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Factors on Spatial Heterogeneity of the Grain Production Capacity in the Major Grain Sales Area in Southeast China: Evidence from 530 Counties in Guangdong Province

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Abstract: Grain security is an essential issue for countries across the world. China has witnessed over the last decades not only a rapid growth in the volume of the grain production, but also a divergence in its geographical distributions. Existing studies on the influencing factors of grain production have overlooked thus spatial heterogeneity. This paper investigates the factors that cause the geographical heterogeneity in grain output levels in Guangdong province of China, in terms of land, labor and capital. To address the spatial attenuation effect of the influencing factors, we use the Geographically Weighted Regression (GWR) on samples of different spatial ranges, which include a total of 530 southern counties from 2015 to 2017. The results show that (a) the effect of land endowment on grain output vary across the east and the west, and between coastal and inland areas; (b) the effect of labor endowment on grain output are inconsistent in the sign and magnitude of the estimates across counties; (c) the effect of agricultural capital on grain production shows heterogeneity spatially (across the east and the west) and economically (across developed and less developed regions). We then analyze the potential mechanism behind this spatial heterogeneity, as well as its policy implications.

Keywords: grain main sales area; spatial heterogeneity; agricultural informatization



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1. Introduction

Since its reform and opening, China has witnessed rapid economic and social developments in the southeastern coastal area. As industrialization, urbanization, and population agglomeration advance accordingly, the de-agriculturalization and de-grainization of arable land has gradually become an issue. The southeastern coastal provinces face serious shortage of agricultural products and have become the main sales area of grains. Although the de-agriculturalization and the de-grainization of cultivated land in this area are mainly the results of market allocation of land resources, the Chinese government has set policy goals to “maintain the food security in the main sales area.” Therefore, it is theoretically significant and empirically valuable to study the evolution of the grain production and the effects of factor endowments on grain output in the main sales areas. It is also important to understand the underlying mechanism of the spatial changes in grain production in the southeastern coastal provinces and to formulate effective policies to incentivize county-level grain production to satisfy the huge demand in the main sales area. Historical evidence across the world shows that all the main sales areas of grain have experienced rapid economic development, scientific and technological progress, and reduction of rural industries brought about by global urbanization [1–3]. Agricultural sectors across the globe have followed a similar trend of spatial aggregation [4]. Decline in

rural population was the first element to bring about a shrinking of agricultural production. In China, the application of mechanical technology and fertilizers has been shown to offset the decline in food production caused by the outflow of rural labor [5]. In the context where de-agriculturalization and de-grainization have gradually become one of the main characteristics of land use in China [6], the food security issue and the shortage of agricultural production factors are increasingly significant [7–10]. Given that change in land use is a process of human-induced spatial change, it is essential to take it into account the difference and complexity in the distribution of land-use patterns [11–14] and to precisely measure the different effects of changes in factors, such as labor, land and, technology, on food production in different regions [15–18].

Existing studies have shown that the grain production areas in China have been shifting over time, and that the grain production across regions has a certain degree of spatial correlation. There is also a large body of literature that investigates different factors affecting grain output. These factors include regional advantages in grain production, rural economic structure and factor returns, crop scale and efficiency, nonagricultural employment opportunities, arable land per capita, and so forth. However, the influencing factors across regions are greatly different. For instance, Zhang et al. (2011) pointed out that human factors (e.g., changes in land-use structure, changes in farmers' behavioral patterns, and environmental pollution) and changes in precipitation intensity are the main contributing factors to the changes in the spatial pattern of grain production in Jiangsu province of China [19]. Zheng et al. (2014) concluded that there is a large heterogeneity in the changes in grain production across regions in China: the areas of grain production in most regions are declining; the decrease in arable land and the shift from grain to cash crops are the main reasons for this decline, whereas the increase in the multiple cropping index has eased this downward trend; and in some special cases, there are even small jump-ups in the areas of grain production due to the sharp increase in the multiple crop index and the relatively small pressure on economic structural adjustments [20]. Zhang et al. (2017) indicated that in the past three decades, the grain output in China has shown a spatial pattern of “(going) down in the south and up in the north,” and the main cause of cross-provincial differences in grain output is the areas of production [4]. In fact, one influencing factor may promote grain output growth in one location but inhibit it in another location [21]. Spatial heterogeneity can yield different results in land-use changes from different observation locations [22]. Therefore, to correctly characterize the heterogeneity of grain production, it is essential to incorporate it into the driving factor model to better predict future scenarios and support planning and decision-making [23].

