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Land Use Policy and Food Security

Edited by
Dingde Xu, Shili Guo and Shaoquan Liu

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Guest Editors

Dingde Xu

Shili Guo

Shaoquan Liu



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Guest Editors

Dingde Xu
College of Management
Sichuan Agricultural
University
Chengdu
China

Shili Guo
College of Economics
Southwestern University of
Finance and Economics
Chengdu
China

Shaoquan Liu
Mountain Development
Research Center
Institute of Mountain
Hazards and Environment
Chinese Academy of Sciences
Chengdu
China

Editorial Office

MDPI AG
Grosspeteranlage 5
4052 Basel, Switzerland

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Article

How Does China's Agricultural Subsidy Policy Drive More Commercially Productive Small Farmers? The Role of Farmland Scale, Labor Supply, and Cropping Structural Change

Jian Zhang ¹, Awais Jabbar ² and Xin Li ^{1,*}

¹ Research Center for Land Use and Ecological Security Governance in Mining Areas, China University of Mining and Technology, Xuzhou 221116, China; zhangjian89@cumt.edu.cn

² College of Economics and Management, Three Gorges University, Yichang 443002, China; awaisjabbar@ctgu.edu.cn

* Correspondence: 6172@cumt.edu.cn

Abstract: This study investigated the impact of China's agricultural subsidy policy on farmers' commercial production, indicated by sales market participation. A nationally representative survey data, panel Tobit model, IV Tobit model, and the Correlated Random Effects (CRE) approach were used. The findings reveal that farmers receiving agricultural subsidies have improved crop sales' share of total output value. Mechanism analysis reveals that agricultural subsidies have driven up farmland scale and increased agricultural labor supply in production, incentivizing the motive for profit maximization among farmers. Meanwhile, agricultural subsidies also encourage farmers to cultivate more grain crops. Policymakers should continue deepening the reform of agricultural subsidies and promoting farmer specialization and commercial production. Moderate-scale operation of farmland should be one of the targets of agricultural subsidies.

Keywords: agricultural subsidy; land use change; farmland scale; commercial production; China

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1. Introduction

The shift from subsistence-based smallholder farming to a focus on agricultural commercialization is a crucial pathway for achieving agricultural advancement and economic growth in developing nations [1–5]. Commercial production, rather than being confined to self-consumption, represents a smallholder economy where farmers achieve a separation between production and consumption, thereby improving resource allocation efficiency [3,6,7]. Agricultural commercial production can be measured in different dimensions, such as the orientation towards profit maximization, an entrepreneurial spirit, and the proportion of market-oriented crops. Some scholars have used the share of total farm output sold as an indicator to measure commercial production [8,9].

However, in developing countries, small farming systems often encounter various challenges to commercialization, including inadequate market infrastructure, outdated public transportation, and a lack of strong motivation for profit maximization [7,10]. The lag in public infrastructure construction makes it difficult to transport agricultural products to the market efficiently and cost-effectively. It also leads to poor information flow, making it difficult for farmers to obtain market information. This increases transaction costs and reduces farmers' willingness to enter the market, thereby limiting the sales and marketization level of agricultural products [11].

China's farming landscape is dominated by small-scale systems, with over 91% of agricultural operators being smallholders managing less than one hectare of land [12]. Although farm households have achieved significant agricultural advancements through mechanization and improvements in pesticide and fertilizer technologies, they still face challenges such as low levels of agricultural specialization and weak motivation for profit

maximization [13,14]. These issues have raised concerns for the Chinese government regarding who will farm the land.

Grain crops are essential to China's food security. They provide essential nutrients and energy to the population, ensuring that people have access to basic sustenance. In the past decade, China's average consumption of cereals and the three main staple crops (wheat, corn, and rice) has reached 207 million tons and 255 million tons, respectively, representing 22.5% and 24.9% of global consumption [15]. According to the National Bureau of Statistics of China¹, the total production of the main grain crops (rice, wheat, corn, barley, sorghum, buckwheat, and oats.) in China reached 633.24 million tons in 2022. However, due to its large population, China still has to import a substantial volume of main grains. This import volume has shown a rapid upward trend since 2000, transforming China from a net exporter to a net importer [16]. In 2019, China's imports of wheat, barley, corn, rice, and soybeans accounted for 5.11%, 20.69%, 4.53%, 12.05%, and 59.26% of the world's total imports, respectively [16]. Moreover, due to higher domestic production costs, the imported grain prices are lower than domestic grain prices, thus squeezing the sales of China's local farmers' agricultural products and hindering their commercial production [17].

China has implemented a nationwide agricultural subsidy policy since 2004 as an important policy to encourage farm households to grow grain crops. This policy extensively covers small farm households and includes "direct grain subsidy", "comprehensive input subsidy", and "quality seed subsidy" [18,19]. Numerous studies have focused on the impact of China's agricultural subsidy policy on grain production, agricultural productivity, and farm households' income [18,20–23]. However, none of them have yet paid attention to the impact of these subsidy policies on smallholders' commercial productive behavior, especially the sales market participation to obtain economic profits, which is of great significance for enhancing farm households' motivation to engage in agricultural production and addressing the future challenge of who will cultivate the land [3,5]. Whether China's agricultural subsidy policy can incentivize farm households' commercial production is an important aspect of evaluating its effectiveness and impact on sustainable agricultural development.

Despite the fact that many studies have focused on the factors influencing farm households' market participation from perspectives such as information access, off-farm employment, infrastructure development, credit accessibility, and risk preference [3,5,24–27], only a few articles have focused on the impact of agricultural subsidy policies on farm households' output market participation [28,29]. Sibande et al. [28] found that Malawi's subsidized fertilizer increased farmers' output market participation, such as the amount of maize sold and maize commercialization. Fujimoto and Suzuki [29] found that the Tanzanian government's subsidy for inorganic fertilizers enhanced seeds, increasing both the likelihood of farmers selling their crops and the revenue generated from those sales. However, there has been no research on the impact of China's agricultural subsidy policy on farm households' participation in the agricultural output market participation.

We therefore analyze the effect of China's agricultural subsidy policy on farm households' output market participation, an important indicator to measure commercial production. We analyze how agricultural subsidies change the cropping structure of crops with different levels of marketization, promote scale farming, and increase agricultural labor supply to reveal the potential mechanisms by which agricultural subsidies impact commercial production. The paper employs a panel Tobit model, and the instrument variable (IV) Tobit model integrated with the Correlated Random Effect (CRE) approach was also adopted to avoid endogeneity. We adopt three round panel data from the 2015, 2017, and 2019 China Family Database (CFD), as well as the China Household Finance Survey (CHFS). The dataset includes 24,678 rural household samples from 29 provinces throughout China.

Our study fills in the gaps in the literature in several ways. First, we focus on the impact of direct grain subsidies on farm households' output market participation in developing countries, while most current studies primarily focus on the impact of agricultural input

subsidies. Second, a theoretical framework on the impact of agricultural subsidies on farm households' commercial production was constructed from the perspectives of crop structure adjustment and agricultural specialization. This framework is crucial for understanding the pathways through which agricultural subsidies affect the market-oriented transformation of smallholders. Third, unlike previous studies that mainly use indicators like whether farmers participate in market sales and the sales volume, we use the proportion of agricultural product sales to the total sales revenue as a relative indicator to measure the degree of farmers' commercial production. Moreover, we further distinguish between cash and grain crops' market participation.

The remainder of the article is structured as follows: Section 2 provides an overview of the background, while Section 3 details the theoretical framework. Section 4 introduces the econometric models. In Section 5, we present and discuss the results. The article concludes with Section 6, which presents our final thoughts.

2. Background

2.1. China's Agricultural Subsidy Policy

The characteristics of agriculture, such as its vulnerability, political significance, and nature as a public good, determine that most countries begin to support and protect agriculture when industrialization reaches a certain stage. In recent decades, China has increased its investment in agriculture to develop technology and improve agricultural production conditions, leading to significant improvements in agricultural mechanization, irrigation rate, and fertilization usage. Agricultural machinery is widely used in various stages of production, from sowing and field management to harvesting, especially for grain crops [30]. China has built a large number of canals and waterways to improve irrigation conditions. Through the development of high-standard farmland and other land improvement projects, agricultural production conditions have also been enhanced [31]. Additionally, the rapid industrialization of China has made pesticides, fertilizers, and other production materials more affordable for farmers, greatly boosting grain production capacity [32,33].

After the 21st century, China reached a point where it was ready to support agriculture through industrial development and began exploring mechanisms and policies for supporting and subsidizing agriculture. For example, in 2002, the government launched crop seed subsidies, and in 2004, it implemented direct grain farmer subsidies. In 2006, a comprehensive subsidy for agricultural inputs was introduced, forming an agricultural subsidy system that includes "direct grain subsidy", "comprehensive input subsidy", and "quality seed subsidy" [18,19]. By 2014, the amounts of the three agricultural subsidies peaked at CNY 155.65 billion (see Figure 1). After 2014, the total subsidy amount decreased and eventually stabilized at CNY 12.049 billion in 2018.

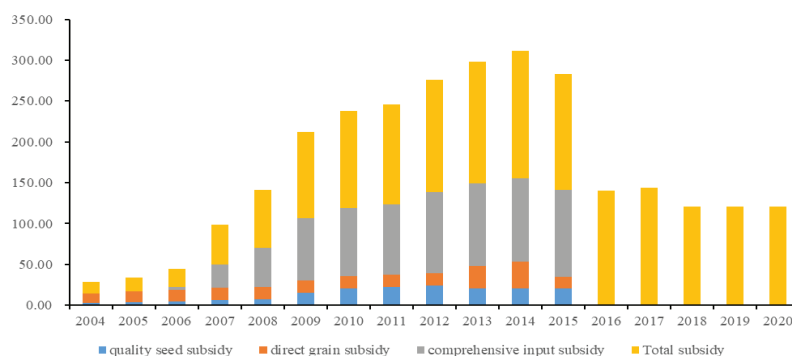


Figure 1. Statistics of agricultural subsidies in China. Source: Calculation from Committee of China Agriculture Yearbook, 2006–2021.

To implement differentiated support policies for its provinces, China has classified them into three categories: main grain-producing areas, grain balance areas, and main grain-selling areas [34]. The major grain-producing regions consist of 13 provinces and autonomous regions: Liaoning, Heilongjiang, Jilin, Hebei, Inner Mongolia, Shandong, Jiangsu, Anhui, Jiangxi, Henan, Hubei, Hunan, and Sichuan. The main grain-producing areas primarily focus on crops such as rice, wheat, corn, barley, sorghum, buckwheat, and oats. Although grain is also grown in the grain balance areas and main grain-selling areas, these regions have less arable land, and some of the farmland is used for growing cash crops, such as vegetables and melons. Generally, major grain-producing areas receive more agricultural subsidies. Statistically, the amount of “direct grain subsidy” allocated to major grain-producing areas accounts for 76.55% of the total direct grain subsidy allocation [34]. However, since this subsidy is primarily based on the area of contracted land or the taxed grain cultivation area rather than the actual grain input or output, current studies have found that agricultural subsidies have limited incentive effects on farm households’ grain production [18,21,35]. One reason is that the subsidies are mostly allocated to land contractors instead of agricultural producers, given the challenges in determining actual production and input [20,23].

To improve the targeting, precision, and effectiveness of the policy, in 2015, the central government began to reform the three agricultural subsidies and selected certain counties and cities in five provinces—Anhui, Hunan, Shandong, Zhejiang, and Sichuan—to conduct pilot reforms. In 2016, based on the experiences gathered from these pilots, the central government merged the three agricultural subsidies into a single “agricultural support and protection subsidy”. The policy objectives were adjusted to support arable land fertility protection and promote moderately scaled grain operations. The reform allocated 80% of the “comprehensive input subsidy”, along with “direct grain subsidy” and “quality seed subsidy”, to support the protection of arable land fertility. The subsidy recipients were principally farmers with land contracting rights [23]. The remaining 20% of the “comprehensive input subsidy”, with pilot funds for large grain farmers and incremental funds from the three agricultural subsidies, were used to promote moderately scaled grain operations. The “agricultural support and protection subsidy” is not only an income subsidy, but also a production-linked subsidy. Particularly for large-scale farmers, the increased subsidies after the reform are tied to their farm size regarding subsidy conditions, amounts, and methods [23].

2.2. *Small Farmers’ Commercial Production in China*

In the production process, farmers generally deal with two markets: the market for factors or inputs and the market for commodities or outputs. Production material input, land leasing, and rural credit fall under the factor market, while agricultural commercial production is the behavior of farmers participating in the output market. Over four decades of economic progress have led to China’s rural economy slowly shifting from an administrative focus to a market-driven approach [36]. Statistics indicate that the net income of Chinese farm households rose from CNY 481 in 1990 to CNY 3955 in 2010, and further increased to CNY 8761 in 2022 [37]. Farmers can afford the inexpensive industrial products brought about by industrial development, such as fertilizers and pesticides, and tend to overuse these inputs [38]. In 2020, 34.08% of farm households rented their farmland [39].

China’s agricultural product market underwent reforms relatively early, and farmers can now freely sell the agricultural products they produce. Since 2004, China has implemented a minimum purchase price policy for rice and wheat, ensuring that farmers do not incur losses from growing grain and do not face difficulties selling it, thus ensuring price stability in grain production [17]. Cash crops have more marketization than grain crops, and their prices fluctuate significantly [12]. Farmers can sell their agricultural products directly in the market, hand them over to intermediaries, or adopt contract farming as a sales method. Generally, the price of agricultural products sold directly by farmers is higher than that of those sold by intermediaries. However, Chinese farm households still face many ob-

stacles to commercial production. For example, many part-time farmers make production decisions based on maximizing total income rather than maximizing agricultural profits, and they lack enough motivation to participate in the output market [5,9]. Rural credit market constraints and high production input costs for farmers are significant barriers. Moreover, due to inadequate infrastructure and a shortage of intermediaries to facilitate transactions and negotiations, farmers continue to encounter high transaction costs [4,13]. Because market grain prices are higher than purchase prices, many farmers retain grain for their consumption, which reduces the degree of marketization of agricultural products.

3. Theoretical Framework

China's agricultural subsidies are directly linked to income and production inputs, and farmers must focus on grain production. These subsidies can potentially influence farmers' commercial production in three ways. First, China's agricultural subsidies can increase farmers' operational farmland scale by encouraging them to rent land and cultivate abandoned land [23], increasing the supply of agricultural labor by farm households [19], then incentivizes them towards specialization, leading to commercial production focused on profit maximization [14]. Economic theory suggests that specialization brings advantages in technical and economic efficiency, driving farmers to concentrate on the agricultural products with the highest comparative advantage. Additionally, it allows them to quickly grasp market demand and price changes, adjust their production plans based on market signals, and incorporate more advanced agricultural technologies and equipment. This strategy significantly boosts the commercial production [40,41]. Recent studies have confirmed the impact of China's agricultural subsidy policies on the scale of agricultural operations, adoption of agricultural technology, and agricultural commercialization. For example, Yi et al. [42] found that China's agricultural subsidies have increased smallholders' farm sizes. Hu et al. [43] found that a larger farm size positively affects farmers' willingness to adopt new agricultural technologies. Zou et al. [44] found that China's agricultural subsidies can affect farm households' on-farm and off-farm labor allocation, such as inhibiting labor migration and increasing agricultural labor supply. Li et al. [14] found that farmers' decisions on farm commercialization and production specialization interact. Fan et al. [45] found that China's agricultural subsidies promoted smallholders' commercial pulse farming.

Second, agricultural subsidies change the crop structure by encouraging farmers to plant grain crops rather than cash crops. The subsidy policy requires that farm households plant grain crops to obtain the subsidies. For example, Fan et al. [23] and Pan et al. [46] all found that agricultural subsidies encourage farmers to grow more grain crops and suppress non-grain cultivated land production using Chinese rural sample households. Compared to cash crops, the marketization of food crops is relatively low. Therefore, agricultural subsidies in China, through adjustments in crop planting, may inhibit farmers' commercial production activities.

Through the above theoretical analysis, we considered the promotion effects of agricultural subsidies on commercial production due to agricultural specialization and the potential inhibitory effects of planting structure adjustments. However, we believe the former effect is more significant. Therefore, this paper constructs the theoretical framework shown in Figure 2 and proposes the following research hypotheses.

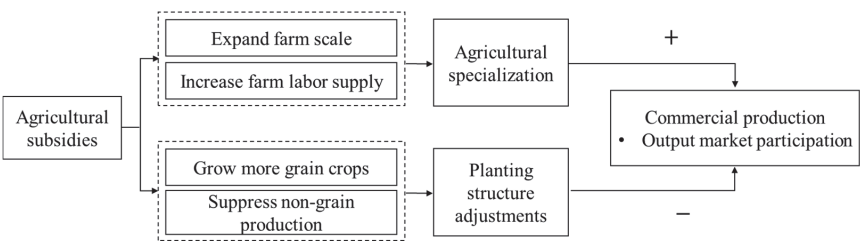


Figure 2. The impact pathways of agricultural subsidies on farmers’ agricultural commercial production.

H1. *China’s agricultural subsidies will positively affect farmers’ commercial production and improve their output market participation.*

H2. *China’s agricultural subsidies promote the commercialization of agriculture by facilitating large-scale land operations and professionalizing the agricultural labor force.*

H3. *China’s agricultural subsidies may increase the planting area of grain crops with a lower degree of market orientation for farmers, thereby indirectly inhibiting their tendency towards commercialization.*

4. Data and Method

4.1. Data

This study uses the Chinese Family Databases (CFD) dataset and the China Household Finance Survey and Research Center (CHFS) for the years 2015, 2017, and 2019. This database was compiled by institutions including Zhejiang University, Southwestern University of Finance and Economics, and Nanjing Audit University. To ensure quality and national representation, the survey utilized a combination of stratified sampling, a three-stage approach, and probability proportional to size (PPS) methods. Using this approach, the compiling institutions gathered data from farm households and village leaders (local grassroots figures) across 29 provinces, with Xinjiang and Tibet (Xizang) being the exceptions. The dataset included comprehensive information on Chinese rural households, covering various aspects including family composition, employment, income and expenses, agricultural production, market involvement, land utilization and transfer, migration and urbanization, financial activities, social security, and education.

During the data-cleaning process, we merged village-level questionnaires with household-level questionnaires and removed data from households not engaged in agricultural production and data with missing outliers. This resulted in a final dataset of 24,678 household samples, with 5922 from 2015, 9637 from 2017, and 9119 from 2019. We converted all income and price variables from 2019 and 2017 to their 2015 equivalents by deflating them with the consumer price index specific for rural residents in each province.

Table 1 is a description of the variables in the study. We can see that the proportion of farmers’ agricultural product sales to their total output value is 52.7%, indicating that more than half of the farmers’ crop output is sold, yet almost half of the agricultural products are still consumed by the households. The average agricultural subsidy received by each farm household is CNY 546.1. We can also see that, overall, the area sown with grain crops accounts for more than 90% of the total sown area. On average, each household manages only 12.33 mu (less than 1 hectare) of land, indicating that the land area operated by farmers is still relatively small. Moreover, each household spends an average of 133.86 days on agricultural production.

Table 1. Variables and definitions.

Variable	Description	Mean	Standard Division
Dependent variable			
Share of crop sales to total output value	The proportion of crop sales revenue to the total production value, %	0.527	0.437
Intermediary variable			
Proportion of grain crop area	The proportion of grain crop area to the total sown area, %	0.927	0.382
Farm size	Total farmland area cultivated by farmers, mu	12.33	52.73
Agricultural labor supply	Time input of household agricultural labor, days	133.86	324.66
Explanatory variables			
Agricultural subsidy	Total agricultural subsidies received by farmers, CNY	546.1	1314.50
Owned farmland per capita	The per capita contracted land area owned by households, mu	2.62	5.369
Age, household head (HH)	The age of the HH, year	56	11.528
Male head	=1 if the HH is male; 0 otherwise	0.89	0.313
HH, junior high school education	=1 if the head received junior high school or higher education; 0 otherwise	0.45	0.497
Off-farm employment	=1 if the head is engaged in off-farm employment; 0 otherwise	0.480	0.500
Farm technology access	=1 if family members receive agricultural technology training; 0 otherwise	0.121	0.326
Agricultural machinery asset	Value of farming machinery such as tractors, planters, and harvesters owned by the family, yuan	4052	24,826.4
Village characteristics			
Per capita income at the village level	The average income per person in the village, CNY	8956	11,110
New farm entity	=1 if there are family farms, cooperatives, and agricultural businesses in the village	0.290	0.454
Distance to the local market, kilometers	The proximity of the village to the nearest farmer's market, a kilometer	7.67	14.86
Western region ^a	Farm household resides in the western part of China	0.238	0.426
Central region ^b	Farm household resides in the central part of China	0.289	0.453
Eastern region ^c	Farm household resides in the eastern part of China	0.217	0.412
Northeastern region ^d	Farm household resides in the northeastern part of China	0.119	0.323
Instrument variable			
Expenditures of agriculture at the provincial level	The provincial-level agricultural, forestry, and water conservancy fiscal expenditures in 2014, billion CNY	44.79	19.62
Number of Observations		24,678	

Note: The income variable has been deflated using the price index. ^a Western region encompasses the provinces of Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, and Ningxia. ^b Central region encompasses the provinces of Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. ^c Eastern region encompasses the provinces of Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. ^d Northeastern region encompasses the provinces of Liaoning, Jilin, and Heilongjiang.

In terms of the explanatory variables, we observe that male household heads are prevalent in China, and the average age of household heads is 56, nearing the retirement age of 60. The educational level of Chinese farmers is generally low, with less than 50% of household heads having completed junior high school or higher. Additionally, 48% of household heads are engaged in off-farm employment. Only 12.1% of farmer households have received agricultural technology training, while the average value of agricultural assets owned by farmer households is CNY 4052.

4.2. Estimation Strategy

Since not all farmers sell agricultural products, the variable “Share of crop sales to total output value” is truncated and censored on the left side, making estimates using ordinary least squares (OLS) potentially biased [47]. Therefore, the Tobit model with corner solutions was chosen [48]. It is important to recognize that panel Tobit models can be categorized into fixed- and random-effects models. However, models that incorporate unconditional fixed effects tend to show bias. As a result, in line with Zheng [47], we employed a random-effects model to achieve maximum likelihood estimation. The model can be specified as:

$$Y_{ijt}^* = \alpha_0 + \alpha_1 Sub_{ijt} + \alpha_2 X_{ijt} + \alpha_3 T_t + \varepsilon_{ijt} \quad (1)$$

$$Y_{ijt} = \begin{cases} Y_{ijt}^*, & Y_{ijt}^* > 0 \\ 0, & Y_{ijt}^* < 0 \end{cases} \quad (2)$$

where i , j , and t represent household i in village j during period t , respectively. Y_{ijt}^* is the latent variable represented by the share of crop sales to total output value, to capture farmers’ commercial production. Y_{ijt} is the actual sales proportion of agricultural products, measured as the proportion of crop sales revenue to the total production value, with values ranging from 0 to 1. Sub_{ijt} represents China’s agricultural subsidy, which is the total agricultural subsidies received by farmers.

X_{ijt} are the control variables that affect the farmers’ output market participation. Drawing from existing literature and considering data availability, the control variables in Equation (1) encompass individual attributes, including the gender of the household head, age and its square [49], and educational status, as well as family characteristics such as land endowment, off-farm employment, farm technology access, and agricultural machinery asset [24,25,50,51]. Village characteristics such as per capita income at the village level and distance to the market were included in the model [3,52,53] (see Table 1). T_t is the time dummy variable. α_0 is a constant term; α_1 , α_2 , and α_3 are coefficients to be estimated; and ε_{ijt} is an error term.

4.2.1. Controlling for Endogenous Regressor

Since farmers’ participation in the output market is not random, it is necessary to address endogeneity issues to obtain consistent estimates [3,5]. Farmers more actively involved in the agricultural product sales market may have larger farm sizes and invest more in agricultural production, which can, in turn, affect their access to agricultural subsidies. Therefore, the subsidy variable Sub_{ijt} in Equation (1) may be correlated with the error term ε_{ijt} . We will use the Instrumental Variable (IV) Tobit model to solve the endogenous problem.

There are two estimation techniques for estimating the IV Tobit model: maximum likelihood and two-stage methods. Compared to the two-stage method, the maximum likelihood approach assumes that the random error term follows a normal distribution, making parameter estimation more efficient in large samples [53,54]. However, the downside is that the iterative process is more complex. Therefore, this study adopts the more efficient maximum likelihood method. The IV Tobit model requires at least one instrumental variable, which affects potentially endogenous variable agricultural subsidies received by farmers, but not the commercial production variable share of crop sales to the total output value. We utilized provincial-level fiscal expenditures on agriculture, forestry, and water conservancy in 2014 as the IV. Agricultural subsidies² fall under this fiscal expenditure.

Consequently, the regional expenditures in these categories influence the grain subsidies farming households receive. Furthermore, it is improbable that agricultural spending at the provincial level would be directly associated with other time-varying elements that influence the error term in the model of output market participation. The previous study [53] confirms the validity of this variable as an instrument. Although the IV Tobit model method does not provide a direct test for the validity of instrumental variables [51],

one can test the validity of the IV after running a two-stage least squares (2SLS) estimation. The findings indicate that both the minimum eigenvalue statistic and the F-statistic are 15.0356, which exceeds the threshold of 10. This allows us to reject the null hypothesis of “weak instruments”.

4.2.2. Controlling for Unobserved Heterogeneity

To estimate nonlinear panel models effectively, the covariates need to be independent of unobserved heterogeneity. This independence allows the model to be approached as a random effects model. However, ensuring that unobserved heterogeneity is orthogonal and uncorrelated with other covariates poses a challenge. The Correlated Random Effects (CRE) approach, introduced by Mundlak [55] and Chamberlain [56], addresses this by relaxing the strict exogeneity assumption, allowing for some dependence between unobserved heterogeneity and covariates, though still under certain restrictions. This approach entails adding the time averages of the variables that change over time as extra explanatory variables to address unobserved heterogeneity that does not vary with time [57].

5. Results and Discussion

5.1. Main Results

Table 2 reports the factors influencing farm households’ sales market participation. Column (1) shows the results from the random effect panel Tobit model, and column (2) shows the results from the IV Tobit model. The average marginal effects for the panel Tobit model were reported. For both models, China’s agricultural subsidy was found to have a significantly positive effect on farmers’ sales market participation, implying that the subsidy has improved the share of crop sales to total output value by farm households. The results support our hypothesis that agricultural subsidies have driven more commercial-oriented activity. Especially from model (1), a 10 percent increase in agricultural subsidies received by farmers has improved 0.15 percent of the share of crop sales to the total output value.

Among the control variables, farmers’ contracted land per capita positively impacts their participation in sales markets. This suggests that households with abundant land resources are more inclined to sell a larger share of their agricultural products. The age of the household head is found to have an inverted U-shaped relationship with sales market participation, indicating that middle-aged household heads are more likely to engage in market sales of agricultural products. This result is similar to that of Feng and Heerink [58], who found the life cycle effect of farm households’ land rental market and labor market participation.

Farm households that have received agricultural technology training are more likely to participate in the sales market. Farmers frequently enhance their production and sales skills and access market information through agricultural technology training provided by the Chinese government, cooperatives, and other sources [7]. The variable agricultural machinery asset is positive and significant at a 1% level, which means that farm households with rich, productive assets are more likely to participate in the sales market.

The positive and significant coefficient of per capita income at the village level implies that households in richer villages have higher sales market participation. Finally, the coefficient of distance to the market is negative and significant, which means that farm households living far away from the villages are less likely to participate in the output market. This finding is similar to those of Woldeyohanes et al. [3].

The two-time dummies, the year 2019 and year 2017, all show a positive and significant effect on farmers’ agricultural output market participation, which means that farmers’ output market participation gradually increases over time. Finally, the three regional dummies, the central, eastern, and northeastern regions, all show significant and positive effects on farmers’ agricultural output market participation. This implies that, compared with the western region, the other regions have more developed agricultural markets.

Table 2. Influencing factors affecting farm households' sales market participation.

	Random Effect Panel Tobit Model (1)	IV Tobit Model (MLE) (2)
Agricultural subsidy (log)	0.015 *** (0.001)	0.160 *** (0.016)
Contracted land per capita (log)	0.066 *** (0.010)	0.052 *** (0.014)
Age, HH	0.013*** (0.002)	0.008 *** (0.003)
Square of age, HH	−0.0001 *** (0.00002)	−0.00008 *** (0.00003)
Male head	−0.008 (0.018)	−0.022 (0.024)
HH, junior high school education	−0.0005 (0.126)	0.012 (0.017)
Off-farm employment	0.013 (0.011)	0.015 (0.014)
Farm technology access	0.035 *** (0.008)	0.048 *** (0.013)
Agricultural machinery asset (log)	0.005 *** (0.001)	0.002 (0.002)
Per capita income at village level (log)	0.018*** (0.005)	0.020 *** (0.005)
Distance to the market (log)	−0.023 *** (0.005)	−0.033 *** (0.006)
Mean of time-varying variables	Controlled	Controlled
Year 2017 ^a	0.089 *** (0.008)	0.075 *** (0.012)
Year 2019 ^a	0.135 *** (0.008)	0.094 *** (0.024)
Central region ^b	0.121 *** (0.010)	0.047 *** (0.012)
Eastern region ^b	0.132 *** (0.011)	0.195 *** (0.014)
Northeast region ^b	0.222 *** (0.014)	0.037 (0.024)
Constant	−0.638 *** (0.081)	−0.393 ** (0.160)
Chi ²	3695.71	3314.18
Prob > chi ²	0.000	0.000
Loglikelihood	−24,669.95	−96,249.42
Number of observations	24,678	24,678

Source: China Household Database (CFD) and the China Household Finance Survey and Research Center (CHFS), 2015, 2017, and 2019. When taking the logarithm of variables such as agricultural subsidy and agricultural machinery asset, which have zero values, 0.00001 was added to avoid the impact of missing values. For the IV Tobit model, the validity of the IV was tested after running a two-stage least squares (2SLS) estimation, and both the minimum eigenvalue statistic and the F-statistic were 15.0356, which is greater than 10, allowing us to reject the null hypothesis of “weak instruments”. Significance levels: **: 5%, ***: 1%. The coefficients shown represent the average partial effects (APEs), calculated using the margins command in Stata. We did not report the results for the mean of time-varying variables for brevity. ^a The 2015 survey data are excluded in order to use it as a control dummy for comparison purposes. ^b The Western region is omitted from the regional dummies to serve as a control.

5.2. Robustness Check

To ensure the reliability of the previous estimates, several additional robustness checks were conducted. The results of these checks are presented in Table 3.

Table 3. Agricultural subsidy and sales market participation: Robust check.

	Revenue of Crop Sold (log) (1)	Share of Crop Sales for Grain Crop (%) (2)	Share of Crop Sales for Cash Crop (%) (3)
Agricultural subsidy (log)	1.562 *** (0.245)	0.405 *** (0.056)	0.670 *** (0.231)
Control variables	Controlled	Controlled	Controlled
Time dummies	Controlled	Controlled	Controlled
Regional dummies	Controlled	Controlled	Controlled
Chi ²	7018.02	796.12	800.26
Prob > chi ²	0.000	0.000	0.000
Loglikelihood	−21,365.85	−1039.55	−1226.65
Number of observations	24,678	20,055	5260

Source: China Household Database (CFD) and the China Household Finance Survey and Research Center (CHFS), 2015, 2017, and 2019. When taking the logarithm of variables such as agricultural subsidy and agricultural machinery asset, which have zero values, 0.00001 was added to avoid the impact of missing values. Estimation results are based on the IV Tobit model. We did not report the results for control variables for brevity. Significance levels: ***: 1%. For model (2), 4623 farm households are excluded from the model because they do not engage in grain crop production. Similarly, in model (3), 19,418 households are removed from the model because they do not grow cash crops. The coefficients shown represent the average partial effects (APEs), calculated using the margins command in Stata.

First, we replaced the share of crop sales with total output value with the revenue from crops sold by farm households, as the latter represents marketed surplus. We can see that agricultural subsidies have a positive and significant effect on the revenue of crops sold by farm households, with a 1% increase in agricultural subsidies leading to a 1.562% increase in agricultural product sales revenue.

Second, farmers' commercial production can be measured by the share of crop sales for grain crops and the share of crop sales for cash crops separately, and it can be seen whether agricultural subsidies have simultaneously increased the marketization level of these two types of crops. Results from model (2) and model (3) show that agricultural subsidies have simultaneously increased the sales proportion of both grain and cash crops. Moreover, compared to grain crops, agricultural subsidies have a greater impact on increasing the sales proportion of cash crops. This is because cash crops have a higher degree of marketization. Estimation results demonstrate agricultural subsidies' robustness in enhancing farmers' commercial production.

5.3. Mechanism Analysis

In the theoretical part, we hypothesize that agricultural subsidies affect farmers' participation in the agricultural output market by adjusting the cropping structure and promoting agricultural specialization. To test this, we further examine the impact of agricultural subsidies on these two effects. Regarding cropping structure adjustment, we assess the impact of agricultural subsidies on the proportion of grain crop planting area to the total planting area. Regarding specialization, we evaluate the impact of agricultural subsidies on farmland scale and agricultural labor supply. Results are reported in Table 4.

The results show that the coefficient of agricultural subsidy in model (1) is positive and significant, which means that agricultural subsidy has increased the proportion of sown area for grain crops. This finding is consistent with Yi et al. [20] and Fan et al. [23], who found that China's agricultural subsidy increased the planting area of grain crops. The main reason is that agricultural subsidies are coupled with grain production. However, because the marketization level of grain crops is lower than that of cash crops, the agricultural subsidies that have promoted an increase in the proportion of the planting area for grain crops have also, to some extent, reduced the level of marketization of farm households.

Table 4. Agricultural subsidy and sales market participation: mechanism analysis.

	Cropping Structure Adjustment	Specialization of Agricultural Production	
	Proportion of Sown Area for Grain Crops (1)	Farm Scale (log) (2)	Agricultural Labor Supply (log) (3)
Agricultural subsidy (log)	0.015 ***	0.013 ***	0.160 ***
Time dummies	Controlled	Controlled	Controlled
Regional dummies	Controlled	Controlled	Controlled
Chi ²	3695.71	3641.07	3314.18
Prob > chi ²	0.000	0.000	0.000
Loglikelihood	−24,669.95	−26,847.06	−96,249.42
Number of observations	24,678	24,678	24,678

Source: China Household Database (CFD) and the China Household Finance Survey and Research Center (CHFS), 2015, 2017, and 2019. When taking the logarithm of variables such as agricultural subsidy and agricultural machinery asset, which have zero values, 0.00001 was added to avoid the impact of missing values. Estimation results are based on the IV Tobit model. We did not report the results for control variables for brevity. Significance levels: ***, 1%. The coefficients shown represent the average partial effects (APEs) calculated using the margins command in Stata.

From model (2) and model (3) in Table 4, we can see that agricultural subsidies have both positive and significant effects on farmers’ farmland scale and agricultural labor input in production, which proves the hypothesis that agricultural subsidy has improved the agricultural specialization of farm households. Our finding is consistent with Fan et al. [23], who found that China’s agricultural subsidy policy enhanced the expansion of large-scale farming. Through enlarging farmland scale and encouraging more agricultural laborers to employ agricultural production, agricultural subsidies strengthen smallholders’ motivation to maximize profit through output market participation. The increase in the labor supply in the agricultural sector also implies that agricultural subsidies have raised the returns to agricultural labor, encouraging family laborers to remain in the agricultural field rather than shifting to off-farm employment [19,44].

6. Conclusions and Policy Implications

This study utilizes a nationally representative rural survey dataset to examine the effect of Chinese agricultural subsidy policy on farmers’ engagement in commercial production, as indicated by their participation in sales markets. The study employs a panel Tobit model, an instrumental variable Tobit model based on the maximum likelihood method, and the Correlated Random Effect (CRE) approach for model estimation and addressing endogeneity issues. Robustness checks confirmed the reliability of the research findings, and the mechanism analysis revealed that agricultural subsidies impact agricultural commercialization through specialization and adjustments in crop planting structures.

The findings of the sales market participation model show that agricultural subsidies received by farm households have significantly improved their commercial production, guided by the increasing share of crop sales to total output value. Agricultural subsidies have also been proven to increase farmers’ sales of agricultural products in the market and the proportion of sales from grain crops and cash crops. Further mechanism analysis reveals the positive effects of agricultural subsidies in promoting commercial production by increasing farmland scale and agricultural labor input. However, since agricultural subsidies are primarily aimed at grain crop cultivation with a lower degree of marketization among farmers, these subsidies have also somewhat restrained commercial production.

The policy implications are as follows: first, the agricultural subsidy policy is necessary for the Chinese government to change the current small farming system where farmers operate on a small scale, with low-level market participation and a limited degree of specialization. Therefore, it is crucial to continue deepening the reform of agricultural subsidies and implement more precise and effective subsidy policies targeting grain producers to boost their enthusiasm and ensure national food security. At the same time, agricultural subsidies should play a positive role in increasing farmland scale and agricultural labor

input in agriculture, thereby promoting farmers to be specialized and enhancing their profit-maximizing production. Second, agricultural subsidy policies should be adjusted to support the adoption of modern agricultural technologies and management methods. For example, subsidies should be provided for the use of high-quality seeds and grain production technologies, as well as for machinery, to increase the profitability and competitiveness of grain crop cultivation.

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Notes

- ¹ Source: National Bureau of Statistics of China, Announcement of the National Bureau of Statistics of China on the Grain Production Data for 2022. https://www.stats.gov.cn/sj/zxfb/202302/t20230203_1901673.html (accessed on 10 September 2024)
- ² China's agricultural subsidy was initially allocated to each province based on the area of grain cultivation and the grain output. Each province then oversaw the distribution to local (city and county level) governments. Additionally, some provinces offered extra subsidies depending on their local financial conditions.

References

1. Pingali, P.L.; Rosegrant, M.W. Agricultural commercialization and diversification: Processes and policies. *Food Policy* **1995**, *20*, 171–185. [CrossRef]
2. Barrett, C.B. Smallholder market participation: Concepts and evidence from eastern and southern Africa. *Food Policy* **2008**, *33*, 299–317. [CrossRef]
3. Woldeyohanes, T.; Heckeleei, T.; Surry, Y. Effect of off-farm income on smallholder commercialization: Panel evidence from rural households in Ethiopia. *Agric. Econ.* **2017**, *48*, 207–218. [CrossRef]
4. Yaseen, A.; Bryceson, K.; Mungai, A.N. Commercialization behaviour in production agriculture: The overlooked role of market orientation. *J. Agribus. Dev. Emerg. Econ.* **2018**, *8*, 579–602. [CrossRef]
5. Zhang, J.; Mishra, A.K.; Hirsch, S. Market-oriented agriculture and farm performance: Evidence from rural China. *Food Policy* **2021**, *100*, 102023. [CrossRef]
6. Ume, C. The role of improved market access for small-scale organic farming transition: Implications for food security. *J. Clean. Prod.* **2023**, *387*, 135889. [CrossRef]
7. Zhang, J.; Mishra, A.K. ICT adoption, commercial orientation and productivity: Understanding the digital divide in Rural China. *Smart Agric. Technol.* **2024**, *9*, 100560. [CrossRef]
8. Carletto, C.; Corral, P.; Guelfi, A. Agricultural commercialization and nutrition revisited: Empirical evidence from three African countries. *Food Policy* **2017**, *67*, 106–118. [CrossRef]
9. Ogutu, S.O.; Qaim, M. Commercialization of the small farm sector and multidimensional poverty. *World Dev.* **2019**, *114*, 281–293. [CrossRef]
10. Mirzaei, O.; Micheels, E.T.; Boecker, A. Product and marketing innovation in farm-based businesses: The role of entrepreneurial orientation and market orientation. *Int. Food Agribus. Manag. Rev.* **2016**, *19*, 99–130.
11. Wu, Q.; Guan, X.; Zhang, J.; Xu, Y. The role of rural infrastructure in reducing production costs and promoting resource-conserving agriculture. *Int. J. Environ. Res. Public Health* **2019**, *16*, 3493. [CrossRef] [PubMed]
12. Han, J. Following the thought of “Village, Agriculture and Farmers” from General Secretary Xi Jinping’s and implementing the strategy of rural revitalization. *Manag. World* **2018**, *34*, 1–10. (In Chinese)
13. Huang, J.; Rozelle, S. The emergence of agricultural commodity markets in China. *China Econ. Rev.* **2006**, *17*, 266–280. [CrossRef]
14. Li, L.; Varua, M.E.; Komarek, A.M.; Shankar, S.; Bellotti, W.D. The interplay of production commercialisation and specialization: An empirical study on Chinese smallholders. *China Agric. Econ. Rev.* **2017**, *9*, 504–521. [CrossRef]
15. Li, Y.; Zhang, W.; Ma, L.; Wu, L.; Shen, J.; Davies, W.J.; Dou, Z. An analysis of China’s grain production: Looking back and looking forward. *Food Energy Secur.* **2014**, *3*, 19–32. [CrossRef]

16. Zhao, F.; Sun, P.; Zhang, J. Modeling the grain import trade: A cointegration analysis of China's panel data. *Discret. Dyn. Nat. Soc.* **2021**, *2021*, 3673282. [CrossRef]
17. Qian, J.; Ito, S.; Zhao, Z. The effect of price support policies on food security and farmers' income in China. *Aust. J. Agric. Resour. Econ.* **2020**, *64*, 1328–1349. [CrossRef]
18. Huang, J.; Wang, X.; Zhi, H.; Huang, Z.; Rozelle, S. Subsidies and distortions in China's agriculture: Evidence from producer-level data. *Aust. J. Agric. Resour. Econ.* **2011**, *55*, 53–71. [CrossRef]
19. Zhang, J.; Mishra, A.K.; Hirsch, S.; Li, X. Factors affecting farmland rental in rural China: Evidence of capitalization of grain subsidy payments. *Land Use Policy* **2020**, *90*, 104275. [CrossRef]
20. Yi, F.; Sun, D.; Zhou, Y. Grain subsidy, liquidity constraints and food security—Impact of the grain subsidy program on the grain-sown areas in China. *Food Policy* **2015**, *50*, 114–124. [CrossRef]
21. Huang, J.; Yang, G. Understanding recent challenges and new food policy in China. *Glob. Food Secur.* **2017**, *12*, 119–126. [CrossRef]
22. Yang, T.; Chandio, A.A.; Zhang, A.; Liu, Y. Do farm subsidies effectively increase grain production? Evidence from major grain-producing regions of China. *Foods* **2023**, *12*, 1435. [CrossRef] [PubMed]
23. Fan, P.; Mishra, A.K.; Feng, S.; Su, M.; Hirsch, S. The impact of China's new agricultural subsidy policy on grain crop acreage. *Food Policy* **2023**, *118*, 102472. [CrossRef]
24. Renkow, M.; Hallstrom, D.G.; Karanja, D.D. Rural infrastructure, transactions costs and market participation in Kenya. *J. Dev. Econ.* **2004**, *73*, 349–367. [CrossRef]
25. Fan, Q.; Salas Garcia, V.B. Information access and smallholder farmers' market participation in Peru. *J. Agric. Econ.* **2018**, *69*, 476–494. [CrossRef]
26. Minviel, J.J.; Latruffe, L. Effect of public subsidies on farm technical efficiency: A meta-analysis of empirical results. *Appl. Econ.* **2017**, *49*, 213–226. [CrossRef]
27. Burchfield, E.K.; de la Poterie, A.T. Determinants of crop diversification in rice-dominated Sri Lankan agricultural systems. *J. Rural Stud.* **2018**, *61*, 206–215. [CrossRef]
28. Sibande, L.; Bailey, A.; Davidova, S. The impact of farm input subsidies on maize marketing in Malawi. *Food Policy* **2017**, *69*, 190–206. [CrossRef]
29. Fujimoto, T.; Suzuki, A. Do fertilizer and seed subsidies strengthen farmers' market participation? Evidence from Tanzania's subsidy program. *Rev. Dev. Econ.* **2024**, *28*, 339–359. [CrossRef]
30. Chi, Y.; Zhou, W.; Wang, Z.; Hu, Y.; Han, X. The influence paths of agricultural mechanization on green agricultural development. *Sustainability* **2021**, *13*, 12984. [CrossRef]
31. Peng, J.; Zhao, Z.; Chen, L. The impact of high-standard farmland construction policy on rural poverty in China. *Land* **2022**, *11*, 1578. [CrossRef]
32. Huang, W.; Jiang, L. Efficiency performance of fertilizer use in arable agricultural production in China. *China Agric. Econ. Rev.* **2019**, *11*, 52–69. [CrossRef]
33. Jabbar, A.; Liu, W.; Wang, Y.; Zhang, J.; Wu, Q.; Peng, J. Adoption and Impact of Integrated Soil Fertility Management Technology on Food Production. *Agronomy* **2022**, *12*, 2261. [CrossRef]
34. Li, X.C. Comprehensive Effectiveness Study of China's Grain Subsidy Policy. Ph.D. Thesis, Hunan Agricultural University, Changsha, China, 2021. (In Chinese).
35. Gale, H.F.; Lohmar, B.; Tuan, F.C. China's New Farm Subsidies. USDA-ERS International Agriculture and Trade Outlook No. (WRS-0501), 2005, 16p. Available online: <https://www.ers.usda.gov/publications/pub-details/?pubid=40444> (accessed on 10 October 2024).
36. Huang, J.; Ding, J. Institutional innovation and policy support to facilitate small-scale farming transformation in China. *Agric. Econ.* **2016**, *47*, 227–237. [CrossRef]
37. Committee of China Agriculture Yearbook. *China Agriculture Yearbook 2022*; China Agriculture Press: Beijing, China, 2023. (In Chinese)
38. Yu, X.; Schweikert, K.; Li, Y.; Ma, J.; Doluschitz, R. Farm size, farmers' perceptions and chemical fertilizer overuse in grain production: Evidence from maize farmers in northern China. *J. Environ. Manag.* **2023**, *325*, 116347. [CrossRef]
39. Committee of China Agriculture Yearbook. *China Agriculture Yearbook 2020*; China Agriculture Press: Beijing, China, 2021. (In Chinese)
40. Sekyi, S.; Quaidoo, C.; Wiafe, E.A. Does crop specialization improve agricultural productivity and commercialization? Insight from the Northern Savannah Ecological Zone of Ghana. *J. Agribus. Dev. Emerg. Econ.* **2023**, *13*, 16–35. [CrossRef]
41. Jabbar, A.; Liu, W.; Wang, Y.; Zhang, J.; Wu, Q.; Peng, J. Exploring the impact of farmer field schools on the adoption of sustainable agricultural practices and farm production: A case of Pakistani citrus growers. *Agronomy* **2022**, *12*, 2054. [CrossRef]
42. Yi, H.; Guo, D.; Wang, H.; Yi, G.; Min, L. Money for operator: The impact of linked agricultural subsidy on incomes. *Sci. Rep.* **2024**, *14*, 13554. [CrossRef]
43. Hu, Y.; Li, B.; Zhang, Z.; Wang, J. Farm size and agricultural technology progress: Evidence from China. *J. Rural Stud.* **2022**, *93*, 417–429. [CrossRef]
44. Zou, B.; Mishra, A.K.; Luo, B. Grain subsidy, off-farm labor supply and farmland leasing: Evidence from China. *China Econ. Rev.* **2020**, *62*, 101293. [CrossRef]

45. Fan, L.I.; Zhang, H.J.; Khan, N.A.W.A.B. Commercial cash crop production and households' economic welfare: Evidence from the pulse farmers in rural China. *J. Integr. Agric.* **2022**, *21*, 3395–3407.
46. Pan, S.; Di, C.; Qu, Z.; Ali Chandio, A.; Rehman, A.; Zhang, H. How do agricultural subsidies affect farmers' non-grain cultivated land production? Evidence from the fourth rural Chinese households panel data survey. *Econ. Political* **2024**, *41*, 1–24. [CrossRef]
47. Zheng, L. Big hands holding small hands: The role of new agricultural operating entities in farmland abandonment. *Food Policy* **2024**, *123*, 102605. [CrossRef]
48. Tobin, J. Estimation of relationships for limited dependent variables. *Econom. J. Econom. Soc.* **1958**, *26*, 24–36. [CrossRef]
49. Han, W.; Fu, Y.; Sun, W. Farmland Transfer Participation and Rural Well-Being Inequality: Evidence from Rural China with the Capability Approach. *Land* **2023**, *12*, 1318. [CrossRef]
50. Bezu, S.; Kassie, G.T.; Shiferaw, B.; Ricker-Gilbert, J. Impact of improved maize adoption on welfare of farm households in Malawi: A panel data analysis. *World Dev.* **2014**, *59*, 120–131. [CrossRef]
51. Wang, X.; Xu, Z.; Li, G.; Zhuo, Y.; Zou, W. Farmland transfer and income distribution effect of heterogeneous farmers with livelihood capital: Evidence from CFPS. *Land* **2023**, *12*, 1398. [CrossRef]
52. Xu, Q.; Lu, Y.F.; Zhang, H.C. Have Agricultural Support and Protection Subsidies Encouraged Large-scale Farmers to Grow Grain? An Analysis Based on Data from Fixed Observation Points of the Ministry of Agriculture and Rural Affairs in China. *China Rural Econ.* **2020**, *424*, 15–33. (In Chinese)
53. Newey, W.K. Efficient estimation of limited dependent variable models with endogenous explanatory variables. *J. Econom.* **1987**, *36*, 231–250. [CrossRef]
54. Chesher, A.; Kim, D.; Rosen, A.M. IV methods for Tobit models. *J. Econom.* **2023**, *235*, 1700–1724. [CrossRef]
55. Mundlak, Y. On the pooling of time series and cross section data. *Econom. J. Econom. Soc.* **1978**, *4*, 69–85. [CrossRef]
56. Chamberlain, G. Multivariate regression models for panel data. *J. Econom.* **1982**, *18*, 5–46. [CrossRef]
57. Wooldridge, J. *Econometric Analysis of Cross Section and Panel Data*, 2nd ed.; MIT Press: Cambridge, MA, USA, 2010; pp. 461–465.
58. Feng, S.; Heerink, N. Are farm households' land renting and migration decisions inter-related in rural China? *NJAS-Wagening. J. Life Sci.* **2008**, *55*, 345–362. [CrossRef]

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Article

Can Land Transfer Alleviate Multidimensional Relative Poverty in Rural Areas?

Benjian Wu ¹, Yiyuan Rong ¹, Xinyu Liang ¹, Haibo Zhu ^{2,*} and Xue Shi ^{1,*}

¹ School of Economics, Minzu University of China, Beijing 100081, China; wubenjian@muc.edu.cn (B.W.); 22300092@muc.edu.cn (Y.R.); 24300090@muc.edu.cn (X.L.)

² Agricultural Information Institute, Chinese Academy of Agricultural Sciences, Beijing 100081, China

* Correspondence: zhuhaibo@caas.cn (H.Z.); 19300126@muc.edu.cn (X.S.)

Abstract: After eliminating absolute poverty, China's anti-poverty efforts have shifted towards multidimensional relative poverty. This study uses microdata from the Chinese Academy of Agricultural Sciences (CAAS) from 2012 to 2021, applies the Kakwani index to construct a multidimensional relative poverty indicator, and uses an endogenous transformation model to analyze the impact of land transfer on multidimensional relative poverty in rural areas. The study found that (1) land transfer can effectively reduce the multidimensional relative poverty of farm households. (2) Land transfer has a better mitigating effect on young farmers, farmers with higher literacy levels, and farmers who have not acute poverty. (3) Land transfer alleviates multidimensional relative poverty by increasing agricultural mechanization, business income, off-farm employment, and wage income. (4) The effects of land transfer out and land transfer in on the dimensions of multidimensional relative poverty are heterogeneous.

Keywords: multidimensional relative poverty; land transfer; sense of relative deprivation; inequality of opportunity

1. Introduction

With the comprehensive victory of poverty eradication, the center of gravity of China's anti-poverty problem has shifted from getting rid of absolute poverty to managing relative poverty. Relative poverty means not only the lack of necessities of life but also the difficulty in reaching the general level of society and thus being excluded from society; it includes multiple dimensions, such as income, opportunities, subjective feelings, etc. [1–6]. Rural areas have always been the main battlefield of poverty management. Land, as the key to agricultural production, is not only a factor of farm output but also an important asset and resource for farmers. The family contract responsibility system, introduced in 1978, has enabled farmers to obtain relatively independent rights to land management and income, which has dramatically enhanced farmers' enthusiasm for production, promoted the increase in agricultural output, and solved the problem of food and clothing. However, along with the rapid development of industrialization and urbanization, the benefits of the land management mode centered on the household contract responsibility system have been gradually depleted. Some new problems have arisen, such as the difficulty in realizing mechanized production due to fragmented land management, the low degree of organization of the agricultural industry, the low efficiency of the farm output, etc. [7]. In 1984, the release of the Circular on the Rural Work of 1984 marked the policy signs of a loosening with regard to rural land transfer. The Amendment to the Constitution of the People's Republic of China and the Land Management Law enacted in 1988 provided a legal basis for rural land transfer. The Rural Land Contracting Law passed in 2003 specified the main body, principles, and modes of land transfer, marking China's land transfer step into standardization and institutionalization. In 2014, the innovation of the rural land property right system of "three-rights separation" further facilitated land transfer. The

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revised Law of the People's Republic of China on Rural Land Contracting, which came into force in 2019, further clarified the legal effect of "three-rights separation" in a legal sense and continued to promote rural land transfer. It continues to encourage the transfer of rural land. Land transfer can optimize the allocation of land, labor, capital, and other resources, improve agricultural production efficiency, and increase farmers' income [8]. However, in considering the impact of the land transfer on rural residents in terms of subjective feelings, equality of opportunity, etc., not enough attention has been paid to whether the land transfer affects the multidimensional relative poverty of rural residents, and if so, whether it relieves or exacerbates the multidimensional relative poverty in rural areas.

The reason for the above questions is that the impact of land transfer on farmers' multidimensional relative poverty is controversial in theory and practice. Theoretically, whether the land is transferred in or out, the flow of land elements realizes the reallocation of resources and improves the efficiency of agricultural land use, thus realizing the value of land appreciation [9–13]. Agricultural subsidies, land value, and other benefits pursued by land lessees promote the specialization of agricultural production. In contrast, urban employment opportunities and wage levels promote the non-farm production of land lessors. Both land lessees and land renters can increase their income, reduce the incidence of poverty, improve subjective well-being, and alleviate multidimensional relative poverty [14–18].

At the same time, the relevant literature has begun to reflect on the negative impacts that land transfer is likely to have on multidimensional relative poverty. Unregulated behaviors such as blind forced transfer in the land transfer process may harm farmers' rights and interests [19]. The insufficient revenue effect of land transfer may lead to the risk of farmers facing a lower level of wealth [20]. The problem of inequitable distribution of revenues may also aggravate relative poverty [21]. The study of the effect of land transfer after dividing farmers into groups according to income found that although land transfer can alleviate the income gap between farmers in the two extremes and the low-end group, it exacerbates the income gap between the high-income and middle-income groups, i.e., the reduction in the income gap effect generated by the land transfer is realized through the depletion of the middle group's interests [22]. Class competition in land transfer can jeopardize the interests of farmers in the lower classes. The higher the class of farmers, the more the opportunities and the greater the power to choose land transfer; therefore, they gain more from land transfer.

In comparison, farmers in the lower class are limited by various factors, such as resources, ability, and other opportunities to enter the land transfer, which are also lower [23]. Hence, land transfer exacerbates the degree of relative poverty in rural areas. As a single factor, the transfer of land alone does not have a significant poverty reduction effect on extremely multidimensional, relatively poor households [24]. Although land transfer allows farmers to improve their business incomes, the problem of the fragmentation of agricultural operations still exists and requires farmers to enhance their vulnerability [25].

Why is the poverty reduction effect of land transfers controversial? Answering this question requires further clarification of the substance and root causes behind the problem. Multidimensional relative poverty is more multidimensional and hidden than absolute poverty, which involves the satisfaction of "basic needs" [26]. Compared to absolute poverty, multidimensional relative poverty emphasizes "relative", "exploitation", and "exclusion" [3,5]. In contrast to relative poverty, the concept of multidimensionality not only points to income disparity but also includes issues such as lack of access to resources and capabilities [1], lack of rights [2], vulnerability [4], and relative deprivation of subjective feelings [27–29]. Most existing studies measure the impact of land transfer on relative poverty based on absolute or relative income [7,10,12], but rarely consider "income inequality, inequality of opportunity, relative deprivation, and risk of return to poverty" as a whole in multidimensional relative poverty and do not explore the impact of land transfer on it. Liu et al. have explored this point [20], but their analytical framework of multidimensional relative poverty is different from ours, which focuses more on inequality in each dimension. We believe that assessing the impact of land transfer only on the income dimension of

farmers is one-sided, because relative poverty also includes aspects such as individual capacity and subjective well-being, and a comprehensive assessment of these is conducive to recognizing the integrated impact of land transfer. Second, land transfer involves both landlords and tenants, but the existing literature does not discuss the different impacts on both sides of land transfer. Zhang et al. only examine the impacts of land transfer on the income dimension of landlords and tenants [10]; Yu et al. discuss the impacts of land transfer on the incidence of the relative poverty of landlords and tenants [14]; neither study discusses the impacts on multidimensional relative poverty. We believe that a separate study of land transfer lessors and lessees can help the government guide farmers to make the right decisions and is also a useful addition to existing studies. In this paper, we use data from the Chinese Academy of Agricultural Sciences (CAAS) for four consecutive surveys (one every three years) from 2010 to 2021, which cover micro-information, such as basic information, housing and living conditions, household property and finances, livelihood strategies, household consumption, and empowerment of farming households. We incorporate income inequality, inequality of opportunity, the risk of returning to poverty, and subjective relative deprivation into the relative poverty analytical framework; treat multidimensional relative poverty as a whole to assess the comprehensive impact of land transfer; use an endogenous switching regression model to circumvent sample selection bias and endogeneity; and construct a counterfactual to assess the impact of land transfer on multidimensional relative poverty. In the further discussion section, we first test several mechanisms by which land transfer affects multidimensional relative poverty in rural areas to refine our theory. Li et al. also explored the saving mechanism by which land transfer affects multidimensional relative poverty [11], but we test and find some new impact mechanisms. Second, we discuss the impact of land transfer on the four sub-indicators of multidimensional relative poverty separately, so that we know clearly the actual role that land transfer plays in mitigating inequality dimensions; thus, we can clarify the effect of the path of land transfer on multidimensional relative poverty, supplement the existing studies, and refine our theory. Previous studies have only explored the impact of land transfer on some of the single indicators of multidimensional relative poverty and have not comparatively analyzed different dimensions of relative poverty [16,17,21,23]. In addition, absolute poverty is the absolutely indivisible “core” of the concept of poverty [30]; so, we discuss the impact of land transfer on farmers’ absolute income and income inequality in detail; this is used to cross-corroborate with previous studies. Finally, and very importantly, the characteristics of the data we use may limit the applicability of our conclusions. Since our sample is not a full sample and only covers poorer areas, our findings may not be applicable in areas with better economic standards, and similarly, certain findings are not applicable in our case [21]. Our findings are relatively more informative to the rulers and farmers in poorer regions.

In conclusion, this paper proposes a new theoretical framework to study the impact of land transfer on multidimensional relative poverty in rural areas and tests the theory with empirical evidence from less developed regions in China, thereby providing some references to the Chinese experience in anti-poverty work in developing countries and less developed regions worldwide.

2. Theoretical Analysis and Research Hypotheses

Land transfer has impacted the alleviation of multidimensional relative poverty in rural areas through land transfer in and land transfer out. Firstly, from the perspective of land transfer in, land transfer in solves the problem of land fragmentation, promotes rural land development in the direction of scale and intensification, and raises the level of agricultural industrialization and agricultural productivity, thereby increasing the operating income of land-contracting farmers. At the same time, low-income farmers have also received as many dividends as possible due to increased agricultural production and income, which has dramatically raised the property income of this group and narrowed the income gap between farmers. Secondly, land transfer can promote the formation

and development of new agricultural subjects, meet the demand for land for farmers' entrepreneurship, and stimulate farmers with technology and capital with which to return to their hometowns to start their businesses. At the same time, land transfer has prompted farmers to actively broaden the supply and marketing markets for agricultural products, enriching the sales channels for agricultural products and increasing the sensitivity of farmers to the obtaining of information and opportunities. However, it is worth noting that in the short term, land transfers can exacerbate unequal opportunities for farmers due to inadequate rural infrastructure and insufficient public services. Thirdly, for land contractors, to improve the efficiency of agricultural production and the yield of agricultural products, they will introduce advanced planting technology and modern management experience, which to a certain extent reduces the impact of asymmetric agricultural information, lack of planting technology and other factors, and reduces the risk of returning to poverty due to agricultural risks. Fourthly, in land transfer, welfare indicators such as farmers' income, comprehensive literacy, and rural infrastructure and environment are raised and improved; this dramatically changes farmers' perception of themselves and their evaluation of life, thus helping to eliminate their subjective sense of deprivation.

Firstly, from the perspective of land transfer, land transfer can release a large amount of surplus rural labor force and promote the transfer of the rural labor force to urban areas to obtain a wage income and property income, thus reducing income inequality. Secondly, land transfer has expanded the scale of non-farm employment for rural households. On the one hand, the migration of farm households to urban areas for work has led to the enjoyment of relatively high-quality education opportunities and higher welfare protection for their migrant children in the cities, alleviating inequalities in education opportunities and infrastructure; on the other hand, farm households have been able to improve their human capital through continuous exposure to new industries, and this has facilitated the proximity of farm households to medical care, reducing the risk of returning to poverty due to illness and "minor illnesses becoming major illnesses". However, because of the household registration system, migrant workers cannot enjoy the benefits of urban residency and the corresponding social security after moving to the cities; so, land transfer has a limited effect on alleviating inequality of opportunity in the short term. Thirdly, after the transfer of land, the agricultural production methods of farmers, which were characterized by self-sufficiency, have changed dramatically, and the degree of social integration of farmers has been further strengthened. At the same time, in the integration process, farmers' knowledge and feasibility have been greatly enhanced, thereby raising their class identity and reducing their subjective sense of deprivation.

Based on the above analysis, this paper proposes:

Hypothesis 1. *Both land transfer in and land transfer out effectively alleviate multidimensional relative poverty in rural areas.*

Hypothesis 2. *Land transfer in alleviates multidimensional relative poverty mainly by increasing business income and mechanized farming. Land transfer out alleviates multidimensional relative poverty mainly by increasing wage income and off-farm employment.*

Land transfer is an essential basis for realizing the large-scale operation of rural land, developing characteristic modern agriculture, and promoting the high-quality development of agriculture; in real life, the development of land transfer is facing multiple dilemmas, which are manifested in the following ways: firstly, the scale of agricultural land is relatively small, and it is not easy to realize the large-scale operation in the short term; according to the data of the Third Agricultural Science and Technology Research Institute (ASTRI), China has 230 million existing farming households, and the average household land operation scale is less than 10 acres of farmland; this is the case for as much as 91% of the households. Secondly, the quality of the agricultural operator could be better; the development quality of the new agricultural operator needs to be improved; the function of farmers' professional

cooperatives could be more robust; and the phenomenon of virtualization and alienation is serious. Thirdly, the construction of agricultural supporting facilities is lagging, hindering disaster prevention and mitigation and the improvement agricultural productivity. Due to farmers' lack of professional judgment of the market, homogenized planting is common; coupled with the effects of typhoons, droughts, floods, and other disasters, the economic returns obtained by land-transferring farmers in the short term are limited. At the same time, after the land is transferred out, the rural labor force is transferred to live in towns and cities and can enjoy the convenience brought by high-quality public services in the cities, and, with the overall rise in China's labor costs in recent years, the income of migrant workers can be improved. Based on the above analysis, this paper proposes:

Hypothesis 3. *Land transfer out alleviates multidimensional relative poverty more than land transfer in.*

For land transfer households, land transfer promotes large-scale management. It increases agricultural productivity and farm incomes, and on the one hand, land transfer satisfies the self-realization needs of farm households and increases their welfare, thus significantly reducing the subjective sense of relative deprivation. Land transfer mainly increases farm household business income and reduces wage income, which can reduce income inequality. On the other hand, after land transfer, the farm households' main activities are concentrated in the countryside. In contrast, the lack of essential public services, such as education and health care, and the inadequacy of the social security system, tend to exacerbate inequality of opportunity. In addition, although farmers can now use agricultural insurance to avoid agricultural risks, rural insurance coverage needs to be completed, and some farmers need a strong sense of insurance. Hence, the mitigating effect of land transfer on the risk of returning to poverty is limited.

For land transfer households, land transfer releases many land-bound rural laborers and promotes non-agricultural employment. On the one hand, after transferring land, farmers' modes of production and life and ideological concepts have changed dramatically. Whether it is local non-agricultural employment or off-site non-agricultural employment, this promotes the integration of farm households into society, strengthens their own class identity, and reduces their sense of relative deprivation. In addition, after the transfer of land, farmers can obtain not only land rental income but also non-agricultural employment income; compared with rural farming, "depend on the sky to eat," rural migrant workers who migrate to the city obtain a more stable wage income, which can reduce the risk of returning to poverty. On the other hand, most rural migrant workers who go to the city are engaged in low-end manufacturing, construction, and service industries, and their wages are low. In addition, due to the existence of the urban–rural dualistic system, the rural migrant workers who go to the city are unable to enjoy the same children's education and social security policies as the urban residents, and the effect of land transfer on the inequality of income and opportunity is limited. Based on the above analysis, this paper proposes:

Hypothesis 4a. *Land transfers have the most significant mitigating effect on relative deprivation, the second most excellent mitigating effect on income inequality; they exacerbate inequality of opportunity and have a minor impact on the risk of returning to poverty.*

Hypothesis 4b. *Land transfers have the most significant mitigating effect on the sense of relative deprivation, the second most significant mitigating effect on the risk of returning to poverty, and a limited mitigating effect on inequality of income and opportunity.*

After the transfer of agricultural land, farmers can choose to expand the scale of their land operations, introduce modern agricultural production technology, develop intensive specialty agriculture, and become new agricultural management bodies. Alternatively, they can leave the countryside and seek diversified city careers. Comparatively speaking, the

new generation of farmers born after 1980 have generally received nine years of compulsory education and have a solid ability to accept new knowledge, new technologies, and new information. Whether it is to become the main body of a new type of agricultural management or to seek non-agricultural employment in the city, they have a more significant advantage in terms of human capital than farmers born before 1980, and the role of multidimensional relative poverty alleviation is also more important. Secondly, farmers with higher literacy levels have more vital learning abilities and higher acceptance of new things. It will be easier for them to change their livelihood after land transfer, whether they turn into new agricultural management subjects or engage in non-agricultural employment, and compared with farmers with lower literacy levels, farmers with higher literacy levels who carry out land transfer have a more significant alleviating effect on relative poverty. Finally, the limitations of poorer farmers with weak human capital, limited physical capital, lack of social capital, insufficient financial capital, and high vulnerability to poverty make it relatively difficult to transition livelihoods after land transfer. Relative poverty alleviation is limited, i.e., land transfer is more effective in alleviating the relative poverty of other farmers relative to farmers with higher poverty levels. Based on the above analysis, this paper proposes:

Hypothesis 5. *The effect of land transfer is greater on younger farmers, more literate farmers, and non-family farmers.*

Logical framework diagram is shown in Figure 1.

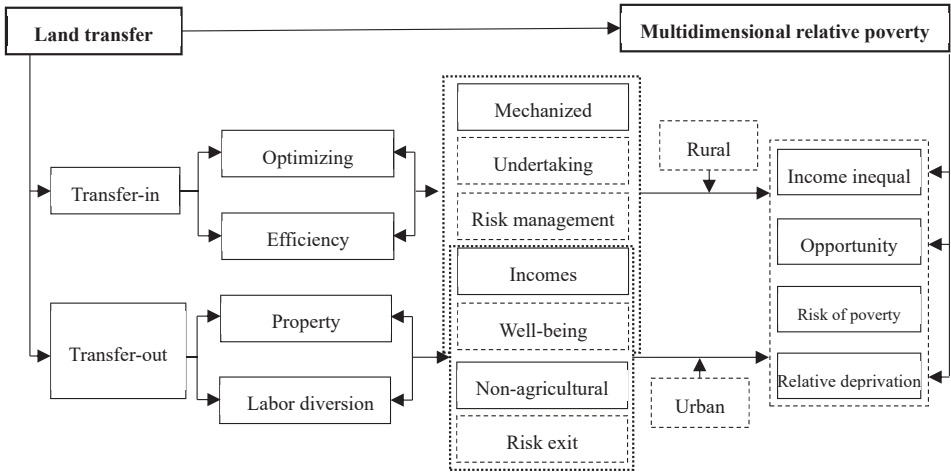


Figure 1. Logical framework diagram.

3. Materials and Methods

3.1. Data Sources

The data in this paper come from the sample survey data of the Chinese Academy of Agricultural Sciences (CAAS) in 7 poor counties, including Huize, Wuding, Panzhou, Zheng'an, Luonan, Zhen'an and Qingshui counties in 4 provinces, including Yunnan, Guizhou Shaanxi and Gansu provinces, from 2010 to 2021(In the first round of 2010, there was no Qingshui County in Gansu). Then, the balanced panel data were obtained for two consecutive periods after preprocessing the data and eliminating the outliers, finally obtaining 2062 valid data samples covering 1031 households in 124 poor villages in 7 counties. Finally, 2062 valid data samples covering 1031 households in 124 poor villages in 7 counties were obtained. ¹Among them, the proportion of poor households was 35.01%, and the proportion of land transfer was 31.28%, of which the proportion of land transfer in

was 17.99% and the proportion of land transfer out was 12.8%. Before poverty eradication, the rural poor population in the above counties accounted for a large proportion of the population; so, this database is used to study the impact of the land transfer system on relative poverty in poor rural areas in China with a good representation.

3.2. Research Method

3.2.1. Endogenous Switching Regression Model (ESR)

The decision to participate in land transfer is a “self-selection” based on the farmers’ own characteristics and comparative advantage analysis, and there are some unobservable factors, such as the farmers’ production preferences, management skills, entrepreneurship, etc., that simultaneously affect the decision to transfer land and multidimensional relative poverty. Neglecting this problem and simply using OLS to directly estimate the equations will lead to biased estimates of the parameters. The treatment of the self-selection problem that is often used in the existing literature is PSM, but this method does not address the endogeneity of omitted variables due to the unobservable factors. Another more commonly used method, the instrumental variable (IV) method, is able to address the estimation bias due to omitted variables to some extent, but it does not take into account the heterogeneity of the treatment effects. With this in mind, this paper empirically examines the impact of land transfer on multidimensional relative poverty using endogenous switching regression (ESR) modelling following Lokshin and Sajaia [31].

According to the random utility model of Becnerril and Abdulai [32], it is known that whether a farmer chooses to participate in land transfer depends on the difference between the utility of land transfer U_{1i} and the utility of not carrying out land transfer U_{0i} . If $D_i^* = U_{1i} - U_{0i} > 0$, then the farmer chooses land transfer. This paper defines the decision equation of whether farmers participate in land transfer as:

$$D_i^* = \Phi(Z_i) + \mu_i \quad (1)$$

If $D_i^* > 0$, then $D_i = 1$; otherwise, the subscript base, cap D , end base, sub i , equals 0 (1), where D_i^* to the asterisk operator is the latent variable, and D_i^* equals one indicates that the first i farmer household participated in land transfer, and $D_i = 0$ denotes that the first i farmer household did not join in land transfer; Z_i is a vector of exogenous explanatory variables, including the respondents’ characteristics, household characteristics, and county characteristics, and μ_i is a randomized disturbance term. To measure the effect of land transfer on multidimensional relative poverty, this paper constructs a multidimensional relative poverty model for farm households, as follows:

$$repov_i = X_i\beta_i + \delta D_i + \varepsilon_i \quad (2)$$

(2) where the dependent variable $repov_i$ is the multidimensional relative poverty of the farm households; X_i is the control variable; D_i is the farmer household i indicating whether they participate in land transfer; ε_i is the random perturbation term. Whether a farm household participates in the land transfer or not may be affected by certain unobservable factors, such as the attention to land policy and the propaganda and mobilization efforts of local cadres, which are related to the explanatory variables ($repov_i$); these are correlated, leading to Equation (10) above, in which D_i is associated with ε_i correlation; thus, the direct estimation of Equation (10) may lead to sample estimation bias due to the sample self-selection problem.

The corresponding multidimensional relative poverty models for participating and non-participating land-transferring farmers are shown below, respectively:

$$repov_{im} = X_{im}\beta_{im} + \sigma_{\mu m}\rho_{\mu m} + \varepsilon_{im} \text{ if } D_i = 1 \quad (3)$$

$$repov_{in} = X_{in}\beta_{in} + \sigma_{\mu n}\rho_{\mu n} + \varepsilon_{in} \text{ if } D_i = 0 \quad (4)$$

In Equations (11) and (12), $repov_{im}$, $repov_{in}$ denote the multidimensional relative poverty of the farmers who participated in land transfer and those who did not, respectively. X_{im} and X_{in} denote the factors affecting the multidimensional relative poverty of farm households. ε_{im} and ε_{in} are randomized perturbation terms. In order to solve the problem of sample selection bias caused by unobservable variables, this paper introduces the inverse Mills ratio ($\rho_{\mu m}, \rho_{\mu n}$) and its covariance [$\sigma_{\mu m} = cov(\mu_i, \varepsilon_{im}), \sigma_{\mu n} = cov(\mu_i, \varepsilon_{in})$] and applies the full information great likelihood estimation method to compute Equation (1) and Equations (3) and (4) jointly.

The average treatment effect of farmers' participation in land transfer is estimated by comparing the expected value of multidimensional relative poverty between the farmers who participated in land transfer and those who did not participate in land transfer under actual and counterfactual hypothetical scenarios.

Multidimensional Relative Poverty Expectations of Farmers Participating in Land Transfers:

$$E[repov_{im} | D_i = 1] = X_{im}\beta_m + \sigma_{\mu m}\rho_{im} \quad (5)$$

Multidimensional Relative Poverty Expectations of Non-Participating Land-Transferring Farmers:

$$E[repov_{in} | D_i = 0] = X_{in}\beta_n + \sigma_{\mu n}\rho_{in} \quad (6)$$

Considering the counterfactual assumptions in both cases, the multidimensional relative poverty expectations of farmers participating in land transfer in the absence of land transfer are:

$$E[repov_{im} | D_i = 0] = X_{im}\beta_m + \sigma_{\mu m}\rho_{im} \quad (7)$$

Multidimensional Relative Poverty Expectations of Non-Participating Farmers in the Presence of Participating Land Transfers:

$$E[repov_{in} | D_i = 1] = X_{in}\beta_n + \sigma_{\mu n}\rho_{in} \quad (8)$$

Through Equations (15) and (16), the multidimensional relative poverty treatment effect for farmers participating in land transfer is:

$$ATT = E[repov_{im} | D_i = 1] - E[repov_{im} | D_i = 0] \quad (9)$$

Similarly, the multidimensional relative poverty treatment effect for farmers not participating in land transfer is:

$$ATU = E[repov_{in} | D_i = 1] - E[repov_{in} | D_i = 0] \quad (10)$$

This paper utilizes ATT_i , ATU_i the average of the mean values to assess the average treatment effect of two types of farmers' participation in land transfer on multidimensional relative poverty.

3.2.2. Mediating Effects Model

In this paper, we analyze the impact of land transfer on relative poverty by using household cultivated area (land size), household business income (ope_income), non-farm employment (occupy), and wage income (Aincomej) as mediating variables, and the mediating effect model is shown below:

$$repov_{it} = \alpha_0 + \alpha_1 \frac{lend}{rent}_{it} + \alpha_2 X_{it} + \varepsilon_{it} \quad (11)$$

$$Z_{it} = \sigma_0 + \sigma_1 \frac{lend}{rent}_{it} + \sigma_2 X_{it} + \varepsilon_{it} \quad (12)$$

$$repov_{it} = \beta_0 + \beta_1 Z_{it} + \beta_2 \frac{lend}{rent}_{it} + \beta_3 X_{it} + \varepsilon_{it} \quad (13)$$

where Z_{it} represents the mediating variable, and according to Baron and Kenny [33], α_1 represents the total effect of land transfer on relative poverty; β_2 reflects the direct effect of land transfer on relative poverty; $\sigma_1\beta_1$ reflects the size of the mediating effect; if α_1 , β_1 , β_2 are all significant, but β_2 is smaller than small α_1 , this indicates a partial mediation effect; if α_1 , β_1 are significant and β_2 is not significant, this indicates a fully mediated effect.

3.3. Variable Selection and Description

3.3.1. Dependent Variable

For relative poverty (repov), relative poverty includes income inequality (inc_sd), inequality of opportunity (opp_sd), risk of returning to poverty (povertyp), and subjective relative deprivation (Rdep); this paper uses the entropy method to synthesize the relative poverty index of each family after measuring its income inequality, opportunity inequality, risk of returning to poverty, and subjective relative deprivation index.

1. Income Inequality (inc_sd)

In this paper, we refer to Deaton [34] and apply the Kakwani index to measure income inequality, which is calculated as follows:

First, the household per capita income (including wage income, business income, transfer income, and property income) is logarithmized, and each household's per capita income is compared with households with higher per capita incomes than their own to derive the household's income inequality index. Let Y represent a group; in this paper, there is the same annual range of all farm families in a group; the sample size is n ; the group of families in the logarithm of the per capita income is in ascending order; and the per capita income logarithmic distribution of the group of families is $Y = (y_1, y_2, \dots, y_n)$, according to the definition:

$$RD(y_j, y_i) = \begin{cases} y_j - y_i, & y_j > y_i \\ 0, & y_j \leq y_i \end{cases} \quad (14)$$

By summing $RD(y_j, y_i)$, summing over j , and dividing by the mean of the log of the per capita income of the n households, then the income inequality y_i is:

$$RD(y_j, y_i) = \frac{1}{n\mu_Y} \sum_{j=i+1}^n (y_j - y_i) = \gamma_{y_i}^+ \frac{(\mu_{y_i}^+ - y_j)}{\mu_Y} \quad (15)$$

where μ_Y is the mean of the log per capita income of all the family households in group Y , and $\mu_{y_i}^+$ is the log of the per capita income in Y over y_i , the mean of the log of per capita income for the sample in Y , and $\gamma_{y_i}^+$ is the percentage of the samples in Y whose per capita income exceeds y_i samples in Y as a percentage of the total samples in Y .

2. Unequal Opportunities (opp_sd)

Inequality of opportunity includes inequality of opportunity in education and training, inequality of opportunity in health, inequality of opportunity in employment, and inequality of social security. As it is restricted by data availability, this paper sums up variables such as whether family members participate in training, whether they participate in health insurance, whether they have access to the Internet, and the rate of the family members' employment outside the home and applies the Kakwani index method to calculate accounting inequality (opp_sd).

3. Risk of Returning to Poverty (povertyp)

In this paper, we measure the risk of returning to poverty by measuring the vulnerability of each household to poverty, drawing on Houghton and Khandker [35], by calculating the probability of falling into poverty, and by calculating the probability of a future household's per capita income falling below the poverty line, as shown below:

$$Povertyp_{i,t} = Pr(Y_{i,t+1} \leq poor) \quad (16)$$

where *Poverty* $p_{i,t}$ represents the first i household in the t period and the probability of returning to poverty, i.e., the future probability that household per capita income $Y_{i,t+1}$ will fall below some established national poverty line. Future income is measured by the observable variable X_i and the error term e_i . Future income is determined by the observable variables and the error term and is calculated using the following formula:

$$Y_{i,t+1} = f(X_i, a_t, e_i) \quad (17)$$

Equation (18) can be obtained by joining Equations (16) and (17):

$$Poverty p_{i,t} = Pr[Y_{i,t+1} = f(X_i, a_t, e_i) \leq poor] \quad (18)$$

Referring to the estimation approach of Koomson et al. [36], the three-stage feasible generalized least squares method is used to estimate the household income equation with the following formula:

$$\ln Y_{i,t} = a_t X_{i,t} + e_{it} \quad (19)$$

where $Y_{i,t}$ represents the first i household in the t period's income, and $X_{i,t}$ is an individual or household observable variable. In the text, the $Y_{i,t}$ logarithm of per capita household income is used, $X_{i,t}$. Variables such as household size, age, marital, work status, and family dependency ratio are used to calculate household income $\hat{Y} = Y_{i,t}$ and the residual term $\sigma_{e,i}$, which are used to compute the residual term.

The log expectation of per capita household income $\hat{E}$ and variance $\sigma_{e,i}^2$ is estimated, as shown below:

$$\hat{E} = (\ln Y_i | X_i) = X_i \hat{\alpha} \sigma_{e,i}^2 = X_i \hat{\beta} \quad (20)$$

Assuming that the logarithm of per capita household income follows a normal distribution, the formula for calculating the risk of returning to poverty is shown below:

$$\widehat{Poverty} p_{i,t} = Pr(\ln \widehat{Y}_i \leq \ln poor) = \Phi \left(\frac{\ln poor - X_i \hat{\alpha}}{\sqrt{X_i \hat{\beta}}} \right) \quad (21)$$

where $\ln poor$ is the logarithm of the national poverty line, drawing on Michaud [37], which uses the 2015 World Bank poverty line standard of USD 1.90, adjusted for exchange rates of USD 4503.31, as the income poverty line standard.

4. Subjective Sense of Relative Deprivation (Rdep)

Subjective relative deprivation was measured by variables such as “Do you feel that your family is poor compared to other families in your village?”; it was dimensionless to facilitate comparisons between the variables, and it took values between 0 and 5.

3.3.2. Core Explanatory Variables

The core explanatory variable in this paper is “whether or not the land is transferred in or out”, and to further analyze whether land transfer in or land transfer out has a greater impact on multidimensional relative poverty, the variables “whether or not the land is transferred in” are chosen, respectively. To further analyze whether land transfer in or land transfer out has a greater impact on multidimensional relative poverty, the variables “whether there is land transfer in” and “whether there is land transfer out” are used to conduct basic regression analysis of multidimensional relative poverty.

3.3.3. Control Variables

In addition to the core explanatory variables, there is a need to further control for other factors affecting multidimensional relative poverty. The control variables selected for this paper are respondent household-level control variables and household-level control variables. The household-level control variables are age, age squared (age2), marital status (marriage), gender, and years of schooling (year). The household-level control variables are

the number of members, depratio, house_area, and access to water throughout the year. The variables in question have been selected as control variables for two reasons. Firstly, they have been chosen in order to draw on the control variables chosen in previous studies, as referenced in [11,14,20,23]. Secondly, these variables are correlated with both explanatory and interpreted variables. For example, the older the farmer, the more likely he or she is to rent out the land. Furthermore, age is also one of the factors affecting multidimensional relative poverty. It should be additionally noted that control variables at the district level were not included in the analysis due to the limitations of the dataset. However, this is not the most important reason for their exclusion. The counties investigated by CAAS are all poor counties in the northwest of China, and as a result, their basic conditions are relatively similar. Furthermore, the counties surveyed are all once-poor counties in China, and as such, no control variables measuring regional differences were added.

3.3.4. Other Variables

Other variables selected for this paper include household cultivation area (land size), household cultivation area = free cultivation area + land inflow area – land outflow area, household operating income (ope_income), non-farm employment (occupy), and whether the household is poor (poorhh).

3.3.5. Tool Variables

In this paper, we select “distance of villages from county towns” and “average land transfer rate in the county where farmers are located (except for farmers)”, and the above variables are selected as instrumental variables, based mainly on the following considerations: firstly, the closer the distance to county towns, the more convenient the transportation is, and the more likely that farmers can easily sell their agricultural products or transfer to employment. First, the closer the distance to the county town, the more convenient the transportation, the easier it is for farmers to sell agricultural products or transfer employment, and the greater the possibility of participating in land transfer. The farmers’ willingness and decision making regarding land transfer will be influenced by the surrounding farmers, and when the average land transfer rate in a county other than the farmer’s is higher, the more the farmer tends to transfer land. Second, neither the distance from the farmer’s village to the county town nor the average land transfer rate in a county other than the farmer’s directly affects the farmer’s relative poverty level. Descriptive statistics of variables is shown in Table 1.

Table 1. Descriptive statistics of variables.

Variable Name	Variable Description	Master Sample	Average Value		Difference (the Result of Subtraction) B-A
			No Land Transfer (A)	Land Transfer (B)	
Repov	Multidimensional relative poverty	0.587	0.597	0.564	−0.033 ***
Inc_sd	Income inequality	0.812	0.817	0.801	−0.016 ***
Opp_sd	Inequality of opportunity	0.619	0.616	0.626	0.010
Povertyp	Risk of poverty	0.489	0.494	0.479	−0.015 ***
Rdep	Sense of relative deprivation	0.575	0.59	0.541	−0.050 ***
Gender	Men = 1, Women = 0	0.654	0.644	0.675	0.031
Age	Logarithm of age	3.95	3.961	3.924	−0.037 ***
Age2	Logarithm of age squared	15.66	15.754	15.453	−0.300 ***
Eduyear	Educational attainment	6.059	5.887	6.427	0.540 **
Marriage	Married or not. 1 for married, 0 for unmarried	0.915	0.902	0.944	0.042 ***

Table 1. Cont.

Variable Name	Variable Description	Master Sample	Average Value		Difference (the Result of Subtraction) B-A
			No Land Transfer (A)	Land Transfer (B)	
Avail_water	Regular access to water throughout the year. 1 for yes, 0 for no	0.819	0.828	0.798	−0.029
Member	Number of family members	3.503	3.481	3.553	0.073
Depratio	Family dependency ratio	0.147	0.146	0.151	0.005
House_area	Size of house occupied	144.450	145.470	142.330	−3.145
Ao_income	Operating income	2.487	3.717	1.927	1.790 ***
Aincomej	Wage income	0.370	0.435	0.341	0.094
Tool	Mechanized farming	0.382	0.431	0.360	0.071 **
Occupy	Occupation. Nonfarm payrolls at 1, agricultural payrolls at 0	0.269	0.254	0.302	0.048 *
Poorhh	Whether or not the household is poor and established. 1 for yes, 0 for no	1.650	1.636	1.681	0.045
Distance	Distance of villages from the county town	483.185	513.459	416.675	−96.784 **
Alandrent	Average land transfer rate in the county where the farmer is located (other than the farmer)	0.311	0.301	0.331	0.030 ***

① *, **, and *** indicate significance at 10%, 5%, and 1% statistical levels, respectively; ② A and B indicate the group of non-participating farmers and the group of participating farmers, respectively; ③ A and B denote the group of non-participating farmers and the group of participating farmers, respectively.

4. Results

4.1. Baseline Regression

The estimated results of the treatment effect of land transfer on the multidimensional relative poverty of farm households are shown in Tables 2–4, where scenarios (a) and (b) represent the factual results of the multidimensional relative poverty for farm households with and without land transfer, corresponding to Equations (3) and (4), respectively; (c) and (d) represent the results of the counterfactual assumptions, corresponding to Equations (9) and (10), respectively.

Table 2. Analysis of treatment effects of land transfer on multidimensional relative poverty of farm households.

Repov		Land Transfer (1)		No Land Transfer (2)	ATT (3)	ATU (4)
Land-transferring farmers	(a)	0.590	(c)	0.690	−0.100 ***	
		(0.003)		(0.002)		
Farmers without land transfer	(d)	0.581	(b)	0.621		−0.040 ***
		0.002		(0.002)		(0.003)

① *, **, and *** indicate significance at 10%, 5%, and 1% statistical levels, respectively; ② values in parentheses are standard errors; ③ ATT and ATU denote the average treatment effects of land-transferring and non-land-transferring farmers, respectively.

Table 3. Analysis of treatment effects of land transfers on multidimensional relative poverty of farm households.

Repov	Land Transfer (1)		Land Not Transferred (2)		ATT (3)	ATU (4)
Land transferred to farmers	(a)	0.570	(c)	0.686	−0.116 ***	
		(0.002)		(0.003)	(0.004)	
Land not transferred to farmers	(d)	0.318	(b)	0.591	−0.273 ***	
		0.001		(0.002)	(0.002)	

① *, **, and *** indicate significance at 10%, 5%, and 1% statistical levels, respectively; ② values in parentheses are standard errors; ③ ATT and ATU denote the average treatment effects of land-transferring and non-land-transferring farmers, respectively.

Table 4. Analysis of treatment effects of land diversion on multidimensional relative poverty of farm households.

Repov	Land Transfer (1)		Land Not Transferred (2)		ATT (3)	ATU (4)
Land transferred out to farmers	(a)	0.575	(c)	0.697	−0.122 ***	
		(0.003)		(0.004)	(0.005)	
Farmers who have not transferred their land	(d)	0.545	(b)	0.618	−0.074 ***	
		0.002		(0.002)	(0.002)	

① *, **, and *** indicate significance at 10%, 5%, and 1% statistical levels, respectively; ② values in parentheses are standard errors; ③ ATT and ATU denote the average treatment effects of land-transferring and non-land-transferring farmers, respectively.

4.1.1. Analysis of the Treatment Effect of Land Transfer on the Multidimensional Relative Poverty of Farm Households

As can be seen from Table 2, the average treatment effect of land transfer on the multidimensional relative poverty pairs of farm households is significantly negative at the 1% level. Under the consideration of the counterfactual hypothesis, when the land-transferring farmers do not implement the land-transferring behavior, their multidimensional relative poverty increases by 0.0997, with an increase ratio of 16.90%; when the non-land-transferring farmers carry out the land-transferring behavior, the level of their multidimensional relative poverty is reduced by 0.0400, with a decrease ratio of 6.44%. This proves that land transfer can significantly reduce the multidimensional relative poverty of farm households. The results support the findings of previous studies [11,14,20] and also validate Hypothesis 1 of this study.

4.1.2. Analysis of the Treatment Effects of Land Transfers on the Multidimensional Relative Poverty of Farm Households

As can be seen from Table 3, the average treatment effect of land transfer on the multidimensional relative poverty pairs of farm households is significantly negative at the 1% level. Under the consideration of the counterfactual hypothesis, when land-transferring farmers do not implement land-transferring behavior, their multidimensional relative poverty increases by 0.1158, with an increase ratio of 20.32%; when land-transferring farmers do not implement land-transferring behavior, their multidimensional relative poverty level decreases by 0.2727, with a decrease ratio of 46.18%. This proves that land transfer can significantly reduce the multidimensional relative poverty of farm households. Hypothesis 2 is verified.

4.1.3. Analysis of the Treatment Effect of Land Transfer on Multidimensional Relative Poverty of Farm Households

As can be seen from Table 4, the average treatment effect of land transfer on the multidimensional relative poverty pairs of farm households is significantly negative at the 1% level. Considering the counterfactual hypothesis, when the land-transferring farmers do not implement the land-transferring behavior, their multidimensional relative poverty increases by 0.1218, with an increase ratio of 21.17%; and when the non-land-transferring farmers carry out the land-transferring behavior, their level of multidimensional relative poverty decreases by 0.0735, with a decrease ratio of 11.89%. This proves that land transfer can significantly reduce the multidimensional relative poverty of farm households. Hypothesis 2 is verified.

4.1.4. Comparative Analysis of the Treatment Effects of Land Transfer in and Land Transfer Out on Multidimensional Relative Poverty Among Farm Households

The comparison shows that both land transfer in and land transfer out can significantly reduce the multidimensional relative poverty of farm households, and the average impact of land transfer out on multidimensional relative poverty is larger than the average impact of land transfer in on multidimensional relative poverty, which is consistent with the findings of previous studies [20,21], and Hypothesis 3 is confirmed. For non-land-transferring households, the mitigating effect of choosing land transfer in the future on multidimensional relative poverty is greater than that of land transfer out, probably because the current land transfer in rural areas is insufficient, and the scale of the transfer is small, while the wages of migrant workers are rigid; in the context of rural revitalization, rural infrastructures will be improved and constructed, and it will be more profitable to carry out land transfer in the future than to carry out land transfer out.

4.2. Robustness Tests

To verify the robustness of the empirical results, this paper adopts a change in the empirical method and deletes part of the sample to test the robustness of the above findings, respectively. Tables A1 and A2 report the results of the scored propensity matching method (PSM), panel fixed effects, and ordinary least square (OLS) regressions, respectively. Columns (1), (2), and (3) indicate that after one-to-one matching, land transfer significantly reduces the multidimensional relative poverty of the farm household at the 1% level, for both land transfer in and land transfer out. Columns (4), (5), and (6) show that after fixing for individual and time effects, either land transfer in or land transfer out reduces multidimensional relative poverty. Columns (7), (8), and (9) show that land transfers reduce multidimensional relative poverty at the 5% significance level, depending on the random effects. By comparing the size of the coefficients in land transfers in and land transfers out across methods, land transfers out have a greater mitigating effect on multidimensional relative poverty, which is consistent with the results of the previous benchmark regression and proves that the results of the benchmark regression are somewhat robust.

Considering that there are a small number of farm households in the total sample that have both land transfer in and land transfer out behaviors; by excluding this part of the 22 samples, the remaining samples are subjected to endogenous switching regression analysis, which yields the results shown in Table A3; columns (1), (2), and (3) show that relative to land-transferring farmers, if they do not participate in land transferring, their multidimensional relative poverty increases by 0.0973. Both the land transfer in and land transfer out can effectively reduce the multidimensional relative poverty of farm households, and land transfer out has a greater effect on the alleviation of multidimensional relative poverty of farm households, which is consistent with the results of the benchmark regression and confirms that this paper has good robustness.

4.3. Heterogeneity Analysis

From columns (1) and (2) in Table 5, it can be seen that there is age heterogeneity in the impact of land transfer on multidimensional relative poverty, and the participation of the new generation of farmers born after 1980 in land transfer has a greater mitigating effect on relative poverty than those born before 1980, and the participation of the farmers born before 1980 in land transfer reduces multidimensional relative poverty by 0.0207 units. The participation in land transfer by the new generation of farmers born after 1980 reduces multidimensional relative poverty by 0.0546 units, which is 0.0339 units more than the multidimensional relative poverty of the farmers born before 1980. From columns (3) and (4) in Table 5, it can be seen that there is heterogeneity in the educational qualifications in the impact of land transfer on multidimensional relative poverty; the farmers with junior high school education and above participate in land transfer to alleviate relative poverty more than those with elementary school education, and for the farmers with elementary school education who participate in land transfer, multidimensional relative poverty is reduced by 0.0252 units, while for the farmers with junior high school education and above who participate in land transfer, multidimensional relative poverty is reduced by 0.0328 units, which is 0.0076 units more than the multidimensional relative poverty of the farmers with junior high school education and above. From columns (5) and (6) in Table 5, compared to the farmers in acute poverty, the participation of non-acutely poor households in land transfer has a more significant effect on alleviating multidimensional relative poverty; the participation of poor households in land transfer is not effective in alleviating multidimensional relative poverty, while the participation of non-poor households in land transfer significantly reduces multidimensional relative poverty at the 10% level, which may indicate that the effect of alleviating multidimensional relative poverty through land transfer has a household capital condition limit [38]. In summary, this paper tests Hypothesis 5.

Table 5. Heterogeneity analysis of the impact of land transfer on multidimensional relative poverty in rural areas.

Variable Name	Repov (Multidimensional Relative Poverty)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Before 1980	After 1980	Primary	Junior High or Above	Poor	Non-Poor
Land_rent	−0.021 *	−0.055 *	−0.025 *	−0.033 **	−0.013	−0.0210 *
(Land transfer)	(−2.488)	(−2.104)	(−2.233)	(−2.840)	(−0.887)	(−2.462)
_cons	−2.009	0.421	0.190	0.174	1.193 *	−0.006
	(−1.104)	(0.224)	(0.235)	(0.288)	(2.188)	(−0.010)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
N	927	91	575	480	290	739
R ² _p	0.126	0.151	0.050	0.048	0.088	0.083

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② *t*-test values are in parentheses.

5. Discussion

5.1. Mechanism Analysis

Table 6 reports the results of the mediating effect of land transfer on the impact of land transfer on the multidimensional relative poverty of farm households; column (2) shows that land transfer significantly promotes the mechanized farming of farm households at the 1% level; column (3) shows that land transfer reduces the multidimensional relative poverty of farm households, but not significantly, while mechanized farming significantly reduces the multidimensional relative poverty of farm households at the 10% level. According to Baron and Kenny’s mediation effect study [32], by comparing the magnitude of the coefficients in columns (1) and (3), it can be seen that the mediation effect of mechanized farming is established, i.e., land transfer improves the level of mechanized farming of farm households and thus mitigates multidimensional relative poverty. Column (4) shows that

land transfer significantly increases farm household operating income at the 10% level; column (5) shows that land transfer reduces the multidimensional relative poverty of farm households, but not significantly, while operating income significantly reduces the multidimensional relative poverty of households at the 1% level. By comparing the magnitude of the coefficients in columns (1) and (5), it can be seen that the mediating effect of farm operating income is established, i.e., land transfer raises the level of farm business income, thus alleviating multidimensional relative poverty.

Table 6. Analysis of mediating effects of land transfers.

Variable Name	Mediating Effects of Mechanized Farming			Intermediation Effects of Business Income	
	(1)	(2)	(3)	(4)	(5)
Intermediary variable	Repov (Multidimensional relative poverty)	Tool (mechanized farming)	Repov (Multidimensional relative poverty)	Ao_income (Operating income)	Repov (Multidimensional relative poverty)
Rent (Land transfers)	−0.025 ** (−2.993)	0.326 *** (5.497)	−0.005 (−0.568)	2.039 ** (2.633)	−0.008 (−0.966)
Tool (mechanized farming)			−0.013 * (−2.376)		
Ao_income (Operating income)					−0.001 ** (−2.856)
_cons	0.590 *** (55.098)	−3.360 (−1.439)	0.733 *** (53.022)	−21.076 * (−2.088)	1.198 ** (3.018)
Control variable	Yes	Yes	Yes	Yes	Yes
N	2060	1029	1938	2060	2060
R ² _p	0.153	0.030	0.125	0.003	0.071

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② *t*-test values are in parentheses.

Table A4 reports the results of the mediating effect of land transfer on the multidimensional relative poverty of farm households. Column (2) shows that land transfer significantly promotes the non-farm employment of farm households at the 1% level, i.e., after land transfer, most of the farm households tend to choose to go to the city to engage in non-farm employment; column (3) shows that land transfer and non-farm employment at the same time significantly reduce the multidimensional relative poverty of farm households at the 5% level, i.e., land transfer and non-farm employment can reduce the multidimensional relative poverty of farm households. By comparing the size of the coefficients in columns (1) and (3), the mediating effect of non-farm employment is established and is a partial mediating effect, i.e., the transfer of land improves the level of non-farm employment of farm households and thus alleviates the multidimensional relative poverty. Column (4) shows that land transfer significantly increases the wage income of farm households at the 10% level; column (5) shows that land transfer significantly reduces the multidimensional relative poverty of farm households at the 1% level, while income significantly reduces the multidimensional relative poverty of households at the 1% level. By comparing the size of the coefficients in columns (1) and (5), it can be seen that the wage income is a partially mediated effect, i.e., land transfer raises the level of wage income and thus alleviates the multidimensional relative poverty of farm households. Wage income thus alleviates multidimensional relative poverty.

5.2. Impact of Land Transfer on the Dimensions of Multidimensional Relative Poverty of Farm Households

Tables 7 and A5 report the regression results of the impact of land transfer on each dimension of the multidimensional relative poverty of farm households. Columns (1), (2), and (3) show that land transfers significantly reduce farm household income inequality at the 5% level, which is consistent with the findings of most studies [7,10,12], but also

inconsistent with the findings of some studies [21]. We believe that the reason for the inconsistency may be that the study by Wang et al. included multidimensional relative poverty in some of the more affluent rural areas, and that land transfers in affluent places may become an exploitative tool for the rich, leading to the Matthew effect. Our study mainly examines the effect in relatively poor areas; so, our conclusions may be more applicable to poor areas.

Table 7. Impact of land transfer on each dimension of multidimensional relative poverty of farm households.

Variable Name	Inc_sd (Income Inequality)			Opp_sd (Unequal Opportunities)		
	(1)	(2)	(3)	(4)	(5)	(6)
Land_rent (Land transfer)	−0.014 ** (−3.001)			0.015 (1.595)		
Lend (Land transfer)		−0.007 (−1.137)			−0.001 (−0.119)	
Rent (Land transfers)			−0.015 * (−2.310)			0.034 ** (2.822)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
_cons	1.324 *** (5.400)	1.391 *** (5.671)	1.313 *** (5.320)	0.110 (0.233)	0.046 (0.098)	0.219 (0.462)
N	2060	2060	2060	2060	2060	2060
R ² _p	0.036	0.033	0.034	0.146	0.144	0.151

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② *t*-test values are in parentheses.

The effect of land transfer on income inequality is negative, but not significant in terms of empirical evidence. The possible reasons for this are that the current land transfer system and vocational training system are not well developed, land rents are low, and most rural migrant workers lack specialized knowledge and skills and can only take up jobs in manufacturing, construction, and low-end services if they go to work in the city, where wages are relatively low. Although land transfer has an obvious income-generating effect, it contributes relatively little to narrowing the income gap between farm households and reducing income inequality. Land transfer significantly reduces income inequality among farm households at the 10% level. Columns (4), (5), and (6) show that land diversion significantly increases inequality of opportunity at the 5% level. Columns (7), (8), and (9) show that land transfer significantly reduces the risk of returning to poverty among farmers at the 1% level, which is consistent with the findings of previous studies [17], where land transfer out reduces the risk of returning to poverty for farm households at the 10% level, while land transfer in does not have a significant effect on the risk of returning to poverty for farm households; the probable reason is that the current agricultural insurance mainly covers cash crops, such as paddy, wheat, and maize, with insufficient insurance coverage; coupled with the fact that the agricultural sector is vulnerable to natural disasters, the short-term effect of land transfer on poverty return risk mitigation is limited. Columns (10), (11), and (12) show that land transfer significantly reduces subjective relative deprivation at the 10% level, and both land transfer in and land transfer out can significantly reduce the subjective relative deprivation of farmers. Hypotheses 4a and 4b were tested.

5.3. Impact of Land Transfer on the Dimensions of Farm Household Income

We discuss in detail the impact of land transfers on absolute income by categorizing income into wage income, business income, transfer income, and property income and regressing them separately. Tables 8 and A6 report the results. As can be seen from the results, the effect of land transfers on total income is positive and significant, but the effect of transfers in is better than the effect of transfers out. The results of the regressions of wage income and business income show that land transfer increases the wage income

of those who transfer out but decreases the wage income of those who transfer in; it increases the business income of those who transfer in but has a negative effect on those who transfer out. This point is in line with the conclusions drawn in the section on the analysis of the mechanism, and again confirms Hypothesis 2. The data results in (10), (11), and (12) suggest that the transfer of land may lead to a loss of transfer income for the transferor, the mechanism of which we have not yet identified. The data results for the property income component are well explained because renting out land is itself a source of property income.

Table 8. Impact of land transfer on income.

Variable Name	Averincome (Total Income)			Aincomej (Salary Income)		Ao_Income (Operating Income)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Land_rent (Land transfer)	0.468 *** (6.737)			0.186 * (2.069)			2.608 ** (3.266)
Lend (Land transfer)		0.379 *** (4.185)			0.605 *** (5.331)		
Rent (Land transfers)			0.409 *** (4.568)			−0.303 * (−2.577)	
_cons	−5.717 (−1.595)	−6.897 (−1.912)	−5.302 (−1.468)	4.094 *** (5.631)	−18.792 *** (−3.835)	−19.042 *** (−3.852)	−2.526 (−0.390)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2062	2062	2062	2062	2062	2062	2062
R ² _p	0.030	0.027	0.027	0.022	0.029	0.026	0.002

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② t-test values are in parentheses.

Tables 9 and A7 report the regression results of the impact of land transfer on the dimensions of income inequality. Columns (1), (2), and (3) show that land transfer reduces wage income inequality at the 10% level, where land transfer out is able to reduce wage income inequality of farm households at the 1% level, while land transfer in is able to increase wage income inequality of farm households at the 1% level. Columns (4), (5), and (6) show that land transfer significantly reduces business income inequality at the 1% level, where land transfer out increases business income inequality at the 1% level, while land transfer in significantly reduces business income inequality at the 10% level. Columns (7), (8), and (9) show that land transfer in significantly increases transfer income inequality at the 1% level. Columns (10), (11), and (12) show that land transfer significantly reduces property income inequality at the 1% level, where land transfer out significantly reduces property income inequality for farm households at the 1% level, while land transfer in significantly increases property income inequality for farm households at the 10% level.

Table 9. Impact of land transfer on income inequality.

Variable Name	Incj_sd (Wage Income Inequality)			Inco_sd (Operating Income Inequality)		
	(1)	(2)	(3)	(4)	(5)	(6)
Land_rent (Land transfer)	−0.009 * (−2.054)			−0.021 *** (−5.959)		
Lend (Land transfer)		−0.040 *** (−6.119)			0.011 * (2.468)	
Rent (Land transfers)			0.022 *** (3.309)			−0.047 *** (−10.695)
_cons	0.941 *** (119.711)	0.556 *** (13.678)	0.550 *** (13.454)	1.415 *** (7.947)	1.436 *** (8.020)	1.313 *** (7.485)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
N	2062	2062	2062	2062	2062	2062
R ² _p	0.015	0.059	0.051	0.024	0.019	0.039

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② t-test values are in parentheses.

6. Conclusions

6.1. Results and Conclusions

Land transfer not only realizes the flow of production factors among farmers and enables an efficient allocation of resources, it also promotes the upgrading of the agricultural industry and the transformation of farmers' livelihood strategies. Based on theoretical analysis, this study uses the endogenous transformation model to examine the impact of land transfer on multidimensional relative poverty in rural areas and draws the following main conclusions:

(1) Land transfer can effectively alleviate the multidimensional relative poverty of farmers on both sides of the transfer, and the alleviating effect on the land lessor is better than the alleviating effect on the land lessee. (2) Although the direction of the effect is the same, the alleviation pathways of land transfer are different for the lessor and the lessee. For the lessee, land transfer promotes the mechanization of agricultural production and improves farm income and production efficiency; for the lessor, land transfer induces farmers to engage in non-agricultural production work, increasing wage income and thus alleviating multidimensional relative poverty. (3) Land transfer has the largest mitigating effect on the lessee's sense of relative deprivation and the second largest mitigating effect on income inequality; this exacerbates inequality of opportunity and at the same time has an insignificant mitigating effect on the risk of returning to poverty. Land transfer has the largest mitigating effect on the lessor's sense of relative deprivation, the second largest mitigating effect on the risk of returning to poverty, and an insignificant mitigating effect on income inequality and inequality of opportunity. (4) Land transfers have a greater mitigating effect on younger, better educated farmers or those who are not acute poverty.

6.2. Policy Recommendations

Based on the theoretical analysis of land transfer as well as the analysis of empirical results, this study suggests that policy makers should consider the following recommendations that may be able to alleviate the multidimensional relative poverty of farmers in developing countries or less developed regions.

(1) The impact of land transfer on alleviating farmers' multidimensional relative poverty is significant and cannot be ignored. The conclusions drawn from this study support the findings of most studies on land transfer and relative poverty, which agree that land transfer is conducive to alleviating farmers' multidimensional relative poverty, and at the same time, we find that land transfer also promotes the level of mechanized agricultural cultivation. Therefore, policymakers can promote rural land transfer through government policies, such as formulating a set of policies and regulations on land transfer as in China or formulating a policy on the transfer of land development rights (TDR) to promote land transfer, as in the United States. However, policy makers need to pay special attention to formulating different policies according to different countries' conditions in order to maximize the impact of land transfer. In addition, more attention should be paid to power struggles that may arise in land transfer, such as friction between land ownership and management, which, if not addressed by policymakers, may lead to policy distortions that may cause the actual effects of the policy to be seriously different from those intended.

(2) This study addresses the heterogeneous effects of land transfers, which deserve to be investigated. As indicated in the empirical results and conclusions section, the effect of land transfers on alleviating multidimensional relative poverty is likely to be better for younger, better educated farmers and farmers who have escaped absolute poverty. This finding can help policymakers in their decision making to achieve poverty reduction goals. Firstly, policies should be biased in favor of the elderly by developing more age-friendly policies, such as the provision of government financial support or risk guarantee funds for elderly land transferees, in order to reduce the sense of exploitation and the risk of returning to poverty among the elderly population. Secondly, since farmers in developing countries and less developed regions tend to have low levels of education, governments need to improve the overall accessibility of land transfer policies, try to make land transfer policy

documents as easy to understand as possible, and pay attention to farmers with lower levels of education when implementing land transfer policies. Finally, the government should adopt different land transfer policies for farmers with different levels of poverty. Since farmers who have higher levels of poverty having a level of assets that is too low, giving them the right to freely transfer their land at this time will increase their risk of returning to poverty. What they should be thinking about at this point is how to get out of acute poverty and raise their asset levels, rather than entering the land exchange market. Premature entry into the land market would most likely lead them to acute poverty and greater exploitation and inequality. Policymakers must therefore take this into account by screening the financial status of farmers, protecting those who are poor themselves, avoiding land transactions as much as possible, and lifting them out of acute poverty by helping them to build their own agricultural capacity.

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Appendix A

Table A1. Robustness test of substitution empirical methods.

Repo (Multidimensional Relative Poverty)	Score propensity Matching (PSM)			Panel Fixed Effect		
	ATT					
	(1)	(2)	(3)	(4)	(5)	(6)
Land_rent	−0.027 ***			−0.0216 **		
(Land transfer)	(−2.410)			(−2.903)		
Rent		−0.021 ***			−0.024 **	
(Land transfers)		(−2.240)			(−2.902)	
Lend			−0.050 *			−0.043 ***
(Land transfer)			(−3.550)			(−4.331)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixation	Not	Not	Not	Yes	Yes	Yes
Fixed time	Not	Not	Not	Yes	Yes	Yes
N	1527	2060	1029	1527	2060	1527
R ² _p	0.010	0.016	0.013	0.013	0.015	0.013

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② *t*-test values are in parentheses.

Table A2. Robustness test of substitution empirical methods.

Repov (Multidimensional Relative Poverty)	Ordinary Least Squares (OLS)		
	(7)	(8)	(9)
Land_rent (Land transfer)	−0.021 ** (−2.765)		
Rent (Land transfers)		−0.028 *** (−3.336)	
Lend (Land transfer)			−0.035 *** (−3.486)
Control variable	Yes	Yes	Yes
Individual fixation	Not	Not	Not
Fixed time	Not	Not	Not
N	1527	2060	1527
R ² _p	0.012	0.015	0.013

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② *t*-test values are in parentheses.

Table A3. Robustness test for deleted partial samples.

Repov (Multidimensional Relative Poverty)	ATT		
	(1)	(2)	(3)
Land_rent (Land transfer)	−0.097 *** (0.004)		
Rent (Land transfers)		−0.085 *** (0.004)	
Lend (Land transfer)			−0.129 *** (0.005)

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② values in parentheses are standard errors.

Table A4. Analysis of mediating effects of land transfers.

Variable Name	Intermediation Effects of Nonfarm Payrolls			Intermediation Effects of Wage Income	
	(1)	(2)	(3)	(4)	(5)
Intermediary variable	Repov (Multidimensional relative poverty)	Occupy (Non-farm payrolls)	Repov (Multidimensional relative poverty)	Aincomej (Wage income)	Repov (Multidimensional relative poverty)
Lend (Land transfer)	−0.034 *** (−3.493)	0.190 *** (5.537)	−0.029 ** (−2.903)	0.301 *** (3.529)	−0.038 *** (−3.820)
Occupy (Non-farm payrolls)			−0.029 ** (−3.272)		
Aincomej (Wage income)					−0.012 *** (−4.694)
_cons	0.685 (1.715)	4.979 *** (3.545)	0.829 * (2.073)	−23.148 * (−2.300)	1.244 ** (3.153)
Control variable	Yes	Yes	Yes	Yes	Yes
N	2060	2060	2060	2060	2060
R ² _p	0.129	0.124	0.137	0.003	0.079

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② *t*-test values are in parentheses.

Table A5. Impact of land transfer on each dimension of multidimensional relative poverty of farm households.

Variable Name	Povertyp (Risk of Returning to Poverty)			Rdep (Subjective Sense of Relative Deprivation)		
	(7)	(8)	(9)	(10)	(11)	(12)
Land_rent (Land transfer)	−0.005 * (−2.230)			−0.039 *** (−3.384)		
Lend (Land transfer)		−0.011 *** (−3.880)			−0.048 *** (−3.361)	
Rent (Land transfers)			0.001 (0.120)			−0.027 * (−2.200)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−0.038 (−0.323)	−0.010 (−0.083)	−0.014 (−0.115)	0.728 (1.230)	0.925 (1.569)	1.875 *** (3.464)
N	2060	2060	2060	2060	2060	2060
R ² _p	0.560	0.563	0.558	0.368	0.368	0.433

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② *t*-test values are in parentheses.

Table A6. Impact of land transfer on income.

Variable Name	Ao_Income (Operating Income)		Atincome (Transfer Income)			Apincome (Property Income)		
	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Land_rent (Land transfer)			−0.054 (−0.896)			1.656 *** (12.800)		
Lend (Land transfer)	−0.292 (−0.281)			0.024 (0.306)			2.206 *** (15.414)	
Rent (Land transfers)		4.737 *** (4.672)			−0.166 * (−2.105)			−0.557 *** (−3.594)
_cons	−74.205 (−1.771)	−60.209 (−1.440)	6.359 * (2.213)	6.392 * (2.224)	−1.001 * (−2.078)	−6.279 (−0.984)	−12.735 (−1.782)	−1.750 * (−2.080)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2062	2062	2062	2062	2062	2062	2062	2062
R ² _p	0.0015	0.003	0.023	0.023	0.022	0.118	0.182	0.017

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② *t*-test values are in parentheses.

Table A7. Impact of land transfer on income inequality.

Variable Name	Inct_sd (Transfer Income Inequality)			Incp_sd (Property Income Inequality)		
	(7)	(8)	(9)	(10)	(11)	(12)
Land_rent (Land transfer)	0.002 (0.405)			−0.027 *** (−13.806)		
Lend (Land transfer)		−0.004 (−0.667)			−0.053 *** (−22.814)	
Rent (Land transfers)			0.013 * (2.135)			0.006 * (2.486)
_cons	0.197 (0.794)	0.198 (0.799)	1.017 *** (26.225)	1.051 *** (10.594)	1.152 *** (12.356)	1.113 *** (10.777)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
N	2062	2062	2062	2062	2062	2062
R ² _p	0.023	0.023	0.021	0.027	0.063	0.004

Notes: ① *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; ② *t*-test values are in parentheses.

Notes

- ¹ The proportion of the sample in each county: 15.32% in Luonan County, Shaanxi Province; 16.49% in Zhen'an County, Shaanxi Province; 11.74% in Qingshui County, Gansu Province; 15.23% in Huize County, Yunnan Province; 14.65% in Wuding County, Yunnan Province; 13.48% in Zheng'an County, Guizhou Province; 13.48% in Panzhou County, Guizhou Province; and 13.09%.

