Analysis of the Spatial Effect of Capital Misallocation on Agricultural Output—Taking the Main Grain Producing Areas in Northeast China as an Example

Shuai Qin, Hong Chen *, Tuyen Thi Tran and Haokun Wang

College of Economics and Management, Northeast Forestry University, Harbin 150040, China; 15225145321@nefu.edu.cn (S.Q.); tranthi_tuyen@yahoo.com (T.T.T.); whk@nefu.edu.cn (H.W.)
* Correspondence: chenhong@nefu.edu.cn; Tel.: +86-139-3644-1436

Abstract: Increasing agricultural output by reducing capital misallocation is a capital-saving strategy, as it does not require the usage of additional inputs. Based on the panel data of 36 prefecture-level cities in northeast China from 2011 to 2020, this paper uses the spatial Durbin model to test the impact of capital mismatch on agricultural output and its mechanisms. We found that capital misallocation is prevalent in prefecture-level cities, showing a spatial distribution characteristic of “north-south confrontation and central collapse”, with a significant spatial spillover effect. A one-unit increase in capital misallocation leads to a 16.00% decrease in local agricultural output and a 1.80% decrease in adjacent areas. However, with the optimization and upgrading of the agricultural industry and agricultural technology progress, the inhibitory effect of capital misallocation on the growth of agricultural output is constantly weakening. The above conclusion still holds after a series of robustness tests. The conclusion of this paper provides policy inspiration for promoting the rational allocation of factors between cities and regions, coordinating regional coordinated development, and then promoting the sustainable growth of agricultural output.

Keywords: capital misallocation; agricultural output; spatial spillover; Northeast China

1. Introduction

COVID-19 has raised global concerns about sustainable agriculture development [1] due to the lack of normal resource circulation in the short term and the deepening of resource mismatch [2,3]. Agriculture is often deemed a national security priority by countries, as its products are necessary for the existence of society [4]. Under the condition of fixed resource endowment, the reallocation of factors is an important factor to promote the improvement of agricultural productivity [5,6]. However, compared with developed countries, the imperfect market system in developing countries leads to widespread factor misallocation [7]. Among various production factors, capital misallocation has been documented as a prevailing empirical phenomenon in China, inhibiting the increase in agricultural output [8,9]. As one of the three black soil belts in the world, Northeast China has contributed the most to China’s grain production increase in recent years, and it is also the ballast stone of China’s food security [10]. However, due to the lag in regional market segmentation and factor market reform, the issue of agricultural capital mismatch in Northeast China still exists, which not only reduces agricultural total factor productivity [11,12] but also inhibits growth in the agricultural output [13]. With the continuing outbreak of the COVID-19 pandemic and the intensification of the Russia–Ukraine conflict, reducing the impact of capital misallocation on agricultural output in Northeast China has become one of the important means to ensure China’s food safety and even the world’s food security.

The impact of capital misallocation on agricultural production is a hot topic that scholars are paying increasing attention to. From the perspective of the research scope, scholars’ existing results based on the perspectives of farmers, regions, and countries show that...
capital misallocation inhibits the improvement of agricultural production levels [14–16]. For example, Stephen et al. (2020) used the survey data of Vietnamese farmers and found that improving capital misallocation can increase their production efficiency by 4.00% [17]. Chen (2012) pointed out that the improvement of China’s agricultural capital misallocation has left the agricultural productivity in the eastern, central, western, and northeastern regions with room for an increase of 3%–61% [18]. Using data from the World Agricultural Census, Adamopoulos et al. (2014) showed that effectively eliminating capital and land misallocation can increase farm productivity by around 25% in both poor and rich countries [19].

In terms of research methods, most of the existing results are based on the research framework of Hsieh et al. (2009) [20] (HK model for short) or Aoki (2012) [21], focusing on the impact of capital misallocation on local agricultural production, ignoring the spillover effect brought about by the spatial mobility of factors. For example, Zhu et al. (2011) believed that under the condition of locking technology, eliminating capital and labor misallocation can increase China’s agricultural total factor productivity by more than 20% based on the extended HK model [15]. Zheng et al. (2019) used the adjusted Aoki model to establish that factor misallocation leads to an average annual loss of more than 5% of China’s agricultural output [13].

The main purpose of this paper is to explore the spatial spillover effect of capital misallocation on agricultural production at the prefecture-city level and identify its mechanism so as to provide a valuable theoretical basis for policymakers to eliminate capital misallocation and promote the synchronous growth of agricultural output between prefecture-city level.

Prior studies regarding the effect of capital misallocation on agricultural production have gradually increased in number in recent years, deepening the understanding of such issues. Compared with previous studies, the marginal contribution of this paper includes three aspects.

Firstly, we explore the impact of capital misallocation on agricultural production at the prefecture level. The major existing achievements are concentrated at the regional and national levels [15,16]. Considering that there are significant regional differences with regard to agricultural capital misallocation in China, and prefecture-level scale analysis has policy guidance on a smaller spatial scale, it is necessary to study the relationship between capital misallocation and agricultural production at the prefecture level.

Secondly, we aim to fill the research gap regarding the spatial spillover effect of capital misallocation on agricultural production. With the improvement in regional market integration and the steady progress of factor marketization reform, the spatial mobility of capital factors has been continuously enhanced. Previous literature has also proved that agricultural production has obvious spatial relevance [22]. However, existing literature only considers the impact of capital misallocation on local agricultural production, ignoring the effect on agricultural production in adjacent cities [18]. Therefore, the spatial mobility of factors should be taken into account to analyze the impact of capital misallocation on agricultural production.

Finally, the mechanism of capital misallocation affecting agricultural production is revealed. Previous studies focused on the causes of capital misallocation [23,24], but there are few studies on how capital misallocation plays a role in agricultural production. In view of this, based on the panel data of 36 prefecture-level cities in Northeast China from 2011 to 2020, this paper measured and analyzed the degree of agricultural capital misallocation. Based on this, the spatial Durbin model was used to test the spatial spillover effect of capital misallocation on agricultural output at the prefecture level. Additionally, we further analyzed the mechanism of capital misallocation affecting agricultural output.

The rest of this paper is arranged as follows. Section 2 presents the model construction, data sources, and variable selection. Section 3 lists the research results based on three aspects: firstly, we introduce the status quo of agricultural output and capital misallocation in 36 prefecture-level cities, followed by the use of the space Durbin model to verify the
capital matching spatial spillover effects on agricultural output. Finally, the mechanism of capital misallocation on agricultural output is tested. Section 4 contains the discussion. The conclusion and suggestions can be found in Section 5.

2. Materials and Methods
2.1. Research Methods
2.1.1. Spatial Autocorrelation Test
“The First Law of Geography” holds that everything is related to everything else, but close things are more related to each other [25]. The global Moran index is the most commonly used index to judge the spatial association of things [26]. Therefore, this paper uses it to test whether there is a spatial correlation of variables. The formula is as follows:

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

(1)

In Formula (1), \( n \) is the number of cities at the prefecture level, taking 36, while \( x_i \) and \( x_j \) represent the observations of cities \( i \) and \( j \), respectively. \( \bar{x} \) is the sample mean, \( S^2 \) is the sample variance, and \( W_{ij} \) is the column element in row \( i \) of the spatial weight matrix. The value of Moran’s \( I \) ranges from \(-1\) to 1, and the larger the value is, the stronger the spatial correlation is. When Moran’s \( I \) is greater than 0, it indicates a positive spatial correlation, that is, the high (low) value is adjacent to the high (low) value. Moran’s \( I \) less than 0 indicates a negative spatial correlation, that is, high (low) values are adjacent to low (high) values. Moran’s \( I \) being equal to 0 means spatial random distribution and no spatial correlation.

