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Special Issue Reprint

Agricultural Land Management to Meet Future Global Food Demand

Edited by
Uttam Khanal and Sanzidur Rahman

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This is a reprint of articles from the Special Issue published online in the open access journal *Land* (ISSN 2073-445X) (available at: https://www.mdpi.com/journal/land/special_issues/agricultural_land_food).

For citation purposes, cite each article independently as indicated on the article page online and as indicated below:

Lastname, A.A.; Lastname, B.B. Article Title. *Journal Name* **Year**, *Volume Number*, Page Range.

ISBN 978-3-7258-0539-6 (Hbk)
ISBN 978-3-7258-0540-2 (PDF)
doi.org/10.3390/books978-3-7258-0540-2

Contents

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Article

Agricultural Water Use Efficiency: Is There Any Spatial Correlation between Different Regions?

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Abstract: Affected by global climate change and water shortages, food security continues to be challenged. Improving agricultural water use efficiency is essential to guarantee food security. China has been suffering from water scarcity for a long time, and insufficient water supply in the agricultural sector has seriously threatened regional food security and sustainable development. This study adopted the super-efficiency slack-based model (SBM) to measure the provincial agricultural water use efficiency (AWUE). Then, we applied the vector autoregression (VAR) Granger causality test and social network analysis (SNA) method to explore the spatial correlation of AWUE between different provinces and reveal the interprovincial transmission mechanism of spillover effects in AWUE. The results show the following: (1) In China, the provincial AWUE was significantly enhanced, and the gaps in provincial AWUE have widened in the past 20 years. (2) There were apparent spatial heterogeneity and correlations of provincial AWUE. The provinces with higher AWUE were mainly located in economically developed and coastal areas. (3) The correlation of AWUE between provinces showed significant network structure characteristics. Fujian, Hebei, Jiangsu, Shandong, and Hubei Qinghai were central to the network, with high centrality. (4) The AWUE spatial correlation network could be divided into four blocks. Each block played a different role in the cross-provincial transmission of spillover effects. Therefore, it is necessary to manage the agricultural water resources and improve water use efficiency from the perspective of the network.

Keywords: agricultural water use efficiency; undesirable super-efficiency SBM model; vector autoregression (VAR) Granger causality test; social network analysis (SNA); spatial correlation network

Citation: Zhi, Y.; Zhang, F.; Wang, H.; Qin, T.; Tong, J.; Wang, T.; Wang, Z.; Kang, J.; Fang, Z. Agricultural Water Use Efficiency: Is There Any Spatial Correlation between Different Regions? *Land* **2022**, *11*, 77. https://doi.org/10.3390/land11010077

Academic Editors: Uttam Khanal and Sanzidur Rahman

Received: 9 December 2021
Accepted: 4 January 2022
Published: 5 January 2022

1. Introduction

Water is indispensable and irreplaceable for human well-being and socio-economic sustainability. Among the 17 Sustainable Development Goals (SDGs) published by the United Nations General Assembly in 2015, at least 4 goals are related to the sustainable utilization and management of water resources, namely, SDG-6, SDG-7, SGD-12, and SDG-13 [1]. However, due to the rising water demands associated with population growth and economic development, coupled with diminishing water supplies caused by climate change and contamination, water is becoming scarce in most regions of the world [2,3]. The recent literature demonstrates that nearly half of the global population faces severe water scarcity, which directly conflicts with the above SDGs [4]. The agriculture sector is the largest water user globally, accounting for approximately 70% of global water withdrawal due to irrigation [5]. Insufficient water resources have posed a substantial threat to agricultural production and food security [6]. In addition, backward agricultural irrigation technology, extensive water use patterns, and low water use efficiency have further intensified water scarcity [7]. Thus, sustainable agricultural water resource management is related to regional food security and closely linked to economic development, ecological security, and quality of life [8,9]. When water supplies are limited, agricultural production should maximize net income per unit of water used rather than per land unit [10]. Evaluating and improving agricultural water use efficiency (AWUE) are also the basis for promoting regional water resource management [11,12].

Widening water demand and supply gaps have been a significant challenge for China. China has been suffering from water scarcity for a long time [13], whose per capita water supply is less than 2200 m^3, only one quarter of the world average [14]. Since 1998, agricultural water use in China has consumed over 60% of the total national water consumption [15], and this figure is as high as 80–90% in some arid regions, such as Ningxia and Xinjiang. Meanwhile, there has been severe conflict between water availability and food production in China, feeding 21% of the world's population needs with only 6% of the global freshwater resources [16]. As one of the largest agricultural countries, the improvement in AWUE in China could contribute to global sustainable water utilization and food security [17].

Generally, AWUE refers to the ratio of physical and economic output to water resource input during agricultural production, a broad concept of physiological, agronomic, and engineering processes, and management practice [18]. Many studies evaluated AWUE with a single-factor index. They focused on the ratio between crop biomass or grain production and the amount of water consumed by crops, including rainfall, the irrigation water applied, and crop transpiration [19–21]. Thus, AWUE also reflects the production ability of water resources, such as crop water productivity, irrigation water productivity, and generalized water productivity [22]. It was later recognized that water alone as the only input could not produce the necessary outputs in the production process. Other inputs are also essential in AWUE assessment [23]. Therefore, the total factor water use efficiency measured by multiple input models has entered the mainstream. The frequently used assessment methods are stochastic frontier analysis (SFA) and data envelopment analysis (DEA) [24,25]. Compared with SFA, DEA is a non-parametric evaluation model and does not require any distributional assumptions about efficiency [26], avoiding the influences of subjective factors on water resource efficiency assessment. In addition, improved DEA models can even deal with both desirable and undesirable outputs simultaneously, significantly improving the accuracy of resource use efficiency evaluation [27]. At present, DEA models have been widely used globally to assess the water use efficiency of a decision-making unit (e.g., farm, enterprise/company, irrigation district, industrial/agricultural sector) [25,28,29].

The spatial difference and correlation of water use efficiency have attracted significant attention in recent years. On the one hand, water use efficiency exhibits noticeable regional variation. The literature has shown that water use efficiency is sensitive to meteorological factors, such as temperature, precipitation, and moisture [30]. Water use efficiency increases with atmospheric CO_2 but declines with increasing atmospheric evaporative demand [31]. Water use efficiency is also influenced by socio-economic factors. The value of AWUE is higher in developed areas than in undeveloped areas in China [13]. On the other hand, water use efficiency has demonstrated a significant spatial correlation. The AWUE of one region is related to the geographical conditions and the economic development level, which is likely to be influenced by the neighboring regions [32]. The adjacent regions' agricultural production behaviors also affect the local region's AWUE, resulting in spatial spillover effects on the local region [13]. Awareness of spatial correlation among regional AWUE is essential for improving water utilization efficiency.

The temporal and spatial patterns of AWUE are related to various natural and socio-economic elements, which are types of agricultural ecosystems, agricultural production factors, and agricultural water resource management measures [3,25]. Agricultural production factors will flow spontaneously from the area with a low factor return rate to a high factor return rate [33]. In contrast, the management departments will actively guide the cross-region transfer of technology, information, talents, and goods to promote sustainable water use and regional synergy development [34,35]. Due to the cross-regional mobility of the agricultural production factors, various regions' agricultural water resource utilization may present close connections. As the scope of factors' mobility continues to expand, an increasing number of regions have shown relevance in AWUE, and the spatial correlation of AWUE shows a network characteristic [36,37]. Meanwhile, the spatial correlation network of AWUE could reflect the distribution pattern of spillover effects related to certain factors [38], which could guide the improvement in AWUE. However, this important feature is often ignored in AWUE studies. Utilizing this information on the spatial correlation of AWUE may help implement effective measures to improve AWUE.

In the spatial correlation of AWUE, different nodes (regions) have various resource (such as information, technology, knowledge, and talents related to water saving) control capabilities, resulting in diverse network structures [39]. Due to the spillover effects, the nodes with strong power may influence various other nodes and be in the central position of the network. Creating solid links among regions can enhance mutual learning and sharing of resources and advice [40]. Moreover, nodes similar to one another are better able to communicate information and apply the same governance [41]. For the whole network, centralization helps form groups and build support for collective action, such as the fast spread of particular water-saving technologies [42]. In contrast, over-centralization may not be conducive to long-term planning and problem solutions [43]. Thus, it is necessary to investigate the spatial network structure related to AWUE and propose appropriate strategies to improve AWUE.

This study aimed to explore the spatial correlation of AWUE between different provinces in China and provide support for the designation of agricultural water resource management strategies. In this study, AWUE is defined as a total factor water efficiency index. The super-efficiency slack-based model (SBM) with undesirable outputs and the social network analysis (SNA) method were used to: (1) evaluate AWUE at the province level within and beyond China, and (2) investigate the characteristics of the spatial correlation network of AWUE.

2. Materials and Methods

The analysis process for the spatial correlation of AWUE is illustrated in Figure 1.

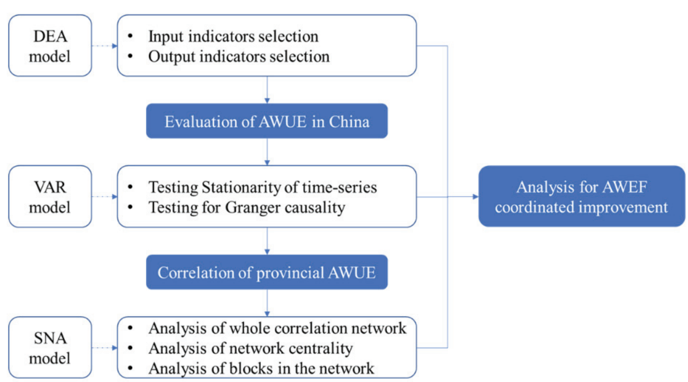

Figure 1. Technical route for analysis of spatial correlation network of agricultural water use efficiency (AWUE).

Firstly, to assess the AWUE of provinces in China, the super-efficiency SBM with undesirable outputs was used. This model is an improved DEA method and needs to select the appropriate input and output indicators for the production efficiency evaluation.

Secondly, the vector autoregression (VAR) Granger causality test model was used to analyze the dynamic connections between different provinces in China.

Thirdly, to investigate the characteristics of the spatial correlation network of AWUE, the SNA model was used. In particular, the centrality and block analysis can reveal the core provinces which influence the coordinated improvement in AWUE.

2.1. Undesirable Super-Efficiency SBM Model

DEA is a non-parametric evaluation method for measuring the relative efficiency of units where they have multiple inputs and outputs [44]. The primary analysis unit is defined as the decision-making unit (DMU). The efficiency value of a DMU is the distance from the DMU to the best-practice frontier. The frontier shows the maximum of diverse outputs with different input combinations or views the minimum combination of necessary inputs for diverse outputs. DMUs below the frontier are considered inefficient, while DMUs on the frontier are regarded as efficient. The traditional radial and angle DEA models calculate the efficiency according to a certain input–output proportion, ignoring the excess in inputs and shortfalls in outputs, which are likely to deviate from the efficiency measurement. The slack-based model (SBM) [45] was applied to avoid the slack problem of inputs and outputs, which belongs to a non-radial and non-angle DEA model. Moreover, when using conventional SBM-DEA models, the efficiency values of all DMUs are within the range of zero to one. This means that we fail to rank the DMUs with an efficiency value of one. Then, the super-efficiency model in DEA was proposed to exclude each observation from its own reference set, making it possible to obtain efficiency scores that exceed one [46]. Thus, the super-efficiency SBM model with undesirable outputs is suitable for the AUWE assessment in this study, which is defined as follows:

$$\rho = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \overline{x_i}/x_{i_o}}{1 + \frac{1}{S_1+S_2}\left[\sum_{p=1}^{S_1}\left(y_p^g / y_{p_o}^g\right) + \sum_{q=1}^{S_2}\left(y_q^b / y_{q_o}^b\right)\right]} \tag{1}$$

$$s.t.\begin{cases} \overline{x} \geq \sum\limits_{j=1,j\neq o}^{n} x_{ij}\lambda_j, \quad y_p^g \leq \sum\limits_{j=1,j\neq o}^{n} y_{pj}^g\lambda_j, \quad y_q^b \leq \sum\limits_{j=1,j\neq o}^{n} y_{qj}^b\lambda_j \\ \overline{x} \geq x_{io}, \quad y_p^g \leq y_{po}^g, \quad y_q^b \geq y_{qo}^b \\ \sum\limits_{j=1,j\neq o}^{n} \lambda_j = 1, \quad y^g \geq 0, \quad y^b \geq 0, \quad \lambda \geq 0 \\ i = 1,2,\cdots m; \ p = 1,2,\cdots S_1; \ q = 1,2,\cdots S_2; \ j = 1,2,\cdots n \end{cases} \tag{2}$$

where ρ represents the AWUE value, n is the number of evaluation units, m is the input elements, S_1 and S_2 are the number of desirable and undesirable outputs, $\overline{x}$, y^g, and y^b are slack variables for inputs, desirable outputs, and undesirable outputs, and λ is the envelope multiplier. If $\rho \geq 1$, the DMU is on the agricultural production frontier and DEA effective. If $0 < \rho < 1$, it means the DMU is not DEA effective, and there is still potential to improve the agricultural water use efficiency in the evaluation unit.

2.2. Social Network Analysis

SNA is a sociological research method used to investigate the relationships of actors, which consists of a set of nodes (actors) and ties (relationships between actors) [47]. SNA has also invented graph-theoretic properties to characterize structures, positions, links, and dyadic properties of the overall "shape" [39]. The AWUE of provinces is embedded in a social network by formal or informal relationships, and their changes are affected by the social network [48]. In the spatial correlation network of AWUE, the "nodes" are provinces, which present the AWUE of a particular region, and "ties" are the connection between these provinces, which show the spillover effects of factors related to AWUE. This section contains two parts: firstly, establishing the correlations in the AWUE in different provinces using the VAR Granger causality test; secondly, constructing the spatial correlation network of provincial AWUE with the method of SNA.

2.2.1. Vector Autoregression (VAR) Granger Causality Test

This step addresses the correlation among variables, which discusses a relationship between two nodes. In general, the influence of AWUE in different provinces has a lag, which means that the WUE information during a specific period in one area can predict the changing trend of WUE in the other regions [37]. Therefore, this paper used the VAR Granger causality test to build the dynamic correlation between provincial AWUE in China and construct a spatial correlation network matrix.

Firstly, the time series of AWUE in any given two provinces x, y were defined as $\{x_t\}$ and $\{y_t\}$, respectively. Secondly, two VAR models were constructed to test whether there is an interaction between the AWUE of the two regions.

$$x_t = \alpha_1 + \sum_{i=1}^{m} \rho_{1,i} x_{t-i} + \sum_{i=1}^{n} \sigma_{1,i} y_{t-i} + \varepsilon_{1,t} \tag{3}$$

$$y_t = \alpha_2 + \sum_{i=1}^{p} \rho_{2,i} x_{t-i} + \sum_{i=1}^{q} \sigma_{2,i} y_{t-i} + \varepsilon_{2,t} \tag{4}$$

where α_i, ρ_i, and σ_i $(i = 1, 2)$ are the parameters to be estimated, $\varepsilon_{i,t}$ $(i = 1, 2)$ represents the residual terms, which obeys the standard normal distribution, m, n, p, and q are the lag orders of the autoregressive terms. Through Equation (3), we can test whether the AWUE in region x is affected with a lag by its AWUE and the AWUE in region y. If the test result rejects the null hypothesis, the historical information of sequence $\{y_t\}$ is helpful to explain the variable change of sequence $\{x_t\}$, which means that $\{y_t\}$ is the Granger cause of $\{x_t\}$, and then create a directed link from region y to region x. According to this method, the links between all pairs of two regions in the study area are tested, and the spatial correlation network map of provincial AWUE is obtained. It should be noted that the stationarity test of time series was carried out by a unit root test model, the ultimate hysteresis order was set to an order of 2, and 1% was used as the significance test standard.

2.2.2. Spatial Correlation Network Characteristics

This step analyzes the spatial correlation network structure of provincial AWUE with two indicators: overall network characteristics and network centrality analysis [38,49,50]. This paper used the software UCINET (v 6.659) to obtain them.

(1) Overall network characteristic analysis

Four items were used to describe the overall network characteristics: network affinity, network density, network efficiency, and network hierarchy.

Network affinity describes the sum of all the actual connections in the network, which reflect the overall scale of the network. It is represented by M.

Network density measures the degree of cohesion in the network. The more connections there are in the provincial AWUE, the greater the network density. It is expressed as Equation (5). D represents the network density, N is the number of nodes in the network, and $N(N-1)$ is the maximum potential connection.

$$D = \frac{M}{N(N-1)} \tag{5}$$

Network efficiency refers to the connection efficiency between nodes in the network. The lower the network efficiency, the more redundant lines and overflow channels there are, and the more stable the whole network.

Network hierarchy reflects the asymmetric accessibility in the network. The higher the network hierarchy, the more rigid the network. The network hierarchy is calculated by Equation (6). H represents the network hierarchy, K is the group number of symmetric reachable points in the network, and $Max(K)$ is the number of groups of maximum possible reachable points.

$$H = 1 - \frac{K}{Max(K)} \quad (6)$$

(2) Network centrality analysis

Three parameters are used to describe the power of the nodes: point centrality, betweenness centrality, and closeness centrality. In a network, power means influence [47], and there is a positive relationship between centrality and power [51].

Point centrality measures the degree of association between a node and other nodes, indicating the degree to which a node is in the center of the network. The province with a higher point centrality has more connections with other provinces in the AWUE network and is likely to be the center node of the network. Point centrality (*De*) is calculated by Equation (7).

$$De = \frac{L}{N(N-1)-1} \quad (7)$$

where L stands for the number of provinces directly connected to the other; this centrality has two types in directed graphs: in-degree and out-degree. The former refers to the incoming spillover effects of factors related to AWUE from other provinces. In contrast, the latter is the outgoing spillover effects to other provinces.

Betweenness centrality indicates the mediation and bridge function, investigating how a node can control the communication between other nodes. It evaluates the number of times a node acts as a bridge along the shortest path between two other nodes, indicating the node's control ability of the overall network [52]. It is represented by C_b and is calculated by Equation (8).

$$C_b = \sum_{j}^{n}\sum_{k}^{n} b_{jk}(i);\ \ j \neq k \neq i,\ j < k \quad (8)$$

Closeness centrality refers to the closeness of a node to all other nodes in the network, which reflects the ability of a node to not be controlled by other nodes in the entire network.

2.2.3. Block Model Analysis

The block model is a primary social, spatial clustering analysis method [53]. It can explore the network's internal structure, investigate the position and role of each node in the block, evaluate the path of sending and receiving information between blocks, and conduct descriptive analysis. According to the block model, the social network is divided into four sections: bidirectional block, agent block, net beneficial block, and net spillover block. We used the CONCOR module in UCINET to finish the block model analysis. The maximum depth was set to 2. The focus on the standard was set to 0.2, dividing the 30 provinces into 4 blocks.

2.3. Data Source

In terms of the measurement of AWUE, five variables related to agricultural production were selected as input indicators, and the output indicators were from two aspects of desirable outputs and undesirable outputs, as shown in Table 1. For the availability and validity of the data, this research selected 30 provinces in China as the study area, excluding Hong Kong, Macao, Taiwan, and Tibet, and chose 2000 to 2019 as the research period.

Table 1. Input and output indicators in the assessment of agricultural water use efficiency.

Input and Output Elements	Variables	Unit
Input indicators	(I1) agricultural water use	10^8 m^3
	(I2) total sown area for crop	10^3 hm^2
	(I3) total power of agricultural machinery	10^4 kw
	(I4) labor force in agricultural production	10^4 persons
	(I5) fertilizer content application	10^4 t
Desirable output indicators	(O1) added value of agriculture	10^8 RMB
Undesirable output indicators	(O2) COD, TN, and TP emission from agriculture	10^4 ton

Since this paper evaluated agricultural water use efficiency, water withdrawal in the agricultural sector (irrigation, forestry, farming, and fishery) was the primary input indicator. As irrigation accounts for most of the agricultural water, this article prioritized the production factors related to the planting industry, such as crop sown area, agricultural machinery power, and fertilizer. In addition, the labor force was also included as an input element. Corresponding to the water use in the agricultural sector, we selected added value of agriculture as a desirable output indicator. To eliminate the influence of interannual price changes, we used the comparable price index to re-calculate the price based on the year 2000. Meanwhile, the undesirable output was mainly considered the non-point source pollution caused by agricultural production.

The data relating to the AWUE assessment were obtained from the *China Water Resources Bulletin*, *China Rural Statistical Yearbook*, and *China Statistical Yearbook*, covering 2000–2019. The discharges of agricultural non-point source pollution mainly come from crop fertilization, livestock breeding, and straw burning, which are estimated through the discharge of the pollution loads of chemical oxygen demand (COD), total nitrogen (TN), and total phosphorus (TP). The inventory analysis method was used to assess the above three indicators [54].

3. Results

3.1. Spatial and Temporal Differentiation of AWUE in China

3.1.1. Average AWUE of 30 Provinces

As shown in Table 2, all the average values of provincial AWUE were less than one, meaning that the agricultural water resource usage was inefficient at the province level. Thus, there is still room for improvement in agricultural water use in China.

Table 2. Average agricultural water use efficiency in China from 2000 to 2019.

Province	Efficiency	Rank	Province	Efficiency	Rank
Beijing	0.625	2	Henan	0.415	9
Tianjin	0.398	11	Hubei	0.258	20
Hebei	0.358	13	Hunan	0.222	22
Shanxi	0.216	23	Guangdong	0.368	12
Inner Mongolia	0.178	28	Guangxi	0.190	27
Liaoning	0.346	14	Hainan	0.494	3
Jilin	0.270	16	Chongqing	0.464	6
Heilongjiang	0.278	17	Sichuan	0.278	18
Shanghai	0.657	1	Guizhou	0.237	21
Jiangsu	0.469	5	Yunnan	0.212	25
Zhejiang	0.477	4	Shaanxi	0.460	7
Anhui	0.211	26	Gansu	0.264	19
Fujian	0.438	8	Qinghai	0.136	30
Jiangxi	0.215	24	Ningxia	0.159	29
Shandong	0.326	15	Xinjiang	0.410	10

There are distinct spatial disparities in AWUE among different provinces. In the past twenty years, the top five provinces with the highest average AWUE were Shanghai (0.657), Beijing (0.765), Hainan (0.494), Zhejiang (0.477), and Jiangsu (0.469). These five provinces are located in economically developed regions or coastal areas with abundant precipitation. In contrast, the bottom five districts with the lowest average AWUE were Qinghai (0.136), Ningxia (0.159), Inner Mongolia (0.178), Guangxi (0.190), and Anhui (0.211). These five provinces are mainly in arid and semi-arid areas with less precipitation, comparatively backward agricultural water technology, and large agricultural non-point pollution discharge [55]. The average AWUE in Shanghai was about five times that of Qinghai.

3.1.2. Temporal Evolution of the Provincial AWUE

The AWUE of most provinces has increased significantly over time, which means that the agricultural water use efficiency has considerably improved (Figure 2). In 2000, the AWUE of all 30 provinces was less than 0.4. In 2019, the AWUE in more than 50% of the provinces was more than 0.6. It is worth noting that the AWUE of 11 provinces gradually exceeded 1 since 2015, which indicates that agricultural water usage in these provinces had reached an utterly efficient state.

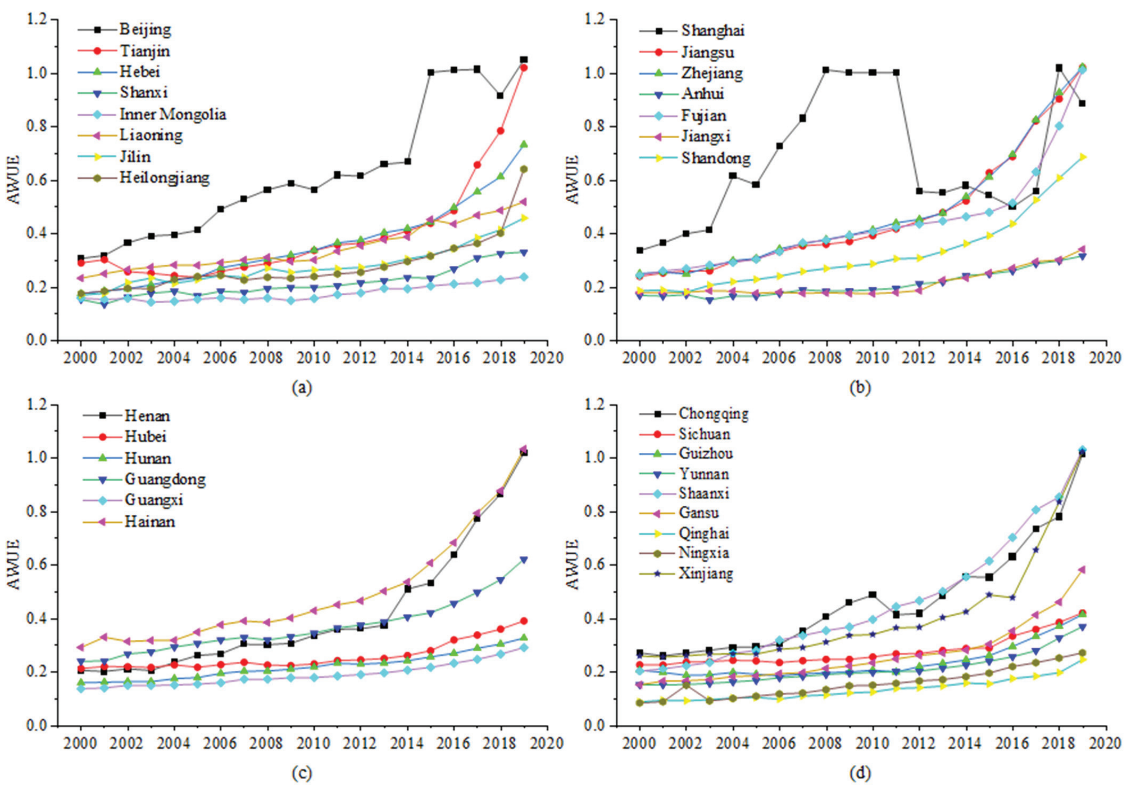

Figure 2. Temporal trends of provincial agricultural water use efficiency (AWUE) in China from 2000 to 2019. The above four charts are listed separately according to the geographical location of the province within (**a**) North China (8 provinces), (**b**) East China (7 provinces), (**c**) South China (6 provinces), and (**d**) West China (9 provinces).

In addition, the change trajectories of AWUE presented noticeable differences. The AWUE in most provinces experienced a process of first rising slightly and then rising drastically. The AWUE in Beijing and Shanghai started to increase around 2005, reaching 1 in 2015 and 2008. Meanwhile, the AWUE in most provinces such as Tianjin, Hebei, Jiangsu, Zhejiang, Fujian, Shandong, Henan, Hainan, Shaanxi, Gansu, and Xinjiang entered a stage of significant improvement since 2011 and exceeded 1 in 2019. Moreover, there are some provinces where AWUE has been low, with a minimal increment during the observation, including Inner Mongolia, Anhui, Guangxi, Qinghai, and Ningxia.

The average value of AWUE in China presented a significant increasing trend between 2000 and 2019. The variable coefficients of AWUE rose from 2000 to 2008 and reached a peak in 2008. Then, they decreased between 2009 and 2012 and increased again later (Figure 3). The fluctuations in variable coefficients revealed that the gaps in AWUE between the 30 provinces were the smallest in 2000 and the widest in 2008. Moreover, the gaps in the provincial AWUE are currently in the expanding stage. The spatial imbalance of China's agricultural water use efficiency is significant.

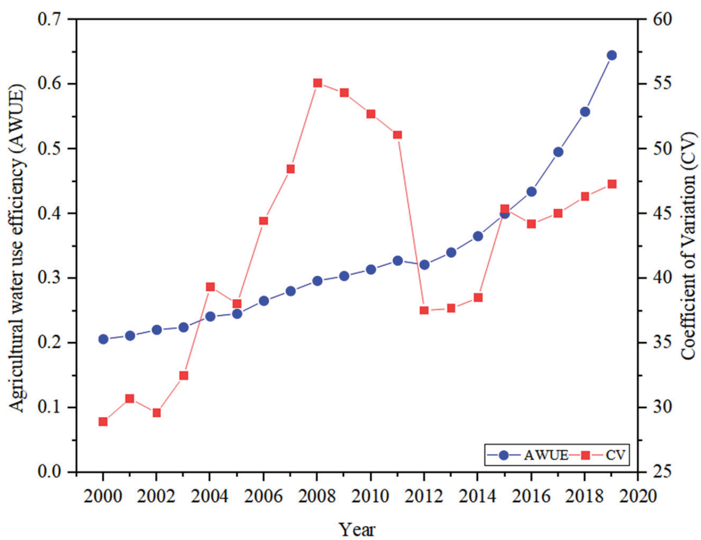

Figure 3. Average AWUE and the variable coefficients of AWUE in China.

3.1.3. Spatial Distribution of AWUE in 30 Provinces

To further analyze the spatial pattern of AWUE, the spatial distribution map of the AWUE of the 30 provinces in 2019 is plotted and shown in Figure 4. Overall, it is clearly illustrated that the AWUE in China presented apparent spatial aggregation and spatial variability at the provincial scale. According to the evaluation results of AWUE in 2019, we found that provinces with AWUE greater than one were mainly in southeastern and northwestern China. Provinces with AWUE lower than 0.4 were primarily in southwestern, south central, and northwestern China. The major grain-producing areas in northeast China, e.g., Heilongjiang, Jilin, and Liaoning, had AWUE between 0.4 and 0.7. Moreover, provinces whose AWUE was 0.6–0.8 were mainly concentrated on the Huang-Huai-Hai Plain [56], such as Hebei and Shandong in East China. The lowest AWUE was found in Inner Mongolia with 0.240 in 2019, followed by Qinghai (0.248) and Ningxia (0.273), all of which are arid provinces with water resource per unit area less than 20×10^4 m^3/km^2.

3.2. Spatial Correlation Network of AWUE in China

With the VAR Granger causality test (1% significance level), the spatial correlation matrix of AWUE in China was established. Then, the network map was drawn to show the structure and pattern of the spatial correlation network of AWUE, as shown in Figure 5. The spatial correlation of China's interprovincial AWUE presents a typical network structure. There are no isolated nodes in the whole spatial correlation network, which indicates that correlations of the agricultural water utilization of provinces in China have transcended geographically adjacent areas and evolved to form a massive spatial network. In other words, due to the frequent mobility of production factors related to AWUE, there has been a close correlation of AWUE between geographically non-adjacent regions. Therefore, the improvement in AWUE in any province will affect other provinces through the network.

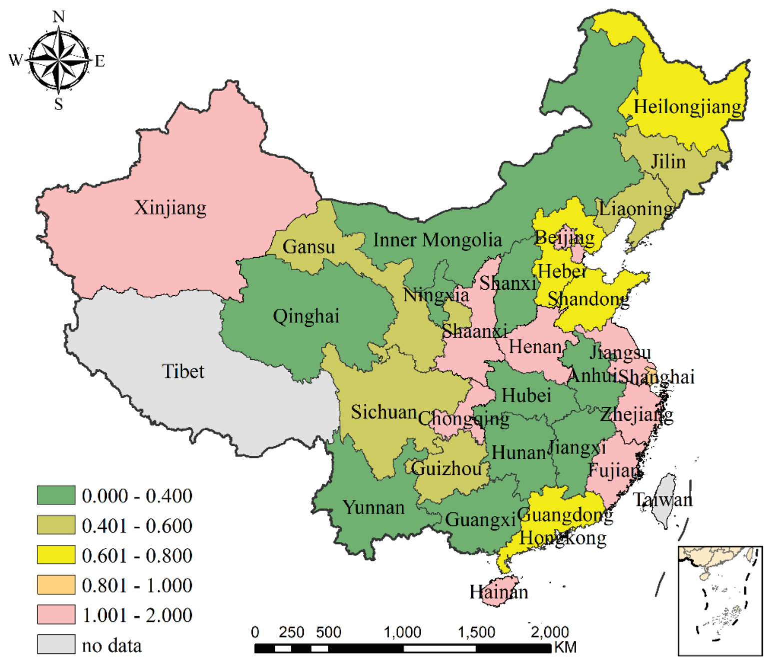

Figure 4. Agricultural water use efficiency of 30 provinces in China in 2019.

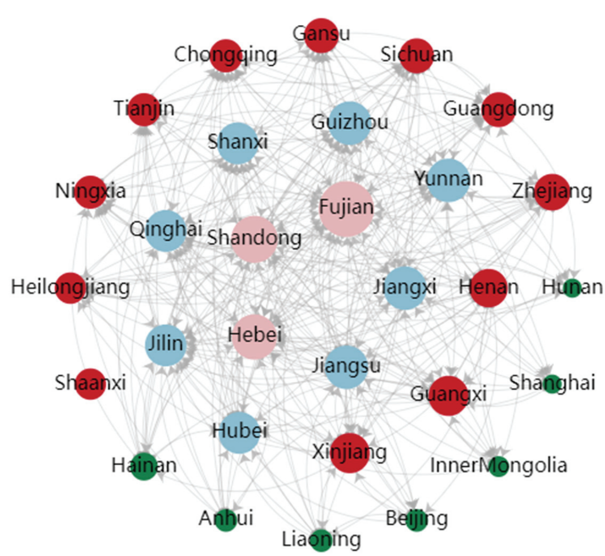

Figure 5. Spatial correlation network of agricultural water use efficiency in China.

3.2.1. Overall Network Characteristics and Evolution Trend

Table 3 shows the overall features of the spatial correlation network of AWUE. Meanwhile, to study the evolution trend of the interprovincial AWUE spatial correlation network, this paper divided the whole sample investigation period into two stages, with 2000–2009 and 2010–2019.

Table 3. Overall characteristics of interprovincial agricultural water use efficiency spatial network.

Item	2000–2009	2010–2019	2000–2019
Network affinity	136	200	301
Network density	0.156	0.230	0.346
Network efficiency	0.746	0.616	0.404
Network hierarchy	0.537	0.242	0
Average distance	2.302	2.045	1.789
Clustering coefficient	0.210	0.305	0.371

The potential maximum spatial correlation of the spatial correlation network of AWUE in the 30 provinces is 870 (30×29). From 2000 to 2019:

(1) The total actual spatial correlation (network affinity) was 307, and the network density was 0.346, indicating that the level of spatial correlation in the provincial AWUE in China was not high. There is still enormous scope to improve the interprovincial correlation of AWUE in the network.

(2) The network correlation was 1, meaning all 30 provinces were in the spatial correlation network of AWUE, and the accessibility and connectivity of the whole network were good. The AWUE of each province always had direct or indirect links with that of other provinces, presenting significant spillover effects of production factors related to AWUE.

(3) The network hierarchy was 0, indicating that there was no rigid network structure, and there was a close interrelation between these provinces.

(4) The network efficiency was 0.397, reflecting that there were many redundant links in the network, and the spatial spillover effects of AWUE had a multiple superposition phenomenon. The more redundant and invalid connections there are, the stabler and more robust the network is, and the slower the transmission speed among the nodes.

(5) The average distance and clustering coefficient of the network were 1.775 and 0.378, implying that the spatial correlation network of AWUE in China had prominent small-world characteristics. The short average distance revealed that we could establish a connection between any two nodes in the network through 1–2 intermediary provinces. The high clustering coefficient indicated a frequent connection and interaction in the provincial AWUE.

From the perspective of evolution, the features of the spatial correlation network of AWUE in China show a noticeable variation (Table 3). The network affinity and density in 2010–2019 were higher than in 2000–2009. The network efficiency and hierarchy in 2010–2019 were lower than in 2000–2009. With the growth of AWUE in China, the spatial correlations of AWUE in different provinces have risen significantly, indicating that the spillover effects of interprovincial agricultural water use efficiency have been enhanced.

3.2.2. Centrality Analysis

The point centrality, betweenness centrality, and closeness centrality of the spatial correlation network of AWUE in China were calculated to reveal the status and role of each province (Table 4).

Table 4. Central analysis of spatial correlation network of agricultural water use efficiency in China.

Province	Point Centrality				Betweenness Centrality		Closeness Centrality	
	Out-Degree	**In-Degree**	**Centrality**	**Rank**	**Centrality**	**Rank**	**Centrality**	**Rank**
Beijing	7	5	37.931	27	1.029	23	61.702	27
Tianjin	11	8	55.172	20	1.969	16	69.048	20
Hebei	8	18	79.310	2	6.927	4	82.857	2
Shanxi	8	16	72.414	10	2.505	12	78.378	10
Inner Mongolia	7	5	34.483	28	1.474	17	60.417	28
Liaoning	11	2	44.828	25	0.442	29	64.444	25
Jilin	5	19	75.862	4	2.145	14	80.556	4
Heilongjiang	8	10	55.172	21	4.201	9	69.048	21
Shanghai	7	4	34.483	29	2.672	10	60.417	29
Jiangsu	17	8	79.310	3	4.319	8	82.857	3
Zhejiang	14	7	62.069	17	1.233	21	72.500	17
Anhui	11	2	44.828	26	0.66	28	64.444	26
Fujian	9	23	82.759	1	8.909	1	85.294	1
Jiangxi	12	13	68.966	13	8.797	2	76.316	13
Shandong	14	13	75.862	5	4.798	5	80.556	5
Henan	20	1	72.414	11	1.052	22	78.378	11
Hubei	15	8	75.862	6	2.601	11	80.556	6
Hunan	2	8	34.483	30	0.886	25	60.417	30
Guangdong	3	16	65.517	15	0.385	30	74.359	15
Guangxi	9	13	72.414	12	1.333	19	78.378	12
Hainan	14	2	55.172	22	0.917	24	69.048	22
Chongqing	3	16	65.517	16	1.465	18	74.359	16
Sichuan	13	6	62.069	18	0.707	27	72.500	18
Guizhou	11	13	75.862	7	4.407	7	80.556	7
Yunnan	11	14	75.862	8	2.220	13	80.556	8
Shaanxi	14	3	55.172	23	0.770	26	69.048	23
Gansu	11	8	51.724	24	1.299	20	67.442	24
Qinghai	8	16	75.862	9	7.640	3	80.556	9
Ningxia	4	15	58.621	19	2.140	15	70.732	19
Xinjiang	14	9	68.966	14	4.579	6	76.316	14
Mean	10.033	10.033	62.989	–	2.816	–	73.401	–

The average out-degree, in-degree, and point-degree of each province in China were 10.033, 10.033, and 62.989, respectively. The top nine provinces with the highest point centrality were Fujian, Hebei, Jiangsu, Jilin, Shandong, Hubei, Guizhou, Yunnan, and Qinghai. Their degree centrality value exceeded 80, which indicates that these provinces had many more connections with other regions and played the role of central actors in the network. As shown in Figure 6, the nodes representing these provinces had more links and were in the center of the network. Meanwhile, Beijing, Inner Mongolia, Liaoning, Shanghai, Anhui, Hunan, and Hainan had low ranks of point centrality and acted as marginal actors in the whole network.

In terms of spillover and reception among the provinces (Figure 7), Henan, Jiangsu, Hubei, Shandong, Zhejiang, Hainan, Shaanxi, and Xinjiang were overflowing with higher out-degree, indicating these areas had more impacts on AWUE in the rest of the provinces than the rest of the provinces on themselves. Meanwhile, Fujian, Jilin, Hebei, Shanxi, Guangdong, Chongqing, and Qinghai were mainly beneficial with high in-degree, meaning that the AWUE levels of these provinces were primarily affected by other regions. The spillover and reception of Shandong, Jiangxi, and Guizhou were nearly equal.

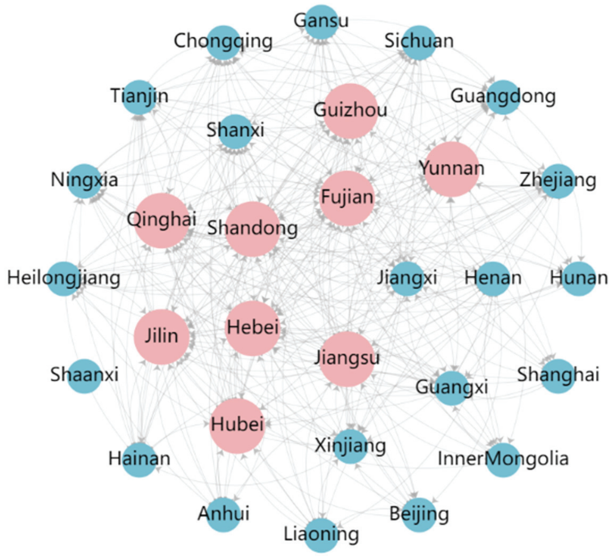

Figure 6. Network diagram corresponding to point centrality.

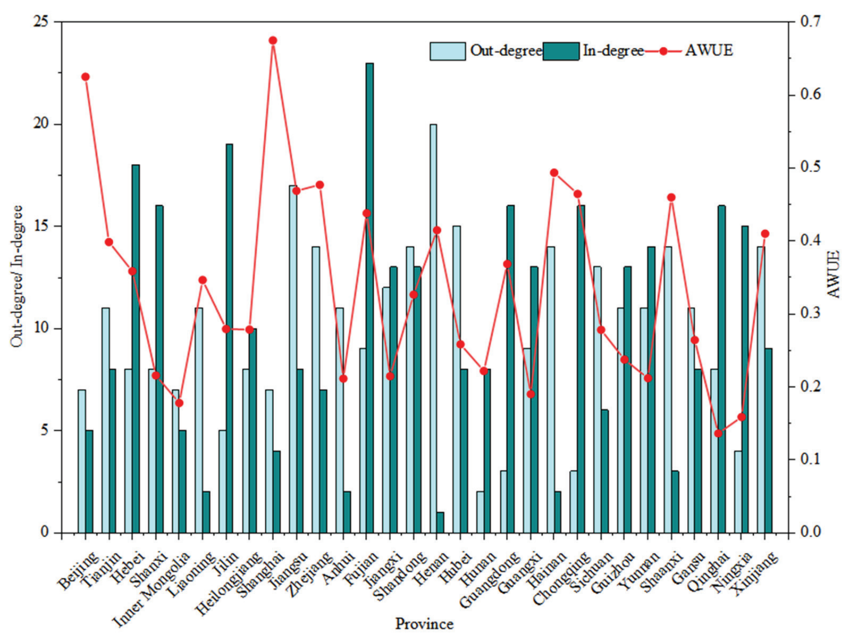

Figure 7. Spillover and reception correlation network of agricultural water use efficiency (AWUE) in China.

In general, provinces with high average AWUE were likely to have higher out-degree than in-degree, suggesting that regions with higher AWUE would have more significant spillover effects of factors related to AWUE, which would benefit the improvement in AWEU in other areas. On the contrary, provinces with low AWUE would have higher in-degree and lower out-degree, and other districts may affect their AWUE.

However, provinces with high AWUE, such as Fujian and Chongqing, did not have apparent spillover effects as expected and had absorbed advanced experience from others through high in-degree. Meanwhile, provinces with low AWUE, such as Liaoning, Anhui, and Hubei, had more spillover effects than receiving effects. Considering these three regions are main grain-producing areas in China, we must promote them to receive spillover effects of factors related to effectively using water.

The average betweenness centrality in the network was 2.816, and nine provinces had a higher value than that (Figure 8). The betweenness centrality in Fujian, Jiangxi, Qinghai, and Hebei was about 7, indicating that these four provinces had controlled more than seven transmission channels in the spatial correlation network of AWUE in China. The betweenness centrality in Shandong, Xinjiang, Guizhou, Jiangsu, and Heilongjiang was more than 4. Provinces with high betweenness centrality play a role as a "bridge" in the network, meaning they are critical nodes for disseminating and exchanging information technology related to agricultural water utilization.

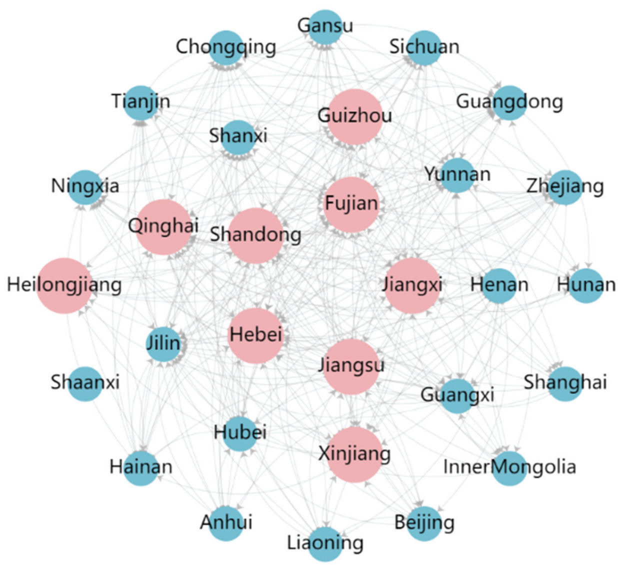

Figure 8. Network diagram corresponding to betweenness centrality.

There are slight differences between the rankings of the centrality degree and betweenness centrality of the 30 provinces in the network.

The average closeness centrality of the nodes in the network was 73.401, and more than 50% of the provinces had a higher value than that, which indicates the whole network was relatively balanced. As shown in Figure 9, Fujian, Hebei, Jiangsu, Jilin, Shandong, Hubei, Guizhou, Yunnan, and Qinghai ranked higher in closeness centrality, meaning they had a short distance to other nodes and could communicate with other provinces quickly in the network.

By comparing the point centrality, betweenness centrality, and closeness centrality of the spatial correlation network of AWUE in China, we found that Fujian, Hebei, Jiangsu, Shandong, Guizhou, and Qinghai had high point centrality, centrality, and closeness centrality at the same time. These provinces were essential nodes in the network and could play a vital role in improving AWUE.

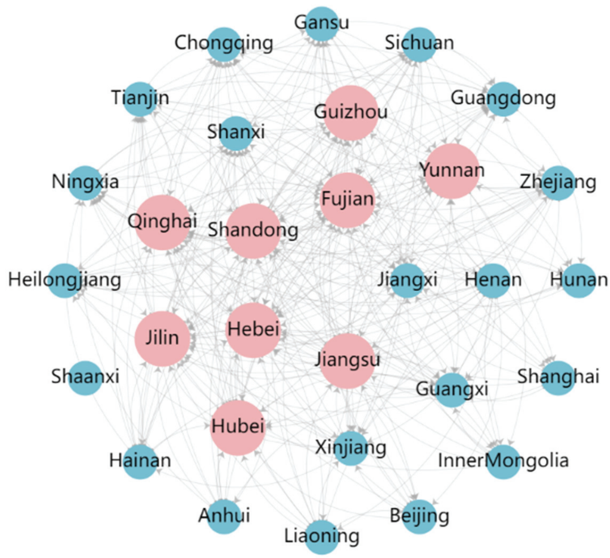

Figure 9. Network diagram corresponding to closeness centrality.

3.2.3. Block Model Analysis

The total correlation in the network was 301. The number of correlations within blocks was 63, with a ratio of 20.93%. Meanwhile, the correlation out of blocks was 238, with a ratio of 79.07%, meaning that the spillover effects between blocks were more significant (Table 5). Moreover, the net spillover block, bidirectional spillover block, and agent block contained most of the nodes and links in the spatial correlation network of AWUE.

Table 5. Spillover effect of agricultural water use efficiency spatial correlation block in China.

Block	Reception		Spillover		Expected Internal Relationship Ratio %	Actual Internal Relationship Ratio %	Block Properties
	Intra Block	Out of Block	Intra Block	Out of Block			
I	8	32	8	75	24	10	Net Spillover Block
II	34	43	34	106	31	24	Bidirectional Spillover Block
III	19	119	19	44	28	30	Agent Block
IV	2	44	2	13	7	13	Net Beneficial Block

Block I had eight nodes: Beijing, Inner Mongolia, Liaoning, Shanghai, Zhejiang, Anhui, Jiangxi, and Hainan. There were 83 spillover relations in block I, and 75 issuing spillover relations to other blocks. The expected internal relationship was 24%, while the actual internal proportion was 10%. Therefore, block I was named the net spillover block, whose members are more likely to send spillover effects on AWUE to other blocks. Among the members, Inner Mongolia, Liaoning, Jiangxi, and Anhui are major grain-producing areas in China, contributing about 20% of the grain production. Beijing, Shanghai, Zhejiang, and Hainan have high agricultural water use efficiency levels.

Block II had ten nodes: Tianjin, Jiangsu, Shandong, Henan, Hubei, Sichuan, Guizhou, Shaanxi, Gansu, and Xinjiang. There were 140 spillover relations in block II, 34 spillover connections within the block, and 106 spillover relations to other blocks. The expected internal relationship proportion was 31%, more than the actual relationship proportion of 24%. Therefore, we called block II the bidirectional spillover block. Members in this block likely have bidirectional spillover effects on nodes inside and outside. Jiangsu, Henan, and Hubei are also major grain-producing provinces.

Block III had nine nodes: Hebei, Shanxi, Jilin, Heilongjiang, Guangdong, Guangxi, Chongqing, Yunnan, and Qinghai. There were 63 spillover relations in block III, 19 within this block, and 44 issuing spillovers to other blocks. The expected internal relationship was 28%, while the actual internal proportion was 30%. According to the above characteristics, block III was classified as the agent block, which plays the role of an "intermediary" and "bridge" in the correlation network. Provinces in this block are evenly distributed in the northeast, northwest, southwest, southeast, and north central subregions of China, which is conducive to the spread of the spillover effects of AWUE across provinces.

Block IV had three nodes: Fujian, Hunan, and Ningxia. There were only 15 spillover relations in this block, 2 within the block, 44 receiving spillover relations in other blocks, and 13 sending spillover relations to other blocks. The expected internal relationship proportion was 7%, and the actual relationship proportion was 13%, meaning block IV was classified as the net beneficial block. Provinces in the net beneficial block mainly receive the spillover effects of other blocks. Fujian's food demand is great, but the local grain output is small, whose external food dependence is high.

Then, the density matrix was calculated to further analyze the spillover effects of AWUE between the four blocks in the network. According to the results in Table 3, the density of the whole spatial correlation network of AWUE was 0.346. If the density of each block in the density matrix is higher than 0.346, the corresponding value in the image matrix is 1; otherwise, the value is 0. The results are shown in Table 6.

Table 6. Density matrix and image matrix of agricultural water use efficiency in China.

Block	Density Matrix				Image Matrix			
	I	II	III	IV	I	II	III	IV
I	0.143	0.375	0.486	0.417	0	1	1	1
II	0.188	0.378	0.867	0.433	0	1	1	1
III	0.194	0.100	0.264	0.778	0	0	0	1
IV	0.125	0.133	0.222	0.333	0	0	0	0

Block I and block II mainly overflowed to block III and block IV, which meant that the former two blocks had substantial spillover effects of AWUE on the latter two blocks. Meanwhile, block III mainly overflowed to block IV. Moreover, only block II overflowed to itself, which suggests that the AWUE of nodes in this block had a significant correlation.

Figure 10 shows the transmission mechanism of spillover effects of factors related to agricultural water utilization between the four blocks. The net spillover block (block I) was the "engine" of the AWUE spatial correlation network, driving changes in agricultural water use efficiency in other members of the network. The net spillover block mainly sent spillover effects of factors related to agricultural water utilization to block II and block III. The bidirectional spillover block (block II) was the "steering wheel" of the network, leading to improving agricultural water resource management. The agent block (block III) was the "bridge" of the network, coordinating the exchange and dissemination of information and technology concerning water resources among the provinces. The net beneficial block (block IV) was the weak link of the whole network due to the low level of AWUE or the great import of agricultural products from other blocks.

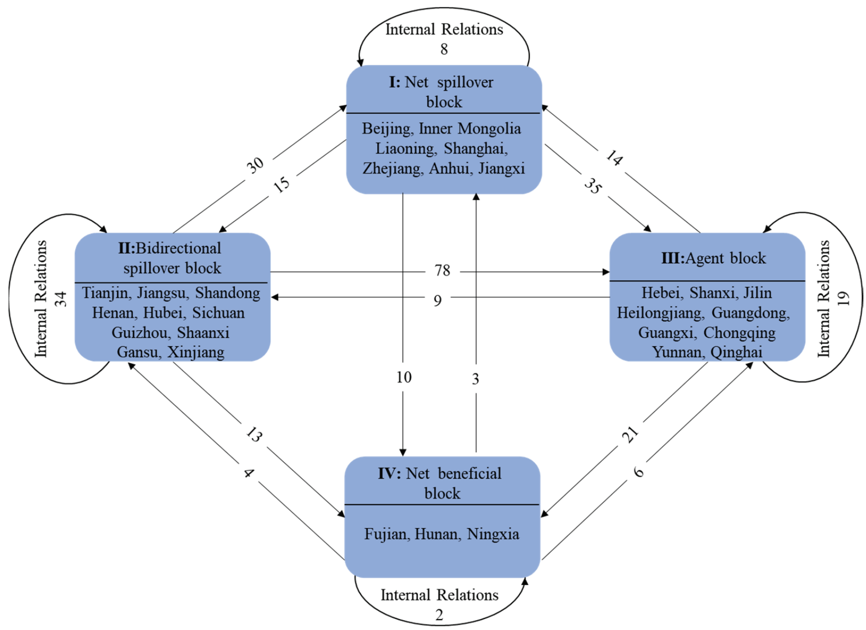

Figure 10. Spatial correlation between the four blocks.

4. Discussion

4.1. Discussion of Overall Level of Provincial AWUE

The overall agricultural water use efficiency of China was at a low level. This result is consistent with the research conclusion of Wang et al. [13]. The main reasons for this were the backward irrigation technology, extensive water use pattern, and inefficient agricultural water management. Only 1.1% of rural residents in major irrigation districts have adopted modern water-saving technology [57], meaning there is great potential for AWUE improvement. In addition, using chemical fertilizers will increase the grain yield, but excessive use of them will affect the soil and water environment through non-point source pollution [32]. Therefore, water-saving management and reducing non-point source pollution should be involved when implementing measures to improve agricultural water use efficiency.

4.2. Discussion of the Temporal Trend of AWUE

On the one hand, the evaluation value of AWUE is determined by the ratio of inputs and outputs. Due to the rapid increase in the economic outputs of the agricultural sector, and the reduction in non-point source pollution, AWUE in certain provinces showed a significant upward trend, such as Beijing, Shanghai, Jiangsu, and Zhejiang. On the other hand, AWUE reflects the condition of water conservancy facilities, the application of water-saving measures, farmers' awareness of water saving, etc. [13]. Economically developed or major grain-producing provinces always have advanced agricultural water use technology and information, causing their AWUE to have apparent temporal trends. In addition, policies related to agricultural production also introduce significant drives for AWUE improvement. In 2011, the Decision on Accelerating the Reform and Development of Water Conservancy, released by the CPC Central Committee and State Council, required the government to pay great attention to water conservancy construction and establish the rational allocation and efficient utilization system of water resources. In 2015, the Planning of National Agriculture Sustainable Development (2015–2030) was issued by the China Ministry of Agriculture, which aims to increase the effective utilization coefficient of farmland irrigation water. Therefore, provincial AWUE showed growth after 2011 and 2015. Due to regional differences in policy implementation measures and standards, there would be regional differences in the effects of the above policies on AWUE.

4.3. Discussion of Spatial Pattern of AWUE

The spatial performance of AWUE is primarily determined by the regional climate and agricultural system characteristics [56]. In general, the southern subregions are rich in precipitation and have well water resource endowment, which would benefit crop growth. Moreover, developed provinces always have advanced agricultural production technology and higher value-added agricultural products, which results in increased economic outputs per unit of water use. Thus, provinces with high AWUE values were located in southeastern China, while provinces with low values were mainly located in southwestern, south central, and north central China. Meanwhile, neighboring provinces always have similar geographical conditions and close communication, conducive to spreading spatial spillover effects between the adjacent areas [13,22,32].

However, the AWUE in several major grain-producing areas was low, including Hubei, Hunan, Jiangxi, and Anhui. Since it is often necessary to input a lot of irrigation water to ensure grain outputs, redundancy and shortage of irrigation water are the main reasons for low AWUE [58]. Moreover, the economic value per unit area for growing wheat and rice is lower than that for planting vegetables, fruits, and other cash crops.

4.4. Discussion of Spatial Correlation of Provincial AWUE

In the context of regional coordinated development, mobility of agricultural production factors has become more frequent [59], resulting in closer connections of resource utilization efficiency between different regions [38]. Each province could receive and send spillover effects of factors concerning agricultural water utilization, resulting in a significant correlation of AWUE between provinces. Meanwhile, with the increase in connections of AWUE between different provinces, the whole network became more robust.

The role of a particular province in the network may be related to its position in the national agricultural system. Figure 11 shows the ranking of provinces in agricultural economic outputs, grain outputs, and AWUE. Hebei, Jiangsu, Jilin, Shandong, and Hubei are major grain-producing areas from functional zoning. Provinces with a high added value of agriculture and large grain outputs may export many agricultural products to other provinces. Along with the frequent agricultural products trade, information and technology related to agricultural water utilization would be widespread. The AWUE in these provinces is more likely to correlate with other regions. From water use efficiency, agricultural sectors in Jilin, Shandong, Hubei, Guizhou, Yunnan, and Qinghai consumed water with low-level efficiency. To alleviate their water shortage, they had urgent needs to absorb information, technology, and the experience of water management from other regions [37]. Accordingly, the low-AWUE provinces would receive more spillover effects of water use efficiency from high-AWUE regions, resulting in the value of in-degree mostly in low-AWUE areas being higher than the value of out-degree.

Beijing and Shanghai are highly developed cities and have a high average value of AWUE. However, their agricultural outputs are significantly smaller than in other areas. Hebei has replaced Beijing's network functionality and has provided many resources for developing the Beijing-Tianjin-Hebei region [60]. Shanghai's network functionality was also replaced by Jiangsu [38]. For Inner Mongolia and Liaoning, their crop yield and economic output are high, and their agricultural water use efficiency is at the middle level. However, they are located in northern China and face severe water shortages. Correspondingly, it is more challenging to improve their water use efficiency, resulting in fewer connections between these provinces and others in AWUE.

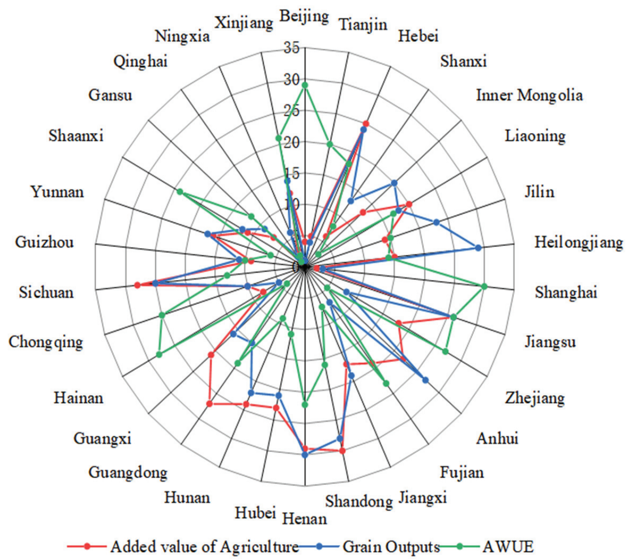

Figure 11. Ranking of average value of added value of agriculture, grain outputs, and AWUE (agricultural water use efficiency) in China from 2000 to 2019. (For comparison and display purposes, the highest value rank is 30, and the lowest value rank is 1.).

Fujian, Jiangxi, Qinghai, Hebei, Shandong, Guizhou, Jiangsu, Xinjiang, and Heilongjiang had high betweenness centrality, playing the role of a "bridge" to promote the dissemination of information, experience, knowledge, and technology concerning water use efficiency in the network. Most of the above provinces are major agricultural production regions. Generally, major grain-producing provinces are more sensitive to water shortages and are willing to adopt new management strategies and technology to improve agricultural water use efficiency [61]. For example, Jiangxi and Xinjiang are the primary agricultural production areas in China, and there is great demand for agricultural water. Xinjiang is even located in arid northwestern China. The two provinces are pilot regions for water rights trading. They have accumulated rich experience in water saving and constructed an advanced platform for the exchange and communication of water resource information [62]. They could assume the role of a bridge to promote the interactions of AWUE in other provinces.

Provinces in the net spillover block were mainly major grain-producing areas or had high levels of AUWE. They always possessed an advanced agricultural water management capacity and could drive the whole spatial correlation network, such as Inner Mongolia and Shanghai. Provinces within the middle level of AWUE mainly belonged to the bidirectional spillover block, which could receive spillover effects from other areas to improve AWUE and send helpful knowledge and information to others. Members in the agent block were more complex, including nodes with a high value, median value, and low value of AWUE. Therefore, this block can serve as a transfer station for agricultural water use efficiency information.

5. Conclusions

Affected by global climate change and water shortages, food security continues to be challenged. Improving agricultural water use efficiency and increasing the outputs of per unit water usage are essential to guarantee global food security. This article used the undesirable super-efficiency SBM model to measure the AWUE of 30 provinces in China from 2000 to 2019. Then, we investigated the spatial correlation of provincial AWUE with the social network analysis (SNA) method. The results found that:

(1) The overall agricultural water use efficiency in China was inefficient, and there is still great potential to improve it. The focus of sustainable agricultural water resource management included the broad application of water-saving technology and strict control of water pollution.

(2) All the provinces had experienced increasing AWUE in the past 20 years, but with apparent gaps. The growth rate of AWUE experienced a slight increase first and then a substantial increase. Provinces with higher AWUE were primarily located in the east, while the lower-AWUE areas were located in central and western China.

(3) There was a strong spatial correlation in provincial AWUE in China, presenting a typical network structure. It was necessary to manage water resources from a system and network perspective and improve coordinated agricultural water use efficiency.

(4) Fujian, Hebei, Jiangsu, Jilin, Shandong, Hubei, Guizhou, Yunnan, and Qinghai had high centrality in the network. Improvement in AWUE should pay more attention to the province with high centrality in the network and promote the spillover effects of agricultural water utilization between different regions.

(5) The nodes and links in the network were highly concentrated in the net spillover block, bidirectional spillover block, and agent block. We should focus on the driving role of the net spillover block, which is the power source of the improvement in AWUE in the whole network. Moreover, it is needed to strengthen the transmission of the bidirectional spillover block and agent block to promote the coordinated development of AWUE.

Therefore, when formulating relevant measures and policies to improve agricultural water use efficiency, they must pay attention to the spatial correlation of water resource utilization in different provinces to promote the common improvement in water use efficiency in all provinces.

Author Contributions: Conceptualization, Y.Z. and H.W.; methodology, T.Q.; software, T.Q.; validation, F.Z. and J.T.; formal analysis, Z.W. and H.W.; writing—original draft preparation, Y.Z. and F.Z.; writing—review and editing, Y.Z.; visualization, J.K., Z.F. and T.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 51861125101; the Fundamental Research Funds for the Central Universities, grant number 2018B710X14; the Postgraduate Research & Practice Innovation Program of Jiangsu Province, grant number KYCX18_0512; Projects of the National Social Science Foundation of China, grant number 20BGL191, and the Zijin Cultural Talent Project in Jiangsu Province, grant number PDJPC[2020]No.96.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The methods for the collection and preprocessing of the data are presented in Section 2. Data used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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Article

Food Waste Reduction from Customers' Plates: Applying the Norm Activation Model in South Korean Context

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Abstract: Researchers have pointed out the urgent need to tackle food waste from customers' plates, considering its environmental and socioeconomic impacts. Nonetheless, little is known about reducing food waste from customers' plates in the restaurant context. The present research successfully addressed how customers can reduce food waste by using the Norm Activation Model (NAM). A customer survey was employed to collect quantitative data to verify the hypotheses of this study. The NAM of this study involved awareness of environmental impact (of the restaurant industry), ascribed responsibility for food waste, and moral norm for food waste reduction as predictors for food waste reduction intention. In addition, this study adopted self-efficacy to food waste reduction as a moderator on the path from the moral norm for food waste reduction to food waste reduction intention. Our empirical results supported all the hypotheses suggested in the research model. Consequently, the findings of this study adequately explained how restaurant customers form their intention to reduce food waste and thus provided important clues about how it can be encouraged. For example, based on the findings, a nudging message may be displayed on the restaurant wall to raise customers' self-efficacy, saying, "Saving the earth is as easy as finishing your food or taking it home".

Keywords: food waste; norm activation model; self-efficacy; restaurant

Citation: Kim, W.; Che, C.; Jeong, C. Food Waste Reduction from Customers' Plates: Applying the Norm Activation Model in South Korean Context. *Land* **2022**, *11*, 109. https://doi.org/10.3390/land11010109

Academic Editors: Uttam Khanal and Sanzidur Rahman

Received: 18 December 2021
Accepted: 7 January 2022
Published: 10 January 2022

1. Introduction

Food waste is increasingly drawing public attention, causing adverse environmental and socioeconomic impacts [1]. The foodservice industry discharges substantial food waste globally [2,3]. For example, the foodservice industry generates about 12% of the 28 EU countries' total food waste [4]. US foodservice wastes up to 40% of the nation's total [5], implying considerable resource, energy, and environmental costs. The literature indicates that out-of-home dining results in more incredible food waste than home dining [6,7]. Nevertheless, foodservices have received much less scholarly attention than households in terms of food waste [6]. Further, foodservices have been studied much less than hotels regarding environmental impacts [2].

Although there is no official data available about amount of the food waste from the foodservices in South Korea, the food waste from households has been reported as decreasing every year [8] as households should pay costs in proportion to the amount of the food waste discharged. This policy is equally applied to the foodservices in South Korea. However, the cause of the problem lies in the fact that the foodservice operators directly pay the costs, not customers. Hence, customers are not directly rewarded by reducing their plate waste. It would be the fundamental reason people tend to be less motivated to reduce their food waste in restaurants than at home.

Undoubtedly, food waste is at the center of the harmful environmental influence of foodservices. Moreover, the food waste from foodservices is perfectly edible but discarded simply because it is no longer wanted [9]. This phenomenon is especially true for Korean food as typical Korean meals are served with several side dishes, which are a default option and thus easily left behind. Food waste causes climate change, land and water pollution, biodiversity loss, overharvesting, fossil fuel consumption, and many others [10]. The landfill is the most common method of food waste disposal in Korea, as most countries do [10]. In other words, food goes back to land, where it came from, as waste that pollutes the land, water, and air. Thus, there is need to intervene to reduce food waste, which is mostly 'edible,' in the foodservice sector [11]. Filimonau and De Coteau [12] asserts that continuous scholarly support is required to help foodservice managers in reveal the significance and determinants of effective mitigation of food waste.

In a broad sense, food waste is defined to include not only perfectly edible parts but also inedible parts (e.g., eggshells) and occasionally edible parts (e.g., potato skins, cucumber peels) [13]. However, given that the latter two food waste types are mostly unavoidable in the value-adding process in foodservices, this study pays particular attention to the perfectly edible food waste generated by restaurant customers. It is critical to address reducing edible food waste in the environmental perspective and the socioeconomic perspective [14], given that 11% of the world population are in hunger as of 2017 [15]. In this sense, restaurant customers' food waste reduction can be viewed from a moral viewpoint [11,16]. Accordingly, this study adopted the Norm Activation Model (NAM), which includes moral norm as a key driver of prosocial behavior [17], to predict restaurant customers' food waste reduction intention. The NAM is considered the most influential theory in the environmental literature [18].

This study is the first attempt to predict restaurant consumers' food waste reduction intention through their moral norm formation process. In addition, this study adopted self-efficacy to food waste reduction as a moderator on the path from the moral norm for food waste reduction to food waste reduction intention. Self-efficacy is a self-appraisal of one's capacity to organize and guide the actions essential to deal with certain situations [19]. Therefore, it follows that when customers believe they are capable of behaving in the ways required to mitigate food waste, their moral norm will drive them more strongly to form food waste reduction intention. By revealing the central roles of the moral norm and self-efficacy in forming customers' food waste reduction intention, this study contributes to drawing scholarly as well as managerial attention to how to simulate customers' moral norm and self-efficacy to food waste reduction, which is a win-win-win for the foodservices, customers, and the general public.

In sum, as the first study adopting the NAM in explaining restaurant customers' food waste reduction intention, this study aimed to verify (1) whether the NAM can successfully explain restaurant customers' food waste reduction intention, and (2) whether customers' self-efficacy to food waste reduction enhances the effect of their moral norm for food waste reduction on their food waste reduction intention in the South Korean restaurant context.

2. Literature Review and Hypotheses

2.1. Food Waste

The term "food waste" is interchangeably used with "food loss" by some scholars [20]. However, it is more practical to distinguish "food waste" from "food loss" as "food waste" represents the food lost at the consumption stage, whereas "food loss" represents the food lost at the value-adding stage [16,21]. Thus, food waste takes place at the household level as well as foodservice level. In the foodservice context, "food waste" refers to the food waste from customers' plates [22]. Given the growing dining-out trend, fueled by the advance of the foodservice industry and growth in income, increasing amount of edible food waste has been the focus of media, often blaming both foodservice businesses and their customers [12,21]. Witzel et al. [23] investigated Northern and Western European consumers, and applying cluster analysis led to the relationship between food-related lifestyle and food waste. Janssen et al. [24] examine the Dutch customer's household food management and food waste relation. Customers' overfull purchase behavior is the main reason for household food waste (Janssen et al.) [24]. Özbük [25] extension the theory of planned behavior by included price perception and food taste to discuss customers' food waste behavior in a restaurant. Goh and Je [26] applied theory planned behavior to explain the Generation Z hotel employees' food wastage motivation. Their research also points out that using fresh food material to improve customer satisfaction renders hotel employees ascribed responsibility for food waste [26].

It implies that both foodservice operators and customers share responsibilities in reducing edible food waste. They can easily cooperate to reduce edible food waste from customers' plates since it is a relatively low-hanging fruit [27] compared to reducing food loss in the kitchen. Studies show that consumers are the biggest generator of food waste [28], and the wasted food can be avoided mainly by consumers' environment-considerate behaviors [29,30]. Certainly, foodservice operators can facilitate their customers' environment-considerate behaviors [31]. Fortunately, restaurants are gradually paying attention to exemplary restaurant cases of food waste reduction [16].

2.2. Norm Activation Model

Developed by Schwartz [32], Norm Activation Model (NAM) has been extensively adopted to explain various prosocial behaviors [33,34], including energy saving behavior (e.g., Wittenberg, Blöbaum, and Matthies [35]), sustainable transport behavior (e.g., Bamberg, Hunecke, and Blöbaum [36]), environmental complaint behavior (e.g., Zhang, Liu, and Zhao [37]), and recycling behavior (e.g., Han and Hyun [38]). Prosocial behavior refers to the behavior intended to benefit other people or the general public [33]. In this regard, food waste reduction is undoubtedly a type of prosocial behavior [39]. Therefore, the NAM is the suitable theoretical model to explain food waste reduction behavior. However, no study has empirically verified restaurant customers' food waste reduction intention using the NAM.

The NAM consists of three antecedents that predict people's prosocial behavior. Namely, they are awareness of consequences (AC), ascribed responsibility (AR), and personal norm (PN) [32]. AC is defined as "whether someone is aware of the negative consequences for others or for other things one values when not acting pro-socially" [33] (p. 426). AR indicates "feelings of responsibility for the negative consequences of not acting pro-socially" [33] (p. 426). PN refers to a feeling of a "moral obligation to perform or refrain from specific actions" [33] (p. 426). The original norm activation model proposes that when people are aware of the negative consequences of not acting pro-socially (i.e., AC), they are likely to feel joint responsibility for the consequences of their non-prosocial behavior (i.e., AR). Thus, they would have a moral obligation to quit the non-prosocial behavior or adopt the alternative prosocial behavior (i.e., PN) [32]. Consequently, such felt moral norm would lead people to protect the environment [32,33,40].

As mentioned, food waste reduction should be considered as a type of prosocial behavior. Therefore, following the NAM, the more people are aware of the negative consequences of the foodservice industry (i.e., AC), the more they will feel responsible for the negative consequences of wasted foods (i.e., AR). In turn, the more people feel responsibility for the negative consequences of wasted foods (i.e., AR), the more they will feel a moral obligation to reduce food waste (i.e., PN). Finally, this felt moral obligation would induce people to form food waste reduction intention.

Whereas the original model suggests sequential influences (i.e., AC $\rightarrow$ AR $\rightarrow$ PN $\rightarrow$ prosocial behavior), some scholars have suggested both AC and AR as the predictors of PN [35] since AC initially triggers a person's moral obligation (i.e., PN) [41]. As such, previous studies have shown inconclusive viewpoints and each of the viewpoints has its own sound theoretical bases and empirical supports [35]. Therefore, the mediation model was adopted as the proposed model of this study to embrace both viewpoints. Using this well-proven theoretical model of the NAM, the following hypotheses were suggested in the context of customers' food waste in restaurants.

Hypothesis 1 (H1). *Awareness of environmental impact of the foodservice industry positively affects ascribed responsibility for food waste.*

Hypothesis 2 (H2). *Awareness of environmental impact of the foodservice industry positively affects moral norm for food waste reduction.*

Hypothesis 3 (H3). *Ascribed responsibility for food waste positively affects moral norm for food waste reduction.*

Hypothesis 4 (H4). *Moral norm for food waste reduction positively affects food waste reduction intention.*

2.3. Self-Efficacy to Food Waste Reduction

Self-efficacy represents a personal belief in one's capability to act to tackle certain situations [19]. It leads people to exert greater efforts to engage in and maintain certain behaviors [19,42]. In other words, the more people believe they are capable of taking actions to achieve certain goals, the more they tend to take the actions. As such, self-efficacy motivates people to engage in specific behaviors. Therefore, with the same level of the moral norm for food waste reduction, those with higher self-efficacy to food waste reduction would form stronger food waste reduction intention than those who have lower self-efficacy. Thus, integrated into the NAM, this motivational effect of self-efficacy would work as a moderator as follows.

Hypothesis 5 (H5). *Self-efficacy to food waste reduction will enhance the positive impact of moral norm for food waste reduction on food waste reduction intention.*

Figure 1 graphically illustrates the study constructs and hypotheses suggested above.

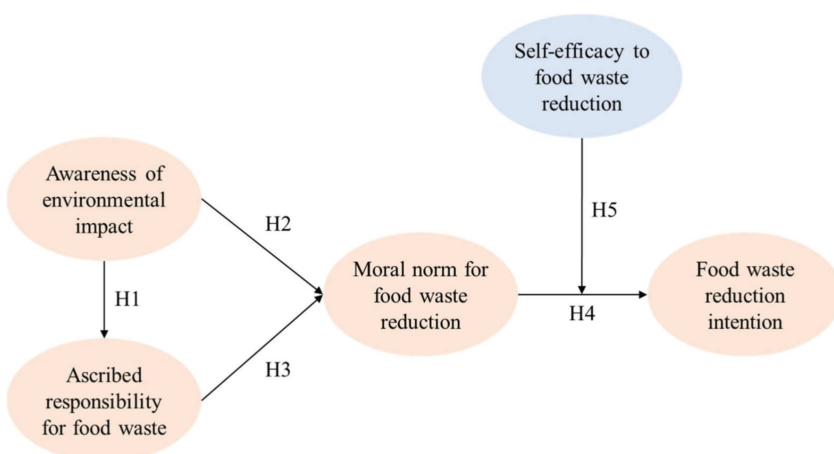

Figure 1. The proposed conceptual model.

3. Method

3.1. Measures

The measures of this study were borrowed from previous research in the environmental psychology and consumer behavior literature. All the constructs were measured with multiple items in a seven-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (7). Three items were used to measure awareness of environmental impact (e.g., "The restaurant industry causes pollution, climate change, and exhaustion of natural resources", "The restaurant industry may have a huge environmental impact on the atmosphere, soil, and water", "The restaurant industry causes environmental deteriorations (e.g., excessive waste generation, waste of food materials)") [43]. Ascribed responsibility for food waste was evaluated with three items (e.g., "I feel jointly responsibility for reducing food waste while eating out at restaurants", "I feel jointly responsibility for the negative consequences of not practicing efforts to reduce food waste while eating out at a restaurant", "I feel jointly responsibility for the environmental pollution and ecological damage problems caused by not practicing efforts to reduce food waste while eating out at a restaurant") [44]. Four items were utilized to measure moral norm for food waste reduction (e.g., "It is contrary to my principles when I have to discard food", "I have been raised to eat all food I have taken myself", "Leaving leftovers give me a bad conscience", "It is contrary my principles when I have to discard food") [9]. Food waste reduction intention was evaluated with three items (e.g., "I try to eat all food that I have ordered", "The next time when I eat out at a restaurant, I intend to not throw food away", "The next time when I eat out at a restaurant, I will try to leave as little food as possible") [9]. Lastly, four items were adopted to assess self-efficacy to food waste reduction (e.g., "There are simple things I can do that reduce the negative consequences of food waste", "I can change my daily routines to prevent the problem caused by food waste", "My individual actions will contribute to a solution of the problem caused by food waste", "Changes in my daily routines will contribute to reducing the negative con-sequences of food waste") [45].

Along with these measures, the questionnaire included the research description and questions asking the respondent's demographic profiles. The face validity of the measures was tested by two foodservice academics and two industry professionals. Since all the measures adopted in this study had been well verified in various study contexts, no major modification was made. Just slight wording changes on the questions were made to make them clearer and easier to understand and finally the questionnaire was confirmed with a thorough review from the foodservice academic experts, who are professors in a hospitality program in a university in South Korea.

3.2. Data Collection and Respondent Profiles

The South Korean restaurant distinguished from other countries restaurant is the typical Korean meals offer the side dished, the most classic example is Hanjongshik. It means Korean consumers have potential food waste behavior. According to this situation, we decided to explore South Korean consumers. The data for this study were collected through the biggest online panel survey firm in South Korea. The firm's database has more than 1.4 million panel members, including all types of Koreans, from which the samples were randomly selected through the firm's random sampling algorithm. Then, the firm's system emailed an online invitation to the sampled panel members. Receiving the invitation, they accessed and filled out the online questionnaire. Only those who had dined out in a restaurant within the last three months were qualified to complete the survey. The description of the research was provided at the beginning of the questionnaire. Through this process, 315 usable responses were obtained. Because there were no incomplete or inconsistent responses, all the 315 data points remained for the analysis.

Of the 315 samples, 50.2% were female while 49.8% were male. The mean age was about 43.7 years old. 22.8% were in the 40′s, 20.0% were in the 30′s, 19.7% were in the 50′s, 19.4% were in the 20′s, and 18.1% were in 60′s. Regarding education level, 65.7% reported a bachelor′s degree, 13.7% reported graduate school or higher, 11.1% reported a high school diploma, and 9.5% reported an associate degree. Lastly, in terms of monthly income, 36.8% reported an income less than US$2500, followed by 29.6% between US$2501–4500, 17.4% between US$4501–6500, 8.9% between US$6501–8500, and 7.3% over US$8501. Overall, the samples appeared to well represent typical restaurant customers in South Korea.

4. Results

4.1. Measurement Model Evaluation

A confirmatory factor analysis (CFA) was conducted to evaluate the fit of the measurement model to the data and verify the reliability, convergent validity, and discriminant validity of the measures [46]. As shown in Tables 1 and 2, the results of the CFA showed that the measurement model adequately fits the data (χ^2 = 259.534 (df = 108, p < 0.001, χ^2/df = 2.403), RMSEA = 0.067, CFI = 0.969, IFI = 0.969, TLI = 0.961). All the measures significantly loaded on their associated constructs at p < 0.001. The composite reliability values of the constructs were all above the recommended cutoff of 0.700, ranging from 0.842 to 0.952, showing satisfactory internal consistency of the measures for each construct [47]. The average variance extracted (AVE) values of the constructs all exceeded the suggested cutoff of 0.500 [47], ranging from 0.574 to 869. It indicated that the measures of each construct had adequate convergent validity [48]. Lastly, satisfactory discriminant validities of the constructs were established since the AVE value of each construct was above the squared correlations with the other constructs [48].

Table 1. Measurement model assessment.

Constructs and Measures	Loading
Awareness of environmental impact (CR = 0.923, AVE = 0.800)	
The restaurant industry causes pollution, climate change, and exhaustion of natural resources.	0.882
The restaurant industry may have a huge environmental impact on the atmosphere, soil, and water.	0.904
The restaurant industry causes environmental deteriorations (e.g., excessive waste generation, waste of food materials).	0.897
Ascribed responsibility for food waste (CR = 0.952, AVE = 0.869)	
I feel jointly responsibility for food waste reduction while eating out at a restaurant.	0.904
I feel jointly responsibility for the negative consequences of not practicing efforts to reduce food waste while eating out at a restaurant.	0.954
I feel jointly responsibility for the environmental pollution and ecological damage problems caused by not practicing efforts to reduce food waste while eating out at a restaurant.	0.938
Moral norm for food waste reductio (CR = 0.842, AVE = 0.574)	
I feel guilty about poor people when I leave leftover food.	0.612
Leaving leftovers give me a bad conscience.	0.762
I have been raised to eat all food I have taken myself.	0.789
It is contrary my principles when I have to discard food.	0.847
Food waste reduction intention (CR = 0.934, AVE = 0.826)	
The next time when I eat out at a restaurant, I will try to eat all food that I order.	0.930
The next time when I eat out at a restaurant, I intend to not throw food away.	0.917
The next time when I eat out at a restaurant, I will try to leave as little food as possible.	0.878
Self-efficacy to food waste reduction (CR = 0.933, AVE = 0.777)	
There are simple things I can do to reduce the negative consequences of food waste.	0.823
I can change my daily routines to prevent the problem caused by food waste.	0.861
My individual actions will contribute to a solution of the problem caused by food waste.	0.926
Changes in my daily routines will contribute to reducing the negative consequences of food waste.	0.912

Note: All standardized loadings were significant at p < 0.001.

Table 2. Results of the confirmatory factor analysis and correlations (n = 315).

Construct	(a)	(b)	(c)	(d)	(e)	CR	AVE
(a) Awareness of environmental impact	-	0.101 [b]	0.073	0.008	0.048	0.923	0.800
(b) Ascribed responsibility for food waste	0.318 [a]	-	0.430	0.358	0.437	0.952	0.869
(c) Moral norm for food waste reduction	0.270	0.656	-	0.493	0.316	0.842	0.574
(d) Food waste reduction intention	0.092	0.598	0.702	-	0.494	0.934	0.826
(e) Self-efficacy to mitigate climate crisis	0.219	0.661	0.562	0.703	-	0.933	0.777
Mean	4.43	5.30	4.83	5.75	5.62		
SD	1.24	1.19	1.20	1.10	0.94		

Goodness-of-fit statistics:
χ^2 = 259.534 (df = 108, p < 0.001, χ^2/df = 2.403),
RMSEA = 0.067, CFI = 0.969, IFI = 0.969, TLI = 0.961

[a] Correlation
[b] Squared correlation

Note: CR = composite reliability; AVE = average variance extracted; SD = standard deviation; RMSEA = root mean square error of approximation; CFI = comparative fit index; IFI = incremental fit index; TLI = Tucker-Lewis index.

4.2. Structural Model Analysis and Hypotheses Testing

A structural equation modeling (SEM) was conducted to test the hypothesized relationships in the structural model. The model was shown to fit the data well (χ^2 = 151.903 (df = 60, p < 0.001, χ^2/df = 2.532), RMSEA = 0.070, CFI = 0.974, IFI = 0.974, TLI = 0.966). As shown in Table 3 and Figure 2, the suggested causal relationships satisfactorily accounted for the variance in food waste reduction intention (R^2 = 0.542). 47.6% of the total variance in moral norm for food waste reduction and 10.1% of the total variance in ascribed responsibility for food waste were accounted for by its antecedent(s).

Table 3. Results of the structural equation modeling (n = 315).

	Independent Construct	Dependent Construct	Coefficient	t-Value
H1	Awareness of environmental impact	Ascribed responsibility for food waste	0.318	5.425 ***
H2	Awareness of environmental impact	Moral norm for food waste reduction	0.032	0.607
H3	Ascribed responsibility for food waste	Moral norm for food waste reduction	0.679	8.833 ***
H4	Moral norm for food waste reduction	Food waste reduction intention	0.736	9.101 ***

Total variance explained (R^2):
R^2 for ascribed responsibility for food waste = 0.101
R^2 for moral norm for food waste reduction = 0.476
R^2 for food waste reduction intention = 0.542

Goodness-of-fit statistics:
χ^2 = 151.903 (df = 60, p < 0.001,
χ^2/df = 2.532), RMSEA = 0.070,
CFI = 0.974, IFI = 0.974,
TLI = 0.966
*** p < 0.001

Note: RMSEA = root mean square error of approximation; CFI = comparative fit index; IFI = incremental fit index; TLI = Tucker-Lewis index.

The SEM results showed that awareness of environmental impact significantly and positively affected ascribed responsibility for food waste ($ß$ = 0.318, p < 0.001), supporting H1. However, awareness of environmental impact did not significantly affect moral norm for food waste reduction (H2) ($ß$ = 0.032, p > 0.05). An additional mediation test revealed that this insignificant effect was resulted from a full mediation by ascribed responsibility for food waste. Specifically, when the path from ascribed responsibility for food waste to moral norm for food waste reduction was constrained to zero, the effect of awareness of environmental impact on moral norm for food waste reduction became significant ($ß$ = 0.267, t = 4.05 (p < 0.001)). The χ^2 difference between the original model and the constrained model ($\Delta\chi^2(1)$ = 135.681) was significant at p < 0.001, indicating that the mediation effect was highly significant. Going back to the original model, ascribed responsibility for food waste significantly and positively affected moral norm for food waste reduction ($ß$ = 0.679, p < 0.001) and, in turn, moral norm for food waste reduction significantly and positively affected food waste reduction intention ($ß$ = 0.736, p < 0.001), supporting H3 and H4.

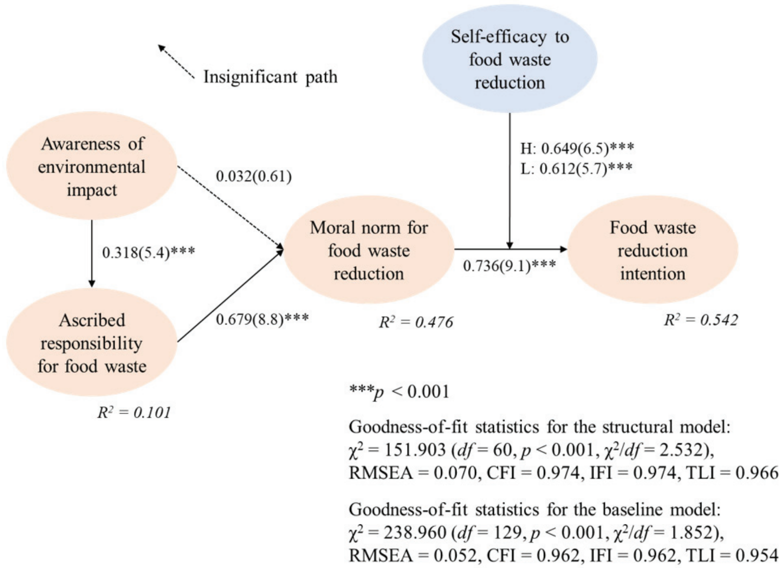

Figure 2. The structural model results.

Next, the indirect effects of the mediating constructs were tested. As in Table 4, awareness of environmental impact ($ß = 0.183$, $p < 0.05$) and ascribed responsibility for food waste ($ß = 0.500$, $p < 0.01$) showed a significant positive indirect impact on food waste reduction intention. In addition, awareness of environmental impact showed a significant positive indirect impact ($ß = 0.216$, $p < 0.05$) on moral norm for food waste reduction. Lastly, in terms of the total effect, the findings showed that moral norm for food waste reduction exerted the greatest effect on food waste reduction intention ($ß = 0.736$, $p < 0.01$), followed by ascribed responsibility for food waste ($ß = 0.500$, $p < 0.01$), and awareness of environmental impact ($ß = 0.183$, $p < 0.05$).

Table 4. Results of the indirect and total effect assessment.