References

- Chambers, R. Poverty and livelihoods: Whose reality counts? *Environ. Urban.* **1995**, *7*, 173–204. [CrossRef]
- Zhang, J.; Chen, Q.; Chen, H.; Feng, Z. How Does Farmland Tenure Security Affect Rural Household Income? Empirical Evidence of China's Survey Data. *Sustainability* **2023**, *15*, 5645. [CrossRef]
- Zhang, F.; Wang, X. Impact of new rural cooperative medical system on the maternal and child's healthcare status in Lingshui county. *Matern. Child Health Care China* **2013**, *28*, 3229–3237.
- Zhang, X.; Liu, H.; Wang, D. Relative Poverty Scale Measurement and Trend Analysis Between Provinces in China. *Soc. Indic. Res.* **2023**, *169*, 629–645. [CrossRef]
- Zhang, Q. Retreat from Equality or Advance towards Efficiency? Land Markets and Inequality in Rural Zhejiang. *China Q.* **2008**, *195*, 535–557. [CrossRef]
- Xie, T.; Xiong, C.; Xu, Q.; Zhou, T. The impact of social pension scheme on farm production in China: Evidence from the China Health and Retirement Longitudinal Survey. *Int. J. Environ. Res. Public Health* **2022**, *19*, 2292. [CrossRef]
- Zhang, L.; Feng, S.; Heerink, N.; Qu, F.; Kuyvenhoven, A. How do land rental markets affect household income? Evidence from rural Jiangsu, PR China. *Land Use Policy* **2018**, *74*, 151–165. [CrossRef]
- Lu, H.; Xie, H. Impact of changes in labor resources and transfers of land use rights on agricultural non-point source pollution in Jiangsu Province, China. *J. Environ. Manag.* **2018**, *207*, 134–140. [CrossRef]
- Wang, Y.; Chen, Y.; Li, Z. Escaping poverty: Changing characteristics of China's rural poverty reduction policy and future trends. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 694. [CrossRef]
- Zhang, W.; Zhao, S.; Wang, J.; Xia, X.; Jin, H. Rural Land Circulation and Peasant Household Income Growth—Empirical Research Based on Structural Decomposition. *Sustainability* **2024**, *16*, 6717. [CrossRef]
- Li, C.; Jiao, Y.; Sun, T.; Liu, A. Alleviating multi-dimensional poverty through land transfer: Evidence from poverty-stricken villages in China. *China Econ. Rev.* **2021**, *69*, 101670. [CrossRef]
- Udimal, T.B.; Liu, E.; Luo, M.; Li, Y. Examining the effect of land transfer on landlords' income in China: An application of the endogenous switching model. *Heliyon* **2020**, *6*, e05071. [CrossRef] [PubMed]
- Li, G.; Cui, X.; Pan, L.; Wang, Y. Land transfer and rural household consumption diversity: Promoting or inhibiting? *Land* **2023**, *12*, 203. [CrossRef]
- Yu, W.; Guan, G.; Wang, Y.; Wang, Q. An analysis of the poverty reduction effects on land transfer: Evidence from rural areas in China. *PLoS ONE* **2024**, *19*, e0298243. [CrossRef] [PubMed]
- Zheng, B.; Gu, Y.; Zhu, H. Land tenure arrangements and rural-to-urban migration: Evidence from implementation of China's rural land contracting law. *J. Chin. Gov.* **2020**, *5*, 322–344. [CrossRef]
- Zhou, Z.; Tan, L.; Qu, L.; Li, Y.; Chen, X. The impact of rural land transfer on the living satisfaction of middle-aged rural residents and the implications: A perspective of land attachment. *Habitat Int.* **2024**, *148*, 103085. [CrossRef]
- Zhao, X.; Lan, F.; Guo, M.; Zhang, L. Differences in the impact of land transfer on poverty vulnerability among households with different livelihood structures. *Front. Sustain. Food Syst.* **2024**, *8*, 1425762. [CrossRef]
- Ma, X.; Qiu, T.; Qian, Z. The role of government in farmland transfer: Referee or player?—Empirical evidence from households' satisfaction about farmland transfer in Jiangsu, Hubei, Guangxi and Hei Longjiang Provinces. *Economist* **2016**, *11*, 83–89.
- Wang, W.; Wang, Y.; Shen, Y.; Cheng, L.; Qiao, J. The role of multi-category subsidies in cultivated land transfer decision-making of rural households in China: Synergy or trade-off? *Appl. Geogr.* **2023**, *160*, 103096. [CrossRef]
- Liu, S.; Xu, H.; Deng, L. Does land transfer help alleviate relative poverty in China? An analysis based on income and capability perspective. *Appl. Econ.* **2024**, *57*, 1–13. [CrossRef]
- Wang, X.; Xu, Z.; Li, G.; Zhuo, Y.; Zou, W. Farmland transfer and income distribution effect of heterogeneous farmers with livelihood capital: Evidence from CFPS. *Land* **2023**, *12*, 1398. [CrossRef]
- Galiani, S.; Schargrodsky, E. Land property rights and resource allocation. *J. Law Econ.* **2011**, *54*, S329–S345. [CrossRef]
- Li, M.; Zheng, Z.; Zheng, J.; Yang, D.; Wang, T. The effect and mechanism of farmland transfer on the multidimensional relative poverty of rural women. *Front. Environ. Sci.* **2023**, *11*, 1276195. [CrossRef]
- Pemberton, S.; Arriaga-García, G.J. Poverty and social exclusion. *Stud. Companion Soc. Policy* **2022**, *32*, 216–221.
- Li, G.; Cai, Z.; Liu, J.; Liu, X.; Su, S.; Huang, X.; Li, B. Multidimensional poverty in rural China: Indicators, spatiotemporal patterns and applications. *Soc. Indic. Res.* **2019**, *144*, 1099–1134. [CrossRef]
- Yao, Y. Study on Changes in the System of Guaranteeing the Subsistence Right for the Disabled in China (1978–2020)—Based on NVivo Qualitative Analysis Against the Poverty Alleviation Context. *J. US-China Public Adm.* **2021**, *18*, 133–139. [CrossRef]
- Alkire, S.; Foster, J. Counting and multidimensional poverty measurement. *J. Public Econ.* **2011**, *95*, 476–487. [CrossRef]
- Hulme, D.; Shepherd, A. Conceptualizing chronic poverty. *World Dev.* **2003**, *31*, 403–423. [CrossRef]

29. Wang, W.; Luo, X.; Zhang, C.; Song, J.; Xu, D. Can land transfer alleviate the poverty of the elderly? Evidence from rural China. *Int. J. Environ. Res. Public Health* **2021**, *18*, 11288. [CrossRef]
30. Sen, A. Poor, relatively speaking. *Oxf. Econ. Pap.* **1983**, *35*, 153–169. [CrossRef]
31. Lokshin, M.; Sajaia, Z. Maximum likelihood estimation of endogenous switching regression models. *Stata J.* **2004**, *4*, 282–289. [CrossRef]
32. Becerril, J.; Abdulai, A. The impact of improved maize varieties on poverty in Mexico: A propensity score-matching approach. *World Dev.* **2010**, *38*, 1024–1035. [CrossRef]
33. Baron, R.M.; Kenny, D.A. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Personal. Soc. Psychol.* **1986**, *51*, 1173. [CrossRef] [PubMed]
34. Deaton, A. Measuring poverty in a growing world (or measuring growth in a poor world). *Rev. Econ. Stat.* **2005**, *87*, 1–19. [CrossRef]
35. Houghton, J.; Khandker, S.R. *Handbook on Poverty+ Inequality*, 1st ed.; World Bank Publications: Washington, DC, USA, 2009; pp. 231–237.
36. Koomson, I.; Villano, R.A.; Hadley, D. Effect of financial inclusion on poverty and vulnerability to poverty: Evidence using a multidimensional measure of financial inclusion. *Soc. Indic. Res.* **2020**, *149*, 613–639. [CrossRef]
37. Michaud, P.C. Optimal Financial Knowledge and Wealth Inequality. *J. Political Econ.* **2017**, *125*, 431–477.
38. Adamopoulos, T.; Brandt, L.; Chen, C.; Restuccia, D.; Wei, X. Land security and mobility frictions. *Q. J. Econ.* **2024**, *139*, 1941–1987. [CrossRef]

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Article

The Impact of Farmers' E-Commerce Adoption on Land Transfer: Evidence from Ten Provinces across China

Yitao Wang, Weidong Wang *, Xuemei Jiang and Hui Wang

School of Economics and Management, Beijing Forestry University, Beijing 100083, China; wangsomnus@bjfu.edu.cn (Y.W.); jiangxm@bjfu.edu.cn (X.J.); huiwang@bjfu.edu.cn (H.W.)

* Correspondence: wangwd2019@bjfu.edu.cn

Abstract: Rural e-commerce is rapidly expanding in rural China, profoundly affecting the agricultural and rural development of China. This paper focuses on the impact of farmers' e-commerce adoption on land transfer, aiming to reveal the role of farmers' e-commerce adoption in promoting rural transformation. Based on the 2020 Comprehensive Survey of Rural Revitalization in China conducted by the Chinese Academy of Social Sciences, this study employs the method of least squares and propensity score matching to evaluate the impact of farmers' e-commerce adoption on land-transfer behaviors in China. The results indicate that farmers' e-commerce adoption promotes farmers' participation in land transfer, significantly facilitating farmers' land transfer in and increasing the area of land acquired. Additionally, farmers' e-commerce adoption also promotes the trend of standardization and contractualization in land transfer, significantly increasing the probability of farmers signing formal agreements, clarifying lease terms, and renting land to strangers when acquiring land. This study can provide some theoretical inputs for policies to promote the development of agricultural land markets in developing countries and for policy formulation to promote e-commerce development.

Keywords: farmers' e-commerce adoption; land transfer; rural development; agricultural innovation; China

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1. Introduction

Developing countries generally face the problem of agricultural land fragmentation, which significantly constrains the transformation and development of agriculture and limits the rise of farmers' incomes [1,2]. Exploring effective ways to promote the transfer of agricultural land to achieve large-scale operations has become a topic of widespread concern in the academic community. Developing countries in South Asia, Africa, and other regions have adopted land reform policies to improve the situation of land fragmentation, and scholars are also actively researching the problem of land fragmentation and countermeasures to promote land transfers [3–5]. China, as the largest developing country in terms of economic size, faces even more prominent problems of rural land fragmentation and small-scale and scattered operations. The average per capita arable land area is less than 1 hectare [6]. Previous studies have shown that in 2003, the average land operation scale per rural household in China was 7.5 mu, with an average of 5.7 plots per household. By 2018, the per capita arable land area per household in the country was less than 7.5 mu, with a slight decrease in the average number of plots per household, but still around 5.5 plots [7]. The decentralized and small-scale land management model is no longer able to fully meet the needs of the large market and modernization. Also, land fragmentation will lead to the waste of arable land resources, increase agricultural production costs, and indirectly inhibit the increase in farmers' income [8,9].

Land transfer is one of the important means to solve land fragmentation and promote the centralized and contiguous operation of land [10] as well as to optimize land resource allocation and improve agricultural productivity. In recent years, the government has

attached great importance to the transfer of rural land contract management rights, issuing a series of documents, laws, and regulations to encourage farmers to carry out land transfers that are compatible with the current level of scientific and technological production. The government has also clearly regulated the ways and means of land transfer [11]. At the same time, rural society in China is characterized by a focus on kinship and personal relationships, and most of the land is traded among acquaintances, with a low proportion of paid and written contractualized transfers [12]. Scholars believe that land transfer among acquaintances is a kind of land transfer with low marketization and standardization [13,14]. Non-market land transfer hinders land integration, hinders the development of agricultural transfer markets, and is more likely to cause transaction disputes between farmers, limiting the increase in farmers' income [15,16]. Therefore, promoting land transfer and integration and facilitating the transition of land transactions to marketization and standardization is one of the means to promote the development of rural construction towards modernization.

Meanwhile, rural e-commerce is developing rapidly. According to the China Rural Digital Development Report, by 2022, online retail sales in rural China reached 2.17 trillion yuan. Studies have confirmed that adopting e-commerce can have a significant impact on the welfare of rural households. Some scholars believe that the entry of e-commerce into rural areas can effectively increase farmers' income. For instance, Qiu and Zhou [17] analyzed the positive impact of e-commerce development on rural residents' income from the perspective of effective demand and supply docking. Zeng et al. [18] found that participating in rural e-commerce can promote farmers' income growth by increasing profit margins and sales volume. Some scholars believe that adopting farmer e-commerce can narrow the urban–rural income gap by promoting farmers' income growth [17,19]. Existing research confirms that rural households participating in rural e-commerce improve their income structure, raise their living standards, and increase their risk awareness. The adoption of rural e-commerce by farmers improves the information asymmetry in traditional agricultural markets and enables farmers to obtain more information about product markets and sales channels [18,20,21]. This is conducive to reducing transaction costs and increasing farmers' production and operation income. With the increase in farmers' income, budget constraints are alleviated, making it more likely for them to transfer in land. Higher incomes for farmers have eased budgetary constraints, making it more likely that they will switch land. At the same time, due to the evaluation mechanism of the e-commerce platform, the adoption of e-commerce makes farmers have higher requirements for the quality and reputation of their products, and they are likely to ensure the quality of their products by renting land and operating their own business [22].

In addition, the adoption of e-commerce by rural households deepens the embedding of internal market mechanisms in rural areas, and the contractualization and standardization of land transfer will continue to improve. Existing studies have mostly explored the drivers of land transfer from other perspectives. Few studies have examined the impact of e-commerce adoption by farmers on land transfers [23]. Even if it does, it only mentions that e-commerce adoption affects land transfers, without specifically analyzing how it affects land transfers [24]. Based on this, this paper argues that e-commerce adoption by farmers is an important driving force to promote land transfer as well as contractualization and standardization of the transfer market. This paper will use nationally representative China Rural Revitalisation Survey (CRRS) data covering ten provinces to empirically reveal the impact of e-commerce adoption by farmers on their land-transfer participation and land-transfer marketization behaviors. Then it can provide feasible theoretical references to optimize the allocation of agricultural land resources and promote the transformation of the countryside into a modernized countryside. This study also provides a reference for other developing countries to cope with the problem of land fragmentation and promote land transfer, which helps other countries to optimize the allocation of resources, promote the transformation and upgrading of the rural economy, and improve the income of farmers, thus accelerating the modernization and development process of other developing countries. It also provides new research perspectives on the development of e-commerce

in these countries, which helps them formulate policies for e-commerce development and helps other countries better plan and manage their own rural e-commerce development.

The main contributions of this research include the following: First, it enriches the relevant literature on the socioeconomic impact of rural household e-commerce adoption, providing theoretical support for predicting the development of China's rural land market under the new era background. Existing research has mainly focused on studying the impact of rural e-commerce adoption on farmers' income [25–27], the urban–rural income gap [28], farmers' happiness [29], farmers' quality of life [12], and other welfare aspects, with relatively few studies on the impact of rural household e-commerce adoption on land transfer. Second, this study focuses on e-commerce, which has a widespread impact in rural China, enriching the literature on the driving factors of land transfer and providing a new perspective for research on land-transfer issues in other developing countries. Last, unlike the existing literature that mainly studies the impact of rural e-commerce on farmers at the village level, this study focuses on individual households, enriching the research on the welfare performance of rural e-commerce adoption at the household level.

The rest of this paper is organized as follows. Section 2 presents the theoretical analysis and research hypothesis. Section 3 introduces the materials and methods used in this study, and describes the variables. Section 4 presents the analysis results. Section 5 provides a discussion.

2. Theoretical Analysis and Research Hypotheses

Information is an important factor influencing the effective and rational allocation of resources in a market economy. In traditional markets, there is often asymmetric information, where one party possesses more and higher-quality information while the other party has less. In agricultural markets, farmers are often at a disadvantage in terms of information, receiving delayed and distorted market information [18]. However, the development of e-commerce has enhanced the information exchange between farmers and consumers, reducing information asymmetry. With the adoption of e-commerce, farmers can access market information timely and comprehensively, understand the market demand for agricultural products as well as consumer evaluations and needs, and adjust product supply accordingly. This reduces information search costs, improving their disadvantaged position [30,31]. Furthermore, e-commerce platforms can eliminate intermediary links, allowing farmers to set higher prices for their products [32]. With the dual mechanism of cost reduction and price increase, farmer incomes have significantly increased compared to before, allowing for more budget allocation to go toward land (Figure 1).

With the adoption of e-commerce, not only can farmers have a deeper and more timely understanding of the needs of the agricultural market, but consumers can also more accurately find agricultural products that meet their needs for purchase through the e-commerce channel. Then the goods provided by farmers and the goods needed by consumers can be more effectively matched, which helps to realize the matching of supply and demand, and thus increases the demand for agricultural products [33]. As the rational peasant, driven by profit, rural households will further expand the supply of their products through multiple channels, of which, in the context of easing budget constraints, scaling up operations through land transfers is a viable option [34]. Farmers may also expand the supply of their products by acting as middlemen, and there are also farmers who may choose to invest capital inputs in their existing land rather than expanding to increase outputs. However, it can be inferred that none of these farmers will choose to rent out their existing land. And so, on balance, the adoption of e-commerce by farmers will encourage them to rent land.

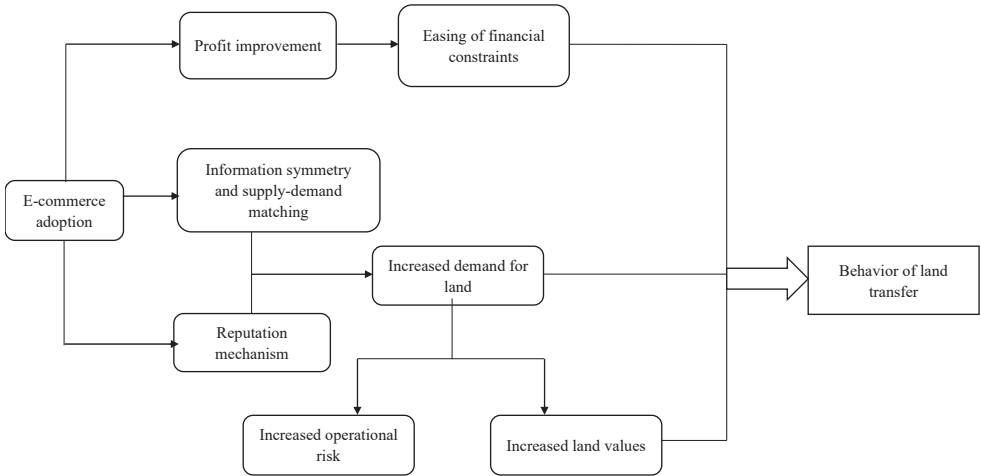


Figure 1. Logical framework diagram.

At the same time, e-commerce has a product display mechanism and a reputation incentive mechanism, and the orders can directly display previous consumers’ evaluations of the products so that consumers can understand the quality of the products before purchasing [35,36]. This mechanism directly influences whether new customers will make purchases and whether old customers will repurchase, reinforcing the impact of agricultural product quality on consumer decisions [37]. Therefore, as rational peasants, farmers will value reputation evaluations, quality control, and product quality. To reduce the risk of product quality issues, compared to purchasing products of unknown quality from others, farmers will tend to internalize the risk by leasing more land for their own cultivation and, therefore, will promote the transfer of agricultural land. Based on this, the following research hypothesis is proposed:

Hypothesis 1. *The adoption of e-commerce will promote the transfer of agricultural land through profit enhancement, supply–demand matching, and reputation mechanisms.*

Further, e-commerce sales have made traditional agricultural production more closely linked to the market, and as farmers expand their production, they need to be more sensitive to market information and respond to changes in the market. Otherwise, they may face a backlog of products or even losses. This means that compared to farmers who have not adopted e-commerce sales, farmers who adopt e-commerce sales face relatively higher risks in production and operation. In addition, the participation of farmers in e-commerce represents the development of local e-commerce, increasing consumer demand for local agricultural products and prompting an increase in the transfer price of agricultural land rights [24]. This enhances the value represented by the land itself, further emphasizing the importance of land value to land transferees. With the adoption of e-commerce, land transactions become more active. The inevitable increase in transaction volume will inevitably bring more disputes [38]. From both the perspective of rising land value and the perspective of risk, farmers are more cautious when transferring land, preferring standardized and contractual means to ensure their rights. Therefore, to some extent, the adoption of e-commerce prompts farmers’ land-transfer behavior to become more market-oriented, preferring a contractual mode dominated by the market rules of the stranger society.

Hypothesis 2. *The adoption of e-commerce will promote farmers to transfer land through more market-oriented and contractual means.*

3. Materials and Methods

3.1. Data Sources

This study utilizes data from the “China Rural Revitalization Survey” (CRRS), conducted by the Rural Development Institute of the Chinese Academy of Social Sciences from August to September 2020. The sample for this survey was drawn in accordance with the principle of multi-stage stratified random sampling. Considering the economic development and agricultural production of each province, provinces were randomly selected at a ratio of one-third in each of the eastern, central, western, and northeastern regions, and a total of ten provinces were selected. Counties were randomly sampled based on per capita GDP, with efforts made to cover the entire province spatially. Using the same sampling method, townships and villages were randomly selected based on their local economic development levels. Finally, sample households were randomly selected based on rosters provided by village committees. The selected provinces were Guangdong, Zhejiang, Shandong, Anhui, Henan, Heilongjiang, Guizhou, Sichuan, Shaanxi, and Ningxia Hui Autonomous Region. The survey covered 50 counties (cities) and 156 townships (towns), resulting in a total of 3830 completed household survey questionnaires.

3.2. Research Method

This study will first utilize the empirical analysis framework based on ordinary least squares (OLS) to estimate the impact of farmers’ adoption of e-commerce on land transfer. The specific model setting is as follows:

$$Y_i = \alpha + \delta Ecommerce_i + \beta X_i + \eta_i + \varepsilon \quad (1)$$

In Equation (1), Y_i represents the dependent variable of interest in this study, indicating the situation of land transfer; $Ecommerce$ indicates whether farmers adopt e-commerce; δ represents the degree of influence of farmers’ adoption of e-commerce on land-transfer behavior; X represents other control variables; β represents the coefficients of control variables; η_i represents provincial fixed effects; and ε represents the random disturbance term.

In reality, rural households carry out various behaviors related to land transfer as the result of subjective initiative, not a random event. The individual characteristics of households and family characteristics will also affect the behavior of farmers related to land transfer. If we ignore these potential factors, the resulting estimates are biased. To overcome the sample selection problem, this study introduces propensity score matching (PSM). The core idea of PSM is to match farmers who adopt e-commerce and those who do not based on observed farmer characteristics, ensuring that the two groups of farmers are in a balanced and comparable state. Subsequently, the differences in land management behaviors between the two groups of farmers are further compared. Specifically, the propensity score obtained by farmers participating in e-commerce is the probability of farmers participating in e-commerce under certain conditions. Before calculating the impact of e-commerce adoption on land market development, it is necessary to calculate the propensity score matching values based on the probit model. The specific model setting is as follows:

$$P(Z_i) = P(Ecommerce = 1|Z_i) = \Lambda(Z_i'\beta) = \exp(Z_i'\beta) / (1 + \exp(Z_i'\beta)) \quad (2)$$

In Equation (2), $P(Ecommerce = 1|Z_i)$ represents the propensity score matching value for farmers participating in e-commerce, where Z_i is the matching variable. After calculating the propensity score matching values, various matching methods can be used to match farmers who adopt e-commerce with those who do not. This study employs methods such as 1:1 nearest neighbor matching, kernel matching, and radius matching. Once the matching is completed, the impact of farmers’ adoption of e-commerce on land market development can be assessed. Typically, the average treatment effect of the treated (ATT)

is calculated to characterize the impact of farmers’ adoption of e-commerce. The specific model setting is as follows:

$$ATT = E(Y_1|Ecommerce = 1) - E(Y_0|Ecommerce = 1) = E(Y_1 - Y_0|Ecommerce = 1) \tag{3}$$

In Equation (3), Y_1 represents the land transfer status of farmers who adopt e-commerce, and Y_0 represents the land transfer status of farmers who do not adopt e-commerce.

3.3. Variable Selection and Description

Dependent variable: The dependent variable of interest in this study is the situation of land transfer, mainly characterized by two categories of indicators. The first category is the participation of farmers in land transfer, including whether farmers engage in land transfer (1 = yes; 0 = no), whether they engage in land transfer in (1 = yes; 0 = no), the scale of land transfer in (in mu), whether they engage in land transfer out (1 = yes; 0 = no), and the scale of land transfer out (in mu). The second category is the market-oriented behavior of land transfer, including whether farmers have signed written agreements (1 = yes; 0 = no), whether they have specified the lease term (1 = yes; 0 = no), whether they receive or pay monetary rent (1 = yes; 0 = no), and whether they rent land to acquaintances or rent land from acquaintances (1 = yes; 0 = no).

Core explanatory variable: Referring to previous measures of farmers’ adoption or participation in agricultural e-commerce [39], the core explanatory variable of interest in this study is measured by whether farmers operate products through online transactions at home (1 = yes; 0 = no). According to the descriptive statistical analysis of variables (Table 1), 6.3% of the 3726 farming households sell their agricultural products online.

Table 1. Descriptive statistics for variables.

Variable	Variable Description	Sample Size	Mean	Std.
Dependent Variables				
Land Transfer	1 = Yes, 0 = No	3627	0.536	0.499
Land Transfer Out	1 = Yes, 0 = No	3595	0.324	0.468
Written Agreement	1 = Yes, 0 = No	1133	0.643	0.475
Clearly Defined Lease Term	1 = Yes, 0 = No	1133	0.605	0.489
Cash Rent Collection	1 = Yes, 0 = No	1002	0.965	0.184
Transfer to Acquaintances	1 = Yes, 0 = No	905	0.534	0.499
Land Transfer In	1 = Yes, 0 = No	3580	0.249	0.432
Written Agreement	1 = Yes, 0 = No	885	0.349	0.477
Clearly Defined Lease Term	1 = Yes, 0 = No	881	0.359	0.480
Cash Rent Payment	1 = Yes, 0 = No	646	0.952	0.214
Transfer from Acquaintances	1 = Yes, 0 = No	849	0.802	0.399
Core Explanatory Variable				
E-commerce Adoption	Whether products are sold online; 1 = Yes, 0 = No	3726	0.063	0.243
Control Variables				
Gender of Household Head	1 = Male; 0 = Female	3827	0.934	0.248
Education of Household Head	1 = High school and above; 0 = Below high school	3830	0.152	0.359
Age of Household Head	Year	3816	55.019	11.236
Ethnicity of Household Head	1 = Han ethnicity; 0 = Minority ethnicity	3830	0.875	0.330
Household Head as Village Cadre	1 = Yes, 0 = No	3830	0.070	0.255
Number of Labor Force in Family	Population aged 14–64	3830	2.863	1.338
Proportion of Children in Family	Proportion of the population under 14	3540	0.265	0.426
Proportion of Elderly in Family	Proportion of the population over 64	3540	0.198	0.408

Control variables: To further eliminate the potential influence of omitted factors, drawing on previous research [12,40], this paper also controls for individual characteristics

of farmers (such as gender of household head, education, age, ethnicity, and holding village cadre positions) as well as household characteristics (such as the proportion of children, the proportion of elderly, and the number of labor force). These control variables were chosen with the following considerations in mind: when the head of the household is more educated, he or she has more opportunities for off-farm employment, is better financed, and is more likely to transfer land. When the household head is older, he or she has reduced physical strength and is, therefore, less likely to transfer land. Considering that the increase in the number of children under the age of 14 and the number of elderly people over the age of 64 creates a burden on households, it is expected that these households will be less likely to lease land. However, when the farmer has a larger number of household laborers, the head of the household is a man or a village cadre, they are more likely to lease land. Additionally, this study also controls for provincial fixed effects in empirical estimation.

Table 2 reveals that the proportion of land transfer among farmers who adopt e-commerce is slightly higher than those who do not. As Figure 2 shows, farmers who adopt e-commerce have significantly higher proportions of land transfer in and larger areas of acquired land compared to those who do not adopt e-commerce. As Figure 3 shows, the proportion of land transfer and the area of land transferred among farmers who adopt e-commerce are slightly lower than those who do not.

Table 2. Preliminary relationship between farmers’ e-commerce adoption and farmland-transfer behavior.

E-Commerce Adoption	Land Transfer	Land Transfer In	Land Transfer In Area	Land Transfer Out	Land Transfer Out Area
Adoption	0.570	0.372	40.245	0.273	1.917
Non-Adoption	0.531	0.245	11.404	0.323	2.278
Difference	0.039	0.127 ***	28.841 ***	−0.050	−0.361

Note: *** indicates significance at the 1% level.

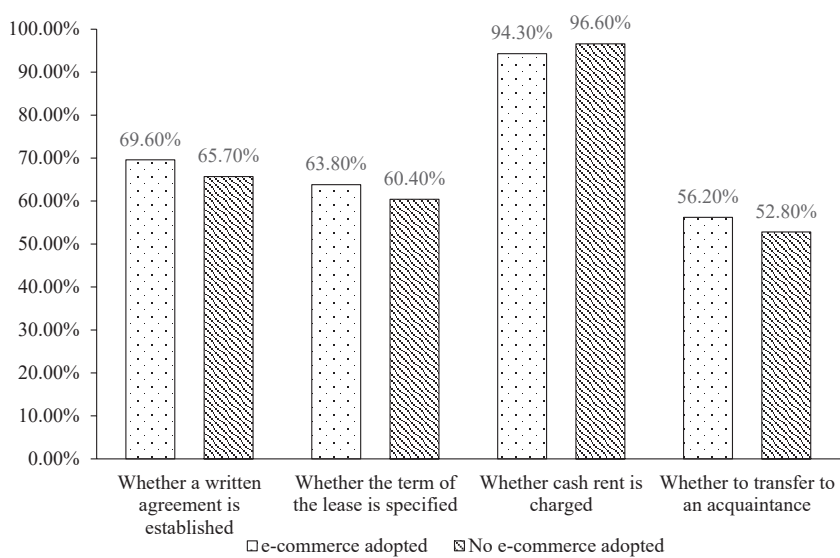


Figure 2. Marketability of land turnout under different e-commerce adoption.

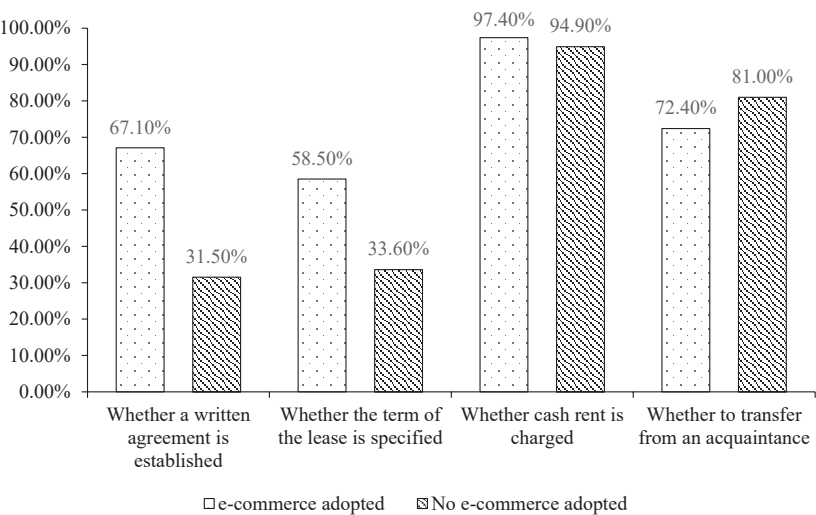


Figure 3. Marketization status of land transfers under different e-commerce adoption.

4. Results

4.1. Baseline Regression

This paper initially explores the impact of farmers’ adoption of e-commerce on their participation in land-transfer behavior based on the framework of ordinary least squares (OLS) empirical analysis. The estimation results in Table 3 demonstrate that the adoption of e-commerce by farmers has a significant impact on their participation in land transfer, primarily manifested in promoting farmers’ acquisition of land, leading to an 11.1% increase in the probability of leasing land. The adoption of e-commerce by farmers increases the probability of renting land by 11.1 percent, with an average probability of land transfer of 24.9%, making this result economically significant. However, the baseline regression results did not reveal a significant impact of farmers’ adoption of e-commerce on their land-transfer-out behavior.

Table 3. The impact of farmers’ adoption of e-commerce on their participation in land transfer.

Explanatory Variables	Dependent Variables:		
	Land Transfer (1 = Yes; 0 = No) (1)	Land Transfer In (1 = Yes; 0 = No) (2)	Land Transfer Out (1 = Yes; 0 = No) (3)
E-commerce Adoption	0.052 (1.47)	0.111 *** (3.63)	−0.020 (−0.62)
Gender of Household Head	0.048 (1.52)	0.169 *** (5.27)	−0.097 ** (−2.87)
Education of Household Head	−0.041 (−1.65)	−0.094 *** (−4.33)	0.035 (1.56)
Age of Household Head	−0.001 (−1.29)	−0.005 ** (−5.72)	0.004 *** (4.11)
Ethnicity of Household Head	0.04 (1.54)	0.046 * (2.00)	−0.003 (−0.13)
Household Head as Village Cadre	−0.049 (−1.41)	0.003 (0.09)	−1.83 (0.019)
Proportion of Children under 14 in Family	−0.059 * (−2.27)	−0.058 * (−2.53)	0.009 (0.39)
Proportion of Elderly over 64 in Family	−0.013 (−0.61)	−0.0189 (−0.99)	0.003 (0.15)
Number of Labor Force in Family	−0.016 (−1.84)	0.007 (0.95)	−0.026 ** (−3.10)
Provincial Fixed Effects	controlled	controlled	controlled
Observations	3260	3246	3246
R-squared	0.006	0.015	0.015

Notes: (1) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; (2) T-values are shown in parentheses.

4.2. Robustness Analysis

4.2.1. Replacement of Dependent Variables

In order to test the robustness of the baseline model, this paper firstly replaces the explanatory variables with land area of transferred in and transferred out to estimate the model. The results are shown in Table 4. From the estimation results, it can be observed that after replacing the dependent variables, the adoption of e-commerce by farmers has a significant positive impact on the area of land transferred in. Specifically, the adoption of e-commerce by farmers leads to a significant increase in the area of land transferred in by over 26 mu. However, the impact on the area of land transferred out is not significant. This is consistent with the results of the baseline regression.

Table 4. The impact of farmers’ adoption of e-commerce on the area of land transferred.

Explanatory Variables	Dependent Variables:	
	Land Transferred In Area (1)	Land Transferred Out Area (2)
E-commerce Adoption	26.010 *** (4.96)	−0.035 (−0.06)
Gender of Household Head	8.369 (1.52)	−0.051 (−0.08)
Education of Household Head	−0.467 (−0.13)	0.488 (1.10)
Age of Household Head	−0.555 *** (−4.00)	0.055 ** (3.29)
Ethnicity of Household Head	7.276 (1.87)	0.377 (0.80)
Household Head as Village Cadre	6.753 (1.29)	−0.860 (−1.37)
Proportion of Children under 14 in Family	−3.067 (−0.79)	−0.531 (−1.13)
Proportion of Elderly over 64 in Family	−3.011 (−0.93)	−1.035 ** (−2.66)
Number of Labor Force in Family	−0.311 (−0.23)	−0.634 *** (−3.96)
Provincial Fixed Effects	controlled	controlled
Observations	3229	3246
R-squared	0.033	0.009

Notes: (1) *** $p < 0.01$, ** $p < 0.05$; (2) T-values are shown in parentheses.

4.2.2. Propensity Score Matching

In the second step of the robustness test in this paper, the impact of farmers’ adoption of e-commerce on their participation in land transfer is validated through propensity score matching. To ensure the quality of matching between the ‘treatment group’ and the ‘control group’ in propensity score matching, it is necessary to check the common support conditions of the matching. If the common support is too narrow, it will result in too much sample loss and ineffective matching. The common support requires that there is sufficient overlap between the propensity score values of the ‘treatment group’ and the ‘control group’, i.e., there should be a substantial ‘common support domain’. This paper further calculates the sample loss under different propensity score methods to determine how many samples have propensity score values within the common support domain. Under 1:1 nearest neighbor matching, kernel matching, and radius matching, when the dependent variables of interest are whether to engage in land transfer, whether to transfer in land, transfer in area, whether to transfer out land, transfer out area, and land operating area, the sample loss is between 5% and 6%. This means that there are enough samples with propensity score matching values within the common support domain. Therefore, it is reasonable to believe that the estimation bias caused by the lost samples is very small.

Given the differences between farmers who adopt e-commerce and those who do not at the individual and household levels, as evidenced in the results before matching in Table 5, it is clear that there are significant differences in endowment characteristics between these two types of farmers. Such differences may introduce biases in the estimation when using the least square method. After matching, except for the variable ‘transfer to acquaintances’, the standardized biases of other explanatory variables are all less than 10%, with many variables showing standardized biases of less than 3%. This is significantly lower than the standardized biases before matching. Additionally, it can be observed that the differences in endowment characteristics between the ‘treatment group’ and the ‘control group’ have shifted from significant before matching to non-significant after matching. These results indicate that the matched samples have similar characteristics, and the overall bias has been significantly reduced, thus passing the balance test.

Table 5. Balance test results of dependent variables before and after matching.

Dependent Variable	Matching Status	Pseudo R ²	LR Statistic	p-Value	Mean Bias
Land Transfer	Before Matching	0.028	44.68	0.000	17.900
	After Matching	0.005	2.740	0.841	4.500
Land Transfer In	Before Matching	0.027	43.38	0.000	17.300
	After Matching	0.000	0.220	1.000	1.500
Transfer In Area	Before Matching	0.027	43.38	0.000	17.300
	After Matching	0.000	0.220	1.000	1.500
Land Transfer Out	Before Matching	0.029	45.91	0.000	18.100
	After Matching	0.003	1.920	0.927	4.300
Transfer Out Area	Before Matching	0.041	70.96	0.000	18.200
	After Matching	0.002	1.530	0.997	2.800
Sign Written Lease In	Before Matching	0.022	11.91	0.008	24.200
	After Matching	0.007	1.540	0.673	9.900
Specify Lease Term	Before Matching	0.022	12.00	0.007	24.400
	After Matching	0.004	1.40	0.705	9.400
Pay Cash Rent	Before Matching	0.016	7.30	0.063	19.500
	After Matching	0.001	0.20	0.978	1.700
Transfer to Acquaintances	Before Matching	0.018	8.840	0.032	22.100
	After Matching	0.004	00.90	0.826	7.800
Sign Written Lease Out	Before Matching	0.050	21.50	0.001	26.500
	After Matching	0.005	0.840	0.991	5.300
Specify Lease Term	Before Matching	0.046	20.30	0.002	25.600
	After Matching	0.008	1.190	0.977	6.100
Collect Cash Rent	Before Matching	0.048	19.28	0.004	25.400
	After Matching	0.012	1.660	0.948	9.100
Transfer to Acquaintances	Before Matching	0.056	20.12	0.003	27.500
	After Matching	0.024	3.070	0.800	11.900

Notes: The propensity score matching method used in the table is 1:1 nearest neighbor matching. The paper also conducted balance tests using kernel matching and radius matching methods, and the results are highly consistent with the conclusions in Table 5. Due to space limitations, they are not presented here.

Therefore, both the common support test and the balance test are passed, indicating that the estimation results obtained based on propensity score matching are reliable.

Table 6 presents the results using 1:1 nearest neighbor matching, kernel matching, and radius matching. The results show that the adoption of e-commerce by farmers does not have a robust positive significant effect on their participation in land transfer or land transfer out. However, the adoption of e-commerce by farmers has a significant positive effect on their land transfer in and the increase in transfer in area, both at the 1% significance level. Moreover, there is no significant difference in the magnitude of the coefficients compared to the estimates from ordinary least squares. Overall, the conclusions from Table 6 further confirm the significant promoting effect of farmers’ adoption of e-commerce on their participation in land transfer.

Table 6. Effects of farmers’ adoption of e-commerce on their participation in land transfer under propensity score matching (PSM).

Dependent Variable	Adoption of E-Commerce	1:1 Nearest Neighbor Matching	Kernel Matching	Radius Matching
Land Transfer	Adopt E-commerce	0.577	0.577	0.577
	Not Adopt E-commerce	0.523	0.519	0.520
	Difference	0.055	0.058 *	0.057
Land Transfer In	Adopt E-commerce	0.376	0.376	0.376
	Not Adopt E-commerce	0.256	0.259	0.260
	Difference	0.119 ***	0.117 ***	0.115 ***
Transfer In Area	Adopt E-commerce	41.050	41.050	41.050
	Not Adopt E-commerce	11.492	13.114	13.140
	Difference	29.558 ***	27.936 ***	27.910 ***
Land Transfer Out	Adopt E-commerce	0.277	0.277	0.277
	Not Adopt E-commerce	0.329	0.295	0.294
	Difference	−0.052	−0.018	−0.017
Transfer Out Area	Adopt E-commerce	1.938	1.938	1.938
	Not Adopt E-commerce	2.138	1.994	1.986
	Difference	−0.200	−0.064	−0.048

Notes: (1) *** $p < 0.01$, * $p < 0.1$. (2) The estimated results in the table are the Average Treatment Effects (ATT).

4.3. Heterogeneity Analysis

4.3.1. Individual Heterogeneity Analysis

Previous regressions treated farmers as homogeneous individuals. However, in reality, farmers with different characteristics may exhibit heterogeneity in their adoption of e-commerce. According to other studies, farmers’ education level and whether they are engaged in non-agricultural employment often influence their land-transfer behavior [22,41–43]. Therefore, this section will focus on the heterogeneity effects of farmers’ education level and employment status. Education level is divided into two groups: low-education-level group (below high school) and high-education-level group (high school and above); employment status is divided into off-farm employment and agricultural employment. The results of the heterogeneity tests for the two groups are shown in Tables 7 and 8, respectively.

Table 7. Heterogeneity analysis based on educational levels.

Dependent Variable	Land Transfer		Land Transfer in		Land Transfer out	
	Low-Educated (1)	High-Educated (2)	Low-Educated (3)	High-Education (4)	Low-Educated (5)	High-Educated (6)
E-commerce Adoption	0.112 *** (2.73)	−0.082 (−1.19)	0.135 *** (3.69)	0.070 (1.25)	0.024 (0.62)	−0.124 * (−1.91)
Control Variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	2737	512	2717	509	2725	510
R-Squared	0.008	0.036	0.035	0.033	0.017	0.026

Notes: (1) *** $p < 0.01$, * $p < 0.1$; (2) Values in parentheses are t-values.

As shown in Table 7, the adoption of e-commerce has a greater impact on the participation of low-educated farmers in land transfer, significantly promoting this group to engage in land transfer. Specifically, it positively encourages this group to acquire land, and the effect is significant at the 1% level. However, the effect on the participation of highly educated farmers in land transfer is relatively minor, only reducing the probability of these farmers transferring out land at the 10% level. This could be because highly educated

farmers, compared to low-educated ones, have a higher level of cognitive understanding, possess more knowledge about markets and sales, and have stronger skills. Hence, the marginal utility brought about by the adoption of e-commerce is relatively lower for them.

Table 8. Heterogeneity analysis based on employment status.

Dependent Variable	Land Transfer		Land Transfer in		Land Transfer out	
	Off-Farm Employment (1)	Agricultural Employment (2)	Off-Farm Employment (3)	Agricultural Employment (4)	Off-Farm Employment (5)	Agricultural Employment (6)
E-commerce Adoption	0.091 * (1.87)	0.026 (0.52)	31.946 *** (5.56)	20.894 ** (2.43)	−0.001 (−0.00)	−0.027 (−0.03)
Control Variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	1391	1854	1375	1847	1386	1845
R-Squared	0.017	0.010	0.040	0.024	0.012	0.014

Notes: (1) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; (2) Values in parentheses are t-values.

Table 8 shows that the adoption of e-commerce has a significant positive impact on off-farm employed farmers in terms of land transfer and land transfer in. This might be due to the fact that farmers with off-farm employment in their work have higher incomes compared to full-time agricultural farmers and, therefore, have a higher budget to invest in more land for agricultural production, which aligns with hypothesis 1. Meanwhile, the result is economically significant as e-commerce adoption increases the probability of low-education-level farmers renting land by 13.5%.

4.3.2. Regional Heterogeneity Analysis

Due to the disparities in development among different provinces in China, the impact of rural household e-commerce adoption on their participation in land transfer may vary across different regions. According to previous understanding, economically developed provinces typically have better communication infrastructure, which leads to faster dissemination of information even before the adoption of rural e-commerce. Moreover, these provinces often exhibit a higher degree of implementation of government policies related to land, reducing the likelihood of further influence from rural e-commerce adoption. Conversely, this might not be the case in central and western regions. Among the ten sampled provinces in this study, Heilongjiang, Henan, and Anhui belong to the central region; Zhejiang, Shandong, and Guangdong belong to the eastern region; and Sichuan, Guizhou, Shaanxi, and Ningxia belong to the western region. After the regional delineation, regional heterogeneity analysis is conducted.

Among the 3830 surveyed rural households, a total of 1928 households engaged in land transfer, as shown in Table 9. Columns (1) to (3) indicate that in central and western regions, rural household e-commerce adoption significantly promotes land transfer, while it has no significant effect in the eastern region. The specific impact can be observed in columns (4) to (9): the probability of a household farmer adopting e-commerce transferring in land increased significantly in both the central and western regions, by 13.5 percent and 18.6 percent, respectively, whereas rural households in the eastern region do not experience a significant impact. This indicates that the influence of e-commerce adoption on land-transfer behavior among rural households in the eastern region is lower compared to those in the central and western regions, which aligns with our hypothesis. This means that in the eastern part of the country, the economy and the market are more developed, and the education level of farmers is higher, which means that agricultural e-commerce adoption plays a very limited role in mitigating information asymmetry. Meanwhile, due to the average probability of farmland transfer in being 24.9%, this result also has economic significance.

Table 9. Regional heterogeneity analysis based on region.

Dependent Variable	Land Transfer			Land Transfer in			Land Transfer out		
	Eastern (1)	Central (2)	Western (3)	Eastern (4)	Central (5)	Western (6)	Eastern (7)	Central (8)	Western (9)
E-commerce Adoption	−0.020 (−0.32)	0.118 * (1.77)	0.094 * (1.71)	0.035 (0.74)	0.135 ** (2.12)	0.186 *** (4.04)	−0.040 (−0.67)	0.064 (1.05)	−0.043 (−0.85)
Control Variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	845	975	1429	921	1029	1518	842	967	1426
R-Squared	0.030	0.035	0.006	0.023	0.097	0.033	0.045	0.028	0.013

Notes: (1) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; (2) Values in parentheses are t-values.

4.4. Further Analysis

Having established that e-commerce adoption significantly promotes rural households' engagement in land transfer, a natural extension of the inquiry arises: does rural household e-commerce adoption act as a driver for land transfer toward marketization? This paper further explores this question empirically based on research data.

Four dimensions are employed to measure the degree of marketization of land transfer: whether a written agreement is signed, whether the lease term is clearly defined, whether monetary rent is used, and whether the transferee is an acquaintance. These are used as dependent variables, focusing on rural households engaging in land transfer. The empirical analysis based on least squares method results (Table 10) indicates that rural household e-commerce adoption significantly facilitates land transfer toward marketization.

Table 10. Impact of e-commerce adoption on land-transfer marketization.

	Signed Agreement	Defined Lease Term	Monetary Rent	Transferee
	(1)	(2)	(3)	(4)
E-commerce Adoption	0.336 *** (6.19)	0.228 *** (4.09)	0.027 (1.03)	−0.067 * (−1.68)
Control Variables	Controlled	Controlled	Controlled	Controlled
Observations	855	851	631	823
R-Squared	0.085	0.045	0.053	0.030

Notes: (1) *** $p < 0.01$, * $p < 0.1$; (2) Values in parentheses are t-values.

Specifically, rural households adopting e-commerce are 33.6% more likely to sign agreements and 22.8% more likely to define lease terms, with these effects being significant at the 1% level. Moreover, e-commerce adoption leads to a significant 6.7% decrease in the probability of land transfer with acquaintances, significant at the 10% level. These findings reveal that when rural households adopt e-commerce to sell products, they tend to engage in more market-oriented transfer behaviors, thus propelling China's rural land market towards standardization and contractualization.

Further estimation of the impact of rural household e-commerce adoption on the marketization of land transfer was conducted using propensity score matching. The results are presented in Table 11.

The conclusions drawn from 1:1 nearest neighbor matching, kernel matching, and radius matching methods support the results obtained from OLS estimation, indicating that e-commerce adoption enhances the probability of rural households engaging in land transfer through more contractual and modernized means. Specifically, for rural households involved in land transfer, e-commerce adoption significantly increases the probability of signing written agreements and defining lease terms. Moreover, under 1:1 nearest neighbor matching, there is a significant increase in the probability of rural households paying cash rent when acquiring land.

Table 11. Impact of rural household e-commerce adoption on marketization of land-transfer behavior under PSM.

Explained Variable	E-Commerce Adoption	1:1 Nearest Neighbor Matching	Kernel Matching	Radius Matching
Signed Agreement	Adopt E-commerce	0.718	0.718	0.718
	Not Adopt E-commerce	0.535	0.436	0.439
	Difference	0.183 **	0.282 ***	0.280 ***
Defined Lease Term	Adopt E-commerce	0.620	0.620	0.620
	Not Adopt E-commerce	0.501	0.459	0.471
	Difference	0.119 *	0.151 **	0.149 **
Monetary Rent	Adopt E-commerce	0.972	0.972	0.972
	Not Adopt E-commerce	0.895	0.951	0.951
	Difference	0.077 **	0.021	0.020
Transferee Acquaintance	Adopt E-commerce	0.718	0.718	0.718
	Not Adopt E-commerce	0.734	0.760	0.759
	Difference	−0.015	−0.042	−0.041

Notes: (1) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (2) The estimated results in the table are the Average Treatment Effects (ATT).

5. Discussion

5.1. Conclusions and Discussion

The continuous development of rural factor markets is a central part of rural transformation, and land factors are an important part of rural factor markets. Therefore, exploring how the adoption of new technologies contributes to the factorization of agricultural land is an important prerequisite for understanding how the process of rural transformation takes place. This study, based on data from the Comprehensive Rural Revitalization Survey (CRRS) conducted by the Chinese Academy of Social Sciences, investigates the impact of rural household e-commerce adoption on land transfer. Utilizing both ordinary least squares (OLS) and propensity score matching (PSM) methods, empirical results demonstrate that rural household e-commerce adoption significantly facilitates land transfer by promoting both the likelihood and the scale of land influx. Moreover, rural household e-commerce adoption enhances the marketization of rural land transfer by increasing the probability of signing written agreements, defining lease terms, and transferring land to strangers. This indicates a shift towards more contractual and standardized practices in the rural land-transfer market. Additionally, regional heterogeneity analysis reveals that the influence of rural household e-commerce adoption on land transfer is more pronounced in the central and western regions compared to the eastern region. Furthermore, individual heterogeneity analysis indicates that households with lower education levels and engaged in non-agricultural activities are more likely to participate in land transfer after adopting rural e-commerce.

5.2. Policy Recommendations

The policy implications of this article are as follows. Firstly, as of 2020, only 6.3% of Chinese rural households utilize e-commerce channels to sell agricultural products, indicating significant room for improvement in agricultural product sales through e-commerce channels. China’s digital infrastructure is now very well developed, with the world’s largest fiber-optic network and the world’s largest 5G network in terms of speed and scale [44]. In the context of the digital economy, the ability to use e-commerce platforms to increase incomes depends largely on the digital literacy of farmers. Therefore, further expansion of rural e-commerce needs to strengthen the capacity of farmers to utilize emerging technologies [45,46]. Secondly, while e-commerce adoption can facilitate the transfer of agricultural land and lead to further concentration of agricultural land, it may further induce new inequalities. For example, previous studies have found that agriculture can play an important buffering role as a ‘reservoir’ when non-farm employment is hit [47,48].

When rural laborers in non-farm employment face negative economic shocks, they are likely to return to their home villages with the expectation that agricultural production will secure their daily lives. However, since land management rights have been transferred, agricultural production cannot serve as the last barrier to secure their livelihoods. Therefore, the relevant authorities should further reform China's household registration system so that peasants working in the cities can access equal public services as urban residents. Thirdly, given the differential impact of e-commerce adoption on the land-transfer behavior of farmers in different regions of China, relevant policies and resource inputs aimed at promoting e-commerce adoption among farmers should be tilted towards less developed regions.

5.3. Limitations and Future Prospects

This study has the following limitations. On the one hand, although we used PSM to identify the impact of farmers' e-commerce adoption on their land-transfer behaviors, there are still unobservable factors that both influence farmers' e-commerce adoption and land-transfer behavior. Therefore, future research can try to find a more appropriate identification strategy to carry out the analysis. On the other hand, the e-commerce adoption behaviors of farmers are not homogeneous, as some farmers apply for registration of online shops for sales, while others just post product information on social platforms to promote sales. Therefore, even if they all belong to e-commerce adoption, farmers' behaviors are different, so future research can further expand the impact of different e-commerce behaviors on land transfer.

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References

1. Hung, P.; MacAulay, T.G.; Marsh, S. The economics of land fragmentation in the north of Vietnam. *Aust. J. Agric. Resour. Econ.* **2007**, *51*, 195–211. [CrossRef]
2. Manjunatha, A.; Anik, A.; Speelman, S.; Nuppenau, E. Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in India. *Land Use Policy* **2013**, *31*, 397–405. [CrossRef]
3. Niroula, G.; Thapa, G. Impacts and causes of land fragmentation, and lessons learned from land consolidation in South Asia. *Land Use Policy* **2005**, *22*, 358–372. [CrossRef]
4. Tan, S.; Heerink, N.; Qu, F. Land fragmentation and its driving forces in China. *Land Use Policy* **2006**, *23*, 272–285. [CrossRef]
5. Leeuwen, M. Renegotiating customary tenure reform—Land governance reform and tenure security in Uganda. *Land Use Policy* **2014**, *39*, 292–300. [CrossRef]
6. Huang, J.; Ding, J. Institutional innovation and policy support to facilitate small-scale farming transformation in China. *Agric. Econ.* **2014**, *47*, 227–237. [CrossRef]
7. Liu, T.; Qian, L. Experiences and insights on the governance of agricultural land fragmentation in developed countries—Taking Germany, France, the Netherlands and Japan as examples. *Acad. J. Zhongzhou* **2023**, *7*, 58–66.
8. Wan, G.; Cheng, E. Effects of land fragmentation and returns to scale in the Chinese farming sector. *Appl. Econ.* **2001**, *33*, 183–194. [CrossRef]
9. Wang, S.; Li, D.; Li, T.; Liu, C. Land Use Transitions and Farm Performance in China: A Perspective of Land Fragmentation. *Land* **2021**, *10*, 792. [CrossRef]

10. Wang, Y.; Li, X.; Lu, D.; Yan, J. Evaluating the impact of land fragmentation on the cost of agricultural operation in the southwest mountainous areas of China. *Land Use Policy* **2020**, *99*, 105099. [CrossRef]
11. Gong, M.; Yi, K. Contracted Land Rights, Agricultural Subsidies and Farmers' Land Transfers—An Empirical Test Based on CHFS Data. *Contemp. Econ. Res.* **2023**, *3*, 98–108.
12. He, X.; Jiang, T.; Guo, L.; Gan, L. A study on the development of farmland transfer market and farmers' behaviour in transferring farmland in China—Based on the data of farmers' survey in 29 provinces from 2013 to 2015. *Manag. World* **2016**, *6*, 79–89.
13. Deininger, K.; Jin, S. Securing property rights in transition: Lessons from implementation of China's rural land contracting law. *J. Econ. Behav. Organ.* **2009**, *70*, 22–38. [CrossRef]
14. Wang, H.; Riedinger, J.; Jin, S. Land documents, tenure security and land rental development: Panel evidence from China. *China Econ. Rev.* **2015**, *36*, 220–235. [CrossRef]
15. Kong, X.; Xu, Z. Analysis of Influencing Factors on the Choice of Transfer Objects by Farmers Transferring Land—An Empirical Analysis Based on a Comprehensive Perspective. *China Rural Econ.* **2010**, *12*, 17–25+67.
16. Jiang, S.; Su, Q. The Rent Stratification Phenomenon in Agricultural Land Transfer and Its Root Causes. *Issues Agric. Econ.* **2013**, *34*, 42–48+110–111.
17. Qiu, Z.; Zhou, Y. Mechanism analysis of the role of e-commerce on rural households' income increase—A micro test based on the effective matching of demand and supply. *China Rural Econ.* **2021**, *4*, 36–52.
18. Zeng, Y.; Guo, H.; Jin, S. Is e-commerce beneficial to farmers' income?—Evidence from Shuyang, Jiangsu Province. *China Rural Econ.* **2018**, *2*, 49–64.
19. Li, X.; Li, J. A Study on the Impact of Digital Economy Development on Rural-Urban Income Gap. *J. Agrotech. Econ.* **2022**, *2*, 77–93.
20. Pool, B. How Will Agricultural E-Markets Evolve? In Proceedings of the USDA Outlook Forum, Washington, DC, USA, 22 February 2001; pp. 22–23.
21. Bonfadelli, H. The Internet and Knowledge Gaps: A Theoretical and Empirical Investigation. *Eur. J. Commun.* **2002**, *17*, 65–84. [CrossRef]
22. Deng, X.; Xu, D.; Zeng, M.; Qi, Y. Does labor off-farm employment inevitably lead to land rent out? Evidence from China. *J. Mt. Sci.* **2019**, *16*, 689–700. [CrossRef]
23. Wang, Y.; Yang, A.; Li, Y.; Yang, Q. Effect of e-commerce popularization on farmland abandonment in rural China: Evidence from a large-scale household survey. *Land Use Policy* **2023**, *135*, 106958. [CrossRef]
24. Qin, F.; Wang, J.; Xu, Q. How can the digital economy boost farm incomes?—Evidence from rural e-commerce development. *China Econ. Q.* **2022**, *22*, 591–612.
25. Yang, B.; Wang, X.; Wu, T.; Deng, W. Reducing farmers' poverty vulnerability in China: The role of digital financial inclusion. *Rev. Dev. Econ.* **2023**, *27*, 1445–1480. [CrossRef]
26. Liu, M.; Min, S.; Ma, W.; Liu, T. The adoption and impact of E-commerce in rural China: Application of an endogenous switching regression model. *J. Rural Stud.* **2021**, *83*, 106–116. [CrossRef]
27. Wang, B.; Shao, X.; Yang, X.; Xu, H. How does land transfer impact rural household income disparity? An empirical analysis based on the micro-perspective of farmers in China. *Front. Sustain. Food Syst.* **2023**, *7*, 1224152. [CrossRef]
28. Li, L.; Zeng, Y.; Ye, Z.; Guo, H. E-commerce development and urban-rural income gap: Evidence from Zhejiang Province, China. *Pap. Reg. Sci.* **2021**, *100*, 475–494. [CrossRef]
29. Wu, B.; Li, Z.; Gong, R.; Zhu, H. Can rural e-commerce development improve farmers' subjective well-being? *J. China Agric. Univ. (Soc. Sci. Ed.)* **2023**, *40*, 129–146.
30. Zhang, J.; Zhang, X. A Study of the Impact and Mechanisms of Internet Use on the Decision to Transfer Agricultural Land—Micro Evidence from CFPS. *China Rural Econ.* **2020**, *3*, 57–77.
31. Aker, J.; Ghosh, I.; Burrell, J. The promise (and pitfalls) of ICT for agriculture initiatives. *Agric. Econ.* **2016**, *47*, 35–48. [CrossRef]
32. Li, Q.; Zhu, P.; Zheng, J. Can participation in e-commerce promote green production of facility vegetable growers?—A micro study based on five cities and eleven counties in Shandong Province. *Chin. J. Popul. Resour. Environ.* **2024**, *34*, 106–118.
33. Wang, X.; Huang, H. Analysis of Legal Countermeasures for Risk Prevention of Rural E-commerce in the Era of Big Data. *Agric. Econ.* **2021**, *7*, 116–118.
34. Jia, C. An empirical study on the impact of rural e-commerce development on farmers' income in the context of common wealth. *J. Commer. Econ.* **2023**, *7*, 88–91.
35. Jin, S.; Li, H.; Li, Y. Preferences of Chinese consumers for the attributes of fresh produce portfolios in an e-commerce environment. *Br. Food J.* **2017**, *119*, 817–829. [CrossRef]
36. Benn, Y.; Webb, T.; Chang, B.; Reidy, J. What information do consumers consider, and how do they look for it, when shopping for groceries online? *Appetite* **2015**, *89*, 265–273. [CrossRef] [PubMed]
37. Zhao, X.; Gao, Q. A Study on the Influencing Factors and Mechanism of Agricultural Products' Online Purchase Intention—An Analysis Based on the Perspective of Reference Effect. *J. Beijing Technol. Bus. Univ. (Soc. Sci.)* **2016**, *31*, 42–53.
38. Guo, L. Mediation of land disputes and its institutional improvement in the context of rural revitalisation. *J. Huazhong Univ. Sci. Technol. (Soc. Sci. Ed.)* **2022**, *36*, 23–30.
39. Wang, Y. Has e-commerce participation improved the economic access of farm households?—Differences between Poor and Non-Poor Households. *China Rural Econ.* **2019**, *7*, 37–50.

40. Zhang, L.; Cao, Y.; Bai, Y. The impact of the land certificated program on the farmland rental market in rural China. *J. Rural Stud.* **2022**, *93*, 165–175. [CrossRef]
41. Kung, J. Off-Farm Labor Markets and the Emergence of Land Rental Markets in Rural China. *J. Comp. Econ.* **2002**, *30*, 395–414. [CrossRef]
42. Rahman, S. Determinants of agricultural land rental market transactions in Bangladesh. *Land Use Policy* **2010**, *27*, 957–964. [CrossRef]
43. Ma, Z.; Ran, R.; Xu, D. The Effect of Peasants Differentiation on Peasants' Willingness and Behavior Transformation of Land Transfer: Evidence from Sichuan Province, China. *Land* **2023**, *12*, 338. [CrossRef]
44. Duan, G.; Liu, X.; Huang, Y. How Digital Infrastructure Development Impacts the Development of New Quality Productivity in the Enterprise. *Financ. Econ.* **2024**, 1–13. Available online: <http://kns.cnki.net/kcms/detail/36.1005.F.20240608.1949.002.html> (accessed on 7 June 2024).
45. Liu, B.; Zhou, J. Digital Literacy, Farmers' Income Increase and Rural Internal Income Gap. *Sustainability* **2023**, *15*, 11422. [CrossRef]
46. Gao, Y.; Zang, L.; Sun, J. Does computer penetration increase farmers' income? An empirical study from China. *Telecommun. Policy* **2018**, *42*, 345–360. [CrossRef]
47. Bai, Y.; Cao, Y.; Liu, C.; Zhang, L. Re-conceptualising the role of employment buffers in the agricultural sector—Evidence from rural labour employment before and after the New Crown Pneumonia epidemic. *Chin. Rural Econ.* **2022**, *6*, 65–87.
48. Fallon, P.; Lucas, R. The Impact of Financial Crises on Labor Markets, Household Incomes, and Poverty: A Review of Evidence. *World Bank Res. Obs.* **2002**, *17*, 21–45. [CrossRef]

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Article

Effects of Conservation Tillage on Agricultural Green Total Factor Productivity in Black Soil Region: Evidence from Heilongjiang Province, China

Mei Zhang, Hanye Zhang, Yun Deng and Chuanqi Yi *

College of Economics and Management, Northeast Agricultural University, Harbin 150030, China; z10967@neau.edu.cn (M.Z.); s220801024@neau.edu.cn (H.Z.); s230801017@neau.edu.cn (Y.D.)

* Correspondence: 16118116@njau.edu.cn

Abstract: The implementation of conservation tillage is crucial for the preservation and utilization of black soil. This study examined 297 new agricultural management entities in five pilot counties in the black soil region of northeast China. Using the SBM-Undesirable model, this study measured and evaluated the agricultural green total factor productivity (AGTFP) of these entities. We further employed the Tobit model to explore the impact of conservation tillage on the AGTFP. The findings revealed that the average AGTFP value of the sample entities was 0.4364, indicating a generally low degree of AGTFP that exhibited significant variation. Improvement in input indicators (such as machinery) and undesirable output indicators (such as net carbon emissions) was particularly needed. Additionally, conservation tillage had a significant positive impact on AGTFP, with a higher number of applied technologies correlating with increased productivity. Material subsidies for conservation tillage offered greater direct cost relief and had a stronger positive effect on AGTFP in comparison with cash subsidies. Furthermore, apart from policy factors, key production and operation characteristics—such as access to agricultural materials—also significantly influenced AGTFP. The results of this study offer a valuable decision-making framework and scientific reference for countries in black soil regions worldwide, enabling them to enhance the conservation and sustainable utilization of this vital resource.

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Keywords: AGTFP; conservation tillage; new agricultural management entities; black soil region

1. Introduction

Black soils, found predominantly at middle and high latitudes worldwide, are renowned for their exceptional fertility and high organic matter content, making them vital to global agricultural production [1]. Black soils compose 19% of the world's farmland, with the four major black soil regions serving as key areas for agricultural production [2]. Black soils are mineral soils that have a black surface horizon, enriched with organic carbon that is at least 25 cm deep [3]. According to the WRB classification, black soils comprise Chernozems, Kastanozems, and Phaeozems [4]. Particular types of black soil vary from country to country and region to region, but the protection of this valuable resource is a consensus widely held worldwide [5]. The 2015 Paris Agreement emphasizes mitigating the impacts of climate change, prompting countries to set goals related to carbon neutrality and ecological protection [6]. Black soils play a critical role in global carbon regulation and climate adaptation due to their exceptional carbon sequestration capacity [7,8]. According to the Global Soil Organic Carbon Sequestration Potential map, the world's 725 million hectares of black soil hold 8.2% of the global soil organic carbon stock and can sequester up to 10% of global soil organic carbon potential [9]. Therefore, black soil is crucial for ensuring food security and ecological stability and achieving global carbon neutrality [10,11]. Given projected population growth and increasing food consumption, global food demand and the urgency of managing carbon emissions will escalate over the next 40 years [12,13].

Consequently, maximizing the effectiveness of black soil in order to balance agricultural, environmental, and economic needs (while adapting to climate change) remains an urgent and critical research focus [14,15].

The black soil region of northeast China is one of the world's four major black soil regions, encompassing 1.09 million square kilometers and accounting for about one-fifth of the total global black soil area [16]. This region not only is the cornerstone of agricultural development in northeast China but also serves as China's granary, playing a crucial role in ensuring national food security [17]. However, on one hand, extensive exploitation and irrational traditional farming practices over an extended period have led to significant soil degradation and loss of organic carbon in the black soil region [18]. Soil erosion in this zone affects 275,900 square kilometers, representing roughly 27% of the total area. Many black soils have lost half of their organic carbon stocks, weakening their carbon sequestration capacity [19]. Such a decline in soil organic carbon stocks exacerbates soil fertility degradation and reduces land productivity [20]. On the other hand, improper use of heavy machinery has intensified soil compaction in recent years. Issues such as soil hardening, consolidation, and diminished water and moisture retention capacity in the drylands of the black soil zone have also worsened [21]. These challenges have severely limited the sustainable utilization of black soil in northeast China, impacting regional food production, as well as economic and social development [22]. Conventional farming practices threaten the stability of soil ecosystems [23], but conservation tillage represents a progressive farming approach that can enhance the soil's structure. This method integrates no-tillage, minimum-tillage, straw mulching, and crop rotation practices [24–26]. Conservation tillage minimizes soil disturbance by leaving at least 30% of the soil surface covered with residue, thereby reducing soil erosion [27,28]. It represents a significant reformation of conventional tillage methods, offering substantial benefits such as carbon sequestration and a reduction in emissions [29,30]. This practice increases soil organic carbon, reduces the risk of soil erosion [31], and fosters a better soil environment, thereby enhancing crop yields with minimal environmental impact [32,33]. Currently, in China, conservation tillage is a crucial measure being taken to curb soil erosion and promote the restoration of degraded black soil croplands. China has developed a system of policies to support the popularization and application of conservation tillage in its nationwide plan for northeastern black soil. The "Outline of the Northeast Black Soil Conservation Plan (2017–2030)" emphasizes technological innovation and integrated demonstrations of conservation tillage. The "Implementation Program of the National Black Soil Protection Project (2021–2025)" lists the promotion of conservation tillage in black soil regions as a major measure and task. The "Action Plan for Conservation Tillage on Black Soil in Northeast China (2020–2025)" outlines detailed arrangements for the comprehensive promotion and application of conservation tillage in suitable areas. Furthermore, China has enacted the only special legislation dedicated to black soil protection among the world's major black soil countries, with the Black Soil Protection Law emphasizing the promotion of conservation tillage technology tailored to local conditions.

Existing studies have demonstrated that conservation tillage technology can foster agricultural technological progress and generate both economic and ecological benefits by optimizing the efficiency of resources' allocation [34]. On one hand, conservation tillage provides clear economic benefits. Buehren et al. (2019) suggested that conservation tillage techniques can improve farmers' production and crop yields, thereby increasing their income [35]. Contemporary conservation tillage technology encompasses a variety of new methods, such as reduced tillage, no-tillage, and stubble mulching. Ogieriakhi et al. (2022) found that no-tillage technology, which boasts a more streamlined production process than conventional methods, can increase net farm income by reducing labor input and machinery operating costs [36]. On the other hand, conservation tillage can bring about ecological benefits such as soil consolidation and enhanced soil carbon sequestration capacity. Pisani et al. (2020) suggested that strip-tillage can reduce the loss of nutrients like nitrogen, phosphorus, and potassium through surface runoff by improving the soil

structure [37]. Field surveys have indicated that conservation tillage can also help to preserve local biodiversity [38,39]. Although most scholars have an optimistic view of the economic and ecological effects of conservation tillage, some controversy remains. For example, Jussi et al. (2006) found that no-till technology, when used for corn cultivation in northern Colorado and oat and wheat cultivation in Finland, resulted in lower yields than conventional methods when under optimal conditions. They noted that even though production costs decreased, these savings did not compensate for the reduced yields, potentially overshadowing associated environmental benefits [40]. Government support is a crucial factor in promoting conservation tillage technology. The USDA's Environmental Quality Incentives Program (EQIP), which provides technical assistance and incentive payments, encourages farmers to protect cropland quality. Evaluations by Claassen (2008) and Wunder (2008) found that the program significantly improved the ecological quality of U.S. plantations [41,42]. Greiner (2009) and Bopp (2019) suggested that compensation policies, which offer both technical assistance and financial support, can offset the costs of adopting new technologies and enhance economic returns. This dual support motivates farmers to protect cropland quality more effectively [43,44]. Johnston (2021) and others also suggested (as early as 2002) that if the promotion of conservation tillage technology is not accompanied by corresponding support subsidies, farmers will reduce their input of other factors in order to control costs. Or in order to ensure their yield, farmers may increase their use of fertilizers and other pollution-producing factors of production, meaning the marginal gains made through the promotion of technologies for increasing production and greening will continue to diminish or even disappear [45]. Other factors may also influence the protection of cropland quality by affecting farmers' behavior. Mishra et al. (2022) proposed that there is a significant positive correlation between planting area (i.e., scale) and the behaviors that farmers exhibit to protect quality [46]. Tey et al. (2012) concluded that farmers with land titles exhibited stronger and more stable conservation behaviors compared with those of farmers who only have land management rights; leased land was shown to be less conducive to high levels of conservation behavior by the farmers leasing such land [47]. Asfaw (2017) and Darkwah (2019) noted that external conditions, such as the availability of technical extension services and the degree of professionalism, also positively influence farmers' conservation behaviors [48,49]. The existing research systematically evaluating the effect of conservation tillage in the black soil region is relatively limited, and the index used for evaluation is singular, failing to reflect the multiple roles played by conservation tillage in the conservation and utilization of black soil. Additionally, regional differences in economic development and environmental conditions affect the adoption of conservation tillage techniques, making it essential that we conduct comprehensive assessments that are tailored to local contexts. Finally, we must improve the integration of research across disciplines and the diversity of indicators used to evaluate the effects of conservation tillage.

This study introduces the concept of agricultural green total factor productivity (AGTFP) as a metric for assessing the effects of conservation tillage on both the economic and the ecological aspects of agricultural production in black soil regions. AGTFP is recognized as an effective measure of the balance between agricultural economic performance and ecological health [50]. Improving AGTFP is essential in addressing the challenge of balancing agricultural economic growth with environmental sustainability [51]. It reflects the environmental costs associated with agricultural production and provides an objective evaluation of the combined economic and ecological impacts of conservation practices in black soil regions. Understanding and measuring AGTFP is crucial for promoting green agriculture [52]. Compared with traditional total factor productivity (TFP), AGTFP offers a more comprehensive and accurate assessment of the efficiency with which production inputs are converted into desirable economic outputs, while also accounting for undesirable outputs such as surface source pollution and carbon emissions [53]. This approach considers both the positive and the potentially negative impacts of agricultural activities on black soil arable land. Furthermore, the slack-based measure (SBM) model,

which includes undesirable outputs, allows for the evaluation of input redundancies, undesirable outputs, and output deficiencies. This detailed calculation of AGTFP highlights areas in which improvements can be made, providing valuable insights into sustainable agricultural practices.

This paper is structured as follows. First, we analyze how conservation tillage in the black soil region influences the agricultural green total factor productivity (AGTFP) of new agricultural management entities; we do so through integrating theories of environmental regulation, the effects of substitution, and technological advancements. Second, we provide an empirical overview of the application of conservation tillage in five pilot counties, detailing the input–output dynamics of 297 new agricultural management entities. Third, we construct the SBM-Undesirable model to measure and evaluate AGTFP among these entities. Finally, we use the Tobit model to investigate the impact of conservation tillage technology on AGTFP, verifying our theoretical analysis and providing a basis for optimizing the protection and utilization of black soil.

2. Analysis of Theoretical Mechanisms

2.1. Environmental Regulatory Perspective

Based on the theory of environmental regulation, conservation tillage technology in the black soil region impacts the input–output status and AGTFP of new agricultural management entities in two main ways: “compliance costs” and the “innovation effect.” On one hand, adopting conservation tillage technology in response to government mandates increases input costs, creating “compliance costs” that can limit AGTFP under certain conditions [52]. Compared with traditional methods like burning straw or removing it from the field, returning straw to the field is more complex and incurs higher labor and machinery costs. Although organic fertilizers are relatively inexpensive, their large-scale application requires additional labor or rented machinery [53]. Technologies such as no-till and deep plowing necessitate the use of multifunctional large-scale agricultural machinery, thereby increasing the demand for green production services such as aerial pest control and plant protection and leading to additional costs related to purchasing or leasing machinery and services. Under financial constraints, these increased costs may force entities to reduce their input of other production factors, which will affect the resource allocation capacity and efficiency. To cover these higher total production costs and achieve economic goals, entities might increase fertilizer usage to improve production quality and ensure revenue covers expenses; however, this has the potential to exacerbate surface pollution and carbon emissions. On the other hand, the application of conservation tillage technology can create an “innovation compensation” effect, partially offsetting “compliance costs,” improving output, and thus increasing AGTFP [54]. The green production factors introduced by conservation tillage technology are more effectively converted into comprehensive outputs. Organic fertilizers improve production and reduce pollution [55], while large-scale no-till seeders and deep-tillers offer higher operational efficiency and have a minimal negative impact on the physicochemical properties of black soil arable land [56]. This leads to increased economic output while controlling surface pollution and carbon emissions [57].

2.2. The Effect of Technology

Conservation tillage technology offers both economic and ecological benefits, increases comprehensive output, and enhances the AGTFP of new agricultural management entities by transforming traditional rough production methods into modern green production methods [58,59]. From a micro perspective, improvements in technical efficiency and the alignment of technological progress with production needs both determine the level of AGTFP [60]. The greening and high efficiency with which production factors are input—both brought about by conservation tillage technology—align well with the research, development, and application of technological progress, thereby enhancing AGTFP [61]. Promoting conservation tillage technology in the black soil region can increase food production, mitigate surface pollution, and reduce carbon emissions without changing

the input of other resources. From a macro perspective, the influence of conservation tillage technology needs to be further expanded, and the technological transformation of the entire industry has not yet been achieved. However, business entities can still leverage such positive technological effects to achieve remarkable profits [62].

2.3. The Substitution Effect

Conservation tillage technology can replace expensive, inefficient, and pollution-producing production factors via the substitution effect [63], thereby reducing input costs and controlling surface pollution and carbon emissions and ultimately improving the AGTFP of new agricultural management entities. Compared with traditional farming methods, conservation tillage involves fewer production processes, reducing the demand for and cost of manual labor and mechanical operations. The operational efficiency of large-scale agricultural machinery used in conservation tillage is higher, making it a direct substitute for manual labor, traditional rotary plows, and other expensive and inefficient small-scale machinery. The increased application of organic fertilizers and conservation tillage improves the quality of black soil arable land, reducing the need for chemical fertilizers during crop growth [64]. Organic fertilizers, such as manure compost or biological fertilizer, have a direct substitution effect on nitrogen, phosphorus, and potassium blended fertilizers [65]. Consequently, fertilizer inputs, surface pollution, and carbon emissions are controlled.

2.4. The Technology Agglomeration Effect

The effects of different combinations of conservation tillage techniques on the AGTFP of new agricultural management entities vary. First, the “environmental regulation” and substitution effects of individual technologies are less pronounced than those of combined technologies. A singular technology can only address a specific issue related to black soil cultivation, and at this stage, the marginal utility of conservation tillage technology is still in the early stages of incremental increase. The “innovation compensation” effect created by a single technology has limited ability to cover the “compliance costs” and may even produce a negative “environmental regulation” effect. A single technology can only substitute a certain expensive, inefficient, and highly polluting factor, resulting in a minimal substitution effect. Second, different technologies and their combinations produce varying technological effects. As shown in Table 1, under the premise of not exceeding the economic capacity of the operational entity and based on the actual condition of the cultivated land, combining conservation tillage technologies can optimize their comprehensive effect. The more integrated and numerous the technologies applied, the more they compensate for each other’s shortcomings, promote mutual reinforcement, and produce a synergistic effect, thus optimizing the overall impact.

Table 1. Description of conservation tillage technologies in black soil region.

Conservation Tillage Technologies	Specific Measures	Roles and Effects
Straw-returning	Incorporating harvested straw back into the soil through plowing or mulching.	Boost soil fertility and reduce chemical fertilizer use while maintaining or increasing crop yields [66,67].
Organic fertilizer	Use specialized machinery to apply organic fertilizer made from harmlessly treated livestock and poultry manure or composted with straw.	Increase microbial diversity and population to stabilize the soil ecosystem [68]. Enhance soil organic matter, etc., to restore soil productivity [69]. Reduce chemical fertilizer use to mitigate surface pollution [70].
No-tillage seeding	Planting seeds directly into the soil without prior tilling.	Simplify seeding for efficiency, extend crop growth [71]. Reduce soil disturbance, stabilize soil structure, and minimize nutrient runoff [72].

Table 1. Cont.

Conservation Tillage Technologies	Specific Measures	Roles and Effects
Deep plowing	Turning over the soil to a greater depth than conventional plowing to break up compacted layers.	Reduce soil bulk and compaction in the tillage layer to increase water content and holding capacity [73–75]. Improve crop drought resistance [76].
No-tillage seeding + straw-returning	Conservation tillage technology portfolios.	Soil urease, alkaline phosphatase, dehydrogenase, and invertase activities were higher and more effective at increasing soluble nutrients in the soil [77].
Deep plowing + straw-returning		Increase soil alkaline dissolved nitrogen, quick-acting potassium, and other nutrients effectively [78]. Promote root system development [79]. Enhance soil water content, improve crop drought resistance [80].
No-tillage seeding + straw-returning + organic fertilizer		Enhance the levels of quick-acting phosphorus, enzymes, and microorganisms [81].
Deep plowing + straw-returning + organic fertilizer		Enhance soil physical and chemical properties to promote crop root growth [82]. Increase soil organic matter content and yield [83].

Source: Technical Guidelines for the Action Plan for Conservation Tillage of Black Soil in Northeast China 2023.

Figure 1 demonstrates the mechanisms of conservation tillage technology impact on AGTFP in black soil region.

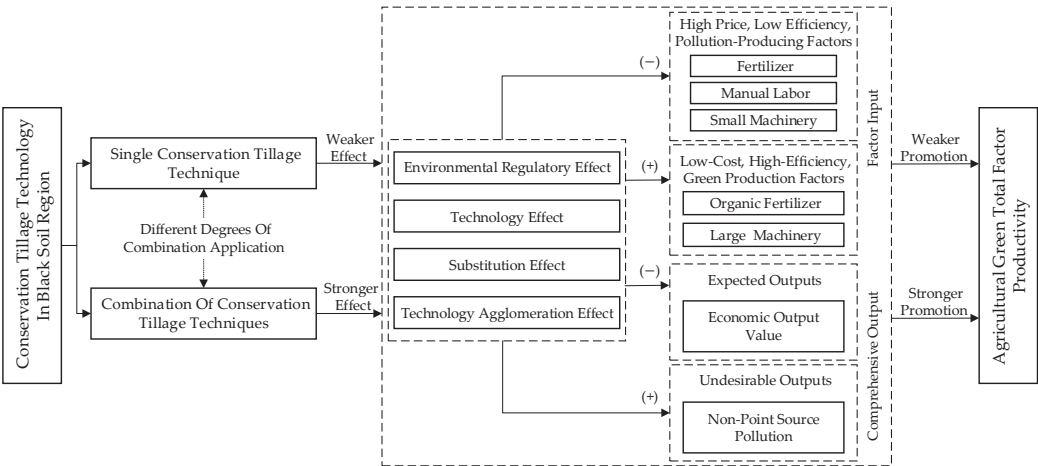


Figure 1. Mechanisms of conservation tillage technology impact on AGTFP in black soil region.

3. Materials and Methods

3.1. Data Sources and Sample Profile

3.1.1. Overview of the Research Area

Heilongjiang Province is renowned for its vast expanse of black soil arable land, named the northeast black soil region. This province plays a crucial role as a strategic grain reserve and the cornerstone of China’s grain commodities, thus emphasizing the importance of protecting black soil and ensuring comprehensive grain production. To this end, Heilongjiang Province has focused on pilot projects in counties (cities) with concentrated arable land that is suitable for conservation tillage. These projects aim to promote the protection and utilization of black soil throughout the province, with key areas including

Keshan, Longjiang, and Yi'an counties in Qiqihar City and Beilin and Lanxi counties in Suihua City. The establishment of pilot counties for black soil protection in Heilongjiang involved a meticulous process. This process included county-level declarations, municipal recommendations, and provincial evaluations, taking into account factors such as the extent of black soil arable land, agricultural production conditions, and the professional capacity of agricultural technology and machinery departments. In response to central and provincial government directives on black soil protection, Qiqihar City issued the "Nenjiang River Basin Efficient Eco-agriculture Black Soil Protection and Utilization Project Planning (2020–2025)" directive. This plan provides guidance for the protection and utilization of black soil across counties. Similarly, Suihua City included black soil protection in its 13th Five-Year Plan for Ecological Environmental Protection and has continued to emphasize it in the 14th Five-Year Plan through the Black Soil Strength Enhancement Project. Consequently, Qiqihar City and Suihua City have designated Keshan County, Longjiang County, Yi'an County, Beilin District, and Lanxi County as national-level key protection areas for black soil. Among them, Longjiang and Lanxi are black soil protection whole-establishment promotion counties. At the same time, they are counties in which the eradication of poverty is of great concern, meaning government funding is adequate and timely. The implementation of the pilot policy in these two counties is different in strength and scope from projects in other pilot counties (districts).

This study focuses on the effectiveness of conservation tillage in Keshan County, Longjiang County, Yi'an County, Beilin District, and Lanxi County. These areas were selected based on their shared natural environmental conditions and varied forms of policy implementation. The conclusions and recommendations derived from this study will be both representative and comprehensive.

3.1.2. Data Sources

The "Action Plan for Conservation Tillage in the Black Soil of Northeast China (2020–2025)" prioritizes maize production in the northeast China region (Heilongjiang Province, Jilin Province, Liaoning Province, and the eastern part of the Inner Mongolia Autonomous Region) for the promotion and application of conservation tillage. The data for this study were collected via field research conducted in July and August 2022 in five pilot counties involved in black soil conservation and utilization projects: Keshan, Longjiang, and Yi'an in Qiqihar City and Beilin and Lanxi in Suihua City. Questionnaires were distributed primarily to new agricultural management entities involved in corn cultivation, focusing on their production input and output status as of 2021. A total of 319 questionnaires were distributed, with 297 valid responses retained after screening out 22 invalid ones, resulting in a validity rate of 93%. Among the valid questionnaires, 74 were from Longjiang County, 62 from Yi'an County, 57 from Keshan County, 53 from Beilin District, and 51 from Lanxi County.

Our field research involved discussions with staff from the Agriculture and Rural Affairs Bureau, Agricultural Economics Stations, Agricultural Machinery Stations, and Agricultural Technology Extension Centers of each pilot county. We collected relevant policy documents in order to appraise the current status, effectiveness, and challenges of black soil protection programs. This research also included a questionnaire used to evaluate the new agricultural management entities' level of production and their influence on pilot black soil protection programs. The questionnaire comprised three sections: the first covered the input and output status of production, the second assessed production activities affected by policy (including types of conservation tillage technology and the implementation of compensation policies) and gathered feedback on knowledge of and satisfaction with these policies, and the third focused on the characteristics of the production and management subjects. Before conducting the research, the team confirmed that they thoroughly understood the research content, survey questions, and questionnaire structure. They also received training in interview techniques and efficient record keeping to ensure the authenticity and completeness of each questionnaire.

3.1.3. Overview of Conservation Tillage in Each Sample

The Regulations on the Protection and Utilization of Black Soil in Heilongjiang Province detail the responsibilities of pilot counties to carry out the scientific application of chemical and organic fertilizers, promoting practices such as straw returning, reduced tillage, no-tillage seeding, and deep plowing. These counties have further refined such guidelines on the application of protective tillage technology based on these regulations. For example, the Implementation Plan for the Suihua City Black Soil Protection Project (2021–2025) emphasizes integrating agro-mechanical and agro-technical methods, categorizing the implementation of deep tillage and organic fertilizers, and increasing the return of organic matter like straw and animal manure. The pilot counties (districts) adapted their black soil protection programs to local conditions, considering their specific black soil arable land and basic agricultural production conditions, as well as the professional capabilities of their agronomy and agricultural machinery sectors. Field research observed various combinations of conservation tillage technologies involved in actual production. The application of these technologies in the sample area is summarized in Table 2.

Table 2. Application of conservation tillage technologies in the sample.

Degree of Combination	Technologies	Quantities	Proportion
Not applied	No conservation tillage technology applied	54	18.18%
Single	Only straw-returning	20	6.73%
	Only organic fertilizer	23	7.74%
Combined	No-tillage seeding + straw-returning	69	23.23%
	Deep plowing + straw-returning	77	25.93%
	No-tillage seeding + straw-returning + organic fertilizer	30	10.10%
	Deep plowing + straw-returning + organic fertilizer	24	8.08%
	—	297	100%

3.2. Empirical Model Construction

3.2.1. SBM-Undesirable Model Construction

In this study, the SBM-Undesirable model was utilized to measure the AGTFP of new agricultural management entities. This DEA-derived model, which is widely used for assessing green productivity, energy efficiency, and environmental efficiency, addresses technological inefficiency through estimating the frontier surface [40]. First, it resolves the input and output slackness that features in traditional DEA models by eliminating inefficiency due to slack. Second, it evaluates productivity by considering non-expected outputs [84]. Third, its non-angularity avoids bias from differences in angle selection, thereby better reflecting productivity [85]. Last, it retains the DEA model’s dimensionless quality, not requiring unified input–output dimensions. The construction of the SBM-Undesirable model proceeds as follows.

Suppose there are n decision-making units (DMUs) in the production system, each with m inputs, s_1 desirable outputs, and s_2 undesirable outputs. These can be represented by the following vectors:

$$x \in R_m, y^g \in R_{s1}, y^b \in R_{s2} \tag{1}$$

We can then define the matrices X, Y^g, Y^b as

$$\begin{aligned} X &= [x_1, x_2, \dots, x_n] \in R_{m \times n} \\ Y^g &= [y^{g1}, y^{g2}, \dots, y^{gn}] \in R_{s1 \times n} \\ Y^b &= [y^{b1}, y^{b2}, \dots, y^{bn}] \in R_{s2 \times n} \end{aligned} \quad (2)$$

In Equation (2), $X > 0$, $Y^g > 0$, and $Y^b > 0$, which transforms the above set as follows:

$$p = \left\{ (x, y^g, y^b) \mid x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0 \right\} \quad (3)$$

In Equation (3), $\lambda \in R_n$ is a vector of weights, and $\lambda \geq 0$ represents constant returns to scale (CRS), or variable returns to scale (VRS) if the equation also satisfies $\lambda \geq 0$ and $\Sigma\lambda = 1$. $x \geq X\lambda$ means that the actual inputs are greater than the production frontier inputs, $y^g \leq Y^g\lambda$ means that the actual desirable outputs are less than the production frontier desirable outputs, and $y^b \geq Y^b\lambda$ means that the actual undesirable outputs are greater than the production frontier undesirable outputs. The SBM-Undesirable efficiency model for a particular decision unit (x_0, y_0^g, y_0^b) can be expressed as

$$\begin{aligned} P^* &= \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b} \right)} \\ \text{s.t.} \quad &\begin{cases} x_0 = X\lambda + S^- \\ y_0^g = Y^g\lambda - S^g \\ y_0^b = Y^b\lambda + S^b \\ s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0 \end{cases} \end{aligned} \quad (4)$$

In Equation (4), s^- , s^g , and s^b represent slack variables for inputs, desirable outputs, and undesirable outputs, respectively. The objective function p^* strictly decreases with respect to s^- , s^g , and s^b . When $s^- = s^g = s^b = 0$, there exists an optimal solution of the function, $p^* = 1$, which indicates that the DMU is suitably efficient. If $0 \leq p^* < 1$, the efficiency (i.e., green production inefficiency) has diminished in the DMU. This inefficiency can be improved by adjusting the inputs and outputs, with potential improvement determined by the proportion of slack variables to the respective inputs and outputs.

Green production inefficiency can be decomposed into input inefficiency and output inefficiency, expressed as follows.

Input inefficiency:

$$IE_x = \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}, \quad (i = 1, 2, \dots, m) \quad (5)$$

Expected output inefficiency:

$$IE_g = \frac{1}{s_1} \sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g}, \quad (r = 1, 2, \dots, s_1) \quad (6)$$

Undesirable output inefficiency:

$$IE_b = \frac{1}{s_2} \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b}, \quad (r = 1, 2, \dots, s_2) \quad (7)$$

In Equations (5)–(7), $\frac{s_i^-}{x_{i0}}$ is a non-negative number representing the relative shrinkable proportion of the DMU's item i inputs. Similarly, $\frac{s_r^g}{y_{r0}^g}$ is a non-negative number indicating

the relative expandable proportion of the DMU's item r expected outputs, and $\frac{S_r^b}{y_{r0}^b}$ is a non-negative number denoting the relative shrinkable proportion of the DMU's item r undesirable outputs.

3.2.2. Tobit Model Construction

In this study, the Tobit model was chosen to explore the effect of conservation tillage on the AGTFP of new agricultural management entities in the black soil region. The Tobit model is suitable for situations in which explanatory variables are constrained and has broadly been used in studies on green productivity, environmental efficiency, and technological efficiency [86]. The reasons for selecting the Tobit model are twofold: first, the values of AGTFP range between 0 and 1, making it a constrained explanatory variable; second, the explanatory variables are continuous within these constraints, truncated at both ends but continuous in the middle. Tobit model-based estimation uses the latent variable Y^* and must meet the basic assumptions of the classical linear model, with the error term following a normal homoskedastic distribution. To address normality issues, this study followed the method of Jiang et al. (2023) by standardizing the dependent variable using the Z-value [87]. To handle potential heteroskedasticity, heteroskedasticity-robust standard errors were used, per the method of White (1980) [88]. The Tobit model was constructed as follows:

$$Y_i^* = \alpha + \beta x_i + \mu_i, \mu_i \sim N(0, \sigma^2)$$

$$Y_i = \begin{cases} Y_i^*, & 0 \leq Y_i^* \leq 1 \\ 0, & Y_i^* < 0 \\ 1, & Y_i^* > 1 \end{cases} \quad (8)$$

In Equation (8), Y_i^* denotes the latent variable, α is the constant term, β is the coefficient to be estimated, x_i denotes the independent variable, μ_i is the random disturbance term, and Y_i denotes the dependent variable.

3.3. Variable Selection and Descriptive Statistics

3.3.1. Variable Selection and Descriptive Statistics for the SBM-Undesirable Model

In line with China's "Peak Carbon and Carbon Neutral Strategy", scholars have included carbon emissions as undesirable outputs in the AGTFP accounting system [40]. Conservation tillage technology can increase carbon sinks while reducing carbon emissions [89]. Therefore, this study used net carbon emissions (carbon emissions minus carbon sinks) and surface pollution as indicators of undesirable outputs. The explanation and descriptive statistics of the input–output index system are presented in Table 3. Surface pollution from maize cultivation is primarily a result of fertilizer and pesticide runoff, agricultural film residue, and straw returned to the field [90]. Since the use of agricultural film in the samples was minimal (less than 5% of samples featured it in small amounts), this study focused on the total nitrogen and phosphorus emissions from fertilizer and pesticide runoff and returned straw in order to characterize agricultural surface pollution.

$$E_{ij} = \sum EU_i * \rho_{ij} * (1 - \mu_j) * C_{ij}(EU_{ij}, S) \quad (9)$$

In Equation (9), E_{ij} is the emission of agricultural pollutant, including total nitrogen (TN) and total phosphorus (TP). EU_i is the corresponding fertilizer use of unit i , and ρ_{ij} is the pollution intensity coefficient of pollutant j produced by unit i , varying with different fertilizer types. μ_j represents the fertilizer utilization efficiency, influenced by soil properties, fertilizer characteristics, organic fertilizer application, and conservation tillage techniques. C_{ij} is the discharge coefficient of pollutant j produced by unit i , which is affected by unit and spatial characteristics (environment, climate, management measures, etc.).

In this study, carbon emissions are accounted for from sources such as fertilizers, pesticides, irrigation, tillage, straw return, and diesel machinery. The increase in carbon

sinks is attributed to soil and biological carbon sequestration resulting from no-tillage, straw return, and other conservation tillage techniques.

$$NCE_i = \sum CE_i - \sum CF_i = \sum_j E_{ij}\theta_{ij} - \left[(1 - \alpha) \sum_k S_{ik}\theta_{ik} + (1 - \beta) \sum_k S_{ik}\rho_{ik} \right] \tag{10}$$

Table 3. AGTFP input–output index system and descriptive statistics.

Type of Variable	Variable	Description	Mean	Standard Deviation
Input variable	Land	Corn planting area (hm ²)	97.3691	133.8124
	Labor	Total own and hired labor hours (h)	2839.3833	4170.9578
	Seed	Total cost of purchased seeds (10,000 yuan)	8.0334	9.9889
	Pesticide	Total cost of purchased pesticides (10,000 yuan)	2.3910	3.2281
	Machinery	Total cost of own and hired machinery (10,000 yuan)	12.2263	20.1863
	Fertilizer	Total input of base fertilizer, seed fertilizer, and top dressing (t)	66.2578	88.7720
Expected output variable	Total agricultural production	Total income from corn production (10,000 yuan)	191.1290	265.6771
Undesired output variables	Non-point source pollution	Total nitrogen and phosphorus emissions (t)	26.3924	37.9033
	Net carbon emission	Carbon emissions minus carbon sequestration (t)	142.4054	195.7664

In Equation (10), NCE_i is the net carbon emission of unit i , E_{ij} is the total amount of carbon source j for unit i , and θ_{ij} is the carbon emission coefficient for unit i . α is the coefficient for the inverse synergistic effect of no-tillage and straw return on soil carbon sequestration, and β is the coefficient for the effect of these practices on slowing biological carbon sequestration. S_{ik} is the area in which conservation tillage technology k is applied, and θ_{ik} and ρ_{ik} are the annual rates of soil carbon sequestration and biological carbon sequestration for conservation tillage technology k , respectively.

3.3.2. Variable Selection and Descriptive Statistics for the Tobit Model

Based on the specific metrics of black soil conservation tillage implemented in the five pilot counties studied (Keshan County, Longjiang County, Yi'an County, Beilin District, and Lanxi County), this study combined the production and operation characteristics of each sample subject and their impact on AGTFP levels. Considering the comprehensibility of the questionnaires and the availability of data, the selected variables and descriptive statistics are presented in Table 4.

Table 4. Tobit model variable description and descriptive statistics.

Type of Variable	Variable	Description	Effect Direction	Mean	Standard Deviation
Dependent variable	AGTFP	Range of values [0,1]	/	0.4364	0.2214
Independent variable	Application of conservation tillage techniques	Not applied = 1, only straw-returning = 2, only organic fertilizer = 3, no-tillage seeding + straw-returning = 4, deep plowing + straw-returning = 5, no-tillage seeding + straw-returning + organic fertilizer = 6, deep plowing + straw-returning + organic fertilizer = 7	+	4.0565	1.7820

Table 4.
 Cont.

Type of Variable	Variable	Description	Effect Direction	Mean	Standard Deviation
Control variable	Subsidies for conservation tillage	No compensation = 1, cash subsidy = 2, material subsidy = 3	+	1.9919	0.6564
	Access to agricultural materials	Purchase by oneself = 1, purchase by cooperatives and village departments = 2, shipment from fixed agricultural company = 3	+	1.8226	0.8839
	Adoption of agricultural socialized services	Not adopted = 0, adopted = 1	+	0.5323	0.5010
	Degree of farmland fragmentation	Very decentralized = 1, more decentralized = 2, concentrated = 3	+	1.3634	0.8873
	Quality of farmland	Below average = 1, medium = 2, above average = 3	+	2.1613	0.6790
	Suitability of farmland for mechanized operations	More than half unsuitable = 1, More than half suitable = 2, all suitable = 3	+	1.7182	0.7500
	Age of person in charge	Actual age of the person in charge (years)	−	46.2581	8.4680
	Education level of person in charge	Elementary school and below = 1, secondary school or middle school = 2, college and above = 3	+	1.7892	0.8021
	Proportion of managers	Range of values (0.00%,100.00%]	+	0.8082	0.2551
	Presence of village cadres among members	None = 0, yes = 1	+	0.4516	0.4997

4. Results

4.1. Analysis of AGTFP Measurement Results

As shown in Table 5, the results indicated that the degrees of improvement in each input factor, surface pollution, and net carbon emissions were all negative, signifying a need for reduction. On average, the improvement required in each input factor was less than 50%, highlighting the strong contribution of each factor to overall output. This statistic indicated that most new agricultural management entities in the sample were able to source high-quality agricultural resources and demonstrate modernized production and operation capabilities, exhibiting strong decision making and resource allocation skills. The standard deviation in the degree of improvement in factors revealed significant variations among the entities. This disparity was influenced by factors such as differences in resource allocation capacities, varying levels of technological maturity in black soil protection methods, and the varying impacts of policy among the entities.

Table 5.
 Degree of improvement needed in input–output indicators for the total sample.

Descriptive Statistics	Land	Labor	Seed	Pesticide	Machinery	Fertilizer	Non-Point Source Pollution	Net Carbon Emission
Mean	−14.23%	−14.17%	−28.28%	−35.29%	−45.29%	−11.07%	−6.73%	−18.18%
Maximum	−34.09%	−55.16%	−83.77%	−77.03%	−93.00%	−53.00%	−51.87%	−59.33%
Standard deviation	0.1064	0.1525	0.2563	0.2713	0.3242	0.1289	0.1189	0.2189

Analyzing the input factors further, machinery inputs showed the highest mean need for improvement at 45.29%; this was likely due to recent increases in oil prices. The need for improvement in labor input was lesser, with a mean of 14.17% but a maximum value of 55.16%, suggesting a need to enhance the use of machinery in some production processes. Improvement in both fertilizer input and surface pollution emissions was relatively limited, with means of 11.07% and 6.73%, respectively, indicating positive pollution control behaviors among the entities. However, some entities still exhibited a great need for improvement, up to 53.00% for fertilizer input and 51.87% for surface pollution, highlighting the importance of enhancing conservation tillage technology. The mean requirement for improvement in net carbon emissions was 18.18%, but some entities showed values as high as 59.33%, indicating substantial potential for carbon sequestration and the reduction in emissions through improved conservation tillage practices in the black soil region.

The results of slack input and output indicators for new agricultural management entities, taking into account differing applications of conservation tillage technology, are presented in Table 6. As the degree of application progressed from “not applied” to “deep plowing + straw returning + organic fertilizer”, labor, pesticide, machinery, fertilizer, non-point source pollution, and net carbon emissions all showed a decreasing trend. However, in the “traditional rotary tillage with straw” group, both machinery and fertilizer use increased. This increase was attributed to the additional production processes and machinery costs associated with rotary plowing, which also failed to achieve adequate straw decomposition. The levels of improvement for land and seed inputs were affected by factors beyond technology, thus not strictly correlating with the extent to which technology was adopted.

Table 6. Average degree of improvement needed in input–output indicators under different technology portfolios.

Descriptive Statistics	Land	Labor	Seed	Pesticide	Machinery	Fertilizer	Non-Point Source Pollution	Net Carbon Emission
Not applied	−22.10%	−27.09%	−29.75%	−71.16%	−69.15%	−22.00%	−28.37%	−35.58%
Only straw-returning	−27.75%	−24.24%	−46.67%	−58.06%	−74.86%	−28.38%	−45.57%	−41.62%
Only organic fertilizer	−17.86%	−21.64%	−47.71%	−43.59%	−61.30%	0.00%	−18.06%	−22.65%
No-tillage seeding + straw-returning	−12.91%	−11.72%	−21.55%	−34.69%	−53.32%	−7.86%	−11.15%	−20.59%
Deep plowing + straw-returning	−11.72%	−9.37%	−31.16%	−26.76%	−42.28%	−7.37%	−7.16%	−14.83%
No-tillage seeding + straw-returning + organic fertilizer	−15.57%	−5.60%	−32.45%	−26.23%	−41.63%	−0.79%	−3.87%	−11.21%
Deep plowing + straw-returning + organic fertilizer	−6.99%	−3.54%	−21.86%	−18.97%	−34.11%	−0.37%	−1.36%	−7.24%

4.2. Analysis of the Effect of Conservation Tillage on AGTFP

In this study, we employed the Tobit model and used Stata15.1 software to estimate the impact of conservation tillage technology and other influencing factors on the AGTFP levels of the new agricultural management entities in the selected research areas. In Table 7, the first column contains the names of variables, the second column contains descriptions of these variables, and the third column shows the regression coefficient and standard deviation of these variables in the Tobit model.

Table 7. Tobit model results: impact of conservation tillage on AGTFP.

Variables	Description	Coefficient
<i>Ln tech</i>	Application of conservation tillage techniques	0.0100 ** (0.0044)
<i>Ln subs</i>	Subsidies for conservation tillage	0.0913 ** (0.0348)
<i>Ln mate</i>	Access to agricultural materials	0.0093 ** (0.0041)
<i>Ln serv</i>	Adoption of agricultural socialized services	0.0438 * (0.0170)
<i>Ln frag</i>	Degree of farmland fragmentation	0.0462 ** (0.0174)
<i>Ln qual</i>	Quality of farmland	0.0036 (0.0020)
<i>Ln mech</i>	Suitability of farmland for mechanized operations	0.0578 ** (0.0262)
<i>Ln age</i>	Age of person in charge	−0.0019 (0.0009)
<i>Ln educ</i>	Education level of person in charge	0.0154 ** (0.0075)
<i>Ln mana</i>	Proportion of managers	0.0578 * (0.0318)
<i>Ln cadr</i>	Presence of village cadres among members	0.0587 (0.0363)
<i>_cons</i>	constant term	0.5561 *** (0.1376)

Note: *, **, and *** indicate significant at the 10%, 5%, and 1% levels, respectively, with standard deviations in parentheses. Table 8 is the same.

According to the regression results in Table 7, conservation tillage technology had a significant positive impact on the AGTFP levels of new agricultural management entities. The greater the application and combination of this technology, the more pronounced the enhancement of AGTFP. The estimated coefficients of each control variable’s effect on AGTFP aligned with our theoretical expectations. Specifically, subsidies for conservation tillage, access to agricultural materials, adoption of agricultural socialized services, degree of farmland fragmentation, suitability of farmland for mechanized operations, education level of persons in charge, and the proportion of managers all positively and significantly affected AGTFP levels. The quality of cultivated land did not pass the significance test, likely because all cultivated land in the sample area was high-fertility black soil, making differences in quality insufficient to impact AGTFP. The age of the person in charge also did not pass the significance test; this may be because land transfer, land trusteeship, and socialized services mitigated the influence of the characteristics of the person in charge on AGTFP. Additionally, whether or not there were village cadres among members did not pass the significance test; this was likely because current policies were more transparent and new agricultural management entities had greater social capital and information resources than ordinary farmers, which reduced the influence of village cadre membership.

To further ensure the reliability of the Tobit model’s regression results, this study conducted robustness tests using model substitution, explanatory variable substitution, and reduced-tail regression. Model (I) replaced the Tobit model with the CLAD model, relaxing the normal homoskedasticity assumption. Model (II) reported the regression results of the test by substituting explanatory variables. The application of organic fertilizer, which can represent green production [91], was substituted into the model using normalized

data on the organic fertilizer used by new agricultural management entities. Model (III) employed reduced-tail regression, trimming 2.5% of outliers before and after analysis to minimize their impact on conclusions. The results in Table 8 consistently demonstrate a significant positive impact of conservation tillage technology on AGTFP across all test variations, affirming the robustness of this study’s findings.

Table 8. Robustness test results: evaluating the impact of conservation tillage on AGTFP using various models and methods.

Variables	Model (I) AGTFP	Model (II) Organic Fertilizer Application	Model (III) AGTFP
<i>Ln tech</i>	0.1206 *** (0.0256)	0.1090 *** (0.0551)	0.0906 ** (0.0028)
<i>Ln subs</i>	0.0001 ** (0.0269)	0.0002 ** (0.0463)	0.0797 *** (0.0071)
<i>Ln mate</i>	0.0194 * (0.0104)	0.0040 ** (0.0015)	0.0108 ** (0.0030)
<i>Ln serv</i>	0.0693 ** (0.0335)	0.0411 ** (0.0157)	0.0613 ** (0.0138)
<i>Ln frag</i>	0.0712 ** (0.0350)	0.0450 * (0.0245)	0.0638 ** (0.0144)
<i>Ln qual</i>	0.0034 (0.0010)	0.0013 (0.0006)	0.0069 (0.0001)
<i>Ln mech</i>	0.0548 ** (0.0269)	0.0559 ** (0.0277)	0.0661 ** (0.0132)
<i>Ln age</i>	−0.0026 (0.0019)	−0.0318 (0.0011)	−0.0108 (0.0001)
<i>Ln educ</i>	0.0131 * (0.0074)	0.0178 * (0.0094)	0.0166 ** (0.0038)
<i>Ln mana</i>	0.0349 ** (0.0158)	0.0609 ** (0.0308)	0.0502 (0.0137)
<i>Ln cadr</i>	0.0534 (0.0372)	0.0629 (0.0460)	0.0678 (0.0177)
<i>_cons</i>	0.6163 *** (0.1393)	0.5563 *** (0.1380)	0.6331 *** (0.1006)

5. Discussion

Against the backdrop of escalating environmental pollution and resource depletion induced by the development of the traditional agricultural industry, black soil is deteriorating, and agriculturally efficient and ecologically friendly practices have become crucial in the pursuit of global agricultural sustainability [92]. Considered the “breadbasket of the world” [93], black soil plays a crucial role in global food production [94]. According to the International Food Policy Research Institute (IFPRI), 30% of global wheat production, 26% of soybean, and 16% of corn come from black soil cropland [95]. These soils, rich in organic matter and fertility, not only support food production but also have a high capacity for organic carbon sequestration, making them vital for adapting to and mitigating climate change [96]. Despite covering only 5.6% of the global soil area, black soils hold 8.2% of the world’s soil organic carbon (SOC) reserves and contribute 10% of total global SOC sequestration potential [15]. However, many black soils have lost over half of their carbon stocks, thus negatively impacting regional ecological stability and food security [97]. The Status of the World’s Soil Resources Report has identified increasing soil erosion, organic carbon loss, nutrient imbalances, acidification, and pollution in black soils globally [98]. Intensive human development and exploitation have further degraded these soils’ natural

fertility, reducing the depth of the tillage layer and compromising soil properties and ecological functions [99]. Scholars are increasingly advocating for conservation tillage and better protection of black soil as solutions to these issues [100].

This study built on the existing research by introducing agricultural green total factor productivity (AGTFP) as a key indicator used to assess the combined economic and ecological impacts of conservation tillage in black soil regions in order to investigate the significant effect of conservation tillage on agricultural green total factor productivity (AGTFP) in the black soil zone, thereby filling the research gap left by existing studies. The AGTFP clarifies the mechanisms through which conservation tillage enhances the sustainable production capacity of black soil, supplementing existing theories on black soil conservation and utilization. Subsequently, in this study, we constructed an analytical framework within which to examine the impact of conservation tillage on AGTFP for new agricultural management entities in black soil regions, based on the “Longjiang model” in Heilongjiang Province. Our theoretical analysis was grounded in theories of environmental regulation, the substitution effect, and the technology effect; it examined the economic and ecological impacts of conservation tillage using factor inputs, desirable outputs, and undesirable outputs. Empirically, this study used the SBM-Undesirable model to measure and evaluate AGTFP, analyzing the need for improvement in different input and output elements. The Tobit model was employed to quantify the effect of conservation tillage on AGTFP, providing a basis for evaluating its effectiveness in the black soil region. Additionally, China’s unique national-level legislation on black soil protection, featuring clear legal and institutional frameworks at both central and local levels, provided a context for this analysis. The study’s findings offered empirical insights and decision-making references for global black soil conservation efforts and the development of conservation tillage programs tailored to black soil environments worldwide.

In order to promote black soil conservation and utilization and to enhance the application of conservation tillage in the black soil region, we provide the following policy recommendations.

1. Comprehensive strategies for integrated black soil protection:

Several pilot counties and districts in Heilongjiang Province have integrated black soil protection into their national economic and social development plans [7]. However, some areas lack specialized projects for black soil protection, focusing instead on conservation tillage, planting, and recycling projects. These areas need to improve their allocation of financial resources and the efficiency of their project management [101]. Regional governments at or above the county level should develop specialized policies and projects for black soil protection and utilization, strengthening leadership, organizational structures, coordination mechanisms, and supervision to continually expand their overall impact.

2. Enhancing the role of new agricultural management entities in black soil protection:

New agricultural management entities should play a leading role in black soil protection, leveraging their production efficiency and radiation-driven capabilities. They should capitalize on opportunities presented by land trusteeship and agricultural socialization services by efficiently conducting conservation activities on their own transferred arable land [102]. Additionally, this study proposed that these entities should provide technical conservation tillage services to small-scale farmers, expanding protected areas through government-funded purchases and publicly promoting black soil protection [103]. The government should support new agricultural management entities by optimizing production operations (thereby enhancing their ability to apply conservation tillage techniques) and providing necessary production services. Forms of support may include subsidies for no-tillage planters, large-scale tilling machines, and agricultural materials like organic fertilizers. Maintaining the feasibility of conservation tillage technology and the provision of external services (along with centralized purchasing channels for quality-controlled agricultural materials) is essential to ensure that production inputs are of acceptable price and quality.

3. Promotion of integrated conservation tillage techniques

Heilongjiang Province emphasizes the promotion and implementation of conservation tillage technology, exploring the “Longjiang model” for black soil protection in drylands [104]. However, challenges include fragmented conservation tillage methods across programs and insufficient promotion of integrated approaches. The results of this study showed that the rate of adoption of the three integrated conservation tillage technologies was low, indicating a lack of systematization. To address this, the authors propose further advancements in scale, standardization, and science in order to achieve a transformation of black soil management. The pilot counties’ governments and agricultural technology departments should implement the most suitable combinations of technology for the restoration and enhancement of local black soil fertility by considering actual conditions. Numerous studies have compared the effects of physical processes on soil physicochemical properties using both conventional and conservation tillage methods [105,106]. They have also emphasized the importance of soil organic cover and nutrient management in improving soil quality and crop yields, but they have overlooked the opportunity to mix technologies within conservation tillage [107,108]. To improve the overall quality of soils’ structures, agricultural extension and policy-making bodies must thoroughly understand regional black soil quality and its challenges, promoting and combining different technologies to address specific issues and optimization goals. Gathering and addressing feedback from users of this technology on the positive impact of conservation tillage is crucial for refining promotion strategies. Training new agricultural management entities in conservation tillage techniques will increase their awareness of, willingness to adopt, and ability to apply these technologies, thus facilitating integrated application and combination of different techniques.

4. Expanding material subsidies for black soil conservation

Heilongjiang Province has established subsidies in the form of cash subsidies for conservation tillage operations, material and chemical subsidies for organic fertilizer and spreading services, and government-funded conservation tillage services [109]. However, few new agricultural management entities benefit from these subsidies and services. To improve this, the integration of planting and feeding cycle projects and black soil conservation projects should be furthered, that we might increase the input of organic fertilizers to expand their coverage. Combining subsidies for organic fertilizer with support for producers who do not receive free fertilizer and seeding services may enhance this effect. Cooperation between agronomy and soil fertilizer departments and local organic fertilizer manufacturers may improve the bargaining position of business entities. Agricultural machinery departments should designate new agricultural management entities with large-scale and robust service capacities and high proficiency in conservation tillage technology as primary providers of conservation tillage services in the region. This approach aims to systematize government procurement services effectively. Some scholars have also suggested the establishment of a mechanism that accounts for black soil resources within existing systems that account for natural resources [110]. Additionally, cash subsidies for conservation tillage operations should be adjusted based on actual disbursement and recipient satisfaction levels.

5. Enhancing and refining supporting policies for black soil protection

Integrated management and comprehensive policies for typical black soil protection and utilization areas should be implemented in order to improve the construction of policies. Establishing a robust mechanism for policy coherence and reinforcing supportive systems are crucial to ensure the comprehensiveness and alignment of policies [92]. Previous studies have focused on standardizing evaluation criteria [111,112]; however, the results of this study suggest that real-time monitoring and measures for preventing and restoring sustainable management should also be included. Governments in pilot areas should establish systematic and regular monitoring mechanisms, including key indicators such as soil properties, black soil layer thickness, erosion, organic matter

content, and quality grading. A dynamic database tracking black soil quality changes should be developed and continually improved, integrating existing monitoring data into a nationally unified database. Implementing a robust early warning system for black soil quality, featuring clear standards and alert levels, is essential for timely intervention. Increasing special funds for black soil protection and utilization, along with enhancing technical and management capacities, is necessary. The establishment of a wide-coverage, rapid-response exchange and cooperation platform for black soil protection and utilization is also recommended.