2.1.2. Econometric Model Construction
As there are extensive and close economic relations between prefecture-level cities, they show a strong correlation in economic development. Some empirical studies have shown that there are differences in the contribution of agricultural output among different regions [27], and agricultural production may also have obvious spatial correlations [22]. As confirmed by Wu (2010) [28] and Wang et al. (2021) [29], the trans-regional mobility of agricultural production factors in China leads to a significant spatial effect on agricultural output. However, traditional econometric models fail to consider the spatial effect of agricultural output, and their regression results may be biased [28,30]. Therefore, it is necessary to test and control the possible spatial correlation between capital mismatch and agricultural output.

To date, the most used and mature spatial panel econometric models are the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM). SLM is mainly used to analyze whether the dependent variable has a spatial spillover effect. SEM mainly analyzes the spatial influence of error terms. SDM includes lag terms of both dependent and independent variables, and parameter estimation of independent variables and error terms are not affected by increasing or missing spatial dependence of variables [31]. Concurrently, SDM can measure the spillover effects of variables within and between regions, namely direct effects and indirect effects, and can further and comprehensively analyze the impact of capital mismatch on agricultural output. However, which spatial econometric model should be used in the analysis needs to be determined based on the results of the LR and Wald tests. Therefore, this paper constructs a general spatial econometric model.

\[ y_{it} = \rho \sum_{j=1}^{n} W_{ij} y_{jt} + \beta X_{it} + \phi \sum_{j=1}^{n} W_{ij} x_{it} + \mu_i + \nu_t + \epsilon_{it} \]  

(2)

In Formula (2), \( i \) and \( t \) represent regions and years, respectively. \( y_{it} \) represents the agricultural output of the prefecture-level city \( i \) in year \( t \). \( X_{it} \) is the set of explanatory
variables. \( \beta \) is the vector of the parameters to be evaluated for the explanatory variable, \( \rho \) is the spatial lag coefficient of the explained variable, and \( \rho \) is the spatial regression coefficient of the explanatory variable. \( \mu \) and \( \nu \) represent space and time effects, respectively. The \( \epsilon_{it} \) is subject to the random error term of independent homometry, and \( W_{ij} \) is the spatial weight, expressed as the penultimate of the shortest distance between cities.

2.2. Variable Selection

2.2.1. Dependent Variable

Agricultural output: Stable agricultural output is a necessary condition for sustainable agricultural development [32]. Especially under the framework of resource and environment constraints, further improvement of agricultural output capacity is considered a key link for achieving sustainable agricultural development [33]. Agricultural output is expressed in two ways, one in terms of crop yield and the other in terms of agricultural output value. Considering that this paper mainly focused on generalized agricultural research, the aggregate yield of different types of crops is relatively impractical. Therefore, the total output value of agriculture, forestry, animal husbandry, and fisheries (\( \text{Agrout} \)) measured by constant price in 2011 was selected as the representative variable of agricultural output at the municipal level.

2.2.2. Independent Variables

Capital misallocation: Capital misallocation refers to the fact that capital cannot flow freely according to the market rules due to the existence of external factors, which leads to the unequal marginal output of the same unit of capital input—that is, to deviation from the Pareto optimal state. Capital misallocation will not only reduce total factor productivity in agriculture but also inhibit the growth of agricultural output [15]. Based on the research framework by Aoki (2012) [21], this paper uses the relative misallocation coefficient of capital to measure the level of capital misallocation. The specific estimation process is as follows:

\[
\text{Miscap} = \frac{(K_i/K)}{(s_{it}\beta_{K}/\hat{\beta}_K)}
\]  

In Formula (3), \( \text{Miscap} \) is a relative misallocation factor for capital. \( \text{Miscap} \) equal to 1 indicates that capital investment in the \( i \) region has reached an effective state, and \( \text{Miscap} \) greater than 1 (\( \text{Miscap} \) less than 1) indicates excessive (insufficient) capital factor investment. \( K_i \) and \( K \) represent the stock of agricultural capital in the \( i \) region and in all sample areas, respectively. \( s_{it} \) indicates that the output of the \( i \) region accounts for the share of the total sample output. \( \hat{\beta}_K \) represents the output-weighted capital contribution. \( \beta_{K} \) is the elasticity of the capital factor output in the \( i \) region, estimated by the C-D production function with constant scale compensation. The output variable in this function is the total output value of agriculture, forestry, animal husbandry, and fisheries measured at constant prices in 2011. Labor input indicates the agricultural employees of the prefecture-level cities. The proxy variable of land input is the sown area of crops. Capital investment is the agricultural capital stock of each city; it should be noted that the agricultural capital in this article only refers to material capital in a narrow sense, mainly using the perpetual inventory method to measure the stock of agricultural capital, which refers to the year-end monetary value of tangible fixed assets that can be reused in the agricultural production process. The expression of this method is \( K_t = (I_t/P_t) + K_{t-1} (1 - \delta) \), where \( K_t \) and \( K_{t-1} \) are the stock of agricultural capital for the current year and the previous year, respectively. This is the investment of the current year, expressed by the total agricultural fixed capital formation, \( P_t \) is the agricultural production material price index, and \( \delta \) is the depreciation rate, the value of which is 9.6% [34]. On this basis, the elasticity of capital output in prefecture-level cities is estimated by the panel fixed-effect model, and the result is substituted into Formula (3) to obtain the capital relative misallocation coefficient of each prefecture-level city.
2.2.3. Control Variables

To make the model more robust and accurate in measuring the relationships between core variables, this paper also controlled the following variables.

Mechanization level. Agricultural mechanization has helped to promote the large-scale operation of China’s agriculture, which not only promotes the growth of agricultural output [35] but also promotes the sustainable development level of agriculture [36]. Previous studies found that a 1% increase in agricultural mechanization would lead to a 1.28% increase in agricultural output [37]. Therefore, improving the level of agricultural mechanization is an important way to guarantee the stable growth of agricultural output. In this work, the total power of agricultural machinery in prefecture-level cities was used to measure the level of mechanization.

Irrigation level. Water shortage in China is threatening the growth of agricultural output and the promotion of sustainable agricultural development [38,39]. The improvement of irrigation level is beneficial for improving the level of drought resistance in crops, which has become an important constraining factor of agricultural production. In this paper, the ratio of effective irrigated area to sown area of crops is used to measure the level of agricultural irrigation.

Fertilizer. As a decisive factor in increasing agricultural production, chemical fertilizers play an important role in China’s agricultural production. However, the excessive use of chemical fertilizers will lead to an increase in agricultural production costs and the aggravation of non-point source pollution, restricting the improvement in the sustainable agricultural development level [36]. The input of chemical fertilizer in this paper is calculated by the net amount of chemical fertilizer used for agricultural production in the current year.

Agricultural practitioners. The previous literature found that rural labor transfer and population aging lead to insufficient agricultural labor input, which has a negative effect on agricultural output [40,41]. This paper uses the number of agricultural employees to represent the level of agricultural labor input.

Sown area of crops. The cultivated land area is the key factor restricting the growth of agricultural output. The decrease in the cultivated land area will lead to a significant decline in agricultural output [42]. In this paper, crop sown area is taken as a proxy variable of cultivated land area.

