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The Impact of Factor Price Change on China's Cotton Production Pattern Evolution: Mediation and Spillover Effects

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Abstract: Cotton is an important agricultural crop and strategic resource. China is currently the country with the largest global cotton production and consumption, but few studies have systematically analyzed the dynamic relationship between factor price change (FPC) and cotton production pattern evolution (CPPE). Based on provincial panel data from the main cotton planting areas from 1985 to 2021, this paper used spatial econometric models to empirically analyze the impact of FPC including labor price, production material cost, and mechanical cost on CPPE from the perspective of mechanical substitution difficulty. The findings are that (1) FPC significantly affected CPPE, specifically the rise of labor price induced the demand for mechanical substitution, resulting in a significant cotton agglomeration effect; (2) spatial econometric analysis found that FPC had a significant spatial spillover effect on CPPE in adjacent regions; and (3) the transfer analysis found that higher mechanical substitution difficulty exerted an inhibitory effect on cotton planting, leading to a gradual shift of the main cotton planting areas from the Yangtze River Basin and Yellow River Basin with high labor prices to the Northwest Inland region with lower labor prices. Updating the production technology and improving the efficiency of cotton specialization are effective strategies. The results are valuable for policy making related to the development of China's cotton industry.

Keywords: factor price change; mechanical substitution difficulty; cotton production pattern; spatial spillover effect



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1. Introduction

Cotton serves as a major source of income in the global agricultural and textile sectors, bridging the gap between the two industries [1]. As one of the world's primary raw materials for the textile industry, cotton has significantly promoted the industry's growth. It creates employment opportunities for individuals and fosters economic development. Furthermore, cotton has played a crucial role in promoting the development of the economy and society, profoundly making a significant contribution to the economies of numerous developing nations [2,3]. China is globally recognized as the leading producer and consumer of cotton. In 2023, China's cotton production reached 5.618 million tons, accounting for over 25% of global production. China's cotton continues to supply high-quality textiles to countries worldwide, contributing to the enhancement of human health and well-being [4–6]. Cotton, besides grain, is the most important agricultural crop and strategic resource, which was once a traditionally advantageous economic crop industry [7], playing a crucial economic role by serving as a bulk agricultural product and raw material for the textile industry [8,9]. China's cotton industry has gradually formed a “tripartite equilibrium” pattern supported by three major cotton planting areas: the Yellow River cotton region, the Yangtze River cotton region, and the Inner Northwest cotton region [10]. China

has achieved significant success in cotton cultivation, but at the same time, there has been a rapid decline in traditional cotton planting areas in the Yangtze River and Yellow River basins, while there has been a rapid increase in the Northwestern Inland region [11,12]. Within a span of forty years, the main cotton-producing areas have shifted from the Yangtze River Basin and Yellow River Basin to the Northwestern region, specifically Xinjiang and Gansu. Apart from agricultural regions, the cotton cultivation areas in Xinjiang and Gansu have increased by 888.59% and 179.83%, respectively, while other provinces have experienced a significant decrease. For instance, seven provinces and municipalities, including Shanxi, Jiangsu, Zhejiang, Shandong, Henan, Sichuan, and Shaanxi, have experienced a reduction of over 90% in cotton planting areas. Meanwhile, Hebei, Anhui, Jiangxi, and Hubei have seen decreases of 60% to 80%. This shift has preliminarily established a pattern where the cotton industry in China is now centered around Xinjiang [13–16].

Cotton is a type of industrial raw material, so factor price is the main factor affecting a country's cotton competitiveness [17]. Given that cotton production exhibits both labor-intensive [18] and capital-intensive characteristics [13,19], it is influenced by various factors, including land, labor, capital, and technology. With economic globalization, market opening, and policy adjustments, factor prices have fluctuated, leading to a continuous decline in cotton production. Recently, there has been a persistent increase in expenses related to cotton production, while the comparative benefits have continuously decreased, further contributing to the decline in cotton production. In 2018, the cost of cotton production in China was more than three times that of the United States and four times that of India [20]. In 2023, China produced a total of 5.618 million tons of cotton, which was 362,000 tons less than the previous year, indicating a decrease of 6.1%. Consequently, it is important to increase cotton production yields. Cotton production in the United States and Australia is highly mechanized, resulting in minimal labor costs. In contrast, countries such as China, Turkey, and Uzbekistan have lower levels of mechanization in cotton production, leading to higher labor inputs [21]. Specifically, the degree of mechanization is particularly crucial in cotton production [22].

Research on the impact of FPC on CPPE is relatively scarce. Current studies primarily focus on the following areas: (1) Exploring the spatial pattern of cotton production. Several studies have investigated the cotton production pattern at different scales, such as nation, basin, province, district, and municipal levels [23]. (2) Exploring the driving factors contributing to cotton yields has always been a widely discussed topic. Existing academic studies have discussed the impacts of the influencing factors, such as market price, target price policy [3], subsidy [24], climate change [25–27], soil fertility [28,29], and technology [6,30]. Understanding these factors is crucial for improving agricultural productivity. For instance, market prices, subsidies, and target price policies can enhance cotton producers' enthusiasm for cotton production, leading to higher yields. An increase in daytime maximum temperatures accelerates cotton photosynthesis, leading to increased yields [31]. Additionally, technologies such as plastic film mulching, close planting, and drip irrigation under mulching play significant roles in boosting cotton production. (3) Numerous studies have identified a mechanism for enhancing agricultural productivity, suggesting that the mechanization of agricultural production could free up labor from farms. Han et al. (2013) [32] found that advanced agricultural mechanization production improved crop cultivation efficiency, making it a crucial factor in increasing cotton yields in Aksu City, Xinjiang, except for warming. Zhou et al. (2024) [33] demonstrated that the combination of nitrogen fertilization and agricultural mechanization can further enhance cotton yields. However, these studies tend to focus on singular outcomes and have not explored the relation between labor price, material cost, mechanical cost, and crop production pattern using a spatial economic model with enhanced accuracy. The extent to which changes in factor prices influence cotton production in neighboring areas across the entire cotton production region remains unquantified.

This study utilizes a spatial economic model to effectively reveal the spatial relationships between the local area's FPC and the adjacent area's CPPE. Due to significant

differences in natural conditions, resource endowments, and economic environments across different regions, agriculture production exhibits distinct spatial characteristics [34,35]. That is, the production behaviors and outcomes in the adjacent areas often influence each other. For example, factor price changes in a local area may affect the agricultural decisions of neighboring areas. Therefore, utilizing spatial econometric methods can explore spatial correlation and heterogeneity, thereby analyzing the driving factors affecting the cotton production pattern from a spatial perspective. Measuring the spatial relationship between FPC and CPPE is crucial for providing a more comprehensive understanding of cropping structure change. In summary, the impact of FPC on the evolution of cotton patterns in China remains unclear. The relationship between FPC and cotton pattern evolution has rarely been explored at regional scales. There are notable gaps in the literature concerning how FPC affects CPPE. To address these research gaps, this study focuses on the driving mechanisms of FPC on CPPE. Based on this, we develop a theoretical framework linking FPC and CPPE. To reveal the impact of FPC on cotton pattern evolution, this study employs Moran's I and spatial economic models to address the following aspects: (1) to assess how FPC influences CPPE and its associated heterogeneity, and (2) to identify the influence mechanism of FPC on CPPE through mechanical substitution.

The rest of the manuscript is structured as follows: Section 2 introduces the theoretical framework; Section 3 presents the methodology; Section 4 outlines the spatial regression analysis; and Section 5 discusses the conclusions and policy implications.