6. Conclusions

This study initially analyzed the mechanisms through which conservation tillage affected the AGTFP of new agricultural management entities in the black soil region, drawing on theories of environmental regulation effect, substitution effect, and technology effect. It provided an overview of the application of conservation tillage technology in the black soil region and assessed the input–output status of these new agricultural management entities in pilot counties based on empirical research. Furthermore, the SBM–Undesirable model and Tobit model were constructed to measure and evaluate the AGTFP of these entities, analyzing the impact of conservation tillage technology on AGTFP. This empirical analysis substantiated our theoretical framework and presented a basis upon which to optimize the conservation and utilization of black soil. Our specific conclusions were as follows.

AGTFP levels and their variations: The AGTFP of new agricultural management entities in the research region showed significant imbalance and fluctuation. The average AGTFP value was 0.4364, indicating a generally low and greatly varying level. This suggested a need for substantial improvements in the efficiency of resources' allocation, input–output conversion, and the application of green production technology. The disparities in AGTFP levels among different enterprises highlighted the significant impact of production and management characteristics and black soil conservation practices. Improvement was needed in all input–output indicators, ranked as follows by the mean value of the degree of improvement required: machinery > pesticides > seeds > net carbon emissions > land > labor > fertilizers > non-point source pollution.

Impact of conservation tillage: Conservation tillage had a significantly positive impact on AGTFP, with the impact increasing with the number of technical measures applied. Different technology combinations yielded varying effects on AGTFP. When only one technology was used, the AGTFP from straw returning was lower than that from organic fertilizer. Combining two technologies, the AGTFP from no-tillage seeding + straw returning was lower than that from deep plowing + straw returning. When all three technologies were combined, the AGTFP from no-tillage seeding + straw returning + organic fertilizer is lower than that from deep plowing + straw returning + organic fertilizer. Overall, conservation tillage technology enhanced AGTFP, with stronger effects as more technologies and complex combinations were applied.

Influence of government subsidies and other factors: Government subsidies for black soil protection significantly increased AGTFP. Subsidies for organic fertilizer and its supporting services and government-funded conservation tillage services provided more direct financial relief and a stronger impact on AGTFP than cash subsidies. Apart from policy factors, production and operational characteristics also affected AGTFP. Factors such as access to agricultural materials, adoption of agricultural socialized services, the degree of farmland fragmentation, the suitability of farmland for mechanized operations, the education level of the person in charge, and the proportion of managers all had significantly positive effects on AGTFP.

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References

1. Liao, X.; Yao, Q.; Wan, X.; Wang, J.; Li, Z. Theoretical Basis and Technical Path for the Regional All-for-One Customization Model of Black Soil Granary. *J. Geogr. Sci.* **2022**, *32*, 2147–2169. [CrossRef]
2. Lupwayi, N.Z.; May, W.E.; Kanashiro, D.A.; Petri, R.M. Soil Bacterial Community Responses to Black Medic Cover Crop and Fertilizer N under No-Till. *Appl. Soil Ecol.* **2018**, *124*, 95–103. [CrossRef]
3. FAO. *Global Status of Black Soils*; FAO: Rome, Italy, 2022.
4. IUSS Working Group WRB. World Reference Base for Soil Resources. In *International Soil Classification System for Naming Soils and Creating Legends for Soil Maps*, 4th ed.; International Union of Soil Sciences: Vienna, Austria, 2022.
5. Durán, A.; Morrás, H.; Studdert, G.; Liu, X. Distribution, Properties, Land Use and Management of Mollisols in South America. *Chin. Geogr. Sci.* **2011**, *21*, 511–530. [CrossRef]
6. Huang, M.-T.; Zhai, P.-M. Achieving Paris Agreement Temperature Goals Requires Carbon Neutrality by Middle Century with Far-Reaching Transitions in the Whole Society. *Adv. Clim. Chang. Res.* **2021**, *12*, 281–286. [CrossRef]
7. Wang, W.; Deng, X.; Yue, H. Black Soil Conservation Will Boost China's Grain Supply and Reduce Agricultural Greenhouse Gas Emissions in the Future. *Environ. Impact Assess. Rev.* **2024**, *106*, 107482. [CrossRef]
8. Amelung, W.; Bossio, D.; de Vries, W.; Kögel-Knabner, I.; Lehmann, J.; Amundson, R.; Bol, R.; Collins, C.; Lal, R.; Leifeld, J.; et al. Towards a Global-Scale Soil Climate Mitigation Strategy. *Nat. Commun.* **2020**, *11*, 5427. [CrossRef]
9. Zhang, J.; Liu, M.; Zhang, B. Environmental Policy Integration and Performance: The Effectiveness of China's One Permit Management Reform. *Environ. Impact Assess. Rev.* **2023**, *98*, 106951. [CrossRef]
10. Wiesmeier, M.; Urbanski, L.; Hobbey, E.; Lang, B.; Von Lützow, M.; Marin-Spiotta, E.; Van Wesemael, B.; Rabot, E.; Ließ, M.; Garcia-Franco, N.; et al. Soil Organic Carbon Storage as a Key Function of Soils—A Review of Drivers and Indicators at Various Scales. *Geoderma* **2019**, *333*, 149–162. [CrossRef]
11. Liu, X.; Zang, J.; Fu, Y.; Pan, X.; Meng, D.; Zhu, Y.; Sun, T. Influences of Conservation Tillage on Soil Macrofaunal Biodiversity and Trophic Structure in the Mollisol Region of Northeast China. *Catena* **2024**, *236*, 107750. [CrossRef]
12. Godfray, H.C.J.; Beddington, J.R.; Crute, I.R.; Haddad, L.; Lawrence, D.; Muir, J.F.; Pretty, J.; Robinson, S.; Thomas, S.M.; Toulmin, C. Food Security: The Challenge of Feeding 9 Billion People. *Science* **2010**, *327*, 812–818. [CrossRef]
13. Ray, D.K.; Sloat, L.L.; Garcia, A.S.; Davis, K.F.; Ali, T.; Xie, W. Crop Harvests for Direct Food Use Insufficient to Meet the UN's Food Security Goal. *Nat. Food* **2022**, *3*, 367–374. [CrossRef]
14. Chen, Y.; Miao, J.; Zhu, Z. Measuring Green Total Factor Productivity of China's Agricultural Sector: A Three-Stage SBM-DEA Model with Non-Point Source Pollution and CO₂ Emissions. *J. Clean. Prod.* **2021**, *318*, 128543. [CrossRef]
15. Bai, Z.; Zhang, X.; Xu, J.; Li, C. Can Farmland Transfer Reduce Fertilizer Nonpoint Source Pollution? Evidence from China. *Land* **2024**, *13*, 798. [CrossRef]
16. Zhang, S.; Yang, S.; Xiong, S.; Guo, L.; Wang, Y.; Huang, X.; Sun, M.; Ding, Z. Origin and Depositional Background of the Holocene Black Soil in Northeast China: Evidence from Grain-Size Analysis and Optically Stimulated Luminescence Dating. *Catena* **2024**, *239*, 107963. [CrossRef]
17. Han, Z.; Deng, M.; Yuan, A.; Wang, J.; Li, H.; Ma, J. Vertical Variation of a Black Soil's Properties in Response to Freeze-Thaw Cycles and Its Links to Shift of Microbial Community Structure. *Sci. Total Environ.* **2018**, *625*, 106–113. [CrossRef] [PubMed]
18. Li, H.; Zhu, H.; Qiu, L.; Wei, X.; Liu, B.; Shao, M. Response of Soil OC, N and P to Land-Use Change and Erosion in the Black Soil Region of the Northeast China. *Agric. Ecosyst. Environ.* **2020**, *302*, 107081. [CrossRef]
19. Gu, Z.; Xie, Y.; Gao, Y.; Ren, X.; Cheng, C.; Wang, S. Quantitative Assessment of Soil Productivity and Predicted Impacts of Water Erosion in the Black Soil Region of Northeastern China. *Sci. Total Environ.* **2018**, *637–638*, 706–716. [CrossRef] [PubMed]
20. Wen, D.; Liang, W. Soil Fertility Quality and Agricultural Sustainable Development in the Black Soil Region of Northeast China. *Environ. Dev. Sustain.* **2001**, *3*, 31–43. [CrossRef]

21. Yan, Y.; Kuang, W.; Zhang, C.; Chen, C. Impacts of Impervious Surface Expansion on Soil Organic Carbon—A Spatially Explicit Study. *Sci. Rep.* **2015**, *5*, 17905. [CrossRef]
22. Xu, X.Z.; Xu, Y.; Chen, S.C.; Xu, S.G.; Zhang, H.W. Soil Loss and Conservation in the Black Soil Region of Northeast China: A Retrospective Study. *Environ. Sci. Policy* **2010**, *13*, 793–800. [CrossRef]
23. Hu, X.; Liu, J.; Liang, A.; Li, L.; Yao, Q.; Yu, Z.; Li, Y.; Jin, J.; Liu, X.; Wang, G. Conventional and Conservation Tillage Practices Affect Soil Microbial Co-Occurrence Patterns and Are Associated with Crop Yields. *Agric. Ecosyst. Environ.* **2021**, *319*, 107534. [CrossRef]
24. Chen, Y.; Liu, S.; Li, H.; Li, X.F.; Song, C.Y.; Cruse, R.M.; Zhang, X.Y. Effects of Conservation Tillage on Corn and Soybean Yield in the Humid Continental Climate Region of Northeast China. *Soil Tillage Res.* **2011**, *115–116*, 56–61. [CrossRef]
25. Hartmann, M.; Six, J. Soil Structure and Microbiome Functions in Agroecosystems. *Nat. Rev. Earth Environ.* **2023**, *4*, 4–18. [CrossRef]
26. Lu, J.; Zhang, W.; Li, Y.; Liu, S.; Khan, A.; Yan, S.; Hu, T.; Xiong, Y. Effects of Reduced Tillage with Stubble Remaining and Nitrogen Application on Soil Aggregation, Soil Organic Carbon and Grain Yield in Maize-Wheat Rotation System. *Eur. J. Agron.* **2023**, *149*, 126920. [CrossRef]
27. Kumar, S.; Kadono, A.; Lal, R.; Dick, W. Long-Term No-Till Impacts on Organic Carbon and Properties of Two Contrasting Soils and Corn Yields in Ohio. *Soil Sci. Soc. Am. J.* **2012**, *76*, 1798–1809. [CrossRef]
28. Archer, D.W.; Halvorson, A.D.; Reule, C.A. Economics of Irrigated Continuous Corn under Conventional-Till and No-Till in Northern Colorado. *Agron. J.* **2008**, *100*, 1166–1172. [CrossRef]
29. Li, Y.; Xue, C.; Chai, C.; Li, W.; Li, N.; Yao, S. Influencing Factors and Spatiotemporal Heterogeneity of Net Carbon Sink of Conservation Tillage: Evidence from China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 110913–110930. [CrossRef] [PubMed]
30. Sullivan, D.G.; Strickland, T.C.; Masters, M.H. Satellite Mapping of Conservation Tillage Adoption in the Little River Experimental Watershed, Georgia. *J. Soil Water Conserv.* **2008**, *63*, 112–119. [CrossRef]
31. Xing, S.; Zhang, G.; Wang, C.; Zhang, N.; Chen, S. Effects of Straw Incorporation on Soil Erosion Resistance along a Land Degradation Gradient in the Black Soil Region of China. *Catena* **2023**, *231*, 107365. [CrossRef]
32. Busari, M.A.; Kukal, S.S.; Kaur, A.; Bhatt, R.; Dulazi, A.A. Conservation Tillage Impacts on Soil, Crop and the Environment. *Int. Soil Water Conserv.* **2015**, *3*, 119–129. [CrossRef]
33. Joseph, K.X.; Issahaku, Z. Effects of Soil Conservation Technologies in Improving Soil Productivity in Northern Ghana. *J. Soil Sci. Environ. Manag.* **2015**, *6*, 158–167. [CrossRef]
34. Robertson, M.; Llewellyn, R.; Mandel, R.; Lawes, R.; Bramley, R.G.V.; Swift, L.; Metz, N.; O'Callaghan, C. Adoption of Variable Rate Fertiliser Application in the Australian Grains Industry: Status, Issues and Prospects. *Precis. Agric.* **2012**, *13*, 181–199. [CrossRef]
35. Buehren, N.; Goldstein, M.; Molina, E.; Vaillant, J. The Impact of Strengthening Agricultural Extension Services on Women Farmers: Evidence from Ethiopia. *Agric. Econ.* **2019**, *50*, 407–419. [CrossRef]
36. Ogieriakhi, M.O.; Woodward, R.T. Understanding Why Farmers Adopt Soil Conservation Tillage: A Systematic Review. *Soil Secur.* **2022**, *9*, 100077. [CrossRef]
37. Pisani, O.; Liebert, D.; Bosch, D.D.; Coffin, A.W.; Endale, D.M.; Potter, T.L.; Strickland, T.C. Element Losses from Fields in Conventional and Conservation Tillage in the Atlantic Coastal Plain, Georgia, United States. *J. Soil Water Conserv.* **2020**, *75*, 376–386. [CrossRef]
38. Choudhary, M.; Sharma, P.C.; Jat, H.S.; McDonald, A.; Jat, M.L. Soil Biological Properties and Fungal Diversity under Conservation Agriculture in Indo-Gangetic Plains of India. *J. Soil Sci. Plant Nutr.* **2018**, *18*, 1142–1156. [CrossRef]
39. Chan, K.Y. An Overview of Some Tillage Impacts on Earthworm Population Abundance and Diversity—Implications for Functioning in Soils. *Soil Tillage Res.* **2001**, *57*, 179–191. [CrossRef]
40. Lankoski, J.; Ollikainen, M.; Uusitalo, P. No-till Technology: Benefits to Farmers and the Environment? Theoretical Analysis and Application to Finnish Agriculture. *Eur. Rev. Agric. Econ.* **2006**, *33*, 193–221. [CrossRef]
41. Claassen, R.; Cattaneo, A.; Johansson, R. Cost-Effective Design of Agri-Environmental Payment Programs: U.S. Experience in Theory and Practice. *Ecol. Econ.* **2008**, *65*, 737–752. [CrossRef]
42. Wunder, S.; Engel, S.; Pagiola, S. Taking Stock: A Comparative Analysis of Payments for Environmental Services Programs in Developed and Developing Countries. *Ecol. Econ.* **2008**, *65*, 834–852. [CrossRef]
43. Greiner, R.; Patterson, L.; Miller, O. Motivations, Risk Perceptions and Adoption of Conservation Practices by Farmers. *Agric. Syst.* **2009**, *99*, 86–104. [CrossRef]
44. Bopp, C.; Engler, A.; Poortvliet, P.M.; Jara-Rojas, R. The Role of Farmers' Intrinsic Motivation in the Effectiveness of Policy Incentives to Promote Sustainable Agricultural Practices. *J. Environ. Manag.* **2019**, *244*, 320–327. [CrossRef]
45. Johnston, R.J.; Boyle, K.J.; Loureiro, M.L.; Navrud, S.; Rolfe, J. Guidance to Enhance the Validity and Credibility of Environmental Benefit Transfers. *Environ. Resour. Econ.* **2021**, *79*, 575–624. [CrossRef]
46. Mishra, A.K.; Shinjo, H.; Jat, H.S.; Jat, M.L.; Jat, R.K.; Funakawa, S.; Sutaliya, J.M. Farmers' Perspectives as Determinants for Adoption of Conservation Agriculture Practices in Indo-Gangetic Plains of India. *Resour. Conserv. Recycl. Adv.* **2022**, *15*, 200105. [CrossRef]
47. Tey, Y.S.; Brindal, M. Factors Influencing the Adoption of Precision Agricultural Technologies: A Review for Policy Implications. *Precis. Agric.* **2012**, *13*, 713–730. [CrossRef]

48. Asfaw, D.; Neka, M. Factors Affecting Adoption of Soil and Water Conservation Practices: The Case of Wereillu Woreda (District), South Wollo Zone, Amhara Region, Ethiopia. *Int. Soil Water Conserv.* **2017**, *5*, 273–279. [CrossRef]
49. Darkwah, K.A.; Kwawu, J.D.; Agyire-Tettey, F.; Sarpong, D.B. Assessment of the Determinants That Influence the Adoption of Sustainable Soil and Water Conservation Practices in Techiman Municipality of Ghana. *Int. Soil Water Conserv.* **2019**, *7*, 248–257. [CrossRef]
50. Zhang, H.; Guo, X. Farmland Rental Market, Outsourcing Services Market and Agricultural Green Productivity: Implications for Multiple Forms of Large-Scale Management. *Land* **2024**, *13*, 676. [CrossRef]
51. Xu, Q.; Zhu, P.; Tang, L. Agricultural Services: Another Way of Farmland Utilization and Its Effect on Agricultural Green Total Factor Productivity in China. *Land* **2022**, *11*, 1170. [CrossRef]
52. Liu, Y.; Feng, C. What Drives the Fluctuations of “Green” Productivity in China’s Agricultural Sector? A Weighted Russell Directional Distance Approach. *Resour. Conserv. Recycl.* **2019**, *147*, 201–213. [CrossRef]
53. Wang, Y.; Zhu, Y.; Zhang, S.; Wang, Y. What Could Promote Farmers to Replace Chemical Fertilizers with Organic Fertilizers? *J. Clean. Prod.* **2018**, *199*, 882–890. [CrossRef]
54. Qin, W.; Niu, L.; You, Y.; Cui, S.; Chen, C.; Li, Z. Effects of Conservation Tillage and Straw Mulching on Crop Yield, Water Use Efficiency, Carbon Sequestration and Economic Benefits in the Loess Plateau Region of China: A Meta-Analysis. *Soil Tillage Res.* **2024**, *238*, 106025. [CrossRef]
55. Xu, J.; Yang, A.; Yan, Y.; Xu, Y.; Tang, M.; Li, P.; Zhao, L.; Zhang, X.; Ren, Z. Quantification and Identification of Microplastics in Organic Fertilizers: The Implication for the Manufacture and Safe Application. *Water Air Soil Pollut.* **2024**, *235*, 169. [CrossRef]
56. Gozubuyuk, Z.; Sahin, U.; Ozturk, I.; Celik, A.; Adiguzel, M.C. Tillage Effects on Certain Physical and Hydraulic Properties of a Loamy Soil under a Crop Rotation in a Semi-Arid Region with a Cool Climate. *Catena* **2014**, *118*, 195–205. [CrossRef]
57. Kassam, A.; Friedrich, T.; Derpsch, R. Global Spread of Conservation Agriculture. *Int. J. Environ. Sci.* **2019**, *76*, 29–51. [CrossRef]
58. Yan, J.; Zhang, Y.; Hua, X.; Yang, L. An Explanation of Labor Migration and Grain Output Growth: Findings of a Case Study in Eastern Tibetan Plateau. *J. Geogr. Sci.* **2016**, *26*, 484–500. [CrossRef]
59. Teng, Y.; Pang, B.; Zhang, M.; Guo, X. Driving Mechanism of Farmers’ Green Production Behavior under Normalization of COVID-19 Prevention and Control: A Case Study in China. *Front. Public Health* **2022**, *10*, 826846. [CrossRef] [PubMed]
60. Shen, Y.; Hu, P.; Hou, Y.; Ying, Z.; Wang, G. Research on the Supervision Mechanism and Effect of Environmental Regulation–Re-Estimation Based on China’s Corn Planting Fertilizer Pollution. *Pol. J. Environ. Stud.* **2022**, *31*, 4313–4330. [CrossRef] [PubMed]
61. Tang, M.; Cao, A.; Guo, L.; Li, H. Improving Agricultural Green Total Factor Productivity in China: Do Environmental Governance and Green Low-Carbon Policies Matter? *Environ. Sci. Pollut. Res.* **2023**, *30*, 52906–52922. [CrossRef]
62. Li, H.; Lin, Q.; Wang, Y.; Mao, S. Can Digital Finance Improve China’s Agricultural Green Total Factor Productivity? *Agriculture* **2023**, *13*, 1429. [CrossRef]
63. Chaghazardi, H.R.; Jahansou, M.R.; Ahmadi, A.; Gorji, M. Effects of Tillage Management on Productivity of Wheat and Chickpea under Cold, Rainfed Conditions in Western Iran. *Soil Tillage Res.* **2016**, *162*, 26–33. [CrossRef]
64. Song, W.; Shu, A.; Liu, J.; Shi, W.; Li, M.; Zhang, W.; Li, Z.; Liu, G.; Yuan, F.; Zhang, S.; et al. Effects of Long-Term Fertilization with Different Substitution Ratios of Organic Fertilizer on Paddy Soil. *Pedosphere* **2022**, *32*, 637–648. [CrossRef]
65. Li, X.; Fang, J.; Shagahaleh, H.; Wang, J.; Hamad, A.A.A.; Alhaj Hamoud, Y. Impacts of Partial Substitution of Chemical Fertilizer with Organic Fertilizer on Soil Organic Carbon Composition, Enzyme Activity, and Grain Yield in Wheat–Maize Rotation. *Life* **2023**, *13*, 1929. [CrossRef]
66. Ning, Y.; Wang, X.; Yang, Y.; Cao, X.; Wu, Y.; Zou, D.; Zhou, D. Studying the Effect of Straw Returning on the Interspecific Symbiosis of Soil Microbes Based on Carbon Source Utilization. *Agriculture* **2022**, *12*, 1053. [CrossRef]
67. Chen, P.; Xu, J.; Zhang, Z.; Nie, T.; Wang, K.; Guo, H. Where the Straw-Derived Nitrogen Gone in Paddy Field Subjected to Different Irrigation Regimes and Straw Placement Depths? Evidence from ¹⁵N Labeling. *Agric. Water Manag.* **2022**, *273*, 107921. [CrossRef]
68. Jin, L.; Jin, N.; Wang, S.; Li, J.; Meng, X.; Xie, Y.; Wu, Y.; Luo, S.; Lyu, J.; Yu, J. Changes in the Microbial Structure of the Root Soil and the Yield of Chinese Baby Cabbage by Chemical Fertilizer Reduction with Bio-Organic Fertilizer Application. *Microbiol. Spectr.* **2022**, *10*, e0121522. [CrossRef]
69. Huang, M.; Fu, H.; Kong, X.; Ma, L.; Liu, C.; Fang, Y.; Zhang, Z.; Song, F.; Yang, F. Effects of Fertilization Methods on Chemical Properties, Enzyme Activity, and Fungal Community Structure of Black Soil in Northeast China. *Diversity* **2020**, *12*, 476. [CrossRef]
70. Dou, X.; He, P.; Zhu, P.; Zhou, W. Soil Organic Carbon Dynamics under Long-Term Fertilization in a Black Soil of China: Evidence from Stable C Isotopes. *Sci. Rep.* **2016**, *6*, 21488. [CrossRef]
71. Wang, X.; Wang, X.; Geng, P.; Yang, Q.; Chen, K.; Liu, N.; Fan, Y.; Zhan, X.; Han, X. Effects of Different Returning Method Combined with Decomposer on Decomposition of Organic Components of Straw and Soil Fertility. *Sci. Rep.* **2021**, *11*, 15495. [CrossRef]
72. Huang, W.; Wu, J.; Pan, X.; Tan, X.; Zeng, Y.; Shi, Q.; Liu, T.; Zeng, Y. Effects of Long-Term Straw Return on Soil Organic Carbon Fractions and Enzyme Activities in a Double-Cropped Rice Paddy in South China. *J. Integr. Agric.* **2021**, *20*, 236–247. [CrossRef]
73. Schneider, F.; Don, A.; Hennings, I.; Schmittmann, O.; Seidel, S.J. The Effect of Deep Tillage on Crop Yield—What Do We Really Know? *Soil Tillage Res.* **2017**, *174*, 193–204. [CrossRef]

74. Zhou, M.; Liu, C.; Wang, J.; Meng, Q.; Yuan, Y.; Ma, X.; Liu, X.; Zhu, Y.; Ding, G.; Zhang, J.; et al. Soil Aggregates Stability and Storage of Soil Organic Carbon Respond to Cropping Systems on Black Soils of Northeast China. *Sci. Rep.* **2020**, *10*, 265. [CrossRef] [PubMed]
75. Zhang, B.-Y.; Dou, S.; Guo, D.; Guan, S. Straw Inputs Improve Soil Hydrophobicity and Enhance Organic Carbon Mineralization. *Agronomy* **2023**, *13*, 2618. [CrossRef]
76. Yuan, L.; Gao, Y.; Mei, Y.; Liu, J.; Kalkhaje, Y.K.; Hu, H.; Huang, J. Effects of Continuous Straw Returning on Bacterial Community Structure and Enzyme Activities in Rape-Rice Soil Aggregates. *Sci. Rep.* **2023**, *13*, 2357. [CrossRef]
77. Yan, S.; Jiang, H.; Li, J.; Yan, C.; Ma, C.; Zhang, Z.; Gong, Z. Effect of Short-Term Organic Matter Returns on Soil Organic Carbon Fractions, Phosphorus Fractions and Microbial Community in Cold Region of China. *Agronomy* **2023**, *13*, 2805. [CrossRef]
78. Huang, C.; Huang, H.; Huang, S.; Li, W.; Zhang, K.; Chen, Y.; Yang, L.; Luo, L.; Deng, L. Effects of Straw Returning on Soil Aggregates and Its Organic Carbon and Nitrogen Retention under Different Mechanized Tillage Modes in Typical Hilly Regions of Southwest China. *Agronomy* **2024**, *14*, 928. [CrossRef]
79. Wang, S.; Zhao, Y.; Wang, J.; Zhu, P.; Cui, X.; Han, X.; Xu, M.; Lu, C. The Efficiency of Long-Term Straw Return to Sequester Organic Carbon in Northeast China's Cropland. *J. Integr. Agric.* **2018**, *17*, 436–448. [CrossRef]
80. Zhang, Y.; Zou, J.; Osborne, B.; Dang, W.; Xu, Y.; Ren, Y.; Dang, S.; Wang, L.; Chen, X.; Yu, Y. Effect of Straw Return on Soil Respiration in Dryland Agroecosystem of China: A Meta-Analysis. *Ecol. Eng.* **2023**, *196*, 107099. [CrossRef]
81. Han, J.; Song, X.; Fu, H.; Liu, C.; Yang, F. Effects of the Decomposition Agent Application on the Physicochemical Properties and Microbial Community Structure of Wheat Straw-Returning Soil. *Environ. Technol. Innov.* **2024**, *35*, 103668. [CrossRef]
82. Du, Y.; Cui, B.; Zhang, Q.; Wang, Z.; Sun, J.; Niu, W. Effects of Manure Fertilizer on Crop Yield and Soil Properties in China: A Meta-Analysis. *Catena* **2020**, *193*, 104617. [CrossRef]
83. Li, Z.; Liu, H.; Wang, T.; Gong, P.; Li, P.; Li, L.; Bai, Z. Deep Vertical Rotary Tillage Depths Improved Soil Conditions and Cotton Yield for Saline Farmland in South Xinjiang. *Eur. J. Agron.* **2024**, *156*, 127166. [CrossRef]
84. Niu, H.; Zhang, Z.; Xiao, Y.; Luo, M.; Chen, Y. A Study of Carbon Emission Efficiency in Chinese Provinces Based on a Three-Stage SBM-Undesirable Model and an LSTM Model. *Int. J. Environ. Res. Public Health* **2022**, *19*, 5395. [CrossRef]
85. Liu, J.; Kang, X.; Wang, W. Fintech's Impact on Green Total Factor Productivity of High Carbon Enterprises. *Emerg. Mark. Financ. Trade* **2024**, *60*, 744–768. [CrossRef]
86. Guo, Y.; Hu, Y.; Shi, K.; Bilan, Y. Valuation of Water Resource Green Efficiency Based on SBM–TOBIT Panel Model: Case Study from Henan Province, China. *Sustainability* **2020**, *12*, 6944. [CrossRef]
87. Jiang, M.; Paudel, K.P.; Mi, Y.; Li, J. Farmland Transfer and Rural Financial Structure: Evidence from China. *Int. Rev. Financ. Anal.* **2023**, *90*, 102897. [CrossRef]
88. White, H. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica* **1980**, *48*, 817–838. [CrossRef]
89. López-Garrido, R.; Díaz-Espejo, A.; Madejón, E.; Murillo, J.M.; Moreno, F.; Moreno, F. Carbon Losses by Tillage under Semi-Arid Mediterranean Rainfed Agriculture (SW Spain). *Span. J. Agric. Res.* **2009**, *7*, 706–716. [CrossRef]
90. Wang, M.; Jiang, T.; Mao, Y.; Wang, F.; Yu, J.; Zhu, C. Current Situation of Agricultural Non-Point Source Pollution and Its Control. *Water Air Soil Pollut.* **2023**, *234*, 471. [CrossRef]
91. Wang, A.; Hussain, S.; Yan, J. Evaluating the Interlinkage between Pesticide Residue Regulation and Agricultural Green Total Factor Productivity: Empirical Insights Derived from the Threshold Effect Model. *Environ. Dev. Sustain.* **2024**, 1–28. [CrossRef]
92. Lu, S.; Zhuang, J.; Sun, Z.; Huang, M. How Can Rural Digitalization Improve Agricultural Green Total Factor Productivity: Empirical Evidence from Counties in China. *Heliyon* **2024**, *10*, e35296. [CrossRef]
93. Zhu, M.; Cheng, G.; Zhang, X.; Guo, Y.; Wu, Y.; Wang, Q.; Wang, H.; Wang, W. Shelterbelts Increased Soil Inorganic Carbon but Decreased Nitrate Nitrogen, Total Phosphorus, and Bulk Density Relative to Neighbor Farmlands Depending on Tree Growth, Geoclimate, and Soil Microbes in the Northeast China Plain. *Catena* **2023**, *231*, 107344. [CrossRef]
94. Teng, Y.; Pang, B.; Guo, X. Study on the Quality Improvement on Black Land in Northeast China under the Environment of Sustainable Agricultural Development. *Kybernetes* **2021**, *52*, 809–827. [CrossRef]
95. IFPRI. *Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 1.1*; IFPRI: Washington, DC, USA, 2019.
96. Ma, S.; Wang, L.-J.; Jiang, J.; Zhao, Y.-G. Land Use/Land Cover Change and Soil Property Variation Increased Flood Risk in the Black Soil Region, China, in the Last 40 Years. *Environ. Impact Assess. Rev.* **2024**, *104*, 107314. [CrossRef]
97. Zhang, F.; Han, P.; Wu, L.; Tian, Z. Quantitative Evaluation and Evolution Characteristics of Consistency Level of Black Soil Conservation Policy, Taking China's Black Soil Protection Policy as an Example. *Land* **2024**, *13*, 800. [CrossRef]
98. FAO. *Healthy Soils Are the Basis for Healthy Food Production*; FAO: Rome, Italy, 2015.
99. Cui, N.; Ba, X.; Dong, J.; Fan, X. Does Farmland Transfer Contribute to Reduction of Chemical Fertilizer Use? Evidence from Heilongjiang Province, China. *Sustainability* **2022**, *14*, 11514. [CrossRef]
100. Savary, S.; Waddington, S.; Akter, S.; Almekinders, C.J.M.; Harris, J.; Korsten, L.; Rötter, R.P.; Van den Broeck, G. Revisiting Food Security in 2021: An Overview of the Past Year. *Food Secur.* **2022**, *14*, 1–7. [CrossRef] [PubMed]
101. Ren, Z.; Han, X.; Feng, H.; Wang, L.; Ma, G.; Li, J.; Lv, J.; Tian, W.; He, X.; Zhao, Y.; et al. Long-Term Conservation Tillage Improves Soil Stoichiometry Balance and Crop Productivity Based on a 17-Year Experiment in a Semi-Arid Area of Northern China. *Sci. Total Environ.* **2024**, *908*, 168283. [CrossRef] [PubMed]

102. Ke, C.; Huang, S.-Z. The Effect of Environmental Regulation and Green Subsidies on Agricultural Low-Carbon Production Behavior: A Survey of New Agricultural Management Entities in Guangdong Province. *Environ. Res.* **2024**, *242*, 117768. [CrossRef] [PubMed]
103. Zheng, L. Big Hands Holding Small Hands: The Role of New Agricultural Operating Entities in Farmland Abandonment. *Food Policy* **2024**, *123*, 102605. [CrossRef]
104. Miao, X.; Li, Z.; Wang, M.; Mei, J.; Chen, J. Measurement of Cultivated Land Ecosystem Resilience in Black Soil Region of Northeast China under the Background of Cultivated Land Protection Policy in China: Case Study of Qiqihar City. *J. Clean. Prod.* **2024**, *434*, 140141. [CrossRef]
105. Smerald, A.; Kraus, D.; Rahimi, J.; Fuchs, K.; Kiese, R.; Butterbach-Bahl, K.; Scheer, C. A Redistribution of Nitrogen Fertiliser across Global Croplands Can Help Achieve Food Security within Environmental Boundaries. *Commun. Earth Environ.* **2023**, *4*, 315. [CrossRef]
106. Ardenti, F.; Capra, F.; Santelli, S.; Lucini, L.; Tabaglio, V.; Fiorini, A. Potential of Conservation Tillage, Cover Crops, and Digestate Application as Integrated C Farming Practices for Processing Tomato. *Soil Tillage Res.* **2024**, *244*, 106213. [CrossRef]
107. Nunes, M.R.; van Es, H.M.; Schindelbeck, R.; Ristow, A.J.; Ryan, M. No-till and Cropping System Diversification Improve Soil Health and Crop Yield. *Geoderma* **2018**, *328*, 30–43. [CrossRef]
108. Teng, Y.; Pang, B.; Xu, H.; Liu, X. The Behavioral Decisions of Stakeholders Related to Agricultural Film Recycling under the Improvement of Black Land Quality in Northeast China. *J. Clean. Prod.* **2024**, *452*, 141899. [CrossRef]
109. Tang, Z.; Song, W.; Zou, J. Farmland Protection and Fertilization Intensity: Empirical Evidence from Preservation Policy of Heilongjiang's Black Soil. *J. Environ. Manag.* **2024**, *356*, 120629. [CrossRef] [PubMed]
110. Wang, J.; Xing, Q.; Tong, Y.; Wang, Z.; Li, B. Establish Governance Systems for Securing Black Soils in China Based on a New Law. *Soil Secur.* **2023**, *13*, 100112. [CrossRef]
111. Ma, J.; Shi, P. Remotely Sensed Inter-Field Variation in Soil Organic Carbon Content as Influenced by the Cumulative Effect of Conservation Tillage in Northeast China. *Soil Tillage Res.* **2024**, *243*, 106170. [CrossRef]
112. Hyun, J.; Yoo, G. Modification of the RothC Model to Evaluate the Inconsistent Effect of Conservation Tillage on SOC Stock and a Suggestion of a National-Scale Assessment Framework. *Sci. Total Environ.* **2024**, *907*, 168010. [CrossRef]

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Article

Study on the Spatial Effects of Grain Change on Food Security of Feed from the Perspective of Big Food

Qiang Chen, Zhiming Yu, Hua Deng and Haitao Wu *

School of Business Administration, Zhongnan University of Economics and Law, Wuhan 430073, China; 15527032018@163.com (Q.C.); 202101080017@stu.zuel.edu.cn (Z.Y.); 17771304881@163.com (H.D.)

* Correspondence: wuhan_haitao@aliyun.com

Abstract: Using panel data from 30 provinces in China from 2005 to 2020, this paper uses a spatial double difference model to evaluate the policy impact of the “grain-to-feed” policy on feed grain production in pilot areas and adjacent spatial areas. Research has found that the “grain-to-feed” policy has a significant impact on the feed grain production in pilot areas and can significantly increase the feed grain production in pilot areas by about 2.71 million tons. The “grain-to-feed” policy has strengthened the positive connection between pilot areas and adjacent pilot areas, increased feed grain production, and has a significant spatial spillover effect. Robustness analysis shows that whether using different methods to measure spatial adjacency or using different standards to distribute subsidies, the “grain-to-feed” policy can significantly increase feed grain production, narrow the supply and demand gap of feed grain, and ensure feed grain security. Further analysis shows that the “grain-to-feed” policy can not only ensure the security of feed grain for the current and next periods but also promote the increase in farmers’ income, which is long-term and sustainable. Compared with non-pilot areas, the “grain-to-feed” policy can mitigate the negative impact of wage–price signals on feed grain production in pilot areas. It is recommended that government departments accelerate the transformation of food security concepts, establish a “Big Food Perspective”, gradually promote the pilot of the “grain-to-feed” policy nationwide, increase the subsidy amount of the “grain-to-feed” policy, increase financial support for scientific and technological research and achievement transformation in the field of feed grain, prevent the impact of economic price signal fluctuations on feed grain production, and effectively ensure the security of feed grain in China.

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1. Introduction

Food security is a “national priority” [1]. The continuous improvement and diversity of grain production are not only an important measure to ensure China’s food security but also an important means to ensure global food security [2]. According to the latest data from the World Bank, China will produce more than 632 million tons of grain in 2021, maintaining first place in the global grain production ranking for ten consecutive years. According to the data of China Statistical Yearbook 2023, China’s per capita grain consumption in 2021 exceeded 480 kg, far higher than the Food and Agriculture Organization of the United Nations proposed “400 kg per capita grain consumption” food security warning line. Although China’s grain output has been increasing year annually, the supply and demand of feed grain have been in a tight balance for a long time, so it is urgent to ensure the security of feed grain [3].

Effective protection of the security of feed grain plays a key role in achieving high-quality economic and social development, especially in stabilizing prices and ensuring people’s livelihoods [4]. The 2022 China and Global Food Policy Report found that the eating habits of Chinese residents are quietly changing, and the trend of balanced and

diversified food structure is obvious. The main performance is that the demand for rations continues to decline, and the demand for feed grain is increasing [3]. Therefore, it is urgent to improve the supply of feed grain and ensure its security.

However, China's domestic feed grain supply growth is slow, with long-term dependence on imports to maintain feed grain security [5]. According to the data of the "China Feed Industry Yearbook 2020", the average annual growth rate of China's domestic feed grain output from 2014 to 2019 was 2.96%, and it is noteworthy that the growth rate of domestic feed grain output in 2019 changed from positive to negative growth for the first time. At the same time, statistics from the General Administration of Customs of China show that the import amount of soybeans and corn, China's main feed grain, continued to increase in 2023, with 99.41 million tons of soybeans and 27.13 million tons of corn imported, accounting for 78% of the total grain imports. Therefore, China's food security problems mainly appear in domestic feed grain production, among which soybeans and corn are the key [6]. Therefore, this paper mainly focuses on the study of feed grain yield changes in various provinces in China. First, the feed grain trade among various provinces is easily subject to the macro-control of the central government. Second, the international trade in feed grain is vulnerable to the impact of the international environment, especially the impact of major emergencies such as the COVID-19 pandemic and the Russia–Ukraine war.

The study of food security from the perspective of feed grain yield coincides with the concept of the "Big Food Perspective". "Big Food Perspective" is one of the important concepts that ensure food security in the world [7]. The "Big Food Perspective" refers to the formation of a wide range, variety, and nutritious food concepts [8]. In terms of food security, the "Big Food Perspective" refers to ensuring the quantity security, structural security, and nutritional security of food, of which the security of grain planting structure is particularly important [9]. Combined with the current situation of China's high grain output and low feed grain output, the "Big Food Perspective" requires optimizing China's grain planting structure, increasing the output of feed grain, and ensuring the security of feed grain. It is the establishment of the "Big Food Perspective" that has changed the traditional food security concept of the Chinese government "taking rations as the key link" and prompted the Chinese government to pay more attention to ensuring the security of feed grain [10]. Therefore, there is a very close relationship between the "Big Food Perspective" and the research content of this paper. The establishment of the "Big Food Perspective" promoted the in-depth implementation of the "grain-to-feed" policy and improved the output of feed grain, which provided a new perspective and practical support for this paper to study the impact of "grain-to-feed" policy on the output of feed grain.

Under the guidance of the "Big Food Perspective," the Chinese government has issued a series of policies to ensure the security of feed grain, and the "grain-to-feed" policy is one of them. Since 2017, China's ration output has increased annually. Although ration security has been effectively guaranteed, problems such as contradictions in grain planting structure have become increasingly prominent, especially in the planting area, and the yield of corn and soybeans urgently needs to be optimized and adjusted. To this end, under the guidance of the "Big Food Perspective," the Ministry of Agriculture and Rural Affairs of China fully implemented the "grain-to-feed" policy in 17 provinces in 2017. Its policy aim is to optimize the grain planting structure, increase the output of feed grain, and ensure the security of feed grain. In terms of policy content, taking silaged corn as an example, the policy of "grain-to-feed" requires subsidies according to the actual storage capacity of silaged corn, and the subsidy for each ton of silaged corn is about CNY 60. So the implementation of the "grain-to-feed" policy has not only greatly increased the planting area and output of feed grain but also effectively promoted an increase in farmers' income.

However, in the process of implementing the "grain-to-feed" policy, many thorny problems have also been encountered, which is not conducive to the realization of the policy purpose. First, the "grain-to-feed" policy has high requirements for agricultural machinery and equipment, and corn as a feed grain must be harvested with large special machinery and equipment, which increases the planting cost of farmers. Second, the

“grain change to feed” policy has higher requirements for agricultural technology, and the production of feed grain corn must rely on scientific production technology, such as the fermentation technology of silage corn, which ordinary farmers find difficult to master. Therefore, whether the “grain-to-feed” policy can achieve the expected policy objectives still needs scientific empirical testing. Furthermore, China’s neighboring provinces are closely connected in space, and the impact of the “grain-to-feed” policy on the spatial adjacent areas is also worthy of further exploration. Therefore, can the “grain-to-feed” policy have a significant impact on the output of feed grain in the pilot areas? How big is the policy impact? Can the “grain-to-feed” policy have a significant impact on the output of feed grain in adjacent areas? Do the policy effects differ significantly depending on the types of neighboring areas? Next, this study launches a more detailed and in-depth exploration of the above issues.

Compared with previous studies, this study may provide some marginal contributions in the following aspects. First, it fills the gap in existing research to some extent. Few of the previous studies directly discussed the implementation effect of the “grain-to-feed” policy; in particular, there is a certain research gap in the empirical analysis of the implementation effect of the “grain-to-feed” policy. The research in this paper has filled the gap of empirical analysis of the effect of the “grain-to-feed” policy on feed grain output to a certain extent, which is of great significance. Second, it expands a new research perspective. From the “Big Food Perspective”, this paper reveals the direct and indirect effects of the “grain-to-feed” policy on the local and neighboring areas, which provides a new research perspective for the existing research. Third, it enriches the research content. This study not only established a comprehensive theoretical analysis framework of the “grain-to-feed” policy but also used the spatial differential method to accurately estimate the size of the effect of the “grain-to-feed” policy on the feed grain output in local and neighboring areas and even decomposed the spatial effect to accurately capture the difference of the spatial effect. Fourth, it provides new empirical evidence. Compared with the country panel data used in previous studies, this study uses the provincial panel data of the latest year as the research object, which is not only updated in time but also has a finer granularity.

2. Literature Review

2.1. International Cutting-Edge Research

Food security is a top priority for all countries in the world. The existing international research on food security mainly focuses on four aspects: food loss reduction, agricultural big data construction, climate change response, and legal protection.

2.1.1. Food Loss Reduction

Food loss reduction is one of the important ways to ensure food security. Promoting food loss reduction and ensuring food security has reached a consensus around the world. Food loss reduction mainly includes two aspects: one is to reduce food waste, and the other is to reduce the loss of food production and post-production. Among them, food waste mainly occurs in developed countries and primarily occurs in the household consumption link. In Germany, 12 million tons of food go to waste every year, more than half of which is wasted by households [11]. The UK wastes enough food each year to fill 3600 Olympic-size swimming pools, 70% of which is wasted by households [12].

In order to reduce food waste in household consumption link, developed countries have introduced a series of targeted policy measures according to their national conditions. First, they will strengthen legal and institutional safeguards. Italy introduced the Anti-Food Waste Law in 2016, introducing the concept of reducing food waste into national legislation for the first time [13]. Japan, on the other hand, introduced the Food Reuse Law, which supports the recycling of wasted food into feed and fertilizer. Second, they will strengthen basic research and promote technological innovation. Through its self-developed automatic food sorting system, the United States can accurately distinguish low-quality food from high-quality food in the food recycling process and reduce food waste [14]. Third, they

will provide financial support. The New Zealand government provides a large amount of money every year to turn wasted food into other products, such as making beer from uneaten bread [15]. Fourth, they will promote the circulation of surplus food. Japan has launched “food bank” activities to provide surplus and unused food at the consumption link to people in need [16]. The fifth is to carry out publicity and education to raise awareness of food saving. South Korea has launched a nationwide campaign to reduce food waste [17].

Different from food waste in household consumption linked in developed countries such as Europe and the United States, food loss in developing countries such as Asia, Africa, and Latin America is concentrated in production and post-production. About half of Fiji’s food losses come from production [18]. In Brazil, on average, 14 percent of food is lost each year before it reaches the market [19]. To address food loss in the production and post-production sectors, different developing countries have adopted measures suitable for their national conditions in light of local conditions. First, they will promote infrastructure development. The Senegalese government is investing USD 400 million in food storage and logistics infrastructure [20]. Second, they will strengthen scientific and technological support. Vietnam is vigorously supporting high-tech agriculture, speeding up agricultural mechanization and processing of agricultural products [21]. Third, they will increase policy support. Brazil has implemented a number of public food security policies, from food production to consumption, which are critical to reducing food losses [22]. The fourth is to raise our awareness of the economy. Turkey has implemented a food loss awareness program, which has resulted in a 20% increase in producers’ awareness of conservation and a 40% reduction in food losses during production and post-production [23].

2.1.2. Agricultural Big Data Construction

At present, scientific and technological innovation has become a new driving force to promote the development of the food industry. New production factors represented by big data have produced good results in international practice, effectively ensuring food security. From simple sensor information collection to large-scale crop identification and disaster warning, the innovative application of big data in the field of food security is increasingly large. Remote sensing early warning technology implemented in Cambodia, Vietnam, Thailand, and Indonesia has not only effectively increased the area and willingness of farmers to grow food but also increased the annual income of each farmer by an average of 255 euros [24]. India and Germany have used big data platforms to provide farmers with food farming decisions, significantly improving food production efficiency. An agricultural big data insurance policy implemented in Kenya shows that the application of big data technology can significantly reduce the losses caused by uncertainty in food production, resulting in a 20% increase in farmers’ willingness to grow food and a 16% increase in income [25].

2.1.3. Addressing Climate Change

The food sector is globally recognized as the most sensitive to climate change, and it has reached a broad consensus around the world to strengthen response to the impact of climate change in the food sector. Since the Food and Agriculture Organization of the United Nations formally put forward the concept of climate-smart agriculture in 2010, foreign scholars have extensively discussed the theory and practice of climate-smart agriculture. As a leader in climate-smart agriculture, the United States is modernizing its digital irrigation infrastructure to cope with drought and ensure food security by developing new varieties of corn and soybeans that are more resistant to heat [26]. Canada has effectively responded to the impact of global climate change by using straw returning, fallow, crop rotation, and the establishment of green buffer zones in farmland [27]. France uses remote sensing and network monitoring technology to strengthen the intelligent management of food production by accurately monitoring climate change [28]. By spraying self-developed plant growth promoters such as carrageenan on rice, the Philippines has effectively improved the

typhoon resistance of rice, increasing the average yield per mu by about 20% and effectively ensuring food security [29]. Australia is strengthening its resilience to climate change by developing a climate change-based drought index and infrared heat signal system to monitor the growth of food crops [30].

2.1.4. Legal Protection

Legal protection is an important means for countries to ensure food security. Through the implementation of the new Agricultural Promotion Act, the United States has strengthened policy incentives in the field of food production and circulation, reduced the institutional cost of high-quality food supply, improved the global competitiveness of food production, and ensured food security [31]. Through the Common Agricultural Policy (CAP), the EU has unified the management of agriculture in its member states and ensured food security by directly subsidizing food production, enhancing the resilience of the food system, and emphasizing biodiversity [32]. In order to strengthen the legal guarantee of its food security, Japan has formed a legal guarantee system for food security based on the Basic Law on Food, Agriculture, and Rural Areas and supplemented by special legislation [33]. Among them, the Basic Law on Food, Agriculture, and Rural Areas provides overall planning and comprehensive guarantee for legal guarantee of Japan's national food security, and special legislation such as the Law on Stabilizing the Supply, Demand, and Price of Major Grains provides provisions and coordination on specific areas and specific issues. The establishment of this legal guarantee system not only realizes the absolute security of domestic rice supply but also helps to make full use of foreign resources and effectively protect domestic food security.

2.2. Comparison of Domestic and Foreign Studies

In addition to the above four aspects of research, China and foreign scholars also pay more attention to the study of grain structure transformation. Foreign studies on the transformation of grain structure mainly focus on the structural security of grain quantity, variety, and region. Among them, Fukase and Martin et al. (2020) believe that with the improvement of per capita consumption level, the structural problem of the difference between food consumption demand and food production and supply quantity in Mexico becomes prominent [34]. Kimura et al. (2008) found obvious variety differences in Japan's grain structure, in which rice is the least dependent on imports, and crops such as soybean and corn are underproduced and vulnerable to changes in the international price mechanism [35]. Saleh (2012) found that in recent years, the grain structure of Egypt has obvious regional differences, and the difference in grain production between the eastern and western regions is gradually expanding [36].

The research on grain structure transformation in China started late, and there are not many studies and discussions on grain structure transformation in the existing literature, which mainly focus on the discussion of ideas and plans for grain structure transformation [37]. Brandt et al. (2008) believe that the key point of China's grain structure transformation is to adjust the proportion of grain crop planting structure, especially to increase the area and yield of feed crops such as corn silage, alfalfa, and oats. Few studies have discussed the impact of policies related to the grain structure transformation, especially the impact of the "grain-to-feed" policy on feed food security from the perspective of empirical analysis. This gives this paper the opportunity to fill the existing research gap to some extent.

In summary, the existing research has the following shortcomings. First, the existing studies lack sufficient attention to the security of feed grain. The existing research mainly focuses on ensuring ration security, and there are few discussions on ensuring the security of feed grain. Second, the discussion on ensuring the security of feed grain has not gone far enough. Although some countries have begun to pay attention to the impact of feed grain on the transformation of grain structure, the existing studies are more focused on qualitative analysis and lack scientific quantitative research. Third, the existing studies

have ignored the spatial impact of policies to ensure the security of feed grain. The existing studies mainly focus on the impact of feed policy on the local area, ignoring the potential impact of feed policy on neighboring areas. The above deficiencies urgently need to be supplemented and improved by relevant research.

3. Theoretical Analysis

3.1. Research Hypothesis

The “grain-to-feed” policy aims to increase the production of feed grain by enhancing farmers’ production enthusiasm and leveraging economies of scale. On the one hand, this policy can reduce farmers’ planting costs, increase their income, boost their enthusiasm for growing feed grain, and expand the planting area and supply of feed grain [38]. On the other hand, the policy facilitates the integrated development of planting and breeding industries, optimizes the agricultural industry structure, and creates economies of scale, which both reduces the cost of feed grain and increases its demand [39].

In terms of boosting farmers’ production enthusiasm, compared to ration grain, feed grain has a higher yield per acre and simpler production processes, which can significantly reduce farmers’ planting costs and increase their income, thereby enhancing their production enthusiasm. For instance, the average yield per acre of silage corn is 2.9 tons, with an average purchase price of CNY 365 per ton, leading to an income of CNY 1058.5 per acre. In contrast, the average yield per acre of grain corn is 538 kg, with an average purchase price of CNY 1320 per ton, resulting in an income of CNY 710.2 per acre. Thus, compared to traditional ration crops, planting feed grain provides a higher yield per acre and increases income by CNY 348.3 per acre, greatly enhancing farmers’ production enthusiasm. Additionally, silage corn eliminates the need for harvesting, threshing, and drying, reducing the opportunity cost for farmers, increasing their chances and income from non-farming work, and further boosting their enthusiasm for planting feed grain. The increased enthusiasm for production helps to expand the planting area of feed grain and increase its production.

Regarding the economies of scale in agriculture, the “grain-to-feed” policy promotes the deep integration of planting and breeding industries, achieving integrated production, expanding agricultural production scale, and leveraging economies of scale. According to the theory of industrial integration, the integration of upstream and downstream industries in the same industrial chain can not only reduce the production costs of each individual industry through economies of scale but also effectively improve the quality and demand for each industry’s products through supply–demand alignment. The realization of agricultural economies of scale reduces the cost of feed grain, increases its demand, and indirectly boosts its production. Based on this, the theoretical hypothesis of this paper is as follows:

H1. *The implementation of the “grain-to-feed” policy can effectively increase the production of feed grain in pilot areas.*

China is vast, with significant differences in natural resource endowments and economic development levels across regions. This results in the “grain-to-feed” policy having varying spatial effects in different areas, exhibiting clear spatial heterogeneity.

Regarding natural resource endowments, there are considerable differences in arable land quality, topography, and climate conditions across China’s regions, leading to distinct spatial heterogeneity in the policy’s implementation. For instance, the climate in the Northwest region of China is arid, the terrain is at a higher altitude, and the quality of arable land is lower, limiting the capacity for ration grain production and making it more suitable for feed grain crops. Consequently, the spatial driving effect of the “grain-to-feed” policy may be relatively better in these areas.

Regarding economic development levels, there are significant disparities in industrial development levels and farmers’ income levels across China, leading to distinct spatial heterogeneity in the policy’s implementation. For example, in the southeastern coastal areas of China, the level of non-agricultural industry development is higher, farmers’

non-agricultural income levels are higher, and their willingness to engage in agricultural production is lower. Therefore, the spatial driving effect of the “grain-to-feed” policy is poorer in these areas.

In summary, the significant differences in arable land quality, topography, climate conditions, economic development levels, and farmers’ income levels across China’s regions result in distinct spatial driving effects of the “grain-to-feed” policy, leading to spatial heterogeneity. Based on this, the theoretical hypothesis of this paper is as follows:

H2. *There is significant spatial heterogeneity in the implementation of the “grain-to-feed” policy.*

3.2. Impact Pathways

The production of feed grain is inseparable from the input and allocation of production factors such as agricultural inputs, land, labor, and technology. The in-depth implementation of the "grain to feed" policy will greatly increase the input of various production factors, drive the sustained growth of feed grain output, and ensure the safety of feed grain. Figure 1 depicts the influence path of the "grain to feed" policy to improve the output of feed grain.

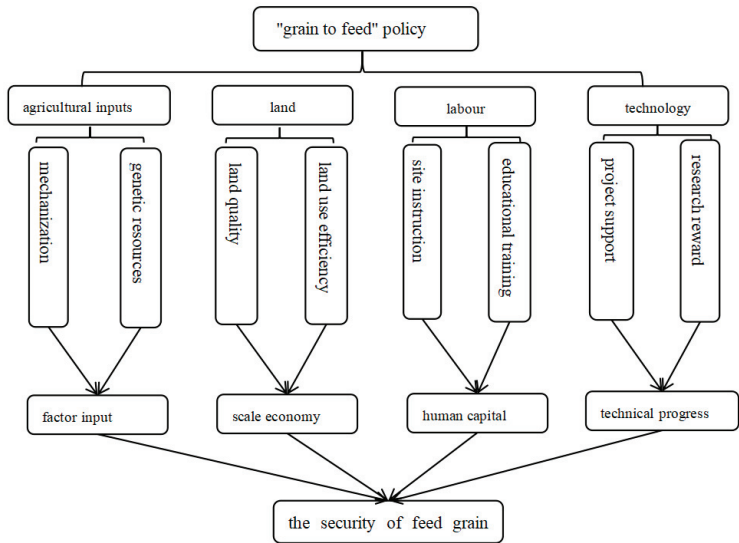


Figure 1. The impact pathways of the “grain-to-feed” policy to improve the output of feed grain.

The implementation of the “grain-to-feed” policy has driven more agricultural inputs into the production of feed grain. This policy not only enhances the mechanization level of feed crop cultivation but also optimizes the genetic resources of feed grain. Feed crops require a high level of mechanization, and the “grain-to-feed” policy provides special subsidies for the purchase of agricultural machinery for feed crops. Additionally, it actively explores the introduction of financial leasing and financing leasing to support pilot areas in improving the modern equipment capabilities for feed grain production, thereby increasing the mechanization level of feed crop cultivation and boosting feed grain production.

At the same time, the “grain-to-feed” policy promotes the cultivation of special varieties such as silage corn and high-yield, high-quality feed grain varieties, further increasing feed grain production.

The implementation of the “grain-to-feed” policy has not only improved land quality but also enhanced the utilization efficiency of land resources. Feed grain, such as alfalfa, helps with soil nitrogen fixation. Planting feed grain can improve the land quality of medium- and low-yield fields, increasing soil organic matter content by about 20%. This

improvement in land quality is also beneficial for the subsequent increase in feed grain production. Compared to ration grain, feed grain requires fewer production processes and has shorter production cycles. This allows for more inter-cropping with other crops, thereby improving land utilization efficiency and increasing feed grain production.

The implementation of the “grain-to-feed” policy helps improve farmers’ grain cultivation techniques and increases their human capital. On the one hand, the policy supports agricultural technicians in visiting villages and providing on-site guidance on corn silage techniques. On the other hand, it encourages agricultural training institutions to offer free feed crop cultivation training to farmers. This enhances farmers’ technical skills in growing feed crops, increases their human capital, and ultimately boosts feed grain production.

The “grain-to-feed” policy has promoted the investment of more technological elements. To address the technical shortcomings in feed crop cultivation, the policy provides special financial support for research on technologies such as biological fermentation feed preparation, grass–livestock energy (fertilizer) cycling, and grass–livestock efficient coupling. This support has effectively increased feed grain production.

4. Methodology

4.1. Data Sources and Selection of Variables

This study uses spatial panel data for 30 provinces in China (excluding Tibet and Taiwan) from 2005 to 2020 for the empirical analysis. The data were obtained from the China Feed Industry Statistical Yearbook and the China Statistical Yearbook.

4.1.1. Dependent Variable

This paper uses the total annual feed grain production of each province during the sample period as a proxy variable for feed grain security. Currently, the China Statistical Yearbook does not have a dedicated metric for feed grain production. The existing literature estimates feed grain production using three main methods: the variety input method, the gross reduction method, and the direct coefficient method. Each method calculates feed grain production from different perspectives, offering unique insights.

Given the aim of this paper to estimate feed grain production across various provinces in China, and considering the availability of data and the actual feed production process, the variety input method is employed. Feed grain involves numerous varieties, with soybeans, corn, tubers, and bran accounting for the majority. Thus, it is practical to use the production of soybeans, corn, tubers, wheat, and rice, which are applicable for feed grain production, to represent the output level of feed grain. The calculation of feed grain production is as follows:

$$Y_{it} = a \times S_{it} + b \times C_{it} + c \times T_{it} + d \times W_{it} + e \times R_{it} \quad (1)$$

In Equation (1), Y_{it} represents the feed grain production of province i in year t . S_{it} , C_{it} , T_{it} , W_{it} , and R_{it} denote the production of soybeans, corn, tubers, wheat, and rice, respectively, for province i in year t . a represents the conversion rate for corn into feed production, set at 70%. b is based on the soybean meal rate of 79% from the Chinese Ministry of Agriculture database. c is determined to be 40% for tubers based on studies [40]. d and e are set at 23% and 10%, respectively, following research findings by Yao et al. (2022) for wheat and rice bran rates [41]. Therefore, the total feed grain production data in this paper includes feed production, with higher total feed grain production indicating sufficient feed grain supply and greater feed grain security.

4.1.2. Policy Variables

In 2015, Document No. 1 of the Central Committee proposed a “grain-to-fodder” policy. Subsequently, Document No. 1 of the Central Committee in 2017 proposed that the “grain-to-fodder” policy should be further promoted and that the “grain-to-feed” policy should continue to be subsidized on a pilot basis. At this time, the pilot counties of the “grain-to-feed” policy were expanded from the original 30 counties to 431 counties. They

were mainly concentrated in Hebei, Liaoning, Jilin, Heilongjiang, Guangxi, Yunnan, Anhui, Shandong, Henan, and other large corn production and feed processing provinces [42]. Up to this point, the “grain-to-feed” policy has realized its policy effectiveness. Therefore, this study selects the above provinces as the policy treatment group and 2017 and later as the policy treatment period and constructs the “grain-to-feed” policy treatment variables.

4.1.3. Control Variables

To accurately assess the policy effect of the “grain-to-feed” policy on the security of feed grain, this study controlled the influence of relevant factors from the three levels of residents’ consumption, industrial structure, and regional development, respectively. This study chose the ratio of per capita consumption expenditure of urban and rural residents to control for the impact of residents’ consumption levels. The larger the ratio of per capita consumption expenditure of urban and rural residents, the more prominent the phenomenon of urban–rural consumption inequality; the higher the consumption level of urban areas, the greater the demand for meat, eggs, milk, and other products, resulting in an increase in the production of grain for fodder. The proportion of the total agricultural output value to the total regional agricultural, forestry, animal husbandry, and fishery output value is used as a proxy variable for industrial structure [43]. A larger ratio indicated more food-based agricultural production and less food production for feed. In contrast, the larger the sown area of crops, the greater the production of food for feed while guaranteeing the absolute security of regional food rations. The main factors affecting grain production for feed at the regional development level include the level of fiscal revenue, urbanization, population growth rate, and proportion of talented people [44]. The regional public budget revenue was selected to control the effect of economic development on grain feed production. Higher fiscal revenues indicate a more developed economy, higher demand for high-quality protein food, and more production of feed grain. Similarly, the higher the level of urbanization, the greater the production of food for feed. The higher the population growth rate, the higher the demand for food and the greater the production of food. The demand for meat, eggs, and milk shows a tendency to increase and then decrease as the level of education and learning increases. The reason for this is that the increase in education level firstly brings about a significant increase in income, which will increase people’s consumption and demand for meat, eggs, and milk. However, excessive intake of meat, eggs, and milk will lead to obesity and over-nutrition; out of the consideration of health and nutritional balance, the demand for meat, eggs, and milk from highly educated and high-income people gradually decreases. Therefore, with the more highly educated people above the tertiary level in a region, the impact on the production of feed grain is uncertain and needs to be determined on a case-by-case basis.

4.1.4. Spatial Weighting Matrix

Usually, the closer the spatial distance, the closer the spatial connection between the provinces, the more distant the spatial distance between provinces. This spatial connection can be either a spatial spillover effect through imitation and learning, exchange and communication, technology diffusion, or a spatial siphoning effect through coordination and matching, industrial support, or other mechanisms. To accurately capture the spatial effect of the “grain-to-feed” policy on feed grain security, this study constructs an inverse geographic distance weight matrix for the spatial distance between different provinces. $W_{ij}^1 = 1/d_{ij}$ is the matrix used as the basis for analyzing the spatial relationship between similar provinces.

Additionally, spatial spillover effects are more likely to occur between spatially neighboring provinces. To avoid Hainan Province becoming an “isolated island”, this study artificially sets Hainan Province with Guangxi and Guangdong Province according to the de facto neighboring relationship. Similarly, both collaboration and competition exist between provinces with similar distances and development levels; therefore, their spatial relationships are relatively close. Therefore, this study additionally constructs a spatial

neighbor weight matrix and an economic–geographical distance weight matrix to ensure the robustness of the analysis results.

In terms of data processing, we avoided the effects of inflation and price increases. Using 2000 as the base period, the gross domestic product (GDP) and price index were used to deflate various types of gross product and income consumption data, respectively. To minimize the effect of magnitude and excessive variance, data from various areas were logarithmized to reflect the effect of changes in elasticity. Descriptive statistics for all variables are shown in Table 1.

Table 1. Descriptive statistics of all variables.

Variable	Mean	Standard Deviation	Minimum	Median	Maximum	Sample Size
Output of feed grain	447.5	453.5	4.970	290.8	3209	480
“Grain-to-feed” policy	0.100	0.310	0	0	1	480
The ratio of per capita consumption Expenditure	2.380	0.430	1.510	2.320	3.920	480
The ratio of the agricultural output value	0.510	0.090	0.320	0.500	0.790	480
The sown area of crops	8.170	1.120	4.490	8.500	9.610	480
The level of fiscal revenue	19.40	19.48	0.340	14.35	121.8	480
Urbanization	0.550	0.140	0.270	0.530	0.900	480
Population growth rate	4.980	2.820	−4.480	5.010	11.78	480
The proportion of talented people	0.110	0.070	0.030	0.100	0.500	480

Source: China Statistical Yearbook, Statistical Yearbook by Province.

The results of descriptive statistics show that, overall, the mean and median of all variables do not differ significantly, indicating that the sample is more evenly distributed and that the possibility of bias in the estimation results caused by extreme values and outliers is low. Locally, the difference between the maximum and minimum values is relatively large, indicating that spatial heterogeneity is more evident, and there is the possibility of high-value–high-value clustering and low-value–low-value clustering, which requires spatial correlation tests.

4.2. Spatial Correlation Test Methods

A spatial correlation test of feed grain production in each province was conducted before the spatial analysis. To enhance the reliability of the test results, this study used the global Moran [45] and the Geary index [46] to test whether there is a spatial correlation in feed grain production in each province. The global Moran index is between −1 and 1, reflecting the overall spatial correlation of feed grain production. The closer the absolute value of the global Moran index is to 1, the stronger the spatial correlation, and the closer it is to 0, the weaker the spatial correlation. The Gillet index ranges from −2 to 2, with a value greater than 1 indicating negative spatial correlation, a value equal to 1 indicating spatial irrelevance, and a value less than 1 indicating positive spatial correlation.

Table 2 shows the Moran and Geary indices for the production of feed grain in each province under the three different spatial weighting matrices. The results show that (1) no matter which spatial weight matrix is used, the Moran index is all greater than 0, and the Gilley index is less than 1, indicating that there is a significant positive correlation between the production of feed grain. That is, the closer the spatial relationship between the provinces, the more obvious the spatial spillover effect of the production of feed grain, the existence of high-value–high-value agglomeration, and the low-value–low-value agglomeration. (2) The test statistics under the three spatial weight matrices are all significant, indicating that the geographic location relationship is an important factor influencing the spatial diffusion effect of feed grain production. With the implementation of regional integration strategies, the relationship between economic and social development in geographically proximate provinces is becoming stronger. Therefore, the inverse geographic

distance weight matrix can accurately portray the real spatial impact of the “grain-to-feed” policy on feed grain security.

Table 2. Global spatial correlation.

Test statistics	Economic Geographic Weight Matrix		Inverse Geographical Distance Weight Matrix		Adjacent-Weight Matrix	
	Moran’s I	Geary’s c	Moran’s I	Geary’s c	Moran’s I	Geary’s c
	0.464 ***	0.531 ***	0.457 ***	0.554 ***	0.471 ***	0.527 ***

Source: China Statistical Yearbook, Statistical Yearbook by Province. Note: *** represent significance at the 10%, 5%, and 1% levels, respectively. Due to the length of this study, this paper will not report the results of the annual global spatial correlation test, local spatial correlation test, and Moran scatter plot; these can be obtained upon request from the author if necessary.

4.3. Spatial Double-Difference Econometric Modeling

Assumptions y_1 denotes provinces that are part of the “grain-to-feed” policy pilots and y_0 denotes provinces that are not part of the “grain-to-feed” policy pilot. y_{it} denotes the production of feed grain in province i in period t . x_{it} denotes the vector of observable variables for province i in period t . For each province, there are two states before (b) and after (a) the implementation of the “grain-to-feed” policy, so the results before and after the two different types of provinces are as follows:

$$y_{it,0}^a = y_{it,0}^b + w_i D_{it} \beta \tag{2}$$

$$y_{it,1}^a = y_{it,0}^a + \alpha \tag{3}$$

Among Equations (2) and (3), the w_i is the $1 * n$ the spatial weight matrix that represents the spatial relationship between the provinces. D_{it} is $nt * 1$ the vector of $D_{it} = 1$ denotes a province that is a pilot province in period t , and $D_{it} = 0$ indicates a non-pilot province in period t . Parameter α denotes the direct treatment effect of the “grain-to-feed” policy, parameter β denotes the spatial treatment effect of the “grain-to-feed” policy in all regions and is mainly determined by $w_i D_{it}$. The parameter α denotes the direct treatment effect of the policy, and the parameter β denotes the spatial treatment effect of the policy on all regions. The above equation can be obtained by taking the above equation into the spatial panel benchmark model [47]:

$$y_{it} = \rho w_i y_{it} + \gamma w_i x_{it} + \vartheta x_{it} + (\alpha + W\beta) D_{it} + v_{it} \tag{4}$$

$$v_{it} = \lambda w_i v_{it} + \varnothing_i + \theta_t + \varepsilon_{it} \tag{5}$$

Among Equations (4) and (5), the W is an $nt * nt$ matrix of dimensions, which is w_i expanded over the spatio-temporal relationships to represent the spatio-temporal relationships between regions. $\varnothing_i$ denotes individual fixed effects and θ_t denotes time-point fixed effects. ε_{it} is a $nt * 1$ dimensional vector of error terms. The parameters ρ , γ , and λ denote the explanatory variables, the explanatory variables, and the corresponding parameters of the error terms on the space, respectively. A spatial Durbin model is used when $\lambda = 0$ is the spatial Durbin model; when $\lambda = 0$ and $\gamma = 0$ is the spatial autoregressive model; and when $\gamma = 0$ and $\rho = 0$ is the spatial error model.

To avoid model selection bias, a parallel trend test was performed first. Second, fixed and random effects were chosen based on the Hausman test. Finally, LR, Wald, and LM tests were performed to determine whether the spatial Durbin model can be reduced to a spatial autoregressive model or a spatial error model.

4.4. Decomposition of Spatial Processing Effects

In model (2), the $W\beta D_{it}$ denotes the average spatial treatment effect of the “grain-to-feed” policy for all regions. In practice, the treatment effects of a policy may differ

across regions. For the pilot policy regions, the direct treatment effect of the FFS policy was stronger, and the spatial treatment effect was relatively weaker. For non-policy pilot areas, the spatial treatment effect is clearly stronger as it is the only policy effect affecting this type of area. In this case, the parameter β as an estimate of the average spatial treatment effect of the policy across all regions would underestimate the true spatial treatment effect of the policy.

To assess the magnitude of the policy spatial treatment effect more accurately, each period's W matrix was decomposed as follows:

$$W = W_{T,T} + W_{T,NT} + W_{NT,T} + W_{NT,NT} \quad (6)$$

where $D_t^D = \text{diag}(D_{it})$ is a matrix whose main diagonal is D_{it} diagonal matrix of $D_t^C = \text{diag}(\tau - D_{it})$ and τ is a unit vector with element 1. $W_{T,T} = D_t^D * W * D_t^D$ denotes the spatial treatment effect of the policy pilot region on itself. $W_{T,NT} = D_t^D * W * D_t^C$ denotes the spatial treatment effect of the non-policy pilot region on the treatment region. $W_{NT,T} = D_t^C * W * D_t^D$ denotes the spatial treatment effect of the policy pilot region on the non-policy pilot region. $W_{NT,NT} = D_t^C * W * D_t^C$ denotes the spatial treatment effect of the non-policy pilot region on itself. Theoretically, $W_{T,NT}$ and $W_{NT,NT}$ are close to zero; therefore, we focused on the sizes of the $W_{T,T}$ and $W_{NT,T}$.

5. Results

5.1. Empirical Models

As there is a spatial correlation in the production behavior of feed grain among different provinces, the production of feed grain in a province is not only affected by its own "grain-to-feed" policy. However, it may also be affected by the implementation of the "grain-to-feed" policy in spatially related provinces. In particular, the spatial interactions between the implementation behaviors of the grain-to-feed policy in this province and other provinces reflect the spatial spillover effect of the grain-to-feed policy. To assess this effect accurately, the following spatial double-difference econometric model was constructed:

$$yield_{it} = \rho w_i yield_{it} + \gamma w_i X_{it} + \vartheta X_{it} + (\alpha + w_i \beta) policy_{it} + \varnothing_i + \theta_t + \varepsilon_{it} \quad (7)$$

In the above equation, the $yield_{it}$ denotes the total amount of feed grain production in province i in period t . $policy_{it}$ denotes whether province i is a pilot area of the "grain-to-fodder" policy in period t . X_{it} denotes the vector set of control variables, including the ratio of urban and rural residents per capita consumption expenditures and the proportion of agricultural production, gap_{it} ; the share of agricultural production, $agri_{it}$; the crop sown area (log), $\ln sonw_{it}$; the level of fiscal revenue, $fiscal_{it}$; the urbanization level, $urban_{it}$; the population growth rate, pop_{it} ; and the talent ratio, $college_{it}$. $\varnothing_i$ denotes individual fixed effects, θ_t denotes time-point fixed effects, and ε_{it} denotes random disturbance term. ρ , γ , and β are the spatial lag coefficients. ρw_i , γw_i , and $w_i \beta$ represents the spatial lag effect.

5.2. Model Testing

A parallel trend test was performed before the spatial correlation test to ensure that the use of the spatial double-difference method was justified. Figure 2 shows a parallel trend plot obtained using the ordinary double-difference method. The results show that, except for 2014, the parallel trend hypothesis is satisfied in the pilot and non-pilot areas of the "grain-to-feed" policy from 2005 to 2016. The reason for the anomaly in 2014 is that the state temporarily increased the minimum purchase price in the main grain-producing areas in 2014, and the pilot areas of the "grain-to-feed" policy happened to be among them. The state canceled the temporary corn storage policy in 2015, which led to a return to parallel feed grain production in the main grain-producing regions and other regions after 2015.

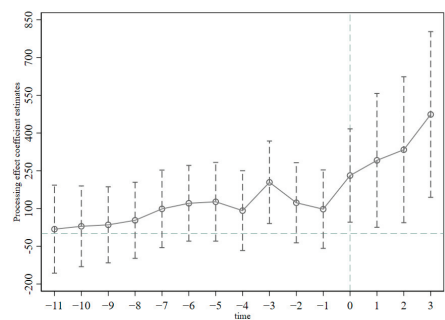


Figure 2. Parallel trend chart.

5.3. Empirical Results

In this study, the inverse geographic distance matrix is first chosen for the empirical analysis. Hausman test results show that the chi2 value of the spatial lag model (SAR) is 79.47 with a *p*-value of 0.0001, and the chi2 value of the spatial Durbin model (SDM) is 29.78 with a *p*-value of 0.028. Therefore, regardless of the spatial empirical model adopted for the estimation, the fixed-effects model estimates that efficiency is better than the random effects. Under fixed effects analysis, the LR test results show that the spatial Durbin model (SDM) cannot be transformed into a spatial lag model (SAR) or spatial error model (SEM). The chi2 value for determining whether SDM could be transformed into SAR was 38.04, with a *p*-value of 0.0001, and the chi2 value for determining whether SDM could be transformed into SEM was 39.12, with a *p*-value of 0.0001. The test of the joint significance of the spatial coefficients using the Wald statistic indicates that the SDM cannot be simplified to either SAR or SEM. The chi2 value for determining whether the SDM can be simplified to SAR was 39.79, with a *p*-value of 0.0001, and the chi2 value for determining whether the SDM can be simplified to SEM was 37.42, with a *p*-value of 0.0001. In summary, it is optimal to use the fixed-effects SDM as the final explanatory model for spatial double differences. The estimation results are shown in Table 3.

Table 3. Regression results of different spatial econometric models.

Variable	Output of Feed Grain			
	SDM-Main	SDM-Wx	SAR	SEM
“Grain-to-feed” policy	271.483 *** (33.85)	−330.179 *** (65.29)	202.357 *** (30.11)	193.917 *** (32.06)
The ratio of per capita consumption expenditure	46.315 (42.04)	49.911 (87.68)	77.885 ** (38.74)	80.687 ** (38.17)
The ratio of the agricultural output value	−242.715 (202.26)	1014.205 ** (469.07)	−425.807 ** (204.64)	−431.769 ** (204.52)
The sown area of crops	272.654 *** (70.99)	217.719 (172.68)	281.329 *** (65.14)	305.690 *** (63.80)
The level of fiscal revenue	11.303 *** (0.91)	7.952 *** (2.57)	11.348 *** (0.83)	11.134 *** (0.80)
Urbanization	686.347 * (399.15)	−410.757 (619.51)	845.809 *** (260.34)	727.788 *** (238.85)
Population growth rate	11.704 (8.02)	−9.821 (13.68)	17.029 *** (5.98)	17.201 *** (5.84)
The proportion of talented people	−396.920 (323.53)	−840.999 * (500.28)	−870.064 *** (253.87)	−900.248 *** (249.60)
R2	0.543		0.584	0.556
Log-likelihood	−3035.7254		−3054.7461	−3055.2878

Source: China Statistical Yearbook, Statistical Yearbook by Province. Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity robust standard error in parentheses.

5.4. Analysis of Results

The results in Table 3 show that after stronger controls for other disturbances, the implementation of the “grain-to-feed” policy reduced the production of feed grain by about 3.3 million tons in adjacent districts without the policy. Combined with the hypothesis of parallel trends, it can be seen that if the “grain-to-feed” policy is not implemented, the output of feed grains in the adjacent districts without the policy will increase slowly according to the change in parallel trends. However, after the implementation of the policy, because the “siphon effect” of the policy is greater than the diffusion effect, the output of feed grain in the adjacent districts without the implementation of the policy is reduced. This is mainly because the higher the output of feed grain in the pilot area of the “grain-to-feed” policy, the greater the market competitiveness, the stronger the supply capacity of feed grain in the adjacent non-pilot districts, and the lower the output of feed grain in the adjacent non-pilot districts.

In contrast, the higher the share of agriculture in the region, the stronger the promotion effect on the production of feed grain in spatially neighboring regions. For every 1% increase in the share of agriculture, the production of feed grain in adjacent regions increases by 10.14 million tons on average. A higher share of agricultural output in the region’s agriculture, forestry, fisheries, and services implies a lower share of forestry, fisheries, and services. To meet a region’s demand for meat, eggs, milk, and other proteins, the demand for feed grain from neighboring regions will increase; thus, feed grain production in neighboring regions will be significantly higher. Similarly, the higher the financial income of a region, the more developed the economy; the more robust the demand for meat, eggs, milk, and other high-quality proteins, and the greater the demand for feed grain in neighboring regions. For every CNY 100 million increase in the region’s fiscal revenue, feed grain production in neighboring regions increased by an average of 80,000 tons.

In terms of main effects, the GFS policy significantly increased the production of feed grain in the pilot districts. From the coefficients of the “grain-to-feed” variables, on average, the implementation of the “grain-to-feed” policy can significantly increase the production of feed grain in the pilot areas by about 2.71 million tons. Subsidizing the “grain-to-feed” policy can effectively increase farmers’ incentives to grow fodder grains, thus increasing the overall production of fodder grains. The larger the area planted with crops, the more adequate the supply of feed grain. For every 1% increase in the crop planting area, the supply of feed grain increases by 2.72 million tons on average. Under the condition of ensuring the absolute security of food rations, the larger the area under crop cultivation, the more area that can be used for growing feed grain crops, and the higher the output of feed grain. The higher the local fiscal revenue, the greater the feed grain production. For every CNY 100 million increase in fiscal revenue, feed grain production increases by 110,000 tons, on average. The higher the local fiscal revenue, the greater the infrastructure investment available to promote feed grain production, and the higher the production of feed grain. The coefficients of the consumption expenditure ratio, urbanization rate, population growth rate, and talent share variables are not significant at the 5% level. However, they are significant in the SAR and SEM models, indicating that further robustness tests need to be carried out.

6. Further Analysis

6.1. Robustness Tests

To ensure the robustness of the results, this study adopted the economic–geographical distance weight matrix and the adjacency weight matrix based on the fixed-effects double-difference SDM model for the robustness test to mitigate the interference of different spatial adjacencies on the estimation results. In addition, the difference between supply and demand (demand minus supply) of feed grain was used to replace feed grain supply as a proxy variable for feed grain security to enhance the persuasiveness of the impact mechanism of the “grain-to-feed” policy on feed grain security. The estimated results are presented in Table 4.

Table 4. Robustness test.

Variable	Output of Feed Grain				Supply and Demand Difference of Feed Grain	
	Economic Geographic Weight Matrix		Adjacent-Weight Matrix		Inverse Geographical Distance Weight Matrix	
	Main	Wx	Main	Wx	Main	Wx
“Grain-to-feed” policy	217.362 *** (33.80)	−98.436 ** (46.07)	245.481 *** (39.74)	−96.431 (68.42)	−194.462 *** (34.72)	334.143 *** (66.91)
The ratio of per capita consumption expenditure	79.331 * (40.81)	52.478 (68.45)	72.323 * (43.36)	−13.372 (75.32)	45.819 (43.15)	−123.444 (90.33)
The ratio of the agricultural output value	−494.364 ** (202.86)	564.142 * (325.17)	−393.613 * (207.05)	129.009 (392.12)	−225.722 (207.68)	−1335.44 *** (488.69)
The sown area of crops	180.364 ** (75.80)	830.991 *** (168.41)	344.945 *** (70.42)	42.461 (132.77)	−75.512 (72.81)	590.689 *** (173.67)
The level of fiscal revenue	13.488 *** (1.01)	1.233 (1.68)	10.791 *** (0.94)	3.698 ** (1.63)	−10.034 *** (0.93)	1.776 (2.19)
Urbanization	−6.856 (449.84)	523.955 (585.66)	782.586 * (404.23)	−393.036 (606.24)	−55.020 (410.02)	−141.991 (638.82)
Population growth rate	11.113 (8.17)	0.230 (11.66)	24.174 *** (8.20)	−12.465 (12.31)	3.208 (8.24)	19.102 (14.13)
The proportion of talented people	−834.102 ** (376.33)	−285.129 (570.06)	−417.135 (364.86)	−820.354 (535.52)	302.626 (332.70)	512.692 (508.75)
R2	0.5566		0.5309		0.3838	
Log-likelihood	−3038.3523		−3050.5651		−3047.4082	

Source: China Statistical Yearbook, Statistical Yearbook by Province. Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity robust standard error in parentheses.

The results in Table 4 show that, in terms of main effects, the “grain-to-feed” policy is effective in increasing fodder grain production in the policy pilot areas, regardless of the spatial weighting matrix. Similarly, the conclusion that the larger the area planted with local crops and the higher the fiscal revenue, the higher the production of feed grain is robust to the estimation of different spatial weighting matrices. When only the dual spatial adjacencies of economy and geography are considered, the share of local agriculture and the proportion of talented people have significant impacts on the production of feed grain in the region. The higher the share of agricultural output in the region’s agriculture, forestry, fisheries, and services sectors, the lower the feed grain production. For every one percentage point increase in the share of agriculture, feed grain production decreases by approximately 4.94 million tons. The higher the share of agriculture, the lower the share of the forestry, animal husbandry, fishery, and service industries; the smaller the demand for local feed grain, and the lower the supply of feed grain. The more highly educated the local talent, the lower the feed-grain production. For every 1% increase in the proportion of talent, feed grain production is reduced by 8.34 million tons on average. With the growth in learning, people pay more attention to the adjustment of diet structure, the lower demand for high-protein substances, and the subsequent reduction in feed grain production. When considering only spatial adjacency, the higher the population growth rate, the greater the feed grain production. For every one percentage point of population growth, feed grain production increased by approximately 240,000 tons. This is because protein is a fundamental part of the human food system, and population growth inevitably increases the demand for protein intake, thus boosting feed grain production. Adopting the difference between the supply and demand of feed grain as an explanatory variable also proves that the “grain-to-feed” policy can effectively guarantee the security of feed grain in the pilot areas, and the effect of the policy has initially appeared. On average,

the implementation of the “grain-to-feed” policy can significantly reduce the difference between the supply and demand of feed grain in the pilot areas by about 1.94 million tons. Similarly, an improvement in regional financial income can also effectively increase the supply of feed grain, narrow the difference between the supply and demand of feed grain in the region, and guarantee the security of feed grain. For every CNY 100 million increase in fiscal revenue, the difference between the supply and demand for feed grain in the region will be reduced by approximately 100,000 tons on average.

Regarding the spatial effect, the results of the estimation by choosing the economic and geographical weight matrix and the difference between the supply and demand of feed grain show that the grain-to-feed policy, while promoting an increase in the production of feed grain in the pilot areas, replaced the production of feed grain in some neighboring areas. In the context of establishing a unified national market, the increase in feed grain production in the pilot areas effectively releases potential space for the development of other industries in the neighboring areas, which is conducive to the formation of an integrated, left-right, and right-right supporting industrial system. From the estimation results of the economic geography weight matrix alone, the larger the area of crop cultivation in the region, the higher the output of feed grain in economically and geographically similar regions. To ensure the absolute security of the food ration, the larger the crop planting area, the higher the land utilization efficiency, and the more advanced the planting technology. Through the effect of technology diffusion, planting technology in neighboring areas has also improved, and the area that can be used for planting fodder grain crops has increased accordingly, resulting in a significant increase in fodder grain production. In terms of the difference between the supply and demand of feed grain, the higher the proportion of agriculture in a region, the more conducive it is to reduce the difference between the supply and demand of feed grain in neighboring regions in space. The higher the proportion of agriculture in a region, the higher the production of feed grain in spatially neighboring regions, the smaller the difference between supply and demand, and the safer the feed grain. This conclusion corroborates the previous estimation results. Taken together, the estimation results of this study are robust.

6.2. Decomposition of Effects

To further explore the differences in the magnitude of the effect of the food-for-feed policy on spatially adjacent pilot and non-pilot areas, this study decomposed the spatial effects of the food-for-feed policy on spatially adjacent areas. Table 5 shows the estimation results using the inverse geographic distance weight matrix, economic–geographic weight matrix, and the difference between the supply and demand of food as the dependent variable.

The results in Table 5 show that when fodder grain production was the subject of the study, the direct effect of the food-for-feed policy on the pilot areas was always positive, regardless of the matrix used. Meanwhile, the spillover effect of the policy pilot areas on spatially neighboring pilot areas was significantly positive, and the spatial effect on non-pilot areas was insignificant. Taking the inverse geographic distance weight matrix as an example, after the implementation of the grain-to-feed policy, the grain output of the pilot areas themselves increased by an average of 1.17 million tons, and the grain output of the spatially adjacent pilot areas increased by an average of 449.47 million tons, which is an obvious policy effect. The overall negative spatial effect of pilot regions on neighboring regions is mainly caused by the fact that there are more non-pilot regions, and the spatial effect of pilot regions on non-pilot regions is insignificant. In particular, it should be noted that the negative impact of the policy on the output of feed grain in adjacent non-pilot districts does not mean that the implementation of the policy is ineffective. Because we found that there is a significant and positive promoting effect between the feed grain output in the pilot area and the adjacent pilot area, it also means that we can reduce the negative impact of the “grain-to-feed” policy on the feed grain output in the adjacent non-pilot districts by expanding the implementation scope of the “grain-to-feed” policy.

Table 5. Effect decomposition.

Variable	Output of Feed Grain		Supply and Demand Difference of Feed Grain	
	Inverse Geographical Distance Weight Matrix	Economic Geographic Weight Matrix	Inverse Geographical Distance Weight Matrix	Economic Geographic Weight Matrix
“Grain to feed” policy	116.685 *** (44.34)	128.694 *** (36.03)	−28.727 (45.58)	−39.616 (36.96)
Pilot area to pilot area	44,946.87 *** (12,982.32)	895.376 *** (174.83)	−50,289.3 *** (13,339.87)	−986.149 *** (179.16)
Pilot areas versus non-pilot areas	1640.725 (3697.41)	64.158 (52.90)	−2130.546 (3805.46)	−15.190 (54.27)
The ratio of per capita consumption expenditure	32.098 (41.34)	36.866 (40.74)	76.568 * (41.08)	69.967 * (40.34)
The ratio of the agricultural output value	−200.030 (205.03)	−247.094 (201.63)	−248.455 (203.30)	−202.900 (199.15)
The sown area of crops	299.718 *** (72.21)	271.954 *** (71.39)	−142.593 ** (71.56)	−118.296 * (70.46)
The level of fiscal revenue	11.668 *** (0.94)	11.812 *** (0.92)	−10.556 *** (0.93)	−10.760 *** (0.91)
Urbanization	567.615 (397.39)	739.482 * (391.88)	357.734 (397.64)	151.917 (391.09)
Population growth rate	9.065 (8.68)	11.798 (8.55)	2.666 (8.64)	0.097 (8.48)
The proportion of talented people	−458.195 (325.44)	−458.744 (319.71)	280.269 (323.76)	292.135 (316.86)
R2	0.5528	0.5653	0.3742	0.3927
Sample size	480	480	480	480

Source: China Statistical Yearbook, Statistical Yearbook by Province. Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity robust standard error in parentheses.

When using the difference between feed grain supply and demand as the dependent variable for estimation, it was found that after the implementation of the grain-to-feed policy, the policy effect of the pilot regions on neighboring pilot regions was more obvious. Overall, the implementation of the grain-to-feed policy has significantly promoted feed grain security between the pilot regions and spatially neighboring pilot regions. By imitating and learning from the successful experiences of neighboring pilot regions, healthy competition has been formed among the pilot regions of the grain-to-feed policy, which has effectively increased the total output of fodder grains in the pilot regions and strongly guaranteed the security of fodder grains.

6.3. The Impact on Farmers’ Income

The “grain-to-feed” policy should not only guarantee the security of feed grain but also be able to promote farmers’ income. Any policy reform that reduces farmers’ income is unsustainable. In order to verify the sustainability of the “grain-to-feed” policy, this paper further analyses the impact of the “grain-to-feed” policy on the per capita disposable income of rural residents. At the same time, any policy reform that widens the income gap between urban and rural areas is not conducive to social stability. Therefore, the text also analyses the impact of the “grain-to-feed” policy on the ratio of urban residents’ income to rural residents’ income, and the results are shown in Table 6.

Table 6. Impact of “grain-to-feed” policies on farmers’ income and income inequality.

Variable	Farmers’ Income		The Ratio of Urban to Rural Residents’ Income	
	Main	Wx	Main	Wx
“Grain-to-feed” policy	966.899 *** (166.29)	−683.717 (458.59)	−0.080 *** (0.02)	0.026 (0.05)
The ratio of per capita consumption expenditure	−132.994 (202.20)	1708.914 *** (561.25)	0.238 *** (0.02)	0.045 (0.07)
The ratio of the agricultural output value	2518.089 ** (1005.07)	−6660.82 ** (2919.25)	−0.264 ** (0.12)	0.105 (0.34)
The sown area of crops	−2258.57 *** (348.06)	−1508.65 (1040.87)	−0.122 *** (0.04)	−0.105 (0.11)
The level of fiscal revenue	45.203 *** (4.83)	87.068 *** (16.11)	0.002 *** (0.001)	0.001 (0.01)
Urbanization	−30,201.3 *** (1933.23)	4108.997 (6148.71)	−0.729 *** (0.22)	−3.631 *** (0.68)
Population growth rate	5.482 (42.35)	−73.352 (135.07)	−0.001 (0.001)	0.046 *** (0.02)
The proportion of talented people	993.088 (1588.78)	−5949.66 * (3579.55)	0.057 (0.18)	0.653 (0.42)
R2	0.186		0.494	
Sample size	480		480	

Source: China Statistical Yearbook, Statistical Yearbook by Province. Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity robust standard error in parentheses.

The results in Table 6 show that the “grain-to-feed” policy was effective not only in raising the income of farmers in the pilot areas but also in narrowing the urban–rural income gap in the pilot areas. After the implementation of the “grain-to-feed” policy, the income of rural residents in the pilot areas increased by CNY 967, and the income ratio between urban and rural residents decreased by 0.08 units. Therefore, the “grain-to-feed” policy is not only sustainable but also conducive to social stability. On the one hand, it is because the production of feed grain is higher than that of ration grain, which increases farmers’ farm income, and on the other hand, it is because the subsidies under the “grain-to-feed” policy increase farmers’ transfer income. At the same time, we also found that the impact of the “grain-to-feed” policy on farmers’ incomes and the urban–rural income gap in the neighboring areas of the pilot was not significant. On the one hand, the “grain-to-feed” policy reduced the production of feed grain in the neighboring areas, thus decreasing the farmers’ operating incomes. On the other hand, however, it may also encourage farmers in neighboring areas to migrate to urban areas for work and increase their wage income, thus having a non-significant impact on farmers’ income in neighboring areas and on the urban–rural income gap.

6.4. Impact of the Amount of Policy Subsidies

In addition to clearly delineating the pilot areas, the “grain-to-feed” policy mainly encourages and guides farmers to plant feed grain through policy subsidies. According to the requirements of the “grain-to-feed” Work Implementation Programme of the Ministry of Agriculture of China, the amount of subsidies under the “grain-to-feed” policy in each province is mainly determined by the planting area and storage volume of feed grain. In 2017, China’s central financial administration arranged a total of RMB 2 billion in subsidies for the “grain-to-feed” policy, which was used to subsidize farmers who planted feed grain on 10 million mu and cooperatives who collected and stored 30 million tonnes of feed grain. At the same time, the central government broke down the tasks of 10 million mu and

30 million tonnes to 17 provinces and regions according to the factor method. Therefore, this paper estimates the amount of central financial subsidy for different provinces and regions according to their planting area and storage tasks and discusses the impact of the subsidy amount of the “grain-to-feed” policy on the output of feed grain accordingly. The results are shown in Table 7.

Table 7. Impact of the number of subsidies under the “grain-to-feed”.

Variable	Output of Feed Grain			
	Main	Wx	Main	Wx
Subsidies for planting area	133.806 *** (23.17)	−168.907 *** (45.87)		
Subsidy for storage volume			146.529 *** (23.69)	−166.898 *** (45.72)
The ratio of per capita consumption expenditure	47.028 (43.36)	47.366 (90.81)	47.250 (43.15)	49.730 (90.29)
The ratio of the agricultural output value	−256.991 (207.20)	1029.535 ** (469.57)	−255.964 (206.21)	985.700 ** (467.53)
The sown area of crops	288.640 *** (73.52)	163.391 (184.34)	286.941 *** (73.25)	217.568 (184.33)
The level of fiscal revenue	10.386 *** (0.95)	9.277 *** (2.63)	10.378 *** (0.95)	9.392 *** (2.62)
Urbanization	540.443 (420.77)	−227.816 (652.55)	528.481 (417.74)	−212.280 (647.15)
Population growth rate	12.301 (8.27)	−7.447 (14.25)	12.275 (8.23)	−6.788 (14.18)
The proportion of talented people	−575.595 * (332.57)	−777.284 (520.06)	−559.187 * (331.06)	−809.206 (517.60)
R2		0.536		0.529
Sample size		480		480

Source: China Statistical Yearbook, Statistical Yearbook by Province. Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity robust standard error in parentheses.

The results in Table 7 show that the grain-to-feed policy subsidy funds, whether disbursed on the basis of planting area or storage volume, were effective in increasing the production of feed grain in the pilot areas. Controlling for other factors, for every CNY 100 million subsidy from the “grain-to-feed” policy, the production of feed grain in the pilot areas increased by 1.34 million tonnes and 1.46 million tonnes, respectively. Therefore, the conclusion is that the “grain-to-feed” policy has contributed to increasing feed grain production and ensuring feed grain security is robust.

6.5. Impact of Economic Price Signals

In addition to the impact of the number of subsidies under the “grain-to-feed” policy, economical price signals in pilot and non-pilot areas also have an impact on farmers’ behavior in growing feed grain. Since China has a minimum purchase price policy for feed grain and feed grain prices fluctuate from region to region, it is difficult to use feed grain price signals to reflect the real market situation. Instead, we use the average wage of urban private sector workers in each province to indirectly reflect economic price signals in different regions in order to compare the impact of economic price signals in pilot provinces with those in non-pilot provinces.

The results in Table 8 show that the higher the wage–price signals, the lower the production of feed grain, but the implementation of the “grain-to-feed” policy in the pilot areas effectively mitigates the negative impact of wage–price signals on feed grain

production compared to the non-pilot areas. The higher the wage–price signals, the higher the opportunity cost for farmers to grow feed grain, and the more likely they are to go out to work, which reduces the cultivation of feed grain and lowers the production of feed grain. Compared with the non-pilot areas, the implementation of the “grain-to-feed” policy in the pilot areas increased farmers’ income from cultivating feed grain and reduced their opportunity cost of cultivating feed grain, thus mitigating the negative impact of the wage–price signal on feed grain production. Thus, the impact of wage–price signals on feed grain production varied across regions, with the negative impact of wage–price signals on feed grain production being weaker in the pilot regions than in the non-pilot regions.

Table 8. Impact of economic price signals.

Variable	Output of Feed Grain		Output of Feed Grain in the Next Period	
	Main	Wx	Main	Wx
“Grain-to-feed” policy	210.346 *** (48.56)	−198.881 * (101.48)	96.059 *** (21.90)	−40.553 (43.47)
Wage–price signal	−299.768 * (154.12)	36.845 (221.50)		
Wage–price signal * “grain-to-feed” policy	60.876 (67.59)	−284.173 (185.65)		
The ratio of per capita consumption expenditure	0.819 (63.80)	−138.755 (166.35)	−11.351 (29.02)	50.114 (59.06)
The ratio of the agricultural output value	−21.753 (291.19)	949.038 (689.59)	−143.101 (135.38)	−83.972 (313.03)
The sown area of crops	260.566 *** (98.77)	122.856 (244.64)	12.914 (48.19)	−30.102 (114.62)
The level of fiscal revenue	10.676 *** (1.27)	13.043 *** (3.82)	0.026 (0.62)	−0.673 (1.36)
Urbanization	−251.665 (595.02)	1022.458 (1081.49)	19.349 (277.72)	639.069 (423.52)
Population growth rate	7.299 (8.95)	−6.752 (15.00)	8.112 (5.33)	3.380 (9.02)
The proportion of talented people	−129.084 (342.92)	−1187.03 ** (544.56)	17.655 (212.95)	−935.388 *** (325.83)
R2	0.211		0.63	
Sample size	360		450	

Source: China Statistical Yearbook, Statistical Yearbook by Province. Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity robust standard error in parentheses.

Finally, this paper also considers the long-term impact of the “grain-to-feed” policy and examines the impact of the “grain-to-feed” policy on the production of feed grain in the next period. The results in Table 8 show that the “grain-to-feed” policy can effectively increase the production of feed grain in the next period. This is mainly due to the fact that the “grain-to-feed” policy has increased farmers’ confidence and expectation of growing feed grain, thus increasing the production of feed grain in the next period, which further indicates that the implementation of the “grain-to-feed” policy has a stable, sustained and long-term effect.

7. Conclusions and Discussion

7.1. Conclusions

Using the panel data of 30 provinces in China from 2005 to 2020, this paper selects a spatial double difference to difference model to assess the policy impact of the “grain-to-

feed" policy on the production of feed grain in pilot areas and spatially adjacent areas. It is found that the spatial distribution of feed grain production in each province in China has obvious spatial dependence and spatial agglomeration, which is characterized by the agglomeration of high values and high values and the agglomeration of low values and low values. The "grain-to-feed" policy can significantly increase the output of feed grain in the pilot areas with a certain degree of precision. To a certain extent, the "grain-to-feed" policy has reduced the production of feed grain in neighboring regions, indicating that the "siphoning effect" of the "grain-to-feed" policy on feed production in neighboring regions is greater than the spillover effect, exacerbating the impact of the policy on feed production. The results of the decomposition of spatial effects show that the policy has enhanced the positive linkages between the pilot areas and neighboring pilot areas, increased feed grain production, and had an obvious spatial spillover effect. The "grain-to-feed" policy intensified the negative linkage between the pilot areas and the neighboring non-pilot areas and reduced the production of feed grain, showing a certain "siphoning effect". The "siphon effect" is greater than the spillover effect, which is the root cause of the reduction in feed grain production in neighboring regions as a result of the "grain-to-feed" policy.

The results of the robustness test show that, regardless of the method used to measure spatial proximity, the "grain-to-feed" policy can significantly increase the production of feed grain in the pilot areas, reduce the gap between supply and demand of feed grain in the pilot areas, and guarantee the security of feed grain in the pilot areas. The "grain-to-feed" policy can not only guarantee the security of feed grain but also promote farmers' income increase, which has certain sustainability. Whether subsidies are granted based on the area planted with feed grain or the amount of feed grain harvested and stored, the "grain-to-feed" policy can significantly increase the production of feed grain in the pilot areas and guarantee the security of feed grain in the pilot areas. Due to the obvious differences in economic price signals in different regions, the implementation effect of the "grain-to-feed" policy in different regions is also obviously different. Compared with the non-pilot areas, the "grain-to-feed" policy can reduce the negative impact of wage-price signals on feed grain production. Finally, the "grain-to-feed" policy has the potential to increase feed grain production not only in the current pilot period but also in the next period, with a certain degree of long-term persistence.

7.2. Comparative Analysis with Existing Studies

Compared with previous studies, this paper will provide new insights for research related to the field of food structural transformation. First, this paper provides a new research direction for studies related to food structure transformation. Most of the studies related to food structure transformation have argued that the food structure should be transformed from ration crops to cash crops. This paper argues that, in addition to the transformation of ration crops to cash crops, ration crops can also be transformed to feed crops, which guarantees food security and improves farmers' incomes. Secondly, this paper fills the gap in analyzing the spatial effect of the "grain-to-feed" policy to a certain extent. The related research on the "grain-to-feed" policy mainly focuses on the direct effect of the "grain-to-feed" policy, but this paper not only examines the effect of the "grain-to-feed" policy on the production of feed grain in the pilot area but also examines the effect of the "grain-to-feed" policy on the production of feed grain in spatially adjacent areas. Thirdly, this paper provides a new research method for the study of spatial effect decomposition from the perspective of economics. At present, the research on spatial effect decomposition mainly focuses on statistics, and this paper is one of the few studies that apply spatial effect decomposition to economics.

7.3. Policy Recommendations

Based on the conclusions of this paper, this paper suggests that the government departments concerned should improve and perfect the "grain-to-feed" policy in the following aspects so as to give full play to the effectiveness of the "grain-to-feed" policy

and realize the objectives of the “grain-to-feed” policy: (1) Accelerate the change in the perspective of food, and comprehensively set up the “Big Food Perspective”. Perspective influences attitudes, and attitudes change behaviors. It is necessary to accelerate the transformation of the traditional food perspective of “taking rations as an outline”; establish the new perspective of “food, economy, forage and grass diversification as a whole”; and pay more attention to the production of non-ration crops such as feed grain, and so on. (2) Further expand the scope of implementation of the “grain-to-feed” policy. The “grain-to-feed” policy can effectively increase the production of feed grain in pilot areas, but it is slightly insufficient to guarantee the security of feed grain in non-pilot areas. In order to make up for this shortcoming, it is suggested that the implementation scope of the “grain-to-feed” policy be expanded further, starting from the main grain-producing areas, gradually expanding to the balanced production and marketing areas, and finally realizing the national promotion. (3) Increase the implementation of the “grain-to-feed” policy. On the one hand, it is suggested to increase that the number of subsidies for the “grain-to-feed” policy be increased, the financial fund integration in the grain field be strengthened, and the financial fund “reservoir” for the “grain-to-feed” policy be expanded. On the other hand, it is suggested to expand the subsidy standard of the “grain-to-feed” policy, and in addition to the two standards of planting area and storage volume of feed grain, it is suggested to increase the indicators of scientific and technological research and development rate of feed grain and the rate of transformation of achievements, so as to strengthen the financial support for scientific and technological research and development of feed grain and the transformation of achievements. (4) Strengthening the response to the impact of fluctuating economic price signals on feed grain production. It is recommended that priority be given to implementing the “grain-to-feed” policy in regions with large fluctuations in economic price signals so as to mitigate the negative impact of high wage prices on feed grain production.

7.4. Research Limitations and Areas for Future Research

Due to the absence of data and other objective reasons, the limitations of this paper are also obvious, which are mainly reflected in the following points: First, this paper lacks corresponding micro-analysis, especially the micro-analysis from a single farmer or farm. Second, this paper lacks an in-depth discussion on the impact of “grain-to-feed” policy subsidies on the ecological environment and social costs. In particular, there is a lack of in-depth analysis of the dependence of subsidies locking in high input production systems with associated social and environmental costs. Third, it does not take into account the effective response of local governments to the “grain-to-feed” policy. For example, local governments in non-policy pilot areas may reduce or circumvent the main responsibility of food security by “withdrawing counties and combining districts”. Fourth, this paper lacks the impact of international trade rules on the “grain-to-feed” policy, especially how to guide the subsidy direction of the “grain-to-feed” policy toward the “green box” policy.

Looking forward to the future, the subsequent relevant research can be supplemented and improved in the following aspects: First, in the research field, the “grain-to-feed” policy can be expanded to other policies, such as the “Northeast black land protection and utilization” policy. Second, the research dimension is expanded from the dimension of feed grain output to the dimension of quality and structure. The third is to broaden the research data from the provincial level to the prefecture-level city, county, family, and individual levels. The fourth is to broaden the research methods from multi-stage DID to intensity DID to continuously enrich the relevant research on food security in China.

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References

- Xu, D.; Deng, X.; Guo, S.; Liu, S. Labor migration and farmland abandonment in rural China: Empirical results and policy implications. *J. Environ. Manag.* **2019**, *232*, 738–750. [CrossRef]
- Fan, M.; Shen, J.; Yuan, L.; Jiang, R.; Chen, X.; Davies, W.J.; Zhang, F. Improving crop productivity and resource use efficiency to ensure food security and environmental quality in China. *J. Exp. Bot.* **2012**, *63*, 13–24. [CrossRef] [PubMed]
- Wang, H.; Zhang, M.; Cai, Y. Problems, challenges, and strategic options of grain security in China. *Adv. Agron.* **2009**, *103*, 101–147.
- Deng, X.; Xu, D.; Zeng, M.; Qi, Y. Does Internet use help reduce rural cropland abandonment? Evidence from China. *Land Use Policy* **2019**, *89*, 104243. [CrossRef]
- Li, J.; Li, Z. Physical limitations and challenges to Grain Security in China. *Food Secur.* **2014**, *6*, 159–167. [CrossRef]
- Cui, K.; Shoemaker, S.P. A look at food security in China. *npj Sci. Food* **2018**, *2*, 4. [CrossRef]
- Makkar, H.P.S. Feed demand landscape and implications of food-not feed strategy for food security and climate change. *Animal* **2018**, *12*, 1744–1754. [CrossRef] [PubMed]
- Gallo, M.; Ferrara, L.; Calogero, A.; Montesano, D.; Naviglio, D. Relationships between food and diseases: What to know to ensure food safety. *Food Res. Int.* **2020**, *137*, 109414. [CrossRef]
- Lu, Y.; Zhang, Y.; Hong, Y.; He, L.; Chen, Y. Experiences and lessons from Agri-Food system transformation for sustainable food security: A review of China's practices. *Foods* **2022**, *11*, 137. [CrossRef]
- Bryden, W.L. Mycotoxin contamination of the feed supply chain: Implications for animal productivity and feed security. *Anim. Feed. Sci. Technol.* **2012**, *173*, 134–158. [CrossRef]
- Jörissen, J.; Priefer, C.; Bräutigam, K.R. Food waste generation at household level: Results of a survey among employees of two European research centers in Italy and Germany. *Sustainability* **2015**, *7*, 2695–2715. [CrossRef]
- Lowenberger, A.; Mauer, J.; de Laski, A.; DiMascio, M.; Amann, J.; Nadel, S. *The Efficiency Boom: Cashing in on the Savings from Appliance Standards*; ACEEE: Washington, DC, USA; ASAP: Boston, MA, USA, 2012.
- Fattibene, D.; Recanati, F.; Dembska, K.; Antonelli, M. Urban food waste: A framework to analyse policies and initiatives. *Resources* **2020**, *9*, 99. [CrossRef]
- Ceryes, C.A.; Antonacci, C.C.; Harvey, S.A.; Spiker, M.L.; Bickers, A.; Neff, R.A. “Maybe it’s still good?” A qualitative study of factors influencing food waste and application of the EPA Food recovery hierarchy in US supermarkets. *Appetite* **2021**, *161*, 105111. [CrossRef] [PubMed]
- Mason, L.; Boyle, T.; Fyfe, J.; Smith, T.; Cordell, D. National food waste assessment. In *Final Report*; Institute for Sustainable Futures, University of Technology Sydney: Ultimo, Australia, 2011; pp. 78–80.
- Nomura, A. The shift of food value through food banks: A case study in Kyoto, Japan. *Evol. Inst. Econ. Rev.* **2020**, *17*, 243–264. [CrossRef]
- Zamri, G.B.; Azizal NK, A.; Nakamura, S.; Okada, K.; Nordin, N.H.; Othman, N.; Akhir, F.N.M.D.; Sobian, A.; Kaida, N.; Hara, H. Delivery, impact and approach of household food waste reduction campaigns. *J. Clean. Prod.* **2020**, *246*, 118969. [CrossRef]
- Pratt, S. Minimising food miles: Issues and outcomes in an ecotourism venture in Fiji. *J. Sustain. Tour.* **2013**, *21*, 1148–1165. [CrossRef]
- Pereira PA, A.; Martha, G.B.; Santana, C.A.; Alves, E. The development of Brazilian agriculture: Future technological challenges and opportunities. *Agric. Food Secur.* **2012**, *1*, 4. [CrossRef]
- Faye, A.; Dièye, M.; Diakhaté, P.B.; Bèye, A.; Sall, M.; Diop, M. *Senegal-Land, Climate, Energy, Agriculture and Development: A Study in the Sudano-Sahel Initiative for Regional Development, Jobs, and Food Security*; Center for Development Research, University of Bonn: Bonn, Germany, 2021.
- Nguyen, T.C.N. *The Development of Vietnam’s Industrial Clusters and New Challenges in the Post-COVID Scenario*; Università Ca’ Foscari Venezia: Venice, Italy, 2022.
- Berchin, I.I.; Nunes, N.A.; de Amorim, W.S.; Zimmer GA, A.; da Silva, F.R.; Fornasari, V.H.; Sima, M.; de Andrade, J.B.S.O. The contributions of public policies for strengthening family farming and increasing food security: The case of Brazil. *Land Use Policy* **2019**, *82*, 573–584. [CrossRef]
- Kör, B.; Krawczyk, A.; Wakkee, I. Addressing food loss and waste prevention. *Br. Food J.* **2022**, *124*, 2434–2460. [CrossRef]

24. Ledien, J.; Sorn, S.; Hem, S.; Huy, R.; Buchy, P.; Tarantola, A.; Cappelle, J. Assessing the performance of remotely-sensed flooding indicators and their potential contribution to early warning for leptospirosis in Cambodia. *PLoS ONE* **2017**, *12*, e0181044. [CrossRef]
25. Saeed, M.; Arshed, N. Big Data Analytics Technology Adoption in Kenya Insurance Industry: A Systematic Literature Review. *Asian Bull. Big Data Manag.* **2023**, *3*, 1–17. [CrossRef]
26. Zhao, J.; Liu, D.; Huang, R. A review of climate-smart agriculture: Recent advancements, challenges, and future directions. *Sustainability* **2023**, *15*, 3404. [CrossRef]
27. Gan, Y.; Liang, C.; Campbell, C.A.; Zentner, R.P.; Lemke, R.L.; Wang, H.; Yang, C. Carbon footprint of spring wheat in response to fallow frequency and soil carbon changes over 25 years on the semiarid Canadian prairie. *Eur. J. Agron.* **2012**, *43*, 175–184. [CrossRef]
28. Martos, V.; Ahmad, A.; Cartujo, P.; Ordoñez, J. Ensuring agricultural sustainability through remote sensing in the era of agriculture 5.0. *Appl. Sci.* **2021**, *11*, 5911. [CrossRef]
29. Gatto, M.; Naziri, D.; San Pedro, J.; Bénédicte, C. Crop resistance and household resilience—the case of cassava and sweetpotato during super-typhoon Ompong in the Philippines. *Int. J. Disaster Risk Reduct.* **2021**, *62*, 102392. [CrossRef]
30. Afuye, G.A.; Kalumba, A.M.; Orimoloye, I.R. Characterisation of vegetation response to climate change: A review. *Sustainability* **2021**, *13*, 7265. [CrossRef]
31. Mozaffarian, D. Dietary and policy priorities for cardiovascular disease, diabetes, and obesity: A comprehensive review. *Circulation* **2016**, *133*, 187–225. [CrossRef]
32. Candel, J.J.; Breeman, G.E.; Stiller, S.J.; Termeer, C.J. Disentangling the consensus frame of food security: The case of the EU Common Agricultural Policy reform debate. *Food Policy* **2014**, *44*, 47–58. [CrossRef]
33. Qureshi, M.E.; Dixon, J.; Wood, M. Public policies for improving food and nutrition security at different scales. *Food Secur.* **2015**, *7*, 393–403. [CrossRef]
34. Fukase, E.; Martin, W. Economic growth, convergence, and world food demand and supply. *World Dev.* **2020**, *132*, 104954. [CrossRef]
35. Kimura, Y.; Inoue, T.; Yin, F.; Tsuzaki, K. Inverse temperature dependence of toughness in an ultrafine grain-structure steel. *Science* **2008**, *320*, 1057–1060. [CrossRef] [PubMed]
36. Saleh, S. 3D crustal structure and its tectonic implication for Nile delta and greater Cairo regions, Egypt, from geophysical data. *Acta Geod. Geophys. Hung.* **2012**, *47*, 402–429. [CrossRef]
37. Hou, D.; Wang, X. Measurement of agricultural green development level in the three provinces of Northeast China under the background of rural vitalization strategy. *Front. Public Health* **2022**, *10*, 824202. [CrossRef] [PubMed]
38. Irvan, I.P.; Yuliarmi, N.N. Analysis of impact factors on farmers income. *Int. Res. J. Manag. IT Soc. Sci.* **2019**, *6*, 218–225. [CrossRef]
39. Smith, S. The foundations, continuing evolution, and outcomes from the application of intellectual property protection in plant breeding and agriculture. *Plant Breed. Rev.* **2019**, *43*, 121–213.
40. Sawicka, B.; Michałek, W.; Pszczółkowski, P. The relationship of potato tubers chemical composition with selected physiological indicators. *Zemdirb.-Agric.* **2015**, *102*, 41–50. [CrossRef]
41. Yao, W.; Gong, Y.; Li, L.; Hu, X.; You, L. The effects of dietary fibers from rice bran and wheat bran on gut microbiota: An overview. *Food Chem. X* **2022**, *13*, 100252. [CrossRef]
42. Cao, Z.; Huang, Y.; Hao, J. Multi-suitability comprehensive evaluation of crop straw resource utilization in China. *Res. Environ. Sci.* **2018**, *31*, 179–186.
43. Zhang, H.; Wu, D. The impact of transport infrastructure on rural industrial integration: Spatial spillover effects and spatio-temporal heterogeneity. *Land* **2022**, *11*, 1116. [CrossRef]
44. Liu, X.; Xu, Y.; Engel, B.A.; Sun, S.; Zhao, X.; Wu, P.; Wang, Y. The impact of urbanization and aging on food security in developing countries: The view from Northwest China. *J. Clean. Prod.* **2021**, *292*, 126067. [CrossRef]
45. Moran, P.A. Notes on continuous stochastic phenomena. *Biometrika* **1950**, *37*, 17–23. [CrossRef] [PubMed]
46. Geary, R.C. The contiguity ratio and statistical mapping. *Incorp. Stat.* **1954**, *5*, 115–146. [CrossRef]
47. Elhorst, J.P. Applied spatial econometrics: Raising the bar. *Spat. Econ. Anal.* **2010**, *5*, 9–28. [CrossRef]

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Article

Influencing Factors of Peasant Households' Willingness to Relocate to Concentrated Residences in Mountainous Areas: Evidence from Rural Southwest China

Jia Zhong ^{1,2}, Qian Cao ³, Ruiyin Chen ^{2,4}, Shaoquan Liu ², Zhaoyang Lian ², Hui Yu ^{2,*} and Ningchuan Zhou ¹

¹ School of Emergency Management, Xihua University, Chengdu 610039, China; zhongjia@mail.xhu.edu.cn (J.Z.); zhouningchuan@stu.xhu.edu.cn (N.Z.)