	Indirect Effect of	
On	**Awareness of Environmental Impact**	**Ascribed Responsibility for Food Waste**
Moral norm for food waste reduction	0.216 *	–
Food waste reduction intention	0.183 *	0.500 **
Total effect on food waste reduction intention: β awareness of environmental impact = 0.183 * β ascribed responsibility for food waste = 0.500 ** β moral norm for food waste reduction = 0.736 **	* $p < 0.05$, ** $p < 0.01$	

4.3. Invariance Model Test

A metric invariance test was conducted to evaluate the hypothesized moderating effect of self-efficacy to food waste reduction. The respondents were separated into high and low self-efficacy to food waste reduction groups through a K-means cluster analysis. 187 respondents were clustered into the high group and 128 into the low group. In turn, a baseline model involving both the high and low groups were created. Our results showed that the baseline model satisfactorily fit the data ($\chi^2 = 238.960$ ($df = 129$, $p < 0.001$, $\chi^2/df = 1.852$), RMSEA = 0.052, CFI = 0.962, IFI = 0.962, TLI = 0.954). Table 5 and Figure 2 show the detailed results of the baseline model test. Subsequently, the baseline model was compared with the nested model where the path from moral norm for food waste reduction to food waste reduction intention was constrained to be equivalent. As expected, our results showed that the influence of moral norm for food waste reduction on food waste reduction intention differed significantly between the high and low self-efficacy groups ($\Delta\chi^2(1) = 4.70$, $p < 0.05$), supporting H5. The χ^2 difference test was shown in Table 5.

Table 5. Results of the invariance model assessment.

Linkage	**High SMCC Group (n = 187)**		**Low SMCC Group (n = 128)**		**Baseline Model (Freely Estimated)**	**Nested Model (Equally Constrained)**
	β	***t*-Value**	β	***t*-Value**		
Moral norm for food waste reduction → Food waste reduction intention	0.649	6.448 ***	0.612	5.719 ***	χ^2 (129) = 238.960	χ^2 (130) = 243.658 [a]
Chi-square difference test: [a] $\Delta\chi^2$ (1) = 4.70, $p < 0.05$ (H5: Supported) ***$p < 0.001$			Goodness-of-fit statistics for the baseline model: χ^2 = 238.960 (df = 129, $p < 0.001$, χ^2/df = 1.852), RMSEA = 0.052, CFI = 0.962, IFI = 0.962, TLI = 0.954			

Note: SMCC = self-efficacy to mitigate climate crisis.

5. Discussions

5.1. Discussions and Implications

The current research tested the relationship of awareness of environmental impact. Ascribed responsibility of food waste, moral norm for food waste reduction, self-efficacy to food waste reduction, and food waste reduction intention, modeled restaurant consumers' food waste reduction intention through the moral norm formation process. The hypothesis also explored the mediate and moderate effect and robust evidence of the relationship between self-efficacy to food waste reduction and its direct determinants. The norm activation model in this research act as a firm theoretical framework that illuminates the restaurant consumer's moral obligation and food waste reduction intention. The Seoul metropolitan government implement the "Pay as You Throw" system to encourage its people to reduce food waste [49]. Moreover, as mentioned in the literature review, the restaurant should make the customer aware that wasting food is not a good habit. It also has irreversible environmental consequences [40].

The three antecedents of the norm activation model (awareness of the environmental impact, ascribed responsibility for food waste, the moral norm for food waste reduction) were adopted to explain the energy-saving behavior [35,37,38]. The goal of the restaurant is to avoid food wastage [16,31]. The findings of this study revealed that ascribed responsibility for food waste fully mediated the relationship between awareness of environmental impact (of the foodservice industry) and moral norm for food waste reduction. This result is in line with previous studies that took such sequential relationships in green research (e.g., Meng, Chua, Ryu, and Han [50]; Steg and De Groot [41]). As mentioned in the literature review and hypotheses section, this study adopted the mediation version of the NAM, where both AC and AR affect PN [35], to embrace both rivaling versions of the NAM. The findings of this study indicate that the sequential version of the NAM is more appropriate in the context of this study. It means that when customers are aware of the environmental damage caused by the foodservice industry, they are more likely to feel joint responsibility for the negative consequences of their food waste. This feeling leads them to feel moral norm to reduce their food waste. Therefore, arousing people's attention to potential environmental impacts of foodservices is certainly the first step to reduce customers' food waste. Then, people will feel responsibility for their plate waste and, in turn, form moral norm to decrease it. As shown in Figure 2, the awareness of environmental impact is not significant to the moral norm for food waste reduction. This result differs from some prior studies [35,41]. This result may be explained by customers' lack of knowledge about restaurant food waste. Xu et al. [51] analyzed the Chinese restaurant and detected the consumer's food taste and the big meal directly influences customer's dishes waste. Combined with this research finding, the restaurants need to know food tastes yucky and more significant portions are not pro-environment behavior. The most critical point is consumers didn't become aware that they didn't eat the not tasty food or order overfilled dishes is environmentally unfriendly behavior. As a South Korean situation, the restaurant inquiry about the consumers' need to freebie or not. According to the analysis results, customers' self-efficacy to food waste reduction enhanced the effect of moral norm for food waste reduction on food waste reduction intention. It indicates that with the same level of moral norm, the customers who recognize there are simple things they can do to reduce their plate waste would develop stronger intention to reduce plate waste than those who do not. This finding indicates that foodservice managers should make it easy and convenient for customers, for example, to order just as much food as they can finish and choose the right menu that suits their taste. Managers can even make customers feel proud of taking leftover food home, for example, by putting a message saying "I am proudly saving the earth" on a takeout bag. The restaurant can make rules like "Pay as You Throw" [49]. Moreover, perhaps restaurants offer reduced-sized plates, or encouraging eco-friendly "take-home" containers can solution the leftovers problem. On the other side, government policymaking plays a key background role in food waste.

Filimonau et al. [52] pointed out that it is challenging for foodservice managers to identify food waste and measure its exact amount. However, our society would not expect managers to reduce food waste by 100%. We just hope they do their best in reducing food waste together with their customers. Whatever the result would be, the general public would appreciate their efforts and sincerity since people would believe the joint effort by managers and customers will eventually produce meaningful results in our society. The ultimate outcome to the restaurant would be their improved image as a restaurant of "good influence" besides better financial outcomes through saved costs and improved operational efficiency, coming from increased customer traffic owing to improved reputation. Customers are smarter and increasingly environment-sensitive than ever before.

Research suggests customers' food waste reduction intention would not be enough to predict their actual actions. For example, Dolnicar, Juvan, and Grün [53] suggested some interventions can promote customers' actual food waste reduction behavior such as using a stamp collection booklet for zero plate waste or a flyer asking customers to help in reducing food waste in hotel buffets. Elhoushy [54] highlighted the importance of having motivational balance for an intention to lead to an action. In other words, in a case where a customer has conflicting motivations to avoid carrying doggy bags as well as to leave zero plate waste, the probability for the customer to take leftover home would be less than in a case where the customer has compatible motivations. To induce customers' intention to actual action, managers should be able to remove customers' conflicting motivations by changing their perceptions on food waste reduction practices such as carrying takeout bags, asking to take back unwanted side dishes, ordering just enough food to eat, and so on. Those are great practices to be proud of, not to be shame of. It is scientifically and ethically correct. Therefore, it is what socially responsible foodservices should do in this era of climate crisis.

Further, foodservices may consider providing customers with an option to choose their portion size as pizzerias do. This practice can help customers to order right amount of food for them to finish. This practice will not necessarily reduce foodservices' revenue since a half portion size does not mean a half price. Involving some fixed costs, a half-size menu is reasonable to be priced, for example, around 75% of the price of a whole-size menu. This practice would be especially welcomed by female one-person household customers, who are steadily increasing in number globally. They are sensitive not only about healthy diet but also about environment-friendliness and, critically, they are active in online communication [55].

5.2. Limitations and Future Research

This study includes the following limitations. First, the present study used the responses from South Korean customer samples. This may lead to a concern about the generalizability of the results. Future research may extend this study by test a similar conceptual model in other countries as food waste is a global matter. Second, like other socio-psychological studies dealing with people's decision-making processes (e.g., Ajzen [56]; Perugini and Bagozzi [57]), this study investigated customers' general decision formation. Future research may measure customers' actual food waste reduction behaviors to assess their behavioral changes. Third, in this study, the impact of restaurant types (e.g., fine dining, casual dining, fast casual) was not considered. It increases the generalizability of the results. Fourth, the current research uses the questionnaire to discuss consumers' potential behavior. Fifth, future studies can research the relationship between government policy and norm activation model theory. However, future research may focus on some specific types of foodservices when interested in finding type-specific results.

6. Conclusions

When tested in the context of food waste from restaurant customers' plates, the norm activation model revealed moral norm for food waste reduction as the most influential antecedent of customers' food waste reduction intention (R^2 = 54.2%, see Table 3). It implies that when customers feel guilty or uncomfortable about leaving food behind, they are more likely to intend to finish all the food on their plates or take it home. The previous research shows that the preventive measures of food waste is stakeholders (e.g., government, local enterprise, restaurant industry and so no) make a comprehensive action plan to promote restaurant pro-environment programs [58]. Especially, there is some change of food waste since COVID-19 pandemic [59–63]. Given that making customers happy is a basic role of foodservice managers, they should make customers feel comfortable by helping them not to leave food behind. Managers can help customers to order just as much as they can finish or to take leftover food home easily and comfortably, or rather proudly. It is apparent that if managers can do so, the amount of food waste from customers' plates will be decreased dramatically. At first glance, managers may think sales volume would decrease. However, in the long run, such socially responsible practices will certainly pay back to them since customers these days are increasingly becoming sensitive about climate change and socially responsible management of all types of businesses [64,65]. Further, consumers are today widely connected to so many people online to spread good word of mouth so easily and quickly than ever before.

Author Contributions: Conceptualization, W.K.; methodology, W.K.; writing—original draft preparation, W.K.; writing—review and editing, C.C.; visualization, C.C.; supervision, C.J.; project administration, C.J.; funding acquisition, C.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Because of the observational nature of the study, and in the absence of any involvement of therapeutic medication, no formal approval of the Institutional Review Board of the local Ethics Committee was required. Nonetheless, all subjects were informed about the study and participation was fully on a voluntary basis. Participants were ensured of confidentiality and anonymity of the information associated with the surveys. The study was conducted in accordance with the Helsinki Declaration.

Informed Consent Statement: Not applicable.

Data Availability Statement: The dataset used in this research are available upon request from the corresponding author. The data are not publicly available due to restrictions i.e., privacy or ethical.

Conflicts of Interest: The authors declare no conflict of interest.

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Article

Spatio-Temporal Patterns of the Land Carrying Capacity of Tibet Based on Grain Demand and Calorie Requirement

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Abstract: Tibet constitutes a major part of the Qinghai–Tibet Plateau (QTP) and is a typical ethnic minority (e.g., Tibetan) and ecologically fragile area in the world. Land resources are one of the most important foundations of food production, and Tibet's increasingly multi-type food demands are putting new pressure on land resources. However, there is still debate on how many people can be supported with the food production in Tibet. Investigating the land carrying capacity (LCC) in Tibet is very important for maintaining food security and formulating sustainable land management and utilization. Based on an analysis of the unique characteristics of the local farming, pastoral production, and dietary consumption, the spatio-temporal patterns of theLCC in Tibet in 2000–2019 were quantitatively assessed against the grain demands and calorie requirements at three different standards of living (i.e., basic prosperity, comprehensive moderate prosperity, and affluence). The dietary consumption was characterized by the high consumption of grains and meat products, and the low consumption of fruits and vegetables. The LCC in Tibet has continued to increase. The LCC in approximately 60% of the counties increased, with the high-LCC counties concentrated mainly in the Yarlung Zangbo River—Nyangqu River—Lhasa River area, and municipal districts and pastoral counties generally experiencing a low LCC. The load on land resources (LoL) in Tibet exhibited the characteristic of overall balance with local overloads and increasing tensions. More than 50% of the counties experienced population overload, mainly in municipal districts and pastoral counties. Food surplus was mainly found in farming counties, while the food production in pastoral counties was generally unable to meet the calorie demand. Considering the important role of land use in maintaining regional food security and ecological security, the conversion of grassland to cultivated land, the occupation of cultivated land, and the phenomenon of cultivated land was used to non grain should be avoided. Trans-regional transport of food should be strengthened to meet the calorie needs in population overload areas in the future. Our study provides a perspective for evaluating the pressure of land resources. The result can provide a reference for realizing the balance of grain and calorie supply–demand and lay a foundation for formulating sustainable land use policies in the QPT.

Keywords: land carrying capacity; load on land resources; food supply–demand balance; spatio-temporal patterns; Tibet

Citation: Zhang, C.; Yang, Y.; Xiao, C.; You, Z.; Song, X. Spatio-Temporal Patterns of the Land Carrying Capacity of Tibet Based on Grain Demand and Calorie Requirement. *Land* **2022**, *11*, 380. https://doi.org/10.3390/land11030380

Academic Editors: Uttam Khanal and Sanzidur Rahman

Received: 25 January 2022
Accepted: 1 March 2022
Published: 4 March 2022

1. Introduction

Since the late 20th century, the population–land relationship focusing on population, resources, environment, and development has become an increasingly important topic in geography, resources sciences, and other scientific disciplines [1,2]. As a major tool for describing the limitations to development and a major means for assessing the population–land relationship, the land carrying capacity (LCC) has become a major measure of sustainable development [1,2]. The resources and environmental carrying capacity (RECC) has gained increasing attention in research areas such as regional planning, ecosystem services assessment, and sustainable development, especially in the balance of food supply and demand [3–5]. Land resources are the basis for the sustenance and development of human society. LCC, a measure of the population size that can be sustained by the current land resources, is a traditional hot topic in research on RECC [6].

The Qinghai–Tibet Plateau (QTP) occupies a unique ecogeographical position, serves as a major barrier protecting the ecological security in China, and is among the areas in the world that are most sensitive to climate change [7]. Moreover, the QTP is a major gathering area for ethnic minorities (e.g., Tibetan) and an area where agricultural–pastoral cultures intersect. The issues of resource environment and food security in the QTP have always received high attention from the government and scholarly community. Because of the unique geographical environmental limitations and the impact of stringent ecological protection policies, the grain production on the QTP does not meet the local consumption demand [8]. Maintaining a food supply–demand balance in the QTP has received high attention from the Chinese Central Government. In his Congratulatory Letter to the Second QTP Comprehensive Scientific Expedition Team of the Chinese Academy of Sciences, for example, Chinese President Xi Jinping highlighted the necessity of further efforts to investigate the resources and environmental carrying capacity (including LCC), disaster risk, and other problems in the plateau [9]. Tibet constitutes a major part of the QTP, and securing food supply–demand balance is of important strategic significance for securing the ecological barrier, promoting stable development in the border areas, and protecting China's homeland security.

Focusing on the population size that can be sustained by current land resources, Park et al. first introduced the concept of LCC in 1921 [10]. With nearly a century's development, LCC research has gradually broadened its scope from analysis of grain supply–demand balance to research on food supply–demand balance, with the concepts of cereal equivalent and nutrient equivalent gradually introduced into relevant research [11,12]. The dietary consumption of Chinese residents has changed since the country succeeded in building a moderately prosperous society, and this has led to increasing research on dietary consumption [13–16] and the emergence of LCC research based on food consumption demand [17,18]. For Tibet, research has been conducted on the individual factors of RECC—such as water resources [19], ecology [20], and grassland [21]—and on the overall RECC [22–24]. In particular, long-standing research has been conducted on the LCC in Tibet. In the 1980s, the Commission for Integrated Survey of Natural Resources of the Chinese Academy of Sciences [25] was the first to study the LCC in theQTP. Shang [26] predicted the maximum output of agricultural crops and meat products using an agricultural ecological zone method, and the results showed that Tibet would be short of approximately 50 thousand tons of grain per annum in 2025. In the 1990s, Liu [27] assessed the land resources and investigated the potential capacity of agricultural production in the middle reaches of the Yarlung Zangbo river. Entering the 21st century, Zeng simulated the population carrying capacity in Tibet during 1985–2005, and the results showed that Tibet would face severe population overload in the future [28]. In recent years, Wang et al. [29] and Hao et al. [30] used nutrient equivalent to estimate the LCC in Tibet. Existing research has provided reference methods for LCC research, but there are controversies over whether the land resources in Tibet are overloaded. In addition, the food consumption level is often assumed to be temporally constant, and there is space for improvement with the measurement of effective calorie supply.

In fact, in the vast geographical area of China, different regions differ in food production and dietary consumption; thus, LCC research based on regional food production structure and dietary consumption characteristics can reveal more truthfully the regional levels of load on land resources (LoL). As a unique agricultural geographical unit of China, Tibet consists of farming, pastoral, and farming–pastoral, counties with unique food production and consumption characteristics [31]. In terms of geographical environment and land use in Tibet, the terrain slopes from northwest to southeast and is complex and diverse. The climate is cold and dry in the northwest, and warm and humid in the southeast. The land use type is mainly grassland (about 65% of the total land), and cultivated land are scarce (merely 0.3% of the total land). In particular, there are obvious regional differences between planting and animal husbandry. In terms of socioeconomics, both urbanization and economic development have great potential. In fact, the problems of land resources utilization and food security in Tibet are typical of mountainous–pastoral areas and underdeveloped areas.

Generally, livestock products (mainly beef, mutton, and dairy products) have constituted a major part of the dietary consumption of Tibetan residents, while the local grain production does not satisfy the local demand. The per capita share of grain was only 300 kg in 2019 in Tibet, less than 65% of the national average. In recent years, Tibet has enjoyed rapid socioeconomic development and increasing communication with other Chinese provinces; Meanwhile, the food consumption levels of Tibetan farmers and herdsmen have increased, and their dietary structures have become increasingly diversified. In particular, the consumption demand for rice, wheat, vegetables, and fruits has increased [8]. However, there remain prominent problems, such as imbalanced dietary structures. Overall, Tibet produces only a limited range of plant foods, while the supply of livestock products is constrained by increasingly stringent policies on animal husbandry [32], resulting in prominent structural problems in food supply and demand. Particularly, grazing exclusion increased grazing pressure in unfenced areas, and lowered the satisfaction of herders and food production [33]. Investigating the LCC in Tibet by considering only the demand for grain or the demand for food in individual scenarios cannot reveal the true state and future trends of food supply–demand balance.

In Tibet, food security is not only related to the lives of residents, but also has special significance in socio-economic development, ethnic unity, and border security. After the COVID-19 pandemic, the port blockade led to the interruption of food markets, supply chains, and trade. The issue of “food security” has once again been raised [34]. It is particularly important to consider the security of the food supply considering its own food production capacity. From a long-term perspective, exploring the LCC of Tibet, an area with interlaced farming–pastoral culture and fragile ecological environment, and clarifying the relationship between population and food production–consumption in this area will help promote the sustainable use of land resources on the QTP and socio-economic as well as ecological sustainable development.

Therefore, the present study was aimed at investigating the spatio-temporal patterns of the LCC in Tibet against the grain demands and calorie requirement at different standards of living. This study attempted to answer the following questions. (1) What are the characteristics of the residents’ dietary consumption structure? (2) What is the population size that can be sustained by the land resources (or the LCC)? (3) What is the spatial–temporal pattern of the LoL level? Considering that food is a bond of land resource utilization and human demand, the balance of food supply and demand can not only reflect the degree of food security, but the pressure of the population on land resources. To achieve the research objective and answer the research questions, this study analyzed the food consumption levels and estimated the effective calorie supply levels in Tibet using food production and consumption data and a food–calorie conversion model. The spatio-temporal patterns of the LCC in Tibet in the past nearly two decades (2000–2019) at three spatial scales (i.e., provinces, cities/prefectures and counties) were assessed systematically against different standards of living using an LCC model from two perspectives: population–grain balance that considers the supply and demand for grain only, and calorie supply–demand balance that considers the supply and demand for all major categories of livestock and plant foods. The aim was to quantitatively reveal the LoL and provide scientific support for food security and sustainable development in ecologically fragile areas (e.g., the QTP) across the globe.

2. Study Approach, Materials and Methods

2.1. Study Approach

LCC is essentially a measure of the balance between human consumption and food production, and that between human demand and resources supply. The present study focused on the quantities of land resources and the population. First, the effective calorie supply and dietary nutrition levels were estimated using a food–calorie conversion model based on an analysis of the characteristics of land use and farming and pastoral production. Then, the LCC and LoL levels in Tibet were assessed against the different food demand and calorie requirement levels at different standards of living using an LCC model. Figure 1 shows the theoretical framework of our study.

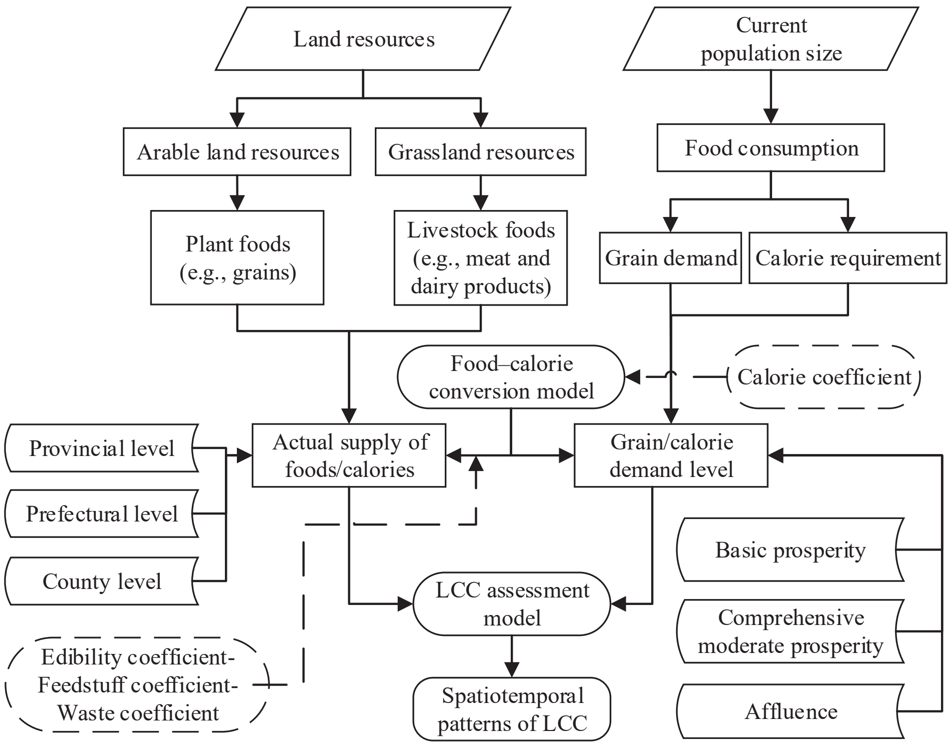

Figure 1. Study framework and approach.

2.2. Research Methodology

2.2.1. Food–Calorie Conversion Model

Foods differ in calorie content, and a consistent measurement of food supply and demand levels was realized using the food–calorie conversion model:

$$Energy = \sum F_i \times Cal \tag{1}$$

where *Energy* is the calorie supply level, F_i is the *i*th category of food (see Table 1), and *Cal* is the calorie contained in the *i*th category of food. For estimating the calorie intake on the consumption side, food edibility was considered and estimated using an edibility coefficient. On the supply side, food edibility (as measured using the edibility coefficient) and food waste (measured using a food waste coefficient) were considered. For livestock foods, feedstuff (measured using a feedstuff coefficient) was considered. Table 1 gives the food–calorie conversion parameters for the major categories of foods.

Table 1. Food–calorie conversion parameters for major categories of foods.

Foods	Calorie Coefficient (kcal/100 g)	Edibility Coefficient	Waste Coefficient (%)	Feedstuff Coefficient
Rice	347	0.78	10	/
Wheat	339	0.85	10	/
Highland barley	342	0.85	10	/
Beans	390	0.9	4	/
Roots and tubes	77	0.85	15	/
Rapeseed	899	0.4	4	/
Peanut	899	0.45	4	/
Vegetables	73	0.85	15	/
Apple	54	0.76	15	/
Pear	50	0.82	15	/
Pork	395	1	6	2.53
Beef	125	1	6	0.28
Mutton	203	1	6	0.28
Cow milk	54	1	1.5	0.1
Sheep milk	59	1	1.5	0.1

2.2.2. LCC Model

Based on the characteristics of food production in Tibet, the LCC was analyzed against grain demand and calorie requirement using the following model:

$$LCC = \begin{cases} CLCC = C/C_{PC} \\ ELCC = E/E_{PC} \end{cases} \tag{2}$$

$$LCCI = \begin{cases} CLCCI = Pa/CLCC \\ ELCCI = Pa/ELCC \end{cases} \tag{3}$$

where CLCC is the LCC estimated against grain demand, ELCC is the LCC estimated against calorie requirement, C is the grain production, E is the calorie supply, C_{PC} is the per capita grain demand, E_{PC} is the per capita calorie requirement (Table 2), P_a is the current population size, LCCI is the LCC index, CLCCI is the LCCI estimated against grain demand and measures the degree of population–grain balance, and ELCCI is the LCCI estimated against calorie requirement and measures the degree of calorie supply–demand balance. LCCI values are classified into three levels and six sub-levels (Table 3) for describing the LoL level.

Table 2. Grain demand and calorie requirement levels in Tibet at different standards of living.

Standard of Living	Grain (kg/person/y)	Calories (kcal/person/y)
Basic prosperity	340	2400
Comprehensive moderate prosperity	400	3000
Affluence	440	3500

2.2.3. Definitions of Food Demand and Calorie Requirement Levels

The quantities of grain and calories required for maintaining the basic physiological activities of Chinese residents have usually been estimated to be 400 kg/person/y and 2400 kcal/person/y, respectively [25]. Considering that different types of counties in Tibet differ in grain demand and that the ratio between farming and pastoral populations has been sustained at 7:3, and referencing the grain demand in pastoral counties estimated by existing research (200 kg/person/y) [35], the amount of grain required for maintaining a basic prosperity standard of living in Tibet is estimated to be 340 kg/person/y. Considering that the food consumption structure in Tibet will become increasingly similar to the overall food consumption structure in China, i.e., the grain demand for feedstuff and industrial purposes will increase, the per capita share of grain required for maintaining a comprehensive moderate prosperity standard of living and an affluent standard of living was estimated to be 400 kg/y and 440 kg/y (total of all grain uses, such as feed, seed, processing, losses waste), respectively. To reveal more accurately the degree of population–grain balance in different types of counties in Tibet, the grain demand in the farming counties was assumed to be equal to that in Tibet, and the ratio between farming and pastoral populations in farming–pastoral counties was assumed to be 5:5. On this basis, the grain demand was estimated against the three different standards of living (i.e., basic prosperity, comprehensive moderate prosperity, and affluence. Pastoral counties have low or no grain output, and the degree of population–grain balance in these counties was not analyzed. The calorie requirement was also estimated against the three different standards of living (Table 2).

Table 3. Classification of LoL levels and sub-levels according to the value of LCCI.

LoL Level	LoL Sub-Level	LCCI Value Range
Food surplus	Abundant surplus	≤0.5
	Surplus	0.5–0.875
Balanced supply and demand	Overall balance with small surplus	0.875–1.0
	Overall balance with small overload	1.0–1.125
Population overload	Overload	1.125–1.5
	Severe overload	>1.5

2.3. Data Sources and Treatment

(1) The food production structure in Tibet is relatively simple, with ten main categories of plant foods (e.g., rice, wheat, highland barley, beans, roots and tubers, rapeseed, peanut, vegetables, apple, and pear) and five main categories of livestock foods (beef, mutton, cow milk, sheep milk, and pork). The food output data for 2000–2019 came mainly from the statistics yearbooks of Tibet and its cities (prefectures). (2) The food consumption data came mainly from the statistics yearbooks of Tibet and China. Considering that the data for urban and rural food consumption in the statistics yearbooks after 2017 have included the major categories of food consumption quantities, the average data for 2017–2019 were used to measure the current food consumption levels, and the calorie intake levels in Tibet were calculated using the food–calorie conversion model fed by the consumption data for 43 subcategories of foods. (3) The population data came from the Tibet Statistics Yearbooks and China Population and Employment Statistics Yearbooks for the study time period. (4) The calorie coefficients and edibility coefficients for the major categories of foods came from the China Food Composition 2009 [36]. The waste coefficients (covering waste in mainly the storage and distribution links) and feedstuff coefficients were based on previous studies [37,38] and adjusted according to the actual farming and pastoral production structure in Tibet. (5) The definition of county types in the Tibet Statistics Yearbooks (Table 4) was used.

Table 4. Classification of Tibetan counties.

Type	Quantity	Name
Farming county/district	35	Chengguan*, Duilongdeqing*, Dazi*, Nimu, Qushui, Mozhugongka, Sangzhuzi, Nanmulin, Jiangzi, Dingri, Sajia, Lazi, Bailang, Renbu, Dingjie, Jilong, Nielamu, Zuogong, Mangkang, Luolong, Bianba, Bayi, Milin, Motuo, Bomi, Chayu, Lang, Naidong*, Zhanang, Gongga, Sangri, Qiongjie, Luozha, Jiacha, Longzi
Pastoral county/district	15	Dangxiong, Zhongba, Saga, Seni*, Jiali, Nierong, Anduo, Shenzha, Bange, Baqing, Nima, Shuanghu, Geji, Gaize, Cuoqin
Farming–pastoral county/district	24	Linzhou, Angren, Xietongmen, Kangma, Yadong, Gangba, Karuo*, Jiangda, Gongjue, Leiwuqi, Dingqing, Chaya, Basu, Gongbujiangda, Qusong, Cuomei, Cuona, Langkazi, Biru, Suo, Pulan, Zhada, Gaer, Ritu
Counties/district in the Yarlung Zangbo River—Nyangqu River—Lhasa River (YNL) development area	18	Chengguan*, Duilongdeqing*, Dazi*, Linzhou, Nimu, Qushui, Mozhugongka, Sangzhuzi, Nanmulin, Jiangzi, Lazi, Xietongmen, Bailang, Naidong, Zhanang, Gongga, Sangri, Qiongjie

Note: Regions with a * are urban areas (districts) and regions without a * are counties, according to China's differentiation criteria between counties and urban areas.

3. Study Area

Tibet is located in the southwest of the QTP (26°50′~36°53′ N, 78°25′~99°06′ E), and borders with India, Nepal, Bhutan, Bangladesh, and other countries. The average altitude is more than 4000 m, known as the roof of the world. The terrain slopes from northwest to southeast and is complex and diverse. The climate is cold and dry in the northwest and warm and humid in the southeast [39]. Tibet serves as a major barrier protecting the ecological security in China.

Tibet is one of the 34 provincial-level administrative regions in China and is the second largest province at 1.23 million km^2, accounting for one-eighth of the geographic expanse. Tibet has a vast territory, but a sparse population [22]. However, as of 2019, its population was 3.506 million people (86% are Tibetan), only accounting for 0.25% of China's population. At same time, the natural growth rate of the population reached 10.1‰ in Tibet, which is three times that of China's (3.3‰). Tibet's GDP was CNY 169.78 billion, accounting for only 0.17% of China's GDP. The per capita disposable income is CNY 19,501, only 63.45% of China's. Its urbanization rate is 31.5%, less than half of China's (68.5%). The economy and urbanization level of Tibet lags behind China's level. The land use type in Tibet is mainly grassland (about 65% of the total land area), of which Naqu City has the largest grassland area (Figure 2). Forests are mainly distributed in southeastern Tibet (about 10.38% of the land area). Cultivated land and construction land (which, combined, account for 0.40% of the land area) are mainly distributed in the Yarlung Zangbo River—Nyangqu River—Lhasa River area. Water area and water conservancy facilities account for about 4.56%, and other unused land accounts for about 14.71%. Above all, Tibet has the characteristics of mountainous–pastoral–underdeveloped areas and border areas. The rapid population growth and socioeconomic development will bring new challenges to the food supply and new pressure on land resources.

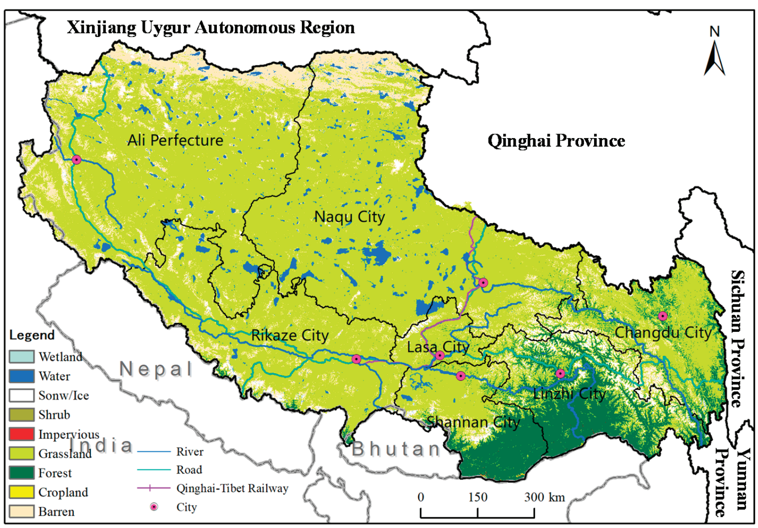

Figure 2. Land use map of Tibet in 2019 [40].

4. Results

4.1. Food Consumption and Dietary Nutrition

The dietary consumption in Tibet is dominated by grains, with a high consumption of livestock products. At the present stage, grains (97.15% cereals) ranked first in terms of the food consumption by Tibetan residents (227.07 kg/person/y), followed by vegetables (42.40 kg/person/y) and meat products (29.07 kg/person/y). Meat consumption was dominated by beef (56.54%), followed by pork (22.94%) and mutton (18.46%). Edible oil and dairy products ranked fourth (17.63 kg/person/y) and fifth (16.13 kg/person/y), respectively. The per capita per year consumption of grains was 1.76 times the national average (97.93 kg higher than the national average). The consumptions of sugar, edible oil, dairy products, and meat products were higher than the national averages, being 2.74, 1.79, 1.32, and 1.05 times the national averages, respectively. The consumptions of pork, poultry, eggs, dried and fresh fruits, and aquatic products were significantly lower than the national averages. The dietary consumption exhibited the overall characteristics of high consumption of grains and livestock products and low consumption of fruits and vegetables (Figure 3).

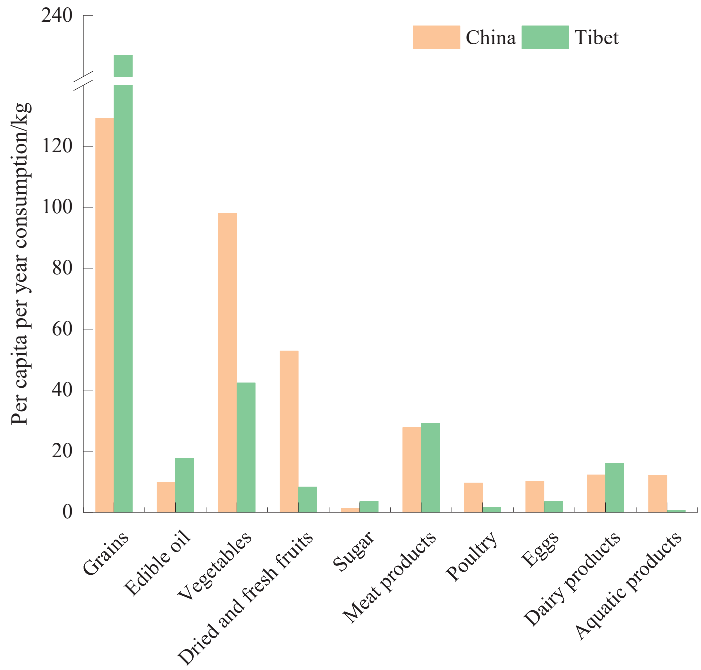

Figure 3. Consumptions of major categories of foods in Tibet vs. China. Note: China refers to the average level of the whole of China, while Tibet refers to the average level of Tibet.

Urban and rural food consumption levels differed considerably, and the dietary structure in Tibet was remarkably different from the overall situation in China. The urban and rural grain consumptions were 239.07 and 191.50 kg/person/y, respectively, with the urban consumption being 1.25 times the rural consumption. The consumptions of all major categories of foods by rural residents were lower than those by urban residents, except that the consumption of sugar by rural residents was 0.83 kg/person/y higher than for urban residents. In particular, the consumptions of poultry, dried and fresh fruits, eggs, vegetables, and meat products by rural residents were lower than 40% of those by urban residents. The consumptions of edible oil and dairy products by rural residents were only 67.29% and 69.28%, respectively, of those by urban residents. The urban and rural consumptions of grains, edible oil, dairy products, and sugar in Tibet were 1.57 and 1.74 times, 1.57 and 2.38 times, 7.40 and 4.27 times, and 2.73 and 2.29 times the national averages, respectively. The consumptions of vegetables, fruits, and eggs by rural residents in Tibet were 30%, less than 10%, and 21%, respectively, of the national average rural consumptions. The meat consumption by urban residents in Tibet was 1.8 times the national average urban consumption, whereas that by rural residents was only 81% of the national average rural consumption.

Calorie intake differed insignificantly between urban and rural residents, with plant foods being the major source of calories. The per capita calorie intakes of urban and rural residents were 2960 and 2986 kcal, respectively, with the latter being slightly higher than the former. Plant foods were the major source of calorie intake by both urban and rural residents, with grains accounting for the largest share (about 60%), followed by vegetable oil (approximately 14%) and vegetables and confections (merely 4% each). Livestock foods accounted for nearly 18% of the total calorie supply, which were dominated by meat and dairy products, accounting for 10% and 4% of the total, respectively. For rural residents, grains accounted for nearly 75% of the total calorie intake, and vegetable oil accounted for 8%. Livestock foods accounted for approximately 11% of the total calorie intake, which were dominated by animal oil and meat, each accounting for about 4% of the total calorie intake (Figure 4).

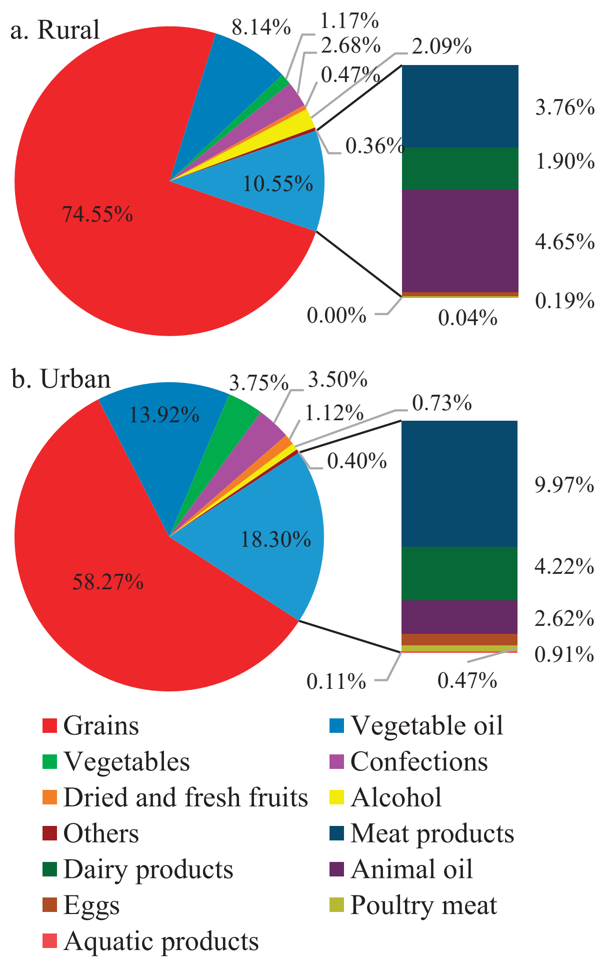

Figure 4. Composition of the sources of calorie intake by (**a**) rural and (**b**) urban residents in Tibet. Note: in the part of food consumption, meat products include pork, beef, mutton meat; poultry meat includes chicken, duck, and goose meat.

4.2. LCC

4.2.1. LCC Based on Grain Demand

In 2000–2019, the grain production in Tibet increased from 962.23 thousand tons to 1047.06 thousand tons, and the LCC gradually increased when estimated against the grain demand. This translates into an increase in the LCC at the basic prosperity standard of living from 2830.10 thousand persons to 3079.57 thousand persons. The LCC in 2019 estimated against the comprehensive moderate prosperity and affluent standards of living was 2617.64 and 2379.67 thousand persons, respectively (Figure 5).

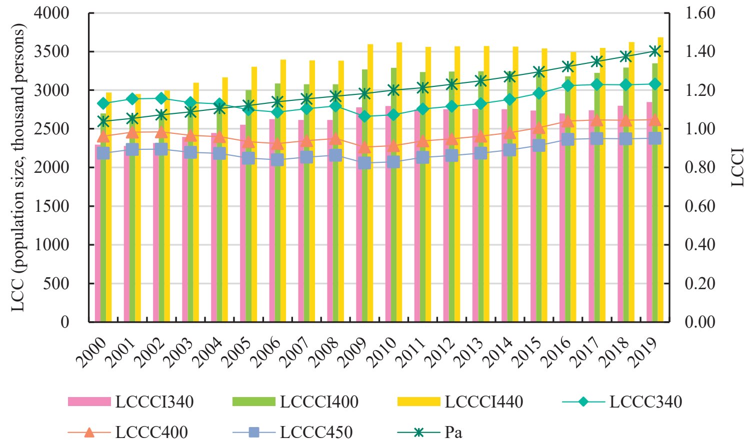

Figure 5. LCC and LCCI in Tibet estimated against grain demands at different standards of living. Note: CLCC340, CLCC400, and CLCC450 indicate the LCC estimated against the three grain demand levels of 340, 400, and 450 kg, respectively, and CLCCI340, CLCCI400, and CLCCI450 indicate the LCCI estimated against the three grain demand levels, respectively.

For the LCC in individual cities/prefectures (Figure 6a), at the basic prosperity standard of living, Rikaze City had the highest LCC of 1025 thousand persons in 2000, followed by Lasa City (565 thousand persons), Shannan City (490 thousand persons), Changdu City (465.8 thousand persons), Linzhi City (more than 200 thousand persons), and the two pastoral cities/prefectures of Naqu City (30.7 thousand persons) and Ali Prefecture (17.8 thousand persons). In 2019, the LCC in four cities/prefectures (Lasa City, Shannan City, Naqu City, and Ali Prefecture) decreased to 460.1 thousand, 483.0 thousand, 24.1 thousand, and 14.5 thousand persons, respectively. The LCC in the other three cities/prefectures increased: Rikaze City achieved the highest increase (274.4 thousand persons), followed by Changdu City (90.4 thousand persons) and Linzhi City (10.4 thousand persons).

For the LCC in individual counties, at the basic prosperity standard of living, six counties (Linzhou, Sangzhuzi District, Jiangzi, Lazi, Bailang, and Duilongdeqing District) had a high LCC of above 100 thousand persons in 2000, while the farming–pastoral counties (Yadong, Zhada, Ritu, and Gaer counties) had a low LCC of less than 10 thousand persons because of low grain output. In 2019, the number of counties with an LCC of higher than 100 thousand persons increased to 11, with 5 farming counties (Sangzhuzi District, Jiangzi, Bailang, Lazi, and Gongga) having an LCC in the range of 100–250 thousand persons. However, farming–pastoral counties such as Yadong, Ritu, Zhada, and Gaer, and some municipal districts, still had a low LCC because of low grain output (Figure 7a). For temporal variations, compared with 2000, 41 non-pastoral counties (most located in farming regions) achieved increases in LCC. In particular, Linzhou, Dingqing, Angren, Karuo District, Jiangda, and Bailang achieved an increase of higher than 50 thousand persons. In contrast, municipal districts (including Dazi, Naidong, Chengguan, and Duilongdeqing District) experienced decreases in LCC because of the impact of urbanization.

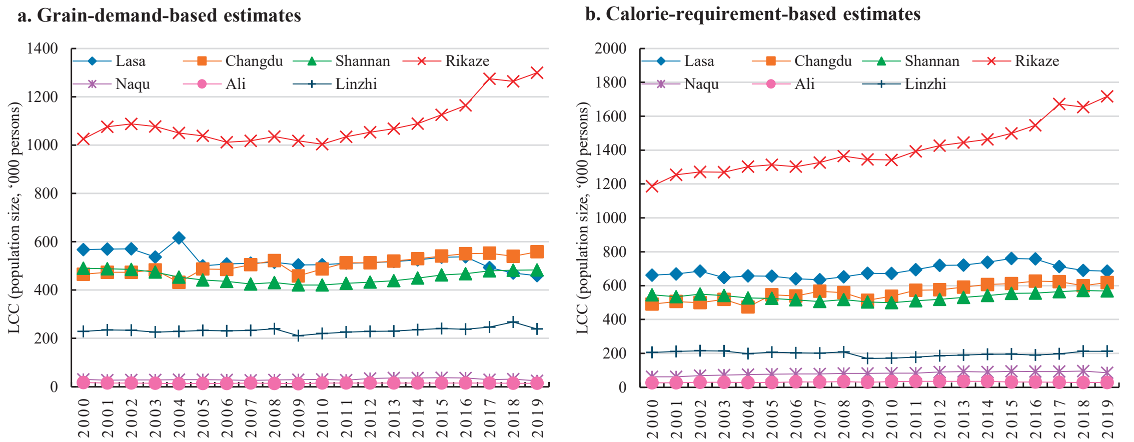

Figure 6. LCC in individual cities/prefectures estimated against the grain demands (**a**) and calorie requirements (**b**) at the basic prosperity standard of living.

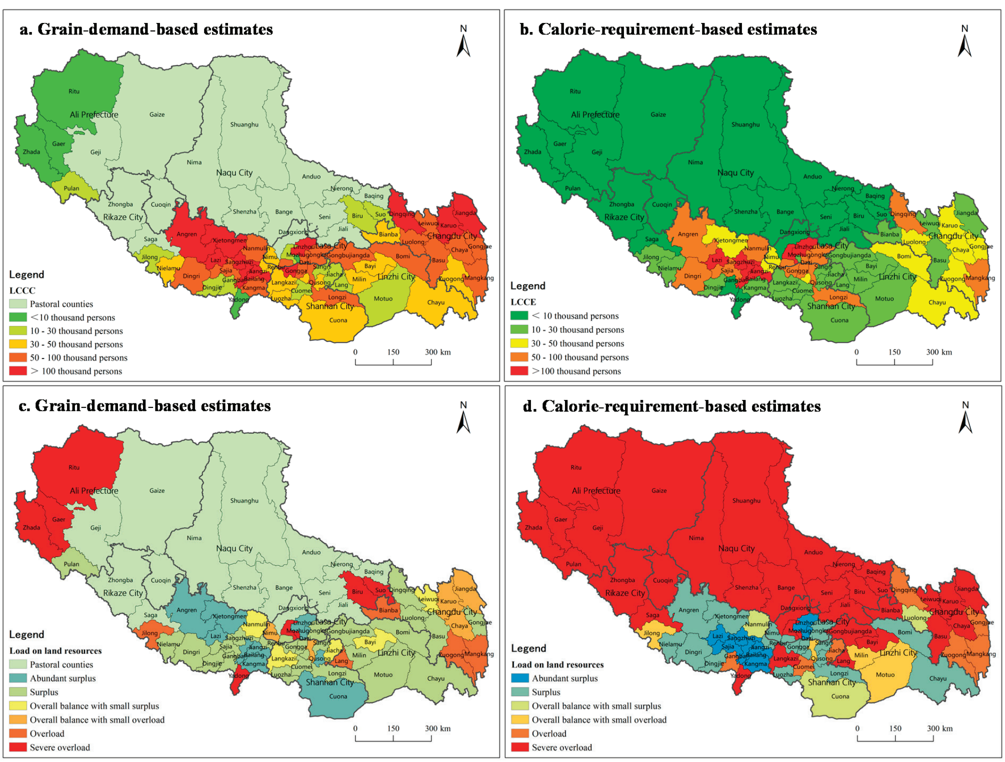

Figure 7. Spatial pattern of LCC and LoL in Tibet estimated against the basic prosperity standard of living in 2019.

4.2.2. LCC Based on Calorie Requirement

In 2000–2019, the meat output in Tibet increased from 149.30 thousand tons to 277.50 thousand tons, and the milk output increased from 204.00 thousand tons to 466.6 thousand tons, with livestock products being a major source of calorie supply. The calorie supply increased from 2.79 × 10^{12} kcal/y to 3.43 × 10^{12} kcal/y, and the LCC gradually increased when estimated against the calorie requirement. At the basic prosperity standard of living, the LCC increased from 3184.97 thousand persons to 3913.80 thousand persons. At the comprehensive moderate prosperity and affluent standards of living, the LCC reached 3131.04 and 2683.75 thousand persons, respectively, in 2019 (Figure 8).

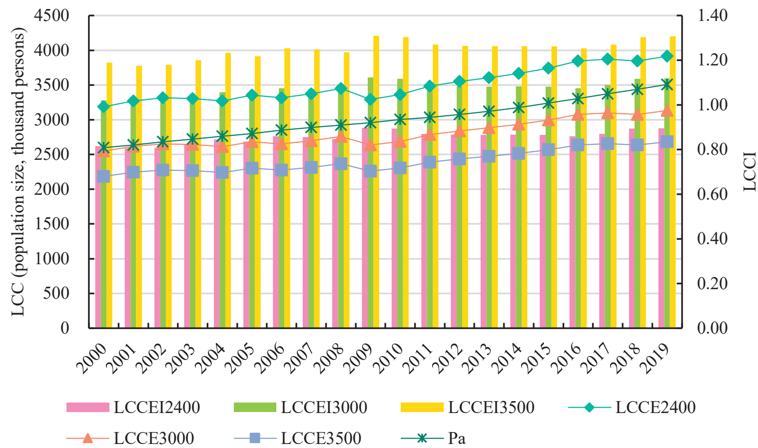

Figure 8. LCC and LCCI in Tibet estimated against the calorie requirements at different standards of living. Note: ELCC2400, ELCC3000, and ELCC3500 indicate the LCC estimated against the three calorie intake levels of 2400, 3000, and 3500 kcal, respectively, and ELCCI2400, ELCCI3000, and ELCCI3500 indicate the LCCI estimated against the three different calorie intake levels, respectively.

For the LCC in individual cities/prefectures, at the basic prosperity standard of living, Rikaze City had the highest LCC (1186.60 thousand persons) in 2000, followed by Lasa City (661.11 thousand persons), Changdu City (491.20 thousand persons), Shannan City (545.88 thousand persons), Linzhi City (204.79 thousand persons), and the two pastoral cities/prefectures of Naqu City (60.89 thousand persons) and Ali Prefecture (26.52 thousand persons). In 2019, the LCC in Rikaze City increased to 1717.97 thousand persons, followed by Lasa City (686.02 thousand persons), Changdu City (617.11 thousand persons), Shannan City (568.13 thousand persons), Lizhi City (212.72 thousand persons), and the two pastoral cities/prefectures of Naqu City (85.81 thousand persons) and Ali Prefecture (28.00 thousand persons). The seven cities/prefectures differed in LCC temporal variations. In particular, Rikaze City enjoyed the largest increase (531.37 thousand persons), followed by Changdu City (125.91 thousand persons). The LCC in Lasa City first increased and then decreased, experiencing an insignificant overall increase during the period. The LCC in Naqu City and Ali Prefectures remained at low levels, with the increases being insignificant (Figure 6b).

For the LCC in individual counties, six farming and farming–pastoral counties (Sangzhuzi District, Linzhou, Lazi, Duilongdeqing District, and Bailang) had a high LCC of above 100 thousand persons in 2000, whereas pastoral counties such as Gaize, Baqing, Cuoqin, Shenzha, and Gaer of Ali Prefecture had a low LCC of less than 10 thousand persons because of limited food output. As of 2019, the spatial pattern of the LCC in individual counties varied insignificantly. The number of counties with an LCC of above 100 thousand persons increased to eight. The counties with a low LCC were mainly concentrated in Ali Prefecture and Naqu City. A total of 23 counties had an LCC of less than 10 thousand persons, including Nierong, Shenzha, Zhada, Baqing, Shuanghu, and Gaer (Figure 7b). Compared with 2000, the LCC increased in 43 counties. The counties with a low LCC were mainly pastoral counties and municipal districts such as Chengguan District.

4.3. LoL

4.3.1. LoL Based on Grain Demand

At the basic prosperity standard of living, the LCCI in Tibet increased from 0.92 to 1.14 in 2000–2019, i.e., the LoL changed from the overall balance with small surplus sub-level to the population overload level, and the population–grain relationship became increasingly strained. At the comprehensive moderate prosperity standard of living, the LCCI fell in the range of 1.08–1.47, i.e., the LoL changed from the overall balance with small overload sub-level to the severe overload sub-level. At the affluent standard of living, the LoL changed from the overload sub-level to the severe overload sub-level (Figure 5).

For LCCI in individual cities/prefectures, at the basic prosperity standard of living, the LCCI in all seven cities/prefectures increased in 2000–2019. In particular, the LCCI in Lasa City increased from 0.71 to 1.57, with the LoL increasing from the surplus sub-level to the severe overload sub-level. The LCCI in Linzhi City increased from 0.63 to 0.99, with the LoL changing from the surplus sub-level to the overall balance with small overload sub-level. The LCCI in Rikaze City fell in the range of 0.59–0.70, and in Shannan City fell in the range of 0.64–0.79, with the LoL remaining at the surplus sub-level. The LCCI in Changdu City fell in the range of 1.17–1.38, with the LoL remaining at the overload sub-level. Naqu City and Ali Prefecture were dominated by pastoral production and experienced a strained population–grain relationship, with the LoL remaining at the severe overload sub-level. The LoL in Lasa City, Changdu City, Naqu City, and Ali Prefecture was at the severe overload sub-level in 2019; the LoL in Linzhi City was at the overload sub-level, with a large load on land resources. The LoL in Shannan and Rikaze Cities was at the overall balance with small surplus and surplus sub-levels, respectively, experiencing a small load on land resources. At the affluent standard of living, only the LoL in Rikaze City was at the surplus sub-level; in Linzhi city it was at the overload sub-level, and in Shannan City it increased to the overall balance with small overload sub-level (Figure 9a).

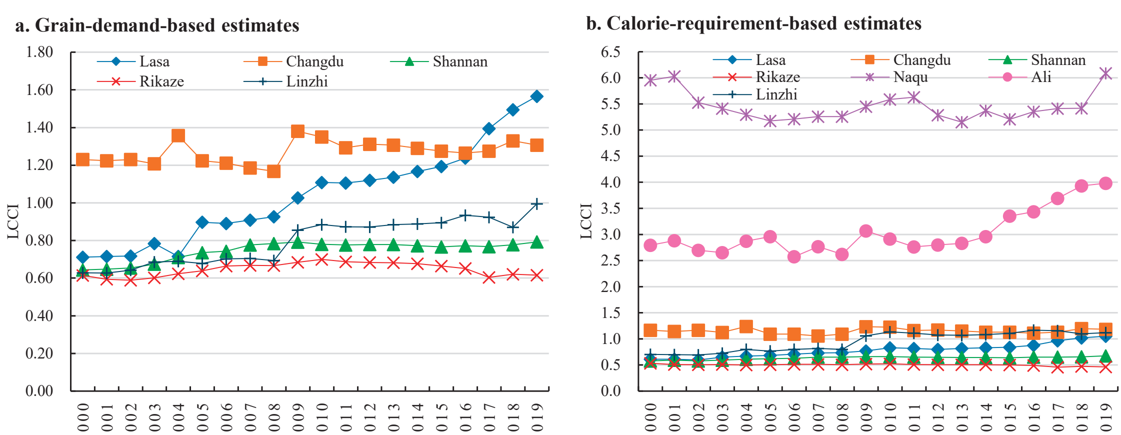

Figure 9. LoL in individual cities/prefectures estimated against the grain demands (**a**) and calorie requirement (**b**) at the basic prosperity standard of living. Note: the food production in Naqu City and Ali Prefecture is mainly beef, mutton and milk, with limited grain output, and the LoL estimated against the grain demands is above 10 and 4, respectively. Not shown in figure (**a**).

For the LCCI in individual counties, at the basic prosperity standard of living, the numbers of farming and farming–pastoral counties with an LoL at the food surplus, balanced supply and demand, and population overload levels changed from 38, 9, and 12 in 2000 to 36, 10, and 13 in 2019, respectively, with most counties enjoying a food surplus (Figure 10a). In 2019, the LoL in Chengguan District, Gaer, Biru, Zhada, Suo, Yadong, Duilongdeqing District, and Ritu was at the severe overload sub-level, experiencing a strained population–grain relationship (Figure 7c). The numbers of counties with an LoL at the levels of food surplus, balanced supply and demand, and population overload were 25, 9, and 25, respectively, at the comprehensive moderate prosperity standard of living and 20, 11, and 28, respectively, at the affluent standard of living. Nearly half of the county facing population overloaded (Figure 11a).

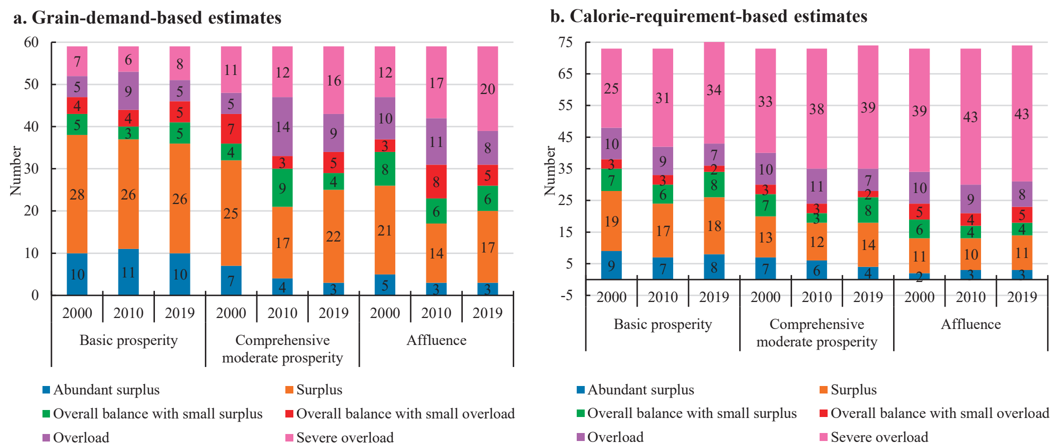

Figure 10. LoL in individual counties estimated against the grain demand (**a**) and calorie requirements (**b**) at different standards of living. Note: the label on the columns is the number of counties.

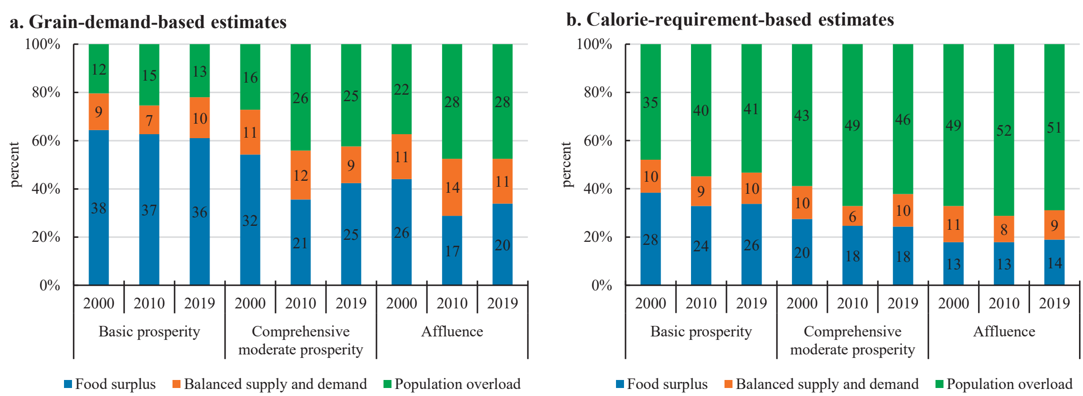

Figure 11. Percentage of LoL level in individual counties estimated against the grain demand (**a**) and calorie requirements (**b**) at different standards of living. Note: the label on the columns is the number of counties.

Restricted by the limited grain production capacity and rapid population growth rate, the LoL in Tibet is overloaded to varying degrees. It is difficult to meet the food demand of local residents in terms of grain. With the increase in the food demand level in the future, a large amount of grain from inland China will be needed, particularly in the pastoral and farming–pastoral counties, as well as in municipal districts with a high urbanization rate. At the same time, the LOL in Shannan City and Rikaze City is relatively low. There is a certain grain surplus, which is an important grain supply base for Tibet.

4.3.2. LoL Based on Calorie Requirement

At the basic prosperity standard of living, the LCCI in Tibet increased from 0.82 to 0.90 in 2000–2019, with the LoL changing from the surplus sub-level to the overall balance with small surplus sub-level, but remaining low. At the comprehensive moderate prosperity standard of living, the LCCI fell in the range of 1.02–1.12, with the LoL always remaining at the overall balance with small overload sub-level. At the affluent standard of living, the LoL always remained at the overload sub-level (Figure 8).

For the LoL in individual cities/prefectures, at the basic prosperity standard of living, the LCCI in Rikaze City decreased slightly, but the LCCI in the other six cities/prefectures increased by different degrees in 2000–2019. In particular, the LCCI in Ali Prefecture increased from 2.79 to 3.99, with the LoL always remaining at the severe overload sub-level and continuing to increase. The LCCI in Lasa City increased from 0.61 to 1.05, with the LoL changing from the surplus sub-level to the overall balance with small overload sub-level. The LCCI in Linzhi City increased from 0.7 to 1.12, with the LoL changing from the surplus sub-level to the overall balance with small overload sub-level. The LCCI in the other four cities/prefectures varied insignificantly. In 2019, the LoL in Rikaze and Shannan cities was at the abundant surplus and surplus sub-levels, respectively, and the LoL in Changdu and Naqu cities was at the overload and severe overload sub-levels, respectively. For the LCCI in individual cities/prefectures in 2019 estimated against different standards of living, the LoL estimated against the comprehensive moderate prosperity standard of living in Naqu City and Ali Prefecture was at the severe overload sub-level, in Lasa, Changdu, and Linzhi cities was at the overload sub-level, and in Rikaze and Shannan cities was at the surplus sub-level. At the affluent standard of living, the LoL in Rikaze and Shannan cities was at the surplus and overall balance with small surplus sub-levels, respectively, and in the other five cities/prefectures was at the severe overload sub-level (Figure 9b).

For the LoL in individual counties, at the basic prosperity standard of living, the numbers of counties with an LoL at the food surplus, balanced supply and demand, and population overload levels increased from 28, 10, and 35 in 2000 to 26, 10, and 41 in 2019, respectively. The major characteristic of the temporal variations during this period is the increased number of overloaded counties (Figure 10b). In 2019, the number of severely overloaded counties reached 34, mainly consisting of pastoral (15) and farming–pastoral (14) counties. The 21 counties with surplus land resources were mainly farming counties and also included five farming–pastoral counties (Linzhou, Kangma, Qusong, Angren, and Xietongmen) (Figure 7d). In 2019, the numbers of counties with an LoL at the food surplus, balanced supply and demand, and population overload levels were 18, 10, and 46, respectively, at the comprehensive moderate prosperity standard of living, and 14, 9, and 51, respectively, at the affluent standard of living, with nearly 70% of the counties experiencing population overload and a large LoL (Figure 11b).

The LCC in Tibet has increased after considering the supplementation of foods other than grains. As we are aware, the calorie content of non-grain food per unit mass is lower than grain. Compared with grain demand, the spatial difference of LoL is more obvious than when estimated against the calorie requirement. In Tibet, where grassland is the main land use (about 70% of the land area), beef and mutton meat and milk play an important role in calorie supply, especially in pastoral counties. The unique land use and animal husbandry-based production activities determine the animal-based food supply mode in pastoral counties, and the total calorie value of the food supply is low. Therefore, the LCC is low in pastoral counties, and the LoL is relatively large. These counties face the pressure of population overload, and the amount of extraterritorial food, especially grain, is required. On the contrary, after considering other food (no grains), farming counties have improved calorie supply capacity, which is mainly characterized by food surplus. For municipal districts, the population overload is mainly caused by the huge permanent resident population.

5. Conclusions and Discussion

Based on an analysis of the characteristics of farming and pastoral production, the regional differences in Tibet, and of the dietary structure of Tibetan residents, the spatio-temporal patterns of the LCC in Tibet in 2000–2019 were assessed quantitatively at three different spatial scales (i.e., provinces, cities/prefectures and counties) based on the grain demands and calorie requirements at three different standards of living (i.e., basic prosperity, comprehensive moderate prosperity, and affluence) using a food–calorie conversion model and an LCC model. The major contributions of the present study were as follows. (1) Based on the comparative analyses, the dietary consumption characteristics and calorie intake levels in Tibet were summarized. (2) The LCC in Tibet was estimated based on both grain consumption and calorie requirements, and the spatio-temporal patterns of the LCC were analyzed. (3) The spatial patterns of the LoL in Tibet were analyzed against different standards of living.

The results revealed the following. (1) The dietary structure in Tibet is characterized by the high consumption of grains and livestock products and low consumption of fruits and vegetables, with the per capita grain consumption being 1.76 times the national average. The food consumption pattern is the reflection of Tibet's social and economic development stage and its unique food production structure. According to Bennett's law [41,42], with the income increasing, the consumption of starchy staple food (cereals, roots and tubers) will decrease relatively, and the consumption of high-nutrition food (livestock products, fruits and vegetables, etc.) will increase. For Tibet, the relatively lagging level of socioeconomic development has resulted in grain-based food consumption. Animal husbandry-based agricultural production activities lead to high meat consumption and relatively low fruit and vegetable consumption. The urban and rural dietary consumption levels differ remarkably. The consumptions of grains and sugar by rural residents are higher than those by urban residents, whereas the consumptions of most other foods by rural residents are less than 40% of those by urban residents, and are significantly lower than the national average rural consumptions. The urban and rural calorie intake levels differ insignificantly, with both being approximately 3000 kcal/person/d. Plant foods are the major source of calorie intake, with grains accounting for a high proportion of calorie intake by urban (60%) and rural (75%) residents.

(2) The LCC in Tibet has been improving and is generally sustained at the balanced supply and demand level. At the basic prosperity standard of living, the grain demand-based LCC in Tibet increased to 3079.6 thousand persons in 2019, and the calorie requirement-based LCC (also considering livestock products and other foods) increased to 3913.8 thousand persons. With increasing population growth, the grain demand-based LCCI and calorie requirement-based LCCI have increased, but remained at approximately 1.0, with the LoL being at the overall balance with small overload and overall balance with small surplus sub-levels, respectively. The LoL estimated against the comprehensive moderate prosperity and affluent standards of living is at the overall balance with small overload and severe overload sub-levels, respectively, indicating an off-balance, strained food supply–demand relationship.

(3) The temporal variations in LCC differ between the cities/prefectures in Tibet, and there are significant spatial differences, with the LoL in some areas being at the severe overload sub-level. Since 2000, the grain demand-based LCC in Lasa City, Shannan City, Naqu City, and Ali Prefecture has decreased at different degrees. Overall, at the basic prosperity standard of living, the LCC in Rikaze City fell in the range of 1000–1700 thousand persons, the LCC in Lasa, Changdu, and Shannan Cities fell in the range of 450–700 thousand persons, the LCC in Linzhi City fell to 200 thousand persons, and the LCC in the two pastoral cities/prefectures of Naqu City and Ali Prefecture is at a low level of below 100 thousand persons. The LCCI in all seven cities/prefectures has increased with the population growth. Rikaze and Shannan cities have exhibited a relatively eased calorie supply–demand relationship, and the other five cities/prefectures have exhibited population overload to different degrees.

(4) More than half of the counties experienced increases in the LCC. Most farming and farming–pastoral counties exhibited a basically balanced population–grain relationship; however, nearly half of the counties exhibited a strained calorie supply–demand relationship. Since 2000, the grain demand-based LCC in 41 of the 59 farming and farming–pastoral

counties has increased, with the high-LCC counties concentrated mainly in the YNL area. At the basic prosperity standard of living, the number of counties with grain surplus has decreased slightly; however, 60% of the counties have a grain surplus of different degrees. At the comprehensive moderate prosperity and affluent standards of living, nearly half of the counties have exhibited a strained population–grain relationship. The calorie requirement-based LCC in 43 of the 74 counties has increased, with the low-LCC counties being mainly pastoral counties and municipal districts. At the basic prosperity standard of living, the number of counties with an off-balance, strained calorie supply–demand relationship has increased, with approximately 55% of the counties exhibiting population overload of different degrees. At the comprehensive moderate prosperity and affluent standards of living, more than 60% of the counties have exhibited a strained food supply–demand relationship and an increased LoL.

The LCC in Tibet exhibits the characteristic of "overall balance with local overloads and increasing tensions". The counties experiencing population overload include municipal districts with high urbanization levels, and most pastoral counties. These counties/districts have a high population density or a simple agricultural production structure, thus experiencing a low level of self-sufficiency in terms of calorie supply. For pastoral counties dominated by livestock product production, the LCC is low because of the low calorie volume produced by a unit of land resources, resulting in an off-balance, strained calorie supply–demand relationship. Therefore, ensuring stable, effective food imports is an important option for alleviating the LoL in these municipal districts and pastoral counties.

The results of the LCC in this study are lower than those of Hao et al. [30]. This difference is mainly on the calorie supply side, and we use more detailed parameters. The calorie coefficient of grain is mainly calculated based on the proportion of highland barley, wheat, and rice (mainly highland barley). Meat and dairy are also refined into subcategories. Such coefficients make the results more accurate, because the calorie per unit of pork is 3.16 times that of beef and 1.95 times that of lamb. In a previous study [30], 391.5 kcal/kg was used for the calorie content of meat. We also consider both the feedstuff coefficient in relation to pork meat production and the edible portion of the food, so our study is closer to the actual calorie supply level in Tibet. This difference is also reflected in the consumption side. As we explained in the data processing, this study combines the consumption data of fine class foods (43 kinds), so the calorie intake level is also lower than the results of Wang et al. [29].

It should be noted that agricultural production activities and food consumption in Tibet are unique. In terms of social economy, Tibet is still underdeveloped compared with the whole country. However, as Tibet has historically achieved comprehensive poverty alleviation, the income of residents, regional transportation conditions, and agricultural/animal husbandry production conditions have been greatly improved. On the other hand, with the change of social environment, the scope and frequency of cultural exchanges between agricultural and pastoral areas, Tibet, and inland China have increased, and the food consumption structure and demands of residents have also changed with those exchanges [43]. All of these factors will promote the development of the local food consumption structure as well as the food consumption structure on a larger geographical scale [44,45].

The demands for vegetables, fruits, and other plant foods in Tibet are expected to increase in the future because of the unique agricultural production and food consumption structures, and the fact that Tibet is still socioeconomically underdeveloped and is undergoing transformations in dietary consumption structure [46]. In 2000–2019, the ratio of the sown area of vegetables and fruits to the sown area of all crops in Tibet increased from 3% to 10%. Because of the impact of policies on pastoral production, the ratio of the sown area of green fodders increased from 2% to 14%, whereas that of grain crops decreased from 87% to 68%. The changes in consumption demand and policies on pastoral development have brought new pressure on the grain production in Tibet and posed a new challenge to the grain supply security.

The limitations and future research of the study are as follows. (1) Because of the availability of limited statistical data, the measurement of the food supply did not include poultry, eggs, or aquatic products. In addition, the present study was based on the current productivity (food output) of land resources, without considering the potential improvement in land productivity. On the consumption side, more in-depth analysis of the trends of food consumption in Tibet is necessary. (2) In fact, supply and demand are two inseparable aspects of LCC and food security. An in-depth analysis of the future consumption demands for foods, especially plant foods, in Tibet will be conducted as the next step, so that the pressure posed by population growth and dietary consumption variations on land resources can be understood systematically. On the production side, the potential for improving the productivity of highland barley and other major grain crops can be investigated further [47] so that the upper limit of the local food supply can be analyzed, thus providing a basis for assessing the food supply–demand balance in Tibet. (3) Another future research direction is the scientific planning of the development of crop farming and animal husbandry, and fine-tuning of the ratio of grain crop to non-grain crop farming, in order to realize the sustainable development of farming and pastoral production and coordinate the ecological and economic benefits with food security based on a scientific understanding of the upper limit of the LCC. Investigating the food production–consumption and LCC of other regions belonging to the QTP (such as Nepal and the Qinghai province of China), and conducting horizontal comparisons to propose the third-pole dimension of food security and land use sustainability policy on a larger scale, would be meaningful.

Author Contributions: C.Z. wrote the manuscript text and contributed to the graphics; Y.Y., C.X., Z.Y. and X.S. contributed to the revision of the methods, data processing, results, and discussion of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Second Tibetan Plateau Scientific Expedition and Research Program (STEP) (Grant No. 2019QZKK1006), the National Natural Science Foundation of China (Grant No. 42130508), and the Chinese Academy of Sciences (Grant No. ZDRW-XH-2021-3).

Institutional Review Board Statement: Not available.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request to authors.

Conflicts of Interest: The authors declare no conflict of interest.

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Climate, Environment and Socio-Economic Drivers of Global Agricultural Productivity Growth

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Abstract: Growth in total factor productivity (TFP) indicates the sustainable and/or judicious use of scarce resources, including non-renewables. This paper identifies sources of growth in global agricultural TFP and its finer components, ranging from climate, production environment, and socio-economic factors, using a panel data of 104 countries, covering a 45-year period (1969–2013); and, finally, projects changes in TFP from increased climate variability. The results revealed that global agricultural productivity grew consistently at a rate of 0.44% p.a., driven by technological progress and mix-efficiency change, with negligible contributions from technical- and scale-efficiency changes; albeit with variations across regions. Both long-term and short-term climatic factors and the natural production environment significantly reduce global agricultural productivity, whereas a host of socio-economic factors have a significant but varied influence. The projected increased level of future climate variability will significantly reduce future agricultural productivity. Policy implications include investments in crop diversification, education, agricultural spending, number of researchers, and country specific R&D.

Keywords: Färe–Primont TFP index; technical-, scale- and mix-efficiency changes; climate change; socio-economic factors; determinants; multivariate Tobit model

Citation: Rahman, S.; Anik, A.R.; Sarker, J.R. Climate, Environment and Socio-Economic Drivers of Global Agricultural Productivity Growth. *Land* **2022**, *11*, 512. https://doi.org/10.3390/land11040512

Academic Editor: Marta Debolini

Received: 10 March 2022
Accepted: 31 March 2022
Published: 1 April 2022

1. Introduction

Technological change is an important factor in economic growth and development. Historical experience suggests that technology, by raising the productivity of factors (e.g., labor, capital, land, and other natural resources), plays an important role in economic growth [1]. The major technological breakthrough in agricultural history was the development of high-yielding modern varieties of rice and wheat, which are highly responsive to inorganic fertilizers, pesticides/insecticides, effective soil management, and water control [2]. The overwhelming belief in the pursuit of this 'high-input payoff' model of agricultural development, known as the 'green revolution' (GR), is due to its potential for increasing food-grain productivity and employment, as well as income; thereby, alleviating poverty and hunger [3]. However, this pioneering scientific method-based modern agriculture has overlooked the sustainability of this input-intensive production system. In fact, GR technology enabled rapid global food-grain output growth by bringing more land under cultivation, as well as by increasing the efficiency of the inputs used, but not by increasing total factor productivity (TFP) growth [4,5], which can contribute towards the sustainability of the production system [6]. The modern agricultural production process does not adequately address sustainability issues and increasing environmental concerns, including biodiversity loss, greenhouse gas emissions, and reduced availability of fertile soils and clean water [7–9]. Since the mid-1980s, there has been reduced returns from different inputs, which Singh [10] characterized as high input-use and a decelerating productivity growth phase for India. The concern is even greater today because, to meet global food requirements, production needs to increase 2.5 fold by 2050 [11].

There is a need for sustainable intensification of the agricultural production system that does not require trade-offs between productivity and other ecosystem services [11–13]. In other words, the global food production system requires TFP growth, which will ensure increased productivity, while maintaining the sustainability of the system and contributing towards poverty reduction [14–16]. Exploration of agricultural TFP, not only provides information about the diversity of agricultural growth, but increased TFP can ensure increased agricultural production, while reducing environmental externalities, which is also important for increasing the resilience and ensuring sustainability of the farming system [6]. Moreover, given the changing nature of climate and weather, concerns about their effects on agriculture and livelihoods are increasing globally [17,18]. Therefore, TFP growth in agriculture has become more critical than ever.

Researchers believe that agricultural productivity growth is the most effective long-term strategy to tackle the problems of poverty, hunger, and malnutrition [19], which are amenable through devising policies and investments in agriculture [20]. Abbott et al. [21] noted that the global spike in food prices during 2008–2009 was largely due to declining agricultural productivity and cereal crop failure in food exporting economies, which are likely to be repeated more frequently and with higher intensity in the future, owing to increasing anomalies in climate, weather events, and other factors; thereby, threatening agricultural sustainability [22,23]. However, the declining yield trend can be addressed through adjusting production systems, technology, and/or input combinations. In this respect, examination of TFP change is appropriate, because it allows decomposition of total production growth into various components (technology, efficiency, and scale changes) and enables identification of specific sources of productivity growth, thereby leading to better policy prescriptions [24]. Increased TFP has implications beyond national boundaries and can help in achieving internationally set development targets, including the sustainable development goal (SGD). For instance, to attain SDG2 (zero hunger) there is a target of doubling productivity in smallholder farms by 2030. TFP growth will also help in achieving sustainability related SGD targets, viz. SGD 12 (responsible consumption and production) targeting the strengthening of scientific and technological capacities (i.e., use of modern technologies in production); SDG 13 (climate action) focusing on resilience and adaptive capacity to climate-related hazards and natural disasters (i.e., climate change adaptation in production); and SDG 15 (life on land), which is aimed at ensuring conservation, restoration, and sustainable use of ecosystems.

Conventionally, agricultural policies, whether designed at the regional or country level, are targeted at attaining higher productivity, so that enough food is produced [25]. Most Asian countries have followed the Asian path of productivity growth, where land productivity increased faster than labor productivity in the early period, followed by fairly rapid growth of labor productivity, even after the mid-1980s [26]. On the contrary, the Common Agricultural Policy of the European Union focused on mechanization of agriculture to boost labor productivity, as labor supplies were relatively scarce in these economies. Japan followed the European path (i.e., increasing labor productivity), which is closely related to an increase in farm size and mechanization. Although the policies of various regions were different, the goal was to increase total agricultural productivity. There are examples of support policies, such as innovation policies related to agriculture, captured in the OECD’s classification as part of the General Services Support Estimate (GSSE), and other policies (environmental regulations or taxes), which may also influence producers’ decision-making and ultimately influence productivity and sustainability outcomes in agriculture [27]. African farmers faced more discriminatory agricultural policies than in other parts of the world [28]. Nevertheless, different agricultural policies in Sub-Saharan Africa, e.g., national and international agricultural research investment policies, economic policy reforms, and irrigation investments, had a positive and significant effect on total factor productivity [29].

Literature is available which provides valuable insights on the effects of climate change on agricultural production (e.g., [18,24,30–32]) and productivity (e.g., [33,34]). However, research on climate change and TFP is confined to a specific region or country, e.g., Ryan [35], Mullen and Cox [36], and Salim and Islam [33] focused on a specific Australian region. Liang et al. [37] explored impacts on US agriculture, whereas Kunimitsu et al. [38] studied the effects in Japan. Furthermore, there are limitations in terms of the scope of analysis, content coverage, methodology applied, and identification of determinants of agricultural productivity [20]. Although climate, weather, agro-ecological and socio-economic factors influence agricultural land use change and/or production [30,31], the exact nature and magnitude of their influence on productivity and efficiency is not clear. Lobell and Field observed that the literature did not duly emphasize climate change effects on agriculture, despite the increasing trend in surface temperature rise over the past few decades [30]. The dominant trend in the literature is to model changes in crop production, as explained by different climatic variables (mainly rainfall and temperature) and natural factors (soil quality) only (e.g., [22,30,31,39]), but they do not consider the influence of socio-economic and other factors [40]. Some even proxied weather by rainfall only while exploring the impact of climate change on farm cost (e.g., [35]) or TFP (e.g., [34]). Mullen and Cox [37] explained TFP variations in Australian broadacre agriculture through time trends, which is an even more distant proxy. In their subsequent work, Mullen and Cox [41] used pasture growth based on rainfall data to supplement weather. Most importantly, the TFP measures used in these studies have their own limitations. For instance, Liang et al. [37] used Wang et al.'s [42] estimates for US agriculture, where TFP was defined simply as the ratio of output to input. In the case of Western Australia, Salim and Islam [33] used TFP measured through the Tornqvist index method, whereas Kunimitsu et al. [38] applied the Tornqvist–Theil index for paddy production in Japan. Mullen and Cox [36] adopted the Divisia indices of aggregate output to aggregate input. All these are biased measures and do not possess the required features of multiplicative completeness or transitivity, and the scope to decompose estimated TFP growth into finer components of associated efficiency measures is limited [43].

Finally, and most importantly, the aforementioned studies lack a holistic approach, as none has explicitly explored the impacts of climate change, the production environment, and relevant socio-economic factors together, which are driving global agricultural productivity and efficiency changes over time and, hence, carry little interest in the policy arena. Rather, efforts are limited to exploring the impact of climatic variables only along with research and development (e.g., [33,37]). Alternatively, TFP-focused global-level studies did not try to explain the growth factors, particularly climatic factors. Avila and Evenson [44] and Fuglie [4] concentrated only on technology and human capital index to explain TFP growth, and Fuglie [4] admitted that due to 'left-out' variables (such as, climate change, production environment, and other socio-economic factors), the results may suffer from omitted variable bias. Furthermore, the future possible effect of the changing climate and associated anomalies on TFP is yet to be explored in the literature. Although, Anik et al. [45] circumvented all of the aforementioned weaknesses and provided an estimate of global agricultural TFP growth and efficiency changes, they did not attempt to identify the determinants and/or drivers of these changes, which is important for policy purposes. They also did not conduct any predictive analysis regarding future climate variability on agricultural TFP.

Given these backdrops, the main objectives of the present study were to (a) jointly identify the influences of climate change, natural production environment, and socio-economic factors on global agricultural productivity growth and its finer components (i.e., technical-, scale-, and mix-efficiency changes); and (b) predict the effect of future climate variabilities on global agricultural productivity. To achieve these objectives, we used the TFP and efficiency estimates of Anik et al. [45], which are based on a panel data of 104 countries, covering a 45-year period (1969–2013). Our study revealed three important insights and/or contributions to the existing literature: (i) established linkages, including magnitude and direction, amongst climate, production environment and socio-economic factors with global agricultural productivity and its efficiency components; (ii) identified synergies amongst agricultural productivity and various efficiency components; and (iii) provided the magnitude and direction of agricultural TFP change from future climate variabilities.

Although we explored different potential dimensions of agricultural productivity, due to a lack of the necessary data covering a long time-series for the majority of the countries investigated in this study, we could not explore two potential dimensions. The first one is related to waste management in agriculture from the viewpoint of the circular economy and the bioeconomy. While agriculture is both a cause and effect of climate change, it also contributes to climate change mitigation and resilience, since all the inputs from its production process are not lost, and the concept of circular economy addresses this. Although several notable related works are available (e.g., [46,47]), more rigorous work regarding these themes aimed at exploring the linkages, and possible policy options are suggested for future research.

Another crucial research area is related to the role of agricultural trade in TFP growth. Trade can enable a country to explore markets beyond its own geography and gain through comparative advantages originating from various factors, including natural and bio-physical factors and the institutional culture and skills that farmers possess over time. Edwards [48] noted that countries having greater trade barriers experienced slower productivity growth. Farmers of a middle-income country producing traditional and non-traditional crops, and those producing only traditional crops, are facing different international trade effects on crop yields [49]. They also revealed that exporting channels include international technology and knowledge spillovers because of trade and also gains in productivity, due to product specialization in trade. In global market exports, the EU countries held comparative advantages in exporting products of animal origin, whereas the US had comparative advantages in the exports of cereals, preparations of cereals, oilseeds, oleaginous fruits, and meat products [50]. Future studies focusing on the linkages between international trade, comparative advantages of an individual country, and TFP growth in agriculture could unpack new insights and knowledge on the subject matter.

2. Methodology

2.1. TFP Index and Its Components

We utilized the estimated values of TFP, technical-, scale-, and mix-efficiency indices from Anik et al. [45], who applied O'Donnell's [51] Färe–Primont index (FPI) approach, and produced estimates of TFP and its six finer components (i.e., technical change, technical efficiency change, scale efficiency change, mix efficiency change, residual mix efficiency change, and residual scale efficiency change). The advantage of the FPI method is that it only requires specification of the production technology (i.e., output and/or input distance functions), and it is free from any restrictive assumptions related to the nature of production technology, optimizing behavior of the firms, structure of markets and prices, and it also satisfies the condition of multiplicative completeness and transitivity of index number theory [52]. Anik et al. [45] constructed all relevant input and output variables, using the FAOSTAT database to estimate output oriented TFP and efficiency changes for 104 countries where agriculture contributed at least 4% of the GDP and/or 4% of total employment, covering a period of 45 years (1969–2013).

The estimation used eight outputs and five inputs, which circumvented aggregation issues, a common concern in global level TFP studies [53,54]. The panel-data series used in this study covered the period 1969–2013. This is because, prior to 1969, many data points were missing for most of the variables for many countries. In addition, although data from FAOSTAT for production inputs and outputs are available up to 2018 (i.e., prior to COVID-19, since data from the pandemic period are not considered as normal years), other data variables used to identify determinants of TFP change and its components are not available for most of the countries in the sample. Moreover, we believe that, since our study covers a historically long period of 45 years covering 137 countries, adding another 5 years of data, with incomplete information, would not have any discernible impact on the main conclusions and policy implications drawn from this study.

2.2. Determinants of TFP Change and Its Components: A Multivariate Tobit Analysis

Having the estimates of TFP and efficiency change indices in hand, which are censored in nature, we applied a multivariate Tobit model (MVTOBIT) to identify the determinants/drivers jointly influencing agricultural TFP and its efficiency components. Furthermore, the model enables testing correlations between error terms of different equations, which ultimately will inform how countries substitute or compliment TFP and its efficiency components. The general form of the model can be written as

$$Y_{it}^{*} = \gamma' X_{it} + \mu_{it} \quad (1)$$

where Y_i^* is the estimated value of TFP or its various components (log transformed) for country i in year t; x_{ijt} is the vector of different explanatory variables j of country I in time t; ε_i is the error. In any equation, Y_i^* equals the actual level of TFP of its components (Y_i); whereas for other countries, Y_i^* is an index reflecting potential score, such that

$$\begin{aligned} Y_{it} &= Y_{it}^{*} \quad if\ \gamma' X_{it} + \mu_{it} > 0 \\ &= 0 \quad\ \ if\ \gamma' X_{it} + \mu_{it} < 0 \end{aligned} \quad (2)$$

We developed four equations for TFP change index (dTFP) and its output-oriented components: technical efficiency change index (dOTE), scale efficiency change index (dOSE), and mix-efficiency change index (dOME). The general form of the four equations can be written as

$$\begin{gathered} dTFP_{it}^{*} = \gamma' X_{dTFP_{it}} + \mu_{dTFP_{it}} \\ dTFP_{it} = Maximum\left(dTFP_{it}^{*}, 0\right)\ (the\ usual\ Tobit\ specification\ as\ in\ 2) \\ dOTE_{it}^{*} = \gamma' X_{dOTE_{it}} + \mu_{dOTE_{it}} \\ dOTE_{it} = Maximum\left(dOTE_{it}^{*}, 0\right)\ (the\ usual\ Tobit\ specification\ as\ in\ 2) \\ dOSE_{it}^{*} = \gamma' X_{dOSE_{it}} + \mu_{dOSE_{it}} \\ dOSE_{it} = Maximum\left(dOSE_{it}^{*}, 0\right)\ (the\ usual\ Tobit\ specification\ as\ in\ 2) \\ dOME_{it}^{*} = \gamma' X_{dOME_{it}} + \mu_{dOME_{it}} \\ dOME_{it} = Maximum\left(dOME_{it}^{*}, 0\right)\ (the\ usual\ Tobit\ specification\ as\ in\ 2) \end{gathered} \quad (3)$$

A list of the explanatory variables and their estimation procedures are presented in Table 1.

