Temporal and Regional Differences and Empirical Analysis on Sensitive Factors of the Corn Production Cost in China

Shumiao Ouyang 1,*, Jie Hu 1, Minli Yang 2,3, Mingyin Yao 1 and Jinlong Lin 1,*

1 College of Engineering, Jiangxi Agricultural University, Nanchang 330045, China; hujie@jxau@163.com (J.H.); mingyin800@126.com (M.Y.)
2 College of Engineering, China Agricultural University, Beijing 100083, China; qyang@cau.edu.cn
3 China Agricultural Mechanization Development Research Center, China Agricultural University, Beijing 100083, China
* Correspondence: q1605636164@163.com (S.O.); rincy@jxau.edu.cn (J.L.)

Abstract: The corn production cost (CPC) in China is related to national food security. However, there are few studies on the temporal and regional differences (TRD) and sensitive factors in the CPC. In this paper, the TRD of the corn production cost across various regions, as well as over the entirety of the country from 2008 to 2018, is presented. It is based on the GIS exploratory spatial data analysis method (ESDA). Simultaneously, a spatial panel model is established to conduct an empirical analysis of the main factors affecting the CPC. The results from the period in question show that the CPC in China and the three major production regions present a fluctuating growth trend, mainly associated with the increase in labor prices. Moreover, the CPC exhibits significant spatial differences, and demonstrates an overall trend of gradual increase from the east to the west. Over time, the number of relatively high-cost provinces has increased. All are located in southern mountainous and hilly corn areas. In addition, the CPCs of various regions are spatially correlated. Factors such as the scale of land management, the degree of mechanization, and socioeconomic conditions have a significantly negative impact on the CPC in China. Furthermore, the labor structure has a notably positive impact on the CPC.

Keywords: corn production cost; temporal and regional differences; sensitive factors; spatial panel model

1. Introduction

The development of grain production is interconnected not only with the economic benefit of Chinese farmers, but with the country’s grain security as well. In addition to opportunities, there have also been severe challenges in grain production after Chinese accession to the WTO. In 2018, Chinese grain stocks continued to rise as a result of the Chinese grain supply, while the demand gap was less than 45 million tons and Chinese grain imports exceeded 115 million tons [1]. The aforementioned situations constitute the strange phenomenon of the Chinese grain “three-quantity increase” [2]. The occurrence of this phenomenon may be attributed to the ceiling effect of Chinese agricultural product prices and the squeeze effect of rising cost floors [3]. China is both the second largest corn producer and consumer in the world, just after the United States. Corn production has continuously been exceeding rice output since 2012 and, thus, ranking first in Chinese grain output. In 2018, Chinese grain output was 658 million tons, of which corn made up 257 million tons, accounting for 39.09% of the total output [1]. From the above information, it may be concluded that corn occupies an important position in Chinese food security. In addition, it can also be concluded that the level of the CPC has a significant impact on the international competitiveness of Chinese corn. According to natural resource endowments and production conditions, the “Maize Advantage Regional Layout Plan” [4] divides Chinese corn planting areas into the northern spring corn area, the Huang-huai-hai summer corn area, and southern hilly corn area. The corn planting areas in the three
major regions account for 47.74%, 37.67%, and 10.24% of the total planting area [1]. In these three regions, the CPCs are too high, while the benefits are too low [5]. In turn, this severely affects the international competitiveness of Chinese corn production. Therefore, studying the temporal and spatial differences and causes of the CPC has both theoretical and practical significance for improving the efficiency of corn production, extensively reducing the CPC in various regions of China, improving the international competitiveness of Chinese corn and increasing the incomes of grain farmers.

Previous studies concerning the CPC had mainly focused on the following aspects. Firstly, the focus was placed on the analysis of the comparative advantage of the CPC [6–8]. In other words, studies compared the differences in corn production cost structure between China and other developed countries based on either macro data or field survey data. Secondly, previous research dealt with the cost efficiency analysis of corn production [9,10]. The DEA and other quantitative analysis methods were utilized to measure the cost efficiency index of corn production and analyze the contribution of factor inputs to cost efficiency. Lastly, analysis regarding variation in the CPC was conducted [11–13]. Considering the economic development cycle and other factors, studies examined the laws and trends of changes in the CPC. However, few studies analyzed the spatial distribution and change characteristics of the CPC from a spatial perspective. With respect to research related to sensitive factors, most scholars tended to discuss them at the theoretical level [14–19], proposing that factors such as the scale of land management, labor, technical conditions, and the economic environment significantly affect the CPC. Furthermore, many scholars conducted quantitative analyses [15,16], where the research methods primarily included descriptive statistical analysis, the double logarithmic linear regression model, stochastic frontier cost function model, etc. All the above methods commonly assumed that the regional variables were independent of each other and thus failed to consider the possibility of spatial dependence.

Due to the previously discussed research gap, this article attempts to use statistical and ESDA analysis methods to systematically explore the characteristics of the temporal and regional differences of the CPC in China. Additionally, from the perspective of spatial autocorrelation, this paper aims to construct a spatial panel model to analyze the influence mechanism of sensitive factors for the CPC. The research results have significant value for correctly understanding the changes in China’s CPC, adjusting and formulating relevant policies to reduce CPC, and improving the comparative advantages and market competitiveness of China’s corn production.

2. Materials and Methods

2.1. Research Methods

This paper adopts Excel 2010 and ArcGIS 10.2, a processing tool for spatial analysis. It combines the above mentioned with global spatial autocorrelation and local spatial autocorrelation methods in order to analyze the temporal and regional differences in the CPC. Additionally, it is used to build a spatial panel model to study the factors affecting the production costs of corn.