² Institute of Mountain Hazards and Environment, Chinese Academy of Sciences, Chengdu 610299, China; chenruiyin@imde.ac.cn (R.C.); liushq@imde.ac.cn (S.L.); lianzhy@imde.ac.cn (Z.L.)

³ College of Geography and Planning, Chengdu University of Technology, Chengdu 610059, China; caoqian@stu.cdut.edu.cn

⁴ POWERCHINA Chengdu Engineering Corporation Limited, Chengdu 611130, China

* Correspondence: yuhui1276617803@126.com; Tel.: +86-134-3818-1790

Abstract: Relocating poor people in mountainous areas to centralized settlement sites is an important poverty alleviation policy implemented by China and a key measure to promote stable poverty alleviation and sustainable rural development for the poor. Based on the survey data of 405 peasant households in the Panxi Area in 2021, this study constructed a structural equation model (SEM) to explore the influencing factors of peasant households' willingness to relocate to a concentrated residence. The results showed the following: (1) Of the 405 peasant households surveyed, 20.98% were unwilling to move to centralized resettlement sites, making it more difficult to carry out the relocation policy for poverty alleviation. (2) Living environment, living conditions, important social groups, the economic benefits, living benefits, and survival benefits brought by concentrated residences, governments, and the village committees significantly influenced the willingness to relocate to a concentrated residence. In contrast, agricultural income, ecological benefits, and value benefits brought by the concentrated residence had little effect on the willingness to relocate to a concentrated residence. (3) Land force, human force, cognitive force, and national force significantly positively affected the peasant households' willingness to relocate to a concentrated residence. This study is of great significance in promoting the implementation of poverty alleviation and relocation policy, improving the efficiency of relocation and promoting the wellbeing of peasant households.

Keywords: concentrated residence; rural; influencing factors; mountainous areas; SEM

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1. Introduction

With the rapid development of urbanization and industrialization, the rural structure is constantly adjusted to meet the needs of agricultural modernization. As a form of rural structural adjustment, the relocation of peasant households to concentrated residences plays an important role in improving the efficiency of land use in rural areas, enhancing the level of rural public services and improving the level of rural production and the quality of life of peasant households [1]. In essence, encouraging peasant households to choose to reside in a concentrated residence is the process of rural housing reconstruction. Rural housing reconstruction is key to sustainable development. In the background of new rural construction, concentrated rural settlement (CRS) has been widely promoted [2]. Most scholars believe that the concentrated residence of peasant households is a new type of community residence with complete basic and supporting facilities, which scatters peasant households living in natural villages [3]. Among them, the concept of "population migration", focused on the sharing of urban civilization by farmers [4], the concept of "village-to-community", focused on rural transformation [5], and the concept of "land

intensification”, focused on improving the efficiency of land use [6]. This study defines the concept of peasant households’ concentrated residences from multiple perspectives, that is, under the support of government policies, to promote the relocation of peasant households in poor areas to a concentrated settlement planned and constructed by the government, intending to promote improvement in the quality of life of peasant households, the intensive use of land, and the efficiency of agricultural production, focusing on lifting peasant households out of poverty. Compared with the dispersed living form of peasant households, promoting the concentrated residence of peasant households is an effective means of rural revitalization, which can enhance the development of rural areas and promote the coordinated development of urban and rural areas [7].

The advantages of the concentrated residence policy, which is promoted and controlled by governments at all levels from top to bottom, lie in the low cost required by peasant households and the direct and effective improvement of their living conditions [8]. As the main force and the ultimate beneficiary of the concentrated residence, peasant households’ willingness has a fundamental impact on the effectiveness of the concentrated residence policy. In reality, because some local governments have harmed the immediate interests of farmers and ignored the wishes of farmers by carrying out the policy of concentrated residence, conflicts between the government and farmers have arisen, which has reduced the wishes of farmers to live in concentrated residence [9,10]. This impedes the process of concentrated residence. Peasant households’ willingness to relocate is the core problem that affects the process of realizing the concentrated residence policy [11]. Understanding peasant households’ willingness and its influencing factors is an important guarantee to promote the process of concentrated residence. Many factors affect the peasant households’ willingness to relocate to a concentrated residence, including internal and external factors. Internal factors are summarized as individual characteristics (such as gender, age, education level) [12–14], household characteristics (such as household size, household income and expenditure, labor force) [15,16], and cultural characteristics (such as life expectancy, risk perception) [17–19]. External factors include attitudes of important social groups (such as family members, relatives, friends, and neighbors) [20–22], existing living conditions (such as the quality of houses, the years of construction of houses, the materials of houses) [23,24], living environment (such as natural disasters, the quality of cultivated land, infrastructure conditions) [25–28], and policy environment (such as the attitude and behavior of the government and village committee) [29,30]. Many domestic and foreign scholars have analyzed the factors affecting peasant households’ willingness to relocate to a concentrated residence through questionnaires and interviews [16,25]. The most common measurement models used are the Probit and Logit models [28,31]. The structural equation model (SEM) has been used increasingly in recent years [32], but mainly for studies on the plains. The Logit and Probit models are used to model the relationship between the dependent and independent variables; however, they cannot fit the complex nonlinear data well [33]. As a powerful statistical analysis tool, the structural equation model (SEM) can deal with many dependent variables simultaneously, allowing both independent variables and dependent variables to contain measurement errors and taking into account the direct and indirect relationships among multiple variables. This model can compensate for the deficiency in the Logit model and the Probit model, as they can only measure the direct effect among variables but cannot measure the intermediate effect and the total effect among variables [34]. To date, few studies have used the SEM model to determine the factors influencing peasant households’ willingness to relocate to a concentrated residence in mountainous areas.

Most scholars have paid attention to the concentrated residence of peasant households under the influence of meteorological disasters, such as floods and typhoons [35,36]. However, there are few that focus on poor peasant households concentrating their lives in regions threatened by geological disasters with the help of the government’s policy. Most of these study areas are in the plains, and only some scholars have explored the influencing factors of peasant households’ willingness to relocate to a concentrated residence in moun-

tainous areas [37–40]. However, due to the differences in geographic location, resource conditions, development bases, and other factors, the rural areas in mountainous areas have lower economic development than the plains. Thus, the development of rural areas in mountainous regions deserves more attention, and the research on the influencing factors of peasant households' willingness to relocate to a concentrated residence in mountainous areas should also be given more attention. In economically developed plains, concentrated residences will generally increase peasant households' income to different degrees and speed up the urbanization process, and peasant households in these areas are more willing to do so. In remote mountainous areas where the economy is underdeveloped, the willingness of the peasant households is generally low if the policy is implemented in rural areas where farming is the main activity [3]. This dramatically slows down the government's progress in promoting the policy, thus leading to these economically underdeveloped areas missing development opportunities, eventually forming a vicious circle. Although the proportion of the world's poor has declined in recent years, the problem of poverty remains acute [41]. Statistics show that many poor people live in mountainous regions with poor natural and essential conditions [42]. In 2019, there were still 5.51 million poor people in rural China, mainly in the remote mountainous areas of central and western China [43]. Promoting the centralization of peasant households in mountainous areas in China will significantly eradicate poverty among the country's peasant households and develop the country's villages.

Against this background and based on the field survey data of 405 peasant households in Sichuan Province, the southwestern mountainous area of China, the influencing factors of peasant households' willingness to relocate to a concentrated residence and the relationship of the influencing factors were explored. This study presents a structural equation model, in order to provide some reference for relevant policies to promote peasant households in mountainous areas to live in concentrated residences.

2. Theoretical Analysis and Research Hypotheses

2.1. The Theory of Planned Behavior

According to the theory of planned behavior, human behavior results from well-thought-out planning, and its variables include behavioral attitudes, subjective norms, perceived behavioral control, and behavioral will [44]. Behavioral attitude reflects an individual's belief and evaluation of behavior results, such as peasant households' rational cognitions about the implementation of the concentrated residence policy, including economic rationality, ecological rationality, survival rationality, and value rationality [45], defined as "cognitive force" in the study. Individual cognition has a significant predictive effect on their intention [46], and peasant households' expectation of the result of concentrated residence will affect their own will and behavior. Subjective norms refer to individuals' social pressure when deciding whether to act [47]. Especially in ethnic minority areas, where blood and geographic ties are predominant, peasant households will consider whether the important social groups (family, relatives, friends, neighbors) around them support their relocation to a centralized settlement, defined as "human force" in this study. If these important social groups around them support peasant households' relocation behavior, then to a certain extent, it will strengthen peasant households' decision-making confidence. Perceived behavioral control refers to the individual's perception of the difficulty of performing a certain behavior, which reflects the actual control conditions. For example, peasant households' willingness to relocate to a concentrated residence is affected by the environment of their residence (agricultural production, living, and ecological conditions) [16], defined as "land capacity" in this study. If the natural and living environments are poor, it will strengthen the farmers' willingness to live together [48]. From the perspective of the theory of planned behavior, the following hypotheses are proposed in this paper:

H1. *Land force has a positive effect on the peasant households' willingness to relocate to a concentrated residence.*

H2. *Human force has a positive effect on the peasant households' willingness to relocate to a concentrated residence.*

H3. *Cognitive force has a positive effect on the peasant households' willingness to relocate to a concentrated residence.*

2.2. The Social Cognitive Theory

Social cognitive theory emphasizes the interaction between the individual and the environment, which holds that human behavior and cognitive processes are formed by interacting with the environment. The theory emphasizes individual cognitive factors, including belief, memory, expectation, motivation, and self-reinforcement, essential in understanding and coping with the social environment [49]. Bandura put forward a three-dimensional interactive learning theory based on social cognitive theory: environment, behavior, and humans are mutually causal, and each has a two-way interactive and decisive relationship [18]. If the environmental conditions in which peasant households live cannot meet their living development needs, they will improve their living conditions [50]. Peasant households will imagine whether living conditions and quality of life will improve if they move into a concentrated residence with the government's help [51]. If the results are expected to be better, this will strengthen the peasant households' willingness to relocate to a concentrated residence. Families, relatives, friends, and neighbors are the people who have most contact with the peasant household. They are important channels for farmers to obtain information. The access to information will affect the peasant households' cognition about the concentrated residence [52]. At the same time, they also provide significant emotional support for peasant households. When peasant households are faced with decision-making confusion, the support of these important social groups will remove some of the worries and concerns of peasant households, further strengthening peasant households' willingness to relocate to a concentrated residence. From the perspective of the social cognitive theory, the following hypotheses are proposed in this paper:

H4. *Land force has a positive promoting effect on peasant households' cognitive force about concentrated residences.*

H5. *Human force has a positive promoting effect on peasant households' cognitive force about concentrated residences.*

H6. *Cognitive ability plays a mediating role in land force, human force, and willingness to relocate to a concentrated residence.*

2.3. The Policy Process Theory

The policy process theory emphasizes policymaking, implementation, evaluation, and the interaction of various stakeholders in this process. As the main body of policymaking, the national government's behavior and attitude (such as policy orientation, value orientation, and decision-making efficiency) will directly affect the content and quality of policy [53]. Generally speaking, in the course of implementing state policy, it will bring a series of changes and influences to the important groups in society (such as enterprises, social organizations, and citizens) and the environment outside the place of residence (such as natural environment, social, and economic environment) [54]. Faced with some remote and poor mountainous areas with poor living environments and fragile ecological environments, traditional poverty alleviation measures may not be sufficient to achieve significant results [55,56]. In order to improve the living conditions of the poor households in these areas and realize poverty alleviation, the policy of poverty alleviation and relocation came

into being. Implementing the policy is conducive to improving the land use efficiency and the living conditions of peasant households in mountainous areas by promoting the concentration residence of poor peasant households in mountainous areas [57]. The attitude and strength of the local government and village committee in publicizing the policy will also affect the degree of trust and support of the important social groups (families, relatives, friends, and neighbors) in the policy [58], defined as “national force” in this study. The range and intensity of the improvement of the living conditions and the perception and attitude of the important social groups around peasant households to the policy are all related to the policy support, and it indirectly affects the farmers’ willingness to live in a centralized way. From the perspective of the policy process theory, the following hypotheses are proposed in this paper:

- H7.** National force has a positive effect on land force.
- H8.** National force has a positive effect on human force.
- H9.** The relationship between land force, human force, and peasant households’ willingness to relocate to a concentrated residence is moderated by national force.

The research framework is shown in Figure 1.

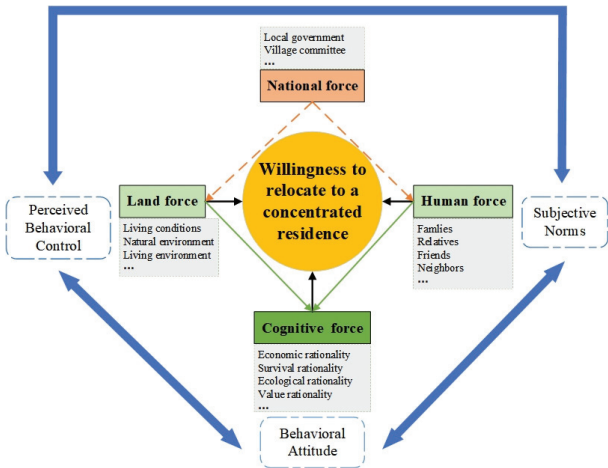


Figure 1. Theoretic analysis framework.

3. Data and Methods

3.1. Data Source

Sichuan is a large agricultural province with a rural population of 42.92 million, 52.31% of the province’s resident population in 2019 [59]. The proportion of mountainous areas in Sichuan is over 77%, which profoundly impacts agricultural production and rural development in Sichuan. By the end of 2018, there were still more than 700,000 poor people, 1782 poor villages, and 38 poor counties in Sichuan Province, mainly concentrated in deeply impoverished areas of the province’s mountainous ethnic minorities (Tibetans and Yi) [33]. The Panxi Area, located in the mountainous area of southwestern Sichuan Province, was chosen as the study area in this study. The Panxi Area is the largest Yi settlement of Yi people in China, with an average altitude of 2500 m, rugged terrain, and inconvenient transport. Compared with rural areas in the plains, the development of rural areas in mountainous regions is slower and more difficult, which is closely related to the terrain. The mountainous terrain of the Panxi Area restricts contact and communication between the mountainous countryside and the outside world, leading to closed information and

limited economic development in the mountainous countryside. At the same time, the mountainous countryside is threatened by geological disasters in the mountainous regions, which further exacerbates the problem of poverty in the Panxi Area [43,60]. In response to the poverty problem in the Panxi Area, the government in Sichuan has taken a series of practical measures to lift people out of poverty and has also actively promoted the work of poverty alleviation and relocation in inhospitable areas. The policy of relocation for poverty alleviation is a crucial way to address the issue of poverty where “the local environment cannot support the local people”. However, the mountain environment’s particularity, the ecological environment’s fragility, and the complexity of national culture all affect the progress of poverty alleviation relocation work to varying degrees [55]. Accelerating the progress of the policy of relocation for poverty alleviation in the Panxi Area is of great significance for achieving rural poverty eradication in the region.

The data used in this paper were mainly from a questionnaire survey conducted by the research team in August 2021. The 2016–2020 period was the phase of China’s poverty eradication campaign, and the policy of relocation for poverty alleviation, implemented in China in 2019, has made remarkable progress, laying a solid foundation for China to fully realize its poverty eradication goal in 2020. Therefore, the research designed in this study covered the basic situation of individuals and families, willingness to relocate, living place conditions, and knowledge of poverty alleviation and relocation policies at the end of 2019, and each questionnaire involved face-to-face interviews with farmers for 30–60 min. The research samples mainly adopted stratified sampling, followed by equal probability random sampling to ensure the typicality and representativeness of the selected samples [33]. The process is as follows: Firstly, according to the results of the coupling of the mountain disaster risk evaluation grade and spatial conflict [61], the conflict level was sorted and divided into four categories and combined with the national major function-oriented zones; Yanyuan County, Xichang City, Puge County, and Miyi County were selected as the sample area. Secondly, all townships in the study area were divided into two groups according to the sorting of contradiction rank (with the county median as the division standard, one group with a high contradiction rank and one group with a low contradiction rank), and two sample townships were randomly selected from the four sample areas. Then, two villages were randomly selected from each sample township in the same way. Finally, 25–30 households were randomly selected from the roster in each sample village using a random number table [45]. According to the above process, 16 villages and 405 peasant households were chosen. The distribution map of sample counties and villages is shown in Figure 2.

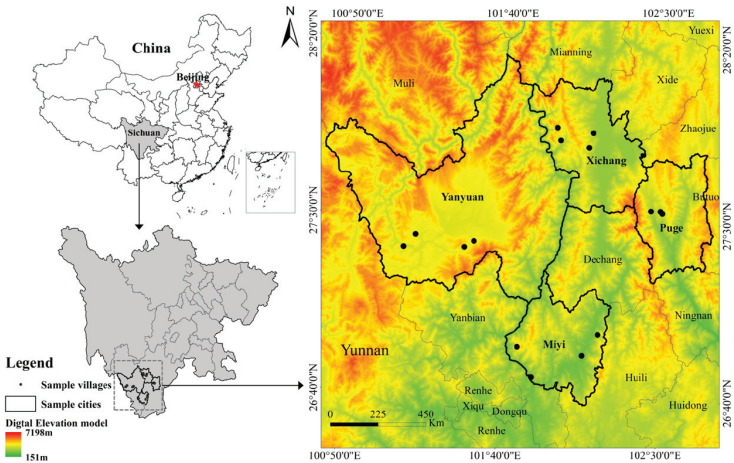


Figure 2. Distribution map of sample counties and villages.

3.2. Selection of the Model Variables

3.2.1. Descriptive Statistical Analysis of Respondents

Among the 405 peasant households, 56.54% were more willing to move to a concentrated residence at the bottom than to live scattered on the hill, and 55 were highly willing to live in a concentrated residence. However, at the same time, 20.98% of peasant households were unwilling to move to centralized resettlement sites, and 22.47% were generally unwilling to live in a concentrated residence. As for the willingness to move to a town or village concentrated residence, almost 40% of peasant households chose not to do so. The above indicates that in the villages in the sample are, although the majority of peasant households were willing to live in a concentrated residence, there were still some peasant households who were reluctant to move to centralized resettlement sites, which to a certain extent made it more challenging to carry out the policy of relocation for poverty alleviation. Of the 405 peasant households, 74.57% were of Yi ethnicity, with an average age of 47.44 years, mostly male, and 42.72% were illiterate. Most peasant households were in relatively good health, with 73.83% working purely in agriculture and 62 households working part time, with an average of one elderly person and one child per household. Overall, the village populations were many middle-aged Yi males engaged in agricultural work, with a low level of education and a heavy family burden (Table 1).

Table 1. Descriptive statistics of the respondents.

Variable	Definition	Mean	SD ^c
Gender	Respondents' gender (female = 1, male = 0)	0.316	0.466
Ethnicity	Respondents' ethnicity (Han = 1, Yi = 2, Tibetan = 3, other = 4)	1.746	0.436
Age	Respondents' age (year)	47.444	15.171
Education	Respondents' education level (year)	3.724	3.999
Health	Respondents' health level (1 = very healthy–5 = very unhealthy)	2.273	1182
Occupation	Respondents' occupation (1 = full-time farming, 2 = part-time farming, 3 = wage labor, 4 = other occupations)	1.509	1.089
Family scale	Total family population in 2019 (person)	4.624	1.747
Elderly people	Household count of individuals aged 64 and older (number of the persons)	0.615	0.787
Children	Household count of children aged under 6 (number of persons)	0.515	0.804
Family labor	Household labor force count within the age range of 16–64 (number of persons)	1.760	1.173

Note: ^c SD = standard deviation.

3.2.2. Selection of Variables

The dependent variable was concentration living willingness (Y1–Y3), which referred to the subjective attitude or psychological tendency of peasant households toward residing in a concentrated residence under the national poverty alleviation policy. The dependent variable was measured by the choice of residence type and the place of residence of the peasant households [62].

As the target of the national poverty alleviation policy, peasant households' willingness to relocate to a concentrated residence is influenced by internal and external factors, mainly including personal, natural, social, and economic factors. Referring to existing studies and considering the actual situation of the study area [26,55,63–66], five independent variables were summarized as follows (Table 2): (1) Land force (DL1–DL6): Peasant households in mountainous areas usually live in remote areas where the local natural environment, living environment, arable land, and infrastructure conditions are insufficient to meet their daily production and living needs and where geological disasters threaten their living space. In such cases, peasant households preferred to move to centralized resettlement sites with the government's help. (2) Human force (RL1–RL3): As the largest Yi settlement area in the country, ethnic minority peasant households in the Panxi Area are usually linked by blood and geographic ties. Peasant households' family members, relatives, friends, and neighbors, as an important social group within peasant households, have an important influence on whether they choose to live in a concentrated residence or not by their support for the peasant households' behavioral decision making. (3) Cognitive force (RZL1–RZL5): Peasant households exhibit certain characteristics of rational economics when making decisions,

and their rational cognition is often a complex process in which multiple rationalities are intertwined. Therefore, this study focused on the economics, ecology, survival, and values of rational cognition to measure peasant households' cognitions regarding concentrated residence. (4) National force (GL1–GL3): The local government and village committee are the implementers of the national poverty alleviation policy, and the implementation process and its effect are affected by the willingness of peasant households to relocate. At the same time, the intensity of peasant households' willingness to relocate to a concentrated residence was directly related to the behavior and attitude of the local government and village committee. Therefore, when considering the variable of national force, this study mainly considered the attitudes and propaganda behaviors of local governments and village committees.

Table 2. Influencing factors of peasant households' willingness to relocate to a concentrated residence.

Latent Variables	Observation Variables	Definition	Mean	SD ^c
Land force	Housing quality	DL1: Do you feel that the quality of the housing you live in is not good? ^a	3.479	1.089
	Geological hazards	DL2: Do earthquakes, landslides, mudslides, and other disasters occur frequently where you live? ^a	2.800	1.211
	Infrastructure conditions	DL3: Do you think the infrastructure in the village is in poor condition? ^a	3.217	1.07
	Living environment	DL4: Do you think the living environment is poor where you live? ^a	3.128	1.098
	Land quality	DL5: Do you think the land is infertile and the quality of the arable land is poor? ^a	2.926	1.043
	Agricultural income	DL6: Do you feel that income from farming is low where you live? ^a	3.472	1.03
Human force	Support from relatives and friends	RL1: Do you think your relatives and friends will support you in relocation? ^a	3.462	0.996
	Neighborhood support	RL2: Do you think your neighbors will support you in relocation? ^a	3.390	1.003
	Family support	RL3: Do you think your family will support you in relocation? ^a	3.449	1.079
Cognitive force	Economic rationality 1	RZL1: Do you think that concentrated residence will improve the standard of living of families? ^a	3.699	0.807
	Economic rationality 2	RZL2: Do you think that concentrated residence will improve the living conditions of families? ^a	3.891	0.825
	Ecological rationality	RZL3: Do you think that concentrated residence will be conducive to the efficient use of land? ^a	3.560	0.957
	Survival rationality	RZL4: Do you feel that concentrated residence will be good for future generations? ^a	3.837	0.916
	Value rationality	RZL5: Do you think it is a good thing for the government to organize concentrated residence for poverty alleviation? ^a	3.474	0.979
National force	Local government support	GL1: Do you feel that your local government supports you in relocation? ^a	3.617	0.847
	Village committee support	GL2: Do you feel that your village committee will support and guide you in your relocation? ^a	3.615	0.881
	Policy advocacy	GL3: Have you been informed by village cadres about the policy of relocation for poverty alleviation? ^a	3.398	1.098
Willingness to relocate to a concentrated residence	Form of living	Y1: Would you prefer to move to a concentrated residence than to live scattered in the hills? ^b	3.457	1.039
	Choice of living 1	Y2: Would you like to move to a concentrated residence in the town? ^b	2.985	1.156
	Choice of living 2	Y3: Would you like to move to a concentrated residence in the village? ^b	2.985	1.051

Note: ^a Likert 5-point scale, where 1 means strongly disagree and 5 means strongly agree; ^b Likert 5-point scale, where 1 means very unwilling and 5 means very willing; ^c SD = standard deviation.

3.3. Methods

The structural equation model (SEM) is a statistical methodology based on statistical analysis techniques to explore and analyze complex multivariate research data, consisting of a measurement model and a structural model [34]. The measurement model is to describe the relationship between latent variables and measured variables, and its specific formula is as follows:

$$X = V_x\psi + \omega \tag{1}$$

$$Y = V_y\phi + \theta \tag{2}$$

where θ is uncorrelated with ψ , ϕ , or ω , and ω is uncorrelated with ψ , ϕ , or θ . V_x and V_y are the factor loading on the indicator variable (x , y). In contrast, ω and θ are the measurement errors of the exogenous observation index X and the endogenous observation index Y , respectively. ψ and ϕ are the exogenous latent variable and endogenous latent variable, respectively.

The structural model focuses on describing the relationship between two or more latent variables and is formulated as follows:

$$\phi = \beta\phi + \delta\psi + \eta \tag{3}$$

where β is the $n \times n$ coefficient matrix representing the relationship between the endogenous latent variables; δ is the $n \times m$ coefficient matrix representing the effect of the exogenous latent variables on the endogenous latent variables. η denotes the residual term of the structural equation, reflecting the unexplained part of ϕ in the equation [33]. Analysis of the models in this study was carried out using AMOS 22.0.

Based on the research hypotheses and the construction of the theoretical model framework presented in the previous section, the initial model of structural equations for the factors affecting peasant households' willingness to relocate to a concentrated residence in mountainous areas was constructed in AMOS 22.0 (Figure 3). e1–e20 are the measurement errors for each observed variable, and e21–e24 are the portion of the endogenous latent variables that cannot be explained or predicted by the exogenous latent variables, known as residuals or disturbance. The number 1 denotes the fixed parameter in the model.

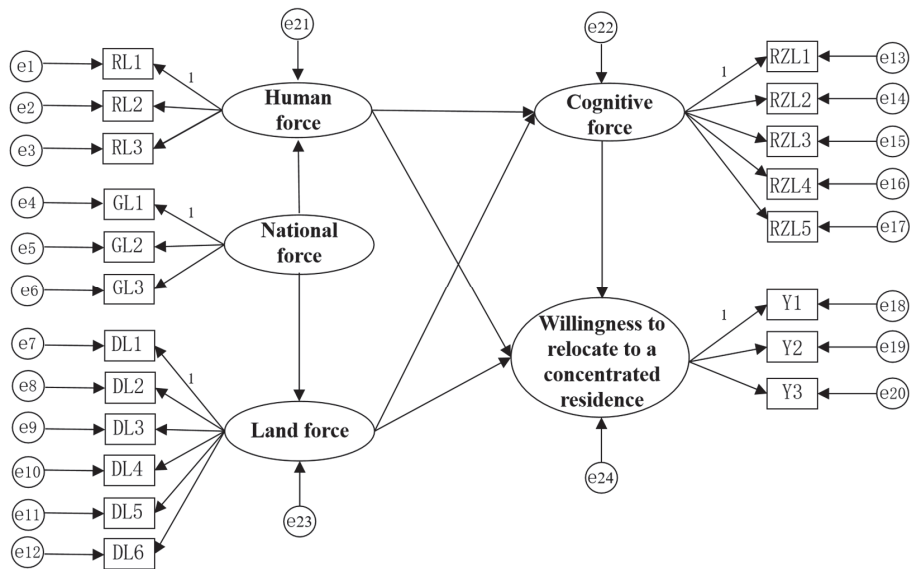


Figure 3. Initial model of structural equation.

4. Results

4.1. Validity and Reliability

In this study, each dimension’s internal consistency was first analyzed using Cronbach’s α reliability test. An α value below 0.6 is generally considered implausible, between 0.6 and 0.7 is plausible, between 0.7 and 0.8 is more plausible, between 0.8 and 0.9 is very plausible, and between 0.9 and 1 is extremely plausible [67]. As seen in Table 3, the Cronbach’s α value for the total scale is 0.871, and the Cronbach’s α values for all dimensions are within the range of 0.7–0.9, thus indicating that the questionnaire used in this study had good internal consistency and good reliability. For validity analysis, factor analysis was used in this study for validation. The KMO (Kaiser–Meyer–Olkin) value for the total scale is 0.848 (>0.6), the KMO values for the four layers of the scale are all higher than 0.6, and the p value is $0.000 < 0.05$, which passes the Bartlett sphere test. Thus, the questionnaire data are acceptable and suitable for factor analysis. In this study, four principal factors were extracted using principal component analysis and rotated by the maximum variance method to explain the factors better, and the cumulative variance contribution is relatively high (Table 4). Thus, it indicates that the questionnaire has good structural validity.

Table 3. Analysis of reliability and validity of questionnaire.

Latent Variables	Observation Variables	Cronbach's Alpha	KMO	Bartlett's Test of Sphericity		
				Approximate Chi-Square	Degree of Freedom	p Value
Land force	DL1, DL2, DL3, DL4, DL5, DL6	0.818	0.866	706.892	15	0.000
Human force	RL1, RL2, RL3	0.893	0.749	712.814	3	0.000
Cognitive force	RZL1, RZL2, RZL3, RZL4, RZL5	0.743	0.787	472.674	10	0.000
National force	GL1, GL2, GL3	0.769	0.672	366.175	3	0.000
Willingness to relocate to a concentrated residence	Y1, Y2, Y3	0.808	0.748	698.660	3	0.000
Overall		0.871	0.848	2370.574	136	0.000

Table 4. Factor loading matrix after rotation.

		Factor			
		1	2	3	4
Land force	DL1	0.685	0.118	0.086	−0.020
	DL2	0.679	0.071	0.026	0.013
	DL3	0.774	−0.047	0.055	0.029
	DL4	0.777	0.157	0.108	0.122
	DL5	0.697	0.124	0.022	0.113
	DL6	0.693	−0.184	0.028	0.016
Human force	RL1	0.087	0.78	0.193	0.339
	RL2	0.042	0.858	0.131	0.266
	RL3	0.051	0.837	0.231	0.242
Cognitive force	RZL1	0.06	0.237	0.746	0.151
	RZL2	0.132	0.103	0.832	−0.048
	RZL3	−0.065	0.089	0.669	0.147
	RZL4	0.101	0.063	0.706	0.128
	RZL5	0.311	0.348	0.429	−0.302
National force	GL1	0.127	0.161	0.093	0.818
	GL2	0.079	0.284	0.119	0.806
	GL3	0.029	0.364	0.137	0.644
Cumulative variance contribution rate				68.136%	

4.2. Fitting and Adaption of Models

As shown in Table 5, the goodness-of-fit indices of the initial model, such as CMIN/DF, GFI, IFI, TLI, and CFI, are smaller than the reference value, which does not satisfy the

criteria and, thus, needs to be modified. In general, the measurement model should be revised according to the modification indices (MI), in descending order, and only one at a time, and the cycle continues until most of the fitness metrics reflecting goodness-of-fit values align with the reference value criteria [68]. Using AMOS 22.0 software, the initial model was modified according to MI, and after adding three paths in turn, the modified model was obtained (Figure 4). Three paths of e5 ↔ e15, e17 ↔ e19, and e17 ↔ e20 passed the significance test and have positive values, indicating that the local village committee supported and guided the peasant households to relocate in favor of the efficient use of land, and the peasant households agreed that relocation was a good thing. They were more willing to relocate to the centralized resettlement sites in the village or the town for centralized residence.

Table 5. Model fit indices.

Evaluation Indices	CMIN/DF	GFI	IFI	TLI	CFI	NFI	RMSEA	PGFI	PNFI
Initial Model	3.356	0.874	0.893	0.874	0.892	0.854	0.076	0.765	0.733
Modified model	2.447	0.910	0.935	0.923	0.935	0.895	0.060	0.787	0.063
Fit standard	≤3	>0.9	>0.9	>0.9	>0.9	>0.9	≤0.08	>0.5	>0.5

Note: CMIN/DF = χ^2/df , GFI = goodness-of-fit index, IFI = incremental fit index, TLI = Tucker–Lewis index, CFI = comparative fit index, NFI = normed fit index, RMSEA = root mean square error of approximation, PGFI = parsimony goodness-of-fit index, PNFI = parsimony-adjusted NFI.

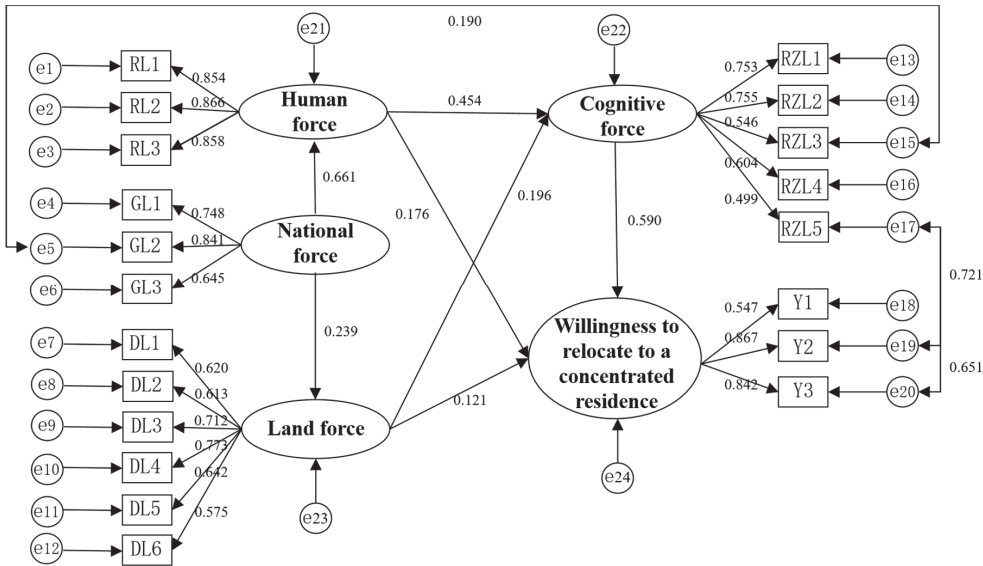


Figure 4. Modified model of structural equation.

With the modified model, CMIN/DF = 2.447 (<3), RMSEA = 0.060 (<0.08), the test results of GFI, IFI, TLI, and CFI are all higher than 0.9, and the NFI = 0.895, which is close to 0.9; in addition, the values of PNFI and PGFI are all higher than 0.5. Therefore, all the indicators of the modified model comply with the standard, indicating that the model's overall fitness is good.

4.3. Modified Model Results

4.3.1. Modified Measurement Model Results

The non-standardized regression coefficients were calculated using the maximum likelihood method, and the results of the modified measurement model are shown in Table 6. The standard deviation and critical values of housing quality, support from relatives and

friends, local government support, and form of living are blank because these four factors are assumed to have an inevitable effect on peasant households’ willingness to relocate to a concentrated residence when the model was initially constructed, so they are set as fixed parameters.

Table 6. Fitting results of measured model.

Items			NSE	¹ SE	CR	² SE
DL1	←	Land force	1			0.620 ***
DL2	←	Land force	1.1	0.111	9.909	0.613 ***
DL3	←	Land force	1.128	0.102	11.031	0.712 ***
DL4	←	Land force	1.258	0.108	11.603	0.773 ***
DL5	←	Land force	0.993	0.097	10.262	0.642 ***
DL6	←	Land force	0.878	0.093	9.433	0.575 ***
RL1	←	Human force	1			0.854 ***
RL2	←	Human force	1.022	0.048	21.183	0.866 ***
RL3	←	Human force	1.089	0.052	20.935	0.858 ***
RZL1	←	Cognitive force	1			0.753 ***
RZL2	←	Cognitive force	1.024	0.077	13.284	0.755 ***
RZL3	←	Cognitive force	0.863	0.087	9.967	0.546 ***
RZL4	←	Cognitive force	0.91	0.083	10.937	0.604 ***
RZL5	←	Cognitive force	0.796	0.086	9.211	0.499 ***
GL1	←	National force	1			0.748 ***
GL2	←	National force	1.170	0.083	14.167	0.841 ***
GL3	←	National force	1.118	0.094	11.877	0.645 ***
Y1	←	Willingness to relocate to a concentrated residence	1			0.547 ***
Y2	←	Willingness to relocate to a concentrated residence	3.621	0.321	11.278	0.867 ***
Y3	←	Willingness to relocate to a concentrated residence	3.197	0.285	11.223	0.842 ***

Note: NSE = non-standardized estimate; ¹ SE = standard error; CR = critical ratio; ² SE = standardized estimate; *** significant at *p* < 0.001.

(1) Among land force (DL1–DL6), the path coefficient of housing quality is fixed at 1, and the standardized regression coefficient is 0.620. The standardized regression coefficients of the living environment, infrastructural conditions, land quality, geological hazards, and agricultural income of the place of residence are 0.773, 0.712, 0.642, 0.613, and 0.575, respectively. All six factors significantly positively affect peasant households’ willingness to relocate to a concentrated residence. Specifically, a bad living environment is the primary influencing factor, followed by poor infrastructure conditions in the settlement. This indicates that if the primary living conditions of the place do not meet the daily needs of the farmers, the farmers will be more willing to move to a centralized resettlement site with better conditions. The poor land quality in the settlement, coupled with the threat of geological hazards, may strengthen peasant households’ willingness to relocate to a concentrated residence. Low agricultural income in the settlement has a significant positive effect on the willingness of peasant households to relocate to a concentrated residence. However, its effect is relatively small compared with other land force factors. This may be because some peasant households carry out other odd jobs besides growing crops to supplement their income.

(2) Among the three observed variables reflecting human force (RL1–RL3), the standardized regression coefficients of the support from peasant households’ relatives and friends, neighbors, and family are higher than 0.85, all of which significantly positively affect peasant households’ willingness to relocate to a concentrated residence. This indicates that peasant households will have a stronger desire to live in concentrated residences if their relatives, friends, neighbors, and families supported them in relocating with the government’s help. Human beings are complex, and the behavioral intentions of peasant households are not entirely determined by themselves but also influenced by important social groups in the individual’s society (e.g., family, relatives, friends, and neighbors). The behavior, opinions, and attitudes of these important social groups close to the peasant household often significantly positively impact the peasant household.

(3) The standardized regression coefficients of the five observed variables of cognitive force (RZL1–RZL5) are 0.753, 0.755, 0.546, 0.604, and 0.499, respectively, which indicates that the rational cognitions (economic rationality, ecological rationality, survival rationality, and value rationality) of peasant households regarding relocation all positively affect the peasant households' willingness to relocate to a concentrated residence. Among them, farmers pay more attention to economic rationality; that is, whether the living standard of their own families and the living conditions of their families will be improved after relocating to the centralized resettlement sites, which are the primary driving forces for the willingness of peasant households to live in a concentrated residence, followed by RZL4 (survival rationality). In contrast, the cognitions of RZL3 (ecological rationality) and RZL5 (value rationality) have a slighter positive influence on the peasant households' willingness to relocate to a concentrated residence with the other cognitive force factors, probably because they are not closely related to peasant households' interests.

(4) Among national force (GL1–GL3), the path coefficient of local government support is fixed at 1 with a standardized regression coefficient of 0.748, and the standardized coefficients of village committee support and policy advocacy are 0.841 and 0.645, respectively. These three factors have a significant and positive effect on peasant households' willingness to relocate to a concentrated residence. Among them, the behavior and attitude of the village committee significantly positively impact the peasant households' willingness to relocate to a concentrated residence. If the village committee supported and guided peasant households to relocate, it would significantly strengthen peasant households' willingness to relocate to a concentrated residence. Most of the sample villages are in remote mountainous areas, where peasant households receive information in a closed manner, and the support and publicity of the local government and village committee would strengthen peasant households' understanding of and trust in the relocation policy. Therefore, the attitude of the local government and the publicity of the relocation policy by village cadres also have a significant positive effect on the willingness of peasant households to live in a concentrated residence.

(5) Among the three observed variables reflecting the willingness to relocate to a concentrated residence, the path coefficient in the form of living is fixed at 1, with a standardized regression coefficient of 0.547. The standardized regression coefficients of Y1 and Y2 (choice of living) are 0.867 and 0.842, respectively. This suggests that the three factors affecting the preference of a concentrated residence and the willingness to live in centralized resettlement sites in a town or a village will also positively influence peasant households' willingness to relocate to a concentrated residence.

4.3.2. Modified Structural Model Results

The standardized path coefficients and fitting results of the structural model are shown in Table 7. Land force significantly positively affects the willingness to relocate to a concentrated residence (path coefficient of 0.121, $p < 0.01$). This indicates that the production, living, and ecological spatial conditions of the place where peasant households live are poor, affecting their daily production and living activities. These factors strengthen peasant households' willingness to relocate to a concentrated residence; thus, H1 is verified. Human force has a significant positive effect on the willingness to relocate to a concentrated residence (path coefficient of 0.176, $p < 0.001$), indicating that in addition to peasant households' attitudes, the support of peasant households' family members, friends, relatives, and neighbors in relocating will play a role in encouraging and motivating to a certain extent, which could strengthen the confidence and willingness of peasant households to choose to live in a centralized residence; thus, H2 is verified. Cognitive force significantly positively affects the willingness to relocate to a concentrated residence (path coefficient of 0.590, $p < 0.001$). The direct effect is much higher than that of land force and human force, indicating that the more comprehensive rational cognitions of peasant households about the impacts of relocating to the concentrated resettlement sites and the more long-term consideration, the more it will strengthen peasant households' willingness to relocate to a

concentrated residence; thus, H3 is verified. The path coefficients of the influence of land force and human force on cognitive force passed the significance test at the 1% level with standardized coefficients of 0.196 and 0.176, respectively, indicating that the rational cognitions of peasant households on the impact of the relocation policy is positively influenced by land force and human force; thus, H4 and H5 are verified. The path coefficients of the influence of national force on land force and human force were significant at the 1% level with standardized coefficients of 0.239 and 0.661, respectively, indicating that national force positively contributes to human force and land force. Thus, H7 and H8 are verified.

Table 7. Fitting results of structural model.

Items			NSE	¹ SE	CR	² SE
Willingness to relocate to a concentrated residence	←	Land force	0.049	0.017	2.819	0.121 **
Willingness to relocate to a concentrated residence	←	Human force	0.056	0.015	3.693	0.176 ***
Willingness to relocate to a concentrated residence	←	Cognitive force	0.263	0.035	7.565	0.590 ***
Cognitive force	←	Human force	0.324	0.042	7.758	0.454 ***
Cognitive force	←	Land force	0.176	0.052	3.394	0.196 ***
Human force	←	National force	0.888	0.081	10.967	0.661 ***
Land force	←	National force	0.254	0.066	3.872	0.239 ***

Note: NSE = non-standardized estimate; ¹ SE = standard error; CR = critical ratio; ² SE = standardized estimate; *** significant at *p* < 0.001; ** significant at *p* < 0.01.

In order to explore the relationship between the latent variables further, the direct, indirect, and total effects between the variables are analyzed next. As shown in Table 8, the total effects of land force, human force, cognitive force, and national force on peasant households’ willingness to relocate to a concentrated residence are 0.095, 0.141, 0.263, and 0.150, respectively. The indirect effects of land force, human force, and national force on peasant households’ willingness to relocate to a concentrated residence are 0.046, 0.085, and 0.150, respectively. The direct effects of land force and human force on the cognitive force are 0.176 and 0.324, and the direct effects of national force on land force and human force are 0.254 and 0.888, respectively. The direct effects of national force on land force and human force are 0.254 and 0.888, respectively. Through the analysis, it can be seen that the support of national force may directly increase the support of human force and also have a specific role in promoting the improvement of land conditions. At the same time, it may indirectly strengthen the willingness of local peasant households to live in a concentrated residence by improving their cognitive force. Therefore, H7, H8, and H9 are verified. The total effect of cognitive force on peasant households’ willingness to relocate to a concentrated residence is 0.263, and local peasant households’ willingness to relocate to a concentrated residence depends mainly on peasant households’ rational cognitions of relocation.

In order to test the mediating role of cognitive force between land force, human force, and the willingness to relocate to a concentrated residence, this study used AMOS 22.0 to conduct the mediating effect test by the Bootstrap method (Bootstrap was set to 2000 times, and the confidence interval was taken as 95%) [69]. In analyzing the mediating effect of land force and human force on the willingness to relocate to a concentrated residence, the confidence intervals of the indirect effect are [0.057, 0.122] and [0.017, 0.081], respectively. Since none of the confidence intervals contain 0, it indicates that the mediating effect of cognitive force between land force and human force and the willingness to relocate to a concentrated residence exists significantly, and thus, H6 is verified. The indirect effect of human force on peasant households’ willingness to relocate to a concentrated residence is higher than that of land force.

Table 8. Comprehensive analysis of overall impact effects among variables.

Variables	Land Force			Human Force		
	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
Land force						
Human force						
Cognitive force	0.176		0.176	0.324		0.324
Willingness to relocate to a concentrated residence	0.049	0.046	0.095	0.056	0.085	0.141

Variables	Cognitive Force			National Force		
	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
Land force				0.254		0.254
Human force				0.888		0.888
Cognitive force					0.333	0.333
Willingness to relocate to a concentrated residence	0.263		0.263		0.150	0.150

5. Discussion

Based on the survey data of peasant households in the Panxi Area, located in the south-western mountainous area of China, this study analyzed peasant households’ willingness to relocate to a concentrated residence and the essential personal and family characteristics of peasant households. Then, a structural equation model was constructed to analyze the relationship between national force, human force, land force, cognitive force, and the willingness to relocate to a concentrated residence, and explored the main factors affecting peasant households’ willingness to relocate to a concentrated residence in mountainous areas. Compared with previous studies, this study has made the following novel contributions: Firstly, the research perspective is innovative. The construction of the theoretical model in this study is not based on a single theory but on a combination of three theories, namely, the theory of planned behavior, social cognition theory, and policy process theory, and has creatively constructed the theoretical model of “national force—human force—land force—cognitive force—willingness to relocate to a concentrated residence” from the perspective of the peasant households. Second is the innovation of the research content. The relationships between national force, human force, land force, cognitive force, and the willingness to relocate to a concentrated residence in mountainous areas in this study were not only empirically analyzed, but the direct, indirect, and total effects between the variables were also explored, which revealed in greater depth the mechanisms influencing the willingness to relocate to a concentrated residence, by using survey data of rural peasant households in southwestern China. Third is the innovation of the research method. Most existing studies about the influencing factors of peasant households’ willingness to relocate to a concentrated residence use traditional regression analyses, such as logit and probit models, which cannot measure the intrinsic relationship between the factors. The SEM model used in this study can analyze multicausal and multifunctional relationships and simulate the factors’ intrinsic logical relationships. In addition, there are some similarities and differences between the results of this study and those of existing studies.

This study obtained conclusions consistent with those of Montpetit (2017), Alam (2019), and Meng et al. (2023) [21,47,52]. That is, important social groups (family, relatives, friends, and neighbors) significantly impact the willingness of peasant households to relocate. When important social groups support peasant households’ decision making, it strengthens their confidence and motivation to implement the decision to some extent. In addition, these findings are consistent with research hypothesis H2, which agrees that human force has a positive effect on peasant households’ willingness to relocate. The important social groups of family members, relatives, friends, and neighbors play the roles of core, extended, and geographical relationships, respectively, in the social relationships of peasant households. Together, they form the social support network of the peasant households and profoundly impact the life, production, and development of peasant households. In this study, in villages inhabited by Yi people in the Panxi Area, peasant households are mostly linked

by blood relationships and kinship, so peasant households in a village are very trusting of each other. If peasant households have the support of their neighbors, relatives, and friends when making decisions, it will greatly enhance their motivation to participate in it. Obtaining information from important social groups has been a common cognitive pathway in society, and people also infer information from their decisions and attitudes. Peasant households' value-based decisions resulted from interactions with these important social groups [70]. Junquera (2022) argued that peasant households' social relations affected their decision making, and that changes in social relations and rural structure were interrelated, so policymakers from the local to national level should recognize the contribution of peasant households' diverse social support networks to rural development and pay attention to the role of important social groups in guiding important social groups [71], which is in line with this study's conclusions.

Many countries have provided multifaceted government interventions to alleviate poverty [54,58,72], and while these strategies are cost-effective, policies aiming to reduce poverty tend to prioritize economic interventions. However, poverty alleviation policies that only consider economic support are limited in helping poor households. Leonardo et al. (2022) argued that there is also a need to consider addressing the psychological and social barriers of poor households [73], which is consistent with this study's consideration of several factors of peasant households' cognitive force, both of which pay attention to the psychological expectations and rational cognitions that peasant households have of the government's poverty alleviation policies. This is consistent with hypothesis H3, which agrees that cognitive force has a positive effect on peasant households' willingness. Hoang et al. (2024) argued that the government's human support and living support could help reduce multidimensional poverty among mountainous peasant households [72]. That is consistent with the results of this study and hypothesis H9, which agrees that the behavior (such as the construction of resettlement areas) and attitudes (support and encouragement) of the local government and village cadres were conducive to strengthening the peasant households' motivation to participate in the government's poverty alleviation policies and to cooperate with the government, which in turn, would help them to combat poverty. Both this study and Whitaker et al. concluded that government policies impacted the wellbeing of peasant households in mountainous areas. However, in contrast to the results of this study and hypothesis H7, Whitaker et al. (2024) attributed the low wellbeing of peasant households in two mountainous regions in Italy to the implementation of government policies and regulations, which did not improve the wellbeing of peasant households in mountainous areas [66]. This may be because the policies and regulations implemented in rural mountainous areas in Italy were designed for the plains and did not apply to mountainous areas. The consequence of such implementation was that it eroded peasant households' trust in government institutions. However, the research hypothesis H7 indicates that national force has a positive effect on land force. This shows that when the government formulates poverty alleviation policies for poor peasant households in mountainous areas, they should consider the local conditions and consider the peasant households' real needs and development requirements from the peasant households' perspective.

In addition, this study has certain limitations that can be addressed in future research. For example, this paper only discussed the peasant households' willingness to relocate to a concentrated residence and the influencing factors of all peasant households in the study area; however, whether there is any heterogeneity in the willingness to live in a concentrated residence and its influencing factors among peasant households of different genders, ethnicities, and occupations must to be further explored. There are many factors affecting peasant households' willingness to relocate to a concentrated residence; however, this study only explored the impact of important social groups in the human force on the peasant households' willingness to relocate, without taking into account the individual characteristics of farmers, family characteristics, and cultural characteristics. The authors will attempt to construct other models to study this in the future. Additionally, further study will explore the simulation of the location and construction of ideal resettlement areas

based on the factors that affect peasant households' willingness to relocate to a concentrated residence in mountainous areas.

6. Conclusions and Implications

6.1. Conclusions

Promoting the relocation of poor peasant households in mountainous areas to concentrated residences is necessary for the successful implementation of the national poverty alleviation strategy and rural revitalization. This study explored the factors that influence peasant households' willingness to relocate to a concentrated residence by constructing a structural equation model using data collected through a questionnaire survey of 405 peasant households in 2021 in the Panxi Area. The following major conclusions have been drawn:

(1) In the 16 villages surveyed in the Panxi Area, there were still 20.98% of peasant households in mountainous areas who were unwilling to choose the concentrated residence. (2) The poor living environment and infrastructure conditions in the places where peasant households lived, the support of important social groups (family, relatives, friends, and neighbors), economic benefits (the improvement of living standards and living conditions) brought by concentrated residence, and the support and guidance of the local government and village committee were important factors that strengthened peasant households' willingness to relocate to a concentrated residence. (3) Low agricultural income, ecological benefits and value benefits brought by concentrated residence, slightly influenced the peasant households' willingness to relocate to a concentrated residence. (4) Land force, human force, and cognitive force all had a significant positive effect on the willingness to relocate to a concentrated residence, and the mediating role of cognitive force between land force and human force and the willingness to relocate to a concentrated residence existed significantly.

6.2. Policy Implications

(1) The national government plays a crucial role in relocation [74]. Hypotheses H7, H8, and H9 of this study prove that the support of national force directly impacts human force and land force, and the relationship between land force, human force, and peasant households' willingness to relocate to a concentrated residence is moderated by national force. It shows that in promoting the relocation of peasant households to centralized resettlement sites, it is essential to pay attention to the influence of the attitudes and behaviors of the local government and the local village committee on the peasant households. In implementing national policies, local governments should make appropriate adjustments to policies in light of the actual local situation and feedback from the public to meet better local development needs and the interests of the public. Village committees should assist the government in the specific implementation of relocation work, such as assisting in and resetting relocation targets. At the same time, village cadres should do a good job of publicizing the policy, so that peasant households have a comprehensive understanding of the relocation policy and can strengthen their understanding of and support for the state's policy, thus strengthening their willingness to relocate to a concentrated residence.

(2) Peasant households' cognitive force plays a crucial role in the decision-making process of moving to a centralized settlement. Hypotheses H3 and H6 in this study prove that cognitive force has a significant positive effect on the willingness of peasant households to live in centralized resettlement sites, and the direct effect is much higher than that of land force and human force. There is a significant mediating effect between land force, human force, and the willingness to relocate to a concentrated residence. It shows that before carrying out relocation work, it is essential to guide peasant households to understand the relocation policy correctly. In addition, farm households are more concerned about the economic benefits brought by concentrated residence [75]. Therefore, local governments and village committees can improve the acceptance and satisfaction of peasant households in mountainous areas with the relocation policy by strengthening the construction of

concentrated residences and providing employment support, so that peasant households will willingly and actively participate in the relocation work with the correct knowledge.

(3) The importance of social support networks to individuals cannot be overstated. Important social groups, such as family, relatives, friends, and neighbors, play different roles in an individual's life and form an important part of an individual's social support network [76]. This study proves that the indirect effect of human force on peasant households' willingness to relocate to a concentrated residence is higher than that of land force. It shows that in carrying out relocation work, it is essential to pay more attention to the influence of important social groups on the individual peasant household's behavioral decisions and cognitive abilities. Important social groups can enhance peasant households' willingness to relocate to a concentrated residence in many ways, such as by providing them with detailed information on the benefits of concentrated residence, guiding them to develop an optimistic mindset, and assisting them in moving. These measures will help dispel the doubts and worries of the peasant households and boost their confidence and expectations, thereby facilitating the smooth implementation of concentrated residence.

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References

1. Zhou, L.; Wang, L.; Su, K.; Bi, G.; Chen, H.; Liu, X.; Yang, Q. Spatiotemporal characteristics of rural restructuring evolution and driving forces in mountainous and hilly areas. *Land* **2022**, *11*, 848. [CrossRef]
2. Peng, Y.; Zhu, X.; Zhang, F.; Huang, L.; Xue, J.; Xu, Y. Farmers' risk perception of concentrated rural settlement development after the 5.12 Sichuan Earthquake. *Habitat. Int.* **2018**, *71*, 169–176. [CrossRef]
3. Deng, X. Chongqing Village-Type Farmers Concentration Building Mechanism on Study. Master's Thesis, Chongqing Technology and Business University, Chongqing, China, 2016.
4. Ellenbogen, N.R.; Trivic, Z. Dynamic place attachment in the context of displacement processes: The socio-ecological model. *Cities* **2024**, *148*, 104862. [CrossRef]
5. Feng, Y.; Li, J.; Feng, D. Research on spatial restructuring of farmers' homestead based on the "Point-Line-Surface" characteristics of mountain villages. *Land* **2023**, *12*, 1598. [CrossRef]
6. Long, H.; Zhang, Y.; Ma, L.; Tu, S. Land use transitions: Progress, challenges and prospects. *Land* **2021**, *10*, 903. [CrossRef]
7. Han, Q.; Guo, Z.; Kumar, R.; Kumar, A. An empirical approach for enhancing farmers' concentrated residence strategies: A case study in Jiangsu Province, China. *Ecol. Indic.* **2024**, *158*, 111361. [CrossRef]
8. Miltenburg, E.M.; van de Werfhorst, H.G.; Musterd, S.; Tieskens, K. Consequences of forced residential relocation: Early impacts of urban renewal strategies on forced relocatees' housing opportunities and socioeconomic outcomes. *Hous. Policy Debate* **2018**, *28*, 609–634. [CrossRef]
9. Ruming, K.; Melo Zurita, M.d.L. Care and dispossession: Contradictory practices and outcomes of care in forced public housing relocations. *Cities* **2020**, *98*, 102572. [CrossRef]
10. Steven, O. Sustainable developmentality: Interrogating the sustainability gaze and the cultivation of mountain subjectivities in the central Indian Himalayas. *Geoforum* **2021**, *127*, 209–221. [CrossRef]
11. Shi, Y. Analysis and Measures on Farmers' Willingness of Collective Living: Taking Nanhu District of Jiaying City, Zhejiang Province for Example. Master's Thesis, Shanghai Jiao Tong University, Shanghai, China, 2015.

12. Cheteni, P.; Khamfula, Y.; Mah, G. Gender and poverty in South African rural areas. *Cogent Soc. Sci.* **2019**, *5*, 1586080. [CrossRef]
13. Bukvic, A.; Barnett, S. Drivers of flood-induced relocation among coastal urban residents: Insight from the US east coast. *J. Environ. Manag.* **2023**, *325*, 116429. [CrossRef] [PubMed]
14. Kalantari, R.; Pakravan-Charvadeh, M.R.; Rahimian, M. Multi-level factors influencing climate migration willingness among small-scale farmers. *Front. Environ. Sci.* **2024**, *12*, 1434708. [CrossRef]
15. Wu, J.; Zhang, J.; Yang, H. Impact of relocation in response to climate change on farmers' livelihood capital in minority areas: A case study of Yunnan Province. *Int. J. Clim. Chang. Str.* **2023**, *15*, 790–809. [CrossRef]
16. Grüner, B. Two close-to-nature lifestyles, one benefit for the cultural landscape: Comparing lifestyle movers and lifestyle farmers in the remote European Eastern Alps. *Mt. Res. Dev.* **2023**, *43*, R1–R11. [CrossRef]
17. Stark, O.; Budzinski, W.; Kosiorowski, G. The pure effect of social preferences on regional location choices: The evolving dynamics of convergence to a steady state population distribution. *J. Reg. Sci.* **2019**, *59*, 883–909. [CrossRef]
18. Cai, J.; Hu, S.; Que, T.; Li, H.; Xing, H.; Li, H. Influences of social environment and psychological cognition on individuals' behavioral intentions to reduce disaster risk in geological hazard-prone areas: An application of social cognitive theory. *Int. J. Disast. Risk Reduct.* **2023**, *86*, 103546. [CrossRef]
19. Wang, J.; Wang, P.; Zhu, C.; Wang, Y.; Zhou, Z. Impact of different models of relocating coal mining villages on the livelihood resilience of rural households—A case study of Huaibei City, Anhui Province. *Land* **2023**, *12*, 2169. [CrossRef]
20. Gallardo-Peralta, L.P.; de Roda, A.B.L.; Ángeles Molina-Martínez, M.; Schettini Del Moral, R. Family and community support among older Chilean adults: The importance of heterogeneous social support sources for quality of life. *J. Gerontol. Soc. Work* **2018**, *61*, 584–604. [CrossRef]
21. Alam, A.; Miller, F. Slow, small and shared voluntary relocations: Learning from the experience of migrants living on the urban fringes of Khulna, Bangladesh. *Asia Pac. Viewp.* **2019**, *60*, 325–338. [CrossRef]
22. Plys, E. Reasons for relocating to assisted living: The push, the pull, and decision control. *Innov. Aging* **2019**, *3*, S638. [CrossRef]
23. Mizrak, S.; Turan, M. Effect of individual characteristics, risk perception, self-efficacy and social support on willingness to relocate due to floods and landslides. *Nat. Hazards* **2023**, *116*, 1615–1637. [CrossRef] [PubMed]
24. Rebecchi, A.; Gola, M.; Riva, A.; Capolongo, S. Can housing conditions and features affect well-being? A review through indoor environmental quality aspects and mental health implications. *Eur. J. Public Health* **2023**, *33*, 160–715. [CrossRef]
25. Qian, Z. Displaced villagers' adaptation in concentrated resettlement community: A case study of Nanjing, China. *Land Use Policy* **2019**, *88*, 104097. [CrossRef]
26. Sina, D.; Chang-Richards, A.Y.; Wilkinson, S.; Potangaroa, R. What does the future hold for relocated communities post-disaster? Factors affecting livelihood resilience. *Int. J. Disast. Risk Re.* **2019**, *34*, 173–183. [CrossRef]
27. Fattah Hulio, A.; Varghese, V.; Chikaraishi, M. Analyzing the preferences of flood victims on post flood public houses (PFPH): Application of a hybrid choice model to the floodplains of southern Pakistan. *Clim. Risk Manag.* **2023**, *42*, 100571. [CrossRef]
28. Xie, H.; Wu, Q.; Li, X. Impact of labor transfer differences on terraced fields abandonment: Evidence from micro-survey of farmers in the mountainous areas of Hunan, Fujian and Jiangxi. *J. Geogr. Sci.* **2023**, *33*, 1702–1724. [CrossRef]
29. West, J.S.; Price, M.; Gros, K.S.; Ruggiero, K.J. Community support as a moderator of postdisaster mental health symptoms in urban and nonurban communities. *Disaster Med. Public* **2013**, *7*, 443–451. [CrossRef]
30. Palagi, S.; Javernick-Will, A. Institutional constraints influencing relocation decision making and implementation. *Int. J. Disast. Risk Reduct.* **2019**, *33*, 310–320. [CrossRef]
31. Nguyen-Anh, T.; Nong, D.; Leu, S.; To-The, N. Changes in the environment from perspectives of small-scale farmers in remote Vietnam. *Reg. Environ. Chang.* **2021**, *21*, 98. [CrossRef]
32. Chaulagain, S.; Pizam, A.; Wang, Y.; Severt, D.; Oetjen, R. Factors affecting seniors' decision to relocate to senior living communities. *Int. J. Hosp. Manag.* **2021**, *95*, 102920. [CrossRef]
33. Zhong, J.; Liu, S.; Huang, M.; Cao, S.; Yu, H. Driving forces for the spatial reconstruction of rural settlements in mountainous areas based on Structural Equation Models: A case study in Western China. *Land* **2021**, *10*, 913. [CrossRef]
34. Rosseel, Y.; Loh, W.W. A structural after measurement approach to structural equation modeling. *Psychol. Methods* **2022**, *29*, 561–588. [CrossRef] [PubMed]
35. Mortreux, C.; Safrade Campos, R.; Adger, W.N.; Ghosh, T.; Das, S.; Adams, H.; Hazra, S. Political economy of planned relocation: A model of action and inaction in government responses. *Glob. Environ. Chang.* **2018**, *50*, 123–132. [CrossRef]
36. Daly, P.; Mahdi, S.; Mundir, I.; McCaughey, J.; Amalia, C.S.; Jannah, R.; Horton, B. Social capital and community integration in post-disaster relocation settlements after the 2004 Indian Ocean Tsunami in Indonesia. *Int. J. Disast. Risk Reduct.* **2023**, *95*, 103861. [CrossRef]
37. Chen, Y.; Lü, B.; Chen, R. Evaluating the life satisfaction of peasants in concentrated residential areas of Nanjing, China: A fuzzy approach. *Habitat. Int.* **2016**, *53*, 556–568. [CrossRef]
38. Li, Y.; Feng, X. Influence of housing resettlement on the subjective well-being of disaster-forced migrants: An empirical study in Yancheng City. *Sustainability* **2021**, *13*, 8171. [CrossRef]
39. Karani, I.; Papada, L.; Kaliampakos, D. Energy poverty signs in mountainous Greek areas: The case of Agrafta. *Int. J. Sustain. Energy* **2022**, *41*, 1408–1433. [CrossRef]
40. Duglio, S.; Salotti, G.; Mascadri, G. Conditions for operating in marginal mountain areas: The local farmer's perspective. *Societies* **2023**, *13*, 107. [CrossRef]

41. Ma, L.; Wang, S.; Wästfelt, A. The poverty of farmers in a main grain-producing area in Northeast China. *Land* **2022**, *11*, 594. [CrossRef]
42. Li, D.; Yang, Y.; Du, G.; Huang, S. Understanding the contradiction between rural poverty and rich cultivated land resources: A case study of Heilongjiang Province in Northeast China. *Land Use Policy* **2021**, *108*, 105673. [CrossRef]
43. Xiao, Y.; Yin, K.; Pan, L. Study on the change of livelihood capital of poverty alleviation farmers in hilly and mountainous areas of southwest china and its regulation on people's anxiety. *Int. J. Neuropsychoph.* **2022**, *25*, A78. [CrossRef]
44. Sussman, R.; Gifford, R. Causality in the theory of planned behavior. *Personal. Soc. Psychol. Bull.* **2019**, *45*, 920–933. [CrossRef] [PubMed]
45. Zhang, F.; Zhou, W.; He, J.; Qing, C.; Xu, D. Effects of land transfer on farmer households' straw resource utilization in rural Western China. *Land* **2023**, *12*, 373. [CrossRef]
46. Keer, M.; van den Putte, B.; Neijens, P. The role of affect and cognition in health decision making. *Brit. J. Soc. Psychol.* **2010**, *49*, 143–153. [CrossRef]
47. Meng, Z.; He, J.; Xu, D. How do peer effects affect the transformation of farmers' willingness and behavior to adopt biogas? *J. Clean. Prod.* **2023**, *415*, 137857. [CrossRef]
48. Lee, S.S.; Kim, Y.; Roh, T. Pro-environmental behavior on electric vehicle use intention: Integrating value-belief-norm theory and theory of planned behavior. *J. Clean. Prod.* **2023**, *418*, 138211. [CrossRef]
49. Li, M.; Hua, Y. Integrating social presence with social learning to promote purchase intention: Based on social cognitive theory. *Front. Psychol.* **2022**, *12*, 810181. [CrossRef]
50. Hesam, M.; Roshan, G.; Grab, S.W.; Shabahrami, A.R. Comparative assessment of farmers' perceptions on drought impacts: The case of a coastal lowland versus adjoining mountain foreland region of northern Iran. *Theor. Appl. Climatol.* **2021**, *143*, 489–503. [CrossRef]
51. Novira, N.; Maxriz, J.; Astuti, A. The socio-economic impact of relocation policy to the communities affected by the mount sinabung eruption: A preliminary study. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *683*, 012094. [CrossRef]
52. Montpetit, M.A.; Nelson, N.A.; Tiberio, S.S. Daily interactions and affect in older adulthood: Family, friends, and perceived support. *J. Happiness Stud.* **2017**, *18*, 373–388. [CrossRef]
53. Wehner, L.E.; Thies, C.G. Leader influence in role selection choices: Fulfilling role theory's potential for foreign policy analysis. *Int. Stud. Rev.* **2021**, *23*, 1424–1441. [CrossRef]
54. Nagle Alverio, G.; Hoagland, S.H.; Coughlan de Perez, E.; Mach, K.J. The role of international organizations in equitable and just planned relocation. *J. Environ. Stud. Sci.* **2021**, *11*, 511–522. [CrossRef] [PubMed]
55. Cao, M.; Xu, D.; Xie, F.; Liu, E.; Liu, S. The influence factors analysis of households' poverty vulnerability in southwest ethnic areas of China based on the hierarchical linear model: A case study of Liangshan Yi autonomous prefecture. *Appl. Geogr.* **2016**, *66*, 144–152. [CrossRef]
56. Martin, A.; Petersen, M. Poverty alleviation as an economic problem. *Camb. J. Econ.* **2019**, *43*, 205–221. [CrossRef]
57. Wang, W.; Lan, Y.; Wang, X. Impact of livelihood capital endowment on poverty alleviation of households under rural land consolidation. *Land Use Policy* **2021**, *109*, 105608. [CrossRef]
58. Rivera, J.P.R. A nonparametric approach to understanding poverty in the Philippines: Evidence from the family income and expenditure survey. *Poverty Public Policy* **2022**, *14*, 242–267. [CrossRef]
59. Qu, X.; Zhou, W.; He, J.; Xu, D. Land Certification, Adjustment Experience, and Green Production Technology Acceptance of Farmers: Evidence from Sichuan Province, China. *Land* **2023**, *12*, 848. [CrossRef]
60. Fang, Y.; Zhu, F.; Qiu, X.; Zhao, S. Effects of natural disasters on livelihood resilience of rural residents in Sichuan. *Habitat. Int.* **2018**, *76*, 19–28. [CrossRef]
61. Qiang, M. Analysis of the Spatial Conflicts of the National Land and Its Influencing Factors. Master's Thesis, Institute of Mountain Hazards and Environment, Chinese Academy of Sciences, Chengdu, China, 2018.
62. Habibah, U.; Hassan, I.; Iqbal, M.S.; Naintara, N. Household behavior in practicing mental budgeting based on the theory of planned behavior. *Financ. Innov.* **2018**, *4*, 28. [CrossRef]
63. Guo, Y.; Liu, Y. Poverty alleviation through land assetization and its implications for rural revitalization in China. *Land Use Policy* **2021**, *105*, 105418. [CrossRef]
64. Klärner, A.; Knabe, A. Social networks and coping with poverty in rural areas. *Sociol. Rural.* **2019**, *59*, 447–473. [CrossRef]
65. Liu, Y.; Deng, W.; Peng, L. The coupling mechanism between the suitable space and rural settlements considering the effect of mountain hazards in the upper Minjiang River basin. *J. Mt. Sci.* **2020**, *17*, 2774–2783. [CrossRef]
66. Whitaker, S.H. The impact of government policies and regulations on the subjective well-being of farmers in two rural mountain areas of Italy. *Agr. Hum. Values* **2024**, *1*–19. [CrossRef]
67. Zhao, D.; Chen, L.; Liu, Y.; Liu, C.; Gao, W.; Miao, S. A new scale to assist in evaluating architectural proposals on the natural dimension based on psychometrics. *Sustain. Cities Soc.* **2024**, *100*, 105037. [CrossRef]
68. Saris, W.E.; Satorra, A.; van der Veld, W.M. Testing Structural Equation Models or detection of misspecifications? *Struct. Equ. Model.* **2009**, *16*, 561–582. [CrossRef]
69. Valente, M.J.; Gonzalez, O.; Miočević, M.; MacKinnon, D.P. A note on testing mediated effects in Structural Equation Models: Reconciling past and current research on the performance of the test of joint Significance. *Educ. Psychol. Meas.* **2016**, *76*, 889–911. [CrossRef]

70. Braun, D.; Lascelles, K. Involving and supporting families, friends, and carers during a mental health crisis. *Lancet Psychiat.* **2024**, *11*, 586–587. [CrossRef]
71. Junquera, V.; Rubenstein, D.I.; Grêt-Regamey, A.; Knaus, F. Structural change in agriculture and farmers' social contacts: Insights from a Swiss mountain region. *Agr. Syst.* **2022**, *200*, 103435. [CrossRef]
72. Hoang-Duc, C.; Nguyen-Thu, H.; Nguyen-Anh, T.; Tran-Duc, H.; Nguyen-Thi-Thuy, L.; Do-Hoang, P.; To-The, N.; Vu-Tien, V.; Nguyen-Thi-Lan, H. Governmental support and multidimensional poverty alleviation: Efficiency assessment in rural areas of Vietnam. *J. Econ. Inequal.* **2024**, 1–40. [CrossRef]
73. Leonardo, W.; van de Ven, G.W.J.; Kanellopoulos, A.; Giller, K.E. Addressing social, psychological and economic barriers helps people out of extreme poverty. *Nature*, 2022; *online ahead of print*. [CrossRef]
74. Wang, P.; Lyu, L.; Xu, J. Factors Influencing Rural Households' Decision-Making Behavior on Residential Relocation: Willingness and Destination. *Land* **2021**, *10*, 1285. [CrossRef]
75. Zhang, Z.; Wen, Y.; Wang, R.; Han, W. Factors influencing rural households' willingness of centralized residence: Comparing pure and nonpure farming areas in China. *Habitat. Int.* **2018**, *73*, 25–33. [CrossRef]
76. Cugmas, M.; Ferligoj, A.; Kogovšek, T.; Batagelj, Z. The social support networks of elderly people in Slovenia during the COVID-19 pandemic. *PLoS ONE* **2021**, *16*, e0247993. [CrossRef] [PubMed]

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Article

Harnessing the Power of Mechanization: A Multivalued Treatment Effect Analysis on Productivity for Chinese Smallholders

Zhenbang Ma ¹ and Huichun Sun ^{2,*}¹ School of Finance, Nankai University, Tianjin 300350, China; 1120231232@mail.nankai.edu.cn² School of Business Administration, Zhongnan University of Economics and Law, Wuhan 430073, China

* Correspondence: hcsun@zuel.edu.cn

Abstract: Developing countries, in their pursuit of the Sustainable Development Goals, are intensifying their efforts to promote agricultural mechanization, with China at the forefront, through comprehensive policy revisions aimed at enhancing mechanization levels. This study employs multivalued treatment effect (MVTE) and quantile treatment effect (QTE) methodologies to assess the impact of agricultural mechanization on labor and land productivity while also examining the effects across different farm sizes and moderating influences. Leveraging data from the 2016 China Labor-force Dynamics Survey, the findings indicate that semi-mechanized and full-mechanized farming, compared to no-mechanized farming, significantly boost labor and land productivity for both average and lower-to-mid-level productivity farmers. Disaggregated analysis by farm size shows that larger farms benefit significantly from semi-mechanized and full-mechanized farming in terms of increased labor and land productivity. However, the incremental benefits of varying levels of mechanization on productivity are observed only in labor productivity for farmers with mid- and upper-level productivity and for those in the largest farm size group. Additionally, land transfer status, government subsidies, and the intensity of clan culture are found to significantly influence the productivity effects of agricultural mechanization in China. Consequently, it is imperative to reorient agricultural policies towards enhancing the efficiency and cost-effectiveness of mechanization, especially considering the constraints on labor and land availability and the need to minimize the environmental impact of agricultural production. In light of these discussions, this paper presents policy implications for sustainable agricultural mechanization.

Keywords: agricultural mechanization; labor and land productivity; multivalued treatment effect; quantile treatment effect; moderating effect; Chinese smallholders

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1. Introduction

Maintaining and boosting agricultural productivity and income for smallholder farmers is a critical issue in many developing nations [1]. The second Sustainable Development Goal (SDG), which focuses on ending hunger and promoting sustainable agriculture, specifically targets a doubling of agricultural productivity and the income of small-scale food producers by 2030 [2]. The connection between agricultural productivity and income is well established, especially for smallholder farmers. Amidst high rates of rural-to-urban migration and an aging rural population, agricultural mechanization is key to increasing the productivity of smallholder farms, thus supporting their economic sustainability and the broader goals of sustainable agricultural development [3,4].

Since 1998, China has implemented agricultural machinery purchase subsidy policies, leading to a significant increase in the total power of agricultural machinery from 45,207.5 million kW to 105,622.1 million kW between 1998 and 2020 [5]. While mechanization shields smallholder farms from escalating labor costs, there is a growing concern that China may be overinvesting in agricultural machinery. For instance, in 2016, China used

91.54 standard tractors per thousand hectares of arable land, compared to only 27.51 in the United States [6,7]. However, a common oversight in the literature is the pivotal role of farm size. In the United States, less than 10% of farms are smaller than 10 acres, whereas, in China, at least 80% of farms are below this threshold, with land often divided into spatially separated plots [8]. The productivity and profitability derived from standard tractors vary by farm scale and plot size due to scale economies in machinery capacity. Therefore, a critical question that requires further exploration is the extent to which agricultural mechanization is linked to productivity and how this relationship might differ based on farm size in developing countries.

Agricultural mechanization is widely recognized for its positive impact on production, primarily through increased yields and output. Studies have shown that improved access to mechanization services in Ghana and the increased use of self-owned and purchased machinery services in China significantly raise crop yields [9,10]. Wang et al. further support this by demonstrating that machinery use in China leads to substantial yield increases for a variety of crops, including wheat, corn, Japonica rice, soybean, cotton, and rapeseed [11]. Belton et al. attribute the rapid rise in agricultural mechanization in Myanmar to improvements in operational speed, timeliness, weather risk management, and reduced grain loss during harvest [12]. However, it is crucial to note that farms operating on a similar scale can exhibit significant yield differences due to variations in input use efficiency, such as fertilizer application intensity. Consequently, output alone is an insufficient measure of agricultural productivity, especially when detailed information on input use and costs is lacking. This limitation also affects the assessment of the profitability and welfare impacts of agricultural mechanization on smallholder farmers.

The literature on agricultural mechanization and its impact on production efficiency is varied. Some studies emphasize the positive role of mechanization in increasing farmers' income and crop revenue by improving economies of scale [13–16]. It is also noted for its potential to alleviate poverty in regions like Zambia when implemented effectively. [14,17]. On the other hand, there is an ongoing debate about the extent to which small farms in developing countries, including those in China, can leverage the full benefits of mechanization due to the scale of available machinery [8]. The high cost of equipment is seen as a significant obstacle for these smaller operations [18]. Additionally, evidence indicates that medium-sized farms might gain more from mechanization compared to their smaller and larger counterparts, as the smallest farms typically depend more heavily on manual labor for crops [19]. This brief overview suggests that agricultural mechanization primarily benefits by alleviating rural labor deficits and leveraging scale economies of machinery. The complex interplay between mechanization and productivity, especially concerning farm size, requires deeper exploration, particularly for smallholder farmers in developing countries.

China, the world's largest developing country, has made agricultural mechanization a key driver for productivity and income growth in rural areas. The 2004 Law on the Promotion of Agricultural Mechanization, along with subsequent policies, has heightened focus on mechanization, leading to a 3.73% average annual growth rate of mechanization from 2004 to 2016 [20]. Despite a slowdown in growth since 2016, indicating a potential overinvestment in agricultural mechanization, China's Ministry of Agriculture and Rural Affairs unveiled in December 2021 plans to stabilize agricultural machinery power at around 1.1 billion kW by 2025, prioritizing optimization over expansion [21].

Facing challenges from urbanization, an aging rural population, and the rise in non-agricultural employment, which increase agricultural costs and hamper productivity, China's household-level agricultural production remains stable, contributing 29.4% to annual household income on average in 2021, with crop-planting households even more dependent on farming for income [22,23]. Agricultural mechanization in China is at a pivotal moment, demanding strategic actions that align with sustainable development and the Sustainable Development Goals. While past policies have focused on augmenting the power of agricultural machinery, there is an urgent need to shift focus towards optimizing current

machinery usage, improving mechanization efficiency, and achieving cost-effectiveness, especially in light of labor and land limitations and environmental considerations.

This study aims to address three key objectives: first, to assess how agricultural mechanization can boost labor and land productivity across different productivity levels; second, to analyze whether the impact of mechanization varies by farm size; and third, to explore the influence of land transfer status, government subsidies, and regional cultural differences on the productivity effects of agricultural mechanization. We expect to find that farmers with diverse characteristics will show asymmetric behaviors in the relationship between mechanization adoption and productivity. Utilizing data from the 2016 China Labor-force Dynamics Survey [24], encompassing 2581 rural households across 200 villages, our research reveals that semi- and full-mechanized farming, compared to no mechanization, improves labor and land productivity for average and lower-to-mid-level productivity farmers. Notably, for farmers with larger farm sizes, the adoption of semi- and full-mechanized farming significantly enhances labor and land productivity. However, the incremental benefits of different mechanization levels are only observed in labor productivity for farmers with mid-level productivity and those in the largest farm size group. These findings provide significant guidance for policymakers and stakeholders as they work towards promoting agricultural mechanization and enhancing the sustainability of smallholder farms in developing countries.

This paper makes significant contributions to the existing literature. First, it diverges from previous studies that have concentrated on a binary view of mechanization or the use of mechanization services by farmers, instead exploring the spectrum of no-, semi-, and full-mechanized farming [10,25–29]. Our analysis estimates the multivalued impact of the three mechanization strategies on labor and land productivity. Second, we leverage multivalued treatment effect (MVTE) models and quantile treatment effect (QTE) models to tackle selection bias in the mechanization adoption and assess the varied effects of mechanization in a nuanced context [30–32]. Additionally, our research underscores that the impact of mechanization is contingent upon productivity levels and farm sizes, a critical insight that is often overlooked, despite evidence indicating that larger farms and those expanding are more inclined to adopt mechanization [33,34]. This dimension is crucial for understanding the differential adoption and impact of mechanization within countries.

The rest of this paper is structured as follows: Section 2 provides the background; Section 3 details methodology; Section 4 presents the data and descriptive statistics; Section 5 displays the empirical results and its corresponding discussions; and Section 6 concludes with policy implications.

2. Background

Between 2010 and 2016, China experienced notable progress in agricultural mechanization, propelled by strategic government initiatives and technological innovations. In this section, we will discuss the key developments in agricultural mechanization, the promotion strategies that boosted mechanization levels and improved workforce capabilities, as well as the pivotal impact of non-agricultural labor on the adoption of agricultural technology and the enhancement of productivity.

2.1. Agricultural Mechanization Development

Between 2010 and 2016, China's agricultural mechanization saw remarkable progress, supported by strong data and legislative measures. The Chinese government prioritized agricultural mechanization, leading to a series of policy initiatives and subsidy measures. The "Agricultural Mechanization Promotion Law" of 2004 underscored the state's commitment to technological innovation and the dissemination of mechanization technology in agriculture. This was complemented by large-scale policy subsidies for agricultural machinery from 2005 onwards, which significantly accelerated the agricultural development.

By 2016, China's agricultural machinery power had reached 11.06 billion kilowatts, a 2.63% increase from the previous year, with the number of tractors reaching 21.44 million

units and the corresponding agricultural implements reaching 40.29 million sets. There was a notable year-on-year growth in the ownership of large and medium tractors, with increases of 12.47% and 4.24%, respectively, and the number of implements corresponding to tractors with power above 58.8 kilowatts increased by 9.65% [35].

From 2005 to 2015, the level of mechanization for major crops experienced rapid growth. By 2016, the comprehensive mechanization rate had risen to an estimated 65–66%, representing a 2–3 percentage point increase from 2015, which concluded the “Twelfth Five-Year Plan” period. This period was particularly marked by significant advancements in the mechanization of critical crops such as wheat, rice, and corn. Additionally, the advocacy for green and eco-friendly agricultural machinery emerged as a defining characteristic of this timeframe. In 2016, approximately 180,000 units of machinery, equipped with functionalities like recycling and removal, solid–liquid separation, and film residue recovery, were introduced. The establishment of the first batch of 28 full mechanization demonstration counties across the nation reached significant milestones. These included a consistent rise in the operational volume of agricultural machinery and a hastened push towards mechanization in hilly and mountainous regions. These demonstration counties have since served as a beacon, offering scalable and valuable experiences for the broader advancement of agricultural mechanization across the country.

The swift development of agricultural mechanization in China between 2010 and 2016 not only amplified agricultural production efficiency but also secured national food safety. It laid a solid material and technical foundation for the modernization of agriculture and the execution of rural revitalization strategies. This era of agricultural mechanization development was a culmination of policy promotion, technological innovation, market demand, and government subsidies, signifying a new phase in the evolution of China’s agricultural mechanization.

2.2. Mechanization Promotion

China is tackling the challenge of inadequate worker qualifications in agricultural machinery operations through a comprehensive strategy that aims to enhance both mechanization levels and worker competencies. This strategy is executed through a structured promotion system and collaborative efforts across national and local levels, thereby boosting agricultural production efficiency and modernization.

The four-tier agricultural mechanization promotion system in China is crucial for devising technology promotion strategies, implementing key projects, and converting scientific and technological achievements into practical applications. These non-profit institutions are distinguished by their public service mission, setting them apart from other service organizations.

Agricultural machinery cooperatives, established under the “Farmers’ Professional Cooperatives Law”, are pivotal in upgrading worker qualifications. Operating on principles of self-management and shared risks and benefits, these cooperatives offer a suite of services including mechanized production, harvesting, the initial processing of agricultural products, as well as information, technology, maintenance, training, and consulting services. While they generate income from services, their primary goal is to serve their members and increase agricultural production efficiency rather than to maximize profits.

The Chinese government has introduced policies and regulations to foster the transformation and upgrading of the agricultural mechanization and equipment industry. These initiatives aim to establish an efficient mechanized production system, promote mechanization-compatible crop varieties, and create conditions for full-process mechanization and large-scale production. By encouraging the integration of information technology in agricultural machinery and operations, the quality and efficiency of agricultural machinery operations are significantly enhanced.

Acknowledging the small-scale nature of Chinese rural landholdings, China emphasizes the use of medium and small-sized machinery in the mechanization process, often operated by more professional villagers or those with extensive experience within agri-

cultural machinery cooperatives. This approach ensures that the qualification issue is less critical than the level of mechanization, as each rural household can select the appropriate level of mechanization to meet their needs, supported by promotion organizations, cooperatives, company personnel, and other rural family members.

2.3. Contributions of Non-Agricultural Labor Force

When examining agricultural mechanization, the primary goals are to boost productivity and decrease the labor required for farming tasks. However, it is essential to recognize the significant interplay between mechanization and non-agricultural labor. This relationship is not just important but also pivotal, as non-agricultural labor can influence the adoption and advancement of agricultural mechanization within specific economic and social contexts.

The “semi-agricultural, semi-non-agricultural” employment model is a strategic adaptation to the seasonal demands of agricultural labor, which results in periods of low demand and prompts rural workers to seek non-agricultural work during the off-season [36]. This model helps maintain a balance between agricultural and non-agricultural work. The Chinese government’s initiative to redirect surplus agricultural labor into non-agricultural sectors, as detailed in the State Council’s “Notice on the Promotion of Employment Planning (2011–2015)”, has significantly increased job opportunities in rural areas. This policy has been instrumental in localizing non-agricultural employment, providing workers with the flexibility and variable work schedules necessary to engage in peak agricultural activities alongside their non-agricultural jobs. The 2016 third agricultural census data, compared to 2018, show a relatively low average household ownership of key agricultural machinery, highlighting the reliance on non-agricultural labor to support agricultural work, especially when mechanization is limited [37].

The influence of non-agricultural employment on agricultural productivity extends beyond just labor availability. During our research period, internet usage in rural China was not as widespread, emphasizing the importance of knowledge and information exchange for the adoption of new agricultural technologies. Non-agricultural workers, through their interactions in various work environments, are more likely to acquire and disseminate knowledge that advances agricultural technologies, thereby enhancing productivity. Despite concerns that non-agricultural work might impede the adoption of labor-intensive advanced practices [31], China’s agricultural technology extension organizations and agricultural machinery cooperatives coordinate technology promotions and operations, reducing the need for every household to undergo agricultural machinery operation training.

Economically, non-agricultural employment significantly impacts agricultural production efficiency by increasing remittances and raising household income levels [38]. This income growth can alleviate income constraints for family members remaining in agriculture, enabling them to invest in more capital-intensive and labor-saving agricultural production factors to enhance labor productivity. While there is evidence that increased non-agricultural income can lead to increased agricultural investment [39,40], it is also observed that farmers may allocate these funds to home construction, children’s education, and other durable goods consumption [41]. However, in the context of small-scale farming in China, where farmers tend to purchase mechanical services rather than machinery for self-operation, the financial support from non-agricultural labor effectively increases investment in agricultural production, particularly in covering the costs of mechanical services, to a certain extent.

3. Econometric Specification

In this study, we followed the framework to specify the impact of agricultural mechanization on labor and land productivity [31,42]. In the MVTE model, for each household i ($i = 1, \dots, N$), we observed Y_i (labor and land productivity), T_i (multivalued mechanization strategy, where $T = 1$ for no-mechanized farming, $T = 2$ for semi-mechanized farming,

and $T = 3$ for full-mechanized farming), and X_i (the vector of pre-treatment covariates, such as age, education, gender, farm size, and household size). The set (Y_{i1}, Y_{i2}, Y_{i3}) indicates the potential productivity level for each household i where $T_i = t$ and $t \in \{1, 2, 3\}$, given that only one of Y_{it} is observed once a specific mechanization strategy is selected. Each observed outcome Y_i can be written as a function of the treatment indication D_{it} and potential outcome Y_{it} as follows:

$$Y_i = \sum_{t=1}^3 D_{it}(T_i)Y_{it}, \quad D_{it}(T_i) = \begin{cases} 1, & \text{if } T_i = t \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Let m and n denote the distinct mechanization strategies, such that the treatment effect (τ) of strategies m versus n can be expressed as the difference between potential outcomes associated with these strategies:

$$\tau = E(Y_{im} - Y_{in}), \quad m, n \in t = \{1, 2, 3\} \quad (2)$$

The MVTE model employs the ignorability and overlap assumptions to create the semblance of randomness [42]. The ignorability assumption implies that the choice of mechanization strategy is uncorrelated with the crop income outcomes. This assumption holds once we partial out a rich set of observed pre-treatment characteristics (X) by drawing on the existing literature. The overlap assumption requires that, for the setting of covariates (X) in the assumed population, there is a chance of seeing households in all mechanization strategy groups in contrast. We used the multinomial logit (MNL) model to estimate the generalized propensity score (GPS) as the conditional probability of a household belong to a particular mechanization strategy group conditioning on X_i [43] and employ the GPS to weigh observations and estimate the treatment effects.

Given the selected covariates (X), the conditional expectations of the potential productivity outcomes for mechanization strategies m and n are $E[Y_{it}|X_i] = E[Y_i|T_i = t, X_i] = \beta_{0t} + X_i' \beta_{1t}$, where $t = m$ and n , respectively. Therefore, the average treatment effect (ATE) of adopting mechanization strategy m versus n over the whole population can be estimated as follows:

$$ATE_{mn} = \frac{1}{K} (E[Y_{im}|X_i] - E[Y_{in}|X_i]) \quad (3)$$

where K refers to the total number of observations that take part in the treatment $T_i = m$ and $T_i = n$, $m, n \in t = \{1, 2, 3\}$. We employed an inverse-probability-weighted regression adjustment (IPWRA) estimator to estimate both average treatment effects as the IPWRA estimator has a double-robust property to ensure the treatment effects estimated are consistent and unbiased [30,32].

We also study a weighted quantile regression approach for estimating the conditional quantile labor and land productivity. Let $F_{Y_t}(Y)$ be the distribution function of the potential productivity outcomes $Y(t), t = \{1, 2, 3\}$. For $0 < \tau < 1$, the τ th quantile of the T potential productivity outcomes are $q(\tau) = \{q_1(\tau), q_1(\tau), q_2(\tau)\}'$, where $q_t(\tau) = F_{Y_t}^{-1}(\tau) = E[F_{Y_t|X}(Y_t|X)]$, and $F_{Y_t}(Y)$ is assumed to be continuous. Therefore, the quantile treatment effect (QTE) of adopting mechanization strategy m versus n over the whole population can be estimated as follows:

$$QTE_{mn,\tau} = \frac{1}{K} (q_m(\tau) - q_n(\tau)) \quad (4)$$

where K refers to the total number of observations that take part in the treatment $T_i = m$ and $T_i = n$, $m, n \in t = \{1, 2, 3\}$. Again, we form GPSs generated from an MNL model and construct the IPWRA estimator by using an inverse-probability-weighted regression adjustment scheme. The quantile regression framework estimates the heterogeneity in treatment effects at the lower (0.25), median (0.5), and upper (0.75) quantiles of the distribution of labor productivity and land productivity, which allow us to obtain a more

complete picture of the multivalued treatment effects of agricultural mechanization on the productivity outcomes.

The productivity effects of agricultural mechanization are significantly influenced by the land transfer status of farmers, the extent of government subsidies received, and the variations in clan culture within their local regions. Consequently, it is anticipated that farmers with different combinations of these characteristics will exhibit asymmetrical relationships between mechanization adoption and productivity. To test this hypothesis, we incorporate interaction terms into our analysis. The specific model is as follows:

$$Y_i = \alpha_0 + \alpha_1 \text{Mechanization}_i \times \text{Moderator}_i + \alpha_2 \text{Mechanization}_i + \alpha_3 \text{Moderator}_i + \sum \text{Controls}_i + \sum \text{Province}_i + \varepsilon_i \quad (5)$$

where Y_i represents, respectively, labor productivity and land productivity, and moderator variables are employed to adjust the relationship between mechanization and productivity outcomes. These moderators include the household's land transfer status, the government subsidy receipt, and the intensity of clan culture in the village of residence. The land transfer status is quantified by the proportion of the household's contracted land to the total arable land. The receipt of government subsidies is measured using a binary variable from the survey data, indicating whether the household has received any government subsidies. The intensity of clan culture in the village is assessed by the population proportion of the most common surname in the village.

4. Data and Descriptive Statistics

We use China Labor-force Dynamics Survey (CLDS) data collected in 2016 for empirical analysis [24]. The data were collected and owned by the Center for Social Survey at Sun Yatsen University, Guangzhou, China. A multistage cluster, stratified, and probability-proportional-to-size sample of China labor force was surveyed, and the surveys provided information on households and individuals in both rural and urban communities in China (except Hong Kong, Taiwan, Macau, Tibet, and Hainan). Screened by the questions about agricultural operations in 2015, the dataset used in this study includes a total of 2581 farmer households involved in crop planting in 2015. This sample comprises 834 households adopting no mechanized farming (i.e., farm machines are not used at any production stages), 1077 adopting semi-mechanized farming (i.e., farm machines are used at some production stages), and 670 adopting full-mechanized farming (i.e., farm machines are used at every production stage).

First, it is important to note that our analysis, which concentrates on grain crops, is limited by the CLDS 2016 data that provided information on agricultural income rather than direct agricultural output. Therefore, we used the crop income (output value) per unit of labor or land to represent labor and land productivity [44,45]. We define crop income as returns over cash costs, which is the value of the crop outputs produced by the household minus the value of paid-out costs of crop planting. The crop outputs are valued even if a small portion of the production is consumed by the farmer's household rather than sold on the market. Given that most small farms in China rent or share the machinery they use [46], the depreciation costs can be neglected [47]. This measure of income based on returns over cash costs adequately represents the crop income available to the household at the end of the cropping season. The survey instrument elicited information on a household's 2015 wage income, property income, transfer income, and, most importantly, agricultural income after subtracting all expenses, and, in this study, we focus on agricultural income for crop planting farmers.

We further examine agricultural labor productivity and land productivity through crop income per effective agricultural labor and per mu, where 1 mu equals 1/15 hectare. Agricultural labor productivity is usually measured by the number of units of outputs produced per unit of labor or the number of hours effectively worked in the process of production. However, the reported change in the number of hours does not always reflect the change in technology and, therefore, productivity [48]. We employ a questionnaire item inquiring, "Last year, how many people in your household were engaged in agricultural

production for more than three months?”. Using this, we developed an effective agricultural labor indicator. We defined all eligible laborers in a household who worked in agricultural production for over three months as constituting one unit of agricultural labor. Those who did not meet this threshold are counted as 0.5 units, and we aggregated these to determine the total effective agricultural labor force for each household. This approach allows us to quantify the labor contribution to agriculture, taking into account the varying degrees of engagement with agricultural activities. An increase in the productivity of effective agricultural labor results in an increase in the net cash farm income at no additional monetary cost. Expressed in monetary units, crop income per effective agricultural labor is used in our analysis to explore the effect of agricultural mechanization on labor productivity.

Agricultural land productivity, as the most applicable productivity measure in the context of cropping activities, measures the crop production generated by a given unit of land. An increase in land productivity reflects a higher output per unit of land and higher farm income. Therefore, in this study, we used the crop income per mu to represent the agricultural land productivity in monetary units.

To capture the labor and land productivity, we calculated the per effective agricultural labor and per mu crop income for each household and used their logarithmically transformed values in the analysis. Agricultural mechanization was assumed to help foster labor and land productivity and, therefore, the productivity in monetary units. Figure 1 demonstrates the means and 95% confidence intervals of labor and land productivity by the mechanization strategies. With an upgrade in mechanization strategy, labor productivity increases consistently, while land productivity exhibits a difference between no-mechanized farming and mechanized farming with no notable incremental increase.

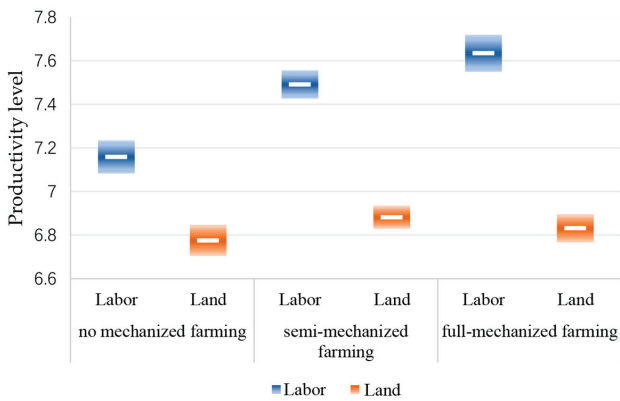


Figure 1. Productivity across the three mechanization strategies with 95% confidence intervals. The labor and land productivity are measured by using the logarithmically transformed value of per effective agricultural labor and per mu crop income for each household.

Figure 2 displays how the labor and land productivity are distributed by the mechanization strategies. By using kernel density estimation to create smooth approximations, we are able to visualize and compare the productivity distributions for different mechanization strategies. For labor productivity, the peak shifts to the right and becomes lower as the mechanization level improves, which implies that the labor productivity distribution has a higher average and a higher variance with mechanized farming. However, as revealed in Figure 2, there is no notable change among the peak values of land productivity distributions, while the concentration from the peak grows much more intense as the mechanization level improves. We note that the observed difference between the labor and land productivity distribution changes can be attributed to different farm sizes and the different ways that agricultural practices are involved with mechanization based on farm size as reported by the surveyed smallholder farmers. In this sense, the disaggregated

analysis by farm size of the productivity improvement effect of agricultural mechanization is necessary and imperative.

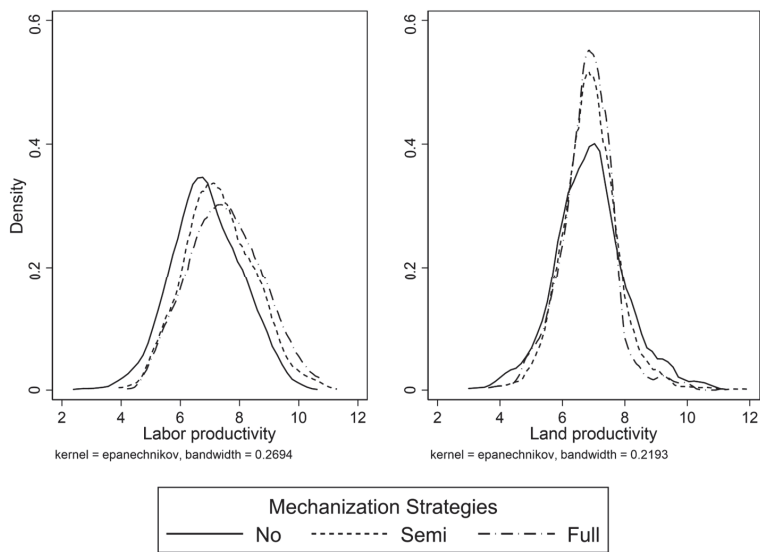


Figure 2. Kernel density plots of labor and land productivity for different mechanization strategies.

As shown in Table 1, we find that almost 68% of farms (1747 out of 2581) adopt agricultural mechanization, while 26% of them apply full-mechanized farming. If we narrow our focus and categorize the data based on farm size into three tertiles, the distribution of the adoption of mechanization strategies among the three groups show that, as expected, smaller farms are less likely to adopt mechanization, while larger farms are more likely to.

Table 1. Farm-size characteristics and distribution of agricultural mechanization strategy.

Variables	Mean (mu)	S.D. (mu)	Obs. on Mechanization Strategies			Total Obs.
			No	Semi	Full	
Farm size	7.88	6.39	834	1077	670	2581
lower tertile	2.89	0.83	399	350	179	928
median tertile	6.17	1.17	277	359	221	857
upper tertile	15.55	6.26	158	368	270	796

Furthermore, to control the spatial changes in mechanization level and productivity level in crop production, Table 2 shows the regions and provinces of China covered in our analysis, as well as the corresponding distributions of farm sizes and mechanization levels of the sample farms from these regions. The inter-regional distinctions of distributions of the farm size and the mechanization level were not drastic in our sample, but Western China, where small farms account for a higher proportion, has a lower rate of mechanization applications. In all, farm size plays an active role in agricultural mechanization adoption, but how the farm size influences the productivity improvement effect of agricultural mechanization needs more in-depth study.

We also utilize the question, “What is the situation regarding the mechanized production tools used by your household?”, which provides options such as ownership, co-purchase, rental, borrowing, and other arrangements. This question is integrated into our regression model to gain insights into the diverse methods that farmers utilize mechanization and its effect on production efficiency.

Table 2. Geographic distribution of farm size and agricultural mechanization strategy.

Region	Province	Farm Size (Tertile)			Mechanization Strategy			Obs.
		Lower	Median	Upper	No	Semi	Full	
eastern	Tianjin; Hebei; Liaoning; Jiangsu; Zhejiang; Fujian; Shandong; Guangdong; Guangxi	419	349	318	284	494	308	1086
central	Shanxi; Neimenggu; Jilin; Anhui; Heilongjiang; Jiangxi; Henan; Hubei; Hunan	227	256	310	225	363	205	793
western	Sichuan; Chongqing; Guizhou; Yunnan; Shanxi; Gansu; Ningxia; Xinjiang	282	252	168	325	220	157	702

We acknowledge that regional factors like soil conditions, climate, irrigation, and predominant crop types could influence the impact of mechanization on productivity. To account for these, we included them as control variables in our model. Specifically, for irrigation conditions, we relied on responses to “From January 2015 to now, has the growth period (before harvest) of crops in this village required irrigation?” and “From January 2015 to now, what has been the main irrigation method in this village?”. Soil improvement conditions were identified through the question “Has soil modification been implemented in this village?”. The dummy variable for region was used to control climatic variations.

The scope of mechanized farming in this study is confined to grain crops. Drawing from the 2016 White Paper on Agricultural Mechanization Development in China, we note that, while the mechanization level for economic crops is lower than for grain crops, the overall mechanization rate for major national crops is anticipated to be between 65 and 66% [35]. Thus, we believe that our focus on grain crops will not significantly skew the results due to crop type differences.

Table 3 presents summary statistics for the main variables used in our empirical analysis. The average household head is 55 years and has an education level between primary school and middle school. The average household has 4.68 members and owns 2.11 mu of crop land per family member. An amount of 63% of households have land use certificates issued by the government.

Table 3. Variable definitions and descriptive statistics.

Variables	Definitions	Mean	S.D. ¹	Min	Max
Dependent variables					
Labor productivity	Log of crop income per effective agricultural labor	7.57	1.11	3.00	11.29
Land productivity	Log of crop income per mu ²	6.83	0.93	3.22	10.77
Treatment variable					
Mechanization strategies	1 = no-mechanized farming; 2 = mechanized farming	1.68	0.47	1	2
	1 = no-mechanized farming; 2 = semi-mechanized farming; 3 = full-mechanized farming	1.94	0.76	1	3
Control variables					
Age	Age of household head (HH) in years	54.97	10.54	24	96
Gender	1 if HH is male, 0 otherwise	0.92	0.26	0	1
Education	Educational levels ³ of HH in years	2.53	0.98	1	9
Health status	Self-reported health status (from 1 = very unhealthy to 5 = very healthy)	2.53	1.05	1	5
Household size	Number of people in a household	4.68	2.01	1	16
Farm size per labor	Farm size cultivated by a household (mu/labor)	2.11	2.50	0.13	30
Land use certificate	1 if household receives a formal land use right certificate, 0 otherwise	0.63	0.48	0	1
Migrant worker	The proportion of migrant worker among labor aged between 15 and 64 in a village (%)	0.28	0.20	0.01	1
Planting plan	1 if there exists a planting plan in a village, 0 otherwise	0.29	0.45	0	1

Table 3. Cont.

Variables	Definitions	Mean	S.D. ¹	Min	Max
Pest control	1 if there exists pest control service in a village, 0 otherwise	0.37	0.48	0	1
Agri-tech training	1 if there exists agri-technology training service in a village, 0 otherwise	0.69	0.46	0	1
Cooperative	1 if there exists an agricultural cooperative in a village, 0 otherwise	0.27	0.44	0	1
Distance to town	Log of (distance from household location to town + 1)	1.71	0.66	0	3.93
Machine ownership	1 if fully household-owned, 2 co-owned, 3 fully leased, 4 borrowed, 5 mixed owned and leased/borrowed, 6 mixed owned and co-owned, 7 other, 8 no machinery used	4.62	2.56	1	8
Mechanization services	1 if there is mechanization service in a village, 0 otherwise	0.13	0.33	0	1
Irrigation	1 if the growth period (before harvest) of crops in a village required irrigation, 0 otherwise	0.71	0.45	0	1
Irrigation method	1 if flood, 2 if drip, 3 if sprinkler, 4 if other irrigation methods, 5 if no irrigation needed	2.55	1.77	1	5
Soil modification	1 if there is soil modification in a village, 0 otherwise	0.13	0.33	0	1
Eastern	1 if household locates in Eastern China, 0 otherwise	0.42	0.49	0	1
Central	2 if household locates in Central China, 0 otherwise	0.31	0.46	0	1
Western	3 if household locates in Western China, 0 otherwise	0.27	0.45	0	1

¹ S.D. refers to standard deviation. ² 1 mu = 1/15 hectare; ³ 1 = illiterate; 2 = primary school; 3 = middle school; 4 = high school; 5 = vocational high school; 6 = technical school; 7 = technical secondary school; 8 = college; 9 = bachelor.

5. Results and Discussions

5.1. The Effect of Dichotomous Mechanization Strategies

We first estimate the impact of agricultural mechanization on the labor and land productivity by considering a dichotomous decision of farm machine use (Table 4). The GPS with the MNL model is applied where the dependent variable is, whether or not the farm uses machines. Following previous studies [30,42], we further estimate the percentage change in the ATE and the QTE to make the interpretation of the coefficient estimates straightforward.

Table 4. Average treatment effect and quantile treatment effects of adopting mechanization (IPWRA estimator).

Labor Productivity			Land Productivity	
	ATE	% Δ	ATE	% Δ
MF vs. NMF	0.180 (0.051) ***	2.824	0.159 (0.054) ***	2.370
	QTE (Q25)	% Δ	QTE (Q25)	% Δ
MF vs. NMF	0.297 (0.064) ***	4.493	0.362 (0.076) ***	6.026
	QTE (Median)	% Δ	QTE (Median)	% Δ
MF vs. NMF	0.223 (0.055) ***	3.022	0.176 (0.082) **	2.617
	QTE (Q75)	% Δ	QTE (Q75)	% Δ
MF vs. NMF	0.134 (0.077) *	1.628	0.062 (0.053)	0.846

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; robust standard error in parentheses. MF refers to mechanized farming; NMF refers to no-mechanized farming; % change is calculated by expressing the treatment effects as the percentage of the estimated potential outcome means.

As displayed in the first column, adopting agricultural mechanization can increase labor productivity by 2.824% on average, compared to no-mechanized farming. In addition to mean treatment effects, estimating quantile treatment effects reveals that the agricultural mechanization affects the smallholder farmers at the lower end of the labor productivity distribution differently than it affects those in the middle and those at the upper end. To be more precise, the mid-level farmers see a significant 3.022% increase in labor productivity, the lower-end farmers achieve a significant 4.493% increase, while the impact is considerably less pronounced, at a mere 1.628% increase on the upper quantile farmers.

Similarly, mechanized farming significantly increases land productivity by 2.370% on average. For lower-end farmers, mechanized farming increases land productivity by 6.026%, compared to no-mechanized farming. Upper-end farmers do not appear to derive statistically significant benefits from agricultural mechanization in terms of land productivity.

The estimated mean treatment effects agree with the existing literature regarding the effect of agricultural mechanization on productivity improvement [9–12], while the estimated quantile treatment effects further reflect a more versatile and informative relationship between agricultural mechanization and labor/land productivity. However, these results still fail to reflect on both the effect of various agricultural mechanization levels and the effect variation in farm sizes, both of which will be further demonstrated below.

5.2. The Effect of Three Types of Mechanization Strategies

By applying the MVTE model, we are able to assess the heterogeneous effects of mechanization in a multivalued context. Table 5 reports the estimation results for Equations (3) and (4), controlling additional variables that may influence the agricultural productivity and regional heterogeneity. Again, we calculate the percentage change in the ATE and the QTE to ease understanding.

Table 5. Average treatment effect and quantile treatment effects of adopting mechanization strategy *m* vs. adopting mechanization strategy *n* (IPWRA estimator).

<i>m</i> vs. <i>n</i>	Labor Productivity		Land Productivity	
	ATE	% Δ	ATE	% Δ
SMF vs. NMF	0.186 (0.055) ***	2.499	0.178 (0.058) ***	2.654
FMF vs. NMF	0.256 (0.061) ***	3.439	0.152 (0.063) **	2.266
FMF vs. SMF	0.070 (0.050)	0.918	−0.026 (0.048)	−0.378
	QTE (Q25)	% Δ	QTE (Q25)	% Δ
SMF vs. NMF	0.297 (0.069) ***	4.493	0.356 (0.081) ***	5.926
FMF vs. NMF	0.297 (0.083) ***	4.493	0.370 (0.089) ***	6.159
FMF vs. SMF	0.000 (0.067)	0.000	0.015 (0.090)	0.236
	QTE (Median)	% Δ	QTE (Median)	% Δ
SMF vs. NMF	0.167 (0.073) ***	2.467	0.160 (0.084) *	2.379
FMF vs. NMF	0.310 (0.094) ***	5.040	0.176 (0.085) **	2.617
FMF vs. SMF	0.143 (0.077) **	2.565	0.015 (0.038)	0.218
	QTE (Q75)	% Δ	QTE (Q75)	% Δ
SMF vs. NMF	0.049 (0.088)	0.790	0.081 (0.057)	1.105
FMF vs. NMF	0.118 (0.085) ***	3.244	0.032 (0.058)	0.437
FMF vs. SMF	0.069 (0.088) **	2.448	−0.049 (0.056)	−0.661

*** *p* < 0.01, ** *p* < 0.05, * *p* < 0.1; robust standard error in parentheses. SMF refers to semi-mechanized farming; NMF refers to no-mechanized farming; and FMF refers to full-mechanized farming. The % change is calculated by expressing the treatment effects as the percentage of the estimated potential outcome means.

For labor productivity, as shown in the second and third columns of Table 5, we find significantly positive average treatment effects of agricultural mechanization on productivity when compared with no-mechanized farming. The output indicates that changing the mechanization strategy from no-mechanized farming to semi-mechanized farming results in a significant enhancement in labor productivity by 2.499%, and the effect of changing the mechanization level from no to full-mechanized farming is a 3.439% increase in labor productivity. The 0.25 quantile results indicate that semi- and fully mechanized agriculture raises labor productivity equally by 4.493% for the lower-end farmers. The median results show that the labor productivity gap between semi-mechanized or fully mechanized agriculture and non-mechanized agriculture is 2.467% and 5.040%, respectively, with a significant incremental impact of agricultural mechanization of 2.565%. In contrast, for the upper quartile of farmers, the 0.75 quantile results show that they only reap significant benefits from fully mechanized farming, which improves their labor productivity.

Our results show that, compared to no-mechanized farming, farmers with the lower labor productivity benefit most from mechanization, while no statistically significant

incremental effect is found from semi- to full-mechanized farming. This is reasonable given that the farm performance with the lower productivity labor is far from being economically or technically efficient, and any small changes in how farm operations are performed, either through semi- or full-mechanized farming, will lead to large increases in output and income, therefore improving the labor productivity. When the labor productivity upgrades from lower quantile to mid-level, not only will both semi- and full-mechanized farming significantly improve labor productivity relative to no-mechanized farming, but there will exist a significant incremental effect of mechanization on labor productivity improvement. Farmers with mid-level labor productivity may have relatively better access to and understand new knowledge and farmer training, such that they may better grasp the general level of farm management required by the full-mechanized farming [49], hence enjoying the incremental effect of mechanization on labor productivity. However, it is only full-mechanized farming that significantly enhances labor productivity among the higher-labor-productivity farmers. This insight prompts a deeper investigation into the production constraints confronting smallholder farmers in China. These farmers may have reached a level of technical efficiency where only full mechanization can further propel productivity gains. This scenario is particularly relevant in developing countries, where limitations on inputs beyond labor, such as farm size, can impede the enhancement of marginal labor productivity even with semi-mechanization. The constraints on land and other factors of production mean that the potential for labor productivity improvement through partial mechanization is limited, and, thus, only the transition to full mechanization can break through these barriers and unlock additional efficiency.

For land productivity, compared to no-mechanized farming, results displayed in the fourth and fifth columns of Table 5 show that semi- and full-mechanized farming significantly increase land productivity by 2.654% and 2.266%, respectively. The estimated quantile treatment effects indicate that lower-end farmers benefit much more in land productivity from semi- or full-mechanized farming than mid-level farmers. The difference (5.926%, 6.159%) is more than twice as much as those for the mid-level farmers (2.379%, 2.617%). An increase in land productivity is synonymous with more efficient farming practices with agricultural machinery, that is, if everything else is held equal. Based on the law of diminishing marginal productivity, the additional return generated by an upgrade in agricultural mechanization level declines the higher the land productivity is. One in particular is that, failing to reject hypotheses and joint hypotheses that state that semi- and full-mechanized farming bring the same treatment effects within and across means and quantiles, we cannot conclude that a higher level of mechanization has a larger improvement effect on land productivity. The result can also be observed in Figure 3. Though farmers are expected to benefit more from adopting a high level of mechanization, the finding suggests that no incremental effect of agricultural mechanization has been found on land productivity in our analysis.

As intuition would suggest, smallholder farmers, even with higher land productivity in our analysis, are not necessarily technically efficient. To explain the non-existence of the land productivity improvement effect of mechanization for the upper-end farmers, the farmers may need to use more of a certain type of input, such as agricultural infrastructure improvement and land holding increase through land consolidation, to reach prescribed technical efficiency upgrades. Thus, simply implementing the policy on the basis of the positive mean treatment effects might have caused unintended consequences on individual farmers.