2.3. Predicting Future TFP under Different Climatic Scenarios: A Sensitivity Analysis

Using the parameter estimates of the aforementioned MVTOBIT model, we predicted change in global agricultural TFP up to 2033. The predict command available in STATA 16 software enables both in-sample and out-of-sample forecasting. The out-of-sample prediction process requires forecasting explanatory variables, which we did for each country, using the annual compound growth rate estimated as the parameter β in $lnY = \alpha + \beta t$ (where y is the relevant explanatory variable and t is time) of the existing in-sample data. The assumption is that the explanatory variables will follow the same rate of growth in the future as experienced over the past 45 years (1969–2013). Therefore, the projected values of the explanatory variables can be considered as the natural change over the next 20 years (2014–2033) and provide us with the counterfactual scenario. This is because, along with this natural growth rate of explanatory variables, we assumed additional changes in climatic variables and developed four different models. The first of these is the 'counterfactual model', where we assumed the natural growth rate for all the explanatory variables, including climate variables. In the second model (Model 2), to capture the impact of increased rainfall and temperature variabilities, we imposed a 1% additional change in total rainfall and mean temperature variabilities annually on top of the counterfactual model. In the third model (Model 3), we imposed a 0.1% additional change in LTP and LTT annually, on top of the counterfactual model. In the final model (Model 4), we incorporated changes in Models 2 and 3, simultaneously, on top of the counterfactual model. All other remaining explanatory variables followed the natural growth rate, as explained previously.

Table 1. Definition and construction of the determinants.

Variables	Description of Variables
	Technology enhancing variables
Researcher	Agricultural researchers defined as '000 FTEs, collected from IFPRI's ASTI database.
Spending	Total agricultural spending, defined as share of Agricultural GDP, collected from IFPRI's ASTI database.
	Institutional capacity variables
Literacy	Log of literacy rate defined as share of people aged 15 years and above, collected from World Bank Data Bank (https://data.worldbank.org/indicator/SE.ADT.LITR.ZS; accessed on 21 February 2021). The data are available for different time periods for different countries. The standard interpolation method was applied to fill missing data.
Employment	Log of employment in agriculture, defined as share of total employment. The standard interpolation method was applied for missing years. A constant value of 4% (minimum threshold level for a country to be selected as a sample in our analysis) was applied to those countries where the method was not applicable because they had only one or no observations.
Economic openness	Log of trade, which is the sum of exports and imports of goods and services, measured as share of total GDP. Information compiled from the World Bank's national accounts data and OECD National Accounts data files.
	Socio-economic variables
Crop diversification	Log of Herfindahl index of crop diversification, which is constructed using land area under the different crops available at FAOSTAT. A zero value means complete diversification, and a value of 1 means complete specialization.
Dummy for income category (base = upper-middle income countries)	Based on GNI per capita. World Bank classifies countries into four categories, and three dummy variables are used: dummy for low income country (=1 for countries belonging to low income category, 0 otherwise); dummy for low-middle income country (=1 for low-middle income category countries, 0 otherwise); and dummy for high income country (=1 for the high income category, 0 otherwise).
	Agro-ecological and physical location variables
Elevation	Log of mean elevation (meters above sea level), available at https://www.pdx.edu/econ/country-geography-data; accessed on 7 June 2020.
Dummy for country's location in a typical weather regime (base = temperate zone)	The countries were classified into three broad typical weather regimes, and dummies for two regimes were used. These are dummy for arid and semiarid regions (=1 if the country belongs to arid and semi-arid region, 0 otherwise), and dummy for tropical sub-tropical regions (=1 if the country belongs to tropical and sub-tropical region, 0 otherwise). Some countries fall into multiple categories. The classification is available at: https://www.cia.gov/library/publications/the-world-factbook/fields/284.html; accessed on 17 December 2018
Climatic variables	Under this category four variable are used. The first four are climatic variables used to represent climate change and are constructed by exploring the World Bank's Climate Change Knowledge Portal (https://climateknowledgeportal.worldbank.org; accessed on 3 April 2020); whereas the fifth one represents the impact of climate change, and was collected from The International Disaster Database (available at: https://www.emdat.be; accessed on 25 March 2020).

Table 1. *Cont.*

Variables	Description of Variables
Long-term-precipitation–LTP (mm)	As climate is the average weather over a long period of time [39] and as the IPCC [55] considered 30 years as an example of a long time-period, a 30-year moving average (starting from 1901) of total annual rainfall was used, in logarithmic form.
Rainfall variability (mm)	Log of standard deviation of monthly rainfall per year is estimated using monthly total rainfall data.
Long-term-mean-temperature–LTT (0C)	Similarly to LTP, a log of the 30-year moving average (starting from 1901) of mean annual temperature is used as a measure of climate change.
Temperature-variability (0C)	The annual temperature variability is estimated as the difference between monthly maximum and minimum average temperature.
Regional dummy (base = Middle East and North Africa (MENA))	The countries belonged to six different regions, and, therefore, five dummies were constructed. These are dummy for Sub-Saharan Africa (SSA) = 1 if the country belongs to SSA, 0 otherwise; dummy for South Asia (SA) = 1 if the country belongs to SA, 0 otherwise; dummy for Latin America and Caribbean (LAC) =1 for LAC countries, 0 otherwise; dummy for East Asia and the Pacific (EAP) =1 if the country belongs to EAP, 0 otherwise; and dummy for Europe and Central Asia (ECA) = 1 if the country belongs to ECA, 0 otherwise.
Year	An integer variable represents time, t = 1 for 1969, 2 for 1970, and so forth.

3. Results

3.1. Global Agricultural TFP Change and Its Components

The estimated global agricultural TFP indices and its various components are presented in Table 2. The global TFP grew annually at a rate of 0.44%, and the estimated level was 0.20. The global technical efficiency level was estimated at 0.91, scale efficiency level at 0.97, mix-efficiency level at 0.78, residual- scale-efficiency level at 0.37, and residual-mix-efficiency level at 0.29, respectively.

Table 2. Total factor productivity and efficiency levels in global agriculture.

TFP and Its Components	Geometric Mean	Growth Rate (%)
Max-TFP level	0.75	0.23
Technical efficiency level	0.91	0.05
Scale efficiency level	0.97	0.04
Mix-efficiency level	0.78	0.32
Residual scale efficiency level	0.37	0.19
Scale–mix efficiency level	0.29	0.55
Total factor productivity level	0.20	0.44

The geometric mean of agricultural TFP and its components across regions and different categories are presented in Table 3. At the global level, the geometric mean of the TFP change index for the last four and half decade was 1.014, meaning the output increased at a higher rate than inputs. For the other three TFP components, i.e., technical-, scale-, and mix-efficiency changes, the index values remained less than unitary. The TFP change index values across all the categories are statistically significant.

3.2. Climate, Production Environment, and Socio-Economic Drivers of Productivity Change

Table 4 presents the joint estimates of the determinants of the TFP change and its three efficiency components by applying the MVTOBIT model. The key hypothesis in this multivariate analysis is that the 'correlation of the disturbance term between any pair of equations is zero $\left(i.e.\ \rho_{jk} = 0\right)$'. We found all correlations to be positive and significantly different from zero. This implies that complementary relationships exist amongst TFP and its three efficiency components, i.e., growth in TFP or any of its components is associated with growth in another component. The signs associated with the time variable imply that technical-, scale-, and mix-efficiency grew significantly over time.

Table 3. Geometric mean of TFP change and its components for different categories.

Country Categories	TFP Change Index *	Technical Efficiency Change Index	Scale Efficiency Change Index	Mix-Efficiency Change Index
		Income classes		
Low income countries	1.001	0.940	0.980	0.944
Low middle income countries	0.975	0.879	0.965	0.947
Upper-middle income countries	1.105	0.916	0.978	1.041
High income countries	1.236	0.963	0.995	1.012
		Production environment: land elevation		
Low elevation (185.39 MASL)	0.851	0.901	0.964	0.942
Medium elevation (503.19 MASL)	1.147	0.914	0.977	0.959
High elevation (1252.73 MASL)	1.068	0.921	0.981	0.981
		Production environment: weather regime/zone		
Arid and semiarid	0.975	0.892	0.968	0.859
Tropical and subtropical	1.083	0.915	0.976	0.979
Temperate	0.803	0.922	0.972	1.017
		Region/geographic location		
SSA	0.913	0.881	0.964	0.878
SA	0.791	0.981	0.982	1.015
ECA	1.516	0.975	0.991	1.109
LAC	0.964	0.922	0.979	1.024
EAP	1.231	0.926	0.979	1.006
MENA	0.928	0.868	0.967	0.874
Global	1.014	0.912	0.974	0.960

Note: * We conducted a one-way ANOVA test and found that the TFP change index across all the categories was significantly different at a 1% level of significance.

3.2.1. Socio-Economic Factors Explaining TFP Growth and Its Components

The negative signs on the coefficient of the Herfindahl index of crop diversification imply that crop diversification positively contributed towards TFP growth, technical-, and mix-efficiency changes. A 1% increase in crop diversity index will increase the likelihood of an increase in TFP, technical-, scale-, and mix-efficiency by 0.585%, 0.031%, and 0.074%, respectively (Table 4).

To understand whether the growth in TFP and its three components across countries belonging to different income classes is different, countries were categorized into four income classes, following the World Bank classification. Except for the mix-efficiency change index, high-income countries had the highest index values compared to the other three income classes (Table 3). However, the econometric analysis revealed that, compared to the upper-middle income countries, low-income countries attained significantly higher growth in TFP and its three components, and that the high-income countries experienced significantly higher technical- and scale-efficiency growth. However, for low-middle income countries, the mix-efficiency change was significantly lower than for the upper-middle income countries (Table 4).

Table 4. Joint estimation of the determinants of TFP change and its components.

Variables	MVTOBIT (Marginal Effects)			
	TFP Change Index	**Technical Efficiency Change Index**	**Scale Efficiency Change Index**	**Mix-Efficiency Change Index**
Technology enhancing variables				
Spending	0.043 ***	0.006 *	0.002 *	−0.003
Researcher	0.006	0.005 ***	0.0003	0.010 ***
Institutional capacity variables				
Literacy	0.010	−0.019 ***	0.003 *	0.021 ***
Employment	0.023 ***	0.004 ***	−0.001	0.007 ***
Economic openness	0.004	−0.002 **	0.002 ***	0.0003
Socio-economic variables				
Crop diversification	−0.585 ***	−0.031 **	−0.007	−0.074 ***
Income class dummy (base = upper-middle income countries)				
Low income	0.112 ***	0.031 ***	0.015 ***	0.030 ***
Low middle income	0.016	−0.003	0.001	−0.011 *
High income	0.024	0.033 ***	0.008 ***	0.009
Production environment and weather regime dummy (base = temperate zone)				
Land elevation	0.046 ***	−0.024 ***	0.006 ***	−0.051 ***
Square of land elevation	−0.003 ***	0.002 ***	−0.0002 *	0.005 ***
Arid and semiarid	0.126 ***	0.006	0.005 ***	−0.015 ***
Tropical and subtropical	0.203 ***	0.015 ***	0.006 ***	0.045 ***
Climatic variables				
LTP	0.016	−0.021 ***	0.004 ***	0.004
Rainfall variability	−0.139 ***	0.002	−0.004 ***	−0.051 ***
LTT	−0.056 ***	−0.011 ***	−0.002	−0.013 ***
Temperature variability	−0.021 ***	−0.011 ***	−0.002 *	−0.017 ***
Region/Geographic location dummy (base = MENA)				
SSA	0.068 ***	−0.004	−0.010 ***	0.011
SA	0.047 *	0.030 ***	−0.004	0.063 ***
ECA	0.301 ***	0.074 ***	0.009 ***	0.103 ***
LAC	0.146 ***	0.054 ***	0.0005	0.081 ***
EAP	0.260 ***	0.045 ***	−0.002	0.073 ***
Year	0.0002	0.0004 ***	0.0001 ***	0.0003 *
Model diagnostic				
LR χ^2 (92)	2547.31 ***			
Log likelihood	248.36			
ρ_{12}	0.329 ***			
ρ_{13}	0.223 ***			
ρ_{14}	0.345 ***			
ρ_{23}	0.098 ***			
ρ_{24}	0.356 ***			
ρ_{34}	0.243 ***			
N	4680			

Note: ***, ** and * indicate significance at 1%, 5% and 10% level respectively.

3.2.2. Role of Technology-Enhancing and Institutional Capacity Variables in TFP Change and Its Components

The positive sign on the coefficient of employment variable in the TFP, technical-, and mix-efficiency change model implies that a 1% increase in the quantity of agricultural labor increases the likelihood of an increase in TFP, technical-, and mix-efficiency efficiency change by 0.023%, 0.004%, and 0.007%, respectively (Table 4). Our results reveal that a 1% increase in the adult literacy rate increases the likelihood of a 0.003% and 0.021% increase in scale- and mix-efficiency change, while technical efficiency is likely to be reduced by 0.019% (Table 4). Contrary to the common notion of the efficiency-enhancing role of education, in many instances empirical literature was inconclusive about the relationship between the two, while some noted a negative relationship [56,57]. A commonly mentioned reason is the wider livelihood domain beyond agriculture, which is more likely to be explored by educated farmers.

To capture the impact of economic openness on TFP and its associated components, an explanatory variable, defined as the ratio of trade (sum of exports and imports of goods and services) with GDP was included. The coefficient on this variable has a positive sign in the scale efficiency change equation, but negative sign in the technical efficiency change equation (Table 4). The implication is that the likelihood of enhancing scale efficiency is significantly higher in open economies.

Agricultural spending (measured as the share of agricultural GDP) positively increases the likelihood of TFP growth, technical-, and scale-efficiency improvements. Similarly, increase in the number of agricultural researchers increases the likelihood of an increase in technical- and mix efficiency changes (Table 4).

3.2.3. Climate, Agroecology, and Weather Regimes as Drivers of TFP and Its Components

We incorporated four variables to represent climate change: two of these are to capture the long-term change in climate, i.e., a 30-year moving average of annual mean temperature (LTT) and annual total rainfall (LTP), whereas the remaining two capture annual variations in total rainfall and mean temperature.

Among these four variables used to represent climate change, except the LTP variable in the scale-efficiency equation, all coefficients have negative signs, especially where the effect is significant. The estimated marginal effects with the variable LTP imply that a 1% increase in LTP is associated with a likelihood of 0.021% reduction and 0.004% increase in the technical- and scale-efficiency change indices, respectively. We also found that a 1% increase in LTT is associated with the likelihood of a 0.056%, 0.011%, and 0.013% decrease in TFP, technical-, and mix-efficiency change indices, respectively, which is in-line with Rahman and Anik's [58] findings about agriculture in Bangladesh. Moreover, climatic vulnerability, in the form of increasing LTP and LTT, creates risk and uncertainty, which can negatively contribute to efficiency. Annual mean temperature and total rainfall variations have severe implications on agriculture, as expected. Except for rainfall variation in the technical efficiency change equation, both variables have a significant growth reducing role across equations, with relatively higher marginal effects of variation in annual total rainfall (Table 4). Increasing precipitation within the growing season may cause crop loss, particularly in tropical and sub-tropical countries that are prone to flood. Within a certain temperature range, crop growth is positively and linearly related with temperature. However, beyond the base and the upper threshold temperature, growth is affected, and the relationship is inverse for temperature between optimum and a ceiling levels [59]. Increasing temperature in the growing season has an adverse effect on yield [60].

Based on the mean elevation of the landscape, the countries were divided into three categories, and countries belonging to the medium elevation category had the highest level of TFP change, whereas the high elevation countries had the highest technical-, scale-, and mix-efficiency changes (Table 3). To further investigate the dynamics between land elevation and agriculture performance, we included land elevation and squared land elevation as explanatory variables and found a significant negative effect of both across four equations. With increasing land elevation, TFP first increases. However, as land elevation increases at an increasing rate, the TFP level then reduces. A similar pattern was observed with the scale-efficiency change model. However, the relationship was opposite for the technical- and mix-efficiency change models (Table 4).

Based on weather regime, we classified the countries into three categories, and the descriptive statistics presented in Table 3 show that the arid and semiarid region was the worst performing. The econometric analysis shows that, compared to the temperate zone, the likelihood of growth in TFP and its three efficiency components is significantly higher in the tropical and subtropical zone. The arid and semiarid region also showed significantly higher TFP and scale-efficiency changes than the temperate region, although the mix-efficiency change was relatively higher in the temperate zone than the arid and semiarid zones (Table 4).

3.2.4. TFP and Its Components across Regions

TFP and its three different components have regional patterns. Among the regional dummies, except for scale-efficiency change in SSA, all showed a positive effect, especially where the effect is significant, implying that the likelihood of increase in TFP and its efficiency components is significantly higher in these regions compared to the base region, MENA (Table 4).

3.3. Predicting Impact of Future Climate Change on TFP: Sensitivity Analysis

Table 5 presents predicted TFP based on parameter estimates of the MVTOBIT model up to 2033, under four different climatic scenarios. For all four models, the predicted TFP in 2033 is significantly higher compared to the baseline year of 2013, but the TFP increases more in the counterfactual model, where no additional climate variabilities are assumed. The bottom two rows of Table 5 show the mean-differences in TFP between the counterfactual and other three models, which shows that with any additional climatic variabilities, the TFP reduces significantly from its natural rate of change, i.e., the counterfactual model.

Table 5. Predicted changes in TFP index under different scenarios.

Year/Time-Period	**TFP Change Index**			
	Counterfactual Model [1]	**Model 2 [2]**	**Model 3 [3]**	**Model 4 [4]**
Terminal year, 2013	1.038			
Projected final year, 2033	1.102	1.098	1.102	1.098
% change from 2013 to 2033	+6.20	+5.75	+6.19	+5.74
t-test statistics	5.201 ***	4.766 ***	5.192 ***	4.757 ***
Mean difference with the counterfactual model (%)	Not applicable	−0.431	−0.009	−0.440
t-test statistics	Not applicable	48.949 ***	29.052 ***	49.680 ***

Note: [1] changing at the same rate as observed from 1969 to 2013. [2] 1% additional change in annual rainfall and temperature variabilities on top of the counterfactual model. [3] 0.1% additional change in LTP and LTT annually, on top of the counterfactual model. [4] combined changes in Models 2 and 3, on top of the counterfactual model. *** indicate significance at 1% level.

4. Discussion

Although the estimated annual TFP growth rate was below a modest level (Table 2), an important and encouraging feature of this rate is that global agriculture has maintained this positive rate of growth over four and half decades, which certainly contributed towards enhancing global food security. The econometric analysis also confirmed that, over the years, TFP and its three efficiency components increased significantly (Table 4). Meanwhile, the estimated high values of technical- and scale-efficiency indices, and relatively lower values of mix-efficiency index, imply that global agriculture has performed well, in terms of operating at a technically efficient and optimal scale, but lacked the ability to derive economies of scale, by changing optimal input and output mixes (Table 2). The estimated geometric mean of TFP change index implies that during the last four and half decades, global agricultural output increased at a higher rate than the input growth, which is encouraging. However, the estimated less than unitary values for the three efficiency components imply that global agriculture is not only incapable of optimizing economies of scale and judiciously deciding on input-output mixes, it also failed to enhance technical efficiency to its maximum level; along with notable regional differences (Table 3). The existence of notable regional differences is further confirmed by the significant effects of production environment (i.e., land elevation and weather regime) and regional dummies in the econometric analysis (Table 4).

Farming is sensitive to topography, as both climatic variables (precipitation and temperature) and associated changes are related to elevation and extreme topography and can severely affect plant growth [61]. For instance, low temperature at higher elevation can progressively increase plant duration [62]. Farm management practices become complex and different at higher elevation as the topography is also complex [63]. Alternatively, at mid-elevations, precipitation and temperature are likely to be at a level that is optimal for crop growth [61], and we observed relatively higher TFP change index values for countries located at medium elevation level (Table 3). These dynamisms can probably explain the positive sign in the TFP change index, where, as elevation increases at an increasing rate, TFP reduces (Table 4).

Weather regime dummies significantly influence changes in TFP and its three efficiency components. Sachs [64] highlighted the importance of physical geography while explaining growth differences across regions. Compared to the tropics, the yield of major agricultural crops is higher in the temperate zone [65]. However, when it comes to inputs, except for labor, use of other inputs (e.g., fertilizer, machinery) is much lower in the tropics [65], as is the level of agricultural technology use [64].

Similarly, regional dummies are critical in explaining changes in TFP and its efficiency components, as is evident from Tables 3 and 4. The positive associations with regional dummies imply that the TFP in MENA has changed at a relatively lower rate than in other regions, except for technical efficiency for the SSA region. The findings in the literature about regional patterns are mixed. For instance, while Fuglie [5] noted that SSA has the lowest agricultural TFP growth, Headey et al. [20] observed that SSA has been doing remarkably better in recent years. Ludena et al. [53] noted that the TFP for MENA between 1981 and 2000 was much lower than the LAC, SSA, and SA regions.

The growth reducing role of increasing temperature (Table 4) is consistent with the literature, reporting increasing temperature as a major threat to agricultural production and yield [31,66]. Zhao et al. [67] analyzed historical trends in production and climatic variables and demonstrated the impact of increasing temperature on agricultural production. Finally, they argued for the importance of understanding temperature impacts while formulating agricultural policies. Our econometric analysis also confirmed a growth reducing role for both temperature and rainfall variabilities (Table 4), which is in line with previous literature. For instance, Lansigan et al. [68] discussed the different short- and long-term agronomic impacts of climatic variability. Such variabilities do not only have bio-physical impacts, but also contribute to associated risks and uncertainties (e.g., shifting dates of plantation and other farming activities). Pest and disease infestations vary according to seasonal variations in weather parameters [69]. Most importantly, although climatic variations are forcing changes in agricultural cycle [70] and the literature argues for proper forecasting [68] and adaptive strategies [70], farmers fail to cope properly with environmental changes [70]. The forecasted TFP under different climatic scenarios presented in Table 5 implies that, although agricultural TFP will increase in the future following past growth patterns, any additional changes in climate are likely have a significant growth-reducing role.

In such situations, agricultural spending for R&D becomes critical, as we observed in our results (Table 4). However, globally there has been a relatively low allocation to this sector, which is an unfortunate trend, given the proven positive effect of investment in R&D in enhancing food security and employment. For instance, Rahman and Salim [71] found a positive impact of R&D expenditure on technical change, technical- and scale-efficiency changes, and TFP in Bangladesh, which is also consistent with the findings of Coelli et al. [72]. Anik et al. [16] highlighted the importance of technology capital through investments in R&D, to obtain a higher level of agricultural productivity growth in South Asia.

Crop diversification significantly contributes in increasing TFP, technical-, and mix-efficiency changes (Table 4). In the literature, there is ample empirical evidence that crop diversification positively contributes to farming efficiency [73] and income [74], while reducing variability in income [75]; and that it ultimately can contribute to agricultural growth [76]. The strategy further helps in building resilience against a changing climate [77].

The importance and role of labor and its productivity in agricultural growth and development is repeatedly mentioned in many countries' policy documents (e.g., [78,79]). We also found that increasing employment in agriculture positively contributes to TFP growth, technical-, and mix-efficiency change (Table 4). However, in general, for several reasons, including the increasing use of agricultural technology and mechanization that leads to increased labor productivity, and the growth in the non-farming sector creating more lucrative job opportunities beyond the farm sector, employment in agriculture is showing a downward trend globally, which again points towards the need to enhance agricultural productivity through R&D. Furthermore, our results for the literacy variable establish the importance of human capital development, which is possible through education. However, we also saw a negative influence of literacy on technical efficiency (Table 4). In fact, the nexus between education and agricultural productivity and efficiency is ambiguous [57]. For instance, while some observed a production, profitability, and efficiency enhancing role of education (e.g., [58,80]), Hasnah et al. [81] reported a negative relationship.

5. Conclusions and Policy Implications

Globally, the agricultural sector was successful in maintaining a modest level of positive TFP growth rate, mainly through reaping the benefits of technological progress and deriving economies of scale by optimally changing input and output mixes. There were many more factors, including natural resources, that led to the concentration of production and specialization. The revealed complementary relationships amongst TFP and its three efficiency components imply that growth over time in TFP, or any of its components, is associated with growth in another component. This insightful finding is a methodological improvement, which is not found in the conventional literature exploring determinants of TFP. For instance, the land-rich and resourceful Central Asian countries specialized in grain and cotton production [82], and African countries concentrated on traditional agricultural products (e.g., cocoa, coffee, cotton, fish and fish products, fruits, legumes, and tea, etc.) [83]. However, it failed to improve regarding technical efficiency changes and the ability to operate at an optimal scale, although the actual levels of technical and scale efficiency were quite high at the beginning but became stagnant over time. A wide range of climate, production environment, and socio-economic factors exert significant and varied influences on TFP growth and its efficiency components. Climatic variables have a robust effect across models, particularly the variation in annual mean temperature and annual total rainfall. Alarmingly, future TFP projections show that any incremental variabilities in climatic variables will have a further growth-reducing effect.

Therefore, based on the observations of the varied performance of TFP and its components and findings from the econometric analysis, the following policy implications are suggested: At the strategic level, the main thrust should be geared towards technological progress and mix-efficiency improvements, while special attention needs to be paid to remove stagnancy in pure technical and scale efficiency changes at the global level. First, investment in agriculture, particularly in R&D activities needs to increase, which has been on the decline in many economies. Second, research and extension organizations have a vital role to play in promoting crop diversification, through identifying and developing appropriate crop diversification portfolios suited to each agro-ecology and its socio-economic settings. Third, the above two strategies need to be backed up with a favorable institutional and policy environment, particularly given that the existing low institutional efficiency and low adoption rate of innovative agricultural technologies remains a worldwide phenomenon [84]. Enhanced institutional efficiency will specifically contribute to a higher scale- and mix-efficiency. Fourth, due to its undisputed role, investment is needed in education, particularly in the developing economies and focusing on agriculture. Finally, there is strong evidence that increasing temperature and volatility in climatic variables are adversely affecting TFP growth. Therefore, given the regional variations in TFP performance, country and region-specific research and policies to mitigate and adapt to climate change should have topmost priority. Although various climate-smart agricultural technologies are being developed and advocated, their adoption is subjected to several socio-economic, political, and institutional constraints [85,86]. Crop insurance may be an effective instrument, and has been suggested across different agricultural settings, including pastoral regions of Kenya and other East African countries [87]. While, the Indian policy of banning conventional urea, and producing neem-coated urea only, is a successful example of enhancing both nitrogen use efficiency and farm efficiency [88], the recent Sri Lankan policy of banning fertilizers and agro-chemicals has created an economically and politically chaotic situation [89].

Governments, alone, may not be capable of bringing about the required changes in the agricultural future; rather, international donors, development partners, and private sectors need to contribute as well. Furthermore, individual farmers and/or farm managers in their respective countries also have an important role to play by implementing the economic optimization of their production process, by adopting appropriate/modern technologies and improving technical, scale, and mix-efficiencies, while acknowledging the limitations posed by climate change and the natural production environment within which they are operating.

Author Contributions: Conceptualization, S.R. and A.R.A.; methodology, S.R. and A.R.A.; software, A.R.A.; formal analysis, A.R.A.; data collection, A.R.A. and J.R.S.; data curation, A.R.A. and J.R.S.; writing—original draft preparation, A.R.A. and J.R.S.; writing—review and editing, J.R.S.; supervision, S.R.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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Article

The Effect of the Major-Grain-Producing-Areas Oriented Policy on Crop Production: Evidence from China

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Abstract: As a powerful actor in the global food system, China experienced a significant drop in crop production from 1998 to 2003, which posed a substantial threat to national food security and led to the establishment of 13 major grain-producing areas (MGPA). Although some qualitative research has found that the MGPA policy plays an important role in ensuring the national food security, quantitative evidence on the effect of the MGPA policy and its potential mechanism remains scarce. Based on China's interprovincial panel data from 1998 to 2018, this study used a difference-in-differences (DD) estimation strategy to analyze the treatment effect of the MGPA policy by taking the assignment of 13 MGPA as a quasi-experiment. The results showed that the enforcement of the MGPA policy significantly increased crop production, especially in terms of grain, rice and wheat yields. The average grain yields were raised by 27.5%. The results of the event study analysis showed that the treatment effects were sustainable in the following years of the policy implementation. This study also explored alternative causal channels and found that the MGPA policy raised crop yields mainly by expanding planting areas, improving the level of mechanization and increasing transfer payments. These findings demonstrate the effectiveness of the MGPA policy in increasing crop production in a developing country setting, which could enlighten policymakers in some less well-developed countries on boosting crop production and maintaining food security.

Keywords: major grain-producing areas; crop production; food security; China

Citation: Hua, W.; Chen, Z.; Luo, L. The Effect of the Major-Grain-Producing-Areas Oriented Policy on Crop Production: Evidence from China. *Land* **2022**, *11*, 1375. https://doi.org/10.3390/land11091375

Academic Editors: Sanzidur Rahman and Uttam Khanal

Received: 7 July 2022
Accepted: 14 August 2022
Published: 23 August 2022

1. Introduction

"Food security" literally translates as "grain security" in Chinese, which is not only related to the security of a country, but also to world peace and social stability [1]. The United Nations post-2015 sustainable development agenda has set the eradication of hunger as one of important targets of the 17 Sustainable Development Goals (SDGs) in 2030. However, nearly 750 million people were exposed to severe levels of food security globally in 2019, and the number of people with food insecurity has been slowly increasing since 2014 (FAO, 2020). It was estimated that between 720 and 811 million people went hungry in 2020 according to the State of Food Security and Nutrition in the World 2021 report. Meanwhile, in addition to the climate change [2] and economic inequality [3], the widespread of COVID-19 pandemic also triggered a crisis on the global food security [4]. The COVID-induced economic shock has threatened food security by reducing incomes and disrupting supply chains, resulting in people's reduced availability and affordability of food in both higher and lower-income countries [5]. Therefore, transformations to increase the productive capacity and stability of agricultural production are urgently needed, which requires the building of a knowledge base to support.

As a powerful actor in the global food system, China has traditionally struggled to feed its large population. China feeds approximately 18% of the world population with only 8% of the global cultivated land (FAO, 2020). It is evident that China's food security is closely related to the stability of the global food system. To ensure its food security, the Chinese government has long put it high priority on the national political agenda [6]. However, from 1998 to 2003, China experienced a significant drop in crop production with the production of rice, wheat and corn in 2003 falling down almost 18 percent from the harvest in 1998. It posed a substantial threat to the national food security. After this crop production crisis, 13 major grain-producing areas (MGPA) were established by Ministry of Finance China, and a package of MGPA-oriented policies was implemented in the 13 regions. Although some qualitative research has found that the MGPA regions play an important role in ensuring the national food security and improving the production capacity [7,8], quantitative evidence on the effect of the MGPA policy and its potential mechanism remains scarce. Quantitatively verifying the efficacy of the implementation of the MGPA policy is important for China, as the ineffectiveness of such agricultural policy may deepen China's food crisis and threaten its food security. Furthermore, if the MGPA policy failed to increase China's crop production sustainably, the international crop price would increase as a result of increased crop imports from China. This would threaten the food security of low-income countries. Thus, the effectiveness of China's MGPA policy is not only a concern nationally but globally too.

A line of literature closely related to our work studies a certain set of factors affecting agricultural production. The theoretical and empirical literature acknowledges that the determinants of agricultural production can be categorized into mainly four types: physical factors (e.g., terrain, topography and climate), infrastructural factors (e.g., irrigation, roads and crop insurance), technological factors (e.g., farm machinery, pesticides and chemical fertilizer) and institutional factors (e.g., land tenure, land tenancy and land reforms). In terms of physical factors, they are defined as some natural resources including biophysical framework of soils, water, temperature, flora and fauna. It is worth mentioning that these factors do not work in isolation but the agricultural activity of a place is the product of combinations of different physical factors [9–11]. In terms of infrastructural factors, following the World Bank Report (1994), the definition of agricultural infrastructure was narrowed down to comprise long-lived engineered facilities and other services which include roads, electricity supplies and telecommunication. As illustrated by empirical studies, roads, electricity supplies, telecommunication and other infrastructure are important stimulants to agricultural output [12–15]. In terms of technological factors, empirical studies have found the adoption of improved agricultural technologies remains to be a promising strategy to achieve food security in many developing countries [16–18]. Institutional factors, which refers to the particular system under which land is owned and managed, have a direct bearing on agricultural production [19]. In practice, many developing countries have implemented many institutional reforms in agriculture sector, including providing security of tenure, computerization of land records and ceilings on agricultural holdings. Many of these institutional reforms have been empirically evaluated their effectiveness [20,21]. Despite the growing interests and enthusiasm for analyzing agricultural production from the perspectives of physical, infrastructural and technological dimensions, many studies note that these practices are still finite and farmers in developing countries are faced with a challenging environment [22], hence more focus should be on the role of institutional factors in agriculture. In particular, for China's MGPA policy, an institutional reform of redistributing regions for agricultural production, the research on its effectiveness still remains scarce. Given these, there is dire need to investigate the impact of the institutional factors on agricultural production.

Another strand of literature related to our analysis is research on the agricultural production in the MGPA regions. So far, many studies have been done to understand the agricultural production in the MGPA regions. Zhang et al. [23] estimated the grain production efficiency of the 13 MGPA regions between 2008 and 2017 and found that the overall level of total factor productivity of grain production in China's MGPA regions was relatively high and fluctuated, with an average annual rise rate of 1.85%. Yang et al. [24] identified the efficiency of the crop insurance in increasing crop production of the MGPA regions which exhibit a higher level of spatial farming risk accumulation and larger natural disaster pressures on farmers. Zhang et al. [25] empirically estimated the impact of the farmland protection on the security of grain supply in the MGPA areas using the panel data from 2010 to 2019 and found that the protection of cultivated land resources positively impacted the security of grain supply. Although all results in these studies have shown a significant increase in crop production in the MGPA regions, none of them empirically examined the causality between the establishment of the MGPA policy and crop production. The MGPA policy pertains to land management practices as it involves the allocation of land resources for agricultural growth. Theoretically, the exchange of inputs may avoid resource misallocation, which achieves higher marginal products and therefore improves input elasticities in agriculture [26].The effective land and resource governance systems that provide improved access, control, and rights to land and other natural resources is a necessary condition for achieving stable crop production [27]. Besides, land management practices are often with some production-oriented policies, which can be categorized as input support [28,29] (e.g., subsidies for fertilizers and seeds and farm equipment), output support [30,31] (e.g., countercyclical payments and price incentives), technical support [32,33] (e.g., extension services and investment in structural development) and financial support [34,35] (e.g., cash subsidies, loan aid and insurance aid). Although the four types of agricultural policies often interact with each other, previous studies have rarely treated them as a whole to investigate their impact on crop production.

Although China's food security is now guaranteed [6], in the long run, it is still faced with great challenges such as the rapid urbanization and spatial mismatch in agriculture resources. The rapid urbanization coincides with a large-scale transfer of China's cropland to "marginal land", which substantially imperiled food security and environmental sustainability [36]. This urbanization trend has led a large number of people to migrate from rural areas to cities. This rural-to-urban migration pattern intensifies the abandonment of cultivated land, while increasing its non-agricultural use [37]. Furthermore, a serious spatial mismatch exists between grain production and farmland resources in China, which also poses a threat to China's food security [38]. Thus, identifying the impact of the MGPA policy on crop production and clarifying its mechanism could provide insightful policy implications for alleviating food crisis in the future.

Given the above practical and theoretical background, to our knowledge, systematic empirical evidence on the effectiveness of the implementation of the MGPA policy remains scarce. Therefore, the objectives of this study are twofold: (i) The first is to investigate the effects of the MGPA policy on crop production by carrying out a difference-in-differences (DD) estimation and taking the assignment of 13 MGPA as a quasi-experiment based on China's interprovincial panel data from 1998 to 2018. To consolidate the reliability of the baseline results, several robustness checks are also performed. (ii) The second objective is to identify alternative causal channels of the treatment effects of the MGPA policy in terms of agricultural planting areas, mechanization level and transfer payments using a causal steps approach. This analysis could shed new light on maintaining food security from a perspective of land management practice.

2. Major-Grain-Producing-Areas Oriented Policy in China

China's production of rice, wheat and corn fell to around 400 million tons in 2003, down almost 18 percent from the record harvest of 486 million tons in 1998, according to statistics from the US Department of Agriculture. Meanwhile, this food crisis was accompanied by a growing population and shrinking arable land area. To eliminate the threat to food security, 13 major grain-producing areas were established at the end of 2003 by the Ministry of Finance China. These areas were Heilongjiang, Liaoning, Jilin, Inner Mongolia, Hebei, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hubei, Hunan, and Sichuan. Before 2003, the MGPA regions had been unofficially identified and were slightly different from those announced in 2003. Specifically, Guangdong, Guangxi, Zhejiang, Gansu and Shanxi had been classified as MGPA pre-2003, however, they were not included in the list of 2003. Figure 1 illustrates the geographic distribution of the MGPA regions in China. Dark grey areas indicate the 13 MGPA regions, and white areas the non-MGPA regions. The 13 MGPA regions cover 64% of the geographical area, are home to more than 50% of the population, and produce 75.4% of China's grain output [7]. Geographically, seven of the 13 MGPA regions are located in northern China, which is to the north of the Qinling-Huai line[1]. This is consistent with the current observation that China's agricultural center is shifting from the south to the north, especially to the northeast of China.

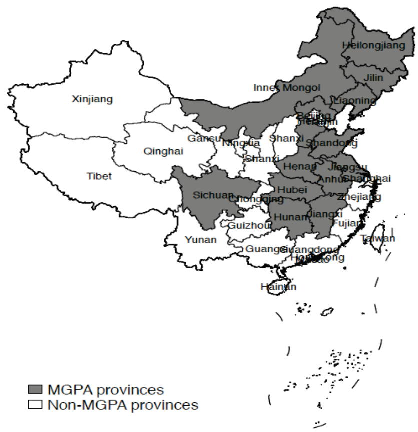


Figure 1. MGPA provinces.

The establishment of the MGPA is supplemented by some MGPA-specific policies. After carefully sorting out the MGPA oriented policies during our research period from 1998 to 2018, as Table 1 shows, we classify these policies into three types: production support, market management and natural resources management. Such classification is based on the food and agriculture policy classification of FAO. Among these MGPA oriented policies, several MGPA-specific policies are widely recognized. In terms of the production support policy, rewarding counties that produced large harvests, was added to the MGPA policy package in 2005. Specifically, a county was deemed to have produced a large harvest when its average yearly crop yields for the past five years were above 200 thousand tons and commodity crops above 5000 tons. Also, when a county's yields were ranked in the top 100 of all areas in the MGPA, it received some extra bonus subsidy from the central government. This MGPA-specific policy not only increased the willingness of farmers to plant crops, but also reduced the financial pressure on local government. In terms of the agricultural risk management policy, subsidies for the disaster prevention and mitigation in agriculture were implemented in 2012. The central government implemented for the first time the subsidy policy for agricultural disaster prevention and mitigation by subsidizing six key technologies for winter wheat, northern corn and southern early rice production. Abdur and Wang [39] found that these policies played an important role in helping farmers restore production and living. For the value-chain-development oriented policy, China formulated a plan for the construction of a high-quality grain industry (2004–2010) immediately after identifying the 13 MGPA regions. This policy was designed to accelerate the upgrading of the grain industry for the 13 MGPA regions by cultivating superior crop breeds, promoting the construction of standard farmland, improving agricultural mechanization and advancing disease and pest control techniques. Meanwhile, it also incorporated technology advancement into the existing agricultural value chain through better training, financing and fertilizer. As for the conservation and management of resources policy, the central government of China officially launched the Action Plan for the Zero Increase of Fertilizer Use in 2015. The goal of this plan was to reduce the fertilizer use without reducing food production especially in the MGPA regions. Lastly, the establishment of grain production functional area in 2017 scientifically demarcated the grain production functional areas of rice, wheat and corn, the production and protection areas of soybean, cotton and rapeseed, and management of groundwater overexploitation funnel areas in North China.

In general, the MGPA policy can be summarized as following features: (i) The spatial agglomeration of the MGPA regions. China's agricultural center had been in the south for a quite long time and the traditional pattern of grain transportation was from the southern regions to the northern regions during the long-term historical accumulation of agricultural production [40]. However, with the establishment of MGPA policy, seven of the 13 MGPA regions are located in northern China and the spatial pattern of the food production has shifted from transporting grain to the north to relying mainly on the northern regions as a result of the conversion of farmland in the southern regions, the expansion of cultivated land in the northern regions [41], the transfer of agricultural labor to non-agricultural industries [42] and the adjustment of the planting structure [40]. The regions with high grain output per capita are now concentrated in northern and eastern China, while regions with low grain output per capita are mainly in southern and western China [43]. The proportion of grain output in 15 northern provinces in the national grain output has increased from 45.65% in 2000 to 59.22% in 2020, while for the southern areas, it declined from 54.35% in 2000 to 40.78% in 2020. In addition, the MGPA regions agglomerate to the relatively less developed areas when compared with the non-MGPA regions. Existing studies indicate that the MGPA regions sacrifice their economic development for China's food security [44]. In contrast, the food supply of the non-MGPA regions is largely supported by the MGPA regions' grain production, and the development of the non-MGPA regions is more economic-oriented. For example, Zhejiang was not included in the 2003 list, despite being one of the unofficial major grain-producing provinces and having better agricultural resources. Zhejiang was not included on the list because it may take more economic responsibility with its well-equipped industry and intensified city groups. (ii) The comprehensiveness of the MGPA policy. The MGPA policy is not merely a land management practice for reallocating land resources for food production. It is also followed by a comprehensive MGPA-regions-specific agricultural policies. The MGPA policy has multiple areas of action, mainly including financial subsidies (e.g., rewarding the county for large harvests), technical support (e.g., upgrading local agricultural infrastructure) and input support (e.g., promoting the adoption of superior crop breeds). These integrated sub-policies support and complement each other to increase grain output. In terms of the source of funds, formal financial institutions are less interested in financing the agricultural sector because it is a high-risk business with high transaction costs, asymmetric information and low profits [45]. However, the funds for implementing the MGPA policy are provided by both the central financial budget and local supporting funds, which can safeguard the stability and sustainability of the MGPA policy from financial constraints. In addition, the MGPA policy is also a dynamic policy which, through successive reforms, has adapted to new challenges faced by China's agriculture. The Chinese government has so far created and implemented a series of MGPA sub-policies to meet new challenges such as addressing national market fluctuations and price volatility, using natural resources in a more sustainable manner and contributing to climate change mitigation.

Table 1. The brief summary of the MGPA oriented policy.

	Policy Classification	Policy Sub-Classification	Policy	Time	Policy Specification
MGPA oriented agricultural policy	Production support	Production subsidy	Rewarding counties that produce large harvests.	2005	When a county's yields were ranked in the top 100 of all areas in the MGPA, it will receive some extra bonus subsidy from the central government.
			The subsidy policy for soil testing and fertilizer recommendation.	2005	Focusing on five segments of "testing, formulating, producing, supplying and fertilizing", agricultural agencies launched soil testing, formulated scientific fertilization scheme and generalized the scientific technique of fertilization.
			Supporting policies for agricultural standardized production.	2006	The subsidy funds were mainly used for the integration of grain production standards, the publicity of standards, the construction of core demonstration areas, the establishment of leading enterprises and and the brand cultivation.
			The construction of large grain commodity bases.	2007	More than 60 large grain commodity bases have been built in several areas of the MGPA to upgrade local agricultural infrastructure and strengthen scientific and technological support for grain production.
			The construction of high standard farmland.	2010	It is a key measure to consolidate and improve grain production capacity and ensure national food security, which mainly focuses on arable land protection, soil fertility improvement, and efficient water-saving irrigation.
	Market management	Agricultural risk management	Subsidies for the disaster prevention and mitigation in agriculture.	2012	Special funds were allocated to provide subsidies for the implementation of drought resistant technique in the northeast region and the implementation of "one spraying and three prevention" technique in the winter wheat producing areas.
		Value chain developments	The construction of high-quality grain industry.	2004	The plan was designed to improve the quality of grain production by cultivating superior crop breeds, promoting the construction of standard farmland, improving agricultural mechanization and advancing disease and pest control techniques.
			The construction of modern agriculture demonstration zone.	2010	Taking green and recycling agriculture as the leading industry, it strived to build a pilot area with efficient grain production and quality improvement, a model area for sustainable development in agriculture.
	Natural resources management	Conservation and management of resources	A pilot scheme for agricultural resources recuperation.	2014	Returning farmland to forests and grasslands for steep slopes, seriously desertified farmland and important water sources areas. Carrying out comprehensive management of groundwater overexploitation funnel areas in North China.
			Policy of reducing fertilizer application and increasing efficiency.	2015	It was designed to reduce the amount of fertilizers and increase the efficiency on the premise of stable food production growth and adequate protection of food security.
		Land policy	The establishment of grain production functional area.	2017	It was aimed to scientifically demarcate the grain production functional areas of rice, wheat and corn, and the production and protection areas of soybean, cotton, rapeseed, sugar cane and natural rubber.

3. Methodology and Data

3.1. Regression Model

3.1.1. Difference-in-Differences Model

In order to identify the effect of the MGPA policy, a difference-in-differences model (DD) is widely used as an effective method for separating the time trend effect and the policy effect [46]. DD is a quasi-experimental design that makes use of longitudinal data from treatment and control groups to obtain an appropriate counterfactual to estimate a causal effect. It is typically used to estimate the effect of a specific intervention or treatment by comparing the changes in outcomes over time between the intervention group and the control group. In our analysis, the provincial variations in the adoption of MGPA policy enables us to carry out DD analysis. Specifically, there are two groups of provinces: those designated as MGPA (treated provinces) and those not (control provinces). There are two sample periods, pre-MGPA and post-MGPA, with the pre-MGPA period ranging from 1998 to 2004 and the post-MGPA period ranging from 2005 to 2018. The grain yield of MGPA provinces was compared to that of non-MGPA provinces (the first difference) before and after the implementation of the MGPA policy (the second difference).

The DD estimation specification is as follows:

$$Y_{it} = \alpha + \beta(D_i \times T_t) + \gamma Z_{it} + \lambda_i + \delta_t + \varepsilon_{it} \tag{1}$$

where Y_{it}, our measure of grain yield from province i in year t, is proxied by grain yield, rice yield and wheat yield; D_i indicates whether the province has been designated as MGPA i.e., $D_i = 1$ if province i is a MGPA province and $D_i = 0$ if province i is a non-MGPA province; $T_t = 1$ indicates the post-treatment period and $T_t = 0$ indicates the pre-treatment period[2]; Z_{it} are other independent variables; λ_i are province fixed effects, capturing province i's time-invariant characteristics, such as natural, climate and geographic features; δ_t are year fixed effects, capturing all yearly shocks common to all provinces, such as monetary policy and business cycles; ε_{it} is the error term.

One concern with the above specification is that province-specific annual variations may bias the estimation. One of these potential variations is natural disaster. Specifically, if grain yield was affected by some specific disasters, the estimates could be mistakenly attributed to the implementation of the MGPA policy. For example, during China's 2008 snow storms, the excessive snowfall and ice in February paralyzed the southern provinces and badly damaged their crops. To address such province-specific annual variations, we followed the approach of Li et al. [47] and included the interaction of province i and year t ($\lambda_i \times \delta_t$) into Equation (1). We therefore used the following equation for DD estimation to account for province-fixed, year-fixed and province-specific annual effects:

$$Y_{it} = \alpha + \beta(D_i \times T_t) + \gamma Z_{it} + \lambda_i + \delta_t + \mu(\lambda_i \times \delta_t) + \varepsilon_{it} \tag{2}$$

3.1.2. Event-Study Difference-in-Differences Model

DD relies on the parallel trends assumption which requires that in the absence of treatment, the difference between the treatment and control group is constant over time [46]. Despite the estimated coefficients of treatment effects being statistically significant in the DD estimation, the parallel trends assumption might still be a cause of concern. One estimation strategy widely used is to implement an "event-study difference-in-differences" estimator (ET-DD) [48]. The ET-DD estimation can also show the dynamic effects of the MGPA policy on crop production if the parallel trends assumption is satisfied. The specification of the ET-DD estimation model is:

$$Y_{it} = \alpha + \sum_{k=-6}^{14} \beta_k(D_i \times T_t) + \gamma Z_{it} + \lambda_i + \delta_t + \mu(\lambda_i \times \delta_t) + \varepsilon_{it} \tag{3}$$

where k describes the year before or after the enactment of the MGPA policy and $k = 0$ is normalized to 2004. In the regressions, $k = -1$ is left out as the reference year of 2003.

3.1.3. Propensity Score Matching Method

China exhibits appreciable regional differences across its huge territory and some of these differences are closely associated with the enactment of the MGPA policy. It suggests that the MGPA policy is more easily implemented in provinces with developed agricultural resources. If so, this reduces the comparability between the treatment and control provinces and confounds our estimation. To provide a good counterfactual for the treatment provinces in the period studied, the propensity score matching (PSM) method was used to mitigate selection bias by matching observations of treatment provinces with control provinces. Besides, PSM can also serve as a robustness check of our baseline estimation using DD method. Following Rosenbaum and Rubin [49], the PSM is modeled as:

$$p(X) = Pr(D = 1|X) = E(D|X) \tag{4}$$

where D = 0, 1 is an indicator of whether the province has been assigned as a MGPA province; X is a vector of pre-treatment characteristics.

Following Heckman et al. [50], we let Y_1 be the grain yield if the province i is a MGPA province (D = 1) and Y_0 if the province i is a non-MGPA province (D = 0). Thus, the average treatment effect on the treated (ATT) is specified as:

$$ATT = E(Y_1 - Y_0|D = 1) = E(Y_1|D = 1) - E(Y_0|D = 1) \tag{5}$$

Then the treatment effects based on the propensity score is estimated as follows:

$$ATT = E(Y_1|D = 1, p(X)) - E(Y_0|D = 0, p(X)) \tag{6}$$

3.2. Indicators and Variable Selection

3.2.1. Explained Variables

As discussed in Section 2, the major grain-producing areas were established as a result of China's falling grain production. The MGPA policy is aimed at increasing grain-oriented production. Hence we select the yearly provincial grain yield as the outcome of interest, which is defined as the output of grain, wheat, maize, sorghum, tubers, soybean and several other crops by China Agricultural Statistical Yearbooks. Besides, rice and wheat yield are also incorporate as two supplementary dependent variables because they are the two most important crops [51]. In 2021, the outputs of rice and wheat were respectively 21.29 million tons and 13.70 million tons, both ranking the highest in the world and accounting for about 55% of China's total food production. The increase of grain yield is expected to be mainly illustrated by the increase of the rice and wheat yield. Therefore, the estimation of the MGPA policy's effect on the two supplementary dependent variables can also serve as a robustness check for our baseline regression which employs the yearly provincial grain yield as the explained variable .

3.2.2. Key Explanatory Variable

According to the DD model setting, the core explanatory variable of this paper is the implementation of the MGPA policy, which is a dummy variable. Specifically, the core explanatory variable equals to 1 when the province has been designated as a MGPA province and 0 if province is a non-MGPA province. In addition, a dummy variable is often used in regression analysis to distinguish different treatment groups [52]. In our paper, whether the province has been assigned as a MGPA province is our interest. In other words, we just focus on whether the MGPA policy has been implemented, which does not involve building an explicit index system for the implementation of the MGPA policy. Therefore, a dummy variable can represent the implementation status with two distinct categories in our analysis.

3.2.3. Control Variables

A number of control variables relating to crop production have been included. Fertilizer consumption and pesticide consumption per mu[3] are two important inputs for agricultural production [53]. As China's agricultural growth has mainly been attributed to the improvement of productivity, especially the improvement of mechanization level in agriculture [26], the fixed asset which is closely related to the investment of technical equipments in agriculture is also included. Research shows that participation in rural non-farm activities exerts a pronounced impact on agriculture, household farm decisions and household food security [54]. Hence, non-agricultural income earned from non-farm activities has been included as a control variable. Following Janvry et al. [55], non-agricultural income was measured as the farmer's wage income per capita[4]. Due to the fact that the agricultural production system can benefit from participation in trade through the introduction of new skills and techniques [56], trade openness which is defined as the ratio of a province's sum of exports and imports to that province's GDP is also incorporated. The rate of urbanization is also included because a person's diet and demand for agricultural products will be transformed by urban expansion [57]. Zhong et al. [58] suggest that the frequent use of modern technologies resulting from the industrial revolution has increased crop yields, thus we included industrialization which is measured as the ratio of the output in the secondary industry to GDP. Lastly, rural financial efficiency also affects agricultural yields by extending agriculture-oriented financial services to farmers. Following Wang and Sun [59], we use the ratio of yearly rural loans to deposits as an indicator of rural financial efficiency, with data obtained from Chinese Rural Credit Cooperatives (1998–2018).

A threat to the identification is that the treatment effects would be confounded when there were other policies being enacted around the same time as implementation of the MGPA policy. After studying Chinese government documents, we found two agricultural policies that may have biased the estimation. One was the enactment of Law of Rural Land Contract (LRLS) in 2002[5], which enabled farmers to legally transfer, re-contract, enter into share-holding ventures and exchange the rights of land use. The other was the abolition of China's agricultural tax in 2006[6], which had been in existence over 2600 years. Existing studies have found that these two policies can affect farmers' grain production [60,61]. To relieve any confounding effects of these policies, two dummy variables were included. *LRLS* indicated the enactment of Law of Rural Land Contract in 2002 and *Tax* indicated the abolition of agricultural tax in 2006.

3.3. Data Sourcing

Our list of provinces designated as MGPA was derived from an official Ministry of Finance of the People's Republic of China document from December 2013, "The Plan for the Reform and Improvement of Agricultural Development.". The 13 MGPA were Heilongjiang, Liaoning, Jilin, Inner Mongolia, Hebei, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hubei, Hunan, and Sichuan. During the sample period, this list remained unchanged.

In order to estimate the treatment effects, a balanced panel of provincial data was constructed to estimate the effects of interest. The sample periods covered 1998 to 2018, as Chongqing was separated from Sichuan and designated a provincial-level municipality in 1997. In almost all cases, data were collected from various sources, including China Rural Statistical Yearbooks (Ministry of Agriculture, 1998–2018), National Agricultural Product Cost and Revenue Survey Data books (Ministry of Agriculture, 1998–2018), China Agricultural Statistical Yearbooks (Ministry of Agriculture, 1998–2018), China Statistical Yearbooks on Environment (Ministry of Environment, 1998–2018), and China Statistical Yearbooks (NBSC, 1998–2018). In addition, all economic variables were deflated using 1997's CPI. Detailed descriptive statistics are presented in Table 2.

Table 2. Descriptive statistics of variables.

Variables	Definition of Variables	Mean	S.D.	Min	Max
Grain	Annual grain yields (log)	16.16	1.23	12.74	18.15
Rice	Annual rice yields (log)	5.11	2.45	−2.30	7.94
Wheat	Annual wheat yields (log)	4.10	2.40	−3.22	8.22
Pesticide	Pesticide use per 10,000 yuan of the primary industry output (log)	−7.81	1.15	−11.68	−5.73
Fertilizer	Fertilizer use per 10,000 yuan of the primary industry output (log)	−1.18	0.62	−6.14	3.59
Fixed-asset investment	Fixed-asset investment per capita (log)	5.91	0.69	3.48	7.62
Non-agricultural income	Non-agricultural income per capita (log)	6.76	0.97	3.49	9.07
Trade openness	The ratio of a province's sum of exports and imports to that province's GDP	0.29	0.37	0.02	1.70
Urbanization	The ratio of urban population to rural's	0.43	0.18	0.10	0.90
Industrialization	The ratio of the secondary industry output to GDP	0.44	0.08	0.19	0.60
Rural financial level	The ratio of annual rural loans to deposits	0.68	0.14	0.33	1.97
Grain planting areas	Grain planting areas per capita (log)	0.09	0.06	0.00	0.38
Wheat planting areas	Wheat planting areas per capita (log)	0.02	0.02	0.00	0.06
Rice planting areas	Rice planting areas per capita (log)	0.02	0.02	0.00	0.10
Transfer payment	Transfer payment per capita (log)	5.26	1.25	2.58	8.13
Mechanization	Mechanization level per capita (log)	−0.04	0.81	−1.57	9.49

4. Results

4.1. Tests for Some Statistical Problems

To check for the variable collinearity, we perform a variance inflation factor (VIF) analysis, which has been widely used to test collinearity. The VIF test results of the explanatory variables in this study are summarized in Table 3. Among all variables, the largest VIF value is 2.75. Generally, a VIF above 4 indicates that multicollinearity might exist, therefore multicollinearity is free from concern in our analysis.

Table 3. The result of VIF test.

Variables	Pesticide	Fertilizer	Fixed-Asset Investment	Non-Agricultural Income	Trade Openness	Urbanization	Industrialization	Rural Financial Level
VIF	2.03	1.28	2.50	2.75	1.73	2.05	1.30	1.12
$\frac{1}{VIF}$	0.49	0.78	0.40	0.36	0.58	0.49	0.77	0.89

To verify whether the regression model contains a heteroskedastic error, White's test proposed by White [62], has been widely used. White's test, which compares the estimated variances of regression coefficients under homoskedasticity with the ones under heteroskedasticity, has an asymptotic chi-squared distribution and works well in large samples [63]. We perform a White's test and the p-value is 0.492, suggesting that the null hypothesis of homoscedasticity or no heteroscedasticity should be accepted. For the possible autocorrelation, a test proposed by Wooldridge [64] is very attractive because it requires relatively few assumptions and is easy to implement [65]. The result of the Wooldridge test shows that p-value is 0.0751, indicating that there is no first-order autocorrelation at a 5% confidence level in our linear panel-data model. Besides, following most empirical studies using panel data, all our empirical estimation is built on a robust-standard-errors technique for panel regression which is invented by Hoechle [66]. The code program presented by Hoechle not only could enable the estimates to be heteroskedasticity consistent but also make the standard error estimates be robust to general forms of cross-sectional and temporal dependence, i.e., autocorrelation. Therefore, the statistical problems of the heteroscedasticity and autocorrelation are relieved by using the estimation program.

In terms of the linearity and adequacy of the model setting, on the one hand, our select of control variables are based on the literature review (Section 3.2) and hence these control variables' linear relationship with the dependent variable has been examined by previous studies. Besides, the adequacy of the model can be partly illustrated by R^2, and the R^2 of our baseline regression model is above 92%, as reported in the baseline regression, suggesting that at least 92% of variance in the dependent variable that can be explained by the independentvariables. Therefore, the performance of our regression model is good. On the other hand, linearity in parameters within linear regression requires that model equation has correct functional form specification. This can be evaluated through Ramsey RESET test [67] which evaluates whether linear regression fitted values non-linear combinations explain dependent variable. If linear regression fitted values non-linear combinations explain dependent variable, then model equation has incorrect functional form specification. The result of Ramsey RESET test reported in Table 4 shows that the linearity is valid and model specification is correct.

Table 4. The results of White's test, Wooldridge test and Ramsey RESET test.

Test	Null Hypothesis	For χ^2-Statistic	p-Value
White's test	There is no heteroscedasticity.	555.000	0.492
Wooldridge test	There is no first-order autocorrelation.	3.385	0.076
Ramsey RESET test	Model has no omitted variable.	1.660	0.175

For the normality, the assumption requires a normal distribution that applies only to the residuals, not to the independent variables as is often believed [68]. We have tested the residuals' normality of the model and the result below (Table 5) shows that the residuals of our model are normally distributed.

Table 5. The results of skewness/kurtosis tests for normality.

Variable	Observations	Pr(skewness)	Pr(kurtosis)	χ^2	p-Value
Residuals	535	0.359	0.944	0.870	0.647

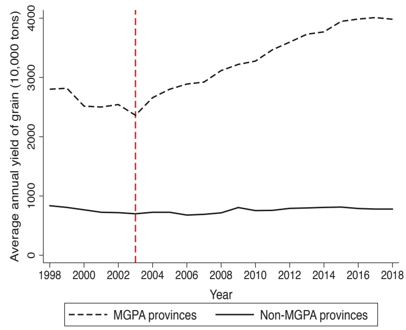
H0: the variable is normally distributed.

Lastly, in terms of the endogeneity which may result from the omission of variables, errors-in-variables, and simultaneous causality [64], we have employed an instrumental variables (IV) estimation in the section of robustness check to relieve potential endogeneity and our baseline results remain significant after using an IV estimation. IV estimation is a widely used approach to relieve potential endogeneity in many empirical studies [69]. Besides, to avoid the omission of variables, we also include some topographic and meteorological factors that may affect crop production in the section of robustness check and our baseline results remain significant after controlling for other variables. Such treatment could relieve the potential estimation bias resulted from the endogeneity.

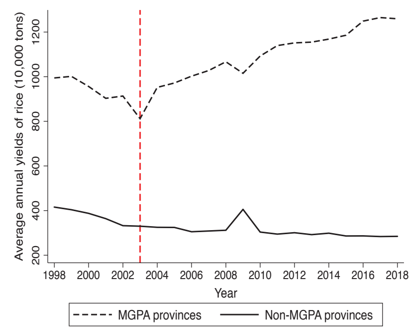
4.2. DD Estimation

Figure 2 shows the annual yield of grain, rice and wheat in the treated and control groups, namely MGPA and non-MGPA provinces. These graphs show that the yields for the three crops approximately perform some similarity in the years before the enactment of the MGPA policy, which agrees with the parallel historic paths assumption of DD estimation. The trends tentatively suggest that the MGPA provinces saw a higher output growth after 2003 than the non-MGPA provinces, and this will be examined in more detail next.

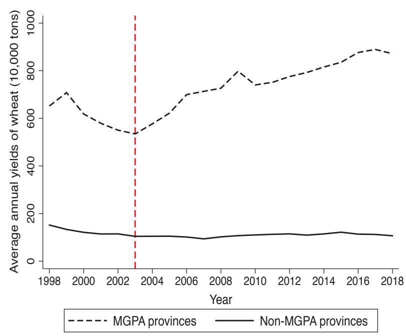
Table 6 shows the results for grain, rice and wheat. Columns (1), (3) and (5) include the controls of province-specific annual effects except year and province effects to reduce the estimation bias caused by potential province-specific annual variations. To control for other ongoing policies that may bias the estimation, columns (2), (4) and (6) also include the dummy variables for the two agricultural policies discussed above. The coefficients for the treatment effects, $D_i \times T_t$, are all positively significant suggesting that across the three crops, the implementation of MGPA policy increased crop yields, with an average increase of 27.5% for grain yields, 47.8% for rice yields and 35.5% for wheat yields. These treatment effects seem to be greater than expected, but are better explained after controlling other independent variables (planting areas per capita, mechanization and transfer payment per capita) in the following mechanism analysis which explores the potential causal channels of the treatment effects.



(**a**) Grain



(**b**) Rice



(**c**) Wheat

Figure 2. Yields of grain, rice and wheat.

In addition to the baseline result, there are also several interesting findings concerning factors affecting crop production. First, the positive relationship between crop production and pesticide use is valid for all three crops. However, only wheat production is positively associated with fertilizer use. The non-significant estimates for grain and rice yields may be attributed to the overuse of fertilizer. Chemical fertilizer overuse is common and serious in China with fertilizer use already severely exceeding international standards [70]. Second, the statistically significant coefficients for urbanization agree with previous findings showing that crop production increases with urban expansion because people's diets and demand for agricultural products are changed and diversified food consumption needs greater crop production [57]. Third, improving rural finances is beneficial to the increase in crop production. China has many smallholder farmers who are extremely vulnerable to unexpected events, so rural financial services, such as agricultural insurance, could protect farmers when these events occur and therefore encourage farmers to increase their investment in crops.

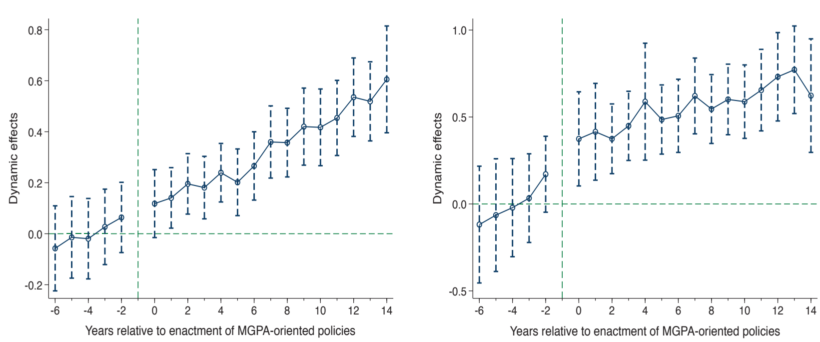
Table 6. The baseline DD estimation.

Dep. Var.: Yields	Grain		Rice		Wheat	
	(1)	(2)	(3)	(4)	(5)	(6)
$D_i \times T_t$	0.271 ***	0.275 ***	0.481 ***	0.478 ***	0.350 ***	0.355 ***
	(0.027)	(0.027)	(0.055)	(0.055)	(0.106)	(0.107)
Pesticide	0.275 ***	0.280 ***	0.178 ***	0.174 ***	0.535 ***	0.524 ***
	(0.029)	(0.029)	(0.056)	(0.054)	(0.163)	(0.160)
Fertilizer	0.016	0.022	0.032	0.017	0.214 *	0.231 *
	(0.020)	(0.022)	(0.032)	(0.029)	(0.124)	(0.126)
Fixed-asset investment	0.099 ***	0.095 ***	−0.040	−0.042	0.372 ***	0.362 ***
	(0.030)	(0.030)	(0.064)	(0.066)	(0.112)	(0.111)
Non-agricultural income	−0.008	−0.010	0.243 ***	0.249 ***	1.071 ***	1.083 ***
	(0.063)	(0.065)	(0.073)	(0.069)	(0.195)	(0.195)
Trade openness	−0.116	−0.115	−0.172	−0.168	1.025 ***	1.030 ***
	(0.090)	(0.090)	(0.105)	(0.105)	(0.318)	(0.318)
Urbanization	−0.429 ***	−0.374 ***	−0.221 **	−0.339 **	−0.862 **	−0.750 **
	(0.093)	(0.087)	(0.153)	(0.149)	(0.417)	(0.372)
Industrialization	−0.023	0.082	0.727 *	0.372	−2.007 ***	−1.812 **
	(0.231)	(0.227)	(0.387)	(0.387)	(0.762)	(0.811)
Financial level	0.166 ***	0.164 ***	0.156 *	0.167 *	0.242 *	0.237 *
	(0.054)	(0.053)	(0.087)	(0.091)	(0.101)	(0.100)
LRLS		Yes		Yes		Yes
Tax		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	555	555	535	535	535	535
R^2	0.929	0.927	0.986	0.986	0.962	0.962

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

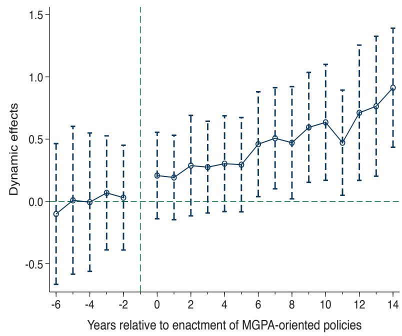
4.3. ET-DD Estimation

Figure 3 shows the estimated coefficients along with the 95% confidence intervals for the dynamic treatment effects. The coefficients for the pre-MGPA years (k = −2~k = −6) are all statistically distinguishable from zero, suggesting that the parallel trends assumption holds. After the implementation of MGPA policies, there is an immediate and lasting increase in grain and rice yields implying that the treatment effects of the MGPA policy are sustainable. For wheat yields, the treatment effect becomes significant six years after the policy's implementation. Such a delayed treatment effect may be attributed to farmers being less motivated to plant wheat as a result of its decreasing profitability[7].



(**a**) Grain (**b**) Rice

Figure 3. *Cont.*



(**c**) Wheat

Figure 3. Tests for parallel trends.

4.4. PSM-DD Estimation

When selecting matching covariates, one rule for selection is that the covariates are meant to be predictors of post-intervention outcomes, which are not themselves affected by the event [50]. To this end, our matching covariates include rural family size, sex ratio, educational attainment and agricultural land per capita. To improve the sample efficiency of the estimates [71], we removed treated observations whose propensity scores were out of the range of those of the control groups. The PSM-DD estimates based on the matched sample are shown in Table 7. The coefficients of the treatment effect ($D_i \times T_t$) for grain, rice and wheat are all positively significant whether controlling for province-specific annual effects or two other ongoing policies. The magnitudes of the coefficients are quite similar to the results of the DD estimation. Thus, our baseline findings from the DD estimation remain valid after using the PSM-DD for mitigating selection bias.

Table 7. The PSM-DD estimation.

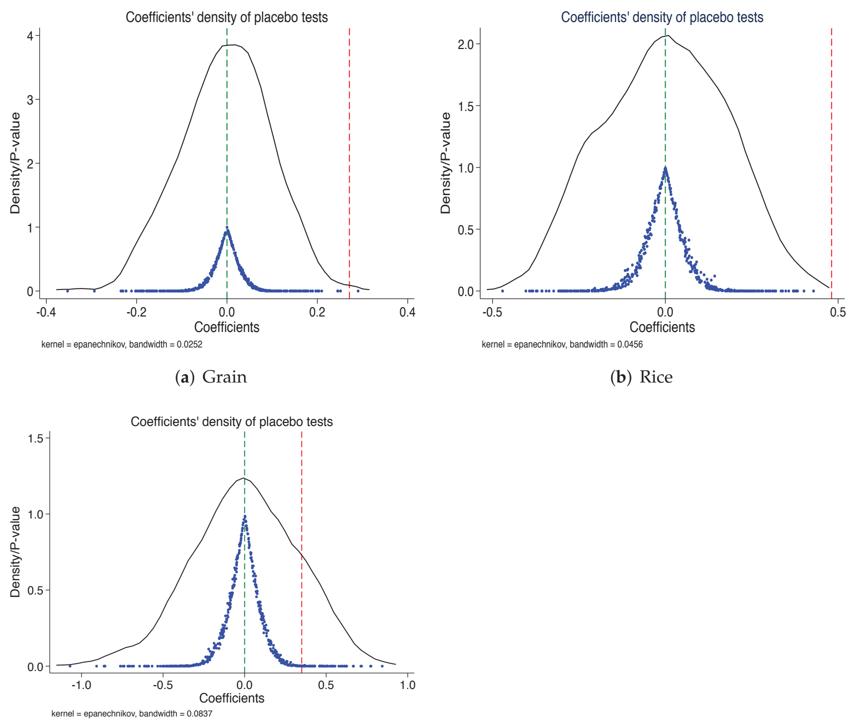
Dep. Var.: Yields	**Grain**		**Rice**		**Wheat**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$D_i \times T_t$	0.246 ***	0.253 ***	0.448 ***	0.442 ***	0.382 ***	0.383 ***
	(0.026)	(0.025)	(0.054)	(0.054)	(0.107)	(0.108)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
LRLS		Yes		Yes		Yes
Tax		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	546	546	526	526	526	526
R^2	0.928	0.926	0.987	0.987	0.963	0.963

Standard errors in parentheses. *** $p < 0.01$.

4.5. Robustness Checks

In this section, we perform three further robustness checks on our baseline findings. They are placebo tests using alternative treatment provinces, an instrumental variables estimation using local annual production of raw coal as the instrumental variable for the enactment of the MGPA policy, and case studies using synthetic control methods.

Placebo tests: To verify DD estimation, Chetty et al. [72] recommended using "fake" treatment groups, namely, randomly assigning policy shocks to sample areas. Specifically, for our estimation sample, 13 fake MGPA provinces were randomly selected from the 31 provinces and the remaining 18 provinces become fake control groups. Then, a series of fake treatment variables i.e., $D_i^{fake} \times T_t$, were constructed based on that random assignment. Given that these randomly constructed treatment provinces were not necessarily implemented with real MGPA oriented policies, the outcome of interest should be insignificant. In other words, any significant coefficients for fake treatment effects, β^{fake}, would suggest the invalidity of our baseline DD estimation. Following the method of Cai et al. [73], to rule out bias from any rare events, we carried out this random data generating procedure for 500 times. Figure 4 shows the kernel density of 500 random estimates and associated p-values for grain, rice and wheat yields. The mean values of the fake treatment effect for three crops are all around zero, specifically, the mean coefficient is -0.001 for grain, 0.003 for rice and 0.001 for wheat. The distribution center of 500 random estimates for three crops are all close to zero and their associated p-values are mostly larger than 0.1. Our real coefficients for treatment effects, represented by the red line, clearly differ from that of the placebo tests. Thus, these results again lend support to our baseline DD estimation.



(**a**) Grain (**b**) Rice (**c**) Wheat

Figure 4. Placebo tests.

Instrumental variables (IV) estimation: Using IV estimation can help remove potential bias arising from the pre-existing differences between the treatment and control groups [74]. Specifically, instrumental variables can rule out the pre-trends caused by confounders between the treatment and control groups [47]. In this study, we selected local annual production of raw coal as the instrumental variable for the enactment of the MGPA policy. There are two reasons that display the validity of using this instrumental variable. First, the origin of most coal is plant debris in wetlands from hundreds of millions of years ago in swampy forests. Hence, regions that have a large production capacity of raw coal are often agriculture-friendly places with rich natural resources, and MGPA policy is more likely to be implemented in such provinces. Second, to our knowledge, there is no direct relationship between the production of raw coal and crop yields.

Table 8 shows the two-stage least squares (2SLS) regression of the instrumental variables estimation. The first-stage results are presented in columns (1), (3) and (5). The coefficients of the instrumental variable, $Rawcoal_i \times T_t$, are all significantly positive suggesting that the large production capacity of raw coal is a valid indicator for the enactment of MGPA policies. Columns (2), (4) and (6) show the second-stage results for grain, rice and wheat, respectively. The treatment effects remain statistically positive and significant, with the magnitude of coefficients being even bigger. These 2SLS results imply that our baseline findings in DD estimation are robust.

Table 8. Instrumental variables estimation.

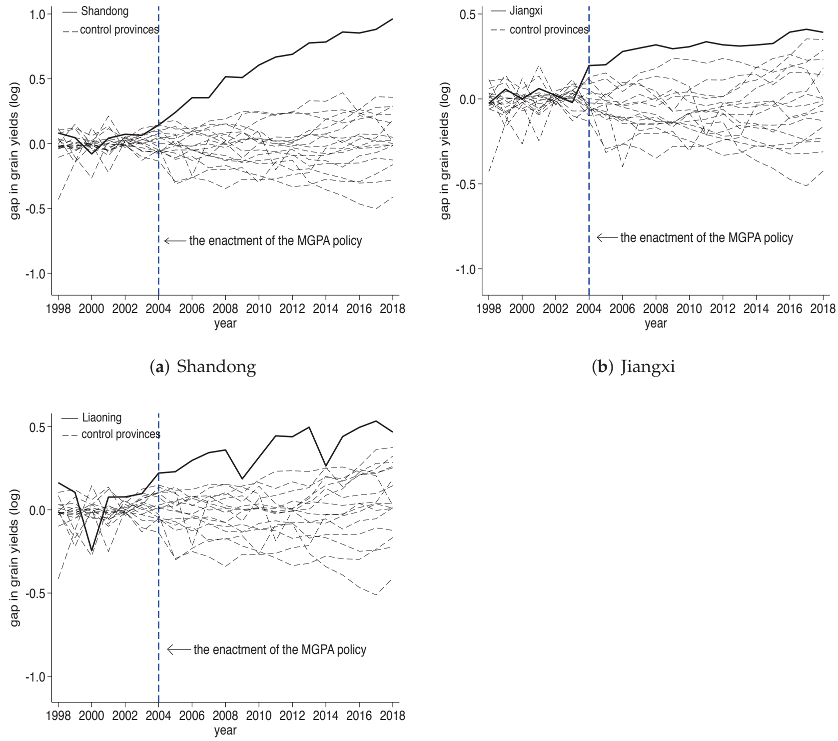
	Grain		**Rice**		**Wheat**	
Dep. Var.:	$D_i \times T_t$	**Grain Yields**	$D_i \times T_t$	**Rice Yields**	$D_i \times T_t$	**Wheat Yields**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Rawcoal_i \times T_t$	0.055 ***		0.052 ***		0.052 ***	
	(0.010)		(0.002)		(0.010)	
$D_i \times T_t$		1.332 ***		1.072 ***		3.116 ***
		(0.231)		(0.360)		(0.962)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	571	571	550	550	563	563
R^2	0.783	0.927	0.784	0.978	0.782	0.873

Standard errors in parentheses. *** $p < 0.01$.

Synthetic control methods: The synthetic control method, proposed by Abadie et al. (2007) [75], can effectively be used for comparative studies when exact matches are unavailable, which offers a sensible generalization of DD estimation [76]. We carried out comparative case studies focusing on the grain yields of three MGPA provinces. The three provinces were Shandong, Jiangxi and Liaoning, located in three traditional agricultural zones, specifically the Yellow River, Huai River and Hai River, the middle reaches of the Yangtze River, and the northeast of China.

We first constructed a synthetic Shandong, Jiangxi and Liaoning from the donor pool, all the non-MGPA provinces. The synthetic Shandong, Jiangxi and Liaoning mirrored the values of the predictors[8] of grain yields in real Shandong, Jiangxi and Liaoning before the establishment of MGPA. We then estimated the treatment effect of the MGPA policy on grain yields as the difference in grain yields between case provinces and their synthetic versions in the years after the MGPA were established. Figure A1 shows that the post-intervention growth paths of the three provinces significantly increased over the growth paths of their synthetic versions.

We further carried out a series of placebo tests confirming that our estimated treatment effects for the three case provinces were unusually larger relative to the distribution of fake treatment effects obtained from applying the same synthetic control analysis to the donor provinces. Figure 5 shows the results of the placebo tests for Shandong, Jiangxi and Liaoning. The dotted lines show the difference in grain yields between each province in the donor pool and their synthetic versions. The superimposed solid lines indicate the differences for case provinces. As the graphs show, the estimated difference for case provinces during the 2004–2018 period was unusually larger relative to the distribution of the differences for the donor provinces. These results illustrate the link between the MGPA policy and grain yields, which further support our baseline findings.



(**a**) Shandong (**b**) Jiangxi

(**c**) Liaoning

Figure 5. Synthetic control methods.

Controls for other variables: It is evident that the agricultural activity is closely related to some topographic and meteorological factors. To test the validity of our baseline result, several topographic and meteorological variables are incorporated into the regression analysis. Given the data accessibility at the provincial level, relief degree of land surface (RDLF), surface water resources (SF), sunshine hours (SH), temperature (TEM) and precipitation (Pre) are included as control variables. Following Feng et al. [77], RDLS is defined as the topographic relief above the horizontal surface of average elevation in a certain area, and it is an important index for evaluating environment conditions[9]. The dataset uses provinces as the statistical unit and is based on 1 km $\times$ 1 km raster data for extraction which serves as a macro scale regional assessment [78]. The surface water resources data is collected from China Water Statistical Yearbook (1998–2018). The data of sunshine hours, temperature and precipitation are collected from China Meteorological Data Network.

Table 9 reports the result of controlling for the topographic and meteorological factors. The coefficients for the treatment effects, $D_i \times T_t$, are still positively significant and similar to the baseline results, suggesting that the treatment effect of the MGPA policy is still significant even after controlling the topographic and meteorological factors. One interesting finding is that RDLS is negatively associated with the agricultural output, which shares the similar conclusion of Krummel and Su [79].

Table 9. Controls for other variables.

Dep. Var.:	Grain		Rice		Wheat	
	(1)	(2)	(3)	(4)	(5)	(6)
$D_i \times T_t$	0.277 ***	0.277 ***	0.496 ***	0.496 ***	0.346 ***	0.346 ***
	(0.026)	(0.026)	(0.055)	(0.055)	(0.109)	(0.109)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
RDLS	−5.258 ***	−5.258 ***	−13.296 ***	−13.296 ***	−10.102 ***	−10.102 ***
	(1.785)	(1.785)	(3.741)	(3.741)	(9.205)	(9.205)
SF	−0.027 **	−0.027 **	−0.010	−0.010	−0.006	−0.006
	(0.014)	(0.014)	(0.017)	(0.017)	(0.043)	(0.043)
SH	0.002	0.002	0.024	0.024	−0.838	−0.838
	(0.154)	(0.154)	(0.205)	(0.205)	(0.529)	(0.529)
TEM	0.114	0.114	−0.123	−0.123	−0.224	−0.224
	(0.177)	(0.177)	(0.235)	(0.235)	(0.542)	(0.542)
Pre	0.139	0.139	−0.188	−0.188	−0.173	−0.173
	(0.085)	(0.085)	(0.153)	(0.153)	(0.305)	(0.305)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	571	571	550	550	563	563
R^2	0.985	0.985	0.987	0.987	0.962	0.962

Standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

Controls for other cultivated land spatial planning schemes: A threat to the identification is that the treatment effects would be confounded by some other cultivated land spatial planning schemes. After studying Chinese government documents, we found two land spatial planning schemes that may have biased the estimation. One is the cultivated land balance program (CLB). In 1999, given the magnitude of the cultivated land loss in China, the National Bureau of Land Management (the predecessor of the MLRC) adopted the CLB of maintaining the existing amount of cultivated land nationally. CLB focused particularly on the balance between cultivated land losses by construction occupation and cultivated land supplement. According to this approach, if a plot of cultivated land was replaced by construction, the land developer should create another plot of cultivated land [80]. Another one is the main functional areas planning (MFAP) which incorporated national nature reserves, world cultural and natural heritage sites, national scenic attractions and forest parks into the national list of prohibited development areas. Specifically, it divided the national land space into four main functional areas: optimized development areas, key development areas, restricted development areas and prohibited development areas. It was aimed to effectively improve the efficiency of space utilization and realize the goal of sustainable development, which also incorporated the space utilization of arable lands [81]. Therefore, both land planning programs had the potential to involve the redistribution of cultivated land and confound the treatment effect of the MGPA policy. To relieve any confounding effects of the two land planning programs, two dummy variables for the implementation of these land planning programs were included. CLB indicates the enactment of the cultivated land balance program and $MFAP$ indicates the implementation of the main functional areas planning.

Table 10 shows the estimation result of controlling for the cultivated land balance program and the main functional areas planning. The coefficients for the treatment effects, $D_i \times T_t$, are still positively significant, suggesting that the contribution of the MGPA policy to the increase in grain production is still significant even after controlling the potential confounding effect of other land spatial planning schemes. For the empirical comparison between the MGPA policy and other land spatial planning schemes, it may require systematic evaluation and is waiting for future research.

Table 10. Controls for other cultivated land spatial planning schemes.

Dep. Var.:	Grain		Rice		Wheat	
	(1)	(2)	(3)	(4)	(5)	(6)
$D_i \times T_t$	0.296 ***	0.293 ***	0.415 ***	0.415 ***	0.285 **	0.288 **
	(0.025)	(0.025)	(0.042)	(0.042)	(0.105)	(0.106)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
CLB	0.155 ***		0.158 *		0.256 *	
	(0.042)		(0.084)		(0.149)	
MFAP		0.178 ***		0.093 **		0.101
		(0.033)		(0.041)		(0.104)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	571	571	550	550	563	563
R^2	0.982	0.982	0.985	0.985	0.956	0.956

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.6. Alternative Causal Channels

The analysis so far has provided evidence that the MGPA policy can significantly increase local grain, rice and wheat yields. In this section, we will further explore the causal channels of such positive treatment effects in terms of agricultural planting areas, mechanization level and transfer payments using the causal steps approach built by Heerink et al. (2006) [82]. The analysis of causal channels here only focuses on grain yields and the results for rice and wheat can be found in the Appendix A.

Expanding planting areas: Column (1) of Table 11 shows the first-step results, suggesting that the implement of the MGPA policy significantly increased local grain planting area per capita. Specifically, the grain planting area increased by 2.7% on average, with the figures for rice and wheat being 0.92% and 0.48%, respectively (in Appendix A Tables A1 and A2).

Column (3) of Table 11 shows the second-step results. The coefficients of $D_i \times T_t$ and planting area per capita are all positively significant at the 1% level indicating that, combined with the first-step result, the causal channel of expanding planting areas is statistically valid for grain. The coefficient of $D_i \times T_t$ fell from 0.271 (column (2)) to 0.166 after controlling for planting area per capita. This consolidates the idea that the implementation of the MGPA policy raised grain yields by increasing planting areas. This is also the case for the increase in rice yields with the treatment effect decreasing from 0.48 to 0.39 when the rice planting area is included in regression. However, no causal link was found between wheat yields and expanding planting areas.

Table 11. Channel 1—expanding planting areas.

Dep. Var.:	Planting Area per Capita	Grain Yields	Grain Yields
	(1)	(2)	(3)
$D_i \times T_t$	0.027 ***	0.271 ***	0.166 ***
	(0.003)	(0.027)	(0.048)
Planting area per capita			3.895 ***
			(1.410)
Control Variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes
N	555	555	555
R^2	0.940	0.984	0.987

Standard errors in parentheses. *** $p < 0.01$.

Improving mechanization level: Column (1) of Table 12 shows that the estimated impact of the MGPA policy on local mechanization, $D_i \times T_t$, was significant and positive. Specifically, the implementation of the MGPA policy improved local mechanization by 21.8%. This can be attributed to the MGPA-preferred agricultural machinery subsidies, a sub-project of the MGPA policies. Many studies suggest that agricultural mechanization in China, and especially in MGPA, has been accelerated by the government's increase of the subsidy for agricultural machinery purchases since 2004 [83].

The coefficients in the first two rows of column (3) are significantly positive. The treatment effect, the coefficient of $D_i \times T_t$, in regression (3) is slightly smaller than that in regression (2). These results suggest that the treatment effect of the MGPA policy is partially caused by boosting mechanization. For rice, such a causal channel exists, however, it is statistically insignificant for wheat.

Table 12. Channel 2—improving mechanization.

Dep. Var.:	Mechanization	Grain Yields	Grain Yields
	(1)	(2)	(3)
$D_i \times T_t$	0.218 ***	0.271 ***	0.263 ***
	(0.040)	(0.027)	(0.027)
Mechanization			0.037 *
			(0.021)
Control Variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes
N	555	555	555
R^2	0.783	0.984	0.985

Standard errors in parentheses. * $p < 0.1$, *** $p < 0.01$.

Increasing transfer payments: As column (1) in Table 13 shows, the transfer payments for MGPA have increased by 30.2% since the enactment of the MGPA policy. The second-stage results in columns (2) and (3) illustrate that the causal channel that the MGPA policy boosts grain yields by increasing the transfer payments to MGPA farmers. Such direct financial support can be realized in many ways, including rewarding counties for producing a large harvest. This MGPA-specific policy not only motivates farmers to plant more crops, but also reduces the financial pressure on local governments. Heilongjiang, one of the MGPA, was offered a 21.13 billion yuan reward in total from 2005 to 2013. Meanwhile, Heilongjiang has doubled its crop yields in under five years.

The causal channel for transfer payments is very obvious for wheat yields. The results, reported in Appendix A Table A2, show that the treatment effect falls from 0.350 to 0.244 when including the transfer payments into the baseline DD regression. Combined with the fact that the profit from planting wheat is shrinking, expanding direct transfer payments for wheat-growing farmers has become one of the few effective ways of increasing their motivation to plant the crop. However, for rice, there is no robust causal link between rice yields and increased transfer payments.

Table 13. Channel 3—increasing transfer payments.

Dep. Var.:	Transfer Payment	Grain Yields	Grain Yields
	(1)	(2)	(3)
$D_i \times T_t$	0.302 ***	0.271 ***	0.229 ***
	(0.059)	(0.027)	(0.026)
Transfer payment per capita			0.140 ***
			(0.023)
Control Variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes
N	555	555	555
R^2	0.942	0.984	0.986

Standard errors in parentheses. *** $p < 0.01$.

5. Discussion

5.1. The Policy Recommendations

The global food security challenge is straightforward in the context of the climate change and widespread of COVID-19 pandemic. As China feeds approximately 18% of the world population, China's food security is closely related to the stability of the global food system. In the long run, China's stable food production is still faced with great challenges, e.g., the rapid urbanization and spatial mismatch in agriculture resources. Looking back to history, China experienced a significant drop in crop production in 2003 which posed a substantial threat to national food security. After this crop production crisis, 13 MGPA regions were established by Ministry of Finance China. However, the empirical evidence of such land management practice's effect on crop production remains unclear. Identification of the mechanism that how the MGPA policy affect crop production will provide important policy implications for maintaining food security from a perspective of land management practices.