2.2.4. Other Variables

Agricultural industry upgrade. The upgrading of the agricultural industry is the process of the formation, development, and decline of the agricultural industry. It represents the evolution trend of the agricultural industry from a low value-added state to a high value-added state [43]. In most of the literature, the proportion of non-agricultural output value is adopted to measure industrial upgrading according to Petty-Clark’s law. Therefore, this paper draws on the research of Chen et al. (2018) [44] and uses the proportion of the total output value of the secondary and tertiary industries in GDP as a proxy variable of agricultural industrial upgrading.

Agricultural technology progress. Agricultural technological progress refers to the continuous use of advanced agricultural technology to replace backward agricultural technology, in order to promote the development of agricultural productivity. In recent years, the contribution rate of technological progress to China’s agricultural development has reached over 50% [45]. Referring to previous research results [46], the contribution rate of agricultural scientific and technological progress is used as a characterization index of agricultural technological progress.

2.3. Data Sources

In accordance with the principle of availability and objectivity of data, 36 prefecture-level cities in three northeastern provinces (Heilongjiang, Jilin, and Liaoning) in the past decade (2011–2020) were selected as the research scope, with a total of 360 sample sizes. The
data mainly came from the Liaoning Statistical Yearbook, the Jilin Statistical Yearbook, and the Heilongjiang Statistical Yearbook, statistical yearbooks of each city and its Statistical Bulletin of National Economic and Social Development. To eliminate the influence of heteroscedasticity, we completed logarithm processing for variables other than Miscap and Irrigation. In order to eliminate the influence of heteroscedasticity, the absolute numbers in the article are logarithmic. The descriptive statistics of each variable are shown in Table 1. It can be seen that the mean value of most variables is greater than the standard deviation, indicating that the degree of data dispersion is not high, and the next step can be analyzed.

Table 1. Variable indicators and descriptive statistics.

| Variable Type   | Variable | Obs | Mean  | Min  | Max  |
|-----------------|----------|-----|-------|------|------|
| Dependent variable | Agrout  | 360 | 108.71 | 0.57 | 430.06 |
| Independent variable | Miscap | 360 | 0.64  | 0.01 | 2.25  |
| Area            | 360      | 640.52 | 58.00 | 2746.82 |
| Mechan          | 360      | 292.19 | 15.24 | 1636.43 |
| Fertilizer      | 360      | 12.69  | 0.33  | 48.56  |
| Labor           | 360      | 50.40  | 1.50  | 152.20 |
| Irrigation      | 360      | 0.32   | 0.01  | 1.06   |
| Upgrade         | 360      | 0.68   | 0.16  | 0.93   |
| Tech            | 360      | 33.57  | 10.01 | 59.53  |

3. Results

3.1. Dynamic Evolution of Agricultural Output

Figure 1 is the kernel density map of agricultural output in 36 cities drawn using the stata17.0 software to characterize its evolution characteristics. The level of agricultural output is reflected by the left and right translation of the position of the curve. The shape represents the convergence or diffusion degree, and the kurtosis represents the divergence or polarization trend. Firstly, the overall position of the curve fluctuates to the left from 2011 to 2020, indicating that the agricultural output capacity continues to decline, and the proportion of cities in low-value areas shows the characteristics of expansion, which is in line with the actual situation of “increasing production but not increasing income” of agriculture in major grain-producing areas [47]. Secondly, the kernel density curve has undergone the evolution process from a single peak to a double peak. In 2020, the distribution characteristics of the double peak are obvious, but the height difference between the side peak and the main peak is large, which means that the polarization phenomenon of agricultural output is increasing and the agricultural output is changing from convergence to diffusion. Thirdly, the peak height fluctuates from a wide peak to a sharp peak, indicating that the spatial difference in agricultural output between cities is gradually narrowing and evolving, and its range reduced from CNY 40.89 billion in 2011 to CNY 29.18 billion in 2020. Finally, the trailing end of the curve keeps shrinking on the right side, and the ductility of the distribution tends to shrink to some extent, indicating that the difference between the cities in the high-value region and the average level of agricultural output is narrowing. In general, the agricultural output capacity at the prefecture level is declining and polarized, and the spatial difference still exists, although it shows a narrowing trend. Therefore, the spatial effect should be included in the econometric regression model of agricultural output.
3.2. Spatial-Temporal Evolution Analysis of Agricultural Capital Misallocation

According to Formula (3), the closer the misallocation coefficient of agricultural capital is to 1, the more reasonable the capital allocation is. Since the capital misallocation coefficient is greater than or less than 1, in order to better display its spatial distribution characteristics, the calculation results were subtracted from 1, and the absolute value was taken: the smaller the absolute value, the lighter the capital mismatch in the prefecture-level city. According to the absolute value, the degree of misallocation was divided into three different levels: mild $[0, 0.30]$, moderate $[0.30, 0.60]$, and high $[0.60, +\infty]$. Concurrently, ArcGIS10.8 software was used for spatial visualization of the absolute value results from 2011 to 2020 (Figure 2).

From the perspective of time evolution, there is a widespread misallocation of agricultural capital at the prefecture-city level. Although the degree tends to decline, there is still room for further improvement. Among the cities, the number of cities with mild misallocation increased from 7 in 2011 to 11 in 2020, with the proportion rising from 19.44% to 30.56%, and the proportion of cities with high levels of misallocation decreased from 33.33% and 47.22% in 2011 to 27.78% and 41.67% in 2020, respectively. It was proved that more than two-thirds of the cities have moderate or high levels of agricultural capital misallocation, and only one-third of the cities have a low degree of agricultural capital misallocation. From the perspective of spatial evolution, agricultural capital misallocation in prefecture-level cities has significant spatial agglomeration characteristics, and the spatial pattern changes greatly. In 2011, the cities with a low degree of agricultural capital misallocation formed a large-scale agglomeration trend in the south of Heilongjiang Province and the southeast of Jilin Province, while the cities with a moderate and high degree were mainly distributed in the east and west sides of Heilongjiang Province, presenting the spatial distribution characteristics of “low in the middle, high in the east and west”. With the improvement in regional market integration, the barriers of market segmentation to factor flow are gradually reduced, and the problem of inter-municipal agricultural capital misallocation is effectively alleviated. By 2020, the number of cities with mild agricultural capital misallocation increased by 57.14%, mainly distributed in the northern part of Heilongjiang Province, the southern part of Jilin Province, and most cities in Liaoning Province, presenting a spatial pattern of “low in the central part and high in the north and south”.

Figure 1. Kernel density of agricultural output from 2011 to 2020.
Heilongjiang Province, the southern part of Jilin Province, presenting a spatial pattern of "low in the central part and high in the north and south". It is 0.160, and it passes the 1% significance level test, indicating that there is a siphon effect in the process of regional agricultural development, that is, high agricultural output areas will attract the surrounding areas of production factors, improve the region’s output level, but exert a negative impact on neighboring areas’ agricultural output. The regression coefficient of capital misallocation on agricultural output is −0.160, and it passes the 1% significance level test, indicating that capital misallocation will cause a loss in agricultural output. The coefficient of the spatial lag of capital misallocation will cause a loss in agricultural output. The coefficient of the spatial lag on agricultural output is \(-\rho\) passes the 1% significance level test, indicating that there is a spatial spillover effect of agricultural output. Its value is less than zero, indicating the existence of a negative spatial correlation effect, which may indicate that there is a siphon effect in the process of regional agricultural development, that is, high agricultural output areas will attract the surrounding areas of production factors, improve the region’s output level, but exert a negative impact on neighboring areas’ agricultural output. The regression coefficient of capital misallocation on agricultural output is \(-0.160\), and it passes the 1% significance level test, indicating that capital misallocation will cause a loss in agricultural output. The coefficient of the spatial lag