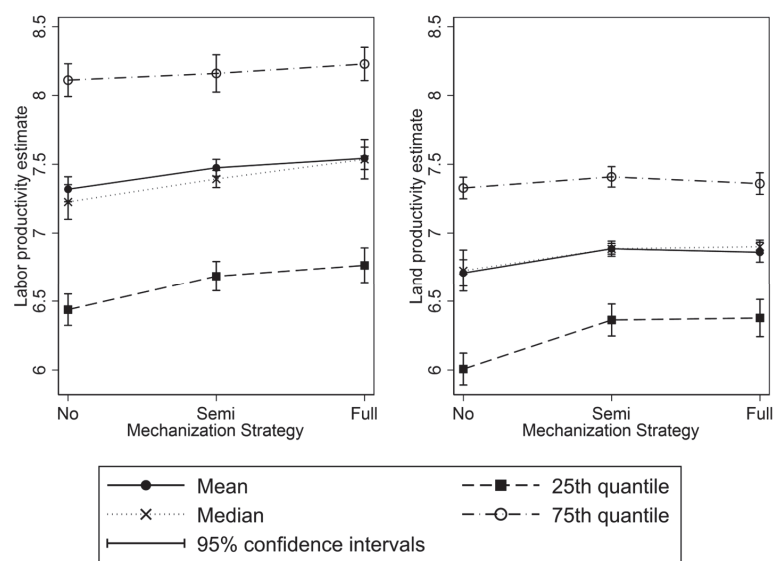


Figure 3. Estimated means and quantiles for mechanization strategies.

5.3. Disaggregated Analysis by Farm Size

Results displayed in Table 6 show that there exist heterogeneous effects of mechanization adoption on productivity by farm size. Farmers in the highest tertile of farm size are more likely and able to adopt agricultural machinery, therefore benefiting most from mechanized farming on both labor and land productivity. The significantly positive impacts of mechanization, though much smaller, sustain for the farmers in the median tertile of farm size, but diminish for the farmers in the lowest tertile of farm size. And no incremental effect of the agricultural mechanization is found for farmers in these two groups.

Table 6. Disaggregated analysis by farm size (IPWRA estimator).

<i>m</i> vs. <i>n</i>	Labor Productivity		Land Productivity	
	ATE	% Δ	ATE	% Δ
lower tertile				
SMF vs. NMF	0.055 (0.083)	0.780	0.009 (0.086)	−0.127
FMF vs. NMF	0.014 (0.092)	0.198	−0.042 (0.093)	−0.594
FMF vs. SMF	−0.041 (0.090)	−0.577	−0.051 (0.091)	−0.720
median tertile				
SMF vs. NMF	0.267 (0.077) ***	3.645	0.202 (0.074) ***	3.029
FMF vs. NMF	0.256 (0.096) ***	3.494	0.172 (0.092) *	2.579
FMF vs. SMF	−0.011 (0.082)	−0.145	−0.030 (0.079)	−0.437
upper tertile				
SMF vs. NMF	0.357(0.106) ***	4.530	0.406 (0.105) ***	6.492
FMF vs. NMF	0.500 (0.103) ***	6.345	0.510 (0.102) ***	8.155
FMF vs. SMF	0.143 (0.073) *	1.736	0.104 (0.071)	1.562

*** $p < 0.01$, * $p < 0.1$; robust standard error in parentheses. SMF refers to semi-mechanized farming; NMF refers to no-mechanized farming; and FMF refers to full-mechanized farming. The % change is calculated by expressing the treatment effects as the percentage of the estimated potential outcome means.

For labor productivity, relative to no-mechanized farming, semi-mechanized farming increases that of farmers in the highest tertile of farm size by 4.530%, while full-mechanized farming significantly increases labor productivity by 6.345% with a notably and significantly incremental effect of agricultural mechanization. For land productivity, both full- and semi-mechanized farming bring the largest significant increases of 6.492% and 8.155%,

respectively, to farmers in the largest farm size group, which are more than twice the size of effects for farmers in the median tertile of farm size, though no incremental effect is found. On one hand, mechanization can vastly reduce the time and effort of many agricultural production practices. Larger land holdings enable the more proper and better utilization of agricultural machines which further improve labor productivity [50,51]. On the other hand, along with the standardized improved seed use, chemical fertilizer use, and pesticide use, the adoption of agricultural mechanization can provide more efficient input management and therefore confer the competitive benefits to smallholding farmers from the efficiencies gained by land productivity improvement [52,53]. Thus, the disaggregated analysis by the farm size of agricultural mechanization on productivity offers the smallholding farmers a key means to eke out a sustainable, high-productivity agricultural production.

Figure 4 illustrates the confidence interval outcomes for the quantile treatment effects of mechanization on both labor and land productivity, segmented into three tertiles based on land size. The semi-mechanized versus no-mechanized comparison is denoted by the blue line/area, while the full-mechanized versus no-mechanized comparison is indicated by the orange line/area. The sequence from left to right represents an ascending order of land size, with the corresponding regression results showing an overall trend of increasing significance across farm size tertiles. This suggests that the efficacy of mechanization is contingent upon its harmonious integration with land size.

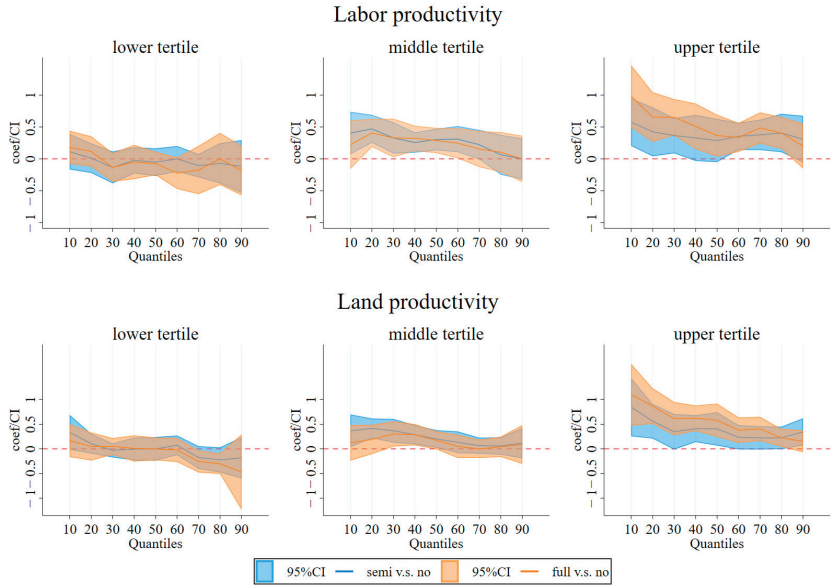


Figure 4. Quantile treatment effects of mechanization on labor and land productivity across tertiles of land size.

Within the upper tertile, the estimated effects for full mechanization exceed those for semi-mechanization, and they exhibit greater statistical significance, indicating the superiority of full mechanization over semi-mechanization. In the medium land size tertile, the impacts of full and semi-mechanization are comparatively indistinguishable. Regardless of the land size, the downward trajectory observed in the quantile treatment effect results, along with the diminishing significance, implies that mechanization has a more substantial marginal effect on the productivity of low-productivity farmers, encompassing both labor and land aspects.

5.4.
Moderating Effects

The productivity effects of agricultural mechanization are significantly influenced by several key factors, including the land transfer status of farmers, the receipt of government subsidies, and the prevalence of clan culture in the local region. Specifically, the land transfer status is measured by the ratio of a household’s contracted land to its total cultivated land. The presence of government subsidies is indicated by a dummy variable derived from survey data, reflecting whether the household has received any subsidies. The intensity of clan culture in a village is quantified by the population proportion of the most common surname within the village. In our regression analysis shown in Table 7, we controlled for provincial fixed effects and employed robust standard errors.

Table 7.
 Moderating effects.

	(1)	(2)	(3)	(4)	(5)	(6)
	Labor Productivity	Land Productivity	Labor Productivity	Land Productivity	Labor Productivity	Land Productivity
Contracted * Mechanization	0.069 *** (0.014)	0.150 *** (0.053)				
Contracted	−0.003 (0.022)	−0.289 ** (0.118)				
Subsidy * Mechanization			0.132 ** (0.056)	0.107 * (0.055)		
Subsidy			−0.195 * (0.115)	−0.200 * (0.113)		
ComLastNam * Mechanization					−0.150 (0.104)	−0.190 * (0.101)
ComLastNam					−0.054 (0.233)	0.270 (0.226)
Mechanization	0.140 *** (0.029)	0.076 *** (0.028)	0.066 (0.051)	0.016 (0.049)	0.229 *** (0.052)	0.170 *** (0.050)
Constant	7.469 *** (0.489)	7.367 *** (0.585)	7.592 *** (0.500)	7.493 *** (0.587)	7.560 *** (0.518)	7.349 *** (0.598)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.395	0.133	0.395	0.132	0.397	0.132
N	2581	2581	2581	2581	2581	2581

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; robust standard error in parentheses; ComLastNam denotes the prevalence of the dominant last name within the village’s population, reflecting clan culture.

As detailed in Table 7, the findings reveal that households that have acquired additional land through transfers experience an increased effect of mechanization on labor and land productivity. This suggests that larger landholdings facilitate the more efficient use of machinery and improved resource management, thereby enhancing both productivity measures.

Furthermore, the receipt of government subsidies is found to significantly amplify the enhancing effect of mechanization on both land and labor productivity. Subsidies are crucial in making mechanization more affordable and in promoting the adoption of advanced technologies, which, in turn, leads to substantial improvements in productivity across both dimensions.

In contrast, a more prevalent clan culture tends to diminish the land productivity-enhancing effects of mechanization. This reduction may be attributed to the adherence to traditional farming practices, social patterns of resource allocation, or a resistance to innovation within these communities. These findings highlight the intricate interplay of factors when integrating mechanization into agricultural practices, emphasizing the necessity of considering socio-economic and cultural factors in the quest for enhanced agricultural efficiency and productivity.

6. Conclusions

Given the substantial improvement in the mechanization level of major economic crops, China's agricultural mechanization remains in a developmental phase. To achieve sustainable agricultural production, it is imperative to scrutinize the impact of agricultural mechanization on the productivity of China's smallholder farmers. This analysis is essential for formulating continuous development measures and strategies aimed at promoting the adoption of mechanization and enhancing its economic impact on agricultural production. Utilizing data from the 2016 China Labor-force Dynamics Survey (CLDS), this study employs a multivalued mechanization framework—encompassing no-mechanized, semi-mechanized, and full-mechanized farming—to investigate the impact of agricultural mechanization in China. This framework addresses the uneven distribution of mechanization efforts among smallholder farmers, overcoming information loss about the nature of mechanization's impact.

By applying the MVTE model and QTE model, we explore the average treatment effect, quantile treatment effect, the disaggregated analysis by farm size, and the moderating effect of agricultural mechanization on both labor and land productivity. This approach provides extensive and nuanced insights into the relationships between agricultural mechanization and labor/land productivity. The empirical results are as follows:

The empirical results show that (1) general agricultural mechanization significantly improves both labor and land productivity on average, particularly for lower- and mid-level productivity farmers; (2) the multivalued mechanization framework reveals that, compared to no-mechanized farming, both semi- and full-mechanized farming have significantly positive impacts on labor and land productivity for lower- and mid-level productivity farmers; (3) disaggregated analysis by farm size indicates that, compared to no-mechanized farming, both semi- and full-mechanized farming significantly increase labor and land productivity for farmers with larger farm sizes; (4) the incremental productivity improvement effect of different levels of mechanization is observed in labor productivity for farmers with mid- and upper-level labor productivity and for those in the largest farm size group; and (5) land transfer status, government subsidies, and the intensity of clan culture significantly influence the productivity effects of agricultural mechanization in China. According to the empirical results, there are four policy implications.

Firstly, addressing the potential overinvestment in agricultural mechanization, our analysis suggests that the efficiency of agricultural machinery is crucial, which is related to the actual production capacity when factors such as production quality control, agricultural labor, and farm size are considered. Given the fragmented and scattered landholdings in China, it is essential to assist smallholder farmers of all productivity levels by providing access to highly adaptable and reliable machinery. Policy tools that improve machine-appropriate agricultural practices and promote the integration of agricultural machinery and agronomy are vital for enhancing the crop-output expansion and national food security effects of sustainable agricultural mechanization.

Secondly, the level of agricultural mechanization for lower productivity farmers in China should be further improved. The empirical results show a significant improvement effect of mechanization on both labor and land productivity for lower productivity farmers, where small farm size has not yet become a major limitation of production. More policy attention should be directed towards the initial adoption of mechanization for these farmers, rather than comprehensive mechanization plans. However, a basic plan for the structure and cultivation of the agricultural labor force is needed to assist farmers in becoming aware of, adopting, and improving the use of mechanization to boost production efficiency, income, and welfare in the near future as labor and land productivity upgrade.

Thirdly, the productivity improvement effect and incremental effect of agricultural mechanization vary among the three farm size groups in our analysis. Consistent with many related studies, this result implies that enlarging the farm size would enhance the productivity improvement effect of mechanization, given that larger farms permit a better use of agricultural machinery. While China has been promoting land consolidation, implement-

ing an overall plan for the development of high-standard farmland, establishing functional areas for grain production and protected areas to produce important agricultural products, and efforts to cultivate socialized service organizations and agricultural cooperation that help farmers rent or share machinery should be further strengthened. This guidance is essential for steering smallholding farmers onto the track of modern agriculture.

Above all, government subsidies are instrumental in rendering mechanization more affordable and in catalyzing the adoption of cutting-edge technologies, which are essential for markedly boosting productivity in both land and labor. In tandem with this, acknowledging and addressing the cultural nuances that shape mechanization outcomes are critical. Policymakers must craft strategies that not only alleviate the resistance to mechanization in communities with deeply rooted traditional practices but also actively promote the adoption of modern farming techniques. Moreover, incorporating socio-economic and cultural considerations into policy formulation is imperative for bolstering agricultural efficiency and productivity. By adopting a holistic approach, mechanization initiatives can be better aligned with the distinct needs and circumstances of various farming communities, fostering a more effective and inclusive trajectory for agricultural advancement.

Our study, though insightful, is bound by the data available up to 2016. Beyond this point, China's agricultural mechanization has advanced markedly, especially with the pronounced increase in micro-tiller sales, which captured 30.54% of the market share in 2021. Additionally, the total power of agricultural machinery increased to 10.71 billion kilowatts in 2021, marking a 1.42% rise and signaling further developments in mechanization that our research does not encompass. Nevertheless, our findings lay a robust foundation for subsequent research and policy formulation. China's "14th Five-Year Plan" for agricultural mechanization aims to maintain the total machinery power at approximately 11 billion kilowatts by 2025. This plan emphasizes the refinement of machinery allocation, the enhancement of operational environments, and the establishment of a comprehensive agricultural machinery socialized service system. It also underscores the advancement towards larger, smarter, and more versatile agricultural machinery, aligning with the broader initiative to converge mechanization with information and intelligent technologies. We aspire for our research to catalyze effective mechanization strategies in developing countries and to enrich the international dialogue on agricultural modernization.

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References

1. Sun, Z.; Li, X. Technical efficiency of chemical fertilizer use and its influencing factors in China's rice production. *Sustainability* **2021**, *13*, 1155. [CrossRef]
2. Food and Agricultural Organization of the United Nations (FAO). Productivity and efficiency measurement in agriculture: Literature review and gaps analysis. In *Publication Prepared in the Framework of the Global Strategy to Improve Agricultural and Rural Statistics*; FAO: Rome, Italy, 2017. Available online: <https://openknowledge.fao.org/server/api/core/bitstreams/dcd4edfc-f7d5-4872-8996-5612c87446d6/content> (accessed on 1 December 2024).
3. Chi, Y.; Zhou, W.; Wang, Z.; Hu, Y.; Han, X. The influence paths of agricultural mechanization on green agricultural development. *Sustainability* **2021**, *13*, 12984. [CrossRef]
4. Jiang, X.; Yin, G.; Lou, Y.; Xie, S.; Wei, W. The impact of transformation of farmers' livelihood on the increasing labor costs of grain plantation in China. *Sustainability* **2021**, *13*, 11637. [CrossRef]

5. Li, W.; Wei, X.P.; Zhu, R.X.; Guo, K.Q. Study on factors affecting the agricultural mechanization level in China based on structural equation modeling. *Sustainability* **2019**, *11*, 51. [CrossRef]
6. Li, Q.Y.; Chen, G.M.; Li, Z.Q.; Xu, L.L. Evaluation of missile electromagnetic launch system based on effectiveness. *J. Intell. Fuzzy Syst.* **2021**, *41*, 6517–6526. [CrossRef]
7. Yao, C.S.; Hou, F.A.; Chen, H.Y. Logical relation and its policy implications between agricultural mechanization and food security: Based on a contrastive study of the cost and benefit of three main grain crops between China and the United States. *J. Chin. Agric. Mech.* **2021**, *42*, 1–8. (In Chinese)
8. Foster, A.D.; Rosenzweig, M.R. Are There Too Many Farms in the World? Labor-market Transaction Costs, Machine Capacities and Optimal Farm Sizes. *J. Political Econ.* **2022**, *130*, 3. [CrossRef]
9. Benin, S. Impact of Ghana's agricultural mechanization services center program. *Agric. Econ.* **2015**, *46*, 103–117. [CrossRef]
10. Zheng, H.; Ma, W.; Zhou, X. Renting-in cropland, machinery use intensity, and land productivity in rural China. *Appl. Econ.* **2021**, *53*, 5503–5517. [CrossRef]
11. Wang, X.; Yamauchi, F.; Huang, J. Rising wages, mechanization, and the substitution between capital and labor: Evidence from small scale farm system in China. *Agric. Econ.* **2016**, *47*, 309–317. [CrossRef]
12. Belton, B.; Win, M.T.; Zhang, X.; Filipski, M. The rapid rise of agricultural mechanization in Myanmar. *Food Policy* **2021**, *101*, 102095. [CrossRef]
13. Takeshima, H. Mechanize or exit farming? Multiple-treatment-effects model and external validity of adoption impacts of mechanization among Nepalese smallholders. *Rev. Dev. Econ.* **2018**, *22*, 1620–1641. [CrossRef]
14. Abass, A.; Amaza, P.; Bachwenkizi, B.; Alenkhe, B.; Mukuka, I.; Cromme, N. Adding value through the mechanization of post-harvest cassava processing, and its impact on household poverty in north-eastern Zambia. *Appl. Econ. Lett.* **2017**, *24*, 579–583. [CrossRef]
15. Ma, W.; Renwick, A.; Grafton, Q. Farm machinery use, off-farm employment and farm performance in China. *Aust. J. Agric. Resour. Econ.* **2018**, *62*, 279–298. [CrossRef]
16. Zhou, X.; Ma, W.; Li, G.; Qiu, H. Farm machinery use and maize yields in China: An analysis accounting for selection bias and heterogeneity. *Aust. J. Agric. Resour. Econ.* **2020**, *64*, 1282–1307. [CrossRef]
17. Adu-Baffour, F.; Daum, T.; Birner, R. Can small farms benefit from big companies' initiatives to promote mechanization in Africa? A case study from Zambia. *Food Policy* **2019**, *84*, 133–145. [CrossRef]
18. Mujawamariya, G.; Kalema, E. Limited usage of mechanical equipment in small-scale rice farming: A cause for concern. *J. Agric. Environ. Int. Dev.* **2017**, *111*, 5–21. [CrossRef]
19. Qiu, T.; Choy, S.B.; Luo, B. Is small beautiful? Links between agricultural mechanization services and the productivity of different-sized farms. *Appl. Econ.* **2021**, *54*, 430–442. [CrossRef]
20. Yao, C.S. Research of improving China's agricultural mechanization quality in the context of supply-side structural reform. *J. Chin. Agric. Mech.* **2019**, *40*, 1–4. (In Chinese)
21. Fang, S.L.; Huang, Z.H. 70th anniversary of the founding of the PRC: The transition, influence factor and trend of China's agricultural mechanization. *Issues Agric. Econ.* **2019**, *10*, 36–49. (In Chinese)
22. Agricultural and Rural Development Institute, China Agricultural University and China Economic Trends Research Institute, Economics Daily. 2022 China Agriculture and Rural Development Trend Report (21 January 2022). Available online: http://www.moa.gov.cn/ztl/ymksn/jrbdbd/202201/t20220121_6387414.htm (accessed on 1 February 2022). (In Chinese)
23. Lai, Z.H.; Chen, M.Q.; Liu, T.J. Changes in and prospects for cultivated land use since the reform and opening up in China. *Land Use Policy* **2020**, *97*, 104781. [CrossRef]
24. Cai, H.; Sun Yat-sen University. China Labor-Force Dynamics Survey (CLDS). 2016. Available online: <https://isg.sysu.edu.cn/node/353> (accessed on 30 May 2023).
25. Amoozad-Khalili, M.; Rostamian, R.; Esmailpour-Troujeni, M.; Kosari-Moghaddam, A. Economic modeling of mechanized and semi-mechanized rainfed wheat production systems using multiple linear regression model. *Inf. Process. Agric.* **2020**, *7*, 30–40. [CrossRef]
26. Mohammed, K.; Batung, E.; Saaka, S.A.; Kansanga, M.M.; Luginaah, I. Determinants of mechanized technology adoption in smallholder agriculture: Implications for agricultural policy. *Land Use Policy* **2023**, *129*, 106666. [CrossRef]
27. Zheng, H.; Ma, W.; Guo, Y.; Zhou, X. Interactive relationship between non-farm employment and mechanization service expenditure in rural China. *China Agric. Econ. Rev.* **2022**, *14*, 84–105. [CrossRef]
28. Zou, B.; Mishra, A.K. Modernizing smallholder agriculture and achieving food security: An exploration in machinery services and labor reallocation in China. *Appl. Econ. Perspect. Policy* **2024**, *46*, 1662–1691. [CrossRef]
29. Lu, Q.; Du, X.; Qiu, H. Adoption patterns and productivity impacts of agricultural mechanization services. *Agric. Econ.* **2022**, *53*, 826–845. [CrossRef]
30. Cattaneo, M.D.; Drukker, D.M.; Holland, A.D. Estimation of multivalued treatment effects under conditional independence. *Stata J.* **2013**, *13*, 407–450. [CrossRef]
31. Issahaku, G.; Abdulai, A. Household welfare implications of sustainable land management practices among smallholder farmers in Ghana. *Land Use Policy* **2020**, *94*, 104502. [CrossRef]
32. Ma, W.L.; Renwick, A.; Bicknell, K. Higher intensity, higher profit? Empirical evidence from dairy farming in New Zealand. *J. Agric. Econ.* **2018**, *69*, 739–755. [CrossRef]

33. Foster, A.D.; Rosenzweig, M.R. *Are Indian Farms Too small? Mechanization, Agency Cost, and Farm Efficiency*; Unpublished Manuscript Presented at the Department of Economics, Brown University and Yale University. 2011. Available online: https://www.bu.edu/econ/files/2009/09/Rosenzweig_Seminar-Paper.pdf (accessed on 6 June 2024).
34. Hornbeck, R.; Naidu, S. When the levee breaks: Black migration and economic development in the American South. *Am. Econ. Rev.* **2014**, *104*, 963–990. [CrossRef]
35. White Paper on Agricultural Mechanization Development in China 2016. China Agricultural Mechanization Association (CAMA). 2017. Available online: <http://www.cama.org.cn/secondPage/getDetails/43/1078> (accessed on 5 December 2024). (In Chinese).
36. Chen, Y.S. Time Allocation of the Rural Labor from a Perspective of Farming Season: Farming and Off-farm Employment. *Chin. J. Popul. Sci.* **2017**, *5*, 75–86. (In Chinese)
37. Gai, Q.; Li, C.; Zhang, W.; Shi, Q. From smallholders to large-scale farmers: Land rental and agricultural productivity. *Econ. Res. J.* **2023**, *5*, 135–152. (In Chinese)
38. Gartaula, H.; Niehof, A.; Visser, L. Shifting perceptions of food security and land in the context of labour out-migration in rural Nepal. *Food Secur.* **2012**, *4*, 181–194. [CrossRef]
39. Goodwin, B.K.; Mishra, A.K. Farming Efficiency and the Determinants of Multiple Job Holding by Farm Operators. *Am. J. Agric. Econ.* **2004**, *86*, 722–729. [CrossRef]
40. Damon, A.L. Agricultural Land Use and Asset Accumulation in Migrant Households: The Case of El Salvador. *J. Dev. Stud.* **2010**, *46*, 162–189. [CrossRef]
41. Davis, J.; Lopez-Carr, D. Migration, Remittances and Smallholder Decision-making: Implications for Land Use and Livelihood Change in Central America. *Land Use Policy* **2014**, *36*, 319–329. [CrossRef]
42. Ma, W.L.; Zhu, Z.K.; Zhou, X.S. Agricultural mechanization and cropland abandonment in rural China. *Appl. Econ. Lett.* **2021**, *29*, 526–533. [CrossRef]
43. Imbens, G.W.; Wooldridge, J.M. Recent developments in the econometrics of program evaluation. *J. Econ. Lit.* **2009**, *47*, 5–86. [CrossRef]
44. Li, G.; Feng, Z.; Fan, L. Is the Small-sized Rural Household More Efficient? The Empirical Evidence from Hubei Province. *China Econ. Q.* **2010**, *9*, 1. (In Chinese)
45. Qian, L.; Hong, M. Non-agricultural Employment, Land Transfer and Changes in Agricultural Productivity—An Empirical Analysis Based on CFPS. *Chin. Rural Econ.* **2016**, *12*, 2–16. (In Chinese)
46. Ma, J.J.; Zhao, J.; Wu, B.J.; Zhu, H.C. Providing outsourcing services or transferring land and servicing for themselves: A case study on the development and transition of agricultural machinery cooperatives. *China Soft Sci.* **2019**, *7*, 35–46. (In Chinese)
47. Yi, Q.; Chen, M.Y.; Sheng, Y.; Huang, J.K. Mechanization services, farm productivity and institutional innovation in China. *China Agric. Econ. Rev.* **2019**, *11*, 536–554. [CrossRef]
48. Shumway, C.R.; Fraumeni, B.M.; Fulginiti, L.E.; Samuels, J.D.; Stefanou, S.E. *Measurement of U.S. Agricultural Productivity: A 2014 Review of Current Statistics and Proposals for Change*; Working Paper Series WP 2015-12; School of Economic Science, Washington State University: Pullman, WA, USA, 2015. Available online: <http://digitalcommons.unl.edu/ageconfacpub/136> (accessed on 10 October 2023).
49. Sims, B.G.; Hilmi, M.; Kienzle, L. *Agricultural Mechanization: A Key Input for Sub-Saharan Africa Smallholders*; Integrated Crop Management: Rome, Italy; FAO: Rome, Italy, 2016; Volume 23, pp. 1–44. Available online: <https://agris.fao.org/search/en/providers/122621/records/6473afa713d110e4e7a932cc> (accessed on 10 September 2023).
50. Muyanga, M.; Jayne, T.S. Revisiting the farm size-productivity relationship based on a relatively wide range of farm sizes: Evidence from Kenya. *Am. J. Agric. Econ.* **2019**, *101*, 1140–1163. [CrossRef]
51. Jette-Nantel, S.; Hu, W.Y.; Liu, Y.M. Economies of scale and mechanization in Chinese corn and wheat production. *Appl. Econ.* **2019**, *52*, 2751–2765. [CrossRef]
52. Sims, B.; Heney, J. Promoting smallholder adoption of conservation agriculture through mechanization services. *Agriculture* **2017**, *7*, 64. [CrossRef]
53. Takeshima, H.; Liu, Y.Y. Smallholder mechanization induced by yield-enhancing biological technologies: Evidence from Nepal and Ghana. *Agric. Syst.* **2020**, *184*, 102914. [CrossRef]

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Article

Quantitative Change or Qualitative Change: The Impact of Whole-Region Comprehensive Land Consolidation on Cultivated Land Security—Based on Panel Data from Townships in Zhejiang Province

Jin Li ¹, Yongpeng Ding ², Ming Jing ^{3,*}, Xiangyu Dong ^{4,5}, Jiayi Zheng ⁶ and Luoyu Gu ²

¹ School of Business, Zhejiang Wanli University, Ningbo 315100, China; Rachelli@zwwu.edu.cn

² School of Economics and Management, Zhejiang A&F University, Hangzhou 311300, China; 2023606021001@stu.zafu.edu.cn (Y.D.); 201903090202@stu.zafu.edu.cn (L.G.)

³ Fudan Institute of Belt and Road & Global Governance, Fudan University, Shanghai 200433, China

⁴ School of Humanities and Law, Zhejiang A&F University, Hangzhou 311300, China; xiangyu@zafu.edu.cn

⁵ Research Academy for Rural Revitalization of Zhejiang Province, Zhejiang A&F University, Hangzhou 311300, China

⁶ WTO and Hubei Development Research Center, Zhongnan University of Economics and Law, Wuhan 430073, China; zhengjiayi@zuel.edu.cn

* Correspondence: Ming_jing@fudan.edu.cn; Tel.: +86-13162337001

Abstract: Land consolidation is a crucial strategy for optimizing land use structure and ensuring cultivated land security and food safety. Since 2019, Zhejiang Province has been piloting and exploring Whole-Region Comprehensive Land Consolidation (WRCLC). However, there remains an insufficient understanding of the feasibility of WRCLC in ensuring cultivated land security and its potential for synergy with other policies. This study utilizes panel data from 707 townships in Zhejiang Province spanning from 2013 to 2022. By categorizing cultivated land security into two dimensions—quantity and quality—this study employs a double machine learning approach to evaluate the impact of WRCLC policies on township cultivated land security. The results indicate that implementing WRCLC significantly enhances both the quantity and quality of cultivated land. A heterogeneity analysis reveals that WRCLC is particularly effective in improving the quality of cultivated land in non-major grain-producing areas and low economic development areas. Furthermore, examining policy synergies indicates that agricultural mechanization and agricultural industry integration policies work well in conjunction with WRCLC, thereby enhancing both the quantity and quality of cultivated land. However, the synergy with rural tourism policies improves cultivated land quality without effectively increasing cultivated land quantity.

Keywords: whole-region comprehensive land consolidation; cultivated land; double/debiased machine learning; policies synergy

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1. Introduction

Cultivated land, as a fundamental resource for food production, directly influences total food output through changes in both quantity and quality [1]. However, due to irrational land use planning and the unchecked expansion of construction land, issues such as the reduction in cultivated land area and declining land quality have become increasingly severe [2]. According to the Third National Land Survey conducted in 2021, the area of cultivated land in China has decreased by 11.3 million hectares since 2009.¹ In the context of a global food supply–demand imbalance, China, as one of the most populous countries in the world, faces a significant responsibility to ensure the security of its cultivated land and food production [3,4].

The severe situation of cultivated land security and its far-reaching impacts have attracted widespread attention from scholars both domestically and internationally, resulting in a substantial body of research. The early literature primarily focused on the security of cultivated land quantity [5–7]. However, relying solely on changes in cultivated land area is insufficient to systematically assess the impact of socioeconomic development on cultivated land security. With the advancement of remote sensing technology, which offers extensive accessibility and detailed spatial information, new perspectives have been provided for evaluating the security of cultivated land quality [8,9]. Cultivated land (in both quantity and quality) is a unique natural resource closely linked to a country's food security, and is critical in promoting regional sustainable development [10,11]. Cultivated land security requires not only sufficient land area but also high-quality and sustainable production capacity to meet future development needs [11,12]. Therefore, this study defines cultivated land security as the ability of a region's cultivated land quantity and quality to meet the long-term demands of socioeconomic development and food production [12–14]. Specifically, the concept of cultivated land security in this paper includes both cultivated land quantity security and cultivated land quality security. The former refers to the adequacy and stability of the land area. The latter focuses on the sustainability of land quality.

Research on land use and cultivated land security has mostly focused on traditional land consolidation models, including cultivated land pattern optimization and farmland protection policies [15,16]. Molnárová et al. (2023) reviewed 93 studies on the impact of land consolidation and found that only 56% of the cases reported positive effects, indicating significant contradictions in the conclusions of such studies [17]. Furthermore, traditional land consolidation mainly uses engineering measures to address inefficient or unused land, focusing on the adjustment of farmland and rural demolition [18]. This approach not only neglects the importance of ecological restoration, but also fails to ensure the sustainable use of rural cultivated land resources. WRCLC, as a key component of China's new phase of land system reform, addresses the entire process, life cycle, and all elements of land use. WRCLC aims to minimize land use conflicts between land projects by formulating detailed land use plans. Additionally, WRCLC requires that the newly created cultivated land area in the project area be at least 5% of the original cultivated land area. Although some scholars have already paid attention to the impact of pilot policies on cultivated land, research methods are limited to theoretical and case analyses [19,20], lacking empirical evaluations of policy effects using large sample data. Additionally, the research scope is still confined to single township samples [21,22], which may lead to biased conclusions. WRCLC, primarily implemented at the township level, is a systematic governance project encompassing the interconnected ecosystems of mountains, waters, forests, fields, lakes, and grasslands. Its land management measures include the concentrated layout of cultivated land and the development of tourism, health care, and facility agriculture within parts of the consolidated area. Land consolidation is closely related to industrial development [23,24]. However, there is limited understanding of how WRCLC affects cultivated land security from the perspective of policy synergy, especially in rural areas with lower levels of food security.

According to the aforementioned analysis, previous research has looked at the connection between cultivated land security and land consolidation. The mitigating effects of comprehensive land consolidation on land degradation have also been studied by some academics. However, three key issues remain unresolved. First, most existing research focuses on theoretical discussions and case studies from rural areas. Few studies use remote sensing technology and big data samples to assess the impact of WRCLC on cultivated land security. Second, past research has not conducted heterogeneous analyses of the effects of WRCLC on cultivated land security under varying natural, economic, and social conditions. Third, in influencing cultivated land security, does WRCLC conflict with or complement other agricultural industrial policies?

To address these knowledge gaps, this study constructs a theoretical framework for the synergy between WRCLC and agricultural industrial policies. Using panel data

from 707 townships in Zhejiang Province, China, we employ a double machine learning approach to assess the impact of WRCLC on cultivated land security. We aim to investigate the following scientific questions: (1) Can WRCLC, which encompasses all processes, cycles, and factors of land use, enhance cultivated land quantity and quality in rural areas? (2) Is there heterogeneity in the effects of WRCLC on cultivated land security across different topographical features, economic development levels, and grain-producing areas? (3) How does WRCLC affect cultivated land security under various agricultural policy synergies? This study presents a fresh viewpoint on the connection between cultivated land security and comprehensive land consolidation. The findings can guide and inform the development of more effective land consolidation modes in other countries and regions.

The structure of this paper is organized as follows: Section 2 presents the research hypothesis based on theoretical analysis. Section 3 describes the technical processes, methods, and data sources used in the study. Section 4 employs a dual machine learning approach to assess the impact of WRCLC on cultivated land security. Section 5 analyzes the heterogeneity of WRCLC's impact on cultivated land security under different scenarios. Section 6 discusses the synergistic effects of agricultural industry policies on cultivated land security. Section 7 presents the discussion of the paper. Finally, based on the research findings, policy recommendations are made, followed by a discussion of the study's limitations and directions for future research.

2. Policy Background and Theoretical Analysis

2.1. Policy Background

Three major phases can be distinguished in China's current land consolidation. The first stage focuses on land development and consolidation, primarily targeting agricultural land to increase cultivated area and improve irrigation facilities. The second stage extends the scope of land consolidation from farming to construction land. It aims to address issues such as fragmented rural farmland, disordered spatial layouts, and inefficient land resource utilization. The third stage is characterized by comprehensive land consolidation, which innovatively incorporates ecological protection and restoration into the consolidation process. This approach seeks to promote projects that consider all elements and phases of land management. Compared to previous efforts, WRCLC encompasses more diverse and specific measures. First, at the planning level, it uses townships as basic units to optimize cultivated land layouts, ensure sufficient cultivated land, and integrate protection with ecological restoration. Second, at the implementation level, WRCLC focuses on consolidating fragmented plots into larger, contiguous areas of cultivated land. This increases utilization efficiency and production potential. Additionally, it enhances irrigation infrastructure and improves soil quality through high-standard farmland construction and low-quality land transformation, thereby elevating the overall quality of cultivated land.

The WRCLC policy created stringent indicators and a negative list to guarantee the efficient application of policies and the sensible distribution of land. Regarding indicators, the policy mandates that the new cultivated land area in consolidation zones must be at least 5% of the existing cultivated land area. For adjustments involving permanent basic farmland, the newly designated area must also be at least 5% of the adjusted area. The negative list enforces strict land use regulations. It prohibits actions that harm the ecological environment, such as deforestation, excavation, filling of lakes, and the conversion of cultivated land into artificial landscapes. In addition, schedules for consolidation projects and construction work must be arranged appropriately to prevent haste and mechanical copying, as well as the emergence of image projects and political performance projects. To promote WRCLC, Zhejiang Province has introduced supportive policies. These include the reclamation of permanent basic farmland, optimization of land layout, reserved construction indicators for project areas, and incentives for new construction plans (see Figure 1).

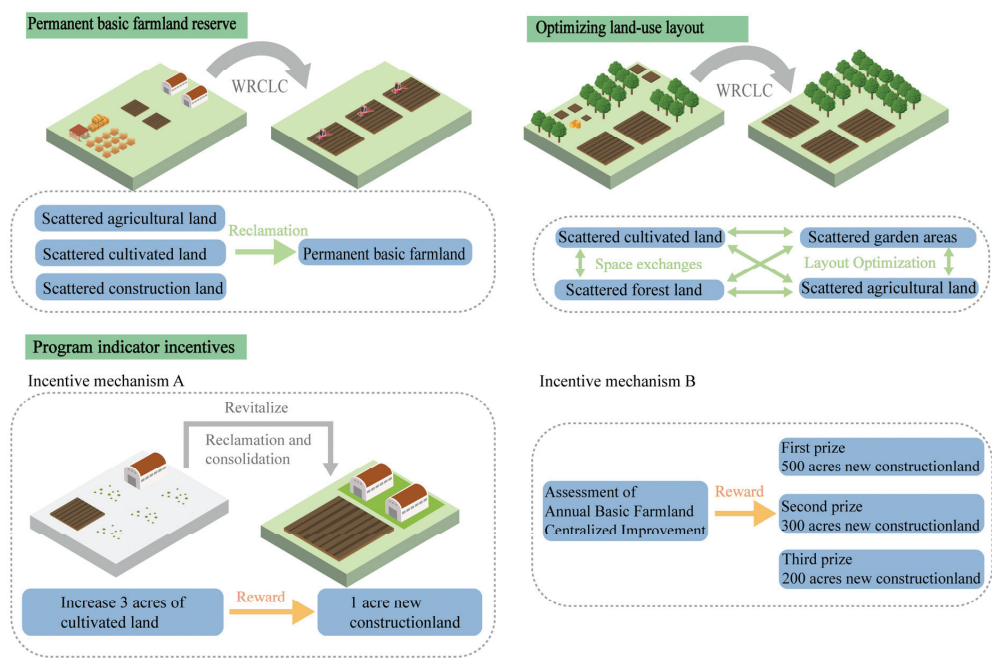


Figure 1. Policy measures for the WRCLC policy.

2.2. Theoretical Analysis

2.2.1. Direct Effect

Traditional land consolidation models mainly focus on land development and utilization, often resulting in issues such as a lack of unified planning, intense competition, and disordered development. As a new policy in land system reform, WRCLC emphasizes the need to address issues such as cultivated land fragmentation, quality degradation, and disordered spatial layout in rural areas. This is achieved through the development of village and townland planning that encompasses the entire space, all elements, and the full life cycle. From the perspective of policy planning, the WRCLC policy primarily promotes the dual improvement of both the quantity and quality of cultivated land through three major measures: agricultural land consolidation, construction land consolidation, and ecological restoration. The first is the specific plan for agricultural land consolidation. WRCLC alleviates issues of abandoned and idle farmland through measures such as merging small fields into larger ones and land transfer, while ensuring a steady increase in the amount of cultivated land through moderate-scale farming [18,25]. At the same time, WRCLC improves the quality of medium- and low-yield lands through high-standard farmland construction, land leveling, and soil improvement [26]. The second is the specific plan for the construction land consolidation. WRCLC aims to balance urban and rural land use to prevent urban expansion from encroaching on cultivated land [27]. Moreover, WRCLC increases cultivated land area and enhances land connectivity by reclaiming inefficiently used construction land and demolishing fragmented rural residential plots [28]. The third is the specific plan for ecological restoration. WRCLC restores land ecosystems through measures such as soil and water conservation, vegetation restoration, and the construction of ecological corridors to prevent soil erosion and protect cultivated land resources [29]. Additionally, WRCLC restores cultivated land functionality and enhances irrigation and drainage capabilities through the ecological reclamation of mining sites and soil pollution remediation [30,31]. In summary, we propose the following hypothesis:

Hypothesis 1. *The WRCLC policy has a positive impact on cultivated land security.*

2.2.2. Policy Synergy Effects

Policy synergy is essentially a systematic approach that ensures the consistency and complementarity of policy objectives. It enhances the convergence of policy content, improves resource utilization efficiency, and strengthens the coordination of policy implementation bodies. The aim is to maximize overall policy benefits. On the agricultural level, the impact of land policy on cultivated land resources is fundamental. However, this impact also depends on synergy with other policies to amplify the effects of individual policies [32].

Firstly, agricultural mechanization, which replaces traditional farming methods with mechanized tools, better meets the needs of large-scale development [33]. However, the promotion of agricultural mechanization faces challenges in the context of an aging agricultural workforce and cultivated land fragmentation [34,35]. From the perspective of policy synergy, on the one hand, the WRCLC policy promotes the consolidation and concentration of cultivated land through land reclamation measures. This approach promotes the adoption of agricultural mechanization, thereby preventing cultivated land abandonment due to labor shortages [36]. On the other hand, according to the theory of economies of scale, agricultural mechanization contributes to reducing production costs and optimizing resource allocation. This will effectively mitigate soil compaction caused by the excessive use of fertilizers and pesticides, thus promoting the sustainable use of cultivated land [37,38]. Secondly, the construction of characteristic agricultural towns aims to promote the integration of agricultural industries and the development of full industry chains. An organic synergy between production, living, and nature is made possible by this approach, which encourages the deep integration of primary, secondary, and tertiary businesses. From the perspective of policy synergy, on the one hand, the WRCLC policy promotes the rational allocation of land resources, meets the needs of rural industrial integration, and facilitates industrial clustering and concentrated pollution control [39]. On the other hand, internal agricultural industry integration, through exploring new agricultural models such as “rice–shrimp co-cultivation” and “rice–fish symbiosis”, improves resource use efficiency and enhances land quality [40]. At the same time, the extension of the industry chain enhances the value of agricultural products, promotes the application of green agricultural technologies, and reduces the risk of land degradation [41]. Thirdly, rural tourism, as a new industry expanding the functions of agriculture, relies on natural landscapes such as rice fields and terraced fields to develop ecological tourism and agricultural experiences, thereby promoting cultivated land protection [42]. From the perspective of policy synergy, on the one hand, the WRCLC policy ensures the rational allocation of land for rural tourism, safeguarding both cultivated land security and the sustainable development of the tourism industry [43]. On the other hand, rural tourism provides additional income for farmers and strengthens cultural identity, thus preventing rural population decline and cultivated land abandonment [44,45]. At the same time, the development of rural tourism contributes to the improvement of rural infrastructure, including water, electricity, roads, communications, and the internet, promotes high-standard farmland construction, and enhances land quality [46]. Based on this, the following hypothesis is proposed. The theoretical analytical framework of this paper is shown in Figure 2.

Hypothesis 2. *Policy synergy helps enhance the positive impact of the WRCLC policy on cultivated land security.*

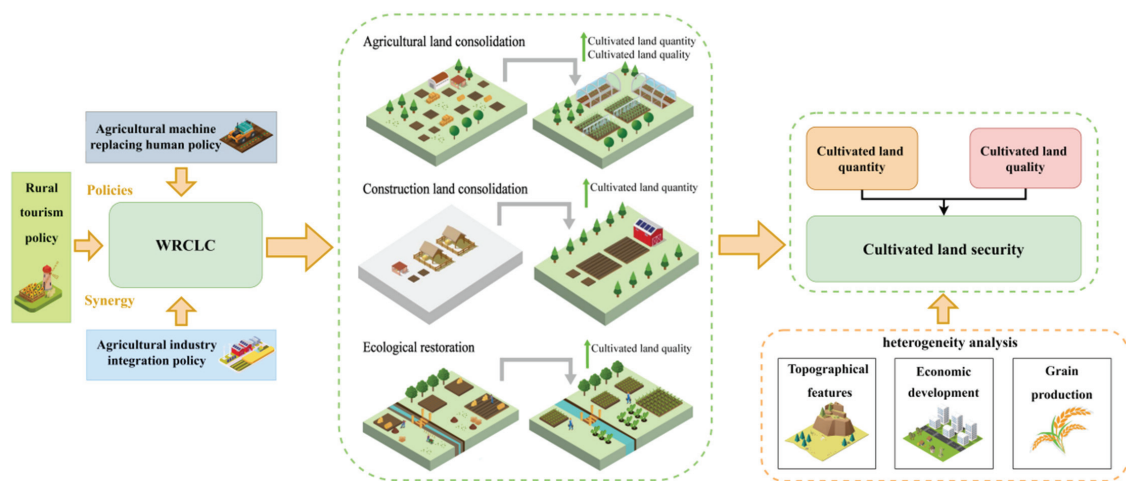


Figure 2. Theoretical analysis framework.

3. Study Design and Data Sources

3.1. Summary of the Research Area

Figure 3 shows the geographical location, distribution of land types, and distribution of pilot townships in Zhejiang Province. Zhejiang Province is situated on the southeast coast of China, in the southern wing of the Yangtze River Delta. Its latitudes range from 27°02' N to 31°11' N, while its longitudes range from 118°01' E to 123°10' E. The specific geographical location of Zhejiang Province is shown in Figure 3a. The area is distinguished by a humid climate that is influenced by the monsoon, with pleasant temperatures, distinct seasons, lots of sunshine, and copious amounts of rainfall. With a land size of 105,500 square kilometers, Zhejiang has an average annual temperature between 15 °C and 18 °C, 1100 to 2200 h of sunshine, and 1100 to 2000 mm of precipitation. This land area comprises 74.6% mountainous terrain, 5.1% water bodies, and 20.3% flat land, leading to the colloquial saying “seven mountains, one water, and two fields”. The distribution of different land types in Zhejiang Province is shown in Figure 3b. This topography underscores the province’s significant economic development and the food security challenges posed by land resource scarcity.

In response to issues such as chaotic rural spatial layouts, fragmented farmland distribution, and ecosystem degradation, Zhejiang Province took the lead in 2018 by issuing the “Opinions on Implementing Comprehensive Land Consolidation and Ecological Restoration Projects” from the Zhejiang Provincial People’s Government Office. In 2019, WRCLC pilot projects were initiated at the township level, focusing on five main tasks: overall rural land use planning, farmland improvement, remediation of inefficient construction land, ecological and environmental restoration, and the establishment of a democratic management mechanism for rural land. This model has achieved successful outcomes in cities such as Hangzhou, Ningbo, Huzhou, and Jinhua, and it has been promoted nationwide. Subsequently, the Ministry of Commerce issued a notice on launching pilot projects for comprehensive land consolidation, marking the beginning of national pilot initiatives. At present, Zhejiang Province, as a pioneer in implementing comprehensive territorial land consolidation measures, has initiated four groups of pilot projects. Among other things, the Natural Resources Department of Zhejiang Province announced the first and second of CLC pilot projects in Zhejiang Province in 2019 and 2020, a total of 497 pilot projects. In 2021, China’s Ministry of Natural Resources released a national list of CLC pilot projects, with a total of 42 pilot projects in Zhejiang Province. Subsequently, in 2022, the Natural Resources Department of Zhejiang Province released a list of 56 township land consolidation pilot projects under the “11350 Project”. After excluding pilot projects in urban streets, duplicate

projects, and projects with serious data deficiencies, a total of 258 pilot townships were covered in this study. The specific distribution of the pilot townships is shown in Figure 3c.

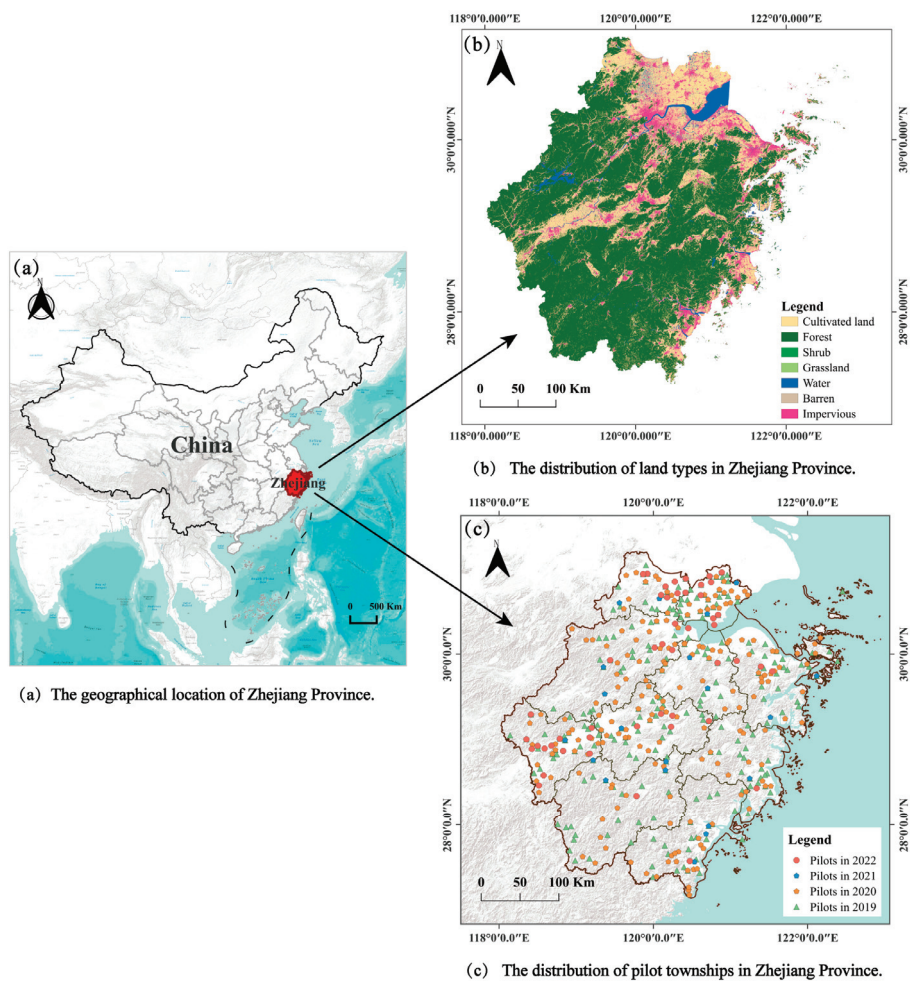


Figure 3. The geographical location of Zhejiang Province, the distribution of land types, and the distribution of pilot townships. (a) The geographical location of Zhejiang Province. (b) The distribution of land types in Zhejiang Province. (c) The distribution of pilot townships in Zhejiang Province.

3.2. Data Sources

The information about pilot townships for CLC in Zhejiang Province was obtained from the official websites of the Department of Natural Resources of Zhejiang Province and the Ministry of Natural Resources of China (<https://zrzyt.zj.gov.cn>, accessed on 1 March 2023). Township-specific data, including the size of the administrative area and the number of industrial enterprises, were compiled from the “China County Economy Statistical Yearbook (Township Volume)” for the period 2014–2023. County-level control variables were extracted from the “Zhejiang Statistical Yearbook” for the period 2014–2023. Missing values in these statistical yearbooks were imputed using linear interpolation and moving average methods. The National Tibetan Plateau Data Center provided the temperature and precipitation information (<https://data.tpdac.ac.cn>, accessed on 31 July 2024), with a spatial resolution of 1 km. Township population data were obtained from the LandScan

Global Population Database (<https://landscan.ornl.gov>, accessed on 1 May 2023), with a spatial resolution of 1 km. Net primary productivity (NPP) and enhanced vegetation index (EVI) data were sourced from NASA EOS/MODIS (<https://www.earthdata.nasa.gov/>, accessed on 1 January 2024), with a spatial resolution of 500 m. Township cultivated land area data were sourced from the Zenodo data platform (<https://zenodo.org/records/8176941>, accessed on 1 August 2023), with a spatial resolution of 30 m.

In the data processing process, first, this study constructed a basic township-level panel dataset by collecting township-level data from statistical yearbooks. Subsequently, based on the administrative divisions of the counties where the townships are located, county-level statistical data were matched with township data to enrich the township-level panel dataset. Next, using satellite remote sensing data obtained from public platforms and ArcGIS 10.8.2 software, different resolution raster spatial data were spatially mapped to the vector boundary data of each township in Zhejiang Province. These data were then aggregated within the township boundaries to generate township-level spatial geographic data. Finally, based on township names and year information, the statistical yearbook data were accurately matched and merged with the processed spatial geographic data, resulting in a complete township-level panel dataset for Zhejiang Province.

3.3. Variable Measure

3.3.1. Dependent Variable

This study selects cultivated land security as the dependent variable, which is divided into two dimensions: cultivated land quality and quantity. The quantity of cultivated land is represented by the area of cultivated land in townships (Unit: km²). For the quality of cultivated land, we reference the research by Zhou Xiaoping et al. (2024) and use the vitality of the cultivated land system as a proxy variable for cultivated land quality [47]. This vitality is constructed based on Net Primary Productivity (NPP) and the Enhanced Vegetation Index (EVI). The rationale for using cultivated land system vitality lies in its representation of the system's metabolic capacity or primary productivity, which is typically reflected by the growth status and biomass of aboveground vegetation. The EVI, which enhances vegetation signals by incorporating the blue band, effectively indicates vegetation coverage and health. Meanwhile, NPP represents the net accumulation of organic matter after subtracting plant respiration from Gross Primary Productivity (GPP), effectively reflecting the production capacity of vegetation communities. Considering the significant variations in crop growth both within a year and between years, this study calculates the annual averages of NPP and EVI, normalizes these values through extreme value normalization, and combines them equally to represent the vitality of the cultivated land system.

3.3.2. Core Independent Variable

This study constructs the key independent variable WRCLC, which indicates the setting of the WRCLC pilots, based on the information released by the Natural Resources Department of Zhejiang Province and the Ministry of Natural Resources of China. Specifically, if a township is designated as a WRCLC pilot during the study period, it will be classified as a treatment group, while the undesignated townships will serve as a control group. For the treatment group townships, WRCLC takes the value of 1 in the founding year of the WRCLC pilot project and in subsequent years, otherwise it is 0. For the control group townships, WRCLC takes the value of 0 for all years.

3.3.3. Control Variables

Cultivated land security is influenced not only by climate conditions such as temperature and precipitation [48], but also by socioeconomic factors, including human activities and industrialization [13,49]. Therefore, in the regression analysis, this study incorporates factors such as township-level temperature, precipitation, population density, and the number of industrial enterprises as control variables to mitigate endogeneity issues caused by omitted variables. Specifically, the control variables selected in this study include both

township-level and county-level variables. The township-level variables consist of the following: (1) Population Density (persons/km²): The number of residents in a township divided by the area of the administrative region. (2) Industrial Development Level: The number of industrial enterprises, represented in logarithmic form. (3) Precipitation (mm): annual average precipitation in townships. (4) Temperature (°C): annual average temperature in townships. At the county level, the variables are as follows: (1) Economic Development Level (10,000 yuan): Per capita regional GDP. (2) Compulsory Education Penetration Rate: The percentage of the population at the end of the year that is enrolled in conventional secondary and primary schools. (3) Government Intervention Level: The ratio of local fiscal revenue to regional GDP. (4) Industrial Structure: The proportion of secondary industry value contributed to tertiary industry value added. (5) Agricultural Development Level: The share of regional GDP that comes from the combined output value of forests, fisheries, agriculture, and animal husbandry. (6) Technological Innovation Level (applications/10,000 persons): The proportion of approved patent applications to the overall population at the end of the year.

3.3.4. Policy Synergy Variables

Based on the theoretical analysis in the previous section, it was found that agricultural mechanization, agricultural–industrial integration, and rural tourism development all have a synergistic effect with the WRCLC policy, which impacts the cultivated land security of townships. Additionally, considering that the WRCLC policy is implemented at the township level, this paper selects three types of pilot policies at the township level as proxy variables. The definitions of these three policy variables are as follows: (1) Agricultural Mechanization (AM) Policy: This paper uses the Zhejiang Province Agricultural Machinery Replacement Pilot Townships as the proxy variable for agricultural mechanization policy. The reason for this is that the policy primarily focuses on promoting agricultural machinery technology and equipment and cultivating agricultural machinery service entities, effectively improving the level of agricultural mechanization in townships. (2) Agricultural Industry Integration (AII) policy: the pilot policy for characteristic agricultural townships in Zhejiang Province serves as a proxy variable for agricultural industry integration policy. This policy promotes the integrated development of agricultural production, agricultural product processing, and agricultural services, leveraging the multifunctionality of agriculture and the region’s characteristic agricultural industries. It plays an important role in promoting agricultural industry integration at the township level. (3) Rural Tourism (RT) Policy: The pilot policy for tourism-themed townships in Zhejiang Province is used as a proxy variable for rural tourism policy. This policy relies on the unique natural landscapes and rich cultural resources of townships, promoting the construction of tourism public service facilities, with the aim of forming a comprehensive rural tourism industry system. This is a key policy for supporting rural tourism development in townships. In terms of variable assignment, the paper constructs three dummy variables, AM_{it} , AII_{it} , and RT_{it} for these three types of township pilot policies. Specifically, the dummy variable is assigned a value of 1 for the year a township is designated as a pilot, and for subsequent years, it is 0. For non-pilot townships, the dummy variables always take the value of 0. The descriptive statistics for all variables are shown in Table 1.

Table 1. Descriptive statistics of the variables.

Type	Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent variable	Cultivated land quality	7070	60.257	13.990	1.844	88.929
	Cultivated land quantity	7070	20.639	21.671	0.100	192.578
Core independent variable	WRCLC policy	7070	0.132	0.338	0.000	1.000

Table 1. Cont.

Type	Variable	Obs	Mean	Std. Dev.	Min	Max
Control variables	Population density	7070	375.660	513.784	1.312	5001.249
	Industrial development level	7070	4.319	1.918	0.000	9.880
	Precipitation	7070	1334.897	344.824	97.972	2501.282
	Temperature	7070	16.942	1.049	12.815	20.203
	Economic development level	7070	7.586	3.050	1.490	26.737
	Compulsory education penetration rate	7070	0.106	0.021	0.061	0.189
	Government intervention degree	7070	0.085	0.022	0.022	0.171
	Industrial Structure	7070	0.980	0.324	0.149	2.317
	Agricultural development level	7070	0.105	0.060	0.003	0.316
Policy synergy variable	Technological innovation level	7070	40.599	27.742	2.568	262.046
	Agricultural machines policy	7070	0.086	0.280	0.000	1.000
	Agricultural industry integration policy	7070	0.036	0.186	0.000	1.000
	Rural tourism policy	7070	0.034	0.180	0.000	1.000

3.4. Model Specification

The purpose of this study is to evaluate how the WRCLC pilot policy has affected the quantity and quality of agricultural land. Previous research has primarily employed traditional causal inference models; however, some limitations and drawbacks of these models can compromise the accuracy of the conclusions [50,51]. The double/debiased machine learning method proposed by Chernozhukov et al. (2018) effectively addresses the shortcomings of traditional models [52]. On the one hand, the application of machine learning to handle high-dimensional, nonlinear data reduces the risk of model misspecification. On the other hand, double machine learning employs instrumental variables, two-stage residual regression, and subsampling methods to mitigate “regularization bias”, thereby ensuring the unbiased estimation of treatment effects [50]. Based on this, the present study adopts the DML approach to evaluate the effects of the WRCLC policy.

The partial linear model for double machine learning is constructed as follows:

$$Y_{it} = \theta_0 D_{it} + g(X_{it}) + U_{it}, E(U_{it}|X_{it}, D_{it}) = 0 \tag{1}$$

$$D_{it} = m(X_{it}) + V_{it}, E(V_{it}|X_{it}) = 0 \tag{2}$$

In Equation (1), i represents the township, t represents the year, Y_{it} denotes cultivated land quantity and quality of townships, D_{it} serves as the policy variable for WRCLC, and θ_0 is the treatment coefficient. X_{it} denotes a set of high-dimensional control variables, $\hat{g}(X_{it})$ are estimated using machine learning algorithms, and U_{it} is the error term. To address the potential bias introduced by regularization in machine learning algorithms, an auxiliary regression, as shown in Equation (2), is constructed.

Furthermore, drawing upon Chernozhukov et al. (2018), a more generalized interaction model is established to estimate the policy effects [52]:

$$Y_{it} = g(D_{it} + X_{it}) + U_{it}, E(U_{it}|X_{it}, D_{it}) = 0 \tag{3}$$

$$D_{it} = m(X_{it}) + V_{it}, E(V_{it}|X_{it}) = 0 \tag{4}$$

The treatment effects obtained from this model are: $\theta_0 = E[g(D_{it} = 1|X_{it}) - g(D_{it} = 0|X_{it})]$. The specific estimation methods for the relevant parameters are consistent with those used in the partial linear model.

To examine the impact of policy synergy on the quantity and quality of cultivated land in rural towns, this study establishes the following model:

$$Y_{it} = \theta_1 D_{it} \times R_{it} + g(X_{it}) + U_{it}, E(U_{it}|D_{it} \times R_{it}, X_{it}) = 0 \tag{5}$$

In Equation (5), $D_{it} \times R_{it}$ denotes the interaction term between the WRCLC policy and other policy variables and θ_1 is the treatment coefficient. The specific functional form of $g(X_{it})$ and its estimates $\hat{g}(X_{it})$ are estimated using machine learning algorithms.

4. Empirical Results and Analysis

4.1. Baseline Regression Results

The influence of the WRCLC policy on the quantity and quality of cultivated land is estimated in this study using a DML approach. Table 2 presents the baseline regression results. The sample split ratio is set at 1:4, and the random forest algorithm is utilized to predict and solve both the main and auxiliary regressions. Models (1) and (2) use partial linear models for estimation. From Model (1), it is evident that the impact coefficient of the WRCLC policy on cultivated land quantity is 1.217, significant at the 1% level. The results from Model (2) indicate that the impact coefficient of the WRCLC policy on cultivated land quantity is 0.678, which is also positively significant at the 1% level. This suggests that implementing WRCLC can effectively increase the area of cultivated land in townships and improve its quality. Models (3) and (4) utilize interactive models for regression analysis, yielding similarly positive and significant results at the 1% level, thus validating Hypothesis 1 and Hypothesis 2.

Table 2. Baseline regression.

Var.	(1) Partial Model Cultivated Land Quantity	(2) Partial Model Cultivated Land Quality	(3) Interactive Model Cultivated Land Quantity	(4) Interactive Model Cultivated Land Quality
WRCLC	1.217 *** (0.248)	0.678 *** (0.187)	1.161 *** (0.211)	4.664 *** (0.195)
Controls	Yes	Yes	Yes	Yes
Id	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	7070	7070	7070	7070

Note: *** indicates statistical significance at 1% level; values in parentheses represent robust standard error.

4.2. Robustness Checks

4.2.1. Parallel Trends Test

This study evaluates how the WRCLC policy affects cultivated land quantity and quality by adopting a DML approach. A parallel trends test is necessary to satisfy the prerequisites for using the DID research methodology. Figures 4 and 5 display the parallel trends test results, indicating that the coefficients for the policy effects before the implementation of the WRCLC policy are not significant. This supports the parallel trends assumption for the DID research methodology employed in this study, by indicating that there were no appreciable differences between the control and treatment groups prior to the policy’s implementation. Furthermore, starting from the second year after the policy’s implementation, the regression coefficients show positive significance, indicating that the WRCLC policy effectively enhances cultivated land quantity and quality in rural areas.

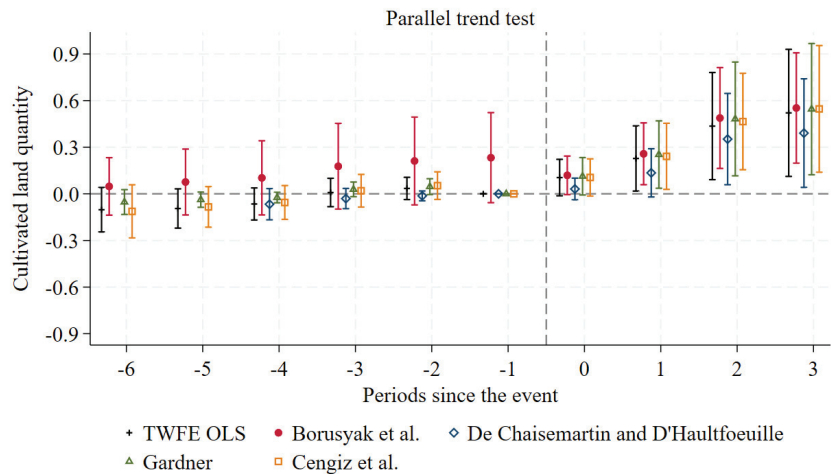


Figure 4. Parallel trends test (cultivated land quantity) [53–56].

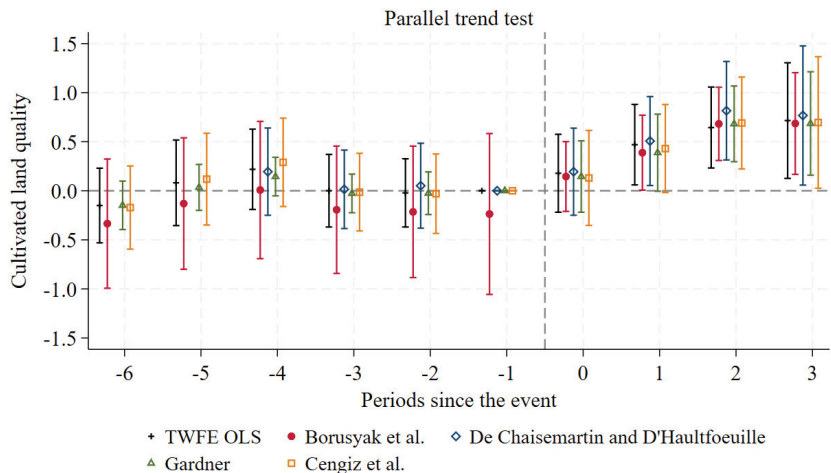


Figure 5. Parallel trends test (cultivated land quality) [53–56].

4.2.2. Adjustment of the Study Period

To mitigate the potential influence of samples spanning an extensive time frame on the research findings, this study confines the analysis to a three-year window before and after policy implementation, ensuring symmetry in the sample time periods. As shown in Table 3, when the study period is adjusted to 2016–2022, the WRCLC policy still demonstrates a significantly positive effect on cultivated land quantity and quality, reinforcing the robustness of the previous conclusions.

Table 3. Robustness checks results (1).

Var.	(1) Adjustment of the Study Period	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cultivated Land Quantity	Cultivated Land Quality	Cultivated Land Quantity	Cultivated Land Quality	Cultivated Land Quantity	Cultivated Land Quality	Cultivated Land Quantity	Cultivated Land Quality
WRCLC	1.121 *** (0.270)	0.441 ** (0.176)	1.220 *** (0.247)	0.654 *** (0.185)	1.547 *** (0.315)	0.792 *** (0.244)	0.928 *** (0.210)	0.566 *** (0.175)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19	No	No	No	No	Yes	Yes	No	No
County–Year	No	No	No	No	No	No	Yes	Yes
Observations	4949	4949	7070	7070	7070	7070	7070	7070

Note: ***, ** indicate statistical significance at 1% and 5% levels, respectively; values in parentheses represent robust standard error.

4.2.3. Winsorization

Considering that outliers in the regression sample may affect the unbiasedness of the regression results, we apply winsorization to all variables (excluding the core explanatory variable) at the 1% levels, replacing values above the upper quantile and below the lower quantile, and conduct regression analysis. After removing outliers, the results in Table 3 show that the regression results are still significantly positive.

4.2.4. Exclusion of COVID-19 Impact

To disentangle the potential influence of the COVID-19 pandemic, a significant event that occurred in 2020, on township cultivated land quantity and quality, this study follows existing research by constructing a dummy variable for COVID-19 (assigning the value of 1 for 2020 and subsequent years, and 0 for other years) and incorporating it into the regression model for control [57]. As shown in Table 3, after controlling for the COVID-19 impact, the regression coefficients remain significantly positive, confirming the robustness of the previous conclusions.

4.2.5. Consideration of County–Year Interactive Fixed Effects

To further validate the robustness, this study employs a method that controls for county–year interactive fixed effects. As shown in Table 3, after controlling for county–year interactive fixed effects, the coefficients remain significantly positive, demonstrating the reliability of the previous findings.

4.2.6. Alternative Estimation Models

This study employs the traditional staggered difference-in-differences (Staggered DID) method, along with two robust Staggered DID estimation techniques, to conduct robustness checks and effectively mitigate estimation bias arising from heterogeneous policy effects at different time points [58,59]. To this end, we use these three model types to re-estimate the average treatment impact of the policy implementation. As shown in Table 4, following the model adjustments, the coefficients for the WRCLC policy remain positively significant, thereby confirming the robustness of our conclusions.

Table 4. Robustness checks results (2).

Var.	(1)	(2)	(3)	(4)	(5)	(6)
	Staggered DID		Robust Estimation of Staggered DID			
	Cultivated Land Quantity	Cultivated Land Quality	Sun and Abraham Cultivated Land Quantity	Sun and Abraham Cultivated Land Quality	Callaway and Sant’Anna Cultivated Land Quantity	Callaway and Sant’Anna Cultivated Land Quality
WRCLC	0.318 *** (0.116)	0.438 *** (0.149)	0.316 *** (0.066)	0.444 *** (0.119)	0.364 ** (0.166)	0.320 * (0.191)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Id	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7070	7070	7070	7070	7070	7070

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively; values in parentheses represent robust standard error.

4.2.7. Resetting Machine Learning Models

This study re-estimates the models by altering the sample split ratio and machine learning methodologies, in order to lessen the effect of model specification bias on the estimation outcomes. The findings in Tables 5 and 6 show that the conclusion on the WRCLC policy is unaffected by changes to the sample split ratio and machine learning methodologies. This policy promotes simultaneous improvements in cultivated land quantity and quality, thereby confirming the reliability of the original findings.

Table 5. Robustness checks results (3).

Var.	(1)	(2)	(3)	(4)	(5)	(6)
	Kfold = 3 Cultivated Land Quantity	Kfold = 8 Cultivated Land Quantity	Lassocv Cultivated Land Quantity	Gradboost Cultivated Land Quantity	Elasticcv Cultivated Land Quantity	Svm Cultivated Land Quantity
WRCLC	1.284 *** (0.277)	1.131 *** (0.234)	0.305 *** (0.074)	2.928 *** (0.463)	0.321 *** (0.082)	3.491 *** (0.686)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Id	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7070	7070	7070	7070	7070	7070

Note: *** indicates statistical significance at 1% level; values in parentheses represent robust standard error. “Kfold = 3” indicates a sample split ratio of 1:2; “Kfold = 8” indicates a sample split ratio of 1:7; “Lassocv”, “Gradboost”, “Elasticcv”, and “Svm” represent different machine learning methodologies.

Table 6. Robustness checks results (4).

Var.	(1)	(2)	(3)	(4)	(5)	(6)
	Kfold = 3 Cultivated Land Quantity	Kfold = 8 Cultivated Land Quantity	Lassocv Cultivated Land Quantity	Gradboost Cultivated Land Quantity	Elasticcv Cultivated Land Quantity	Svm Cultivated Land Quantity
WRCLC	0.722 *** (0.188)	0.587 *** (0.187)	0.315 *** (0.116)	1.111 *** (0.257)	0.350 *** (0.117)	2.063 *** (0.334)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Id	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7070	7070	7070	7070	7070	7070

Note: *** indicates statistical significance at 1% level; values in parentheses represent robust standard error. “Kfold = 3” indicates a sample split ratio of 1:2; “Kfold = 8” indicates a sample split ratio of 1:7; “Lassocv”, “Gradboost”, “Elasticcv”, and “Svm” represent different machine learning methodologies.

4.3. Endogeneity and Placebo Test

4.3.1. Endogeneity Test

When evaluating the policy effects of the WRCLC, potential endogeneity issues such as omitted variable bias, reverse causality, and selection bias may arise. First, regarding omitted variables, this study has accounted for factors that may influence cultivated land quantity and quality at the township level, controlling for both time-fixed effects and individual fixed effects to mitigate endogeneity arising from omitted variables. Second, to address reverse causality, this study conducted regressions with lagged control variables, which helped alleviate the endogeneity issues stemming from reverse causality. Third, this study applied Propensity Score Matching (PSM) to address sample self-selection bias. This study estimated propensity scores using township-level characteristics as covariates and employed a one-to-one matching method ($k = 1$). After excluding samples that violated the common support assumption, this study re-estimated using a double machine learning (DML) approach. The results from Models 3 and 4 in Table 7 indicate that, after addressing the endogeneity issues related to sample self-selection, the WRCLC policy continues to show a positive and significant impact on both the quality and quantity of cultivated land. Finally, this study used instrumental variable methods to further mitigate endogeneity issues. Based on the research of Chernozhukov et al. (2018) [52], this study constructs a partially linear instrumental variable model using DML, as specified below:

$$Y_{it} = \theta_0 D_{it} + g(X_{it}) + U_{it} \tag{6}$$

$$Z_{it} = m(X_{it}) + V_{it} \tag{7}$$

Table 7. Endogeneity test.

Var.	(1)	(2)	(3)	(4)	(5)	(6)
	Control Variables Cultivated Land Quantity	Lagged One Period Cultivated Land Quality	PSM-DML Cultivated Land Quantity	Cultivated Land Quality	Instrumental Cultivated Land Quantity	Variable Methods Cultivated Land Quality
WRCLC	1.177 *** (0.283)	0.830 *** (0.203)	0.478 *** (0.175)	1.632 *** (0.353)	1.414 *** (0.338)	0.507 ** (0.233)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Id	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6363	6363	6673	6673	6363	6363

Note: ***, ** indicate statistical significance at 1% and 5% levels, respectively; values in parentheses represent robust standard error.

In Equations (6) and (7), Z_{it} serves as an instrumental variable for D_{it} . This study used the lagged variable of the comprehensive land rehabilitation pilot policy as an instrumental variable to conduct endogeneity tests, thereby addressing endogeneity issues. The results of the endogeneity tests in Models 5 and 6 of Table 7 indicate that, after mitigating the endogeneity concerns, the WRCLC policy continues to significantly enhance both cultivated land quantity and quality.

4.3.2. Placebo Test

To eliminate potential confounding factors in the relationship between the WRCLC policy and its impact on cultivated land quantity and quality, this study conducted two types of placebo tests. First, using a “pseudo-treatment period” and re-estimating the effects, this study conducted a time placebo test by moving the WRCLC policy’s implementation date forward by one to six years. The results shown in Figure 6 indicate that, within a 95% confidence interval, the placebo effects are no longer significant. Second, this study conducted a spatial placebo test by randomly assigning part of the sample to a “pseudo-treatment group” through 500 iterations of random sampling, while the remaining samples served as a “pseudo-control group”. According to Figure 6’s results, the estimated

treatment effect is an extreme value that is on the right tail of the placebo effect distribution. Therefore, the core conclusion of this study is not a result of random chance, and other unknown confounding factors are insufficient to establish a causal relationship with our primary findings.

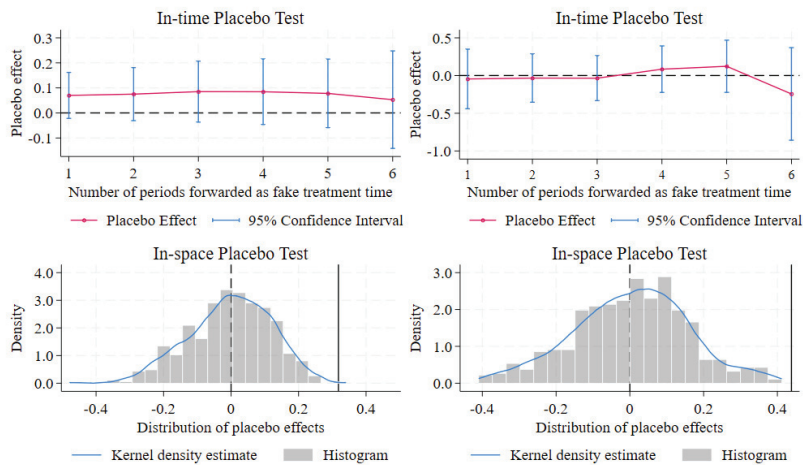


Figure 6. The results of placebo test.

5. Heterogeneity Analysis

5.1. Topographical Heterogeneity

The Zhejiang Provincial County (City) Socio-Economic Statistical Yearbook classifies the county-level cities of Zhejiang Province into three categories based on topography: plain counties, hilly counties, and mountainous counties. Accordingly, this paper further classifies townships in Zhejiang Province into plain and non-plain regions. Specifically, if a township is located in a plain county, it is categorized as the plain region group. If a township is located in a hilly or mountainous county, it is categorized as the non-plain region group. Based on this classification, the paper conducts regressions on the sample by groups to analyze the topographic heterogeneity.

As shown in Figure 7, the impact of the WRCLC policy on cultivated land security exhibits topographical heterogeneity. Regarding cultivated land quantity, the WRCLC policy significantly increases the quantity of cultivated land in towns across all topographical zones. Moreover, the effect of the policy on increasing cultivated land quantity is greater in non-plain areas compared to plain areas.

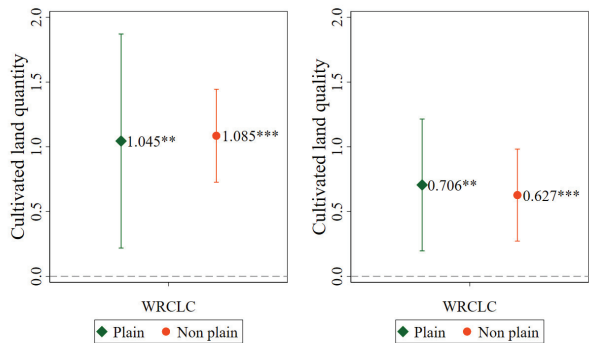


Figure 7. Results of topographic heterogeneity analysis. ***, ** indicate statistical significance at 1% and 5% levels, respectively.

Regarding cultivated land quality, the WRCLC policy appears to enhance cultivated land quality more effectively in plain areas than in non-plain areas. This indicates that the WRCLC policy prioritizes improvements in cultivated land quality in plain regions, while focusing on increasing cultivated land quantity in non-plain regions.

5.2. Economic Development Heterogeneity

In Zhejiang Province, the term “26 mountainous counties” specifically refers to the counties under the jurisdiction of the cities of Quzhou and Lishui, and 26 counties including Chun’an, Yongjia, Pingyang, Cangnan, Wencheng, Taishun, Wuyi, Pan’an, Sanmen, Tiantai, and Xianju. These 26 counties, as an important part of Zhejiang, account for approximately 45% of the provincial land area and about 15% of the permanent population. However, the economic development level in these “26 mountainous counties” is below the provincial average. Based on the above classification, this paper categorizes townships located within the “26 mountainous counties” as the low economic development group, while other townships are classified as the high economic development group. The paper then conducts regressions by groups based on this classification.

As illustrated in Figure 8, the impact of the WRCLC policy on cultivated land security varies across regions with different economic development levels. In terms of cultivated land quantity, the WRCLC policy demonstrates a more pronounced positive effect in areas with lower economic development compared to those with higher economic development levels. Regarding cultivated land quality, the WRCLC policy does not lead to significant improvements in cultivated land quality in areas with higher economic development levels. A possible explanation for this is that, in economically developed regions, the value of land is higher, leading to relatively higher costs for land consolidation investments, which can hinder the effective implementation of WRCLC projects.

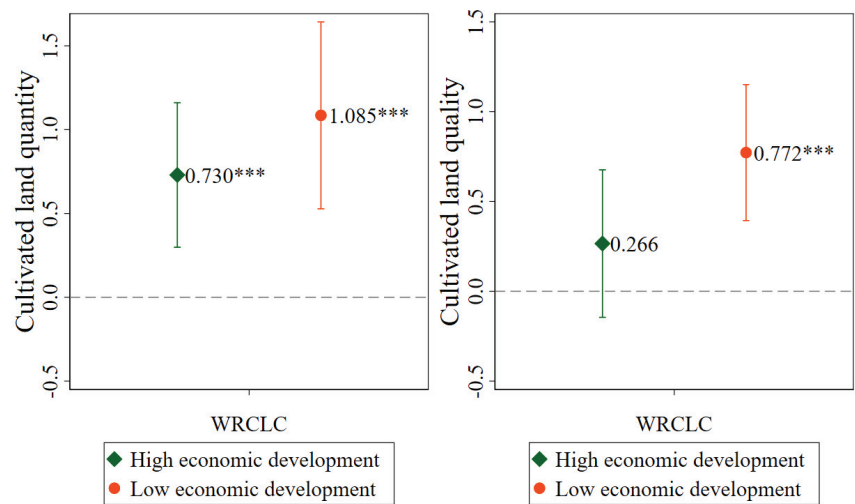


Figure 8. Results of economic development heterogeneity analysis. *** indicates statistical significance at 1% level.

5.3. Heterogeneity of Grain-Producing Functional Zones

According to the “Major Grain-Producing Counties” list of Zhejiang Province, this paper groups all counties into major and non-major grain-producing categories. Building on this classification, the paper identifies whether a township belongs to a major grain-producing area based on its location within a county-level city, and then performs regressions by groups accordingly.

As shown in Figure 9, the impact of the WRCLC policy on cultivated land security varies across different grain-producing functional zones. In terms of cultivated land quantity, implementing the WRCLC policy in major grain-producing regions results in a more significant increase in cultivated land quantity compared to non-grain-producing regions. Regarding cultivated land quality, the WRCLC policy significantly improves cultivated land quality in non-grain-producing regions, while its effects on cultivated land quality in major grain-producing regions are not as pronounced. This may be due to the generally higher quality of cultivated land and more developed agricultural infrastructure in major grain-producing areas, making the improvements from land rehabilitation less noticeable.

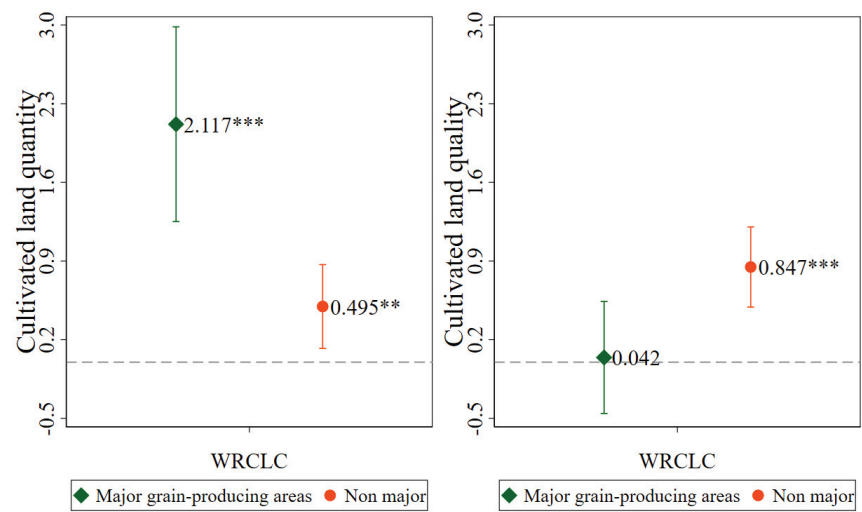


Figure 9. Results of grain-producing functional zones heterogeneity analysis. ***, ** indicate statistical significance at 1% and 5% levels, respectively.

From the standpoint of guaranteeing food security, the WRCLC policy can significantly enhance cultivated land quantity in major grain-producing regions, effectively contributing to an overall increase in regional grain production and thus ensuring regional food security. Additionally, the WRCLC policy can simultaneously improve the cultivated land quantity and quality in non-grain-producing regions, further enhancing local self-sufficiency in food production and realizing the goal of “zero hunger”.

6. The Impact of Policy Synergy on Cultivated Land Security

6.1. The Impact of Policy Synergy on Cultivated Land Quantity

This study examines the effects of policy synergy on cultivated land quantity and quality in rural areas by constructing interaction terms. The results presented in Figure 10 indicate that the coefficient for the impact on cultivated land quantity increases from 1.217 to 2.570 and 2.717, respectively, when the WRCLC policy is coordinated with the AM policy and AII policy, achieving statistical significance at the 1% level. This suggests that the measures for WRCLC and the development of agricultural mechanization can form a complementary relationship, thereby promoting an increase in cultivated land quantity in rural areas. Additionally, the coordinated advancement of agricultural industry integration and WRCLC can effectively enhance the quantity of cultivated land, contributing to food security. It is noteworthy that when the WRCLC policy is coordinated with RT policies, the coefficient for the impact on cultivated land quantity decreases to 0.493 and is no longer statistically significant. This may be attributed to the fact that the development of rural tourism significantly stimulates the construction of homestays and tourism facilities, which can encroach on cultivated land resources [60]. Furthermore, the focus on creating

aesthetically pleasing landscapes in rural tourism may lead to issues that indirectly alter the nature of cultivated land.

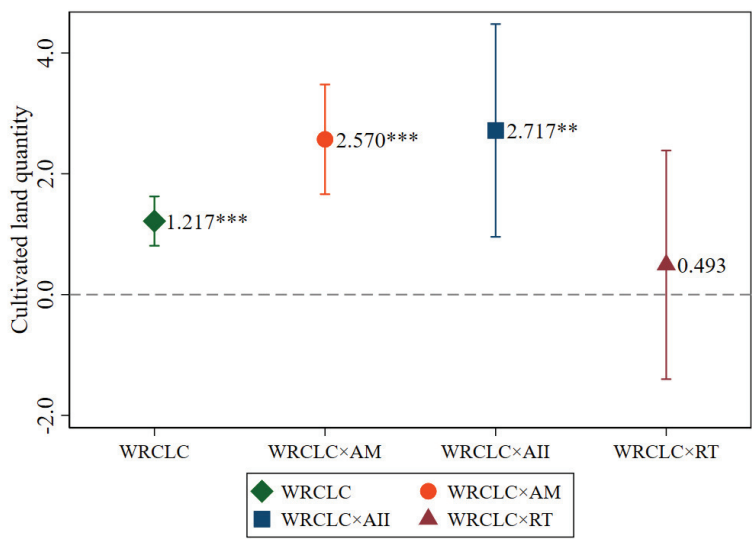


Figure 10. Results of the impact of policy synergy on the quantity of cultivated land. ***, ** indicate statistical significance at 1% and 5% levels, respectively.

6.2. The Impact of Policy Synergy on Cultivated Land Quality

The results shown in Figure 11 indicate that the enhancement of cultivated land quality is positively significant when the WRCLC policy is coordinated with the three types of policies. The impact coefficients increase from 0.678 to 1.485, 1.382, and 1.329, respectively. These findings validate that the coordination of agricultural mechanization, agricultural industry integration, and rural tourism development policies with the WRCLC policy effectively promotes the improvement of cultivated land quality in rural areas.

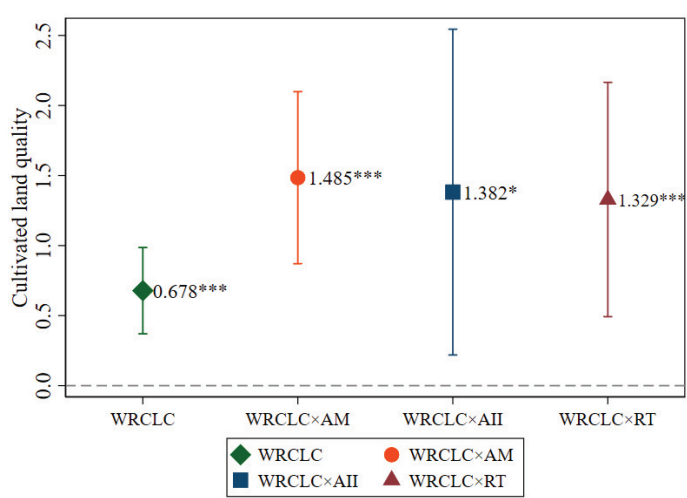


Figure 11. Results of the impact of policy synergy on the quality of cultivated land. ***, * indicate statistical significance at 1% and 10% levels, respectively.

7. Discussion

The research findings indicate that WRCLC can enhance cultivated land security. Existing studies on land use and cultivated land security have mainly focused on traditional land consolidation models, but the conclusions are inconsistent [17]. Traditional land consolidation typically uses engineering measures to improve inefficient or unused land, primarily on a project-by-project basis, focusing on land adjustment and rural reconstruction, without considering ecological restoration projects [18,61]. Additionally, in some regions, traditional land consolidation is seen as a tool to provide land use quotas, overlooking the protection of cultivated land and agricultural ecosystems, which makes it difficult to ensure the security of rural cultivated land [62]. WRCLC emphasizes the holistic scope of consolidation, the comprehensive nature of the consolidation targets, and the systematic implementation of consolidation measures, providing an important guarantee for achieving cultivated land security [19]. In terms of scope, WRCLC takes townships as the basic unit for implementation, promoting planning, design, and consolidation at the regional level. Regarding the consolidation targets, WRCLC focuses on all elements of the landscape—mountains, water, forests, fields, lakes, and grasslands—within the region, coordinating the optimization of land resource allocation. In terms of measures, WRCLC systematically implements three key actions: agricultural land consolidation, construction land consolidation, and ecological restoration. Therefore, WRCLC not only contributes to increasing the quantity of cultivated land but also addresses improvements in land quality, and the sustainable use of cultivated land [19,20]. Although some scholars have already recognized the significant impact of WRCLC on cultivated land security, existing studies primarily use theoretical analysis or case study methods to qualitatively explore the relationship between the two [63,64]. Furthermore, due to limitations in data availability, existing research often focuses on single pilot township samples [21,22], which may raise doubts about the reliability of the conclusions. To address the limitations of previous studies, this research innovatively combines spatial data analysis methods with econometric causal inference techniques. Using ArcGIS 10.8.2 software, satellite remote sensing images are processed into data with numerical characteristics, forming township-level panel data with a time series. This approach effectively resolves the issue of limited research samples and improves the accuracy of the findings.

In terms of model selection, current research predominantly relies on traditional difference-in-differences (DID) models [26,65], which may lead to biased policy evaluation results. In contrast, this study uses township-level panel data and treats the WRCLC policy as a quasi-natural experiment, employing the double machine learning (DML) method for causal inference. This approach aims to examine the impact of WRCLC on cultivated land security from a more micro and precise perspective. DML offers significant advantages in variable selection and model estimation [52]. On the one hand, since the cultivated land security is influenced by various natural, economic, and social factors, this study includes ten covariates such as population density, temperature, and precipitation, while controlling for township-fixed and year-fixed effects. This helps to avoid estimation bias caused by omitted variables, improving the accuracy of policy effect evaluation. The DML approach, by employing machine learning and regularization algorithms, automatically selects the most predictive and relevant subset of control variables from the pre-selected high-dimensional set. This not only effectively resolves the issue of redundant control variables in traditional models, but also alleviates estimation bias caused by insufficient key control variables [66]. On the other hand, thanks to its advantages in handling nonlinear data, DML can effectively mitigate model specification errors [50,66], thus providing more robust estimates.

Existing research has primarily focused on the analysis of individual land adjustment policies, with less attention given to the exploration of policy synergy effects. However, from the perspective of regional development needs, single policies often fail to achieve their expected outcomes. Only through the synergy effect of multiple policies can regional policy goals be more effectively realized [67–69]. Meanwhile, scholars have identified that

agricultural mechanization, agricultural industrial integration, and rural tourism development all have significant impacts on land security [37,38,70–73]. Therefore, based on existing research, this study selects three pilot policies implemented at the township level in Zhejiang Province: the AM policy, the AII policy, and the RT policy. By constructing interactive terms, this study further examines the impact of policy synergy on cultivated land security within the framework of WRCLC. The results show that during the implementation of WRCLC, the synergy with the AM policy and the AII policy both significantly improved the quantity and quality of cultivated land in townships. Notably, however, the synergy between the WRCLC policy and the RT policy does not show a significant effect on the improvement of cultivated land quantity, which contrasts with the findings of previous studies [74]. Field surveys reveal that tourism-oriented rural development models, emphasizing projects such as “study tours” and “sightseeing”, have led to a rapid increase in land demand for infrastructure development. When there is insufficient land for rural construction, it often results in the cultivated land encroachment. Furthermore, tourism development has caused local farmers to shift from traditional agricultural activities to tourism-related industries (such as operating homestays and providing catering services), leading to cultivated land abandonment. Therefore, during the development of the tourism industry, the government should firmly establish awareness of cultivated land protection, strictly review land for tourism construction, and ensure the protection of cultivated land quantity and the stability of its quality. Additionally, in the process of implementing comprehensive land consolidation, the government should carefully plan tourism land and construction projects, optimize the layout of the tourism industry, improve land use efficiency, and promote a high-efficiency balance between tourism development and farmland protection [75]. The government should also establish a well-functioning land transfer system, encourage part-time farmers to lease out their cultivated land and enhance the scale of cultivated land management.

8. Conclusions and Implications

8.1. Research Conclusions

Based on panel data from 707 townships in Zhejiang Province from 2013 to 2022, this study employs the DML approach to estimate the impact of WRCLC on cultivated land. Meanwhile, the heterogeneous impact of WRCLC on cultivated land security is examined under different geographic characteristics, economic development levels, and grain functional zone scenarios. Additionally, this study incorporates the AM policy, the AII policy, and the RT policy into the WRCLC policy analytical framework, to explore the effects of policy synergy on cultivated land security in townships. The main findings are as follows:

(1) After the implementation of WRCLC, pilot townships saw significant improvements in both the quantity and quality of cultivated land, further ensuring cultivated land security. This conclusion remains valid after a series of robustness, endogeneity, and placebo tests. Therefore, Hypothesis 1 is confirmed.

(2) Heterogeneity analysis shows that the policy effects of WRCLC are minimally affected by geographic features, with significant improvements in cultivated land quantity and quality occurring in townships, regardless of terrain conditions. However, there is some heterogeneity in the policy effects across different economic development levels and grain-producing functional zones. Specifically, WRCLC is more effective in improving cultivated land quality in non-grain-producing areas and regions with lower economic development levels.

(3) From the perspective of policy synergy, when the AM policy is synergized with the WRCLC policy, as well as when the AII policy is synergized with the WRCLC policy, cultivated land quantity and quality in townships experience significant improvements. However, the synergy between the RT policy and the WRCLC policy only leads to enhancements in cultivated land quality, without effectively increasing the quantity of cultivated land.

8.2. Policy Implications

Based on the above discussions, the research policy implications are as follows:

(1) Zhejiang Province's WRCLC promotes improvements in the cultivated land security of townships, offering new perspectives for innovating land rehabilitation models and addressing food security issues. The Zhejiang Province should continue to explore and optimize new models of WRCLC at the township level, while further promoting the establishment of pilot programs across the country. In the process of policy implementation, it is essential to base actions on the protection of basic farmland and ecological red lines. Measures such as the consolidation of agricultural land and construction land, along with ecological protection and restoration efforts, should be employed to enhance the role of land consolidation in ensuring cultivated land security.

(2) Through a heterogeneity analysis, it has been found that the impact of WRCLC in Zhejiang Province on cultivated land security varies based on geographical characteristics, regional economic development levels, and grain-producing functional zones. In the subsequent policy implementation, particular attention should be paid to improving cultivated land quality in economically developed areas and major grain-producing regions, avoiding an imbalanced focus solely on quantity at the expense of quality.

(3) WRCLC, as a systematic project encompassing all elements and processes, can play a synergistic role with relevant agricultural industry policies during its implementation, promoting cultivated land security. First, it is essential to promote the synergy between the AM policy and the WRCLC policy, advancing the concentrated, contiguous rehabilitation of cultivated land and large-scale operations. This will improve the input structure of production factors through agricultural mechanization, ensuring the sustainable use of cultivated land. Second, the government should utilize the policy synergy between the AII policy and the WRCLC policy. To improve the effectiveness of the use of cultivated land resources, the government ought to support the internal integration of the agricultural sector. Additionally, the government should promote the extension of the agricultural value chain to facilitate the adoption of green agricultural technologies that improve cultivated land quality. Finally, during the synergic advancement of the RT policy and the WRCLC policy, the government should place a high emphasis on cultivated land protection, strengthening the management of both the quantity and quality of cultivated land. The government should establish a negative list based on field investigations, and strictly review the approval process for tourism construction land to ensure that cultivated land resources are not excessively occupied. Simultaneously, during the implementation of WRCLC, the government should reasonably plan tourism land and related construction projects, optimize the spatial layout of the tourism industry, enhance land use efficiency, and achieve a win-win situation for tourism development and cultivated land protection. Furthermore, the government should establish and improve the land transfer system, encourage part-time farmers to participate in land transfers, and promote large-scale farming operations, thereby improving the efficiency and sustainability of land use.

8.3. Research Limitations and Prospects

This study, based on WRCLC, expands the research on the relationship between land consolidation and cultivated land security. It employs a DML approach to scientifically evaluate the policy effects of WRCLC. From a policy synergy perspective, it explores the impact of the synergy between the WRCLC policy and other agricultural industry policies on cultivated land security. While this study has made certain contributions, several limitations remain, warranting further investigation. Firstly, the mechanisms through which WRCLC influences cultivated land security are complex and multifaceted, involving factors such as production, livelihood, and ecology. Future research should delve deeper into the interactions between these factors to obtain a more comprehensive understanding and develop a more systematic theoretical framework. Secondly, this study's sample is limited to Zhejiang Province, thus, the generalizability of the results is constrained by regional limitations and the lack of sample diversity. Subsequent research should consider

expanding the sample to include data from townships across the country, in order to better explore the effects of WRCLC on cultivated land security, thereby providing more comprehensive and representative empirical analysis. Lastly, the influence of multiple factor combinations on a single outcome is systematic and complex, making it difficult to conduct a detailed analysis using the interactive terms approach. Future research could consider adopting qualitative comparative analysis (QCA) to uncover the specific configuration pathways through which different factor combinations affect cultivated land security. Additionally, based on causal asymmetry, the QCA method could be used to identify the core conditions that lead to low levels of cultivated land security, thus providing theoretical insights for optimizing the WRCLC policy.

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Notes

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References

1. Li, Q.; Liu, G. Is land nationalization more conducive to sustainable development of cultivated land and food security than land privatization in post-socialist Central Asia? *Glob. Food Secur.* **2021**, *30*, 100560. [CrossRef]
2. Ling, L.; Tang, H.; Chen, X.; Li, S.; Han, X. Spatial zoning and effect evaluation of county high-standard farmland siting delineation for sustainable cultivated land use in China: A case study in Dali, Shaanxi. *Ecol. Indic.* **2024**, *167*, 112647. [CrossRef]
3. Kinnunen, P.; Guillaume, J.H.A.; Taka, M.; D’odorico, P.; Siebert, S.; Puma, M.J.; Jalava, M.; Kummu, M. Local food crop production can fulfil demand for less than one-third of the population. *Nat. Food* **2020**, *1*, 229–237. [CrossRef]
4. Lu, D.; Wang, Z.; Su, K.; Zhou, Y.; Li, X.; Lin, A. Understanding the impact of cultivated land-use changes on China’s grain production potential and policy implications: A perspective of non-agriculturalization, non-grainization, and marginalization. *J. Clean. Prod.* **2024**, *436*, 140647. [CrossRef]
5. Deng, X.; Huang, J.; Rozelle, S.; Zhang, J.; Li, Z. Impact of urbanization on cultivated land changes in China. *Land Use Policy* **2015**, *45*, 1–7. [CrossRef]
6. Yao, Z.; Zhang, L.; Tang, S.; Li, X.; Hao, T. The basic characteristics and spatial patterns of global cultivated land change since the 1980s. *J. Geogr. Sci.* **2017**, *27*, 771–785. [CrossRef]
7. Li, W.; Wang, D.; Liu, S.; Zhu, Y. Measuring urbanization-occupation and internal conversion of peri-urban cultivated land to determine changes in the peri-urban agriculture of the black soil region. *Ecol. Indic.* **2019**, *102*, 328–337. [CrossRef]
8. Karthikeyan, L.; Chawla, I.; Mishra, A.K. A review of remote sensing applications in agriculture for food security: Crop growth and yield, irrigation, and crop losses. *J. Hydrol.* **2020**, *586*, 124905. [CrossRef]
9. Chen, X.; Lin, C.; Hou, X.; Wu, Z.; Yan, G.; Zhu, C. The impact of land consolidation on arable land productivity: A differentiated view of soil and vegetation productivity. *Agric. Ecosyst. Environ.* **2022**, *326*, 107781. [CrossRef]
10. Qi, X.; Fu, Y.; Wang, R.Y.; Ng, C.N.; Dang, H.; He, Y. Improving the sustainability of agricultural land use: An integrated framework for the conflict between food security and environmental deterioration. *Appl. Geogr.* **2018**, *90*, 214–223. [CrossRef]
11. Liu, L.; Zhou, D.; Chang, X.; Lin, Z. A new grading system for evaluating China’s cultivated land quality. *Land Degrad. Dev.* **2020**, *31*, 1482–1501. [CrossRef]
12. Sun, X.; Xiang, P.; Cong, K. Research on early warning and control measures for arable land resource security. *Land Use Policy* **2023**, *128*, 106601. [CrossRef]
13. Uisso, A.M.; Tanrivermis, H. Driving factors and assessment of changes in the use of arable land in Tanzania. *Land Use Policy* **2021**, *104*, 105359. [CrossRef]

14. Yawson, D.O. Estimating virtual land use under future conditions: Application of a food balance approach using the UK. *Land Use Policy* **2021**, *101*, 105132. [CrossRef]
15. Chen, L.; Zhao, H.; Song, G.; Liu, Y. Optimization of cultivated land pattern for achieving cultivated land system security: A case study in Heilongjiang Province, China. *Land Use Policy* **2021**, *108*, 105589. [CrossRef]
16. Perrin, C.; Clément, C.; Melot, R.; Nougaredes, B. Preserving farmland on the urban fringe: A literature review on land policies in developed countries. *Land* **2020**, *9*, 223. [CrossRef]
17. Molnárová, K.J.; Sklenička, P.; Bohnet, I.C.; Lowther-Harris, F.; Brink, A.; Moghaddam, S.M.; Fanta, V.; Zástěra, V.; Azadi, H. Impacts of land consolidation on land degradation: A systematic review. *J. Environ. Manag.* **2023**, *329*, 117026. [CrossRef]
18. Guo, Y.; Wang, J. Land Consolidation in Rural China: Historical Stages, Typical Modes, and Improvement Paths. *Land* **2023**, *12*, 491. [CrossRef]
19. Fan, Y.; Jin, X.; Zhang, X.; Sun, Y.; Han, B. Mechanism Analysis and Case Study of Comprehensive Land Consolidation in the Whole Region from the Perspective of Rural Reconstruction. *China Land Sci.* **2021**, *35*, 109–118. [CrossRef]
20. Zhou, X.; Shen, D.; Gu, X.; Li, X.; Zhang, S. Comprehensive Land Consolidation in the Whole Region of Metropolis and Multifunctionality of Cultivated Land: An Analysis Based on the “Context-Structure-Behavior-Outcome” Framework. *China Land Sci.* **2021**, *35*, 94–104. [CrossRef]
21. Ao, J.; Zhang, F.; Li, H.; Wu, X.; Xie, Z.; Li, P.; Zhang, T. Changes in Cultivated Land and Its Benefit Evaluation Before and After Comprehensive Land Consolidation in the Whole Region of the Western Sichuan Plain. *J. China Agric. Univ.* **2020**, *25*, 108–119. [CrossRef]
22. Liu, Y.; Dai, L.; Long, H. Theories and practices of comprehensive land consolidation in promoting multifunctional land use. *Habitat Int.* **2023**, *142*, 102964. [CrossRef]
23. Yao, H. Research on the Linkage between Land Consolidation and Rural Industrial Development Based on Land Spatial Planning. *Acad. J. Humanit. Soc. Sci.* **2022**, *5*, 51–56. [CrossRef]
24. Wang, G.; Li, X.; Gao, Y.; Zeng, C.; Wang, B.; Li, X.; Li, X. How does land consolidation drive rural industrial development? Qualitative and quantitative analysis of 32 land consolidation cases in China. *Land Use Policy* **2023**, *130*, 106664. [CrossRef]
25. Zheng, J. Governance of Land Fragmentation through Village-Community Coordination: Mechanisms and Benefits—A Case Study of “Small Fields into Large Fields” in Anhui Province. *J. Nanjing Agric. Univ. (Soc. Sci. Ed.)* **2024**, *24*, 99–109. [CrossRef]
26. Zhang, D.; Yu, L.; Wang, W. Promoting effect of whole-region comprehensive land consolidation on rural revitalization from the perspective of farm households: A China study. *Land* **2022**, *11*, 1854. [CrossRef]
27. Li, Y.; Wu, W.; Liu, Y. Land consolidation for rural sustainability in China: Practical reflections and policy implications. *Land Use Policy* **2018**, *74*, 137–141. [CrossRef]
28. Zhou, Y.; Li, X.; Liu, Y. Cultivated land protection and rational use in China. *Land Use Policy* **2021**, *106*, 105454. [CrossRef]
29. Liu, B.; Xie, Y.; Li, Z.; Liang, Y.; Zhang, W.; Fu, S.; Yin, S.; Wei, X.; Zhang, K.; Wang, Z.; et al. The assessment of soil loss by water erosion in China. *Int. Soil Water Conserv. Res.* **2020**, *8*, 430–439. [CrossRef]
30. Liu, X.; Cai, Z.; Xu, Y.; Zheng, H.; Wang, K.; Zhang, F. Suitability evaluation of cultivated land reserved resources in arid areas based on regional water balance. *Water Resour. Manag.* **2022**, *36*, 1463–1479. [CrossRef]
31. Fang, H. Effect of soil conservation measures and slope on runoff, soil, TN, and TP losses from cultivated lands in northern China. *Ecol. Indic.* **2021**, *126*, 107677. [CrossRef]
32. Lambin, E.F.; Meyfroidt, P.; Rueda, X.; Blackman, A.; Börner, J.; Cerutti, P.O.; Dietsch, T.; Jungmann, L.; Lamarque, P.; Lister, J.; et al. Effectiveness and synergies of policy instruments for land use governance in tropical regions. *Glob. Environ. Chang.* **2014**, *28*, 129–140. [CrossRef]
33. Zhou, X.; Ma, W. Agricultural mechanization and land productivity in China. *Int. J. Sustain. Dev. World Ecol.* **2022**, *29*, 530–542. [CrossRef]
34. Lu, H.; Xie, H.; Yao, G. Impact of land fragmentation on marginal productivity of agricultural labor and non-agricultural labor supply: A case study of Jiangsu, China. *Habitat Int.* **2019**, *83*, 65–72. [CrossRef]
35. Wang, X.; Yamauchi, F.; Huang, J.; Rozelle, S. What constrains mechanization in Chinese agriculture? Role of farm size and fragmentation. *China Econ. Rev.* **2020**, *62*, 101221. [CrossRef]
36. Ma, W.; Zhu, Z.; Zhou, X. Agricultural mechanization and cropland abandonment in rural China. *Appl. Econ. Lett.* **2022**, *29*, 526–533. [CrossRef]
37. Zhu, Y.; Zhang, Y.; Piao, H. Does agricultural mechanization improve agricultural environment efficiency? Evidence from China’s planting industry. *Environ. Sci. Pollut. Res.* **2022**, *29*, 53673–53690. [CrossRef]
38. Tian, X.; Li, W.; Li, R. The Environmental Effects of Agricultural Mechanization: Evidence from the Agricultural Machinery Purchase Subsidy Policy. *Chin. Rural Econ.* **2021**, *09*, 95–109.
39. Han, H.; Yang, D. Research on the Spatial Spillover Effect of Agricultural Industry Agglomeration on the Growth of Agricultural Green Total Factor Productivity. *J. Arid Land Resour. Environ.* **2023**, *37*, 29–37. [CrossRef]
40. Zhang, Y.; Huang, Y. Research on the Impact of Geographic Indication Brand Participation on the Quality and Safety of Agricultural Products. *J. Huazhong Agric. Univ. (Soc. Sci. Ed.)* **2022**, *05*, 123–135. [CrossRef]
41. Zhu, G.; Jiao, L.; Liu, X. Industry Chain Participation, Technology Choice, and Farmers’ Green Production Behavior. *Econ. Rev.* **2022**, *08*, 88–97. [CrossRef]

42. Qiao, W.; Chai, Y.; Wang, J.; Li, C. Analysis of the Process and Mechanism of Land Use Transformation in Tourism-Oriented Rural Areas in the Suburbs of Metropolis: A Case Study of She Village in the Suburbs of Nanjing. *Prog. Geogr.* **2024**, *43*, 1060–1073. [CrossRef]
43. He, S.; Fang, X.; Yang, G. Can Comprehensive Land Consolidation Promote Rural Industrial Transformation? Evidence from Some Villages in Hubei Province. *China Land Sci.* **2022**, *36*, 107–117. [CrossRef]
44. Weyland, F.; Colacci, P.; Cardoni, A.; Estavillo, C. Can rural tourism stimulate biodiversity conservation and influence farmer's management decisions? *J. Nat. Conserv.* **2021**, *64*, 126071. [CrossRef]
45. Ammirato, S.; Felicetti, A.M.; Raso, C.; Pantera, B.A.; Violi, A. Agritourism and sustainability: What we can learn from a systematic literature review. *Sustainability* **2020**, *12*, 9575. [CrossRef]
46. Guo, Z.; Zeng, Y. Optimization of County-Level Government Supply Behavior and Performance Improvement Mechanism for Agricultural Infrastructure: A Case Study of High-Standard Farmland Construction. *J. Northwest AF Univ. (Soc. Sci. Ed.)* **2023**, *23*, 146–154. [CrossRef]
47. Zhou, X.; Liang, Y.; Li, X.; Chai, Y. The spatiotemporal evolution and driving factors of farmland system health: Taking the middle and lower reaches of the Yangtze River as an example. *J. Nat. Resour.* **2024**, *39*, 1174–1192. [CrossRef]
48. Park, S.; Lim, C.H.; Kim, S.J.; Isaev, E.; Choi, S.E.; Lee, S.D.; Lee, W.K. Assessing climate change impact on cropland suitability in Kyrgyzstan: Where are potential high-quality cropland and the way to the future. *Agronomy* **2021**, *11*, 1490. [CrossRef]
49. Ke, N.; Zhang, X.; Lu, X.; Kuang, B.; Jiang, B. Regional disparities and influencing factors of eco-efficiency of arable land utilization in China. *Land* **2022**, *11*, 257. [CrossRef]
50. Wang, R.; Peng, F.; Li, W.; Wang, C. Can Breaking Rigid Payment Guarantees Reduce Corporate Financing Costs? *Manag. World* **2022**, *38*, 42–64. [CrossRef]
51. Zhang, T.; Li, J. Network Infrastructure, Inclusive Green Growth, and Regional Disparities: Causal Inference Based on Double Machine Learning. *J. Quant. Tech. Econ.* **2023**, *40*, 113–135. [CrossRef]
52. Chernozhukov, V.; Chetverikov, D.; Demirer, M.; Duflo, E.; Hansen, C.; Newey, W.; Robins, J. Double/debiased machine learning for treatment and structural parameters. *Econom. J.* **2018**, *21*, C1–C68. [CrossRef]
53. Borusyak, K.; Jaravel, X.; Spiess, J. Revisiting event-study designs: Robust and efficient estimation. *Rev. Econ. Stud.* **2024**, *91*, 3253–3285. [CrossRef]
54. De Chaisemartin, C.; d'Haultfoeuille, X. Two-way fixed effects estimators with heterogeneous treatment effects. *Am. Econ. Rev.* **2020**, *110*, 2964–2996. [CrossRef]
55. Gardner, J. Two-stage differences in differences. *arXiv* **2022**, arXiv:2207.05943. [CrossRef]
56. Cengiz, D.; Dube, A.; Lindner, A.; Zipperer, B. The effect of minimum wages on low-wage jobs. *Q. J. Econ.* **2019**, *134*, 1405–1454. [CrossRef]
57. Tang, F. China's Local Laffer Curve: Autonomous Reduction in Deed Tax Rates and Urban Fiscal Capacity. *Econ. Sci.* **2024**, *03*, 42–69. [CrossRef]
58. Sun, L.; Abraham, S. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *J. Econom.* **2021**, *225*, 175–199. [CrossRef]
59. Callaway, B.; Sant'Anna PH, C. Difference-in-differences with multiple time periods. *J. Econom.* **2021**, *225*, 200–230. [CrossRef]
60. Xu, G.; Zhao, C.; Liu, Y.; Wan, P. Research on the trade-offs/synergies of multifunctional cultivated land in rural tourism destinations from a new perspective on tourism resources: A case study of Zhongyuan township, Jiangxi province. *J. Nat. Resour.* **2024**, *39*, 804–822. [CrossRef]
61. Yin, Q.; Sui, X.; Ye, B.; Zhou, Y.; Li, C.; Zou, M.; Zhou, S. What role does land consolidation play in the multi-dimensional rural revitalization in China? A research synthesis. *Land Use Policy* **2022**, *120*, 106261. [CrossRef]
62. Cai, X.; Yang, S. Exploration on the Path of Whole-region Comprehensive Land Consolidation under the Background of Rural Revitalization. *Asian Agric. Res.* **2023**, *15*, 1–6. [CrossRef]
63. You, H.; Zhang, J.; Xia, S. Land optimization for comprehensive regional land consolidation based on the trade-off between ecological value and the realization potential of ecological product value. *J. Nat. Resour.* **2023**, *38*, 2950–2965. [CrossRef]
64. Jin, X.; Luo, X.; Zhou, Y. On the basic logic, key issues, and main relationships of comprehensive regional land consolidation. *China Land Sci.* **2022**, *36*, 1–12. [CrossRef]
65. Demirdogen, A. Land consolidation, cropland use, and vegetation productivity. *Agribusiness* **2024**, *40*, 641–660. [CrossRef]
66. Yang, Y.; Yuan, X.; An, J.; Su, Q.; Chen, B. Drivers of ecosystem services and their trade-offs and synergies in different land use policy zones of Shaanxi Province, China. *J. Clean. Prod.* **2024**, *452*, 142077. [CrossRef]
67. Kosow, H.; Weimer-Jehle, W.; León, C.D.; Minn, F. Designing synergetic and sustainable policy mixes—a methodology to address conflictive environmental issues. *Environ. Sci. Policy* **2022**, *130*, 36–46. [CrossRef]
68. Yang, H.; Zou, R.; Hu, Y.; Wang, L.; Xie, Y.; Tan, Z.; Zhu, Z.; Zhu, A.X.; Gong, J.; Mao, X. Sustainable utilization of cultivated land resources based on “element coupling-function synergy” analytical framework: A case study of Guangdong, China. *Land Use Policy* **2024**, *146*, 107316. [CrossRef]
69. Wei, C.; Wu, Z.; Xing, J.; Jin, G. Trade-off or synergy? Dynamic analysis and policy insights on land use functions in China. *Environ. Impact Assess. Rev.* **2024**, *105*, 107399. [CrossRef]

70. Ge, K.; Zou, S.; Lu, X.; Ke, S.; Chen, D.; Liu, Z. Dynamic evolution and the mechanism behind the coupling coordination relationship between industrial integration and urban land-use efficiency: A case study of the Yangtze River Economic zone in China. *Land* **2022**, *11*, 261. [CrossRef]
71. Ghadami, M.; Dittmann, A.; Pazhuhan, M.; Firouzjaie, N.A. Factors affecting the change of agricultural land use to tourism: A case study on the southern coasts of the Caspian Sea, Iran. *Agriculture* **2022**, *12*, 90. [CrossRef]
72. Li, Y.; Filimonau, V.; Wang, L.; Cheng, S. Tourist food consumption and its arable land requirements in a popular tourist destination. *Resour. Conserv. Recycl.* **2020**, *153*, 104587. [CrossRef]
73. Lupi, C.; Giaccio, V.; Mastronardi, L.; Giannelli, A.; Scardera, A. Exploring the features of agritourism and its contribution to rural development in Italy. *Land Use Policy* **2017**, *64*, 383–390. [CrossRef]
74. Yuan, H.; Wang, Q. Evolution model of tourism and ecological symbiosis and ecological security assessment: A case study of the key ecological function area in Huangshan, Anhui Province, China. *Tour. Trib.* **2022**, *37*, 25–38. [CrossRef]
75. Wang, J.; Yuan, J.; Wang, L. Sustainable development of tourism from the perspective of food security: Scientific connotation and strategic orientation. *Tour. Trib.* **2023**, *38*, 5–8. [CrossRef]

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Article

Digital Economy, Factor Allocation, and Resilience of Food Production

Yue Xie ¹, Ruikuan Yao ^{2,*}, Haitao Wu ² and Mengding Li ^{3,*}¹ Institute of Geographical Sciences, Henan Academy of Sciences, Zhengzhou 450052, China; xieyue@igs-has.cn² School of Business Administration, Zhongnan University of Economics and Law, Wuhan 430073, China; z0003961@zuel.edu.cn³ School of Economics and Management, Hubei University of Arts and Science, Xiangyang 441053, China

* Correspondence: yaoruikuan@stu.zuel.edu.cn (R.Y.); limd@hbuas.edu.cn (M.L.); Tel.: +86-199-3948-1411 (R.Y.)