This paper focuses on exploring the impact of the MGPA policy on food security from the perspective of crop (grain, rice and wheat) production. The baseline results of this paper demonstrated that the establishment of the MGPA regions provided favorable conditions for increasing crop production. This result is consistent with the findings of the research on the relationship between land management policy and food production, which finds that the effective land and resource governance system that provides improved access, control, and rights to land and other natural resources is a necessary condition for achieving stable crop production [27]. Therefore, the implementation of the MGPA policy is without doubt a successful land management policy for achieving food security. Given the uncertainty in future trends of global food production due to a series of challenges, China should continue to consolidate policy support in the MGPA regions. Meanwhile, the fact that natural resources, especially land resources, is irreversible [84] reminds policymakers that they should fundamentally recognize the value of natural resources in the MGPA regions. Then the future policy preference in agriculture should be given more to the MGPA regions. Besides, the features of the MGPA policy could provide some policy implications for maintaining food security by some land management practice. First, as the MGPA policy is followed by some sub-policies which aim at dealing with different issues in China's agriculture at different times, the land management policy should be a dynamic policy which could be adaptive to new challenges faced by agricultural production. The reason is that the global food problem concerns the dynamics of economic growth, trade policy and even climate change [53]. The land management practice must be designed for continual improvement and adjustment to meet the needs of a changeable environment. Second, the MGPA policy is not merely for reallocating land resources for food production, but an integrated policy which is combined with some monetary and technical support policies. Similarly, such finding is acknowledged by Barry and Augustinus [85], who find that the comprehensive land policies which utilize sub-policies with different domains could exert a larger impact. Hence, the design of land management policy should incorporate other policy packages. In this way, these integrated sub-policies support and complement each other to realize the policy objective.

The findings in investigating alternative causal channels of the treatment effect found that the MGPA policy raised crop yields mainly by expanding planting areas, improving the level of mechanization and increasing transfer payments. It is evident that the irreversible land resource is the most important factor for agricultural production. However, in the context of China's rapid urbanization, the expansion of large cities and regions that have experienced rapid economic growth and urban development, causing the loss of cultivated land [86,87]. Hence, the policies designed to protect cultivated land, especially in the MGPA regions, are urgently needed. To preserve arable land, it is necessary not only to maintain quantity but also to improve quality, and to keep the double red line of quantity and quality [88]. It is also necessary to invest in agricultural research as agricultural technology is considered the main driver in solving China's shortage of arable land [89]. In terms of the second causal channel of improving the level of mechanization, it is consistent with many empirical research's finding. For example, Gong finds that over the past 25 years, China's agricultural growth has mainly been attributed to the improvement of productivity, especially the improvement of mechanization level in agriculture [26]. Therefore, the government should enhance the knowledge and skills of adult members, including household head, to adopt the latest mechanization technologies for land management. Agricultural policy should also focus on promoting agricultural mechanization technologies that are economically viable and friendly to females and older people to increase the adoption of agricultural mechanization. For the last causal channel of increasing transfer payments, it is also in keeping with the conclusion of Hu et al. that the financial support significantly improves agricultural TFP growth [90]. With the easy access to financial support, farmers can use these financial resources to adopt and foster technology innovations, which are well documented to improve agricultural production [91]. Local governments and banks should continue to improve the financial support for farmers, particularly the usage of financial services in rural areas and in agricultural production. In addition, paying attention to the financial services usage and the availability of credit to individuals with real needs is effective in promoting agricultural production.

5.2. The Methods' Applicability and Results' Reliability

In this paper, the DD model has been employed as a starting point for identifying the treatment effect of the MGPA policy. The applicability of this method is illustrated by other research on identifying treatment effects in policy analysis (see Cheng et al. [92]; Tan et al. [93] and Wang [94]). In general, different from the case of randomized experiments that allow for a simple comparison of treatment and control groups, DD is an evaluation method used in non-experimental settings, which has been widely used in economics, public policy, health research, management and other fields. The use of the DD model is detailedly discussed by Fredriksson et al. [95]. Due to the DD model relies on the parallel trends assumption which requires that in the absence of treatment, the difference between the treatment and control group is constant over time [48], an ET-DD model was employed to not only perform a parallel trends but also served as a robustness check for the baseline DD estimation. Although the DD method is a common strategy for evaluating the effects of policies or programs that are instituted at a particular point in time, sometimes the cross-sectional difference may reduce the comparability between the treatment and control group which eventually leads to a biased estimate. To relieve such concern and provide a good counterfactual for the treatment group, the PSM method was used to mitigate selection bias by matching observations of treatment provinces with control provinces. Such treatment has gained popularity in many empirical studies [96,97].

Although the results in this study could be comparable with the previous findings arguing that land management policy is one of the major driving forces for agricultural development [27,98], however, this research has certain drawbacks. First, agricultural production is a complicated process which is influenced by many factors. The results will be more unbiased if these factors, especially some climatic and topographic factors, are comprehensively considered. Second, this paper evaluated the effectiveness of the MGPA policy merely from the perspective of crop production. However, the indicator system for the MGPA policy can be improved and the results will be more reliable if future research is built in other perspectives. Third, this study used provincial data and could only provide insights into practice at the level of provincial areas and could not be refined at the municipal level. One possible direction for future work is to use more detailed county data, even micro-data to study the effectiveness of the MGPA policy.

6. Conclusions

Based on China's interprovincial panel data from 1998 to 2018, this study used a difference-in-differences (DD) estimation strategy to analyze the treatment effect of the MGPA policy by taking the assignment of 13 MGPA as a quasi-experiment. It primarily draws the following conclusions: (i) the MGPA policy did indeed increase crop production, specifically, grain, rice and wheat yields, and such positive treatment has been sustainable over the long term. Across the three kinds of crops, the MGPA policy led to an average rise of 27.5% for grain yields, 47.8% for rice yields and 35.5% for wheat yields. (ii) After the implementation of the MGPA policy, there is an immediate and lasting increase in grain and rice yields, however, for wheat yields, the treatment effect became significant six years after the policy's implementation. Such a delayed treatment effect may be attributed to farmers' being less motivated to plant wheat as a result of its decreasing profitability in the first few years after the policy implementation. (iii) The MGPA policy has increased grain yields mainly by expanding planting areas, improving mechanization levels and increasing transfer payments. Specifically, due to the establishment of the MGPA regions, the grain planting area increased by 2.7% on average, with the figures for rice and wheat being 0.92% and 0.48%, respectively. The implementation of the MGPA policy improved local mechanization by 21.8% and increased the transfer payments by 30.2%. These findings from the evaluation of the MGPA policy greatly increase understanding of how land management policies positively affect crop production in such a large developing country. Given the great similarity to agriculture production in developing countries, these findings may enlighten policymakers in some less well-developed countries on boosting crop production and eradicating hunger.

Author Contributions: Conceptualization, W.H.; methodology, W.H.; software, W.H.; validation, W.H. and L.L.; data curation, W.H.; writing—original draft preparation, W.H.; writing—review and editing, W.H., L.L. and Z.C.; visualization, W.H.; funding acquisition, L.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by The National Key Research and Development Program of China (Grant no. 2018YFE0107000) and Ministry of Science and Technology of the People's Republic of China (Grant no. 2016YFD0201306).

Institutional Review Board Statement: Not applicable.

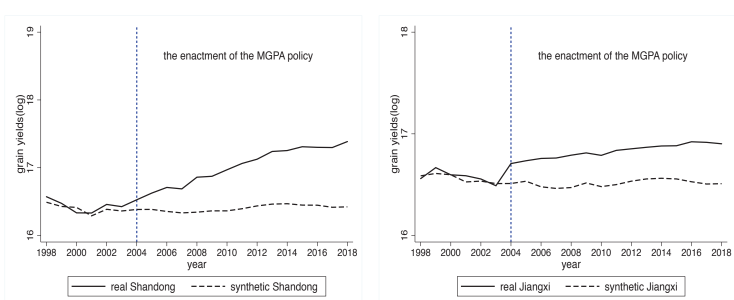
Informed Consent Statement: Not applicable.

Data Availability Statement: The data were collected from various sources, including China Rural Statistical Yearbooks (Ministry of Agriculture, 1998–2018), National Agricultural Product Cost and Revenue Survey Data books (Ministry of Agriculture, 1998–2018), China Agricultural Statistical Yearbooks (Ministry of Agriculture, 1998–2018), China Statistical Yearbooks on Environment (Ministry of Environment, 1998–2018), and China Statistical Yearbooks (NBSC, 1998–2018).

Acknowledgments: We would like to express our great gratitude to Xi Yang from Gansu State Grid for her companion in drafting the manuscript.

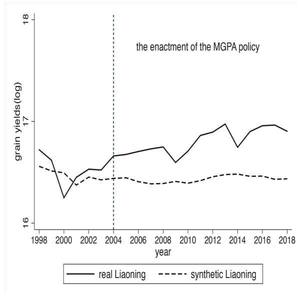
Conflicts of Interest: The authors declare no conflict of interest.

Appendix A



(**a**) Shandong (**b**) Jiangxi

Figure A1. *Cont.*



(**c**) Liaoning

Figure A1. Synthetic control methods without placebo tests.

Table A1. The channels of rice.

	Channel 1			Channel 2			Channel 3		
Dep. Var.:	**Planting Area per Capita**	**Rice Yields**	**Rice Yields**	**Mechanization**	**Rice Yields**	**Rice Yields**	**Transfer Payments**	**Rice Yields**	**Rice Yields**
$D_i \times T_t$	0.009 ***	0.481 ***	0.391 ***	0.218 ***	0.481 ***	0.475 ***	0.302 ***	0.481 ***	0.483 ***
	(0.001)	(0.055)	(0.064)	(0.040)	(0.055)	(0.055)	(0.059)	(0.055)	(0.061)
Planting area per capita			9.752 ***						
			(1.953)						
Mechanization						0.029 **			
						(0.043)			
Transfer payment									−0.006
									(0.041)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	537	535	535	555	535	535	555	535	535
R^2	0.942	0.986	0.987	0.783	0.986	0.987	0.942	0.986	0.986

Standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

Table A2. The channels of wheat.

	Channel 1			Channel 2			Channel 3		
Dep. Var.:	**Planting Area per Capita**	**Wheat Yields**	**Wheat Yields**	**Mechanization**	**Wheat Yields**	**Wheat Yields**	**Transfer Payments**	**Wheat Yields**	**Wheat Yields**
$D_i \times T_t$	0.005 ***	0.350 ***	0.339 ***	0.218 ***	0.350 ***	0.351 ***	0.302 ***	0.350 ***	0.244 **
	(0.001)	(0.106)	(0.109)	(0.040)	(0.106)	(0.106)	(0.059)	(0.106)	(0.104)
Planting area per capita			2.297						
			(5.167)						
Mechanization						−0.003			
						(0.057)			
Transfer payment									0.365 ***
									(0.083)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	537	535	535	555	535	535	555	535	535
R^2	0.942	0.986	0.987	0.783	0.986	0.987	0.942	0.986	0.986

Standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

Notes

1 The geographical dividing line of North-South China is formed by the Qinling Mountains and the Huai River, which are also environmental features affecting climate regulation, soil conservation, water maintenance and biodiversity conservation.

2 In this paper, the enactment year of MGPA policy is set to 2004 because the official release of MGPA documents was on 3 December 2003 and the MGPA policy started in 2004.

3 Mu is a Chinese unit of land measurement. It is commonly 806.65 square yards (0.165 acre, or 666.5 square meters).

4 The income is classified into four types: (i) income earned from agriculture, forestry, livestock, and fishery; (ii) income earned from self-employment in non-farm activities such as industry, transportation, construction, and services, (iii) income earned from formal or informal wage, including salary, allowance, bonus, dividend, and other kinds of remuneration, and (iv) other non-productive incomes, such as pensions, transfers, grants/subsidies, rents, and financial income. (ii) and (iii) are normally considered as non-farm household income.

5 This law was formulated in accordance with the Constitution for the purpose of stabilizing and improving the two-level management system based on household contract management, giving the people long-term and guaranteed land use rights, and protecting the legitimate rights and interests of the parties to the rural land contract.

6 For a long time, China's industrialization and modernization have benefited from agricultural tax. However, agricultural tax was cancelled due to the decline of the relative importance of agricultural tax in the whole fiscal revenue.

7 From 2008 to 2016, the profit from planting wheat decreased from 164.51 yuan per mu to 21.29 yuan per mu. This fall was mainly a result of the slow upward trend of wheat price relative to the rapid rise in planting costs. Meanwhile, the profit from planting rice is about 13 times higher than that of wheat.

8 The predictors of grain yields are rural household size, sex ratio, educational attainment, agricultural land per capita, and grain yields in 1998, 2000 and 2002.

9 RDLS is defined as follows: $RLDS = ALT/100 + \{((Max(H) - Min(H)) \times (1 - P(A)/A))\}/500$, where RDLS is relief degrees of land surface; ALT is the average elevation in a grid cell (m); Max(H) and Min(H) represent the highest and lowest altitudes in this grid cell respectively (m); P(A) is the area of flat land (km^2); and A is the total area of the extraction unit.

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Does Economic Growth Lead to an Increase in Cultivated Land Pressure? Evidence from China

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Abstract: With economic growth, people's living standards improve, and more cultivated land is needed to meet food demand. Meanwhile, the economic growth and urban expansion in China since 1978 has led to the loss of considerable amounts of cultivated land. Thus, the contradiction between "economic growth" and "food security" becomes increasingly prominent. Studying the impact of economic growth on cultivated land population support pressure is the basis for easing this problem. This study uses the cultivated land pressure index to represent cultivated land population support pressure, and explores the relationship between economic growth and cultivated land pressure based on the panel data of 31 provinces in China from 2000 to 2017. The feasibility generalized least squares estimation and the fixed effect model based on Driscoll and Kraay standard errors are used. The results show that: (1) the impact of economic growth on cultivated land pressure is an N-shaped or U-shaped curve; and (2) there are regional differences in the impact of economic growth on cultivated land pressure. The cultivated land pressure in economically developed regions and main grain production regions responds slowly to the impact of economic growth. Therefore, some policy recommendations are put forward, such as paying attention to cultivated land protection and controlling disorderly urban expansion.

Keywords: economic growth; cultivated land pressure; food security; Kuznets curve

Citation: Wu, X.; Wang, Y.; Zhu, H. Does Economic Growth Lead to an Increase in Cultivated Land Pressure? Evidence from China. *Land* **2022**, *11*, 1515. https://doi.org/10.3390/land11091515

Academic Editors: Uttam Khanal and Sanzidur Rahman

Received: 13 August 2022
Accepted: 7 September 2022
Published: 8 September 2022

1. Introduction

Food is the foundation of human survival and development, and food security attracts worldwide attention [1]. Food production is inseparable from cultivated land, and sufficient cultivated land is an important foundation for ensuring food security [2,3]. However, rapid economic growth and urbanization consume a large amount of cultivated land, which leads to a decrease in cultivated land and a threat to food security [4,5]. As a country with a large population and little cultivated land, China's food security has attracted considerable attention. In 1995, Lester R. Brown published a report entitled "Who Will Feed China?", which alerted people to pay attention to the food security and cultivated land pressure [6]. Since then, scholars have increased their research in related fields [7–9].

At the end of 2017, China's cultivated land area was 134.88 million hm^2, ranking third in the world [10]. However, China is the country with the largest population in the world. According to the statistics of FAO, China successfully feeds 19.25% of the global population with only 8.61% of the global cultivated land. In 2017, the global per capita cultivated land area was 0.18 hm^2, while this index was only 0.096 hm^2 in China [3]. China's cultivated land is under great pressure to support its population. In addition, over the past 40 years, China experienced rapid urbanization and economic growth, which exacerbated food insecurity in China. From 1978 to 2017, the GDP increased from 367.87 billion yuan (USD 21.85 billion at the exchange rate of 1978) to 83,203.59 billion yuan (USD 12,323.17 billion at the exchange rate of 2017), and the urbanization rate increased from 17.92% to 60.24% in China. A large number of studies show that urban expansion would encroach on cultivated land [11,12].

This phenomenon is more pronounced in developing countries, such as China, Vietnam, and India [13–15]. Statistics from the Ministry of Housing and Urban–Rural Development in the People's Republic of China show that 13,258.14 km^2 of cultivated land was occupied by urban construction in China from 2000 to 2017.

In recent years, global food insecurity increases significantly under the influence of the COVID-19 pandemic, the Russia–Ukraine conflict, weather extremes, and water scarcity [16–19]. The latest edition of the "State of Food Security and Nutrition in the World" report notes that almost 924 million people faced severe levels of food insecurity in 2021, 207 million more than in 2019 [20]. Under the unstable international situation, trade is restricted, and nations relying on imports are vulnerable to food supply shocks [17]. The statistics of FAO show that China is one of the top ten cereal importers in the world, and its cereal imports in 2020 were about 20% lower than in 2019. The Chinese government begins to advocate using its own cultivated land to feed its population. Xi Jinping, the president of the People's Republic of China, says that "The rice bowls of Chinese people must always be held in their own hands, and the rice bowls are mainly filled with Chinese grains". It is particularly important to coordinate the relationship between economic growth and cultivated land pressure in China. However, the grain supply capacity in different regions of China is diverse. Regions with economic development and high grain production have stronger grain supply capacity and greater grain supply flexibility. The pressure of cultivated land population support may be less affected by economic growth.

Most studies on the relationship between economic growth and cultivated land pressure are based on the Kuznets curve. A Kuznets curve means that the relationship between two variables is an "inverted U", which refers to the way that as one variable increases, the other variable shows a trend of rising first and then falling. In 1955, Simon Kuznets put forward the hypothesis that the relationship between economic growth and wealth distribution takes an inverted U-shaped curve at the Annual Conference of American Economics [21]. In 1991, Grossman introduced the Kuznets curve into the study of the relationship between economic growth and environmental pollution, and put forward the environmental Kuznets curve (EKC) [22]. Since then, scholars have carried out considerable verification and generalization of the traditional inverted U-shaped EKC, and have proposed various shapes of EKC, such as U-shaped, N-shaped, and inverted-N-shaped [23–29]. The research applications are extended to deforestation, ecological footprint, land use, and other aspects [30–36]. Cultivated land has both production and ecological functions, and it is a valuable natural resource. Converting too much cultivated land into construction land would damage the ecological environment. Some scholars believe that the impact of economic growth on cultivated land pressure first rises and then falls, which is similar to the environmental Kuznets curve (EKC). Qu is the first to propose the hypothesis that there is an "inverted U" Kuznets curve between economic growth and farmland conversion [37]. Many studies verify the "inverted U" and "inverted N" Kuznets curves between economic growth and cultivated land conversion based on the provincial panel data in China [37–40]. However, some scholars believe that the existence of a cultivated land Kuznets curve is limited by time and space, and it is not universal [41]. There are monotonically increasing, monotonically decreasing, U-shaped, N-shaped, and inverted N-shaped curves between economic growth and cultivated land conversion [42].

Existing studies only focus on the impact of economic growth on cultivated land loss [38,40,43], without further considering the food security risks and population support pressure caused by cultivated land loss. Based on this, the cultivated land pressure index is used to represent the pressure of cultivated land population support [44]. Then, the impact of economic growth on cultivated land pressure can be studied. It not only enriches the existing research in theory, but also provides new ideas for formulating cultivated land protection strategies and alleviating cultivated land pressure.

Based on EKC hypothesis and the cultivated land pressure index model, this paper studies the impact of economic growth on cultivated land pressure. The main concerns are as follows: (1) whether economic growth increases cultivated land pressure; and

(2) whether there are regional differences in the impact of economic growth on cultivated land pressure. Compared with the existing research, this paper has two innovations. Firstly, the influence path of economic growth on cultivated land pressure is analyzed theoretically. Secondly, the cultivated land pressure index is used to reflect the pressure of cultivated land food security and population support in the empirical study. This research provides a theoretical basis and practical direction for realizing the "double guarantee" of economic growth and food security.

2. Materials and Methods

2.1. Theoretical Analysis

Research shows that the possible causes of an environmental Kuznets curve (EKC) include the equity of income distribution, international trade, structural changes, technological progress, government governance, and consumer preferences [45]. Cultivated land is an important resource in the environment. Economic structural changes could alter the area of cultivated land occupied by construction. Technological progress could improve land use efficiency. Government policy improvement could restrain the loss of cultivated land, and changes in residents' preferences could increase attention on the ecological function of cultivated land. Some studies have confirmed the influence of these factors [37,46]. Therefore, this paper analyzed the influence of economic growth on cultivated land pressure from the above four aspects.

(1) Economic structural changes. In the era of the agricultural economy, cultivated land was an important means of production. Cultivated land was effectively protected, and cultivated land pressure was small [47]. In the early stage of the industrial economy, land became a key factor to promote economic growth [48]. Urbanization and industrialization transformed large amounts of high-quality cultivated land into construction land [49]. Cultivated land pressure increased rapidly [50]. In the later stage of the industrial economy, land was gradually replaced by capital and labor [51]. The demand for construction land decreased, and cultivated land pressure began to decrease. China entered the later stage of industrialization in 2010 [52], and the area of land requisitioned for construction decreased after reaching the maximum value of 2161.48 km^2 in 2012.

(2) Technological progress. In the early stage of economic development, the technological level was low. The proportion of land elements in industrial production was high, and the construction occupied a large amount of cultivated land. Moreover, the level of agricultural technology was also low, and the grain yield per unit area was low. Thus, cultivated land pressure was great. With the advancement of technology, the input of land elements required for economic growth decreases [53], and the grain yield per unit area and land reclamation technology improves [54]. Cultivated land pressure gradually eases. From 2004 to 2017, China's industrial land use efficiency increased from 0.457 to 0.599 [55]. During the same period, the grain yield per unit area of cultivated land in China increased from 4266.94 kg/hm^2 to 5607.36 kg/hm^2.

(3) Government policy improvement. The focuses of government policies are diverse in different stages of economic and social development. In the beginning stage of reform and opening up, the Chinese government paid attention to economic growth rather than cultivated land protection. With the increasingly serious environmental problems brought by development, the government pays more attention to the ecological environment and sustainable development [56]. In 1998, the "Regulations on the Protection of Basic Farmland" and "Balance between the Occupation and Supplement of Arable Land" were issued, and cultivated land protection measures were gradually tightened [57]. Since then, the Chinese government has issued many policies to continuously strengthen the protection of cultivated land, which effectively control the population support pressure caused by the reduction of cultivated land [4].

(4) Changes in public environmental preferences. The EKC and Inglehart's subjective values hypothesis suggest that as the economy grows, people's priorities shift from economics and materialism to quality of life and subjective wellbeing [58]. Cultivated

land has various ecological functions, such as improving the environment and protecting biodiversity [59,60]. With economic development and income growth, the cultivated land protection gradually attracts public attention.

Based on the analysis, it can be found that the impacts of factors, such as economic structure changes, technological progress, government policy improvement, and public preference changes, on cultivated land pressure are sometimes positive and sometimes negative. Therefore, the relationship between economic growth and cultivated land pressure might be similar to the Kuznets curve. In addition, the territory of China is very vast. There are great differences in the economic development levels and cultivated land-reserve resources in distinct regions. The economically developed regions are mainly distributed on the eastern coast. These regions have limited grain output and are the main grain sales regions. The economically underdeveloped regions are mainly distributed in the central and western regions. The central regions have a flat terrain and are the main grain producing region. The land in the western regions is poor, and most provinces are grain production and sales balance regions. The impact of economic growth on cultivated land pressure may be different in the regions with distinct levels of economic development and grain production and sales.

2.2. Regional Division

Based on theoretical analysis, there are differences in the influence of economic growth on cultivated land pressure in the regions with different economic development levels. In addition, China has a vast territory, and the grain production capacity of different provinces is diverse. The cultivated land pressure in main grain production regions might be less affected by economic growth. Therefore, when analyzing the regional differences in the impact of economic growth on cultivated land pressure, the 31 provinces were divided according to the degree of economic development and the situation of grain production and sales. Referring to Tang (2021) [61], the provinces were divided into developed regions and undeveloped regions based on the median of the average per capita GDP from 2000 to 2017. According to the "National Food Security and Long-Term Planning Framework (2008-2020)" proposed by the China National Development and Reform Commission, the provinces were divided into three categories, including the main grain sales regions, the grain production and sales balance regions, and the main grain production regions. The spatial distributions of each region are shown in Figure 1.

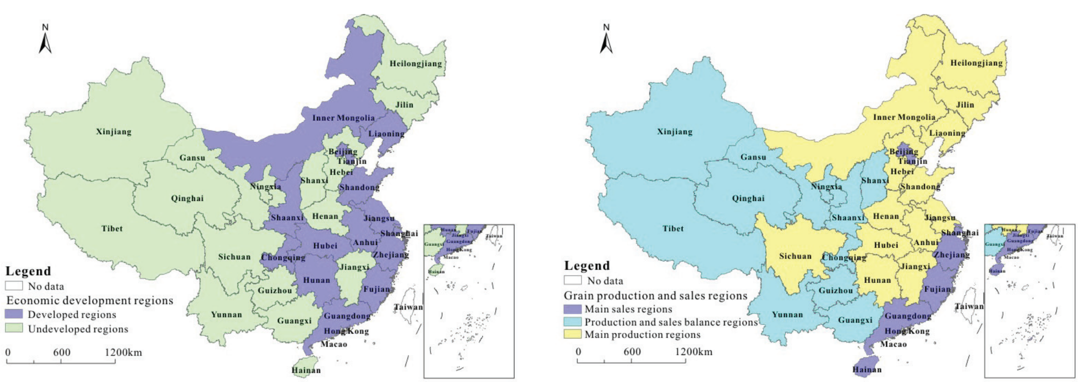

Figure 1. The spatial distributions of regions with different levels of economic development and grain production and sales.

2.3. Models and Variables

2.3.1. Model Settings

Theoretical analysis shows that the impact of economic growth on cultivated land pressure might be positive first and then negative. This is in line with the characteristics of the environmental Kuznets curve (EKC) model, in that the influence direction of the independent variable changes after reaching a certain value. Most studies applying Kuznets curve model employ reduced-form models, in which the explained variable is the quadratic or cubic function of the explanatory variable [62–65]. Simplified EKC models can clearly specify the form of variable relationships and provide empirical explanations for the solution of research problems [66]. However, the model also has limitations. Firstly, the model only reflects the correlation rather than the causality, and there may be a reverse causality problem in the actual situation [67]. Secondly, the symmetry of quadratic function makes the slope of the uphill and downhill parts of the curve the same, which hardly exists in reality. In addition, the shape of the curve and the number of turning points are affected by the model form. Therefore, the quadratic and cubic function models were established to reduce the fitting error caused by the function form. Since the data of 31 specific provinces in China were used, the following fixed effect model was established:

$$CLP_{it} = \alpha + \beta_1 PGDP_{it} + \beta_2 {PGDP_{it}}^2 + \beta_i X_{it} + \delta_i + \lambda_t + \mu_{it} \quad (1)$$

$$CLP_{it} = \alpha + \beta_1 PGDP_{it} + \beta_2 {PGDP_{it}}^2 + \beta_3 {PGDP_{it}}^3 + \beta_i X_{it} + \delta_i + \lambda_t + \mu_{it} \quad (2)$$

where i and t represent the provinces and periods under consideration; CLP_{it} is the cultivated land pressure index; $PGDP_{it}$ is the per capita GDP; α is a constant; β_1, β_2, β_3, β_i are the coefficients to be estimated; X_{it} are control variables, including population (POP_{it}), urbanization rate (UR_{it}), proportion of secondary industry (SI_{it}), proportion of tertiary industry (TI_{it}), effective irrigation rate (EI_{it}), fertilizer application (FA_{it}), pesticide input (PI_{it}), and agricultural machinery power (MP_{it}). POP_{it} and UR_{it}, respectively, reflect the impacts of population growth and urban expansion on cultivated land pressure. SI_{it} and TI_{it} reflect the impacts of industrial structure change on cultivated land pressure. EI_{it}, FA_{it}, PI_{it} and MP_{it} reflect the impacts of agricultural cultivation level and technology on cultivated land pressure. δ_i and λ_t, respectively, denote the region and time effects. μ_{it} is a random error term.

According to different situations of estimation coefficients $\beta_1 - \beta_3$, the different shapes and possible turning points of the Kuznets curve are shown in Table 1.

Table 1. Possible results of the cultivated land pressure Kuznets curve model.

Function Type	β_1	β_2	β_3	Curve Shape	Possible Turning Points
Cubic function	—	—	>0	N or monotonically increasing	$\frac{-\beta_2 \pm \sqrt{\beta_2^2 - 3\beta_1\beta_3}}{3\beta_3}$
	—	—	<0	Inverted N or monotonically decreasing	
Quadratic function	—	>0	=0	U	$-\frac{\beta_1}{2\beta_2}$
	—	<0	=0	Inverted U	
Linear function	>0	=0	=0	Monotonically increasing	—
	<0	=0	=0	Monotonically decreasing	—

2.3.2. Variables Selection

(1) Explained variable. Cultivated land pressure index was used to characterize the cultivated land pressure, which is proposed by Cai Yunlong (2002) [44]. It takes into account the food demand of the population, the grain production capacity, and the area of cultivated land, and it can comprehensively reflect the pressure of cultivated land to ensure population support in a certain region. The cultivated land pressure index is the ratio of

the minimum per capita cultivated land area to the actual per capita cultivated land area, and the basic calculation formula of it is as follows:

$$K_i = \frac{S_{\min i}}{S_i} = \frac{\beta_i \times \frac{Gr_i}{p_i \cdot q_i \cdot k_i}}{S_i} \tag{3}$$

where K_i is the cultivated land pressure index. $S_{\min i}$ is the minimum per capita cultivated land area, which refers to the area of cultivated land required to ensure the normal food consumption of each person under a certain level of grain self-sufficiency and cultivated land production capacity in a certain region ($S_{\min i} = \beta_i \times Gr_i/(p_i \cdot q_i \cdot k_i)$). S_i is the actual per capita cultivated land area, which is the ratio of the total cultivated land area to the total population in a region. β_i is the grain self-sufficiency rate, which refers to the proportion of grain production to grain consumption in the region. Gr_i is the per capita grain demand, usually calculated based on calories consumed or statistics [68,69]. p_i is the grain yield per unit area. q_i is the proportion of grain crop sown area in the total crop sown area. k_i is the multiple cropping index, which represents the ratio of crop sown area to cultivated land area within a year. When $K_i < 1$, the cultivated land grain production is greater than the demand, and there is no cultivated land pressure. When $K_i = 1$, the cultivated land grain production is equal to the demand, and cultivated land pressure is at a critical value. When $K_i > 1$, the cultivated land grain production is less than the demand, and there is cultivated land pressure.

Due to the different levels of economic development, the relationship of grain production and sales among provinces is different. That is to say, there are differences in the economic acquisition capacity of grain in distinct provinces. Referring to Zhu (2016) [70], the first revision of the cultivated land pressure index was carried out by using the economic acquisition capacity of grain. In addition, there are differences in the quality of cultivated land in distinct provinces. Referring to Luo (2016) [71], the second revision of the cultivated land pressure index was carried out by using the standard coefficient of cultivated land productivity. The calculation formula of the revised cultivated land pressure index is as follows:

$$K_i{}' = K_i \times \frac{1}{\theta_i} \times \frac{1}{\sigma_i} = \frac{\beta_i \times \frac{Gr_i}{p_i \cdot q_i \cdot k_i}}{S_i} \times \frac{\overline{X}}{X_i} \times \frac{p \cdot k}{p_i \cdot k_i} \tag{4}$$

where $K_i{}'$ is the revised cultivated land pressure index. θ_i is the grain economic acquisition capacity of province i, which is expressed by the ratio of the per capita GDP of province i to that of the nation ($\theta_i = X_i/\overline{X}$). $\overline{X}$ is the national average per capita GDP. X_i is the per capita GDP of province i. σ_i is the standard coefficient of cultivated land productivity, which is expressed by the ratio of the cultivated land production capacity of province i to that of the nation ($\sigma_i = (p_i \cdot k_i)/(p \cdot k)$). p is the national grain yield per unit area. k is the national multiple cropping index. The meanings of the other indicators are the same as those in formula (3).

(2) Explanatory variable. The explanatory variable of this paper is economic growth. Existing studies mostly use indicators such as GDP, per capita GDP, and GDP growth rate to characterize economic growth [72–75]. Among them, per capita GDP can better reflect the average level of regional economic growth. In recent years, China's economy has developed rapidly, and both population and GDP has grown. Thus, per capita GDP was used to represent economic growth.

(3) Control variables. In the process of economic growth, other factors can affect the pressure of cultivated land population support. Theoretical analysis shows that industrial structure changes and agricultural technology progress would affect cultivated land pressure. Some studies have confirmed the impact of population growth and urbanization on cultivated land [76–78]. In recent years, China's major industries transforms from the secondary industry to the tertiary industry [79]. Firstly, the development of non-agricultural industries may occupy cultivated land, which results in the reduction of cultivated land. Secondly, it may promote the labor force to leave agricultural production and reduce the ef-

ficiency of grain production [80]. In addition, agricultural production technology is rapidly improved, agricultural irrigation and mechanization are popularized, and the inputs of fertilizer and pesticide are increased. The above factors have a significant impact on ensuring the quantity and productivity of cultivated land [76]. Therefore, when analyzing the factors affecting cultivated land pressure, eight control variables were selected, including population, urbanization rate, proportion of secondary industry, proportion of tertiary industry, irrigation rate, fertilizer application, pesticide input, and agricultural machinery power. The explanation of the variables is shown in Table 2.

Table 2. Explanation of the variables.

Variable Types	Variable Names	Variable Connotation	Unit
Explained variable	Cultivated land pressure (CLP)	Cultivated land pressure index	—
Explanatory variable	Economic growth (PGDP)	Per capita GDP (at the price in 2000)	10^4 yuan/person
Control variables	Population (POP)	Total population	10^8 persons
	Urban expansion (UR)	Urban population/total population	%
	Proportion of secondary industry (SI)	Added value of secondary industry/GDP	%
	Proportion of tertiary industry (TI)	Added value of tertiary industry/GDP	%
	Effective irrigation rate (EI)	Effective irrigation area/cultivated land area	%
	Fertilizer application (FA)	Fertilizer application/cultivated land area	10^4 t/hm^2
	Pesticide input (PI)	Pesticide input/cultivated land area	10^4 t/hm^2
	Agricultural machinery power (MP)	Agricultural machinery power/cultivated land area	KW/hm^2

2.4. Data Sources

Since China conducted the third national land survey in 2017, the data of cultivated land area has not been continuously updated. Therefore, the panel data of 31 provinces (excluding Hong Kong, Macao, and Taiwan) in China from 2000 to 2017 were used.

The level of economic development is expressed by per capita GDP (PGDP). The consumer price index (CPI) was used to convert the per capita GDP into a comparable price in 2000. The data on the grain yield per unit area, grain crop sown area, total crop sown area, cultivated land area, population, urbanization rate, proportion of secondary industry, proportion of tertiary industry, irrigation rate, fertilizer application, pesticide input, agricultural machinery power, GDP, and CPI were obtained from the "China Statistical Yearbook (2001–2018)" and the "Provincial Statistical Yearbook". Referring to the existing research, the grain self-sufficiency rate was set as 1 [81]; the per capita grain demand was set as 350 kilos per person in 1981, with an increase of 4 kg per year after 1981 and a decrease of 4 kg per year before 1981 [70]. The descriptive statistics for the data are illustrated in Table 3.

Table 3. Descriptive statistics of the variables.

Variable Names	Mean	Std. Dev.	Min.	Max.	Obs.	Skewness	Kurtosis
CLP	2.2487	2.1445	0.3447	21.3217	558	2.672	16.051
PGDP	2.2412	1.6428	0.2742	9.9292	558	1.629	6.118
POP	0.4273	0.2734	0.0258	1.2141	558	0.608	2.606
UR	48.8493	15.9550	19.4700	89.6000	558	0.579	3.057
SI	42.9756	8.2835	16.8972	61.9603	558	−0.719	3.508
TI	44.5186	8.6279	29.6445	82.6948	558	1.769	7.639
EI	50.6619	22.5083	13.6963	115.2961	558	0.411	2.118
FA	0.0431	0.0215	0.0068	0.1001	558	0.391	2.485
PI	0.0015	0.0013	0.0001	0.0065	558	1.167	4.029
MP	0.6870	0.3773	0.1297	1.7545	558	0.725	2.547

The correlation matrix of the variables and the variance expansion factor (VIF) of the multicollinearity tests are shown in Table 4.

Table 4. The correlation matrix of the variables and the results of the multicollinearity tests.

Variables	CLP	PGDP	POP	UR	SI	TI	EI	FA	PI	MP	VIF
CLP	1.000	—	—	—	—	—	—	—	—	—	—
PGDP	0.042	1.000	—	—	—	—	—	—	—	—	5.66
POP	−0.419 ***	0.025	1.000	—	—	—	—	—	—	—	2.12
UR	−0.113 ***	0.849 ***	−0.079 *	1.000	—	—	—	—	—	—	4.60
SI	−0.400 ***	−0.091 **	0.446 ***	0.026	1.000	—	—	—	—	—	4.38
TI	0.399 ***	0.629 ***	−0.395 ***	0.530 ***	−0.699 ***	1.000	—	—	—	—	7.21
EI	−0.325 ***	0.541 ***	0.229 ***	0.446 ***	0.092 **	0.275 ***	1.000	—	—	—	2.29
FA	−0.369 ***	0.430 ***	0.543 ***	0.353 ***	0.215 ***	0.018	0.612 ***	1.000	—	—	4.27
PI	−0.214 ***	0.332 ***	0.320 ***	0.297 ***	0.063	0.047	0.472 ***	0.764 ***	1.000	—	2.61
MP	−0.132 ***	0.404 ***	0.352 ***	0.294 ***	0.176 ***	0.176 ***	0.620 ***	0.533 ***	0.364 ***	1.000	1.99
Mean VIF	—	—	—	—	—	—	—	—	—	—	3.90

Note: *, **, and *** indicate the significance of 10%, 5% and 1%, respectively.

3. Empirical Results

3.1. Unit Root Tests

The unit root test can prevent spurious regression by testing the stationarity of panel data [82]. Depending on the null hypothesis, unit root tests can be divided into two categories. The first type assumes that each section has the same unit root, including the LLC (Levin–Lin–Chu) test and the Breitung test. The second type assumes that each section has a different unit root, including the IPS (Im–Pesaran–Shin) test, the Fisher-ADF test and the Fisher-PP test. In this paper, four methods are used to test the unit root. The results of the unit root test show that the variables are first-order stable (Table 5), and it is valid to perform regression analysis.

Table 5. Results of unit root tests.

Variables	LLC Test	IPS Test	Fisher−ADF Test	Fisher−PP Test
d(CLP)	−21.306 ***	−18.720 ***	427.301 ***	851.230 ***
d(PGDP)	−5.490 ***	−3.635 ***	101.489 ***	83.893 ***
d(POP)	−7.136 ***	−6.107 ***	149.611 ***	146.907 ***
d(UR)	−10.539 ***	−9.226 ***	208.395 ***	321.182 ***
d(SI)	−8.111 ***	−5.680 ***	139.542 ***	202.138 ***
d(TI)	−10.461 ***	−7.930 ***	173.880 ***	164.494 ***
d(EI)	−19.443 ***	−14.645 ***	300.356 ***	446.513 ***
d(FA)	−10.566 ***	−8.908 ***	193.441 ***	224.793 ***
d(PI)	−9.748 ***	−9.964 ***	227.856 ***	263.869 ***
d(MP)	−14.500 ***	−11.045 ***	229.555 ***	245.916 ***

Note: *** indicates the significance of 1%.

3.2. Basic Estimation Results

In order to ensure the reliability of the regression results, the Hausman test and F statistic are used for model selection. According to the test results, the fixed-effects model is considered to be superior to the random-effects or mixed model. The heteroscedasticity, cross-sectional dependency. and serial correlation tests are necessary for the panel data [83]. The modified Wald test, Frees test, and Wooldridge test are used to check for the above problems, respectively [84–86]. The test results show that the standard fixed-effects model has heteroscedasticity and correlation problems, which may cause estimation inefficiency [87]. Therefore, the estimation method is changed in the robustness test. The basic estimation results are shown in Table 6.

According to the estimation results of the cubic model, the coefficients of $PGDP^3$ are significantly positive at the level of 1%. This shows that with economic growth, the cultivated land pressure increases firstly, then decreases, and increases again finally. There is an N-shaped cultivated land pressure Kuznets curve. According to the estimation results of the quadratic model, the coefficients of $PGDP^2$ are significantly positive at the level of

1%. This shows that with economic growth, the cultivated land pressure first decreases and then increases. When the per capita GDP is about 40,000 yuan/person, the pressure on cultivated land begins to rebound. From 2000 to 2017, the average per capita GDP in each province increased from 8430 yuan/person to 41,270 yuan/person. Hence, the rebound point of cultivated land pressure is approaching.

Table 6. The results of basic estimation.

Variables	Fe_c	Fe_cc	Fe_q	Fe_qc
$PGDP^3$	0.037 *** (9.663)	0.033 *** (6.417)	—	—
$PGDP^2$	−0.337 *** (−5.923)	−0.271 *** (−3.287)	0.193 *** (11.548)	0.246 *** (13.637)
PGDP	0.856 *** (3.215)	0.448 (0.962)	−1.157 *** (−6.427)	−2.172 *** (−9.327)
POP	10.968 *** (6.001)	10.632 *** (5.727)	4.102 ** (2.243)	6.441 *** (3.566)
UR	−0.008 (−0.690)	−0.014 (−1.104)	0.010 (0.797)	−0.011 (−0.876)
SI	0.085 *** (4.428)	0.097 *** (4.820)	0.137 *** (6.816)	0.125 *** (6.165)
TI	0.081 *** (3.788)	0.067 *** (2.848)	0.124 *** (5.453)	0.062 ** (2.534)
EI	−3.098 *** (−4.400)	−3.206 *** (−4.376)	−3.787 *** (−4.980)	−4.003 *** (−5.334)
FA	−27.000 *** (−2.991)	−23.124 ** (−2.469)	−8.406 (−0.878)	−13.375 (−1.392)
PI	453.960 *** (4.400)	479.197 *** (4.453)	433.659 *** (3.872)	452.687 *** (4.050)
MP	−1.038 *** (−3.205)	−1.038 *** (−3.079)	−0.637 * (−1.828)	−0.816 ** (−2.341)
Cons	−7.228 *** (−4.163)	−6.451 *** (−3.350)	−8.212 *** (−4.364)	−4.110 ** (−2.091)
Time−fixed effect	No	Yes	No	Yes
Region−fixed effect	Yes	Yes	Yes	Yes
R^2	0.604	0.612	0.532	0.580
Modified Wald test	46,481.77 ***	24,021.74 ***	89,123.87 ***	28,739.68 ***
Frees test	5.052 *** (0.144)	4.723 *** (0.144)	4.836 *** (0.144)	4.642 *** (0.144)
Wooldridge test	14.076 ***	13.942 ***	14.515 ***	12.895 ***
F test	71.44 ***	28.12 ***	58.75 ***	25.58 ***
F statistic	43.03 ***	40.47 ***	34.93 ***	36.23 ***
Hausman test	118.26 ***	115.44 ***	46.22 ***	48.40 ***
Curve shape	N	N	U	U
Maximum extreme point	1.813	1.019	—	—
Minimum extreme point	4.239	4.386	3.005	4.416
Obs.	558	558	558	558

Note: (1) The data outside the brackets are coefficients, and the data inside the brackets are t values; the critical value of 10% significance is shown in the brackets of the Frees test. (2) Fe_c, Fe_q are the estimation results after controlling the region effect; Fe_cc, Fe_qc are the estimation results after controlling the region effect and the time effect. (3) *, **, and *** indicate the significance of 10%, 5%, and 1%, respectively.

The effects of control variables on cultivated land pressure are basically identical in all models. The impact of population on cultivated land pressure is significantly positive at the level of 5%. This is consistent with the research results of other scholars [88]. It shows that population growth increases the demand for food and the space for construction land, which increases the cultivated land pressure. The impact of urbanization is negative, but not significant. This may be due to the offsetting effect between cultivated land abandonment and the increase in the ratio of grain crops caused by the migration of rural population to cities [76]. On the one hand, urban expansion occupies a large amount of cultivated land, which results in the reduction of cultivated land [11,89]. On the other hand, population urbanization leads to the transfer of labor from agricultural industries to non-agricultural industries, which may force the increase of agricultural operation scale and mechanization, and the proportion of grain crops may increase [90]. The coefficients of the proportion of the secondary industry and the proportion of the tertiary industry are significantly positive at the level of 5%. This shows that the increases of secondary and tertiary industries exacerbate the cultivated land pressure. The coefficients of effective irrigation rate, fertilizer application, and agricultural machinery power are significantly negative. This shows that the improvement of agricultural production level and technology can reduce the cultivated land pressure. However, pesticide input has a positive impact on cultivated land pressure. This may be because China's pesticide input has exceeded the economic optimal level [91].

The increase of pesticide input would lead to many adverse effects and increase the pressure on cultivated land [92].

3.3. Robustness Analysis

3.3.1. Replacement of Explanatory Variable

The per capita disposable income can reflect the wealth level of residents, and can be used to measure economic growth [93]. Therefore, the per capita disposable income (PDI) of residents is selected as the alternative variable of per capita GDP (PGDP) for the robustness test. The estimation results are shown in Table 7.

Table 7. Estimation results of the replacement explanatory variable.

Variables	Fe_c	Fe_cc	Fe_q	Fe_qc
PDI^3	0.370 *** (6.529)	0.283 *** (3.670)	—	—
PDI^2	−1.354 *** (−3.740)	−0.659 (−1.219)	0.945 *** (10.843)	1.289 *** (12.302)
PDI	1.517 ** (2.198)	−0.640 (−0.467)	−2.177 *** (−5.303)	−5.085 *** (−7.819)
POP	9.943 *** (5.132)	9.732 *** (4.929)	3.856 ** (2.184)	6.533 *** (3.642)
UR	−0.007 (−0.563)	−0.012 (−0.911)	0.008 (0.665)	−0.004 (−0.323)
SI	0.092 *** (4.802)	0.092 *** (4.499)	0.119 *** (6.112)	0.094 *** (4.538)
TI	0.085 *** (3.856)	0.064 *** (2.588)	0.098 *** (4.255)	0.055 ** (2.233)
EI	−3.359 *** (−4.591)	−3.801 *** (−4.898)	−3.811 *** (−5.034)	−4.470 *** (−5.853)
FA	−28.534 *** (−3.010)	−26.084 *** (−2.673)	−11.393 (−1.203)	−18.525 * (−1.918)
PI	526.875 *** (5.023)	562.301 *** (5.186)	505.879 *** (4.642)	556.790 *** (5.073)
MP	−1.235 *** (−3.672)	−1.246 *** (−3.549)	−0.803 ** (−2.341)	−1.038 *** (−2.958)
Cons	−7.040 *** (−4.022)	−4.912 ** (−2.379)	−6.265 *** (−3.451)	−2.242 (−1.146)
Time−fixed effect	No	Yes	No	Yes
Region−fixed effect	Yes	Yes	Yes	Yes
R^2	0.574	0.584	0.539	0.573
Modified Wald test	36,987.34 ***	20,376.38 ***	48,921.38 ***	22,332.70 ***
Frees test	4.225 *** (0.144)	4.378 *** (0.144)	4.362 *** (0.144)	4.457 *** (0.144)
Wooldridge test	10.060 ***	9.986 ***	13.568 ***	12.517 ***
F test	63.22 ***	25.05 ***	60.42 ***	24.86 ***
F statistic	37.11 ***	40.91 ***	36.60 ***	37.84 ***
Hausman test	45.87 ***	99.69 ***	48.75 ***	79.93 ***
Curve shape	N	N	U	U
Maximum extreme point	0.872	−0.388	—	—
Minimum extreme point	1.568	1.941	1.152	1.972
Obs.	558	558	558	558

Note: (1) The data outside the brackets are coefficients, and the data inside the brackets are t values; the critical value of 10% significance is shown in the brackets of the Frees test. (2) Fe_c, Fe_q are the estimation results after controlling the region effect; Fe_cc, Fe_qc are the estimation results after controlling the region effect and the time effect. (3) *, **, and *** indicate the significance of 10%, 5%, and 1%, respectively.

After replacing the explanatory variable, the estimation results are consistent with basic estimation. The cubic model shows that as per capita disposable income increases, the cultivated land pressure increases firstly, then decreases, and increases again finally. The estimation results of the squared model show that there is a U-shaped curve relationship between per capita disposable income growth and cultivated land pressure. When the PDI is between 15,000–20,000 yuan/person, the cultivated land pressure starts to rebound. From 2000 to 2017, the average per capita disposable income in each province increased from 4010 yuan/person to 17,620 yuan/person. The rebound points of cultivated land pressure are close to basic estimations. The influence direction and significance of the control variables are basically consistent with basic estimation. This shows that the impact of economic growth on cultivated land pressure is stable.

3.3.2. Change of Estimation Methods

With the existence of heteroscedasticity, cross-sectional dependence, and autocorrelation, the feasibility generalized least squares (FGLS) technique and Driscoll and Kraay standard error are employed [61,94]. Driscoll and Kraay standard errors are produced through weighted heteroskedasticity autocorrelation (HAC), which can effectively address the complications caused by heteroscedasticity, cross-sectional dependence, and autocorrelation [87]. The estimation results after changing the estimation methods are shown in Table 8.

Table 8. Estimation results after changing the estimation methods.

Variables	FGLS_c	FGLS_q	Fe_ccd	Fe_qcd
$PGDP^3$	0.012 ** (2.491)	—	0.033 *** (4.473)	—
$PGDP^2$	−0.011 (−0.171)	0.172 *** (9.834)	−0.271 ** (−2.567)	0.246 *** (6.360)
PGDP	−0.467 (−1.553)	−1.448 *** (−8.478)	0.448 (0.888)	−2.172 *** (−5.755)
POP	5.594 *** (6.033)	5.004 *** (4.955)	10.632 *** (9.856)	6.441 *** (3.356)
UR	−0.008 (−1.150)	0.004 (0.488)	−0.014 ** (−2.339)	−0.011 *** (−2.755)
SI	0.044 *** (3.672)	0.059 *** (5.025)	0.097 *** (6.751)	0.125 *** (8.330)
TI	0.035 *** (2.628)	0.045 *** (3.266)	0.067 * (1.742)	0.062 (1.516)
EI	−1.579 *** (−3.634)	−1.326 *** (−2.670)	−3.206 *** (−3.494)	−4.003 *** (−3.523)
FA	−12.364 *** (−3.271)	−16.843 *** (−4.529)	−23.124 ** (−2.646)	−13.375 (−1.259)
PI	342.547 *** (3.959)	349.341 *** (3.988)	479.197 *** (2.930)	452.687 *** (2.850)
MP	−0.340 ** (−2.038)	−0.165 (−0.909)	−1.038 ** (−2.418)	−0.816 ** (−2.284)
Cons	1.730 (1.389)	1.319 (0.960)	−5.740 * (−1.789)	−0.681 (−0.173)
Time−fixed effect	Yes	Yes	Yes	Yes
Region−fixed effect	Yes	Yes	Yes	Yes
R^2	—	—	0.612	0.580
F/Wald test	4404.25 ***	5169.83 ***	795.44 ***	236.26 ***
Curve shape	N	U	N	U
Maximum extreme point	−3.309	—	1.019	—
Minimum extreme point	3.92	4.209	4.386	4.416
Obs.	558	558	558	558

Note: (1) The data outside the brackets are coefficients, and the data inside the brackets are t values. (2) FGLS_c and FGLS_q are the estimation results with FGLS; Fe_ccd, Fe_qcd demonstrate Driscoll and Kraay standard errors. (3) *, **, and *** indicate the significance of 10%, 5%, and 1%, respectively.

After changing the estimation method, the influence direction and significance of the explanatory variable and control variables are basically consistent with the basic estimation. The N-shaped or U-shaped curve relationship between economic growth and cultivated land pressure is proved to be stable again.

3.4. Endogenous Analysis

There are many factors that affect the pressure of cultivated land. Although the basic estimation has controlled the main influencing factors, there are still some factors that have been missed. In addition, there may also be a reverse causal relationship between the explanatory variable and the explained variable. These may lead to endogeneity problems in the model. The generalized moment estimation (GMM) proposed by Arellano and Bond (1991) can deal with endogeneity problems by introducing a lag of explained variables [95]. In this paper, an improved system generalized moment estimation (sys-GMM) is used for endogenous analysis [96]. The endogenous test results are shown in Table 9.

The results of system generalized moment estimation are basically consistent with basic estimation. Only the influence direction and significance of a few control variables change. In addition, the model passes the serial correlation test (the p value of AR(1) is less than 0.1, the p value of AR(2) is greater than 0.1) and the validity test of instrumental variables (the p value of the Hansen test is greater than 0.1) [97]. Therefore, it can be considered that the estimation results are stable and reliable.

Table 9. Estimation results with generalized moments.

Variables	GMM_ct	GMM_qt	GMM_cr	GMM_qr
L.CLP	0.872 *** (84.645)	0.873 *** (101.989)	0.868 *** (17.452)	0.869 *** (17.639)
$PGDP^3$	0.017 *** (8.869)	—	0.018 * (1.768)	—
$PGDP^2$	−0.146 *** (−6.203)	0.070 *** (9.892)	−0.163 (−1.538)	0.068 * (1.896)
PGDP	0.362 *** (4.989)	−0.393 *** (−7.737)	0.417 (1.348)	−0.350 * (−1.753)
POP	−0.295 *** (−3.313)	−0.406 *** (−5.436)	−0.295 * (−1.699)	−0.372 ** (−2.286)
UR	−0.010 *** (−5.296)	−0.009 *** (−5.769)	−0.011 ** (−2.068)	−0.010 ** (−1.973)
SI	0.013 *** (4.454)	0.019 *** (4.170)	0.012 (1.432)	0.013 (1.366)
TI	0.028 *** (8.977)	0.031 *** (6.181)	0.028 ** (2.466)	0.025 * (1.882)
EI	−1.057 *** (−10.045)	−1.326 *** (−11.241)	−0.954 *** (−2.638)	−1.218 ** (−2.371)
FA	0.532 (0.249)	1.313 (1.311)	0.037 (0.015)	0.145 (0.074)
PI	77.834 *** (2.864)	85.714 *** (4.618)	76.243 ** (2.144)	78.439 ** (2.134)
MP	0.238 *** (2.843)	0.391 *** (9.189)	0.234 * (1.870)	0.370 ** (2.181)
Cons	−0.941 *** (−3.699)	−0.692 * (−1.706)	−0.874 * (−1.679)	−0.179 (−0.247)
AR(1)	−2.38 (0.017)	−2.39 (0.017)	−2.56 (0.011)	−2.54 (0.011)
AR(2)	1.11 (0.269)	1.05 (0.296)	1.19 (0.234)	1.10 (0.272)
Hansen test	23.12 (0.145)	21.01 (0.226)	23.12 (0.145)	21.01 (0.226)
Curve shape	N	U	N	U
Maximum extreme point	1.802	—	1.827	—
Minimum extreme point	3.979	2.814	4.246	2.560
Obs.	527	527	527	527

Note: (1) The data outside the brackets are coefficients, and the data inside the brackets are t values. (2) GMM_ct, GMM_qt are the results of two-step estimation; GMM_cr, GMM_qr are the results of robust estimation. (3) The p values of AR(1), AR(2), and the Hansen test are in parentheses. (4) *, **, and *** indicate the significance of 10%, 5%, and 1%, respectively.

3.5. Heterogeneity Analysis

3.5.1. Different Economic Development Regions

The estimation results of different economic development regions are shown in Table 10.

Table 10. Estimation results for different economic development regions.

Variables	Developed Regions		Undeveloped Regions	
	FE_ccd	FE_qcd	FE_ccd	FE_qcd
$PGDP^3$	0.053 *** (6.647)	—	−0.668 *** (−4.885)	—
$PGDP^2$	−0.642 *** (−4.739)	0.242 *** (5.896)	4.864 *** (6.652)	1.245 *** (6.478)
PGDP	3.006 *** (3.597)	−1.898 *** (−5.305)	−14.291 *** (−8.886)	−8.046 *** (−7.558)
POP	15.051 *** (7.225)	12.546 *** (7.309)	−5.955 ** (−2.720)	−1.804 (−0.699)
UR	−0.004 (−0.806)	−0.007 (−1.263)	0.032 ** (2.570)	0.003 (0.194)
SI	0.077 ** (2.617)	0.294 *** (5.092)	0.179 *** (11.780)	0.135 *** (10.230)
TI	0.012 (0.442)	0.127 ** (3.213)	0.141 *** (5.348)	0.088 *** (3.505)
EI	−3.716 *** (−4.198)	−6.194 *** (−3.421)	1.225 (0.875)	0.038 (0.030)
FA	−76.620 *** (−4.503)	−48.076 *** (−3.611)	−10.096 (−0.750)	2.569 (0.171)
PI	1474.904 *** (5.470)	1022.763 *** (4.473)	−50.447 (−0.668)	95.053 (1.140)
MP	−2.527 *** (−4.674)	−1.636 *** (−3.575)	0.735 (1.611)	0.827 (1.701)
Cons	0	0	5.455 ** (2.271)	5.793 * (2.122)
Time−fixed effect	Yes	Yes	Yes	Yes
Region−fixed effect	Yes	Yes	Yes	Yes
R^2	0.827	0.771	0.415	0.365
F test	1432.66 ***	291.56 ***	87,740.96 ***	5617.11 ***
Curve shape	Increment	U	Decrement	U
Maximum extreme point	—	—	—	—
Minimum extreme point	—	3.922	—	3.231
Obs.	270	270	288	288

Note: (1) The data outside the brackets are coefficients, and the data inside the brackets are t values. (2) Fe_ccd, Fe_qcd demonstrate Driscoll and Kraay standard errors. (3) *, **, and *** indicate the significance of 10%, 5%, and 1%, respectively.

In economically developed regions, the coefficient of $PGDP^3$ in the cubic model is significantly positive, but there is no extreme point. With economic growth, the cultivated land pressure continues to rise. The coefficient of $PGDP^2$ in the square model is significantly positive. With economic growth, the pressure of cultivated land first decreases and then increases. The influence of control variables on cultivated land pressure in developed regions is consistent with basic estimation.

In economically underdeveloped regions, the coefficient of $PGDP^3$ in the cubic model is significantly negative, and there is also no extreme point. As the economy grows, the cultivated land pressure continues to decrease. The estimation result of the squared model shows that the relationship between economic growth and cultivated land pressure in underdeveloped regions is a U-shaped curve. The coefficients of control variables show that their influence direction and significance are different from the regression results with the whole sample. The impact of population growth becomes negative, while the impact of urbanization becomes positive. This might be because the population loss in underdeveloped regions is serious, and the rise in population can increase the agricultural labor force. The effects of effective irrigation, fertilizer application, pesticide input, and agricultural machinery power on cultivated land pressure in underdeveloped regions become insignificant. This shows that the agricultural cultivation technology in underdeveloped regions need to be improved.

Comparing the rebound points of cultivated land pressure in developed regions and underdeveloped regions, it can be found that the rebound point in economically developed regions is larger. This is due to the higher level of agricultural production and technology in developed regions, which delays the rebound of cultivated land pressure.

3.5.2. Different Grain Production and Sales Regions

The estimation results of different grain production and sales regions are shown in Table 11.

From the impact of economic growth on cultivated land pressure, there are differences in distinct grain production and sales regions. The coefficient of $PGDP^3$ in the cubic model is significantly positive in the main sales regions. That is to say, with economic growth, the cultivated land pressure increases firstly, then decreases, and finally increases again. The coefficients of $PGDP^3$ in the cubic model are significantly negative in the production and sales balance regions and the main production regions, and there is no extreme point. As the economy grows, the cultivated land pressure decreases. The coefficients of $PGDP^2$ in the squared model are significantly positive in all regions, and the cultivated land pressure first decreases and then increases with economic growth. The rebound point of cultivated land pressure in the main grain producing regions is much larger than other regions. This shows that the cultivated land in the main production regions has a stronger population support capacity (average cultivated land pressure: production and sales balance regions = 3.686 > main sales regions = 2.514 > main production region = 0.890), which delays the rebound of cultivated land pressure.

The coefficients of the control variables show that the influence direction and significance of a few variables change compared with the basic estimation. The impact of urbanization on cultivated land pressure is positive in the main production regions, but negative in the main grain sales areas. This is because the population urbanization in the main sales regions promotes the improvement of agricultural machinery power and the proportion of grain crops, which eases the cultivated land pressure. However, the high proportion of grain crops planted in the main production regions is highly dependent on labor, and the excessive population loss makes agricultural operations develop in an extensive direction. This is consistent with other scholars' research [76]. The influence of pesticide input on cultivated land pressure is significantly negative in the production and sales balance regions and the main production regions. This is because the pesticide input in these two regions is low (pesticide input per unit of cultivated land: main sales regions = 0.0029 > main production regions = 0.0015 > production and sales balance regions = 0.0005).

Table 11. Estimation results of different grain production and sales regions.

Variables	Main Sales Regions		Production and Sales Balance Regions		Main Production Regions	
	FE_ccd	FE_qcd	FE_ccd	FE_qcd	FE_ccd	FE_qcd
$PGDP^3$	0.076 *** (11.323)	—	−0.223 *** (−3.956)	—	−0.015 * (−1.879)	—
$PGDP^2$	−1.039 *** (−9.227)	0.299 *** (4.937)	2.363 *** (4.922)	0.707 *** (8.364)	0.222 * (2.150)	0.042 ** (2.767)
PGDP	4.611 *** (6.919)	−2.760 ** (−2.867)	−9.605 *** (−7.616)	−5.856 *** (−11.789)	−1.311 ** (−2.914)	−0.584 *** (−3.962)
POP	10.370 *** (4.048)	12.447 *** (5.408)	−0.885 (−0.138)	7.835 (1.407)	3.308 *** (4.985)	4.069 *** (6.525)
UR	0.008 (0.742)	−0.059 * (−1.951)	−0.035 (−1.033)	−0.045 (−1.344)	0.002 (0.324)	0.001 (0.272)
SI	0.124 (0.638)	0.779 ** (3.260)	0.180 ** (3.018)	0.189 *** (3.355)	0.027 ** (2.912)	0.016 ** (2.466)
TI	0.002 (0.009)	0.484 * (2.329)	0.133 ** (2.557)	0.135 ** (2. 650)	0.018 (1.480)	0.010 (0.802)
EI	−4.625 *** (−3.664)	−7.054 ** (−3.683)	−4.520 (−1.589)	−4.394 (−1.638)	−0.664 (−1.758)	−1.032 ** (−2.614)
FA	−1.031 (−0.045)	10.732 (0.470)	−3.352 (−0.205)	6.334 (0.382)	−11.268 *** (−3.134)	−11.395 *** (−3.221)
PI	130.368 (0.564)	−73.659 (−0.371)	−1800.000 *** (−5.121)	−2100.000 *** (−7.533)	−202.606 ** (−2.683)	−193.238 ** (−2.618)
MP	−4.592 ** (−2.954)	−3.064 * (−1.968)	1.040 (1.087)	0.505 (0.546)	0.290 (1.733)	0.261 (1.590)
Cons	−5.438 (−0.294)	−39.526 * (−2.061)	7.640 (0.949)	2.833 (0.435)	0.163 (0.194)	−0.227 (−0.295)
Time−fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Region−fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.891	0.846	0.555	0.527	0.463	0.443
F test	436.79 ***	85.41 ***	213.74 ***	201.87 ***	779.63 ***	365.65 ***
Curve shape	N	U	Decrement	U	Decrement	U
Maximum extreme point	3.794	—	—	—	—	—
Minimum extreme point	5.342	4.619	—	4.144	—	6.924
Obs.	126	126	198	198	234	234

Note: (1) The data outside the brackets are coefficients, and the data inside the brackets are t values. (2) Fe_ccd and Fe_qcd demonstrate Driscoll and Kraay standard errors. (3) *, **, and *** indicate the significance of 10%, 5%, and 1%, respectively.

4. Conclusions

Land is of great significance for ensuring food security and promoting economic development. Under the influence of many uncertain factors, such as the COVID-19 pandemic, the Sino–US trade friction, and the Russia–Ukraine conflict, global food security is seriously threatened. The issue of using limited cultivated land resources to guarantee food security and ensure “the rice bowl must be held in our own hands” has become a research hotspot. Based on the cultivated land pressure index and Kuznets curve model, this study analyzes the impact of economic growth on cultivated land pressure. The conclusions are as follows: (1) The relationship between economic growth and cultivated land pressure is an N-shaped or U-shaped curve in China from 2000 to 2017. When the per capita GDP is about 40,000 yuan/person, the cultivated land pressure rebounds. (2) There are regional differences in the impact of economic growth on cultivated land pressure. The per capita GDP at the rebound points of cultivated land pressure in economically developed regions and major grain producing regions are relatively high.

The research of this paper shows that economic growth and cultivated land pressure are sometimes synchronized and sometimes decoupled. With economic growth, the cultivated land pressure would fluctuate. Cultivated land pressure is affected by many factors, such as population growth, industrial structural changes, technological progress, government policies, and awareness of cultivated land protection. At the current stage, the cultivated land pressure is facing a rebound period from reduction to increase. We should always be vigilant. More attention should be paid to cultivated land protection, and cultivated land pressure should be controlled. Only in this way can we prevent cultivated land pressure from long-term synchronous growth with the economy.

Thus, the following policy recommendations are put forward: (1) We must pay attention to cultivated land protection in the process of economic growth. A decrease in cultivated land pressure is supported by many factors, such as industrial structural changes, technological progress, and increased awareness of cultivated land protection. Only by directing more capital and technology to cultivated land protection in the process of economic development can we effectively control the cultivated land pressure. Some specific measures should be implemented, including improving the compensation system of cultivated land protection, increasing subsidies for the purchase of agricultural machinery, and supporting the development of modern seed industry. (2) We must also prevent an increase of cultivated land pressure caused by urban expansion. By implementing land use control and national land and space planning, the impact of disorderly urban expansion on cultivated land pressure might be weakened. Meanwhile, improving the economical and intensive utilization of urban construction land can reduce the occupation of cultivated land for construction, which might alleviate cultivated land pressure. In practice, it is necessary to strictly delineate and adhere to the control lines of urban development boundaries, permanent basic farmland, and ecological protection. Only in this way can we guide the orderly development of cities and effectively protect cultivated land and ecological environment.

There are some limitations in this study. Firstly, this paper only analyzes the relationship between economic growth and cultivated land pressure at the provincial level, due to the availability of data. However, some provinces have broad jurisdictions, and there are differences in economic growth and cultivated land pressure within the province. Taking cities or counties as the basic research unit can more accurately reflect cultivated land pressure and its influencing factors, which is a research direction worthy of being carried out in the future. Secondly, this paper does not pay attention to the spatial correlation of the cultivated land pressure and its influencing factors. However, grain production and sales, economic development level, and population mobility may have spatial characteristics, which is also a content worthy to study.

Author Contributions: Conceptualization, H.Z. and X.W.; methodology, H.Z. and Y.W.; software, Y.W.; validation, H.Z. and X.W.; formal analysis, H.Z. and Y.W.; investigation, H.Z. and Y.W.; resources, H.Z. and X.W.; data curation, Y.W.; writing—original draft preparation, H.Z. and X.W.; writing—review and editing, H.Z., X.W. and Y.W.; visualization, Y.W.; supervision, H.Z. and X.W.; project administration, H.Z. and X.W.; funding acquisition, H.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Fund (13BGL149) and the Statistical Development Special Project of Sichuan Social Science Fund (SC19TJ024).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analyzed in this study. These data can be found at: https://data.stats.gov.cn/, https://www.fao.org/faostat/zh/#data/RL, and https://data.cnki.net/Yearbook/Navi?type=type&code=A, accessed on 15 March 2022.

Conflicts of Interest: The authors declare no conflict of interest.

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Article

Land Productivity and Agri-Environmental Indicators: A Case Study of Western Balkans

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Abstract: Due to the environmental radicalization of European politics, which is reflected in the European Green Deal, Farm to Fork strategy, and new CAP 2023–2027, this paper aims to determine the impact of agri-environmental indicators on soil productivity based on the land productivity function model. The paper focuses on the Western Balkans countries, which are in the process of European integration and which, in the coming period, need to harmonize their agricultural policy with the CAP. First, the aggregate Cobb–Douglas production function has been used to create a land productivity function. Then, the sources of land productivity growth have been calculated, which can be particularly interesting in the context of agri-environmental indicators, such as fertilizer use and livestock density. The research results showed that land productivity is the most elastic concerning changes in the number of livestock units per hectare. Consequently, reducing livestock units had a markedly negative effect on productivity. In addition, the research results showed that using mineral fertilizers is a crucial source of growth in land productivity in these countries. These results imply that the creators of the agricultural policy must carefully assess the pace at which they will harmonize ecological and economic goals, especially if they take into account the current Ukraine crisis that can disrupt the food market.

Keywords: agri-environmental indicators; fertilizer use; European Green Deal; CAP 2023–2027

Citation: Đokić, D.; Matkovski, B.; Jeremić, M.; Đurić, I. Land Productivity and Agri-Environmental Indicators: A Case Study of Western Balkans. *Land* **2022**, *11*, 2216. https://doi.org/10.3390/land11122216

Academic Editors: Uttam Khanal and Sanzidur Rahman

Received: 31 October 2022
Accepted: 1 December 2022
Published: 6 December 2022

1. Introduction

In the last few years, there has been an environmental radicalization of European politics, which is also present in the new proposal of the Common Agricultural Policy (CAP) for 2023–2027. Several important events preceded such changes. The Birds Directive (79/409/EEC) was adopted in 1979. In addition, the Green Paper (1985) is very significant, emphasizing the importance of environmental awareness of farmers and support for areas essential for preserving rural environments. Furthermore, the Nitrate Directives (91/676/EEC), whose aim is to reduce water pollution due to using nitrogen fertilizers, is particularly interesting for this paper. Indeed, the first significant turning point was Agenda 2000, which declared the new CAP goals, which include integration with environmental protection goals and sustainable agriculture promotion, and finally, the previous CAP reform in 2013 tried to respond to new concerns such as climate change, animal welfare, food safety, and the sustainable use of natural resources by including greening of payments to make agriculture more sustainable. According to [1], the new CAP will be vital to securing the future of agriculture and forestry and achieving the objectives of the European Green Deal. The first sentence in the brief overview of the new CAP suggests a strong connection with the European Green Deal. In addition, the Farm to Fork strategy (F2F) stands out as a special strategy that should provide a fair, healthy, and environmentally friendly food system [2]. One of the main goals of F2F is to create a sustainable food system that should have a neutral or positive environmental impact. As Schebesta and Candel (2020) [3] pointed out some precision targets should be achieved by 2030: a reduction of chemical and hazardous pesticides by 50% and a reduction of fertilizer use by 20%. This new state of European policies is particularly interesting for Western Balkan (WB) countries in the European integration process, which includes harmonization with EU policies and strategies. Potentially, this radicalization of EU policies, specifically CAP, could be very harmful to the agricultural sector's economic performance in countries with lower development levels.

These changes in agricultural policy and its goals are the critical motive for choosing this topic. In the context of ecology, it is exciting to analyze the use of mineral fertilizers and the intensification of livestock production due to the opposition of economic and ecological goals. In addition, it is interesting to analyze land productivity in countries with primary economic goals, such as the Western Balkans countries, which will have to harmonize their agricultural policy. Moreover, due to the specific political circumstances (the Ukraine crisis) disrupting the food supply chain, research examining the sources of productivity growth is crucial due to the need for increased food production.

So, this paper is focused on the agricultural sector of Albania, Bosnia and Herzegovina, North Macedonia, Montenegro, and Serbia. More precisely, the main focus is on land productivity and its interrelation with agri-environmental indicators: fertilizer use and livestock density. Therefore, this paper aims to determine the influence of fertilizer use intensification and livestock density on land productivity growth in WB countries. In order to quantify this influence, the land productivity function will be estimated. The application of this model to determine the impact of agri-environmental indicators on the growth of land productivity is the main contribution of this paper (in addition to the quantification of the impact itself). This research fills the gap in the literature that focuses on agricultural productivity because it looks at this phenomenon in the context of environmental goals, not just economic ones. This is particularly important for countries that have yet to adapt their agricultural policy to achieve environmental goals, such as the WB countries.

This paper is structured as follows. Section 2 provides a literature review on land productivity and agri-environmental indicators. Section 3 describes productivity and land productivity function, while the Sections 4 and 5 show results and discussion. The main conclusions are summarized in Section 6.

2. Literature Review

According to Kurduys-Kujawska et al. (2021) [4], productivity in agriculture is a measure of resource efficiency. This definition is crucial because of agriculture's global challenges, such as food security, natural resources degradation, and climate change adaptation and mitigation. Fuglie (2018) [5] points out that improving agricultural productivity is essential regarding global food security. Furthermore, the author claims that the rising agricultural productivity in developing countries increases income and encourages broader economic development. Improving the productivity of agriculture is very important due to the reduction of poverty through providing food security and higher income for farmers. Improving agricultural productivity is particularly significant in the case of countries where the agricultural sector is very important and where there is a large gap between the productivity of the agricultural sector and other sectors of the economy [6]. One of the most comprehensive studies of the partial productivity of agriculture was conducted by Yamada and Ruttan (1980) [7]. They analyzed the partial agricultural productivity of 41 states in 1970, and results showed significant differences in levels of partial productivity among these groups. Sharma, Rao, and Shepherd (1990) [8] observed partial productivity for different regions of the world in 1975 and 1980 and concluded that developed countries achieved higher levels of agricultural productivity than developing countries. In addition, they showed that the differences are more significant in the case of labor productivity than in the case of land productivity. Many authors have analyzed the agricultural sector of the WB. For example, Gajić et al. (2015) [9] compared the production performance of the countries of the Danube region. They showed that higher levels of partial productivity of agriculture are characteristic of EU countries in this region than WB. A similar conclusion is reached by Birovljev et al. (2017) [10]. They showed significant differences in the production and export performance of agriculture of the EU and the Central European Free Trade Agreement (CEFTA) countries (which are WB countries also). Therefore, they point out that it is necessary to create adequate agricultural policy instruments to improve the agricultural sector's performance in these countries before EU accession.

In order to increase productivity, especially land productivity, producers (and policymakers) usually decide to intensify chemical inputs' use, potentially endangering the environment and fostering land degradation. According to Xie et al. (2019) [11], crop production intensification in the developing world began with the Green Revolution. The Green Revolution significantly impacted the widespread use of new, input-responsive seeds and irrigation, fertilizer, and pesticides to increase cereal crop yields and improve food security [12]. With the activities of the Green Revolution, the main agricultural crop productivity more than doubled. The doubling of global food production in the previous decades was accompanied by the intensive use of inputs [13]. Although agricultural intensification led to the increasing productivity of land and volume of food supply, the negative impact on the environment, especially land, was also present. Land is a multifunctional, nonrenewable resource, and its limits are finite [14]. Moreover, besides producing food, fiber, fodder, and biofuel, the land performs many other vital functions, such as climate regulation, flood management, water quality, soil functionality, and cultural landscape and recreation. However, the land used nowadays is not sustainable and causes degradation [15,16]. Taddese (2018) [17] considers land degradation a complex phenomenon induced by natural and socio-economic factors and refers to the loss of biological and economic productivity of the land. The causes of land degradation are numerous, but in the case of agriculture, the negative impacts on land are mainly related to intensive agricultural production. According to ELD (2015) [18], 52% of agricultural land is already moderately or severely damaged by land degradation, and in the next 25 years, it is predicted that further degradation could reduce land productivity by 12% and thus lead to a 30% rise in prices of agricultural products. Agricultural intensification considers producing more per unit of input, and it is a way to increase agricultural productivity and food production [12]. According to Kopittke et al. (2019) [19] intensive agricultural production has so far significantly degraded the soil. The main forms of this degradation include the loss of organic matter, soil pollution due to excessive use of fertilizers, release of the greenhouse effect, loss of biodiversity, etc. Land degradation caused by intensive agricultural production can have a long-term negative impact on ensuring food security in the future. In order to increase agricultural production, the excessive use of agrochemical inputs had negative effects on the environment and human health [20]. Therefore, it is necessary to apply a sustainable method of agricultural production that will enable the recovery of soil, human health, and at the same time, food security.

As awareness of environmental problems caused by agricultural production grows, the number of methods for analyzing this problem is also growing. For example, the European Commission, together with all member states, defined a set of 28 agri-environmental indicators covering various areas that can be used to assess the impact of agriculture on the environment [21]. An empirical assessment of agriculture's environmental effects represents a problem that includes the inability to define and quantify all the impacts of agricultural production on the environment.

3. Materials and Methods

In the last decade, the total factor productivity (TFP) index has been mainly used to measure productivity [22]. The DEA method is the most common, based on which it is possible to obtain the Malmquist TFP index [23]. In addition, authors often decide to use the Färe–Primont Index to estimate agricultural total factor productivity growth [24,25].

However, in the second half of the 20th century, the focus of agricultural economists was mainly on the determinants of the growth of agricultural production and productivity. Very often, authors estimated aggregate agricultural Cobb–Douglas type production function [26–28], which can be presented in the following form:

$$y = A\prod_{i=1}^{n} x_i^{\beta_i} \tag{1}$$

where y—agricultural production; x_i—inputs; A, β_i—estimated parameters.

When the Cobb–Douglas production function is considered in agricultural economics, in many papers, five inputs (the most common are: labor, land, capital, fertilizers and livestock) and one output (value of agricultural production) were taken [29,30]. It can be presented as:

$$\ln Y = \alpha + \beta_1 \ln X_w + \beta_2 \ln L + \beta_3 \ln X_c + \beta_4 \ln X_f + \beta_5 \ln X_l + \gamma \tag{2}$$

where Y—output, X_w—labor; L—land; X_c—capital; X_f—fertilizers; X_l—livestock units; γ—residual.

This model is very useful for determining the causes of production growth. However, there is one more important advantage: it is possible to create a function of partial (land or labor) productivity of agriculture [31–33] simply by dividing the whole function with values for labor or land. As a main aim of this paper is the analysis of land productivity, this function can be expressed as:

$$\ln\frac{Y}{L} = \alpha + \beta_1 \ln\frac{X_w}{L} + \beta_2 \ln\frac{X_c}{L} + \beta_3 \ln\frac{X_f}{L} + \beta_4 \ln\frac{X_l}{L} + \gamma \tag{3}$$

where Y/L—land productivity, X_w/L—labor per land; X_c/L—capital per land; X_f/L—fertilizers use; X_l/L—livestock density; γ—residual.

In the context of modern times, this model can be suitable for determining the impact of agri-environmental indicators on land productivity. Based on the European Commission [21], agri-environmental indicators are the use of mineral fertilizers (*Mineral fertilizer consumption*) and livestock density (*Cropping patterns, Livestock patterns*) (among other 28 indicators presented in Table A1). Indeed, the biggest drawback of the Cobb–Douglas production function is that it shows constant returns to scale. In addition, this function is based on the unrealistic assumption of perfect competition in the factor market. However, in this paper, the model is used to approximate the impact of agri-environmental indicators on land productivity.

After estimation of the land productivity function, it is possible to determine the contribution of individual production factors to the growth of land productivity:

$$r_{Y/L} = \sum_{i=1}^{n} \beta_i r_i + \gamma \tag{4}$$

where $r_{Y/L}$—growth rate of land productivity, r_i—growth rate of use of production factors per land, β_i—coefficients, γ—residual.

This is precisely the most significant advantage of this model. It should also be noted that other models measure land productivity, but they belong more to the domain of agronomy and technology [34].

In the analysis, all data were collected from FAOSTAT [35] due to the lack of data from national statistics. Besides this, data for economic relevance for agriculture were collected from World Bank [36] and Agricultural Policy Plus (APP) [37] databases. Countries included are Albania, Bosnia and Herzegovina, North Macedonia, Montenegro, and Serbia (all of them are WB countries that are still in the process of European integration). The observed period is 2006–2018 due to missing data in the period before.

4. Results

Figure 1 shows indicators of agriculture's economic relevance in the Western Balkans and the EU countries. The lowest share of agriculture in employment is in Montenegro (8% on average), which is expected considering that some other parts of the economy, such as tourism, are far more important for the economy of this country and that the resource potentials are relatively unfavorable for agricultural production. In Serbia, Bosnia and Herzegovina, and North Macedonia, the share of employees ranges from 10 to 20%, which is four to five times higher than the EU average [38]. In Albania, the share of employment in agriculture is at a very high level (39%).

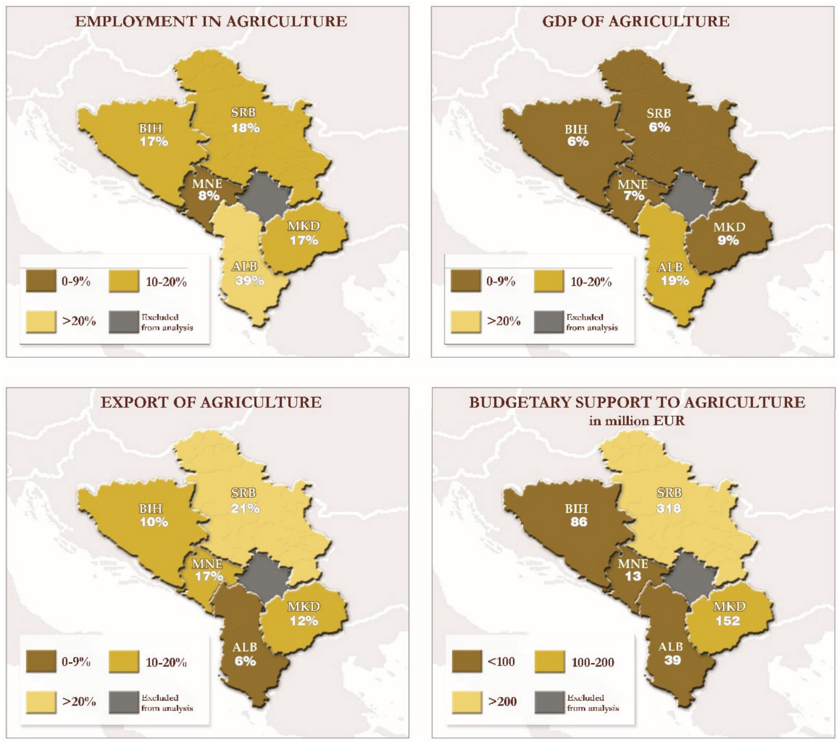

Figure 1. Economic relevance of agriculture in Western Balkans countries. Source: own research on the basis of FAOSTAT, World Bank, and APP Plus.

Note: Employment in agriculture and Export of agriculture (data from FAOSTAT) average for period 2005–2018; GDP of agriculture (data from World Bank) average for period 2005–2018; Budgetary support to agriculture (data from APP Plus) for 2019.

As expected, among the countries of the Western Balkans, the largest share of GDP in agriculture was achieved in Albania, and it is about 19% on average. In the other countries of the Western Balkans, the share of the agricultural sector is at a significantly lower level and ranges from 6 to 9%, with the present decline in the importance of the agricultural sector in the formation of GDP. The largest share of agricultural products in the total value of exports is present in Serbia, where one-fifth of the value of exports is agricultural products. Serbia has the largest comparative advantages on the international market, while only Albania has no comparative advantages in exporting these products [39]. The high share of agriculture in employment and GDP formation and the relatively low share of agricultural products in the total export of Albania (about 5%) imply that the greater part of the production is realized on the domestic market. Total budgetary support to the agricultural sector also greatly influences production performance. The largest volume of funds for agriculture is determined in Serbia, while the smallest volume of funds is in Montenegro, which is the smallest country in this sample, with relatively poor performance for agricultural production. Although all the Western Balkans countries aspire to become EU members, and to harmonize their agricultural policy with the CAP, current support from the budget is more directed towards optimal measures from the domestic (national) political economy perspective [40].

Figure 2 shows land productivity in WB countries in international US dollars per hectare and the productivity growth rate (r). Serbia has the highest level of land productivity, around USD 2000 per hectare, while the highest growth was achieved in Albania (3.01%). In Montenegro and North Macedonia, there was a decrease of 3.07% and 0.69%, respectively. Primarily, agroecological and climatic conditions determine these differences in land productivity as well as overall economic development.

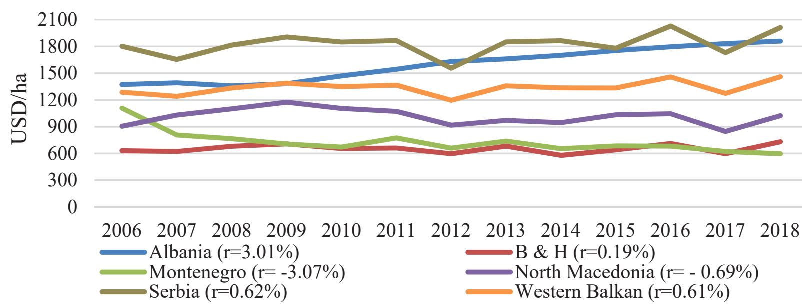

Figure 2. Land productivity in Western Balkans countries. Source: own research on basis of FAOSTAT.

Table 1 shows the regression results for the land productivity function of the WB. The coefficient of determination and the F-test show the validity of the model. All evaluated parameters are statistically significant, except the capital/land ratio. Land productivity is the most elastic in relation to changes in livestock density (0.37) and mineral fertilizer used per hectare (0.24). Both of these variables can be seen as indicators of the intensity of agricultural production.

Table 1. Estimation of land productivity function (OLS model).

Variables	Coefficients	Std. Error	t-Ratio	*p*-Value
const.	1.82	0.430308	4.234422	0.00 ***
Labor/Land	0.16	0.055803	2.804541	0.01 **
Capital/Land	0.02	0.058507	0.333235	0.74
Fertilizers/Land	0.24	0.029196	8.242370	0.00 ***
Livestock/Land	0.37	0.142243	2.602155	0.01 **
R^2			0.76	
Adjusted R^2	0.74			
F (4,73)			56.37	
p-value	0.00			

Note: ***, ** level of significance is 1% and 5%, respectively. Source: own research on basis of FAOSTAT [35].

Table 2 shows an estimation of the contribution of production factors to land productivity change. The most significant influence on land productivity has the use of mineral fertilizer per hectare, among the agricultural inputs. Such results are expected given that the average annual growth rate of mineral fertilizer use per hectare is very high (4.05%) compared to EU-27 (0.7%), which indicates an intensification of production. On the other hand, the decline in the number of employees and the reduction in the number of livestock units per hectare harmed land productivity. The estimated parameter for Labor/Land (0.16) is in line with the study conducted by Khan (1979) [41].

Table 2. Estimation of contribution of production factors to land productivity change.

Inputs	Estimated Parameters (C)	r (Growth Rate)	C x r	Contribution to Land Productivity Change (%)
Labor/Land	0.16	−1.65%	−0.26%	−43%
Capital/Land	0.02	1.81%	0.04%	6%
Fertilizers/Land	0.24	4.05%	0.97%	160%
Livestock/Land	0.37	−1.83%	−0.68%	−111%
Production factors			0.07%	12%
Residual			0.54%	88%
Land productivity growth rate		0.61%	0.61%	100%

Source: own research on basis of FAOSTAT [35].

This indicator could be very interesting from the socio-economic point of view and rural politics because results imply that workers' migration to other sectors has a negative impact on land productivity in WB. All production factors contribute to land productivity change only by 12%, primarily due to the bad influence of livestock unit reduction. Another 88% are linked to residual, which was often explained as technical progress in the past. However, there is still debate about such a conclusion [42].

5. Discussion

As it was explained, in the focus of this paper are land productivity and agri-environmental indicators, so the influence of fertilizer use and livestock density on land productivity will be discussed. The research results clearly showed that land productivity is the most elastic concerning changes in the number of livestock units per hectare, and the decrease in the number of livestock units per hectare had a negative impact on land productivity.