2. Literature and Theoretical Framework

2.1. Effects of Factor Price Change on Cotton Production Pattern Evolution

Agricultural production demonstrates significant spatial agglomeration characteristics [34–37], leading to the formation of specialized cultivation zones, such as wheat belts, corn belts, cotton belts, grape belts, etc. [38]. Cotton production is an industry that demands substantial inputs of labor, land, and planting materials, which is influenced by natural conditions, socio-economic conditions, technological conditions, and policy conditions. Among these influencing factors, factor price change has a particularly significant impact on cotton production. Factor price change refers to the cost change of inputs such as labor, capital, land, and technology. In China, cotton production is concentrated in the Yangtze River Basin, the Yellow River Basin, and the Xinjiang region. With the rapid economic development of the Yangtze River Basin and the Yellow River Basin, labor costs and fixed material costs have risen substantially. Despite farmers increasing their use of pesticides, fertilizers, and seeds, it remains challenging to mitigate the growing labor shortage. Changes in the relative prices of these factors lead to adjustments in the input structure [39,40], ultimately determining the optimal production structure. Hence, farmers in the Yangtze River Basin and the Yellow River Basin have gradually withdrawn from cotton production and switched to crops that have lower labor costs and easier mechanization. Crop switching is an important pathway to achieving sustainable agricultural development. Compared to the Yangtze and Yellow River basins, Xinjiang and Gansu, with their vast planting land and relatively lower labor costs, have comparative advantages in terms of cotton yield per unit, average net income per mu, and cotton irrigation facilities, thereby promoting mechanized cultivation. This encourages farmers in Xinjiang and Gansu to shift towards cotton production, while those in the Yangtze Basin and Yellow River Basin move towards grain production, thereby affecting the regional layout of cotton production [16,20]. Therefore, we propose Hypothesis 1:

Hypothesis 1. *CPPE demonstrates a spatial agglomeration, and The FPC has a significant spatial effect on CPPE.*

2.2. Effects of Factor Price Change on Cotton Production Pattern through Mechanical Substitution Difficulty

Agricultural mechanization improves fieldwork efficiency and land productivity, which is conducive to the adoption of management measures, which, in turn, promotes agriculture yields [41,42]. The difficulty of mechanical substitution in cotton planting is influenced by the complexity of the processes involved [43]. Specifically, the various stages of cotton production, such as planting, field management, and harvesting, are often more complex and delicate compared to those of other crops [33]. For instance, cotton harvesting requires meticulous handling to avoid damaging the cotton fibers, which demands high precision and flexibility from machines. Additionally, the height and structure of different cotton varieties vary greatly, further increasing the complexity of mechanical usage. Although mechanization can improve efficiency and reduce costs, fully replacing manual labor in cotton cultivation remains a formidable challenge due to these complexities. Han et al., (2013) [32] found that advanced agricultural mechanization production improved crop cultivation efficiency, resulting in increasing cotton yields in Xinjiang. Xinjiang has flat agricultural lands that are suitable for mechanized operation and large-scale production. The mechanized cotton harvesting productivity in Xinjiang, China, is at a leading level domestically, but it is still lower than that of major cotton-producing countries such as the United States and Brazil. In summary, the transition from manual labor to mechanized systems in cotton farming is hindered by the intricate nature of the required tasks. With the continuous increase in labor costs, regions with higher mechanical substitution difficulties may struggle to maintain their production levels, leading to a spatial shift in cotton cultivation from high labor cost regions to those with lower labor costs. This dynamic process underscores the importance of technological advancements to overcome these challenges and ensure sustainable cotton production. Therefore, we propose Hypothesis 2:

Hypothesis 2. *The higher difficulty of mechanical substitution exerted an inhibitory effect on cotton production.*

The mechanism analysis is presented in Figure 1.

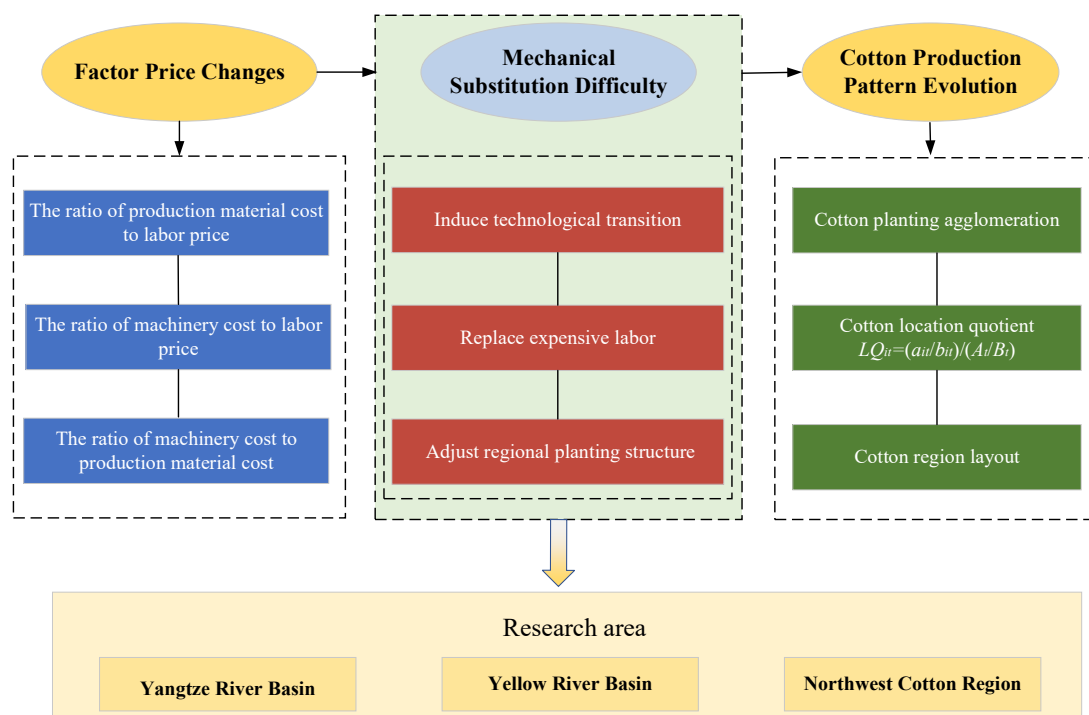


Figure 1. The mechanism of FPC affecting CPPE.

3. Methodology and Data Sources

3.1. Methodology

3.1.1. Benchmark Model

To reveal the influencing mechanism of *FPC* on *CPPE*, the ordinary least squares (OLS) model for the impact of *FPC* on *CPPE* is set as follows:

$$CPPE_{it} = \alpha + \beta_1 FPC_{it} + \beta_2 Dcs_{it} + \beta_3 Z_{it} + \varepsilon_{it} \quad (1)$$

In the formula, *CPPE_{it}* represents the cotton production pattern evolution, which is measured by the location quotient (*LQ*) for province *i* in year *t*. *FPC_{it}* represents the factor price change, which includes labor price, production material cost, and mechanical cost. *Dcs_{it}* represents the difficulty of mechanical substitution. *Z_{it}* refers to the control variable group, which is divided into two groups in this study.