Abstract: This paper systematically explores the impact of the digital economy on the resilience of food production and its mechanism of action based on panel data from 30 provincial-level administrative regions in China from 2011 to 2022. This study shows that the digital economy significantly enhances the ability of the food production system to cope with external shocks by improving resource allocation efficiency and mitigating factor mismatch. Specifically, the digital economy directly improves the stability and resilience of food production through the widespread application of digital technology; at the same time, it indirectly contributes to the enhancement of food production resilience by alleviating the mismatch of labor and capital factors. Heterogeneity analyses show that there are regional differences in the impact of the digital economy, in which the main food-producing regions benefit more significantly due to their agricultural resource advantages and policy support, and the improvement of food production resilience in the central region is particularly prominent. This study provides an important theoretical basis and practical reference for exploring the potential of the application of digital economy in agriculture and formulating policies to enhance food production resilience.

Keywords: digital economy; factor mismatch; food production resilience; food security

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1. Introduction

Food production forms the bedrock of economic development, while food security is fundamental not only to social stability and public well-being, but also to sustainable economic and social progress. For a country as populous as China, the importance of food security is even more self-evident. In 2023, China's total food output reached 695.41 million tons, achieving 20 consecutive years of abundant harvests. This milestone highlights the success of supportive government policies and ongoing innovations in agricultural technology. Food security has consistently been a strategic priority for China, with central government policy documents repeatedly emphasizing the critical role of food production. However, the world is undergoing unprecedented transformations, accelerated by the frequent occurrence of geopolitical conflicts, public health emergencies, and intensified climate change. These factors pose significant challenges to food production [1], threatening the stability of food supplies and drawing increased attention to the resilience of food production systems. Food production resilience refers to the capacity of the system to maintain stability and recover rapidly from external shocks such as climate change, natural disasters, and market volatility. It involves not only stable food output, but also the continuity of supply chains and the safeguarding of farmers' incomes [2]. Establishing a

resilient food production system capable of effectively responding to uncertainty and risk is crucial to ensuring food security under complex conditions. As external challenges grow increasingly intricate, enhancing resilience requires exploring innovative technologies and new models beyond traditional policy approaches [3].

The rise of the digital economy presents new opportunities for enhancing the resilience of food production. The digital economy, characterized by the use of information technology and data resources, relies on technologies such as big data, artificial intelligence, and blockchain to reshape traditional production and consumption models, optimizing resource allocation. Beyond its transformative impact on the manufacturing and service industries, the digital economy is increasingly demonstrating immense potential in agricultural production [4]. At this pivotal moment of technological innovation and industrial restructuring, the Chinese central government has prioritized the integration of the digital economy with traditional agriculture. Policies like the Rural Revitalization Strategy Plan (2018–2022) and the Digital Agriculture and Rural Development Plan (2019–2025) explicitly promote the acceleration of agricultural informatization and digital transformation, the establishment of a modern agricultural industry system, and the enhancement of agriculture's comprehensive competitiveness to ensure food security. Can the digital economy truly drive improvements in food production resilience? If so, how can we maximize its positive spillover effects to enhance food production resilience? Furthermore, how do these effects vary across different regions? These questions demand urgent scientific analysis. Assessing food production resilience accurately and evaluating the digital economy's potential as a driver of resilience from a factor allocation perspective hold significant theoretical and practical implications for future policies. Such analysis will contribute to building resilient food systems, ensuring food security, and advancing the construction of a strong agricultural nation. Based on this, this study explores the relationship between the digital economy and the resilience of food production with the help of the panel data of 30 provincial-level administrative regions in China from 2011 to 2022, using a two-way fixed-effects model, so as to reveal in depth the effect and mechanism of the digital economy on the resilience of food production.

2. Literature Review

The current literature on topics related to this study follows three primary lines of inquiry.

2.1. Relevant Studies on the Digital Economy

The first line of inquiry examines the digital economy itself. As a major driving force behind global economic transformation, the digital economy encompasses a wide range of digital technologies, including the internet, mobile networks, e-commerce, and artificial intelligence. These technologies significantly reshape global economic structure and influence development trajectories by enhancing productivity, optimizing resource allocation, and accelerating innovation [5]. With rapid advancements in digital technologies, academic discussions on the digital economy have grown increasingly sophisticated, encompassing multiple dimensions, from foundational theories to practical applications. In foundational research, scholars have focused on defining and constructing theories around the digital economy. At its core, the digital economy is rooted in advancements in information and communication technology (ICT), dating back to the 1950s, and has expanded significantly with the rise of the internet and mobile technologies. It spans not only traditional economic activities related to production and consumption, but also emerging areas such as the platform economy and the attention economy [6]. This theoretical framework has gained broad support in the literature, with scholars emphasizing how the digital economy is transforming market operations and reshaping competitive dynamics, allowing firms to

innovate and adapt rapidly in the global market [7]. In terms of impact mechanisms, the rapid growth of the digital economy is largely driven by economies of scale and the spillover effects of the ICT industry. By enhancing the efficiency of traditional industries, the digital economy not only accelerates overall economic growth but also brings about fundamental changes in production and consumption patterns [8]. This transformation is not limited to developed economies; it also has a profound impact on developing countries, providing unique opportunities to leapfrog traditional development pathways [9].

To accurately assess the contribution of the digital economy to national and regional economies, scholars have developed various measurement methods, ranging from foundational theories to specific indicator frameworks. One approach is the “Digital Economy Satellite Account” (DESA), which integrates digital products and services into the national economic accounting system. By constructing Digital Supply and Use Tables (DSUT), this method captures the value-added processes of “intangible assets” and “free digital services” within the digital economy, providing a foundation for more comprehensive statistical evaluation [10]. Another method focuses on applying the Net Present Value (NPV) approach to valuing data assets. By treating data as a non-productive asset, this approach facilitates a more precise evaluation of its long-term economic benefits [11]. Regarding indicator construction, some studies have developed comprehensive evaluation index systems for the digital economy, assessing its performance across multiple dimensions. By introducing a multidimensional evaluation framework that includes “digital users”, “digital platforms”, “digital innovation”, and “digital industries”, researchers have constructed regional digital economy indices to reflect disparities in development across regions [12]. This method quantifies the digital economy development levels of various provinces and cities and highlights the uneven development of the digital economy between regions. Data mining technologies also offer new perspectives for measuring the digital economy. Through the application of big data and deep learning techniques, some studies have proposed data-mining-based methods for measuring the digital economy. By analyzing and processing big data, this approach better reflects trends and changes in digital economic development across regions, particularly gaining traction in studies of China’s digital economy [13]. At the international level, regions such as the European Union have adopted the “Digital Economy and Society Index” (DESI) to monitor digital economy development among member countries. DESI encompasses not only the use of digital technologies, but also the impact of the digital economy on societal development, providing a comprehensive indicator system for assessing the contribution of digital transformation to the overall economy [14].

2.2. Relevant Studies on the Agricultural Resilience and Food Production Resilience

The second area of focus is research on agricultural and food production resilience. Agricultural resilience is a multifaceted concept that captures the ability of agricultural systems to endure and adapt to natural, social, and economic disruptions. Early research on agricultural resilience primarily concentrated on the sustainability of agro-ecosystems, investigating how to preserve the fundamental functions of agricultural production systems amidst environmental changes. However, as global climate change, market volatility, and social dynamics increasingly influence agriculture, scholars have recognized that agricultural resilience extends beyond ecological systems. It now encompasses the adaptive and recovery capacities of the broader socio-ecological framework [15]. In developing agricultural resilience, social and economic dimensions have emerged as pivotal areas of study. Assessing agricultural resilience requires an integrated approach that considers ecological shifts alongside the complexities of agricultural supply chains and the influence of socio-economic structures [16]. Generally, agricultural resilience consists of three essential components: resistance, adaptability, and recovery capacity. Resistance pertains to

a system's capacity to remain stable in response to short-term disturbances, adaptability highlights the system's evolving responses to long-term environmental changes, and recovery capacity reflects the agricultural system's ability to safeguard its core functions through structural adjustments amid significant external disruptions [17].

In recent years, scholars have advocated for agricultural resilience frameworks that account for multi-scale complexities—spanning farm, regional, and national levels—and examine the interconnections among ecological, social, and economic factors from a comprehensive perspective. This approach is essential for addressing future uncertainties in agriculture effectively [18]. Food production resilience, originally an offshoot of agricultural resilience, has evolved significantly over time. Early studies primarily focused on the capacity of food production systems to sustain food supply amidst environmental challenges like natural disasters and climate change. With the intensification of global climate change, food production resilience has been redefined as a more comprehensive concept that integrates production management, supply chain stability, and socio-economic considerations [19]. As this field has developed, research on food production resilience has expanded from narrow, single-dimensional analyses to multidimensional perspectives that encompass not only ecosystem health, but also social equity and economic efficiency [20]. The globalization of food trade has further complicated food production systems, particularly in terms of supply chain dynamics. Enhancing the resilience of these systems through policy initiatives, market adaptations, and other strategic measures has become crucial. Increasingly, researchers are highlighting the importance of harmonizing resilience across both regional and global food production systems to address resilience disparities [21].

With the progression of agricultural industrialization, food production systems have become increasingly dependent on centralized supply chain structures. While this intensive production model enhances efficiency, it also amplifies vulnerability to external shocks, including natural disasters and market fluctuations [22]. The resilience of contemporary food production systems hinges not only on ecological and economic stability, but also on factors such as social organization, policy backing, and market dynamics. Enhancing food production resilience involves fostering diversified agricultural models and adaptive supply chain management, which bolsters adaptability across scales—from local to global—to secure food availability [18]. Assessing food production resilience demands a comprehensive approach that integrates ecological, economic, and social dimensions. Recent research has produced various indicator frameworks and tools to evaluate resilience in food production. Ecologically, resilience is assessed through the diversity of land-use practices and the sustainability of ecosystem services. Economically, key indicators include market price stability and resource use efficiency. Social resilience, meanwhile, is shaped by policy support, technological innovation, and the effectiveness of social organization, all of which influence the capacity of food production systems to adapt and respond to external shocks [23,24].

2.3. Relevant Studies on the Impact of the Digital Economy on the Resilience of Food Production

The third area of research explores the impact of the digital economy on food production resilience. With the rapid expansion of the digital economy, various digital technologies are becoming increasingly integrated into agriculture, significantly influencing the resilience of food production systems. Tools such as big data, the Internet of Things (IoT), and artificial intelligence (AI) enhance the adaptive capacity of food production systems, enabling them to respond more effectively to external shocks, including climate change, market fluctuations, and policy shifts. Specifically, these digital tools optimize resource efficiency and streamline production processes, which not only reduce resource waste, but also help mitigate environmental impacts [4]. Data-driven management practices also enable more

precise environmental predictions, assisting in minimizing the effects of natural disasters on food production [25]. Economically, the digital economy greatly improves the efficiency and profitability of food production. Digital supply chain management has enhanced transparency and flexibility within supply chains, reducing information asymmetry. By facilitating better access to market data, digital tools empower agricultural producers to align their production decisions with market demand, thereby lowering the risk of economic losses [26]. On a social level, digital technologies have advanced knowledge dissemination and fostered innovation within agricultural communities. Digital platforms not only provide farmers with technical support and policy updates, but also enhance collaboration within agricultural networks, strengthening the social resilience of these systems when facing external challenges [27]. The digital economy enhances food production resilience through several mechanisms. First, advancements in digital technology support precision agriculture and smart farming, optimizing resource utilization within food production systems. This improved efficiency allows farmers to better respond to environmental changes and natural disaster risks [28]. Second, the digital economy bolsters the transparency and flexibility of agricultural supply chains. Digital supply chain management systems enhance the efficiency of each stage—production, transportation, and sales—enabling rapid adaptation to market shifts and unforeseen events, thereby strengthening supply chain resilience. Real-time supply chain monitoring allows farmers and agricultural businesses to adjust promptly based on market demand, mitigating economic losses due to overproduction or shortages [29]. Additionally, digital platforms and technology facilitate faster dissemination and adoption of agricultural innovations. Through these platforms, farmers gain easier access to information on emerging technologies, accelerating their practical application and boosting the innovation and adaptability of food production systems. This mechanism for technology dissemination not only raises production efficiency, but also strengthens the system's capacity to adapt to environmental shifts [30].

Existing research offers valuable insights for this study; however, certain limitations persist in research perspectives and methodologies. First, a localized theoretical framework for food production resilience, specifically suited to China's distinctive agricultural and socio-economic context, remains underdeveloped. Further investigation is needed to refine evaluation methods for food production resilience and to explore the mechanisms influencing it. Second, much of the literature has examined the digital economy's impact on food production resilience, primarily from the perspective of agricultural system factors, such as technological innovation and risk mitigation, often overlooking other critical factors in the production process. This paper seeks to address these gaps by making two key contributions: 1. Using a time-series Markov process model to quantitatively measure regional food production resilience, this study analyzes how digital-era transformations drive resilience through the digital economy, thereby contributing to research on the digital economy's role in agriculture. 2. By empirically examining the digital economy's impact on food production resilience and its internal mechanisms, this study offers new empirical evidence to inform discussions on digital economy development and strategies for enhancing industry resilience.

3. Theoretical Analysis and Research Hypotheses

3.1. *Direct Effects of the Digital Economy on Food Production Resilience*

The emergence and rapid development of the digital economy have had substantial direct effects on agricultural production. From an economic standpoint, technological progress and gains in total factor productivity are key drivers of economic growth. The Solow Growth Model posits technological advancement as a critical factor for long-term economic growth, with technology functioning as an exogenous variable that plays a deci-

sive role in output increases [31]. Digital technologies introduce exogenous technological advancements to agriculture, enabling a shift from labor-intensive to technology-intensive production models. This transition improves agricultural output efficiency and stability, minimizes production waste, and directly strengthens the food production system's resilience against natural disasters and resource limitation [4,32]. Additionally, technological innovation drives production transformation, enhancing the adaptability of agricultural systems to external changes. The theory of economies of scale further highlights that as production scales expand, unit production costs decrease, thus boosting efficiency and competitiveness. In grain production, the digital economy fosters economies of scale through optimized supply chain management. Technologies like big data, IoT, and blockchain increase transparency and efficiency within agricultural supply chains, reducing waste and uncertainties in distribution [33]. Digital platforms enable farmers to connect directly with markets, minimizing intermediaries and transaction costs. This streamlined approach facilitates market access for small-scale producers and contributes to a more stable food supply [34]. Digital technologies also facilitate automation and standardization in large-scale production, enabling producers to maintain consistent quality across scale and benefit from economies of scale. This approach, which combines large-scale production with supply chain optimization, enhances the food production system's resilience to external shocks. Furthermore, the digital economy enables more precise supply chain management, reducing logistics and warehousing costs and allowing a broader range of agricultural entities to achieve economies of scale. By expanding market access through e-commerce and other digital channels, the overall efficiency of the grain supply chain improves [35]. Through optimized supply chain processes, the digital economy directly fosters economies of scale in agriculture, strengthening food production resilience [36].

Based on this, Hypothesis 1 is proposed:

Hypothesis 1. *The digital economy can enhance the resilience of food production.*

3.2. Indirect Effects of the Digital Economy on Food Production Resilience

Both formal and informal institutional barriers—such as the urban–rural dual structure and imperfections in factor markets—create substantial mismatches in labor and capital allocation within the agricultural sector [37]. Factor allocation theory and total factor productivity theory emphasize that effectively matching production factors like labor and capital is essential for improving production efficiency. Endogenous growth theory and empirical research further indicate that factor mismatches not only reduce production efficiency, but also hinder long-term economic growth and the resilience of production systems [38–40]. Current research suggests that the digital economy can reduce barriers to factor mobility, facilitating a more rational allocation of resources between urban and rural areas [41]. As shown in Figure 1, on one hand, digital technologies improve labor supply–demand matching in agriculture, significantly reducing labor mismatch. This technological progress enhances agricultural productivity by optimizing production processes and strengthening information flows, which mitigates the adverse effects of labor mismatches on food production resilience. Additionally, with advancements in artificial intelligence and automation, the demand for repetitive labor in agriculture decreases, while the need for highly skilled labor increases, further reducing labor mismatches and enhancing the flexibility and adaptability of food production systems [42]. By improving labor allocation, the digital economy also promotes sustainable agricultural development, stabilizing food production systems when facing external shocks. Moreover, the digital economy spurs the development of financial technology and improves transparency in capital allocation, facilitating more efficient capital flow and utilization, which, in turn,

boosts agricultural production efficiency. Beyond addressing capital mismatches, the digital economy also injects new momentum into sustainable agricultural development. By incorporating digital technologies, capital resources are more effectively directed toward critical stages of agricultural production, thereby enhancing the resilience of food production systems [43].

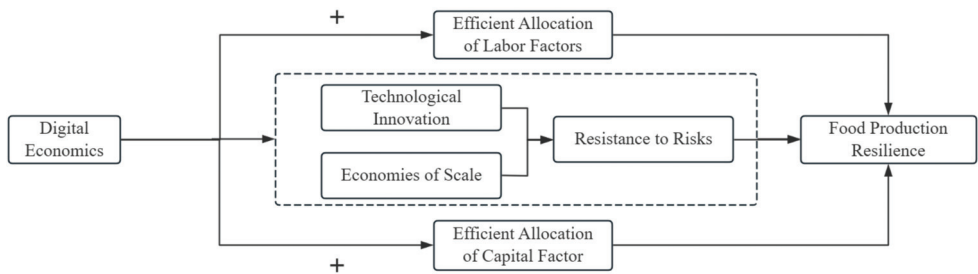


Figure 1. Mechanism by which the digital economy enhances food production resilience.

Accordingly, the following hypotheses are proposed:

Hypothesis 2a. *The digital economy enhances the resilience of food production by mitigating labor factor mismatch.*

Hypothesis 2b. *The digital economy enhances the resilience of food production by mitigating capital factor mismatch.*

4. Research Design

4.1. Variable Selection

4.1.1. Dependent Variable

Using food production resilience (Fpr). combined with the previous analysis, this paper argues that the resilience of food production can be understood as the ability of the food production system to rely on internal and external dynamics to resist internal disturbances and external shocks in order to reshape the new development path, including the pre-disaster resistance, to maintain the stability of the basic functions, the adaptive power in the disaster to adjust or change the mode of production, and the post-disaster reconstruction power for sustainable development. The food production system is a typical complex dynamic system, whose resilience is demonstrated not only by its short-term response to external shocks, but also by its performance over long-term changes. Time series analysis methods can effectively capture the dynamic characteristics of food production, and the Markov process model can reveal the system’s path dependency and self-recovery capabilities. This method allows for a quantitative analysis of the relationship between production volatility and long-term trends, thereby assessing system resilience [44]. The specific steps are as follows:

First, establish the Markov process model. In the food production system, yield changes often exhibit path dependency. This path dependency stems from the accumulation of technology, the use of inputs, and the long-term development of the ecological environment during agricultural production. These factors collectively result in notable continuity and inertia in food production [45]. The Markov process model can effectively describe such dynamic changes. Changes in per capita food production can be represented by the following equation:

$$Y_{it} = \sum_{j=1}^k \beta_M^j Y_{i,t-1} + \gamma_M X_{it} + \varepsilon_{Mit} \quad (1)$$

where Y_{it} represents the per capita food production of region i at time t . $Y_{i,t-1}$ represents the per capita food production in the previous period, reflecting the time dependence of yield; X_{it} represents other variables affecting food production, such as climatic conditions, agricultural policies, and technological inputs; ε_{it} is a random disturbance term. This model can not only capture historical changes in food production, but also predict future yields based on previous data.

Second, calculate the conditional expectation and variance. To further assess the resilience of food production systems across regions, the conditional expectation and conditional variance of food production need to be calculated. The conditional expectation represents the expected value of future food production under given external conditions, reflecting the system's recovery ability in response to external shocks. The conditional variance represents the volatility of food production, while smaller volatility indicates higher system stability. By analyzing the conditional expectation, the future stability of food production can be evaluated, while the conditional variance reflects the potential degree of fluctuation when the system faces external shocks.

Using the assumption of zero mean for the random error term, estimate the conditional expectation prediction value for region i at time t :

$$\mu_{it}^1 = E(Y_{it} | Y_{i,t-1}, X_{it}) = \sum_{j=1}^k \beta_M^j Y_{i,t-1} + \gamma_M X_{it} \quad (2)$$

Derive the second central moment using the residuals. Summarizing previous studies, the residuals of the first central moment are used to estimate the variance equation [46]. The form of the variance equation is as follows:

$$\varepsilon_{Mit}^2 = \sum_{j=1}^k \beta_V^j Y_{i,t-1} + \gamma_V X_{it} + \varepsilon_{Vit} \quad (3)$$

where ε_{Mit}^2 is the square of the first-order residuals, β_V^j represents the coefficient in the variance equation, and γ_V represents the coefficients of other influencing factors.

Similarly, following the assumption of zero mean of the random error term ε_{Vit} , the conditional variance of food production in area i at time t can be estimated:

$$\mu_{it}^2 = \sum_{j=1}^k \beta_V^j Y_{i,t-1} + \gamma_V X_{it} \quad (4)$$

This sets the food security threshold. In this study, the internationally recognized food security baseline (400 kg/person/year) is used as the food security threshold. To measure the capacity of each region to maintain food security at different times, the probability of food production exceeding the security threshold can be calculated using the following formula:

$$Fpr_{it} = \rho_{it} = P(Y_{it} \geq Y^*) = F\left(\frac{Y_{it} - \mu_{it}^1}{\mu_{it}^2}\right) \quad (5)$$

Here, Y^* represents the food security threshold, while F denotes the distribution function (e.g., normal distribution), which calculates the probability that the yield exceeds this security threshold. This paper applies this approach to quantify the capacity of regional food production systems to maintain a stable output under external shocks. That is, the core explanatory variable of the paper is food production resilience (Fpr).

4.1.2. Core Explanatory Variable

Digital Economy Level (Dig): The digital economy level is the main explanatory variable. Building on prior research [47], this study constructs a digital economy evaluation index system based on three dimensions: digital infrastructure, digital industry development, and digital inclusive finance (see Table 1). Digital infrastructure, represented by metrics such as the number of domain names and IPv4 addresses, serves as a crucial foundation for technology application, diffusion, and digital economy growth. Digital industry development, measured by indicators like the number of IT enterprises and websites per 100 enterprises, drives social production efficiency and supports industrial transformation and upgrading. Digital inclusive finance, assessed using the Peking University Digital Inclusive Finance Index, encompasses efficient payment services and accessible financial resources, essential components of the digital economy. These include the breadth of coverage, depth of use, and digitalization indices. The breadth of coverage index measures the geographic and demographic reach of financial services; the depth of use index assesses the actual use and depth of financial services; and the digitization index reflects the level of digitalization and innovation in financial services. All indicators are positive, and their aggregate measurement is achieved via principal component analysis.

Table 1. Evaluation index system for digital economy level.

Primary Indicators	Secondary Indicators	Tertiary Indicators	Indicator Attribute
Digital Economy Level	Digital Infrastructure	Number of domain names (10,000)	+
		Number of IPv4 addresses (10,000)	+
		Number of internet broadband access ports (10,000)	+
		Mobile phone penetration rate (per 100 people)	+
	Digital Industry Development	Length of optical cable per unit area (km/km ²)	+
		Number of information technology companies	+
		Number of companies with websites (per 100 companies)	+
		Proportion of companies engaged in e-commerce activities (%)	+
	Digital Inclusive Finance	E-commerce sales (billion yuan)	+
		Software business revenue (billion yuan)	+
		Breadth of coverage index	+
		Depth of use index	+
		Digitalization index	+

4.1.3. Mechanism Variables

Labor and capital factor mismatch (Lmi and Kmi): The mechanism variables include labor factor mismatch index (Lmi) and capital factor mismatch index (Kmi). With a constant land endowment assumption, this study focuses on the allocation efficiency of labor and capital. Factor mismatch indices serve as key indicators of allocation efficiency. Most existing studies apply the Solow residual method, as described by Bai Junhong and Liu Yuying (2018) [48], to determine the factor mismatch index. Assuming that regional production functions adhere to the constant returns-to-scale Cobb–Douglas (C-D) form, this paper employs a panel model with varying intercepts and slope coefficients to estimate the output elasticities of agricultural capital and labor in each region, subsequently calculating labor and capital factor mismatch indices as follows:

$$Lmi_{it} = 1/\gamma_{li} - 1, Kmi_{it} = 1/\gamma_{ki} - 1 \tag{6}$$

In Equation (6), γ_{li} and γ_{ki} represent the labor and capital price distortion coefficients for region i, respectively, calculated as follows:

$$\gamma_{li} = (\frac{L_i}{L})/(\frac{s_i\beta_{Li}}{\beta_L}), \gamma_{ki} = (\frac{K_i}{K})/(\frac{s_i\beta_{ki}}{\beta_k}) \tag{7}$$

In Equation (7), s_i represents the share of regional agricultural output in the total agricultural output of the entire economy; $\frac{L_i}{L}$ and $\frac{K_i}{K}$ represent the shares of actual labor and capital usage in the total labor and capital usage of the entire economy for the region, respectively; $s_i\beta_{L_i}$ and $s_i\beta_{K_i}$ represent the proportion of labor and capital allocated efficiently in region i , respectively; and β_{L_i} and β_{K_i} denote the output elasticity of labor and capital, respectively, for the region. After calculating the labor price distortion coefficient γ_{L_i} and capital price distortion coefficient γ_{K_i} from Equation (7), the mechanism variables, labor factor mismatch index (Lmi) and capital factor mismatch index (Kmi), of this paper can be calculated by combining them with Equation (6).

Considering that the index may contain negative values, this paper takes the absolute value of the index. Agricultural output involved in the calculation is represented by the total output value of agriculture, forestry, animal husbandry, and fishery; the stock of agricultural capital is measured using the perpetual inventory method, represented by multiplying the proportion of fixed-asset investment in agriculture, forestry, animal husbandry, and fishery to the total social fixed capital stock, with a depreciation rate of 9.6%. The stock of agricultural labor is represented by the number of people employed in agriculture, forestry, animal husbandry, and fishery.

4.1.4. Control Variables

Drawing on the existing literature, this paper includes the following control variables in the regression analysis: industrial structure (Is), level of agricultural mechanization (Aml), fiscal support for agriculture (Fsa), urbanization rate (Ur), and agricultural management scale (Sab). The industrial structure is represented by the share of value added by the primary industry in the region's GDP; the agricultural mechanization level is captured through the logarithm of total agricultural machinery power in the region, as agricultural facilities and equipment can influence producers' operational decisions, thereby impacting food production resilience; and fiscal support for agriculture is measured by the proportion of expenditure on agriculture, forestry, and water affairs relative to the general local government budget. Government support through economic policies and other measures may affect agricultural development, which in turn influences food production resilience; urbanization rate is assessed by the proportion of the urban population, as urbanization can impact food system resilience by altering rural labor structures; and agricultural management scale is represented by the sown area per laborer, a key factor affecting agricultural production efficiency, and thus influencing food production resilience.

4.2. Model Specification

Building on the theoretical analysis above, and accounting for the unique characteristics of the sample data (which passed the Hausman test), this paper employs a fixed effects model to investigate the impact of the digital economy on food production resilience. The model specification is as follows:

$$Fpr_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 Controls_{it} + \mu_i + \omega_t + \varepsilon_{it} \quad (8)$$

In Equation (8), Fpr_{it} and Dig_{it} represent the dependent variable of food production resilience and the explanatory variable of digital economy development level for province i in year t , respectively. $Controls_{it}$ represents other control variables. μ_i and ω_t are dummy variables for province and year, respectively, used to control for individual and time effects, while ε_{it} represents the random disturbance term.

In addition to exploring the direct effect, this paper examines the indirect effect of the digital economy on food production resilience through improvements in factor mismatch. To address the endogeneity concerns between mechanism variables and the dependent

variable—which the mediation effect model cannot fully resolve—and recognizing that an interaction effect model may not comprehensively explain the economic mechanism, this study employs an approach from previous research [49]. Specifically, we directly regress the explanatory variable on the mechanism variable to test for the existence of the mechanism effect. The model specification is as follows:

$$Lmi_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 Controls_{it} + \mu_i + \omega_t + \varepsilon_{it} \tag{9}$$

$$Kmi_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 Controls_{it} + \mu_i + \omega_t + \varepsilon_{it} \tag{10}$$

4.3. Data Sources

This study uses panel data from 30 provinces (including autonomous regions and municipalities) in China for the period of 2011 to 2022. Tibet, Hong Kong, Macau, and Taiwan are excluded due to data availability and comparability constraints. Primary data sources include the China Statistical Yearbook, China Rural Statistical Yearbook, China Rural Management Statistical Annual Report, and individual provincial statistical yearbooks. Data for the “Digital Inclusive Finance Index” is sourced from the Peking University Digital Inclusive Finance Index (2011–2022). Any missing data were supplemented via linear interpolation, and economic indicators were adjusted to 2011 as the base year to ensure comparability. Descriptive statistics for each variable are presented in Table 2.

Table 2. Descriptive statistics of variables.

Variable	Observations	Mean	Standard Deviation	Minimum Value	Maximum Value
Fpr	360	0.460	0.470	0.000	1.000
Dig	360	0.000	0.700	−1.040	3.370
Is	360	0.100	0.050	0.000	0.260
Aml	360	3.340	0.490	1.970	4.130
Fsa	360	0.110	0.030	0.040	0.200
Ur	360	0.600	0.120	0.350	0.900
Sab	360	0.800	0.410	0.210	2.940
Lmi	360	0.370	0.340	0.000	2.550
Kmi	360	0.690	0.910	0.000	5.700

5. Empirical Analysis

5.1. Trends in the Level of the Digital Economy and the Resilience of Food Production

The core explanatory variable in this paper, the level of digital economy, is measured using principal component analysis. Similarly, the resilience of food production, the other key variable, is calculated using Formulas (1)–(5), and its evolution over time is analyzed. The results are presented in Figure 2.

Figure 2 illustrates the national trend in the level of digital economy. Overall, China’s digital economy has shown a steady upward trajectory over the study period, rising from −0.4617 in 2011 to 0.2882 in 2022, marking a notable increase. This suggests that while the digital economy has made significant progress in recent years, its overall development level remains relatively low, indicating it is still in the early stages, with considerable potential for further growth.

Figure 2 also shows the changes in food production resilience at the national level. Overall, China’s food production resilience has remained relatively stable throughout the study period, with occasional fluctuations, but the general trend has been one of stability. This reflects the country’s continued emphasis on the development of the “three rural areas” (agriculture, rural areas, and farmers). In recent years, the steady advancement of the rural revitalization strategy, ongoing agricultural modernization, and the gradual

implementation of the strategy for building a strong agricultural nation have provided a solid foundation for enhancing food production resilience.

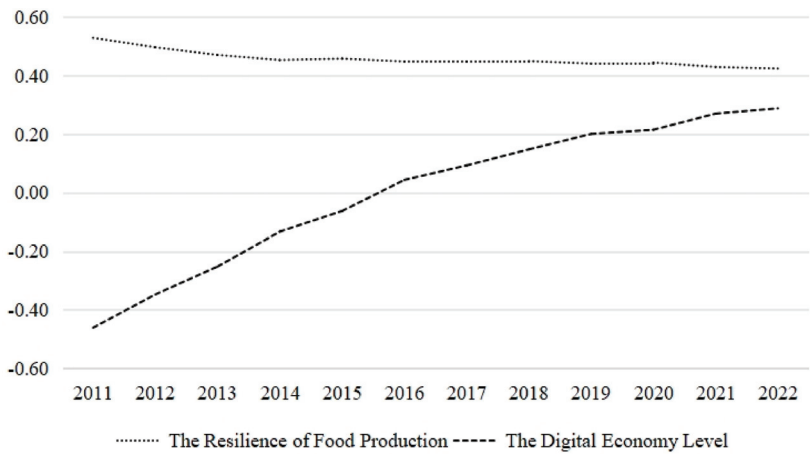


Figure 2. Changes in the level of development of the digital economy and food production resilience (average values).

5.2. Baseline Regression

To ensure the reliability of the estimation results, and to avoid multicollinearity among variables in the regression model, a collinearity diagnostic was first conducted for each explanatory variable. The variance inflation factor (VIF) analysis revealed a maximum value of 2.39, which is well below the threshold of 10, indicating that no multicollinearity concerns are present. Using the baseline regression model, control variables were introduced sequentially to estimate the effect of digital economic levels on food production resilience. The results are presented in Table 3.

In Table 3, the impact of the digital economy on food production resilience is reported. Column (1) presents the OLS regression results without province and year fixed effects; Column (2) includes bidirectional fixed effects but omits control variables; and Column (3) incorporates both bidirectional fixed effects and control variables. According to the baseline regression results in Table 3, the coefficient of the core explanatory variable, digital economic level, is consistently positive and significant at the 1% level, regardless of the inclusion of control variables and bidirectional fixed effects. These findings suggest that digital economic development significantly enhances food production resilience, indicating that higher levels of digital economic development are associated with stronger food production resilience, thereby supporting Hypothesis 1. Specifically, for every 1 unit increase in the level of digital economy development, food production resilience increases by 0.0827 units. As a typical “integrative” economy, the digital economy, when closely integrated with grain production, maximizes both factor-driven and industry-driven effects. On one hand, data serve as a crucial production factor, incorporated into the production function and deeply interwoven with traditional production inputs. This integration reduces information asymmetry, restructures the factor system, and enhances labor productivity. On the other hand, technological advancements spurred by the digital economy drive the transformation of agricultural industry structures, extending the grain industry chain both vertically and horizontally. This expansion overcomes traditional development limitations and helps mitigate the impacts of internal and external shocks on food production.

Table 3. Baseline regression results.

	(1)	(2)	(3)
	Fpr	Fpr	Fpr
Dig	0.2142 *** (0.0331)	0.0592 *** (0.0190)	0.0827 *** (0.0292)
Is			−0.2753 (0.3557)
Aml			0.3419 *** (0.1048)
Fsa			−0.4024 (0.5424)
Ur			−0.5532 (0.3902)
Sab			0.1128 ** (0.0455)
Time Fixed Effects	NO	YES	YES
Province Fixed Effects	NO	YES	YES
_cons	0.4582 *** (0.0232)	0.9762 *** (0.0395)	0.6425 (0.4184)
N	360	360	360
R2	0.105	0.966	0.969

Note: ** and *** indicate significance at the 5% and 1% levels, respectively. Robust standard errors are in parentheses.

5.3. Robustness Tests

(1) Changing the Estimation Method: Different estimation methods can introduce potential biases in model regression outcomes. Since the dependent variable, grain production resilience, ranges between 0 and 1, it fits the criteria for a constrained dependent variable model. Consequently, a panel Tobit model is suitable for this estimation. The results, displayed in Column (1) of Table 4, show that after switching the estimation method, the coefficient for digital economic development remains significantly positive. This finding indicates that digital economic development continues to promote grain production resilience, consistent with the baseline regression results.

(2) Adjusting the Measurement Approach for Core Explanatory Variables. In previous analyses, the principal component method was employed to assess the level of digital economic development, which was then incorporated into the baseline regression model. To further affirm the robustness of these regression results, the entropy method was subsequently used to calculate a composite score for digital economic development, grounded in the previously established evaluation index system. This composite score was then integrated into the baseline regression model as a robustness check, with the results presented in Column (2) of Table 4. After modifying the measurement approach for the core explanatory variable, the estimated coefficient of digital economic development on the resilience of grain production remains positive and statistically significant at the 1% level, supporting the reliability of the baseline regression outcomes.

(3) Adjusting the Time Window. The onset of the COVID-19 pandemic had profound effects on the Chinese economy. To minimize potential distortions in model estimates arising from abnormal data fluctuations during this period, data from 2020 onwards were excluded based on a review of the relevant literature. The baseline regression model was then re-estimated, and the results are shown in Column (3) of Table 4. Following this adjustment to the time window, the effect of digital economic development on grain production resilience remains significantly positive. Overall, the baseline regression results in this study are credible.

Table 4. Robustness test results.

	(1)	(2)	(3)
	Fpr Change in Estimation Method	Fpr Adjustment of Calculation Method	Fpr Adjustment of Time Window
Dig	0.0864 ** (0.0359)	0.4554 *** (0.1519)	0.0710 ** (0.0325)
Is	−0.3503 (0.5119)	−0.0865 (0.3433)	−0.1001 (0.3938)
Aml	0.3578 *** (0.0883)	0.3419 *** (0.1051)	0.2494 ** (0.1025)
Fsa	−0.4317 (0.4910)	−0.2796 (0.5515)	−0.6033 (0.5223)
Ur	−0.3855 (0.3938)	−0.4309 (0.3893)	−0.6651 (0.4630)
Sab	0.1452 *** (0.0473)	0.0998 ** (0.0452)	0.1238 ** (0.0553)
Time Fixed Effects	YES	YES	YES
Province Fixed Effects	YES	YES	YES
_cons	0.5576 (0.3664)	0.5245 (0.4211)	0.9638 ** (0.4780)
N	360	360	300
R2	/	0.969	0.970

Note: ** and *** indicate significance at the 5% and 1% levels, respectively. Robust standard errors are in parentheses.

5.4. Endogeneity Test

Reverse causality, measurement errors, and omitted variables between the dependent and independent variables may lead to endogeneity issues in the model, resulting in biased and inconsistent estimates. This study first examines the impact of digital economic development on food production resilience, noting that enhanced resilience in food production could also, in turn, stimulate regional digital infrastructure improvements and broader adoption of digital technologies in the agricultural sector. Second, while the baseline regression controls for provincial and time-fixed effects—mitigating omitted variables related to regional characteristics constant over time and across provinces—certain province-level factors that could influence food production resilience were not included in the control variables, which may contribute to endogeneity concerns. To address these potential endogeneity issues, two methods are employed.

First, the issue of reverse causality. This study substitutes the current level of digital economic development with its lagged term in the regression model to assess the effect of past digital economic development on current food production resilience. This approach assumes that digital economic growth in the prior period influences current resilience, while the latter is unlikely to impact digital economic development retrospectively. The regression results, presented in Column (1) of Table 5, indicate that even when using the lagged digital economic development level, the estimated coefficient remains significantly positive at the 1% level, which is consistent with the baseline findings.

Second, there is the problem of omitted variables. The instrumental variable method is a primary approach for addressing endogeneity issues; however, its application requires selecting an appropriate instrumental variable that meets both the relevance and exogeneity criteria. Drawing on prior research, this study employs an interaction term between the regional fixed telephone density (i.e., the number of fixed telephones per 100 people in 1984) and the previous year’s national information technology service revenue as the instrumen-

tal variable for digital economy development levels. The reasons are as follows: on the one hand, digital technology is a continuation and development of traditional communication technology, and the widespread use of fixed-line telephones, as a traditional communication tool, has strongly promoted the development of the digital economy, thereby meeting the relevance requirement for an instrumental variable. Concurrently, while fixed telephones were once the primary communication tool, their significance has diminished with the rise of mobile and internet technologies, rendering them unrelated to contemporary food production resilience—a condition that satisfies the exogeneity requirement. Moreover, as seen from the empirical results in Column (2) of Table 5, the instrumental variable passed the exogeneity test and the weak identification test. Therefore, both theoretically and empirically, the choice of this instrumental variable is reasonable. Additionally, the estimated coefficient of the instrumental variable is significantly positive at the 1% level, indicating that the digital economy can enhance food production resilience. This conclusion is consistent with the results of the baseline regression, supporting the credibility of the findings.

Table 5. Endogeneity test results.

	(1)	(2)
	Fpr Lagged 1-Period Dig	Fpr IV
L.Dig	0.0776 *** (0.0264)	0.4298 *** (0.1609)
Is	0.0022 (0.2966)	−0.2754 (0.4152)
Aml	0.3704 *** (0.1178)	0.4189 *** (0.1092)
Fsa	−0.1371 (0.3617)	0.2060 (0.6265)
Ur	−0.3402 (0.2882)	0.8510 (0.7658)
Sab	0.0582 * (0.0340)	0.1933 *** (0.0657)
Time Fixed Effects	YES	YES
Province Fixed Effects	YES	YES
_cons	0.3930 (0.3171)	−1.2564 (0.9565)
K-P rk LM		10.169 ***
K-P rk Wald F		19.139 > 16.38
N	330	360
R2	0.981	0.957

Note: * and *** indicate significance at the 10% and 1% levels, respectively. Robust standard errors are in parentheses.

5.5. Mechanism of Action Tests

The previous analysis has established that digital economic development promotes food production resilience. To further investigate the mechanisms through which the digital economy influences food production resilience, this section examines factor allocation as a key lens, informed by prior theoretical insights. Based on existing research, three primary approaches are commonly employed for mechanism testing: mediation effect models, interaction effect models, and direct regression of the explanatory variable on mechanism variables. However, mediation effect models do not adequately address endogeneity issues between mechanism variables and the dependent variable, and interaction effect models may not fully capture underlying economic mechanisms. Consequently, this study adopts the third approach, with the results detailed in Table 6. Column (1) of Table 6 reports the es-

timated coefficient of the digital economy on labor factor mismatch, showing a significantly negative coefficient. This suggests that the digital economy mitigates labor factor mismatch, thereby improving labor allocation efficiency. Similarly, Column (2) presents the coefficient of the digital economy on capital factor mismatch, which is also significantly negative, indicating that the digital economy reduces capital factor mismatch and enhances capital allocation efficiency. These results, in conjunction with prior definitions of mechanism variables and theoretical analysis, suggest that digital economic development promotes food production resilience by alleviating labor and capital factor mismatches, thus confirming Hypotheses 2a and 2b.

Table 6. Mechanism test results.

	(1)	(2)
	Lmi	Kmi
Dig	−0.2754 ** (0.1178)	−0.8103 ** (0.3328)
Is	−0.9997 (1.6542)	−3.0626 (5.7581)
Aml	−0.1567 (0.3503)	0.0583 (0.6949)
Fsa	−1.1941 (1.7267)	−0.3810 (4.9216)
Ur	−3.1394 * (1.6636)	−6.0703 (3.6975)
Sab	0.0216 (0.1780)	−0.1296 (0.4363)
Time Fixed Effects	YES	YES
Province Fixed Effects	YES	YES
_cons	3.6678 ** (1.7955)	6.8496 ** (3.3668)
N	360	360
R2	0.136	0.107

Note: * and ** indicate significance at the 10% and 5% levels, respectively. Robust standard errors are in parentheses.

5.6. Heterogeneity Analysis

(1) Heterogeneity by grain functional zones: Grain functional zones represent recent adjustments to regional, urban–rural, and human–land relationships within China, embodying strategic shifts in national grain production priorities. To assess the differential impact of digital economic development on grain production resilience across these zones, the sample was divided into major and non-major grain-producing areas for regression analysis, with the results shown in Columns (1) and (2) of Table 7. The coefficients for digital economic development are significantly positive in both major and non-major grain-producing areas; however, the positive effect is more pronounced in major grain-producing areas. This may be attributed to the superior agricultural production conditions in these areas, underpinned by their strategic importance, which enables the digital economy to more effectively bolster agricultural resilience. Furthermore, the state’s recent emphasis on food security, through strategies such as “storing grain in the land and technology” has likely enhanced the benefits accrued by major grain-producing areas.

(2) Heterogeneity by geographic location: Due to differences in foundational conditions and resource endowments across provinces, both digital economic development levels and food production resilience exhibit marked heterogeneity. To further explore whether the impact of the digital economy on grain production resilience varies by geographic region, the sample was segmented into eastern, central, and western regions for regression

analysis. As shown in Columns (3), (4), and (5) of Table 7, the results indicate that the digital economy exerts the strongest effect on food production resilience in the central region, relative to the eastern and western regions. This may be due to the central region’s pronounced comparative advantage in food production, making it more likely to harness the benefits brought about by digital economic development.

Table 7. Results of heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)
	Fpr Major Grain- Producing Areas	Fpr Non-Major Grain- Producing Areas	Fpr Eastern Region	Fpr Central Region	Fpr Western Region
Dig	0.1726 *** (0.0256)	0.0932 ** (0.0418)	0.0084 (0.0172)	0.5312 ** (0.2616)	0.1755 (0.1486)
Is	0.9868 *** (0.1996)	0.3900 (0.5677)	−0.3666 (0.3850)	−4.5557 *** (1.6358)	0.0455 (1.0057)
Aml	−0.1455 *** (0.0337)	0.7437 *** (0.1413)	0.0085 (0.0662)	0.1520 (0.1704)	0.4751 * (0.2405)
Fsa	1.1945 *** (0.3306)	−1.0962 (0.7846)	0.3417 (0.4173)	1.6775 (1.2769)	−1.4742 (1.1307)
Ur	−0.0809 (0.1769)	−1.2744 ** (0.5508)	−0.5558 * (0.3027)	9.0499 *** (1.8262)	0.8353 (0.8866)
Sab	−0.0696 *** (0.0189)	0.2260 *** (0.0851)	0.0405 (0.0365)	0.0815 (0.0986)	0.3507 ** (0.1493)
Time Fixed Effects	YES	YES	YES	YES	YES
Province Fixed Effects	YES	YES	YES	YES	YES
_cons	0.6114 *** (0.1923)	0.3039 (0.5454)	1.4416 *** (0.2248)	−3.5832 *** (1.0192)	−2.1831 ** (1.0303)
N	156	204	156	72	132
R2	0.958	0.936	0.993	0.961	0.948

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

6. Conclusions

Based on panel data from 30 provincial-level regions in China from 2011 to 2022, this paper investigates the effects and mechanisms through which the digital economy enhances food production resilience. Theoretical analysis suggests that the digital economy influences food production resilience through both direct and indirect channels. The empirical findings are as follows:

First, the level of the digital economy has shown steady growth, but significant regional disparities remain. The data reveal that the digital economy index increased from −0.4617 in 2011 to 0.2882 in 2022, highlighting the success of advancements in information infrastructure and technology adoption. However, there is a marked imbalance in development across regions, with the eastern provinces exhibiting far higher levels of digital economy development compared to the central and western regions. The latter still face challenges, particularly in terms of weak digital infrastructure and delayed technology adoption, which hinder further growth in these areas.

Second, while food production resilience has remained relatively stable, there is considerable potential for improvement. This study shows that, despite the stable trend in food production resilience, driven by agricultural modernization and increasing policy support, its growth has not kept pace with the rapid development of the digital economy. This indicates that the current food production system still has significant room to enhance its adaptability and resilience in the face of complex external shocks.

Third, the digital economy has a substantial positive impact on food production resilience. The regression analysis confirms that a 1-unit increase in digital economy

development correlates with a 0.0827-point increase in the food production resilience index. This underscores that the digital economy, through the integration of intelligent technologies, data sharing, and supply chain optimization, enhances the stability and risk resilience of the agricultural system, providing critical support for food security.

Fourth, the optimization of factors of production plays a crucial role. The findings reveal that the digital economy indirectly boosts food production resilience by addressing mismatches in labor and capital allocation. Specifically, the digital economy reduces both labor and capital mismatches, thereby improving resource allocation efficiency. The application of digital technologies not only improves the alignment of supply and demand for production factors, but also strengthens the system's flexibility and adaptability to external shocks.

Fifth, the benefits of digital economy development are unevenly distributed across regions. This study highlights significant regional differences in the impact of the digital economy on food production resilience. In major food production areas, the effect is notably stronger (0.1726) compared to non-major production areas (0.0932). In the central region, the impact coefficient is as high as 0.5312, driven by advantages in agricultural resources and policy support, which far exceed the effects observed in the eastern and western regions. These disparities suggest that regional differences in resource endowment, policy support, and technology adoption result in spatial heterogeneity in the role of the digital economy in enhancing food production resilience.

7. Recommendations and Discussion

7.1. Recommendations

The above research conclusions reveal that the digital economy helps strengthen food production resilience. Moving forward, efforts should be directed toward accelerating digital economic development strategies, enhancing infrastructure, guiding the digital economy to support rural development, and fostering new drivers for growth in the grain industry. Based on these insights, the following policy recommendations are proposed:

First, strengthen digital infrastructure to reduce regional disparities. To address the inadequate digital infrastructure in central and western regions, the government should increase investment in key areas such as 5G networks, the Internet of Things, and data collection systems in rural areas. This will enable the full integration of digital technology into agriculture. Additionally, partnerships between enterprises and local governments should be encouraged to co-develop information infrastructure, ensuring balanced regional development and providing the technical foundation needed for a resilient food production system.

Second, accelerate the digital transformation of agriculture to improve system efficiency. The government should prioritize the promotion of intelligent agricultural technologies, including precision farming, smart machinery, drone monitoring, and smart irrigation. These technologies optimize resource allocation, reduce waste, and enhance efficiency in production. Furthermore, the use of big data and artificial intelligence should be expanded to improve the real-time monitoring and management of the food supply chain, strengthening the stability and resilience of the agricultural system.

Third, optimize the allocation of labor and capital to boost efficiency. By advancing digital inclusive finance, the government can lower financing barriers for agribusinesses and smallholder farmers, addressing the issue of uneven capital distribution. Simultaneously, policies should encourage the flow of skilled labor into high-value agricultural sectors to increase productivity. Digital platforms should be leveraged to connect agricultural producers with labor and capital markets, ensuring an efficient allocation of resources.

Fourth, adopt regionally tailored policies to maximize digital economy benefits. In grain-producing and central regions, the focus should be on promoting intelligent farming

equipment and precision planting techniques to further enhance production resilience. In the eastern region, innovation in digital technologies should be prioritized, while in the western region, infrastructure development must be accelerated to bridge the digital divide. These region-specific strategies will help unlock the full potential of the digital economy in enhancing food production resilience.

Fifth, strengthen digital literacy and provide targeted training for agricultural workers. To address the digital skills gap among rural agricultural workers, the government should implement both online and offline training programs. These programs should focus on helping farmers master digital tools for production and management, thus enhancing their ability to adapt to the digital economy and facilitating the modernization and transformation of the agricultural sector.

7.2. Discussion

This paper provides a comprehensive theoretical and empirical analysis of the impact of the digital economy on food production resilience, shedding light on its mechanisms and offering new insights into this emerging research field. The contributions of this paper can be summarized as follows, highlighting how it advances the understanding of the existing literature:

First, this paper enriches the literature on food production resilience by incorporating the evolving context of the digital economy. Unlike previous studies that primarily focus on the stability of food output or supply chain management, this research systematically investigates the relationship between digital economy development and food production resilience. By employing a Markov process model, it quantifies resilience in terms of dynamic stability and recovery capacity, thereby broadening the theoretical framework for measuring and analyzing food production resilience.

Second, this paper delves into the mechanisms through which the digital economy enhances food production resilience, particularly by alleviating mismatches in labor and capital allocation. While prior research emphasizes the role of technological innovation or policy interventions in agricultural development, this paper uncovers how digital technologies optimize resource allocation, thus improving the capacity of food production systems to withstand external shocks. This represents a novel contribution to understanding the interplay between the digital economy and resource efficiency in the agricultural sector.

Third, the regional heterogeneity analysis reveals that the digital economy has the most pronounced impact in food-producing regions and central China. This finding underscores the strategic importance of the central region within China's food production system, where favorable policy support and abundant agricultural resources amplify the benefits of digital economy development. By linking the effects of the digital economy with regional resource endowments and infrastructure conditions, this paper offers actionable insights for tailoring regional food production policies.

Despite these contributions, this paper has several limitations that warrant further exploration.

First, the measurement of food production resilience primarily focuses on the dynamic changes in food output, which may not fully capture other critical dimensions such as supply chain resilience, market volatility adaptation, and food reserve systems. Since food production resilience is a multidimensional concept, future research could integrate more comprehensive indicator systems that encompass production, distribution, and consumption dynamics, offering a more holistic perspective.

Second, while this paper emphasizes the alleviation of labor and capital mismatches, it does not delve deeply into other potential mechanisms. For instance, the role of digital technologies in improving land-use efficiency, accelerating technology diffusion, or fos-

tering climate adaptation remains underexplored. In light of increasing climate-related challenges, understanding how the digital economy influences crop structure adjustments and climate-resilient practices would provide valuable insights.

Third, this paper focuses on the context of China's digital economy without engaging in cross-national comparisons. It remains unclear whether the digital economy exhibits greater efficiency gains in developed countries or emphasizes inclusivity in developing nations. Comparative studies could illuminate the applicability and limitations of the digital economy under varying institutional and developmental contexts, offering broader policy implications.

In summary, this paper provides robust theoretical and empirical evidence on how the digital economy enhances food production resilience, offering critical insights for both academics and policymakers. By addressing the intersection of digital innovation and agricultural resilience, this paper contributes to the ongoing discourse on leveraging the digital economy for sustainable food systems. Future research could build upon this foundation by incorporating cross-country comparisons, constructing multidimensional indicator systems, and further investigating the intricate mechanisms at play. Such efforts would advance the understanding of the digital economy's role in fostering resilience and inform evidence-based strategies for global food security and economic sustainability.

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References

1. Rasul, G. A framework for addressing the twin challenges of COVID-19 and climate change for sustainable agriculture and food security in South Asia. *Front. Sustain. Food Syst.* **2021**, *5*, 679037. [CrossRef]
2. Benabderrazik, K.; Jeangros, L.; Kopainsky, B.; Dawoe, E.; Joerin, J.; Six, J. Addressing the resilience of tomato farmers in Ghana facing a double exposure from climate and market. *Ecol. Soc.* **2022**, *27*, 26. [CrossRef]
3. Jung, J.; Maeda, M.; Chang, A.; Bhandari, M.; Ashapure, A.; Landivar-Bowles, J. The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. *Curr. Opin. Biotechnol.* **2021**, *70*, 15–22. [CrossRef]
4. Chen, Y.; Hu, S.; Wu, H. The digital economy, green technology innovation, and agricultural green total factor productivity. *Agriculture* **2023**, *13*, 1961. [CrossRef]
5. Hoontrakul, P. Asia's Digital Economy. In *The Asian Century*; Springer: Cham, Switzerland, 2018; pp. 269–312.
6. Sutherland, W.; Jarrahi, M.H. The sharing economy and digital platforms: A review and research agenda. *International. J. Inf. Manag.* **2018**, *43*, 328–341. [CrossRef]
7. Chen, Y. Improving market performance in the digital economy. *China Econ. Rev.* **2020**, *62*, 101482. [CrossRef]
8. Kim, T.Y.; Heshmati, A.; Kim, T.Y.; Kim, E.; Park, J.; Hwang, J. The faster-accelerating digital economy. *Econ. Growth New Perspect. Theory Policy* **2014**, 163–191.
9. Sachs, J.D. Some brief reflections on digital technologies and economic development. *Ethics Int. Aff.* **2019**, *33*, 159–167. [CrossRef]
10. Tatarinov, A. Measuring Digital Economy in National Accounts. *Vopr. Stat.* **2019**, *26*, 5–17. [CrossRef]

11. Jagannathan, U.K.; Kumar, K.M.S. Application for Stochastic Net Present Value (NPV) Estimation and Sensitivity Analysis. In Proceedings of the 2nd Indian International Conference on Industrial Engineering and Operations Management, Warangal, India, 16–18 August 2022. [CrossRef]
12. Xu, Y.; Li, T. Measuring digital economy in China. *Natl. Account. Rev.* **2022**, *4*, 251–272. [CrossRef]
13. Liu, H. Research on measurement of digital economy based on Data Mining. In Proceedings of the 7th International Conference on Intelligent Information Processing, New York, NY, USA, 29–30 September 2022; pp. 1–5.
14. Golinski, M. Measuring the digital economy in the European Union research. In Proceedings of the 2019 4th International Conference on Financial Innovation and Economic Development, Sanya, China, 18–20 January 2019; pp. 155–170. [CrossRef]
15. Tendall, D.; Joerin, J.; Kopainsky, B.; Edwards, P.; Shreck, A.; Le, Q.; Kruetli, P.; Grant, M.; Six, J. Food system resilience: Defining the concept. *Glob. Food Secur.* **2015**, *6*, 17–23. [CrossRef]
16. Stone, J.; Rahimifard, S. Resilience in agri-food supply chains: A critical analysis of the literature and synthesis of a novel framework. *Supply Chain. Manag.* **2018**, *23*, 207–238. [CrossRef]
17. Meuwissen, M.P.M.; Feindt, P.H.; Spiegel, A.; Termeer, C.J.A.M.; Mathijs, E.; De Mey, Y.; Finger, R.; Balmann, A.; Wauters, E.; Urquhart, J.; et al. A framework to assess the resilience of farming systems. *Agric. Syst.* **2019**, *176*, 102656. [CrossRef]
18. Bullock, J.M.; Dhanjal-Adams, K.L.; Milne, A.; Oliver, T.H.; Todman, L.C.; Whitmore, A.P.; Pywell, R.F. Resilience and food security: Rethinking an ecological concept. *J. Ecol.* **2017**, *105*, 880–884. [CrossRef]
19. Hodbod, J.; Eakin, H. Adapting a social-ecological resilience framework for food systems. *J. Environ. Stud. Sci.* **2015**, *5*, 474–484. [CrossRef]
20. Bizikova, L.; Tyler, S.; Moench, M.; Keller, M.; Echeverria, D. Climate resilience and food security in Central America: A practical framework. *Clim. Dev.* **2016**, *8*, 397–412. [CrossRef]
21. Suweis, S.; Carr, J.A.; Maritan, A.; Rinaldo, A.; D’odorico, P. Resilience and reactivity of global food security. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 6902–6907. [CrossRef]
22. Hendrickson, M. Resilience in a concentrated and consolidated food system. *J. Environ. Stud. Sci.* **2015**, *5*, 418–431. [CrossRef]
23. Jacobi, J.; Mukhovi, S.; Llanque, A.; Augstburger, H.; Käser, F.; Pozo, C.; Peter, M.N.; Delgado, J.M.F.; Kiteme, B.P.; Rist, S.; et al. Operationalizing food system resilience: An indicator-based assessment in agroindustrial, smallholder farming, and agroecological contexts in Bolivia and Kenya. *Land Use Policy* **2018**, *79*, 433–446. [CrossRef]
24. Karakoc, D.B.; Konar, M. A complex network framework for the efficiency and resilience trade-off in global food trade. *Environ. Res. Lett.* **2021**, *16*, 105003. [CrossRef]
25. Bharadiya, J.P.; Tzenios, N.T.; Reddy, M. Forecasting of crop yield using remote sensing data, agrarian factors and machine learning approaches. *J. Eng. Res. Rep.* **2023**, *24*, 29–44. [CrossRef]
26. Deichmann, U.; Goyal, A.; Mishra, D. Will digital technologies transform agriculture in developing countries? *Agric. Econ.* **2016**, *47*, 21–33. [CrossRef]
27. Finger, R. Digital innovations for sustainable and resilient agricultural systems. *Eur. Rev. Agric. Econ.* **2023**, *50*, 1277–1309. [CrossRef]
28. Zhong, R.; He, Q.; Qi, Y. Digital economy, agricultural technological progress, and agricultural carbon intensity: Evidence from China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6488. [CrossRef] [PubMed]
29. Bökle, S.; Koenn, L.; Reiser, D.; Paraforos, D.S.; Griepentrog, H.W. 1. Consideration of resilience for digital farming systems. In *Precision Agriculture’21*; Wageningen Academic: Wageningen, The Netherlands, 2021; pp. 25–31.
30. Zhang, Y.; Ji, M.; Zheng, X. Digital economy, agricultural technology innovation, and agricultural green total factor productivity. *Sage Open* **2023**, *13*, 21582440231194388. [CrossRef]
31. Solow, R.M. A contribution to the theory of economic growth. *Q. J. Econ.* **1956**, *70*, 65–94. [CrossRef]
32. Basso, B.; Antle, J. Digital agriculture to design sustainable agricultural systems. *Nat. Sustain.* **2020**, *3*, 254–256. [CrossRef]
33. Zilberman, D.; Lu, L.; Reardon, T. Innovation-induced food supply chain design. *Food Policy* **2019**, *83*, 289–297. [CrossRef]
34. Reardon, T.; Echeverria, R.; Berdegue, J.; Minten, B.; Liverpool-Tasie, S.; Tschirley, D.; Zilberman, D. Rapid transformation of food systems in developing regions: Highlighting the role of agricultural research & innovations. *Agric. Syst.* **2019**, *172*, 47–59.
35. Xiao, L. Research on Supply Chain Management Models from the Perspective of Cross Border E-commerce. *Ind. Eng. Innov. Manag.* **2023**, *6*, 54–59.
36. Pingali, P.L. Green revolution: Impacts, limits, and the path ahead. *Proc. Natl. Acad. Sci. USA* **2012**, *109*, 12302–12308. [CrossRef] [PubMed]
37. Du, Y.; Zhao, Z.; Liu, S.; Li, Z. The impact of agricultural labor migration on the urban–rural dual economic structure: The case of liaoning province, China. *Land* **2023**, *12*, 622. [CrossRef]
38. Romer, P.M. Endogenous technological change. *J. Political Econ.* **1990**, *98*, S71–S102. [CrossRef]
39. Farjoun, E.D.; Machover, M. *Laws of Chaos: A Probabilistic Approach to Political Economy*; Verso Books: Brooklyn, NY, USA, 2020.
40. Flaschel, P.; Franke, R.; Veneziani, R. Labour productivity and the law of decreasing labour content. *Camb. J. Econ.* **2013**, *37*, 379–402. [CrossRef]

41. Zhang, B.; Dong, W.; Yao, J.; Cheng, X. Digital economy, factor allocation efficiency of dual-economy and urban-rural income gap. *Sustainability* **2023**, *15*, 13514. [CrossRef]
42. Frank, M.R.; Autor, D.; Bessen, J.E.; Brynjolfsson, E.; Cebrian, M.; Deming, D.J.; Feldman, M.; Groh, M.; Lobo, J.; Moro, E.; et al. Toward understanding the impact of artificial intelligence on labor. *Proc. Natl. Acad. Sci. USA* **2019**, *116*, 6531–6539. [CrossRef]
43. Jia, X. Digital Economy, Factor Allocation, and Sustainable Agricultural Development. *Sustainability* **2023**, *15*, 54418. [CrossRef]
44. Wu, H.; Noé, F. Variational approach for learning Markov processes from time series data. *J. Nonlinear Sci.* **2020**, *30*, 23–66. [CrossRef]
45. Dawson, N.; Martin, A.; Sikor, T. Green revolution in sub-Saharan Africa: Implications of imposed innovation for the wellbeing of rural smallholders. *World Dev.* **2016**, *78*, 204–218. [CrossRef]
46. Mentz, R.P.; Morettin, P.A.; Toloi, C. On residual variance estimation in autoregressive models. *J. Time Ser. Anal.* **1998**, *19*, 187–208. [CrossRef]
47. Guo, F.; Wang, J.; Wang, F.; Kong, T.; Zhang, X.; Cheng, Z. Measuring China's Digital Financial Inclusion: Index Compilation and Spatial Characteristics. *China Econ. Q.* **2020**, *19*, 1401–1418.
48. Junhong, B.; Yuying, L. Can Outward Foreign Direct Investment Improve the Resource Misallocation of China? *China Ind. Econ.* **2018**, *1*, 60–78.
49. Lijuan, S.; Xiaoxiao, T. The Impact of Digital Financial Inclusion on Farmer's Income Inequality: An Empirical Analysis Based on CFPS Data. *Econ. Rev.* **2022**, *5*, 100–116.

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Article

Digital Economy as a Buffer: Alleviating the Adverse Effects of Land Resource Mismatch on Food Security

Wenjie Li ^{1,2}, Guanyu Guo ^{1,2}, Huangying Gu ^{1,2}, Shuhao Lai ^{1,2}, Yuanjie Duan ³ and Chengming Li ^{1,2,*}

¹ School of Economics, Minzu University of China, Beijing 100081, China; 202204008@muc.edu.cn (W.L.); 23300103@muc.edu.cn (G.G.); 23300127@muc.edu.cn (H.G.); 23300139@muc.edu.cn (S.L.)

² China Institute for Vitalizing Border Areas and Enriching the People, Minzu University of China, Beijing 100081, China

³ School of Economics, Peking University, Beijing 100871, China; 2201110969@pku.edu.cn

* Correspondence: 202101033@muc.edu.cn

Abstract: In the era of the digital economy (DE), technology factors and data factors, like a two-wheel drive, have not only redefined the mode of production but also innovatively reshaped production relations. To examine how the DE can ensure food security (FS) in China, this study explores the negative impacts of land resource mismatch (LRM) on FS, the mechanisms of the impacts, and the critical role played by the DE in mitigating its negative impacts, based on China's provincial-level panel data from 2011 to 2022. This study finds that, first, LRM leads to a reduction in food production, which, in turn, threatens FS, and this conclusion remains robust after a series of robustness tests. Second, the heterogeneity analysis finds that LRM has a greater negative impact on FS in regions with high urbanization levels, regions with a short tenure of officials, and regions that are not major food-producing regions. Finally, in a further analysis, the specific channels and solution paths of the negative impact of LRM on FS are explored in depth. LRM negatively affects the material base and production capacity of food production, including reducing the supply of land, labor, and capital factors for food production; the DE reduces the negative impact of LRM on FS through the use of digital technology and open government data.

Keywords: land resource mismatch; food security; digital economy; digital technology; open government data

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1. Introduction

Food, as the most fundamental subsistence material for the populace, constitutes a crucial strategic material intimately tied to national livelihood and economic security, characterized by the discontinuity of its production process and the irreplaceable nature of its demand [1]. The quantity and quality of arable land are two key factors affecting a country's food production capacity. Therefore, ensuring its security has always been a significant concern, particularly for countries like China, where arable land resources are scarce and ecological and environmental issues are severe. Both of these factors are, in fact, impacted by land resource mismatch (LRM) [2]. LRM refers to the phenomenon where local governments attract foreign investment by offering low industrial land prices and generous land supplies to cultivate the tax base and propel economic development. This often results in a significant conversion of agricultural land into construction land [3], as illustrated in Figure 1. Both domestic and international experience demonstrates that densely populated countries inevitably experience significant losses of arable land during the process of industrialization [4]. Firstly, the growth in population, economic development, housing demands, industrial expansion, and infrastructure construction necessitate vast amounts of land for construction, inevitably encroaching upon arable land [5,6]. For instance, Japan's arable land decreased by 52% between 1955 and 1994, while South Korea's decreased by 46% from 1965 to 1994 [7]. Similarly, according to the Statistical Yearbook

of Urban Construction in China, China's construction land has expropriated an average of 77,766.67 hectares of arable land annually over the past thirteen years. Secondly, the overall quality of land occupied for non-agricultural construction tends to be superior to that of the reclaimed wasteland used as compensation. Additionally, land scarcity often leads to overuse of arable land and excessive fertilizer application, resulting in a decline in the quality of arable land [8]. In 2023, China's food output reached 695 million tons, witnessing a continuous growth for 18 consecutive years. However, in the same year, China's grain imports reached total of 160 million tons, making it the world's largest importer of agricultural products. This suggests that China's food supply is insufficient to achieve a high level of self-sufficiency. Against this backdrop, it is of utmost practical significance to delve deeply into the effective pathways for optimizing land resource allocation and food production and supply, thereby enhancing food security (FS) levels. The advent of the digital economy (DE) has revolutionized agricultural development, with digital technology and data factors continually expanding into rural areas and gradually infiltrating agricultural production, circulation, and other aspects. By integrating these factors, they empower and augment the efficiency of other production factors, achieving a synergistic effect where $1 + 1 > 2$ and providing a more potent leadership and support framework for addressing FS challenges. Based on this premise, this study aims to explore the potential impact of the DE on the phenomenon of LRM, with the objective of identifying a pragmatic path to bolster FS capacity.

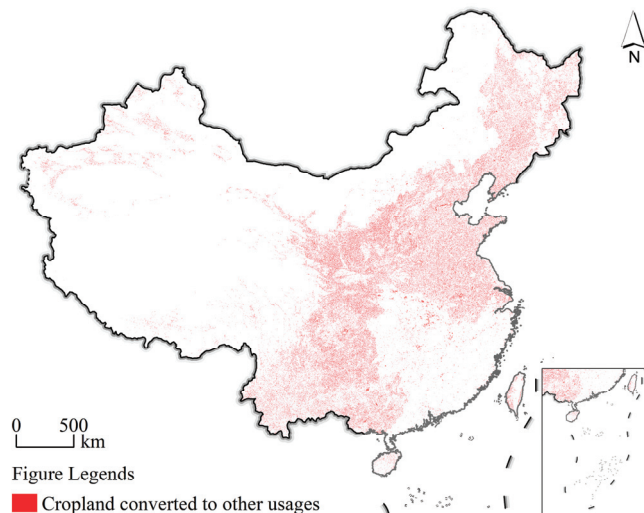


Figure 1. The distribution of arable land has been converted to other uses since 2010.

The important cause of LRM in China lies in the national situation of large numbers of people and small amounts of land, resulting in the fact that most of the available land has already been taken up by arable land, for example, so that land for construction needs to encroach on land with other uses. The direct cause can be traced back to changes in local government behavior as a result of the fiscal decentralization brought about by the tax system reform. Corporate income tax has become the main source of finance for local governments, leading to a keen supply of land for construction at the expense of land for other uses [9]. Specifically, corporate income tax has emerged as the primary revenue source for local governments, prompting them to actively attract foreign investment by offering low industrial land prices and generous land supplies [10]. Over the past two decades, the dedication of substantial quantities of premium arable land towards economic construction has objectively propelled China's swift economic development, albeit resulting in a relative plateau in agricultural growth, as depicted in Figure 2. During the initial phase

of economic construction, spanning from 1992 to 2013, China’s average GDP growth rate stood at an impressive 16.28%. This rapid escalation in economic standing and residents’ incomes rendered the conversion of arable land for non-agricultural purposes feasible. Consequently, scholarly discourse concerning land resource allocation during this era predominantly centered on strategies to empower high-productivity enterprises to secure adequate factor inputs through effective land resource allocation, thereby ensuring an overall augmentation in economic productivity [11]. Consideration of the value of the decolonization of arable land is also limited to the realm of economic value [12]. When high-speed growth is no longer sustainable, the question of whether to continue to invest a large amount of high-quality arable land in industrial, mining, and storage construction becomes a questionable issue. During this period, the non-economic value of agricultural land was gradually emphasized, and the trade-off between economic and agricultural land became a hot topic. On the one hand, the ecological value of agricultural land has received more attention, such as its function of purifying air, preventing soil erosion, and regulating biodiversity [13,14]. On the other hand, the significance of arable land for guaranteeing FS is also recognized, and most of the existing studies show that both population growth and the income of the population place higher demands on the amount of arable land [15]. However, there remains a lack of clarity regarding whether LRM impacts food production, specifically through channels such as decreased land and other essential factors and how to address the FS challenges stemming from such mismatches. This study endeavors to provide answers to these questions, offering a novel perspective on understanding the ramifications of LRM in China and presenting a fresh idea for local governments to mitigate this phenomenon.

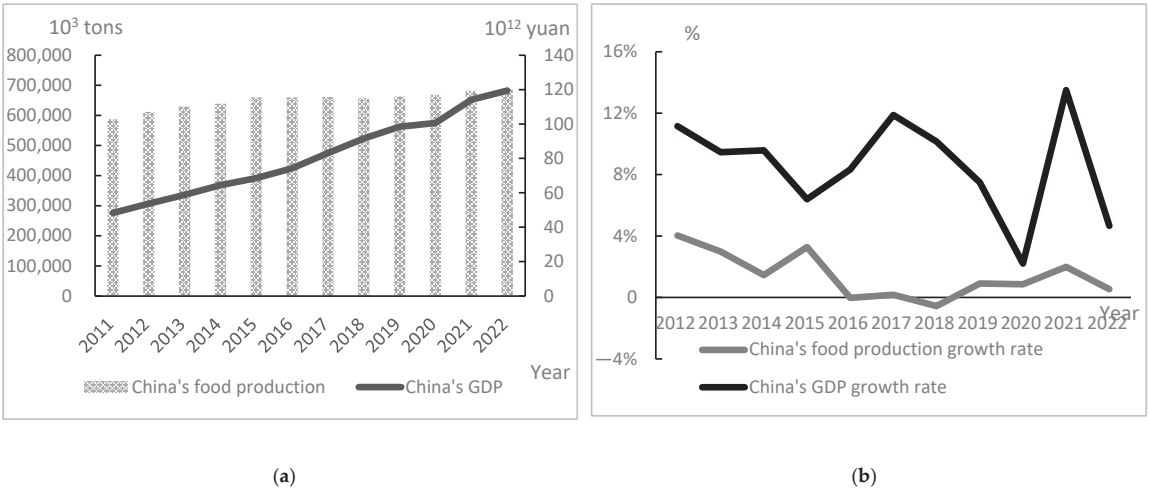
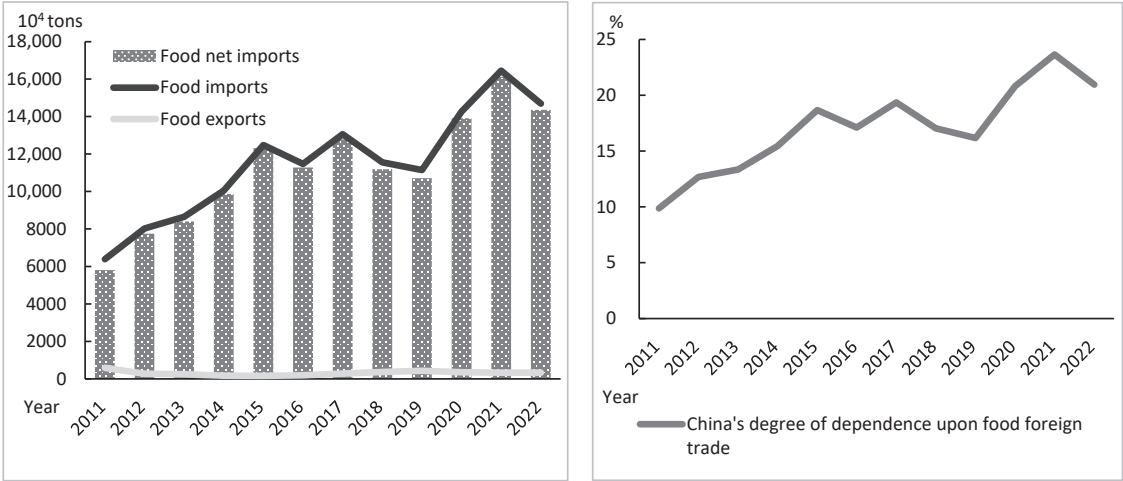


Figure 2. The relationship between food production and economic development in China. (a) China’s total GDP and total food production; (b) China’s food production growth rate and GDP growth rate.

In 1983, the World Food Organization (WFO) articulated that the objective of FS is “to guarantee that all individuals have access to sufficient and affordable basic foodstuffs at all times” [16]. Consequently, the cornerstone of ensuring FS resides in the production and accessibility of food for an entire country’s populace. However, China’s dependence on foreign trade for food has risen over the years, from 10% in 2012 to around 20% in 2022, as shown in Figure 3, which means that FS is not yet fully guaranteed in China. From the perspective of food demand, China’s population, although no longer growing, will remain stable at over 1.4 billion for an extended period. Furthermore, as China’s economy expands and the living standards of its citizens improve, the food consumption structure of the Chinese populace are evolving. Direct food consumption, or the demand for staple foods

like rice and wheat, remains stable. However, indirect food demand, particularly for feed and industrial food products, is on a steady rise. This surge ultimately fuels China’s overall food demand, especially for protein-rich feed consumption. Consequently, the challenge of FS necessitates increasingly effective solutions. From the perspective of food supply, academics have observed that LRM can lead to mismatches in other production factors, such as labor and capital [17,18]. A critical issue that has garnered insufficient attention is the encroachment of farmland and arable land for higher economic gains due to LRM. This phenomenon raises concerns about whether the loss of production factors resulting from such mismatches could further exacerbate adverse impacts on China’s FS. It is imperative to address this question to ensure the sustainability and stability of China’s food supply. Secondly, the empowering role of the DE in agriculture is increasingly recognized in the academic literature as a crucial solution for FS. Studies have demonstrated that precision farming techniques, smart agricultural machinery, and efficient supply chain management facilitated by the DE have significantly enhanced agricultural productivity. These advancements not only improve the efficiency of farming operations but also optimize resource allocation, thereby contributing to increased food production and helping to safeguard FS [19–21]. Given the slow growth in China’s arable land area and the lack of a significant improvement in land quality [22], it is essential to explore whether the DE can mitigate the adverse effects of LRM. By leveraging the DE, we can harness its potential to better position the primary industry as a new growth engine. Addressing the challenges of low output efficiency, environmental constraints, and resource limitations within China’s agricultural industry is crucial. By achieving this, we can increase agricultural productivity and point the way toward ensuring China’s FS and facilitating the transformation of its agricultural sector. This approach offers a promising direction for sustainable agricultural development and FS in China.



(a) (b)

Figure 3. Degree of dependence upon China’s food foreign trade. (a) China’s food imports and exports; (b) degree of dependence upon China’s food foreign trade.

As we enter the DE era, advancements in digital technology have transformed data into a pivotal resource. Data are now universally acknowledged for their substantial economic and social value [23,24], stemming from their characteristics of shareability, reproducibility, and infinite availability. These attributes have shattered the constraints previously posed by limited supplies of traditional production factors, such as land and capital, thereby

facilitating economic growth. Simultaneously, the explosive growth in the scale of data has not only elevated their prominence in the development of the DE but has also significantly impacted the transformation of traditional production modes [25]. This surge has led to the emergence of new industries, business models, and operational methods, solidifying data's role as a crucial production factor driving economic and social development [26]. According to the Internet Development Report 2022, the scale of China's DE industry is stable and good, realizing RMB 50.2 trillion of industrial output value, of which rural online retail sales contribute to RMB 2.05 trillion of innovative revenue growth, an increase of 11.3% year-on-year, which is a good result of the deep integration of the agricultural economy and the DE. In this context, data and digital technology function as the means of production and labor tools for the advancement of the DE. By optimizing resource allocation and enhancing production efficiency, it mitigates the excessive consumption of agricultural resources [27]. For instance, through the utilization of digital agricultural management systems [28], farmers can monitor real-time data such as soil moisture and weather conditions. This enables them to achieve precise fertilization and intelligent irrigation, thereby substantially enhancing the utilization efficiency of farmland. Obviously, the DE can effectively bolster the total factor productivity of agriculture by optimizing the allocation of production factors [29], thereby creating a new growth pole for the agricultural economy [30,31]. Consequently, it is crucial to explore whether the DE can address the challenges posed by the LRM for FS. While scholars have already identified that the development of the DE significantly contributes to FS in China, exhibiting a dampening effect on localized FS and a facilitating effect on neighboring areas' FS [32], the crucial material basis for food production, namely arable land, has not been thoroughly discussed. Therefore, from the perspective of the DE, optimizing the allocation of land resources through digital technology and data factors in order to ensure the security of food production still remains an important topic that needs to be explored and practiced in depth.

Based on this, this study delves into the adverse effects of LRM on FS using China's provincial panel data spanning from 2011 to 2022. Firstly, it is revealed that LRM can decrease food production and pose a threat to FS, a finding that remains significant even after conducting a series of robustness tests. Secondly, this study examines the specific mechanisms through which LRM adversely impacts FS, including the reduction in the supply of land, labor, and capital factors essential for food production. Finally, this study proposes practical recommendations to mitigate these negative impacts, namely leveraging the technology and data factors introduced by digital technology and open data to alleviate the threat posed by LRM to FS.

The research contributions of this study are as follows: Firstly, this study enhances the existing literature on FS. Typically, FS is examined from the perspectives of arable land area, fertilizer application, and mechanical inputs [33–35]. However, the FS issues stemming from the economic and social values underlying LRM have been overlooked by academic circles. This study aims to contribute to the literature by highlighting the negative impacts of LRM on FS. This not only diversifies the academic research on the factors influencing FS but also furnishes policymakers with scientific evidence on optimizing land resource allocation, conserving arable land resources, and safeguarding FS. Second, this study enriches the literature on the consequences of LRM. Existing research on the negative impacts of LRM has shifted from purely economic value comparison to sustainable development perspectives such as ecological value [36,37], but the impacts on FS and its specific channels of action have not yet been subjected to rigorous theoretical and empirical tests. This study explores the impact of LRM on FS and also constructs a multidimensional analytical framework for FS from the perspectives of factors of production such as capital, labor, and technology, which can not only help academics to further develop related research but also provides policymakers with more comprehensive and systematic policy references. Thirdly, this study engages in a discussion on the heterogeneous effects of LRM on FS, revealing that factors such as urbanization, the tenure length of officials, and the role of primary food-producing regions can all exert different impacts on FS.

By analyzing regional heterogeneity, this study assists policymakers in crafting more precise regional development strategies, optimizing the layout of food production, and enhancing the national level of FS. Furthermore, it offers policymakers a more intuitive and specific anticipation of policy outcomes, which can aid in guiding policy formulation and adjustment. Lastly, this study explores the moderating role of the DE in alleviating the adverse effects of LRM on FS. Unlike much of the existing literature that treats the DE as an explanatory variable and examines its impact on food production and resilience [38,39], this study delves into how digital technology and data factors can facilitate food production development through various channels by incorporating moderating variables such as digital technology and open government data. This study not only broadens the research scope concerning the effectiveness of the DE but also presents policymakers with novel ideas for leveraging the DE to propel agricultural modernization.

The research layout of this study is as follows: the second part is the theoretical derivation; the third part is the research design, including the data source, model design, and variable definition; the fourth part is the empirical analysis, including a descriptive test and a basic regression and robustness test with heterogeneity analysis; the fifth part is a further analysis, including a mechanism test and moderating effect analysis; and the sixth part is the conclusion and recommendations.

2. Theoretical Analysis and Research Hypothesis

The rapid expansion of urbanization has created a tremendous demand for land resources. As populations have become increasingly concentrated in urban centers, the need for residential, commercial, and industrial land has surged significantly [40]. This has led to substantial amounts of farmland being repurposed for non-agricultural use. However, these transitions are not always driven by optimal market-based allocations but are frequently influenced by government intervention, which accelerates the conversion of land to non-agricultural purposes. Local governments, motivated by fiscal revenue as a performance indicator, often suppress industrial land prices and increase the availability of construction land, resulting in vast swaths of farmland being transformed into industrial or construction land [41]. This behavior distorts the land market's pricing mechanism, creating a mismatch between agricultural and construction land, which, in turn, causes a considerable loss of arable land and weakens grain production capacity [42]. Consequently, the land resources essential for agricultural production are inadequately safeguarded, directly impacting grain yields and threatening national FS.

Moreover, from the standpoint of externality theory, the inefficient allocation of land resources generates substantial negative externalities [43]. In the course of urbanization, the loss of arable land diminishes the total area available for grain production. For a populous country like China, where arable land is relatively scarce, this represents a serious threat to FS. LRM, by reducing the amount of arable land, leads to decreased grain production, which can result in food supply shortages, price volatility, and a series of chain reactions that ultimately jeopardize national FS. Based on the above, this study proposes the following hypothesis:

H1. *LRM reduces food production, which in turn jeopardizes FS.*

Grain production is, in essence, a complex process involving the input and output of multiple factors. This study uses a production function, where the output is denoted by Y , and the five key production factors, capital, labor, technology, and data, are represented as L_d , K , L_a , T , and D , respectively. This model helps to reveal how changes in these production factors influence grain output.

From the perspective of land resources (L_d), land is an essential factor in agricultural production. LRM directly reduces the amount of land available for grain production [43,44]. In the context of rapid urbanization, a significant portion of high-quality arable land has been converted into industrial and urban construction land, resulting in an insufficient

supply of agricultural land. This mismatch not only decreases the total area of arable land but also creates an imbalance in land use, reducing the overall productivity of the land. Furthermore, the shrinking supply of arable land may limit both the scale and variety of crops that can be cultivated [45]. In regions where land resources are scarce and the quality of arable land is generally low, this mismatch further exacerbates constraints on food production, posing a serious threat to FS.

From the perspective of capital (K), LRM results in insufficient capital investment in agricultural production. Local governments tend to allocate land resources for industrial development, diverting capital that could have been used to enhance agricultural productivity, improve agricultural infrastructure, and promote agricultural technology to more profitable industrial sectors [46]. This lack of investment reduces the profitability and enthusiasm of farmers [46], restricting agricultural technological progress and capital accumulation. As a result, grain production struggles to achieve economies of scale or intensive growth, hindering increases in grain output.

From the perspective of labor (L_a), the flow of labor is also impacted by LRM. As urbanization accelerates, a large number of young rural workers migrate to cities in search of higher incomes and better living conditions [47]. This trend reduces both the quantity and quality of labor engaged in grain production, resulting in an aging workforce [48] and a decline in labor skills. These factors hinder the refined management of agricultural production and the adoption of new technologies, exacerbating the challenges in agricultural production and limiting the total grain supply.

In summary, LRM negatively affects the material base and production capacity of food production by reducing the supply of land, capital, and labor factors, thus endangering the stability of national FS. Therefore, this study proposes the following hypothesis:

H2a. *LRM reduces the availability of land factor for food production, which, in turn, jeopardizes FS.*

H2b. *LRM reduces the availability of capital factors for food production, which, in turn, jeopardizes FS.*

H2c. *LRM reduces the supply of labor factor for food production, which, in turn, jeopardizes FS.*

With the rapid development of digital information technologies and the aggregation of vast amounts of data, “digitalization” has become the prevailing trend [49]. Emerging digital technologies, such as big data, cloud computing, and the Internet of Things, are increasingly penetrating various sectors, reshaping existing production models [50]. The DE enables the digital transformation of traditional agriculture through data and digital technologies. Based on the productivity theory of Marx, the revolutionary breakthrough of technology and the innovative allocation of production factors, namely, the labor force, labor means and labor objects and their optimal combination help to promote the improvement in productivity. Following this theory, the deep integration of data and technology with traditional production factors can not only transform agricultural production methods but also enhance overall productivity.

From the perspective of digital technologies (T), large-scale farming has gradually emerged as the dominant trend in agricultural development within the current context of rural land transfers. Expanding production scales allows farmers and agricultural companies to utilize large machinery and digital technologies for operations, thereby liberating labor [51]. Digital technologies can transcend the limitations of resource scarcity and the obsolescence of traditional agricultural practices [52]. By transforming the business models and operational concepts of modern agricultural enterprises through information technologies, digital solutions can enhance the efficiency of labor and material resources, ultimately improving agricultural productivity [53] and the quality of grain production. For instance, smart agricultural equipment can monitor crop growth throughout the production process and assist in adjusting factors such as light, water, temperature, and soil quality, thereby mitigating the adverse effects of natural variables and ensuring stable crop yields.

This fosters the standardization and scaling of agricultural production, alleviating the constraints of resource scarcity.

From the perspective of data (D), data exhibit characteristics of non-competitiveness and non-exclusivity, thereby overcoming the constraints imposed by the limited supply of traditional production factors [54] and further enhancing productivity levels. Although data have always existed in traditional agriculture, they have often been fragmented and granular, lacking continuity and completeness, which limits their inherent value. In the digital era, these data can now be collected, classified, cleaned, aggregated, and shared through open government data platforms, facilitating widespread application by various stakeholders. For example, on the open government data platforms, there is basic situation information of rural areas under the theme of “agriculture and rural areas”, including the total output value of agriculture, forestry, animal husbandry and fisheries, the production and operation information of agricultural products, etc., tax information, penalty data, and consumption data under the theme of “credit service” and “fiscal and taxation finance”. Based on these open government data, first of all, they help agricultural operators to obtain richer decision-making information, including information on agricultural resources, supply and demand in the agricultural market, and policy information on industrial development, thus helping them to make scientific choices in their decision-making. Furthermore, LRM is often accompanied by insufficient capital investment in agriculture. However, open government data sharing can help alleviate the information asymmetry between banks and enterprises [55], enabling banks to more accurately assess the creditworthiness and production potential of agricultural companies. This increases credit support for agricultural enterprises, facilitating adequate capital investment, expanding production scales, and enhancing total factor productivity, thereby ensuring the sustainability of agricultural production and FS.

Based on the above analysis, this study proposes the following hypothesis:

H3a. Digital technology innovations can mitigate the threat of LRM to FS.

H3b. Open government data can mitigate the threat of LRM to FS.

The theoretical mechanism diagram of this study is shown in Figure 4.

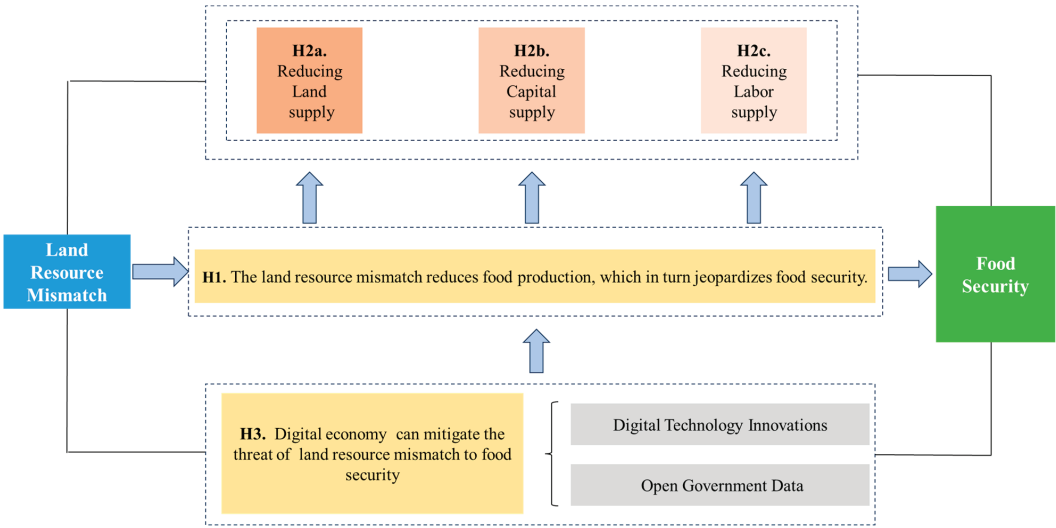


Figure 4. The theoretical mechanism diagram.

3. Research Design

3.1. Data Sourcing

This study selected 30 provinces in China (excluding Tibet due to data availability) as the research focus, covering the period from 2011 to 2022. The relevant data were primarily sourced from the *China Regional Statistical Yearbook*, *Provincial Statistical Yearbooks*, the Wind, and the CSMAR database. After excluding samples with significant missing data, a total of 360 samples were included in this analysis.

3.2. Model Setting

3.2.1. Baseline Regression Model

This study first empirically examined the negative impact of LRM on FS. The model is constructed as shown in Equation (1):

$$FP_{it} = \alpha_1 + \beta_1 LRM_{it} + \gamma_1 \sum Controls_{ijt} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

In this Equation, i represents the city; t represents the year; j represents the type of control variable; FP_{it} is a proxy variable for the level of FS in each province; LRM_{it} is a proxy variable for the degree of LRM in each province; $Controls_{ijt}$ represents various control variables; μ_i and δ_t represent individual fixed effects and time-fixed effects, respectively; and ε_{it} represents the random disturbance term.

3.2.2. Mechanism Effect Model

To examine the specific mechanism through which LRM negatively affects FS, this study followed the two-step method proposed by Jiang (2022) [56] to construct the models shown in Equations (2) and (3):

$$FP_{it} = \alpha_1 + \beta_1 LRM_{it} + \gamma_1 \sum Controls_{ijt} + \mu_i + \delta_t + \varepsilon_{it} \quad (2)$$

$$Mediator_{it} = \alpha_2 + \beta_2 LRM_{it} + \gamma_2 \sum Controls_{ijt} + \mu_i + \delta_t + \varepsilon_{it} \quad (3)$$

3.2.3. Moderating Effect Model

To investigate whether the DE can mitigate the negative impact of urban LRM on FS, this study constructed a moderating effect model, as shown in Equation (4):

$$FP_{it} = \alpha_3 + \beta_3 LRM_{it} + \phi LRM_{it} \times Digital_{it} + \mu Digital_{it} + \gamma_3 \sum Controls_{ijt} + \mu_i + \delta_t + \varepsilon_{it} \quad (4)$$

$Digital_{it}$ represents the DE-related variables that play a moderating role in the relationship between urban LRM and FS.

3.3. Variable Definition and Description

3.3.1. FS Level

This study employed the annual grain output of each province to assess FS levels across different regions. There are two main reasons for using total grain output as a measure of FS. First, as Godfray et al. (2010) [57] pointed out, the most fundamental dimension of global food security is to ensure an adequate supply of food, and an increase in food production has a direct impact on the adequacy of that supply. Second, measuring the total grain output, as opposed to the yield per unit area, can better mitigate various measurement and statistical errors [58]. This is because an increase in the yield per unit area may occur alongside a decrease in the area sown for other crops. Therefore, the total grain output serves as a more direct and accurate indicator of FS.

3.3.2. LRM

The theory of this study is mainly based on the phenomenon of the overprovision of urban industrial land by local governments. Drawing from the methodology in the mainstream literature and utilizing detailed data from the China Statistical Yearbook of

Land and Resources on land concessions by method and land use type at the national level, this study calculated the proportion of industrial, mining, and warehousing land across various concession methods. These proportions were then used as weights to estimate the area of industrial, mining, and warehousing land in the land concessions of each province, followed by the calculation of this area as a percentage of the total land concessions. When a city allocates a large portion of its industrial and warehousing land through negotiated agreements, it becomes more susceptible to issues such as large-scale land occupation by development zones and low entry barriers for enterprises. This can lead to LRM, which may subsequently cause imbalances in the allocation of labor and capital.

3.3.3. DE Variables

In line with the existing literature and the availability of relevant data at the provincial level, this study constructed moderating effect indicators from two directions: technological factors and data factors, labeled as DigTech and Egovertment, respectively.

3.3.4. Control Variables

Drawing from the relevant mainstream literature, this study included control variables such as the rural Engel coefficient, among others. The specific variables used in this study are shown in Table 1.

Table 1. The definition of variables.

Variable Type	Variable Name	Variable Construction
Dependent Variable	FP	The grain, legume, and tuber output of each province in the given year (unit: 10,000 tons).
Independent Variable	LRM	The proportion of land used for industrial, mining, and warehousing purposes in the total land transferred in the given year.
Mechanism Variables	Land	The natural logarithm of the sown area for grain, legumes, and tubers in each province in the given year, plus 1 (unit: 1000 hectares).
	Capital	The natural logarithm of the product of the proportion of agricultural output and the total investment in agriculture, forestry, animal husbandry, and fisheries in the given year, plus 1.
	Labor	The number of people employed in the primary industry in each province in the given year.
Mechanism Variables	DigTech	The natural logarithm of the number of digital innovation patent applications in each province in the given year, plus 1.
	Egovertment	If the province launched an open government data platform in the given year, it is assigned a value of 1; otherwise, 0.
Control Variables	Engel	The rural Engel coefficient.
	AgrMac	The number of agricultural machinery service organizations.
	AgrLoans	Agricultural-related loans.
	Intensity	The intensity of soil and water conservation efforts.
	Emissions	The amount of ammonia nitrogen emissions (tons).
	Resilience	Disaster resilience capacity.

4. Empirical Results

4.1. Descriptive Statistics

As shown in Table 2, the average FS level (FP) was 7.122, with a standard deviation of 1.285, a minimum value of 3.393, and a maximum value of 8.971. This indicates that while China’s overall FS is stable, there are regional differences. The average LRM (LRM) was 0.178, which is relatively low, but it had a standard deviation of 0.048, demonstrating some regional heterogeneity. Notably, the region with the highest degree of LRM reached 0.325, highlighting the need for further optimization of land resource allocation to reduce the mismatch.

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
FP	360	7.122	1.285	3.393	8.971
LRM	360	0.178	0.048	0.099	0.325
Land	360	7.733	1.273	3.861	9.595
Capital	360	3.094	1.318	0	5.05
Labor	360	6.169	1.115	3.091	7.701
DigTech	360	6.505	2.493	0	11.644
Egoverment	360	0.16	0.367	0	1
Engel	360	33.839	6.188	22.615	69.939
AgrMac	360	5869.792	6500.239	32	26,547
AgrLoans	360	9633.435	9250.928	78.761	65,566
Intensity	360	2.25	10.475	0	184.286
Emissions	360	11,607.332	18,549.074	0	75,800
Resilience	360	0.557	0.165	0.1	1

This study mapped the spatial distribution of China’s FS levels and the degree of LRM in 2011 and 2022, respectively. As shown in Figure 5, first, from an overall perspective, regions with higher food production were primarily concentrated in the northeast and central areas, with Heilongjiang Province in the northeast standing out significantly, as its grain output far exceeded that of other provinces. In contrast, some provinces in the southwest had relatively low grain production. This distribution pattern reflects the regional concentration of China’s grain production resources, with the northeast and central regions emerging as key grain-producing areas due to their favorable natural conditions, while the western and southern regions have relatively lower production capacity, constrained by less favorable natural conditions. Second, the severity of LRM varied significantly across regions, with higher levels observed in the northeast and certain western provinces, while other areas experienced lower degrees of mismatch. Finally, when analyzing these maps together, it becomes apparent that LRM in China improved by 2022, while FS levels across the provinces also increased over the past 12 years. This observation prompts an important question: is there an underlying connection between the reduction in LRM and the improvement in FS?

4.2. Baseline Regression

Table 3 presents the baseline regression results of the impact of LRM on FS. In this baseline regression, a progressive regression strategy was used to mitigate potential endogeneity caused by omitted variables. In Column (1), which only controls for province-fixed and year-fixed effects, the LRM coefficient is significantly negative. In Columns (2) and (3), control variables are gradually added, and the regression results show that the LRM coefficient remained significantly negative, indicating that LRM reduces FS levels, thus confirming H1.

Table 3. Baseline regression.

	(1)	(2)	(3)
Variables	FP	FP	FP
LRM	−2.2409 ** (−2.22)	−2.4524 ** (−2.35)	−2.2690 ** (−2.19)
Engel		−0.0051 (−1.23)	−0.0055 (−1.35)
AgrMac		0.0000 *** (3.90)	0.0000 *** (3.58)
AgrLoans		0.0000 ** (2.35)	0.0000 (0.97)

Table 3. Cont.

	(1)	(2)	(3)
Variables	FP	FP	FP
Intensity			0.0003 (0.56)
Emissions			−0.0000 * (−1.82)
Resilience			−0.1286 *** (−2.67)
Constant	7.4469 *** (50.85)	7.4314 *** (37.01)	7.5680 *** (36.90)
Observations	360	360	360
R-squared	0.993	0.993	0.994
Controls FE	YES	YES	YES
Province FE	YES	YES	YES
Year FE	YES	YES	YES
r2_a	0.992	0.993	0.993
F	4.935	8.091	6.040

Note: robust t-statistics are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, the same as below.

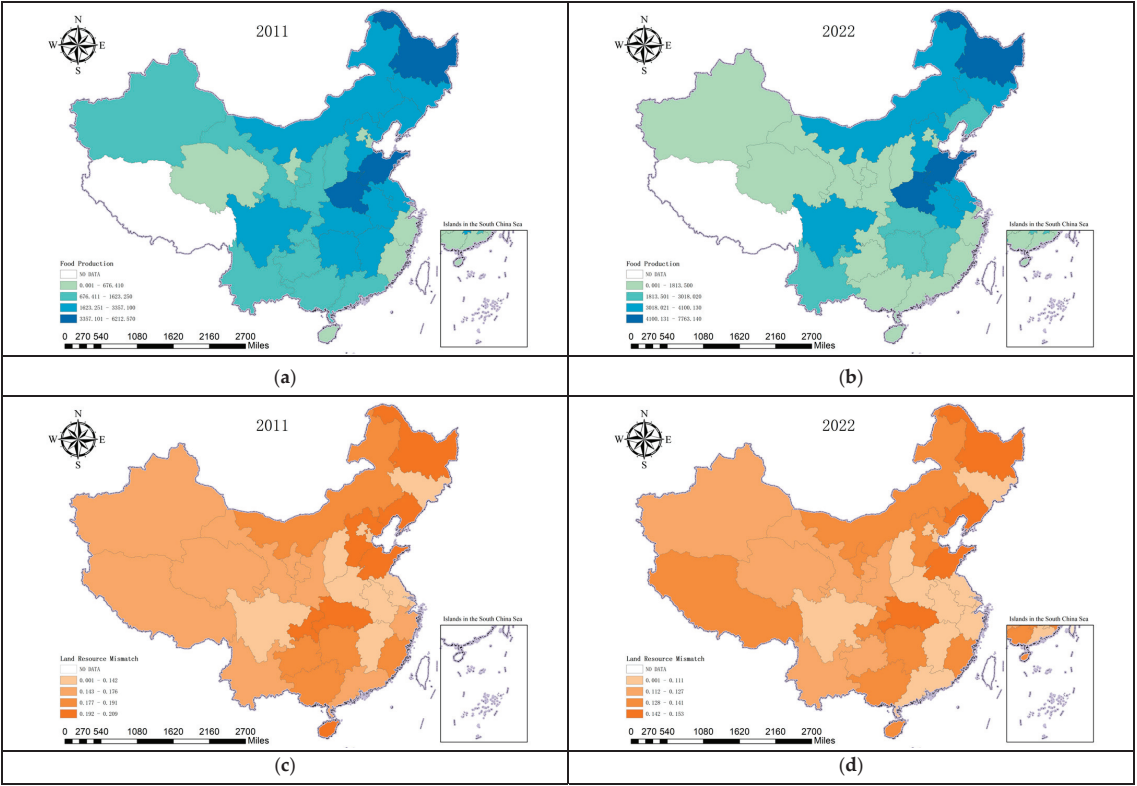


Figure 5. Spatial distribution of the level of food security and the degree of LRM in China. (a) Level of food security in China in 2011; (b) level of food security in China in 2021; (c) degree of LRM in China in 2011; (d) degree of LRM in China in 2022.

4.3. Robustness Tests

4.3.1. Changing the Sample Time

The COVID–19 pandemic led to widespread economic lockdowns and business closures, significantly disrupting primary industry activities. To account for these exceptional circumstances, data from 2020 and 2021 were excluded, and the regression was re-estimated. As shown in Column (1) of Table 4, the LRM coefficient remained significantly negative, affirming the robustness of the main findings.

Table 4. Robustness test results.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	FP	Volatility	lnGrain	FP	FP_w	FP
LRM	−2.6367 ** (−2.36)	1.0901 *** (2.93)	−2.3061 ** (−2.17)			
L.LRM				−3.7193 *** (−3.78)		
LRM_w					−2.1237 ** (−2.22)	
LRM1						−0.0340 * (−1.84)
Constant	7.5876 *** (32.79)	−0.0920 (−1.25)	7.4594 *** (35.41)	7.7483 *** (39.82)	7.5342 *** (39.84)	7.3821 *** (77.65)
Observations	267	360	360	327	327	270
R-squared	0.994	0.631	0.994	0.994	0.995	0.994
Controls						
FE	YES	YES	YES	YES	YES	YES
Province						
FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
r2_a	0.993	0.571	0.993	0.993	0.994	0.993
F	6.129	3.945	6.172	7.576	6.148	21.92

Note: robust t-statistics are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, the same as below.

4.3.2. Changing the Dependent Variable

Due to the significant influence of natural, market, and other socio-economic factors on grain production, it often exhibits some volatility. Therefore, grain production volatility is an important indicator of the stability of grain production. Since cereals are a key subset of food, this study replaced the original dependent variable with grain production volatility (Volatility) and the logarithmic value of grain output (lnGrain) and re-estimated the regression. The results, shown in Table 4, indicate that in Column (2), the LRM coefficient is 1.0901 and is significant at the 1% level, indicating that LRM increases grain production volatility, which may threaten FS. In Column (3), the LRM coefficient is significantly negative, indicating that LRM reduces grain output. These results are consistent with the baseline regression conclusions.

4.3.3. Lagged Independent Variable

To further test the robustness of the main conclusions, the study introduced a one-period lagged independent variable and re-estimated the baseline regression to address potential endogeneity. As can be seen in Column (4) of Table 4, the lagged LRM coefficient was −3.7193 and significant at the 1% level, confirming that even when considering potential dynamic effects, the negative impact of LRM on FS remains robust.

4.3.4. Excluding Extreme Values

To avoid the influence of extreme values on the baseline regression results, this study trimmed the top and bottom 1% of the values for FP and LRM and then re-estimated the regression. Column (5) of Table 4 shows that the LRM_w coefficient remained significantly

negative, indicating that LRM continues to impact grain production negatively, consistent with the baseline results.

4.3.5. PSM Matching

To mitigate potential endogeneity and sample selection bias, the study employed the PSM approach for robustness testing. Control variables from the baseline regression were used as matching variables, and the radius matching method was applied. The results, as shown in Column (6) of Table 4, indicate that the LRM1 coefficient remained significantly negative, further confirming the robustness of the findings.

4.4. Heterogeneity Tests

4.4.1. Heterogeneity in Urbanization Rate

In examining the negative impact of LRM on total grain output, the level of urbanization emerged as an important factor. The study divided the sample into a high-urbanization group (urbanization rate above the mean) and a low-urbanization group (urbanization rate below the mean). As shown in Columns (1) and (2) of Table 5, LRM had a more significant effect on grain output in areas with higher urbanization rates. As discussed earlier, the higher the urbanization rate, the greater the demand for construction land and non-agricultural jobs. Therefore, these areas tend to occupy low-cost arable land for economic development, and due to economies of scale, they attract a wide range of production factors, leading to a faster decline in grain production.

Table 5. Heterogeneity regression result.

	(1) High Urbanization Rate	(2) Low Urbanization Rate	(3) Long Tenure of Officials	(4) Short Tenure of Officials	(5) Major Grain- Producing Area	(6) Non-Major Grain- Producing Area
Variables	FP	FP	FP	FP	FP	FP
LRM	−4.2138 ** (−2.01)	0.8557 (1.28)	−1.2248 (−1.04)	−9.4264 ** (−2.43)	−0.7128 (−1.29)	−3.0132 * (−1.75)
Constant	7.2095 *** (18.02)	7.3479 *** (53.77)	7.4136 *** (31.32)	7.9497 *** (12.28)	8.3286 *** (69.98)	6.9257 *** (20.91)
Observations	194	166	278	82	156	204
R-squared	0.993	0.999	0.994	0.995	0.992	0.988
Controls FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
r2_a	0.990	0.998	0.993	0.989	0.990	0.985
F	3.993	5.383	3.789	1.736	4.225	2.395

Note: robust t-statistics are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, the same as below.

4.4.2. Heterogeneity Based on Officials’ Tenure

To explore the heterogeneity in the negative impact of LRM on grain output based on officials’ tenure, the study divided the sample into a long-tenure group and a short-tenure group based on the median tenure of provincial party secretaries. As shown in Columns (3) and (4) of Table 5, the negative impact of LRM on FS was greater in areas with shorter tenures. This is because local governments have considerable discretion in land transfers, and officials with shorter tenures are more likely to expand industrial land supply to rapidly boost GDP and demonstrate their capabilities. Since FS is not a key performance indicator for officials, it is more likely to be neglected by those with shorter tenures.

4.4.3. Heterogeneity in Major Grain-Producing Areas

China assigns distinct functional roles to its provinces, with major grain-producing regions, like Henan Province, being crucial for national FS. Therefore, China implements

stricter farmland protection policies and provides more generous economic incentives for farmland protection in these areas, reducing the likelihood of farmland being occupied for construction and slowing the decline in grain output. This study classified 13 provinces—Heilongjiang, Henan, Shandong, Sichuan, Jiangsu, Hebei, Jilin, Anhui, Hunan, Hubei, Inner Mongolia, Jiangxi, and Liaoning—as major grain-producing areas based on their designation in 2001. The remaining provinces were classified as non-major grain-producing areas. The regression results, as shown in Columns (5) and (6) of Table 5, indicate that the negative impact of LRM on FS was more pronounced in non-major grain-producing areas.

5. Further Analysis

5.1. Mechanism Effects

As discussed in the theoretical analysis, LRM absorbs essential agricultural resources, such as land, capital, and labor, thereby reducing grain production and threatening FS. To examine these impact pathways, this study employed a two-step approach for mechanism effect testing.

5.1.1. Land Factor

In this study, the natural logarithm of the sown area (in thousands of hectares) of cereals, pulses, and yams in each province in the current year plus one was taken as a proxy variable for the land factor and brought into the mechanism effect model for testing. As seen in the regression results in Column (1) of Table 6, the coefficient of LRM was significantly negative, indicating that LRM reduces the sown area for grain. The imbalance in land allocation results in a large portion of land resources originally designated for grain production being converted into non-agricultural uses, such as industrial, commercial, and residential development. This shift not only reduces the physical space available for food production but also limits the scale and variety of crops that can be cultivated. The growing scarcity of arable land poses a serious threat to the stability and sustainability of grain production, with significant implications for FS, confirming H2a.

Table 6. Influence mechanism regression results.

	(1)	(2)	(3)
Variables	Land	Capital	Labor
LRM	−1.8331 * (−1.91)	−7.7587 ** (−2.36)	−1.5047 ** (−2.45)
Constant	8.0461 *** (43.75)	4.3448 *** (6.92)	6.4394 *** (52.76)
Observations	360	360	360
R-squared	0.997	0.935	0.994
Controls FE	YES	YES	YES
Province FE	YES	YES	YES
Year FE	YES	YES	YES
r2_a	0.997	0.924	0.993
F	8.726	1.183	25.45

Note: robust t-statistics are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, the same as below.

5.1.2. Capital Factor

In this study, the natural logarithm of multiplying the share of agricultural output and investment in agriculture, forestry, livestock, and fisheries in each province in the current year plus one was taken as a proxy variable to calculate the capital factor, which was brought into the mechanism effect model for testing. According to the regression results in Column (2) of Table 6, the LRM coefficient was −7.7587 and significant at the 5% level, indicating that LRM leads to insufficient capital investment in agriculture. Capital is an essential factor in agricultural production, especially with the increasing reliance on mechanization

and infrastructure in modern agriculture. However, local governments often prioritize land allocation for industrial development, which limits agricultural investments and capital supply. This capital shortfall hinders the adoption of new technologies and equipment upgrades, reducing production efficiency and posing a threat to FS, confirming H2b.

5.1.3. Labor Factor

This study took the number of people employed in the primary industry in the current year in each province as a proxy variable for the labor factor and brought it into the mechanism effect model for testing. As shown in the regression results in Column (3) of Table 6, the LRM coefficient was significantly negative, indicating that LRM contributes to rural labor loss. The migration of rural labor to cities has intensified with urbanization. Due to LRM, rural income levels are adversely affected, weakening the ability of rural areas to retain their workforce. As a result, many laborers migrate to cities in search of better opportunities, which exacerbates the challenges in agricultural production and impacts the overall grain supply, confirming H2c.

5.2. Moderating Effects

As discussed in the theoretical analysis, in the era of the DE, the rapid advancement of digital technologies has led to the integration of data into production, distribution, and consumption processes with unprecedented scope and depth, transforming traditional production models. To validate the moderating effects of technology and data factors in alleviating LRM, this study conducted tests on these moderating effects.

5.2.1. Technological Factor

In this study, the natural logarithm of the number of digital innovation patent applications in each province plus one was taken as a proxy variable for the technology factor and brought into the moderating effects model for testing. As shown in the regression results in Column (1) of Table 7, the coefficient for LRMXDigTech was 1.0591 and significant at the 1% level, indicating that the development of digital technologies can mitigate the risks posed by LRM to FS. Digital technology overcomes the limitations of resource scarcity and the backwardness of traditional agricultural techniques. With the advancement of rural land transfers and the expansion of production scales, farmers or agricultural enterprises can utilize digital technologies and large-scale machinery to achieve the precise management of production, improving agricultural efficiency. This trend alleviates the inefficiency in agricultural production caused by LRM, thereby reducing the threat to FS, confirming H3a.

5.2.2. Data Factor

In this study, the policy variable Egovernment was defined as follows: if the province went online with the open government data platform in that year, the value of Egovernment was assigned to 1, and otherwise, it was assigned to 0, and then the moderating effect model was tested. As demonstrated by the regression results in Column (2) of Table 7, the coefficient of LRMXegovernment was significantly positive, indicating that the open government data can mitigate the negative impact of LRM on FS. The open government data break down information barriers between banks and enterprises, enabling agricultural companies to gain sufficient financial support. Moreover, the interaction between open government data and other production factors can generate a multiplier effect. By integrating deeply with digital technologies, agricultural firms can adopt precise and intelligent management practices, optimizing the allocation of agricultural resources. Thus, data factors play an essential role in reducing the risks posed by LRM to FS, supporting H3b.