### Table 2. Results of the space metering model test.

| Test Indicator | Test Method | Statistical Value | p-Value |
|----------------|-------------|-------------------|---------|
| LM test        | LM test no spatial error | 32.94 | 0.001 |
|                | LM test no spatial lag   | 40.70 | 0.001 |
| Robust LM test | Robust LM test no spatial error | 26.90 | 0.001 |
|                | Robust LM test no spatial lag | 34.65 | 0.001 |
| Wald test      | Wald test spatial lag    | 45.54 | 0.001 |
| LR test        | LR test spatial error    | 41.61 | 0.001 |
|                | LR test spatial lag      | 41.29 | 0.001 |
| Hausman test   | Hausman test             | 12.50 | 0.052 |

Based on the above tests, further comparison of the estimated results in Table 3 shows that under the three fixed-effect models, the log-likelihood of the spatial-temporal fixed-effect model is the maximum and sigma2 is the minimum, so the paper chooses the spatial-temporal fixed-effect model as the final analysis model. In the spatial-temporal fixed-effect model, the spatial autocorrelation coefficient of agricultural output \(\rho\) passes the 1% significance level test, indicating that there is a spatial spillover effect of agricultural output. Its value is less than zero, indicating the existence of a negative spatial correlation effect, which may indicate that there is a siphon effect in the process of regional agricultural development, that is, high agricultural output areas will attract the surrounding areas of production factors, improve the region’s output level, but exert a negative impact on neighboring areas’ agricultural output. The regression coefficient of capital misallocation on agricultural output is \(-0.160\), and it passes the 1% significance level test, indicating that capital misallocation will cause a loss in agricultural output. The coefficient of the spatial lag
term is significantly negative at the 1% level, indicating that there is a spatial spillover effect in the impact of capital misallocation on agricultural output; that is, capital misallocation at the local level will bring about losses in agricultural output in neighboring regions. Since the estimated coefficient of SDM is biased, it cannot represent the magnitude of direct impact and spatial spillover effects [48], and the regression result is only a preliminary judgment of the direction of action of the various factors, so the direct, indirect, and total effects of the respective variables on agricultural output need to be further estimated.

### Table 3. SDM model estimation results.

| Variable      | Spatial Fixed Effect | Time Fixed Effect | Spatial-Temporal Fixed Effect |
|---------------|---------------------|-------------------|-------------------------------|
|               | Coefficient         | t-Value           | Coefficient                  | t-Value | Coefficient       | t-Value |
| Miscap        | −0.390 ***          | −7.37             | −0.218 ***                   | −8.42   | −0.160 ***        | −7.22   |
| lnArea        | 1.025 ***           | [5.70]            | −0.193 *                     | [−1.89] | 1.087 ***         | [6.37]  |
| lnMechan      | −0.434 ***          | [−3.09]           | 0.171                        | [1.41]  | −0.398 ***        | [−2.92] |
| lnFertilizer  | −0.051              | [−0.40]           | −0.171                       | [1.61]  | 0.015             | [0.12]  |
| lnLabor       | 0.572 *             | [1.82]            | 0.516 ***                    | [6.16]  | 0.210             | [0.68]  |
| Irrigation    | 0.228               | [0.66]            | −0.401 **                    | [−1.99] | 0.637 ***         | [1.85]  |
| WlnMiscap     | −0.028              | [−0.26]           | 0.0136                       | [0.22]  | −0.073 ***        | [−0.91] |
| WlnArea       | −0.888 ***          | [−3.05]           | −0.782 ***                   | [−3.38] | 0.012             | [0.04]  |
| WlnMechan     | 0.209               | [0.81]            | 0.715 ***                    | [2.69]  | 0.421             | [1.43]  |
| WlnFertilizer | 0.268               | [1.29]            | −0.055                       | [−0.29] | 0.269             | [1.31]  |
| WlnLabor      | 0.322               | [0.50]            | 0.008                        | [0.04]  | −0.444            | [−0.67] |
| WlnIrrigation | −2.050 ***          | [−3.68]           | −1.939 ***                   | [−4.88] | −0.692            | [−1.15] |
| ρ             | −0.023              | [−0.33]           | −0.129 *                     | [−1.74] | −0.257 ***        | [−3.38] |
| sigma2        | 0.145 ***           | [13.42]           | 0.324 ***                    | [13.39] | 0.126 ***         | [13.33] |

R-squared: 0.420 0.556 0.290
log l: −163.504 −308.702 −141.293
N: 360 360 360

Note: * p < 0.1, ** p < 0.05, *** p < 0.01.

### 3.4. Analysis of Spatial Effect Decomposition

On the basis of the previous section, the partial differential method is used to decompose the spatial effects of each driving factor on agricultural output (Table 4). The results show that the direct effect of capital misallocation on agricultural output is −0.160, and through the 1% significance level test, it indicates that capital misallocation will bring losses to local agricultural output. When locking other variables, on average, every 1 unit increase in capital misallocation will lead to a 16.00% decrease in local agricultural output. This is similar to the conclusions in the existing literature [18]. The reason for this is that capital misallocation causes agricultural capital to be allocated to low-efficiency agricultural production activities, which increases the means of production consumed by the same output, hinders the improvement of agricultural production efficiency, and thus inhibits the growth of agricultural output. The indirect effect is significantly negative at the 1% level, indicating that on the premise of controlling other variables, every 1 unit increase in the degree of local capital misallocation will, on average, cause a 1.80% reduction in the agricultural output of neighboring regions. The possible reason for this is that there is strong imitation behavior among local governments [49]. Investment decisions of local governments are easy to use to conduct spatial transmission to surrounding areas through “demonstration and learning effect”, resulting in problems such as repetitive construction and inefficient input, which further inhibits the growth of agricultural output in neighboring areas.

Among the control variables, the direct effect of the mechanization level is significantly positive at the 5% level, indicating that the improvement of the mechanization level has a great promotion effect on the growth of local agricultural output, but its spillover effect is significantly negative, indicating that the inter-regional operation of agricultural machinery has not been effectively popularized in the study area. The direct effect and indirect effect of chemical fertilizer are not significant, which may be due to the improvement of
agricultural technology progress. Increasing the amount of chemical fertilizer is no longer the main way to increase agricultural yield [50], and with the strict implementation of the policy of chemical fertilizer reduction, the amount of chemical fertilizer available is also decreasing. The direct effect of irrigation level was significantly positive. During the study period, the effective irrigated area increased by 3.55% annually, which greatly promoted the improvement in agricultural output. The direct effect of the agricultural sown area was significantly positive, while the indirect effect was negative, but it was not statistically significant. The main reason for this is that the input of agricultural capital has a substitution effect on land resources. In addition, the agricultural sown area in Northeast China is basically fixed, and there was even a decline trend in some years, resulting in a very limited marginal contribution of land to agricultural output [28]. The direct and indirect effects of agricultural employees are not significant, mainly because agricultural production has changed from labor-intensive to capital-intensive [51], and simply increasing the labor force cannot have a significant impact on regional agricultural output.

Table 4. SDM spatial effect decomposition results.

| Variable | Miscap | lnMechan | lnFertilizer | Irrigation | lnArea | lnLabor |
|----------|--------|----------|--------------|------------|--------|---------|
| Direct effects | −0.160 *** | 0.415 *** | −0.001 | 0.671 ** | 1.091 *** | 0.246 |
| Indirect effects | [−6.68] | [3.08] | [−0.01] | [2.06] | [6.55] | [0.80] |
| Total effect | −0.018 *** | −0.460 * | 0.231 | −0.688 | −0.026 | −0.426 |

Note: * p < 0.1, ** p < 0.05, *** p < 0.01, t values are put in parentheses.