3.1.2. Global Moran's I Index

The cotton production pattern exhibits distinct basin characteristics, indicating the presence of spatial autocorrelation and spillover effects in cotton cultivation across various provinces. To examine the spatial correlation and the degree of regional agglomeration in cotton production, this study employs the Global *Moran's I* index to test for spatial autocorrelation [44]. The formula is as follows:

$$Moran's\ I = \left[n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (LQ_{it} - \overline{LQ_t})^2 (LQ_{jt} - \overline{LQ_t}) \right] / \left[\sum_{i=1}^n \sum_{j=1}^n W_{ij} \sum_{i=1}^n (LQ_{it} - \overline{LQ_t})^2 \right] \quad (2)$$

$$W_{ij} = w_{ij} / \sum_{j=1}^n w_{ij} \quad (3)$$

In Formula (2), *LQ_{it}* represents the cotton location quotient for province *i* in year *t*, *LQ_{jt}* represents the cotton location quotient for province *j* in year *t*, *n* is the number of provinces, $\overline{LQ_t}$ is the average of cotton location quotients for all provinces in year *t*, and *W_{ij}* is the binary spatial weight matrix. In this matrix, adjacent provinces in geographical space are assigned a value of 1, non-adjacent provinces are assigned a value of 0, and diagonal elements are set to 0.

Based on the assumption of a normal distribution, the expected value, variance, and standardized value of the Global Spatial Autocorrelation index are constructed, and the formula is as follows:

$$E(Moran's\ I) = 1 / (1 - n) \quad (4)$$

$$Var(Moran's\ I) = (n^2 W_1 + n W_2 + 3 W_0^2) / [W_0^2 (n^2 - 1) + 1 / (n - 1)] \quad (5)$$

$$Z(d) = (Moran's\ I + \frac{1}{n-1}) / \sqrt{var(\frac{1}{1-n})} \quad (6)$$

In Formula (5), *W_i* represents the sum of the values in the *i*-th column of the weight matrix. The significance of spatial correlation is assessed using the standardized value *Moran's I* for *i*. If the standardized value *Z* exceeds the critical value of 1.96 under a normal distribution at the 5% significance level, it indicates a significant spatial correlation.

3.1.3. Spatial Economic Model

The existing literature shows that the cotton production pattern is not only directly affected by the local labor price, material cost, mechanical cost, natural conditions, comparative benefit, and other factors, but also by relevant factors in the neighboring regions. The nature of geography highlights that everything is related to everything else, but near things are more related to each other. The OLS model did not consider spatial dependence and heterogeneity, which may result in sample information distortion. To address this issue, it

is essential to establish a spatial econometric model to analyze the impact of FPC on CPPE. To investigate how FPC affects CPPE, a series of spatial economic models including the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM) were used in this study [45]. The SLM, SEM, and SDM were then used in STATA 16.0 software to identify the spatial effect of FPC with the consideration of the spatial lag or spatial error terms [46]. The spatial economic model equations are as follows:

The spatial lag model (SLM) is expressed as

$$CPPE_{it} = \alpha + \rho \sum_{j=1}^n W_{ij} CPPE_{it} + \beta X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (7)$$

where ρ is the spatial autoregressive coefficient, W_{ij} is the spatial weight matrix, β is a vector of coefficients X_{it} , and X_{it} represents the vector of explanatory and control variables.

The spatial error model (SEM) is expressed as

$$\begin{aligned} CPPE_{it} &= \alpha + \beta X_{it} + \mu_i + \nu_t + \varepsilon_{it} \\ \mu_{it} &= \lambda \sum_{j=1}^n w_{ij} \mu_{jt} + \varepsilon_{it} \end{aligned} \quad (8)$$

where λ is the spatial autocorrelation coefficient of the error term.

The spatial durbin model (SDM) is expressed as:

$$CPPE_{it} = \alpha + \rho \sum_{j=1}^n W_{ij} CPPE_{it} + \beta X_{it} + \gamma \sum_{j=1}^n W_{ij} X_{ij} + \mu_i + \nu_t + \varepsilon_{it} \quad (9)$$

where μ_i and ν_t represent the province-specific and year-specific fixed effects. ε_{it} represents error terms. X_{it} represents the vector of explanatory and control variables, including explanatory variables (PRL , MAL , MAP , Dcs) and control variables (Dar , Pia , Pmy , $Gpad_{t-1}$).

Since the above regression coefficients cannot directly measure the spatial spillover effects of the explanatory variables, the partial differentiation method for spatial regression models proposed by LeSage and Pace effectively solved the problem of reasonable interpretation of the estimated coefficients in spatial econometric models. This method has been widely applied in various research fields. The formula is as follows:

$$Y = (I_n - \rho W)^{-1} (I_n \beta + W \lambda) X + (I_n - \rho W)^{-1} \varepsilon \quad (10)$$

The partial differential matrix of the dependent variable relative to the k -th explanatory variable in different spatial units:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \dots \\ Y_n \end{bmatrix} = \sum_{s=1}^t \begin{bmatrix} K(W)_{11} & K(W)_{12} & \dots & K(W)_{1n} \\ K(W)_{21} & K(W)_{22} & \dots & K(W)_{2n} \\ \dots & \dots & \dots & \dots \\ K(W)_{n1} & K(W)_{n2} & \dots & K(W)_{nn} \end{bmatrix} \begin{bmatrix} X_{1s} \\ X_{2s} \\ \dots \\ X_{ns} \end{bmatrix} + M(W) \varepsilon \quad (11)$$

where I_n is an identity matrix, β_s is the estimated coefficient of the s -th explanatory variable ($s = 1, 2, \dots, t$), and λ is the regression coefficient in WX . $K(W)_{ij}$ represents the impact of explanatory variable X_j on Y_i . $K(W)_{ii}$ represents the impact of the explanatory variable X_i on Y_i .

3.2. Selection of Variables

3.2.1. Explained Variables

Previous studies have generally measured specialization using the planting area of crops. However, relying solely on planting area to determine the distribution patterns of cotton regions can overlook disparities in land resources among different provinces. For instance, provinces like Henan, Hebei, and Shandong have larger cotton planting areas, primarily due to their significantly greater land resources compared to other provinces. Building on the foundational design concept of the spatial Gini coefficient, this study

employs the cotton location quotient (LQ) index to measure $CPPE$. The specific calculation formula is as follows:

$$LQ_{it} = (a_{it}/b_{it}) / (A_t/B_t) \quad (12)$$

where LQ_{it} represents the cotton planting agglomeration, a_{it} is the cotton planting area for province i in year t , b_{it} is the total planting area for all crops for province i in year t , A_t is the total cotton planting area in year t , and B_t is the total planting area for all crops in year t . The higher the value of the location quotient, the higher the concentration degree of cotton planting.

3.2.2. Explanatory Variables

Numerous factors influence cotton production yield, including economic factors, natural conditions, technological advancements, social policies, and others [47–49]. Under market economy conditions, these factors influence cotton production through the price mechanism, specifically reflected in the change of the relative factor prices. Mechanization consistently ranks as one of the most crucial inputs in global cotton production [50]. Cotton growers have adopted mechanization in response to labor shortages and rising wages.