As shown above, there is a rich body of literature that uses spatial econometric methods to explore the spatial pattern of China's grain production [24,25], and some use spatial measurement methods (SAR) based on spatial correlation to consider the spatial relationship between grain production levels and the driving factors. However, the existing literature does not address the boundary issue of special influence. Regardless of whether spatial correlation or spatial heterogeneity is studied, the effect of each driving factor on the surrounding areas should be defined within a boundary, and this boundary should be represented as a radiation attenuation function in the model, but there are few studies providing a reasonable explanation for the sampling range. In view of this, this paper studies the spatial heterogeneity of the factors affecting grain production levels with a sample of 530 counties in Guangdong and its neighboring provinces, and compares the effects on grain production at different scales by establishing three-level buffer zones.

2. Materials and Methods

2.1. Theoretical Analysis

Technological advancement has weakened the role of natural resources in the agricultural production process, while technology and labor have become more and more important. The “invisible hand” directs all mobile factors of production to move to places where the maximum efficiency is achieved, and historical trends indicate that both labor

and technology will aggregate over time to certain regions due to the economies of scale. Land, labor, and technology serve as important driving factors for grain production across counties. What role do these factors have on the evolution of regional grain production? This paper focuses on analyzing the spatial heterogeneity of the impact of land, labor, and technology endowment on grain production at the county level.

2.1.1. Effect of Land Endowment on Regional Grain Output and Its Heterogeneity

Land endowment is the most stable factor of agricultural production. Since a land area is fixed in the short run, change in land endowment reflects more in changes in land property rights and planting structure. Therefore, compared with more mobile factors, such as labor and capital, land endowment is relatively stable. At the micro level, the impact of land endowment on grain production is mainly reflected in the topography, soil fertility, irrigation water, climatic conditions, degree of fragmentation, and changes in planting structure [26–30]. When applied to macro-aggregated data, land endowment is usually represented by the total amount of cultivated land [31] and the stock of agricultural infrastructure [32]. In theory, increase in agricultural land endowment has a positive impact on grain production.

A few studies have found that the level of grain production and the factors of production are spatially heterogeneous [33], which means that the elasticity of grain output to production factors varies in geographical areas. For example, let counties A and B be two adjacent administrative regions, both of which have relatively similar natural resource characteristics (e.g., total area of arable land, topography, and water and soil conditions), and let us assume that the agricultural labor and the agricultural capital market are cleared. Farmers in county A mainly plant double-cropping rice. County B has developed high-value-added characteristic agriculture in recent years, which has led a group of farmers to adjust their planting structure and implement the “double-to-single” planting system, such as shrimp–rice symbiosis and single-cropping rice rotation. Then, when the land endowments of the two counties have increased by the same amount, for example, getting the same amount of high-standard farmland facility construction funds, then the grain output elasticities of A and B will be different in terms of the effect of farmland construction—county A would have a larger output elasticity than county B. This is caused by the difference in the planting structures of the two places. In light of this, this paper proposes the following hypothesis:

Proposition 1. *Increase in land endowment has a positive impact on the level of grain production, but with spatial heterogeneity in terms of magnitude.*

2.1.2. Effect of Labor Endowment on Regional Grain Output and Its Heterogeneity

Agricultural labor is the most active factor in grain production, and is highly mobile. In the past two decades, agricultural labor has evolved from excess to insufficient supply. The main changes on a micro level are the transfer of agricultural labor across regions and industries and the aging labor issue. There are studies on spatial relations in agricultural economics that have already found the spatial spillover effect of labor transfer on the level of food production [34]. They suggest that there exists a turning point in the impact of labor transfer on agricultural ecological efficiency; that is, the effect is not consistently positive or negative. There is spatial heterogeneity in the effect of agricultural labor changes on the level of food output, and the sign and magnitude of the impact also vary across regions. Take counties C and D as examples. County C is located in western Guangdong and is a traditional grain-producing county with sufficient agricultural labor; county D is located on the edge of the Pearl River Delta, with high labor prices and insufficient supply of agricultural labor. Obviously, cultivating new agricultural businesses in county C can support a number of grain farmers, specialized farmer cooperatives, or social organizations of production services. The growth of these organizations will help increase the scale of business operations and radiation belt capabilities of grain farmers in order to increase grain production. However, the cultivation of new agricultural businesses in county