2.1.1. Global Spatial Autocorrelation Method

The global spatial autocorrelation analysis is based on the macro level. Moran’s I is used to compare the average production cost of corn in the country with the cost in each province in order to obtain the correlation of the entire study area. The calculation formulas are

\[
I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}
\]  

(1)
\[ S^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2, \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \]  

(2)

In the formulas, \( n \) is the sum of all research objects. \( x_i \) and \( x_j \) are the values of the corn production cost at the adjacent paired space points. \( \bar{x} \) is the average of all production costs of corn. \( W_{ij} \) is the matrix element in row \( i \) and column \( j \) of the geographical feature spatial weight matrix. Both rows and columns correspond to the spatial unit. The spatial weight matrix of the geographical feature set in this paper is a \((0, 1)\) adjacency standard matrix. The value range of Moran’s \( I \) is \([-1, 1]\). If \( I > 0 \), there is a positive spatial correlation, and objects with similar attributes gather together. Conversely, if \( I < 0 \), negative spatial correlation exists, meaning that spatially adjacent units do not have similar properties. Finally, \( I = 0 \) indicates random distribution with no spatial autocorrelation.

After calculating the Moran’s \( I \) index, the \( p \) value of the standardized statistic \( Z \) value is generally used to test whether there is spatial autocorrelation in the production cost of the regional unit. The calculation formula is

\[ Z = \frac{I - E(I)}{\sqrt{Var(I)}} \]  

(3)

In Formula (3), \( E(I) \) represents the digital expected value, while \( Var(I) \) is the coefficient of variation. In cases where \( Z < 1.96 \) or \( Z > 1.96 \), the global spatial autocorrelation between regions is taken to be significant. Moreover, if \( p \) is less than the given significance level (5% in the present article), the global spatial autocorrelation between regions is considered to be significant.

2.1.2. Local Spatial Autocorrelation Method

The local autocorrelation analysis is employed to analyze the production cost of the main corn planting areas in the country on the micro level. Local Moran’s \( I \) is used to determine whether there is a spatial agglomeration or diffusion state in each province and its surrounding neighbors. This makes up for the lack of global spatial autocorrelation that cannot reflect the spatial and temporal differentiation of the spatial correlation pattern of corn production costs within the region. The calculation formula is

\[ I_i = Z_i \sum_{j \neq i} W_{ij} Z_j \]  

(4)

In the above formula, \( X_i \) and \( X_j \) represent the deviations of the observed value of \( Z_i \) and \( Z_j \) from the mean value. In addition, \( W_{ij} \) is the normalized asymmetric spatial weight matrix.

In situations where the local Moran’s \( I > 0 \) and the significance test (\( p \) value test) is passed, there is a local positive spatial correlation, and the attribute values of the surrounding spatial units are similar. However, when the local Moran’s \( I < 0 \) and the significance test is passed, there is a local negative spatial correlation and the attribute values of surrounding spatial units differ. There are four types of local spatial agglomeration: (1) The HH (high–high) cost zone primarily refers to the relatively high cost of corn production in the province and the surrounding areas. In these areas, the degree of spatial difference is small. (2) The HL (high–low) cost zone represents high corn production cost in the province and low corn production cost in the surrounding area. In this zone, the degree of spatial difference is large. (3) The LH (low–high) cost zone indicates a low corn production cost at the province level and a high corn production cost in the surrounding area. In this zone type, the degree of spatial difference is large. (4) Lastly, the LL (low–low) cost zone refers to the relatively low cost of corn production in the province and surrounding areas. Here, the degree of spatial difference is considered small.
2.1.3. Empirical Model of Sensitive Factors

Corn production represents a complex system, directly affected by not only production factors, such as land and labor, but also closely related to the technical level and socioeconomic conditions [15–23]. In order to explore the impact mechanism of the temporal and spatial differences in China’s corn production costs, this article conducted an empirical analysis of the relevant factors. Taking into consideration the many factors that affect the CPC, this paper relied on existing research results [24–30] and selected four key sensitive factors. Firstly, it took into consideration the scale of land management, measured by the sown area per labor [24,25]. Secondly, it examined the labor force structure, which was recognized as the proportion of the non-agricultural population [26,27]. Thirdly, this paper looked at the degree of mechanization, measured by the comprehensive mechanization level of corn cultivation and harvesting [28]. The final sensitive factor was socio-economic condition, measured by the average annual net income of farmers in each region and the proportion of non-agricultural output value [29,30]. All the above variables are provided in Table 1.

Table 1. Variable meaning and descriptive statistical analysis.

| Variable                  | Variable Meaning                              | Variable Symbol | Description                                                                 | Mean    | S.D.  | C.V  | Min    | Max    |
|---------------------------|-----------------------------------------------|-----------------|----------------------------------------------------------------------------|---------|-------|------|--------|--------|
| Corn production cost      | Corn production cost                          | CPC             | Corn production cost                                                      | 7.470   | 0.282 | 0.038| 6.877  | 8.215  |
| Land management scale     | Sown area per labor                           | Land            | Corn sown area/Number of laborans                                          | 8.868   | 0.877 | 0.099| 7.117  | 10.750 |
| Labor structure           | Proportion of non-agricultural population      | Citizen         | Non-agricultural population/Total population                               | 0.507   | 0.086 | 0.170| 0.291  | 0.696  |
| Degree of mechanization   | Comprehensive Mechanization Level of Corn Cultivation and Harvest | Machine         | 0.4 \times \text{Mechanized farming level} + 0.3 \times \text{Mechanized planting level} + 0.3 \times \text{Mechanized harvesting level} | 0.549   | 0.272 | 0.495| 0.004  | 0.997  |
| Socioeconomic conditions  | Per capita annual net income of farmers        | Income          | (Total income of rural households-various expenses)/Number of permanent residents of the household | 18.160  | 0.439 | 0.024| 17.120 | 19.160 |
|                           | Proportion of non-agricultural output value    | Nonagrigdp      | (The added value of the secondary industry + the added value of the tertiary industry)/GDP | 0.883   | 0.039 | 0.045| 0.759  | 0.956  |

Note: all values are the results after taking the logarithm. The number of observations is 220.