① Due to rising labor costs and the need for more efficient material inputs, such as fertilization methods with fewer but larger applications, farmers can effectively reduce labor expenses. Consequently, substituting labor with material inputs has emerged as a rational strategy for enhancing agricultural yields. To represent the relative prices of material costs to labor costs, we selected the ratio of production material cost to labor price (PRL_{it}). PRL_{it} is calculated as the ratio of production material cost to the average labor cost per unit of area, the equation was as follows:

$$PRL_{it} = \frac{Prod_{it}}{Labor_{it}} \quad (13)$$

② The change in the relative price of mechanization to labor induces the adoption of mechanical technology, leading to technological advancements in machinery and, consequently, increasing agricultural production [51,52]. Therefore, we used the ratio of mechanical cost to labor price (MAL_{it}) to represent the relative prices of mechanization to labor. MAL_{it} is calculated as the ratio of mechanical cost to the average labor input discount per unit of area, the equation was as follows:

$$MAL_{it} = \frac{Mach_{it}}{Labor_{it}} \quad (14)$$

③ The relative price of mechanical costs to production material costs is an important factor affecting cotton yield. It not only directly impacts the efficiency and cost of the production process but also indirectly influences farmers' economic decisions and investment strategies. The ratio of mechanical cost to production material cost (MAP_{it}) is defined as the ratio of mechanical costs to the average production material cost per unit area, the equation was as follows:

$$MAP_{it} = \frac{Mach_{it}}{Prod_{it}} \quad (15)$$

3.2.3. Mediating Variables

Mechanical substitution difficulty (Dcs_{it}) is represented by the ratio of the change in labor input relative to the previous year to the change in mechanical input relative to the previous year. A higher ratio signifies lower substitutability of mechanical input for labor, indicating greater difficulty in replacing labor with machinery. Conversely, a lower ratio indicates lower difficulty in substituting machinery for labor.

3.2.4. Control Variables

① Internal and External Conditions for Cultivation: Natural conditions provide the foundation for cotton cultivation, while irrigation conditions serve as essential requirements and guarantees. According to the relative literature, we have selected three factors to reflect the comparative advantage of cotton cultivation: the natural conditions for agricultural production (Dar_{it}) are indicated by the ratio of the disaster-affected area to the total planting area, the degree of irrigation conditions (Pia_{it}) is indicated by the ratio of effectively irrigated area to the total planting area, and the per-unit yield level (Pmy_{it}) is represented by per-unit yield.

② Comparative benefits of grain and cotton ($Gpad_{it}$): The ratio of net output value per mu of grain to cotton represents the comparative benefits. The net output value is calculated as the per-mu total output value minus the per-mu material costs, which include input costs for production materials and machinery. In terms of the comparative benefits of grain and cotton crops, nine provinces—Henan, Hebei, Shandong, Shanxi, Shaanxi, Gansu, Jiangsu, Anhui, and Xinjiang—use the ratio of wheat planting to the lagged one-period cotton net output value. In contrast, five provinces—Zhejiang, Jiangxi, Hunan, Hubei, and Sichuan—use the ratio of rice planting to the lagged one-period cotton net output value. For these provinces, the net output value for rice is the average net output value across the early, middle, and late seasons.

③ Comparative benefits of oilseeds and cotton: The Yangtze River Basin cotton-producing region uses the ratio of rapeseed to a lagged one-period cotton net output value (Rap_{it-1}). The Yellow River Basin cotton-producing region uses the ratio of peanuts to a lagged one-period cotton net output value (Pea_{it-1}). Xinjiang uses the ratio of beets to a lagged one-period cotton net output value (Bee_{it-1}).

The descriptive statistics of the variables in this paper are presented in Table 1.

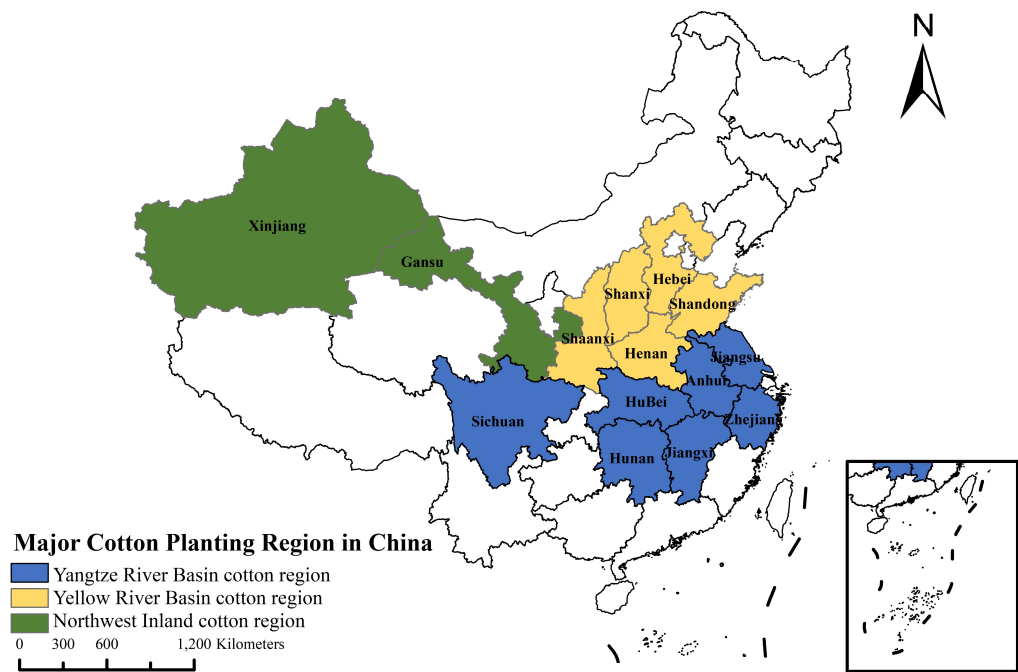
Table 1. Descriptive statistics of variables.

Variables	Symbols	Mean	Standard Deviation	Minimum Value	Maximum Value
Cotton location quotient	LQ	1.653	3.124	0.004	21.857
The average labor price (CNY)	$Labor$	636.687	647.025	0.176	2634.060
The average production material cost (CNY)	$Prod$	254.805	166.218	3.135	1708.580
The average mechanical cost (CNY)	$Mach$	28.928	37.626	0.000	263.830
Cotton planting area (Thousand Hectares)	$Area$	327.256	431.684	0.300	2540.500
Price ratio of production materials cost to labor price	PRL	0.832	1.332	0.015	17.848
Price ratio of mechanical cost to labor price	MAL	0.328	2.846	0.000	50.496
Price ratio of mechanical cost to production materials cost	MAP	0.134	0.248	0.000	2.829
Mechanical substitution difficulty	Dcs	1.928	5.083	0.000	67.395
Proportion of disaster-affected area to total planting area (%)	Dar	0.264	0.148	0.010	0.756
Proportion of effective irrigated area to total planting area (%)	Pia	0.410	0.167	0.222	1.005
Cotton yield per hectare (kilograms per hectare)	Pmy	1073.234	331.842	346.900	2088.470
Comparative benefits of grain and cotton	$GPad_{t-1}$	0.669	3.054	0.066	68.074

3.3. Data Sources

The study area covers 14 provinces in China, including the Yangtze River Basin, the Yellow River Basin, and the Northwest Inland region (Figure 2). The Yangtze River Basin cotton region includes the seven provinces of Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, and Sichuan; the Yellow River Basin cotton region includes the five provinces of Hebei, Shanxi, Shandong, Henan, and Shaanxi; the Northwest Inland cotton region includes the two provinces of Xinjiang and Gansu. The demographics of the major cotton planting regions are provided in Table 2.