D is likely to focus on downstream grain processing firms or local leading enterprises. These organizations with a background of industrial and commercial capital can, on the one hand, increase the value-added and marketization level of agricultural products from the industry optimization perspectives. On the other hand, it is not conducive for increasing and stabilizing grain production and might even aggravate the phenomenon of “de-grainization” of agricultural land. This is due to the differences in the labor prices and industrial bases between the two counties. This paper proposes the following hypothesis:

Proposition 2. *The impact of increase in labor endowment on the level of grain production is spatially heterogeneous, and the magnitude and direction of the effect across regions are different.*

2.1.3. Effect of Technology Endowment on Regional Grain Output and Its Heterogeneity

Generally speaking, the higher the level of agricultural technology in a specific region is, the stronger the grain production capacity is. In terms of spatial relationship, agricultural technology has a high degree of spatial correlation. For example, Yang et al. (2017) showed that the advancement of agricultural frontier technology and technical efficiency can increase food production, and it is manifested as a spatial spillover effect [35]. On the other hand, due to the strong diffusion of agricultural technology, the differences in the industrial structure across counties will promote the development and diffusion of agricultural technology in different directions. For example, the development of local informatization will promote a more flexible allocation of agricultural resources by agricultural producers. This can not only increase the income of grain farmers but also nudge the farmers to be more inclined to nonagricultural and nongrain land use. The result of that is a decline in grain production capacity in counties with high levels of informatization. This shows that in the study of spatial relationships, the difference in industrial structure across counties makes the spillover effects of agricultural technology on grain production either positive or negative. Based on the above analysis, this paper proposes the following hypothesis:

Proposition 3. *The effect of increase in the level of agricultural capitalization on the level of grain production exhibits spatial heterogeneity, and the magnitude and direction of the effect across regions are different.*

2.2. Regression Model, Data, and Sample Range

2.2.1. Regression Model

Spatial heterogeneity refers to the non-uniformity of spatial effects at the regional level due to the heterogeneity of spatial units [36]. This spatial heterogeneity is mainly derived from the differences in geographical conditions of the research objects in each region. These differences in geographical conditions are the result of an overall effect of physical and chemical characteristics, such as topography, light and heat conditions, monsoon climate, and soil composition. These differences are often difficult to control in macroscopic research. Spatial regression is a particularly suitable method to describe spatial heterogeneity, because it combines the geographic location of industrial growth and its driving factors to characterize its spatial changes [37–41]. Similar to nonspatial methods (such as ordinary least squares, OLS), spatial regression produces parameter estimates with clear economic interpretations. These parameter estimates represent the impact of each driving force on industrial growth. Specifically, spatial regression considers the spatial autocorrelation between nearby cells and the location of each observation [42,43]. Spatial autoregressive regression (SAR) and geographically weighted regression (GWR) are two typical spatial regression methods that have been widely applied to the analysis and modeling of land-use change. Representative SAR methods include the spatial lag model (SLM) and spatial error model (SEM). The spatial autocorrelation between observations is considered to reduce the spatial clustering in the model residuals [44]. SAR implicitly solves spatial heterogeneity. In contrast, GWR explicitly solves the problem of spatial heterogeneity by generating position-based regression parameters. It considers local characteristics and the influence of locations [45].

This section describes the geographically weighted regression (GWR) model based on the ordinary least squares (OLS) model and uses the weighted least squares (WLS) method to explore the spatial variability and influencing factors of grain output in Guangdong counties.