If the CPC has spatial autocorrelation characteristics within the study area, there will be setting deviations to use ordinary panel regression model. Therefore, the present paper uses a spatial measurement model for empirical analysis. According to the research requirements, two basic spatial panel models are constructed [31,32]: the spatial lag panel model (SLPDM) and spatial error panel model (SEPDM). Their formulas are as follows:

\[
CPC_{it} = a_0 + a_1 Land_{it} + a_2 Citizen_{it} + a_3 Machine_{it} + a_4 Income_{it} + a_5 Nonagrigdp_{it} + \lambda \sum_{j=1}^{N} w_{ij} CPC_{jt} + \epsilon_{it} \quad (5)
\]

\[
CPC_{it} = \beta_0 + \beta_1 Land_{it} + \beta_2 Citizen_{it} + \beta_3 Machine_{it} + \beta_4 Income_{it} + \beta_5 Nonagrigdp_{it} + \rho \sum_{j=1}^{N} w_{ij} CPC_{jt} + \epsilon_{it} \quad (6)
\]

In Formulas (5) and (6), \(i\) represents each area of the cross section \((i = 1, 2, \ldots, N)\), while \(t\) indicates the time series of the study \((t = 1, 2, \ldots, T)\). Furthermore, the symbol \(w\) is the spatial weight matrix, and \(a_0, a_1, \ldots, a_5\) and \(\beta_0, \beta_1, \ldots, \beta_5\) are the waiting estimated parameters. The symbol \(\epsilon\) represents a random disturbance item that obeys the normal distribution and is independent of each other, while \(\lambda\) is the spatial regression coefficient and \(\rho\) stands for the spatial error coefficient. The CPC represents the production cost of corn, \(Land\) represents the average sown area of labor, while \(Citizen\) indicates the proportion of the non-agricultural population and \(Machine\) represents the comprehensive mechanization.
level of corn cultivation and harvesting. Finally, Income represents the average annual net income of farmers, and Nonagrigdp is the proportion of the non-agricultural output value.

2.2. Data Sources

According to the “Maize Advantage Regional Layout Plan”, China’s dominant corn producing areas are divided into the northern spring corn area, the Huang-huai-hai summer corn area, and the southern mountainous and hilly corn area. Among them, the northern spring corn area includes seven provinces of Inner Mongolia, Liaoning, Jilin, Heilongjiang, Ningxia, Gansu, and Xinjiang. Similar to the previous, the Huang-huai-hai summer corn area includes seven provinces of Hebei, Shanxi, Jiangsu, Anhui, Shandong, Henan, and Shaanxi, while the southern mountain and hilly corn area includes six provinces (regions) of Hubei, Guangxi, Chongqing, Sichuan, Guizhou, and Yunnan. Thus, the research objects of this paper are both the entirety of the country as well as 20 dominant corn producing areas. The selected analysis period is between 2008 and 2018.

The data crucial for this study were gathered from China Statistical Yearbook (2009–2019), Compilation of Costs and Benefits of National Agricultural Products (2009–2019), National Agricultural Mechanization Statistical Yearbook (2008–2018), China Rural Statistical Yearbook (2009–2019), China Regional Economic Statistical Yearbook (2009–2019), and the provincial Statistical Yearbook (2009–2019). The CPC index is based on 2008, while the corn production price index is taken to be a constant price. For the per capita annual net income of farmers, 2008 is selected as the base period, and it is treated as a constant based on the consumer price index of rural residents.

3. Results

3.1. Time Series Characteristics of the CPC

At present, the production cost of food and other agricultural products is primarily defined from the perspective of the economic and accounting cost in Western economics. In the most dependable Compilation of National Agricultural Product Costs and Benefits in China, the cost of agricultural products is largely concentrated in the field of production. However, research concerned with the circulation cost of agricultural products at the national level lacks necessary data support, making the transaction costs are difficult to measure. Therefore, in order to make complete use of the data at the national level, this paper follows relevant research results [33,34] and conducts quantitative analysis primarily from the perspective of accounting costs. The CPC is taken to be the total consumption of production factors per unit of corn output, including material and service costs, labor costs, and land costs. Figure 1 shows the CPC of the country and the three major corn producing areas for the period from 2008 to 2018.

The results show that the CPC in the southern mountainous and hilly area is much higher than that in both the Huang-huai-hai summer corn area and the northern spring corn area. Furthermore, the production cost of the northern spring corn area is slightly higher than that in the Huang-huai-hai summer corn area. The above results are largely the result of the tense human–land relationship in the corn area of the southern mountainous and hilly area [35]. The proportion of mountainous and hilly areas in Yunnan, Guizhou, Sichuan, Guangxi, and other provinces all exceeds 90%. Moreover, the degree of land fragmentation is high, which results in higher labor input level. Noticeably, the CPC is most significantly affected by labor costs [34,35]. Therefore, the CPC in the southern mountainous and hilly area is higher than in other regions.

From 2008 to 2018, the CPC in the three main producing areas manage to maintain an upward trend. However, it fluctuates greatly. The upward trend can be roughly divided into three stages: 2008–2011 as a period of rapid growth, 2012–2014 as a period of relative stability, and 2015–2018 as a period of volatile growth.
Figure 1. Corn production cost of China and three major corn producing areas from 2008 to 2018.

Firstly, the period from 2008 to 2011 is one of rapid growth in corn production cost. During this period, the CPC increases rapidly. The cost in the southern mountain and hilly corn area rises rapidly from 1982.23 CNY/ton (311.21 USD/ton) to 2640.42 CNY/ton (414.55 USD/ton) in 2011, with an average annual growth rate of 10.03%. Furthermore, the cost in northern spring corn area increases from 1473.72 CNY/ton (231.37 USD/ton) to 1748.27 CNY/ton (274.48 USD/ton), which is a cumulative increase of 274.55 CNY/ton (43.10 USD/ton), with an average annual growth rate of 5.86%.