(a)



(b)

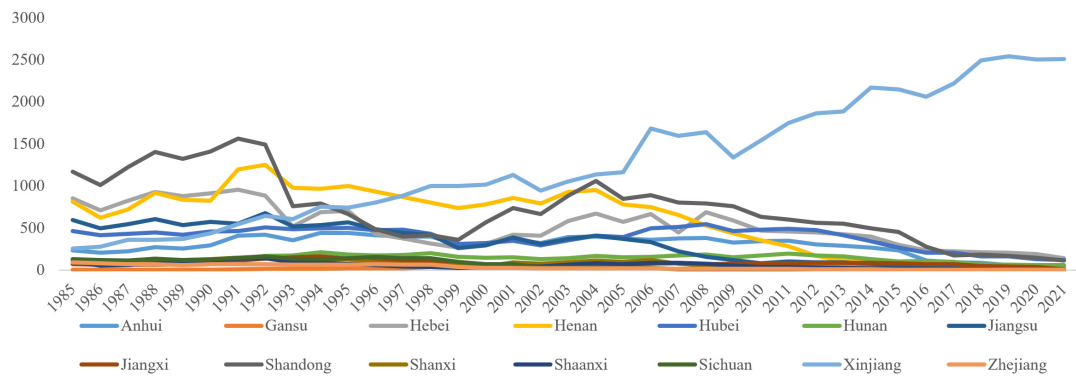


Figure 2. (a) China’s main cotton regions. (b) Change of cotton planting area from 1985 to 2021.

Table 2. Study area population distribution table in 2021.

Major Cotton Planting Region	Province	Population
Yangtze River Basin	Jiangsu	8505
	Zhejiang	6540
	Anhui	6113
	Jiangxi	4517
	Hunan	9883
	Sichuan	8372
	Hubei	5830
Yellow River Basin	Shanxi	3480
	Henan	9883
	Hebei	7448
	Shandong	10,170
	Shaanxi	3954
Northwest Inland	Xinjiang	2589
	Gansu	2490

Based on balanced provincial panel data from 1985 to 2021, this study estimates the impact of FPC on CPPE. To ensure data availability and continuity, the data were sourced from the National Compilation of Cost-Benefit Data for Agricultural Products, the China Statistical Yearbook, and the Statistical Yearbooks of the relevant provinces. The data on indicators such as cotton planting area, crop planting area, cotton yield, disaster-affected area, and effective irrigated area in the main cotton-producing provinces were sourced from the China Statistical Yearbook and the China Rural Statistical Yearbook from 1986 to 2022. The data on indicators such as per-mu total output value, per-mu total cost, per-mu labor cost (based on prevailing rates), and per-mu input costs for cotton at both the national and provincial levels were sourced from the National Compilation of Cost-Benefit Data for Agricultural Products and the Compilation of Cost-Benefit Data for Major Agricultural Products in China Since the Founding of the Nation for the years 1986 to 2022. Additionally, data for certain provinces, including Sichuan, Zhejiang, and Shanxi, were supplemented using interpolation methods for the missing years. It is important to note that prior to the establishment of Chongqing as a separate municipality in 1997, all statistical data were attributed to Sichuan. After 1997, data for Chongqing were collected separately, with the cotton planting area in Chongqing being almost negligible. The percentage-based data for Sichuan remained stable before and after Chongqing's separation, so no adjustments were made to Sichuan's data prior to 1997. The calculation method for the labor cost per mu changed in 1992. Before 1992, the data did not distinguish between regional wage rates and a national unified wage rate. Starting in 1992, data were calculated separately based on regional wage rates and the unified national wage rate. Considering the differences in economic development, data from 1992 onwards were based on regional wage rates. The data sources we used are listed in Table 3.

Table 3. List of data sources.

Variable	Description	Source	Link
<i>LQ</i>	Cotton location quotient	China Statistical Yearbook	https://data.stats.gov.cn/ (accessed on 1 May 2023)
<i>Frb</i>	The ratio of production material cost to labor price	National Compilation of Cost-Benefit Data for Agricultural Products	https://www.ndrc.gov.cn/fzggw/jgsj/jgs/ (accessed on 1 May 2023)
<i>Lfm</i>	The ratio of mechanical cost to labor price	National Compilation of Cost-Benefit Data for Agricultural Products	https://www.ndrc.gov.cn/fzggw/jgsj/jgs/ (accessed on 1 May 2023)
<i>Mbr</i>	The ratio of mechanical cost to production material cost	National Compilation of Cost-Benefit Data for Agricultural Products	https://www.ndrc.gov.cn/fzggw/jgsj/jgs/ (accessed on 1 May 2023)
<i>Dcs</i>	Mechanical substitution difficulty	National Compilation of Cost-Benefit Data for Agricultural Products	https://www.ndrc.gov.cn/fzggw/jgsj/jgs/ (accessed on 1 May 2023)
<i>Dar</i>	The natural conditions for agricultural production	National Bureau of Statistics	https://data.stats.gov.cn/ (accessed on 1 May 2023)
<i>Pia</i>	The degree of irrigation conditions	National Bureau of Statistics	https://data.stats.gov.cn/ (accessed on 1 May 2023)
<i>Pmy</i>	The per-unit yield level	National Bureau of Statistics	https://data.stats.gov.cn/ (accessed on 1 May 2023)
<i>Gpad</i>	Comparative benefits of grain and cotton	National Compilation of Cost-Benefit Data for Agricultural Products	https://www.ndrc.gov.cn/fzggw/jgsj/jgs/ (accessed on 1 May 2023)
<i>Bee</i>	The ratio of beet to cotton net output	National Compilation of Cost-Benefit Data for Agricultural Products	https://www.ndrc.gov.cn/fzggw/jgsj/jgs/ (accessed on 1 May 2023)
<i>Pea</i>	The ratio of peanut to cotton net output	National Compilation of Cost-Benefit Data for Agricultural Products	https://www.ndrc.gov.cn/fzggw/jgsj/jgs/ (accessed on 1 May 2023)
<i>Rap</i>	The ratio of rapeseed to cotton net output	National Compilation of Cost-Benefit Data for Agricultural Products	https://www.ndrc.gov.cn/fzggw/jgsj/jgs/ (accessed on 1 May 2023)

4. Empirical Results

4.1. Spatial Autocorrelation Test

Global Moran's *I* Index was used to examine the spatial autocorrelation of CPPE under the binary spatial weight. As shown in Table 4, the global Moran's index of CPPE across most years from 1985 to 2021 was significantly positive, indicating that CPPE characterizes the presence of spatial autocorrelation. The spatial CPPE in provincial regions initially showed a decline followed by an increase. Neighboring major cotton-producing provinces tend to exhibit similar agglomeration characteristics, with a clear pattern of high-high and low-low agglomeration in cotton production among these provinces.

Table 4. Global Moran's *I* index from 1985 to 2021.

Year	Moran's <i>I</i>	Year	Moran's <i>I</i>	Year	Moran's <i>I</i>
1985	0.230 ** (0.16)	1998	−0.025 (0.084)	2011	0.008 (0.08)
1986	0.141 * (0.159)	1999	−0.015 (0.079)	2012	0.014 (0.078)
1987	0.141 * (0.158)	2000	−0.01 (0.083)	2013	0.016 (0.076)
1988	0.202 ** (0.159)	2001	0.000 (0.085)	2014	0.021 * (0.073)
1989	0.176 * (0.158)	2002	−0.001 (0.09)	2015	0.022 * (0.071)
1990	0.138 * (0.156)	2003	0.006 (0.097)	2016	0.023 * (0.069)
1991	0.133 (0.153)	2004	0.015 (0.101)	2017	0.028 * (0.068)
1992	0.083 (0.147)	2005	0.007 (0.093)	2018	0.031 * (0.067)
1993	−0.032 (0.123)	2006	0.005 (0.086)	2019	0.032 * (0.067)
1994	−0.025 (0.113)	2007	0.008 (0.078)	2020	0.033 * (0.067)
1995	−0.027 (0.115)	2008	0.007 (0.085)	2021	0.035 ** (0.066)
1996	−0.024 (0.099)	2009	0.005 (0.089)		
1997	−0.041 (0.093)	2010	0.005 (0.082)		

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

4.2. Spatial Durbin Model Analysis

Wald and LR tests were used to examine whether the SDM model could be simplified into SAR or SEM models. If the null hypothesis of the Wald test is rejected and the Robust LM-Lag value is significant, then the SDM model is superior to the SAR model. If the null hypothesis of the LR test is rejected and the Robust LM-Lag value is significant, then the SDM model is superior to the SEM model. As shown in Table 5, the results of the Wald and LR tests indicated that both the SLM and SEM models passed the significance tests at the 1% level. Consequently, the null hypothesis was rejected, suggesting that the SDM model cannot be simplified into the SAR or SEM models.