Baseline model. Based on the above discussion of spatial correlation, the assumptions of the GWR model in this paper are (a) the spatial relationship of grain production conforms to the first law of geography—that is, the correlation between neighboring counties is stronger than that in distant counties; (b) the driving factors are non-uniformly distributed, so the effect of one factor has different coefficient estimates in different counties; and (c) the grain output at a specific time and a specific political environment will be affected by land endowment, labor endowment, and technology level. Based on these assumptions, the baseline regression model is

$$Y_i = \beta_0 + \beta_1 Le_i + \beta_2 Ld_i + \beta_3 Ap_i + \beta_4 Dp_i + \beta_5 Ac_i + \beta_6 Ng_i + \varepsilon_i \quad (1)$$

where Y_i is the grain production level in county i , which is measured by the total grain output; β_0 is the intercept term; Ld_i is the degree of land standardization in county i , which is used to characterize the land quality endowment, and it is measured by the ratio of the irrigated arable land area to the total arable land area; Le_i is the total area of arable land in county i , which is also used to characterize the land quantity endowment; Ap_i represents the labor endowment in county i , which is measured by the proportion of the labor force in the agriculture industry in the total population; Dp_i is the degree of nongrainization of labor, which is measured by the number of workers in the vegetable and fruit plantation, forestry, animal husbandry, and fishery sectors in county i ; Ng_i is the area of facility agriculture, that is, the area of cultivated land with facilities such as sprinkler irrigation, drip irrigation, infiltration irrigation, and greenhouse; and Ac_i is the level of agricultural informatization in county i , which is characterized by the proportion of the number of people with telephones in the total population. The specific index composition is shown in Table 1.

Table 1. Index composition.

First-Degree Indices	Second-Degree Indices	Third-Degree Indices	Code
Grain production level	Total grain output	Total grain output (10,000 tons)	Y_i
Land endowment	Degree of land standardization	Irrigated arable land area (thousand hectares)/total arable land area (thousand hectares)	Ld_i
	Total area of arable land	Arable land area (thousand hectares)	Le_i
Labor endowment	Agricultural labor force	Number of workers in the primary industry (10,000 people)/total population (10,000 people)	Ap_i
	Degree of nongrainization of labor	Number of workers in the vegetable and fruit plantation, forestry, animal husbandry, and fishery sectors (10,000 people)	Dp_i
Technology endowment	Area of facility agriculture	Area of facility agriculture (thousand hectares)	Ng_i
	Level of agricultural informatization	Number of people with telephone ownership (10,000 people)/total local population (10,000 people)	Ac_i

2.2.2. Data Collection

Most of the county-level data in the paper are collected from the China County-Level Statistical Yearbook. Some counties and municipalities are not included in the statistical yearbook, and therefore, we collect data in these areas from their regional statistical yearbook, the Third National Agricultural Census: Main Data Bulletin and National Economic and Social Statistics Bulletin. As it is assumed that the samples are spatially correlated, the data collection focuses on Guangdong and its four bordering provinces: Guangxi, Hunan, Jiangxi, and Fujian, constituting a total of 530 county-level regions in five provinces. Guangdong is the country's largest province with the largest permanent residence population and the largest grain sales area.

In addition, this paper constructs four dimensions of variables, including grain production level, agricultural land endowment, agricultural labor endowment, and agricultural technology level. We then descriptively analyze the characteristics of the four dimensions of variables in each province, the relationships between the variables, and comparative analysis across provinces to provide support for the rationality of the model construction. In order to construct a GWR model of spatial heterogeneity, the 3-year average data of 2015, 2016, and 2017 are used to eliminate the influence of climatic factors on grain production. The range method is used to standardize all variables and eliminate dimension factors. The question of interest in this paper is whether there are regional differences in the influencing factors of grain production, and if so, what are the magnitudes and patterns of the differences. The descriptive statistics of the explanatory variables are summarized in Table 2.

Table 2. Descriptive statistics ¹.

Second-Degree Indices	Unit	Code	Max	Min	Mean	Std. Dev.
Total grain output	10,000 tons	Y_i	62.44	0	11.01	11.88
Degree of land standardization	N/A	Ld_i	0.66	0	0.08	0.09
Total area of arable land	1000 hectares	Le_i	2.37	0	0.51	0.58
Agricultural labor force	N/A	Ap_i	0.92	0	0.69	0.19
Degree of nongrainization of labor	10,000 people	Dp_i	155	0	17	23
Area of facility agriculture	1000 hectares	Ng_i	0.38	0	0.67	0.14
Level of agricultural informatization	N/A	Ac_i	80	0	31	40

¹ Notes: N/A refers to "Not Applicable," where the variables are in ratio terms.