Table 7. Moderating effect regression results.

	(1)	(2)
Variables	FP	FP
LRM	−9.7950 *** (−6.23)	−2.2027 (−1.61)
LRMXDigTech	1.0591 *** (4.00)	
DigTech	−0.1739 ** (−3.10)	
LRMXEgoverment		2.0152 ** (2.63)
Egoverment		−0.2872 ** (−2.41)
Constant	8.6553 *** (28.74)	7.5232 *** (26.14)
Observations	360	360
R-squared	0.994	0.994
Controls FE	YES	YES
Province FE	YES	YES
Year FE	YES	YES
r2_a	0.993	0.993
F	1127	335.1

Note: robust t-statistics are in parentheses, *** $p < 0.01$, ** $p < 0.05$, the same as below.

6. Conclusions and Suggestions

6.1. Research Conclusions

This study uses provincial panel data from China spanning from 2011 to 2022 to investigate the negative impact of LRM on FS, examine the impact mechanisms, and highlight the crucial role of the DE in alleviating these negative outcomes. First, the findings reveal that LRM significantly reduces grain production, posing a threat to FS. This conclusion remains robust after a series of robustness checks. Second, this study discusses the heterogeneous effects of LRM on FS, showing that regions with higher urbanization levels, shorter official tenures, and that are non-major grain-producing areas experience a more pronounced negative impact on FS. Lastly, this study explores how LRM impairs FS and offers potential solutions. By diminishing the supply of essential factors such as land, labor, and capital for grain production, LRM undermines the material foundation and productive capacity of the sector. The DE, by providing technological and data resources through digital innovation and open government data, helps mitigate the threat posed by LRM to FS.

6.2. Policy Recommendations

In order to address LRM, policy guidance should be enhanced, and institutions should be optimized. First, land market reforms should be promoted by establishing a comprehensive land market system and improving transaction rules to ensure the efficient allocation of land resources through market mechanisms. Second, the fiscal tax-sharing system should be reformed to reduce local government dependence on land-based financing. This can be achieved by moderately adjusting the system to discourage the transfer of large amounts of arable land for short-term fiscal gain. A diversified local revenue system should be established, with an emphasis on increasing tax revenue sharing and transfer payments to alleviate fiscal pressures on local governments. Finally, a mechanism linking the tenure of officials to the food security accountability system should be established. Considering that the short tenure of officials may exacerbate short-term behaviors in land resource management, it is recommended that food security be incorporated into the performance appraisal system of local officials, especially for non-major food-producing areas and sensitive areas of land resource management, to implement a stricter food security accountability

system and to encourage officials to adopt, during their term of office, land policies that are conducive to the long-term development of food production.

The construction of high-standard farmland should be promoted, and farmland protection should be strengthened. First, investment in high-standard farmland should be increased to boost both production capacity and output efficiency. Land consolidation and agricultural water conservancy projects should be implemented to improve infrastructure and enhance land use efficiency. Second, farmland management systems should be improved with strict land use controls, setting clear boundaries for arable land and ecological protection zones to prevent illegal occupation of high-quality farmland. A robust compensation system for farmland occupation should be established to ensure that any land taken for construction is replaced by land of equal or superior quality. Finally, stringent farmland protection policies should be enforced, farmland quality should be regularly monitored, and damaged farmland should be promptly restored. Illegal activities that harm the quality of farmland should be punished.

Rural employment conditions should be improved, and the supply of labor factors should be increased. First, rural infrastructure can be enhanced by improving roads, water supply, electricity, telecommunications, and other facilities to make rural living more convenient and attractive for labor retention. Second, rural vocational education should be invested in to build a multi-tiered training system that improves the skills and competence of the rural workforce. Various training programs should be provided to help farmers master modern agricultural techniques, thereby increasing productivity and market competitiveness. Finally, young people should be encouraged to return to rural areas by offering policy support and financial incentives for entrepreneurship in modern agriculture and processing industries.

External investment should be attracted to increase agricultural capital supply. First, agricultural investment should be increased through both direct fiscal support and policy-based financial assistance. Government subsidies and funding for agricultural infrastructure should be expanded to boost capital investment in agriculture directly. Financial services such as low-interest loans and credit guarantees should be offered to lower financing costs and encourage further investment in agricultural production. Second, the development of agricultural insurance should be promoted to protect against risks from natural disasters and market fluctuations. The coverage of agricultural insurance should be expanded to ensure more farmers benefit from this financial protection, and additional social capital should be attracted into the agricultural sector to strengthen overall capital supply.

Open government data should be leveraged to improve land resource allocation efficiency and grain production. The government should lead the creation of a comprehensive, authoritative, and user-friendly open government data platform that consolidates information from the agriculture, land, meteorology, and market sectors. Clear standards and access protocols should be established to ensure that key agricultural and land resource data are made available in a timely and accurate manner. Enterprises, research institutions, and individuals should be encouraged to utilize open data to develop intelligent agricultural solutions, such as precision fertilization, smart irrigation, and pest forecasting. Financial institutions should also use these data to better assess the creditworthiness of agricultural operators, promoting innovative financing models like supply chain finance and agricultural insurance linked to futures markets.

Digital technology must be actively utilized to improve agricultural productivity and quality, ensuring national FS. First, investment in rural digital infrastructure should be increased, and internet access should be expanded to ensure farmers and agricultural businesses can easily access digital resources. Agricultural big data centers should be built to gather and analyze information on production, markets, and resources, providing scientific support for agricultural decision-making. Second, developing and using intelligent agricultural machinery, such as autonomous tractors, drones, and smart seeders, should be promoted to enhance production efficiency. The Internet of Things (IoT) technology

should also be employed to monitor soil conditions and crop growth in real time, providing precise production guidance. Finally, digital management capabilities in agriculture can be strengthened by creating integrated platforms for managing production, markets, and resources. Farmers and agricultural employees should be trained in digital skills to ensure they can fully utilize new technologies in their work.

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References

- Chen, R.S.; Kates, R.W. World food security: Prospects and trends. *Food Policy* **1994**, *19*, 192–208. [CrossRef]
- Chen, W.; Wang, G.; Cai, W.; Che, X.; Zhou, W.; Zhang, C.; Zeng, J. Spatiotemporal mismatch of global grain production and farmland and its influencing factors. *Resour. Conserv. Recycl.* **2023**, *194*, 107008. [CrossRef]
- Ju, H.; Zhang, Z.; Zhao, X.; Wang, X.; Wu, W.; Yi, L.; Wen, Q.; Liu, F.; Xu, J.; Hu, S.; et al. The changing patterns of cropland conversion to built-up land in China from 1987 to 2010. *J. Geogr. Sci.* **2018**, *28*, 1595–1610. [CrossRef]
- Dorninger, C.; von Wehrden, H.; Krausmann, F.; Bruckner, M.; Feng, K.; Hubacek, K.; Erb, K.-H.; Abson, D.J. The effect of industrialization and globalization on domestic land-use: A global resource footprint perspective. *Glob. Environ. Chang.* **2021**, *69*, 102311. [CrossRef]
- Zhang, L.; Lu, D.; Li, Q.; Lu, S. Impacts of socioeconomic factors on cropland transition and its adaptation in Beijing, China. *Environ. Earth Sci.* **2018**, *77*, 575. [CrossRef]
- Zeng, L.; Li, H.; Wang, X.; Yu, Z.; Hu, H.; Yuan, X.; Zhao, X.; Li, C.; Yuan, D.; Gao, Y.; et al. China's transport land: Spatiotemporal expansion characteristics and driving mechanism. *Land* **2022**, *11*, 1147. [CrossRef]
- Masayoshi, H.; Hayami, Y. Japan, Republic of Korea and Taiwan, China. In *Distortions to Agricultural Incentives: A Global Perspective, 1955–2007*; Anderson, K., Ed.; World Bank: Washington, DC, USA, 2009.
- Gutser, R.; Ebertseder, T.; Weber, A.; Schraml, M.; Schmidhalter, U. Short-term and residual availability of nitrogen after long-term application of organic fertilizers on arable land. *J. Plant Nutr. Soil Sci.* **2005**, *168*, 439–446. [CrossRef]
- Ding, Y.; McQuoid, A.; Karayalcin, C. Fiscal decentralization, fiscal reform, and economic growth in china. *China Econ. Rev.* **2019**, *53*, 152–167. [CrossRef]
- Gu, H.; Guo, G.; Li, C. Treating the Symptoms as Well as the Root Causes: How the Digital Economy Can Mitigate the Negative Impacts of Land Resource Mismatches on Urban Ecological Resilience. *Land* **2024**, *13*, 1463. [CrossRef]
- Chen, C.; Restuccia, D.; Santaaulàlia-Llopis, R. The effects of land markets on resource allocation and agricultural productivity. *Rev. Econ. Dyn.* **2022**, *45*, 41–54. [CrossRef]
- Azadi, H.; Ho, P.; Hasfiati, L. Agricultural land conversion drivers: A comparison between less developed, developing and developed countries. *Land Degrad. Dev.* **2011**, *22*, 596–604. [CrossRef]
- Milne, R.J.; Bennett, L.P. Biodiversity and ecological value of conservation lands in agricultural landscapes of southern Ontario, Canada. *Landsc. Ecol.* **2007**, *22*, 657–670. [CrossRef]
- Duguma, L.A.; Hager, H. Farmers' assessment of the social and ecological values of land uses in central highland Ethiopia. *Environ. Manag.* **2011**, *47*, 969–982. [CrossRef] [PubMed]
- Yang, S.; Li, D.; Liao, H.; Zhu, L.; Zhou, M.; Cai, Z. Analysis of the Balance between Supply and Demand of Arable Land in China Based on Food Security. *Sustainability* **2023**, *15*, 5706. [CrossRef]
- Shaw, D.J. *World Food Security: A History Since*; Palgrave Macmillan: London, UK, 1945. [CrossRef]
- Jiang, C.; Li, J. Influence of the market supply of construction land on the misallocation of labor resources: Empirical evidence from China. *Land* **2022**, *11*, 1773. [CrossRef]

18. Du, W.; Li, M. The impact of land resource mismatch and land marketization on pollution emissions of industrial enterprises in China. *J. Environ. Manag.* **2021**, *299*, 113565. [CrossRef]
19. Gebbers, R.; Adamchuk, V.I. Precision agriculture and food security. *Science* **2010**, *327*, 828–831. [CrossRef]
20. Shaikh, T.A.; Rasool, T.; Lone, F.R. Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Comput. Electron. Agric.* **2022**, *198*, 107119. [CrossRef]
21. Amentae, T.K.; Gebresenbet, G. Digitalization and future agro-food supply chain management: A literature-based implications. *Sustainability* **2021**, *13*, 12181. [CrossRef]
22. Song, W.; Liu, M. Farmland conversion decreases regional and national land quality in China. *Land Degrad. Dev.* **2017**, *28*, 459–471. [CrossRef]
23. Jones, C.I.; Tonetti, C. Nonrivalry and the Economics of Data. *Am. Econ. Rev.* **2020**, *110*, 2819–2858. [CrossRef]
24. Cong, L.W.; Xie, D.; Zhang, L. Knowledge accumulation, privacy, and growth in a data economy. *Manag. Sci.* **2021**, *67*, 6480–6492. [CrossRef]
25. Li, C.; Xu, Y.; Zheng, H.; Wang, Z.; Han, H.; Zeng, L. Artificial intelligence, resource reallocation, and corporate innovation efficiency: Evidence from China's listed companies. *Resour. Policy* **2023**, *81*, 103324. [CrossRef]
26. Jiang, Z.; Zhang, X.; Zhao, Y.; Li, C.; Wang, Z. The impact of urban digital transformation on resource sustainability: Evidence from a quasi-natural experiment in China. *Resour. Policy* **2023**, *85*, 103784. [CrossRef]
27. Balasundram, S.K.; Shamshiri, R.R.; Sridhara, S.; Rizan, N. The role of digital agriculture in mitigating climate change and ensuring food security: An overview. *Sustainability* **2023**, *15*, 5325. [CrossRef]
28. Karunathilake, E.M.B.M.; Le, A.T.; Heo, S.; Chung, Y.S.; Mansoor, S. The path to smart farming: Innovations and opportunities in precision agriculture. *Agriculture* **2023**, *13*, 1593. [CrossRef]
29. Liu, Y.; Zhao, X.; Kong, F. The dynamic impact of digital economy on the green development of traditional manufacturing industry: Evidence from China. *Econ. Anal. Policy* **2023**, *80*, 143–160. [CrossRef]
30. Zhou, X.; Chen, T.; Zhang, B. Research on the impact of digital agriculture development on agricultural green total factor productivity. *Land* **2023**, *12*, 195. [CrossRef]
31. Yao, W.; Sun, Z. The impact of the digital economy on high-quality development of agriculture: A China case study. *Sustainability* **2023**, *15*, 5745. [CrossRef]
32. Lee, C.C.; Zeng, M.; Luo, K. Food security and digital economy in China: A pathway towards sustainable development. *Econ. Anal. Policy* **2023**, *78*, 1106–1125. [CrossRef]
33. Premnandh, J. Factors affecting food security and contribution of modern technologies in food sustainability. *J. Sci. Food Agric.* **2011**, *91*, 2707–2714. [CrossRef] [PubMed]
34. Li, Y.; Zhang, W.; Ma, L.; Huang, G.; Oenema, O.; Zhang, F.; Dou, Z. An analysis of China's fertilizer policies: Impacts on the industry, food security, and the environment. *J. Environ. Qual.* **2013**, *42*, 972–981. [CrossRef] [PubMed]
35. Jena, P.R.; Tanti, P.C. Effect of farm machinery adoption on household income and food security: Evidence from a nationwide household survey in India. *Front. Sustain. Food Syst.* **2023**, *7*, 922038. [CrossRef]
36. Mirzabaev, A.; Nkonya, E.; von Braun, J. Economics of sustainable land management. *Curr. Opin. Environ. Sustain.* **2015**, *15*, 9–19. [CrossRef]
37. Ma, S.; Swinton, S.M. Valuation of ecosystem services from rural landscapes using agricultural land prices. *Ecol. Econ.* **2011**, *70*, 1649–1659. [CrossRef]
38. Sharma, M.; Joshi, S.; Govindan, K. Overcoming barriers to implement digital technologies to achieve sustainable production and consumption in the food sector: A circular economy perspective. *Sustain. Prod. Consum.* **2023**, *39*, 203–215. [CrossRef]
39. Wang, H.; Li, G.; Hu, Y. The Impact of the Digital Economy on Food System Resilience: Insights from a Study across 190 Chinese Towns. *Sustainability* **2023**, *15*, 16898. [CrossRef]
40. Wu, Y.; Zhang, X.; Shen, L. The impact of urbanization policy on land use change: A scenario analysis. *Cities* **2011**, *28*, 147–159. [CrossRef]
41. Liu, Y.; Fang, F.; Li, Y. Key issues of land use in China and implications for policy making. *Land Use Policy* **2014**, *40*, 6–12. [CrossRef]
42. Jiang, T.; Zhong, M.; Gao, A.; Ma, G. Do Factor Misallocations Affect Food Security? Evidence from China. *Agriculture* **2024**, *14*, 729. [CrossRef]
43. Nasir, J. Misallocation of Land. In *Development Challenges of Pakistan: Constraints and Choices*; Springer Nature: Singapore, 2024; pp. 209–233. [CrossRef]
44. Wang, J.; Lin, Y.; Glendinning, A.; Xu, Y. Land-use changes and land policies evolution in China's urbanization processes. *Land Use Policy* **2018**, *75*, 375–387. [CrossRef]
45. Ramankutty, N.; Mehrabi, Z.; Waha, K.; Jarvis, L.; Kremen, C.; Herrero, M.; Rieseberg, L.H. Trends in global agricultural land use: Implications for environmental health and food security. *Annu. Rev. Plant Biol.* **2018**, *69*, 789–815. [CrossRef] [PubMed]
46. Li, J.; Chu, L. Decentralization versus Centralization: What Ensures Food Security? Empirical Evidence from 170 Prefecture-Level Cities in China's Major Grain-Producing Areas. *Agriculture* **2024**, *14*, 1183. [CrossRef]
47. Ma, L.; Zong, Y.; Wang, X.; Shi, Z.; Zhang, W. Farmland use behavior and its influencing factors from the perspective of population migration. *J. Geogr. Sci.* **2024**, *34*, 439–458. [CrossRef]
48. Guo, Y.; Wang, J. Practices for rural population aging in China: Land-based pension. *Habitat Int.* **2024**, *151*, 103136. [CrossRef]

49. Zhai, C.; Ding, X.; Zhang, X.; Jiang, S.; Zhang, Y.; Li, C. Assessing the effects of urban digital infrastructure on corporate Environmental, Social and Governance (ESG) performance: Evidence from the broadband China Policy. *Systems* **2023**, *11*, 515. [CrossRef]
50. Xu, Y.; Li, C. Digital transformation, firm boundaries, and market power: Evidence from China's listed companies. *Systems* **2023**, *11*, 479. [CrossRef]
51. Wei, S.; Lu, Y. Adoption mode of agricultural machinery and food productivity: Evidence from China. *Front. Sustain. Food Syst.* **2024**, *7*, 1257918. [CrossRef]
52. Balkrishna, A.; Pathak, R.; Kumar, S.; Arya, V.; Singh, S.K. Smart agricultural technology. *Precis. Agric.* **2023**, *5*, 100318. [CrossRef]
53. Stupina, A.A.; Rozhkova, A.V.; Olentsova, J.A.; Rozhkov, S.E. Digital technologies as a tool for improving the efficiency of the agricultural sector. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *839*, 022092. [CrossRef]
54. Shi, Z.; Loh, L.; Wu, H.; Han, D. Smarter and cleaner: How does energy digitalization affect carbon productivity? *Energy Strategy Rev.* **2024**, *52*, 101347. [CrossRef]
55. Xing, Q.; Xu, G.; Wang, Y. Open government data and the cost of debt. *Int. Rev. Financ. Anal.* **2024**, *95*, 103384. [CrossRef]
56. Jiang, T. Mediating effects and moderating effects in causal inference. *China Ind. Econ.* **2022**, *5*, 100–120. [CrossRef]
57. Godfray, H.C.J.; Beddington, J.R.; Crute, I.R.; Haddad, L.; Lawrence, D.; Muir, J.F.; Pretty, J.; Robinson, S.; Thomas, S.M.; Toulmin, C. Food security: The challenge of feeding 9 billion people. *Science* **2010**, *327*, 812–818. [CrossRef]
58. Nan, Y.; Gao, Y.; Zhou, Q. Rural credit cooperatives' contribution to agricultural growth: Evidence from China. *Agric. Financ. Rev.* **2019**, *79*, 119–135. [CrossRef]

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Article

Spatiotemporal Distribution and Driving Mechanisms of Cropland Long-Term Stability in China from 1990 to 2018

Yuchen Zhong ^{1,†}, Jun Sun ^{1,†}, Qi Wang ¹, Dinghua Ou ^{1,2}, Zhaonan Tian ¹, Wuhaomiao Yu ¹, Peixin Li ¹ and Xuesong Gao ^{1,2,*}

¹ College of Resources, Sichuan Agricultural University, Chengdu 611130, China; 2023206046@stu.sicau.edu.cn (Y.Z.); sunj@stu.sicau.edu.cn (J.S.); wq94@stu.sicau.edu.cn (Q.W.); 14340@sicau.edu.cn (D.O.); 71410@sicau.edu.cn (Z.T.); yuwuhamiao123@163.com (W.Y.); lipeixin@stu.sicau.edu.cn (P.L.)

² Key Laboratory of Investigation and Monitoring, Protection and Utilization for Cultivated Land Resources, Ministry of Natural Resources, Chengdu 611130, China

* Correspondence: xuesonggao@sicau.edu.cn

† These authors contributed equally to this work.

Abstract: Long-term stability is crucial in cropland for maintaining stable agricultural production and ensuring national food security. However, relatively few studies have been conducted on the long-term stability of cropland at the national level. This study assessed the long-term stability of cropland in China from 1990 to 2018 using a fine-resolution land use dataset. The experimental results indicated that the average area of unstable cropland in China from 1990 to 2018 amounted to 2.08×10^6 km², 47.31% of the total. The Qinghai–Tibet Plateau exhibited the highest average proportion of unstable cropland at 65.9%, followed by the northern arid and semiarid region, Southern China, and the Yunnan–Guizhou Plateau. The quantity of unstable cropland in China initially declined before increasing, reaching a final growth rate of 5.09%. Furthermore, this study explored the relevant driving factors of cropland’s long-term stability from both natural factors and human activities based on artificial neural networks. The relative importance of distance to vegetation reached a value of 0.30, indicating that it had the most significant influence on the long-term stability of cropland, followed by relief amplitude and soil type. This phenomenon may be attributed to the inadequate execution of the Grain for Green Policy and the requisition–compensation balance of cropland policy, along with the depletion of young and middle-aged laborers due to urban migration from rural areas. Local governments should focus on addressing the unsustainable exploitation of sloped land in rural mountainous or hilly regions while preventing urban developers from appropriating fertile cropland to compensate for less fertile areas.

Keywords: long-term stable cropland; driving mechanisms; spatiotemporal pattern; Grain for Green policy; China

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1. Introduction

As global challenges such as population growth, depletion of natural resources, accelerated climate change, heightened occurrences of extreme weather events, and geopolitical tensions continue to escalate, the issue of global food security has come under significant strain [1–3]. Cropland serves as the cornerstone of food production and security, warranting global attention to its preservation. However, since the 1960s, increasing urbanization has posed a widespread threat to global cropland, leading to its gradual destabilization [4–6]. Existing studies underscore the significance of protecting cropland in developing nations to uphold food security, with a particular focus on China [7–9]. China sustains 21% of the global population, with only 9% of the world’s cropland [10]. However, problems such as the spatial mismatch in cropland distribution and the large-scale transfer of cropland

to marginal land have progressively compromised food security and environmental sustainability in China [11–13]. As a crucial factor in food security, the stability of cropland designated for food production serves as a fundamental pillar in ensuring food security. The long-term stable use of cropland can help improve the sustainability of food production, thereby ensuring food security [14,15].

Existing studies define “long-term stable cropland” as the cropland that has been stably utilized over a long period and distinguish this type of cropland from recently reclaimed cropland or frequently abandoned and reclaimed cropland [16,17]. Research suggests that consistent use of cropland over a prolonged period fosters an optimal environment for crop growth. With appropriate farmland management practices, cropland that has not been abandoned always has higher agro-environmental endowments than newly built or idle cropland [18–21]. Unstable cropland, which is characterized by fluctuating land use and cover changes, deviates from the conventional definitions of cropland and ecological land. It is often disturbed during utilization, which may disrupt the restoration of natural ecosystems and the formation of long-term stable cropland [22,23]. However, the concept of cropland stability and its evaluation have yet to be globally standardized [24].

There are two primary methodological approaches for studying cropland stability: *a priori* evaluation and empirical identification. An *a priori* evaluation involves the establishment of an index system to assess cropland stability based on existing disciplinary knowledge. This method assumes that sufficient prior knowledge can determine the stable utilization of cropland. Previous studies have proposed various approaches to evaluate cropland stability based on different disciplinary backgrounds, reflecting a more developed methodology [24–30]. However, these approaches often lack practical validity and generalizability. In contrast, empirical identification assesses cropland stability based on historical utilization patterns without directly relying on prior disciplinary knowledge, making it an empirical approach [16,17,31]. However, existing research predominantly views the distribution patterns of long-term stable cropland as the geographic scope of specific studies, employing it to analyze other cropland use phenomena rather than systematically summarizing and investigating the long-term stability of cropland and its underlying mechanisms [16,17,32]. Although a few studies have qualitatively discussed the driving mechanisms behind the distribution patterns of long-term stable cropland, there remains a lack of quantitative analyses of specific driving factors [22,33].

Artificial neural networks (ANNs) are vast, continuous-time, dynamic systems characterized by significant nonlinearity, comprising large numbers of interconnected processing units [34]. These networks offer inherent benefits such as self-learning, associative storage, robust generalization capability (i.e., proficient performance on unseen data), and resilience to data errors [35]. Unlike conventional linear regression models, artificial neural networks excel in capturing the complexity and nonlinearity inherent in environmental processes, thereby bridging knowledge and data gaps; this is especially beneficial for analyzing cropland change scenarios [36–39].

Therefore, to fill existing research gaps, this study proposed a method for evaluating cropland stability through the empirical identification of long-term stable cropland (i.e., long-term stability), and employed artificial neural networks to quantitatively analyze the driving mechanisms influencing the long-term stability of cropland. The empirical nature of the proposed method allows for generalization, which also provides an opportunity to validate the efficiency of existing *a priori* evaluation methods by analyzing the underlying driving mechanisms. The major objectives of this study are as follows: (1) to evaluate the cropland long-term stability in China from 1990 to 2018; (2) to analyze the evolution of quantity distribution and spatial pattern of cropland long-term stability across various agricultural zones in China from 1990 to 2018; and (3) to analyze the driving mechanisms behind the cropland long-term stability in China.

2. Materials and Methods

2.1. Study Area

China is located in the eastern part of the Eurasian continent along the western coast of the Pacific Ocean. China's elevation rose sharply from the eastern plains (less than 100 m) to the western mountains (more than 4000 m), with croplands primarily located in the eastern and central plateaus. [40]. Diverse elevations contribute to varied topography, leading to spatial heterogeneity in climate and soil distribution [41–43]. China experiences a mean annual temperature of around 9 °C and a mean annual precipitation of approximately 636 mm. The soils in China exhibit a zonal distribution, characterized by Argosols and Aridisols, primarily in the northern regions, and Anthrosols and Ferralsols, predominately in the southern regions. China has the third-largest global cropland area. However, owing to its substantial population, the per-capita cropland area is less than half the global average [32]. According to the agricultural potential productivity, geographical features, and administrative boundaries, the cropland of China is categorized into nine agricultural zones [44,45], including the Northeast China Plain (NCP), the Huang–Huai–Hai Plain (HHHP), the Loess Plateau (LP), the Northern Arid and Semiarid Region (NASR), the Sichuan Basin and Surrounding Regions (SBSR), the Qinghai–Tibet Plateau (QTP), the Middle–Lower Yangtze Plain (MLYP), the Yunnan–Guizhou Plateau (YGP), and Southern China (SC) (Figure 1).

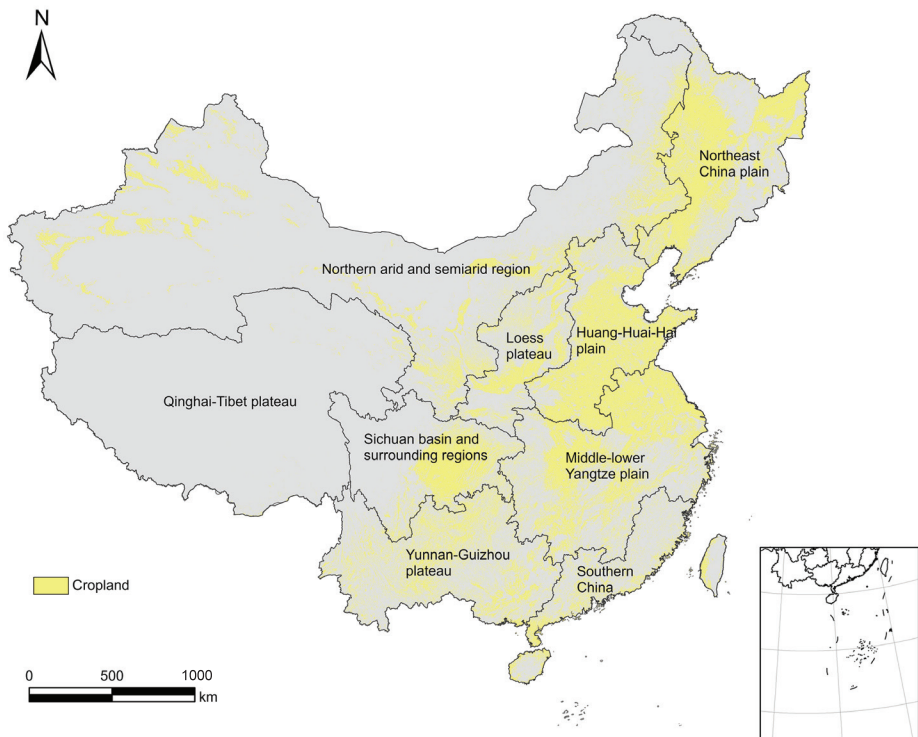


Figure 1. Cropland distribution and agricultural zones in China (2018). Note: Data on cropland distribution in 2018 were obtained from Yang and Huang [46].

2.2. Data Sources

The land use data used in this study were obtained from the China Land Cover Dataset (CLCD), compiled by Yang and Huang [46], which has a time-series range of 1985–2022 and a spatial resolution of 30 m. Digital elevation model (DEM) data were obtained from NASADEM (www.earthdata.nasa.gov) (accessed on 10 October 2023). Annual precipita-

tion and mean annual temperature data were obtained from Peng et al. [47]. Soil organic matter data were obtained from Shangguan et al. [48], drawing upon the Second National Soil Census of China, Harmonized World Soil Database, and additional databases. These data were supplemented by field survey sampling to compile a comprehensive dataset detailing the soil surface properties across China. Soil erosion data were obtained from the Geographic Data Sharing Infrastructure (www.gis5g.com) (accessed on 11 October 2023). Population density and soil type data were obtained from the Resource and Environment Science Data Platform (www.resdc.com) (accessed on 12 October 2023). Notably, the topography and soil properties exhibited minimal changes over a relatively long time-series; thus, the DEM and soil data were static in this study [49]. Owing to limitations in data availability, the population density data for China with a 1 km resolution in 2018 were substituted with data from 2019; this substitution has been allowed in similar studies [50]. Efforts were made to maintain consistency across all data throughout the time-series (Table 1).

Table 1. List of ancillary data used in this study.

Category	Original Spatial Resolution	Year	Data Source
Land use	30 m	1990–2022	Yang and Huang [46]
DEM	30 m	2020	https://www.earthdata.nasa.gov (accessed on 10 October 2023)
Annual precipitation	1 km	1990, 1995, 2000, 2005, 2010, 2015, 2018	Peng et al. [47]
Mean annual temperature	1 km	1990, 1995, 2000, 2005, 2010, 2015, 2018	Peng et al. [47]
Soil erosion	1 km	1990, 1995, 2000, 2005, 2010, 2015, 2018	http://www.gis5g.com (accessed on 11 October 2023)
Population density	1 km	1990, 1995, 2000, 2005, 2010, 2015, 2019	https://www.resdc.cn (accessed on 12 October 2023)
Soil type	1 km	1995	https://www.resdc.cn (accessed on 12 October 2023)
Soil organic matter	1 km	2013	Shangguan et al. [48]

2.3. Cropland Long-Term Stability

We defined cropland long-term stability (LTS) as the ability of a defined cropland to retain its size over an extended period. Thus, any changes in cropland patches, whether shrinking or growing, are considered disturbances, indicating a lack of long-term stability in their use. In contrast to prior studies that assessed the LTS of cropland patches based on historical performance [17], this study evaluated it by summarizing the future performance of cropland patch sizes using historical land use data, grounding this approach in empirical evidence. Drawing on the existing research on cropland abandonment and long-term stable use, we established a 5-year evaluation period [16,32,51].

A spatial offset phenomenon exists in the temporal evolution of land use patches within the same geographic location in the CLCD dataset, hindering the identification of cropland spatial utilization. To accurately assess cropland scale changes and their implications for LTS, we calculated them by quantifying the change in cropland quantity within a 1 km grid. The commonly used fine resolution for analyzing data at the national scale is 1 km [52–54], and this resolution is also the original resolution of most Chinese geospatial datasets selected for this study (Table 1). We employed a 1 km × 1 km grid to partition the CLCD dataset and counted the proportion of cropland within the grid, reflecting both the gain and loss of cropland in the region by proportion change, and used it to calculate the LTS of the cropland. The proportion of cropland ranges from 0 to 1. A proportion of one indicates exclusive arable land, whereas zero denotes its absence, resulting in its exclusion from the calculations.

LTS was calculated based on the fluctuation of the cropland proportion within the 1 km grid over the subsequent five years. The coefficient of variation was used to measure fluctuations in the increase or decrease in the cropland proportion to reflect the shrinking and expansion of cropland patches within the grid.

$$C.V = \frac{\sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}}}{\bar{x}} \times 100 \quad (1)$$

$$LTS = \alpha^{C.V} \quad (2)$$

where x_i is the proportion of cropland within a grid in the i th year; n is the evaluation time period of cropland *LTS*, in this study $n = 5$; $\alpha = 0.98$, which is obtained from trial-and-error. The *LTS* values range from 0 to 1, with higher values indicating greater stability. Based on the distribution of values, the *LTS* was categorized into two types: stable (ranging from 1.0 to 0.7) and unstable (ranging from 0.7 to 0). The calculation was performed using ArcGIS Pro 3.0.2.

2.4. Spatial Autocorrelation Analysis

We conducted a spatial autocorrelation analysis of cropland *LTS* to delineate the spatial distribution patterns. Spatial autocorrelation analysis studies spatial dependence and heterogeneity by exploring spatial correlation patterns, clustering, or hotspots, providing a unique advantage in understanding spatial clustering relationships and inter-regional change characteristics of geographic variables [55,56]. Global Moran's *I* was employed to evaluate the degree of spatial correlation of cropland *LTS* across China, whereas local Moran's *I* was employed to depict the spatial clustering distribution of cropland *LTS* within the grid and its neighbors [57]. The global Moran's *I* is calculated as:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (3)$$

where n is the total number of grids; w_{ij} is the weight matrix that considers the spatial distribution of the spatial unit; x_i and x_j is the cropland *LTS* of grid i and j ; $\bar{x}$ is the average *LTS* of China. Global Moran's *I* value ranges from -1 to 1 : values nearing 1 suggest positive spatial correlation and clustering of cropland *LTS* distributions; values nearing -1 suggest negative spatial correlation and dispersed cropland *LTS* distributions; values nearing 0 indicate no correlation in spatial distribution. *Z*-scores and *p*-values were calculated to denote the statistical significance of spatial differences. *Z*-scores are multiples of standard deviations, whereas *p*-values are probabilities that the observed spatial patterns were created by random processes. Significantly higher (positive) or lower (negative) *Z*-scores and lower *p*-values indicate greater confidence in rejecting the null hypothesis of random processes.

The local Moran's *I* (LISA) is calculated as:

$$I_i = \frac{x_i - \bar{x}}{S_i^2} \sum_{j=1, j \neq i}^n w_{ij} (x_j - \bar{x}) \quad (4)$$

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^n (x_j - \bar{x})^2}{n - 1} \quad (5)$$

LISA identified four local cluster types: High–High, Low–Low, Low–High, and High–Low, based on a threshold of 0 . A pseudo *p*-value was calculated to assess the significance of LISA using a conditional permutation test with 999 permutations. This test involved random permutations of observations, excluding the focal grid i , where $i = 1$, and evaluated how often the neighbor j count reached or surpassed the original value. Global and local Moran's *I* analyses were conducted using ArcGIS Pro 3.0.2.

2.5. Analysis of Driving Mechanisms of Cropland LTS

Given the dual influences of natural and anthropogenic factors, as well as data availability, we selected ten representative variables as potential driving factors of cropland long-term stability and analyzed the underlying driving mechanisms [58]. These variables included elevation, relief amplitude, distance to built-up land, distance to water bodies, distance to vegetation, climate production potential, soil erosion, soil organic matter, soil type, and population density. Elevation and relief amplitude can affect climate and precipitation, thereby indirectly affecting the distribution of cropland [25,59]. The distance to built-up land, water bodies, and vegetation can affect the risk of encroachment by urban and rural residential land expansion to different extents [27] and also influence cropland use owing to their distinct land use functions [60,61]. The climate production potential directly affects the hydrothermal conditions of cropland [62]. Soil erosion can lead to land degradation and fertility loss [28]. Population density serves as both an indicator of anthropogenic disturbance and a resource for agricultural labor [25,63]. Soil type and organic matter content can affect soil fertility and cropland quality [27,64]. Some factors have also been considered in previous studies that evaluated cropland stability, providing an opportunity to validate the effectiveness of their evaluation indicator systems. The specific definitions and calculation methods are shown in Section S1 of the supplementary materials.

Artificial neural networks (ANNs) serve as conceptual computational models for discerning intricate patterns and relationships within datasets, and offer diverse types and architectures [65]. We chose a multilayer perceptron (MLP) as the specific model to analyze the driving mechanisms of LTS in cropland [66,67]. We constructed a three-layer MLP, consisting of input, hidden, and output layers. The input layer is a collection of the assumed driving factors. The output layer was the cropland LTS, expressed as a Boolean value (1 = *stable*, 0 = *unstable*). The hidden layer comprises unobservable neurons, with each neuron's value being a function of one of the predictor variables, and the number of neurons being determined automatically by the model. Cropland LTS data, along with the corresponding data of driving factors in China for each year, were input into the model for training. The model utilizes 50% of the samples for calibration and 50% for validation, terminating the training round once the accuracy reaches the upper limit [68]. The overall percent correct (OPC) of the model predictions and the area under curve (AUC) of the receiver operating characteristic (ROC) curve were calculated to assess the overall accuracy of the model. Higher values of both OPC and AUC indicate better model performance [69–71]. The model was executed using SPSS Modeler 18.0.

3. Results

3.1. Quantitative Differentiation of Cropland LTS in China during 1990–2018

From 1990 to 2018, the number of unstable cropland areas first decreased slightly and then increased slightly, with a turning point occurring in 2000 (Figure 2). On average, the percentage of unstable cropland area was 47.31%, with an overall growth rate of 0.83% from 1990 to 2018. The lowest percentage was observed in 2000 (42.26%), whereas the highest was recorded in 2018 (52.94%). Similar patterns of decreasing and increasing unstable cropland quantities are observed in each agricultural zone. The QTP exhibited the highest average proportion of unstable cropland (65.9%), followed by the NASR, SC, and YGP. Conversely, the HHHP had the lowest average proportion of unstable cropland (22.94%), followed by the NCP, MLYP, and SBSR. The QTP and HHHP exhibited the largest and smallest change rates in the unstable cropland during 1990–2018, at 44.13% and 7.17%, respectively. The LP had the highest positive growth rate (10.65%), followed by the QTP, SBSR, HHHP, and NASR. The NCP showed the largest negative growth rate (−4.65%), followed by the SC, MLYP, and YGP (Figure 2). Areas of stable and unstable cropland for each agricultural zone in each year are presented in Table S1.

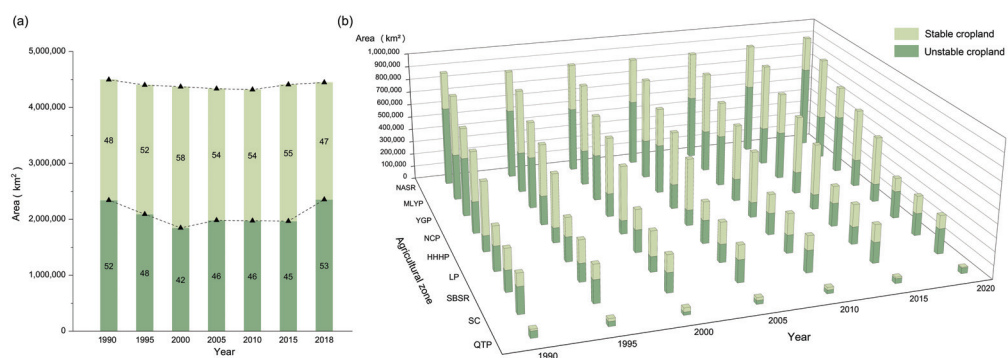


Figure 2. Quantitative differentiation of LTS in China (a) and nine agricultural zones (b) during 1990–2018.

3.2. Spatiotemporal Differentiation of Cropland LTS in China during 1990–2018

The LTS patterns of cropland from 1990 to 2018 exhibited a consistent distribution throughout the study period. Spatially, LTS distribution on cropland exhibited clustering in the NCP, HHHP, MLYP, NASR, LP, QTP, and SBSR. Conversely, the LTS distribution in the SC and YGP appeared fragmented. Unstable cropland situated in areas with a clustered LTS distribution exhibited a trend of initially shrinking and then expanding over the study period. Conversely, unstable cropland located in regions with a dispersed LTS distribution showed a pattern of initial dispersion, followed by clustering over the study period (Figure 3).

The spatial distribution patterns of the local Moran’s I HH and LL values in China mirrored those of stable and unstable croplands. HH values were clustered in the NCP, HHHP, MLYP, and SBSR, whereas LL values were more dispersed, especially in the NASR, LP, YGP, QTP, and SC, with the LP exhibiting greater clustering. Non-significant areas were observed primarily in the YGP and SC groups. Over the study period, HH values underwent expansion and contraction, whereas LH and HL values and non-significant areas gradually expanded, indicating a fragmented clustering pattern (Figure 4).

The average global Moran’s I value for cropland LTS in China from 1990 to 2018 was 0.3375, indicating significant spatial clustering throughout the study period. Following a trend similar to that of the temporal dynamics of the cropland LTS quantity, the global Moran’s I value started at 0.4583 in 1990, declined gradually to its lowest value of 0.3602 in 2010 and then increased to 0.4257 by 2018 (Figure 4). The detailed results of the global Moran’s I calculations are presented in Table S2.

3.3. Relative Importance of Driving Factors of Cropland LTS in China during 1990–2018

The model achieved an OPC of 75.2% with an AUC value of 0.80, indicating high classification accuracy. During the study period, the distance to vegetation had the highest relative importance at 0.30, followed by relief amplitude at 0.16, and soil type at 0.10. The remaining factors, ranked population density, distance to built-up land, soil organic matter, soil erosion, distance to water bodies, elevation, and climate production potential, all had contributions below 0.1 (Figure 5).

An overlay of cropland LTS and distance to vegetation layers revealed that unstable cropland predominantly occurred closer to vegetation in the NASR, NCP, LP, QTP, SBSR, YGP, and SC (excluding areas around provincial capitals), with the HHHP exhibiting a prevalence of unstable cropland in areas farther from the vegetation. In the MLYP, unstable cropland far from vegetation is predominantly distributed in the northeast. Unstable cropland with lower relief amplitude is prevalent in the NCP, NASR, and HHHP, whereas that with higher relief amplitude is predominant in the SBSR, LP, and YGP. Unstable cropland in the SC and MLYP exhibited relatively discrete relief amplitude patterns, whereas the relief amplitude of unstable cropland in the QTP was clustered, with lower values in the

north and higher values in the south. Further analysis revealed two distinct patterns in the distribution of distance to vegetation and relief amplitude in unstable cropland: areas with a shorter distance to vegetation tended to exhibit a higher relief amplitude, and vice versa. These patterns were most common in 2000 (Figure 6). Soil type emerged as the third most influential factor in the LTS of cropland, with unstable cropland predominantly found in red earth (Ferralsols) in the YGP and SC, yellow–brown earth (Luvisols), and loessial soils (Skeletal primitive soils) in the LP, and desert soils in the NASR (Figure 6). Other factors did not exhibit significant patterns within unstable cropland during the study period.

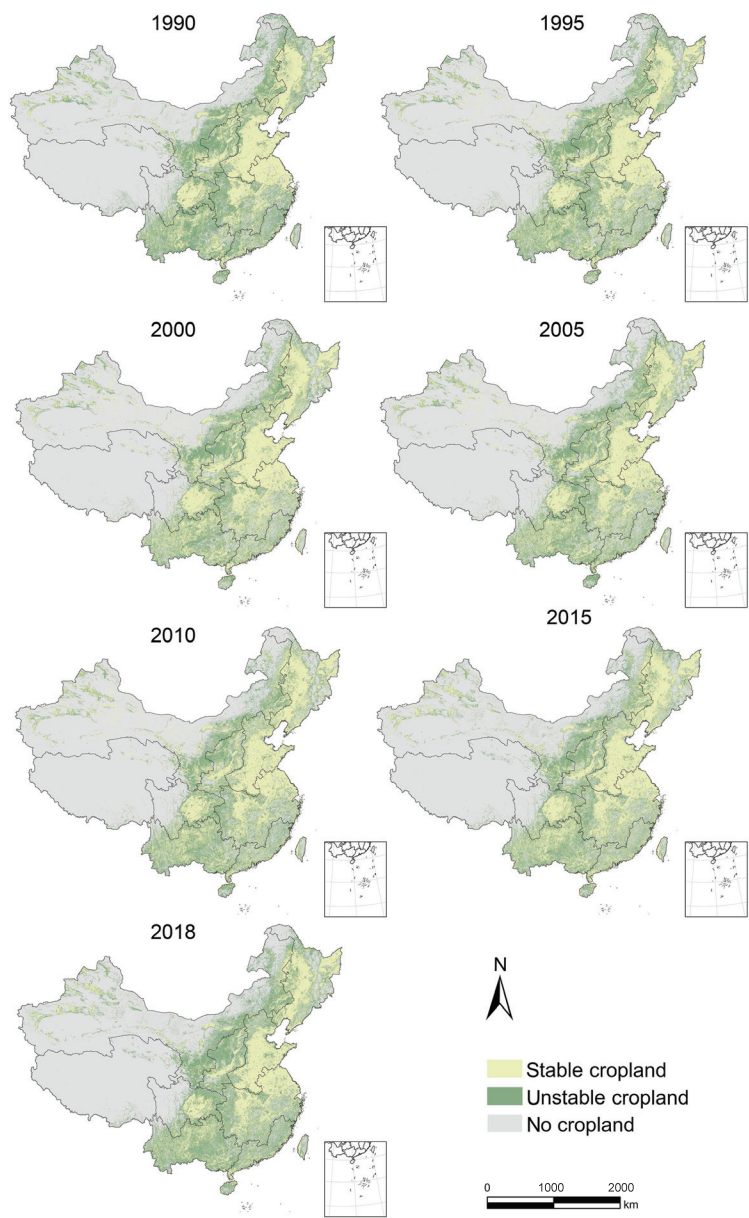


Figure 3. Spatial distribution of cropland LTS in China during 1990–2018.

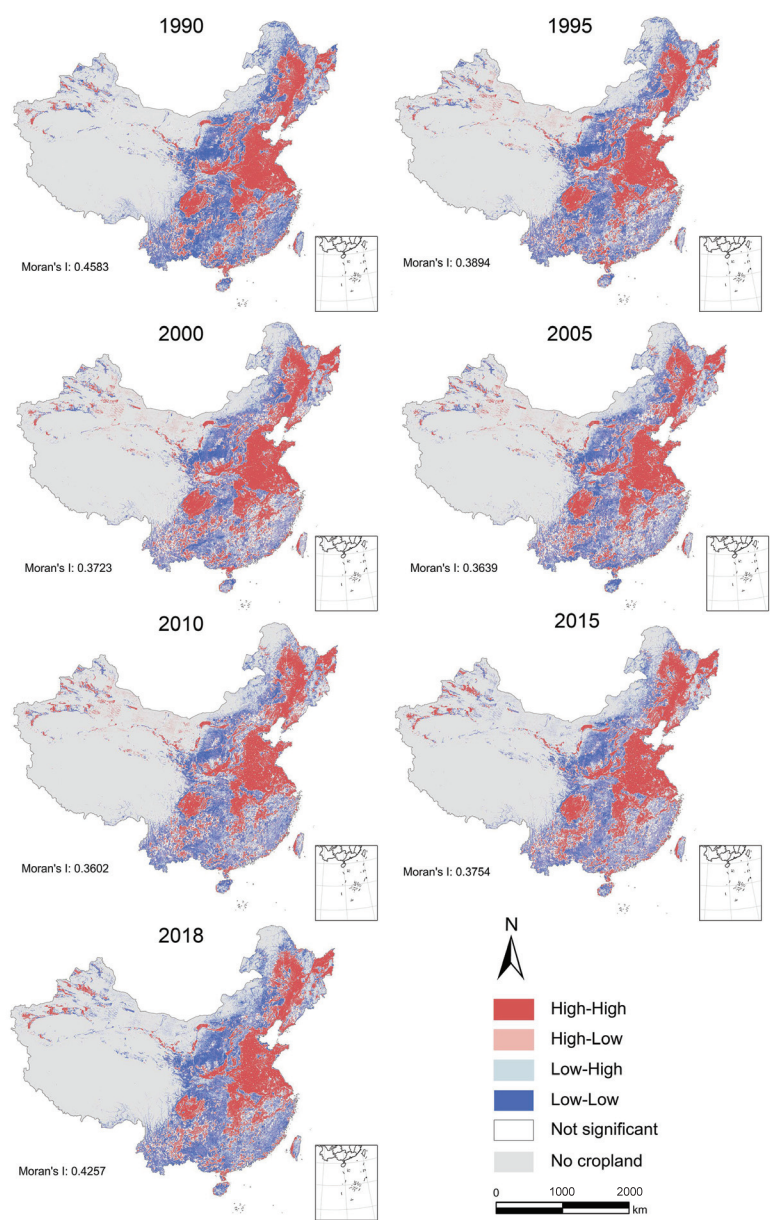


Figure 4. Global Moran's I and spatial autocorrelation of cropland *LTS* during 1990–2018.

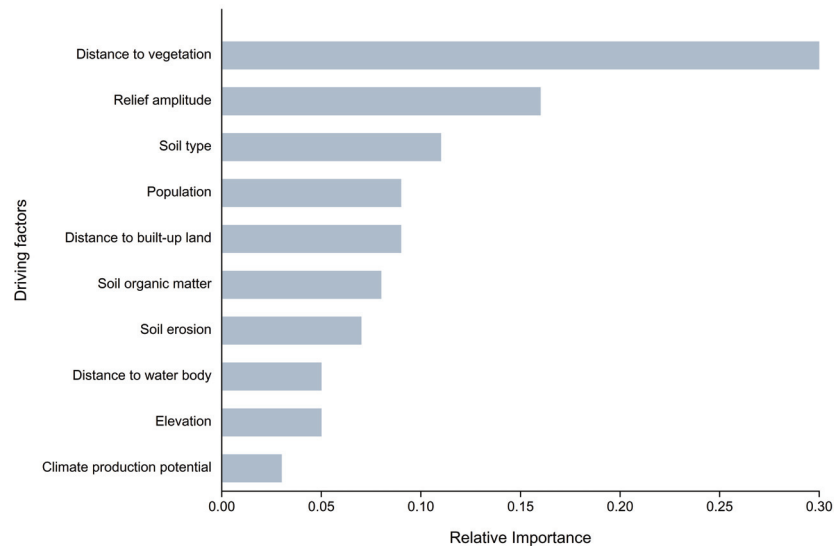


Figure 5. Relative importance of driving factors.

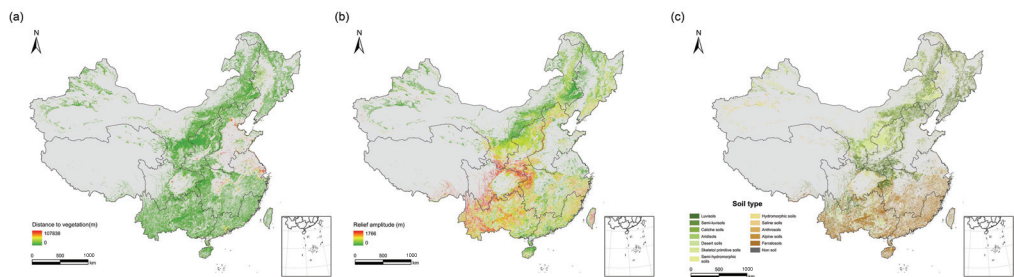


Figure 6. Spatial patterns of distance to vegetation (a), relief amplitude (b), and soil type (c) of unstable cropland in 2000.

4. Discussion

4.1. Comparison to Relative Research

In our study, we evaluated the long-term stability (LTS) of cropland by analyzing the actual fluctuation amplitude of the cropland area per 1 km grid over the next five years. Furthermore, we enhanced the analysis of cropland LTS by integrating it with previous studies in China. The quantity and spatial distribution of stable cropland areas identified in our study aligned closely with those reported by Li et al. [17]. They reported a total area of long-term stable cropland from 2001 to 2019 of approximately 2.08×10^6 km², which closely resembles the stable cropland area in 2018 of approximately 2.09×10^6 km² in our study. This confirms the capacity of our method to accurately depict the long-term stable use of cropland. Liang et al. [24] found that stable cropland, which has remained unchanged for the past 30 years, is predominantly concentrated in the NCP, HHHP, MLYP, and SBSR, which is consistent with the findings of our study. The proportion of unstable cropland productivity in the study by Han et al. [16] was 44.12%, which closely corresponds to the proportion of unstable cropland (46.73%) in our study. However, they overlooked the widespread unstable cropland in the NASR despite the minimal fluctuation in cropland productivity within this agricultural zone. Our findings indicate a significantly greater proportion of unstable cropland compared to the study by Yang et al. [22], which may

by attributed to the coarser resolution (250 m) of the land use data used in their research, leading to the exclusion of unstable cropland in the NCP, HHHP, and MLYP. Notably, Li et al. [17] and Yang et al. [22] employed the same method (sliding-window method) for data processing, but they differed in their interpretation: Li et al. [17] considered anomalous land use changes within the time-series window as errors and filtered them out, whereas Yang et al. [22] interpreted them as indications of unstable use of cropland. The sliding-window method is frequently employed to detect changes in land use dynamics and associated anomalies [72,73]. However, varying identification mechanisms can significantly influence study outcomes, thereby increasing uncertainty. The method we employed mitigated the controversy stemming from divergent interpretations of the sliding-window method, while rectifying errors in the original dataset resulting from spatial offset phenomena, thereby demonstrating better performance.

Our study examined the impacts of specific driving factors on cropland long-term stability, thereby validating the effectiveness of the evaluation indicators proposed in previous studies. For instance, whereas Fan et al. [25] prioritized the distance of cropland to built-up land in their indicator system, our findings emphasize the greater importance of distance to vegetation, a factor overlooked in their study. Kuang et al. [27] suggested that a closer distance to vegetation reduces the risk of cropland being encroached upon by built-up land, thereby promoting stable cropland use. However, our study found significant instability in cropland near vegetation, suggesting that Kuang et al. [27] focused solely on urban expansion, neglecting other potential driving mechanisms. Quantitative analysis of the driving mechanisms behind cropland long-term stability at the national level helped identify the limitations of existing *a priori* evaluation systems when generalized beyond specific regions.

Furthermore, this study quantitatively analyzed the driving mechanisms influencing cropland long-term stability in China using a machine learning model, an approach that has not been employed in previous research [16,17,32,33]. Although Yang et al. [22] qualitatively summarized the various driving mechanisms affecting global cropland long-term stability patterns, their study lacked quantitative insights into the impacts of these mechanisms, resulting in a limited focus on the primary challenges in global cropland stability. In contrast, our study quantified the relative importance of different driving factors, revealing that policy influences and urban expansion could have a greater impact than climate change and ecological disturbances on the long-term stability of cropland in China, as discussed in Section 4.2.

4.2. Driving Mechanisms of Cropland LTS in China

Distinct patterns in the distribution of distance to vegetation and relief amplitude in unstable cropland may reflect two significant social phenomena in China during 1990–2018: the implementation of the Grain for Green Policy and rapid urban expansion (Figure 6). The former corresponds to unstable slope cropland with a low distance to vegetation and high relief amplitude in the LP, SBSR, and YGP, whereas the latter corresponds to cropland in the peri-urban areas in the NCP, HHHP, MLYP, and cities in the SBSR.

The implementation of the Grain for Green project has resulted in varied marginal impacts on yields in agricultural zones such as the SBSR, YGP, and LP, causing instability in the LTS of slope cropland near vegetation in these areas [74]. Upon the conclusion of the local Grain for Green Project, subsidies were gradually withdrawn. Farmers in mountainous and hilly regions confronted with food self-sufficiency challenges often revert to reclaiming land previously designated for forest return or unsuitable slopes to meet their livelihood needs [75]. Nevertheless, rapid urbanization and the outflow of rural labor rendered it unsustainable to maintain these re-cultivated croplands, exacerbating their instability cropland in these areas [76].

Changing patterns of cropland utilization in peri-urban areas can be categorized into two types: rough expansion of built-up land with encroachment on cropland and a requisition–compensation balance approach to adjust the cropland layout [77,78]. Follow-

ing the market-oriented economic reforms in the 1980s, China has pursued an unbalanced urbanization strategy, resulting in significant cropland loss around cities [79]. To mitigate cropland loss, the government introduced a requisition–compensation balance policy in 1996, requiring that any occupied cropland be compensated by an equal or greater amount of additional cropland, ensuring quantitative security in cropland utilization. However, this policy still allows the exchange of low-quality cropland for high-quality ones [80]. Furthermore, the policy, focusing solely on the area, overlooked the effect of slope at vertical levels. Consequently, developers reclaim slopes in peri-urban areas to meet quantity targets after occupying flat croplands for construction purposes. Newly reclaimed croplands are often abandoned because of poor soil conditions, which exacerbates cropland instability in these areas [81].

The global Moran's I value of cropland LTS in China decreased significantly in 1995 and remained low until increasing again in 2018. This trend was driven by the repeated reclamation and abandonment of croplands within the LL value clusters, characterized by cropland proximity to vegetation and sloped terrain. The unstable use of cropland further contributed to the discrete evolution pattern of the LL value clusters (Figure 4).

Our study revealed that soil fertility, as indicated by soil organic matter content, had minimal impact on the LTS of cropland. This could be attributed to China's persistent shortage of cropland resources, prompting operators to utilize land regardless of its fertility, even if this results in excessive chemical fertilizer application [82]. Concurrently, to compensate for the massive encroachment of cropland by rapid coastal urban expansion, substantial new croplands have been reclaimed in the less productive northern regions [83]. The soil type significantly influences the LTS of croplands because soils within these areas are typically unsuitable for cultivation, leading to cropland instability. Our study identified climate factors as minor contributors to cropland LTS, suggesting that, although climate change may have impacted cropland productivity in China [84], it did not significantly alter cropland utilization patterns.

In light of these mechanisms, it is suggested for local governments in the NCP, NASR, LP, QTP, SBSR, YGP, SC, and western MLYP to prioritize thorough investigation of the current conditions of sloped land utilization in rural areas and restructure the utilization strategies for sloped cropland. They could also develop forest food resources (similar to non-wood forest products in Europe) to support farmers affected by the Grain for Green Policy, which ensures their sustainable livelihoods [85,86]. Concurrently, governments in the HHHP and northeastern MLYP should control the unreasonable expansion of built-up land and ensure effective implementation of the cropland requisition–compensation balance policy. The recent policy directive from the Chinese government, which advocates for a net increase in stable-use cropland and sets it as the maximum limit for cropland encroachment, promotes stable cropland utilization in these areas [86]. We recommend integrating quality assessment as a stringent criterion for gained cropland to further enhance its long-term stability in these regions.

4.3. Limitations and Prospects

In this study, the long-term stability of cropland was assessed by calculating the changes in the proportion of cropland over subsequent five years. This method provided empirical validity to our study but also brought about the first limitation. Our approach presumes the current stability of cropland based on its future use, thereby hindering the direct calculation of long-term stability when future land use data (e.g., to assess cropland long-term stability in the current year) are unavailable. This explains why we only assessed cropland long-term stability in China from 1990 to 2018 based on data availability and consistency (the last year of employed land use data was 2022). Future studies may attempt to predict the spatial patterns of cropland long-term stability based on the identified driving mechanisms or adopt methods from other land use simulation studies to predict cropland use changes [50,87].

Additionally, this study calculated the long-term stability of cropland in China using 1 km grids as spatial units, resulting in calculation results with a spatial resolution of 1 km. Although adequate at the national level, this resolution may be insufficient at provincial, river basin, city, and county scales. Furthermore, our method may not fully capture minor changes within 1 km grids, and the effects of cropland fragmentation on productivity and abandonment rates could influence the analysis of the driving mechanisms of cropland long-term stability [88]. Prior studies on long-term cropland stability have predominantly focused on cropland non-agriculturalization (from cropland to non-cropland), neglecting other phenomena such as cropland non-grainization (from food crops to economic crops, such as fruits and herbs) and transformations between paddy fields and dry lands, which may also indicate unstable utilization of cropland [89,90]. Future research should enhance the precision of the cropland use classification to better evaluate the long-term stable use of regional cropland.

Moreover, although this study refers to existing studies on cropland stability and other related research to identify the potential influencing factors, several driving mechanisms remain unexplored. For instance, how do topological relationships among cropland patches (e.g., contiguity and fractal dimensions) affect the long-term stable use of cropland? However, the specific mechanisms underlying these effects require further investigation [27]. Additionally, some factors may exhibit nonlinear effects on cropland long-term stability, such as intensive and large-scale cropland utilization, which may have marginal impacts [91]. Future research could establish thresholds tailored to the characteristics of these new driving factors to enhance the analysis of the driving mechanisms of regional cropland long-term stability.

Finally, this study revealed distinct distribution patterns of cropland long-term stability across different agricultural zones. Although this study conducted a quantitative analysis of the driving mechanisms of cropland long-term stability in China, precise quantitative analyses specific to different agricultural zones remain inadequate. Considering the similarities and differences in the distribution patterns of cropland long-term stability across agricultural zones, adjusting regional boundaries based on China's overall cropland long-term stability distribution, and conducting specific analyses could elucidate the geographical, climatic, cultural, and economic disparities among these regions.

5. Conclusions

In this study, we evaluated the spatiotemporal distribution of the long-term stability of cropland in China from 1990 to 2018, and analyzed its driving mechanisms. Our findings indicate that nearly half of China's cropland was unstable during the study period, with the majority of unstable croplands located in the northern arid and semiarid region, the Loess Plateau, the Qinghai–Tibet Plateau, the Yunnan–Guizhou Plateau, and Southern China. The area of unstable cropland initially decreased and then increased from 1990 to 2018, mirroring trends that are observed in Global Moran's *I* values. Spatial correlation patterns resembled those of cropland long-term stability distribution. High–High values concentrated in the Northeastern China Plain, the Huang–Huai–Hai Plain, the Sichuan Basin, and the northeastern Middle–Lower Yangtze Plain, whereas Low–Low values relatively dispersed in other regions. We identified distance to vegetation and relief amplitude as primary factors influencing cropland long-term stability in China. These patterns potentially explain the instability of marginal cropland in mountainous and hilly areas due to the Grain for Green Policy and rural hollowing, as well as instability in peri-urban regions due to unbalanced urban expansion and improper implementation of the cropland requisition–compensation balance policy. Local governments should prioritize improving the efficiency of the cropland requisition–compensation balance policy in the Huang–Huai–Hai Plain and northeastern Middle–Lower Yangtze Plain, whereas addressing the unintended consequences of the Grain for Green Policy in other regions. Our study underscores the importance of focusing on the long-term stable utilization of cropland to safeguard food security in China.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land13071016/s1>, The Supplementary Material S1 includes definition and calculation of driving factors. Table S1: Stable and unstable cropland areas in China from 1990 to 2018; Table S2: Global Moran's I index and its significance test of cropland LTS in China from 1990 to 2018.

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Abbreviations

The following abbreviations are used in this manuscript:

LTS	long-term stability
NCP	the Northeast China Plain
HHHP	the Huang–Huai–Hai Plain
LP	the Loess Plateau
NASR	the Northern Arid and Semiarid Region
SBSR	the Sichuan Basin and Surrounding Regions
QTP	the Qinghai–Tibet Plateau
MLYP	the Middle–Lower Yangtze Plain
YGP	the Yunnan–Guizhou Plateau
SC	the Southern China
ANN	artificial neural network
MLP	multilayer perceptron
OPC	overall percent correct
ROC	the receiver operating characteristics curve
AUC	area under the ROC curve
CLCD	China Land Cover Dataset

References

1. Lutz, W. Changing population size and distribution as a security concern. In *Facing Global Environmental Change: Environmental, Human, Energy, Food, Health and Water Security Concepts*; Springer: Berlin/Heidelberg, Germany, 2009; pp. 203–213.
2. Mehrabi, Z.; Delzeit, R.; Ignaciuk, A.; Levers, C.; Braich, G.; Bajaj, K.; Amo-Aidoo, A.; Anderson, W.; Balgah, R.A.; Benton, T.G.; et al. Research priorities for global food security under extreme events. *One Earth* **2022**, *5*, 756–766. [CrossRef] [PubMed]
3. Steven, D.; O'Brien, E.; Jones, B.D. *The New Politics of Strategic Resources: Energy and Food Security Challenges in the 21st Century*; Brookings Institution Press: Washington, DC, USA, 2014.
4. Lu, X.; Huang, S. Barriers and solutions to China's cultivated land protection. *Int. J. Environ. Stud.* **2010**, *67*, 223–232. [CrossRef]
5. Vesterby, M.; Heimlich, R.E.; Krupa, K.S. *Urbanization of Rural Land in the United States*; Number 673; US Department of Agriculture, Economic Research Service: Washington, DC, USA, 1994.
6. Wu, Y.; Mo, Z.; Peng, Y. Renewal of land-use term for urbanization in China: Sword of Damocles or Noah's Ark? *Land Use Policy* **2017**, *65*, 238–248. [CrossRef]
7. Li, H.; Song, W. Spatial transformation of changes in global cultivated land. *Sci. Total Environ.* **2023**, *859*, 160194. [CrossRef] [PubMed]
8. Meng, H.; Xing, L.; Hu, J.; Shen, C.; Zhang, H.; Wu, J. Exploring the characteristics and drivers of virtual cropland trade of major agricultural products in China. *J. Clean. Prod.* **2024**, *448*, 141392. [CrossRef]
9. Zhai, J.; Pu, L.; Lu, Y.; Huang, S. Is the boom in staple crop production attributed to expanded cropland or improved yield? A comparative analysis between China and India. *Sci. Total Environ.* **2024**, *933*, 173151. [CrossRef] [PubMed]

10. Liu, Y.; Zhou, Y. Reflections on China's food security and land use policy under rapid urbanization. *Land Use Policy* **2021**, *109*, 105699. [CrossRef]
11. Kuang, W.; Liu, J.; Tian, H.; Shi, H.; Dong, J.; Song, C.; Li, X.; Du, G.; Hou, Y.; Lu, D.; et al. Cropland redistribution to marginal lands undermines environmental sustainability. *Natl. Sci. Rev.* **2022**, *9*, nwab091. [CrossRef]
12. Li, T.; Long, H.; Zhang, Y.; Tu, S.; Ge, D.; Li, Y.; Hu, B. Analysis of the spatial mismatch of grain production and farmland resources in China based on the potential crop rotation system. *Land Use Policy* **2017**, *60*, 26–36. [CrossRef]
13. Li, F.; Wu, S.; Liu, H.; Yan, D. Biodiversity loss through cropland displacement for urban expansion in China. *Sci. Total Environ.* **2024**, *907*, 167988. [CrossRef]
14. Kraemer, R.; Prishchepov, A.V.; Müller, D.; Kuemmerle, T.; Radeloff, V.C.; Dara, A.; Terekhov, A.; Frühauf, M. Long-term agricultural land-cover change and potential for cropland expansion in the former Virgin Lands area of Kazakhstan. *Environ. Res. Lett.* **2015**, *10*, 054012. [CrossRef]
15. Lark, T.J.; Spawn, S.A.; Bougie, M.; Gibbs, H.K. Cropland expansion in the United States produces marginal yields at high costs to wildlife. *Nat. Commun.* **2020**, *11*, 4295. [CrossRef]
16. Han, B.; Jin, X.; Yeting, F.; Chen, H.; Jin, J.; Xu, W.; Ren, J.; Zhou, Y. Trend and spatial pattern of stable cropland productivity in China based on satellite observations (2001–2020). *Environ. Impact Assess. Rev.* **2023**, *101*, 107136. [CrossRef]
17. Li, G.; He, T.; Zhang, M.; Wu, C. Spatiotemporal variations in the eco-health condition of China's long-term stable cultivated land using Google Earth Engine from 2001 to 2019. *Appl. Geogr.* **2022**, *149*, 102819. [CrossRef]
18. Bissett, A.; Richardson, A.E.; Baker, G.; Thrall, P.H. Long-term land use effects on soil microbial community structure and function. *Appl. Soil Ecol.* **2011**, *51*, 66–78. [CrossRef]
19. Li, C.; Li, Y.; Tang, L. The effects of long-term fertilization on the accumulation of organic carbon in the deep soil profile of an oasis farmland. *Plant Soil* **2013**, *369*, 645–656. [CrossRef]
20. Niemiec, M.; Chowaniak, M.; Sikora, J.; Szelag-Sikora, A.; Gródek-Szostak, Z.; Komorowska, M. Selected properties of soils for long-term use in organic farming. *Sustainability* **2020**, *12*, 2509. [CrossRef]
21. Ouyang, W.; Xu, Y.; Hao, F.; Wang, X.; Siyang, C.; Lin, C. Effect of long-term agricultural cultivation and land use conversion on soil nutrient contents in the Sanjiang Plain. *Catena* **2013**, *104*, 243–250. [CrossRef]
22. Yang, R.; Xu, S.; Gu, B.; He, T.; Zhang, H.; Fang, K.; Xiao, W.; Ye, Y. Stabilizing unstable cropland towards win-win sustainable development goals. *Environ. Impact Assess. Rev.* **2024**, *105*, 107395. [CrossRef]
23. Long, Y.; Sun, J.; Wellens, J.; Colinet, G.; Wu, W.; Meersmans, J. Mapping the Spatiotemporal Dynamics of Cropland Abandonment and Recultivation across the Yangtze River Basin. *Remote Sens.* **2024**, *16*, 1052. [CrossRef]
24. Liang, X.; Jin, X.; Dou, Y.; Zhang, X.; Li, H.; Wang, S.; Meng, F.; Tan, S.; Zhou, Y. Mapping sustainability-oriented China's cropland use stability. *Comput. Electron. Agric.* **2024**, *219*, 108823. [CrossRef]
25. Fan, W.; Kong, X.; Men, M.; Xu, H.; Li, C. Evaluation on Cultivated Land Resources Stability in Beijing Daxing District. *China Land Sci.* **2009**, *23*, 48–53+80. (In Chinese)
26. Fan, J.; Wang, L.; Qin, J.; Zhang, F.; Xu, Y. Evaluating cultivated land stability during the growing season based on precipitation in the Horqin Sandy Land, China. *J. Environ. Manag.* **2020**, *276*, 111269. [CrossRef] [PubMed]
27. Kuang, L.; Ye, Y.; Zhao, X.; Guo, X.; Xie, W. Delineation of basic farmland based on the quality and spatial stability: A case study of Yingtan City, China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 88737–88750. [CrossRef] [PubMed]
28. Sui, H.; Song, G.; Liu, W.; Zhang, Y.; Su, R.; Wang, Q.; Ren, G.; Mi, Y. Spatiotemporal variation of cultivated land ecosystem stability in typical regions of Lower Liaohe Plain China based on stress-buffer-response. *Sci. Total Environ.* **2023**, *858*, 160213. [CrossRef] [PubMed]
29. Yan, Y.; Guan, Q.; Shao, W.; Wang, Q.; Yang, X.; Luo, H. Spatiotemporal dynamics and driving mechanism of arable ecosystem stability in arid and semi-arid areas based on Pressure-Buffer-Response process. *J. Clean. Prod.* **2023**, *421*, 138553. [CrossRef]
30. Gao, H.; Gong, J.; Ye, T.; Maier, M.; Liu, J. Constructing cropland ecological stability assessment method based on disturbance-resistance-response processes and classifying cropland ecological types. *Sci. Total Environ.* **2024**, *930*, 172673. [CrossRef] [PubMed]
31. Potapov, P.; Turubanova, S.; Hansen, M.C.; Tyukavina, A.; Zalles, V.; Khan, A.; Song, X.P.; Pickens, A.; Shen, Q.; Cortez, J. Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century. *Nat. Food* **2022**, *3*, 19–28. [CrossRef]
32. Zhang, M.; Li, G.; He, T.; Zhai, G.; Guo, A.; Chen, H.; Wu, C. Reveal the severe spatial and temporal patterns of abandoned cropland in China over the past 30 years. *Sci. Total Environ.* **2023**, *857*, 159591. [CrossRef]
33. He, T.; Li, J.; Zhang, M.; Zhai, G.; Lu, Y.; Wang, Y.; Guo, A.; Wu, C. Uphill cropland and stability assessment of gained cropland in China over the preceding 30 years. *J. Geogr. Sci.* **2024**, *34*, 699–721. [CrossRef]
34. Patterson, D.W. *Artificial Neural Networks: Theory and Applications*; Prentice Hall PTR: Hoboken, NJ, USA, 1998.
35. Pijanowski, B.C.; Pithadia, S.; Shellito, B.A.; Alexandridis, K. Calibrating a neural network-based urban change model for two metropolitan areas of the Upper Midwest of the United States. *Int. J. Geogr. Inf. Sci.* **2005**, *19*, 197–215. [CrossRef]
36. Lakes, T.; Müller, D.; Krüger, C. Cropland change in southern Romania: A comparison of logistic regressions and artificial neural networks. *Landsc. Ecol.* **2009**, *24*, 1195–1206. [CrossRef]
37. Wang, J.; Chen, Y.; Shao, X.; Zhang, Y.; Cao, Y. Land-use changes and policy dimension driving forces in China: Present, trend and future. *Land Use Policy* **2012**, *29*, 737–749. [CrossRef]

38. Panda, K.C.; Singh, R.M.; Singh, S.K. Advanced CMD predictor screening approach coupled with cellular automata-artificial neural network algorithm for efficient land use-land cover change prediction. *J. Clean. Prod.* **2024**, *449*, 141822. [CrossRef]
39. Wen, S.; Wang, Y.; Song, H.; Liu, H.; Sun, Z.; Bilal, M.A. Integrated Predictive Modeling and Policy Factor Analysis for the Land Use Dynamics of the Western Jilin. *Atmosphere* **2024**, *15*, 288. [CrossRef]
40. Office of the Third National Land Resource Survey Leading Group of the State Council. Major Data Bulletin of the Third National Land Resource Survey. Available online: https://www.gov.cn/xinwen/2021-08/26/content_5633490.htm (accessed on 16 May 2024). (In Chinese)
41. Ren, Y.; Liu, J.; Willems, P.; Liu, T.; Pham, Q.B. Detection and Assessment of Changing Drought Events in China in the Context of Climate Change Based on the Intensity–Area–Duration Algorithm. *Land* **2023**, *12*, 1820. [CrossRef]
42. Li, C.; Ou, S. *Soils of China*; Science Press: Beijing, China, 1990. (In Chinese)
43. Yu, D.S.; Shi, X.Z.; Wang, H.J.; Sun, W.X.; Warner, E.D.; Liu, Q.H. National scale analysis of soil organic carbon storage in China based on Chinese soil taxonomy. *Pedosphere* **2007**, *17*, 11–18. [CrossRef]
44. National Agricultural Zoning, C. *Agricultural Resources and Regional Planning in China*; Agriculture Press: Beijing, China, 1991. (In Chinese)
45. Yu, E.; Liu, D.; Yang, J.; Sun, J.; Yu, L.; King, M.P. Future climate change for major agricultural zones in China as projected by CORDEX-EA-II, CMIP5 and CMIP6 ensembles. *Atmos. Res.* **2023**, *288*, 106731. [CrossRef]
46. Yang, J.; Huang, X. 30 m annual land cover and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. [CrossRef]
47. Peng, S.; Ding, Y.; Liu, W.; Li, Z. 1 km monthly temperature and precipitation dataset for China from 1901 to 2017. *Earth Syst. Sci. Data* **2019**, *11*, 1931–1946. [CrossRef]
48. Shangguan, W.; Dai, Y.; Liu, B.; Zhu, A.; Duan, Q.; Wu, L.; Ji, D.; Ye, A.; Yuan, H.; Zhang, Q.; et al. A China data set of soil properties for land surface modeling. *J. Adv. Model. Earth Syst.* **2013**, *5*, 212–224. [CrossRef]
49. Teklay, A.; Dile, Y.T.; Setegn, S.G.; Demissie, S.S.; Asfaw, D.H. Evaluation of static and dynamic land use data for watershed hydrologic process simulation: A case study in Gummara watershed, Ethiopia. *Catena* **2019**, *172*, 65–75. [CrossRef]
50. Liang, X.; Guan, Q.; Clarke, K.C.; Liu, S.; Wang, B.; Yao, Y. Understanding the drivers of sustainable land expansion using a patch-generating land use simulation (PLUS) model: A case study in Wuhan, China. *Comput. Environ. Urban Syst.* **2021**, *85*, 101569. [CrossRef]
51. Yin, B.; Brandão, A., Jr.; Buchner, J.; Helmers, D.; Iuliano, B.G.; Kimambo, N.E.; Lewińska, K.E.; Razenkova, E.; Rizayeva, A.; Rogova, N.; et al. Monitoring cropland abandonment with Landsat time series. *Remote Sens. Environ.* **2020**, *246*, 111873. [CrossRef]
52. Li, F.; Ma, S.; Liu, X. Changing multi-scale spatiotemporal patterns in food security risk in China. *J. Clean. Prod.* **2023**, *384*, 135618.
53. Liu, S.; Xiao, W.; Ye, Y.; He, T.; Luo, H. Rural residential land expansion and its impacts on cultivated land in China between 1990 and 2020. *Land Use Policy* **2023**, *132*, 106816. [CrossRef]
54. Wang, Y.; Wang, J.; Li, F.; Liu, X.; Zhao, D. Can the transition of multiple cropping systems affect the cropland change? *Agric. Syst.* **2024**, *214*, 103815.
55. Tian, G.; Duan, J.; Yang, L. Spatio-temporal pattern and driving mechanisms of cropland circulation in China. *Land Use Policy* **2021**, *100*, 105118. [CrossRef]
56. Wang, L.; Zhang, S.; Xiong, Q.; Liu, Y.; Liu, Y.; Liu, Y. Spatiotemporal dynamics of cropland expansion and its driving factors in the Yangtze River Economic Belt: A nuanced analysis at the county scale. *Land Use Policy* **2022**, *119*, 106168. [CrossRef]
57. Anselin, L. Local indicators of spatial association—LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
58. Wang, Q.; Xiong, M.; Li, Q.; Li, H.; Lan, T.; Deng, O.; Huang, R.; Zeng, M.; Gao, X. Spatially explicit reconstruction of cropland using the random forest: A case study of the Tuojiang River Basin, China from 1911 to 2010. *Land* **2021**, *10*, 1338. [CrossRef]
59. Wang, B.; Cheng, W. Geomorphic influences on land use/cover diversity and pattern. *Catena* **2023**, *230*, 107245. [CrossRef]
60. Prishchepov, A.V.; Müller, D.; Dubinin, M.; Baumann, M.; Radeloff, V.C. Determinants of agricultural land abandonment in post-Soviet European Russia. *Land Use Policy* **2013**, *30*, 873–884. [CrossRef]
61. Zhang, L.; Zhang, K.; Zhu, X.; Chen, H.; Wang, W. Integrating remote sensing, irrigation suitability and statistical data for irrigated cropland mapping over mainland China. *J. Hydrol.* **2022**, *613*, 128413. [CrossRef]
62. Qin, Y.; Liu, J.; Shi, W.; Tao, F.; Yan, H. Spatial-temporal changes of cropland and climate potential productivity in northern China during 1990–2010. *Food Secur.* **2013**, *5*, 499–512. [CrossRef]
63. Klein Goldewijk, K.; Beusen, A.; Van Drecht, G.; De Vos, M. The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12,000 years. *Glob. Ecol. Biogeogr.* **2011**, *20*, 73–86. [CrossRef]
64. Cui, J.; Zhu, M.; Liang, Y.; Qin, G.; Li, J.; Liu, Y. Land use/land cover change and their driving factors in the Yellow River Basin of Shandong Province based on google earth Engine from 2000 to 2020. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 163. [CrossRef]
65. Yilmaz, A.S.; Özer, Z. Pitch angle control in wind turbines above the rated wind speed by multi-layer perceptron and radial basis function neural networks. *Expert Syst. Appl.* **2009**, *36*, 9767–9775. [CrossRef]
66. Darvishi, A.; Yousefi, M.; Marull, J. Modelling landscape ecological assessments of land use and cover change scenarios. Application to the Bojnourd Metropolitan Area (NE Iran). *Land Use Policy* **2020**, *99*, 105098. [CrossRef]
67. Tayyebi, A.; Pijanowski, B.C.; Tayyebi, A.H. An urban growth boundary model using neural networks, GIS and radial parameterization: An application to Tehran, Iran. *Landsc. Urban Plan.* **2011**, *100*, 35–44. [CrossRef]

68. Mozumder, C.; Tripathi, N.K. Geospatial scenario based modelling of urban and agricultural intrusions in Ramsar wetland Deepor Beel in Northeast India using a multi-layer perceptron neural network. *Int. J. Appl. Earth Obs. Geoinform.* **2014**, *32*, 92–104. [CrossRef]
69. Lane, M.M.; Czyzewski, D.I.; Chumpitazi, B.P.; Shulman, R.J. Reliability and validity of a modified Bristol Stool Form Scale for children. *J. Pediatr.* **2011**, *159*, 437–441. [CrossRef]
70. Lee, J.; Oh, Y.G.; Yoo, S.H.; Suh, K. Vulnerability assessment of rural aging community for abandoned farmlands in South Korea. *Land Use Policy* **2021**, *108*, 105544. [CrossRef]
71. Wang, Q.; Ren, Q.; Liu, J. Identification and apportionment of the drivers of land use change on a regional scale: Unbiased recursive partitioning-based stochastic model application. *Agric. Ecosyst. Environ.* **2016**, *217*, 99–110. [CrossRef]
72. Kulanuwat, L.; Chantrapornchai, C.; Maleewong, M.; Wongchaisuwat, P.; Wimala, S.; Sarinnapakorn, K.; Boonya-Aroonnet, S. Anomaly detection using a sliding window technique and data imputation with machine learning for hydrological time series. *Water* **2021**, *13*, 1862. [CrossRef]
73. Li, X.; Gong, P.; Liang, L. A 30-year (1984–2013) record of annual urban dynamics of Beijing City derived from Landsat data. *Remote Sens. Environ.* **2015**, *166*, 78–90. [CrossRef]
74. Feng, Z.; Yang, Y.; Zhang, Y.; Zhang, P.; Li, Y. Grain-for-green policy and its impacts on grain supply in West China. *Land Use Policy* **2005**, *22*, 301–312. [CrossRef]
75. Chen, Y.; Wang, K.; Lin, Y.; Shi, W.; Song, Y.; He, X. Balancing green and grain trade. *Nat. Geosci.* **2015**, *8*, 739–741. [CrossRef]
76. Guo, A.; Yue, W.; Yang, J.; Xue, B.; Xiao, W.; Li, M.; He, T.; Zhang, M.; Jin, X.; Zhou, Q. Cropland abandonment in China: Patterns, drivers, and implications for food security. *J. Clean. Prod.* **2023**, *418*, 138154. [CrossRef]
77. Liu, C.; Song, C.; Ye, S.; Cheng, F.; Zhang, L.; Li, C. Estimate provincial-level effectiveness of the arable land requisition–compensation balance policy in mainland China in the last 20 years. *Land Use Policy* **2023**, *131*, 106733. [CrossRef]
78. Song, W.; Pijanowski, B.C. The effects of China’s cultivated land balance program on potential land productivity at a national scale. *Appl. Geogr.* **2014**, *46*, 158–170. [CrossRef]
79. Cao, S.; Lv, Y.; Zheng, H.; Wang, X. Challenges facing China’s unbalanced urbanization strategy. *Land Use Policy* **2014**, *39*, 412–415. [CrossRef]
80. Liu, L.; Liu, Z.; Gong, J.; Wang, L.; Hu, Y. Quantifying the amount, heterogeneity, and pattern of farmland: Implications for China’s requisition–compensation balance of farmland policy. *Land Use Policy* **2019**, *81*, 256–266. [CrossRef]
81. Chen, H.; Tan, Y.; Xiao, W.; Li, G.; Meng, F.; He, T.; Li, X. Urbanization in China drives farmland uphill under the constraint of the requisition–compensation balance. *Sci. Total Environ.* **2022**, *831*, 154895. [CrossRef]
82. Wu, Y.; Xi, X.; Tang, X.; Luo, D.; Gu, B.; Lam, S.K.; Vitousek, P.M.; Chen, D. Policy distortions, farm size, and the overuse of agricultural chemicals in China. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 7010–7015. [CrossRef]
83. Zuo, L.; Zhang, Z.; Carlson, K.M.; MacDonald, G.K.; Brauman, K.A.; Liu, Y.; Zhang, W.; Zhang, H.; Wu, W.; Zhao, X.; et al. Progress towards sustainable intensification in China challenged by land-use change. *Nat. Sustain.* **2018**, *1*, 304–313. [CrossRef]
84. Piao, S.; Ciais, P.; Huang, Y.; Shen, Z.; Peng, S.; Li, J.; Zhou, L.; Liu, H.; Ma, Y.; Ding, Y.; et al. The impacts of climate change on water resources and agriculture in China. *Nature* **2010**, *467*, 43–51. [CrossRef] [PubMed]
85. Lovrić, M.; Da Re, R.; Vidale, E.; Prokofieva, I.; Wong, J.; Pettenella, D.; Verkerk, P.J.; Mavsar, R. Non-wood forest products in Europe—A quantitative overview. *For. Policy Econ.* **2020**, *116*, 102175. [CrossRef]
86. Central Committee of the Communist Party of China and the State Council. Opinions on Learning and Applying the Experience of the “Thousand Demonstration Villages and Ten Thousand Renovation Villages” Project to Powerfully and Effectively Promote Comprehensive Rural Revitalization. Available online: https://www.gov.cn/zhengce/202402/content_6929934.htm (accessed on 1 July 2024). (In Chinese)
87. Liang, X.; Liu, X.; Li, D.; Zhao, H.; Chen, G. Urban growth simulation by incorporating planning policies into a CA-based future land-use simulation model. *Int. J. Geogr. Inf. Sci.* **2018**, *32*, 2294–2316. [CrossRef]
88. Deng, O.; Ran, J.; Huang, S.; Duan, J.; Reis, S.; Zhang, J.; Zhu, Y.G.; Xu, J.; Gu, B. Managing fragmented croplands for environmental and economic benefits in China. *Nat. Food* **2024**, *5*, 230–240. [CrossRef]
89. Li, X.; Ma, J.; Yang, Y.; Hou, H.; Liu, G.J.; Chen, F. Short-term response of soil microbial community to field conversion from dryland to paddy under the land consolidation process in North China. *Agriculture* **2019**, *9*, 216. [CrossRef]
90. Lu, D.; Wang, Z.; Su, K.; Zhou, Y.; Li, X.; Lin, A. Understanding the impact of cultivated land-use changes on China’s grain production potential and policy implications: A perspective of non-agriculturalization, non-grainization, and marginalization. *J. Clean. Prod.* **2024**, *436*, 140647. [CrossRef]
91. Yan, Z.; Wang, D.; Li, W.; Tong, Z.; Zhu, Y.; Shen, F. Treat and halt: Occurrence of spatially heterogeneous cropland degradation in the peri-urban area. *Environ. Impact Assess. Rev.* **2024**, *104*, 107366. [CrossRef]

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Article

Quantitative Evaluation and Evolution Characteristics of Consistency Level of Black Soil Conservation Policy, Taking China's Black Soil Protection Policy as an Example

Fan Zhang ¹, Peng Han ¹, Ling Wu ^{2,*} and Zhanwei Tian ^{1,*}

¹ School of Engineering College, Northeast Agricultural University, Harbin 150030, China; zhangfan1120@neau.edu.cn (F.Z.); s220702088@neau.edu.cn (P.H.)

² School of Marxism College, Northeast Agricultural University, Harbin 150030, China

* Correspondence: z10349@neau.edu.cn (L.W.); tianzhanwei@neau.edu.cn (Z.T.)

Abstract: Scientifically evaluating China's black soil protection policy and exploring its evolution characteristics are crucial for promoting high-quality and efficient black soil protection projects worldwide. Utilizing the Policy Modeling Consistency (PMC) index model, the effectiveness of China's black soil protection policy system is assessed. Building upon this evaluation, the research delves into the evolution process of the black soil protection policy system, examining its dynamic characteristics across different government levels. Through the application of text mining technology and visual analysis techniques, the study explores four dimensions: keyword co-occurrence, vertical synergy calculation, policy theme identification, and policy tool analysis. The results show the following: (1) The PMC index showed a phased growth trend, and various indicators gradually improved and tended to be stable. (2) Government policies at the same level exhibit progressive evolution patterns in terms of policy keywords and themes. (3) Across different levels of government, there are hierarchical lag evolution rules observed in policy keywords and provincial policy tools. Additionally, policy keywords display vertical synergy evolution patterns. In conclusion, future black soil conservation policies need to reduce hierarchical delays, enhance the coverage and comprehensiveness of policy content, and establish a sound policy feedback mechanism. The conclusions of the study are significant for improving management approaches throughout the black soil zones of the world.

Keywords: black soil protection; evolution characteristics; quantitative evaluation; policy system

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1. Introduction

Black soil is one of the most valuable soil resources on Earth, containing biodiversity and significant amounts of soil organic carbon [1]. It is recognized worldwide as the best land for agriculture and is key to climate action, sustainable and resilient livelihoods, and food security. Since 2017, the FAO, through its Global Soil Partnership, has been actively engaged in the conservation and sustainable management of black soil. It highlights the benefits, challenges, and opportunities of black soil and recommends actions to support a sustainable future for black soil. While countries have started to prioritize the protection of black soil [2], the FAO highlights the significant challenge posed by the absence of effective policies dedicated to black soil preservation. This deficiency not only jeopardizes the quality and health of black soil but also threatens global food security. The FAO underscores the critical importance of governance at both national and subnational levels in safeguarding black soil [3].

As one of the three black soil areas in the world, China has always regarded black soil as China's vegetable basket [4]. In 2022, they produced 18.3% of rice, 33.4% of corn, and 51.8% of soybeans [5]. Only China has a national law in place to protect, conserve, and encourage sustainable management of black soils now. It is hoped that the examples of effective policies can serve as an inspiration for the adoption of improved management

approaches throughout the black soil zones of the world [3]. Therefore, it is necessary to study the policy of black soil protection in China.

It is found that the existing research on black soil protection mainly focuses on the soil characteristics of black soil and the methods and measures of black soil protection. Scholars mainly evaluated black soil from soil quality [6,7], soil productivity [8], and other aspects, and found that there are problems such as soil organic matter decline and soil erosion [9–11] in black soil at present. Given these problems, scholars studied and proposed land use strategies such as three-line defense control mode, pyramid control mode, minimum development, and maximum protection control mode [12], as well as black soil protection technologies such as straw returning to field [13] and conservation tillage [14]. For black soil protection policy, scholars mainly use differences-in-differences and other methods to evaluate the effects of black soil protection policy [15,16], including economic effects and ecological effects.

There are few studies on the policy system of black soil protection; some scholars have carried out preliminary studies on it, such as evaluating the resilience of cultivated land ecosystem in black soil areas under the background of China's cultivated land protection policy [17]. However, cultivated land protection policy pays attention to the protection of the quantity–quality–ecology trinity [18], while black soil protection policy pays more attention to solving the core problems such as soil management and sustainable management, which cannot be equated, so there is still a lack of research on black soil protection policy. As the first country in the world to legislate on black soil protection, the consistency and evolution law of China's black soil protection policy system has not yet formed a scientific and systematic quantitative evaluation and research system, which makes it difficult to provide scientific reference basis for subsequent adjustment and optimization of policy measures, judgment of future trends, and guidance of policy application, and also makes it difficult to provide reference significance for soil management in black soil areas all over the world.

The PMC index model and text mining method can be used to quantitatively study the consistency and evolution characteristics of policy texts. However, there are still several points to be discussed: First, the PMC index model is a method to evaluate the internal consistency of policy by taking the policy text itself as the research object. Compared with the existing DID method for ex-post evaluation of policy effects, the PMC index model focuses more on the policy content itself, and can also analyze the advantages and disadvantages of the policy [19]. Secondly, quantitative text analysis has become a common method for studying policy texts. Quantitative text analysis methods can effectively extract information, recognize emotions, and analyze policy features by focusing on both the external characteristics and content of policy documents [20]. However, when quantitative text analysis is used to study the text content of policy system, most of them only pay attention to the focus of policy or the use of policy tools [21], and do not include keywords, policy themes, policy tools, etc., in a unified research framework to study the characteristics of policy evolution. Thirdly, most of the existing studies focus on the whole policy system, revealing the evolution characteristics of the whole policy system, and lack of hierarchy to explore the evolution characteristics of the same level and the relationship between different levels. Black soil protection policy includes not only the governance at the national level but also the protection at all levels below the national level [3]. There are differences in the evolution rules between policies at the same level and between policies at different levels. Therefore, it is necessary to explore the evolution rules of black soil protection policies at different levels from a multidimensional perspective.

To sum up, to make up for the shortcomings of the existing research, this study takes the black soil protection policy as the research object, uses the PMC index model to evaluate the effectiveness of the black soil protection policy system, divides the evolution stages based on the fluctuation law of policy consistency, and integrates social network analysis, vertical synergy measurement, confusion measurement, text similarity, and other methods. From the four dimensions of keyword co-occurrence, vertical synergy calculation, policy

theme identification, and policy tool analysis, this paper constructs an analysis framework of the evolution law of China’s black soil protection policy system and uses a variety of visualization technologies to reveal the evolution characteristics and development law of the black soil protection policy system. The contributions of this paper are as follows: Firstly, different from the evaluation of policy effect afterward, this paper evaluates the effectiveness of black soil protection policy itself in advance, explores the evolution law, and divides the evolution stage of policy based on the fluctuation law of policy effectiveness. Secondly, integrating keyword co-occurrence, policy theme identification, and policy tool analysis into the same research framework enables a comprehensive exploration of the evolution of policy systems across multiple dimensions, using various methods in text quantitative analysis. Thirdly, it not only discusses the evolution characteristics of policies at the same level of government but also reveals the relationship and evolution rules between policies issued by different levels of government. The conclusions can provide a new research paradigm and theoretical basis for the research of the black soil protection policy system, and provide a theoretical basis and practical reference for optimizing and perfecting black soil protection policy and promoting global black soil protection.

2. Materials and Methods

According to the policy connotation, this paper uses the policy consistency index model to study the effectiveness of black land protection policy, and divides the policy evolution stage. On this basis, from the same level, using text mining, co-word analysis, theme recognition, and other methods to study the evolution of policy keywords and policy themes, policy keywords represent the content focus of policy text, and extracting policy keywords can sort out the policy focus at different levels of government development [22]. Through the mining and analysis of policy themes, we can clearly find the change of policy core direction. At different levels [23], vertical synergy degree calculation and text similarity calculation are used to study the evolution law of policy keywords and policy tools, quantify the vertical synergy of black soil protection policy, and test the synergy degree between policies at different levels [24]. By mining the types and quantities of policy tools, the implementation subjects of policies at different development stages can be clarified [22]. The overall research idea of this paper is shown in Figure 1.

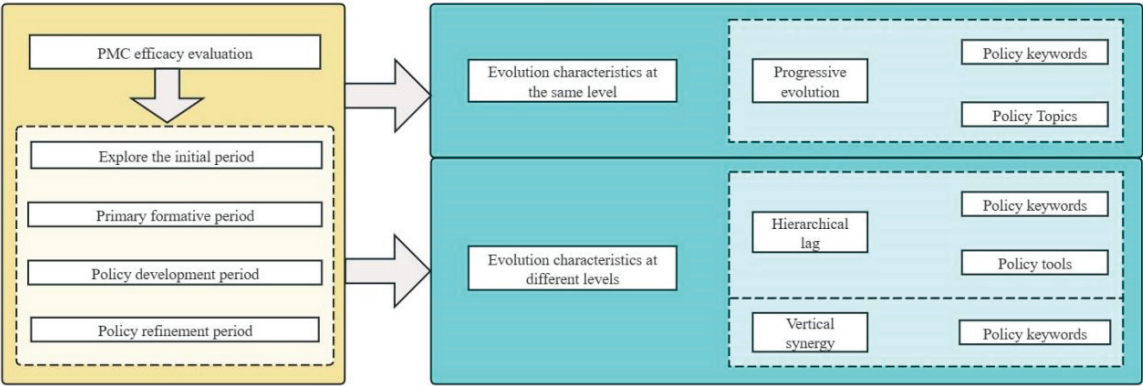


Figure 1. The general research idea of the evolution characteristics of China’s black soil protection policy.

2.1. Research Methods

2.1.1. PMC-Index Model

The evaluation of policy effectiveness is to evaluate the effectiveness of the policy, which can evaluate and analyze the policy content itself, to find the problems existing in the policy, and timely modify and improve it. The policy consistency index model is suitable for the evaluation of policy effectiveness. Its advantage lies in that the variable setting is

based on the comprehensive analysis and mining of the policy text, and the assignment is strictly based on the policy content, which can avoid artificial subjectivity and improve the accuracy of policy quantitative evaluation. Therefore, this paper uses the PMC index model to evaluate the effectiveness of the black soil protection policy.

The evaluation index variable setting is one of the key links of this study, which directly affects the rationality and practicability of the policy evaluation results. Following the hypothesis of “Omnia Mobilis” [25], combining the actual characteristics of black soil protection policies and the analysis conclusions of policy text mining in the previous chapter, and referring to the relevant research of existing scholars [26–31], 9 primary variables and 34 secondary variables are finally determined in this paper, as shown in Table 1.

Table 1. Variables of black soil protection policy.

Main-Variables	Sub-Variables	Main-Variables	Sub-Variables
Policy type (X1)	Laws and regulations Plans, programs Opinions, measures Decision	Policy tool (X6)	Command-and-control tools Economic incentive tools Public participation tools Promotional facilitation tools
Policy release agency (X2)	State Council Ministry of Agriculture and Rural Affairs Other departments Government Agribusiness Farmers	Policy area (X7)	Economy Society Political Technology Supervision and management
Policy receptor (X3)	Rural collective economic organizations New agricultural business entities	Implementation guarantees (X8)	Information promotion Public participation Typical demonstration
Policy function (X4)	Cultivated land quantity protection Restore the quality of arable land Continuous use of black soil resources Long term Medium term Short term	Policy evaluation (X9)	Guiding ideology Basic guidelines Main objective Goal decomposition
Policy timeliness (X5)			

The PMC index is calculated as follows: Firstly, the corresponding values of the secondary variables are obtained by keyword search on the specific contents of the policy text, as shown in Formula (1); secondly, the corresponding secondary variable values under each primary variable are added and divided by the number of secondary variables, to obtain the corresponding primary variable values, as shown in Formula (2); finally, the PMC index score of each policy sample is obtained by adding the primary variable values corresponding to each policy text and dividing by the number of primary variables, as shown in Formula (3).

$$X \sim [0, 1] \tag{1}$$

$$X_t = \frac{\sum_{i=1}^n X_{ti}}{N_t} \quad t = 1, 2, 3, 4, 5 \dots, 10 \tag{2}$$

$$PMC = \sum_{t=1}^k X_t \tag{3}$$

PMC-Surface represents the value of PMC-Index in the form of a stereoscopic image, which can visually show the advantages and disadvantages of the black soil protection policy. PMC surfaces usually depend on the results of PMC matrices. Considering the

symmetry and balance requirements of the matrix [25,32], the PMC matrix is a matrix with 3 rows and 3 columns, and the matrix formula is as follows:

$$PMCSurface = \begin{pmatrix} X_1 & X_2 & X_3 \\ X_4 & X_5 & X_6 \\ X_7 & X_8 & X_9 \end{pmatrix} \tag{4}$$

2.1.2. Quantitative Analysis Method of Policy Text

The policy text on black soil protection has the characteristics of a large number of texts, complex content, and long length. The traditional text analysis method is no longer applicable, and the text mining technology and visual analysis method in the field of information science provide effective tools for studying the dynamic evolution law of black soil protection in China. Among them, text mining is a method that combines machine learning and information retrieval technology to discover and extract implicit knowledge that meets user information needs from large-scale text data [33]; visual analysis can clearly and intuitively present the results of text mining. Therefore, this study comprehensively applies co-word analysis technology, vertical synergy calculation technology, LDA topic modeling and similarity calculation technology in text mining technology, Gephi visualization, LDAvis visualization, and ThemeRiver visualization technology to try to evaluate the policies related to black soil protection before quantification. Specific study methods are described as follows:

(1) Research methods of policy keyword recognition: Policy keywords represent the content focus of policy text, and extracting policy keywords can sort out the policy focus of governments at different levels of development. ROSTCM6 (Version 5.8.0.603) text mining software can mine the selected black soil protection policy text and comb the policy keywords in each policy text. On this basis, Gephi visual view technology can carry out co-word analysis, and then obtain a keyword co-occurrence network.

(2) Vertical synergy means that policy outputs are consistent with the original views of decisionmakers [34]. We classify government policy texts through policymakers to form a database of vertical collaborative assessments. Vertical synergy is calculated according to the proportion of keywords in total word frequency [24], as follows:

$$Sxyi = \frac{\sum_{x=1}^n axyi}{\sum_{x=1}^{\infty} axyi} \tag{5}$$

$$Zxyi = \frac{\prod_{y=1}^3 Sxyi}{\prod_{y=1}^3 Sxy} \tag{6}$$

where x represents the keywords of the policy, y represents a policy dimension, i represents the policy promulgator, $axyi$ represents the total frequency of the policy keywords of dimension y of the policy promulgator i ; $Sxyi$ represents the intensity of policy of dimension y of policy promulgator i ; Sxy represents the intensity of the policy for dimension y in all policy promulgators; and $Zxyi$ represents the synergy degree of policy promulgator i .

(3) The research method of policy theme identification: The policy theme represents the core direction of policy text, and identifying the policy theme provides auxiliary support for studying the law of policy change. Firstly, we use the method of confusion degree measurement to determine the number of policy topics as 4, taking confusion degree as the optimal evaluation model. Secondly, the intensity of the policy theme is calculated to

reveal the keywords that constitute the theme. Finally, the calculation results are visualized by the LDAvis visualization method. The calculation formula is as follows:

$$perplexity(D) = \exp(-\frac{\sum \log p(w|d)}{\sum_{d=1}^M W_d}) \tag{7}$$

$$T_i = \frac{\sum_{d=1}^M P_{id}}{M} \tag{8}$$

where M represents the total number of documents, W_d represents the number of words in the d th document, and the lower the confusion, the better the clustering effect. By analyzing the topic intensity of the policy, we can further understand the relative component of each topic in the policy corpus. The calculation formula is shown in Formula (8). T_i denotes the topic strength of the i th word, and P_{id} denotes the probability of the i th word in the d th document.

(4) Research methods identified by policy tools represent the methods adopted by the government to achieve the established policy goals. Mining policy tools can understand the government’s solution direction to the black soil problem. Text similarity computing technology can mine policy tools included in policy text, and on this basis, ThemeRiver visualization technology can display the mining results. This paper divides policy tools into four types: command and control, economic incentives, information disclosure, and propaganda guidance [35].

2.2. Data Source

The research samples were mainly derived from the national, provincial, and municipal black soil protection policy documents issued from 2004 to 2023, and the text data were preprocessed. The sources of policy text data mainly include (1) official websites of government departments issuing black soil protection policies such as the Ministry of Agriculture and Rural Affairs and provincial agricultural and rural departments; (2) policy big data platforms such as “Beidafabao database” and “Bailu Think Tank”; (3) search engines such as Google and Baidu, which supplement the collected policies. To sum up, a total of 277 copies of black soil protection policy texts were collected. To ensure the relevance of the final adopted documents, excluding documents with low relevance to black soil protection, the number of effective policy texts finally selected was 220, including 36 at the national level, 67 at the provincial level, and 117 at the municipal level. Some of the texts of China’s black soil protection policies are shown in Table 2.

Table 2. Text of China’s black soil protection policy (excerpt).

Release Time	Policy Name	Policy Type	Synopsis
2005	Comprehensive control plan for soil erosion in the black soil area of Northeast China	Planning	Carry out soil erosion control in the black soil area
2017	Outline of Black Soil Conservation Planning in Northeast China (2017–2030)	Planning	It is necessary to take effective measures to protect the black soil
2021	Implementation Plan of the National Black Soil Protection Project (2021–2025)	Scheme	The implementation content and zoning priorities of the national black soil protection project are clarified
2021	Technical Guidelines for Conservation Tillage Action Plan for Black Soil in Northeast China	Guidelines	Promote the four northeastern provinces to do a good job in conservation tillage in 2023
2022	Black Soil Protection Law of the People’s Republic of China	Law	Provide a strong legal guarantee for the protection of black soil

3. Quantitative Evaluation of Policy Consistency of China’s Black Soil Protection

3.1. Results of Policy Consistency Evaluation and Classification of Evolution Stages

Based on the PMC knowledge framework, this paper evaluates the effectiveness of black land protection policy samples collected from 2004 to 2023 at national and provincial levels and analyzes the dynamic mining of issuing subject dimension and policy measure dimension. The PMC index model is used to establish multi-input and output tables of variables, and PMC index results of selected policy texts are obtained. The time-series trends in policy effectiveness levels for each year are shown in Figures 2 and 3.

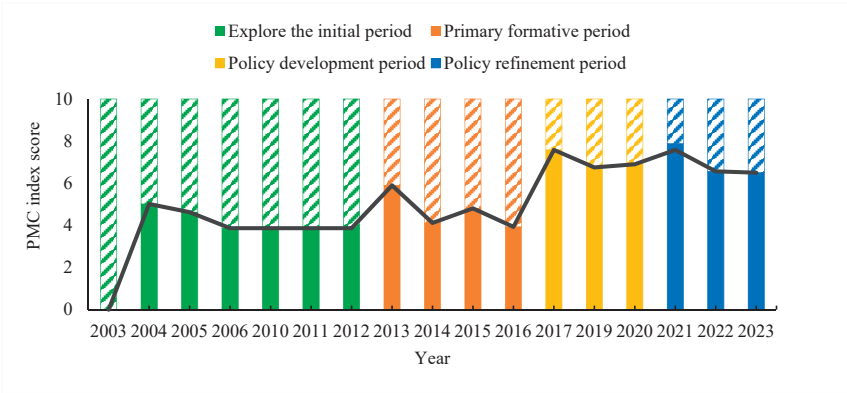


Figure 2. PMC index score results of national black land protection policy.

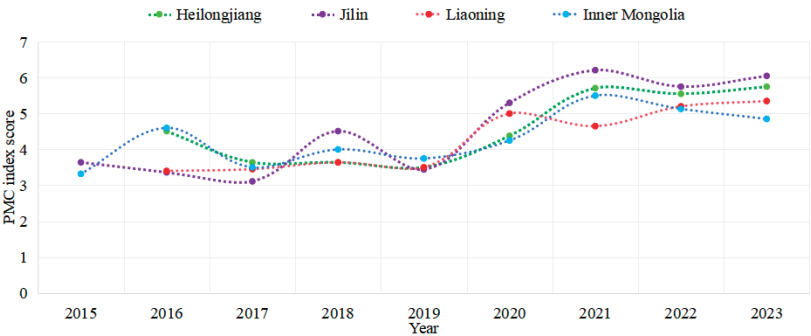


Figure 3. PMC index score results of provincial black land protection policy.

As shown in Figures 2 and 3, the PMC index of black land protection policy shows an overall fluctuation growth trend. According to the change trend of effectiveness evaluation of national black land protection policy, it can be seen that the policy consistency index periodically rises sharply to peak value and then tends to stabilize. The sharp increase in policy effectiveness is due to the large number of issuance of landmark policies and supporting policies. The aggregation of landmark policies and supporting policies will greatly increase the policy effectiveness to peak value, but with the passage of time, the reduction in supporting policies will gradually reduce the policy effectiveness. Therefore, according to the year when the effectiveness of national policies rises rapidly and then rises to the peak, this paper divides the black land protection policy into four development stages: 2004–2012: exploration initial period; 2013–2016: initial formation period; 2017–2021: policy development period; and 2021–now: policy refinement period.

3.2. The Degree of Policy Equilibrium Analysis

Policy equilibrium can be analyzed by the concavity of the PMC surface, which can be measured by using the ratio of the highest peak point value of the surface to the lowest slot point value [36]. A visualization of the PMC surface’s overall score versus the scores for each stage is shown in Figures 4–8. During the initial exploration phase, the concavity of the PMC surface is at its maximum (Figure 4), indicating a lack of policy equilibrium. Among them, the lowest point is the policy receptor dimension, the PMC index score is only 0.2, and the highest point is the policy instrument dimension, the PMC index score is 0.75. It can be seen that in the initial stage of black soil protection, policy tools are used more, but the policy system only covers the single receptor of government. With time, the concavity of the PMC surface tends to smooth, and the equilibrium degree of policy has been gradually optimized and perfected. The policy equilibrium degree is the highest in the policy refinement period. This is because PMC index scores of policy receptors, policy tools, and policy fields are gradually increasing and finally reaching equilibrium, especially the dimension of policy receptors, with the largest increase, from the PMC index score of 0.2 in the initial exploration period to PMC index score of 1 in the policy refinement period. This is because, with the improvement of black soil protection policies, policies have added agricultural enterprises, farmers, rural collective economic organizations, and new agricultural management to policy receptors. That is to say, there are corresponding black soil protection policies for different subjects. These receptors play an important role in the protection of black soil, such as the need to promote agricultural enterprises to accelerate the reduction and efficiency of chemical fertilizers and pesticides, reducing the pollution of black soil; the need to promote farmers to strengthen training and study, improving their quality level; the need for rural collective economic organizations to allocate high-powered machinery, straw returning machinery, and no-tillage seeder, promoting straw returning work.

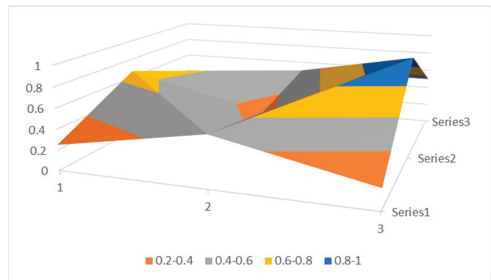


Figure 4. Exploring the surface diagram of the PMC index to explore the initial period.

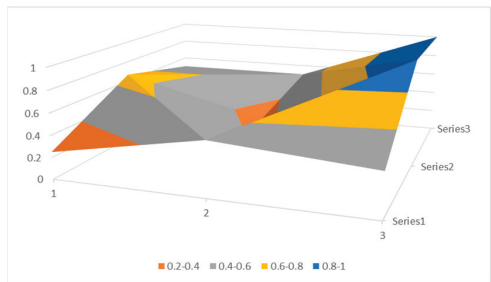


Figure 5. Surface diagram of PMC index in the primary formation period.

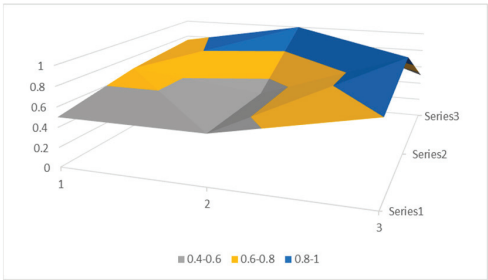


Figure 6. Surface diagram of PMC index during the policy development period.

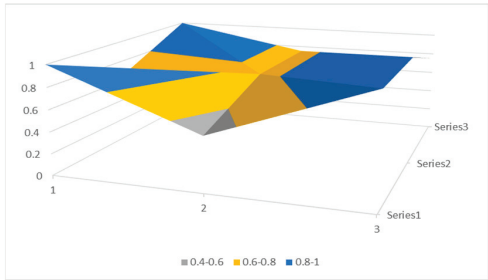


Figure 7. Surface diagram of PMC index during the policy refinement period.

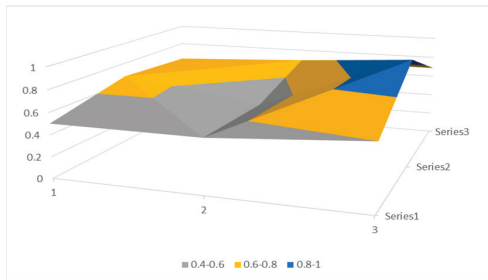


Figure 8. Surface diagram of the overall average PMC index.

It is worth noting that PMC index scores of policy area indicators continue to increase over time, and PMC index scores reach full marks in policy refinement periods. Policy areas are those areas of social development that policies will affect [37]. A more comprehensive policy system should cover economic, social, political, and technical aspects [38]. In the initial period of exploration, the black soil policy only covered the technical aspect, the primary formation period of the policy increased the economic aspect, and in the refinement period of the policy, it covered all four aspects. This is because black soil protection is a complex and systematic project involving rural development, farmers' welfare, and agricultural technology, which should not only consider economic effects such as ensuring comprehensive grain production capacity, but also social effects such as farmers' income, and political factors. For example, the effectiveness of black soil protection has become an important indicator for performance evaluation and political promotion of local government officials in China. Technical aspects are also very important, such as the promotion of conservation tillage and other technologies. To sum up, after entering the policy refinement period, the policy areas covered by China's black soil protection policy have been relatively comprehensive.

4. Research on the Evolution of Black Soil Conservation Policy in China

According to the quantitative analysis of PMC consistency, this paper divides the policy evolution stages into four stages: the initial exploration stage, the primary formation stage, the policy development stage, and the policy refinement stage according to the year when the policy consistency rises rapidly and then rises to the peak. Based on sorting out the policies of each stage, the evolution process of black soil protection policy was summarized and analyzed.

4.1. Exploring the Initial Period (2004–2012)

Exploring the initial period is the stage when the protection of black soil received initial attention, and the main body of policy issuance is mainly a single subject. In 2002, the Premier of the State Council issued important instructions twice, demanding that the prevention and control of soil erosion in black soil areas be placed on the agenda. In 2003, the central budget allocated special funds to support the four northeastern provinces and regions to carry out a three-year pilot project for comprehensive prevention and control of soil erosion in the black soil region of northeast China. During the development period of the system of construction occupation and farmland quality management and protection (2004–2011), black soil protection was first proposed by the Ministry of Agriculture of China, who began to pay attention to the management and protection of black soil quality. However, policies and measures on the protection of black soil quality still need to be further strengthened, and the ecological protection of black soil has not been fully paid attention to. In 2004, the Ministry of Natural Resources reported that China's black soil was suffering from serious damage and erosion, and experts called for the urgent need to formulate policies and regulations to protect the black soil. In 2005, the Ministry of Agriculture proposed, for the first time, the establishment of a long-term mechanism for the rational use and protection of black soil.

Up to 2006, the area of soil and water loss in the black soil area of Northeast China accounted for 27.0% of the total area of the whole region. Given this problem, the *Comprehensive Prevention and Control Plan of Soil and Water Loss in the Black Soil Area of Northeast China* proposed the measures of using both gully and slope control, increasing ground vegetation, rational development, and so on to comprehensively prevent and control the soil and water loss in the black soil area of Northeast China. The trend of soil erosion has been alleviated, but the situation is still grim. In the following five years, although the state in the notice, opinions, outline, and other documents proposed to diffuse hillock areas, hilly areas, and other different characteristics of the black soil area of soil and water loss prevention and control, the black soil problem still remains for the prevention and control of soil and water loss. To better guarantee the economic and social development during the Twelfth Five-Year Plan period, and ensure that the quantity of cultivated land in China is stable and the quality does not decline, in 2012, the Ministry of Land and Resources issued the *Notice on Improving the Level of Cultivated Land Protection and Comprehensively Strengthening the Construction and Management of Cultivated Land Quality*. As China's cultivated land protection enters the transformation and improvement stage, integrating quantity, quality, and ecology, the northeast black soil region is also strengthening engineering measures to improve the regional water and soil conservation capacity.