Table 5. Results of spatial panel model selection.

Model	Test	Statistic	<i>p</i> -Value
SAR & SDM	Wald_spatial	47.61 ***	0.000
	LR_spatial	47.66 ***	0.000
SEM & SDM	Wald_spatial	25.31 ***	0.000
	LR_spatial	58.99 ***	0.000

Note: the applicability test results of the SLM and SEM models are represented by the values of the *t*-statistics for various tests under the SLM model, with *** indicating significance at the 1% level.

To address the issue of spatial autocorrelation, we used the clustered standard error method to analyze the impact of *FPC* on *CPPE*. Table 6 shows the results for the unfixed SDM model estimation, the individual fixed SDM model estimation, and the time and individual two-way fixed SDM model estimation, respectively.

The impact of *PRL* on *CPPE* was significantly negative across all three models, indicating that a higher ratio of production material cost to labor price is detrimental to *CPPE*. Conversely, the effect of *MAL* on *CPPE* was significantly positive under the two-way fixed

SDM model. Similarly, the impact of *MAP* on *CPPE* was significantly positive. This can be attributed to technological advancements that reduce labor and production material input, resulting in a more cost-effective approach. The promoting effect of *FPC* on *CPPE* was mainly driven by mechanical costs. The rapid development of *FPC* played a significant role in influencing the transformation of China's cotton production patterns.

The coefficient of *Dsc* was significantly negative and passed the significance test in three different spatial SDM models. For every 1 unit increase in *Dcs*, the *CPPE* decreases by 0.056 units, indicating that the increase in mechanization difficulty was not conducive to the cotton agglomeration, leading to the migration of the cotton cultivation transfer. Under the two-way fixed effects, the coefficient of $W \times Dsc$ was significantly negative, indicating that the increase in mechanical substitution difficulty in neighboring provinces could result in a decline in the local cotton agglomeration.

The *Dar* was positively correlated with *CPPE*, the *Pia* was negatively correlated with *CPPE*, and the *Pmy* was positively correlated with *CPPE*. Overall, the influence of internal and external circumstances on *CPPE* is uncertain. The impact of $Gpad_{t-1}$ on *CPPE* was significantly negative and passed the significance test in three different spatial SDM models. The primary reason for this outcome is that as the level of mechanization in grain crop operations continues to improve and their profitability increases, the rising labor costs have led to a continuous decline in the net value of cotton compared to grain crops. As rational economic agents, cotton growers would choose grain crops that were easier to mechanize and offer higher profits, and abandon cotton that were more difficult to mechanize and offer lower profits. The coefficient of $W \times Gpad_{t-1}$ was significantly positive, indicating that changes in the comparative returns of grain crops and cotton in neighboring provinces stimulated local cotton cultivation.

Table 6. SDM models regression results.

Variables	Unfixed Effects	Individual Fixed Effects	Two-Way Fixed Effects	Variables	Unfixed Effects	Individual Fixed Effects	Two-Way Fixed Effects
<i>PRL</i>	−0.336 *** (0.056)	−0.335 *** (0.055)	−0.315 *** (0.059)	$W \times PRL$	0.021 (0.122)	0.020 (0.120)	0.109 (0.144)
<i>MAL</i>	0.102 *** (0.024)	0.101 *** (0.024)	0.082 *** (0.025)	$W \times MAL$	−0.014 (0.057)	−0.012 (0.057)	−0.071 (0.062)
<i>MAP</i>	0.216 (0.194)	0.247 (0.191)	0.491 ** (0.228)	$W \times MAP$	−0.733 ** (0.298)	−0.749 ** (0.295)	−0.240 (0.519)
<i>Dcs</i>	−0.032 * (0.017)	−0.034 ** (0.016)	−0.053 *** (0.017)	$W \times Dcs$	0.026 (0.022)	0.029 (0.022)	−0.057 * (0.032)
<i>Dar</i>	0.102 (0.063)	0.113 * (0.062)	0.137 ** (0.061)	$W \times Dar$	0.274 *** (0.093)	0.257 *** (0.092)	0.291 *** (0.112)
<i>Pia</i>	−0.615 ** (0.281)	−0.827 *** (0.274)	−1.436 *** (0.291)	$W \times Pia$	−1.219 *** (0.437)	−1.125 *** (0.435)	−3.578 *** (0.659)
<i>Pmy</i>	0.215 (0.151)	0.210 (0.149)	0.155 (0.152)	$W \times Pmy$	0.227 (0.214)	0.253 (0.212)	−0.239 (0.299)
$Gpad_{t-1}$	−0.156 *** (0.052)	−0.158 *** (0.051)	−0.158 *** (0.056)	$W \times Gpad_{t-1}$	0.187 *** (0.070)	0.195 *** (0.069)	0.124 (0.088)
σ^2	0.325 *** (0.021)	0.316 *** (0.020)	0.295 *** (0.019)	ρ	0.369 *** (0.047)	0.368 *** (0.047)	0.305 *** (0.052)
R^2	0.018	0.004	0.001	N	518	518	518

Note: “***”, “**”, and “*” indicate significance levels of 1%, 5%, and 10%, correspondingly.

4.3. Spatial Spillover Effects Analysis

Using partial differential equations, we decomposed the spatial spillover effects of the SDM model. The impact of *FPC* on *CPPE* can be divided into direct effect, indirect effect, and total effect. The direct effect involves the impact of *FPC* on *CPPE* within the region. The indirect effect represents how local *FPC* influences *CPPE* in adjacent regions, reflecting the spillover effect of *FPC*. The findings are presented in Table 7.

The coefficients of direct and total effects of *PRL* on *CPPE* were significantly negative, which indicated that the level of *PRL* significantly decreases *CPPE* within the region. Simultaneously, the coefficient for the indirect effect of *PRL* was positive, which illustrated that the negative impact of *PRL* on *CPPE* diminishes through its spillover effects, and the main cotton-producing regions tended to move from the provinces with a low ratio of *PRL* to the higher regions. The direct and total effect coefficients of *MAL* on *CPPE* were positive, while the coefficient of the indirect effect of *MAL* was negative, signifying that the main cotton-producing regions tended to transfer from the provinces with higher *MAL* regions to the lower *MAL* regions. The direct, indirect, and total effect coefficients of *MAP* on *CPPE* were positive, suggesting that *MAP* accelerated the *CPPE* in the local province and neighboring provinces. Conversely, the coefficients of the direct, indirect, and total effects of *Dsc* on *CPPE* were all negative and passed the significance level test, indicating that the increase in mechanical substitution difficulty hinders the enhancement of *CPPE* in both the local and neighboring provinces. The coefficients of the direct and total effects of *Pmy* on *LQ* were positive, whereas the coefficient of the indirect effect of *Pmy* was negative. The coefficient of the direct effect of lagged one-period *Gpad* on *CPPE* was negative, and the coefficients for indirect and total effects were positively valued. The reason is that the increase in the lagged one-period *Gpad* can lead farmers to earn higher profits through growing grain crops. Driven by economic benefits, farmers may consequently reduce cotton cultivation and shift to growing grain crops.