2.2.3. Geographical Range of the Study

The GWR model is based on the independent regressions of each sample with cross-sectional data. If we only use the data of Guangdong province, the impact of neighboring counties cannot be accurately estimated, and also the estimation may be biased due to insufficient variability of the structural sample size. Therefore, we address this issue by establishing buffer zones. We use the *ArcGIS 10.6* neighborhood analysis tool to establish four-level buffer areas—R (0 km), S (100 km), M (200 km), and L (400 km)—in the periphery of Guangdong province to analyze the factors affecting grain yield at different scales. Specifically, as shown in Figure 1, the R scale contains Guangdong province, including 123 county-level units; the S scale is the smallest buffer zone, including Guangdong and its adjacent 187 county-level units; the M scale is between L and S, including Guangdong and its surrounding 306 county-level units; and the L scale ranges the largest, including 530 county-level units in the five provinces of Guangdong, Hunan, Zhejiang, Jiangxi, and Guangxi.

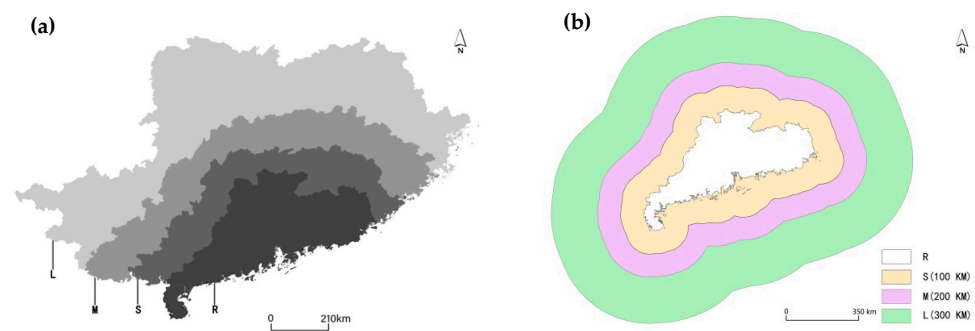


Figure 1. (a,b) Map of the four-level buffer sampling zone.

3. Results

The study obtains a correctly specified variable combination through OLS, and then runs GWR using the same variable combination. Since the OLS model defaults to the same spatial relationship between samples, data with regional differences violate OLS's assumption of global stationarity. In order to evaluate and compare the performances of the OLS and GWR models, the adjusted R^2 and the modified Akaike Information Criterion (AIC) test for a small sample are used.

3.1. Comparative Analysis of the Performances of OLS and GWR Models

A comparison of the performances of the OLS regression and GWR results is summarized in Table 3. Specifications (1)–(4) use OLS regression on the R, S, M, and L scales. Explanatory variables at each scale have different effects on the level of grain production. Under the R scale, the proportion of agricultural labor force (Ap), the area of facility agriculture (Ng), and the level of agricultural informatization (Ac) have a significant correlation with grain output. Under the S scale, the degree of land standardization (Ld), the proportion of agricultural labor force (Ap), and the level of agricultural informatization (Ac) have a significant correlation with grain output. Under the M scale, the proportion of agricultural labor force (Ap) and the level of agricultural informatization (Ac) have a significant correlation with grain output. Finally, under the L scale, the degree of land standardization (Ld), the total area of arable land (Le), the proportion of agricultural labor force (Ap), the area of facility agriculture (Ng), and the level of agricultural informatization (Ac) have a significant correlation with grain production level.

Table 3. Performance comparison of OLS and GWR models under R, S, M, and L scales.

Scale	R	S	M	L
OLS	(1)	(2)	(3)	(4)
R^2	0.52	0.49	0.43	0.36
Adj R^2	0.50	0.47	0.41	0.35
AIC	−903.68	−903.68	−1376.31	−2133.99
Significant variables	Ap, Ng, Ac	Ld, Ap, Ac	Ap, Ac	Ld, Le, Ap, Ng, Ac
GWR	(5)	(6)	(7)	(8)
R^2	0.66	0.63	0.61	0.55
Adj R^2	0.61	0.60	0.58	0.51
AIC	−160.90	−952.70	−1473.02	−2269.33
Residual std. error	1.500	0.057	0.123	0.382
No. of obs.	123	187	306	530