It indicates the extensiveness of agriculture in these countries, where crop production dominates, and livestock production has been stagnant for many years [43]. From an economic point of view, an increase in livestock production would influence the growth of production intensity and, therefore, the growth of land productivity. In all the WB countries, there was a decrease in livestock production in the analyzed period (2006–2018) at an average annual rate of −1% to −2% [35]. In addition, if the livestock density is considered, it is clear that WB countries are far behind EU-27, and a negative growth rate is present in all countries, except Montenegro (Table 3).

Table 3. Livestock unit per hectare (livestock density) in WB countries and EU-27.

	Average 2007–2010	Average 2011–2014	Average 2015–2018	Average	Growth Rate
Albania	0.62	0.62	0.64	0.63	−0.36%
B & H	0.33	0.34	0.31	0.33	−0.58%
Montenegro	0.19	0.28	0.37	0.27	7.65%
N. Macedonia	0.32	0.25	0.25	0.28	−2.76%
Serbia	0.54	0.49	0.48	0.50	−1.14%
EU-27	0.75	0.75	0.76	0.75	0.11%

Source: own research on basis of FAOSTAT [35].

A significant lag in the livestock sector is observed in comparison with the EU countries, especially regarding yields [44]. Although the countries of the WB as a whole have recently achieved some increases in crucial crop and livestock yields and labor productivity over time [38], they are still significantly lagging behind the EU [45]. For example, in Serbia, only one-third of Gross Agricultural Output comes from livestock production. At the same time, since the beginning of the 2000s, the contribution of this sector has decreased significantly, primarily due to the negative development of the meat sector, i.e., negative tendencies in the production of pig and beef meat. The main reasons are the effects of the transition period, poor competitiveness, the poor purchasing power of domestic producers, an inadequate system of incentives, and the disintegration of the value chain [46]. Similar tendencies were followed by all Central and Eastern European Countries where there was a decline in livestock production after 1990, i.e., an orientation towards more extensive sectors. As a result, the contribution of livestock production to the Gross Agricultural Output in these countries does not exceed 50% in these countries, so it is important to note that both labor and land productivity significantly increased for most of these countries after the accession to the EU [46].

In order to improve the performance of livestock production in the WB countries, it is necessary to encourage more intensive production through agricultural policy measures, which would positively affect the food industry [39]. Furthermore, it is very important in ensuring a safe supply of food and reducing import dependence [47], which can be particularly problematic in livestock production in the WB countries. Therefore, in the following period, the focus of short-term policy should be incentives to improve livestock production [48] and improve quality standards to increase competitiveness [49]. Previous research shows that it is easier and faster to start product-level agri-food competitiveness concerning country-level competitiveness [50]. Regional-level competitiveness is also important in creating export opportunities on the international market [51] Therefore, support should be directed toward products with comparative advantages, but also in research and development, which significantly influence competitiveness [52] and higher education that also significantly affect competitiveness and sustainable development [53].

However, insufficient intensification of livestock production can have a positive environmental effect. Namely, livestock contributes to releasing nitrogen, phosphorus, and potassium into the environment as much, if not more, than mineral fertilizer [54]. In addition, traces of antibiotics are noticeable in groundwater due to intensive livestock production [55]. The negative effect of livestock production can further adversely affect the food industry and the regularity in the supply chain of raw materials, which can further lead to economic and social insecurity [56].

The impact of livestock production on the environment depends not only on the livestock density index but also on the agricultural practice itself, so the increase in this index does not necessarily mean increased environmental degradation [57]. However, future policy planning based on the Common Agriculture Policy (CAP) and European Green Deal, adoption of appropriate regulations, the establishment of monitoring of financial instruments, regional cooperation, and improvement of risk management can influence the mitigation of these effects on the environment [56]. The results of previous research show that the WB countries have taken steps towards successful strategic planning of policies in the direction of the CAP, but the applied mechanisms are still not in line with the EU [58], both due to the uncertain moment of entry into the EU and the changing character of the CAP [40]. Because of that, livestock production management will play a significant role in improving environmental performance [59].

Estimates are that the relationship between livestock production and environmental protection will become particularly significant in the future, primarily due to the significant growth in demand for livestock products (mainly meat and milk). The growth of livestock production has, as a rule, in recent years generally led to negative effects on the environment [60]. In order to achieve sustainability, it will be required to strive for a double goal, the growth of livestock production, but also the reduction of negative effects on the environment, and 'sustainable intensifications' will be a solution for 'win–win' outcomes for grasslands, the environment, and smallholders [61].

The key source of agricultural growth in the WB countries was the use of mineral fertilizers in the observed period. This result was expected because the average annual growth rate of mineral fertilizer use was very high due to the intensification of the mineral fertilizer application in the transition period. Mineral fertilizers are one of the most important products in the agricultural industry that provide essential nutrients for crops and increase crop yield, agricultural productivity, and food security [62], but, at the same time, the intensive use of mineral fertilizers harms the environment and human health. The negative impacts of mineral fertilizers are mainly related to their production and application. According to Jensen et al. (2020) [63], the production and application of fertilizers have a wide range of environmental impacts, but the authors state that the most critical impacts are the consumption of valuable natural resources, eutrophication, acidification, and global warming. Namely, the authors assert that the production of mineral fertilizer has a high impact on climate change, resource depletion, and acidification, while eutrophication is a consequence of the mineral fertilizer application. There is evidence that fertilizer use has reached critical environmental limits [64], and it is necessary to consider their application in the coming period. Thus, policymakers in the Western Balkan countries must take this harmful effect into account when creating long-term development strategies.

Furthermore, bearing in mind the evolution of the CAP, it is possible to conclude that over time, due to the increasing degradation of the environment and climate changes, its focus shifted from economic to environmental goals. In addition, for the same reasons, the European Green Deal strategy is within the six priorities of the European Commission for the period 2019–2024. For the agricultural sector, the most important is F2F as a part of the Green Deal. When it comes to the use of mineral fertilizers, according to F2F, excess use of nutrients is a significant source of air, soil, and water pollution and climatic impacts. One of the aims of the Farm to Fork strategy is to reduce fertilizer use by up to 20% till 2030, and some of the objectives of the new CAP 2023–2027 should facilitate the achievement of the Farm to Fork strategy aim related to the reduction of the fertilizer application. So, because all the WB countries are aiming to become a member of the EU and that have a relatively high level of mineral fertilizer use, it is important to raise the level of knowledge about the importance of more sustainable agricultural practices, which is at the center of European policies, strategies, and values.

In addition, recent events indicate that specific problems can be expected in the coming period considering the situation in the mineral fertilizers market. Due to the pandemic and Ukraine crisis, the fertilizer price index rose by 43% from around 890 (25 February 2022) to 1270 (25 March 2022) [65]. Indeed, it is difficult to assess the final effects of this crisis, but there will most likely be some instability regarding the supply of mineral fertilizers on the global market. Certainly, this can be a significant threat to the further growth of agricultural production in WB countries.

In the end, it is important to point out that demand for agricultural products will increase due to population and income growth, and by 2050 it will be necessary to produce 60% more food than today which will create additional pressure on land and other scarce natural resources used in food production. In order to satisfy increasing demand, agricultural production will have to grow, and at the same time, it will have to minimize the environmental impact [66]. Furthermore, considering options to expand cultivated land areas are limited [67], future agricultural production will have to be more productive and sustainable at the same time. Willet et al. (2019) [68] pointed out that the current food system needs to be transformed in terms of productivity, resource use, and environmental effect.

6. Conclusions

Based on the research results, it is possible to summarize three key conclusions. First, the main booster of land productivity growth is the increased use of mineral fertilizers in the countries of the WB. However, considering the environmental consequences of the intensive use of chemical inputs, it is questionable how sustainable this growth is. Second, the decrease in livestock units has had a markedly negative impact on land productivity, implying that policymakers must pay special attention to the livestock sector in these countries. Of course, to increase competitiveness in meat and milk production, it is necessary to develop an adequate strategy that includes agricultural and other economic policies. Indeed, the development of this sector must be sustainable due to the negative environmental impact of intensive animal production. Third, as much as 88% of the increase in land productivity is due to other factors, suggesting that technical progress's influence is crucial for growth. The impact of technical progress on productivity growth will be the subject of future research. In addition, the research focus will be on EU countries. The originality of the research is the application of models that were very often used in the second half of the 20th century to observe the impact of agri-environmental indicators on land productivity which is one of the most critical questions of these days. In addition, the paper contributes to the literature concerning WB's agricultural sector and can influence policymakers' decisions in these countries. However, the paper's main limitations are the lack of a more extended time series of data due to specific regional political events (such as Yugoslavia's breakup) and the limitations of the Cobb–Douglas function itself. In the end, it is essential to emphasize that the creators of the agricultural policy must carefully assess the pace at which they will harmonize ecological and economic goals, especially if they take into account the current Ukraine crisis that can disrupt the food market, especially in the livestock sector and threaten food security in WB.

Author Contributions: Conceptualization, D.Đ. and B.M.; methodology and investigation, D.Đ. and B.M.; writing—original draft preparation, review and editing, D.Đ., B.M., M.J., and I.Đ.; visualization, M.J. and B.M.; supervision, D.Đ., B.M., and I.Đ. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Science Fund of the Republic of Serbia, Program DIASPORA, GRANT No 6406679, AgriNET.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets generated for this study are available on request to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Agri-environmental indicators.

Indicator
1. Agri-environmental commitments
2. Agricultural areas under Natura 2000
3. Farmers' training level and use of environmental farm advisory services
4. Area under organic farming
5. Mineral fertilizer consumption
6. Consumption of pesticides
7. Irrigation
8. Energy use
9. Land use change
10. Cropping patterns, Livestock patterns
11. Soil cover, Tillage practices, Manure storage
12. Intensification/extensification
13. Specialization
14. Risk of land abandonment
15. Gross nitrogen balance
16. Risk of pollution by phosphorus
17. Pesticide risk
18. Ammonia emissions
19. Greenhouse gas emissions
20. Water abstraction
21. Soil erosion

Table A1. *Cont.*

Indicator
22. Genetic diversity
23. High Nature Value farmland
24. Production of renewable energy
25. Population trends of farmland birds
26. Soil quality
27. Water Quality—Nitrate pollution, Pesticide pollution
28. Landscape—state and diversity

Source: European Commision [21].

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Article

Spatial Distribution Pattern, Evolution and Influencing Mechanism of Ecological Farms in China

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Abstract: Nowadays, the challenges of energy depletion, environmental pollution and food security caused by extensive agriculture development are attracting global attention. In China, the construction of ecological farms is a key initiative to effectuate the goal of peaking carbon dioxide emissions and achieving carbon neutrality, contributing to high-quality agricultural development. Based on this, this study selects the national-level ecological farms directories issued by the Ministry of Agriculture and Rural Affairs (MARA) of China in 2021 and 2022, and collects the corresponding economic, social and physical geographic data for GIS spatial analysis and Geodetector. The results are as follows: (1) The distribution of ecological farms in various provinces of China is uneven and spatially clustered. It generally presents a 'high in the east and low in the west with concentrated cores' pattern. The construction scope significantly expanded over time, and the high-value areas of nuclear density are concentrated in East China, with the development core transitioned from East China to Central China. (2) Environmental conditions, industrial foundation, economic and social development level, science and technology level and financial support all significantly affect the spatial distribution of ecological farms in China, among which the science and technology level has the most significant enhancement effect on other factors. (3) Environmental conditions provide the construction basis for ecological farms, while economic and social development level and financial support determine the number of ecological farms. The industrial foundation affects the scale of ecological farms in China, while the level of science and technology eliminates the restrictions of other factors to a certain extent. This study provides a reference for optimizing the spatial distribution pattern of ecological farms in China and promoting ecological agriculture. In addition, it presents a viable approach to safeguarding food security.

Keywords: ecological agriculture; sustainable development; spatial distribution pattern and evolution; Geodetector; influencing mechanism

Citation: Guo, D.; Lin, Y.; Wang, M.; Huang, Z. Spatial Distribution Pattern, Evolution and Influencing Mechanism of Ecological Farms in China. *Land* **2023**, *12*, 1395. https://doi.org/10.3390/land12071395

Academic Editors: Uttam Khanal and Sanzidur Rahman

Received: 10 June 2023
Revised: 5 July 2023
Accepted: 10 July 2023
Published: 12 July 2023

1. Introduction

Nowadays, the rapid development of agriculture is facing the challenges of reducing crop yields and food supply caused by finite natural resources and changing climatic conditions [1,2]. On a global scale, agriculture triggers serious environmental and ecological problems [3]. The excessive use of chemical fertilizers and pesticides has destroyed the environment, a large increase in agricultural irrigation water has led to over-exploitation of water resources and excessive land reclamation has caused soil erosion and land desertification [4,5]. Agricultural production activities are also one of the important sources of greenhouse gas and carbon emissions, which are constantly increasing [6]. These destructive activities result in impaired functioning of agro-ecosystem services and threaten human well-being [7,8]. But at the same time, these challenges have also become an urgent force to promote agricultural transformation [9]. How to improve agricultural productivity and ensure food security is a problem in need of global attention.

With the emergence of systems theory, information theory and cybernetics in the scientific community since the 1940s, agricultural production has been promoted to develop in a comprehensive and systematic direction, and conventional agriculture has gradually shifted towards modern agriculture and ecological agriculture [10]. Various countries worldwide adopted diversified practices to attain sustainable agricultural development, which is the origin of Agroecology. In 1942, the Rodale Institute published *Organic Farming and Gardening* and other publications to promote the idea of organic farming and practiced 'Organic Agriculture' on their farms [11]. In the 1950s, a 'Natural Agriculture' without tillage, fertilizer and pesticide emerged in Japan [12]. In 1974, Mollison and Holmgren of Australia proposed the permanent agriculture method based the ethics of caring for the earth, caring for human beings and sharing surpluses [13]. With the convening of the United Nations Conference on the human environment in 1972, human awareness of ecological and environmental protection gradually increased and sustainable agriculture and green ecological farms became the goals of agricultural development in many countries. In 1981, British scholar Worthington summed up a diversified and nutrient self-sufficient 'Ecological Agriculture' mode based on the practice of European agricultural production [14]. The U.S. federal government proposed the 'Low Input Sustainable Agriculture' in 1988, the 'High Efficiency Sustainable Agriculture' in 1990 and promulgated the 'National Organic Program' in the same year [15]. The EU proposed the concept of 'Multifunctional Agriculture' in 1997, emphasizing the ecological function of agriculture and implementing specific implementation measures in the EU's common agricultural policy [16]. The Japanese government promulgated the Sustainable Agriculture Act in 1999 and the Organic Agriculture Promotion Act in 2006. Since the 21st century, more and more scholars, institutions, groups and governments have paid attention to Agroecology at the international level. In 2014, the Food and Agriculture Organization of the United Nations (FAO) organized an International Symposium on Agroecology to promote the concept and methods of Agroecology and promote the action and policy formulation of Agroecology in various countries [17]. Reviewing the origin, formation and evolution of the concept of Agroecology, it can be found that the principles and propositions for ecological agriculture are similar internationally. The current practice of ecological agriculture aims to optimize the ecological environment, public health and well-being, and to minimize the socio-ecological costs of agriculture, such as soil degradation, water pollution, greenhouse gas emissions and resource exhaustion [18,19]. The essential goal of Agroecological practices includes reducing the consumption of external inputs such as fossil fuels while improving the quality and efficiency of internal inputs. Originating from continuous improvement by experience, experimentation and research, these evolving Agroecological practices improve food security, nutrition and health while adapting to and mitigating climate change without harming ecosystems [20,21]. Currently, ecological agriculture is at a high level of development in many countries. For instance, according to the International Federation of Organic Agriculture Movements (IFOAM), there were 15.6 million hectares of organic farmland in Europe in 2018. The National Agricultural Statistics Service's Census of Agriculture conducted in 2017 revealed that there were 11,650 certified organic farms in the U.S. The market for organic products in the U.S. topped USD 50 billion in 2018 [22].

The studies around Agroecology and ecological farms focus on the construction process and policy formulation of Agroecology, the economic and social effects of Agroecology, the analysis of the influential factors of ecological farms and the path to achieve sustainable agricultural development. For example, Paul et al. analyzed the sustainability challenges faced by Indian agriculture and proposed an analytical framework including scale, affordability and sustainable input to promote the sustainable development of Indian agricultural systems [23]. Pimbert et al. revealed the development dilemma of agricultural ecological practice projects, aiming to explore agricultural production models that support agricultural ecological development [24]. Kujala et al. used the organic agriculture area in Finland as a case study. Through large-scale investigation and comparative analysis, they found that the development of Agroecology in Finland was affected by factors such as planting tradition, farmers' attention and government subsidies [25]. Brown draws on three case studies of civil society organizations promoting sustainable agriculture in India to assess their potential to address contemporary agricultural issues [26]. Research on Agroecology also pays attention to the political, economic, social and cultural impacts brought about by its development. Researchers believe that ecological agriculture is closely related to food security and national governance [27]. Compared with conventional fossil agriculture, Agroecology increases farm income and creates more employment opportunities while helping connect agriculture downstream in the industrial chain, which creates strong links between rural areas and urban consumers [28,29]. To sum up, Agroecology enhances the resilience and sustainability of rural and agricultural areas [30–32]. Moreover, Agroecology has made positive contributions to enriching agricultural landscapes and maintaining biodiversity [17]. However, some scholars argue that developing ecological agriculture may also mean higher input costs, lower output efficiency and potentially higher prices for agricultural products [33–35]. The need for agricultural specialty talents is also a challenge for ecological agriculture [36]. In any case, according to the above studies, Agroecology in modern society is a multifunctional complex integrating production, living and ecology as a comprehensive system composed of nature and human beings [37]. However, few studies have concretely offered solutions for evaluating the development potential of Agroecology in different countries. No consistent criteria have been defined to regulate the development of Agroecology, which, on the contrary, hinders the development of Agroecology and food security.

Corresponding to 'Agroecology' in the West, China began its exploration in modern ecological agriculture in the 1980s, with the term 'China Ecological Agriculture' (CEA) appearing. In the process of rapid modernization, China's agricultural land area is generally decreasing [38], and the service value of agro-ecosystems is also declining [39]. In order to solve these problems, the Chinese government began to carry out ecological agriculture pilot work in nationwide areas. Over time, the level and scope of pilot areas have been continuously enriched, and significant social, economic and ecological benefits have been achieved [40]. The ecological farm is the basic unit of China's ecological agriculture construction following the principles of 'Integration, Coordination, Circulation, Regeneration, and Diversity', which play a leading and exemplary role in green agricultural development. The development of ecological agriculture is an indispensable way to promote the green transformation and development of agriculture, while the construction of ecological farms is providing a stronger carrier for this program. As of 2022, China's gross agricultural product is CNY 5194.2 billion, and more than 1 billion mu of high-standard farmland has been constructed. The number of registered family farms and farmers' cooperatives reached 3.9 million and 2.22 million, respectively, which are potential actors in developing of organic agriculture. In addition, the total number of green food and organic agricultural units nationwide is 27,246 as 102 organic agricultural bases are constructed [41,42].

Currently, there are obvious differences and diversity of China's ecological farms in different regions, and discussions on China's ecological agriculture begin. On the one hand, existing studies have explored the ecological issues faced in the process of China's agricultural development, such as carbon footprint and the risk of pesticide application [34]. On the other hand, researches have discussed more about China's specific ecological agriculture practices and processes, most of which focus on specific provincial cases [43–45]. On a national scale, some researchers apply panel data of China to measure the role of agricultural green production technologies such as water-saving irrigation in reducing carbon emissions [46]. Some scholars, based on Chinese Internet agricultural news, use text analysis methods to explore the differences in ecological agriculture development pattern, but there are large deviations in their data sources [47]. To sum up, the existing research helps us better understand the characteristics of China's ecological farms in the context of digital transformation in rural areas. Nevertheless, they mostly discuss the specific cases of ecological agriculture practice at the provincial level, lacking a macroscopic discussion on the spatial distribution pattern at a national scale. At the same time, as an important carrier of ecological agriculture, the construction of ecological farms will be affected by many factors from the selection of pilot sites and construction practice to evaluation and acceptance, which determine the spatial distribution of ecological farms. Due to the large differences in economic and social development between different regions, coupled with the long construction period of ecological farms, large capital investment and slow return on investment, there are great differences in the spatial distribution of ecological farms in China. How to explain this distribution difference is an urgent problem to be discussed. However, the research on ecological farms is mainly based on qualitative analysis. There is a lack of discussion on the spatial pattern, influential factors and formation mechanism of ecological farms in specific countries or regions, which is not conducive to the formation of holistic cognition and deepening understanding from spatial distribution to internal logic. In addition, due to the large differences in the standards and definitions of ecological agriculture in various regions, and the fact that the accuracy of the diversified data sources cannot be guaranteed, the existing research still has shortcomings in the generalizability of the research results.

Therefore, this study selects the directories of national-level ecological farms released by the MARA. First, spatial analysis methods such as the nearest neighbor index, the imbalance index and kernel density are used to explore the spatial distribution pattern and evolution characteristics of ecological farms in China. At the same time, based on Geodetector, this study analyzes the influential factors of the construction and distribution of ecological farms in China from five aspects: environmental conditions, industrial foundation, economic and social development level, science and technology level and financial support. This study not only fills in the gaps in the current research on the spatial distribution of ecological farms in China but also clarifies the influencing mechanism of the spatial distribution of ecological farms, leading to a better understanding of the development pattern of ecological agriculture. Then, we put forward feasible suggestions for optimizing the spatial distribution of ecological farms and balancing the development of ecological agriculture in China. Furthermore, we present a viable approach for countries that are facing population, ecology and food security issues to develop ecological agriculture.

2. Materials and Methods

2.1. Data Sources

This study selects the first batch and the second batch of national-level ecological farm directories released by the MARA in 2021 and 2022 for spatial analysis, covering 31 provinces and cities in China (data from Hong Kong, Macao and Taiwan are temporarily absent), a total of 432, of which the first batch consisted of 132 directories and the second batch 300. These ecological farms are awarded a national-level title in strict compliance with the 'Technical Specification for the Assessment of Ecological Farm' (NY/T 3667-2020) released by the MARA in 2020, which sets out detailed and strict regulations on land conditions, location selection, surrounding environment, planting and breeding patterns, packaging of agricultural products and farm management. In particular, the technical specification details green development indicators such as livestock and poultry density, pesticide and fertilizer application, water-saving ratio, organic waste recycling, feed composition and other aspects.

Since ecological farms in China are represented as point elements on the provincial scale, we obtain the coordinate data of each ecological farm through the AutoNavi map open platform, then convert and verify them in order to build a spatial attribute database. In particular, the datasets of 2021 and 2022 are constructed using the same methodological basis, and there are no identical data. All maps in this article are based on the standard map No. GS (2020) No. 4619 from the standard map service website of the China Ministry of Natural Resources, whose base map has not been modified.

The construction, operation and acceptance of ecological farms in China require a certain period of time, and the evaluation of agricultural technology also requires a certain development period [48]. Therefore, taking account of the availability and timeliness of data, the cross-sectional data in 2020 are selected to construct the indicator system in the link of Geodetector. The data of each indicator come from the *China Statistical Yearbook*, *China Rural Statistical Yearbook* and *China Science and Technology Statistical Yearbook*.

2.2. Research Methods

2.2.1. The Nearest Neighbor Analysis

The nearest neighbor index R is the ratio of the actual nearest distance to the theoretical nearest distance of a point element in geographic space, which is used to indicate the spatial distribution type (random, uniform or clustered) of point elements. In this study, the nearest neighbor analysis is used to figure out the overall distribution of ecological farms in China. The formula for the index is

$$R = \frac{\bar{r_i}}{\bar{r_j}} = \frac{2\bar{r_i}}{\sqrt{\frac{n}{A}}} \tag{1}$$

where $\bar{r_i}$ denotes the actual nearest distance, $\bar{r_j}$ denotes the theoretical nearest distance, n denotes the total number of ecological farms and A denotes the research area. When $R = 1$, it indicates that ecological farms are randomly scattered throughout the space; $R > 1$ indicates that ecological farms tend to be uniformly spatially dispersed; and $R < 1$ indicates ecological farms tend to be spatially clustered [49].

2.2.2. The Imbalance Index Analysis

The imbalance index S can analyze the distribution balance of ecological farms in various provinces. This study applies the Lorenz curve to figure out the imbalance index S of ecological farms. The formula for the index is

$$S = \frac{\sum_{i=1}^{n} Y_i - 50(n+1)}{100n - 50(n+1)} \tag{2}$$

where n denotes the total number of provinces researched and Y_i denotes the cumulative percentage of ecological farms in the ith province. When $S = 0$, it shows that ecological farms are evenly distributed in each province, and $S = 1$ shows that the ecological farms are concentrated in a certain province. When S is between 0 and 1, a larger value of S indicates a more uneven distribution of ecological farms [50].

2.2.3. Kernel Density Analysis

Kernel density analysis is a nonparametric estimation method that analyzes characteristics of spatial distribution based on the spatial properties of data. This study uses the kernel density formula to analyze the spatial distribution characteristics of ecological farms in China. The higher the kernel density, the denser the ecological farm, and vice versa. The formula is

$$F(x) = \frac{1}{nh^2\pi}\sum_{i=1}^{n} K\left[1 - \left(\frac{(x-x_i)^2 + (y-y_i)^2}{h^2}\right)\right]^2 \tag{3}$$

where h denotes the search radius, $(x-x_i)^2 + (y-y_i)^2$ denotes the distance from the estimated point X to the ith point and n is the total number of ecological farms [51].

2.2.4. Standard Deviation Ellipse Analysis

The standard deviation ellipse (SDE) analysis can reveal the directionality, extension, centrality and spatial form of the spatial distribution of the elements studied. This study applies SDE to analyze the distribution scope, direction changes and gravity center transfer. The formulas are as follows:

$$SDE_x = \sqrt{\frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}{n}}, SDE_y = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}{n}} \tag{4}$$

where SDE_x and SDE_y are the axis lengths in the x and y directions of the standard deviation ellipse. (x_i, y_i) are the coordinates of every ecological farm. $(\bar{x}, \bar{y})$ is the average center of ecological farms' distribution; n is the total number of them. The long axis is the direction with the most spatial distribution, while the short one is the direction with the least spatial distribution [52].

2.2.5. GeoDetector Analysis

GeoDetector is a type of statistical method which mainly compares the total variance of various impact factors in different regions with the total variance in the total region to detect whether their spatial changes are consistent. The formula is

$$q_{DH} = 1 - \frac{1}{n\sigma_H^2} \sum_{i=1}^{m} n_{Di}\sigma_{H_{Di}}^2 \tag{5}$$

where D is the factor selected; H is the dependent variable; q_{DH} denotes the explanatory power of the factor D to the dependent variable H; n and $\sigma_{H_D}^2$ denote the total number of ecological farms and the total variance; m is the classification number of type i factors; and n_{Di} and $\sigma_{H_{Di}}^2$ denote the number and variance of ecological farms for type i factors. According to the principle of Geodetector, the q_{DH} ranges from 0 to 1. And the larger the q value, the stronger the explanatory power of the differentiation factor D for the dependent variable H [53].

3. Results

3.1. The Overall Spatial Distribution Pattern and Evolution Characteristics of Ecological Farms in China

3.1.1. Spatial Agglomeration Analysis

As shown in Figure 1, the vast majority of ecological farms in China are distributed in the southeast side of the Heihe–Tengchong Line, which is a basic dividing line of the physical geography and human geography in China. The distribution of ecological farms on both sides of the line has significant differences and shows a strong agglomeration. The results of the nearest neighbor index analysis in Table 1 show that the actual nearest distance of ecological farms in both 2021 and 2022 is smaller than the theoretical nearest distance. The overall R-value is less than 1 (0.477), which passes the significance test, indicating that ecological farms in China are spatially agglomerating.

Table 1. Analysis results of nearest neighbor index.

Year	Theoretical Nearest Distance/km	Actual Nearest Distance/km	Z	R
2021	106.652	62.210	−8.953	0.593 ***
2022	103.437	53.750	−15.917	0.520 ***
Total	87.099	41.541	−20.798	0.477 ***

Notes: *** represent significance at 1%.

The reduction of the R-value from 0.593 to 0.520 shows that the degree of agglomeration is strengthening, although the scope of ecological farms in China is expanding with more provinces covered. The quantity of ecological farms in different provinces shows significant spatial differentiation. This also tells us that ecological farms have great potential for development, and the ecological farms constructed can drive the synergetic construction of others in the same region.

At the same time, the imbalance index S of ecological farms of the provinces from the first batch (0.699) to the second batch (0.371) shows a decreasing trend, but the overall imbalance index was 0.448. It indicates that even though the distribution scope of ecological farms has expanded over time, the overall distribution is still imbalanced. Thus, the unbalanced state of ecological farms is still relatively serious. It is of necessity to further balance the construction quantity of every province. Specifically, the number of ecological farms in Jiangsu Province currently ranks first in the country, with 50, followed by Zhejiang, Anhui, Shanghai, Hubei and Shandong provinces, each with more than 20 ecological farms. However, a total of 12 provinces have a small number of ecological farms, each of which is less than 10 (Figure 2). Moreover, the two provinces of Tibet and Qinghai have no national-level ecological farms yet. Compared with the pattern of uniform distribution, the Lorenz curve of ecological farms in various provinces shows a clear upward form. The total number of ecological farms owned by the seven provinces with the largest number of ecological farms accounts for more than 50% of the total number of ecological farms in the country. Central China has a high concentration.

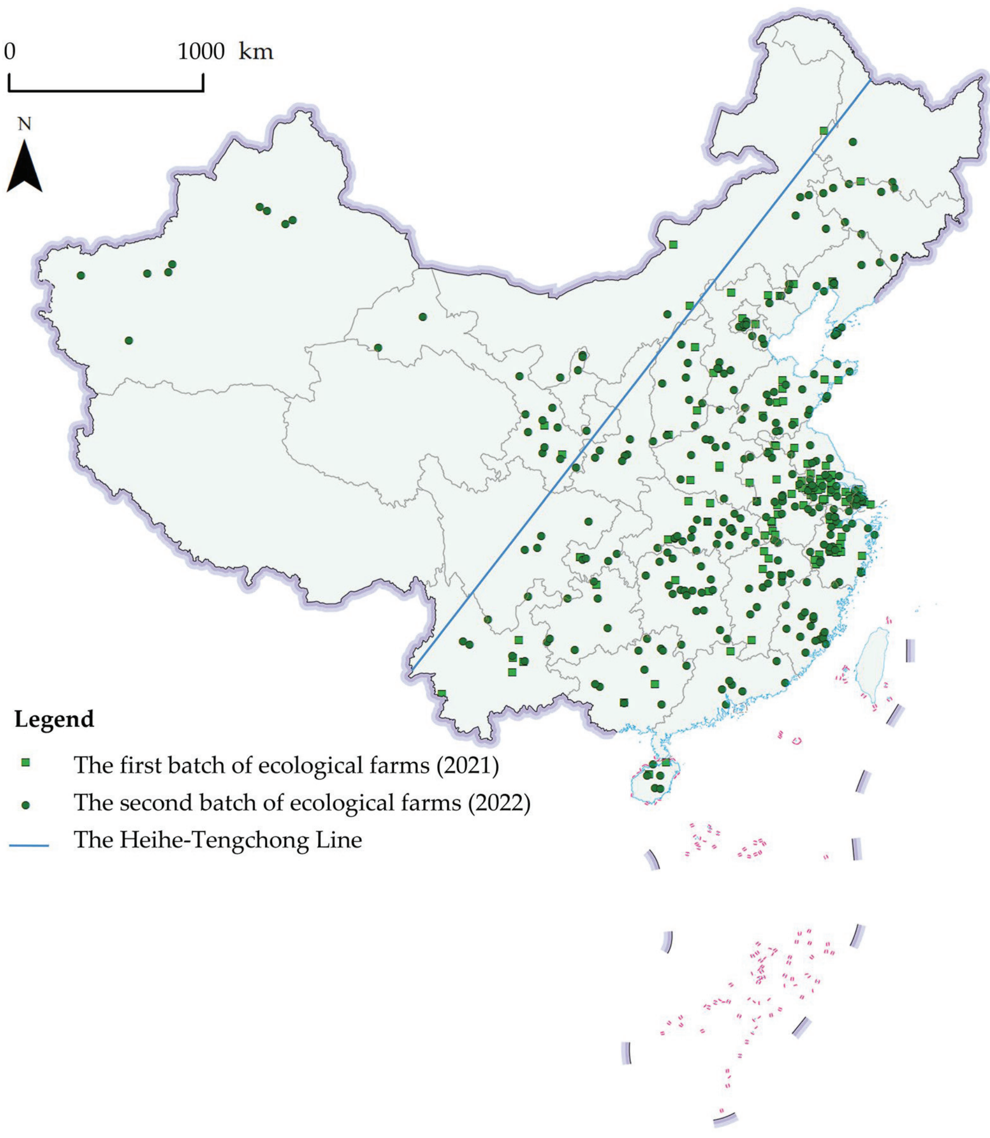

Figure 1. Overall spatial distribution of ecological farms in China. (Data from Hong Kong, Macao and Taiwan are temporarily absent.)

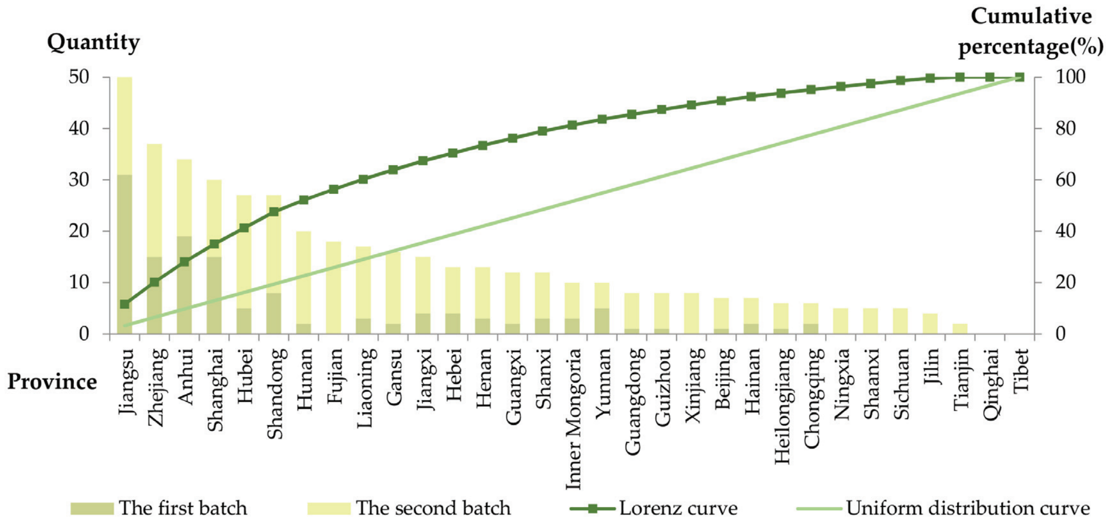

Figure 2. Quantities and Lorentz curve of ecological farms in each province of China. (Data from Hong Kong, Macao and Taiwan are temporarily absent.)

3.1.2. Spatial Density Analysis

The results of kernel density analysis (Figure 3) show that in recent years, the two batches of ecological farms have shown a spatial distribution pattern of 'high in the east and low in the west with a concentrated core', manifesting as a circle structure with the Yangtze River Delta as the core and radiating outward. The area with high nuclear density continues to spread. The first batch of ecological farms formed a high-value area in East China with Yangtze River Delta as the core, which mainly concentrated in the four provinces of Jiangsu, Zhejiang, Anhui and Shanghai. And there are scattered lower-value areas in Central China, North China, South China and Southwest China. Compared with the first batch, the distribution range of the second batch of ecological farms has spread significantly, spreading almost all around the country. At the same time, sub-high-value areas appeared in Hubei Province, Fujian Province and Beijing. The area with high nuclear density expanded to North China and Central China. On the whole, since there are 300 ecological farms in the second batch which account for a relatively high proportion of the total ecological farms, their distribution kernel density also determines the overall spatial kernel density of the current ecological farms to a certain extent.

3.1.3. Spatial Density Analysis

According to the construction sequence of ecological farms in China, its overall scope has gradually expanded. The area of the SDE of ecological farms is obviously enlarged, and both the major axis and the minor axis of the SDE show an increasing trend, with growth rates of 45.82% and 53.79%, respectively. The center of the SDE has moved by 267.118 km (Table 2, Figure 4). These indicate that the agglomeration core area of ecological farms continues to expand, and the distribution center gradually transitions from Huainan City, Anhui Province (East China), to Zhumadian City, Henan Province (Central China), while the current overall distribution center is located in Xinyang City, Henan Province (Central China). The azimuth angle of the SDE of ecological farms has changed from 50.46° to 87.18°, which means that the number of ecological farms in each province, especially the provinces in the east–west direction, has increased more evenly, mainly resulting from the construction of the second batch of ecological farms. Specifically, the number of the second batch of ecological farms in eight provinces and cities including Zhejiang, Hubei, Jiangsu, Shandong, Hunan, Fujian, Shanghai and Anhui exceeded 15, showing a contiguous distribution in the east–west direction.

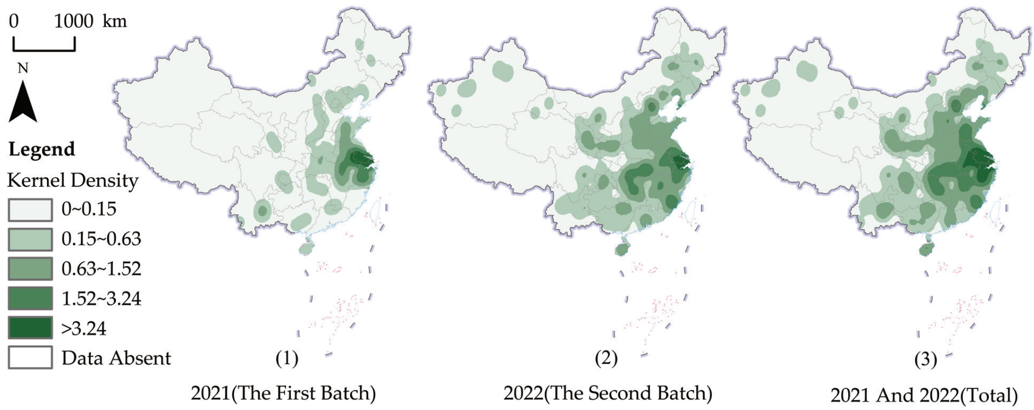

Figure 3. Kernel density estimation programs of ecological farms in China. (Data from Hong Kong, Macao and Taiwan are temporarily absent.)

Table 2. Parameter of standard deviation ellipse of ecological farms in China.

Batch	Area/10,000 km^2	SDEx (°E)	SDEy (°N)	XStdDist /100 km	YStdDist /100 km	Azimuth Angle (°)
First	129.325	116.933	32.029	8.570	12.442	50.461
Second	290.022	114.145	32.473	13.179	18.144	87.179
Total	248.114	114.997	32.337	12.308	16.621	82.495

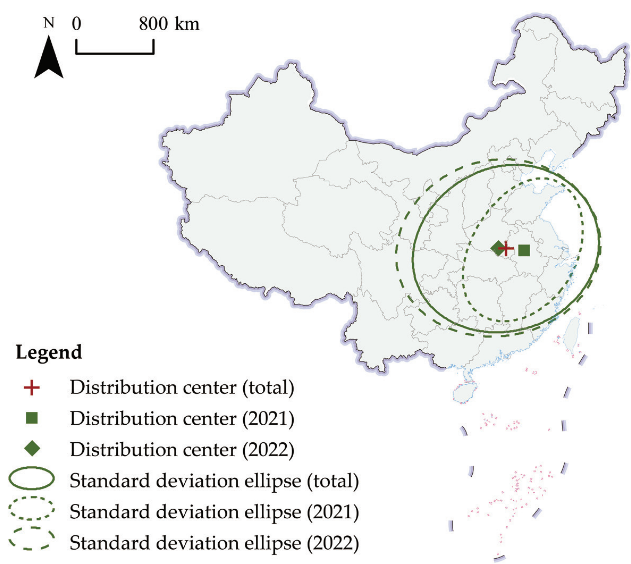

Figure 4. Analysis results of standard deviation ellipse of ecological farms in China. (Data from Hong Kong, Macao and Taiwan are temporarily absent.)

3.2. Analysis of Influential Factors Based on Geodetectors

3.2.1. Construction of the Influential Factor Indicator System

Referring to the existing research results and combined with the actual construction of ecological farms in China, this study mainly explores the influential factors of their spatial distribution from five aspects (Table 3): environmental conditions (A), industrial foundation (B), economic and social development level (C), science and technology level (D) and financial support (E). In terms of environmental conditions, compared with the conventional decentralized agricultural production, the construction of ecological farms requires contiguous land. According to the 'Technical Specification for the Assessment of Ecological Farm' issued by the MARA, an area greater than 2 hm^2 is one of the basic conditions for application of an ecological farm. So, the farmland density (A1) of the region can be a factor to measure the environmental conditions, which is the ratio of sown area to administrative area of each province. At the same time, the water resource endowment is another significant factor to agricultural development, which is measured by the amount of water resources per unit administrative area (A2). The road network density (A3) reflects the traffic basis of ecological farm construction. Industrial foundation (B) is also an important factor in the construction of ecological farms. The number of agricultural legal entities (B1) indicates the scale of agriculture in the region. At the same time, due to the strict and scientific construction standards of ecological farms, leading enterprises with great scale and strength are the key players in the construction and operation of ecological farms. Therefore, the number of leading agricultural enterprises (B2) is also one of the important influential factors, and the degree of agricultural modernization (B3) is the technical basis for the construction of ecological farms, expressed by the total power of agricultural machinery per unit area [54]. Per capita GNP (C1) and the size of the resident population (C2), which are important indicators to measure the regional economic and social development level (C), can reflect the market demand of ecological farms and the social investment in the construction of ecological farms [44]. In terms of science and technology level (D), agricultural technological innovation is an important drive for the construction of ecological farms, and there is a demand for R&D expenditure on the application of science and technology. Therefore, R&D expenditure (D1) could reflect the intensity of scientific and technological activities that contribute to ecological agriculture from every sector. Meanwhile, the Internet access rate (D2) reflects the digital development level of a region to a certain extent [48,55]. As for financial support (E), financial support is another important drive for the construction of ecological farms, measured by total fiscal expenditure (E1) and agriculture-related expenditure intensity (E2) [56]. As the convergence of the primary sector with the secondary and tertiary sectors is a distinctive feature of ecological farms, and as infrastructure construction is also an indispensable condition, we are concerned with the overall fiscal expenditure of the government.

Based on the selected factors, this study adopts the Jenks Natural Breaks Classification to discretize the data of each factor, which are divided into five levels. Following the classification results, we adjust the classification of a few critical data of B2, C1, D1 and D2 in order to get a better discretization result. Finally, the schematic diagram of the discretization result of different influential factors is drawn as follows (Figure 5). According to the number N of ecological farms in every province from left to right, it can be seen that there is a certain gradient differentiation among the influential factors in different provinces, which shows a trend from small to large as a whole.

Table 3. Influential dimensions and factors of the construction of ecological farms in China.

Dimensions	Factors	Definitions	Unit
Environmental conditions (A)	Farmland density(A1)	The ratio of farmland area to administrative area	%
	Water resource endowment (A2)	Water resources per unit administrative area	t/km
	Road network density (A3)	Road length per unit administrative area	km

Table 3. *Cont.*

Dimensions	Factors	Definitions	Unit
Industrial foundation (B)	The number of agricultural legal entities (B1)	Total number of legal entities in agriculture, forestry, animal husbandry and fishery	Number
	The number of leading agricultural enterprises (B2)	Number of national-level key leading enterprises in agricultural industrialization by province	Number
	The degree of agricultural modernization (B3)	Total power of agricultural machinery per unit administrative area	kW/km^2
Economic and social development level (C)	Per capita GNP (C1)	Per capita gross national product by province for the year	10 thousand CNY
	The size of the resident population (C2)	The size of the resident population at the end of the year	Number
Science and technology level (D)	R&D expenditure (D1)	R&D expenditure by province for the year	10 thousand CNY
	Internet access rate (D2)	Number of Internet access ports per unit administrative area	Number/km^2
Financial Support (E)	Total fiscal expenditure (E1)	Total financial expenditure by province for the year	Billion CNY
	Agricultural expenditure intensity (E2)	Expenditure on agricultural, forestry and water affairs per unit administrative area	Billion CNY

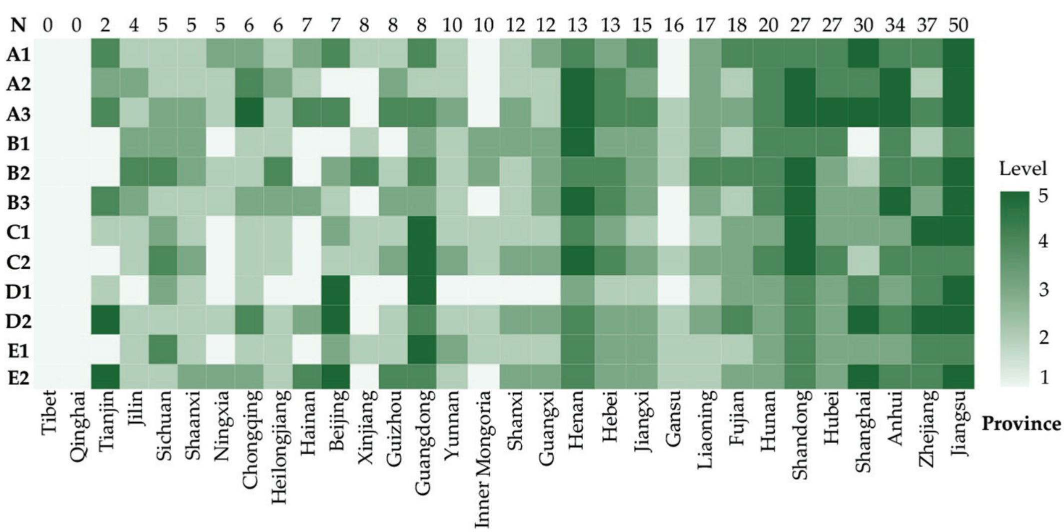

Figure 5. Discretization results of every influential factor in different provinces. (Data from Hong Kong, Macao and Taiwan are temporarily absent.)

3.2.2. Factor Detection Analysis

The analysis results of Geodetector (Table 4) show that the values of the selected twelve factors are all greater than 0 and are positive factors, of which nine are significant at the 0.05 level and one is significant at the 0.1 level. The q value represents the explanatory power of each influential factor. The q value of all factors is higher than 0.2, among which the q value of nine factors exceeds 0.4, up to 0.556, showing that all factors have strong explanatory power. The factors are sorted according to the q value from high to low, which are A1 (0.556) > B1 (0.496) > C1 (0.485) > D1 (0.462) > C2 (0.447) > E1 (0.447) > A2 (0.438) > B2 (0.435) > A3 (0.410) > B3 (0.392) > D2 (0.355) > E2 (0.226).

Table 4. Single-factor detection results.

Factors	q Value	Rank
Farmland density (A1)	0.556 **	1
Water resource endowment (A2)	0.438 **	7
Road network density (A3)	0.410 **	9
The number of agricultural legal entities (B1)	0.496 **	2
The number of leading agricultural enterprises (B2)	0.435	8
The degree of agricultural modernization (B3)	0.392 *	10
Per capita GNP (C1)	0.485 **	3
The size of the resident population (C2)	0.447 **	5
R&D expenditure (D1)	0.462 *	4
Internet access rate (D2)	0.355 *	11
Total fiscal expenditure (E1)	0.447 **	6
Agricultural expenditure intensity (E2)	0.226	12

Notes: *, ** represent significance at 10%, 5%, respectively.

In factor interaction detection, the types of enhancement between factors include bifactor enhancement and nonlinear enhancement. Bifactor enhancement means $q(X_1 \cap X_2) > \mathrm{Max}(q(X_1), q(X_2))$, while nonlinear enhancement means $q(X_1 \cap X_2) > q(X_1) + q(X_2)$. The result of factor interaction detection (Figure 6) shows that the combined explanatory power of any two factors after interaction is stronger than that of a single factor, whose enhancement types are mostly bifactor enhancement. Among the 66 bifactor combinations formed by 12 factors, the q values of the three factor combinations of 'D1∩B1', 'B1∩A1' and 'E1∩D1' all exceed 0.9, which has high explanatory power. The number of factor combinations with a q value exceeding 0.8 reaches 20 (Table 5). Among these factor combinations, the science and technology level (D) appears most frequently. The number of factor combinations containing the D1 factor is eight, while the number of factor combinations containing the D2 factor is six, so these two factors have a greater strengthening effect on other factors. This shows that the science and technology level of the region can eliminate the constraints of environmental conditions, industrial foundation and other factors on the development and construction of ecological farms.

Table 5. The top 20 factor combinations with the highest explanatory power after interaction.

Factor Combination	q Value	Factor Combination	q Value	Factor Combination	q Value
D1∩B1	0.921	C3∩B1	0.856	D1∩A2	0.831
B1∩A1	0.911	D1∩B2	0.854	E1∩D2	0.825
E1∩D1	0.904	D2∩B1	0.845	D2∩C2	0.823
C2∩A1	0.897	D1∩C2	0.842	E2∩C2	0.822
D2∩A2	0.887	D1∩C3	0.841	E2∩B1	0.818
D2∩B3	0.863	D1∩B3	0.834	E1∩A1	0.801
D2∩B2	0.857	D1∩A1	0.832		

	A1	A2	A3	B1	B2	B3	C1	C2	D1	D2	E1	E2
A1	0.556**											
A2	0.753	0.438**										
A3	0.679	0.540	0.410**									
B1	0.911	0.785	0.856	0.496**								
B2	0.791	0.631	0.657	0.627	0.435							
B3	0.706	0.501	0.509	0.657	0.570	0.392*						
C1	0.717	0.688	0.735	0.798	0.625	0.729	0.485**					
C2	0.897	0.694	0.719	0.759	0.731	0.783	0.718	0.447**				
D1	0.832	0.831	0.841	0.921	0.854	0.834	0.578	0.842	0.462*			
D2	0.643	0.887	0.612	0.845	0.857	0.863	0.797	0.823	0.677	0.355*		
E1	0.801	0.625	0.761	0.785	0.594	0.745	0.766	0.544	0.904	0.825	0.447**	
E2	0.741	0.680	0.607	0.818	0.748	0.662	0.772	0.822	0.646	0.463	0.785	0.226

q value
0.921
0.226

Figure 6. Interaction detection results of factor combination. (The detection results with an underline indicate nonlinear enhancement, while the other detection results are bifactor enhancement. *, ** represent significance at 10%, 5%, respectively).

4. Discussion

4.1. Influence Mechanism of Construction and Distribution Ecological Farms in China

4.1.1. Environmental Conditions as a Fundamental Factor

Environmental conditions provide the natural basis for the construction of ecological farms in China, and the concentration of agricultural natural production resources is an important condition for the high-quality development of agriculture. China has a vast territory where the natural conditions of different regions vary greatly [57,58]. So, farmland density and water resource endowment are the two basic reasons for the uneven distribution of ecological farms. The higher the farmland density in the region and the greater the water resource endowment, the greater the number of ecological farms will be constructed. Compared with conventional scattered agricultural production units, ecological farms are generally larger in size, meaning that their construction requires more land. Most of the provinces in East China, Central China and North China are located in the plains with flat terrain and good terrain conditions. There is more farmland per unit area, so their farmland density ranks among the top in China. Provinces such as Jiangsu, Shandong, Anhui and Hubei have a large number of ecological farms, all of which are more than 20. These provinces are located in the monsoon region with abundant average annual precipitation and a dense river network, which provides sufficient water resources for ecological farms. And the improvement of farmland water conservancy facilities of these provinces further guarantees the supply of agricultural water. In contrast, due to the large number of mountains and plateaus, there is less available farmland in the northwest and southwestern regions of China where the number of ecological farms is generally low. There are currently no farms in Qinghai and Tibet that meet the construction standards. Although the water and heat conditions are sufficient in South China, the number of ecological farms is relatively small as a result of the numerous mountains and hills and low-density farmland. In addition, road network density is another basic condition for the construction of ecological farms [59]. As the most crucial rural infrastructure, the accessibility of rural roads is a basic condition for rural production and living activities. Compared with conventional agriculture, the extension of the industrial chain from production to sales is a perceptible transformation of ecological farms. Well-developed road construction is conducive to market connection and industrial chain integration [60]. The road network density in eastern China is significantly higher than that in western China, which also promotes the construction of ecological farms. However, some rural areas in China are still faced with underdeveloped transportation, and the accessibility of farmland for agricultural machinery is low, which also hinders the modernization of agriculture.

4.1.2. Economic and Social Development Level and Financial Support as Decisive Factors

The government's policy and funding support is a decisive factor in the construction of ecological farms. It is specifically reflected in the normative documents issued by the government that determine the quota allocation for the evaluation of ecological farms in various provinces. In recent years, the MARA has initiated a number of construction standards and technical specifications, guiding agricultural entities to practice the concept of green development. The construction of ecological farms needs to go through working procedures such as government recommendation, material submission, review and release. In 2021, the MARA carried out the evaluation of ecological farms with the Yangtze River Delta as the focus on the basis of comprehensive consideration of the environmental conditions and economic and social conditions of each province. So, the pilot work also directly determines the distribution of ecological farms. Therefore, there are 80 ecological farms in Jiangsu, Anhui, Zhejiang and Shanghai among the first batch of ecological farms, accounting for more than 60% of the country's total. The second batch of ecological farms in 2022 expanded the scope of the pilot project, so that the number of provinces with ecological farms passing the acceptance increases from the 21 to 29. In eastern China, the per capita GDP is relatively high, and the population is dense, leading to high demand for ecological farms and promoting the circulation of factors between ecological farms and the outside world. The government's policy and financial support are also important forces for the reclamation of abandoned farmland. The rapid advancement of urbanization in China has brought about the transfer of rural labor force, triggering a contradiction between the input cost of rural agriculture and the scale of development. Thus, the abandonment of a large amount of farmland restricts the scale of agriculture transformation and development [61]. Against the background of China's territorial planning, strictly adhering to the boundary line of prime farmland protection is a strategic need to ensure national food security. Various policies have been introduced and large funds have been invested to promote the reclamation of abandoned farmland and reduce farmland fragmentation. The increase in expenditure on agriculture, forestry and water affairs is conducive to the improvement of infrastructure such as farmland water conservancy and protection, thereby improving the suitability for agricultural production, which provides a suitable environmental foundation for the construction of ecological farms. In addition, the policy adapting measures to local conditions has further expanded the reclamation of abandoned farmland by increasing financial subsidies to agricultural enterprises and farmers. It is also conducive to the expansion of China's current overall farm area and provides reserve land resources for the construction of ecological farms. Meanwhile, the government's financial support also promotes the development of agricultural science and technology, providing strong support for the construction of ecological farms [62]. Under the MARA's policy guidance, provincial and municipal governments in China provide funding and subsidies to support the construction of ecological farms, with follow-up supervision and eligibility verification. In contrast to conventional agriculture, these funds and subsidies are mainly applied to the purchase of agricultural machinery, compensation for ecological production and tax relief for farms.

4.1.3. Industrial Foundation and Science and Technology Level as Key Factors

Industrial foundation and science and technology level are the key factors in the construction of ecological farms in China. Agricultural enterprises are the basic subjects of agricultural production, among which the leading enterprises are the key subjects of applying agricultural technology to the construction of ecological farms. According to the result of Geodetector, the science and technology level is a vital driving factor for the construction of ecological farms for it can significantly enhance the explanatory power of other factors after interaction. The level of R&D expenditure in economically developed areas is also relatively high, which drives the improvement of local scientific and technological innovation capabilities. And it promotes agricultural development through the transformation, output and application of agricultural technological achievements and further transforms scientific and technological benefits into ecological benefits [63]. Existing studies have shown that there is an agglomeration effect on agricultural R&D investment and agricultural GDP, and it has a certain spillover effect which enables enterprises to conduct technical learning and exchanges based on similar locations and environment [64]. This is mainly reflected in the construction of ecological farms. The cooperation and interaction between agricultural enterprises and scientific research institutions promotes the intelligentization of agricultural production and management, which is one of the most important construction standards of ecological farms. And the technologic exchange between different agricultural enterprises has also improved the scope of agricultural technology application. In addition, with the help of the increasing Internet access rate, the technology acceptance of surrounding farmers has also been improved accordingly after receiving information and training [65]. This also means that the technological practice of the ecological farm does not limit to the interior but expands to the entire surrounding production area. Taking East China and Central China as examples, the agriculture in these two regions has a relatively solid industrial foundation where there are a large number of national-level leading enterprises whose R&D activities are relatively active. A case in point is Shanghai. Although it is not a large agricultural province where the area and density of farmland are very limited, Shanghai's high R&D investment equips it with more active scientific and technological innovation capabilities than other provinces. The ecological farms in Shanghai introduce multiplex modern agricultural technologies to promote agricultural transformation and upgrading, which makes the number of ecological farms rank among the top provinces in China. The application of agricultural science and technology brings great economic, social and ecological benefits.

Above all, the mutual influence of five dimensions of environmental conditions, industrial foundation, economic and social development level, science and technology level and financial support can be represented by Figure 7, which explains the mechanism that affects the spatial distribution of ecological farms in China.

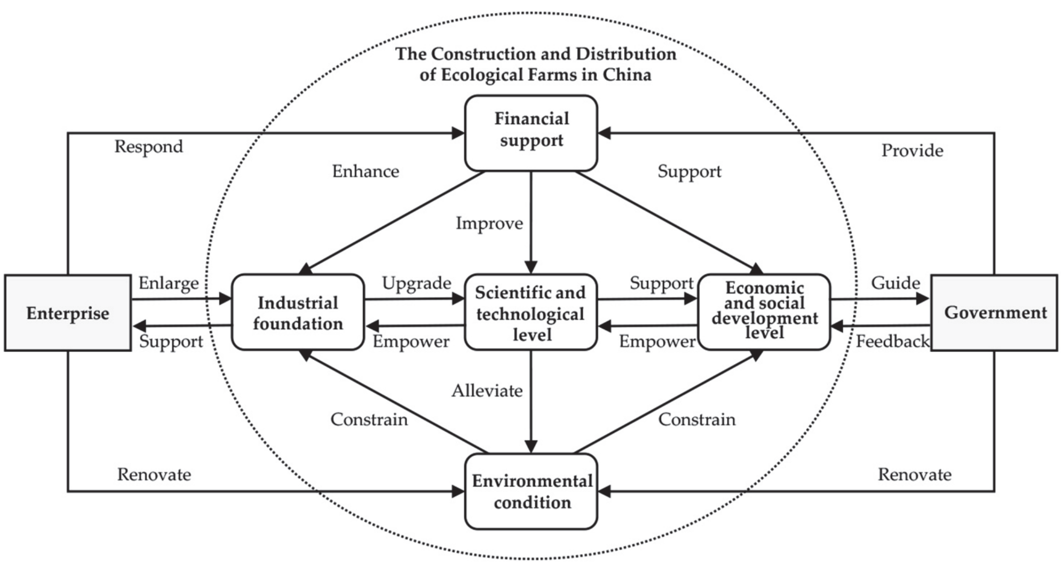

Figure 7. Influencing mechanism of the construction and spatial distribution of ecological farms in China.

4.2. Development and Research Prospects of Ecological Farms

Whether from the development background or specific practice, the principles and specific practices followed by ecological farms in the West are similar to those in China, that is, pay attention to the social and economic effects brought by ecological farms, and strive to explore the development model of ecological agriculture that adapts to its own reality [66–69]. However, in the context of China, the construction of ecological farms is largely influenced by land system, national strategy and local government. Especially in the context of rural revitalization and common prosperity, the practice of ecological agriculture provides an emerging power for promoting the modernization and in-depth transformation of agriculture [70]. Therefore, this study attempts to reveal the spatial distribution and formation mechanism of ecological farms from three aspects: pattern, influential factors and mechanism, so as to provide a systematic and comprehensive analysis for understanding the formation and development of ecological farms in China. At the same time, it reveals a development mode different from Western ecological farms and strengthens the new trend of ecological farm development under the background of rural digitalization in China. We found that the spatial distribution pattern of China's ecological farms in this study is highly consistent with the pattern of agricultural green production efficiency [71]. And it provides possible evidence that ecological agriculture has the potential to promote green production [72]. Based on existing research, we are able to attain a clearer understanding of the irreplaceable role of ecological farms in scientific and technological innovation activities as a part of the private agriculture sector [73]. Moreover, this study focuses on the requisite role of science and technology level in the construction of ecological farms based on Geodetector. It also corresponds with the view of existing research which regards digital transformation and innovation as the core driving force of green agriculture development [74,75]. Thus, China's ecological agriculture has the potential for sustainable development. In recent years, it has gradually played a leading role in the international community and received extensive attention and high evaluation. The research is expected to provide reference for the development of ecological agriculture in other countries around the world, especially in developing countries for which developing ecological agriculture is an effective measure to address population, food and pollution issues.

This study conducts some analysis on the spatial distribution pattern of ecological farms at a national scale. Honestly speaking, there are still some deficiencies in this study. On one hand, since the construction of ecological farms is a continuous work, the development level of ecological farms varies among every province in China, which it is difficult to compare in the same study. This study selects national-level ecological farms and has not yet discussed provincial-level ecological farms whose amount is larger. On the other hand, due to the diversity in environmental conditions and industrial foundation in most provinces, the construction of ecological farms within each province and city is also in a significant imbalance. Therefore, the measurement method based on a fixed indicator system needs further improvement. How to evaluate the construction and spatial distribution of ecological farms more accurately in the future is a problem in need of solution. Above all, safeguarding food security is a systemic project that requires multi-dimensional consideration. Ecological farms play an exemplary role in both strengthening agricultural infrastructure and improving agricultural technology and equipment. In addition, how to establish a sustainable investment and financing mechanism, improve the compensation pattern for ecological production and enhance the training of agricultural specialty talents are also significant issues in need of more attention in the future to safeguard food security and empower rural revitalization.

5. Conclusions

This study explores the spatial distribution patterns of national-level ecological farms in China by spatial analysis. And the Geodetector method is used to deeply analyze the influential factors with relevant economic and social data. The main conclusions of this study are as follows:

(1) The imbalance indexes of China's ecological farm distribution in each province is less than 1, and the second batch has decreased compared with the first batch. The nearest neighbor index is similarly less than 1 but increases with time. This shows that currently the distribution of China's ecological farms in various provinces is relatively

uneven, but the imbalance of ecological farms is weakening with the expansion of the distribution scope, while the agglomeration is increasing. Generally speaking, the distribution of China's ecological farms presents a spatial pattern of 'high in the east and low in the west with concentrated cores'. The high-value areas of core density are mainly concentrated in East China and Central China, which continue to expand. As construction progresses, the overall development focus has gradually shifted from East China to Central China, with the number of ecological farms growing in the provinces that lie on the southwest–northeast direction.

(2) The analysis result of Geodetector shows that the q value of every factor included in the five dimensions of environmental conditions, industrial foundation, economic society, technological level and financial support is more than 0.2, most of which are concentrated above 0.4, meaning that the selected factors have a significant impact on the spatial distribution of ecological farms. When sorting the results of factor detection, the water resource endowment, the number of agricultural legal entities, per capita GDP, R&D expenditure and resident population are the top five influential factors of the distribution of ecological farms. The result of interaction detection shows that R&D expenditure and Internet access rate under the technological level dimension have a significant enhancement effect after interacting with other factors.

(3) As a basic factor, environmental conditions determine the construction foundation of ecological farms. The economic and social development level and financial support are the decisive factors for the construction of ecological farms. The level of economic development affects the number of ecological farms built, while financial support in conjunction with policy from government plays a decisive role in the process of piloting, evaluation and acceptance of ecological farms. The industrial foundation and scientific and technological conditions are the key factors. The technological conditions are based on the original industrial foundation to promote the upgrading of agricultural science and technology. To a certain extent, they can offset the limitations of environmental conditions and enhance the impact of financial support. It has greatly promoted the modernization of ecological farms.

Author Contributions: Conceptualization, D.G., Y.L. and M.W.; Methodology, D.G.; Software, D.G.; Validation, Y.L.; Formal analysis, D.G.; Investigation, D.G. and Z.H.; Resources, M.W.; Data curation, D.G.; Writing—original draft, D.G.; Writing—review & editing, D.G. and Y.L.; Visualization, D.G.; Supervision, Y.L. and M.W.; Project administration, Y.L. and M.W.; Funding acquisition, M.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China, grant number 42271241.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflict of interest.

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Article

Virtual Land and Water Flows and Driving Factors Related to Livestock Products Trade in China

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Abstract: Agricultural trade, which involves the exchange of virtual water and land resources, can effectively regulate the allocation of resources among countries while enhancing the well-being of resource-rich and resource-poor nations. China's animal products trade market concentration is greater, and the livestock industry consumes more water than other agricultural sectors. In order to alleviate the pressure on China's domestic water and land resources and to ensure that Chinese residents have access to animal products, this article examines the trade situation and drivers of virtual water and land resources related to Chinese animal products trade. This study used the heat equivalent method to measure the virtual water and land flows of the import and export of beef, pork, and mutton from 1992 to 2018, which is followed by the gravity model to investigate the factors impacting China's flow of virtual land and water related to livestock products trade. We found that the economic development and the agricultural resources of exporters, as well as China's agricultural employment rates, have a stable beneficial impact on China's livestock imports. The population of importing nations, China's cultivated land area, and the livestock production index of importers and exporters have a positive impact on the export of livestock products from China. Our results remain robust following a series of additional tests.

Keywords: livestock products; gravity model; virtual water; virtual land; economic distance

Citation: Zhou, M.; Wang, J.; Ji, H. Virtual Land and Water Flows and Driving Factors Related to Livestock Products Trade in China. *Land* **2023**, *12*, 1493. https://doi.org/10.3390/land12081493

Academic Editors: Sanzidur Rahman and Uttam Khanal

Received: 12 June 2023
Revised: 24 July 2023
Accepted: 24 July 2023
Published: 27 July 2023

1. Introduction

Recent animal diseases and public health crises have had a significant effect on China's livestock business and animal product supply [1]. Due to African swine fever, China's pork output dropped significantly in 2019. Since the implementation of COVID-19 in 2020, both the volume of imported animal goods into China and the effective supply of animal products have declined. Nonetheless, as China's urbanization process has advanced, the food consumption structure and consumptive mode of locals have altered substantially, with the demand for high-protein, high-nutrition livestock goods such as meat and eggs increasing greatly. Between 1982 and 2018, China's per-capita consumption of livestock products climbed by 37 kg [2], and the country now has the fastest-growing meat consumption [3]. Despite recent years, the consumption of livestock products has expanded dramatically, but there is still a large structural gap in the consumption of animal products, which is impacted by climate, dietary patterns, and other factors. The consumption of animal products has historically been led by pork, whereas mutton has the highest growth rate. In this regard, China outlined in the Central Document No. 1 of 2022 its intention to protect the supply of food basket products for residents, accelerate the expansion of beef and dairy production, and promote the pilot demonstration of the transformation and upgrading of the grassland livestock industry. This demonstrates the nation's increasing importance in the provision of livestock products.

Farmland is necessary for the production of food and livestock products. Countries place a premium on the preservation of arable land. For example, Japan places a premium on the sustainable management of agricultural land [4]. The livestock industry consumes 35% of the world's crop-produced water [5], a third of the global agricultural water [6], and one-fifth of the international food trade [7]. This percentage is expected to rise [8]. China is not only compelled to regulate imports to ease internal food supply and demand problems and resource tensions due to its lack of water and arable land [9], but it must also do so in compliance with international trade laws of comparative advantage. China should employ "two markets, two resources" both domestically and globally in order to secure its national food security [10]. Virtual resources can indicate the amount of resources required to create livestock products, or in a virtual sense, it can be tied to livestock products [11,12]; hence, agricultural trade can conserve virtual resources between trading nations [13].

Statistics show that China's imports of livestock products climbed by 43.4% in the first half of 2020, and the trade deficit for animal products increased by 58.1% to $21.36 billion [14,15]. China's consumption of livestock products as a percentage of total food consumption has increased in recent years, and the average annual growth rate of per-capita consumption of livestock products reached 3.61% from 1982 to 2018 [2]. In addition, there is a high concentration of the import and export market and the influence of uncertainties such as the COVID-19, which will be negative for China's export and import trade of animal products and the protection of local demand for livestock products. Consequently, what elements impact China's livestock trading structure? How can China optimize the nation's trading structure to lower the trade imbalance in livestock products while maintaining domestic demand for animal products? These subjects demand in-depth research. Consequently, the goal of this study is to analyze China's livestock products trade flow variations from 1992 to 2018 by calculating the implicit quantity of virtual water and land resources in trade. The installation of an enlarged gravity model will simultaneously explore the factors that influence the flow of virtual water and land resources in China's livestock trade, recommending the improvement of animal product trade structure. This study theoretically refines the investigation of virtual water and land resources in agricultural product exchanges, expands the use of gravity models, and analyzes the phased effects of trade policy. In practice, the content of this study can explain the flow of virtual water and land in China's international trade in livestock products, provide fact-based policy recommendations for optimizing the trade structure of animal products in China, and offer a fresh perspective for formulating a policy to safeguard China's water and land resources. At the same time, this study also analyzes how to ensure the food safety of Chinese livestock products from the perspective of virtual land and water.

The remaining section is structured as follows. The literature review in Section 2 is brief, Section 3 describes the technique employed in this study, and Section 4 provides empirical results, which is followed by the discussion section. The final section is conclusions and policy recommendations.

2. Literature Review

In recent years, researchers have concentrated on the implicit resource flow underlying agricultural commerce [13,16,17]. Agricultural trade involves a variety of resource exchanges that can effectively regulate the allocation of resources among countries [18], while improving the welfare of resource-rich and resource-deficient countries, and it is one of the most important means of addressing food security in countries with inadequate arable land and water. In addition, identifying the virtual land and water of agricultural trade is an essential component of sustainable agriculture that can reduce the resource use per unit production [19]. Virtual water was first proposed by British researcher Allan (2003) and then evolved into the current idea, which refers to the water resources employed in the production of goods and services [20,21]. In reference to the notion of virtual water, virtual land is the quantity of land required for the production of goods and services [22,23]. Due to the growth of globalization, scholars have become interested in the virtual land and water represented by commodity trading [24,25]. Ali et al. (2017) discovered that agricultural import trade not only significantly alleviated the pressure of Chinese land and water shortages but also preserved global water and land resources [13]. The development of local industrialization facilitates product trade and virtualizes the flow of virtual water to satisfy the needs of local residents despite Iran's relatively limited water resources [26]. This suggests that the essence of international agricultural trade is the transfer of virtual land and water from regions of excess to regions of deficiency.

The study of virtual water and land resources in business has yielded numerous achievements. Hoekstra and Mekonnen (2012) estimate the nation's virtual water flow based on agricultural and industrial goods, and they discovered that some nations rely largely on foreign water resources [6]. Gerbens-Leenes et al. (2013) computed the water footprints of poultry, pork, and beef in China, Brazil, and the United States and discovered that the water footprints of these three animal products varied based on the conversion efficiency, ingredients, and sources of their feed [27]. Brindha (2017) determined the volume of virtual water that was implicitly present in the trade of Indian crops and animal husbandry from 1986 and 2013, with China being the largest importer and Indonesia being the largest exporter of Indian virtual water [28]. In 2012, China was a net importer of virtual land, as determined by Han and Chen (2018), who evaluated the changes in China's overseas trade of virtual land in 2012 [29]. Mekonnen et al. (2019) estimated the amount of virtual water required for the production of livestock products in the United States between 1960 and 2016, and they discovered that less water was consumed per unit of animal products in 2016 [30]. By calculating water footprints for 42 agricultural products and three livestock products in South Korea between 2003 and 2012, Kim and Kim (2019) discovered that the water footprint per ton of beef was approximately 4.2 times that of vegetables per ton [31]. Agriculture trade has helped China and the rest of the globe conserve a significant amount of water and soil resources, according to studies by Shi et al. (2014) and Ali et al. (2017) [13,32]. However, some scholars have also proposed a virtual water trade mystery phenomenon similar to the "Leontief Mystery", namely, that the virtual water trade activities of some countries, such as Greece and India, do not entirely depend on their relative trade endowments, as water flows from relatively scarce regions to relatively abundant regions [32,33]. This is not conducive to the global allocation of water resources in the long term.

In order to examine the effects of agricultural trade, academics have generated significant study findings from the perspective of virtual resources. To explore the impact of virtual water resources on agricultural trade, researchers typically apply enlarged gravitational models [13,16,34,35]. The focus of the experts' research, from the standpoint of the study subjects, was on the analysis of the driving forces of the agricultural trade in foodstuffs, grains, and cotton [13,16,36]. When examining the elements that determine virtual land or water flow, scholars generally analyze economic levels, population size, water and land resources, trade costs, and trade policies, among other aspects [17,37–41].

Similar investigations undertaken by scholars have made substantial progress, giving a solid foundation for this piece. Nonetheless, the following limitations remain in the present research: First, regarding the analysis of trade impact factors in terms of virtual resources, the study subjects are primarily grains and cotton, and research for animal products needs to be expanded. Second, given that the production of grain requires the consumption of land and water resources, feed grain used in the production of livestock products will also consume a certain amount of land and water resource, so international trade in animal products involves a significant amount of land and water resource consumption [42]. Currently, China's water and soil resources are scarce; calculating the amount of virtual land and water in the import and export of livestock products helps to analyze the utilization of soil and water resources in China and the structure of livestock products trade. Third, China's export trade receives less consideration in the study examining effect aspects from the perspective of virtual resources. This study first analyzes the import and export trade situation of Chinese livestock products by calculating the total amount of virtual resources contained in the trade; second, it uses the virtual resources volume included in the trade as dependent variables, using an expanded gravitational model to explore the drivers affecting the trade in China's animal products; and third, it concludes, based on empirical results, that how to optimize the structure of the trade in China's animal products.

3. Methodology and Model Construction

To investigate the factors that affect the flow of virtual water and land resources in China's livestock products trade, it is necessary to first exchange the three animal products, namely beef, pork, and mutton, in China's import and export trade for the corresponding amount of virtual water and land using the heat equivalent method. Following a thorough review of the relevant literature, the appropriate variables and models must be chosen to analyze the market-driving aspects. The larger gravitational model was used in this study to analyze the factors that drive China's trade in animal products.

3.1. Accounting Methodology for Virtual Land

The combination of available studies suggests that the primary estimation approaches for virtual land in commodity are as follows. The heat equivalent approach utilizes the relationship between energy to convert processed agricultural goods into primary products, which is based on the FAO's nutritious ingredient table and the heat balance principle [43]. Thus, to prevent duplication, by exchanging the heat contained in animal products and grain crops, the computation of the multiplication of the units of crops cultivated with the quantity of imports and exports yields the virtual land in the trade of animal products, using heat as a conversion factor [44]. Frequently, the amount of virtual land included in processed products is measured with the product tree approach, which takes a greater quantity of data and employs the value and yield of the products [35,45]. The feed-per-conversion rule is utilized to determine the quantity of virtual land by calculating the feed ratio required in the production of animal products or the material ratio and the output per unit area of grain crops. Similar to Huang et al. (2017) and Yuan et al. (2018), they turned animal products into the feed grain necessary to compute virtual land in their study [46,47]. The majority of Chinese academics calculate feed grain as food directly in exchange for virtual land. Nonetheless, the composition of feed grain is complex, and this method is not particularly exact. In addition, the Food Balance Law is used to estimate national food balances (deficits and surpluses) and future food demand in support of food security policies and initiatives [48].

Based on the advantages and disadvantages of the above methods, this study uses the heat equivalent method to transform animal products into cereal crops according to Liu et al. (2017) [43]. Given that China is the world's top producer of rice and wheat [49], and these two food crops comprise a considerable amount of China's farmed land area, they have been picked for exchange in this article[1]. Based on relevant research and the consumption structure of domestic livestock products [2,8], three animal products, namely beef, pork, and mutton, were chosen as study items. With reference to the current literature and taking into account the extent of trade [2,15], this study screened China's key trade items of animal products, which primarily include Canada, Denmark, France, and a total of 31 nations [14,15][2].

First, this study converts the three animal products to rice based on heat from Yang (2018)'s Chinese Food Composition Table 2018, and the outcome is shown in Table 1 [50]. Following that, the amount of beef, pork, and mutton imported and exported from China is converted into the corresponding amount of rice. Then, using the data on rice seed area and output, we compute the yearly unit area yield of rice. Finally, the amount of virtual land represented by rice for China's annual imports and exports of livestock products is calculated by multiplying the quantity of rice yields by the annual unit area yield of rice.

Table 1. Food calories and calorie conversion result.

Varieties (per 100 g)	Calories (kcal)	Converted to Rice (kg)
Beef	160	0.46
Pork	331	0.96
Mutton	139	0.40
Rice	346	

3.2. Virtual Water Accounting

The amount of water that a crop must consume during production is known as its virtual water content (VWC). Because crops are the main commodities in trade, only direct water use during the crop's growing period is considered for calculating the virtual water content in agricultural trade. A crop's virtual water content is calculated by subtracting its yield from its evaporative emissions during growth. The equation is as follows:

$$W_{nc} = \frac{R_{nc}}{YD_{nc}} \tag{1}$$

where W_{nc} denotes the virtual water content per unit of area n crop c, R_{nc} denotes the average evapotranspiration of crop c in area n, i.e., water demand, and D_{nc} denotes the yield per unit area of crop c in area n.

Therefore, the formula for adjusting crop water requirements between 1992 and 2018 (except 1999) is as follows:

$$W_{tnc} = W_{1999,nc}\frac{YD_{1999,nc}}{YD_{tnc}} \tag{2}$$

where $W_{1999,nc}$ denotes the unit virtual water content of crop c produced in area n in 1999, $YD_{1999,nc}$ denotes the unit area yield of crop c in area n in 1999, and YD_{tnc} is the unit area yield of crop c in area n in year t. The annual area planted and total output of rice were gathered from the annual Chinese statistical yearbooks for this study, and the unit area yield of rice was determined for each year.

Because China is the subject of this study, the virtual water in trade is calculated using China's manufacturing conditions. That is, the measurement of virtual water in export trade indicates China as a producer, whereas it determines China as a consumer in import trade. As a result, the total amount of imported or exported virtual water in China's agricultural trade for the year is the sum of virtual water in all crops imported or exported by China this year. The calculation formula is as follows:

$$VWC_t = \sum\nolimits_c W_{tc} \times T_{tc} \tag{3}$$

where VWC_t represents the total amount of virtual water imported or exported by China in year t, W_{tc} is the amount of water required to produce c crops in China in year t, and T_{tc} is the amount of c crops imported or exported by China in year t.

This article uses the heat equivalent approach to convert the number of beef, pork, and mutton imports and exports based on calories into the amount of virtual water represented by rice for import and export trade. To put it another way, the calorie ratio of imported and exported livestock products and rice is exchanged for the comparable amount of rice, and the equal virtual water is determined using Formula (3).

3.3. Model Construction

This article explores the impact variables on China's livestock trade from the perspective of virtual land. Due to database restrictions, the study period is from 1992 to 2018. The import and export trade data of animal products is extracted from the United Nations Commodity Trade Statistical Database using the HS1992 classification by selecting beef, pork, and mutton. The beef data are obtained by summing up the 0201 and 0202 encoding data in the HS1992 classification, and the pork data are based on the 0203 encoding data, while the lamb data are based on the 0204 encoding data. Using the procedures outlined above, the amount of imported and exported livestock products is converted into the equivalent amount of virtual land and water. This article explores the factors that drive trade in China's livestock products and discusses how to optimize the structure of that trade using an enlarged gravity model. Tinbergen (1962) introduced the gravitational model, which is derived from Newton's law of gravity [51]. The gravitational model permits the consideration of prospective influencing variables such as income, population, geographical distance, and political system within an economic framework. It subsequently evolved into a significant tool for the analysis of trade flows and was increasingly applied to the study of international trade. This study explores the impact factors on China's livestock trade from the perspective of import and export, and it uses the virtual land and water contained in the imported and exported livestock products to analyze trade flows. Hence, This article employs the gravitational model.

Based on neoclassical trade theory, the existing literature and the study aims of this study, the gravity model incorporating trade-influencing factors is as follows.

(1) Economic distance between trading countries

In international trade, both imports and exports involve transportation costs, which are proportional to the economic distance between trading nations. As recent trade transportation costs have been cheap, trade exchanges have grown increasingly accessible [52]. The economic distance, which is the direct-line distance between the countries' capitals divided by the yearly average crude price index, is used to compute the transportation expenses in this study according to Wang et al. (2018) [18].

(2) Population and economic development level

Population growth will raise the need for livestock products, and nations with a high level of economic development will also experience an increase in demand. Wang et al. (2018) and Hu et al. (2021) have confirmed this point [18,38]. Therefore, this study provides demographic data and assesses economic development using GDP per capita in order to assess the impact of population and economic growth on the trade in livestock products.

(3) Agricultural Resources

The imbalance in the distribution of agricultural resources across nations is the fundamental cause of the flow of virtual land and water in the livestock trade. The cultivated land area (i.e., the scope of livestock farming) and labor force play a significant impact in animal product output. Using the research of Zhao et al. (2019), Han et al. (2021), and Tian et al. (2023), this study examined the agricultural resources of countries based on total farmland area and agricultural employment rate [53–55]. In addition, the livestock production index can be used to measure a country's livestock and dairy production; hence, it is also used to measure agricultural resources in this article.

(4) Conditions of commerce

The influence of trade policies on the volume of trade cannot be overstated. A favorable trade policy environment can promote a nation's trade activities and reduce resource allocation distortion, whereas an unfavorable trade policy environment will readily cause trade friction and raise trade costs [56,57]. Accession to the World Trade Organization (WTO) improves international trade and grants advantageous tariffs to the agricultural industry. This study contains the indication of a country's length of WTO membership to show its trading circumstances [10,58]. According to Cornelius and Harald's study (2020), the first four years of a country's accession to the WTO are assigned a value of 1 and the following years are assigned a value of 0 [59].

Table 2 lists the names of the variables and data sources.

Table 2. Variables and data sources.

Name of Variable	Variable Symbols	Data Sources
Economic distance	*dis*	France CEPII database; EPS Database
Economic level	*pgdp*	World Bank Database
Arable land area	*land*	World Bank Database
Population	*pop*	World Bank Database
WTO phase-in effect	*wto1*	World Trade Organization
Length of WTO accession	*wto2*	World Trade Organization
Agricultural employment rate	*aer*	World Bank Database
Livestock production index	*lpi*	World Bank Database

The gravitational models of virtual land are developed as follows based on prior research findings, the goal of this study, and the variables chosen:

$$\begin{aligned} jvltpe_t &= c_1 + \alpha_1 dis + \alpha_2 pgdpe_{it} + \alpha_3 pgdpi_{jt} + \alpha_4 lande_{it} + \alpha_5 landi_{jt} + \alpha_6 pope_{it} \\ &+ \alpha_7 popi_{jt} + \alpha_s wto1_t + \alpha_9 wto2_t + \alpha_{10} aere_{it} + \alpha_{11} aerii_{jt} + \alpha_{12} lpie_{it} + \alpha_{13} lpii_{jt} + \varepsilon_1 \end{aligned} \tag{4}$$

$$\begin{aligned} cvltpe_t &= c_2 + \lambda_1 dis + \lambda_2 pgdpe_{it} + \lambda_3 pgdpi_{jt} + \lambda_4 lande_{it} + \lambda_5 landi_{jt} + \lambda_6 pope_{it} \\ &+ \lambda_7 popi_{jt} + \lambda_s wto1_t + \lambda_9 wto2_t + \lambda_{10} aere_{it} + \lambda_{11} \mathrm{aerii}_{jt} + \lambda_{12} lpie_{it} + \lambda_{13} lpii_{jt} + \varepsilon_2 \end{aligned} \tag{5}$$

where $jvltpe$ and $cvltpe$ denote the number of imported and exported virtual land represented by rice of Chinese livestock products, respectively; dis denotes the economic distance between China and the trading countries (taking logarithms); $pgdpe$ and $pgdpi$ denote the GDP per capita of exporting and importing countries (taking logarithms), respectively; $lande$ and $landi$ represent the total arable land area of exporting and importing countries (taking logarithms), respectively; $pope$ and $popi$ represent the total population of exporting and importing countries (taking logarithms), respectively; $wto1$ represents the policy phase-in effect of WTO accession, and $wto2$ represents the length of time that countries have joined the WTO; *aere* and *aeri* represent the agricultural employment rate in exporting and importing countries, respectively; *lpie* and *lpii* represent livestock production index in exporters and importers, respectively.

The gravitational models of virtual water are constructed as follows:

$$\begin{aligned} vwcjp_t &= c_3 + \beta_1 dis + \beta_2 pgdpe_{it} + \beta_3 pgdpi_{jt} + \beta_4 lande_{it} + \beta_5 landi_{jt} + \beta_6 pope_{it} \\ &+ \beta_7 popi_{jt} + \beta_s wto1_t + \beta_9 wto2_t + \beta_{10} aere_{it} + \beta_{11} aerii_{jt} + \beta_{12} lpie_{it} + \beta_{13} lpii_{jt} + \varepsilon_3 \end{aligned} \tag{6}$$

$$\begin{aligned} vwccp_t &= c_4 + \omega_1 dis + \omega_2 pgdpe_{it} + \omega_3 pgdpi_{jt} + \omega_4 lande_{it} + \omega_5 landi_{jt} + \omega_6 pope_{it} \\ &+ \omega_7 popi_{jt} + \omega_s wto1_t + \omega_9 wto2_t + \omega_{10} aere_{it} + \omega_{11} aerii_{jt} + \omega_{12} lpie_{it} + \omega_{13} lpii_{jt} + \varepsilon_4 \end{aligned} \tag{7}$$

where $vwcjp$ and $vwccp$ represent the volumes of imported and exported virtual water characterized by the rice of Chinese livestock products, respectively; the other variables have the same meanings as in Equations (4) and (5).

4. Empirical Results

4.1. Trend Analysis of Flow Changes of Virtual Land and Water Resources

This article has selected Brazil, France, Germany, and a total of 22 export trading nations and 17 import trading nations for China's trade in livestock products. Figure 1 shows the trend of the total quantity of virtual water and land resources involved in China's import and export trade of animal products from 1992 to 2018 using the methodologies and formulas discussed in Section 3. The import and export of livestock products are equivalent to the import and export of the corresponding water and land resources, and the exchange of resources between the importing and exporting countries is achieved, which is conducive to reducing the environmental burden of the importing countries in terms of its resource consumption. Consequently, the volume of trade in Chinese livestock products and the circulation of virtual water and land resources are consistent. From 1992 to 2018, the number of Chinese imports of animal products and the total volume of imported virtual land and water resources rose. Between 2007 and 2009, the volatility of imports of livestock products increased, which was most likely a result of the 2008 global financial crisis. During 2014–2016, the import of animal goods and virtual water surged dramatically, which may be attributable to a combination of events resulting in a drop in the prices of worldwide herbicide products (beef and mutton). These include cheaper production costs as a result of better endowment of natural resources, the appreciation of the RMB, a drop in international energy prices, which cuts transportation expenses, etc. [60]. China has no discernible export advantage in terms of livestock, and total exports are falling. Before 2008, China sold more virtual land and water, although exports were largely flat after 2008.

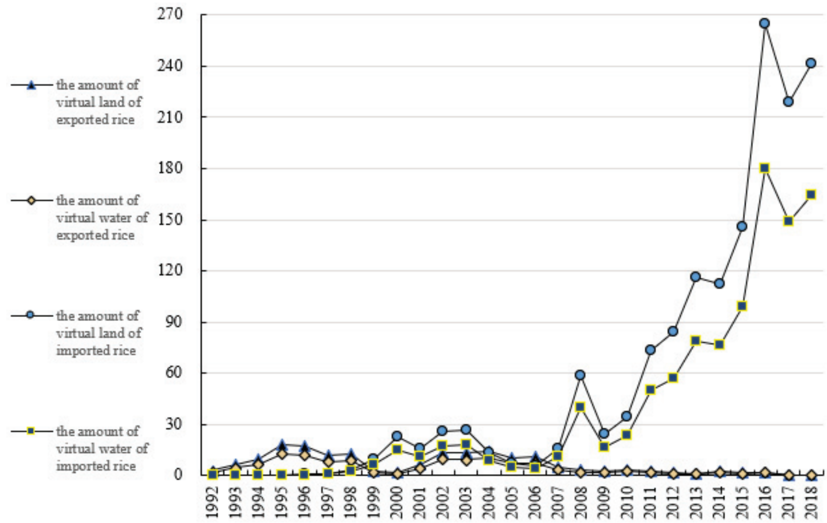

Figure 1. Total amount of virtual water and land resources in China's livestock import and export trade. Note: The unit of virtual land in Figure 1 is thousand hectares, and the unit of virtual water is ten million cubic meters. Data source: UN Comtrade, using HS1992 classification.