Table 7. Results of spatial spillover effects.

Variables	Direct Effect	Indirect Effect	Total Effect	Variables	Direct Effect	Indirect Effect	Total Effect
<i>PRL</i>	−0.311 *** (0.067)	0.032 (0.199)	−0.279 (0.241)	<i>Dar</i>	0.171 *** (0.060)	0.447 *** (0.155)	0.618 *** (0.173)
<i>MAL</i>	0.076 *** (0.028)	−0.067 (0.088)	0.010 (0.105)	<i>Pia</i>	−1.826 *** (0.303)	−5.395 *** (1.015)	−7.221 *** (1.190)
<i>MAP</i>	0.498 ** (0.252)	−0.145 (0.758)	0.354 (0.938)	<i>Pmy</i>	0.134 (0.165)	−0.285 (0.399)	−0.151 (0.478)
<i>Dcs</i>	−0.061 *** (0.018)	−0.098 ** (0.047)	−0.158 *** (0.054)	<i>Gpad_{t−1}</i>	−0.153 *** (0.059)	0.097 (0.123)	−0.056 (0.157)

Note: “***”, “**”, “*” indicate significance levels of 1%, 5%, correspondingly.

4.4. The Transfer Analysis of *CPPE*

To further investigate the distinct causes of transfer in various cotton planting regions, we analyzed provincial panel data from the Yangtze River Basin, Yellow River Basin, and Northwest Inland areas. The empirical findings are presented in Table 8.

The impact of *PRL* on *CPPE* in the Yangtze River Basin, Yellow River Basin, and Northwest Inland cotton regions was negative, which indicates that rising labor expenses did not promote *CPPE* in the three primary cotton planting areas. The impact of *MAL* on *CPPE* in the Yangtze River, Yellow River Basin, and Northwest Inland cotton regions was positive, and the coefficient of *MAL* in the Northwest Inland region was 3.296, which was significantly higher than in the Yangtze River Basin and Yellow River Basin. Compared to the Yangtze River Basin and the Yellow River Basin cotton regions, the lower labor price and advancements in mechanical technology have enhanced the centralization and specialization of cotton production in the Northwest Inland region, so the advantages of the Northwest Inland cotton region become prominent. The impact of *MAP* was significantly negative in the Yangtze River Basin and the Northwest Inland cotton regions but not significant in the Yellow River Basin. The coefficient of *Dsc* in Northwest Inland was −0.020, which was significantly lower than in the Yangtze River Basin and Yellow River Basin. This suggests that cotton production in the northwest was more dependent on mechanization, while cotton production in the Yangtze River Basin and Yellow River Basin was less dependent on mechanization. This discrepancy can be attributed to the scattered nature of cotton planting areas in the Yellow River Basin and the Yangtze River Basin, which is not conducive to mechanization [53]. Xinjiang has a unique ecological environment and flat cotton fields,

creating favorable conditions for the adoption of mechanization [54]. Hence, the main cotton-producing region tended to shift from the Yangtze River Basin and Yellow River Basin with high mechanical substitution difficulty to the Northwest Inland region with low mechanical substitution difficulty. Due to technological advancement, the cotton industry in the Northwest Inland region has rapidly developed [55]. In summary, mechanization is crucial for improving cotton production efficiency. As the level of mechanization increased, the distribution of cotton production was positively affected. The results were consistent with Hypothesis 2.

Table 8. Transfer of CPPE in different regions.

Variables	Yangtze River Basin	Yellow River Basin	Northwest Inland	Variables	Yangtze River Basin	Yellow River Basin	Northwest Inland
<i>PRL</i>	−0.261 *** (0.055)	−0.024 (0.211)	−0.375 (0.278)	<i>W×PRL</i>	−1.239 *** (0.308)	−0.892 * (0.519)	0.123 (0.279)
<i>MAL</i>	0.086 *** (0.017)	−1.313 (2.287)	3.296 * (1.691)	<i>W×MAL</i>	2.955 ** (1.335)	5.695 (6.065)	−4.952 *** (1.664)
<i>MAP</i>	−0.298 * (0.178)	3.197 * (1.724)	−4.527 ** (2.291)	<i>W×MAP</i>	−1.554 *** (0.403)	4.683 (3.451)	4.747 ** (2.288)
<i>Dcs</i>	0.019 (0.015)	0.034 (0.021)	−0.020 (0.024)	<i>W×Dcs</i>	0.046* (0.028)	0.072 (0.050)	0.002 (0.024)
<i>Dar</i>	0.196 *** (0.053)	−0.234 *** (0.074)	0.093 (0.102)	<i>W×Dar</i>	0.455 *** (0.116)	−0.746 *** (0.167)	0.075 (0.102)
<i>Pia</i>	−1.191 *** (0.234)	2.053 *** (0.581)	0.793 (0.596)	<i>W×Pia</i>	−2.519 *** (0.387)	5.554 *** (1.413)	−0.282 (0.599)
<i>Pmy</i>	0.541 *** (0.126)	0.146 (0.188)	0.929 *** (0.332)	<i>W×Pmy</i>	1.552 *** (0.297)	−1.096 ** (0.445)	0.384 (0.339)
<i>Gpad_{t−1}</i>	−0.057 (0.074)	0.019 (0.056)	−0.233 ** (0.119)	<i>W×Gpad_{t−1}</i>	0.345 ** (0.164)	0.232 * (0.139)	−0.034 (0.120)
<i>Rap_{t−1}</i>	−0.016 (0.079)			<i>Rap_{t−1}</i>	0.261 * (0.144)		
<i>Pea_{t−1}</i>		−0.410 *** (0.044)		<i>Pea_{t−1}</i>		−1.416 *** (0.107)	
<i>Bee_{t−1}</i>			0.127 (0.138)	<i>Bee_{t−1}</i>			−0.201 (0.138)
<i>sigma</i> ²	0.083 *** (0.007)	0.058 *** (0.006)	0.081 *** (0.013)	<i>ρ</i>	−0.196 * (0.116)	−0.565 *** (0.096)	0.044 (0.082)
<i>R</i> ²	0.467	0.088	0.859	<i>N</i>	259	185	74

Note: “***”, “**”, and “*” indicate significance levels of 1%, 5%, and 10%, correspondingly.

The impact of *Dar* on CPPE was not significant in the Yellow River Basin and the Northwest Inland cotton regions. The impact of *Pia* on CPPE was significantly negative in the Yangtze River Basin and Yellow River Basin cotton regions, while it was positive in the Northwest Inland cotton region. The impact of *Pmy* on LQ in the Northwest Inland cotton region was higher than in the Yangtze River Basin and the Yellow River Basin, indicating that the climate conditions in Xinjiang and Gansu were more suitable for cotton planting, and the rate of increase in cotton yield per unit area was significantly faster than in the Yangtze River Basin and the Yellow River Basin. The unique comparative advantage of the Northwest Inland cotton region became a crucial factor driving the agglomeration of cotton production. The impact of *GPad_{t−1}* exerted a restraining effect on CPPE in both the Yangtze River Basin and the Northwest Inland cotton regions. In a comparative analysis of oilseed crops with a lagged net value per mu of cotton, *Rap_{t−1}* and *Pea_{t−1}* had an inhibitory effect on CPPE in the Yangtze River Basin and the Yellow River Basin, while *Bee_{t−1}* had a very significant promoting effect on CPPE in the Northwest Inland cotton region. The increasingly high comparative benefits of cotton also became an important factor driving the expansion of cotton planting.