Secondly, the period between 2012 and 2014 is taken to be a relatively stable period with regards to the CPC. During this period, the overall CPC is relatively stable. From 2012 to 2014, the cost per ton in the Southern mountainous and hilly area is 2587.39 (406.22), 2628.97 (412.75), and CNY 2658.59 (USD 417.40). The rate of change in comparison to the previous year is 1.62%. Furthermore, the average annual growth rate of the CPC in the northern spring corn area in the three years does not exceed 2.00%. The change rate of cost compared with the previous year is 2.60% in the Huang-huai-hai summer corn area.

Thirdly, the period from 2015 to 2018 is one of irregular growth with regards to the CPC. From 2015 to 2016, the CPC in three major producing regions declines. However, it begins to increase after 2017. For example, the CPC per ton in the southern mountainous and hilly area is CNY 1992.84 (USD 312.88) in 2017, while the cost increases to CNY 2120.80 (USD 332.97) in 2018. This situation may be associated with the lack of available data after 2018.

The CPC shows a fluctuating upward trend during the research periods. This is the result of the CPC being most significantly affected by labor costs (Table 2), and the elastic coefficient of regional cost to labor input exceeds 0.5 [34,35]. In the past decade or so, labor prices have soared. From 2008 to 2018, China’s labor price increases from 21.60 CNY/day (3.39 USD/day) to 84.89 CNY/day (13.33 USD/day), an increase of nearly four times, which causes the increase in the CPC.
Table 2. Proportion of input of production factors (%).

| Region                        | Labor Cost | Seed Cost | Fertilizer Cost | Pesticide Cost | Mechanical Operation Costs |
|-------------------------------|------------|-----------|-----------------|----------------|---------------------------|
| Nation                        | 42.11      | 6.78      | 28.69           | 2.28           | 15.02                     |
| Northern spring corn area     | 39.90      | 5.93      | 27.53           | 1.80           | 16.96                     |
| Huang-Huai-hai summer corn area | 42.97     | 7.23      | 29.49           | 2.61           | 14.01                     |
| Southern hilly corn area      | 55.52      | 6.06      | 21.60           | 1.51           | 8.24                      |

3.2. Characteristics of Spatial Differences in Corn Production Cost

The CPC of the 20 major maize producing provinces in 2008, 2013, and 2018 is spatially displayed (Figure 2). The results show that the CPC presents a trend of gradual increase from east to west. From the provincial level, we observe the following: (1) Relatively high cost: In 2008, the regions with high production costs are Gansu and Yunnan, accounting for 10% of the studied provinces. In 2018, the high-cost regions are Gansu, Yunnan, Guangxi, and Hebei, accounting for 20% of the examined regions. Among them, the Gansu and Yunnan provinces exceed the national average for 11 consecutive years, ranking among the top costs in all Chinese provinces. (2) Relatively medium cost: In 2008, 8 provinces, including Guangxi, Sichuan, and Shanxi, have moderate production costs, accounting for 40% of the total number of examined provinces. In 2018, there are 7 provinces, including Sichuan, Shanxi, and Shaanxi, which account for 35% of mid-cost regions. (3) Relatively low cost: In 2008, 10 provinces, such as Heilongjiang, Henan, Shandong, and Jiangsu, have lower CPC, accounting for 50% of the studied area. In 2018, there are a total of 9 provinces, including Heilongjiang, Shandong, Anhui, and Jiangsu, with low cost that account for 45% of the total number of examined regions.
In general, provinces with relatively high costs have gradually increased over time. In addition, it can be observed that all increased provinces are situated in the southern mountainous and hilly corn area. Their positioning indicates that the cost gap in this region is widening in comparison to other regions. The main reason for this may be the existence of numerous hills in the southern mountain and hilly provinces, scattered arable land, and the difficulty of mechanization transformation. Although agricultural mechanization has developed rapidly in various regions of China, the process of agricultural mechanization in this region is slow. With the exception of Hubei province, the comprehensive mechanization level of corn cultivation and harvest in 2018 in the southern mountainous and hilly region is below 35%, while the index in most provinces in the northern spring corn region and the Huang-huai-hai summer corn region is 70%. Therefore, agricultural machinery in the southern mountain and hilly area has a lower replacement of labor compared with other regions.
regions. In recent years, labor prices have soared, causing the gap in the CPC between this and other regions to widen further.

3.3. Global Spatial Autocorrelation Analysis of Corn Production Cost

In various provinces in China, the CPC demonstrates clear contiguous distribution characteristics, indicating that it may be dependent on space due to the similarity of natural and socio-economic conditions in neighboring provinces. Therefore, the spatial autocorrelation analysis method can be used to analyze the spatiotemporal pattern of the CPC in China.

Global spatial autocorrelation is capable of describing the overall pattern differentiation characteristics among geographic attributes. Table 3 illustrates the global Moran’s I index and its corresponding Z and \( p \) values of the CPC in China’s 20 main producing provinces from 2008 to 2018. The results indicate that the global Moran’s I index is greater than zero and less than 0.5 during the period from 2008 to 2018. Additionally, the corresponding normal statistic Z value (Z-score) is greater than the critical value of the normal distribution function when the probability is 0.05 (1.96). All pass the significance test. The above mentioned shows that there is a positive autocorrelation relationship in China’s CPC, and similar values are clustered together. In other words, provinces with high production costs are spatially clustered, and provinces with low production costs tend to be adjacent. At the same time, the global Moran’s I index is around 0.4 during the period from 2008 to 2018, indicating that the spatial characteristics of China’s CPC are relatively stable. The aforementioned is the result of the CPC being closely related to natural factors, such as soil and climate. These factors show geographic similarities in China. In addition, by investigating the national and provincial water resources, the weather, and other related statistical data from 2008 to 2018, these data are found to fluctuate within the normal range. Overall, the agricultural production system has strong stability.