Figure 1 also reveals that the virtual water content contained in livestock products is obviously greater than the virtual land contained in livestock, confirming that the livestock industry consumes a lot of water in agriculture [5–7]. China's water resources are also strained by the rapidly growing demand of industrial and residential sectors, with per-capita water resources accounting for less than one-third of the global average [61]. Agriculture is the most water-intensive sector. Overall, China is a net importer of virtual land and water resources, alleviating the shortage of domestic land and water resources by importing livestock products.

Figure 2 illustrates the import share of virtual land for animal products in China in 2018 with a total import volume of 241,744 hm^2 for virtual land. In 2018, Brazil, Germany, Spain, and Canada accounted for nearly fifty percent of all imports. This suggests that China's import market for livestock products is relatively concentrated. China traded animal products with Canada, the United States, New Zealand, and Australia, among other import nations, from 1992 to 2018. These four countries are China's key import markets for livestock products. Moreover, the fluctuations in China's imports of virtual land from these four countries are moderate. This is owing to the superior animal husbandry and economic development of these nations, both of which facilitate the export of livestock products.

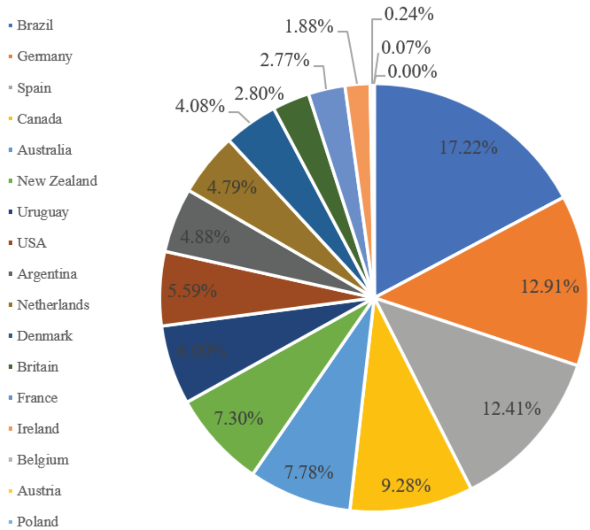

Figure 2. The share of virtual land characterized by rice for imported livestock products in 2018. Note: Since the share of virtual water characterized by rice for imported livestock products in China is consistent with the virtual land, no detailed analysis is performed. Data source: UN Comtrade, using HS1992 classification.

The percentage of China's virtual land exports in 2018 is represented in Figure 3. In 2018, the entire amount of virtual land exported was 0.369 thousand hm^2, which was much less than the volume imported. In 2018, the top exporters were Mongolia, Singapore, Brunei, and Malaysia. In that year, the share of virtual land sent to Mongolia constituted 58.36% of the entire export volume, exceeding 50%. This indicates that the import market for livestock products in China is relatively concentrated in Asia. Prior to 2008, China's principal trading partner for virtual land exports was Russia, a nation with a relatively high export volume. From 1992 to 2018, China's exported to Malaysia, Mongolia, the United Arab Emirates, and Singapore, and there were more exports to Singapore than to the other three.

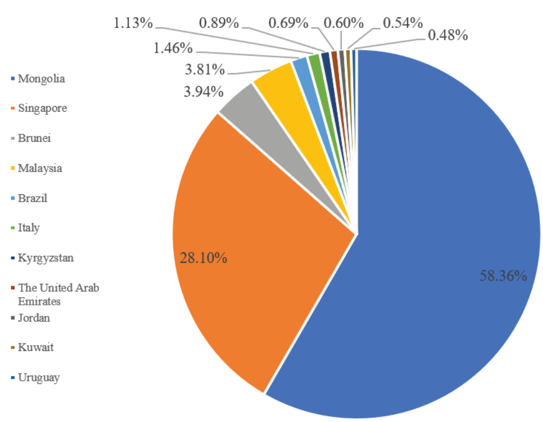

Figure 3. The share of virtual land characterized by rice for exported livestock products in 2018. Note: Since the share of virtual water characterized by rice for exported livestock products in China is consistent with the virtual land, no detailed analysis is performed. Data source: UN Comtrade, using HS1992 classification.

4.2. Descriptive Statistical Analysis

Table 3 gives a descriptive statistical study of the elements that influence China's livestock exports. According to Table 3, the average amount of virtual land in China's livestock export trade is 3.661, and the coefficient of standard deviation is 0.683, indicating that the maximum value of the variable is significantly different from the minimum value and that the export market is highly concentrated. The exporting nations have a very small standard deviation between cultivated land area and population, which is consistent with China's policy of cultivating 1.8 billion acres of land and a growing population. The coefficient of standard deviation between cultivated land area and population in importing nations is bigger than that of exporting countries, suggesting that cultivated land area and population may be the most relevant elements in the trade of livestock products. The average of wto1 is 0.164, while the average of *wto2* is 9.389, indicating that the bulk of China's exports of livestock products entered the WTO earlier than the median. The average agricultural employment rate of the importing and exporting countries varies significantly, with an average of 42.554 in the exporting country, which is nearly three times the average of the importing country, indicating that exporters greatly benefit from the high average agricultural employment rate.

Table 3. Descriptive statistical analysis of the variables in the virtual land model in China's exports of livestock products.

Variable Name	Average	Maximum	Minimum	Standard Deviation	Standard Deviation Coefficient
cvltpe	3.661	9.770	−6.652	2.502	0.683
dis	13.211	15.358	10.818	0.943	0.071
pgdpe	7.623	9.201	5.904	1.057	0.139
pgdpi	9.087	11.129	4.930	1.667	0.183
lande	18.608	18.632	18.599	0.008	0.000
landi	14.221	19.031	6.328	3.232	0.227
pope	20.980	21.055	20.876	0.051	0.002
popi	16.726	19.605	12.520	1.781	0.106
wto1	0.164	1.000	0.000	0.371	2.262
wto2	9.389	24.000	0.000	7.783	0.829
aere	42.554	58.500	26.070	9.761	0.229
aeri	14.834	69.810	0.060	18.186	1.226
lpie	78.085	101.130	38.020	19.110	0.245
lpii	83.492	307.580	7.720	25.560	0.306

Note: When *cvltpe* is the dependent variable, and the exporting country is China, so the variables ending with the letter "e" represent China.

Table 4 presents the descriptive statistical analysis of the variables involved in China's import trade for livestock products. According to Table 4, the mean of virtual land is 5.984, the standard deviation is 0.627, and the highest and minimum values diverge greatly, showing that China's animal product import industry is extremely concentrated. Significant standard variations exist between the cultivated land area and population of the importing and exporting nations. The agricultural land area and population of exporting nations are more volatile, whereas China's agricultural land area and population tend to stable. The average wto1 value is 0.148, while the average *wto2* value is 11.111, showing that the majority of China's imported livestock products entered the WTO earlier. The agricultural employment rates of the importing and exporting countries differ greatly, and the average agricultural employability in China is clearly higher than in the exporting country, but China still imports, indicating that China's livestock production efficiency must be improved.

Table 4. Descriptive statistical analysis of the variables in the virtual land model in China's imports of livestock products.

Variable Name	Average	Maximum	Minimum	Standard Deviation	Standard Deviation Coefficient
jvltpe	5.984	10.782	−6.245	3.754	0.627
dis	13.736	15.360	12.331	0.746	0.054
pgdpe	10.067	11.278	7.808	0.779	0.077
pgdpi	7.623	9.208	5.904	1.057	0.139
lande	15.729	19.031	12.897	1.676	0.107
landi	18.608	18.632	18.599	0.008	0.000
pope	16.999	19.605	14.964	1.306	0.077
popi	20.980	21.055	20.876	0.051	0.002
wto1	0.148	1.000	0.000	0.356	2.405
wto2	11.111	24.000	0.000	7.626	0.686
aere	5.472	25.130	0.060	4.880	0.892
aeri	42.554	58.500	26.070	9.763	0.229
lpie	91.697	115.040	41.120	10.778	0.118
lpii	78.084	101.130	38.020	19.115	0.245

Note: When *jvltpe* is the dependent variable, the importing country is China, so the variables ending with the letter "i" represent China.

4.3. Analysis of the Influencing Factors of Virtual Water and Land Resource Flows

To establish panel data for regression, we have conducted the unit root test firstly to test the stationarity of the data used in this study. Because the trade data used in this study have missing values, that is, the data in this study are unbalanced panel data, so we used Fisher Chi-square (ADF), and Fisher Chi-square (PP). Eviews10.0 was used to conduct the unit root test, and the results are shown in Table 5. The results show that the data met the 5% significance threshold [16].

Table 5. Unit root test results.

	Import Virtual Land and Water			Export Virtual Land and Water	
Variable	**ADF**	**PP**	**Variable**	**ADF**	**PP**
jvltpe	0.000 * (88.392)	0.000 * (220.045)	*cvltpe*	0.048 * (9.591)	0.011 * (53.226)
vwcjp	0.00 * (88.392)	0.000 * (220.044)	*vwccp*	0.048 * (9.591)	0.011 * (52.939)
dis	0.000 * (135.984)	0.000 * (145.510)	*dis*	0.003 * (74.817)	0.000 * (188.307)
gdpe	0.029 * (51.213)	0.000 * (115.997)	*gdpe*	0.049 * (60.654)	0.000 * (91.706)
gdpi	0.000 * (107.639)	0.000 * (70.864)	*gdpi*	0.000 * (96.594)	0.000 * (161.292)
lande	0.000 * (89.527)	0.000 * (87.450)	*lande*	0.000 * (131.874)	0.020 * (65.273)
landi	0.000 * (91.562)	0.035 * (50.438)	*landi*	0.000 * (98.056)	0.000 * (84.148)
pope	0.019 * (53.328)	0.002 * (62.568)	*pope*	0.010 * (68.643)	0.000 * (346.319)
popi	0.020 * (53.043)	0.000 * (267.610)	*popi*	0.011 * (68.296)	0.008 * (69.980)
aere	0.000 * (147.216)	0.000 * (243.898)	*aere*	0.002 * (76.026)	0.026 * (64.052)
aeri	0.000 * (77.538)	0.042 * (49.495)	*aeri*	0.000 * (307.517)	0.000 * (572.109)
lpie	0.000 * (73.595)	0.000 * (198.359)	*lpie*	0.007 * (70.229)	0.000 * (405.255)
lpii	0.000 * (260.509)	0.000 * (313.152)	*lpii*	0.000 * (90.765)	0.025 * (64.140)

Note: * represents that the test was passed at the 5% significance level. t statistics are shown in parentheses. When *jvltpe* and *vwcjp* are the dependent variables, the importing country is China, so the variables ending with the letter "i" represent China. When *cvltpe* and *vwccp* are the dependent variables, the exporting country is China, so the variables ending with the letter "e" represent China.

This work leverages the techniques of prior research and the Poisson pseudo-maximum likelihood estimation approach (ppml) introduced by Silva and Tenreyro (2006) for the estimation of parameters [52,62,63]. Table 6 shows empirical findings.

Table 6. Empirical results of virtual water and land resources characterized by rice for imports and exports.

Variables	*jvltpe*	*cvltpe*	*vwcjp*	*vwccp*
dis	−44.396 *	3.454	−49.822 *	−1.458
	(26.933)	(23.089)	(28.157)	(23.770)
pgdpe	0.392 **	−3.105 *	0.390 **	−2.871 *
	(0.181)	(1.764)	(0.180)	(1.553)
pgdpi	1.295	−0.727 ***	1.505	−0.758 ***
	(1.408)	(0.162)	(1.417)	(0.166)
lande	24.429 ***	5844.697 ***	24.876 ***	5384.731 ***
	(5.561)	(1769.507)	(5.621)	(1468.037)
landi	−3509.658 *	−36.022 ***	−1786.586	−36.044 ***
	(1896.102)	(7.526)	(1637.931)	(7.848)
pope	0.966	286.097	0.761	−2416.128
	(7.901)	(2473.330)	(7.955)	(2082.680)
popi	699.660	28.532 ***	942.147	28.724 ***
	(2410.373)	(10.019)	(2485.176)	(9.970)
wto1	−2.343 ***	0.367	−2.797 ***	0.481
	(0.830)	(0.572)	(0.771)	(0.525)
wto2	0.180	−0.020	0.145	−0.010
	(0.164)	(0.045)	(0.164)	(0.044)
aere	2.948	−12.290	3.169	−10.176
	(2.761)	(12.977)	(2.731)	(11.976)
aeri	21.200 **	−1.142	16.833 *	−1.390
	(9.523)	(1.135)	(9.635)	(1.144)
lpie	2.519 **	13.765 *	2.545 **	20.270 ***
	(1.121)	(7.343)	(1.125)	(7.005)
lpii	2.031	0.583 **	−0.711	0.642 **
	(6.496)	(0.269)	(6.125)	(0.275)
Intercept term	475.221	−1130.341 *	118.428	−473.747
	(552.800)	(673.843)	(514.477)	(545.106)
Number of samples	297	267	301	268
R square	0.485	0.328	0.484	0.381

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, correspondingly. When *jvltpe* and *vwcjp* are the dependent variables, the importing country is China, so the variables ending with the letter "i" represent China. When *cvltpe* and *vwccp* are the dependent variables, the exporting country is China, so the variables ending with the letter "e" represent China.

The economic distance, economic development level of exporting countries, arable land area and livestock production index, as well as WTO phase-in effect and agricultural employment rate of importing countries all pass the significance test, according to the findings. China's imports of livestock goods were positively influenced by the exporting countries' economic development, cultivated land area, livestock production index, and agricultural employment rate of importing countries. The amount of imported virtual land and water would grow by 0.392% and 0.39%, respectively, if the exporting nation's economic level increased by 1%. As there are more exportable resources, the high economic level of exporting nations helps the expansion of international trade. The findings of this study indicate that China's economic level has no significant effect on imports of livestock goods. The unusually large coefficient of cultivated land area in exporting countries significantly influenced China's import of virtual land and water resources. The more arable land there is in the exporting nation, the more favorable it is for the development of livestock husbandry in that nation. The feed grain for animal products and the quality of animal goods would be assured, making exports more possible. The livestock production index of the exporting country is favorable for China's imports, as a high index implies an abundance of livestock products in the exporting country, hence facilitating export commerce. China is better off importing virtual land the greater the agricultural employment rate in the importing country. This may be the outcome of China's high labor input in other agricultural products, such as maize, while it imports livestock products, hence increasing the quantity of imported virtual land.

The arable land area of the importing country had a substantial negative influence only on imported virtual land, with a coefficient of −3509.658, which is extremely significant, while this variable had no effect on the import of virtual water resources. It may be because China's cultivated land area represents China's cultivated soil resources, resulting in a deeper relationship with virtual land. China's imported virtual water and land resources were adversely affected by economic distance and the phasing effect of WTO entry. Geographic distance raises the cost of importing livestock goods, hence reducing Chinese imports of dairy products. The WTO phase-in effect coefficient was negative, indicating that there was a negative impact on China's import of livestock products while China and other trade nations had not joined the WTO. Exporting nations' economic position, the total cultivated land area, the livestock production index, and the agricultural employment rate of importing nations all influenced China's expanding imports of virtual land. In contrast, the duration of China's WTO membership had little impact on China's livestock imports, which was probably due to the fact that the WTO's rules are formulated as fundamental trade facilitation measures.

The economic development level of both importing and exporting countries had a negative impact on China's exported virtual land and water resources, with the exporting country's coefficient being bigger and having a greater influence. This could be explained by the Kuznets curve idea. The importing and exporting countries' economic development levels have reached a U-shaped inflection point, resulting in a negative effect. It may also be related to the increased economic standing of importing nations, which drives the rise in animal husbandry production and decreases the need for imported animal products. Moreover, as their levels of economic development increase, exporting nations will be more likely to meet their domestic water and soil resource needs through imports and preserve their domestic resource and environmental carrying capacity. A significant amount of arable land in importing nations may result in self-sufficiency in livestock products and a decline in demand for imports, which would be adverse to China's export of livestock products, as seen by the negative coefficient of the importing countries' arable land area. The bigger the amount of arable land in the exporting country, the more profitable it was for China to export virtual land and water resources, and this variable's coefficient was relatively large. It appears that the principle of comparative advantage governs the flow of virtual land in China's livestock product trade. China has a substantial amount of arable land and acreage for animal husbandry, resulting in an increase in the number of livestock products. The feed and cereals for livestock goods are guaranteed, and the export quantity and quality of livestock products will be improved, consequently enabling the export of livestock products from China. This indicates that China should maintain its policy of maintaining 18 billion acres of arable land.

Table 6 shows that a 1% rise in the average population of importing countries raised the amount of Chinese exported virtual land and water by 28.532% and 28.724%, respectively. This is due to the fact that the increasing population of the importing nation would boost agricultural product consumption and the consumer structure, resulting in a rise in imports of virtual water and land resources. However, among the influencing elements of China's imported virtual water and land resources, the population of the importing and exporting countries played no substantial role, demonstrating that the demographic component plays a dual role in international commerce. On the one hand, population expansion has increased the domestic division of labor and decreased foreign trade, yet on the other hand, population growth will raise demand and hence enhance international trade [64]. The amount of the impact of population expansion on the rise in demand and intensity of the domestic division of labor also depends on other variables, such as agricultural production technology. This study indicated that the importing country's livestock production index adds to China's export of virtual water resources and has a stronger impact on virtual water exports. Due to the fact that the importing country's livestock business is mostly focused on eggs and dairy products, rather than animal goods, it is forced to buy from other countries, which boosts China's animal products export trade growth. China's strong livestock production index implies that the country prioritizes the growth of livestock and would boost the number and quality of animal goods, allowing it to export more animal products. The increase in the quantity and quality of livestock products is associated with the availability of feed grains and natural grass in the animal husbandry business, which is intimately related to water resources and may have a stronger impact on exports of virtual water [65]. The coefficient of the variable to join the WTO was negative, and two of its correlated variables lacked statistical significance. After countries joined the WTO, barriers to the free flow of commodities, services, and technologies were lifted, increasing agricultural production and decreasing the import demand for livestock products [58], thus discouraging China from exporting livestock products.

4.4. Robustness Tests

To validate the validity of the preceding conclusions, this article replaced the dependent variable with wheat-representing virtual land and water resources. The transformation of three kinds of animal products into wheat was comparable to the transformation of rice. First, the quantities of imported and exported livestock, pork, and mutton from China were changed to wheat. Wheat contains 338 kilocalories per 100 grammes, while 1 kg of beef, pork, and mutton may be turned into 0.47, 0.98, and 0.41 kilos of wheat, respectively. Furthermore, the quantity of wheat was multiplied by the yearly yield per unit area of wheat in China to establish the amount of virtual land for China's annual import and export of livestock products. Calculate the virtual water for the import and export of Chinese livestock products using Section 3's formulas. The trajectory of changes in the total amount of virtual land and water resources represented by wheat in China's livestock product trade was similar to that of rice. There were considerable variations between 2007 and 2009, and the export of virtual land and water in China was stronger before 2008 than after. The export volume remained largely consistent after 2008.

Subsequently, the equation was approximated, and Table 7 shows the estimated findings. The principal findings align with the preceding paragraphs. According to Table 7, the exporting countries' economic development level, the cultivated land area and livestock production index, and the agricultural employment rate of the importing country had a considerable beneficial effect on China's imported virtual land and water resources. In addition, the results revealed that the arable land area of importing countries was not favorable to China's imported virtual land, and the coefficient is −4007.840, indicating a significant effect with a substantial influence. However, it had no significant detrimental effect on the imported virtual water resources. In the interim, the WTO phase-in effect coefficient was negative. In contrast to imported virtual land, imported virtual water was significantly impacted negatively by economic distance. This may be because more than 90% of China's wheat imports come from the United States, Canada, and Australia, and the distance does not prevent the import of China's livestock products [18]. During the sowing of wheat, the change in planting area fluctuates less than water use. When the planting region is reasonably steady, water resources have a stronger impact on wheat planting, and hence, virtual water resources are impacted more.

The export of virtual land and water resources represented by wheat in China is affected by the same empirical findings as the export of virtual land and water resources represented by rice. China's export of virtual land and water was negatively affected by the economic development level and cultivated land area of importing nations. China's export of virtual land and water was positively influenced by the population and livestock production indices of importing nations as well as the total arable land area and livestock production indices of exporting countries. The divergence lies in the fact that the economic development level of exporting countries had a considerable negative influence on exported virtual water but had no effect on exported virtual land. China has limited water and land resources; thus, as its economic development level rises, it will tend to import virtual water rather than export. Due to the fact that arable land can be maintained by returning grass to farmland or forests to farmland, and because it is more difficult and requires a higher technological level to obtain freshwater resources, China's level of economic development has a significant negative impact on the export of virtual water.

Table 7. Empirical results of virtual water and land resources characterized by wheat for imports and exports.

Variables	*jvltwe*	*cvltwe*	*vwcjw*	*vwccw*
dis	−41.865	4.258	−48.044 *	−0.067
	(26.581)	(22.049)	(27.767)	(22.828)
gdpe	0.416 **	−2.861	0.416 **	−2.647 *
	(0.181)	(1.745)	(0.180)	(1.556)
gdpi	1.560	−0.703 ***	1.789	−0.730 ***
	(1.376)	(0.156)	(1.387)	(0.159)
lande	24.570 ***	5510.618 ***	25.019 ***	5095.437 ***
	(5.519)	(1730.382)	(5.588)	(1449.214)
landi	−4007.840 **	−37.218 ***	−2220.257	−37.240 ***
	(1872.182)	(7.204)	(1611.204)	(7.498)
pope	1.001	435.042	0.878	−2208.892
	(7.859)	(2472.452)	(7.928)	(2062.348)
popi	872.342	30.502 ***	1200.386	30.626 ***
	(2376.912)	(10.069)	(2457.817)	(10.024)
wto1	−2.289 ***	0.324	−2.779 ***	0.431
	(0.813)	(0.545)	(0.762)	(0.503)
wto2	0.193	−0.024	0.157	−0.015
	(0.163)	(0.043)	(0.164)	(0.042)
aere	2.842	−10.111	3.141	−8.059
	(2.746)	(12.788)	(2.717)	(11.876)
aeri	24.811 ***	−1.058	20.509 **	−1.283
	(9.325)	(1.095)	(9.478)	(1.106)
lpie	2.513 **	12.596 *	2.550 **	19.012 ***
	(1.079)	(7.160)	(1.082)	(6.824)
lpii	0.738	0.550 **	−2.268	0.604 **
	(6.368)	(0.261)	(6.060)	(0.269)
Intercept term	528.806	−1101.314 *	141.623	−465.638
	(543.751)	(662.721)	(507.787)	(536.836)
Number of samples	297	267	301	268
R square	0.467	0.332	0.465	0.375

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, correspondingly; *jvltwe* and *cvltwe* denote the quantity of imported and exported virtual land characterized by wheat of Chinese livestock products, respectively; *vwcjw* and *vwccw* denote the quantity of imported and exported virtual water characterized by wheat of Chinese livestock products, respectively; other variables have the same meanings as in Equations (4) and (5). When *jvltwe* and *vwcjw* are the dependent variables, the importing country is China, so the variables with the letter "i" are all Chinese. When *cvltwe* and *vwccw* are the dependent variables, the exporting country is China, so the variables with the letter "e" are all Chinese.

5. Discussion

By calculating the amount of virtual water and land resources contained in the import and export trade of Chinese livestock products during 1992 and 2018, the volume of imported animal products shows a general upward trend, the total exports are roughly declining, and the trade deficit is gradually growing [14,15]. China's livestock export trade has no advantages, and China relies more on imports of virtual water and land resources to alleviate domestic water–soil tensions and to meet domestic livestock demand [13,32]. However, there are significant issues with market concentration in the import and export of Chinese livestock products. China's primary exporter of animal products is concentrated in southeast Asia, while the United States, Canada, New Zealand, Australia, and Denmark are the leading importers. This is not conducive to the sustainable development of China's livestock trade and supply, and the structure of animal product trade needs to be optimized.

The results of this study are consistent with Duarte et al. (2019) and Tian et al. (2023), who found that the higher the economic level of the exporters, the more favorable to China's import of livestock products [37,55]. A study by Xia et al. (2022) revealed that the GDP of importers has a positive effect on virtual water flow [16], whereas China's own level of economic development has no discernible impact on its imported virtual water and land resources represented by rice in this study. This may be related to the Kuznets curve theory, where the impact is negligible because China's economic development has reached the top of the inverted U-shaped curve. Among the influence factors of China's imported livestock products, the cultivated land area of the importers has a significant negative impact on the amount of imported virtual land, confirming the research findings of Qiang et al. (2020) that when China's cultivation land area is larger, the country will be largely self-sufficient in livestock products, and import demand will be drastically reduced [66].

The economic distance and WTO phase-in effect variables have a negative impact on the virtual water resources of imported Chinese livestock products. This provides additional support for Wang's (2018) findings that geographical distance increases the cost of importing livestock products [18], thereby limiting Chinese animal product imports. The WTO phase-in effect factor is negative, indicating that China and other trading countries had a negative impact on Chinese imports of livestock products when they were not members of the WTO. This provides a new basis for Wang's (2018) study that it is a significant factor affecting import trade [18]. But this is in contrast to the findings of Cornelius and Harald (2020), who concluded that the coefficient of the WTO was not statistically significant in their study [59]. This may be due to differences in the selection of other control variables or differences resulting from the intensity of the WTO policies on livestock products trade.

Among the influence factors of China's export of livestock products, the cultivated land area of the exporters plays its active role, which means that the larger cultivated soil area of China itself is conducive to the export of Chinese livestock products. In addition this variable coefficient is relatively large and the degree of influence is high, which is consistent with the comparative advantage theory. However, the findings of Liu et al. (2010) demonstrate that China's agricultural land resources are negatively correlated with the net exports of international trade in agricultural virtual water, indicating that there may be an over-development of agricultural lands in China resulting in inefficient land use [67].

6. Conclusions and Policy Recommendations

This article used the heat equivalent method to calculate the amount of virtual land and water represented by rice and wheat in livestock products traded between China and major trading countries between 1992 and 2018, in light of China's increasing consumption of livestock products and its persistent trade deficit. It investigated in depth the changes in the flow of virtual water and land resources between China and the major trading nations as well as employed the gravitational model to examine the factors that affect trade. Among the 22 export trading nations, Singapore, Malaysia, Mongolia, and Brunei were the leading exporters of China's livestock products, while the United States, Canada, New Zealand, Australia, and Denmark were the leading importers among the 17 import trading nations. From 1992 to 2018, both the overall volume of virtual land and water resources represented by rice and wheat, and the quantity of imported livestock products, demonstrated a general upward trend. The volume of animal products imported during 2007–2009 was very variable; however, the increase during 2014–2016 was massively larger. China did not have a substantial advantage in exporting animal products, and total exports tended to drop, with the total amount of exported virtual land and water represented by rice and wheat varying on a regular basis.

The economic development level, cultivated land area, and livestock production index of exporting nations, as well as the agricultural employment rate of importing countries, all had a consistent encouraging influence on the import of virtual land and water. Most influential were the exporting country's cultivated land area and the importing country's agricultural employment rate. Statistically, the WTO phase-in effect, the economic distance, and China's total arable land area were detrimental to the growth of China's livestock product import trade. In addition, the effect was enhanced because the coefficient of the variable of arable land area in importing nations was large. China's export of livestock goods benefited from the population of importing nations, the cultivated land area of exporting countries, and the livestock production index of both importing and exporting countries. The level of economic growth of importing and exporting countries, as well as the cultivated land area of importing countries, had a detrimental effect on China's export of livestock products.

On the basis of the previous conclusion, it is conceivable to conclude that China's import and export trade plans for livestock products can be optimized with greater precision and economic, social, and demographic factors do indeed affect the quantity of virtual land and water imports and exports. The import volume of Chinese livestock products is obviously greater than the export volume, indicating that China mainly relies on imports to meet the demand for livestock products of residents and alleviate the shortage of domestic water and land resources. This indicates that for China, importing livestock products is one of the ways to ensure the consumption of livestock products. The Chinese government should incorporate virtual land and water elements into livestock product safety strategy. China needs to balance the import and export quantity of livestock products as well. It is possible for the trade authorities to carefully select import and export trade partners according to each country's economic development, arable land, transportation costs and animal husbandry production indices so that China can utilize its competitive advantages more effectively. Additionally, the Chinese government encourages residents to modify their food consumption structure or demand, and the livestock production sector should improve the production quality of livestock products to assist the growth of China's export livestock product trade. In particular, the agricultural sector advocate maximizing farmland utilization, and the results show that the land area has a significant impact on the quantity of virtual land and water imports and exports. China can minimize the concentration ratio of imports and exports of livestock products by opening up new import and export markets while retaining great working ties with its current trade partners. China, for example, should expand the interconnection and interaction of agricultural product trade with nations along "the Belt and Road" to ensure food security.

This study's limitation is that virtual land and water are not computed for all livestock products; however, pork, beef, and mutton are chosen as representative of the everyday intake of locals. Future research could study the virtual land and water of all livestock products in order to acquire more precise results. In addition, the net imports and net exports of livestock products are not considered in this study. Only the influence of natural variables, especially arable land, is regarded among the influencing factors. However, climatic circumstances and natural disasters (such as drought) have a significant impact on the livestock industry sector, which consequently impacts the trade of livestock products in importing and exporting countries. Therefore, future study objectives will include the effect of natural disasters on the trade of livestock products.

Author Contributions: Conceptualization, M.Z. and J.W.; methodology, M.Z. and J.W.; software, M.Z.; validation, M.Z.; formal analysis, M.Z., J.W. and H.J.; investigation, M.Z.; resources, M.Z.; data curation, M.Z. and J.W.; writing—original draft preparation, M.Z.; writing—review and editing, M.Z. and J.W.; visualization, M.Z.; supervision, H.J.; project administration, H.J.; funding acquisition, H.J. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by the Social Science Foundation of Shaanxi Province (2022D040), Innovation Capability Support Program of Shaanxi (2023-CX-RKX-136), National Natural Science Foundation of China (72173096), and the Basic Research Program of Natural Science of Shaanxi Province (2021JQ-180).

Data Availability Statement: The data of this study are from the France CEPII database, EPS Database, World Bank Database and World Trade Organization.

Acknowledgments: The authors would like to express their gratitude to EditSprings (https://www.editsprings.cn (accessed on 1 May 2023)) for the expert linguistic services provided.

Conflicts of Interest: The authors of the manuscript entitled "Virtual Land and Water Flows and Driving Factors Related to Livestock Products Trade in China" declare that there is no conflict of interest.

Notes

1 According to the National Bureau of Statistics in 2018, the sown area of rice and wheat in China reached 307.47 $\times$ 10^5, 245.07 $\times$ 10^5 hm^2, respectively.

2 Importing countries: Brazil, Germany, France, Netherlands, Uruguay, Australia, New Zealand, Canada, Denmark, Spain, Belgium, Poland, Austria, USA, UK, Argentina, Ireland. Exporting countries: Brazil, Germany, France, USA, Netherlands, Singapore, Vietnam, Malaysia, Mongolia, Italy, Tajikistan, Japan, Russia, Brunei, UAE, Jordan, Pakistan, Kuwait, Uruguay, Australia, Kyrgyzstan, New Zealand.

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Clan Networks, Spatial Selection, and Farmland Transfer Contracts: Evidence from China

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Abstract: Contracts play a crucial role in the reform of land markets and the process of farmland transfer. This study examines how spatial distance and clan networks impact the choice of farmland transfer contracts based on micro-level survey data from farmer households in China. Our research findings offer valuable insights into the role of contracts as a governance tool in land market reform and provide important implications for policymakers and stakeholders. In this study, we reveal that spatial distance significantly influences the selection of farmland transfer contracts. When farmers face long spatial distances, they tend to prefer written contracts to regulate the transfer relationship. This preference helps to mitigate information asymmetry and cooperation risks, ensuring a more secure and efficient transfer process. Additionally, our findings show that clan networks also play a significant role in the choice of farmland transfer contracts. Strong clan networks in high-density areas often have well-defined social norms and codes of conduct. As a result, farmers in these areas are more likely to opt for written contracts, which provide a formalized framework for governing farmland transfers. Furthermore, the density of the clan network acts as a moderator in the relationship between spatial distance and contract choice. A dense clan network intensifies the influence of spatial distance on contract choice, especially when dealing with long spatial distances. This suggests that social networks and community dynamics play a crucial role in shaping farmers' contract preferences in farmland transfer. In conclusion, this study highlights the importance of contracts as a governance tool in land market reform and provides insights into the influence of spatial distance and clan networks on the choice of farmland transfer contracts. Policymakers and stakeholders involved in land market reforms should consider the findings of this study when designing policies and interventions. By understanding the dynamics surrounding farmland transfer, policymakers can develop more effective strategies to promote secure and efficient land transactions in the context of market-oriented reforms.

Keywords: close spatial distance; long spatial distance; clan network strength; clan network density; written contract; oral contract

Citation: Hong, M.; Long, J.; Zhuo, W. Clan Networks, Spatial Selection, and Farmland Transfer Contracts: Evidence from China. *Land* **2023**, *12*, 1521. https://doi.org/10.3390/land12081521

Academic Editors: Sanzidur Rahman and Uttam Khanal

Received: 3 July 2023
Revised: 28 July 2023
Accepted: 30 July 2023
Published: 31 July 2023

1. Introduction

The continuous development of the market economy has highlighted the importance of the market in resource allocation. A crucial aspect of this development is the establishment of a robust land market system [1]. Creating a land market that facilitates the mobility and flexibility of land resources is essential for optimizing resource allocation and improving production efficiency [2]. In this process of land marketization, farmland transfer plays a vital role in promoting optimal resource allocation and efficiency [3]. The choice of contract by farmers within the land transfer process is of great significance as it ensures smooth transactions and balances the interests of all parties involved. Contracts serve as the economic and legal foundation for agricultural land transfers, stipulating the rights and obligations of both parties and regulating transfer behavior [4]. Therefore, it is crucial to study the factors and mechanisms that influence the selection of farmland transfer contracts in order to optimize the functioning of the farmland transfer market and enhance transfer efficiency.

In the context of farmland transfer, two influential factors are the clan network and spatial distance. The clan network, as a social network, represents a form of social capital formed through connections and cooperation among relatives, friends, and fellow villagers [5]. It plays a vital role in information transmission, trust establishment, and risk sharing in farmland transfer contracts [6]. The presence of a strong and dense clan network facilitates the flow of information among its members, which is essential for making informed decisions during the farmland transfer process. Additionally, the network fosters trust among its members, making them more willing to engage in farmland transfer transactions with each other. The risk-sharing aspect of the clan network ensures that if a transfer does not go as planned, the network members collectively bear the consequences, reducing the overall risk for individual farmers.

On the other hand, spatial distance, as a geographic factor, affects various aspects of farmland transfer transactions [7]. Longer spatial distances between farmers and potential transfer objects can lead to higher transaction costs, as more resources are required for transportation, communication, and coordination. These higher costs can influence the choice of contract, with farmers preferring written contracts to ensure a clear and formalized agreement, given the potential uncertainties associated with long-distance transactions. Additionally, spatial distance affects resource utilization efficiency, as closer proximity allows for easier access to and management of farmland, leading to more efficient production processes.

This study aims to explore how the clan network and spatial distance influence the choice of farmland transfer contracts and analyze their effects to deepen our understanding of the operational principles of the farmland transfer market and farmers' decision-making behavior. By examining the impact of the clan network and spatial distance on contract choice, policymakers can gain valuable insights to optimize the farmland transfer market, promote efficient resource allocation, and foster sustainable development in rural economies.

To conduct the study, field survey data collected from March to April 2023 were utilized to investigate the relationship between clan networks, spatial distance, and the selection of farmland transfer contracts in rural areas. Several innovations were introduced in this research. Firstly, an analysis framework was introduced that incorporated spatial distance, clan networks, and the choice of farmland transfer contracts, enriching the theoretical understanding of contract choice behavior by examining these factors from multiple dimensions. This comprehensive approach allowed for a more nuanced understanding of the factors influencing contract choices among farmers. Secondly, the research took a unique perspective by analyzing the selection of farmland transfer contracts through the lens of clan networks and spatial distance, expanding our knowledge and comprehension of contract choices in the context of farmland transfers. This multi-dimensional analysis provided valuable insights into the interplay between social networks and geographic factors in contract decision-making. Lastly, the use of up-to-date data collected in 2023 ensured timeliness and empirical value, contributing to the study of farmland transfer contract selection. The use of recent data enhanced the reliability and accuracy of the research results, enabling comprehensive theoretical investigations and empirical analyses of the current land market and contract choice behavior.

In conclusion, these innovations contribute to a deeper understanding of the dynamics between clan networks, spatial distance, and the choice of farmland transfer contracts. By shedding light on the interplay between social networks and geographic factors, this study provides valuable information for policymakers aiming to optimize the farmland transfer market, promote efficient resource allocation, and foster sustainable development in rural economies. This study also lays the foundation for more robust theoretical investigations and empirical analyses of the land market and contract choice behavior in the present period.

2. Literature Review and Theoretical Analysis

2.1. Literature Review

Farmland transfer contracts have become a significant subject of study in institutional economics research. Different scholars have emphasized various aspects of contract choices. Marx focused on the consideration of long-term lease contracts versus tenancies at will, highlighting the importance of contract duration [8]. Zhang Wuchang highlighted the role of risk diversification benefits and transaction costs in contract choices, with transaction costs influencing decisions to pursue higher income [9]. Contracts are regarded as a means of addressing shared concerns and solving problems through voluntary and equal communication between parties [10,11]. They help reduce fraud and ensure market operations, but their incompleteness may require adjustments based on real-world conditions [12]. Considering various influencing factors is crucial to ensure the effectiveness and practicality of contracts, especially in the context of farmland transfer.

In the realm of farmland transfer contracts, clan networks and spatial distance emerge as significant influencing factors. Clan networks facilitate communication and cooperation among farmers, enhancing willingness and cooperation in farmland transfer contracts [13]. Empirical research has shown that clan networks impact innovation and entrepreneurship, influencing the competitiveness of farmers' entrepreneurial enterprises and resource acquisition limitations [14,15]. However, clan networks can also have adverse effects on village-level collective economies by promoting labor outflows and reducing the supply of public goods [16]. Their impact on resource allocation efficiency in land transfers varies depending on the local market conditions [17].

Spatial distance, as a geographic factor, also plays a significant role in the choice of farmland transfer contracts. Studies have shown that spatial distance affects consumer demand, industrial upgrading, and collective decision-making processes [18]. Longer spatial distances may lead to reduced consumer psychological ownership and willingness to share, impacting decision-making [19]. Additionally, spatial distance between parties involved in transfers affects contract choices and participation in public affairs, which can be influenced through various communication channels and social networks [20].

In conclusion, understanding the factors influencing the choice of farmland transfer contracts, such as clan networks and spatial distance, is vital for policymakers and researchers. By considering these factors, policymakers can design more effective land market policies, while researchers can deepen their understanding of the dynamics of farmland transfer and contract choices in rural economies.

2.2. Analytical Framework

Harvey's perspective emphasizes that the concept of space is derived from human experience, and geographers focus on studying selected phenomena within space rather than studying everything encompassed by it [21]. Loesch highlights the importance of spatial factors in economic research, particularly in the context of farmland transfer [22].

When there is a long spatial distance between parties involved in farmland transfer and asymmetric information exists, identifying the relevant attributes of the other party becomes challenging, leading to higher transaction costs. These attributes directly influence the choice of transfer contracts. The objective and accurate identification of attributes, such as the relationship network of the other party, often depends on the degree of intimacy in transactions or communication, which is closely related to spatial distance. Differences in spatial distance between the residences of the parties result in variations in transaction frequencies or exchanges [23]. Therefore, spatial distance becomes an important explanatory variable in farmers' contract choices.

From the perspective of spatial distance, a greater spatial distance between the parties in a transfer implies higher transaction costs and more effort needed to address incomplete and asymmetric information [24]. Firstly, communication becomes limited. Longer spatial distances reduce opportunities for face-to-face interaction and communication between farmers and transferees. Language environment, cultural differences, and time–space disparities may further hinder communication, affecting the understanding and negotiation of transfer matters. Secondly, there is an increased risk of default. When significant interests and risks are involved, monitoring and controlling contract performance become necessary. A written contract can provide a clear binding and monitoring mechanism, allowing for tracking and recording contract performance, facilitating the resolution of potential disputes in the future. Conversely, when the spatial distance between the parties is relatively close, transaction costs and the effort required to address incomplete and asymmetric information are reduced [25].

In rural "acquaintance societies", where interpersonal relationships are typically close and neighbors often share long-standing kinship and trust foundations, farmers may be more inclined to choose verbal contracts for land transfers because they believe the other party will honor their commitments. Moreover, oral contracts are simpler and more flexible than written contracts. Farmers can directly communicate and negotiate face-to-face with nearby transfer objects, avoiding the cumbersome preparation and signing of contract documents and the associated costs [26].

As shown in Figure 1, from the perspective of "social spatial distance", the clan network, as a close social network, facilitates information transmission and sharing. In the process of farmland transfer, farmers can acquire information about the land being transferred through the clan network, including details about land quality, the reliability of transfer objects, and fair prices [27]. This information helps farmers make more informed decisions [28].

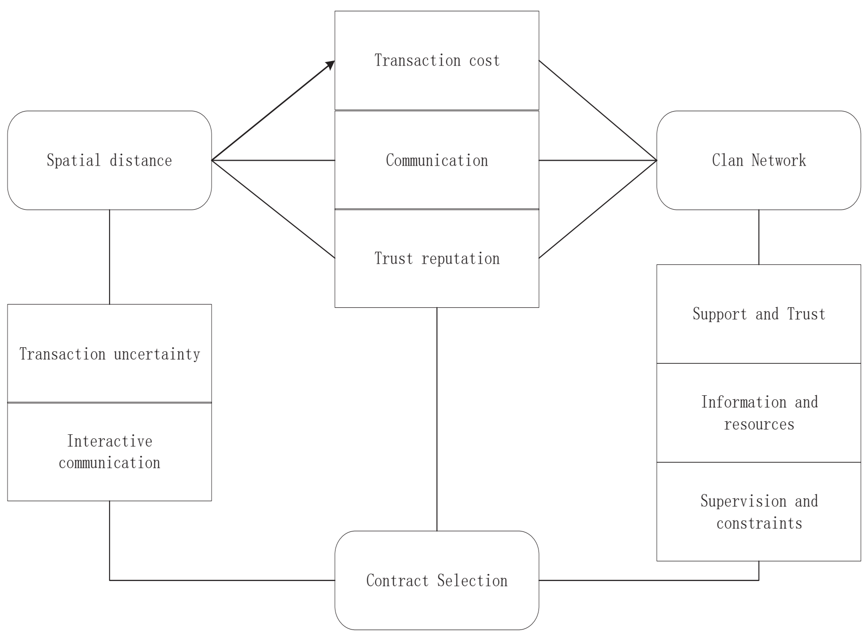

Figure 1. Analysis framework.

Additionally, the clan network serves as a channel for information transmission and communication Illustrated in Figure 1, enabling farmers to gather information about land transfers and assess the credibility and reliability of transfer objects. Moreover, the clan network provides a mechanism for risk sharing in agricultural land transfers. Through the clan network, farmers receive support and assistance from relatives, sharing risks throughout the transfer process. In addition to tangible human, financial, and institutional resources, the clan network represents an influential cultural force [29].

Cultural values not only directly influence individual actions but also shape actors' skills, styles, habits, and abilities. Thus, clan network variables play a significant role in the choice of farmland transfer contracts. This paper distinguishes between clan network strength and clan network density variables. High density in the clan network indicates closer and more efficient connections among members, leading to faster and more effective information transmission. During the process of farmland transfers, farmers can obtain valuable information about potential transfer objects through the clan network, including details about transaction history [30] and reputation [31]. This information exchange within the clan network plays a crucial role in facilitating the decision-making process for farmers, enabling them to make informed choices regarding their land transfer activities [30,31]. This information sharing and transmission deepen their understanding of the transfer objects, instilling greater confidence and dependence. High clan network strength implies closer and more stable relationships among members. Within farmland transfers, clan members have established long-term mutual trust and cooperative relations. The presence of such relationships enhances the willingness of both parties to cooperate and the reliability of contract execution [32].

3. Materials and Methods

3.1. Sample Selection

The data in this article were collected through a field survey conducted by the research team in four counties of Guizhou Province during March and April 2023. To ensure the representation of the research areas, we carefully selected counties based on criteria such as the level of economic development, geographical distribution characteristics, and endowment characteristics of agricultural land resources.

The selected research areas include Meitan County, which is one of the first batches of experimental areas for the reform of the agricultural property rights system determined by the state after the reform and opening up. Guanling County, with Dingyun Community, known as "the first village of China's rural land reform", is also among the selected areas. Sansui County was chosen for its contract documents collected from Miao Village and Dong Village in the river basin, which hold significant research value for re-establishing contract awareness and promoting the spirit of contract. Additionally, Pan County, the first in Guizhou Province to carry out the "three changes" reform in rural areas, was included in the study.

A total of 1250 questionnaires were distributed to the targeted participants, and after excluding farmers who had not experienced land transfer, 1101 valid questionnaires remained, resulting in an effective response rate of 88.80%. The high response rate indicates a good level of participation and engagement from the respondents, enhancing the reliability and representativeness of the data collected for the research. With a large sample size, the research findings can provide valuable insights into the factors influencing the choice of farmland transfer contracts in rural areas.

3.2. Model Selection

The basic model of this paper is set as follows:

$$Contract = \alpha_0 + \alpha_1 Dis\mathrm{tance} + \alpha_2 X + \varepsilon_i \quad (1)$$

$$Contract = \beta_0 + \beta_1 Clan + \beta_2 X + \varepsilon_i \quad (2)$$

$$Contract = \lambda_0 + \lambda_1 Dis\mathrm{tance} + \lambda_2 Clan + \lambda_2 X + \varepsilon_i \quad (3)$$

Among them, *Contract* represents the choice of contract for farmland transfer, *Distance* represents the spatial distance, *Clan* represents the clan network, and *X* represents the control variables, namely individual characteristics of farmers, family endowment characteristics, land cognitive characteristics and village environment characteristics. Model (1) examines the influence of spatial distance on the choice of farmland transfer contract, model (2) examines the influence of clan network on the choice of farmland transfer contract, and model (3) examines the relationship between clan network and the choice of farmland transfer contract in spatial distance and the regulating effect. $\alpha_0 \sim \alpha_2$, $\beta_0 \sim \beta_2$, $\gamma_0 \sim \gamma_2$, $\lambda_0 \sim \lambda_2$ represent the sample regression coefficient, ε_i is a random perturbation term.

3.3. Variable Selection

The incorporation of spatial distance and clan networks as key factors in analyzing the choice of farmland transfer contracts is a significant contribution of this research. By examining the impact of different spatial distances on contract selection, this study aims to shed light on the influence of geographic factors on farmers' decision-making behavior. Additionally, by investigating the role of clan networks, the research seeks to explore the social capital aspect of contract choices and its implications for efficient resource allocation in farmland transfers.

To ensure a comprehensive analysis, this study considers various other factors that may affect contract choice. Individual farmers' characteristics, family endowment, land cognition, and village environment are considered in the analytical model. By including these variables, the research aims to capture the multifaceted nature of contract choices and provide a more holistic understanding of the factors influencing farmers' decision-making in the context of farmland transfer.

The integration of these different factors into the analytical model allows for a more robust examination of the determinants of contract selection. Further, it provides a comprehensive framework that considers both individual and contextual factors, enabling a deeper understanding of the complex dynamics involved in farmland transfer decisions. Through this approach, our research contributes valuable insights to the existing literature on farmland transfer contract choices and provides a solid foundation for policymakers and researchers to optimize the functioning of the farmland transfer market and promote sustainable development in rural economies.

3.3.1. The Variable to Be Explained

The choice of farmland transfer contract serves as the dependent variable in this research. It is assessed based on whether a written contract or an oral contract was signed between the transfer parties. The categorization follows the approach taken by previous studies, such as [18,31,33], and other scholars in the field. In this study, a value of "0" represents an oral contract, while a value of "1" represents a written contract.

The average value of the contract choice variable is 0.530, indicating that, on average, a slightly higher proportion of farmers have opted for written contracts in the context of farmland transfers. This finding suggests that there has been an increase in the prevalence of written contracts over time, likely driven by the government's regulation of the land transfer market and the implementation of land transfer policies. These policies may have prompted farmers to adopt written contracts as a means to ensure legal protection and clarity in their transfer agreements. The prevalence of written contracts may also reflect a growing recognition among farmers of the importance of formalizing their transfer agreements to reduce transaction risks and enhance the security of their land transactions.

3.3.2. Main Explanatory Variables

The main independent variables in this paper are the clan network and spatial distance. Drawing on the research of Jiang, X., Ma, X., et al. (2022) and Wang, A., He, K. et al. (2022), the clan network is divided into two components: clan network intensity and clan network density [16,17].

To measure clan network intensity, the presence of ancestral halls in the village is used as an indicator [34]. Ancestral halls serve as gathering places and centers of activities for clan members, reflecting the strength and cohesion of the clan network. The existence of ancestral halls suggests a higher intensity of the clan network.

Clan network density is measured using the proportion of the population with the largest surname in the village [35]. A higher proportion indicates stronger blood relations and connections among clan members, representing a denser clan network.

As for spatial distance, it is primarily determined by the distance between the farmer and the residence of the transfer object, with reference to the literature of Hong Mingyong (2017) and Hong Mingyong (2018) and the research of various scholars [36,37]. The assessment of spatial distance is based on the responses to questions such as "Where is the home of your land transfer object?" with multiple options provided, including original natural village group, new natural village group, groups outside the village, villages outside the township (town), townships (towns) outside the county (city), and counties (cities) outside. Additionally, the question "What is the distance between your home and the target's home (in kilometers)?" is used to gather information on the spatial distance.

In this study, the distinction between "groups outside the village" serves as the cutoff point for spatial distance. The distance between farmers and transfer objects is categorized into "0" for near spatial distance and "1" for far spatial distance, representing the level of proximity between the two parties [38]. This categorization allows for a clearer understanding of how spatial distance influences contract choices.

3.3.3. Control Variable

To ensure the accuracy and reliability of the regression results, this study incorporates several control variables that may influence the choice of farmland transfer contracts [39]. The inclusion of these control variables is based on the findings of Hong Mingyong (2017) and Hong Mingyong (2018). The control variables encompass various aspects, including the individual characteristics of farmers, family attribute characteristics, land cognitive characteristics, and environmental characteristics of villages.

The individual characteristics of rural households are considered, and variables such as the head of household's level of education (Education), health status (Health), and age (Age) are included. These variables capture the individual attributes that may impact contract choices. For instance, higher levels of education may influence farmers' comprehension of contract terms and their ability to negotiate written contracts.

Family attribute characteristics comprise variables such as whether there are village cadres in the family (Village cadres), the number of migrant workers in the family (Number of migrant workers), and the number of women in the family (Number of women). These variables reflect the family composition and dynamics that could influence contract choices. The presence of village cadres in the family may provide access to information and resources that could influence contract decisions.

Environmental characteristics of the village are represented by variables such as the distance from the village to the nearest expressway entrance (Expressway), the distance from the village committee (Village committee), and the presence of tractor tracks (Tractor track). These variables capture the environmental factors that may affect contract choices. For example, proximity to transportation infrastructure and village administrative centers may influence farmers' access to information and resources relevant to contract negotiations.

Land cognitive characteristics include variables related to farmers' perceptions, such as their understanding of land ownership (Land belongs), their perception of land security (Land security), and their awareness of the certificate of title confirmation (Certificate). These variables capture farmers' cognitive factors that may influence their contract choices. Farmers with a stronger sense of land ownership and perceived land security may be more inclined to choose written contracts for greater protection of their rights.

By incorporating these control variables in the analysis, this study aims to provide a comprehensive examination of the factors influencing the choice of farmland transfer contracts, considering a wide range of individual, family, cognitive, and environmental factors that may shape farmers' decision-making behavior in the context of farmland transfers.

Table 1 presents the processed results, assignments, and descriptive statistics of each variable, providing further details and information for analysis.

Table 1. Descriptive statistics of the whole sample.

Variable Name	Variable Definitions	Average	Std.	Min	Max
Explanatory variable					
Contract Selection	Divided into written contracts (=1) and oral contracts (=0)	0.5304	0.0150	0.000	1.000
Clan network strength	Refer to whether there is an ancestral hall in the village	0.1035	0.0092	0.000	1.000
Clan network density	Proportion of the largest surname in the village	63.5328	0.5231	7	91.000
Spatial distance	The distance between the places of residence of both parties in circulation (Far space distance = 1, near space distance = 0)	0.9272	0.6282	0.000	1.000
Individual characteristics of farmers					
Health	Judge the health status of the head of household (1 is very unhealthy, 3 is average, 5 is very healthy)	3.7639	0.0249	1.000	5.000
Age	Age of head of household	58.0073	0.3709	12.000	93.000
Education	Years of education of the head of household	5.5786	0.1135	0.000	17.000
Family attribute characteristics					
Village cadres	Describe the village cadre family	0.1490	0.0107	0.000	1.000
Migrant workers	Number of migrant workers (person)	1.0845	0.0359	0.000	5.000
Number of women	Number of women (person)	2.0173	0.0340	0.000	8.000
Land cognitive characteristics					
Land belongs	Judging farmers' cognition of land ownership	2.2807	0.0257	1.000	3.000
Land security	Judging farmers' cognition of the social security function of land	0.7920	0.0122	0.000	1.000
Certificate	Determine whether the farmer has the title confirmation certificate	0.5740	0.0149	0.000	1.000
Environmental characteristics of villages					
Expressway	Distance from highway intersection	4.8787	0.1363	0.1000	53.000
Village committee	Distance from the village committee	1.3910	0.0322	0.1000	10.000
Tractor track	Judging whether organic farming	0.6312	0.0145	0.000	1.000

4. Results

4.1. Benchmark Model

To begin, Model I was constructed, incorporating variables representing clan network strength and clan network density, aiming to examine their influence on the selection of farmland transfer contracts. Following this, Model II was developed to investigate the impact of spatial distance on farmland transfer contract choices. Subsequently, Model III simultaneously integrated clan network strength, clan network density, and spatial distance to explore their combined effects on farmland transfer contract choices. Additionally, Models IV, V, VI, and VII successively introduced control variables related to household head characteristics, family endowments, land attributes, and village environmental factors to study the collective impact of clan networks and spatial distance on farmland transfer contract choices as these control variables were introduced.

Based on the findings presented in Table 2 of Model I, Model II, and Model III, several conclusions can be drawn.

In Model I, the variables representing clan network strength and density show a significant positive relationship with the choice of written contracts. This suggests that the clan network, as an informal governing system, operates independently from formal institutions and plays a crucial role in contract selection. The strength and density of the clan network provide social support, trust, and information flow among clan members, which fosters cooperation and trade. Opting for a written contract enhances transparency, predictability, trust, and stability in cooperation. Additionally, the clan network facilitates the assessment of risks and selection of partners through credit and background information obtained within the network. The presence of the clan network ensures social oversight and constraints, promoting transactional responsibility and commitment.

Table 2. Benchmark regression results.

Variable Name	I	II	III	IV	V	VI	VII
Clan network strength	0.7213 ***		0.8299 ***	0.9064 ***	0.8756 ***	0.9090 ***	0.9660 ***
	(0.2194)		(0.2480)	(0.2512)	(0.2556)	(0.2600)	(0.2644)
Clan network density	0.3714 ***		0.5896 ***	0.5863 ***	0.6027 ***	0.6517 ***	0.6664 ***
	(0.0907)		(0.1070)	(0.1081)	(0.1097)	(0.1187)	(0.1235)
Spatial distance		0.6978 ***	0.7374 ***	0.7377 ***	0.7443 ***	0.7290 ***	0.7443 ***
		(0.0549)	(0.0561)	(0.0564)	(0.0567)	(0.0571)	(0.0585)
Health				−0.1785 **	−0.1504 *	−0.1565 *	−0.1872 **
				(0.0889)	(0.0901)	(0.0908)	(0.0925)
Age				−0.0157 **	−0.0162 **	−0.0159 **	−0.0151 **
				(0.0064)	(0.0065)	(0.0066)	(0.0066)
Education				−0.0436 **	−0.0373 *	−0.0369 *	−0.0245
				(0.0206)	(0.0209)	(0.0210)	(0.0216)
Village cadres					−0.4124 **	−0.4216 **	−0.4363 **
					(0.2057)	(0.2067)	(0.2079)
Migrant workers					−0.1719 ***	−0.1564 ***	−0.1660 ***
					(0.0591)	(0.0593)	(0.0600)
Number of women					−0.0738	−0.0793	−0.0804
					(0.0625)	(0.0630)	(0.0632)
Land belongs						−0.0154	−0.0299
						(0.0918)	(0.0933)
Land security						−0.2658	−0.2667
						(0.1742)	(0.1770)
Certificate						0.3867 ***	0.3595**
						(0.1493)	(0.1507)
Expressway							−0.0119
							(0.0170)
Village committee							−0.0617
							(0.0679)
Tractor track							0.4964 ***
							(0.1551)
Constant	−1.2582 ***	−0.4228 ***	−2.6183 ***	−0.7866	−0.5662	−0.7111	−0.8841
	(0.3233)	(0.0760)	(0.3924)	(0.6893)	(0.7099)	(0.8247)	(0.8519)
N	1101	1101	1101	1101	1101	1101	1101
LR chi2 (2)	34.21	254.03	305.31	316.40	330.29	339.44	351.31
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.0225	0.1669	0.2006	0.2079	0.2170	0.2230	0.2308

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively; the robust standard errors are in brackets.

In Model II, the spatial distance variable is found to be significant. Longer spatial distances increase transaction uncertainty, information asymmetry, and lack of trust, which lead to a higher likelihood of choosing written contracts. Written contracts help to clearly define rights and responsibilities, reducing transaction risks in long-distance transactions. On the other hand, shorter spatial distances facilitate direct interaction, communication, and the establishment of trust-based relationships. In familiar village environments, face-to-face communication helps reduce information asymmetry and enhances cooperation, making oral contracts more likely.

In Model III, when clan network strength, clan network density, and spatial distance are simultaneously included, all variables pass the significance test. This indicates that greater clan network strength and density increase the likelihood of farmers choosing written contracts. The presence of a strong and dense clan network positively influences the choice of farmland transfer contracts, emphasizing the role of clan networks in village governance. Furthermore, even with the inclusion of control variables, the impact of clan network and spatial distance on contract choices remains significant, indicating their robust influence.

Overall, the inclusion of clan network and spatial distance variables, along with the control variables, improves the explanatory power of the model. These findings suggest that both clan networks and spatial distance are important factors in determining the choice of farmland transfer contracts, highlighting the significance of social networks and transactional risks in contract decision-making.

The control variables included in the analysis provide additional insights into the factors influencing the choice of farmland transfer contracts. A summary of the control variables and their potential impact is given as follows:

Health status: Farmers in good health may have higher self-confidence and communication skills, making them more likely to engage in verbal communication and negotiations. This could increase the likelihood of choosing oral contracts.

Age: Older individuals tend to have more experience and wisdom, which can contribute to stronger verbal expression and negotiation skills. Therefore, older farmers may be more inclined to choose oral contracts.

Education level: Farmers with lower levels of education may have limited understanding and application of written texts, making them rely more on written contracts to clarify rights and obligations.

Village cadres: Non-village cadres, such as peasant households, may have limited knowledge and experience in law and contracts. This lack of expertise could lead them to prefer written contracts for greater clarity and legal protection.

Number of migrant workers: Farm households with a larger number of migrant workers may find it easier to communicate and confirm agreements through modern means such as phone calls or text messages. This convenience may reduce their reliance on written contracts.

Certificate of title confirmation: Farmers with a certificate of title confirmation have legal protection and recognition of their land rights and interests. This legal security may enhance their negotiation and transaction capabilities, potentially influencing their contract choice.

Environmental characteristics: The presence of a mechanical farm road in the village signifies established norms and requirements for agricultural production and land management. Farmers in such villages may be more likely to choose written contracts to comply with these standards and requirements.

By including these control variables, the analysis accounts for additional factors that could influence contract choice, providing a more comprehensive understanding of the dynamics involved in farmland transfer decisions.

4.2. Endogeneity Test

Spatial distance is typically considered an exogenous variable, meaning its value is not influenced by other intrinsic factors. The spatial distance between farm households and farmland exists objectively and is unrelated to other factors, eliminating the need for selecting instrumental variables in the analysis.

However, the clan network, as an endogenous variable, may suffer from endogeneity problems. To address this issue and ensure the accuracy and consistency of the estimated results, instrumental variables are used to replace the clan network.

In this study, the "ancestral hall" and "proportion of the largest surname" are employed to measure the clan network density and clan network strength, respectively. These variables effectively avoid endogeneity problems arising from self-selection and simultaneity. Nevertheless, there may still be endogeneity concerns due to measurement errors and omitted variables.

To correct for estimation bias caused by potential endogeneity, we adopt instrumental variables referenced from previous research [40]. Specifically, the "proportion of villages with ancestral temples at the township level to all township villages (VI1)" and "the proportion of villages with the first surname at the township level to all township villages (VI2)" are used as instrumental variables for clan network strength and clan network size. These variables are not directly related to the choice of farmland transfer contracts, but they have a certain association with the clan network. By employing these instrumental variables, this study replaces the impact of clan networks on the choice of farmland transfer contracts and addresses potential estimation bias arising from endogeneity concerns.

By incorporating instrumental variables, we aim to strengthen the validity and robustness of our findings, ensuring that the results accurately reflect the relationships between the variables of interest.

The results presented in Table 3 demonstrate that the selection of instrumental variables has successfully passed the validity test. Firstly, the *p*-values of the underidentification test statistics are all below 0.01, leading to the rejection of the null hypothesis at the 1% significance level. This finding indicates that there is no underidentification problem in the instrumental variables chosen. Secondly, the statistics of the weak instrumental variable test are all greater than the critical value of 10%, resulting in the rejection of the null hypothesis of "there is a weak instrumental variable" at the 5% significance level. These results signify that the instrumental variables used in the analysis are sufficiently strong and robust to address the endogeneity issue.

Table 3. Endogeneity test.

Variables	**The First Stage**	**The Second Stage**	**The First Stage**	**The Second Stage**
	Clan Network Strength		**Clan Network Density**	
Clan network strength		0.260 **		
		(0.123)		
Clan network density				0.002 **
				(0.001)
IV1	1.003 ***			
	(0.070)			
IV2			0.002 **	
			(0.001)	
Control variables	Control	Control	Control	Control
Cragg–Donald Wald F	205.755		153.362	
Adj R-squared	(0.157)		(0.122)	
Constant	0.401 *	0.505 ***	0.440 ***	0.439 ***
	(0.011)	(0.020)	(0.042)	(0.042)
N	1101	1101	1101	1101

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively; the robust standard errors are in brackets; the control variables are the same as those in Table 2.

The estimation results reveal that after appropriately controlling for the endogeneity problem, the coefficients of clan network size and clan network strength remain significantly positive. This outcome suggests that the presence of a clan network significantly influences farmers' choices in farmland transfer contracts, which is consistent with the findings of the baseline regression results.

By employing instrumental variables and passing the validity tests, the research findings strengthen the credibility and reliability of our conclusions regarding the impact of clan networks on farmers' decision-making behavior in farmland transfer contract choices. The incorporation of instrumental variables provides a more accurate understanding of the relationships between clan networks and contract choices, contributing to the robustness of our findings.

4.3. Further Analysis

The clan network may play a regulatory role in the relationship between spatial distance and farmland transfer contract choice, and the following equation is constructed:

$$Y = aX + bY + cXM + \varepsilon \tag{4}$$

In the analysis, the dependent variable (Y) represents the choice of farmland transfer contract, specifically distinguishing between written contracts and oral contracts. The independent variable (X) is spatial distance, categorized into long spatial distance and short spatial distance. The moderator variable (M) is the clan network, which plays a moderating role in the relationship between spatial distance and farmland transfer contract choice. To explore the potential interactions, the cross term (XM) of spatial distance and clan network is introduced into the model.

The model development process is as follows: Firstly, the control variables are included in the model to account for other factors that may influence the contract choice. Secondly, the independent variable (spatial distance) and the moderator variable (clan network) are introduced into the model to assess their individual effects. Lastly, the interaction term (spatial distance × clan network) is added to investigate the combined effects of spatial distance and the clan network on farmland transfer contract choices. The results of this analysis are presented in Table 4.

Table 4. Further analysis results.

Variable	VI	VII
Spatial distance	0.9660 ***	1.3945 ***
	(0.2644)	(0.3142)
Clan network strength	0.6664 ***	0.7674 ***
	(0.1235)	(0.2664)
Clan network density	0.7443 ***	0.7168 ***
	(0.0585)	(0.1241)
Spatial distance × Clan network density		−0.1912 **
		(0.0866)
Spatial distance × Clan network strength		0.2070
		(0.2389)
Control variable	Control	Control
Constant	−0.8841	−3.0828 ***
	(0.8519)	(0.4602)
N	1101	1101
LR chi2 (2)	(351.31)	(310.85)
Prob > chi2	0.000	0.0000
Pseudo R2	0.2308	0.2042

Note: ***, ** indicate significance at the 1%, 5% levels, respectively; the robust standard errors are in brackets; the control variables are the same as those in Table 2.

The regression results provide valuable insights into the factors influencing the choice of farmland transfer contracts. The key findings are summarized as follows:

Spatial distance: The coefficient for spatial distance is positive and statistically significant, indicating that greater spatial distance between farmers and transfer objects leads to a higher likelihood of choosing written contracts. This suggests that as the distance between parties involved in the transfer increases, farmers tend to opt for written contracts to mitigate uncertainties and clarify their rights and obligations.

Clan network strength: The interaction term "Spatial distance × Clan network strength" does not show a significant effect on contract choice. This suggests that the strength of the clan network does not significantly influence the relationship between spatial distance and contract choice. Other factors related to clan network density seem to have a more significant impact.

Clan network density: The interaction term "Spatial distance × Clan network density" has a significant effect on contract choice. Clan network density acts as a moderating variable, influencing the relationship between spatial distance and contract choice. When the clan network density is high, farmers are more likely to choose oral contracts, and the impact of spatial distance on contract choice is reduced. A dense clan network facilitates faster and more reliable information transmission, increases trust among members, and provides access to reliable information about transfer objects. As a result, the influence of spatial distance on contract choice is mitigated.

Low clan network density: When clan network density is low, the effect of spatial distance on contract choice may be more pronounced. Greater spatial distances can lead to increased information asymmetry and communication costs, making oral contracts more challenging. In such situations, farmers are more likely to select written contracts to compensate for the lack of information and reduce communication barriers. Therefore, a decrease in clan network density may intensify the impact of spatial distance on contract choice.

In conclusion, both spatial distance and clan network density significantly affect the choice of farmland transfer contracts. The moderating role of clan network density in the relationship between spatial distance and contract choice highlights the importance of social networks in shaping farmers' decisions. These findings contribute to a deeper understanding of the complexities involved in contract choices and the influence of social networks in farmland transfers.

4.4. Robustness Test

4.4.1. Replacement of Explanatory Variables

In this study, the explanatory variables are replaced with the distance variable (DLOR) between the transfer land and the residence of the transfer object, the genealogy variable (Genealogy), and the proportion of the own surname (Own surname), and the estimations are conducted. This method adjusts the selection of explanatory variables and tests the robustness of the research conclusions. The results presented in Table 4 are consistent with the expectations based on the previous baseline regression results.

4.4.2. Replacement of the Estimation Model

To verify the generalizability of the benchmark regressions, robustness testing using probit models is employed, which estimates the probability of binary categories such as written and oral contracts. The results, as shown in Table 5, indicate that as the spatial distance increases and the strength of the clan network increases, farmers are more inclined to choose written contracts. This finding can be attributed to the greater need for written contracts to ensure the reliability and stability of the cooperative relationship and the effective role of the clan network in informal governance. This further confirms the conclusions drawn from the previous baseline regression analysis.

Table 5. Robustness check.

Variable	(1) Replace Variables	(2) Replace the Metering Model
DLOR	0.6325 **	
	(0.3383)	
Genealogy	0.1722 ***	
	(0.1379)	
Own surname	0.1413 ***	
	(0.0450)	
Spatial distance		0.5871 ***
		(0.1558)
Clan network strength		0.3795 ***
		(0.0719)
Clan network density		0.4221 ***
		(0.0308)
Control variable	Y	Y
Constant	−0.8231 ***	−0.3985
	(0.1298)	(0.5017)
N	1101	1101
LR chi2 (2)	203.13	345.90
Prob > chi2	0.0000	0.0000
Pseudo R2	0.1334	0.2272

Note: ***, ** indicate significance at the 1%, 5% levels, respectively; the robust standard errors are in brackets; the control variables are the same as those in Table 2.

5. Discussion

5.1. Key Findings

Clan networks, essential social structures formed through connections and cooperation among relatives, friends, and fellow villagers, play a crucial role in information transmission, trust establishment, and risk sharing in farmland transfer contracts [40–43]. Our research findings underscore the positive influence of clan networks on the choice of farmland transfer contracts. In traditional rural societies, clan networks serve as pivotal channels for transmitting vital information about transfer objects, such as land quality, transaction history, and reputation, enabling farmers to make well-informed decisions. These results align with the works of Hong Mingyong, Yang Xuejiao (2021), and Niu Kunzai, Xu Hengzhou et al. (2022), emphasizing the significant role of clan networks in farmland transfer.

Furthermore, this study reveals that spatial distance significantly impacts the choice of farmland transfer contracts. As a geographic factor, spatial distance affects transaction costs, resource utilization efficiency, and information flow [44]. When facing long spatial distances, farmers tend to opt for written contracts, seeking to mitigate information asymmetry and cooperation risks inherent in such transactions. Written contracts offer clearer protection and regulation of rights and interests, enhancing transaction reliability and stability. These findings are consistent with research conducted by Hong Mingyong (2017) and Hong Mingyong (2018). It is important to note that the context of farmland circulation varies, leading to differences in transaction frequency, information flow for evaluating performance, and consequently, contract choices [35,37].

Additionally, this study identifies the moderating role of clan network density between spatial distance and farmland transfer contract choices. Higher clan network density can mitigate the impact of spatial distance on contract choices. Greater network density facilitates faster and more reliable information exchange, fostering higher levels of trust among members. As a result, farmers find it easier to access reliable information about transfer objects and establish strong trust-based relationships. Thus, increasing clan network density can alleviate the influence of spatial distance on contract choices. These findings align with research conducted by Hong Mingyong and Yang Xuejiao et al. (2021), indicating that clan networks play a regulatory role in the allocation of land transfer resources [39].

5.2. Limitations and Future Prospects

Although this study has conducted an in-depth discussion on the relationship between clan networks, spatial distance, and farmland transfer contract choices, there are still some research deficiencies and directions worthy of further exploration.

On the one hand, this study solely considered the influence of clan networks and spatial distance on the choice of farmland transfer contracts, without incorporating other factors that may also impact farmland transfer, such as policy, economic, and cultural factors. Future research should incorporate these additional factors into the analysis and establish a more comprehensive analytical framework to gain a deeper understanding of the operating mechanisms in the farmland transfer market.

On the other hand, this study utilized cross-sectional data for analysis, which limited its ability to capture changes over time. To address this limitation, future research could employ panel data to compare information at different time points, thereby exploring the dynamic relationships among clan networks, spatial distance, and farmland transfer contract choices. This temporal perspective would provide valuable insights into the evolving nature of these relationships and their implications for the farmland transfer process.

6. Conclusions

The conclusions of this study emphasize the significant impact of spatial distance and clan network characteristics on the choice of farmland transfer contracts, providing crucial insights for policymakers and stakeholders in the farmland transfer market.

Firstly, this study emphasizes the importance of establishing standardized and legally sound practices for farmland transfers. Considering the impact of spatial distance on contract choice, it becomes imperative for governments to formulate regulations and policies that ensure the legality and protection of rights and interests in these transactions.

By creating a transparent and secure environment, such measures will foster confidence and trust among participants, thereby promoting the healthy development of the market.

Secondly, this study highlights the crucial role of strengthening clan networks and information transmission mechanisms. Recognizing the significance of clan network density and strength in contract selection, efforts should be directed towards supporting and enhancing the cohesion and connectivity of these networks. This can be accomplished by providing information resources and assistance, encouraging connections and collaboration among farmers, and reducing information asymmetry and cooperation risks. Strengthening clan networks will facilitate more reliable information exchange and foster smoother transactions within the farmland transfer market.

Lastly, this study proposes the promotion of diversified forms of farmland transfer contracts. Recognizing the varying needs and circumstances of participants, policymakers can facilitate the flexibility of both oral and written contracts. Through the provision of legal support and tailored guidance to different regions and individuals, participants can opt for the contract format that best aligns with their specific preferences and situations. This approach fosters adaptability and customization in contract selection, ultimately enhancing the effectiveness and efficiency of farmland transfers. By offering a range of contract options, the farmland transfer market can better accommodate the diverse needs of stakeholders and contribute to a more dynamic and inclusive agricultural sector.

In conclusion, implementing the suggested measures can enhance the efficiency, fairness, and overall performance of farmland transfer transactions. This will contribute to the development of a robust and sustainable farmland transfer market, benefiting all involved parties and fostering long-term agricultural growth and stability.

Author Contributions: Conceptualization, M.H.; Methodology, J.L.; Formal Analysis, W.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This study is funded by the National Natural Science Foundation of China project "Research on Spatial Distance, Relationship Strength, and Contract Performance Mechanism of Agricultural Land Transfer", with approval number 72163003.

Data Availability Statement: Since the data contained herein were obtained through research conducted by our research group and involves multiple papers, the data are not publicly available.

Conflicts of Interest: The authors declare no conflict of interest.

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Article

The Heterogeneous Effects of Multilevel Centers on Farmland Transfer: Evidence from Tai'an Prefecture, China

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Abstract: Land transfer is an important means to achieve agricultural scale production and improve land use efficiency, as well as an effective way to solve food security issues. Discussing the mechanism of how the multilevel urban centers affect rural farmland transfer can help understand the spatial heterogeneity characteristics of farmland transfer. It is helpful to provide more policy suggestions from the perspective of urban-rural spatial relations and achieve the goal of agricultural and rural modernization. Taking Tai'an prefecture as an example, this study examines the impact of multilevel urban centers on farmland transfer by mediating effect model. The results show that: (1) Distances to urban centers are negatively associated with rural farmland transfer rates, with lower rates farther from urban centers. There are two mechanisms about how the distances to urban centers influence farmland transfer: the first is that the farther a village is from urban centers, the lower the value of its farmland, which leads to lower benefits to those who transferring farmland; the second is that lower opportunity costs of agricultural labor in the villages which farther from cities increase household reliance on farmland, reducing the rates of transferring farmland out. (2) Multilevel centers differentially influence transfers. The higher-level prefectural centers affect farmland transfer through planting structure, while the lower-level county centers affect farmland transfer through off-farm employment. Additionally, the influence of county centers is less stable due to road accessibility. (3) It is critical to additional policy support to both towns and remote villages. Particular focus should be placed on increasing the non-agricultural industries and expanding the agricultural markets of towns. It is also important to enhance infrastructure development to encourage farmland transfer in remote villages.

Keywords: farmland transfer; distance to urban centers; off-farm employment; planting structure; village-level data

Citation: Yang, M.; Sun, T.; Liu, T. The Heterogeneous Effects of Multilevel Centers on Farmland Transfer: Evidence from Tai'an Prefecture, China. *Land* **2023**, *12*, 1858. https://doi.org/10.3390/land12101858

Academic Editors: Sanzidur Rahman and Uttam Khanal

Received: 31 August 2023
Revised: 26 September 2023
Accepted: 27 September 2023
Published: 29 September 2023

1. Introduction

How to efficiently utilize farmland resources for agricultural production and solve the food security problem has always been a hot topic in rural land research globally [1–3]. Large-scale farming is an effective way to efficiently utilize farmland resources, which is conducive to advancing new technologies [4], improving mechanization levels [5], reducing farmland abandonment [6], and enhancing agricultural production efficiency [7]. Therefore, increasing the level of large-scale farming through farmland transfer has always been an important topic discussed by scholars from various countries [7–9].

China has a large population but limited farmland resources, so it is a critical issue to use limited farmland resources to ensure food security, which has also attracted attention from all over the world for a long time [10,11]. China has adopted the collective ownership system of rural farmland. After the implementation of the Household Responsibility

System in 1978, the farmland was divided and allocated to corresponding farmers in China, which led to the fragmentation of land ownership [12]. In recent years, the rural revitalization policy has proposed "modernization of agriculture and rural area". There has been a concerted effort to enhance the level of mechanized agricultural production via farmland transfer. This not only fosters large-scale farming but also addresses the quandary of fragmented land contract rights, consequently elevating agricultural productivity [13]. In China, farmland transfer refers to the transfer of farmland management rights from farmers to other farmers or economic organizations. It is an important means of large-scale farming, which is conducive to improving mechanization levels, improving farmland use efficiency, and ensuring food security [14]. Studying land transfer issues has important practical and policy significance.

The distance between urban centers and villages is an important factor in the study of farmland transfer, which is an inherent locational characteristic of villages. How to overcome the negative impact of unfavorable locations on villages is a topic of both theoretical and practical significance. Most studies argue that farmland transfer is more difficult to occur in remote villages because farmers in peri-urban areas can receive more information and opportunities for off-farm employment. Consequently, driven by the differential in benefits between non-agricultural and agricultural endeavors, these farmers choose off-farm employment, relinquish their contracted lands, and participate in farmland transfer [15,16]. On the contrary, the farmers in remote villages are more dependent on agricultural production, and their enthusiasm for participating in farmland transfer is less. However, some studies have also found that with the urban sprawl development, the conflict between construction land and agricultural land intensifies, and the value of farmland decreases, resulting in a lower farmland transfer rate in peri-urban villages [17]. Discussing the mechanism of how the distance to urban centers affects rural farmland transfer can help resolve the above research contradictions, and provide more policy suggestions for raising the farmland transfer rate in remote villages and achieving large-scale farming.

Despite the considerable attention devoted to the dynamics of farmland transfer in the extant literature, and the exploration of the influence and mechanisms of distance to urban centers on these dynamics, several issues remain unresolved. Firstly, there is a lack of consensus regarding the impact of distance to urban centers on farmland transfer. The studies anchored in the theory of location argue that the closer to the city, the lower the transportation cost, which is conducive to cultivating crops with high prices but not resistant to transportation and storage. Consequently, the agricultural economic returns from such lands are heightened, increasing farmland transfer [18]. On the other hand, studies based on decision-making mechanisms found that theoretically, the closer to the city, the more transaction information farmers can obtain, reducing the transaction cost of farmland transfer and increasing the farmland transfer rate. However, empirical evidence does not robustly present a significant influence of distance to urban centers on farmers' farmland transfer decisions [19]. These different conclusions indicate that more evidence is needed for the impact of distance to urban centers on farmland transfer.

Secondly, there is little information provided about the differences in the impact of multilevel urban centers on farmland transfer. There is heterogeneity in the off-farm employment and agricultural markets of cities at different levels. This heterogeneity inherently influences the radiative effect that urban centers have on farmland transfer. Yet, there is a paucity of research exploring the different impacts of multilevel urban centers on rural farmland transfer. Exploring the heterogeneity is helpful in understanding the influence of different levels of accessibility on rural farmland transfer.

Lastly, the mechanism of how distance to urban centers affects farmland transfer needs more empirical analysis. Although recent studies related to farmland transfer have noticed that distance to urban centers will affect rural farmland transfer and proposed theoretical explanations, they lack empirical testing. This question needs to be solved.

Furthermore, the village level has been conspicuously overlooked in studies of farmland transfer [20]. While a multitude of studies has delved into the determinant factors and mechanisms of farmland transfer decisions at the household or individual level [21–23], and many have elucidated the macroscopic features of farmland transfer at the regional level in China [24], there is also a subset of research focusing on parcel-level factors [25]. However, the study of village-level farmland transfer characteristics and mechanisms is meaningful. Firstly, farmlands within the same village tend to share similar natural features [20]. Secondly, according to the research on farmers' behavior based on the herd effect theory, it is similar in the way agricultural production and employment choices among farmers within the same village [26]. Thirdly, the variation in farmland values within one village is minimal within the same period, resulting in relatively stable prices of farmland [27].

This study aims to examine the impact and mechanisms of distance to urban centers on village-level farmland transfer. The results of this study can help discern the relationship between the evolution of farmland transfer and urban development within the context of urban-rural integration in China. Such insights would subsequently provide more policy recommendations to promote rural revitalization and foster the modernization of agricultural production.

2. Framework and Hypotheses

A voluminous literature has offered valuable insights into the mechanisms of farmland transfer from a cost-benefit perspective and arrived at a fairly consistent conclusion: the rates of farmland transfer increase when the costs of farmland transfer for both transferring in and out decrease and the benefits of farmland transfer increase [28–31]. The costs and benefits of farmland transfer for both sides are influenced by the distance to urban centers. For instance, the classic locational theory suggests that the closer to the city, the lower the transportation costs of agricultural production, the more the economic benefits of agricultural land, and thus the more transferees to transfer in [32]; while the classic dual sector model and the Todaro model suggest that the closer to the city, the more off-farm employment opportunities rural households can obtain, the higher the opportunity costs of agricultural labors, rural households will reduce or abandon agricultural production, and obtain more economic benefits from transferring land out [33]. Figure 1 illustrates these two possible mechanisms of distance to urban centers affecting village land transfer: (a) Agricultural Production Hypothesis; and (b) Off-farm Employment Hypothesis.

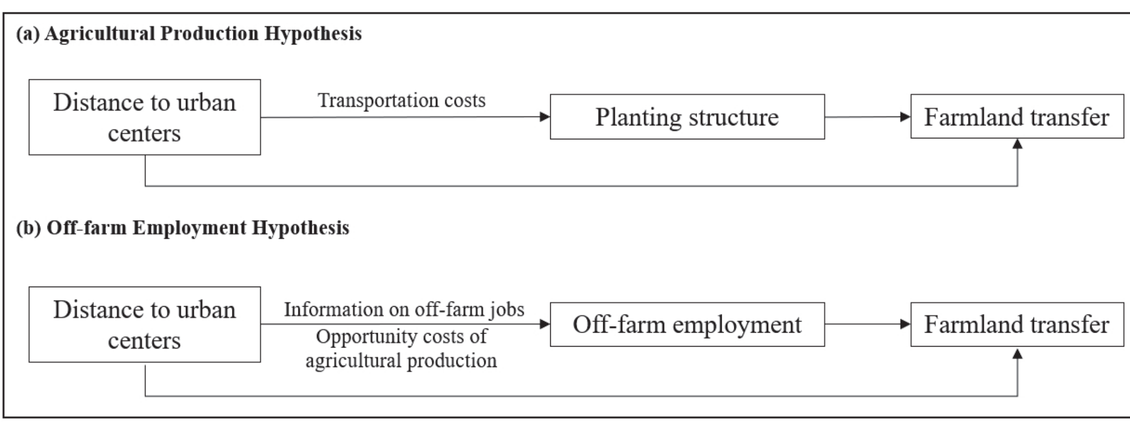


Figure 1. Analysis framework.

While there exists heterogeneity in the impact mechanisms of distance to urban centers on both transferring in and out, their interrelated interests remain consistent. As the distance to urban centers increases, the costs associated with transferring farmland out increase [34], and the benefits of transferring farmland decrease [35]. Consequently, the distance to urban centers has a negative impact on both decisions of farmland transferring in and out, resulting in a lower rate of rural farmland transfer as the distance increases.

Therefore, this study proposes the first hypothesis: The rate of farmland transfer in the village decreases as the distance to urban centers increases, with the village located farther from urban centers exhibiting a lower farmland transfer rate.

Location is the basic geographic characteristic of land, which affects farmland transfer by influencing the benefits of agricultural production of those who transfer farmland [36–38]. The classic agricultural location theory and rent theory argue that the city is the market for agricultural products. The closer to the urban centers, the stronger the market accessibility, which means the lower the transportation costs of agricultural products to the markets. Therefore, crops that are not resistant to transportation and storage but have more economic value tend to gravitate toward the villages near markets [17,18,36]. Under the influence of the homogenization of planting structures and high farmland rents, the degree of intensification of farmland use increases, and the negative impact of high land rents is offset by reducing the marginal cost of agricultural production input [39]. As a result, in the villages surrounding urban centers, the agglomeration of agricultural production of crops with high economic value is facilitated through farmland transfer.

Based on this, this study proposes the second hypothesis: The economic value of farmland decreases with distance to urban centers increasing. As villages are located farther from urban centers, the economic benefits from transferring in are less, leading to a reduced rate of farmland transfer.

In recent years, the studies of rural farmland transfer have also begun to pay more attention to the impact of cities on rural households' decision of farmland transfer [40,41]. The off-farm employment opportunities in the city have a spatial spillover effect [41], and rural households in the villages closer to urban centers can obtain more off-farm employment information and opportunities. Due to the higher benefits of off-farm employment, the opportunity costs of agricultural labor increase, leading rural households to reduce the agricultural input, thereby resulting in farmland abandonment. Abandoning farmland will not bring more benefits to rural households and even increase the risk of being punished [42]. With land rents being comparatively higher near urban areas, the economic incentives drive the households to positively transfer their lands out to these villages. In contrast, households in villages located farther from urban centers have limited access to information about off-farm employment opportunities. The commuting costs of off-farm jobs escalate, reducing the opportunity costs associated with agricultural production [43]. As a result, these households rely more on the agricultural output of their lands and are less likely to transfer farmland out.

Drawing upon the analysis, this study proposes the third hypothesis: As the village is closer to urban centers, the opportunity costs of agricultural labor are higher, leading to an increased rate of farmland transfer. Conversely, as the distance to urban centers increases, rural households rely more on agricultural production, resulting in a decreased rate of farmland transfer.

The urban markets, both for agricultural products and off-farm employment, exert influences on farmland transfer. There exists heterogeneity in the scale of off-farm employment and agricultural markets across different levels of cities [44]. For example, in low-level cities, the proportion of the non-agricultural industry is lower, so it is difficult to promote off-farm employment in these villages and has little influence on rural farmland transfer; while in higher-level cities, the proportion of industrial and service industries is higher and the scale of agricultural market is larger, which not only has a positive effect on rural households' off-farm employment, but also affects the planting structure of suburban villages. Therefore, the influence of the distances to different levels of cities on farmland transfer may be different.

In light of the preceding analysis, this study proposes the fourth hypothesis: There exists a heterogeneous influence of distances to multilevel cities. Specifically, the impact of distance to high-level cities on farmland transfer is stronger compared to that of low-level cities.

Beyond distance to urban centers, other determinant factors such as topography, resource endowment, economic development, population structures, and policy also have impacts that cannot be ignored and should be considered in the empirical analysis. Existing literature has discussed the impact of topography, land quality, and cultivated land area on farmland transfer [31,45,46]. It has been proved that when natural conditions are more favorable and farmland resources are abundant, the rate of farmland transfer increases. Such conditions can diminish the costs of large-scale agricultural production, yielding greater outputs for the same inputs [47]. Some studies have also discussed the impact of economic development on land transfer and found that regional economics or household income has a positive effect on farmland transfer [37,48]. As the income of a rural household increases, the possibility of off-farm employment increases, leading to a greater inclination towards farmland transfer [7], and it is the same in region-level studies [49]. When there is more male and labor population, the comprehensive labor capacity of a household is enhanced, increasing their dependency on land and consequently lowering the rate of farmland transfer [50]. China’s land system is different from Western countries. In Western countries, farmland is privately owned and ownership can be determined by individuals. While in China, farmland is collectively owned [51]. It means that the policy may have a stronger impact on land use in China. When villages benefit from more favorable policies, incentives are generated for the agricultural producers, propelling them to expand the scale of agricultural production and thereby amplifying the rate of farmland transfer [52,53]. As such, when examining the mechanisms through which distance to urban centers impacts farmland transfer, these factors also need to be reflected in empirical analysis.