3.5. Robustness Test

In order to further explain the rationality of the results, this section conducts robustness tests on the empirical results from the following four aspects, and the specific results are shown in Table 5.

Table 5. Results of robust regression.

| Type | Miscap | lnMechan | lnFertilizer | Irrigation | lnArea | lnLabor |
|------|--------|----------|--------------|------------|--------|---------|
| Direct effects | −0.665 *** | −0.620 *** | 0.064 | 0.321 | 0.852 *** | −0.107 |
| Indirect effects | [−7.00] | [−2.89] | [0.38] | [0.64] | [3.78] | [−0.24] |
| Total effects | −0.791 *** | 0.103 | 0.367 | 0.151 | 0.753 ** | 0.092 |
| Direct effects | −0.269 *** | −0.286 * | −0.041 | 0.543 * | 1.067 *** | 0.184 |
| Indirect effects | [−3.43] | [0.24] | [1.46] | [0.18] | [2.11] | [0.10] |
| Total effects | −0.328 *** | −0.118 | 0.101 | −0.514 | 0.705 *** | −0.562 |
| Direct effects | −0.126 *** | 0.117 ** | −0.072 | 0.123 | 0.719 *** | 0.487 *** |
| Indirect effects | [−5.59] | [2.02] | [−1.44] | [0.88] | [10.06] | [3.60] |
| Total effects | −0.141 *** | 0.202 | 0.07 | −0.503 | 0.527 *** | 0.239 |
| Direct effects | −0.275 | [1.48] | [0.71] | [−1.62] | [3.66] | [0.70] |
| Indirect effects | −0.367 *** | −0.225 * | −0.051 | 0.759 ** | 1.117 *** | 0.400 |
| Total effects | [−7.94] | [−1.83] | [−0.48] | [2.55] | [7.14] | [1.47] |
| Direct effects | −0.166 ** | 1.865 *** | −0.572 | 0.631 | −1.311 | 1.766 |
| Indirect effects | [−2.35] | [2.62] | [−0.83] | [0.49] | [−1.36] | [1.19] |
| Total effects | −0.533 | 1.638 ** | −0.623 | 1.401 | −0.195 | 2.166 |

Note: * p < 0.1, ** p < 0.05, *** p < 0.01, t values are put in parentheses.
3.5.1. Shorten the Time Window

China’s economic development has the evolution characteristics of the “five-year plan”; the macro policies within the same planning period are relatively consistent, and the sample observation results are relatively reliable. Therefore, the samples from the most recent 5 years (2016–2020) were used for re-estimation, and we found that the regression coefficients of capital misallocation are significantly negative, which is consistent with the benchmark regression results.

3.5.2. Winsorize

Since the existence of extreme values of variables would affect the accuracy of model estimation, in order to more truly describe the relationship between capital misallocation and agricultural output, the paper divided all variables into 1% upper and bilateral winsorize and re-regression. The results show that the regression coefficient of capital misallocation is still significantly negative, indicating that the impact of capital misallocation on agricultural output is robust.

3.5.3. Replace the Dependent Variable

The total output value of agriculture, forestry, animal husbandry, and fisheries was used as the representative variable of agricultural output above, and some scholars used the total output value of agriculture as a proxy variable [52]. Therefore, the dependent variable was replaced by the total output value of agriculture to continue to test the impact of capital misallocation on agricultural output. The results show that the coefficients of capital misallocation are still significantly negative under different test levels, which once again proves that the empirical results of this paper are robust.

3.5.4. Replace the Weight

The above is mainly based on the spatial geographical distance to construct the spatial weight, ignoring the spatial correlation of economic activities. Therefore, based on existing studies [53], the economic geographical weight matrix is constructed to test the robustness of the above results by taking into account the spatial correlation between the economy and the distance of prefecture-level cities. The results show that the core explanatory variables’ direction and significance of the estimated coefficients do not change fundamentally after the weight is changed, but only the coefficient size is different, which further indicates that the research results are robust and reliable.

3.6. Further Analysis

The empirical conclusion above shows that capital misallocation inhibits the growth of agricultural output and has significant spatial spillover effects. This section mainly analyzes the action path of capital misallocation on agricultural output. Previous studies showed that industrial upgrading is an important factor affecting China’s economic growth [54], and capital misallocation may delay the industrial upgrading and thus affect economic growth, but the existing research results do not fully pay attention to this channel [55]. Compared with the commodity market, the development of China’s factor market is relatively backward, and the allocation of capital factors mainly depends on the government’s administrative means. The government poured capital into non-agricultural fields with a short return and quick results due to incentivization by promotion systems. This led to agricultural capital mainly being manifested as insufficient capital input, especially the shortage of the input of agricultural public goods, which restricts the optimization and upgrading of the agricultural industry [56] and further inhibits the growth of agricultural output. On the other hand, scholars have found that a reduction in capital misallocation will significantly reduce the level of technological progress [20], while technological progress can promote the improvement in agricultural production efficiency, and thus promote the increase in agricultural output [57]. Through the above analysis, this paper argues that, with the optimization and upgrading of the agricultural industry and improvement of
agricultural technology, the negative impact of capital misallocation on agricultural output will be constantly weakened. The specific inspection process is as follows.

3.6.1. Mechanism Test of Agricultural Industry Upgrade

In order to test whether the negative impact of capital misallocation on agricultural output will be weakened with the upgrading of the agricultural industry, the paper introduces the interaction term of capital misallocation and upgrading of the agricultural industry ($Miscap \times Upgrade$) in Formula (2) for verification. The test results are reported in Column (1) of Table 6. The regression results show that the cross term of capital misallocation and agricultural industrial upgrading is significantly positive at the 1% level, indicating that with the optimization and upgrading of the agricultural industry, the inhibition effect of capital misallocation on the growth of agricultural output is gradually weakened. According to the estimation results of the spatial lag term, the negative impact of capital misallocation on agricultural output has a significant spatial spillover effect in cities with reasonable agricultural industrial distribution. Through partial differential method decomposition, the indirect effect accounted for 27.50% of the total effect. In general, the above test results and analysis show that in the process of optimization and upgrading of the agricultural industry, the allocation of agricultural capital is constantly adjusted and optimized, thus weakening its negative effect on agricultural output growth.

**Table 6. Mechanism test of capital misallocation affecting agricultural output.**

| Independent Variable | Dependent Variable: $Agrout$ |
|----------------------|-------------------------------|
| $Miscap$             | $-0.180^{***}$ [−12.82]      | $-0.036$ [−0.48] |
| $Upgrade$            | $-0.629^{***}$ [−4.95]       |                     |
| $Miscap \times Upgrade$ | $0.168^{***}$ [10.19]    |                     |
| $Tech$               | $0.007$ [−0.63]               |                     |
| $W \times Miscap$    | $-0.183$ [−0.94]             | $-0.203$ [−1.01]  |
| $W \times Upgrade$   | $-0.535$ [−0.88]             |                     |
| $W \times Miscap \times Upgrade$ | $0.241^*$ [1.66]    |                     |
| $W Tech$             | $0.018$ [0.74]               |                     |
| Decomposition of interaction term |                     |                     |
| Direct effects       | Indirect effects             | Total effects      |
| Direct effects       | Indirect effects             | Total effects      |
| $0.174^{***}$ [9.96] | $0.066^*$ [1.72]             | $0.240^{***}$ [5.19] | $0.001^{***}$ [7.36] | $0.005$ | $0.006$ [1.11] |
| Control variables    | YES                          | YES                |
| $\rho$               | $-0.261^{***}$ [−3.43]       | $-0.198^{***}$ [−2.58] |
| $\sigma^2$           | $0.098^{***}$ [13.33]        | $0.108^{***}$ [13.36] |
| $N$                  | 360                          | 360                |

Note: * $p < 0.1$, *** $p < 0.01$, $t$ values are put in parentheses.