| Year | Global Moran’s I | Z Value | \( p \) Value |
|------|------------------|---------|--------------|
| 2008 | 0.338            | 3.080   | 0.005        |
| 2009 | 0.360            | 3.262   | 0.001        |
| 2010 | 0.348            | 3.164   | 0.003        |
| 2011 | 0.367            | 3.345   | 0.001        |
| 2012 | 0.367            | 3.310   | 0.002        |
| 2013 | 0.361            | 3.266   | 0.001        |
| 2014 | 0.374            | 3.354   | 0.002        |
| 2015 | 0.375            | 3.373   | 0.001        |
| 2016 | 0.355            | 3.191   | 0.002        |
| 2017 | 0.364            | 3.267   | 0.002        |
| 2018 | 0.347            | 3.130   | 0.003        |

3.4. Local Spatial Autocorrelation Analysis of Corn Production Cost

In order to further explore the aggregation characteristics of China’s CPC at the provincial level, this paper has conducted local spatial autocorrelation analyses and drawn local Moran’s I scatter plots and LISA cluster maps for 2008 and 2018. The scatter plots (Figure 3) indicate that the spatial agglomeration of the CPC has not significantly changed during the 11 years under examination. Furthermore, the LISA cluster diagram (Figure 4), shows that most of the main producing provinces’ CPC are spatially non-significant, while only a small part is significant. There are only “HH” agglomerations (red area) and “LH” agglomerations (blue area). All the areas exhibiting “H–H” clustering characteristics (red areas) are situated in the southern mountainous and hilly area, which is consistent with the actual situation. Additionally, for the period between 2008 and 2018, the number of “HH” clusters decreases by two, accounting for 10% of the total study areas. Conversely, the number of “LH” clusters increases by one, accounting for 5% of the total study areas. The number of provinces in each quadrant reveals little change. Overall, the local heterogeneity
of the CPC has not changed significantly in the study period. This may be connected with
the relative stability of the differences in natural and socio-economic conditions between
the provinces.

![Moran scatter plots of corn production cost in various regions of China in 2008 and 2018.](image1)

**Figure 3.** Moran scatter plots of corn production cost in various regions of China in 2008 and 2018.

![LISA cluster maps of corn production cost in various regions of China in 2008 and 2018.](image2)

**Figure 4.** LISA cluster maps of corn production cost in various regions of China in 2008 and 2018.
Specifically, Xinjiang province has always been a significant “L-H” area, indicating that its CPC is significantly lower than that of the neighboring Gansu and Inner Mongolia provinces. Guangxi province is a notable “HH” area in 2008. However, it has fallen into an insignificant area as of 2018. This example illustrates that the CPC in Guangxi province is at a relatively high level in 2008, and the cost in the neighboring Yunnan and Guizhou provinces is also very high. However, due to the different development speeds of agricultural production in China’s main corn-producing regions, the CPC in Guangxi and its neighboring provinces has declined with regards to their nationwide ranking. Sichuan province shifts from being a “H-H” area in 2008 to a “L-H” area in 2018. This indicates that the CPC in Sichuan and its neighboring provinces, such as Ningxia, Shanxi, and Guizhou provinces, is relatively high in 2008. However, over time, the gap between the CPC in Sichuan province and its neighboring regions gradually widens. The CPC in Sichuan province becomes significantly lower than that of neighboring provinces in 2018. This occurrence is the result of the yield per unit area of corn in Sichuan province growing faster under the conditions of similar climate and planting structure.

3.5. Empirical Analysis of Factors Affecting Corn Production Cost

From the above analysis, the CPC is observed to have significant geographic spatial relevance. Therefore, this paper employed a spatial measurement model to conduct an empirical analysis of sensitive factors affecting the CPC in China for the period between 2008 and 2018. More specifically, this study used LMlag (Robust LMlag) and LMerr (Robust LMerr) to determine which of the two models is more appropriate. Table 4 illustrates that the test values of LMlag, Robust LMlag, LMerr and Robust LMerr are all significant at the 1% level. However, the statistic value of LMlag is greater than that of LMerr, and the statistic value of Robust LMlag is greater than Robust LMerr. These observations suggest that SLPDM is better than SEPDM. Furthermore, the spatial Hausman test is significant at the 1% level, indicating that the spatial panel fixed effects model is more suitable in comparison to the spatial random effects model. Since both the LogL value of the time fixed effects model and the R² value are observed to be the largest, the model fitting effect is taken to be the best one. Therefore, this paper employs the time fixed effects model of the spatial lag panel model to explain the sensitive factors affecting the CPC. In order to observe the impact of various influencing factors on the CPC, the model parameters (model 1 to model 5) are estimated by gradually adding independent variables on the basis of controlling the dependent variables. The test results are provided in Table 5.

Table 4. Model statistical test results.

| Inspection Method | Observations | Statistic | p Value |
|-------------------|--------------|-----------|---------|
| LMlag             | 220          | 83.108    | 0.000   |
| Robust LMlag      | 220          | 14.672    | 0.000   |
| LMerr             | 220          | 82.636    | 0.000   |
| Robust LMerr      | 220          | 14.199    | 0.000   |
| Hausman test      | 220          | 38.50     | 0.000   |
Table 5. Empirical results of factors affecting corn production cost.

| Variables | Model 1       | Model 2       | Model 3       | Model 4       | Model 5       |
|-----------|---------------|---------------|---------------|---------------|---------------|
| Land      | −0.1307***    | −0.1074***    | −0.0051**     | −0.0715***    | −0.0938***    |
|           | (0.0190)      | [−0.1275]     | (0.0174)      | (0.0150)      | (0.0172)      |
| Citizen   | 1.3078***     | 0.5960***     | 1.0308***     | 1.2618***     | 1.2618***     |
|           | (0.2100)      | [0.0887]      | (0.1830)      | (0.0579)      | (0.2250)      |
| Machine   | −0.7672***    | −0.6581***    | −0.6304***    | −0.6304***    | −0.6304***    |
|           | (0.0704)      | [−0.0564]     | (0.0579)      | (0.0580)      | (0.0580)      |
| Income    | −0.8103***    | −0.8644***    | −0.8644***    | −0.8644***    | −0.8644***    |
|           | (0.0739)      | [−1.9699]     | (0.0735)      | (0.0735)      | (0.0735)      |
| Nonagrigo | −2.1014       | −0.7205**     | −0.7205**     | −0.7205**     | −0.7205**     |
|           |               | (0.0888)      | (0.0888)      | (0.0888)      | (0.0888)      |

Note: Standard deviation in parentheses; *** means $p < 0.01$, ** means $p < 0.05$.