3.2. OLS Regression Results

The OLS regression results are summarized in Table 4. Specifications (1)–(4) in Table 4 show how the grain output level changes when each land, labor, or technology endowment factor changes under various geographical scales. We observe that the average value of the variance inflation factor (VIF) is close to 1, indicating that the selection of variables

is reasonable and the collinearity issue is not a concern. As the sample scale increases, the number of significant variables increases, as well as the significance of the variables. Take the degree of land standardization (*Ld*) as an example. Under the R scale, there are no significant changes in grain output when the proportion of irrigated arable land area increases by 1%. However, when we scale up the sample to S, the increase in the degree of land standardization is accompanied with a significant drop in grain production level, at a 5% significance level. Under the M scale and onward, the significance level goes further to 1%, marked with even larger magnitudes of the negative relationship. However, as the sample scale expands, the explanatory power of the variables decreases successively, and the R^2 ranges from 0.52 on the R scale to 0.36 on the L scale (see Table 3). The variance inflation factor (VIF) of each variable is less than 7.5, indicating that there is no collinearity between the variables.

Table 4. OLS regression results (dependent variable: grain output).

Scale		(1) R	(2) S	(3) M	(4) L
<i>Ld</i>	Coefficient	0.14	0.12 **	0.19 ***	2.27 ***
	Std. err.	(0.123)	(0.050)	(0.072)	(1.209)
	VIF	1.82	1.13	1.09	1.07
<i>Le</i>	Coefficient	−0.12	−0.75	1.19	5.87 ***
	Std. err.	(0.102)	(1.241)	(1.329)	(1.113)
	VIF	4.23	4.62	5.75	5.38
<i>Ap</i>	Coefficient	0.18 ***	0.03 **	0.006	−0.13 **
	Std. err.	(0.068)	(0.011)	(0.011)	(0.019)
	VIF	1.74	1.36	1.34	1.23
<i>Dp</i>	Coefficient	0.05	−0.003	−0.04	−0.40
	Std. err.	(0.117)	(0.225)	(0.225)	(0.244)
	VIF	1.97	2.48	2.47	2.99
<i>Ng</i>	Coefficient	0.11 **	0.02	0.006	0.02
	Std. err.	(0.059)	(0.012)	(0.122)	(2.476)
	VIF	2.61	2.28	1.95	1.67
<i>Ac</i>	Coefficient	−0.27 ***	−19.80 ***	−22.70 ***	−34.13 ***
	Std. err.	(0.048)	(2.830)	(2.843)	(10.248)
	VIF	3.54	3.52	4.21	3.20

Notes: Robust standard errors in parentheses. * denotes significant at 10%, ** significant at 5%, and *** significant at 1%.

Based on the OLS regression results, we found that the models under all four scales passed the VIF test, and hence, we cannot reject the hypothesis that the selection of variables is reasonable. Therefore, we continue with the GWRs across sample scales.

3.3. GWR Results

The GWR results show how the grain production of each sample county responds to different factors. Therefore, the estimated coefficients of each sample county under each scale are different. Table 5 shows the robust estimates of the GWR under different scales. Compared with the regression results of the OLS model, the GWR model has a more intuitive and powerful explanation of the factors affecting grain production. The coefficient range of the GWR not only covers the coefficients of OLS regression but also reflects the degree of regional differentiation. It has a stronger explanatory power on the factors affecting grain production, with a smaller standard error and a lower AIC value (the difference is greater than 3). All of the above shows that the fitting of the GWR model is better compared with that of the OLS.

Table 5. GWR regression results (dependent variable: grain output).