3.6.2. Mechanism Test of Agricultural Technology Progress

As with the first test method, the interaction term of capital misallocation and agricultural technology progress ($Miscap \times Tech$) is introduced into Formula (2) to verify whether the improvement in agricultural technology will weaken the inhibition effect of capital misallocation on agricultural output growth. The results in Column (2) of Table 6 show that the interaction term of capital misallocation and agricultural technology progress is significantly positive at the 1% level, which indicates that the improvement of agricultural technology can indeed weaken the negative impact of capital misallocation on agricultural output. However, the spatial lag of the cross-multiplication term is not significant, indicating that there is no spatial spillover effect of agricultural technology progress on the inhibition of capital misallocation. This is closely related to the fragmentation of factor markets between regions and the inability of production factors to flow freely.
4. Discussion

The main purpose of this paper is to reveal the spatial effect of capital mismatching on agricultural output and identify its mechanism based on three aspects. Firstly, the influence of capital mismatch on agricultural production in prefecture-level cities is examined. Secondly, capital mismatches’ spatial spillover effect on agricultural production is established. Finally, capital misallocation is found to affect the path of agricultural production. We referred to the accounting framework of capital misallocation by Aoki (2012) [21] and used the spatial Durbin model to study the above problems. We confirm that there is a widespread capital misallocation at the prefecture level and the spatial spillover effect is significant. However, with the upgrading of the agricultural industry and the improvement of agricultural technology, the negative impact of capital mismatch on agricultural output tends to weaken. The results of this paper are basically consistent with the previous conclusion that factor mismatch affects agricultural production. For example, Zheng (2019) found that there are significant regional differences in agricultural capital misallocation in China, among which the degree of agricultural capital misallocation in northeast China continues to decrease [13]. Chen (2012) found that effectively eliminating capital misallocation in the agricultural sector can greatly improve agricultural output in northeast China [18]. As expected, the empirical results show that the degree of agricultural capital misallocation in northeast China is decreasing, but the misallocation problem still exists. Each unit of increase in the degree of agricultural capital misallocation will lead to a 16.00% decrease in agricultural output. Our conclusions are completely consistent with the research conclusions of the above-mentioned scholars. Notably, we further demonstrate the spatial spillover effect of capital misallocation on agricultural output, that is, an increase in local capital misallocation by one unit leads to a 1.80% reduction in agricultural output in neighboring cities. Concurrently, we also find that the negative impact of capital mismatch on agricultural output will be weakened with the upgrading of the agricultural industry and the progress of agricultural technology. Since agricultural output growth is a necessary condition for sustainable agricultural development [32], our study provides an empirical reference for understanding sustainable agricultural economic development from the perspective of capital mismatch.

Although the misallocation of agricultural capital tends to decrease during the study period, the mismatch still exists. However, what is the cause of agricultural capital mismatch? Previous studies have rarely explained this phenomenon in depth. This paper suggests that the reasons may originate from the following two aspects.

On the one hand, the imperfection of the factor market induces a capital mismatch. Compared with the commodity market, factor market development lags behind due to gradual market reform in China [58,59], especially in financial markets. The effective supply of rural finance has been insufficient for a long time, and farmers lack effective collateral, leading to the problems of low loan availability and high loan cost in agriculture for a long time [60]. For example, Hou and Du (2017) found that the scale of loans available for agricultural production links was only 2.5% of that for industry [61]. Xin et al. (2014) pointed out that the average interest rate of agricultural loans was significantly higher than the profit rate of agricultural production [62]. Financial constraints cause the marginal output of the same unit of capital input to be different and then lead to the capital mismatch problem. The study of Zhu et al. (2011) also showed that the improvement of the financial market helps to reduce the agricultural capital mismatch in inland China (central, western, and northeast China) [15].

On the other hand, government intervention may cause a capital mismatch. Under the dual constraints of the fiscal decentralization system and the “promotion tournament” mode of local government officials, local governments will intervene in the capital market to achieve specific economic goals and to make the actual price of capital deviate from the market price, resulting in the mismatch problem. For example, Wang et al. (2019) found that the government’s intervention in the price of chemical fertilizer distorted the market price of chemical fertilizer, resulting in excessive input of agricultural chemical
fertilizer, which was not conducive to the improvement of the sustainable agricultural development level [63]. Brandt et al. (2013) believed that government intervention in the capital market aggravated the capital mismatch between state-owned enterprises and private enterprises [8]. According to the statistical yearbook data of each province, we found that the gap in municipal financial investment supporting agriculture has expanded from CNY 5.74 billion in 2011 to CNY 12.07 billion in 2020 during the study period. The expansion of the gap means that the marginal cost of agricultural output is different in different cities. That is to say, government intervention measures characterized by financial support for agriculture induce the mismatch of agricultural capital. In Zheng and Ma’s (2021) study, the authors found that government intervention is one of the main causes of factor mismatch in China’s agricultural sector [9].

The contribution of this paper provides an empirical reference for local governments to formulate differentiated policies to reduce capital misallocation in order to promote the growth of the agricultural output and further promote the sustainable development of the agricultural economy. The limitation is that due to the lack of macro statistical data, it is impossible to explore the degree of capital misallocation in each subdivision of agriculture and its impact on the development of the agricultural economy, but this does not affect the generality of our research conclusions. In future research, we plan to conduct sample surveys in various cities to obtain micro-data of agricultural input and output, so as to more accurately grasp the impact of agricultural capital mismatch on agricultural output, and then provide an accurate empirical reference for sustainable agricultural development.

5. Conclusions and Suggestions

Based on the panel data of 36 cities in Northeast China from 2011 to 2020, this paper empirically tested the spatial spillover effect and action path of capital misallocation agricultural output by using the spatial Durbin model and reached the following conclusions:

(1) During the sample period, agricultural output capacity showed a declining trend, and the spatial difference was decreasing, but the polarization was obvious. The degree of agricultural capital misallocation decreased, but the spatial agglomeration was significant, showing a spatial distribution pattern of “low in the middle and high in the north and south”;

(2) The inhibition effect of capital misallocation on agricultural output growth has a significant spatial spillover effect. On average, every 1 unit of increase in capital misallocation will reduce the local agricultural output by 16.00% and neighboring agricultural output by 1.80%;

(3) The negative impact of capital misallocation on agricultural output can be weakened through the optimization and upgrading of the agricultural industry and agricultural technology, and the agricultural industry upgrade has a significant spatial spillover effect, but the spillover effect of agricultural technology progress is not obvious.