3. Data and Methods

3.1. Study Area

This study takes Tai’an Prefecture as the case (Figure 2). Tai’an is located in the middle of Shandong Province. The terrain is mainly plains and hills, with a few mountains in the north and east. Tai’an is surrounded by Jinan Prefecture, Jining Prefecture, Laiwu Prefecture, and Liaocheng Prefecture. It encompasses over 3000 villages spread across six county-level regions: Taishan District, Daiyue District, Xintai City, Feicheng City, Ningyang County, and Dongping County. In 2020, the urbanization rate of Tai’an’s population is approximately 64%, representing a 14-percentage point increase over the past decade. This denotes a significant transformation in the urban-rural relationship. Nonetheless, the agricultural industry plays an important role in the economic system. According to the statistical data of Tai’an in 2020, the total agricultural output value of Tai’an increased by 2.5% compared with last year, the grain yield per unit area is 0.69 tons/hectare, ranking second in the province.

The suitable natural geographic conditions and diversified topographic features indicate that Tai’an has the potential for large-scale agricultural production and may have more cases for farmland transfer on the one hand, and on the other hand, Tai’an is a place with high-speed urbanization and a significant transformation in the urban-rural relationship but still keeps a high-level agricultural production, which may be relative to farmland transfer. These characteristics make Tai’an a proper case for exploring the impact of distance to urban centers on farmland transfer.

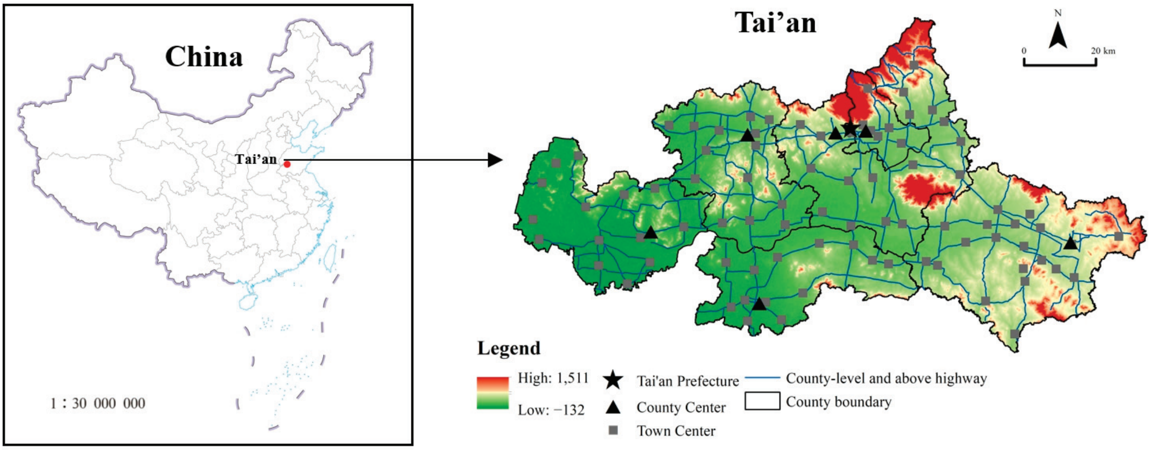


Figure 2. Physical geography and location of Tai'an.

3.2. Data and Model Specification

This study uses several sets of data, including farmland transfer data, geographical data, geophysical characteristics of farmland, economic data, demographic data, and policy. Considering that the period of the farmland transfer data is 2015, most of the datasets are representative of this year. However, due to constraints in data sources, some datasets are representative of 2019. The land transfer data, economic data, and population structure data come from the 2015 village report of Tai'an Prefecture, the geophysical characteristics of farmland are derived from the third national land survey in China, the geographical data are obtained from the Digital Elevation Model (DEM) on the official website of the Geospatial Data Cloud, which shows the land use in 2015, and the policy refers to the historical and cultural towns and villages of Shandong Province and the first batch of rural revitalization demonstration villages announced by Shandong Province before 2019.

In this study, the direct effect of distance to urban centers on farmland transfer and the mediating effect of planting structure and off-farm employment are tested by the Causal Steps Approach [54–56]:

$$Y = \alpha_0 + \alpha_1 X + \delta Z + \varepsilon \tag{1}$$

$$M_1 = \beta_0 + \beta_1 X + \delta Z + \omega \tag{2}$$

$$M_2 = {\beta'}_0 + {\beta'}_1 X + \delta' Z + \omega' \tag{3}$$

$$Y = \gamma_0 + \gamma_1 X + \gamma_2 M_1 + \gamma_3 M_2 + \delta Z + \sigma \tag{4}$$

In Formulas (1)–(4), Y represents the farmland transfer rate, X represents the distance to urban centers, which initially took into account the Euclidean distance, but after modifying the model, the road distance was taken into account, M_1 and M_2, respectively represent the planting structure and off-farm employment, Z represents a series of control variables, α, β, β', γ and δ are the estimated coefficients, ε, ω, ω' and σ are the random error terms.

The first step is to judge whether the total effect (α_1) is significant. The second and third step is to test whether the direct effect and mediating effect (γ_1, $\beta_1\gamma_2$ and ${\beta'}_1\gamma_3$) are significant. Because there are two mediators in this study, it is necessary to repeat Formula (1) twice using different control variables. For more accurate estimates, the percentile and bias-corrected Bootstrap test is used to test the robustness of the mediating effects [56].

3.3. Variables

Table 1 lists the datasets and summary statistics of variables. The dependent variable in this study is the farmland transfer rate. This rate is derived by dividing the number of rural households participating in farmland transfer by the total number of rural households in the village. It can better reflect the level of activity of farmers' participation in farmland transfer. A higher farmland transfer rate indicates more active participation of rural households in farmland transfer, meaning a higher level of farmland transfer within the village. The farmland transfer rate of some villages is 1, which means all the farmland of this village is transferred out.

Table 1. Summary statistics of variables.

Type	Variable	Description	Min	Max	Mean	Standard Deviation
Dependent variable	Farmland transfer rate	The rate of households who participate in farmland transfer to the total households	0	1	0.236	0.269
Independent variables	Distance_P	Distance to the nearest prefecture-level center (km)	2.15	64.35	36.97	13.79
	Distance_C	Distance to the nearest county-level center (km)	0.52	44.01	18.173	9.177
	Distance_T	Distance to the nearest town-level center (km)	0.01	11.70	4.054	1.982
Mediating Variables	Off-farm employment	The proportion of off-farm employment to the total workers	0	1	0.699	0.190
	Planting structure	The proportion of vegetable planting area to the total planting area	0	1	0.189	0.195
Control variables:						
Natural condition	Terrain index	The index according to the terrain index formula [57]	0.29	1.36	0.574	0.169
	Quality	The proportion of the area of high-quality farmland to the total farmland area	0	1	0.725	0.370
	Integrity	Average area of farmland plot (acre)	0.90	495.10	40.213	29.802
	Farmland	The proportion of farmland area to the total area	0.01	0.99	0.777	0.128
Transportation location	Distance_H	Distance to the nearest county-level and above highways (km)	0	16.64	2.826	2.778
Economic factor	Electricity	Per capita electricity consumption (10,000 kWh/person)	0.02	0.05	0.023	0.039
Population structure	Male	The proportion of males to the total population	0.33	0.74	0.515	0.033
	Labor	The proportion of the labor to the total population	0.15	1	0.619	0.106
Policy	Policy support	Whether it is a historical and cultural village or a demonstration village for rural revitalization	0	1	-	-

The distances from villages to the nearest prefectural center, county center, and town center are three independent variables in this study. This study categorizes urban levels based on China's administrative division levels. Within the Chinese administrative hierarchy, prefectures, counties, and townships are classified as the second, third, and fourth levels. The level of the administrative division correlates with its socio-economic status. Typically, a higher-level urban center implies a more advanced economic level, a larger consumer market, and a more expansive non-agricultural employment market [41]. Given that in China, the location of governments largely coincides with market centers [20], thus the urban centers are represented by the governments of prefectures, counties, and towns in this study. This serves as an indicator of the spatial barriers that cities influence the rural farmland transfer. The higher the level of the urban centers, the larger the scale of off-farm employment and agricultural markets. Consequently, there is more negative impact of the distance to the high-level urban centers on rural farmland transfer. Some villages are in the towns but have farmland, and the distances to the town centers are very short.

The mediating variables in this study are the off-farm employment rate and the vegetable planting rate. As the distance to the urban centers decreases, the opportunity costs of agricultural labor rise, leading to a higher off-farm employment rate [58,59]. A higher off-farm employment rate leads to an increased farmland transfer rate. The proportion of off-farm employment in some villages is 1, which means that all the workers have an off-farm job, and the other family members, such as the old people, may do the agricultural work. If there is no family member to do the agricultural work, the probability of households transferring out their farmland will increase. Vegetables are characterized by high economic prices and are not resilient to transport and storage, thus it is suitable for making the vegetable planting rate the variable of planting structure [60]. As the distance to the urban centers decreases, the vegetable planting rate escalates, indicating a higher economic value of the farmland and an increased farmland transfer rate.

The control variables include the following types: natural conditions, transportation locations, economic factors, population structure, and policy. Natural conditions have a direct impact on agricultural production, determining the cost and benefit of agricultural production, thus influencing farmland transfer decisions. The terrain index, the average area of farmland plots, and the proportion of high-quality farmland are used to measure the natural conditions of farmland. In addition, the proportion of farmland area to the total area is used to characterize the abundance of farmland resources. Transportation means the external traffic conditions of the village. The better the transportation, the more convenient the village is to the urban centers, leading to a higher farmland transfer rate [44]. However, some studies have found that roads will cause farmland fragmentation, and the associated facilities will affect the agricultural production conditions of nearby villages, thus having a negative impact on the farmland transfer rate [61]. The distance to the nearest county-level and above highways is used to reflect the traffic situation according to the previous studies [20,62,63]. Economic characterizes the economic level of the village. According to previous studies and the data source, this study uses per capita electricity consumption to reflect the economic level of the village [64]. Population structure affects the agricultural production activities of the village, thus having an impact on the farmland transfer. This paper uses the male rate and labor force rate to characterize gender [44] and age structure [65]. It is expected that the higher the male rate and labor force rate, the stronger the production capacity of farmers with multiple occupations, and the less inclined to participate in land transfer. Policy type is whether the village is a historical and cultural famous village or a rural revitalization demonstration village before 2019. These villages will receive better policy support and more economic subsidies from the local governments [20], which promotes the development of large-scale farming and positively influences households' participation in farmland transfer. This is a binary variable that 1 means the village is a historical and cultural village or a demonstration village for rural revitalization and 0 means it is not.

4. Results

4.1. The Farmland Transfer and Distance to the Urban Centers

In Tai'an Prefecture, farmland transfer is relatively active. After excluding the villages with missing data and anomalies (where the number of households participating in the land circulation exceeds the total number of households), there are 3322 valid samples. Out of these, farmland transfer occurred in 2390 villages, representing approximately 71.94%

of the samples. The average farmland transfer rate is about 23.15%, with the highest rate reaching 100%. The spatial distribution is shown in Figure 3. Notably, villages in the central and southern plains exhibit higher rates of land circulation participation. Most county centers are located in areas with a high concentration of farmer participation. Conversely, a greater number of villages in the western and eastern regions have a 0% participation rate, and these villages tend to be far from the county centers.

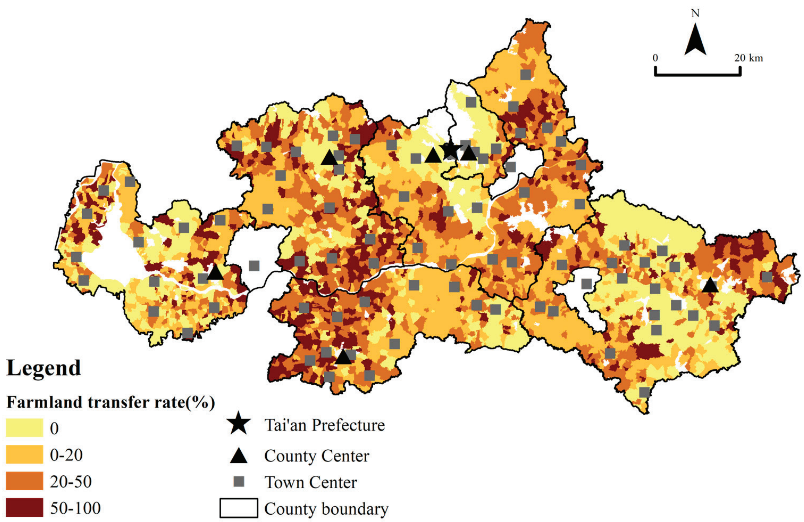
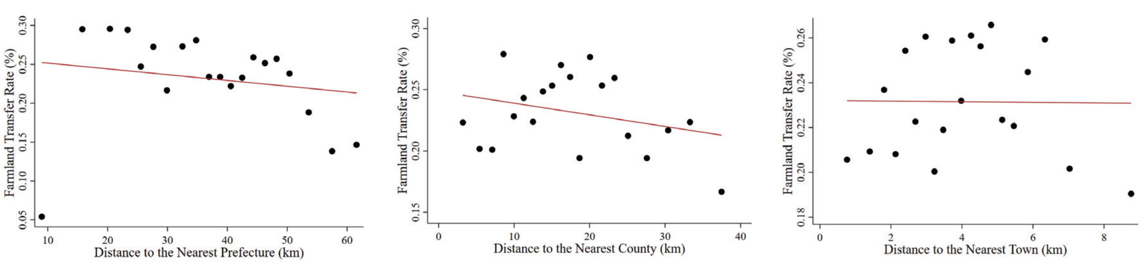


Figure 3. The spatial distribution of farmland transfer rates.

Owing to the limitations of traditional scatterplots in highlighting the relationship between dependent and independent variables when there are large numbers of samples, this study employs binscatter to delineate the relationship between farmland transfer rates and the distance to multilevel centers [66]. Through showing the correlation between the distance to the nearest prefectural center, county center, and town center and the farmland transfer rate by binscatter, it is found that as the distance from a village to the nearest prefectural and county center increases, there is a significant decline in the farmland transfer rate (Figure 4a,b). However, as the distance from a village to the nearest town center increases, the farmland transfer rate does not evidently (Figure 4c).



(**a**) (**b**) (**c**)

Figure 4. The correlation between the distance to the nearest urban center and farmland transfer rate: (**a**) Prefectural center; (**b**) County center; (**c**) Town center.

This is consistent with the existing research results, which indicate that the farther away the village is from the city, especially the prefectural center and county center, the lower the probability of farmland transfer [15]. Moreover, the absolute value of the slope of the fitted line representing the relationship between the distance to the nearest town center and the farmland transfer rate is markedly smaller than that for the distance to the nearest prefectural and county center. This indicates that lower-level urban centers do not exhibit as pronounced an influence as higher-level urban centers. Such a result can explain why extant studies suggest that the distance to town centers has no significant effect on farmers' willingness and decision-making concerning farmland transfer [67]. The presence of high-level prefectures and counties seems to diminish the influence of low-level towns, leading to a nearly horizontal line of the correlation between the distance to the nearest town center and the farmland transfer rate. Nevertheless, it is necessary to examine the effects of three urban centers on farmland transfer together because the fitted line canot refuse the hypothesis that there are mediating effects between town centers and rural farmland transfer. Thus, it is necessary to prove the hypotheses by the mediating effect model.

4.2. Mechanism Analysis

In Section 4.1, through spatial distribution analysis and linear regression, it is discerned that the distance from a village to an urban center, especially the prefectural and county center, might influence the farmland transfer rate. However, this preliminary conclusion needs further rigorous model testing. Consequently, Section 4.2 empirically tests whether the fitting results are valid and calculates the proportion of the mediating effect to the total effect.

Based on the results from Models 1, 2, and 5, it is observed that compared to prefectural and town centers, county centers exert a more pronounced impact on the off-farm employment in villages, subsequently influencing the rural farmland transfer rates. In Model 1, town centers do not exhibit a significant total effect on rural farmland transfer rates at a 90% confidence level. While prefectural centers demonstrate a significant total effect in Model 1, the relationship between prefectural centers and off-farm employment does not pass the significant test at a 90% confidence level in Model 2. Only county centers display the anticipated impact consistently across Models 1, 2, and 5, highlighting the unique role of county centers as urban centers.

This suggests that the higher urban hierarchy does not necessarily translate into a stronger capacity to stimulate the rural population in suburbs to engage in off-farm employment. This finding confirms previous studies suggesting that prefectural centers do not always play a role in promoting off-farm employment in suburbs [68]. Compared to prefectural centers, living in county centers needs a lower level of living costs, and there is a greater emphasis on off-farm employment opportunities that do not necessitate advanced skills, such as those found in the mining and manufacturing sectors in counties [15,20]. Additionally, land rents in villages around counties are lower than those around prefectural centers [15], further facilitating the transition to localized off-farm development.

Models 3, 4, and 5, which explore the mediating path of planting structure, reveal that both county and prefectural centers influence rural farmland transfer through planting structure. However, based on both statistical significance and correlation coefficients, the impact of the prefectural centers is found to be more potent and stable. This indicates two points: firstly, the classic agricultural location theory remains applicable to contemporary rural agricultural studies, and secondly, with the advancements in transportation infrastructure, urban centers still have a spatial influence on rural agriculture. This spatial impact is even more pronounced for urban centers of a higher level. Thus, Prefectural centers possess a larger agricultural product consumption market. Moreover, compared to county centers, these prefectural centers have a higher population density, superior transportation facilities, and an ample consumer base [14]. Such factors favor the development of sightseeing agriculture and leisure agriculture in the surrounding villages, and these types of agriculture require more farmland to create agricultural landscapes and offer ample spaces for visitors, which is highly correlated with farmland transfer.

The total effects of the distance to the nearest town center do not show statistical significance at a 90% confidence level. Moreover, some related studies argue that town centers do not have a significant impact on farmers' decisions of farmland transfer [68]. While villages near towns exhibit a lower proportion of off-farm employment, they possess a higher percentage of vegetable planting area, suggesting there remains a large room for improvement in the off-farm employment markets in the towns. In China, small towns often face problems such as underdeveloped non-agricultural industries and limited growth potential [69]. They fail to absorb the surplus labor force from villages, making it difficult to influence the urbanization of the rural population and the transformation of land use in surrounding villages [20,70]. When compared to prefectures and counties, towns exert a weaker influence on the farmland transfer to villages. This finding holds significant policy implications. Within the hierarchical system of county-township-village, it is necessary to harness the developmental potential of towns, propel the transformation and upgrading of their industrial structures, and enhance their radiation and driving ability in villages.

The control variables nearly show the expected effects. The villages with more suitable natural conditions for agricultural production have higher farmland transfer rates. These villages are endowed with abundant and higher-quality land resources, suitable for large-scale and mechanized farming. As a result, the farmland transfer rates are higher in these villages. However, when the fragmentation of arable land is minimal, the farmland transfer rate decreases. This is because villages with less fragmented farmland do not necessarily require transfer to consolidate land resources, leading to a reduced transfer rate [44]. The higher the economic level of a village, complemented by better infrastructure, the more conducive it is for large-scale agricultural production, and correspondingly, the higher the rate of farmland transfer. The labor force proportion does not pass statistical significance tests at a 90% confidence level, and a higher male proportion negatively affects farmland transfer. Influenced by the traditional model of "men plowing and women weaving" [63], males tend to place a higher value on land assets and are less likely to abandon agricultural production. Policy support received by villages elevates the rate of farmland transfer, indicating that policy backing and economic subsidies positively influence the development of farmland transfer in the villages.

Table 2 proves the first three hypotheses, while the fourth hypothesis is partially validated. To measure the percentage of the mediating effect of the distance to the nearest county center more accurately, this study calculates the proportion of the mediating effect of each variable (Table 3). The results show that about Distance_P, the mediating paths of off-farm employment and planting structure account for 2.33% and 33.45% partly, but only planting structure is statistically significant at a 99% confidence level. About Distance_C, the mediating paths of off-farm employment and planting structure account for 9.28% and 22.27% partly, and the total mediating effect is 31.55%. Numerically, the mediating effect of planting structure has a higher proportion.

The Causal Steps Approach for testing the mediating effect has been criticized for its insufficient test power. To enhance the robustness, this study adopts the percentile and bias-corrected Bootstrap method with stronger test power to test the two mediating paths of the urban distance and sets the resampling times to 5000 according to previous studies [71]. Table 4 shows that the planting structure of county centers cannot pass the test because the 95% confidence intervals include 0, and the other paths pass the test.

This indicates that the mediating effect of county centers on rural farmland transfer rates through planting structure is not robust. Compared to county centers, prefectural centers represent a higher-level market center, possessing a larger agricultural product consumption market. Under the influence of prefectural centers, the path of which county centers affect rural farmland transfer rates through planting structures becomes unstable. Existing studies have also identified that in prefectural centers, there are more consumers for new types of agriculture, such as sightseeing agriculture and leisure agriculture [14,53]. Lower-level urban centers, such as county centers, are unable to provide a sufficiently large consumer base for these new types of agriculture and thus have less capacity to influence rural farmland transfer. This further indicates the intensified role of higher-level urban centers in driving the transformation of village agriculture.

Table 2. The results of mediating effects.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Distance_P	−0.001 **	−0.000	−0.002 ***	−0.003 ***	−0.001 **
	(−2.18)	(−0.91)	(−4.05)	(−12.10)	(−2.13)
Distance_C	−0.001 ***	−0.002 ***	−0.001 **	−0.001 *	−0.001 **
	(−2.60)	(−4.33)	(−2.56)	(−1.69)	(−2.32)
Distance_T	0.000	0.004 **	−0.000	−0.001	0.000
	(0.17)	(2.03)	(−0.08)	(−0.76)	(0.04)
Off-farm employment			0.094 ***	0.007	0.093 ***
			(3.62)	(0.40)	(3.60)
Planting structure	0.223 ***	0.007			0.223 ***
	(9.15)	(0.40)			(9.14)
Terrain index	−0.246 ***	0.282 ***	−0.272 ***	0.002	−0.272 ***
	(−7.29)	(12.38)	(−7.79)	(0.08)	(−7.90)
Integrity	−0.000 ***	−0.000 ***	−0.000	0.001 ***	−0.000 **
	(−2.68)	(−3.69)	(−0.95)	(9.56)	(−2.45)
Quality	0.016	−0.083 ***	0.013	−0.051 ***	0.024 *
	(1.26)	(−9.53)	(0.96)	(−5.53)	(1.84)
Farmland	0.209 ***	−0.212 ***	0.209 ***	−0.084 ***	0.228 ***
	(5.28)	(−7.96)	(5.20)	(−2.97)	(5.73)
Ditance_H	0.013 ***	0.003 *	0.015 ***	0.012 ***	0.012 ***
	(4.40)	(1.76)	(5.17)	(5.82)	(4.29)
Electricity	0.441 ***	0.187 **	0.426 ***	0.012	0.423 ***
	(3.70)	(2.32)	(3.54)	(0.15)	(3.56)
Male	−0.415 ***	0.620 ***	−0.443 ***	0.131	−0.473 ***
	(−2.95)	(6.54)	(−3.10)	(1.31)	(−3.35)
Labor	0.008	0.195 ***	−0.007	0.015	−0.011
	(0.18)	(6.76)	(−0.16)	(0.50)	(−0.25)
Policy	0.142 ***	0.017	0.145 ***	0.023	0.140 ***
	(3.90)	(0.68)	(3.95)	(0.87)	(3.86)
Constant	0.409 ***	0.351 ***	0.438 ***	0.278 ***	0.376 ***
	(4.95)	(6.29)	(5.23)	(4.71)	(4.53)
N	3322	3322	3322	3322	3322
R^2	0.065	0.151	0.046	0.085	0.069

Note: *, **, and *** indicate significance at 0.1, 0.05, and 0.01 levels, respectively. The dependable variables of Models 1–5 are farmland transfer rate, off-farm employment rate, farmland transfer rate, vegetable planting rate, and farmland transfer rate, respectively.

Table 3. The proportion of mediating effects.

Variable		The Coefficient and Proportion of Effects
Distance_P		−0.002 ***
Wherein:	Off-farm employment (%)	2.33
	Planting structure (%)	33.45 ***
	Total mediating effects (%)	35.78 (Only planting structure is significant)
Distance_C		−0.001 ***
Wherein:	Off-farm employment (%)	9.28 ***
	Planting structure (%)	22.27 ***
	Total mediating effects (%)	31.55 ***
Distance_T		No significance
Wherein:	Off-farm employment (%)	-
	Planting structure (%)	-
	Total mediating effects (%)	No significance

Note: *** indicate significance at 0.01 levels, respectively.

Based on Tables 2–4, a mediation effect diagram is illustrated in Figure 5, revealing differences in coefficients across the two mediating paths which pass the tests of the Causal Steps Approach and Bootstrap Method. The first path is that prefectural centers affect the rural farmland transfer through planting structure, and the second path is that county centers affect the rural farmland transfer through off-farm employment.

Table 4. Bootstrap test.

Mediating Variable	Result Type	Acting Path	Point	Bootstrap Std. Err.	Z	P > z	BC-Bootstrap Normal-Based [95% Conf. Interval]	
Off-farm employment	direct	Distance_C → Farmland transfer rate	−0.0012	0.00005	−2.41	0.002	−0.00221	−0.00023
	indirect	Distance_C → Off-farm employment → Farmland transfer rate	−0.0001	0.00005	−2.86	0.004	−0.00024	−0.00004
Planting structure	direct	Distance_C → Farmland transfer rate	−0.0012	0.00051	−2.39	0.017	−0.00222	−0.00022
	indirect	Distance_C → planting structure → Farmland transfer rate	−0.0001	0.00008	−1.75	0.080	−0.00030	0.00002
Planting structure	direct	Distance_P → Farmland transfer rate	−0.0008	0.00039	−2.05	0.040	−0.00159	−0.00004
	indirect	Distance_P → planting structure → Farmland transfer rate	−0.0007	0.00010	−7.13	0.000	−0.00919	−0.00052

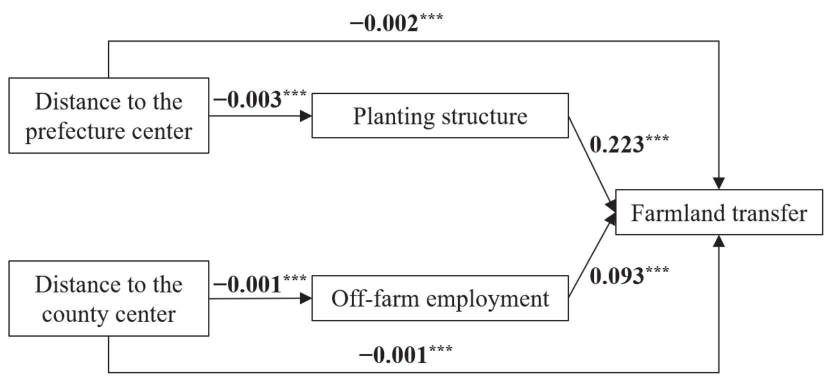


Figure 5. The path coefficients (*** indicate significance at 0.01 levels, respectively).

From the perspective of the coefficients of the total effects, the coefficient of prefectural centers on farmland transfer has a higher absolute value than that of county centers. This discrepancy indicates that, despite different influence paths, higher-level urban centers do indeed exert a more pronounced impact. Considering the coefficients of mediating factors, the coefficient of planting structure on farmland transfer has a higher absolute value than that of off-farm employment. Such differences suggest that in the current context in China, where the disparity in profits between non-agricultural income and agricultural income increases farmers' willingness to transfer out, maximizing the agricultural economic value of farmland and increasing the willingness of transferees to transfer farmland in become even more crucial in improving the farmland transfer rates in villages.

4.3. Robustness Test

The distances from the village to the prefectural, county, and town centers are Euclidean distances, which may not reflect the actual accessibility of the village to the urban centers. Therefore, this paper used the shortest traffic distances from the village to the urban centers to replace the independent variables [20]. The shortest traffic distances from the village to the urban centers are calculated using ArcGIS 10.5 software based on the data of the road network, and then the mediating effect model is run. Table 5 shows the results of the robustness test. The results show that the influence of prefectural centers does not change much, indicating the robustness of the mediating effect. However, the total effect of county centers changes to be not significant at a 90% confidence level. This indicates that when considering the road distance to the urban centers, the interference from higher-level prefectural centers intensifies.

Table 5. The results of mediating effects after changing the independent variable.

Variable	Model 6	Model 7	Model 8	Model 9	Model 10
	Farmland Transfer Rate	**Off-Farm Employment Rate**	**Farmland Transfer Rate**	**Vegetable Planting Rate**	**Farmland Transfer Rate**
Distance_P	−0.001 ** (−2.53)	0.000 (1.16)	−0.002 *** (−4.80)	−0.003 *** (−14.06)	−0.001 *** (−2.60)
Distance_C	−0.001 (−1.65)	−0.001 *** (−4.14)	−0.001 (−1.25)	0.000 (0.75)	−0.001 (−1.39)
Distance_T	−0.001 (−0.51)	0.003 *** (2.75)	−0.002 (−1.11)	−0.004 *** (−2.87)	−0.001 (−0.68)
Off-farm employment			Control	Control	0.098 *** (3.76)
Planting structure	Control	Control			0.240 *** (9.83)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	0.447 *** (5.25)	0.353 *** (6.18)	0.479 *** (5.56)	0.295 *** (4.95)	0.414 *** (4.84)
N	3322	3322	3322	3322	3322
R^2	0.064	0.148	0.046	0.101	0.068

Note: **, and *** indicate significance at 0.05, and 0.01 levels, respectively.

After replacing the independent variables, the same Bootstrap test is conducted for the mediating effect, and the results in Table 6 show that the mediating effect still passes the test. This suggests that even when transitioning from Euclidean to traffic distance, accessibility to prefectural centers still impacts farmland transfer rates by raising the proportion of vegetable planting area.

Table 6. The Bootstrap test after changing the independent variable.

Mediating Variable	Result Type	Acting Path	Point	Bootstrap Std. Err.	Z	P > z	BC-Bootstrap Normal-Based [95% Conf. Interval]	
Planting structure	direct	Distance_P → Farmland transfer rate	−0.00081	0.00040	−2.05	0.040	−0.00159	−0.00004
	indirect	Distance_P → Planting structure → Farmland transfer rate	−0.00072	0.00010	−7.13	0.000	−0.00092	−0.00052

The results that the total effect of county centers does not pass the robustness test does not negate the meaning of prior research regarding the mediating path of county centers, as the impact of county centers on off-farm employment in the suburban villages still passes the test at a 99% confidence level. It means that the transportation of the higher-level urban centers strengthens its positive influence on rural farmland transfer, and suggests that more attention should be paid to the development of transportation infrastructure in county centers to reflect the positive role of county centers in rural farmland transfer.

5. Discussion

This study finds that urban centers have an impact on farmland transfer in villages, but this impact is more prominent in high-level urban centers. Proximity to the urban centers correlates with a higher eagerness among farmers to participate in farmland transfer, leading to a heightened level of farmland transfer. However, this does not mean that the studies concluding that the distance to urban centers has no impact on farmland transfer are meaningless. This study just offers a perspective to discuss the possibility that different paths take place in different places. This study discusses the related issues from the village-level perspective in Tai'an and discusses the different mediating paths of the impact of the distance to urban centers on farmland transfer in villages under varying contexts.

First, the classical agricultural location theory can explain the mechanism of urban centers on the rural farmland transfer through the planting structure. The villages in the suburbs benefit from reduced transportation costs but have high rents. To overcome the negative impact of land rents, crops that are not resistant to transportation and storage but have high economic value are homogenized and scaled up. Thus, the intensity of agricultural production is enhanced, which increases the farmland transfer rates in the villages. Conversely, the villages farther away from urban centers have more dispersed socio-economic activities, leading to diminished farming intensity and lower economic value from agriculture. Besides, there will also be new types of agriculture such as sightseeing agriculture and leisure agriculture near the cities. These new types of agriculture that are combined with the secondary and tertiary industries have more economic benefits but also need stronger urban accessibility to attract more consumers. These new types of agriculture also require capital investment and land resource agglomeration, which increases the farmland transfer rates.

Second, recent studies have also found that the city affects rural land resource reallocation by influencing the sectoral shift of village population employment. This study proves the existence of this mediating path, which can also explain how the distance to urban centers acts as a spatial barrier to affect the development of the farmland transfer, but the results are not robust when we consider the road distance to the urban centers. The city gathers more capital, population, and information, and has stronger mobility of market factors [72]. The flow of factors from urban areas to rural areas has significant spatial heterogeneity [20], and the villages in the suburbs can obtain more off-farm employment information and opportunities than the remote villages, leading to the higher opportunity costs of agricultural labor in the surrounding villages. However, this path is affected by both urban level and transportation facilities. In the higher-level urban centers, such as prefectural centers, there are higher levels of living costs and more jobs that need advanced skills and in the lower-level urban centers, such as town centers, there are less off-farm employment. Transportation strengthens the positive influence of prefectural centers, so only county centers in this study affect the rural farmland transfer through this mediating path and are not robust when using road distance to the nearest city centers.

Finally, the cost-benefit framework is applicable to explain how urban centers influence rural farmland transfer. The farmers in the villages close to the urban centers have more off-farm employment opportunities and have a stronger willingness to obtain more economic benefits from transferring out. Besides, these villages have strong accessibility to the city and low transportation costs [73], which help transferees obtain higher agricultural income through land. This makes them more appealing, attracting more transferees interested in transferring in for agricultural production, which in turn elevates the farmland transfer rates in these villages. The policy also plays a positive role in regulation. The rural revitalization policy proposes "industrial revitalization", which encourages the development of large-scale agricultural production, trains new professional farmers, and offers economic subsidies. These measures have a positive impact on rural farmland transfer. Recent research has also begun to focus on the impact of land property rights on farmland transfer. Findings suggest that land ownership confirmation, guided by policy, has a positive influence on rural farmland transfer [74,75]. The urban influence of this factor should be paid more attention to.

6. Conclusions and Policy Implication

Using Tai'an as a case, this study discusses the mechanisms of the impact of different levels of urban centers on rural farmland transfer rates. The results show that: (1) The closer to the high-level urban centers, the higher the rates of farmland transfer in the village. The county centers attract farmers to off-farm employment and the prefectural centers affect the planting structure of surrounding villages. This increases the opportunity costs of agricultural labor and increases the economic value of agricultural production. As a result, the farmland transfer rate in the village increases. (2) Different levels of urban centers have different impacts. Compared with town centers, county centers have larger off-farm employment market size and higher wage levels, and compared with prefectural centers, county centers have a lower level of living costs and more jobs that need less advanced skills can attract more surplus agricultural labor, and have a more positive impact on rural farmland transfer. (3) Town centers cannot promote off-farm employment and planting structures in the surrounding villages, which means that towns need to further explore their potential for non-agriculture industry and agricultural markets.

Based on the results, this study proposes the following suggestions: First, according to the result that there is no significant impact of the distance to town centers on rural farmland transfer, it is necessary to strengthen the economic function of towns, and fully exert the driving role of off-farm industries and agricultural markets in towns. The impact of towns on the land resource reallocation process in villages is weak, and the radiating potential of towns needs to be paid more attention to. Second, more policy support and preferential subsidies should be given to the remote villages. This involves improving the level of basic infrastructure and advocating for the scaled and intensive development of agriculture. Third, the role of village collectives and agricultural production cooperatives in land integration should be actively played. Existing studies have found that land-scale utilization promoted by village collectives and agricultural production cooperatives in remote villages can achieve greater results and improve agricultural production efficiency [76].

There are three main limitations in this study: (1) Due to the constraints of cross-sectional data, it is difficult to discuss how the urban centers affect the planting structure and off-farm employment of villages in different urbanization stages, and how this change affects the development of the farmland transfer in villages. (2) This study has found that urban centers affect farmland transfer through off-farm employment and planting structure. However, data limitations make it difficult to further discuss other mediating paths, such as new types of agriculture that include sightseeing agriculture and leisure agriculture, which need less distance to the urban centers. This is also a direction for future research. (3) In China, policies affecting land ownership can potentially influence farmland transfer rates. However, due to data limitations, this study can only discuss the impact of policies on farmland transfer from the perspective of policy incentives and economic subsidies. The influence of land ownership confirmation needs further exploration.

Author Contributions: Conceptualization, T.L. and M.Y.; Data curation, M.Y. and T.S.; Formal analysis, M.Y.; Funding acquisition, T.L.; Methodology, T.L. and M.Y.; Project administration, T.L.; Resources, T.L.; Software, M.Y. and T.S.; Supervision, T.L.; Validation, M.Y. and T.L.; Visualization, M.Y. and T.S.; Writing—original draft, M.Y. and T.S.; Writing—review and editing, M.Y. and T.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (42371201).

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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Article

Does Land Fragmentation Affect the Effectiveness of Fiscal Subsidies for Agriculture: Evidence from China

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Abstract: Fiscal and land policies are important tools in developing agriculture in China. Understanding how agricultural subsidies and land fragmentation jointly affect agricultural Total Factor Productivity (TFP) is crucial for building a strong agricultural nation. This paper utilizes microdata from fixed observation points in rural China from 2003 to 2017 and employs panel bidirectional fixed-effect models and moderation-effect models to empirically analyze the impact of agricultural subsidies and land fragmentation on agricultural TFP. The research finds: (1) Agricultural subsidies positively affect agricultural TFP, while land fragmentation leads to decreased agricultural TFP. (2) Land fragmentation hinders the positive effects of agricultural subsidies on agricultural TFP. A 1% increase in land fragmentation could lead to approximately a 3% decrease in the enhancement effect of agricultural subsidies, with significant impacts on households in major grain-producing areas and those primarily engaged in agriculture. (3) There is no evidence that reforms in the "three agricultural subsidies" would alter the combined effect of agricultural subsidies and land fragmentation on agricultural TFP. The obstructive role of land fragmentation cannot be mitigated through the "three agricultural subsidies" reform. The study indicates that the incentivizing role of agricultural subsidies has not been fully realized, and land fragmentation remains a key bottleneck in agricultural development. Fiscal support for agriculture should be coupled with effective land reform policies for synergistic efforts.

Keywords: agricultural development; financial support for agriculture; agricultural subsidies; land fragmentation; agricultural total factor productivity

Citation: Zou, W.; Zhang, Z.; Yang, F. Does Land Fragmentation Affect the Effectiveness of Fiscal Subsidies for Agriculture: Evidence from China. *Land* **2024**, *13*, 43. https://doi.org/10.3390/land13010043

Academic Editors: Uttam Khanal and Sanzidur Rahman

Received: 13 December 2023
Revised: 28 December 2023
Accepted: 28 December 2023
Published: 30 December 2023

1. Introduction

For the first time, the report delivered at the 20th Communist Party of China (CPC) National Congress included the goal of "building a strong agricultural country". It proposed to comprehensively promote rural vitalization, adhere to the priority of agriculture and rural development, consolidate and expand the achievements of poverty alleviation, and accelerate the building of an agricultural power. The important position of agriculture in China has led to the continuous introduction and implementation of various policies to promote high-quality development of agriculture and rural areas. According to the "China Statistical Yearbook" data, since 2003, the scale of national fiscal expenditure on agriculture has grown from CNY 1754.45 billion in 2003 to CNY 22,034.50 billion in 2021. The proportion of agricultural expenditure in the national fiscal expenditure has increased from 7.12% to 8.97%. Notably, from 2018 to 2020, the proportion of agricultural expenditure in the total fiscal expenditure consistently exceeded 9.50%, reaching 9.75% in 2020. From 2004 to 2023, the CPC Central Committee has focused on agriculture, rural areas, and farmers for two decades, issuing the No. 1 central document on agriculture, rural areas, and farmers. Throughout this period, rural residents experienced an average annual real income growth of 6 percent, 1.24 percentage points higher than urban residents. The income ratio between urban and rural residents narrowed from 2.99:1 in 2010 to 2.56:1 in 2020. Grain production has achieved breakthrough growth, and the backward appearance of rural areas has been improved. By the end of 2020, 832 poverty-stricken counties in China were lifted out of poverty, and all 128,000 impoverished villages were removed from the list, achieving a miraculous reduction in poverty by eliminating absolute poverty.

However, while the effectiveness of fiscal support for agriculture policies is becoming evident, China's various agricultural support policies still face issues regarding system, scale, structure, and other aspects. These problems have led to negative phenomena in agricultural development, such as rural marginalization, land idleness, and the last generation of farmers [1,2]. Among these issues, land fragmentation is a key factor hindering agricultural development. Fragmented land can directly lead to a waste of from 3% to 10% of arable land resources, significantly increasing agricultural production costs and severely reducing agricultural production efficiency [3–5]. The intensification of agricultural subsidies and the rise in agricultural production costs are two distinctly opposing factors in improving and increasing agriculture's efficiency. The existence of land fragmentation inevitably negates the positive effects of fiscal support for agriculture. As a country with a long history of agriculture, China's typical characteristics include a large agricultural population and relatively little arable land per capita. The rapid development of modern agriculture, the shift of rural labor to non-agricultural sectors, and an underdeveloped mechanism for urbanites to relinquish their land rights have all exacerbated the issue of land fragmentation. The Central No.1 Document of 2023 emphasizes the need to draw on local experiences of consolidating small plots into larger ones to enhance agricultural operations and combine farmland construction and land consolidation to address the fragmentation issue gradually. So, in the context of China's national conditions with 'small farmers in a large country,' what exactly is the role of agricultural subsidies in agricultural development? Can mere agricultural subsidies be effective? Does land fragmentation lead to efficiency losses in agricultural subsidies? How should land policies and fiscal support for agriculture be coordinated? The answers to these questions are key to clarifying the relationship between fiscal support for agriculture and land reform and are also crucial for China to accelerate its transformation from a large agricultural country to a strong agricultural nation.

Accordingly, we must reassess the impact of agricultural subsidies and land fragmentation on agricultural development. This involves systematically addressing, theoretically and empirically, how agricultural subsidies and land fragmentation affect agricultural development, especially at the household level. Further analysis is conducted on the interactive effects of agricultural subsidies and land fragmentation and their heterogeneous impacts across household characteristics. This helps clarify effective collaborative pathways for land policies and agricultural fiscal support during the rural revitalization phase. Based on this, the paper constructs an input–output model for the agricultural sector that includes the impact of land fragmentation. It attempts to theoretically elucidate the mechanisms through which agricultural subsidies and land fragmentation affect agricultural development. Using microdata from national rural fixed observation points from 2003 to 2017, this study recalculates the Total Factor Productivity (TFP) at the household level and analyzes the individual, interactive, and heterogeneous effects of agricultural subsidies and land fragmentation on agricultural development through panel bidirectional fixed-effect models and moderation effect models. This provides theoretical and empirical support for achieving rural revitalization and accelerating the construction of a strong agricultural nation.

The marginal contribution of this paper is mainly reflected in three aspects: Firstly, this paper develops an input–output model of the agricultural sector, which includes the impact of land fragmentation. The goal is to theoretically explain how agricultural subsidies and land fragmentation affect agricultural total factor productivity. Secondly, land fragmentation is incorporated into the evaluation framework for the effect of agricultural subsidies, focusing on the impact of the economic characteristics of China's smallholder farmers on policy implementation. This is done to provide necessary empirical evidence for subsequent policy formulation and reform. Thirdly, various heterogeneity analyses were conducted to comprehensively depict the interactive effects of agricultural subsidies and land fragmentation on agricultural total factor productivity, considering the characteristics of different regions and households in China. In summary, this paper enhances our theoretical understanding of the mechanisms behind agricultural subsidies and land fragmentation and provides valuable insights into the practical implications for policy development and reform. The heterogeneity analyses contribute to a nuanced understanding of how these factors interact in China's diverse regional and household contexts.

2. Materials and Methods

2.1. Literature Review

From the perspective of international experience and industrial development, the agricultural industry is usually deprived and squeezed in the early stage of a country's economic development and gradually transformed into a sector emphasizing protection in the middle and late stages of economic development [6]. China went through a period of negative agricultural protection (from the 1950s to the 1990s) and a period of agricultural granting balance (from the 1990s to the early 21st century). After 2004, China's agricultural policy underwent a comprehensive transformation [7], and the agricultural tax was completely abolished in 2006. Various agricultural subsidy policies explored and practiced since then, such as subsidies for good crop varieties, direct subsidies for grain farmers, subsidies for farm machinery and tools, and comprehensive subsidies for agricultural supplies, have provided an important driving force for the development of agriculture, farmers and rural areas. Agricultural subsidies play a significant role in promoting agricultural added value and agricultural return on investment, and their role in increasing rural residents' income and driving consumption has been tested many times [8–10].

Furthermore, compared with direct administrative intervention, market-based means such as agricultural subsidies have a more obvious effect on farmers' planting structure adjustment [11]. However, the specific implementation of agricultural subsidy policies has also caused many controversies. It is a common problem that agricultural subsidies cannot improve farmers' willingness to grow grain, and the incentive effect on large-scale and high-income farmers is not obvious [12–14]. The policy evaluation results of Huang et al., 2019 [15] on direct grain subsidies indicate that the small scale of operation mainly caused the lack of enthusiasm of Chinese farmers to grow grain. Although direct grain subsidies would increase farmers' grain planting area in the short term, the increase was limited, and the effect gradually disappeared over time. Even though China's agricultural subsidy standards and total amount have greatly exceeded those of developed countries, there is still a situation of weak agriculture and poor farmers co-existing [16]. Therefore, agricultural development must explore how to make agricultural subsidies play an effective role in avoiding financial and resource waste. In 2016, China merged subsidies for good crop varieties, direct subsidies for grain farmers, and comprehensive subsidies for agricultural supplies into agricultural support and protection subsidies and adjusted the subsidies to actual grain farmers with land management rights (rather than contract rights) to support the protection of cultivated land capacity and appropriate scale grain management. However, concerning the specific policy adjustment of agricultural subsidy reform, Xu et al., 2020 [17] and Yang et al., 2022 [18] both made a comparative analysis of the data before and after the reform and found that the agricultural support and protection subsidy did not have a significant impact on farmers' land transfer behavior on the whole, but only large-scale farmers expanded their land transfer scale. In addition, the planting structure of farmers did not change significantly, and the land rent transformed by subsidies increased the cost pressure of small farmers' land transfer. From an economic perspective, due to the distribution effect between land contractors and operators, the benefits are equally distributed between them no matter to whom the subsidies are given [19]. In addition to this phenomenon in China's agriculture, the agricultural policies of the United States, the European Union, and other countries or regions have had similar effects [20,21]. It can be seen that the effect of agricultural subsidies on agricultural development does not seem to be directly reflected in the promotion of land circulation and increase in land scale, and the reform of a fiscal agricultural support policy aimed only at the subsidy object has not produced the desired effect, so from what dimension to evaluate the policy effect of agricultural subsidies has become a key issue in the implementation process of fiscal agricultural support policy.

In the chapter promoting high-quality development, the 20th CPC National Congress emphasized the importance of "improving the total factor productivity." Considering that China has completed the development status of the initial stage of the agricultural support industry, it is necessary to pay attention to the direct contribution of agriculture to food security and the long-term contribution of economic and social stability in the development process in the next period [22]. Therefore, the study of the effect of agricultural subsidy policies and the efficiency or level of agricultural development should not be limited to the standard of crop yield and the equivalent number of employees but should turn to the qualitative measurement of agricultural production mode, organization mode, and management mode, that is, agricultural total factor productivity. From 1978 to 2016, the annual growth rate of agricultural scientific and technological progress in China was about 3%, much higher than the international average of 1%. Agricultural TFP contributed more than 56% to the total agricultural output value, surpassing the contribution rate of various input factors and becoming an important engine for agricultural development [23]. In the study on agricultural subsidies and agricultural TFP, Li et al., 2021 [24] used provincial panel data from 2003 to 2018 to test the promoting effect of agricultural subsidies on grain TFP and tried to explain it through structural effects and technical effects, and found that the policy effect was better in non-grain-producing areas than in major grain-producing areas. Xu et al., 2023 [25] conducted an empirical study on the impact of the subsidies for farm machinery and tools on agricultural total factor productivity by using the data of fixed observation points in rural areas throughout China from 2007 to 2017 and found that a positive and significant impact does exist, and it is more obvious in plains areas and large-scale farms. Nevertheless, only examining the single effect of agricultural subsidies on agricultural TFP is still a glimpse. Regarding the mechanism of agricultural subsidies, land is an important factor of production closely related to its effect. Whether it is the good seeds, agricultural machinery, and equipment supported by agricultural subsidies or the labor and capital owned by rural residents, they must be combined with land as a factor of production. For farmers engaged in farming, forestry, animal husbandry, fishery, and other agricultural activities, in addition to owning the necessary land (including arable land, forest land, pasture, pond, etc.), the land fragmentation degree directly affects the use of agricultural machinery and tools, the application of agricultural technology and the production efficiency of various labor factors.

Looking back at the history of China's agricultural development, the household contract responsibility system (HRS) divided the scale operation of the production team into small-scale family operations. Under the historical background and development needs at that time, this measure stimulated farmers' enthusiasm for production and greatly improved the efficiency of agricultural production. However, over time, the segmental mode of production and operation undoubtedly hindered the wide use of agricultural machinery, increased agricultural production costs and transaction costs, and reduced the scale economies of agricultural production [26,27]. Drawing on the experience of global agricultural modernization, Germany, the Netherlands, and Japan, as the typical representatives of agricultural powers facing the contradiction between humans and land, have all experienced the development stage of serious land fragmentation and low agricultural production efficiency. Breaking the restriction of land fragmentation has become an important link in their agricultural take-off. Germany's per capita arable land area is only 0.14 hectares (about 2.16 mu). Under the comprehensive management of a series of laws and regulations, from 1949 to 1994, the number of agricultural organizations of less than 10 hectares in Germany was reduced from 1.4 million to 280,000, and the average farm size reached 29.8 hectares, with a cumulative expansion of 3.73 times. It has improved the efficiency of agricultural production while effectively guaranteeing post-war food security[1]. Before the 1950s, the Netherlands could still not meet its demand for agricultural products and needed to import a large amount of food and other agricultural products. But by 2020, after large-scale land management, the number of agricultural operating entities in the Netherlands has dropped from more than 300,000 at the beginning of the 20th century to more than 4000, and the average size of family farms has reached the highest-level set in the European Union. It has promoted the Netherlands' agriculture to a leading position globally [28]. The smallholder peasant economy dominates agricultural operations in Japan, which is close to China regarding resource endowment. In 1960, the average farmland operation scale per household was only 0.88 hectares. However, after implementing effective measures such as farmland construction and land transfer, the average farmland operation area per household reached 2.22 hectares in 2015, nearly three times larger than in 1960. The concentration of agricultural land made the average income of rural residents exceed the national average [29]. It can be found that, as the inevitable result of industrialization and urbanization, the moderate concentration of agricultural land management scale is an important exogenous variable for the development of agricultural industry and an irresistible trend [30,31]. Therefore, the degree of land fragmentation is undoubtedly the key factor affecting agricultural development. The cases of Germany, the Netherlands, and Japan have to some extent given us thoughts on land governance and scale management, but any policy or reform will inevitably have two sides. The national conditions and characteristics of each country determine that the costs and benefits of a certain reform coexist, and opportunities and challenges coexist. Limited by the purpose of this study, the problems and challenges encountered in the land reform process in these countries are also worth discussing in future research. Focusing on the actual situation in China, in 2003, China's average household land management scale was 7.5 mu, the average number of land blocks was 5.7, and the average area of each land block was only 1.3 mu. As of 2018, the average land operation scale of Chinese households has been less than 7.5 mu, and the average number of land blocks per household has still reached 5.5, and even the average number of land blocks per household has reached 9 in mountainous and hilly areas such as Chongqing and Sichuan [32]. China's biggest agricultural feature and national condition is the small-scale peasant economy, which will last a long time [33]. The main contradiction in China's agriculture is the agricultural production mode and production efficiency, and the key is to solve the problem of land fragmentation, achieve scale management, and build a modern production mode to curb the phenomenon of diminishing returns on capital and declining return on investment [27]. Therefore, when exploring the impact of agricultural subsidies on agricultural total factor productivity, it is necessary to measure the degree of land fragmentation to judge how precise measures should be taken to maximize the effect of agricultural subsidies in accelerating the construction of agricultural power.

In summary, existing research has primarily focused on analyzing the impact of agricultural subsidies on single dimensions, such as grain yield, farmer income, land transfer, and land scale, without delving into how agricultural subsidies affect the Total Factor Productivity (TFP), which is critical for long-term agricultural development. Meanwhile, although current studies have identified the influence of both agricultural subsidies and land factors on agricultural development, few have examined the extent of land fragmentation within the context of the impact of agricultural subsidies on agricultural development. In an era where fiscal subsidies are increasing, and land reforms are vigorously underway, exploring the collaborative effect of agricultural subsidies and land fragmentation in agricultural development has clear, practical significance and theoretical value. Based on this, this paper constructs an agricultural sector input–output model that includes the impact of land fragmentation. It attempts to theoretically clarify the mechanisms by which agricultural subsidies and land fragmentation affect agricultural development. Using microdata from fixed observation points in rural China from 2003 to 2017, this study recalculates the TFP at the household level in agriculture. Employing panel bidirectional fixed- and moderation-effect models, it analyzes the individual, interactive, and heterogeneous effects of agricultural subsidies and land fragmentation on agricultural development. This provides theoretical and empirical support for achieving rural revitalization and accelerating the construction of a strong agricultural nation.

2.2. Theoretical Analysis and Research Hypotheses

Suppose that the input–output of the agricultural sector conforms to the Cobb–Douglas form:

$$Y_t = A_t\left[\left(N_t^{\alpha} L_t^{\beta} K_t^{1-\alpha-\beta}\right)^{1-\theta} M_t^{\theta}\right]^{\gamma} I_t^{1-\gamma} \tag{1}$$

where, Y_t is the total agricultural output in period t, N_t is the actual total input of labor in period t, L_t is the actual total input of land in period t, K_t is the actual total input of capital in period t, M_t is the actual total input of intermediate goods in period t, and I_t is the number of peasant households in period t. Accordingly, the total factor productivity A_t is obtained by subtracting the contribution of input factors from the total agricultural output in period t.

If the number of farmers producing a certain crop is fixed in period t, then there is:

$$y_{it} = s_{it}^{1-\gamma}\left[\left(n_{it}^{\alpha} l_{it}^{\beta} k_{it}^{1-\alpha-\beta}\right)^{1-\theta} m_{it}^{\theta}\right]^{\gamma} \tag{2}$$

$$Y_t = \sum\nolimits_{i=1}^{I_t} y_{it} \tag{3}$$

In this case, y_{it}, n_{it}, l_{it}, k_{it}, m_{it} represents agricultural output, labor input, land input, capital input and intermediate product input at the peasant household level, respectively; s_{it} represents the productive capacity of farmer households and $s_{it}^{1-\gamma}$ describes the total factor productivity level at farmer household level; the parameter $\gamma \in (0,1)$ describes the actual control degree by farmers on factors, indicating that farmers with higher productivity can have a higher factor control ability under ideal conditions; the parameters α, β, $1-\alpha-\beta$, θ represent the output elasticity of labor, land, capital and intermediate products in agricultural production, respectively.

From this, it can be obtained that the agricultural total factor productivity at the farmer household level is:

$$s_{it}^{1-\gamma} = \frac{y_{it}}{\left[\left(n_{it}^{\alpha} l_{it}^{\beta} k_{it}^{1-\alpha-\beta}\right)^{1-\theta} m_{it}^{\theta}\right]^{\gamma}} \tag{4}$$

The premise of the Cobb–Douglas production function is the assumption that the return to scale of production is constant when the technical level and factor price are unchanged, that is, $aY = AF(aN, aL, aK, aM)$. At this time, it is assumed that the financial input implemented to the agricultural subsidies at the farmer's level can achieve a multiple of the input growth of various factors. The total agricultural output level under the condition of agricultural subsidies should achieve τ times growth based on y_{it}:

$$\tau y_{it} = s_{it}^{1-\gamma}\tau\left[\left(n_{it}^{\alpha} l_{it}^{\beta} k_{it}^{1-\alpha-\beta}\right)^{1-\theta} m_{it}^{\theta}\right]^{\gamma} \tag{5}$$

However, from the traditional small-scale peasant economy to the agricultural division of labor stage, there is the possibility of increasing returns to scale in agricultural production [34]. In agricultural production practice, agricultural subsidies will change the production level of farmers by affecting the use of agricultural machinery and equipment and the application of agricultural technology, leading to changes in the total factor productivity of farmers, namely:

$$S_{it} = \omega s_{it}^{1-\gamma} \tag{6}$$

At this time, the relationship between agricultural subsidies and the total factor productivity of farmers may be $\omega > 0$, or $\omega < 0$, that is, agricultural subsidies will increase or decrease the total factor productivity of farmers. Because of the research conducted by many scholars using provincial panel data or single subsidy policies, it is proven that agricultural subsidies have a significant positive effect on TFP [25,26]. This paper proposes hypothesis 1 for agricultural TFP at the farm household level:

Hypothesis 1 (H1). *Agricultural subsidies can effectively improve agricultural TFP at the farmer level, that is,* $\omega > 0$.

It can be seen that under the exogenous effect of agricultural subsidies, agricultural output is not only affected by the increase in factor input but also changes with the change in technical level, and the total agricultural output y_{it}^f will increase by $\omega\tau$ times compared with y_{it} that of agricultural subsidies:

$$y_{it}^f = \omega\tau y_{it} = S_{it}\tau\left[\left(n_{it}^{\alpha} l_{it}^{\beta} k_{it}^{1-\alpha-\beta}\right)^{1-\theta} m_{it}^{\theta}\right]^{\gamma} \tag{7}$$

However, due to the existence of land fragmentation, farmers' land input l_{it} in most cases is not in the form of a complete piece of land but in the form of η_{it}^{Large} larger areas of land l_{it}^{Large} and η_{it}^{Small} smaller areas of land l_{it}^{Small} co-input agricultural production activities, namely:

$$l_{it} = \eta_{it}^{\text{Large}} l_{it}^{\text{Large}} + \eta_{it}^{Small} l_{it}^{Small} \tag{8}$$

where, $l_{it}^{Large} > l_{it}^{Small}$; total number of land blocks is $\eta_{it} = \eta_{it}^{\text{Large}} + \eta_{it}^{Small}$. If $\mu_{it} = \frac{\eta_{it}^{Small}}{\eta_{it}}$ expressed as the degree of land fragmentation, $\mu_{it} \in [0, 1]$, that is, the proportion of small land area. The closer it is to 1, the more small-land-area farmers invest in land factors, and the land fragmentation problem is serious. The closer it is to 0, the larger the land area in farmers' land factor input, and the land scale is stronger.

By substituting the degree of land fragmentation μ_{it} into Equation (5), land input can be expressed as:

$$l_{it} = \eta_{it}\left[(1-\mu_{it}) l_{it}^{\text{Large}} + \mu_{it} l_{it}^{Small}\right] \tag{9}$$

By substituting Equation (9) into Equation (7), the total agricultural output, including the degree of land fragmentation, is:

$$y_{it}^f = S_{it}\tau\rho\left[(1-\mu_{it}) l_{it}^{\text{Large}} + \mu_{it} l_{it}^{Small}\right]^{\beta\gamma(1-\theta)} \tag{10}$$

where, $\rho = \left[\left(n_{it}^{\alpha} \eta_{it}^{\beta} k_{it}^{1-\alpha-\beta}\right)^{1-\theta} m_{it}^{\theta}\right]^{\gamma}$, $\rho \geq 0$.

So, $\frac{dy_{it}^f}{d\mu_{it}} < 0$ can be obtained based on Equation (10), that is, the higher the degree of land fragmentation, the lower the total agricultural output under the condition of agricultural subsidies, and the two are negatively correlated. According to the assumption that the return to scale of the production function is unchanged, the decline in the total agricultural output caused by the degree of land fragmentation comes from its negative effect on the total factor productivity, namely $\frac{dS_{it}^f}{d\mu_{it}} < 0$. At this time, due to the input of land fragmentation, the application of large-scale machinery and agricultural science and technology is affected to some extent, which destroys the original large-scale and agglomeration development and makes the total factor productivity at the farmer's level fail to increase to the due degree, which may lead to the gap between the actual output and the theoretical output, that is, $\frac{S_{it}^f}{s_{it}^{1-\gamma}} < \omega$. Accordingly, hypothesis 2 is proposed in this paper:

Hypothesis 2 (H2). *Land fragmentation will hinder the positive effect of agricultural subsidies on farmer-level agricultural TFP, i.e.,* $\frac{S_{it}^f}{s_{it}^{1-\gamma}} < \omega$.

The specific mechanism is as follows Figure 1:

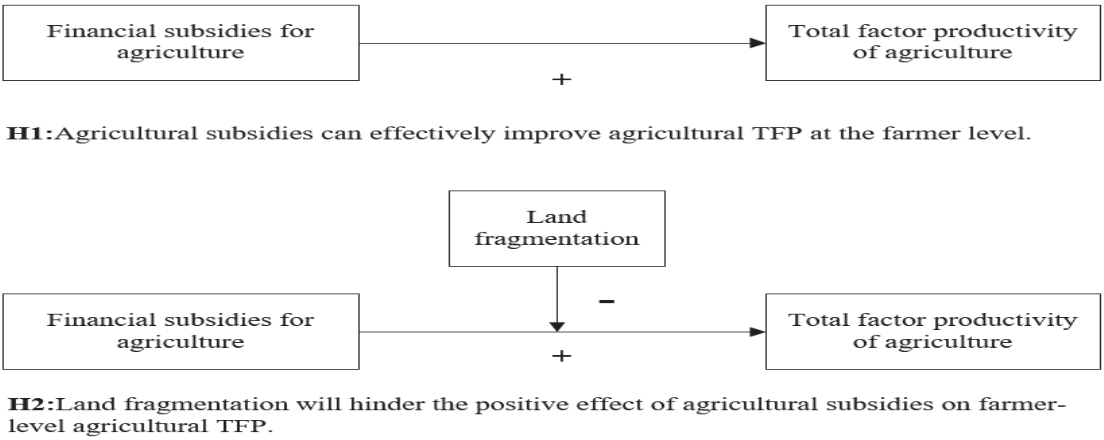

Figure 1. Theoretical Analysis and Research Hypotheses.

2.3. Research Design

2.3.1. Data Source

The national rural fixed observation point data service used in this article is an annual farmer-level tracking survey database led by the Ministry of Agriculture and Rural Affairs of the People's Republic of China. It has national representativeness and authority and is currently China's largest sample size of farmer-level data.

To ensure the availability and continuity of data, this paper selects the data from fixed observation points in rural areas throughout China from 2003 to 2017 for empirical research. After cleaning, sorting, and matching the data of villages and farmers, only the farmers who participate in agricultural production are included in the analysis framework; that is, the agricultural output, labor input, land input, capital input, and intermediate product input all exist and are positive, and the samples with extreme values and abnormal values are reduced by 1%. Finally, 113,507 valid farmer samples are retained.

2.3.2. Model Setting

(1) Model Setting for Measuring Agricultural Total Factor Productivity

The Solow residual accounting method of total factor productivity has experienced many developments. Olley and Pakes, 1996, [35] first proposed the two-step consistent estimation method of total factor productivity. Levinsohn and Petrin, 2003, [36] improved the OP method, enabling researchers to choose proxy variables more flexibly. Wooldridge, 2009, [37] improved the estimation methods of OP and LP, and proposed a one-step estimation method based on GMM, which also considered heteroscedasticity and sequence correlation and could obtain the total factor productivity under robust standard error. Therefore, the Wooldridge method was chosen in this paper to estimate agricultural TFP. Based on the Cobb–Douglas production function, the specific calculation model of agricultural total factor productivity is set as follows:

$$\ln TFP = yit - \alpha \log Wit - \beta \log Xit - \gamma \log Mit \tag{11}$$

where, y_{it} is the agricultural output of farmers i in the year t; W is the free variable, usually the variable that can change such as labor input; X is the state variable, usually land, capital, and other variables that are not easy to change; M is a proxy variable, which is used to represent the unobservable impact of production.

To further reduce the bias of estimating agricultural total factor productivity effectively, we make a series of adjustments based on the Wooldridge method. Firstly, we draw on the study of Wang et al., 2020 [38] to relax the potential assumption that the total agricultural output value is consistent with the intermediate input coefficient and regards the intermediate input as an important factor input. Secondly, to avoid the short-term changes in agricultural total factor productivity caused by technological shocks, the Solow residual method is used to measure agricultural TFP over a long period to weaken the impact of macroeconomic shocks effectively. To sum up, we take the total crop output as the output index, the day of labor entry, the productive fixed assets of farmers and the expenditure of productive services of households as free variables, the actual cultivated land managed by farmers at the end of the year as the state variable, and the total input cost of intermediate goods as the proxy variable. The logarithm of each index is taken to calculate the agricultural total factor productivity at the peasant household level from 2003 to 2017.

(2) Model Setting to Measure the Impact of Agricultural Subsidies and Land Fragmentation on Agricultural TFP

After estimating agricultural total factor productivity, we investigate the impacts of agricultural subsidies and land fragmentation on agricultural total factor productivity by constructing a two-way fixed effect model and a moderating effect model.

First, the two-way fixed effect model can solve the endogeneity problem caused by missing variables as much as possible by controlling some household characteristics that do not change with time but change with individuals and some random characteristics that do not change with individuals but are related to time. The two-way fixed effect model is specified as follows:

$$TFPit = \beta_0 + \beta_1 \ln subsidy_{it} + \theta Xit + \beta_{\mathrm{i}} + \gamma_{\mathrm{t}} + \varepsilon it \tag{12}$$

$$TFPit = \beta_0 + \beta_1 fragment_{it} + \theta Xit + \beta_{\mathrm{i}} + \gamma_{\mathrm{t}} + \varepsilon it \tag{13}$$

where, $TFPit$ is the agricultural output of farmer i in the year t; $subsidy_{it}$ is the agricultural subsidies received by farmer i in the year t, $fragment_{it}$ is the degree of fragmentation of land owned by farmer i in the year t; β_0 is a constant term, and β_1 represents the effects of agricultural subsidies and land fragmentation on agricultural total factor productivity, respectively, in two formulas; X represents a series of control variables, and θ is the corresponding coefficient of each control variable; β_{i}, γ_{t}, respectively, represents individual fixed effect and time fixed effect; ε_{it} represents random interference items.

On this basis, to investigate the interaction between agricultural subsidies and land fragmentation, we introduce the interaction term between agricultural subsidies and land fragmentation based on the two-way fixed effect model and investigate the impact of their interaction on agricultural total factor productivity. The moderating effect model is set as follows:

$$TFPit = \beta_0 + \beta_1 \ln subsidy_{it} + \beta_2 fragment_{it} + \beta_3 Dit + \theta Xit + \beta_{\mathrm{i}} + \gamma_{\mathrm{t}} + \varepsilon it \tag{14}$$

where, Dit denotes the interaction item between agricultural subsidies and land fragmentation, namely $\ln subsidy_{it} * fragmentit$. β_1, β_2 represents the effect of agricultural subsidies and land fragmentation on agricultural total factor productivity, and β_3 is the interaction effect coefficient of the two. The meanings of other symbols are consistent with the previous ones.

As for possible endogeneity problems, we analyze and deal with them as follows: first, there may be some unobservable characteristics at the level of farmers receiving agricultural subsidies, which may lead to endogeneity problems caused by sample self-selection; second, the acquisition of agricultural subsidies will affect the change in total factor productivity of farmers, but the increase in total factor productivity of farmers may also make it easier to obtain agricultural subsidies, so there may be endogenous problems caused by reverse causality. Based on this, to deal with the endogenous problem as much as possible, we construct the average subsidy amount at the provincial level as an instrumental variable and use two-stage least-squares estimation (2SLS). The specific approach is to divide the amount of financial subsidies for agriculture at the provincial level by the effective agricultural irrigation area of the whole province to calculate the amount of average subsidies for the whole province and multiply the actual cultivated land area of households at the end of the year at the farmer's level to obtain the new amount of agricultural subsidies at the farmer's level, and use this as the instrumental variable (IV) to perform two-stage least-squares estimation. Since provincial financial agricultural subsidies are coordinated with the agricultural development status of each province, the implementation situation in previous years, and the needs of rural residents, and the fact that the comprehensive situation in the same region will not change significantly, the number of agricultural subsidies over the years has a certain correlation [25], so the instrumental variable meets the correlation requirements. The acquisition of agricultural subsidies at the farmer's level may be related to farmers' production capacity and factor input. However, there is a large gap between the average amount of subsidies at the provincial level and the level of farmers' production capacity, and there is no significant correlation between the two, so this instrumental variable meets the exogenous requirements. In addition, we replace the estimation method of agricultural total factor productivity in the robustness test to avoid the endogenous problems caused by measurement errors. At the same time, by adding the time dummy variable to characterize the policy impact, we examine whether the exogenous impact of the reform of the three subsidies for agriculture changes the effect of land fragmentation on agricultural subsidies on agricultural total factor productivity.

2.4. Variable Description

2.4.1. Variables Related to Agricultural Total Factor Productivity

Regarding the studies of Ayerst et al., 2020 [39] and Adamopoulos et al., 2022 [40], to obtain the agricultural total factor productivity that represents agricultural development, the following variables are selected for measurement in this paper: (1) Agricultural output. The output index is the total output of crops, mainly wheat, rice, corn, soybean, potato, cotton, oil, sugar, hemp, tobacco, vegetables, fruits, and other planting crops; (2) Land input. Compared with the area contracted by farmers, the area of cultivated land under management at the end of the year decreased the amount of cultivated land transferred and leased to others and increased the amount of cultivated land leased by others, which can more accurately reflect the actual land input of rural households. (3) Labor input. The labor input is measured by labor input day, including the labor days of domestic labor engaged in production activities and labor input by external labor. (4) Capital input. It is composed of the expenditure of farmers' productive fixed assets (such as livestock, large and medium-sized iron and wood farm tools, power machinery for agriculture, forestry, animal husbandry, and fishery, large and medium-sized tractors for transportation, etc.) and household productive services (such as animal power costs, small farm tools purchase and repair costs, machinery operation costs and fixed assets depreciation and repair costs), using the perpetual inventory method to process the original value to get each year's capital input value and taking 2003 as the base period, using the price index of agricultural means of production to carry out the capital input reduction treatment; (5) Input of intermediate goods. It mainly includes the expenditure of intermediate goods related to agricultural activities, such as seeds, seedlings, farm manure, fertilizer, agricultural film, pesticides, water, electricity irrigation, etc. After adding up all kinds of expenses, the CPI index is adjusted to 2003 as the base period.

The descriptive statistics of the variables used to calculate agricultural total factor productivity are shown in Table 1.

Table 1. Describes the descriptive statistics of variables used to measure agricultural total factor productivity.

	Sample Size	Mean	Standard Deviation	Minimum	Maximum
Agricultural output	113,507	4916.24	6270.07	200.16	45,800.14
Land input	113,507	9.07	8.85	0.30	90.00
Labor input	113,507	163.85	140.12	0.34	730.28
Capital input	113,507	10,1876.31	187,323.80	0.19	1,451,132.30
Intermediate inputs	113,507	2049.92	2581.20	51.95	20,469.19

Note: Author's collation.

2.4.2. Core Explanatory and Control Variables

(1) Agricultural subsidies. The annual income received by farmers from state finance includes various kinds of relief, disaster relief, pensions, subsidies related to agricultural activities, as well as subsidies for household appliances to the countryside, subsidies for cars and motorcycles to the countryside, survey subsidies, and other living subsidies. Based on the research needs of this paper, we sum up the agricultural subsidies received by farmers at the level of returning farmland to forest (grass) subsidies, direct grain subsidies, subsidies for good seeds, comprehensive subsidies for the purchase of means of production, subsidies for the purchase and renewal of large agricultural machinery and tools, to obtain agricultural subsidy indicators at the farmer level.

(2) Land fragmentation. There are many indicators in the literature to characterize land fragmentation [41,42]. The single index includes the number of plots, the average area of plots, the average distance between plots, etc. Simpson's index represents the composite index. Since the database does not provide relevant indicators of the specific area of each plot and the distance between different plots, Simpson's index at the farmer's level cannot be calculated. Therefore, combined with the existing research and data characteristics, we integrate the number of plots owned by farmers with the average plot size and measure the degree of land fragmentation at the farmer level with the proportion of land plots less than one mu in the total land plots of farmers.

(3) Control variables. The control variables selected in this paper mainly include family characteristics and village characteristic variables. The family characteristic variables include household grain consumption [2], annual net income, and income from going out to work. Village characteristic variables include total village population and village land scale.

In addition, all income variables (such as agricultural subsidies, annual household net income, and household income from migrant workers) are treated logarithmically, and the CPI index is deflated based on 2003.

The descriptive statistics of variables are shown in Table 2.

Table 2. Descriptive statistics of variables.

	Sample Size	Mean	Standard Deviation	Minimum	Maximum
Total factor productivity in agriculture	113,507	6.214	0.677	1.645	9.974
Farm subsidies	113,507	355.126	563.812	0.050	4116.039
Land fragmentation	113,507	0.655	0.290	0	1
Household grain consumption	113,507	6.619	0.540	5.170	8.087
Annual household net income	113,507	9.795	0.849	7.509	11.702
Household income from migrant workers	113,507	6.429	4.450	0.030	11.628
Total village population	113,507	7.371	0.662	5.595	8.966
Village land scale	113,507	8.574	1.114	5.814	11.358

Note: Author's collation.

2.4.3. Trends of Agricultural Subsidies, Land Fragmentation, and Agriculture Total Factor Productivity

The change trends of three major indicators from 2003 to 2017 are plotted in Figure 2. It can be seen that agricultural subsidies from 2003 to 2017 did not show significant changes from 2003 to 2004. Since the No. 1 central document in 2003 paid attention to the issues of agriculture, rural areas, and farmers, and the official agricultural policy transformation began in 2004, agricultural subsidies have had an obvious upward trend. The overall trend of land fragmentation decreased significantly, but the decrease was small, only from about 0.67 to about 0.62; that is, more than 60% of the land in rural households was less than one mu; China's agriculture total factor productivity at the peasant household level shows a fluctuating upward trend, and its growth rate has slowed down in recent years. Although there are some differences in the values due to the selection of measurement methods and indicators, this changing trend is consistent with the changing trend measured by Wang et al., 2020 [38] using the data of fixed observation points in rural areas across China.

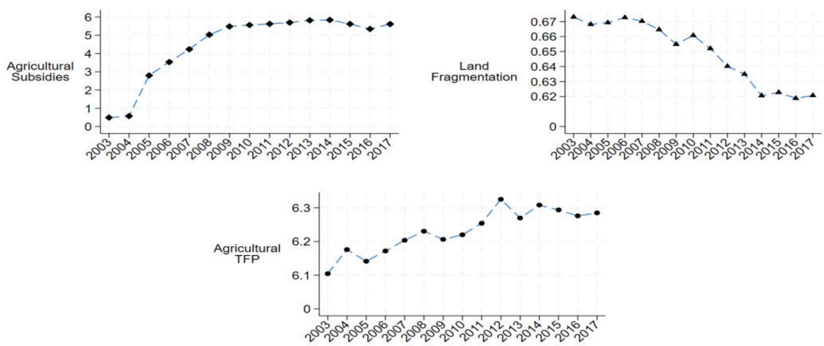

Figure 2. Descriptive Statistics on the Trend of Changes in Main Indicators.

3. Results

3.1. Benchmark Model Regression Results

To clarify the relationship between agricultural subsidies, land fragmentation, and agricultural TFP, we use the two-way fixed effect model and the moderating effect model to identify the single and interactive effects of agricultural subsidies and land fragmentation by controlling the provinces where the households reside and the year of the data survey.

First, Columns 1 and 2 of Table 3 use agricultural subsidies and land fragmentation as single explanatory variables, and the two-way fixed effect model is used to identify the effects of agricultural subsidies and land fragmentation on agricultural TFP. Column 1 reports the effects of agricultural subsidies as an explanatory variable alone. According to the regression results, agricultural subsidies significantly positively affect agricultural TFP, and a 1% increase in agricultural subsidies will increase agricultural TFP by 0.4%. Column 2 presents the separate effect of land fragmentation. Land fragmentation leads to a significant decrease in agricultural TFP, with each 1% increase in land fragmentation leading to a 33.3% decrease in agricultural TFP. This benchmark result indicates that acquiring agricultural subsidies can promote agricultural development and increase the TFP at the farmer level. Hypothesis 1 is supported, but the typical fact is that land fragmentation plays a negative role in agricultural development. On this basis, column 3 is constructed to incorporate both agricultural subsidies and the degree of land fragmentation into the analytical framework. The regression results of column 3 show that adding land fragmentation reduces the influence coefficient of agricultural subsidies on agricultural total factor productivity, and the significance of agricultural subsidies is only marginal, which provides preliminary evidence for the negative effect of land fragmentation on agricultural subsidies.

Table 3. Agricultural subsidies, land fragmentation, and agricultural total factor productivity.

Variables	Explained Variables: Agricultural TFP			
	(1)	(2)	(3)	(4)
Agricultural Subsidies	0.004 *** (0.001)		0.002 * (0.001)	0.023 *** (0.002)
Land fragmentation		0.333 *** (0.014)	0.332 *** (0.014)	0.201 *** (0.017)
Agricultural subsidies × Land fragmentation				0.033 *** (0.002)
Household grain consumption	0.094 *** (0.005)	0.086 *** (0.005)	0.086 *** (0.005)	0.088 *** (0.005)
Annual household net income	0.137 *** (0.004)	0.134 *** (0.004)	0.134 *** (0.004)	0.134 *** (0.004)
Household income from migrant work	0.008 *** (0.001)	0.008 *** (0.001)	0.008 *** (0.001)	0.008 *** (0.001)
Total village population	0.017 ** (0.007)	0.015 ** (0.007)	0.016 ** (0.007)	0.018 *** (0.007)
Village land scale	0.005 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)
Constant term	4.036 *** (0.081)	4.361 *** (0.080)	4.363 *** (0.080)	4.244 *** (0.081)
Province fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Observed values	18,828	18,828	18,828	18,828
Sample size	113,507	113,507	113,507	113,507

Note: *, **, and *** indicate significant differences at the 10%, 5%, and 1% levels, respectively, with robust standard error in brackets.

Considering that agricultural subsidies and land fragmentation have opposite effects on agricultural TFP, to analyze the impact of land fragmentation on agricultural subsidies, we construct the interaction term of agricultural subsidies and land fragmentation and identify the impact of the interaction between the two on agricultural TFP. As can be seen from the results of column 4, the direction of the main effect of agricultural subsidies and land fragmentation is the same as that of the single effect, and there is no significant change in the direction of the influence due to adding another core explanatory variable. At the same time, the interaction term of the two is significantly negative, indicating that at a certain level of financial support for agriculture, the higher the degree of land fragmentation, the more significant the negative reduction effect on agricultural total factor productivity. Specifically, when the degree of land fragmentation increases by 1%, the promoting effect of agricultural subsidies on agricultural TFP decreases by about 3%. Based on the results of the above analysis, hypothesis 2 is supported by sufficient evidence that the degree of land fragmentation will significantly affect the positive role of agricultural subsidies in promoting agricultural development.

Based on the above results, agricultural subsidies significantly positively affect agricultural total factor productivity. However, when land fragmentation is included in the analysis framework, agricultural total factor productivity will decrease significantly. In addition, the interaction between agricultural subsidies and land fragmentation is negative; that is, land fragmentation hinders the positive effect of agricultural subsidies on agricultural TFP. It can be seen that land fragmentation is an important obstacle to agricultural development and the improvement of agricultural total factor productivity. To increase fiscal input for agriculture, it is necessary to combine powerful land reform policies with concerted efforts to give full play to the positive role of fiscal policy in the agricultural field and avoid the low-level utilization of financial resources and land factors.

3.2. Endogeneity Problem Handling and Robustness Test

In the existing literature, few empirical studies combine agricultural subsidies and land fragmentation degrees to examine their impact on agricultural total factor productivity.

Therefore, the robustness of the results needs to be further tested to ensure their authenticity and reliability. Because of data structure and index selection and possible endogeneity problems, we adopt three methods: the instrumental variable method, changing the estimation method of explained variables, and adding the time dummy variable to characterize the policy impact to conduct a robustness test.

(1) Instrumental variable method. Since agricultural subsidies at the farmer's level may be affected by unobservable individual characteristics of farmers, as well as possible reverse-causality problems, we use provincial-level equalization subsidies to replace the farmer-level subsidies and adopt the two-stage least-squares method to eliminate the influence of such endogenous problems as far as possible. The specific approach is as follows: the amount of provincial financial subsidies for agriculture is divided by the effective agricultural irrigation area of the whole province to calculate the amount of provincial average subsidies, and the amount of farmer-level agricultural subsidies is multiplied by the actual cultivated land area of the family at the end of the year, to obtain the new amount of farmer-level agricultural subsidies, replacing the original farmer-level subsidies data. The instrumental variables selected in this paper have passed the necessary tests, and the specific regression results are shown in column 5 of Table 4.

Table 4. Endogeneity Problem Handling and Robustness Test.

Variables	(5) Instrumental Variable Method (Provincial Local Equalization Subsidy)	(6) Replace ATFP with LPACF Method Calculation Result	(7) Replace the ATFP with the OPACF Method	(8) A Year Dummy Variable That Characterizes Policy Shocks
Agricultural subsidies	0.324 *** (0.012)	0.016 *** (0.002)	0.018 *** (0.002)	0.022 *** (0.002)
Land fragmentation	0.031 (0.028)	0.003 (0.017)	0.080 *** (0.016)	0.199 *** (0.017)
Agricultural subsidies × Land fragmentation	0.022 *** (0.006)	0.029 *** (0.003)	0.029 *** (0.002)	0.031 *** (0.002)
Time dummy variable				0.038 (0.092)
Time dummy variable × Agricultural subsidies				0.022 * (0.013)
Time virtual variable × Land fragmentation				0.054 (0.112)
Time dummy variable × Agricultural subsidies × land fragmentation				0.033 * (0.018)
Household grain consumption	0.064 *** (0.006)	0.056 *** (0.005)	0.067 *** (0.005)	0.088 *** (0.005)
Annual household net income	0.087 *** (0.005)	0.106 *** (0.004)	0.122 *** (0.004)	0.134 *** (0.004)
Household income from migrant work	0.006 *** (0.001)	0.008 *** (0.001)	0.008 *** (0.001)	0.008 *** (0.001)
Village population size	0.083 *** (0.015)	0.059 *** (0.007)	0.037 *** (0.007)	0.019 *** (0.007)
Village land size	0.007 (0.005)	0.007 ** (0.003)	0.007 ** (0.003)	0.005 * (0.003)
Constant term		3.583 *** (0.086)	3.992 *** (0.076)	4.233 *** (0.081)
Province fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Observed values	15,159	18,828	18,828	18,828
Sample size	107,490	113,507	113,507	113,507

Note: Column 5 is the estimation result of 2SLS, the F-value of the instrumental variable in the one-stage regression is greater than 10, and the weak instrumental variable test value (Cragg–Donald Wald F statistic) is greater than the critical value of 10%, so there is no weak instrumental variable problem; in addition, the *p*-value of the unidentifiable test (Kleibergen–Paap rk LM statistic) is 0, so there is no unidentifiable problem of the instrumental variables. *, **, and *** indicate significant differences at the 10%, 5%, and 1% levels, respectively, with robust standard error in parentheses.

(2) Replace the explained variables. In the procedures of the LP and OP estimation methods mentioned above, labor may not be able to vary independently of changes in the nonparametric function. To avoid such function dependence problems, Ackerberg et al., 2015 [43] proposed an estimation method that allows for exogenous, series-dependent, unobservable shocks to labor or adjustment costs to labor inputs and more general dynamic effects of labor. The ACF method relies on the same moment conditions compared to the LP and OP methods. However, it controls unobservable productivity through the inverse function of the "conditional" input demand function, which results in the coefficients of variable inputs (e.g., labor) not being identified in the first stage and all input factor coefficients being estimated in the second stage. Accordingly, we use the ACF method to re-estimate farm-level TFP, replacing the explained variables originally estimated by the Wooldridge method. Specific results are shown in column 6 and column 7 in Table 4.

(3) Add the time dummy variable to represent the policy impact. In 2016, the reform of the three subsidies for agriculture was comprehensively extended to the whole country after the pilot implementation. This reform changed the basis of agricultural subsidy payment from the original land contract right to the actual management right, aiming to increase the operating income of farmers who transferred to the land and encourage land transfer behavior among farmers. To further determine whether the adjustment and implementation of national policies will have a substantial impact on the above-estimated results and basic conclusions, we introduce a time dummy variable representing the policy impact, assigning a value of 0 from 2003 to 2015 and 1 from 2016 to 2017, construct a triple interaction term and examine the impact of the policy impact. The specific results are shown in column 8 of Table 4.

To sum up, after adopting the instrumental variable method, changing the estimation method of explained variables, and adding the time dummy variable representing policy impact for the robustness test, the influence direction and magnitude of the interaction terms of agricultural subsidies and land fragmentation did not change. When the degree of land fragmentation increased by 1%, the promoting effect of agricultural subsidies on agricultural total factor productivity would decrease by about 3%. The analysis results and basic conclusions of all kinds of robustness tests are consistent with the previous ones. It is worth noting that after adding the time dummy variable to represent the policy impact, the main effect term or interaction term related to the time dummy variable was only marginally significant or insignificant, indicating that there is no evidence to support that agricultural subsidy reform will affect the joint effect of agricultural subsidy and land fragmentation on agricultural total factor productivity. The obstructive effect of land fragmentation cannot be effectively resolved through the reform of the three subsidies for agriculture, and the effective connection between fiscal policy and land reform still needs to be further explored.

4. Discussion

In the previous analysis, we conducted an analysis based on the data from fixed observation points in rural China from 2003 to 2017 and utilized the two-way fixed effects model and the moderating effect model to examine the impacts of agricultural subsidies and land fragmentation on the total factor productivity of agriculture. In the resulting analysis, it can be found that both Hypothesis 1 and Hypothesis 2 have been confirmed, and the robustness and credibility of the results have been demonstrated using an instrumental variable method and various robustness analyses. We have conducted a comprehensive examination of the fiscal support for agriculture policy, with a focus on observing the overall effect of the policy on farmers. However, our research differs from the studies of Li et al., 2021 [24] and Xu et al., 2023 [25] from the research perspective. Li's research focuses on grain production, while Xu's research focuses on agricultural machinery purchase subsidies. However, we still examine the positive effects of fiscal support policies on agricultural development from an overall perspective. The different research perspectives lead to differences in estimated coefficients, but there is a certain degree of similarity in the basic conclusions. At the same time, our research incorporated land fragmentation into the analysis framework at the farmer level and constructed a moderating effect model. Such research is still rare, and in this paper, our research has obtained further meaningful conclusions.

In further discussion, we will divide it into two parts: mechanism testing and heterogeneity analysis.

4.1. Mechanism Testing

In our research, we incorporated land fragmentation as a factor into the analysis of the effectiveness of fiscal agricultural subsidies, and thus obtained some new conclusions: land fragmentation will become an important factor hindering the effectiveness of fiscal agricultural subsidies. In order to explain the mechanism by which land fragmentation hinders fiscal subsidies for agriculture, we attempt to include the analysis of the mechanism by incorporating the land transfer area at the farmer level. We calculate the difference between the land area obtained by farmers through land transfer and the land area lost through transfer, in order to obtain the net value of land transfer for farmers, which is the actual land transfer area for farmers.

In theory, due to the fact that moderate scale management in agriculture is a common law of agricultural development in various countries around the world [30,31], positive land transfer can promote the scale and agglomeration development of agriculture. Scale effects can reduce agricultural production costs, improve agricultural production efficiency, and thus improve total factor productivity in agriculture. Based on our research, fiscal subsidies for agriculture may increase the willingness of farmers to transfer land, and having more funds will make them more willing to obtain more land through transfer, thereby engaging in larger-scale agricultural production activities and improving agricultural total factor productivity. However, land fragmentation will increase the production and operation costs and land transfer costs of farmers, reduce their willingness to engage in agricultural production, and hinder the further expansion of production paths, thereby reducing agricultural production efficiency and total factor productivity.