4.2. Primary Formation Period (2013–2016)

The preliminary formation period is the stage of starting the first batch of black soil protection and utilization pilot projects. The black soil protection technology was still in the experimental stage, and the coordination trend of black soil protection policy departments was initially formed. In 2013, climate issues adversely affected natural ecosystems and socioeconomic systems, and the black soil problem was raised again. The *Notice on Printing and Distributing the National Adaptation Strategy to Climate Change*, jointly issued by the National Development and Reform Commission and the Ministry of Agriculture and nine other departments, with Jilin Province as the first pilot, proposed to carry out the pilot

demonstration project of black soil protection and governance adaptation in Jilin's main grain-producing areas. Subsequently, in 2015, the policy-issuing department joined the Ministry of Science and Technology and the Ministry of Environmental Protection to jointly issue the *National Agricultural Sustainable Development Plan (2015–2030)* to promote the development of the pilot demonstration area for sustainable development of black soil protection; on this basis, the agricultural machinery purchase subsidy policy issued by Jilin Province proposed black soil protection and issued subsidies for the purchase of agricultural machinery implementing black soil conservation tillage technology. Subsequently, the utilization efficiency of agricultural resources was significantly improved in 2016, and Jilin Province promulgated the *Jilin Province Agricultural Sustainable Development Plan (2016–2030)* to promote the scale expansion process of the black soil protection and utilization pilot.

4.3. Policy Development Period (2017–2020)

During the policy development period, the mainstream technology of black soil protection made obvious progress and began to be popularized and applied in Northeast China. The Ministry of Agriculture and Rural Affairs launched the second batch of pilot projects for black soil protection and utilization, and the policy of black soil protection issued by multiple departments in coordination, had approached maturity. In 2017, China's understanding of black soil problems was deeper, that is, in the past 60 years, the organic matter content of the black soil tillage layer soil had decreased by 1/3, and in some areas by 50%. The National Development and Reform Commission, together with the Ministry of Agriculture, the Ministry of Finance, the Ministry of Water Resources, the Ministry of Land and Resources, and the Ministry of Environmental Protection, issued the *Outline of Northeast black soil Protection Planning (2017–2030)*. Under the condition of clarifying the importance and urgency of black soil protection, they proposed the overall requirements, key tasks, technical modes, and safeguard measures for black soil protection.

In 2020, the Ministry of Water Resources proposed that the area of soil and water loss in the northeast black soil accounted for 19.86% of the total land area, and the control of soil and water loss has achieved success, but the problems of "thinning" of denudation loss, "thinning" of soil organic matter and nutrient element attenuation, and "hardening" of soil structure change and water storage capacity decline have not been completely solved. At the same time, Northeast China's conservation tillage technology has made significant progress, and the overall technical model of the shape, of the key equipment passed, has been in the appropriate area to promote the comprehensive application of the foundation. Accordingly, the Ministry of Agriculture and Rural Affairs and the Ministry of Finance jointly issued the *Action Plan for Conservation Tillage of Northeast black soil (2020–2025)*, to accelerate the popularization and application of conservation tillage, making conservation tillage the mainstream agricultural tillage technology in the suitable areas of Northeast China, realizing the stable improvement of cultivated land quality and comprehensive agricultural production capacity, and enhancing ecological, economic, and social benefits. During this period, based on the locally cultivated land characteristics, the provincial and municipal governments of the four provinces in Northeast China began to promulgate policies to explore technologies and modes more conducive to their development.

4.4. Policy Refinement Period (from 2021 to Now)

In the policy refinement period, multiple departments jointly issued several policies to promote black soil protection as a national project. In 2021, the cultivated land quality of the four provinces (autonomous regions) in Northeast China increased by 0.29 grades compared with five years ago. However, since the black soil cultivated land that has implemented comprehensive treatment measures is still dominated by pilot and demonstration areas, the protected area accounts for a relatively low proportion, and the degradation trend of black soil cultivated land has not been effectively curbed. The Ministry of Agriculture and Rural Affairs, together with six other departments, issued the *Implementation Plan of the National black soil Protection Project (2021–2025)*. The implementation contents of black soil

protection were proposed from the aspects of monitoring and evaluation systems, farmland infrastructure, technology, environment, etc., and black soil protection was formally proposed as a national project. In 2021, the Ministry of Agriculture and Rural Affairs reissued the Technical Guidelines for the *Action Plan for Conservation Tillage of Northeast black soil in 2021* to promote the quality improvement and expansion of conservation tillage in 2021, realize the standardized application of conservation tillage technology, and continuously enhance the soil protection effect.

In 2022, the *Law of the People’s Republic of China on the Protection of black soil* was formally implemented, which is the first law in China and the only law in the world to legislate to protect black soil at the national level, which marks that the protection of black soil in China has officially stepped into the track of legalization. In addition, the provinces and municipalities in Northeast China have issued a large number of detailed policies at the provincial and municipal levels.

5. China’s Black Soil Protection Policy Analysis of the Results of the Dynamic Evolution of the Law

5.1. China’s Black Soil Protection Policy Analysis of the Key Words

5.1.1. Co-Occurrence Network Analysis of Policy Keywords

Through the analysis of the co-occurrence and evolution of keywords in the policies issued by governments at different levels in different periods, we can sort out the key points of policies at different levels of development of governments, and provide auxiliary support for policy research and formulation. The co-occurrence network of policy keywords at different stages of the evolution of national black soil protection policies is shown in Figures 9–12.

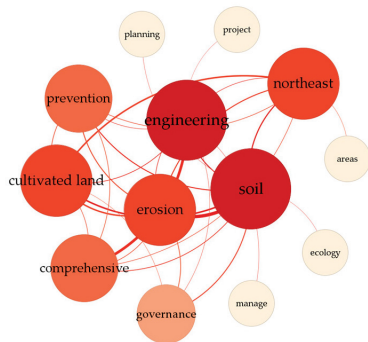


Figure 9. Keyword co-occurrence network of national black soil protection policies from 2004 to 2012.

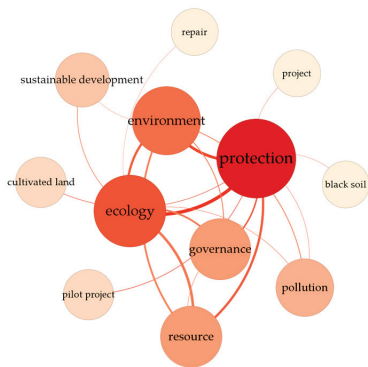


Figure 10. Keyword co-occurrence network of national black soil conservation policies from 2013 to 2016.

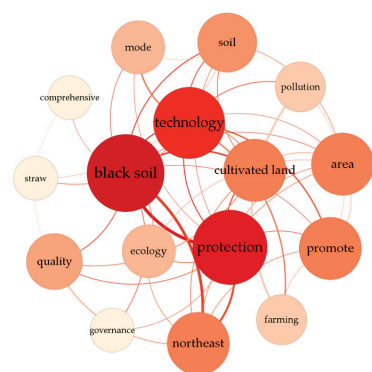


Figure 11. Keyword co-occurrence network of national black soil protection policies from 2017 to 2020.

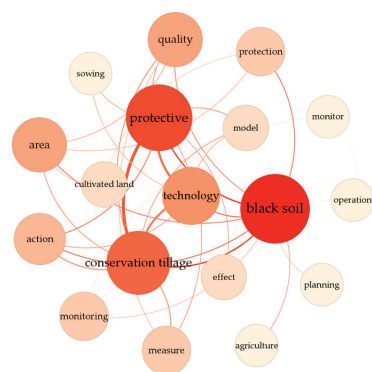


Figure 12. Keyword co-occurrence network of national black soil protection policies from 2021 to the present.

It can be seen from Figure 9 that the “soil” point degree centrality is the highest in the initial exploration period, indicating that the frequency of “soil” appearing in the same policy document with other keywords is the highest, indicating that the black soil protection policy at this stage focuses on the problem of water and soil loss. “Soil”, “erosion”, “prevention”, and “engineering” are at the core of the co-occurrence network, and the edge weights are higher. In this period, the state made great efforts to develop soil erosion control projects, fertile soil projects, and irrigation area reconstruction projects to improve the level of intensive land use, and to establish a long-term mechanism for the rational use and protection of black soil.

As can be seen from Figure 10, the keywords “protection” and “ecology” in the primary formation period have the highest influence on the social network. The protection of black soil has been promoted from solving the problem of soil erosion to improving the ecological environment, improving soil quality, increasing infrastructure, and other agricultural protection. The emergence of keywords such as “pilot” and “governance” is precisely because the report of the 18th National Congress of the Communist Party of China points out that the construction of ecological civilization should be vigorously promoted under the increasingly tight constraints of global resources and environment. Under the key task of protecting cultivated land resources and promoting the sustainable utilization of farmland, strengthening the protection of black soil in Northeast China and improving the land quality has become an indispensable link. This also reflects that the central government’s policy focus on black soil protection at this stage is to “carry out pilot projects” for black soil protection. In 2013, the central government increased capital

investment to carry out pilot projects for black soil protection in Jilin Province, striving to explore effective measures to control soil erosion and restore soil fertility.

It can be seen from Figure 10 that the keywords “black soil”, “protection”, and “technology” have a high degree of centrality during the policy development period, which just shows that in order to accelerate the implementation of the strategy of “storing grain in the land and storing grain in technology” and strengthen the research on black soil protection technology, the state focuses on the technical mode. The keywords “farming”, “promote”, and “northeast” reflect that the pilot work of black soil protection has been extended from Jilin Province to the whole northeast region.

It can be seen from Figure 12 that “conservation tillage” has the highest influence in the keyword network during the policy refinement period, which shows that with the gradual improvement of black soil protection work, conservation tillage technology has become the mainstream tillage technology for black soil protection in Northeast China. Keywords such as “quality”, “technology”, “monitoring”, and “effect” indicate that the black soil protection technology is relatively mature, and the policy focus has been changed to how to promote and implement the black soil protection technology. The next work’s focus is to strengthen the monitoring and evaluation of the quality of black soil cultivated land. Through strict supervision and assessment, centralized and contiguous promotion is realized, and a new pattern of sustainable development in which the black soil is protected during utilization and promoted by protection is formed.

5.1.2. Hierarchical Evolution Analysis of Policy Keywords

The main body of black soil protection policy includes three levels of government at the national, provincial, and municipal levels, and the policy evolution characteristics of the same level of government and different levels of government are also different. To explore the evolution characteristics of the association between the same level and different levels of policies at different development stages, the high-frequency keywords at three levels and four development stages were comprehensively analyzed, as shown in Table 3. It can be seen from the table that there is a law of “progressive evolution” in China’s black soil protection policy from the same level. The progressive evolution process is mainly reflected in the policy content. In the early stage of policy development, the keywords of policy are “prevention” and “pilot”, which reflect the singularity of black soil protection and utilization technology and the locality of the implementation area. In the follow-up development, more black soil degradation problems have been discovered, and the technical model of black soil protection and utilization has been continuously innovated and enhanced. In the later stage of policy development, keywords such as “technology”, “monitoring”, and “northeast” indicate that the black soil protection and utilization technology has mature and supporting technical measures, and the protection scale has been extended from pilot projects in some regions to the whole northeast region.

From the different levels, there are “level lag” and “level transmission” in the early and late development of China’s black soil protection policy. Among them, the lag of hierarchy is mainly reflected in the hierarchy and policy content of the main body of policy issuance. From the perspective of the main body level of policy issuance, most of the policies issued at the initial stage of exploration are limited to the national level, while the provincial and municipal levels begin to promulgate relevant policies at the primary formation stage and policy development stage, respectively. From the perspective of policy content, in the early stage of policy development, the policy keywords “soil” and “ecology” have obvious “hierarchical lag” evolution characteristics; these focuses are the first attention of the central government; local governments will gradually pay attention to them in the subsequent development. In the later stage of policy development, the “hierarchical lag” gradually weakened, gradually showing the evolution characteristics of “hierarchical transmission”, and keywords such as “technology” and “monitoring” appeared in different levels of policy in the same period. To sum up, the evolution law of black soil protection policy is mainly reflected in the same level, and its evolution law conforms to “progressive evolution”.

Between different levels, the early and late stages of policy development show the evolution characteristics of “hierarchical lag” and “hierarchical transmission”, respectively.

Table 3. Keywords at national, provincial, and municipal levels in different periods.

	Explore the Initial Period	Primary Formation Period	Policy Development Period	Policy Refinement Period
National Policy Keywords	“soil” “erosion” “project” “cultivated land” “ecology” “prevention”	“protect” “environment” “ecology” “pilot project”	“black soil” “technology” “protect” “northeast” “soil” “cultivated land”	“farming” “protective” “technology” “conservation tillage” “monitor” “black soil”
Provincial Policy Keywords		“farmland” “ecology” “cultivated land” “protect”	“operation” “straw” “technology” “black soil” “protect” “quality”	“black soil” “protective” “cultivated land” “soil” “monitor” “technology”
Municipal Policy Keywords			“farming” “technology” “soil” “straw” “quality” “promote”	“protective” “black soil” “technology” “farming” “monitor” “assess”

On the basis of studying the evolution characteristics of different levels of government, this paper uses the change of high-frequency word proportion to reflect the change of policy concern and further quantifies the vertical synergy between central black soil protection policy and local government policy, that is, the consistency degree between different levels of policy. On the basis of classifying and merging all the strategy texts, the first 40 high-frequency words in the merged strategy texts are selected as the keywords of the strategy type. Using Equations (5) and (6) to quantify the degree of vertical policy synergy, the results are shown in Figures 13–16. The vertical synergy degree of central government is the highest in the initial formation period and the overall stage, and the vertical synergy degree of Heilongjiang Province is the highest in the policy development period and the policy refinement period.

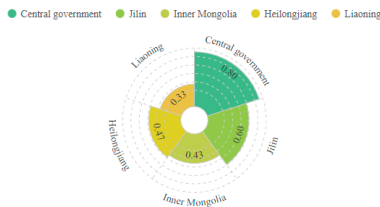


Figure 13. Results of vertical synergy degree of full-stage policies.

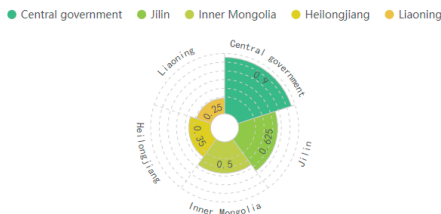


Figure 14. Results of vertical synergy degree of primary formation period.

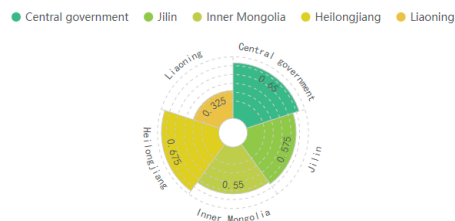


Figure 15. Results of vertical synergy degree of policy development period.

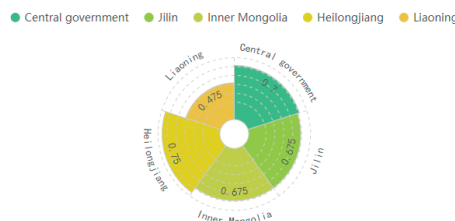


Figure 16. Results of vertical synergy degree of policy refinement period.

As shown in Figure 13, the vertical coordination degree of the central government and local governments at all stages is ranked as follows: Central Government > Jilin Province > Heilongjiang Province > Inner Mongolia Autonomous Region > Liaoning Province. The vertical synergy degree at the national level is 0.8, which is higher than that of the local government. This shows that, compared with local governments, the central government pays more attention to the consistency of policy intentions between upper and lower governments when formulating policies. Second, there is a big gap in the vertical synergy between local governments. The highest vertical synergy degree of Jilin Province is 0.6, which is higher than that of other provinces. This is because Jilin Province set up the first pilot project of black soil protection in China, and later formed a “pear tree model” suitable for black soil protection in Northeast China through exploration. Black soil protection was carried out earlier and policy consistency was strong. On the basis of fully implementing and understanding the purpose of central policy in provincial policies, municipal policies followed its strategic layout.

5.2. Analysis of the Policy Theme of Black Soil Protection in China

Through the excavation and analysis of the policy theme of black soil protection, we can find the change in policy core direction. Figure 17 shows the LDA model recognition results of the national black soil protection policy theme. The red and blue bars on the right side of Figure 17 represent the correlation degree between the word and the theme and the probability of the theme, respectively. The left side figure shows that a total of four themes are identified. To sum up, we extracted the most closely related words and summarized the theme contents of the national black soil protection policy as follows: theme 1 (agricultural protection area), theme 2 (black soil construction), theme 3 (technology promotion), and theme 4 (strengthening ecology). According to the calculation principle of the topic model, the closer the distance, the stronger the relevance. Therefore, as can be seen from Figure 13, theme 1 has the strongest degree of association with theme 2 and the weakest degree of association with theme 4. It can be seen that the protected area is the core of the black soil protection project; compared with this, strengthening the ecological environment accounts for less in the black soil protection project and is in a subsidiary position.

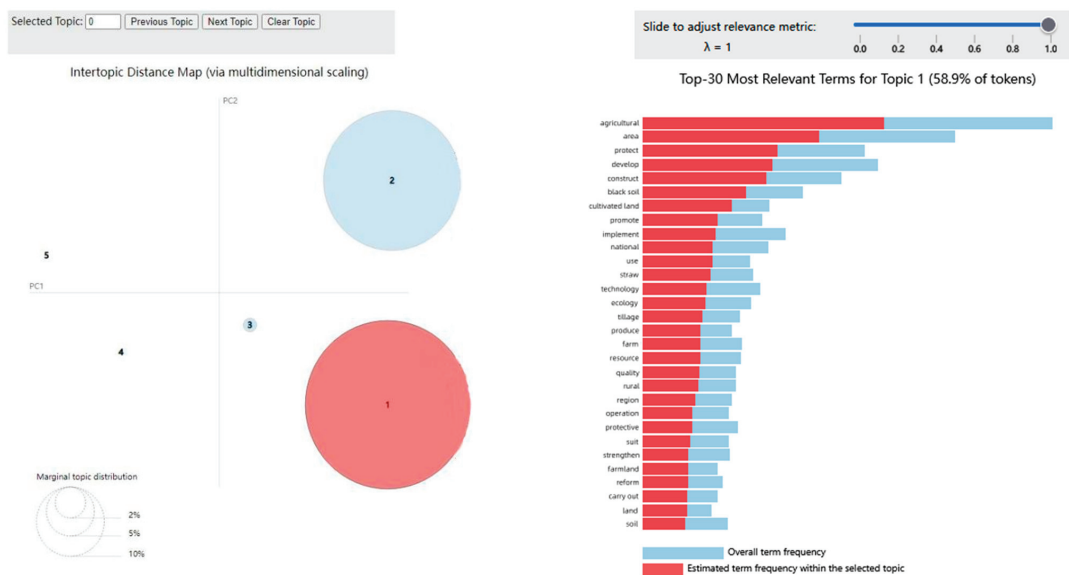


Figure 17. LDA model identification results of national black soil conservation policy themes.

Further identifying the theme of black soil protection policy in different stages, we find that the theme of black soil protection policy in China has the law of “stage evolution”, which is manifested in the core content of black soil protection gradually changing from single to comprehensive. The policy theme in the initial period of exploration is “ecological environment improvement”. Under the background of lack of mature black soil protection technology, it focuses on controlling ecological problems such as soil erosion and desertification of black soil, giving priority to ensuring the quantity of black soil, laying a foundation for the protection and improvement of black soil. The policy themes of the primary formation period are “pilot protection areas”, “strengthening soil quality”, and “black soil protection demonstration areas”. The establishment of pilot and demonstration areas has become a key link in the protection of black soil in this period. Under the background of exploring the most effective methods suitable for black soil protection, the demonstration areas have a demonstration and guidance role, which provides strong support for the comprehensive promotion of black soil protection models.

The policy themes In the policy development period are “conservation technology”, “farming mode”, and “straw returning to the field”. Through the implementation of conservation tillage in the pilot area, and the simultaneous implementation of grain and bean rotation, deep tillage, straw return, and other technical measures, a number of black soil protection and utilization technical models and operation mechanisms suitable for Northeast China were explored and summarized. The policy themes of the policy refinement period are “black soil quality”, “supervision and evaluation”, and “technology promotion”. The establishment of a supervision and evaluation system has become an important task at present. Under the background of mature black soil protection technology and large-scale popularization, perfecting the monitoring index system and evaluation technology of black soil quality can assist in the effective implementation of the black soil protection project.

In order to explore the dynamic evolution characteristics of the policy themes of black soil protection in different development stages of China, this paper comprehensively analyzes the policy themes of four development stages and finds that the policy themes of black soil protection in China have the law of “stage evolution”, which is manifested in the gradual change of the content of black soil protection from single to comprehensive. The policy theme developed from ecological problem management to exploring suitable

technical mode, then combined new farming technology with protection mode, finally improved the supervision feedback mechanism on the basis of comprehensively promoting black soil protection work, and gradually diversified and integrated the content of the black soil protection policy system. Therefore, it shows that the policy theme development of black soil protection policy conforms to the characteristics of stage evolution.

5.3. An Analysis of Policy Tools for China's Black Soil Protection Policy

By mining the types and quantities of policy tools, we can clarify the implementation subjects of policies at different stages of development, and provide auxiliary support for policy research and formulation. The evolution trend of the number of different policy instruments adopted by governments at all levels in the past 20 years is shown in Figure 18. Figure 18 shows that the use of policy instruments is more balanced at all levels of government. This is due to the wide range of subjects implementing the black soil protection policy, including farmers, enterprises, agricultural cooperatives, and government agencies. For example, farmers, the main application subjects of black soil protection technology, have a low overall cultural level, have less cognition of the necessity of black soil protection and the effectiveness of black soil protection technology, and are more suitable for propaganda and guidance policy tools to popularize science among farmers. For the main enterprises of policy regulation and control, some industrial and mining enterprises pollute and destroy the land, and government departments need to control their emission standards, so it is suitable to use command-and-control tools; for the agricultural machinery cooperatives, which are the main body of technology implementation of black soil protection, they are encouraged to purchase and use agricultural machinery equipment conducive to black soil protection, and economic incentive tools are used to purchase agricultural machinery subsidies. Therefore, the use of the four policy tools by governments at all levels has the characteristics of balance and universality.

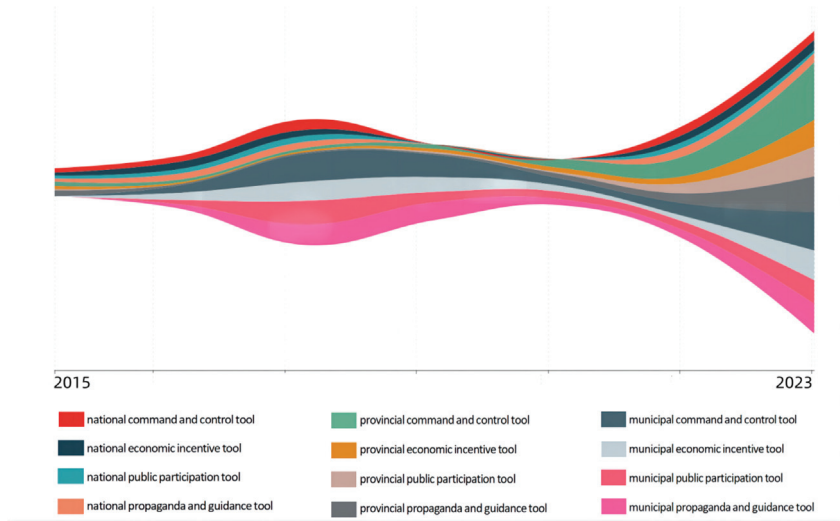


Figure 18. Overall evolution trend chart of policy tool types.

The use of policy instruments is characterized by weak volatility at the national level and strong volatility at the local level. In the early stage, local governments were in a weak position, mostly implementing the black soil protection policies issued by the central government, but in recent years, local governments have gradually occupied a dominant position in the formulation and implementation of black soil protection policies. In the initial period of exploration, the government began to realize the problem of black soil protection, so the number of policy tools was relatively small during this period. In

the primary formation period, the pilot work enabled more government departments to participate in the black soil protection work, so the number of national-level policy tools began to increase, and local governments in pilot areas also issued relevant documents to ensure the implementation of the pilot work, so the number of local policy tools also began to increase. During the policy development period, the state issued policies to explore and popularize the protection technologies and protection models suitable for black soil, and the use of policy tools did not change greatly. At the same time, local governments invested less in exploring new technologies and models, so the number of policy tools available to local governments began to decrease. During the policy refinement period, the black soil Protection Project was formally implemented as a national project, and the number of national policy tools did not fluctuate greatly. At the same time, local governments began to issue black soil protection policies intensively, and local governments gradually occupied a dominant position in the formulation and implementation of black soil protection policies.

We explore the change trend of the use of policy tools at different levels, and display the use of black soil protection policy tools at different periods and levels in the form of thematic river diagrams. The evolution trend of policy tools is shown in Figures 19–21. It can be seen from Figures 19–21 that the changing trend of national-level policy tools is to increase first and then stabilize. The number of four policy tools has increased slowly since 2015. During this period, the black soil protection policy system has initially taken shape. The state mainly uses command-and-control tools and other three types of policy tools to assist government departments in promoting black soil protection. In 2017, China attached great importance to the protection of black soil in Northeast China and clearly proposed to take effective measures to protect black soil. Therefore, during this period, the intensity of issuing policies was strengthened, and the number of policy instruments reached a peak, and then overall tended to be stable. The changing trend of provincial policy tools was increasing and had the characteristics of hierarchical lag. After the relevant policies were promulgated by the state, the provincial government did not respond immediately. Until 2017, the number of provincial policy instruments began to grow slowly, with command-and-control instruments as the main types of instruments, supplemented by the other three types of policy instruments, and lagging behind the use of national-level policy instruments by two years. In 2016, in response to national policies, some cities issued detailed policies based on the current situation of the city, and the number of municipal policy instruments increased. While the state searched for new technologies and models for black soil protection, municipal governments did not respond, and the number of policy tools began to decrease. From 2019 to 2021, the protection of black soil was rapidly promoted, and municipal governments actively responded to this by formulating policies consistent with their own regional characteristics and current situation.

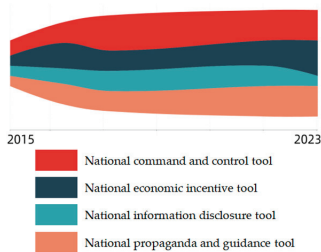


Figure 19. The overall evolution trend of the four types of policy instruments at the national level.

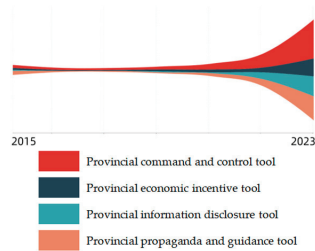


Figure 20. The overall evolution trend of the four types of policy instruments at the provincial level.

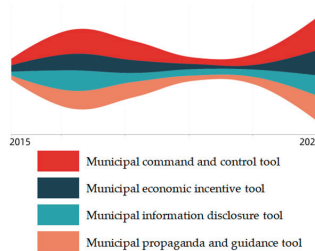


Figure 21. The overall evolution trend of the four types of policy instruments at the municipal level.

6. Research Conclusions

This study used the policy consistency index model to evaluate the effectiveness of the black soil protection policy and comb the evolution process of black soil protection policy in China. At the same time, using quantitative analysis methods such as text mining and text measurement, the dynamic evolution characteristics of black soil protection policy at the same level and different levels were studied from four levels: policy keywords, vertical synergy, policy themes, and policy tools. The following conclusions are drawn:

(1) According to the results of policy effectiveness evaluation, PMC index scores show a phased growth trend as a whole, and each index gradually improves and tends to stabilize. In the early stage of the black soil protection policy, the internal consistency level is relatively low. After the gradual development and refinement of policies in each stage, the consistency index of policies shows a phased upward trend. According to the characteristics of the PMC index rising to the peak and tending to be stable, the evolution stage of black soil protection policy can be divided into an exploration initial period, preliminary formation period, policy development period, and policy refinement period.

(2) From the perspective of the evolution law of policies at the same level, there are progressive evolution characteristics in both policy keywords and policy themes. On the one hand, the logical main line of policy keyword evolution is mainly reflected in the degree of understanding of the black soil problem and the way technological innovation promotes black soil protection and utilization. That is to say, the change in the policy of black soil protection in Northeast China is a process of continuous practice, exploration, and renewal of black soil protection technology, and also a process of policy evolution promoted by agricultural technology progress. On the other hand, the development process of policy theme shows that the content of black soil protection policy gradually changes from single to comprehensive. The policy theme ranges from exploring soil erosion control in the initial period to exploring suitable new models in the initial formation period, then combining new farming techniques with conservation models in the development period, and finally improving the regulatory feedback mechanism in the policy refinement period. Generally speaking, the contents of the black soil protection policy system are gradually diversified and integrated.

(3) From the evolution law of different levels of policies, there is a hierarchical lag evolution law between policy keywords and provincial policy tools, among which policy

keywords also have a vertical synergy evolution law. First of all, the lag of policy keyword hierarchy is mainly reflected in the hierarchy and policy content of policy-issuing subjects. Most of the policies issued in the initial stage of exploration are limited to the national level, while the provincial and municipal governments begin to issue relevant policies in the initial formation stage and policy development stage, respectively. In the early stage of policy development, the keywords “soil” and “ecology” have obvious characteristics of “hierarchical lag” evolution; these focuses have the first attention of the central government, and the local government will gradually pay attention to them in the subsequent development. Secondly, after the promulgation of relevant policies by the state, the response time of provincial governments lags behind, and the number of provincial policy instruments begins to grow slowly in 2017. The types of instruments used are mainly command–control instruments, supplemented by other three types of policy instruments, and lag behind the use of national-level policy instruments by two years. Finally, the vertical coordination degree of central government is higher than that of provincial governments in the process of formulating black soil protection policy.

By reviewing the policy development process, evaluating its effectiveness, and exploring its evolution rules, we find that the black soil protection policy highlights the problems that need to be optimized, such as imperfect incentive measures and imperfect feedback mechanisms. Based on this, this paper proposes the following perfect countermeasures: Shorten the policy delay. Black soil protection policy is a project that needs department coordination, multiparticipation, and linkage to shorten the time delay caused by policy diffusion and implementation among different levels of government as much as possible, and better guarantee the effect of black soil protection policy. In this regard, we can improve the transmission mechanism of policies, improve the implementation mechanism of relevant supporting policies, strengthen policy interaction among different levels of government, and exert efforts to give full play to the incentive and traction role of national policies and provincial policies to municipal, district, and county governments, so as to improve the efficiency of policy implementation and strengthen the continuity and coherence of policies. Strengthen the correlation and coupling between policies, and pay attention to the division of labor, cooperation, and overall consideration among various departments.

Specifically speaking, the adjustment of black soil protection policy should be promoted with the systematic concept, considered as a whole, and the coordination and internal connection among policies such as good governance, repair, good use, and good maintenance of black soil should be emphasized, so as to better grasp the evolution direction of black soil protection policy and provide a guarantee for more efficient promotion of black soil protection work. Strengthen the coverage and comprehensiveness of the policy content: black soil protection involves many aspects such as economy, society, politics, and technology. Expand the coverage of black soil protection policy, improve the comprehensiveness of black soil protection policy, and provide protection to black soil from many aspects, so as to better guarantee national food security.

In general, this paper makes an overall overview and objective evaluation of the policy content text. The research conclusions can provide a new research paradigm and theoretical basis for the research of the black soil protection policy system, and provide a theoretical basis and practical reference for the subsequent optimization and perfection of black soil protection policy to promote the northeast region to solve the bottleneck problem of black soil protection. However, there are still some limitations and deficiencies in the research, such as the following: the PMC index model has limitations in variable selection, universality is still low, some variables cannot adapt to other policies, and the universality of the policy evaluation system can be continued to be strengthened in the future.

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References

- Ma, S.; Wang, L.-J.; Wang, H.-Y.; Zhao, Y.-G.; Jiang, J. Impacts of land use/land cover and soil property changes on soil erosion in the black soil region, China. *J. Environ. Manag.* **2023**, *328*, 117024. [CrossRef]
- Wang, L.; Jia, J.; Zhai, Y.; Wang, J.; Sheng, C.; Jing, Z.; Yan, H.; Fang, J.; Yao, Y. Bibliometric analysis of black soil protection from the perspective of land-use monitoring. *Land* **2022**, *12*, 86. [CrossRef]
- FAO. *Global Status of Black Soils*; FAO: Rome, Italy, 2022. [CrossRef]
- Zhang, S.; Liu, G.; Chen, S.; Rasmussen, C.; Liu, B. Assessing soil thickness in a black soil watershed in northeast China using random forest and field observations. *Int. Soil Water Conserv. Res.* **2021**, *9*, 49–57. [CrossRef]
- National Bureau of Statistics. *2023 China Statistical Yearbook*; China Statistics Press: Beijing, China, 2019.
- Li, X.; Wang, D.; Ren, Y.; Wang, Z.; Zhou, Y. Soil quality assessment of croplands in the black soil zone of Jilin Province, China: Establishing a minimum data set model. *Ecol. Indic.* **2019**, *107*, 105251. [CrossRef]
- Li, Y.X.; Yu, P.J.; Shen, L.C. Soil Quality Assessment of Crop Rotations and Management Practices Based on Minimum Data Set and Soil Quality Indices in the Northeast Plain, China. *Fresenius Environ. Bull.* **2021**, *30*, 8749–8757.
- Xie, Y.; Tang, J.; Gao, Y.; Gu, Z.; Liu, G.; Ren, X. Spatial distribution of soil erosion and its impacts on soil productivity in Songnen typical black soil region. *Int. Soil Water Conserv. Res.* **2023**, *11*, 649–659. [CrossRef]
- Fang, H.; Sun, L. Modelling soil erosion and its response to the soil conservation measures in the black soil catchment, Northeastern China. *Soil Tillage Res.* **2017**, *165*, 23–33.
- Gu, Z.; Xie, Y.; Gao, Y.; Ren, X.; Cheng, C.; Wang, S. Quantitative assessment of soil productivity and predicted impacts of water erosion in the black soil region of northeastern China. *Sci. Total Environ.* **2018**, *637*, 706–716. [CrossRef]
- Wang, X.; Li, S.; Wang, L.; Zheng, M.; Wang, Z.; Song, K. Effects of cropland reclamation on soil organic carbon in China's black soil region over the past 35 years. *Glob. Chang. Biol.* **2023**, *29*, 5460–5477. [CrossRef]
- Xu, X.; Xu, Y.; Chen, S.; Xu, S.; Zhang, H. Soil loss and conservation in the black soil region of Northeast China: A retrospective study. *Environ. Sci. Policy* **2010**, *13*, 793–800. [CrossRef]
- Zhu, F.; Lin, X.; Guan, S.; Dou, S. Deep incorporation of corn straw benefits soil organic carbon and microbial community composition in a black soil of Northeast China. *Soil Use Manag.* **2022**, *38*, 1266–1279. [CrossRef]
- Guo, H.; Zhao, W.; Pan, C.; Qiu, G.; Xu, S.; Liu, S. Study on the influencing factors of farmers' adoption of conservation tillage technology in black soil region in China: A logistic-ISM model approach. *Int. J. Environ. Res. Public Health* **2022**, *19*, 7762. [CrossRef]
- Lin, G.; Lu, X.; Niu, S. Analysis of China's black soil protection policy text under the framework of "policy path policy tools-policy evaluation. *Resour. Sci.* **2023**, *45*, 900–912. (In Chinese) [CrossRef]
- Tang, Z.; Song, W.; Zou, J. Farmland protection and fertilization intensity: Empirical evidence from preservation policy of Heilongjiang's black soil. *J. Environ. Manag.* **2024**, *356*, 120629. [CrossRef]
- Miao, X.; Li, Z.; Wang, M.; Mei, J.; Chen, J. Measurement of cultivated land ecosystem resilience in black soil region of Northeast China under the background of cultivated land protection policy in China: Case study of Qiqihar City. *J. Clean. Prod.* **2024**, *434*, 140141. [CrossRef]
- Tang, H.; Yun, W.; Liu, W.; Sang, L. Structural changes in the development of China's farmland consolidation in 1998–2017: Changing ideas and future framework. *Land Use Policy* **2019**, *89*, 104212. [CrossRef]
- Huang, G.; Shen, X.; Zhang, X.; Gu, W. Quantitative Evaluation of China's Central-Level Land Consolidation Policies in the Past Forty Years Based on the Text Analysis and PMC-Index Model. *Land* **2023**, *12*, 1814. [CrossRef]
- Li, H.; Wei, X.; Gao, X. Objectives setting and instruments selection of circular economy policy in China's mining industry: A textual analysis. *Resour. Policy* **2021**, *74*, 102410. [CrossRef]
- Dai, Y.; Xu, L.; Zhang, X.; Fu, Y.; Dong, W. Promoting sustainable development: A study of China's bicycle sharing industry policies based on text analysis. *Res. Transp. Bus. Manag.* **2024**, *52*, 101085. [CrossRef]
- Yu, W.; Yu, M.; Ding, L. Characteristics and evolution of hierarchical fishery policies in China—A textual analysis based on 5311 policies from 2003 to 2022. *Mar. Policy* **2023**, *155*, 105699. [CrossRef]
- Lin, L.; Chen, Y. Evolution of Chinese original-innovation talent policies: A topic modelling approach. *Technol. Anal. Strateg. Manag.* **2023**, 1–16. [CrossRef]
- Liu, D.; Wang, D. Evaluation of the synergy degree of industrial de-capacity policies based on text mining: A case study of China's coal industry. *Resour. Policy* **2022**, *76*, 102547. [CrossRef]

25. Estrada, M.A.R. Policy modeling: Definition, classification and evaluation. *J. Policy Model.* **2011**, *33*, 523–536. [CrossRef]
26. Sun, W.; Peng, J.; Ma, J.; Zhong, W. Evolution and performance of Chinese technology policy: An empirical study based on “market in exchange for technology” strategy. *J. Technol. Manag. China* **2009**, *4*, 195–216. [CrossRef]
27. Wang, J.; Lin, Y.; Glendinning, A.; Xu, Y. Land-use changes and land policies evolution in China’s urbanization processes. *Land Use Policy* **2018**, *75*, 375–387. [CrossRef]
28. Liu, X.; Zhao, C.; Song, W. Review of the evolution of cultivated land protection policies in the period following China’s reform and liberalization. *Land Use Policy* **2017**, *67*, 660–669. [CrossRef]
29. Zhang, Y.A.; Zhou, Y.Y. New energy vehicle subsidy policy tools mining and quantitative evaluation. *China Popul. Resour. Environ.* **2017**, *27*, 188–197. (In Chinese)
30. Geng, Z.; Zhang, Y.; Lynn, G.; Wang, Y. The measurement of regional science and technology innovation policy. In Proceedings of the 5th International Conference on Information, Communication, and Education Application, ICEA, Tokyo, Japan, 29 November 2015.
31. Kuang, B.; Han, J.; Lu, X.; Zhang, X.; Fan, X. Quantitative evaluation of China’s cultivated land protection policies based on the PMC-Index model. *Land Use Policy* **2020**, *99*, 105062. [CrossRef]
32. Estrada, R.; Arturo, M. The Policy Modeling Research Consistency Index (PMC-Index). 2010. Available online: https://www.researchgate.net/publication/228302925_The_Policy_Modeling_Research_Consistency_Index_PMC-Index (accessed on 1 June 2024).
33. Gentzkow, M.; Kelly, B.; Taddy, M. Text as data. *J. Econ. Lit.* **2019**, *57*, 535–574. [CrossRef]
34. Huang, J.; Shuai, Y.; Liu, Q.; Zhou, H.; He, Z. Synergy degree evaluation based on synergetics for sustainable logistics enterprises. *Sustainability* **2018**, *10*, 2187. [CrossRef]
35. Howlett, M.; Mukherjee, I. *Routledge Handbook of Policy Design*; Routledge: New York, NY, USA, 2018.
36. Liu, Q.; Jia, M.; Xia, D. Dynamic evaluation of new energy vehicle policy based on text mining of PMC knowledge framework. *J. Clean. Prod.* **2023**, *392*, 136237. [CrossRef]
37. Brandl, J.E.; Weimer, D.L.; Vining, A.R. *Policy Analysis: Concepts and Practice*; Prentice-Hall: Englewood Cliffs, NJ, USA, 1989.
38. Hu, F.; Qi, X.N.; Wang, X.Y. Quantitative evaluation of robot industry policies based on PMC index model: Taking eight robot industry policies intelligence as an example. *J. Intell.* **2020**, *39*, 121–129, 161. (In Chinese)

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Article

Farmland Rental Market, Outsourcing Services Market and Agricultural Green Productivity: Implications for Multiple Forms of Large-Scale Management

Heng Zhang ^{1,2} and Xiangyu Guo ^{2,3,*}¹ College of Agriculture, Northeast Agricultural University, Harbin 150030, China; bsh080@neau.edu.cn² Development Research Center of Modern Agriculture, Northeast Agricultural University, Harbin 150030, China³ College of Economics and Management, Northeast Agricultural University, Harbin 150030, China

* Correspondence: guoxy@neau.edu.cn

Abstract: Large-scale management is the key to realizing long-term agricultural growth in smallholder countries. Land-scale management and service-scale management are two forms of agricultural large-scale management. The former is committed to changing the small-scale management pattern, but the latter tends to maintain it. There has been a lack of discussion and controversy about the relationship between the two. From the perspective of market maturity, this paper explores whether the two are complementary or mutually exclusive and how their complementary or mutually exclusive relationship affects agricultural green productivity. The results show the following: Land-scale management and service-scale management are complementary, not superficially contradictory. The benign interaction between the two has a consistent improvement effect on green productivity in both the short and long term, which has spatial spillovers appearing in the long term. The reasons are as follows: The farmland rental market can reverse the inhibitory effect of the current low-maturity outsourcing services market on green productivity. The outsourcing services market can delay the arrival of the inflection point beyond which expansion of farmland rental transactions reduces green productivity, and amplify the positive effect of farmland rental on it. Although the degree of benign interaction between the two forms of large-scale management has gradually increased in recent years, it is still low overall. Agricultural large-scale management in China is still in the stage driven by land-scale management. Smallholder countries such as China need not worry prematurely about which large-scale management path to take, and they should treat both forms of large-scale management with an equal perspective to accelerate the high-level interaction between them.

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Keywords: farmland rental market; outsourcing services market; agricultural green productivity; large-scale management; smallholder countries

1. Introduction

To realize SDGs 1 and 2, rural areas are the focal point, with agriculture being the priority industry. Improving agricultural economic performance and achieving sustainable agricultural development are key to eradicating poverty and hunger. However, there is an incompatibility between agricultural economic growth and environmental sustainability in this process. Agricultural green total factor productivity (TFP) is considered to be an accurate indicator for measuring the balance between agricultural economic performance and ecology [1]. Improving agricultural green TFP is the key to breaking the incompatibility between agricultural economic growth and environmental sustainability [2]. According to the World Population Prospects 2019, per capita farmland in China is approximately 0.097 ha, less than 48% of the world average. Countries with a population of over 100 million and a per capita farmland smaller than China include Japan, Pakistan, Indonesia, Bangladesh, the Philippines and Egypt. It is more difficult to increase agricultural green TFP in the long term in the above smallholder countries because of the high fixed costs

of importing modern factors into traditional production on small-scale farmland [3,4]. Therefore, large-scale management has become one of the important means to increase agricultural green TFP in smallholder countries [5]. The essence of agricultural large-scale management is to enable farmers to obtain scale economies [6]. There are two ways to achieve scale economies in large-scale management. One is to rely on the farmland rental market to expand farm size to obtain internal scale economies. The other is to rely on the outsourcing services market to purchase services to obtain external scale economies [7,8]. That is, “land-scale management” and “service-scale management”.

Two major theoretical schools on agricultural large-scale management have gradually formed. The land-scale management theory advocates changing the pattern of small-scale farming through the transfer and concentration of farmland [9]. However, there is controversy as to whether or not expanding the farm size through the farmland rental market can increase farm productivity [10–12]. Land-scale management has been faced with the challenge of not being the root cause of scale economies, having high transaction costs, etc. [13]. The service-scale management theory advocates improving the productivity of small-scale farmers, enhancing their green production capacity [14–16], pushing them to participate in division of labor economy, through the large-scale supply of services [17] rather than through the expansion of farm size [18]. In China, agricultural outsourcing services are expected to be a new pathway to modernize agriculture in the context of smallholder-dominated agriculture. However, this process also runs the risk of increasing losses in agricultural production and small-scale family producers being cannibalized by capitalism [19,20].

Land-scale management is committed to changing the small-scale management pattern, but service-scale management tends to maintain it by increasing the productivity of small-scale farmers. The two forms of large-scale management have emerged in a seemingly contradictory, substitutive and competitive relationship. However, at the micro level there is evidence that outsourcing services can induce farmers to transfer land to achieve land-scale management [21] and reshape the supply and demand structure of the farmland rental market [22,23]. Whether the relationship between land-scale management and service-scale management is competitive or mutually reinforcing is the first question to be answered in this paper. From the perspective of market rather than individual behavior, this paper establishes a system of indicators to measure the maturity of the farmland rental market and outsourcing services market. It constructs a coupling coordination index and analyses its evolution to measure whether or not the two can interact in a benign way and the degree of benign interaction. The aim of large-scale management is to reduce the cost of introducing modern factors into traditional production and to achieve a green and sustainable increase in agricultural productivity. Therefore, by examining how the farmland rental market and outsourcing services market change each other’s relationship with agricultural green TFP, this paper goes further to answer the second question of how the complementary or mutually exclusive relationship between land-scale and service-scale management affects agricultural green TFP. Addressing the above issues can serve as a reference for policy choices in promoting large-scale management in smallholder countries such as China. It will also be useful for developing countries in eradicating poverty and hunger to realize the Sustainable Development Goals.

The contributions of this study are as follows: (1) From the perspective of market maturity rather than micro-individual behavior, this paper clarifies the possibility and theoretical mechanism of the benign interaction between land-scale and service-scale management. Relatively more convincing conclusions can be provided. (2) It innovatively provides a set of indicators constructed from two aspects of “quantity” and “quality” for measuring the maturity of the farmland rental market or outsourcing services market. (3) Different from the current research split to explore the impact of different forms of large-scale management on agricultural green TFP, this paper examines the impacts and mechanism of the interaction between land-scale and service-scale management on agricultural green TFP. It provides enlightenment into how governments in smallholder countries,

such as China, view the relationship between land-scale and service-scale management and how to coordinate different forms of large-scale management to improve agricultural green productivity.

2. Theoretical Framework

2.1. Mechanisms of Benign Interaction between Farmland Rental Market and Outsourcing Services Market

This paper argues whether and how the farmland rental market and outsourcing services market interact benignly, from the perspective of how they can increase each other's market maturity.

2.1.1. Mechanism of Outsourcing Services Market on Farmland Rental Market

Draw on and improve the analytical approach of Zhang et al. [24]. The dynamic transactions of the farmland rental market under the intervention of the outsourcing services market are illustrated in Figure 1. S is the farmland supply curve, where small-scale farmers are the suppliers. D is the farmland demand curve, where large-scale households such as family farms and cooperatives are the demanders. In the agricultural outsourcing services market, the service suppliers are organizations or individuals with advanced machinery and technology, including large producers, professional service teams, cooperatives and service enterprises. Service suppliers and demanders can sign formal or informal contracts. The outsourcing services market helps to alleviate the constraints of labor, capital and farm size in the production process and increase returns [25]. Therefore, the intervention of the outsourcing services market promotes land renting-in households to continue transferring in farmland, the demand curve D shifts to the right to D' , and inhibits the willingness of land renting-out households to transfer out farmland, the supply curve S shifts to the left to S' . The volume of farmland transactions at equilibrium in the farmland rental market is D_0 and D_1 before and after the intervention of outsourcing services market, respectively. Large-scale farmers on the demand side of farmland have an advantage over small-scale farmers on the supply side of farmland in terms of services purchase price and access to scale economies, due to their larger and relatively contiguous areas of farmland. Therefore, outsourcing services have a greater facilitating effect on demand-side transferring in farmland than an inhibiting effect on supply-side transferring out farmland through the factor constraint relief effect [26]. The shifting distance of the demand curve (T_D) is greater than the shifting distance of the supply curve (T_S), $T_D > T_S$. After the increase in demand for farmland and the decrease in supply, the land rent will increase further to reach a new equilibrium. Therefore, the position of D_1 with respect to D_0 depends not only on T_D and T_S but also on the relative price elasticity of supply and demand for farmland (e_s, e_d).

When $e_s = e_d$, as shown in Figure 1a, $D_1 > D_0$, outsourcing services increase the volume of farmland transactions.

When $e_s > e_d$, as shown in Figure 1b, $D_1 > D_0$, outsourcing services likewise increase the volume of farmland transactions.

When $e_s < e_d$, the impact of outsourcing services on the volume of farmland transactions is uncertain. If the difference in the factor constraint relief effects of outsourcing services on small and large-scale farmers is greater than the difference in land rent increase effects ($T_D - T_S > e_d - e_s$), the volume of farmland transactions increases after the intervention of the outsourcing services market, as in Figure 1c, otherwise the volume of transactions decreases, as in Figure 1d.

In summary, outsourcing services affect the farmland rental market through the effects of factor constraint relief and land rent escalation. In most cases, the intervention of the outsourcing services market can increase the volume of transactions in the farmland rental market and increase the amount of farmland transferred to already highly productive large-scale farmers. The exception to this is when the price elasticity of farmland supply is smaller than that of farmland demand, and when the difference in factor constraint relief

effects of outsourcing services on small and large-scale farmers is greater than the difference in land rent increase effects.

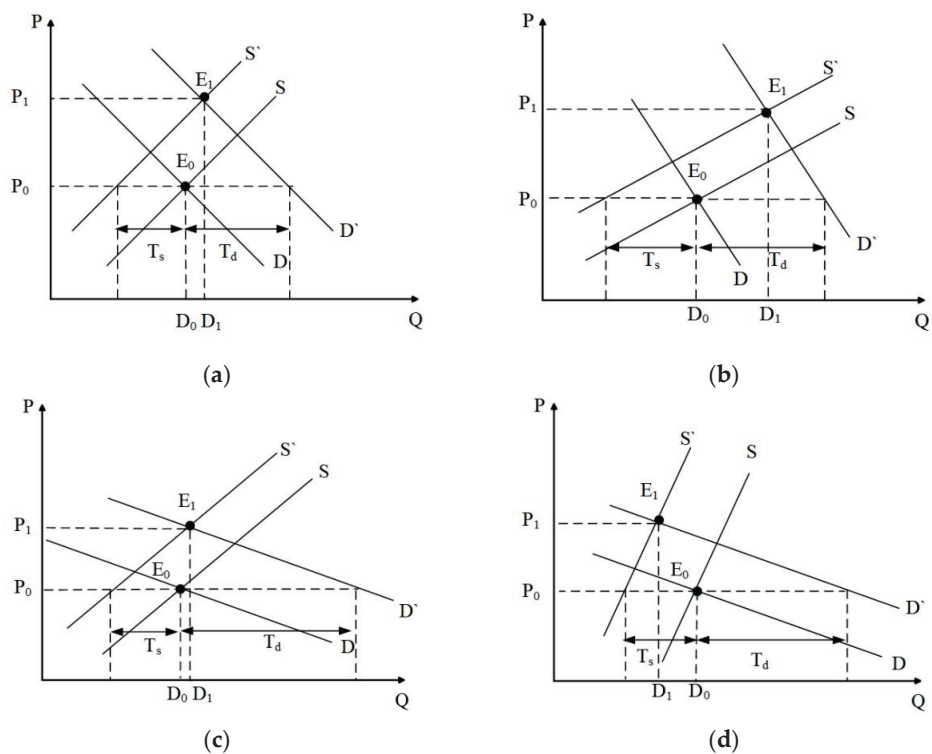


Figure 1. Changes in farmland rental market transactions. (a) $e_s = e_d$; (b) $e_s > e_d$; (c) $e_s < e_d$ and $T_D - T_S > e_d - e_s$; (d) $e_s < e_d$ and $T_D - T_S < e_d - e_s$.

2.1.2. Mechanism of Farmland Rental Market on Outsourcing Services Market

Agricultural production tasks can be divided into production decisions, procurement of farm materials, ploughing, planting, prevention, harvesting, selling, processing, etc. In contrast to individuals performing all tasks independently, the vertical division of labor in agricultural production refers to the specialization of individual farmers in one or more of the above tasks based on their own comparative advantage. Agricultural production outsourcing is the process in which farmers outsource production links in which they do not have comparative advantage to service suppliers with comparative advantage. In general, farmers tend to outsource the in-production stages such as ploughing, planting, prevention and harvesting. When the service providers in the market are more capable, farmers can also outsource the sales or processing links. The Smith–Young Theorem suggests that the division of labor depends on market size, which in turn depends on the division of labor. The market capacity determined by farmers’ demand for the services of any production link is a prerequisite and result in vertical division of labor in agricultural production. With transaction costs being introduced into economics by Coase [27] and becoming an important tool for economic analysis, XiaoKai Yang (Aus) developed the Smith–Young Theorem and introduced transaction costs into the division of labor model. Since then, the theory circle noted the transaction costs implied by the division of labor and its constraints on the division of labor. In the outsourcing services market, expanding the transaction radius brings about an expansion of transaction costs. Economies arising from the division of labor will be dissipated when excessive service transaction costs lead to higher service

costs for the service providers shared by farmers, reduce market capacity and prevent the entry of new service providers and the growth of service type. The transaction costs of the service providers in providing outsourcing services consist of three components: negotiation costs (C_0), moving costs of service providers between farmers (C_m) and moving costs of service providers between plots within individual farmers (C_e). Negotiation costs include information the costs, search costs, bargaining costs, etc., incurred to facilitate transactions. C_m include the efficiency loss of agricultural machinery moving among farmers and the transport costs of service personnel to distribute agricultural materials and coordinate their work among farmers, etc. C_e include the costs of formulating different production schemes for different fertility plots and efficiency loss of agricultural machinery moving between plots, etc. The expression is shown in Equation (1). N represents the number of farmers served by the service provider. S_i represents the amount of service purchased by the i -th farmer. K is the maximum amount of service provided by the service provider. F is the sum of distances between outsourced farmers, f_i is the sum of distances between plots owned by the i -th farmer, c_0 is the unit negotiation cost for the service provider toward each outsourcing farmer, c_m is the unit distance moving cost of the service provider between outsourcing farmers and c_e is the unit distance moving cost of the service provider between plots.

$$\begin{aligned} C_0 &= Nc_0 \\ C_m &= Fc_m \\ C_e &= \sum_{i=1}^N f_i c_e \\ \text{s.t. } \sum_{i=1}^N S_i &= K \end{aligned} \quad (1)$$

The more farmers served and the more land parcels owned by the farmers served, the higher the service transaction costs. Increasing the operating area of farmers, consolidating farmland and reducing farmland fragmentation through the farmland rental market are effective solution paths to reach the maximum service volume of the service provider at the smallest possible transaction cost. Therefore, an increase in the maturity of the farmland rental market can expand the market capacity of outsourcing services by reducing service transaction costs, lowering the services costs apportioned to farmers, etc. This can facilitate the entry of new service providers, increase the variety of services and vertically extend the service chain. Combined with the above analysis, the following hypothesis is proposed:

H1. *The farmland rental market and agricultural outsourcing services market can interact benignly. The two forms of large-scale operation based on these two markets, land-scale management and service-scale management, are not competing or substituting for each other, but complementing each other and developing together.*

2.2. Influence Mechanisms of Benign Interaction between Farmland Rental Market and Outsourcing Services Market on Agricultural Green TFP

Different from the research on the mechanism of a single factor on another factor, this paper addresses the influence mechanism of the relationship between two factors on a single factor. It explores the influence mechanism of the benign interaction between the farmland rental market and outsourcing services market on agricultural green TFP, from the perspective of how the two markets change each other's relationship with agricultural green TFP:

The marginal output of farmland among farmers is different [28]. The farmland rental market can ease farmland mismatches and improve farmland productivity through the reconfiguration of farmland among farmers [29]. Furthermore, a mature farmland rental market can increase green agricultural production by reducing the cost of using green technologies [30,31], reduce fertilizer use by increasing farmers' sensitivity to fertilizer prices [32] and stimulate long-term investment in green production by stabilizing farmland

management rights [33,34]. However, when the farm size is expanded to a certain extent, there is a mismatch among labor, capital, technology and land due to the imperfections of the agricultural factor markets in developing countries such as China [35,36]. The irrational allocation of factors reduces the acquisition of scale economies and violates the original purpose of the existence of the farmland rental market, which instead reduces productivity [37,38]. Therefore, the relationship between the transaction volume of farmland rental (farmland rental market scale) and agricultural green TFP shows an inverted U-shape. However, the outsourcing services market can alleviate the constraints and mismatches of non-land elements due to the expansion of farmland rental market scale. It can then stimulate and amplify the positive impacts of the farmland rental market on agricultural green TFP and delay the arrival of an inflection point where the expansion of farmland rental market scale reduces agricultural productivity.

Theoretically, the existence and maturity of the outsourcing services market can lead to internal and external scale economies for service providers and demanders, respectively. This can reduce the cost of using green technologies in agriculture and the overall cost of production [39]. The outsourcing services market can also reduce chemical inputs through technology direct introduction, spillover, and demonstration [40,41] and improve overall agricultural productivity by contributing to a grain-oriented cropping structure [42]. However, when the agricultural outsourcing services market is at a low maturity stage, the types of services are dominated by in-production machinery services, and service quality measurement standards are dominated by crop yield improvement. Agricultural outsourcing services popularize the use of machinery and increase the use of chemicals purely to improve yields [43]. Furthermore, agricultural outsourcing service is a principal-agent phenomenon that faces moral hazard problems. With high transaction costs and service providers being responsible only for the service content and crop yield, there is a lack of incentive for the application of green technologies in the outsourcing services market. The lack of diversified demand also prevents the expansion of high-end outsourcing services market capacity. Therefore, a low-maturity agricultural outsourcing services market even has a negative impact on agricultural green TFP. However, increased maturity of the farmland rental market expands the scale and contiguity degree of farmland of outsourcing services demanders. This can significantly reduce the transaction costs of service providers, improve their work attitude [44] and increase their incentives for green production [45]. When the large-scale farmers generated by the farmland rental market act as outsourcing service demanders, their diversified demands force the emergence of higher-end services that are more conducive to improving agricultural green productivity. Therefore, the farmland rental market can reverse the negative impact of the low-maturity outsourcing services market on agricultural green TFP and stimulate the potential for service-scale management to exert positive effects. In conclusion, the benign interaction between the farmland rental market and outsourcing services market can keep stimulating each other's potential in improving agricultural production performance and ensuring agricultural sustainability.

Hypothesis 2 is proposed by combining the above analyses:

H2. *The benign interaction between land-scale management and service-scale management can improve agricultural green TFP, through the following mechanism.*

H2a. *The low-maturity outsourcing services market has a negative impact on agricultural green TFP. Increased maturity of the farmland rental market can reverse this negative impact.*

H2b. *Farmland rental market scale and agricultural green TFP have an inverted U-shaped relationship. The agricultural outsourcing services market can delay the arrival of the inverted U-curve inflection point and amplify the positive impact of the farmland rental market on agricultural green TFP.*

(1) Indicator construction and evaluation of market maturity

Market maturity indicates the level of market development. Scale expansion is the “quantitative change” in market development. The improvement of quality and efficiency is the “qualitative change” of market development. To improve the level of market development, it is necessary to take the “quantitative change” of expanding scale and increasing growth rate as a prerequisite and the “qualitative change” of improving development quality, efficiency and governance capacity as the final point. Therefore, this study evaluates the maturity of the two markets by constructing an indicator system from both quantitative (market scale) and qualitative (market quality) aspects. The indicators and weights are shown in Table 1. In the choice of indicators, the transaction volume (I_1) of the farmland rental market and farmland per laborer (I_2) can characterize the development of farmland rental market scale. Promoting the transfer of farmland to cooperatives and enterprises (I_3), which avoids inefficient circulation among small farmers, and increasing the proportion of farmland rented with a transfer contract (I_4), which regulates the farmland rental process, are reflections of the improvement of farmland rental market quality. The output value (I_5) and added value of agricultural support services (I_6) represent the development and expansion speed of the agricultural outsourcing services market scale. The development of agricultural outsourcing services market quality can be measured using four indicators: proportion of service organizations with more invested machinery assets (I_7), proportion of output value (I_8) and added value of agricultural support services (I_9) and proportion of agricultural pre- and post-production service personnel (I_{10}). The reasons are as follows: I_7 represents the service quality. I_8 and I_9 represent the status of the outsourcing services industry. The more prominent the industry status, the higher the efficiency of the services market driving agricultural development, so the higher the development of the services market’s quality will be. I_{10} represents the length of the service chain. Service chain extension is an important feature of improved services market quality.

Table 1. The indicators and weights.

Subsystems	Primary Indicators	Weights			Secondary Indicators	Weights		
		W'	W	U		W'	W	U
Farmland rental market	Market scale	0.39	0.69	0.51	Transaction volume I_1	0.16	0.33	0.23
					Farmland per laborer I_2	0.23	0.36	0.28
	Market quality	0.61	0.31	0.49	Proportion of farmland transferring to cooperatives and enterprises in total transactions I_3	0.44	0.17	0.33
					Proportion of farmland rented with a transfer contract in total transactions I_4	0.17	0.14	0.16
Agricultural outsourcing services market	Market scale	0.46	0.23	0.37	Output value of agricultural various support services per unit sowing area I_5	0.22	0.12	0.18
					Added value of agricultural various support services per unit sowing area I_6	0.24	0.11	0.19
	Market quality	0.54	0.77	0.63	Proportion of service organizations with original value of machinery exceeding 500,000 yuan in total service organizations I_7	0.16	0.12	0.14
					Proportion of output value of agricultural various support services in total agricultural output I_8	0.07	0.10	0.08
					Proportion of added value of agricultural various support services in added value of agriculture I_9	0.17	0.04	0.12
					Proportion of agricultural pre- and post-production support services personnel in total agricultural support services personnel I_{10}	0.14	0.51	0.29

This paper uses the subjective and objective combination of the AHP-entropy weight method to calculate the composite weight. Based on $U = \alpha \cdot W' + (1 - \alpha) \cdot W$. W' is the weight calculated using the highly subjective analytic hierarchy process method (AHP). W is the weight calculated using the highly objective entropy weight method. U is the composite weight. Considering the actual importance of each indicator and experts' advice, α is taken as 0.6. After calculating the composite weights of each indicator, this paper adopts the technique for order preference by similarity to an ideal solution (TOPSIS) to evaluate the maturity of the farmland rental market and outsourcing services market, respectively.

(2) Construction of coupling coordination model

After evaluating the maturity of the two markets separately, the coupling coordination model is constructed to measure the degree of benign interaction between the two markets. Since the coupling degree calculated by the traditional coupling model is not an average distribution function between $[0, 1]$, but is concentrated at the 1 end, this paper uses the improved coupling coordination model proposed by Wang et al. [50]:

$$C = \sqrt{\left[1 - \sqrt{(U_2 - U_1)^2}\right] \times \frac{U_1}{U_2}} = \sqrt{[1 - (U_2 - U_1)] \times \frac{U_1}{U_2}} \quad \text{MAX} U_i = U_2 \tag{2}$$

$$T = \alpha U_1 + (1 - \alpha) U_2 \tag{3}$$

$$CDD = \sqrt{C \times T} \tag{4}$$

U_1 represents the farmland rental market. U_2 represents the outsourcing services market. Equation (2) is the improved coupling model. C is the degree of coupling. T is the coordination index of the two markets. CDD denotes the degree of coupling coordination of the two markets. Generally, $\alpha = 0.5$, which indicates that the two subsystems are equally important. Classification of the coupling coordination evaluation levels is shown in Table 2 [51].

Table 2. Classification of the coupling coordination evaluation levels.

Index Ranges	Coupling Coordination Types	Index Ranges	Coupling Coordination Types
[0, 0.1)	Extreme disorder	[0.5, 0.6)	Bare coordination
[0.1, 0.2)	Severe disorder	[0.6, 0.7)	Elementary coordination
[0.2, 0.3)	Moderate disorder	[0.7, 0.8)	Intermediate coordination
[0.3, 0.4)	Mild disorder	[0.8, 0.9)	Good coordination
[0.4, 0.5)	Near disorder	[0.9, 1.0)	Quality coordination

3.2. Model for Effects and Mechanisms of Benign Interaction between the Two Markets on Agricultural Green TFP

Based on clarifying the specific effects of benign interaction between the farmland rental market and agricultural outsourcing services market on agricultural green TFP, this study empirically demonstrates the mechanisms therein.

(1) Influence effects model

Construct the following two-way fixed effects model:

$$\ln AGTFP_{it} = \alpha_0 + \alpha_1 \ln CDD_{it} + \alpha_2 \sum_{K=1}^7 \ln CON_{Kit} + \mu_i + \nu_t + \varepsilon_{it} \tag{5}$$

In Equation (5), i stands for province and t stands for year. CDD is the coupling coordination degree between the farmland rental market and outsourcing services market measured in the previous section. CON is the control variables, including the proportion of affected area (DIS) to control the natural conditions, the total power of agricultural machinery per unit area (ATL) to control the technological conditions, proportion of government

expenditure on agriculture (*GOE*) to control the policy conditions, proportion of agricultural added value (*AVA*) to control the conditions of industrial and economic development, the planting structure (*PSTR*), pesticide use per unit area (*PES*), and fertilizer use per unit area (*FER*) to control the production conditions. ε_{it} denotes the stochastic disturbance term. μ_i denotes province fixed effect. ν_t denotes year fixed effect. α_1 represents the specific impact of benign interaction between the two markets on agricultural green TFP.

AGTFP stands for agricultural green TFP. Based on the construction of the SBM model considering undesirable outputs, this paper uses the Global Malmquist–Luenberger (GML) index to examine the dynamic changes in efficiency. It converts the sequential *AGTFP* measured by the SBM–GML method into a cumulative growth index with 2009 as 1. In terms of inputs and outputs, inputs include the number of people employed in the primary sector, the total sown area of crops, the total power of agricultural machinery, the amount of fertilizer used and the amount of water used in agriculture. Outputs include desirable and undesirable outputs, the former being characterized by the gross output value of generalized agriculture, and the latter being characterized by agricultural carbon emissions [52]. The formula for estimating agricultural carbon emissions is as follows:

$$E = \sum E_i = \sum T_i \cdot \delta_i \quad (6)$$

E represents the total amount of agricultural carbon emissions. E_i represents the amount of carbon emissions from carbon sources. T_i represents the amount of carbon sources. δ_i represents the carbon emission coefficient of carbon sources. According to the research of Oak Ridge National Laboratory, College of Biology and Technology of China Agricultural University, Institute of Agricultural Resources and Production Environment of Nanjing Agricultural University, IPCC, the carbon emission coefficient of fertilizer is $0.896 \text{ kg} \cdot \text{kg}^{-1}$, that of pesticide is $4.934 \text{ kg} \cdot \text{kg}^{-1}$, that of agricultural film is $5.18 \text{ kg} \cdot \text{kg}^{-1}$, that of diesel fuel is $0.5927 \text{ kg} \cdot \text{kg}^{-1}$, that of ploughing is $312.6 \text{ kg} \cdot \text{km}^{-2}$ and that of agricultural irrigation is $20.476 \text{ kg} \cdot \text{hm}^{-2}$ [53].

(2) Influence mechanism model

This study explores the influence mechanism of benign interactions between the farmland rental market and outsourcing services market on agricultural green TFP, from the perspective of how the two markets change each other's relationship with agricultural green TFP. Firstly, the follow two-way fixed effects model is constructed to examine the average impact of the farmland rental market and outsourcing services market on agricultural green TFP, respectively:

$$AGTFP_{it} = \kappa_0 + \kappa_1 OSM_{it} + \kappa_2 LRM_{it} + \kappa_3 \sum_{K=1}^7 CON_{Kit} + \mu_i + \nu_t + \varepsilon_{it} \quad (7)$$

LRM and OSM are the maturity of the farmland rental market and outsourcing services market measured in the previous section, respectively. $\kappa_1(\kappa_2)$ represents the average influence of changes in maturity of the outsourcing services market (farmland rental market) on agricultural green TFP, controlling for a constant level of farmland rental market (outsourcing services market) maturity.

After clarifying the average effect of each of the two markets on agricultural green TFP, the following threshold model is constructed to verify how the farmland rental market and outsourcing services market change each other's relationship with agricultural green TFP [54]:

$$AGTFP_{it} = \phi_0 + \phi_1 OSM_{it} \times I(LRM_{it} \leq \theta) + \phi_2 OSM_{it} \times I(LRM_{it} > \theta) + \phi_3 \sum_{K=1}^7 CON_{Kit} + \varepsilon_{it} \quad (8)$$

$$AGTFP_{it} = \varphi_0 + \varphi_1 LRM_{it} \times I(OSM_{it} \leq \sigma) + \varphi_2 LRM_{it} \times I(OSM_{it} > \sigma) + \varphi_3 \sum_{K=1}^7 CON_{Kit} + \varepsilon_{it} \quad (9)$$

$I(\cdot)$ is an indicator function that takes the value of 1 for the fulfilment of the condition in parentheses and 0 for the opposite. θ and σ are specific threshold values. Equation (8) is used to examine whether the increased maturity of the farmland rental market reverses the negative impact of the low maturity outsourcing services market on agricultural green TFP. Equation (9) is used to examine whether the increased maturity of the outsourcing services market amplifies the positive impact of the farmland rental market on agricultural green TFP.

To further examine whether the outsourcing services market can delay the arrival of the inflection point beyond which the expansion of farmland rental market scale reduces agricultural green TFP, the following model is constructed:

$$AGTFP_{it} = \omega_0 + \omega_1 LRMS_{it} + \omega_2 LRMS_{it}^2 + \omega_3 \sum_{K=1}^7 CON_{Kit} + \mu_i + \nu_t + \varepsilon_{it} \quad (10)$$

$$AGTFP_{it} = \psi_0 + \psi_1 LRMS_{it} + \psi_2 LRMS_{it}^2 + \psi_3 LRMS_{it} \times OSM_{it} + \psi_4 LRMS_{it}^2 \times OSM_{it} + \psi_5 OSM_{it} + \psi_6 \sum_{K=1}^7 CON_{Kit} + \mu_i + \nu_t + \varepsilon_{it} \quad (11)$$

LRMS stands for farmland rental market scale. Equation (10) constructs the quadratic term of farmland rental market scale to verify whether there is an inverted U-shaped relationship between farmland rental market scale and agricultural green TFP. Equation (11) adds the interaction terms of OSM with the primary and secondary terms of LRMS, respectively, to verify whether the inverted U-shaped relationship between farmland rental market scale and agricultural green TFP changes or how the inverted U-shaped inflection point changes, under the influence of the outsourcing services market.

3.3. Spatial Spillover Model

To examine the spatial spillovers effect of benign interactions between the two markets on agricultural green TFP, this paper constructs the Spatial Durbin Model (SDM), which is more generally applicable:

$$\ln AGTFP_{it} = \beta_0 + \rho W \ln AGTFP_{it} + \beta_1 \ln CDD_{it} + \beta_2 W \ln CDD_{it} + \beta_3 \sum_{K=1}^7 \ln CON_{Kit} + \beta_4 \sum_{K=1}^7 W \ln CON_{Kit} + \mu_i + \nu_t + \varepsilon_{it} \quad (12)$$

Equation (12) is the static SDM. In order to further examine the long-term and short-term differences in the direct and spatial effects of benign interactions between the two markets on agricultural green TFP, this paper constructs the following dynamic SDM:

$$\ln AGTFP_{it} = \gamma_0 + \eta \ln AGTFP_{it-1} + \chi W \ln AGTFP_{it-1} + \rho' W \ln AGTFP_{it} + \gamma_1 \ln CDD_{it} + \gamma_2 W \ln CDD_{it} + \gamma_3 \sum_{K=1}^7 \ln CON_{Kit} + \gamma_4 \sum_{K=1}^7 W \ln CON_{Kit} + \mu_i + \nu_t + \varepsilon_{it} \quad (13)$$

W is the spatial weight matrix. Based on the theoretical analysis, this paper adopts the economic-geographical composite weight matrix. ρ and ρ' are the spatial autoregressive coefficients reflecting the impact of $AGTFP$ in this region on $AGTFP$ in neighboring regions. In Equation (13), $AGTFP_{it-1}$ is the first-order time lag of $AGTFP$. $WAGTFP_{it-1}$ is the first-order time and spatial lag of $AGTFP$. η denotes the one-period lag coefficient, reflecting the impact of the previous $AGTFP$ on the current $AGTFP$. χ is the spatio-temporal lag term coefficient, reflecting the impact of the previous local $AGTFP$ on the current $AGTFP$ of the neighboring region.

In order to retain the economic meaning of the threshold and inflection point values, and the comparability between the coefficients, this paper does not take the logarithm of the variables involved in the mechanism model. It only takes the logarithm of the variables involved in the effect model and the spatial model.

This paper uses the balanced panel data of 30 provinces in China (excluding Hong Kong, Macao, Taiwan and Tibet Autonomous Region) from 2008 to 2021. The original data were sourced from China Rural Business Management Statistics Annual Report, China Tertiary Industry Statistics Yearbook, China Rural Statistics Yearbook, China Agriculture Yearbook, and National Bureau of Statistics of China in the relevant years. Missing data were filled in by interpolation.

4. Estimation and Results Analysis

4.1. Results Analysis of Interaction between Farmland Rental Market and Outsourcing Services Market

(1) Maturity of farmland rental market

The time-series changes in the maturity of the farmland rental market and its subsystems are shown in Figure 3. The scores of overall market maturity, market scale development and market quality development steadily increase from 0.2417, 0.2115 and 0.2637 in 2009 to 0.4367, 0.3604 and 0.5163 in 2021, respectively. The market quality development score has been higher than the scale development score during 2009–2021. The maturity of the farmland rental market has been increasing year by year, and it has passed the stage of market scale expansion including increasing the rate of transfer and the volume of land transactions. It is now at the stage of market quality improvement that includes increasing the rate of land transfer-in of high-capacity subjects, regulating the transaction behavior and lengthening the term of contract.

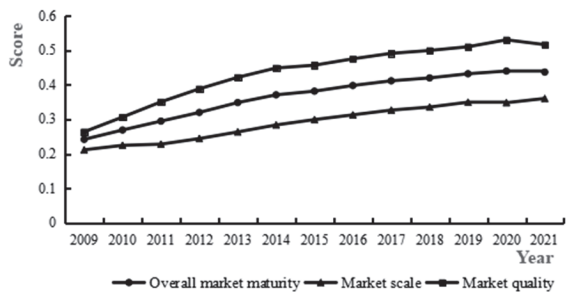


Figure 3. Time-series changes in farmland rental market and its subsystems.

(2) Maturity of agricultural outsourcing services market

The time-series changes in the maturity of the outsourcing services market and its subsystems are shown in Figure 4. The overall maturity, scale development and quality development of the outsourcing services market likewise increased steadily from 2009 to 2021. Except for 2009 and 2010, the market scale development score was higher than the market quality development score in the remaining years. Unlike the farmland rental market, which is at the stage of market-quality development, China’s outsourcing services market is at the primary stage of expanding market scale. It has not yet entered the stage of market-quality development, such as the development of high-value-added back-end agricultural services and the prominence of agricultural services industry status. The reason for this is that, in China, the market-based outsourcing services market started later than the market-based farmland rental market. Moreover, the development of agricultural outsourcing services markets as an alternative path to large-scale management in the context of small-scale farming has only gained importance in recent years.

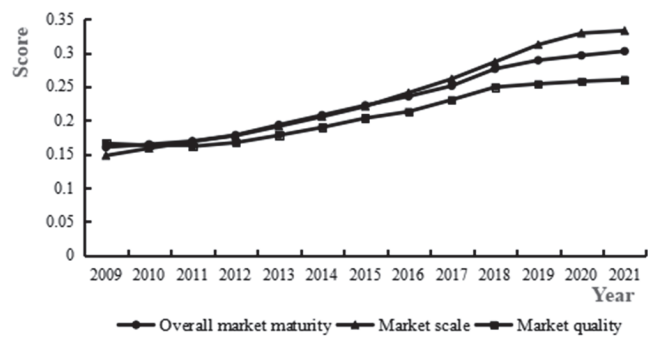


Figure 4. Time-series changes in agricultural outsourcing services market and its subsystems.

(3) Coupling coordination degree between the two markets

Figure 5 shows the time-series change in the coupling coordination degree and relative development degree between the farmland rental market and outsourcing services market. The coupling coordination index between the farmland rental market and outsourcing services market has shown a growth trend from 2009 to 2021. It is now in the stage of bare coordination after experiencing the stage of mild disorder and near disorder, respectively. This growth trend indicates that farmland rental market and outsourcing services market can interact benignly. The two forms of agricultural large-scale management, land-scale and service-scale management formed from the two markets are not competing and substituting for each other, but rather they are complementary to each other. Hypothesis 1 is verified. The relative development degree of the two markets is greater than 1, that is, the maturity of the farmland rental market has been greater than that of the outsourcing services market from 2009 to 2021. This suggests that China is currently at the stage of relying on farmland rental to drive the realization of large-scale management in agriculture. Although the two markets can interact benignly, the degree of this benign interaction is low. From the perspective of factor composition, the reason lies in the imperfection of the outsourcing services market. Furthermore, the imperfection of the service market comes more from its low quality of market development.

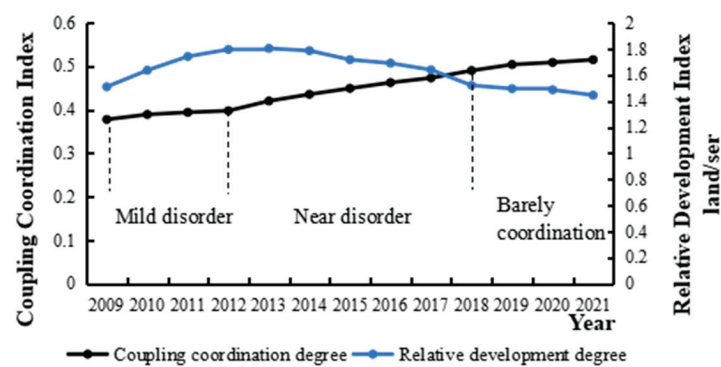


Figure 5. Time-series change in the coupling coordination degree and relative development degree.

Figure 6 shows the time-series changes in the coupling coordination degree between the two markets in different regions. China is divided into eastern, central and western regions according to economic development and geographic location. From 2009 to 2021, the degree of benign interaction between the two markets gradually decreases from the eastern regions to the central and western regions. Low, medium and high agricultural

dependency regions are classified according to the share of agricultural output. The degree of benign interaction between the two markets gradually decreases from low agricultural dependency regions to medium and high agricultural dependency regions. According to the average value of farmland rental market maturity and outsourcing services market maturity, the mode of agricultural large-scale management development can be classified into four types: synchronized development, land-scale management lagging, service-scale management lagging and synchronized lagging. Combined with the degree of coupling coordination of the two markets, the development stage of agricultural large-scale management in each region is shown in Table 3. Low agricultural dependency regions rely on the synchronized development of farmland transfer and services outsourcing to promote large-scale management. In contrast, the two forms of large-scale management are in a low-level cycle in the central regions and the high agricultural dependence regions.

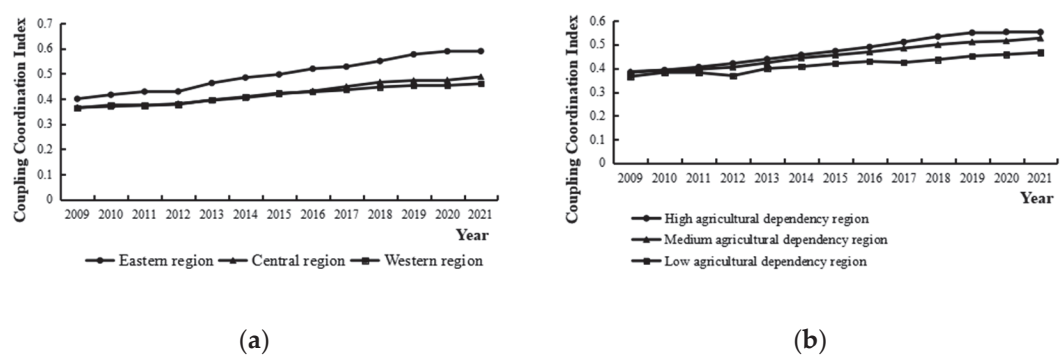


Figure 6. Time-series changes in the coupling coordination degree in different regions. (a) Eastern, central and western regions; (b) High, medium and low agricultural dependency regions.

Table 3. Stage of agricultural large-scale management in each region.

Regions	Development Stage of Agricultural Large-Scale Management
Eastern	Bare coordination—land-scale management lagging
Central	Near disorder—synchronized lagging
Western	Near disorder—service-scale management lagging
High agricultural dependency	Near disorder—synchronized lagging
Medium agricultural dependency	Bare coordination—service-scale management lagging
Low agricultural dependency	Bare coordination—synchronized development

4.2. Benign Interaction between the Two Markets Improves Green Productivity: Effects and Mechanisms

4.2.1. Improved Effect Analysis

The impact results of the coupling coordination between the farmland rental market and outsourcing services market on agricultural green TFP using STATA 17 are shown in Table 4. In the benchmark regression, after controlling for provincial and time effects, the coupling coordination between the farmland rental market and outsourcing services market has a significant positive impact on agricultural green TFP at the 1% level. This means that a 1% increase in the coupling coordination between the two markets will lead to an average increase of 0.67% in agricultural green TFP. Considering some possible endogeneity issues in the benchmark regression, the coupling coordination between the two markets lagged by one period is used as an instrumental variable, and a robust test is conducted using instrumental variable 2-stage least squares estimation (IV-2SLS). The significance of the results remains unchanged after considering endogeneity. Therefore, benign interaction between land-scale management and service-scale management can significantly increase agricultural green TFP.

Table 4. Estimation results of improved effect.

Variables	Benchmark Regression: Two-Way Fixed Effects Model	Robust Test: IV-2SLS
lnCCD	0.6735 *** (5.63)	0.8720 *** (3.17)
lnDIS	−0.0137 (−1.53)	−0.0159 (−1.37)
lnATL	−0.0166 (−0.39)	−0.0211 (−0.59)
lnGOE	−0.1240 ** (−2.17)	−0.1555 *** (−2.96)
lnAVA	0.5489 *** (10.12)	0.5878 *** (9.01)
lnPES	−0.1707 *** (−2.69)	−0.1939 *** (−3.24)
lnFER	−0.3739 *** (−3.71)	−0.4061 *** (−4.41)
lnPSTR	−0.6432 *** (−4.93)	−0.7136 *** (−5.15)
Year	Yes	Yes
Province	Yes	Yes
Hausman P	0.0000	—
Weak instrumental variables test: F-value	—	86.6052
Observation	390	390

Notes: ***, ** indicate rejection of the null hypothesis at the 1%, 5% levels, respectively. Benchmark regression with t-values in parentheses, robust test with z-values in parentheses.

In terms of control variates, the negative effect of natural disasters on agricultural green TFP is not significant, indicating that the impact of natural disasters on Chinese agriculture is gradually weakening. Agricultural mechanization increases agricultural productivity while at the same time substantially increasing carbon emissions. Agricultural mechanization has a non-significant negative impact on agricultural green TFP, suggesting that the desired and non-desired outputs resulting from the advancement of agricultural mechanization in China are offsetting each other. The average effects of agricultural financial expenditure, fertilizer and pesticide application on agricultural green TFP are significantly negative, respectively. This indicates that increasing inputs of all three currently has a greater negative impact on the agricultural environment than a positive impact on agricultural productivity. The higher the dependence of economic development on the primary sector, the higher the agricultural green TFP. Compared with cash crops, food crops have a higher level of mechanization, which increases the overall productivity of agriculture while also increasing the overall carbon emissions of agriculture. Cash crops refer to non-food crops such as cotton, peanuts, sugarcane, vegetables, etc. For example, in 2021 the comprehensive mechanization rates of food crops such as wheat, rice and corn in China were 97.29%, 85.59% and 90.00%, respectively. The comprehensive mechanization rates of cash crops such as oilseed rape, peanuts and sugar cane were 61.92%, 65.65% and 60%, respectively. The results show that the grain-oriented cropping structure reduces green TFP, indicating that the grain-oriented cropping structure increases overall agricultural carbon emissions to a greater extent than it increases overall agricultural productivity.

4.2.2. Improved Mechanism Analysis

This section explores the improved mechanism of benign interactions between the farmland rental market and outsourcing services market on agricultural green TFP from the perspective of how the two markets change each other’s relationship with agricultural green TFP. The aim is to clarify the reasons why the interaction between land-scale management and service-scale management can increase agricultural green TFP.

Farmland Rental Market Optimizes the Relationship between Outsourcing Services Market and Agricultural Green TFP

Putting both the farmland rental market and outsourcing services market into the two-way fixed effects model of the impact on agricultural green TFP, the results are shown in Table 5. When controlling for constant farmland rental market maturity, the average effect of the outsourcing services market on agricultural green TFP is significantly negative. This is due to the low maturity of China’s outsourcing services market. Undesired outputs

from focusing on the form of in-production services and using yield as a measure standard of service quality are greater than desired outputs from high-value-added services and services that alleviate technological constraints. Using the threshold model, this paper discusses the different effect results of the outsourcing services market on agricultural green TFP when the farmland rental market is at different maturity levels. According to the threshold effect test in Table 6, the influence of the outsourcing services market on agricultural green TFP has a threshold feature of the farmland rental market. Table 7 shows that when the farmland rental market is at a low level of maturity (≤ 0.2198), the outsourcing services market maintains a negative impact on agricultural green TFP. The positive impact of the outsourcing services market on agricultural green TFP only become apparent when the farmland rental market maturity crosses the first threshold ($0.2198 < \text{LRM} \leq 0.3536$). The positive impact effect is further increased when the farmland rental market maturity crosses the second threshold (> 0.3536). Therefore, the increasing maturity of the farmland rental market can reverse the negative impact of the low-maturity outsourcing services market on agricultural green TFP and gradually stimulate the potential of the outsourcing services market to improve agricultural green TFP.

Table 5. Estimation results of the impact of the two markets on agricultural green TFP, respectively.

Variables	Agricultural Green TFP
OSM	−1.0571 *** (−3.83)
LRM	1.3599 *** (4.15)
DIS	−0.4880 *** (−3.69)
ATL	0.0447 (0.31)
GOE	−1.4206 (1.36)
AVA	10.1049 *** (8.93)
PES	0.0002 (0.03)
FER	−0.0001 (−0.08)
PSTR	−0.6305 (−1.26)
Year	Yes
Province	Yes
Hausman P	0.0000

Notes: *** indicates rejection of the null hypothesis at the 1% level. The t statistic is in brackets on the right side of the parameter.

Table 6. Results of the threshold test: farmland market as the threshold variable.

Threshold Variable	Number of Thresholds	F-Value	p-Value	Threshold Value	95% Confidence Interval
Maturity of farmland rental market	Single Threshold	45.67	0.0500	0.2198 **	[0.2061, 0.2209]
	Double Threshold	34.35	0.0333	0.3536 **	[0.3458, 0.3551]
	triple threshold	23.83	0.5800	—	—

Notes: ** indicates rejection of the null hypothesis at the 5% level. Bootstrap sampling 300 times.

Table 7. Threshold model estimation results.

Variables	Agricultural Green TFP
OSM	−1.4358 ** (−2.29)
(LRM ≤ 0.2198)	
OSM	0.9177 ** (1.99)
(0.2198 < LRM ≤ 0.3536)	
OSM	2.5779 *** (7.45)
(LRM > 0.3536)	
DIS	−1.1973 *** (−5.92)
ATL	0.3630 * (1.65)
GOE	3.6446 ** (2.32)
AVA	4.5469 *** (2.66)

Table 7. Cont.

Variables	Agricultural Green TFP
PES	−0.0080 (−1.00)
FER	−0.0032 *** (−4.74)
PSTR	−3.3263 *** (−4.48)

Notes: ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively. The t statistic is in brackets on the right side of the parameter.

Outsourcing Services Market Optimizes the Relationship between Farmland Rental Market and Agricultural Green TFP

(1) Delay the arrival of the inflection point beyond which the expansion of farmland rental market scale reduces agricultural green TFP. Expanding market scale is an important precondition for market maturity growth. Table 8 shows the relationship between farmland rental market scale and agricultural green TFP. In model (1), the first-order coefficient of farmland rental market scale is significantly positive and the square term coefficient of it is significantly negative. The slope of the curve is positive (5.000) at the left endpoint of the value range of farmland rental market scale and negative (−4.2431) at the right endpoint. The inflection point of the curve (0.4457) is within the value range of farmland rental market scale (0.0605, 0.7726). The above satisfies the three conditions of the inverted “U” relationship proposed by Haans et al. [55]. Therefore, there is an inverted U-shaped relationship between farmland rental market scale and agricultural green TFP. When the transactions volume of the farmland rental market is low, agricultural green TFP can increase with the expansion of farmland transactions volume, and when the transactions volume crosses the inflection point, agricultural green TFP will be reduced. The interaction term of farmland rental market scale × outsourcing services market is introduced in model (2). Although farmland rental market scale and agricultural green TFP still show an inverted U-shaped relationship, it can be seen that the inflection point of the inverted U-shaped curve is shifted to the right by calculating $\beta_1*\beta_4 - \beta_2*\beta_3(>0)$. This shows that the increase in maturity of the outsourcing services market can delay the arrival of the inflection point where the expansion of the farmland rental market transaction volume reduces agricultural green TFP.

Table 8. Estimation results of inverted U-shaped curve.

Variables	Agricultural Green TFP	
	(1)	(2)
LRMS	5.7850 *** (7.95)	7.0892 *** (5.33)
LRMS ²	−6.4895 *** (−7.54)	−4.7713 *** (−2.62)
LRMS*OSM	—	−8.8469 ** (−2.24)
LRMS ² *OSM	—	5.5822 ** (2.16)
Constant	−1.0578 ** (−2.05)	−1.5517 *** (−2.77)
Controls	YES	YES
Year	YES	YES
Province	YES	YES
R ²	0.8617	0.8812

Notes: ***, ** indicate rejection of the null hypothesis at the 1%, 5% levels, respectively. The t statistic is in the brackets on the right side of the parameter.

(2) Amplify the positive effects of the farmland rental market on agricultural green TFP. The threshold model is also used to explore the different effects of the farmland rental market on agricultural green TFP when the outsourcing services market is at different maturity levels. The tests and results of threshold model in Tables 9 and 10 show that when outsourcing services market maturity is at a low level (≤ 0.1136) and crosses the first threshold ($0.1136 < OSM \leq 0.1898$) and the second threshold (> 0.1898), the

degree of positive impact of the farmland rental market on agricultural green TFP increases from 2.5209 to 3.7356 and 4.5940, respectively. When controlling for constant outsourcing services market maturity, the average impact of the farmland rental market on agricultural green TFP is 1.3599 (Table 6). When the outsourcing services market maturity gradually increases, the improvement of agricultural green TFP by the farmland rental market is not only higher than 1.3599 but also gradually improved. Therefore, the existence and increasing maturity of the outsourcing services market amplifies the positive impact of the farmland rental market on agricultural green TFP, which prompts land-scale management to continuously release the potential of improving agricultural green productivity.

Table 9. Results of the threshold test: services market as the threshold variable.

Threshold Variable	Number of Thresholds	F-Value	p-Value	Threshold Value	95% Confidence Interval
Maturity of outsourcing services market	Single Threshold	41.11	0.0233	0.1136 **	[0.1083, 0.1147]
	Double Threshold	38.30	0.0133	0.1898 **	[0.1858, 0.1904]
	Triple threshold	14.64	0.7633	—	—

Notes: ** indicates rejection of the null hypothesis at the 5% level. Bootstrap sampling 300 times.

Table 10. Estimation results of threshold model.

Variables	Agricultural Green TFP
LRM	2.5209 *** (6.84)
(OSM ≤ 0.1136)	
LRM	3.7356 *** (12.27)
(0.1136 < OSM ≤ 0.1898)	
LRM	4.5940 *** (18.39)
(OSM > 0.1898)	
DIS	−0.7008 *** (−4.29)
ATL	0.3601 ** (2.09)
GOE	3.5558 *** (2.71)
AVA	8.3607 *** (6.05)
PES	−0.0092 (−1.47)
FER	−0.0024 *** (−4.66)
PSTR	−3.8640 *** (−6.72)

Notes: ***, ** indicate rejection of the null hypothesis at the 1%, 5% levels, respectively. The t statistic is in the brackets on the right side of the parameter.

In summary, the farmland rental market and outsourcing services market optimize each other’s relationship with agricultural green TFP, which is the essence of the benign interaction between land-scale management and service-scale management to improve agricultural green productivity. At this point, Hypothesis 2 is fully validated.

4.3. Results Analysis of Spatial Spillover

Table 11 shows the model selection test. The Global Moran’s Index for all years is non-zero and significantly positive between [−1, 1], indicating that there is a significant spatial positive correlation of agricultural green TFP in China from 2009 to 2021. The LM test, LR test, Wald test, and Hausman test are conducted sequentially to determine the valid form of the spatial model. All four tests passed the 5% significance level test, meaning that the fixed-effects Spatial Durbin Model (SDM) is more appropriate for this study and does not degenerate into a Spatial Error Model (SEM) or Spatial Lagged Model (SLR). Table 12 shows the estimation results of the SDM. The estimation results of static and dynamic SDM show that, after considering indirect spatial spillovers, the direct effect coefficients and spatial effect coefficients of the coupling coordination between the farmland rental market and outsourcing services market are both significantly positive. This means that

an increase in the degree of benign interaction between the farmland rental market and outsourcing services market can improve agricultural green TFP, not only in the region but also in the geographically and economically proximate provinces. Hypothesis 3 is verified. The time and spatial lag terms of the explained variables of the dynamic SDM are significant, indicating that the dynamic model setup is reasonable. The dynamic spatial effect decomposition is shown in Table 13. Long-term and short-term effects are in high consistency, and the coefficient of the total effect in the long term is larger than that in the short term. This indicates that the benign interaction between the farmland rental market and outsourcing services market has a more profound long-term effect on agricultural green TFP. Although the spatial spillover of benign interactions between the farmland rental market and outsourcing services market on agricultural green TFP is not obvious in the short term, it is significant in the long term, showing that the knowledge spillover of the outsourcing services market, which is strengthened and optimized by the farmland rental market, cannot be revealed in the short term.

Table 11. Test results related to spatial model selection.

Test Type	Statistics	Results
Global Moran's I	0.614 *** (16.712)	Spatial model
LM_test for no spatial lag	132.191 *** (0.00)	
Robust LM_test for no spatial lag	74.177 *** (0.00)	
LM_test for no spatial error	65.760 *** (0.00)	SDM
Robust LM_test for no spatial error	7.747 *** (0.005)	
Wald_spatial_lag test	19.67 ** (0.0117)	
LR_spatial_lag test	53.50 *** (0.0000)	SDM
Wald_spatial_error test	19.37 ** (0.0130)	SDM
LR_spatial_error test	55.25 *** (0.0000)	SDM
Hausman test	31.05 ** (0.0197)	Fixed effect

Notes: ***, ** indicate rejection of the null hypothesis at the 1%, 5% levels, respectively. Global Moran's I with z values in parentheses, other coefficients with p values in parentheses.

Table 12. Estimation results of static and dynamic SDM.

Variables	Static SDM	Dynamic SDM
L.lnAGTFP	—	0.1223 ** (2.40)
WL.lnAGTFP	—	0.4566 *** (4.41)
lnCCD	1.006 *** (8.73)	0.8694 *** (6.87)
lnDIS	−0.0050 (−1.53)	−0.0042 (−1.26)
lnATL	−0.0053 (−0.13)	−0.0348 (−0.83)
lnGOE	−0.1875 *** (−3.34)	−0.1692 *** (−2.88)
lnAVA	0.6350 *** (11.15)	0.6177 *** (10.21)
lnPES	0.1678 *** (2.75)	0.1747 *** (2.72)
lnFER	−0.3114 *** (−3.28)	−0.3717 *** (−3.80)
lnPSTR	−0.5051 *** (−3.90)	−0.6140 *** (−4.45)
WlnCCD	0.6516 *** (3.20)	0.0832 (0.33)
WlnDIS	0.0033 (0.38)	0.0015 (0.17)
WlnATL	−0.0439 (−0.50)	−0.1137 (−1.27)
WlnGOE	−0.3014 ** (−2.45)	−0.1988 (−1.58)
WlnAVA	−0.1618 (−1.40)	−0.1579 (−1.28)
WlnPES	−0.4769 *** (−2.81)	−0.5611 *** (−3.18)
WlnFER	0.3753 * (1.71)	0.3568 (1.57)
WlnPSTR	0.6052 ** (2.14)	0.8299 *** (2.70)
sigma2_e	0.0098 *** (13.71)	0.0098 *** (14.48)
rho	0.3825 *** (6.37)	0.1458 * (1.77)
Observation	390	390

Notes: ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively. L.lnAGTFP denotes lnAGTFP with a one-period lag. WL.lnAGTFP denotes the first-order time and space lag terms of lnAGTFP. z values in parentheses (the same below).

Table 13. Decomposition of dynamic spatial effects.

Short-Term Effect			Long-Term Effect		
Direct effect	Spatial effect	Total effect	Direct effect	Spatial effect	Total effect
0.8733 *** (7.12)	0.2455 (0.81)	1.1189 *** (3.39)	1.009 *** (6.59)	1.4786 ** (2.44)	2.4880 *** (2.79)

Notes: ***, ** indicate rejection of the null hypothesis at the 1%, 5% levels, respectively.

5. Conclusions

Large-scale management is the key to the long-term improvement of agricultural green productivity in smallholder countries. It is also one of the paths to eradicating poverty in rural areas and ensuring national food security. However, there has been a lack of in-depth discussion and controversy about the relationship between the two agricultural large-scale management forms of land-scale management and service-scale management. From the perspective of market maturity, this study tries to answer the question whether land-scale management and service-scale management are mutually substituted or benignly interacted by evaluating the maturity of China’s farmland rental market and outsourcing services market, constructing the coupling coordination index between the two and analyzing its spatio-temporal evolution trend. Through examining how the farmland rental market and the outsourcing services market change each other’s relationship with agricultural green TFP, this study tries to answer the question of how complementary or mutually exclusive relationships between land-scale management and service-scale management affect agricultural green productivity. The following conclusions are drawn:

First, through scientific calculation, China’s farmland rental market has passed the stage of market-scale expansion and entered the stage of market-quality development in recent years. However, the agricultural outsourcing services market is in the primary stage of market-scale expansion and has not yet entered the stage of market-quality development, such as the development of high value-added back-end agricultural services and the prominence of the agricultural services industry. Therefore, at present, agricultural large-scale management in China is still in the stage driven by land-scale management.

Second, the outsourcing service markets can increase farmland rental market maturity in most cases through the effects of factor constraint relief and land rent escalation. The farmland rental market can increase outsourcing services market maturity by reducing service transaction costs and increasing market capacity. Therefore, land-scale management and service-scale management are not substitutes for each other, but rather are complementary and positively interacting with each other. Although the degree of benign interaction between the two has risen from mild disorder to bare coordination, it is still low overall from 2009 to 2021.

Third, China’s low-maturity outsourcing services market has an inhibitory effect on agricultural green productivity, but the farmland rental market can reverse this negative effect. The expansion of farmland rental market scale has an inverted U-shaped effect on agricultural green productivity, while the outsourcing services market can delay the arrival of the inflection point of this inverted U-shaped relationship and amplify the positive effect of the farmland rental market on agricultural green productivity. Through the above mechanism, the benign interaction between land-scale management and service-scale management has a consistent improvement effect on agricultural green productivity in both the short term and the long term. This improvement effect has spatial spillover that can be seen in the long run, because the knowledge spillover of the outsourcing services market, which is strengthened and optimized by the farmland rental market, cannot be revealed in the short term.

Fourth, the degree of benign interaction between land-scale management and service-scale management gradually decreases from eastern regions to the central and western regions, which also decrease from low agricultural dependency regions to medium and high agricultural dependency regions. It is worth noting that the two forms of large-scale management in the central regions and high agricultural dependency regions do not

complement each other well, and the development of agricultural large-scale management in the two regions is still at the stage of simultaneous lagging of farmland rental and services outsourcing.

According to the conclusions of this paper, China and other smallholder countries need not worry prematurely about which large-scale management form should be taken for agricultural development. In formulating policies to promote agricultural large-scale management, land-scale management and service-scale management both should be treated with an equal perspective, without being overly biased one way. However, policy strategies to support each form of large-scale management should be targeted. For service-scale management, the policy orientation should be to promote the services outsourcing market to guide the service chain forward, backward, to high value-added, to high technology content and to cross-region extension based on ensuring the quantity and quality of in-production services. Therefore, for China, the government should retain the existing subsidies for agricultural socialization services and provide additional financial subsidies and favorable credit support to service providers who provide green production services, carry out smart agriculture, provide high value-added services, etc. For land-scale management, the policy orientation should be to promote the farmland rental market to integrate dispersed land and push forward the transfer of land to efficient entities based on ensuring the smooth flow of land factors. However, because of the high cost of integrating fragmented land, the government should provide appropriate subsidies to agricultural production organizations capable of integrating fragmented land. Through the above targeted policies, land-scale management and service-scale management can achieve a high level of circular interaction. In terms of regional differences, the two large-scale management forms in central regions and high agricultural dependency regions are in a low-level circular state; in particular, the poor advancement of agricultural large-scale management in the latter may have some impact on national food security. Therefore, compared with other regions in China, the governments in the above two regions have more responsibility and should have more urgency to further improve the development scale and quality of the farmland rental market and agricultural outsourcing services market. Subsidies and policies on large-scale management and the construction of new agricultural management subjects, should be appropriately tilted in favor of central and high agricultural dependency regions. The proportion of matching funds from the central government for agricultural construction projects in the above two regions should also be further increased.

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References

1. Lu, X.H.; Jiang, X.; Gong, M.Q. How land transfer marketization influence on green total factor productivity from the approach of industrial structure? Evidence from China. *Land Use Policy* **2020**, *95*, 104610. [CrossRef]
2. Alem, H. The role of green total factor productivity to farm-level performance: Evidence from Norwegian dairy farms. *Agric. Food Econ.* **2023**, *11*, 2. [CrossRef]
3. Foster, A.D.; Rosenzweig, M.R. Microeconomics of Technology Adoption. *Annu. Rev. Econ.* **2010**, *2*, 395–424. [CrossRef] [PubMed]
4. Foster, A.D.; Rosenzweig, M.R. Are there too many farms in the world? Labormarket transaction costs, machine capacities and optimal farm size. *J. Polit. Econ.* **2022**, *130*, 636–680. [CrossRef]

5. Ren, C.C.; Liu, S.; van Grinsven, H.; Reis, S.; Jin, S.Q.; Liu, H.B.; Gu, B.J. The impact of farm size on agricultural sustainability. *J. Clean. Prod.* **2019**, *220*, 357–367. [CrossRef]
6. De Roest, K.; Ferrari, P.; Knickel, K. Specialisation and economies of scale or diversification and economies of scope? Assessing different agricultural development pathways. *J. Rural. Stud.* **2018**, *59*, 222–231. [CrossRef]
7. Young, A.A. Increasing returns and economic progress. *Econ. J.* **1928**, *38*, 527–542. [CrossRef]
8. Fei, R.L.; Lin, Z.Y.; Chunga, J. How land transfer affects agricultural land use efficiency: Evidence from China's agricultural sector. *Land Use Policy* **2021**, *103*, 105300. [CrossRef]
9. Wang, J.Y.; Chen, K.Z.; Das Gupta, S.; Huang, Z.H. Is small still beautiful? A comparative study of rice farm size and productivity in China and India. *China Agric. Econ. Rev.* **2015**, *7*, 484–509. [CrossRef]
10. Manjunatha, A.V.; Anik, A.R.; Speelman, S.; Nuppenau, E.A. Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in India. *Land Use Policy* **2013**, *31*, 397–405. [CrossRef]
11. Ricciardi, V.; Mehrabi, Z.; Wittman, H.; James, D.; Ramankutty, N. Higher yields and more biodiversity on smaller farms. *Nat. Sustain.* **2021**, *4*, 651–657. [CrossRef]
12. Aragón, F.M.; Restuccia, D.; Rud, J.P. Are small farms really more productive than large farms? *Food Policy* **2022**, *106*, 102168. [CrossRef]
13. Kerr, P. Adam Smith's theory of growth and technological change revisited. *Contrib. Political Econ.* **1993**, *12*, 1–27. [CrossRef]
14. Igata, M.; Hendriksen, A.; Heijman, W.J.M. Agricultural outsourcing: A comparison between the Netherlands and Japan. *APSTRACT Appl. Stud. Agribus. Commer.* **2008**, *2*, 29–34. [CrossRef]
15. Deng, X.; Xu, D.D.; Zeng, M.; Qi, Y.B. Does outsourcing affect agricultural productivity of farmer households? Evidence from China. *China Agric. Econ. Rev.* **2020**, *12*, 673–688. [CrossRef]
16. Qing, C.; Zhou, W.F.; Song, J.H.; Deng, X.; Xu, D.D. Impact of outsourced machinery services on farmers' green production behavior: Evidence from Chinese rice farmers. *J. Environ. Manag.* **2023**, *327*, 116843. [CrossRef] [PubMed]
17. Zhang, X.B.; Yang, J.; Thomas, R. Mechanization outsourcing clusters and division of labor in Chinese agriculture. *China Econ. Rev.* **2017**, *43*, 184–195. [CrossRef]
18. Picazo-Tadeo, A.J.; Reig-Martínez, E. Outsourcing and efficiency:: The case of Spanish citrus farming. *Agron. Econ-Blackwell* **2006**, *35*, 213–222. [CrossRef]
19. Qu, X.; Kojima, D.; Nishihara, Y.; Wu, L.P.; Ando, M. Can harvest outsourcing services reduce field harvest losses of rice in China? *J. Integr. Agric.* **2021**, *20*, 1396–1406. [CrossRef]
20. Chen, Y.Y.; Jiao, C.Q. How agricultural contracting services are reshaping small-scale household farming in China. *J. Peasant. Stud.* **2024**, *51*, 339–357. [CrossRef]
21. Zhang, Y.J.; Zhang, J.; Liu, Y.; Zhu, P.X. Agricultural machinery service adoption and farmland transfer-in decision: Evidence from rural China. *Front. Env. Sci.-Switz.* **2023**, *11*, 1195877. [CrossRef]
22. Qian, L.; Lu, H.; Gao, Q.; Lu, H.L. Household-owned farm machinery vs. outsourced machinery services: The impact of agricultural mechanization on the land leasing behavior of relatively large-scale farmers in China. *Land Use Policy* **2022**, *115*, 106008. [CrossRef]
23. Xu, C.H.; Wang, Q.; Fahad, S.; Kagatsume, M.; Yu, J. Impact of Off-Farm Employment on Farmland Transfer: Insight on the Mediating Role of Agricultural Production Service Outsourcing. *Agriculture* **2022**, *12*, 1617. [CrossRef]
24. Zhang, D.; Xu, Z.G.; Liu, J.C. Agricultural production services and land transfer: Whether service scale management postpones land scale management ananalysis from the perspectives of factor constraint mitigation effect and land rent rise effect. *China Rural. Survey* **2022**, *2*, 19–38.
25. Yi, Q.; Chen, M.Y.; Sheng, Y.; Huang, J.K. Mechanization services, farm productivity and institutional innovation in China. *China Agric. Econ. Rev.* **2019**, *11*, 536–554. [CrossRef]
26. Qiu, T.; Shi, X.; He, Q.; Luo, B. The paradox of developing agricultural mechanization services in China: Supporting or kicking out smallholder farmers? *China Econ. Rev.* **2021**, *69*, 101680. [CrossRef]
27. Coase, R.H. The nature of the firm. *Economica* **1937**, *4*, 386–405. [CrossRef]
28. Adamopoulos, T.; Brandt, L.; Leight, J.; Restuccia, D. Misallocation, Selection, and Productivity: A Quantitative Analysis With Panel Data From China. *Econometrica* **2022**, *90*, 1261–1282. [CrossRef]
29. Hsieh, C.T.; Klenow, P.J. Misallocation and Manufacturing Tfp in China and India. *Q. J. Econ.* **2009**, *124*, 1403–1448. [CrossRef]
30. Lu, H.; Xie, H.L. Impact of changes in labor resources and transfers of land use rights on agricultural non-point source pollution in Jiangsu Province, China. *J. Environ. Manag.* **2018**, *207*, 134–140. [CrossRef]
31. Wu, Y.Y.; Xi, X.C.; Tang, X.; Luo, D.M.; Gu, B.J.; Lam, S.K.; Vitousek, P.M.; Chen, D.L. Policy distortions, farm size, and the overuse of agricultural chemicals in China. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 7010–7015. [CrossRef]
32. Ju, X.T.; Gu, B.J.; Wu, Y.Y.; Galloway, J.N. Reducing China's fertilizer use by increasing farm size. *Glob. Environ. Chang.-Human. Policy Dimens.* **2016**, *41*, 26–32. [CrossRef]
33. Goldstein, M.; Udry, C. The Profits of Power: Land Rights and Agricultural Investment in Ghana. *J. Polit. Econ.* **2008**, *116*, 981–1022. [CrossRef]
34. Cao, Y.M.; Bai, Y.L.; Zhang, L.X. The impact of farmland property rights security on the farmland investment in rural China. *Land Use Policy* **2020**, *97*, 104736. [CrossRef]
35. Eswaran, M.; Kotwal, A. Access to capital and agrarian production organisation. *Econ. J.* **1986**, *96*, 482–498. [CrossRef]

36. Binswanger, H.P.; Deininger, K.; Feder, G. Revolt and reform in agricultural land relations. *Handb. Dev. Econ.* **1995**, *3*, 2659–2772.
37. Liu, Y.; Yan, B.J.; Wang, Y.; Zhou, Y.H. Will land transfer always increase technical efficiency in China?—A land cost perspective. *Land Use Policy* **2019**, *82*, 414–421. [CrossRef]
38. Sheng, Y.; Ding, J.P.; Huang, J.K. The Relationship between Farm Size and Productivity in Agriculture: Evidence from Maize Production in Northern China. *Am. J. Agron. Econ.* **2019**, *101*, 790–806. [CrossRef]
39. Li, R.N.; Yu, Y.L. Impacts of Green Production Behaviors on the Income Effect of Rice Farmers from the Perspective of Outsourcing Services: Evidence from the Rice Region in Northwest China. *Agriculture* **2022**, *12*, 1682. [CrossRef]
40. Lu, H.; Duan, N.; Chen, Q.R. Impact of agricultural production outsourcing services on carbon emissions in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 35985–35995. [CrossRef]
41. Yang, Y.F.; Yu, Y.L.; Li, R.N.; Jiang, D.B. Impact of pesticide outsourcing services on farmers’ low-carbon production behavior. *Front. Environ. Sci.* **2023**, *11*, 1226039. [CrossRef]
42. Chai, Q.; Qin, A.Z.; Gan, Y.T.; Yu, A.Z. Higher yield and lower carbon emission by intercropping maize with rape, pea, and wheat in arid irrigation areas. *Agron. Sustain. Dev.* **2014**, *34*, 535–543. [CrossRef]
43. Belton, B.; Win, M.T.; Zhang, X.B.; Filipski, M. The rapid rise of agricultural mechanization in Myanmar. *Food Policy* **2021**, *101*, 102095. [CrossRef]
44. Qu, X.; Kojima, D.; Wu, L.P.; Ando, M. Do Farming Scale and Mechanization Affect Moral Hazard in Rice Harvest Outsourcing Service in China? *Agriculture* **2022**, *12*, 1205. [CrossRef]
45. Chen, Y.J.; Lu, H.; Luo, J.W. How does agricultural production outsourcing services affect chemical fertilizer use under topographic constraints: A farm-level analysis of China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 100861–100872. [CrossRef] [PubMed]
46. Yang, C.; Zeng, W.; Yang, X. Coupling coordination evaluation and sustainable development pattern of geo-ecological environment and urbanization in Chongqing municipality, China. *Sustain. Cities Soc.* **2020**, *61*, 102271. [CrossRef]
47. Wang, S.J.; Ma, H.T.; Zhao, Y.B. Exploring the relationship between urbanization and the eco-environment—A case study of Beijing-Tianjin-Hebei region. *Ecol. Indic.* **2014**, *45*, 171–183. [CrossRef]
48. Fan, Y.P.; Fang, C.L.; Zhang, Q. Coupling coordinated development between social economy and ecological environment in Chinese provincial capital cities-assessment and policy implications. *J. Clean. Prod.* **2019**, *229*, 289–298. [CrossRef]
49. Liu, N.N.; Liu, C.Z.; Xia, Y.F.; Da, B.W. Examining the coordination between urbanization and eco-environment using coupling and spatial analyses: A case study in China. *Ecol. Indic.* **2018**, *93*, 1163–1175. [CrossRef]
50. Wang, S.J.; Kong, W.; Ren, L.; Zhi, D.D.; Dai, B.T. Research on misuses and modification of coupling coordination degree model in China. *J. Nat. Resour.* **2021**, *36*, 793–810. [CrossRef]
51. Li, W.W.; Yi, P.T. Assessment of city sustainability-Coupling coordinated development among economy, society and environment. *J. Clean. Prod.* **2020**, *256*, 120453. [CrossRef]
52. IPCC. *Climate Change 2007: Mitigation of Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change: Summary for Policymakers and Technical Summary*; Cambridge University Press: Cambridge, UK, 2007. Available online: <https://www.ipcc.ch/report/ar4/wg3/> (accessed on 2 November 2023).
53. Liu, D.D.; Zhu, X.Y.; Wang, Y.F. China’s agricultural green total factor productivity based on carbon emission: An analysis of evolution trend and influencing factors. *J. Clean. Prod.* **2021**, *278*, 123692. [CrossRef]
54. Hansen, B.E. Threshold effects in non-dynamic panels: Estimation, testing, and inference. *J. Econom.* **1999**, *93*, 345–368. [CrossRef]
55. Haans, R.F.J.; Pieters, C.; He, Z.L. Thinking about u: Theorizing and testing u- and inverted u-shaped relationships in strategy research. *Strateg. Manag. J.* **2016**, *37*, 1177–1195. [CrossRef]

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