Based on the above research conclusions, the following suggestions are put forward. Firstly, decision-makers should promote the optimization and upgrading of the agricultural industry. The optimization and upgrading of the agricultural industry can effectively reduce the negative impact of capital misallocation on agricultural output. Considering the relatively backward status of China’s agricultural industry, there is still a lot of room for upgrading. Therefore, local cities should reasonably adjust the distribution of agricultural productivity according to their own advantages in resource endowment and establish cross-city regional cooperation mechanisms. Exchange mechanisms in the circulation of agricultural production factors should also be established in personnel training and information services, and they should make full use of the spatial spillover effects generated by various cities to promote the optimization and upgrading of agricultural industries and reduce the upgrading gap. At the same time, infrastructure construction should be increased for agricultural industrial optimization and upgrading to create conditions that foster growth.
Secondly, the authorities should promote research and development and the popularization of agricultural science and technology. The improvement of agricultural technology progress can improve the utilization efficiency of agricultural capital and reduce the adverse effect of capital misallocation on agricultural output. However, the current level of agricultural science and technology is relatively low, and the spatial spillover effect is not significant. Therefore, the authorities should continue to increase investment in agricultural science and technology innovation, actively guide local agricultural colleges and research institutes to carry out scientific and technological innovation activities, and rationally arrange agricultural science and technology extension institutions to improve the dissemination and diffusion speed of agricultural science and technology achievements.

Finally, market-oriented reform of agricultural factors of production should be deepened, giving full play to the decisive role of the market in resource allocation. This would address the situation of market segmentation between regions and promote the improvement of regional market integration. In accordance with the principles of complementing each other’s advantages, sharing benefits and win-win cooperation, the joint circulation of agricultural production factors between prefectures and cities should be strengthened, and the free flow of agricultural capital factors should be promoted.

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

Funding: This research was funded by Heilongjiang Province Ecological Civilization Construction and the Green Development Think Tank Project, grant number 202010; Philosophy and Social Science Research Project of Heilongjiang Province, grant number 21JYB149; Key project of Economic and Social Development of Heilongjiang Province, grant number 21225.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data in this paper come from the statistical yearbook compiled by the National Bureau of Statistics of China (http://www.stats.gov.cn/tjsj/ndsj/, accessed on 30 March 2022). In addition, interested readers can obtain all the data from the corresponding author if required.

Acknowledgments: The authors are particularly grateful to Northeast Forestry University, Harbin, China, for their technical support and extend thanks for the project support given by the fund granting unit.

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

References
1. Jaacks, L.M.; Veluguri, D.; Serupally, R.; Roy, A.; Prabhakaran, P.; Ramanjaneyulu, G. Impact of the COVID-19 pandemic on agricultural production, livelihoods, and food security in India: Baseline results of a phone survey. Food Secur. 2021, 13, 1323–1339. [CrossRef]
2. Pu, M.; Zhong, Y. Rising concerns over agricultural production as COVID-19 spreads: Lessons from China. Glob. Food Secur. 2020, 26, 100409. [CrossRef] [PubMed]
3. Zhang, S.; Chen, C.; Xu, S.; Xu, B. Measurement of capital allocation efficiency in emerging economies: Evidence from China. Technol. Forecast. Soc. Change 2021, 171, 120954. [CrossRef]
4. Beckman, J.; Countryman, A.M. The Importance of Agriculture in the Economy: Impacts from COVID-19. Am. J. Agric. Econ. 2021, 103, 1595–1611. [CrossRef] [PubMed]
5. Gollin, D.; Udry, C. Heterogeneity, Measurement Error, and Misallocation: Evidence from African Agriculture. J. Polit. Econ. 2021, 129, 1–80. [CrossRef]
6. Aragona, F.M.; Restucciabc, D.; Rud, J.P. Are small farms really more productive than large farms? Food Policy 2022, 106, 102168. [CrossRef]
7. Rogerson, R.R. Policy distortions and aggregate productivity with heterogeneous establishments. Rev. Econ. Dyn. 2008, 11, 707–720.
8. Brandt, L.; Tombe, T.; Zhu, X. Factor Market Distortions Across Time, Space and Sectors in China. Rev. Econ. Dyn. 2013, 16, 39–58. [CrossRef]

9. Zheng, H.Y.; Ma, W.L. The role of resource reallocation in promoting total factor productivity growth: Insights from China’s agricultural sector. Rev. Dev. Econ. 2021, 25, 2350–2371. [CrossRef]

10. Zhu, J.; Li, T.X.; Lin, D.Y.; Zhong, F.N. Thinking after “Nine Continuous Increases”: Contribution and Future Potential Analysis of Grain Internal Structure Adjustment. Issues Agric. Econ. 2013, 34, 36–43.

11. Shen, Z.Y.; Tomas, B.; Chen, X.L.; Valdmanis, V. Green growth and structural change in Chinese agricultural sector during 1997–2014. China Econ. Rev. 2018, 51, 83–96. [CrossRef]

12. Han, H.; Li, H.; Zhao, L. Determinants of Factor Misallocation in Agricultural Production and Implications for Agricultural Supply-side Reform in China. China World Econ. 2018, 26, 22–42. [CrossRef]

13. Zheng, H.Y.; Li, G.C.; Zhou, X.S. Factor mismatch and loss of agricultural output in China. J. Nanjing Agric. Univ. Soc. Sci. Ed. 2019, 19, 143–153.

14. Adamopoulos, T.; Brandt, L.; Leight, J.; Restuccia, D. Misallocation, Selection and Productivity: A Quantitative Analysis with Panel Data from China; National Bureau of Economic Research: Cambridge, MA, USA, 2017; No. 20309.

15. Zhou, X.; Shi, Q.H.; Gai, Q.E. Factor Allocation Distortion and Agricultural Total Factor Productivity. Econ. Res. 2011, 46, 86–98.

16. Skevas, T.; Wu, F.; Guan, Z. Farm Capital Investment and Deviations from the Optimal Path. J. Agric. Econ. 2018, 69, 561–577. [CrossRef]

17. Stephen, A.; Loren, B.; Diego, R. Market constraints, mismatch, and productivity in Vietnam agriculture. Food Policy 2020, 94, 101840.

18. Chen, X.B. Resource allocation, total factor productivity and the vision of agricultural economic growth. Reform 2012, 35, 82–90.

19. Adamopoulos, T.; Diego, R. The Size Distribution of Farms and International Productivity Differences. Am. Econ. Rev. 2014, 104, 1667–1697. [CrossRef]

20. Hsieh, C.T.; Klenow, P. Misallocation and Manufacturing TFP in China and India. Rev. Econ. Dev. 2010, 25, 1–11. [CrossRef]

21. Aoki, S. A simple accounting framework for the effect of resource misallocation on aggregate productivity. J. Ipnn. Int. Econ. 2012, 26, 473–494. [CrossRef]

22. Anselin, L.; Lowenberg, D.B.J. A Spatial Econometric Approach to the Economics of Site-Specific Nitrogen Management in Corn Production. Am. J. Agric. Econ. 2004, 86, 675–687. [CrossRef]

23. Liu, S.; Wang, X.Z.; Yang, M.Y.; Wang, Z.L. The Impact of Financial Market Development on Agricultural Factor Misallocation: Household-Level Evidence from China. Math. Probl. Eng. 2021, 2021, 9997438. [CrossRef]

24. Wu, W.W.; Bao, K.X.; Zhang, Y.H. An Empirical Study on the Mismatch Measurement and Influencing Factors of Agricultural Production Factors in Jiangxi Province. Resour. Environ. Yangtze River Basin 2020, 29, 1005–1015.