In Table 5, we first examined the impact of land transfer on agricultural total factor productivity (column 9), and then examined the effects of fiscal subsidies for agriculture and land fragmentation on land transfer (column 10 and 11). Through the results, it can be found that an increase in land transfer area will significantly enhance the total factor productivity of agriculture at the farmer level. For every 1 acre increase in land transfer area, the total factor productivity of agriculture will increase by 1.5%. Focusing on the fiscal agricultural subsidies and land fragmentation that this paper focuses on, it can be found that fiscal agricultural subsidies have a significant positive effect on the area of land transfer, while land fragmentation will have a significant hindering effect on land transfer. This result is consistent with the findings of Xu et al., 2023 [25] and Wu et al., 2016 [3], who also believe that fiscal subsidies for agriculture will promote land transfer, while land fragmentation is an important factor hindering land transfer.

Based on this, we can explain that the mechanism by which land fragmentation hinders fiscal agricultural subsidies may be due to the fact that fiscal agricultural subsidies could have improved the total factor productivity of farmers by promoting land circulation. However, the existence of land fragmentation can hinder the realization of land circulation among farmers, thereby reducing the original policy effect of fiscal agricultural subsidies; as a result, the promotion effect of fiscal subsidies on agricultural development has decreased.

4.2. Heterogeneity Analysis

In the No.1 central document released in 2022, the government clearly stated that it must firmly uphold the two bottom lines of ensuring national food security and preventing large-scale poverty. Through the formulation and implementation of various policies and regulations, China has invested a lot of human resources, material, and financial resources to strictly adhere to the two bottom lines, among which the issuance of fiscal subsidies for agricultural production is of great significance to food production and the prevention of poverty. However, based on previous research, it can be found that land fragmentation does hinder the policy effect of agricultural subsidies. To determine whether this negative effect harms safeguarding the two bottom lines, we will continue to examine farmers' regional heterogeneity and main activity heterogeneity to provide useful references for policy formulation and adjustment.

Table 5. Mechanism Testing.

Variables	(9)	(10)	(11)
	Agricultural TFP	**Transfer**	**Transfer**
Transfer	0.015 *** (0.001)		
Agricultural Subsidies		1.408 *** (0.034)	
Land fragmentation			−1.074 *** (0.053)
Household grain consumption	0.094 *** (0.005)	−0.162 *** (0.015)	0.007 (0.015)
Annual household net income	0.136 *** (0.004)	−0.008 (0.014)	0.069 *** (0.014)
Household income from migrant work	−0.008 *** (0.001)	−0.010 *** (0.002)	−0.013 *** (0.002)
Total village population	0.017 ** (0.007)	0.236 *** (0.018)	−0.012 (0.016)
Village land scale	−0.004 (0.003)	−0.054 *** (0.009)	0.009 (0.009)
Constant term	4.051 *** (0.082)	−3.151 *** (0.267)	−0.290 (0.270)
Province fixed effect	YES	YES	YES
Year fixed effect	YES	YES	YES
Observed values	18,828	18,013	18,828
Sample size	113,507	110,344	113,507

Note: ** and *** indicate significant differences at the 5%, and 1% levels, respectively, with robust standard error in brackets.

4.2.1. Grouping by Regions

Based on the overall characteristics of grain planting, production, and consumption in different provinces and taking into account the differences in grain farming traditions and resource endowments in different regions, the Opinions of The State Council on Further Deepening the Reform of the Grain Circulation System in 2001 divided 31 provinces (autonomous regions and municipalities) into main grain producing areas, main marketing areas, and balanced production and marketing areas[3]. At the same time, differences in topography, climate, temperature, and ecological environment between China's northern and southern regions have also led to different characteristics of regional agricultural development. To investigate the heterogeneity of agricultural subsidies, land fragmentation, and agricultural total factor productivity in different characteristic regions, we divided the main grain-producing areas and non-major grain-producing areas (including the main grain-selling areas and the production–marketing balance areas), the northern regions and the southern regions. Fisher's Permutation test was used to test the differences in the coefficient of interaction terms of the groups.

As can be seen from column 12 and column 13 in Table 6, although the interaction between agricultural subsidies and land fragmentation was significant in both types of regions, the obstruction of land fragmentation to agricultural subsidies was more obvious in major grain-producing regions than in non-major grain-producing regions, where a 1% increase in land fragmentation in major grain-producing areas can reduce the effect of agricultural subsidies on agricultural total factor productivity to 4.1%, which is 2.2% higher than that in non-major grain-producing areas. Columns 14 and 15 in Table 6 compare the effects between the southern and northern regions. In the southern region, the degree of land fragmentation has a more significant inhibitory effect on agricultural subsidies. A 1% increase in land fragmentation will reduce the impact of agricultural subsidies on agricultural TFP by 3.2%, which is higher than the 2.6% in the northern region. However, the difference in the interaction term coefficients between the two is not statistically significant. It can be seen that in different regions, the degree of land fragmentation still shows the inhibitory effect of agricultural subsidies on the improvement of agricultural total factor productivity, especially in the main grain-producing areas, which to a certain extent affects the effective realization of firmly safeguarding the bottom line of national food security.

Table 6. Effects of regional heterogeneity of different rural households.

Variables (Explained Variables Are All ATFP)	**The Type of Area in Which the Household Was Located**			
	(12)	**(13)**	**(14)**	**(15)**
	Major Grain-Producing Regions	**Non-Major Grain-Producing Regions**	**Northern Regions**	**Southern Regions**
Agricultural subsidy	0.024 ***	0.018 ***	0.005 *	0.033 ***
	(0.002)	(0.003)	(0.003)	(0.003)
Land fragmentation	0.146 ***	0.291 ***	0.271 ***	0.168 ***
	(0.019)	(0.028)	(0.025)	(0.023)
Agricultural subsidies × Land fragmentation	0.041 ***	0.019 ***	0.026 ***	0.032 ***
	(0.003)	(0.004)	(0.004)	(0.004)
Household grain consumption	0.092 ***	0.085 ***	0.052 ***	0.125 ***
	(0.006)	(0.008)	(0.007)	(0.007)
Annual household net income	0.134 ***	0.133 ***	0.166 ***	0.106 ***
	(0.005)	(0.007)	(0.006)	(0.006)
Household income from migrant work	0.006 ***	0.011 ***	0.009 ***	0.008 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Village population size	0.012	0.012	0.005	0.045 ***
	(0.009)	(0.010)	(0.010)	(0.009)
Village land size	0.008 **	0.006	0.011 ***	0.000
	(0.003)	(0.005)	(0.004)	(0.004)
Constant term	0.000	4.461 ***	4.313 ***	4.914 ***
	(0.000)	(0.113)	(0.115)	(0.340)
Province fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Observed values	64,352	49,155	49,445	64,062
Sample size	10,207	8621	7989	10,839
Coefficient difference p-value	0.010		0.180	

Note: Fisher's Permutation test obtained the different p-values of the group interaction coefficients, and the results of subsequent group regressions were the same. *, **, and *** indicate significant differences at the 10%, 5%, and 1% levels, respectively, with robust standard error in parentheses.

4.2.2. Grouping by Main Occupations

Under the background of new-type urbanization and all-around deepening of rural reform, the production activities that rural residents participate in are no longer limited to agriculture. In the data of fixed observation points in rural areas across China, the industry in which operating income (or the amount of labor invested) accounts for the proportion of household operating income (or the amount of labor invested in household operation) is identified as the main occupation of household operation. It is especially emphasized that since the sample selection above ensured that all samples were effectively involved in agricultural activities, only agricultural activities accounted for a relatively low proportion of non-agricultural farmers. The typical difference from agricultural-based farmers was whether they depended more on agricultural production or land factors. Data show that there are still 13% of China's rural households mainly based on agricultural production and operation, including many large-scale farmers and vulnerable farmers who are unable to engage in other production and operation activities; this part of vulnerable farmers is also the focus of attention to firmly prevent the large-scale return to poverty.

Comparing column 16 and 17 reveal that compared to households primarily engaged in non-agricultural activities (Table 7), land fragmentation has a more severe obstructive effect on agricultural subsidies in households primarily engaged in agriculture, with a statistically significant difference between the two. Further exploration into different agricultural sectors, distinguishing between households primarily engaged in crop farming and those in forestry, fishery, or animal husbandry (i.e., non-crop farming), reveals that column 18 and 19 show no significant differences in the coefficients of the interaction terms. This indicates that agriculture as a whole is universally affected by land fragmentation. This type of impact does not vary with different agricultural sub-sectors. It can be inferred that land fragmentation severely hampers the effectiveness of agricultural subsidies, affecting the livelihoods of households primarily engaged in agriculture, and is prevalent in various agricultural sub-sectors, including crop farming, forestry, fishery, and animal husbandry. This phenomenon adversely impacts the goal of achieving moderate-scale operation in agriculture and firmly preventing large-scale relapse into poverty.

Table 7. Heterogeneous effects of different farmers' main occupations.

Variables (Explained Variables Are All ATFP)	**Type of Household's Main Occupation**			
	(16)	**(17)**	**(18)**	**(19)**
	Agricultural-Based	**Non-Agricultural Based**	**Planting Based**	**Non-Planting Based**
Agricultural subsidies	0.023 ***	0.021 ***	0.022 ***	0.040 ***
	(0.002)	(0.005)	(0.002)	(0.009)
Land fragmentation	0.164 ***	0.358 ***	0.152 ***	0.236 ***
	(0.018)	(0.037)	(0.018)	(0.061)
Agricultural subsidies × Land fragmentation	0.033 ***	0.018 ***	0.034 ***	0.041 ***
	(0.003)	(0.006)	(0.003)	(0.011)
Household grain consumption	0.081 ***	0.118 ***	0.080 ***	0.084 ***
	(0.005)	(0.011)	(0.005)	(0.018)
Annual household net income	0.160 ***	0.052 ***	0.166 ***	0.151 ***
	(0.005)	(0.010)	(0.005)	(0.014)
Household income from migrant workers	0.011 ***	0.001	0.012 ***	0.010 ***
	(0.001)	(0.001)	(0.001)	(0.002)
Village population size	0.026 ***	0.037 ***	0.020 ***	0.007
	(0.007)	(0.013)	(0.007)	(0.018)
Village land size	0.010 ***	0.014 **	0.006 **	0.044 ***
	(0.003)	(0.007)	(0.003)	(0.009)
Constant term	3.960 ***	4.937 ***	3.987 ***	4.464 ***
	(0.096)	(0.158)	(0.097)	(0.266)
Province fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Observed values	99,104	14,403	90,802	8302
Sample size	17,444	5226	16,664	3445
Coefficient difference *p*-value	0.000		0.190	

Note: ** and *** indicate significant differences at the 5% and 1% levels, respectively, with robust standard error in brackets.

5. Conclusions

In China's new journey towards comprehensively building a socialist modernized nation, the 20th CPC National Congress explicitly put forward the core requirement of enhancing Total Factor Productivity (TFP). Given agriculture's foundational and comprehensive significance in China, improving agricultural TFP is imperative. As an important fiscal policy tool supporting agricultural development, whether it is the complete abolition of agricultural tax, the provision of various agricultural subsidies such as subsidies for high-quality crop seeds, direct subsidies to grain farmers, subsidies for agricultural machinery purchases, comprehensive input subsidies, or the implementation of the "three agricultural subsidies" reform, all reflect the significant role of fiscal support for agriculture in the process of agricultural modernization. However, due to the widespread issue of land fragmentation in China, the full potential of seeds, fertilizers, large machinery, and other scientific technologies is not realized on many fragmented lands, and the scale of farmers' landholdings limits the effectiveness of agricultural subsidies. Thus, in the context of China's national conditions with "small farmers in a large country," what exactly is the role of agricultural subsidies in agricultural development? Can mere agricultural subsidies be effective? Does land fragmentation lead to efficiency losses in agricultural subsidies? How should land policies and fiscal support for agriculture be coordinated? The answers to these questions are key to clarifying the relationship between fiscal support for agriculture and land reform and are also crucial for China to accelerate its transformation from a large agricultural country to a strong agricultural nation.

This paper is based on the data from fixed observation points in rural China from 2003 to 2017 and utilizes the two-way fixed-effects model and the moderating-effect model to examine the impacts of agricultural subsidies and land fragmentation on the total factor productivity of agriculture. The results show: first, agricultural subsidies have a positive effect on the total factor productivity of agriculture, while land fragmentation leads to a decline in agricultural total factor productivity; second, land fragmentation impedes the effect of agricultural subsidies in improving agricultural total factor productivity. A 1% increase in land fragmentation leads to about a 3% decrease in the enhancement effect of agricultural subsidies, particularly affecting households in major grain-producing areas and those primarily engaged in agriculture; third, there is no evidence to support that the reform of the "three agricultural subsidies" will change the combined effect of agricultural subsidies and land fragmentation on agricultural total factor productivity. The hindering effect of land fragmentation cannot be resolved by reforming the "three agricultural subsidies".

The above basic conclusions are of significant theoretical and practical significance for addressing major issues in the coordinated implementation of agricultural subsidies and land reform in China. They also provide useful references for improving the agricultural support policy system and transitioning from a largely agricultural country to a strong agricultural nation. In this study, there are still some shortcomings that will be improved in subsequent research. For example, due to limitations in data availability, this article uses data from 2003 to 2017. If it is possible to obtain the latest data in subsequent research, we will further enrich the research results and conclusions of this article. At the same time, the model selection in this paper only examined the moderating effect of land fragmentation on the fiscal support for agriculture policy, and only used instrumental variables to examine causal identification to a certain extent. In future research, we will optimize identification strategies and use more convincing models to test causal effects.

Based on the research findings, this paper summarizes the following important policy implications:

Firstly, the incentivizing role of agricultural subsidies remains to be fully unleashed. While the scale of China's fiscal support for agriculture continues to expand, the current reform measures have yet to address fundamental issues, often resulting in inefficient outcomes. Agricultural subsidies play a crucial role in pursuing the policy objectives of building a strong agricultural nation and firmly holding the bottom lines. However, there is still room for enhancing their effectiveness. On top of increasing fiscal expenditure, fiscal policies supporting agriculture should focus on integrating and distributing basic elements. It is essential to leverage the multiplier effect of policy implementation effectively. Active use of fund allocation should guide traditional elements like labor and land, as well as higher-order elements like management and data. This approach aims to break through various institutional mechanisms and resource distribution flaws, focusing on enhancing the Total Factor Productivity of agricultural households. Such measures would ensure that agricultural subsidies fully exert their intended role and continue to play an increasingly significant part.

Secondly, land fragmentation is a key bottleneck in agricultural development. Compared to systemic and institutional issues such as corruption and elite capture, the widespread presence of land fragmentation requires more attention due to its obstructive role. Land fragmentation prevents agricultural production from effectively leveraging economies of scale and agglomeration advantages, significantly impeding the transformation of agricultural subsidies into agricultural productivity. This presents a considerable challenge to achieving various urgent targets in China. The solution to the problem of land fragmentation lies in land consolidation and land transfer. Strengthening land consolidation and promoting land transfer not only can fully realize the positive effects of agricultural subsidies, enhance farmers' operational scale, and improve Total Factor Productivity in agriculture, but also can aid in advancing agricultural modernization and accelerating the development of a strong agricultural nation. This contributes to steadfastly maintaining the fundamental goals of ensuring national food security and preventing a large-scale relapse into poverty.

Thirdly, increasing fiscal support for agriculture must be combined with powerful land reform policies to achieve synergistic efforts. Efficiency losses, caused by inherent mechanisms that have not been precisely identified, make relying solely on fiscal policy akin to a tree without roots or a stream without a source. While it may seem effective, the potential for efficiency improvement remains vast. To address these inherent systemic issues, such as land fragmentation, it is necessary for agricultural policies beyond fiscal investment to enhance institutional innovation and reform efforts, thereby clearing obstacles to the effective allocation and functioning of fiscal funds. In agricultural production, land reform not only unleashes the productivity of idle or fragmented land but also sharpens the focus and objectives of agricultural subsidies. This approach helps fully realize fiscal policy's positive impact on the agricultural sector and avoids the inefficient consumption of fiscal resources and land elements.

Author Contributions: Conceptualization, W.Z.; Funding acquisition, W.Z.; Methodology, Z.Z.; Supervision, W.Z.; Visualization, F.Y.; Writing—original draft, Z.Z.; Writing—review and editing, W.Z., Z.Z. and F.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This paper was supported by the National Social Science Foundation of China (NSSFC), "Research on the long-term mechanism of supporting the will and wisdom to solve relative poverty" (Grant No. 20 & ZD168), and the National Natural Science Foundation of China (NNSFC), "Intergenerational Transmission, Neighborhood Effect, and Educational Poverty: Based on the Perspective of Social Network Economics" (Grant No. 71973102).

Data Availability Statement: Data are available from the authors upon request. The data are not publicly available due to [This data is sourced from the Ministry of Agriculture and Rural Affairs of the People's Republic of China. Any individual or organization using this data must apply to the Ministry of Agriculture and Rural Affairs of the People's Republic of China, and we have no right to disclose this data].

Acknowledgments: The authors are grateful to the Editor and the anonymous referees for their helpful comments and suggestions.

Conflicts of Interest: The authors declare no conflicts of interest.

Notes

1. The data is sourced from an article on the Chinese land rule of law research website titled "Rural Land Systems in the UK and Germany" (30 October 2010). Available online: https://illss.gdufs.edu.cn/info/1024/8140.htm (accessed on 30 October 2010).
2. Due to the lack of continuity and completeness in the statistics of the "number of household labor force" indicator in the database since 2009, we use household grain consumption as a proxy variable for household labor force size.
3. There are a total of 13 major grain production areas, 7 major grain sales areas, and 11 balanced production and sales areas in China. Among them, the natural conditions such as geography, soil, and climate in the main grain producing areas are suitable for planting grain crops, ensuring self-sufficiency while also transferring a large amount of commercial grain, including Heilongjiang, Jilin, Liaoning, Inner Mongolia, Hebei, Henan, Shandong, Jiangsu, Anhui, Jiangxi, Hubei, Hunan, and Sichuan. The main grain

sales areas have relatively developed economies, but with a large population and limited land, there is a significant gap in grain production and demand, including Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan. The production and marketing balance area has made limited contribution to the national grain output, but it can basically maintain self-sufficiency, including Shanxi, Ningxia, Qinghai, Gansu, Xizang, Yunnan, Guizhou, Chongqing, Guangxi, Shaanxi and Xinjiang.

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Understanding Resource Recycling and Land Management to Upscale Zero-Tillage Potato Cultivation in the Coastal Indian Sundarbans

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Citation: Goswami, R.; Roy, R.; Gangopadhyay, D.; Sen, P.; Roy, K.; Sarkar, S.; Misra, S.; Ray, K.; Monjardino, M.; Mainuddin, M. Understanding Resource Recycling and Land Management to Upscale Zero-Tillage Potato Cultivation in the Coastal Indian Sundarbans. *Land* **2024**, *13*, 108. https://doi.org/10.3390/land13010108

Academic Editors: Uttam Khanal and Sanzidur Rahman

Received: 15 December 2023
Revised: 14 January 2024
Accepted: 16 January 2024
Published: 19 January 2024

Abstract: Upscaling sustainable intensification (SI) technologies is crucial to enhancing the resilience of fragile farming systems and vulnerable livelihoods of smallholder farmers. It is also critical to shape the future land-use and land-cover changes in a region. Zero-tillage potato cultivation (ZTPC), introduced as an SI intervention in parts of the Indian Sundarbans, has demonstrated promises of rapid upscaling, and thus, changes in the seasonal land-use pattern in the region. This study aims to understand the socioecological complexity of farming systems to comprehend how the nascent stage of ZTPC thrives at the farm level and what preconditions are necessary to upscale them. The objectives are to analyse the farm resource recycling pattern in ZTPC, and map and simulate its system's complexity to strategize ZTPC upscaling in the region. The analysis of farm resource recycling data reveals that ZTPC stability hinges on managing trade-offs in resource allocations, specifically involving straw, organic manure, sweet water, and family labour. The decision to manage such trade-offs depends on farm type characterizations by their landholdings, distance from the homestead, pond, and cattle ownership, competing crops, and family composition. Using a semiquantitative systems model developed through fuzzy cognitive mapping, the study underscores the significance of effective training, input support, enterprise diversification by introducing livestock, timely tuber supply, access to critical irrigation, and capacity building of local institutions as the essential preconditions to sustain and upscale ZTPC. This research contributes a systems perspective to predict agricultural land use within technology transfer initiatives, providing insights into how farm- and extra-farm factors influence resource allocations for ZTPC. Public extension offices must understand the trade-offs associated with straw, organic matter, and harvested water and design differentiated supports for different farm types. The most compelling interventions to upscale ZTPC includes farm diversification by introducing livestock through institutional convergence, pragmatic agroforestry initiatives to enhance on-farm biomass and fuel production, building awareness and integrating alternative energy use to save straw and cow dung, building social capital to ensure access to sweet irrigation water, and developing and/or strengthening farmer collectives to ensure the supply of quality tuber and marketing of farm produce.

Keywords: farm typology; fuzzy cognitive mapping; network analysis; resource trade-off; technology upscaling; Sundarbans; zero-tillage potato

1. Introduction

Smallholder farmers form the backbone of agriculture in many developing nations, playing a vital role in ensuring food security, livelihoods, and overall economic stability, particularly in climatically challenged regions [1–4]. Moreover, the decisions and actions of these smallholders in utilizing natural resources significantly influence the natural resource use in a given region [5]. Despite their importance, smallholder farmers face numerous challenges, including limited arable land and its tenurial status, resource constraints, and environmental vulnerabilities that impact their productivity and sustainability [6]. However, within these challenges lay opportunities to transform smallholder systems into engines of sustainable intensification (SI) [7,8]. Sustainable intensification is a process or system aimed at increasing agricultural yields without causing adverse environmental impacts and converting additional nonagricultural land [9]. Such intensification is envisioned as a pathway to enhance agricultural productivity while minimizing negative environmental impacts, typically by maximizing the yields from limited land, water, and other inputs [10,11]. The integration of SI in smallholder systems is often dependent on the provisions of internal inputs and their efficient utilization [12,13]. There is evidence of the efficient use of endogenous farm resources [14], emphasizing the importance of precisely understanding the on-farm mechanisms of resource use to redesign, sustain, and upscale SI interventions in a given region.

Kharif rice, grown during the monsoon season in the Ganges coastal zone in India, is vital for the food security and livelihoods of small and marginal farmers in the Sundarbans region. However, soil salinity, caused by factors like seawater intrusion and inadequate drainage, affects the rice yield and quality. This postmonsoon salt accumulation in the soil disrupts the availability of water and nutrients to plants and results in large-scale rice monocropping. This situation severely impacts farm cash income and causes a large-scale male out-migration and feminization of agriculture in the region [15,16].

The introduction of additional crops in synergy with rice-based systems provides an opportunity to alter the seasonal land-use pattern, leading to enhanced farm outputs [17]. Zero-tillage potato cultivation (ZTPC) emerged as a promising option for SI in rice-based cropping systems, exhibiting considerable potential in the saline tracts of coastal agroecosystems [18,19]. ZTPC optimises the residual moisture in the paddy field without soil tillage and incorporating straw mulch. This technique enables the growing of additional crop on lands typically left fallow during the winter months, characterised by water scarcity and high soil salinity [20]. Crucially, ZTPC relies on existing farm resources, emphasizing the necessity to comprehend the utilization of endogenous farm resources to sustain ZTPC with minimal or no additional costs. This understanding is important for anticipating the possibilities and constraints associated with upscaling this practice in the region. From the perspective of land-use planning and policy, such endogeneity related to a cropping system's transformation influences the long-term land-use pattern in a given region.

There is a clear disconnect between the scholarly discourse on resource utilization in agricultural sciences and the domains of land-use patterns and land-use policies. This discrepancy is particularly evident in the agrarian societies of developing nations, where agriculture holds a deep-rooted, ancestral significance and serves as a pillar to sustain food security and livelihoods [21]. Consequently, the analytical lenses of 'transaction cost and political economy' and 'ecosystem services' from natural resources may fall short in explaining the future agricultural land use in marginal ecosystems. While these frameworks are applicable in understanding future land-use patterns in extensively cultivated smallholder systems, the current research prefers examining the endogenous mechanism operating within small-scale farms. This approach can explain farm-level land-use patterns, contributing to shape the upscaling of agricultural innovations in a given region. To complement this perspective, the study employs system-level analytical tools, such as semiquantitative modelling, to explain the preconditions for upscaling agricultural innovations, thereby influencing the regional land-use pattern.

The study posits that the incorporation of ZTPC into rice-based cropping systems is primarily shaped by on-farm resource recycling dynamics, which are crucial for sustaining the input requirements of ZTPC across various farm types. This endogenous mechanism, in conjunction with extra-farm factors such as climate stresses and local institutions, determines the feasibility of upscaling ZTPC, thus shaping the future land and natural resource use in the region. Furthermore, our semiquantitative modelling approach establishes a link between the systems management of ZTPC and its potential to impact the livelihoods of smallholders. In doing so, this research fills in a possible void in the existing literature by connecting farm-level decision-making processes and extra-farm interventions with the promotion of sustainable land-use practices and improved rural livelihoods. The Indian Sundarbans, characterised by its saline soils and fragile ecosystem, offers a unique opportunity to explore the implications of on-farm resource recycling and the upscaling of sustainable intensification technologies.

In this article, farm resource recycling is conceptualised as a network of interconnected farm resources [14], and we studied the structural properties of this network to discern the critical importance of specific elements and structures in sustaining the flow of inputs for ZTPC. Then, using a fuzzy cognitive mapping approach, the analysis examined the relationship between on-farm and extra-farm factors that play a role in sustaining and upscaling ZTPC in the region [22]. This combination of on-farm and extra-farm approaches helps us overcome the micro- and macro-level disconnect in the existing literature, enabling the understanding of the relationships between farm-level actions, technology upscaling, and land-use patterns within an agrarian setting.

Addressing these knowledge gaps would significantly enhance our comprehension of how resource recycling can be leveraged to facilitate the upscaling of sustainable intensification technologies such as ZTPC in smallholder systems, especially in salinity-affected areas like the Sundarbans. This study aims to (a) examine how ZTPC is sustained on farms and (b) identify the preconditions for its upscaling in smallholder systems. The outcome of the study might help the extension agencies and self-governing bodies to identify local adaptations and understand the barriers, incentives, and possible policy measures to trigger the widespread adoption of ZTPC across diverse farm types.

2. Research Methodology

2.1. Selection of Case Study Island

The current study purposively selected Satjelia Island, situated in the coastal region of the Indian Sundarbans (Figure 1), where two projects have been implemented from 2022 to 2024 by the Commonwealth Scientific and Industrial Research Organization (CSIRO) in collaboration with Indian collaborators. The project demonstrated a climate-resilient cropping system featuring salinity-resistant, medium-duration paddy varieties in the rainy season, followed by zero-tillage potato cultivation under straw mulch conditions in the winter season for the examination of the impact of sustainable intensification on the performance of cropping systems and farmer incomes. Satjelia is an island under the Gosaba community development block of the South 24 Parganas district, India. The total population of the island is 8757, of which 857 are cultivators, and 1629 are agricultural labourers. The total geographical area of the island is 10.42 km^2, aquaculture/pisciculture is 0.02 km^2, crop land is 6.43 km^2, lakes/ponds are 0.06 km^2, mangrove/swamp area is 0.56 km^2, and rivers/streams/drains are 0.81 km^2. Rice is the predominant crop grown in the rainy season, followed by potatoes and vegetables on small patches of land (Bhuvan Panchayat 3.0; https://villageinfo.in/west-bengal/south-twenty-four-parganas/gosaba/satjalia.html, accessed on 13 December 2023).

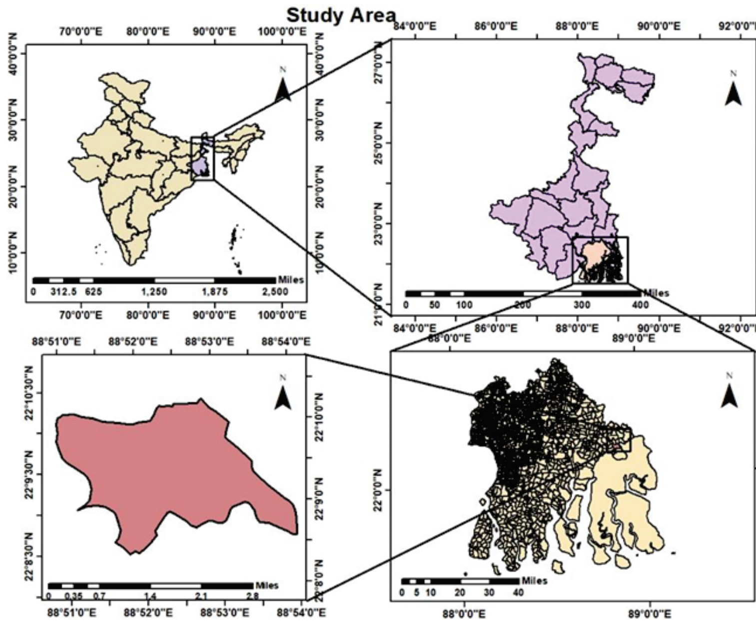


Figure 1. Location map of the study area: Satjelia Island of South 24 Parganas district, India. Clockwise from upper-left: the map of India, map of West Bengal state, map of South 24 Parganas district, and map of Satjelia Island.

2.2. Selection of Respondents

Personal interviews were conducted with 30 purposively selected households that adopted ZTPC on the island and participated in the project actively. Using the primary data and a decision-support tool, the households were categorised into nine distinct farm types (details in Section 3.1 and Table 1). To ensure representation and cooperation, one farm was selected from each farm type in consultation with the community mobiliser. Additionally, for eliciting fuzzy cognitive maps, at least one project beneficiary was deliberately selected from each farm type, considering their alignment with the specific farm type and willingness to participate actively in the mapping exercise.

Table 1. Qualitative description of the farm types (FTs) categorised in the study.

Farm Type (Frequency)	Characteristics
FT-1A (5)	Farms with their own land and at least one cattle and/or many small livestock; cultivate more than 33% of their field in dry seasons, and heavily depend on off-farm income sources as compared to farm income.
FT-1B (7)	Farms with their own land but with no cattle and/or a few small livestock; cultivate more than one crop in dry seasons, covering a substantial area.
FT-2A (2)	Farms with their own land and at least one cattle and/or many small livestock; cultivate less than 33% of their field in dry seasons, and heavily depend on off-farm income sources as compared to farm sources.
FT-2B (2)	Farms with their own land and one cattle or several small livestock; cultivate less than 33% of their field in dry seasons; earn a nearly equal share of off-farm and farm income.
FT-3 (most resourceful) (2)	Farms with their own sizeable land and at least one cattle and/or many small livestock; cultivate more than 33% of their field in dry seasons; earn a nearly equal share of off-farm and farm income.

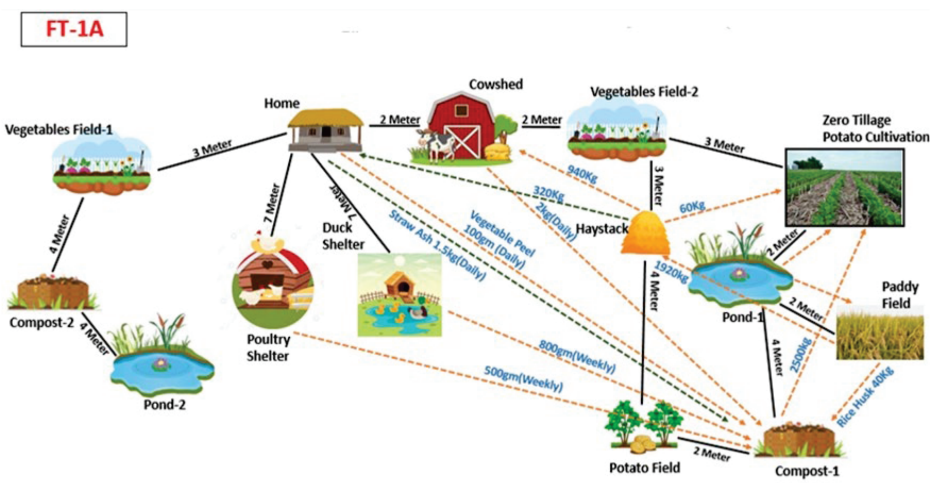
Table 1. *Cont.*

Farm Type (Frequency)	Characteristics
FT-4 (least resourceful) (5)	Farms with their own land but with no cattle and/or a small number of small livestock; cultivate only one crop in their field in dry seasons in a minimal area only.
FT-5 (2)	Landless farms that do not have any land in their name (new generation farmers).
FT-6A (3)	Farms with their own land and small livestock ownership, that cultivate more than 33% of their field in dry seasons, and heavily depend on farm income sources as compared to off-farm sources.
FT-6B (4)	Farms with their own land and at least one cattle and/or many small livestock, but they only cultivate less than 33% of their field in dry seasons, and heavily depend on farm income sources as compared to off-farm sources.

2.3. Data Collection

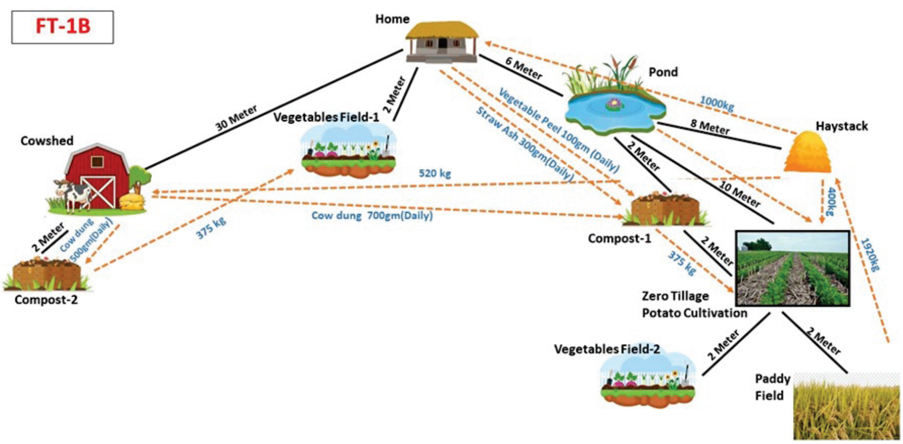
2.3.1. Personal Interviews and Drawing Farm Resource Recycling Maps

The personal interviews with sampled farmers followed a structured interview schedule covering various topics, including household background information, assets and livestock, irrigation access, cropping patterns, income–expenditure details, and farm and off-farm incomes. This information facilitated the allocation of farms to specific farm types using a decision tree developed as part of the project. After the interviews, enumerators visited the farms and drew on-farm resource recycling maps regarding the ZTPC plots on the interview schedule and verified the drawn representations with the farm owners. The redrawn farm resource recycling plans are documented in Figure 2a–i.



(**a**)

Figure 2. *Cont.*



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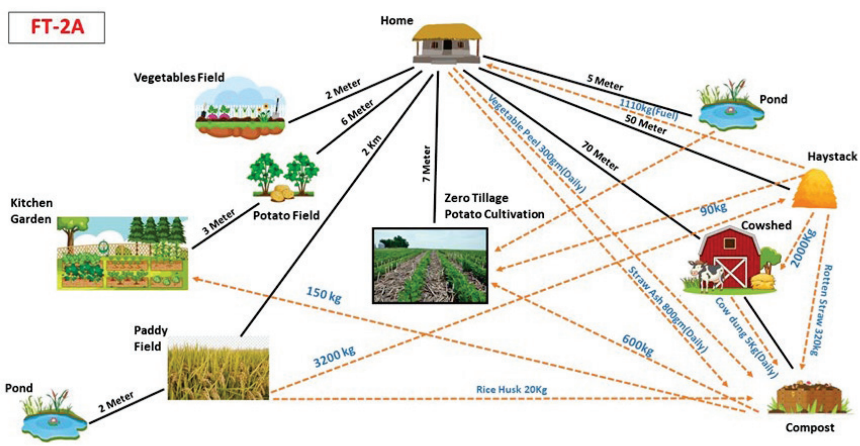

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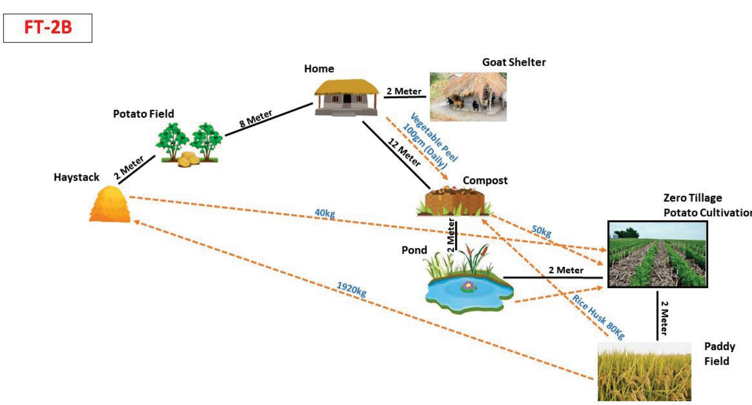
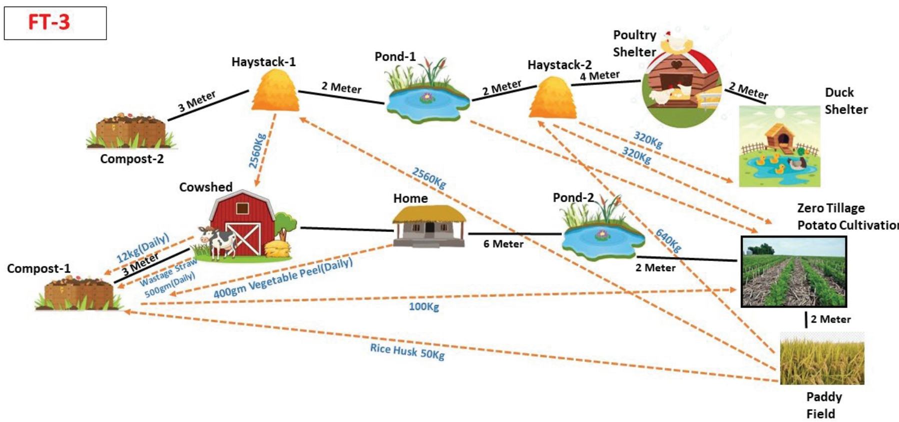
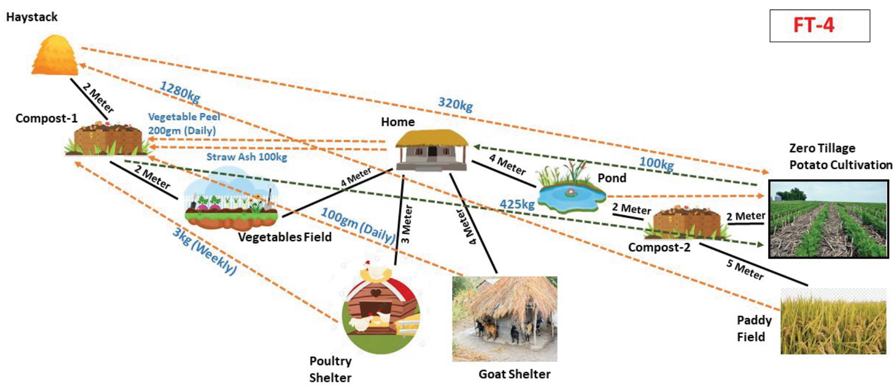


(**d**)

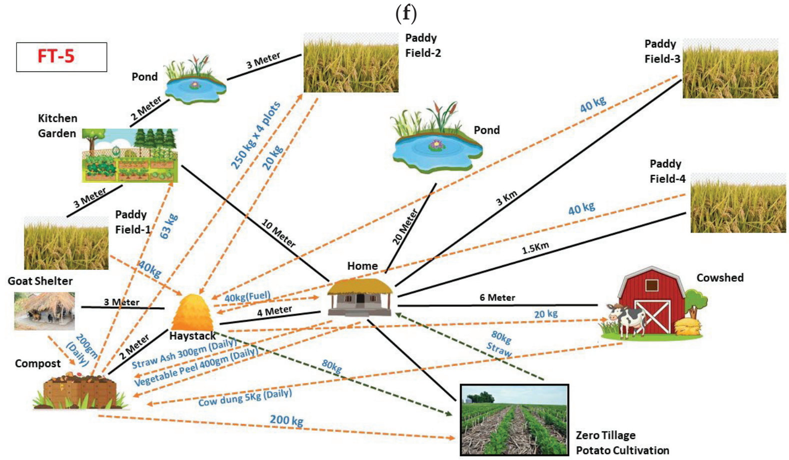
Figure 2. *Cont.*



(e)

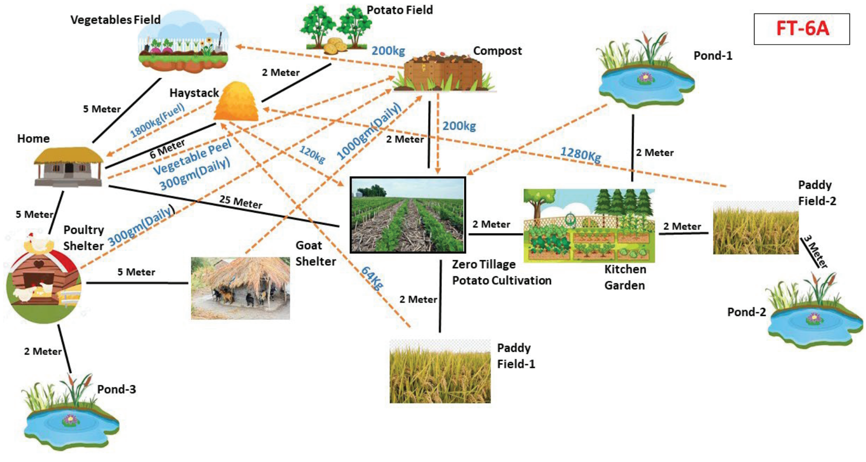


(f)

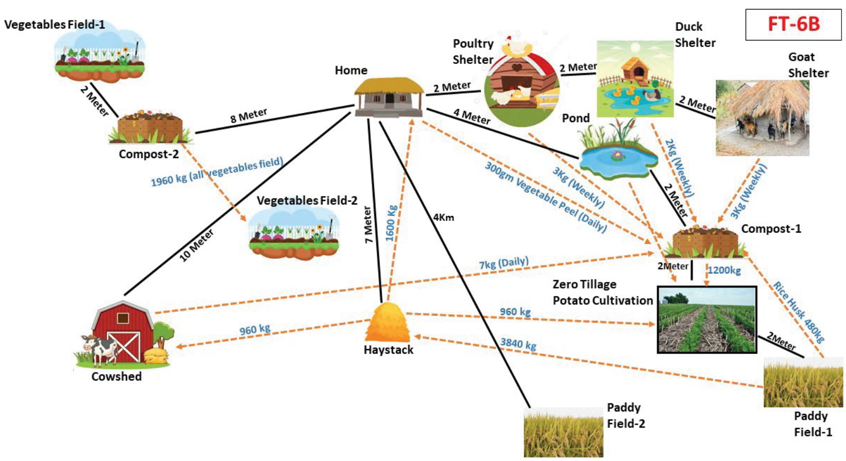


(g)

Figure 2. *Cont.*



(**h**)



(**i**)

Figure 2. Resource flow diagram centred on the ZTPC: (**a**) farm type 1A, (**b**) farm type 1B, (**c**) farm type 2A, (**d**) farm type 2B, (**e**) farm type 3, (**f**) farm type 4, (**g**) farm type 5, (**h**) farm type 6A, and (**i**) farm type 6B. Solid black lines show the distances among farm components. The dotted lines show the direction and magnitude of resource flow among the farm components.

2.3.2. Eliciting the Cognitive Maps from Farmers

Cognitive maps were elicited from a group of representative farmers from each farm type. After gathering the farmers in an open space, facilitators explained the objectives and procedures of the exercise. They started with a focus group discussion on ZTPC, with a checklist to identify possible system elements in the cognitive map. The focus was on understanding the factors driving ZTPC on the island and how both on-farm and extra-farm factors influenced crop yield and associated farm income. Once a consensus on the system elements was reached, facilitators wrote the names of the elements onto rectangular cards. They spread the cards on the open yard and asked the participants to link them with locally available materials. Then, the participants were prompted to assess each dyadic element relationship at two levels: (a) what is the type of relationship between two elements, positive or negative; and (b) what is the strength of the relationship on a scale of 0–10? We deliberately avoided the complexity of requesting ratings on a scale from −1 to +1 (the original method of FCM). Upon completion of the exercise, the participants examined and validated the map. The facilitators ensured that all the participants contribute and validate the final map. A photograph of the map was captured, and a paper copy of the same was prepared. The facilitator also recorded the discussion among the farmers throughout the exercise.

2.4. Data Analysis

2.4.1. Farm Resource Recycling

All the hand-drawn farm resource recycling maps covering all nine farm types were converted into nine weighted adjacency matrices based on their resource flow pattern. These matrices were then combined into a single matrix. Using UCINET 6 network analysis software Version 6.759 [23], the network-level (e.g., density) and node-level (e.g., centrality) properties for all nine resource recycling networks were generated. NetDraw software Version 2.179 [24] generated a combined resource flow network that highlighted its central elements and the magnitude of resource flow among them. Detailed network property definitions can be found in Table S2 (Supplementary Information).

2.4.2. Analysis of the Cognitive Maps

The cognitive map was analysed following the works of Ozesmi and Ozesmi [25] and Gray et al. [26]. However, minor adjustments and adaptations were made to suit the purpose and context of this study. First, we coded the cognitive map developed by the group of farmers into an adjacency matrix, meaning that the elements in the cognitive maps are placed into rows as well into columns. Then, we entered the value of each pair of elements (-1 to +1), as specified by the farmer group, in the corresponding cell of the matrix. This matrix was used to analyse the structure of the cognitive map using UCINET software Version 6.759. On the other hand, we recreated the cognitive map using Mental Modeler software [25] to run the scenario analysis. We analysed the cognitive map to study its structure at the (a) map or network level (e.g., density) and (b) element level (e.g., centrality). The definitions related to the structural analysis of the cognitive map are given in Table S2 (Supplementary Information). The variables having the highest centrality values are the ripple points of the system.

Finally, 'what-if'-type questions were posed about how the system might react to different contexts (scenarios). First, the elements with high centrality values (>mean + one standard deviation) were selected, whose initial values were 'clamped/activated' ('0' means 'not activated' and '1' means 'activated'). The elements and their combinations were identified in consultation with the local experts to specify the scenarios for running the scenario analysis [27]. The activation of elements under a scenario spread through the matrix following the weighted relationships. The resulting values of concepts help in understanding the outcome of a scenario (steady state).

3. Results

3.1. Farm Typology

A predesigned decision-support tool was employed to allocate new farms to specific farm types. We followed the standard technique of farm-type identification in the local context [28] and developed a modified decision-support tool following Hammond et al. [29]. These farm types varied in nature, characterised by various criteria including landholdings, tenurial status, cropping patterns, access to irrigation sources, farm vs. nonfarm income, and migration (Table 1). These distinctive characteristics significantly influence how ZTPC is practised on the farms and impacts farm incomes. While examining the resource recycling patterns centred on ZTPC plots, farms from each of the nine farm types were deliberately selected.

3.2. Farm Resource Recycling

3.2.1. The Nature of the Recycling Network

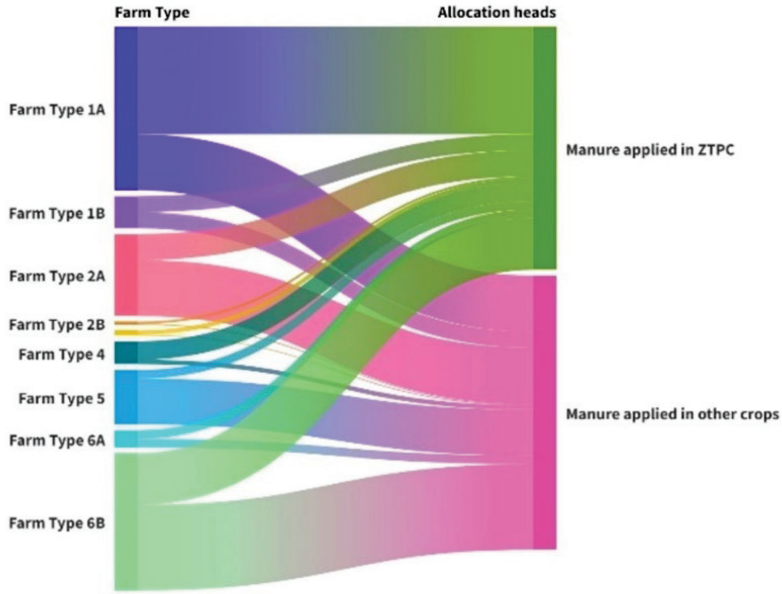
Across different farm types of subtle variations in resource recycling, patterns exist due to contextual factors including landholding and fragmentation, distance from the homestead, pond, and cattle ownership, competing crop demand for manure and irrigation water, and family labour availability. For instance, in FT-1A (Figure 2a), manure application is relatively higher but straw usage is relatively lower than other farm types due to its primary use as cattle feed and fuel (Figure 3b). Biomass for compost preparation is collected from diverse sources such as cattle shed, poultry litter, and household waste. The field's proximity to the homestead and pond also improves the management of ZTPC.

FT-1B (Figure 2b) splits the manure between ZTPC and other vegetable plots (Figure 3b), with straw being used for fuel and animal feed (Figure 3a). FT-2A (Figure 2c) allocates a minimal proportion of straw, but a larger share of compost, to the ZTPC field (Figure 3a,b). FT-2B (Figure 2d) does not own any cattle and allocates a negligible amount of straw or compost to ZTPC (Figures 2d and 3a,b). FT-3 is resource rich and allocates substantial straw for cattle feed (Figure 2e) and limited organic manure to ZTPC (Figure 3a,b). FT-4 (Figure 2f) owns no cattle and allocates a higher proportion but lower volume of organic manure to ZTPC (Figure 3b). FT-5 (Figure 2g) is landless and grows paddy rice in leased plots, selling most straw and using unsold amounts for fuel and mulching in ZTPC (Figure 3a). FT-6A owns no cattle, using limited straw for mulching and the rest as fuel (Figures 2h and 3b). FT-6B (Figure 2i) depends heavily on farm income, and produces sufficient straw for fuel, animal feed, and mulching in ZTPC. Manure is utilised in both ZTPC and for other crops (Figure 3a). FT-1A produces the highest volume of organic manure, allocating a higher proportion to the ZTPC field, unlike other farm types (Figure 3a). FT-5 produces the most paddy straw, which is mainly used for animal feed and fuel. Only a small portion is used in ZTPC, potentially posing a challenge to its upscaling. The proximity of the fields to ponds and homesteads further influences ZTPC management. These observations highlight the importance of manure and straw allocation for the sustainable integration of ZTPC into smallholder systems.

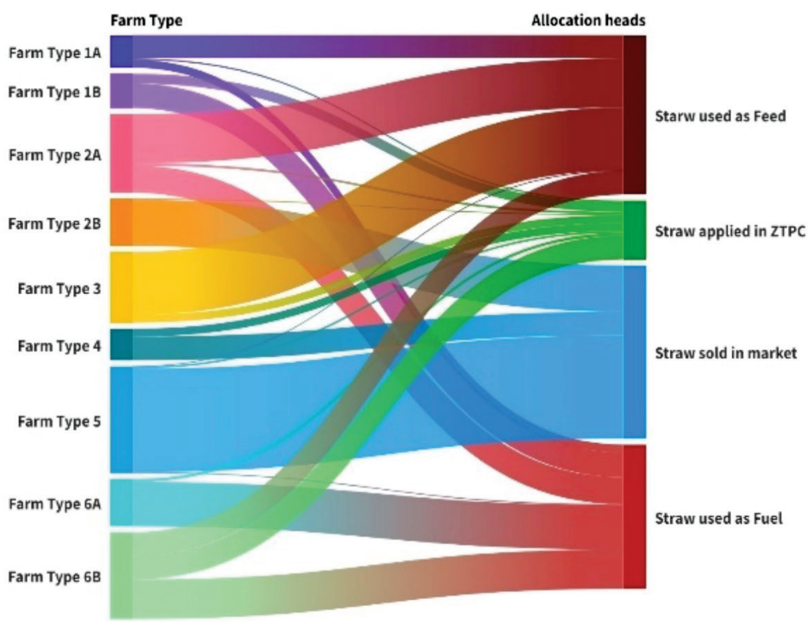
The study analysed the network properties of the nine resource interaction networks and observed the following pattern (Table 2): (a) FT-1A and FT-6A had the highest numbers of elements or components (14 each) directly or indirectly linked to sustaining ZTPC; (b) FT-1B and FT-6B utilised most of their farm components by establishing linkages with other components, resulting in higher-density scores (0.026 and 0.029, respectively); (c) FT-1A and FT-2A relied on off-farm income sources and demonstrated lesser recycling practices; (d) FT-4 lacked resources due to no cattle ownership, limiting manure-based and feed-based linkages; and (e) FT-5 exhibited relationships (indegree and outdegree) reflected in its density score (0.024), despite being landless.

Table 2. Network properties of farm resource recycling patterns across farm types.

	FT-1A	FT-1B	FT-2A	FT-2B	FT-3	FT-4	FT-5	FT-6A	FT-6B
No. of elements	14	10	11	8	12	10	13	14	13
No. of linkages	8	11	4	10	10	8	10	9	12
Density	0.019	0.026	0.010	0.024	0.024	0.019	0.024	0.021	0.029



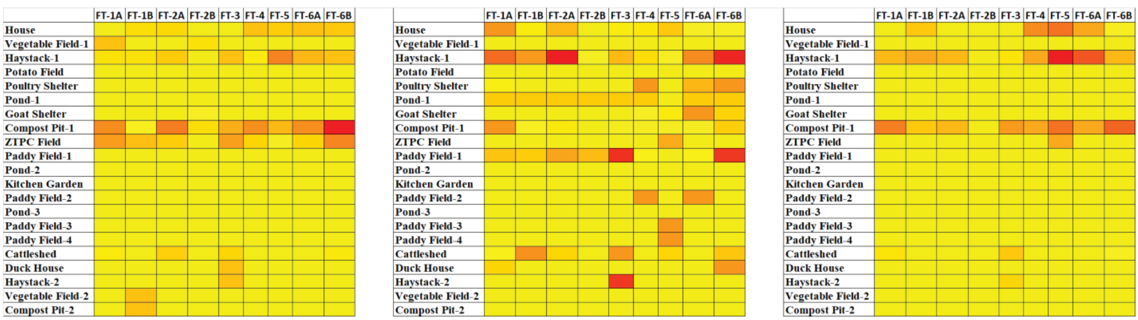
(**a**)



(**b**)

Figure 3. Differential allocation of farm resources by different farm types: (**a**) manure; (**b**) paddy straw.

Figure 4 depicts the indegree, outdegree, and betweenness centralities of farm components in the resource recycling networks, with each type of centrality score normalised for a meaningful comparison. The original data are given in the Supplementary Information (Tables S3–S11). Deeper red colours indicate a higher score, while lighter yellow denotes lower scores. For instance, in Figure 4a, the deep red colour in the 'Compost Pit-1' cell against FT-6B implies a high accumulation of biomass sources in the preparation of on-farm composting. The analysis of individual network properties of farm components across farm types revealed that both the compost pit and ZTPC field properties had the highest indegree centrality, receiving biomass and inputs from diverse sources (Figure 4a). FT-1A and FT-6B, in particular, demonstrated high indegree scores. However, the outdegree scores were more evenly distributed across farm components and farm types (Figure 4b). Paddy fields, haystacks, ponds, and cattle sheds (for those with cattle) were more central, with more resources flowing among the components continuously. FT-1A, FT-6B, and FT-3 had more components with a higher resource outflow potential. The compost pit and haystack properties showed the highest betweenness centrality, directly linking the resource flow to ZTPC (Figure 4c). The house (e.g., kitchen) also plays an important linking function through fuel consumption and household waste production.



(**a**) (**b**) (**c**)

Figure 4. Network properties of all farm types: (**a**) indegree, (**b**) outdegree, and (**c**) betweenness. All weighted values are max–min normalised. Yellow and red colours denote lowest (0) and highest values (100), respectively. See Supplementary Table S1a–c for corresponding cell values.

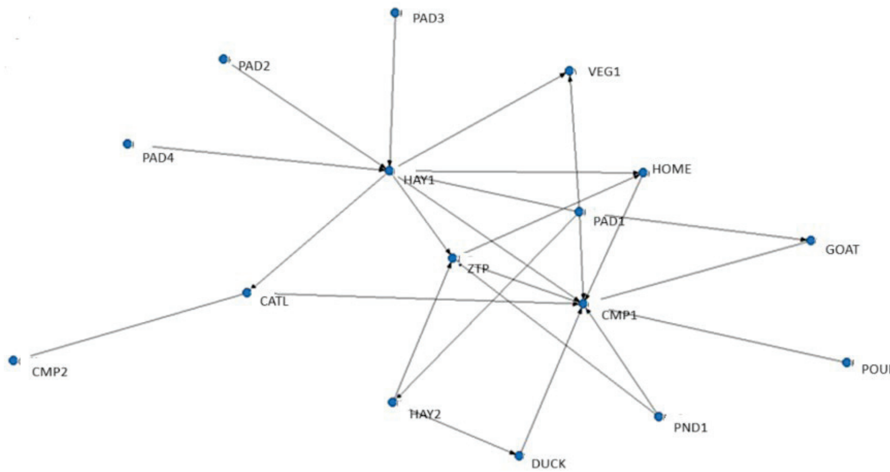
3.2.2. Resource Recycling Network for All Farms

A network with combined resource interactions for all nine farm types (individual networks given as Figure S1a–i) was developed by augmenting components and adding matrices (Figure 5a). The nodes in the diagram are farm components and the linkages (lines) represent the dyadic resource flow between them. The thickness of the lines represents the magnitude of resource flow among farm components. A high magnitude of 2-eigenvector centrality can be observed, which accounts for linkages with more central nodes, for the cattle (CATL), compost (CMP1), home (HOME), paddy field (PAD1), haystack (HAY1), and ZTPC field (ZTP) (Figure 5b). Among these, compost (CMP1) and haystacks (HAY1) showed a higher betweenness centrality (Figure 5c), suggesting that sustaining and upscaling ZTPC is contingent upon the amount of straw and compost sourced from within the farm and applied in the ZTPC field. There is also significant interdependence among the paddy field/s, pond/s, and small livestock, providing necessary biomass and sources of critical irrigation. Furthermore, the thickness of linkages represents the multiplex relationship (linkages between components occurring in more than one farm type), suggesting the critical importance of the following multiplexes: (a) paddy > haystack (straw) > ZTPC > compost; (b) haystack (straw) >home > compost; and (c) cattle > compost > ZTPC.

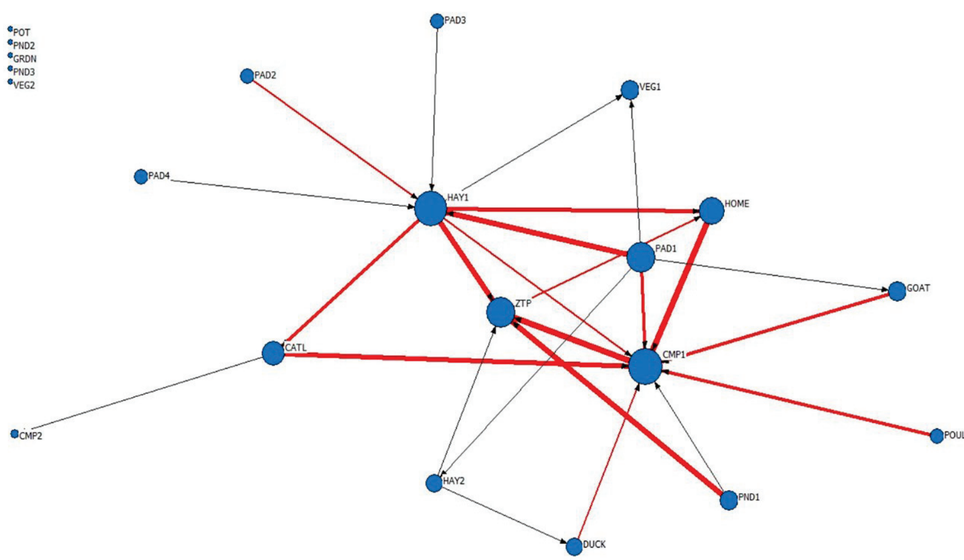
3.3. The Semiquantitative Model for Sustaining and Upscaling ZTPC

3.3.1. The Structural Analysis of the Cognitive Map

The cognitive map was developed using Mental Modeler software (Figure 6). The map represents a network of linked components associated with ZTPC—both causal and consequential—leading to positive impacts on farmers' livelihoods. In the local context, the map conceptualises the 'climatic hazards', project intervention ('CSI4CZ'), 'local institutions' including 'Panchayat' (grassroot-level, self-governing body), 'peer support network', 'land ownership', and more 'acreage' of ZTPC as short-term 'drivers' for the model. The model was extended from increased 'potato production' and 'income' to broader livelihood impacts such as the 'family expenditure', 'investment in next cultivation', 'health expenditure', and 'children's education', which constitute the suite of 'receiver' components in the model.

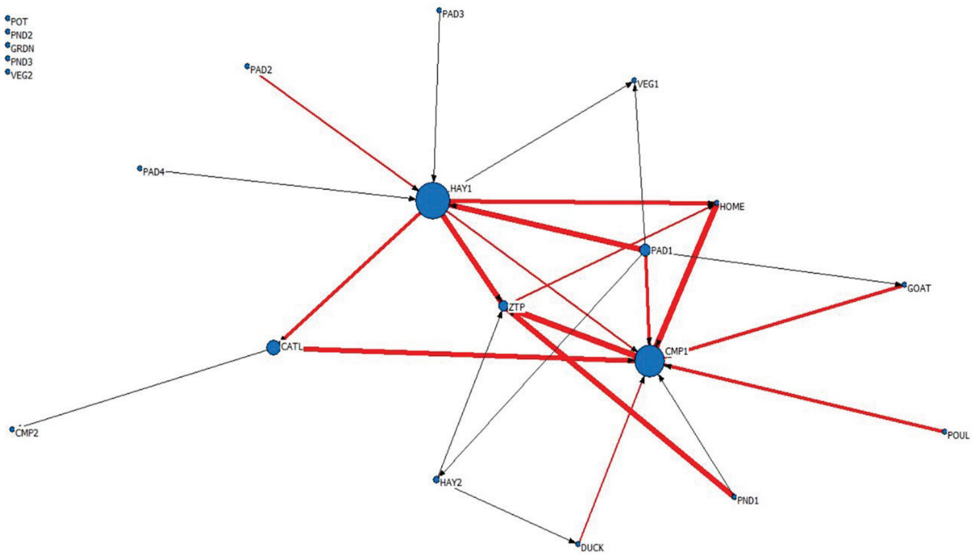


(**a**)



(**b**)

Figure 5. *Cont*.



(**c**)

Figure 5. Combined network diagram of all nine farms: (**a**) nonweighted, (**b**) nodes scaled by 2-eigenvector centrality, and (**c**) nodes scaled by betweenness centrality. Line thickness represents the magnitude of resource flow. Black lines have negligible flow of resources between elements. PAD—paddy; HAY—haystack; PND—pond; GOAT—goat; DUCK—duck; POUL—poultry; CMP—compost; CATL—cattle; ZTP—zero-tillage potato; VEG—vegetable; HOME—home.

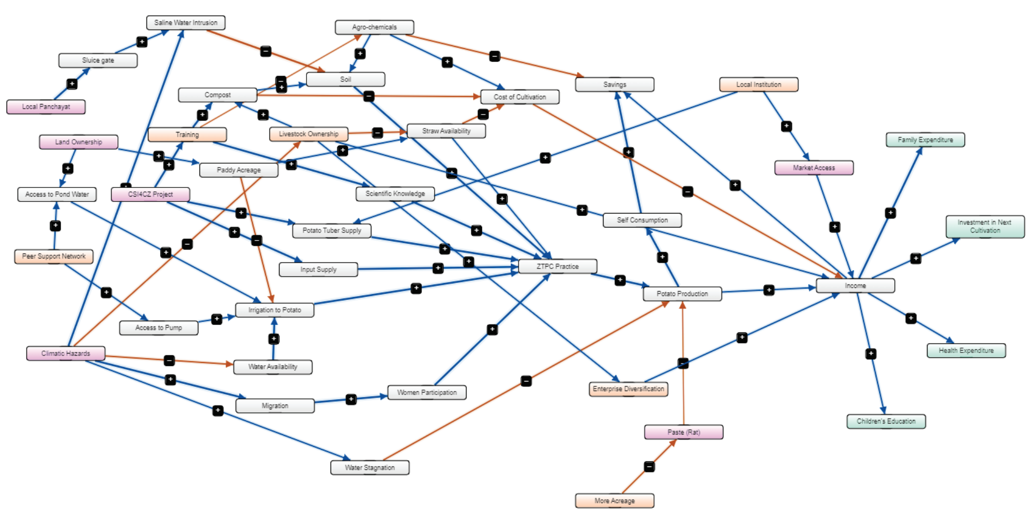


Figure 6. Semiquantitative model developed using fuzzy cognitive mapping for Satjelia Island. Blue and red lines indicate positive and negative relationships between model components, respectively.

In terms of the indegree (i.e., receiving impacts from other components), the 'ZTPC practice' was central (emboldened), with the other components being 'income' and 'savings', 'soil' health, and 'irrigation to potato' at critical stages of growth (Table 3). Regarding the outdegree, the most central components (emboldened) were 'climatic hazards', 'income', 'CSI4CZ' intervention, 'livestock ownership', 'agrochemical' use, and 'training' of farmers.

In terms of (eigenvector) 'centrality', the components that emerged as central were 'ZTPC practice', 'irrigation to potato', 'livestock ownership', 'income', 'climatic hazards', 'soil' health, 'potato production', and 'compost' availability. The high centrality of these elements signifies their critical role in stabilizing the system to impact farmers' livelihoods. These nodes are often used to develop scenarios during the scenario analyses.

Table 3. Component and network properties of the semiquantitative model for integrating and upscaling ZTPC for creating livelihood impact.

Component	Indegree	Outdegree	Centrality	Type
Investment in next cultivation	0.663	0.000	0.663	receiver
Health expenditure	0.730	0.000	0.730	receiver
Family expenditure	0.875	0.000	0.875	receiver
Children's education	0.550	0.000	0.550	receiver
Income	**3.438** *	**3.438**	**6.875**	ordinary
Potato production	1.943	1.711	**3.654**	ordinary
ZTPC practice	**6.172**	0.894	**7.067**	ordinary
Soil	**2.589**	0.867	**3.456**	ordinary
Saline water intrusion	1.741	0.956	**2.697**	ordinary
Climatic hazards	0.000	**3.961**	**3.961**	driver
Water stagnation	0.800	0.593	1.393	ordinary
Training	0.917	**2.046**	**2.962**	ordinary
Agrochemicals	0.290	**2.217**	**2.507**	ordinary
Scientific knowledge	0.894	0.850	1.744	ordinary
Potato tuber supply	1.661	0.889	**2.550**	ordinary
CSI4CZ project	0.000	**2.839**	**2.839**	driver
Self-consumption	0.889	0.867	1.756	ordinary
Savings	**2.281**	0.000	**2.281**	receiver
Sluice gate	0.839	0.830	1.669	ordinary
Local panchayat	0.000	0.839	0.839	driver
Input supply	0.961	0.928	1.889	ordinary
Pest (rat)	0.600	0.456	1.056	ordinary
Irrigation to potato	**3.173**	0.839	**4.012**	ordinary
Access to pond water	1.000	0.811	1.811	ordinary
Access to pump	0.500	0.822	1.322	ordinary
Water availability	0.800	0.900	1.700	ordinary
Peer support network	0.000	1.000	1.000	driver
Compost	1.661	1.381	**3.042**	ordinary
Livestock ownership	0.600	**2.766**	**3.366**	ordinary
Women participation	1.000	1.000	**2.000**	ordinary
Migration	0.850	1.000	1.850	ordinary
Market access	0.800	0.560	1.360	ordinary
Cost of cultivation	1.770	0.600	**2.370**	ordinary
Land ownership	0.000	1.300	1.300	driver
Paddy acreage	0.800	1.440	**2.240**	ordinary
Straw availability	1.400	1.400	**2.800**	ordinary
More acreage	0.000	0.600	0.600	driver
Local institution	0.000	1.500	1.500	driver
Enterprise diversification	0.680	0.770	1.450	ordinary
Whole Network Properties				
Total components	39			
Total connections	58			
Density	0.039			
Connections per component	1.49			
Number of driver components	7			
Number of receiver components	5			
Number of ordinary components	27			
Complexity score	0.714			

* Emboldened values of network components are relatively more central to the model.

The network representing the semiquantitative model is complex, with 39 components and 58 connections. This indicates the multiple pathways in the model's functioning. The complexity score, representing the ratio of 'driver' and 'receiver' components, is close to one, suggesting numerous opportunities for systems interventions.

3.3.2. Scenario Analysis of the Semiquantitative Model

The study conducted a scenario analysis based on the cognitive map (semiquantitative model) generated by FGD participants. Using the centrality scores of the model's components, four distinct scenarios were formulated in consultation with the stakeholders: (1) providing effective training on ZTPC, (2) introducing livestock to diversify the farming systems, along with access to critical irrigation, (3) investing in peer support networks and ensuring the supply of quality potato tuber through local institutions, (4) discontinuing input support with project withdrawals. These scenarios were established using the Mental Modeler's "Scenario" module by triggering the relevant system elements [26] independently and incrementally.

The simulation outputs were combined and synthesised to generate Figure 7. Providing effective training (scenario 1) would lead to the perfection of ZTPC practices and a reduction in the cost of cultivation. Diversifying the system by means of livestock and critical irrigation (scenario 2) would enhance the compost volume, potato production, and farm income. The establishment and/or strengthening of local institutions to ensure the timely supply of quality tuber (scenario 3) would increase potato production and farm income. However, withdrawing project facilities such as the input support (scenario 4) could raise concerns about reduced acreage and tuber production. The red arrows in Figure 7 suggest the fear of immediate reduction in a timely seed supply, precision in practice, and tuber production. Scenarios 1, 2, and 3 may mitigate the immediate fear of a reduction in ZTPC acreage.

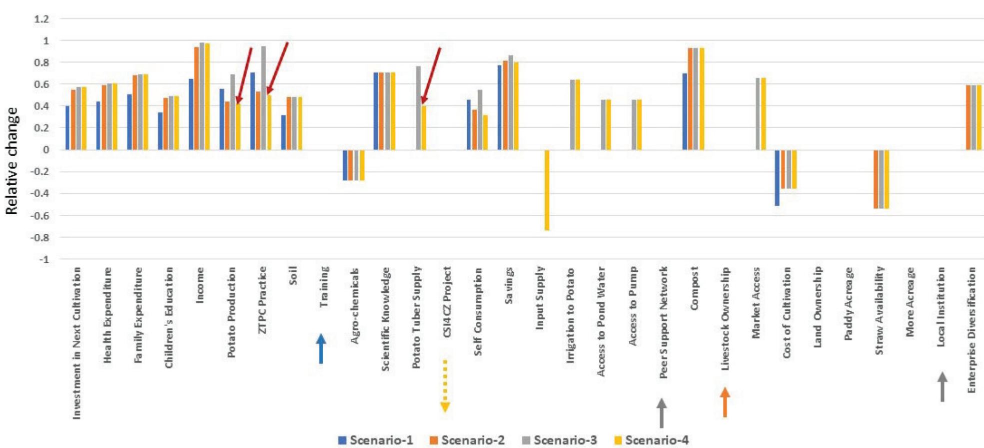


Figure 7. Scenario analysis showing the predicted impact on the system elements under four different scenarios. The x-axis represents the system elements, and the y-axis represents the estimated change in given system components under different scenarios. Values above and below zero are positive and negative changes, respectively.

4. Discussion

4.1. Prologue

Farmers of the Sundarbans often modify their land-use practices in pockets of the regions to efficiently utilise the available natural resources in lean agricultural months. For example, harvested rainwater in small waterbodies is often used for providing critical irrigation to additional crops. Other modifications include farm and enterprise diversifications, engaging in nonfarm activities during lean months, and most importantly, recursive migration to near and distant locations. Thus, there is a hidden nexus of climate, seasonality, natural resource use, farm management, and labour availability. Planned agricultural development often fails to manage the dynamics of natural resource use and human decision making. There are not many examples of upscaling sustainable intensification in the region except for the modified land-use models [30,31]. Donor-supported systems research identified sustainable intensification in the region, coupled with technology integration and upscaling through community-managed, on-farm demonstrations and policy advocacy. In these initial years, the demonstration is at the nascent stage of on-farm practice standardization, and one needs to wait to see the upscaling in the next few years.

4.2. The Trade-Off in Allocating Farm Resources

System-level analytical tools, such as semiquantitative modelling, were used to understand the preconditions for upscaling an innovation like zero-tillage potato cultivation and its impact on regional land use. ZTPC has emerged as an alternative to fallowing (in the wet season) and existing potato cultivation practices in the dry season in the study region. Farmers with access to harvested fresh water traditionally grow an extra crop on small plots after the paddy harvest. Paira cropping (sowing pulses (e.g., lathyrus) before a paddy rice harvest) utilises residual soil moisture for an extra crop [32]. ZTPC offers a more remunerative short-duration crop, especially when critical irrigation opportunities are limited. It aligns with local food habits and acts as a buffer against market volatility. Notably, potatoes are a central component in traditional Bengali cuisine.

The practice of ZTPC largely relies on available resources such as straw (for mulching), organic manure (as a nutrient source), harvested fresh water (for critical irrigation), and family labour (for management). However, there is a trade-off between using these resources for ZTPC and their alternative uses. For example, organic manure, water, and labour can be allocated to competing crops (if there is one). The straw can serve as fuel and cattle feed. Furthermore, decision-making depends on the farm type. Farms with larger plots and paddy acreage may not face critical trade-offs (FT-3). Farms with many cattle and limited alternative energy sources have a higher straw demand (FT-2A and FT-3). Some farmers sell straw and work off farm for cash income. The organic manure allocation varies among competing crops, especially in farms with land and irrigation provisions. For example, FT-1A allocated a sizeable proportion of manure to ZTPC, where FT-2A, FT-5, and FT-6B allocated organic manure to competing crops. Also, cow dung is often used as an energy source (for cooking). Similarly, harvested fresh water has multiple uses, including to irrigate other crops, fishponds, and domestic use. Labour availability depends on the family composition and migration patterns. Such a trade-off in resource allocations is widely reported in studies on integrated systems approaches, such as Value-Ag [33], and understanding such bioeconomic trade-offs may help us design suitable options for intensification [34]. Overlooking such a trade-off might overestimate the outcomes of ZTPC [35].

In summary, the allocation of resources is specific to each farm. Factors such as paddy acreage, pond size, livestock ownership, family labour availability, and ZTPC acreage play a crucial role. The study locations are not yet in that critical stage (except for marginal holdings) where ZTPC acreage emerges as competitive to alternative uses of farm resources.

4.3. The Resource Recycling Plan and Sustaining ZTPC

The sustainability of smallholder farming systems is dependent on the judicious use of scarce resources, especially in underserved regions [36]. Farming systems often undergo endogenous intensification due to resource constraints [37], providing the context of sustainable intensification. In the case of ZTPC, study results found that some farms used their resources more extensively than others by establishing more dyadic linkages, such as FT-1B, 2B, FT-3, FT-5, and 6B. However, the utilisation of linkages accounts for both the inflow (indegree) and outflow (outdegree) of resources, where the outflow is directly related to inputs going into ZTPC. Components like the paddy field, straw (haystack), pond, and cattle shed (manure/compost) exhibited a higher centrality (outdegree) in the resource interaction networks, as more frequent and substantial amounts of resources flowed from these components to others. Among these, straw and manure had the highest betweenness, signifying their crucial role in linking the resource flow from multiple directions and channelling the effects towards ZTPC. The resource interaction network encompassing all the farms also supports these observations (Figure 5b,c).

However, the 'home' (household waste recycling unit) is included in the network encompassing all farm types. This is important since 'home' serves as a significant producer of biomass (household waste) and consumer of straw as fuel. While the research work did not undertake any detailed structural analysis of the networks, from the multiplex relationship (same dyadic linkage existing in several resource recycling networks) represented by linkage thickness, one can anticipate the fundamental importance of the (a) paddy $\rightarrow$ haystack (straw) $\rightarrow$ ZTPC $\leftarrow$ compost; (b) haystack (straw) $\rightarrow$ home $\rightarrow$ compost; and (c) cattle $\rightarrow$ compost $\rightarrow$ ZTPC. Managing these relationships should be a focal point for the upscaling effort of ZTPC in the region. While identifying such motifs for complex systems management is reported in the study of human decision making in sustainable agriculture [38], and very recently in farming system's analysis [14], these are as of now underreported, if not unreported, in the literature on technology transfer and upscaling.

However, recent research in the regional context observes the limitation of the Boserupean imperative of endogenous intensification in farming systems [37] to manage resource constraints, particularly in densely populated areas [39]. Farms in such regions require external support to sustain ZTPC, which can significantly impact the livelihoods of farming families. The study outcomes present this argument, in the form of a desirable systems model that integrates farm-level and extra-farm-level preconditions to upscale ZTPC in and around the demonstrated locations. This necessitated the application of a semiquantitative systems model to identify the preconditions for the successful upscaling of ZTPC.

4.4. The Preconditions for Upscaling ZTPC

Fuzzy cognitive mapping (FCM) is used to develop semiquantitative models of complex systems based on stakeholder knowledge [40]. The cognitive map, representing the model, is then used to simulate the system's behaviour under realistic scenarios to anticipate future outcomes (ex ante assessment). The model, elicited from the FGDs of farmers using FCM, showed the centrality of training, project support (CSIRO Project), timely supply of potato tuber (potato tuber supply), and provision of critical irrigation (irrigation to potato) to crops. These preconditions contribute to the improved precision of the ZTPC practice (ZTPC practice), resulting in a higher potato production and income, ultimately leading to improved livelihoods outcomes. However, to ensure these causal transitions from actions to outcomes, the management of sluice gates to control saline water intrusion and adequate compost application needs to be maintained for soil health. On the other hand, reducing agrochemical application alongside compost application lowers the cost of cultivation and increases savings. A precise ZTPC practice also requires straw availability, which is a function of paddy acreage and livestock ownership. All these central causal components of the model are further driven by climatic hazards, land ownership, local panchayats, and external project support (drivers). The higher centrality of these elements, coupled with field observations and stakeholder consultations, helped us in identifying the four future scenarios (Section 3.3.2). The simulation results suggest that a combination of effective training, system diversification with livestock, provisioning of critical irrigation, and strengthening local institutions to ensure a quality tuber supply on time can sustain and upscale ZTPC for creating a long-term livelihood impact.

Technology integration and upscaling pose complex managerial challenges requiring systems modelling and designs [41] and necessitate suitable governance to manage sustainable transitions in agriculture [42]. Often, managers of natural resource management projects find it difficult to anticipate project outcomes despite having an explicit change theory. They may also fail to identify the most appropriate bundles of intervention to improve complex socioecological systems by introducing promising technologies. This research underscores the necessity of understanding complex systems in proposing future change theories in technology upscaling projects in food and agricultural development [43] in the context of climate change [44], and advocates for the leveraging of novel system analysis tools to explore and simulate uncertain outcomes of systems interventions.

4.5. Linking Resource Recycling with Future Land-Use Pattern and Rural Livelihoods

The paper closes its arguments by linking farm-level resource recycling and systems-level preconditions with land-use patterns in the region under concern. The intensification of agricultural land is one of the most significant forms of modifying land cover. The models for predicting land-use and land-cover (LULC) changes may be dynamic or static, nonspatial or spatial, deductive or inductive, pattern based or agent based [45,46]. However, limited attention has gone into the research on rural LULC changes that examine the land-cover modification process, particularly on the complex relationships between people and their management of land resources [47] in technology-transfer initiatives. This study has particularly addressed this underreported issue and examined farm-level and extra-farm factors influencing future LULC changes on an island of the Indian Sundarbans. For example, a satellite-based approach may capture the cropping intensity dynamics [48] but may not precisely account for how microlevel factors shape the resource allocation for ZTPC. Furthermore, it is difficult to capture how factors in a complex socioecological system interact (captured in the cognitive map) to affect the future upscaling of ZTPC on Satjelia Island. While this study is not a replacement for the predominant methods employed in an LULC study, it may inform and supplement the standard models by providing a systems perspective in predicting agricultural land use.

The current research has shown that paddy acreage, livestock and pond ownership, and family composition form the central nexus in resource allocations for ZTPC. It is known that a combination of effective training, system diversification with livestock, provisioning of critical irrigation, and strengthening local institutions to ensure a quality tuber supply on time can sustain and upscale ZTPC, potentially changing the LULC change in the region. The adoption of ZTPC by approximately 450 farmers in the last two seasons has been recorded.

This change in LULC is also linked to the livelihoods of cash-starved farmers in the region. The expanded acreage makes ZTPC more attractive to the farmers. The net return from one Katha (0.0067 ha) on average is ~INR 400–700, which needs to be enhanced to INR 10,000, which is 15–20% of the average annual cash income in the area (found in a baseline surveys). The study team anticipates that the INR 10,000 target may be achieved by a 200% enhancement in the tuber yield (at least in locations with a higher yield gap), which needs a 3–4 times area enhancement and the selling of potatoes at a 50% enhanced market price. From the application of the smallholder ADOPT model for zero-tillage potato cultivation (not reported here), the project team anticipates that 98% of the farmers are likely to accept ZTPC in the area in the next 7 years. Even if half of the estimated farmers in the immediate vicinity of the project locations adopt the innovation, the number of adopters might stand at 2500–3000. Given the upscaling potential is achieved in terms of acreage, cost reduction, labour engagement, and market price, this might result in an immediate increase of INR 25–30 million (~AUD 0.45–0.55 million) in the hands of local farmers, apart from creating its multiplier effect in the local economy.

However, it may be argued that the extreme vulnerability of the region to climatic variations and perturbations may fundamentally change the findings of the study. First, an untimely rainfall or cyclone may lead to abandonment, crop loss, or even crop failure. Under such crises, livestock often are affected and male members migrate outside the island to earn cash. On the other hand, dry spells and the resultant soil and water salinity might impact the provisioning of critical irrigation. Thus, climatic vagaries might fundamentally change the functioning of the socioecological systems, and thus impact the crop yield, farm economics, straw and organic manure use, and labour and input management.

The studies of complex systems are bound to have methodological limitations, and their external validity is always subject to scrutiny. In the current research, ZTPC receives differential preferences across farm types, posing a challenge to the estimation of its upscaling potential. Farm types are dynamic and may undergo significant changes following perturbations in socioecological systems. Furthermore, populist public service initiatives and market fluctuations can profoundly affect farmer's resource allocation plans related to ZTPC. These effects are difficult to nullify through methodological adjustments. On the other hand, elicited cognitive maps may not account for all potential factors of complex systems, especially those that differ geographically from the study's context. This may be exacerbated if the full participation of participants in the mapping exercise is not ensured. Also, the scenarios employed in the study are ad hoc and not the outcome of socially constructed options in a workshop setting. It is essential to note that this research primarily aimed to establish the rationale of a system design in technology upscaling and does not fall within the framework of action research. The insights derived from the study, however, can be readily adopted and adapted by academics and practitioners in future endeavours.

5. Conclusions

Upscaling sustainable intensification (SI) is crucial to enhance the resilience of fragile farming systems and vulnerable livelihoods in the coastal Sundarbans. Zero-tillage potato cultivation (ZTPC) has been tried as an option for SI as part of CSIRO-supported projects in the Indian Sundarbans. The study explores the socioecological complexity to understand how the nascent stage of ZTPC thrives at the farm level, and what preconditions are necessary to upscale it. The current research concludes that the stabilization of ZTPC depends on the management of resource allocation trade-offs involving straw, organic manure, sweet water, and family labour. However, the decision to manage trade-offs depends on the farm types characterised by their landholdings, distance from the homestead, pond and cattle ownership, competing crops, and family composition.

However, the endogenous intensification style of farm resources has limitations, necessitating external support for ZTPC's sustainability. The semiquantitative systems model, developed using fuzzy cognitive mapping, emphasises the importance of effective training, input support, enterprise diversification by introducing livestock, timely tuber supply, access to critical irrigation, and capacity building of local institutions as essential preconditions to sustain and upscale ZTPC. This research contributes a systems perspective to predicting agricultural land use in the context of technology-transfer initiatives, providing insights into how farm- and extra-farm factors shape resource allocation for ZTPC.

Public extension offices must understand the trade-offs associated with straw, organic matter, and harvested water and design differentiated supports for different farm types. The most compelling interventions seem to be (a) farm diversification by introducing livestock through institutional convergence, (b) pragmatic agroforestry initiative to enhance biomass and fuel production, (c) building awareness and integrating alternative energy use to save straw and cow dung, (d) building social capital to ensure access to sweet irrigation water, and (e) developing and/or strengthening farmer collectives to ensure the supply of quality tuber and the marketing of farm produce.

An increasing adoption of ZTPC in the last two seasons indicates potential LULC change and positively impact the livelihoods of cash-starved farmers in the region. The projected adoption by a significant number of farmers could lead to substantial economic gains and multiplier effects in the local economy, highlighting the transformative potential of ZTPC in the Sundarbans.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land13010108/s1, Figure S1: (a–i) resource interaction network surrounding the zero-tillage potato cultivation fields across farm types; Table S1: Values of different centralities of network elements for different farm types; Table S2: Description of key terms and measurements used in the analysis of resource recycling network and cognitive map; Tables S3–S11: Node properties of different farm elements linked to ZTPC. References [24,49,50] are cited in the supplementary materials.

Author Contributions: Conceptualization, R.G., M.M. (Marta Monjardino) and M.M. (Mohammed Mainuddin); methodology, R.G., R.R. and D.G.; validation, R.G., R.R. and D.G.; formal analysis, R.G. and D.G.; investigation, R.R., D.G., P.S. and K.R. (Kalyan Roy); resources, M.M. (Marta Monjardino), R.G. and S.S.; data curation, R.R., D.G. and R.G.; writing—original draft preparation, R.G., R.R., D.G. and M.M. (Marta Monjardino); writing—review and editing, M.M. (Marta Monjardino), S.S., S.M. and K.R. (Krishnendu Ray); visualization, R.G. and D.G.; supervision, M.M. (Mohammed Mainuddin), M.M. (Marta Monjardino) and R.G.; project administration, M.M. (Mohammed Mainuddin), M.M. (Marta Monjardino), R.G., S.S., K.R. (Krishnendu Ray) and S.M.; funding acquisition, M.M. (Mohammed Mainuddin). All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Australian Centre for International Agricultural Research (ACIAR), Australia through the project 'Mitigating risk and scaling-out profitable cropping system intensification practices in the salt-affected coastal zones of the Ganges Delta—CSI4CZ Phase II' (LWR 2014 073) and the Department of Foreign Affairs and Trade (DFAT), Australia through the SciTech4Climate Indo–Pacific Climate-Smart Agriculture Initiative: Project B: 'Ganges coastal zone climate smart agricultural production' (OD-227626), with a co-investment from the Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia.

Institutional Review Board Statement: The study was conducted following the human research ethics procedure of CSIRO (approval number 013/21 granted on 09 March 2021).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the ongoing nature of the research.

Acknowledgments: We are grateful to the researchers and students at the Ramakrishna Mission Vivekananda Educational Research Institute (RKMVERI) for conducting the demonstrations on salinity-resistant paddy varieties followed by ZTPC and for collecting the agronomic and socioeconomic data during 2022–2024. We also thank the farmers who participated in the interviews.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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ISBN 978-3-7258-0540-2