Scale		(5) R	(6) S	(7) M	(8) L
<i>Ld</i>	Mean value	/	0.61	0.12	0.88
	Std. err.	/	(0.714)	(4.121)	(1.236)
	Min	/	2.874	0.081	0.084
	Max	/	0.061	3.492	8.172
<i>Le</i>	Mean value	/	/	/	5.13
	Std. err.	/	/	/	(5.187)
	Min	/	/	/	−1.363
	Max	/	/	/	31.473
<i>Ap</i>	Mean value	0.14	0.02	/	−0.03
	Std. err.	(0.078)	(0.015)	/	(0.035)
	Min	−0.244	−0.04	/	−0.121
	Max	0.329	0.032	/	0.054
<i>Ng</i>	Mean value	0.08	/	/	/
	Std. err.	(0.107)	/	/	/
	Min	−0.113	/	/	/
	Max	0.343	/	/	/
<i>Ac</i>	Mean value	−0.30 ***	−16.80 ***	−20.43 ***	−30.68 ***
	Std. err.	(0.066)	(2.566)	(10.440)	(11.325)
	Min	−0.441	−25.179	−133.435	−78.974
	Max	−0.222	−14.334	−11.925	−13.689

Notes: Robust standard errors in parentheses. * denotes significant at 10%, ** significant at 5%, and *** significant at 1%.

3.4. Comparative Analysis of the Spatial Heterogeneity of Grain Production in Guangdong Province

The GWR results under all four scales can pass the test, and the explanatory variables can reflect at least 51% of the reasons for changes in grain production (see the adjusted R^2 in Table 3). As the number of observations in the sample increases, there are more statistically significant variables, but the overall explanatory power of the model becomes weaker. Therefore, it is necessary to compare and analyze the coefficient distribution of each explanatory variable under different scales.

Degree of land standardization. According to the distribution of the estimated effect of the degree of land standardization on the total grain output (Figure 2a–c), it can be seen that the degree of land standardization has a positive effect on the total grain output, and the effect varies across regions. Within the sampling ranges of S, M, and L, the promotion effect of land standardization on grain production is enhanced from east to west. The estimated effect of the degree of land standardization expresses the spatial heterogeneity in two aspects: One is that there are differences in output dividends brought about by the improvement of farmland water conservancy facilities. The other aspect is that there are spatial differences in the grain yield rate across land. This gap varies from region to region. Take Guangdong as an example. The western region mainly relies on large-scale production to increase the income per acre of grain crops, while the eastern region mainly improves the income by optimizing the variety structure and increasing the added value of food products. Therefore, the increase in grain production efficiency caused by farmland standardization is more attractive to farmers in western Guangdong but less attractive to farmers in eastern Guangdong. This evidence supports proposition 1.