Model 1 considers the scale of land management to be the basic variable for estimating parameters. The research results suggest that the impact of the scale of land management on the CPC is negative and significant at the 1% level. Furthermore, Model 2 includes the labor structure variable. Its parameter estimate is positive, indicating that growth of the proportion of the non-agricultural population will promote the CPC. Nevertheless, the parameter estimate of the scale of land management is still negative in Model 2. Then, Model 3 considers the variable of the degree of mechanization. The estimated value of its parameter is negative, indicating that the improvement of the comprehensive mechanization level of corn cultivation and harvest has a role in reducing corn production costs. Moreover, Model 4 introduces the per capita annual net income of farmers in the socio-economic condition. Here, the estimated value is significantly negative at the 1% level. Lastly, Model 5 takes into consideration the non-agricultural output value ratio index, and its parameter estimate is significantly negative at the level of 5%, indicating that the increase in the non-agricultural output value ratio can be used to reduce the CPC.

Based on the estimation results of Model 1 to Model 5, the signs of the variables introduced in the model appear not to have changed significantly. The only visible change is observed in the size of the parameter estimate, although the magnitude of the change is not large. All of the above results indicate that, considering the existence of spatial effects, the above sensitive factors have a real impact on the CPC. The parameter estimation results of Model 5 demonstrate the following:

(1) The marginal effect of the scale of land management on the CPC is $−0.0938$, while the coefficient of elasticity is measured at $−0.1114$. The above results show that the scale of land management has a significantly negative impact on the CPC. Furthermore, related research suggests [36–41] that there is a “U-shaped” relationship between the unit cost of crops and the scale of land. In other words, the expansion of the scale of land management’s effect of reducing crop production costs gradually weakens. Therefore, when a certain limit is exceeded, the CPC increases. The results gathered in this paper suggest that China’s land scale is still positioned on the left side of the “U” shape. At this stage, expanding the scale of land management is still the key to reducing the CPC [42].

(2) The parameter estimate and elasticity coefficient of the labor structure are 1.2618 and 0.0856, respectively. The increase in the proportion of non-agricultural population is noted to have a notably positive impact on the CPC. Moreover, the above observations show that the reduction in agricultural labor is one of the main reasons for the increase in the CPC. These results are similar to the research conclusions of Zhang, Y.L. [43] and Alwang, J. [44]. Specifically, from the perspective of the composition of the CPC, labor costs have always accounted for a large proportion of the total CPC [36]. In recent years, as the agricultural population has been shifting to the secondary and tertiary industries, the price
of labor has continuously risen. This especially refers to the increase in the opportunity cost of household labor, which has increased the CPC.

(3) The estimated value of the parameters of the impact of mechanization on the CPC is $-0.6304$, while the elasticity coefficient is measured at $-0.0463$. More specifically, for every 1% increase in the comprehensive mechanization of corn cultivation and harvest, the CPC is reduced by, on average, 0.0463%. The aforementioned indicates that the promotion of agricultural machinery operations reduces production costs. This was proved by related studies, as well [45,46]. Therefore, the higher the level of agricultural mechanization, the stronger the substitution effect of mechanical operations on manual operations, and the less labor is required for agricultural production, which in turn greatly saves labor costs and reduces the total CPC.

(4) In reference to the socio-economic condition, the estimated value of the parameter of farmers’ per capita annual net income to the CPC is $-0.8644$, while the elasticity coefficient is $-2.1014$. The estimated value of the parameter of the proportion of non-agricultural output value to the CPC is measured to be $-0.7205$, and the elasticity coefficient is $-0.0852$. The above results suggest that improved socio-economic conditions can significantly reduce the CPC. Therefore, when the socio-economic level improves, changes in the consumption structure and public perceptions prompt society to utilize and distribute natural resources in a sustainable manner. Furthermore, agricultural development relies more on advanced technology and modern management, while farmers have enough capital to invest in improving production technology. Therefore, the technical input matches the labor input in order to promote the improvement of agricultural mechanization and the reduction of the CPC.

4. Conclusions

Based on the panel data of China’s 20 dominant corn producing provinces, this study employs the ESDA method to explore the TRD of the CPC across the country and in various regions for the period between 2008 and 2018. Furthermore, a spatial panel measurement model is constructed to analyze the influence mechanism of sensitive factors on the CPC. The results firstly indicate that the production costs in China and the three major corn producing regions have a fluctuating upward trend from 2008 to 2018, which is mainly related to the surge in labor prices. Secondly, the CPC is observed to have significant spatial differences and generally show a trend of gradual increase from the east to the west. Over time, the number of relatively high-cost provinces has increased. Moreover, all of these provinces are located in the southern mountainous and hilly corn region, indicating that the gap in the CPC in this region is widening in comparison to other regions. Thirdly, the CPC between various regions has spatial correlation, and the spatial agglomeration characteristics are relatively stable. Lastly, factors such as the scale of land management, labor structure, degree of mechanization, and economic conditions have a considerable impact on the CPC in China. Among the above factors, the scale of land management, the degree of mechanization, and economic conditions have a negative impact on the CPC. Conversely, labor structure has been shown to have a positive impact on the CPC.