25. Tobler, W.R. A Computer Movie Simulating Urban Growth in the Detroit Region. Econ. Geogr. 1970, 46, 234–240. [CrossRef]

26. Chen, Z.; Zhu, H.; Zhao, W.; Zhao, M.; Zhang, Y. Spatial Agglomeration of China’s Forest Products Manufacturing Industry: Measurement, Characteristics and Determinants. Forests 2021, 12, 1006. [CrossRef]

27. Echevarria, C. A Three-factor Agricultural Production Function: The Case of Canada. Int. Econ. J. 1998, 12, 63–75. [CrossRef]

28. Wu, Y.M. Calculation of Input-Output Elasticity of China’s Regional Agricultural Production Factors—Empirical Based on Spatial Econometric Model. China Rural Econ. 2010, 26, 25–37.

29. Wang, F.; Liu, Y.F.; Kong, X.S.; Chen, Y.Y.; Pan, J.W. Spatial-temporal evolution and influencing factors of grain yield at county level in China. Econ. Geogr. 2018, 38, 142–151.

30. Chen, Y.F.; Li, X.D. Spatial-temporal patterns and influencing factors of grain yield change in China. Trans. Case 2013, 29, 1–10.

31. Han, C.G.; Zhang, L. Does the Internet improve resource mismatch in China: A test based on dynamic Spatial Dubin model and threshold model. Explor. Econ. Probl. 2019, 40, 43–55.

32. Zhao, Y.W.; LV, H.M. Construction and Regional Differences Research on Evaluation System of Rural Well-off Construction. Agric. Water Manag. 2016, 37, 9–15.

33. Li, G.C. Green productivity revolution in China’s agriculture: 1978–2008. Econ. Q. 2014, 13, 537–558.

34. Zhang, J.; Wu, G.Y.; Zhang, J.P. Estimation of China’s Interprovincial Material Capital Stock: 1952–2000. Econ. Res. 2004, 68, 35–44.

35. Wang, X.B.; Yamauchi, F.; Otsuka, K.; Huang, J.K. Wage Growth, Landholding, and Mechanization in Chinese Agriculture. World Dev. 2016, 86, 30–45. [CrossRef] [PubMed]

36. Luo, X.W.; Liao, J.; Hu, L.; Zang, Y.; Zhou, Z.Y. Improving the level of agricultural mechanization to promote sustainable agricultural development. Chin. J. Agric. Econ. 2016, 32, 1–11.

37. Zhou, Z.; Kong, X.Z. Effect evaluation and policy direction of agricultural mechanization on Grain output in China. China Soft Sci. 2019, 34, 20–32.

38. Jiang, Y. China’s water security: Current status, emerging challenges and future prospects. Environ. Sci. Policy 2015, 54, 106–125. [CrossRef]

39. Fang, Q.X.; Ma, L. Green T R, Yu Q, Wang T D, Ahuja L R. Water resources and water use efficiency in the North China Plain: Current status and agronomic management options. Agric. Water Manag. 2010, 97, 1102–1116. [CrossRef]

40. Chen, X.W.; Chen, Y.Y.; Zhang, J.J. A Quantitative Study on the Impact of China’s Rural Population Aging on Agricultural Output. China Popul. Sci. 2011, 36, 39–46.

41. Gai, Q.E.; Zhu, X.; Shi, Q.H. The impact of labor transfer on China’s agricultural production. Econ. Q. 2014, 13, 1147–1170.
42. Chen, L.S.; Zhang, D. Empirical analysis on agricultural investment since China’s reform and opening-up. Chin. Rural Econ. 2004, 20, 40–46.
43. Chen, Y.; Kuang, G.L. Review on the theoretical core and research ideas of “industrial upgrading”. Reform 2009, 22, 85–89.
44. Chen, Y.E.; Chen, W. Research on the relationship between agricultural mechanization, industrial upgrading and agricultural carbon emissions: Empirical analysis based on dynamic panel data model. Agric. Technol. Econ. 2018, 37, 122–133.
45. Gao, M.; Song, H.Y. Spatial convergence and functional zone difference of grain production technical efficiency: Also on spatial ripple effect of technological diffusion. Manag. World 2014, 30, 83–92.
46. Yang, X.Y.; Qiao, C.X. Spatial differences and convergence of agricultural industrial structure optimization and upgrading. J. South China Agric. Univ. Soc. Sci. Ed. 2022, 21, 67–80.
47. Wei, H.K. The Structural Contradiction of China’s Agricultural Development and Its Policy Transformation. China Rural Econ. 2017, 33, 2–17.
48. Lesage, J.; Pace, R.K. Introduction to Spatial Econometrics, 1st ed.; CRC Press: Boca Raton, FL, USA, 2009; pp. 45–75.
49. Luo, Y.M.; Fan, L.M. Spatial Characteristics of Income-Increasing Effects of China’s Rural Infrastructure: An Empirical Study Based on Spatial Correlation and Spatial Heterogeneity. Manag. World 2012, 38, 71–87.
50. Su, X.S.; Xu, L. Catastrophe Effect and Risk Assessment of China’s Grain Market-Simulation Analysis Based on Partial Equilibrium Model. Agric. Technol. Econ. 2021, 40, 18–32.
51. Liu, Q.; Yang, Q.Z. The evolution of my country’s agricultural production model during the transition period. Rural Econ. 2013, 31, 46–48.
52. Liu, D.; Zhu, X.; Wang, Y. China’s agricultural green total factor productivity based on carbon emission: An analysis of evolution trend and influencing factors. J. Clean. Prod. 2020, 278, 123692. [CrossRef]
53. Bai, J.H.; Wang, Y.; Jiang, F.X.; Li, J. Flow of research and development factors, spatial knowledge spillover and economic growth. Econ. Res. 2017, 52, 109–123.
54. Gan, C.H.; Zheng, R.G.; Yu, J.J. The impact of China’s industrial structure changes on economic growth and volatility. Econ. Res. 2011, 46, 4–16.
55. Dong, J.C.; Feng, T.; Li, J.J. The impact of factor mismatch between regions in China on the quality of economic development: An empirical test based on a chained multiple mediation effect model. Financ. Trade Res. 2020, 31, 1–12.
56. Jin, F.; Jin, R.X. Analysis of the Spatial Effect of Fiscal Supporting Agriculture Affecting the Change of Agricultural Industrial Structure. Res. Financ. Issues 2020, 42, 82–91.
57. Wei, W.; Wen, C.C.; Cui, Q.; Xie, W. The impact of agricultural technology progress on agricultural energy use and carbon emissions: Analysis based on GTAP-E model. Agric. Technol. Econ. 2018, 37, 30–40.
58. Yang, M.; Yang, F.; Sun, C. Factor market distortion correction, resource reallocation and potential productivity gains: An empirical study on China’s heavy industry sector. Energy Econ. 2018, 69, 270–279. [CrossRef]
59. Fan, G.; Wang, X.; Ma, G. The Contribution of Marketization to China’s Economic Growth. China Econ. 2012, 7, 4.
60. Gao, S.P.; Liu, P. Credit Collateral in rural financial system: Dilemma and outlet. Financ. Res. 2009, 51, 64–72.
61. Hou, T.; Du, Y.K. Performance Evaluation of Agricultural Loans from the Perspective of Industrial Comparison. J. China Agric. Univ. 2017, 22, 180–191.
62. Xin, B.H.; Lian, Y.H.; Tao, J. The Bargaining Power Measurement of Lenders and Lenders in my country’s Rural Lending Market—Analysis Based on Bilateral Stochastic Boundary Model. Agric. Technol. Econ. 2014, 32, 64–73.
63. Wang, X.; Shao, S.; Li, L. Agricultural inputs, urbanization, and urban-rural income disparity: Evidence from China. China Econ. Rev. 2019, 55, 67–84. [CrossRef]