We concluded that the previous decentralized cotton cultivation in the traditional cotton planting provinces in the Yangtze and Yellow River basins has been replaced by specialized cotton cultivation in Xinjiang and Gansu.

5. Discussion

5.1. The Impacts of FPC and Drs on CPPE

This study calculated the impact of factor price change on cotton production patterns among 14 provinces in cotton planting areas, constructing Moran's Index and spatial economic model. Using the spatial Durbin model, this study examines the direct and indirect effects of *FPC* on *CPPE*, comprehensively identifying the spatial effects of key influencing factors.

To examine the spatial spillover impact of driving factors on *CPPE*, Moran's *I* index and spatial economic models were used to estimate the *FPC* including labor price, production material cost, and mechanical cost on *CPPE* from the perspective of mechanical substitution difficulty. Table 4 shows that Moran's *I* index of *CPPE* across most years from 1985 to 2021 was significantly positive, indicating that there was significant spatial autocorrelation in cotton production across different provinces. The impacts of *MAL* (the ratio of mechanical cost to labor price) and *MAP* (the ratio of mechanical cost to production material cost) on *CPPE* were positive; however, the impact of *PRL* (the ratio of production material cost to labor price) on *CPPE* was negative. Table 6 demonstrates that as the mechanical cost increased relative to labor and material costs, the efficiency of cotton production improved, and as the production material cost increased relative to labor prices, the efficiency of cotton production decreased. The empirical results indicated that the rising labor price has been a significant driver for cotton production mechanization, supporting the hypothesis of labor-induced mechanical substitution [40]. The results were consistent with Hypothesis 1. Consistent with our results, Shao et al. (2022) [20] presented that as the cost of labor costs increased, the technological progress in agriculture increased the extent of the economic advantages of managing cotton fields. The results were consistent with Hypothesis 1.

The transfer analysis of *CPPE* revealed the traditional cotton regions of the Yellow River Basin and the Yangtze River Basin had shifted and concentrated towards the North-west Inland region. Table 8 shows that the mechanical substitution difficulty was significantly lower than in the Yangtze River Basin and Yellow River Basin, illustrating that cotton production in the Northwest Inland region was more dependent on mechanization than in the Yangtze River Basin and Yellow River Basin. The reason is that the cotton planting areas in the Yellow River Basin and the Yangtze River Basin were scattered, which was not conducive to mechanization. The full mechanization, technological innovation, and government policy support had a positive influence on the development of the cotton industry in the Northwest Inland region of Xinjiang [56]. Xinjiang has a unique ecological environment and flat cotton fields, creating favorable conditions for the adoption of mechanization [54]. This conclusion was validated by Saliou et al. (2020) [57], who suggested mechanization was essential for the development of agriculture. As the level of mechanization increased, the distribution of cotton production was positively affected. The current study suggested that mechanization was helpful for cotton transfer [58,59]. The results were consistent with Hypothesis 2. The findings regarding the hypotheses are listed in Table 9.

Table 9. The findings regarding the hypotheses.

Hypothesis Number	Hypothesis Content	Research Findings	Results Description
1	<i>CPPE</i> demonstrates a spatial agglomeration, and <i>FPC</i> has a significant spatial effect on <i>CPPE</i> .	The global Moran's index of <i>LQ</i> across most years from 1985 to 2021 was significantly positive, indicating that <i>CPPE</i> has spatial autocorrelation. In spatial analysis, the spatial autoregressive coefficient ρ was significantly positive, and the coefficients of <i>FPC</i> (<i>PRL</i> , <i>MAL</i> , <i>MAP</i>) were significant.	The results support Hypothesis 1
2	The higher difficulty of mechanical substitution exerted an inhibitory effect on cotton production	The coefficient of <i>Dsc</i> is significantly negative, leading to the migration of the cotton region transfer.	The results support Hypothesis 2

5.2. Limitations and Prospects

Considering the limitations of this study, there exist some uncertainties in the above results. First, the data in this study are on a province level during the last 30 years. If the study used lattice-type data, temporal span, or various geographical scales, the result may exhibit different results. Hence, research on the impact of factor price change on cotton production patterns should be expanded to other regional scales and temporal spans. Second, this study verified two core hypotheses, but it did not comprehensively consider all possible influencing factors. Future research could introduce more variables, such as climate change, target price policy, genetic improvements, and other influencing factors. To some extent, these influencing factors will affect the evolution of cotton production patterns. For example, climate changes such as changes in temperature, rainfall, and radiation [60,61] impact cotton yields. Furthermore, this study employs OLS and spatial econometric models to analyze the issue. Future research could utilize more complex dynamic spatial econometric models to capture long-term and short-term effects.

5.3. Policy Implications

Our findings indicated that the transfer of cotton regions reflects the reality of China's cotton production pattern evolution towards regional specialization. By integrating both theoretical and empirical examinations, this study demonstrated that *FPC* significantly impacts *CPPE* through the difficulty of mechanization substitution. The results of this study offered scientific guidance for enhancing the effectiveness of cotton specialization. Based on our findings, we propose several policy implications.

The government should guide cotton cultivation to improve production efficiency, mitigate the negative impact of rising labor costs on cotton production, overcome constraints related to production technology and land scale in inland cotton regions, transform development models, and promote the rational allocation of production factor resources.

The government should focus on guiding and increasing the supply of factors that can replace labor. Simply increasing the supply of production inputs such as fertilizers and pesticides can only improve the output efficiency per unit of land, but it does not alleviate the increasing labor shortage. It is necessary to guide the balanced development of the technology supply market.

We should fully understand the relationship between the integration of the cotton consumption market and the regional specialization of cotton cultivation. Local protectionism exists in the circulation of cotton in different regions, and the cotton market is still somewhat fragmented. Relevant policies for cotton circulation and processing should be scientifically formulated to integrate regional markets, fully utilize the advantages of cotton cultivation in different regions, and promote the deepening of regional specialization in cotton planting and processing.

6. Conclusions

Based on provincial panel data from major cotton planting areas from 1985 to 2021, this paper used spatial autocorrelation tests and spatial econometric models to analyze the impact of *FPC* on *CPPE*. Through the spatial spillover effect analysis using the spatiotemporal SDM model, it examines the direction of the shifts in China's cotton-producing regions. The conclusions are as follows:

The effect of *FPC* on *CPPE* is mainly influenced by the relative prices of mechanical factors themselves, suggesting that the rapid change in relative factor prices is a significant factor driving the change in China's cotton production pattern. The main cotton-producing region tends to shift from the cotton region with high mechanical substitution difficulty to the cotton region with low mechanical substitution difficulty, and the increase in mechanical substitution difficulty is not conducive to the regional agglomeration of cotton. The Northwest Inland cotton region has lower mechanical transaction costs, and its higher mechanization level and lower relative price of labor force promote the transfer of main

cotton planting areas from the Yangtze River Basin and Yellow River Basin to the Northwest Inland region.

Due to the significant spatial spillover effects of technological innovation in mechanization, we can take advantage of these effects to promote the development of the cotton industry. Specifically, mechanization innovation can not only improve the production efficiency in the local region but also promote the adoption of mechanization innovation across broader regions through a demonstration effect in neighboring areas. This spatial spillover effect can break barriers to technology dissemination, allowing more regions to benefit. Therefore, through policy support and promotion activities, encouraging the widespread application of mechanization technology can significantly improve the production efficiency and competitiveness of the cotton industry. When formulating policies, it is crucial to understand the spatial impact of FPC on CPPE from a mechanical substitution. This understanding should guide the development of comprehensive and coordinated cotton production strategies for the Yangtze River Basin, Yellow River Basin, and Northwest Inland.

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