Based on the above analysis, the following policy recommendations are put forward. Firstly, agricultural mechanization technology must be improved and promoted in order to reduce labor costs for corn production. Rising labor costs are the primary reason for the increase in the CPC in China. Thus, reducing the dependence of corn production on manual operations to save labor costs is the main way of lowering the CPC. The above may be achieved by strengthening agricultural machinery research, promoting agricultural mechanization technology, and encouraging farmers to use agricultural machinery for agricultural production. Secondly, this paper suggests the expansion of the land management scale and an increase in the level of large-scale corn production. To fully release the economic benefits of production scale, the paper recommends implementing large-scale planting in the northern spring corn area and the Huang-huai-hai summer corn area according to the local conditions. Furthermore, the transformation of land suitable for machinery
should be accelerated to, in turn, provide conditions for expanding the scale of production. Thirdly, the current study proposes the improvement of social and economic conditions. Farmers should be encouraged to increase their investment in land and technology to match technology input with labor input, thereby reducing the CPC.

Lastly, our study points to the need for further research in three directions. Firstly, our measurement of the CPC is not ideal, as a result of the cost subsidy in corn production not being available in the official statistical data set. Therefore, survey data of grain households, which include the cost subsidy, should be obtained in further studies of the temporal and spatial differences of China’s CPC. Secondly, future research should focus on agricultural mechanization development in the southern mountainous and hilly area, which will aid the reduction of the CPC in this area. Finally, the paper has focused solely on four factors affecting the CPC. Other factors that were not considered may cause spatial differences in the CPC in various regions and demand further study.

**Author Contributions:** S.O.: conceptualization, methodology, visualization, writing—original draft, and writing—review and editing. J.H.: supervision, and writing—review and editing. M.Y. (Minli Yang): supervision, conceptualization, and writing—review and editing. M.Y. (Mingyin Yao): funding acquisition, supervision, conceptualization, and writing—review and editing. J.L.: supervision, and writing—review and editing. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported by the National Natural Science Foundation of China (Grant Nos. 31772072).

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Not applicable.

**Acknowledgments:** The authors sincerely thank the five anonymous reviewers who made valuable comments on this paper.

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

**References**

1. National Bureau of Statistics. *China Rural Statistical Yearbook 2019*; China Statistics Press: Beijing, China, 2019.
2. Huang, J.; Yang, G. Understanding recent challenges and new food policy in China. *Glob. Food Secur.* **2017**, 12, 119–126. [CrossRef]
3. Wu, X.; Xu, J. Drivers of food price in China: A heterogeneous panel SVAR approach. *Agric. Econ.* **2021**, 52, 67–79. [CrossRef]
4. Ministry of Agriculture and Rural Affairs of the People’s Republic of China (former Ministry of Agriculture). Layout planning of conventional and organic rain-fed cereals in Spain. *Energies* **2020**, 13, 3922. [CrossRef] [PubMed]
5. Pandey, R.; Nahar, N.; Pryor, S.W.; Pourhashem, G. Cost and Environmental Benefits of Using Pelleted Corn Stover for Bioethanol Production. *Energies* **2021**, 14, 2528. [CrossRef]
6. Sandhu, H.; Scialabba, E.H.; Warner, C.; Behzadnejad, F.; Fujiwara, D. Evaluating the holistic costs and benefits of corn production systems in minnesota, US. *Sci. Rep.* **2020**, 10, 3922. [CrossRef] [PubMed]
7. Xu, C.; Xia, T.; Wang, J.; Yu, L.; Feng, L. Selectively desirable rapeseed and corn stalks distinctive for low-cost bioethanol production and high-active biosorbents. *Waste Biomass Valorization* **2021**, 12, 795–805. [CrossRef] [PubMed]
15. Chen, F.; Zhao, Y. Determinants and differences of grain production efficiency between main and non-main producing area in china. *Sustainability* **2019**, *11*, 5225. [CrossRef]
16. Latruffe, L.; Bravo-Ureta, B.E.; Carpentier, A.; Desjeux, Y.; Moreira, V.H. Subsidies and technical efficiency in agriculture: Evidence from European dairy farms. *Am. J. Agric. Econ.* **2017**, *99*, 783–799. [CrossRef]
17. Zhang, Z.; Lu, C. Identification of maize yield trend patterns in the north china plain. *Int. J. Plant Prod.* **2020**, *15*, 125–137. [CrossRef]
18. Rani, S.; Sharma, M.K.; Kumar, N. Impact of salinity and zinc application on growth, physiological and yield traits in wheat. *Curr. Sci.* **2019**, *116*, 1324–1330. [CrossRef]
19. Anand, M.; Vivek, K.; Kavya, D. Spatial and Temporal Trends in the Yields of Three Major Crops: Wheat, Rice and Maize in India. *Int. J. Plant Prod.* **2020**, *14*, 187–207. [CrossRef]
20. Wang, X.; Yamauchi, F.; Huang, J. Rising wages, mechanization, and the substitution between capital and labor: Evidence from small scale farm system in China. *Agric. Econ.* **2016**, *47*, 309–317. [CrossRef]
21. Wei, H.H.; Meng, T.Y.; Li, X.Y.; Dai, Q.G.; Zhang, H.C.; Yin, X.Y. Sink source relationship during rice grain filling is associated with grain nitrogen concentration. *Field Crops Res.* **2018**, *215*, 23–38. [CrossRef]
22. Baig, S.M.; Khan, A.A.; Ali, A.; Khan, M.Z.; Ali, G. Enhancing socioeconomic resilience and climate adaptation through value chain development of mountain products in Hindu Kush Himalayas. *Environ. Dev. Sustain.* **2021**, *23*, 8451–8473. [CrossRef]
23. Li, X.; Chen, Y. Projecting the future impacts of China’s cropland balance policy on ecosystem services under the shared socioeconomic pathways. *J. Clean. Prod.* **2020**, *250*, 119489. [CrossRef]
24. Xu, J.W.; Smith, S.; Smith, G.; Wang, W.Q.; Li, Y.H. Glyphosate contamination in grains and foods: An overview. *Food Control* **2019**, *106*, 106710. [CrossRef]
25. Li, P.; Tian, Y.; Wu, J.J.; Xu, W.C. The Great Western Development policy: How it affected grain crop production, land use and rural poverty in western China. *China Agric. Econ. Rev.* **2021**, *13*, 319–348. [CrossRef]
26. Zheng, X.Y.; Liu, W.P.; Xu, Z.G.; Ying, R.Y.; Ye, C.H. Restructuring grain production in China: Regional heterogeneity and its causality. *China Agric. Econ. Rev.* **2018**, *10*, 647–665. [CrossRef]
27. Huang, H.; Yang, M.L.; Huang, G.Q. Construction and evaluation of engineering models for mechanized production of major food crops. *Trans. Chin. Soc. Agric. Eng.* **2013**, *29*, 53–61. (In Chinese)
28. Li, W.; Wei, X.; Zhu, R.; Guo, K.Q. Study on factors affecting the agricultural mechanization level in china based on structural equation modeling. *Sustainability* **2018**, *11*, 51. [CrossRef]
29. Li, M.Y.; Wang, J.J.; Zhao, P.J.; Chen, K.; Wu, L.B. Factors affecting the willingness of agricultural green production from the perspective of farmers’ perceptions. *Sci. Total Environ.* **2020**, *738*, 140289. [CrossRef] [PubMed]
30. Baldoni, E.; Esposti, R. Agricultural Productivity in Space: An Econometric Assessment Based on Farm-Level Data. *Am. J. Agric. Econ.* **2020**, *103*, 1525–1544. [CrossRef]
31. Zhang, L.L.; Xiong, L.C.; Cheng, B.D.; Yu, C. How Does Foreign Trade Influence China’s Carbon Productivity? Based on Panel Spatial Lag Model Analysis. *Struct. Chang. Econ. Dyn.* **2018**, *47*, 171–179. [CrossRef]
32. Hoffer, A.; Humphreys, B.R.; Ruseski, J.E. State cigarette taxes and health expenditures: Evidence from dynamic spatial lag panel models. *Pap. Reg. Sci.* **2019**, *98*, 925–950. [CrossRef]
33. Wongjaikham, W.; Wongsawaeng, D.; Ratnitsai, V.; Kamjam, M.; Assabumrungrat, S. Low-cost alternative biodiesel production apparatus based on household food blender for continuous biodiesel production for small communities. *Sci. Rep.* **2021**, *11*, 13827. [CrossRef] [PubMed]
34. Tian, X.; Yi, F.; Yu, X. Rising cost of labor and transformations in grain production in china. *China Agric. Econ. Rev.* **2020**, *12*, 158–172. [CrossRef]
35. Deng, F.; Zhu, H.; Huang, Y.; Liang, X. The impact of trade on scale efficiency in grain and oil-bearing plant production in china. *Emerg. Mark. Financ. Trade* **2018**, *57*, 1–13. [CrossRef]
36. Wang, Q.; Li, F.; Yu, J.; Fleskens, L.; Ritsema, C.J. Price decline, land rental markets and grain production in the North China Plain. *China Agric. Econ. Rev.* **2021**, *13*, 141–166. [CrossRef]
37. Jin, Y.A.; Qian, W.B.; Wu, B.C. Off-farm employment and grain production change: New evidence from China. *China Econ. Rev.* **2020**, *63*, 101519. [CrossRef]
38. Muyanga, M.; Jayne, T.S. Revisiting the farm size-productivity relationship based on a relatively wide range of farm sizes: Evidence from kenya. *Am. J. Agric. Econ.* **2019**, *101*, 1140–1163. [CrossRef]
39. Ali, D.A.; Deininger, K. Is There a Farm Size-Productivity Relationship in African Agriculture? Evidence from Rwanda. *Land Econ.* **2015**, *91*, 317–343. [CrossRef]
40. Khanna, M.; Chen, L.Y.; Basso, B.; Cai, X.M.; Field, J.; Guan, K.Y.; Jiang, C.; Lark, T.J.; Richard, T.L.; Spawn-Lee, S.A.; et al. Redefining marginal land for bioenergy crop production. *GCB Bioenergy* **2021**, *13*, 1590–1609. [CrossRef]
41. Shi, Y.; Pinsard, C.; Accatino, F. Land sharing strategies for addressing the trade-off between carbon storage and crop production in France. *Reg. Environ. Chang.* **2021**, *21*, 92. [CrossRef]
42. Chou, H.; Li, X.H.; Yu, J.L. China’s Corn Industry: Development Trends and Policy Recommendations. *Issues Agric. Econ.* **2021**, *4–16*. (In Chinese) [CrossRef]
43. Zhang, Y.L.; Wang, Y.H.; Bai, Y.L. Knowing and Doing: The Perception of Subsidy Policy and Farmland Transfer. *Sustainability* **2019**, *11*, 2393. [CrossRef]
44. Alwang, J.; Sabry, S.; Shideed, K.; Swelam, A.; Halila, H. Economic and food security benefits associated with raised-bed wheat production in Egypt. *Food Secur.* **2018**, *3*, 589–601. [CrossRef]

45. Takeshima, H.; Hatzenbuehler, P.L.; Edel, H.O. Effects of agricultural mechanization on economies of scope in crop production in Nigeria. *Agric. Syst.* **2020**, *177*, 102691. [CrossRef]

46. Theuerl, S.; Klang, J.; Prochnow, A. Process disturbances in agricultural biogas production—Causes, mechanisms and effects on the biogas microbiome: A review. *Energies* **2019**, *12*, 365. [CrossRef]