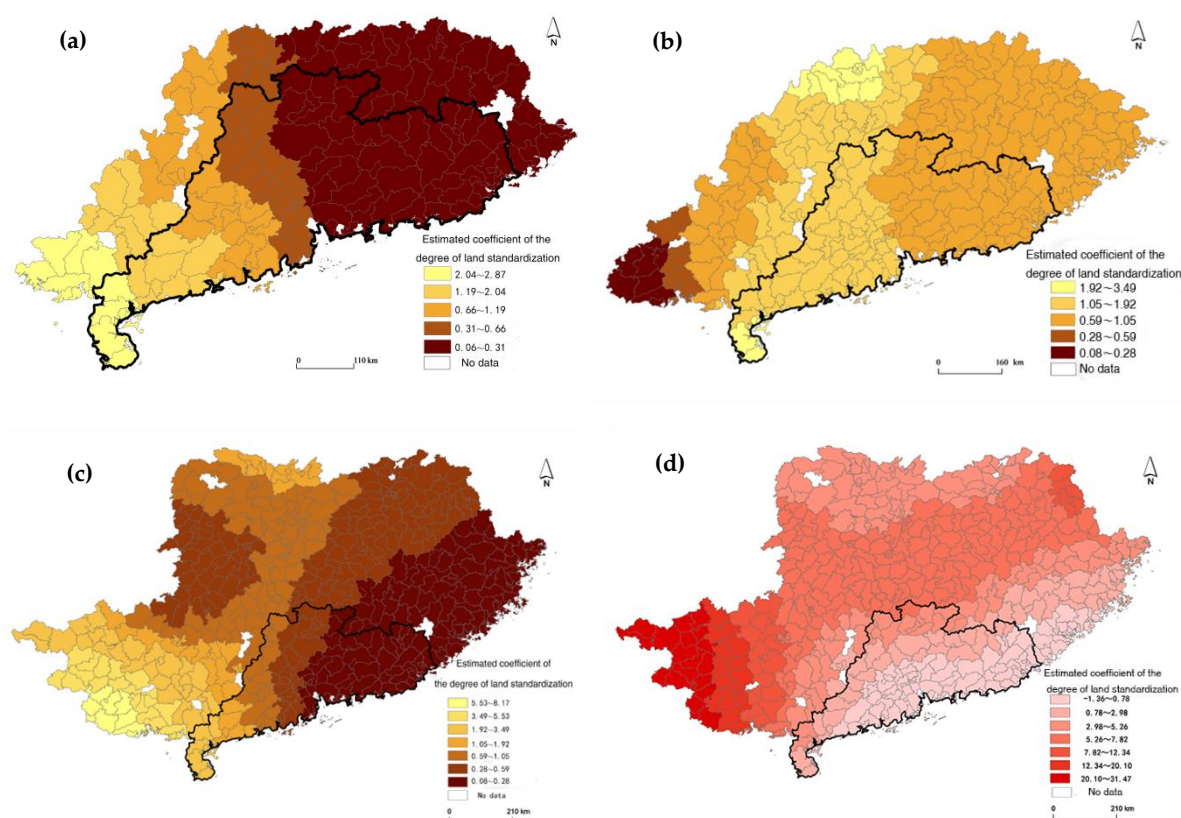


Figure 2. Effect of agricultural land endowment on grain output; (a) Estimated coefficient of the degree of land standardization under the S scale; (b) Estimated coefficient of the degree of land standardization under the M scale; (c) Estimated coefficient of the degree of land standardization under the L scale; (d) Estimated coefficient of the total area of arable land under the L scale.

Total area of cultivated land. It can be seen from Figure 2d that the magnitude and direction of the effect of the total cultivated area on the total grain output vary from place to place. On the whole, in the sampling range of L, the total area of cultivated land in most areas has a positive effect on grain production, and this positive effect has gradually increased from the southern coastal areas to the inland areas. Since the total area of arable land reflects the land's food production potential, the increase in agricultural land's potential is an important means to ensure grain production for areas lacking water resources. Therefore, the effect of the total area of arable land on grain production is very elastic in inland areas where water resources are relatively lacking. However, in Guangdong province, grain production is relatively insensitive to changes in the total cultivated land area. The layout of cultivated land in the southern coastal areas may even have a negative impact on food production. This special case seems to be contradictory to proposition 1, but it is very consistent with the economic reality of the main grain sales area: of the total agricultural output value of Guangdong province, industries with higher yields, such as fishery and fruit industries, account for the majority. These industries have higher demand for agricultural land, and therefore, these high-value-added sectors will absorb more in the allocation of grain production capacity. Over time, an imitation effect will be formed among farmers, and grain production may be crowded out of arable land, which leads to a negative effect. This, in essence, is also consistent with the assumption of proposition 1: the difference in the effect of land endowment on grain production is caused by the difference in the agricultural production structure across different geographical locations.

Distribution of the estimated effect of the proportion of labor force on the total grain output (see Figure 3a–c). Under the sampling scales of R and S, the impact of the proportion of labor on the total grain output varies in magnitudes and signs. In most areas, the regression coefficient is positive, which means that a decrease in the proportion of

agricultural labor will result in a decrease in grain production. However, when we expand the sampling range to L, it is found that a decrease in the proportion of agricultural labor force in the sample counties is correlated with an increase in grain production. This is seen in Guangxi, Jiangxi, Fujian, and central and southern Hunan. This may be due to the “grainization” brought about by the increase in the price of agricultural labor across the country; that is, farmers can use capitals to substitute labor or outsource it in the labor-intensive production process. Therefore, the smaller the rural labor force surplus, the larger the grain planting area and the more grain output. However, the effect of the decrease in the proportion of labor on grain production is inelastic in the southern coastal areas and central areas. The continuing decline in agricultural labor cannot bring about an increase in grain production. This is potentially due to two reasons. First, the price of rural labor in these regions, such as Guangdong, is relatively high, whereas the comparative income of part-time farmers is low, and the phenomenon of decultivation is very prominent. Second, the fragmented farmland conditions in these regions hinder the formation of agricultural production service markets. Farmers cannot outsource some links in the process of production. The heterogeneity of the proportion of labor to grain production is consistent with proposition 2, which states that the increase in labor endowment has a dual effect on the level of grain production, which depends on the local labor price and the agricultural production service market.

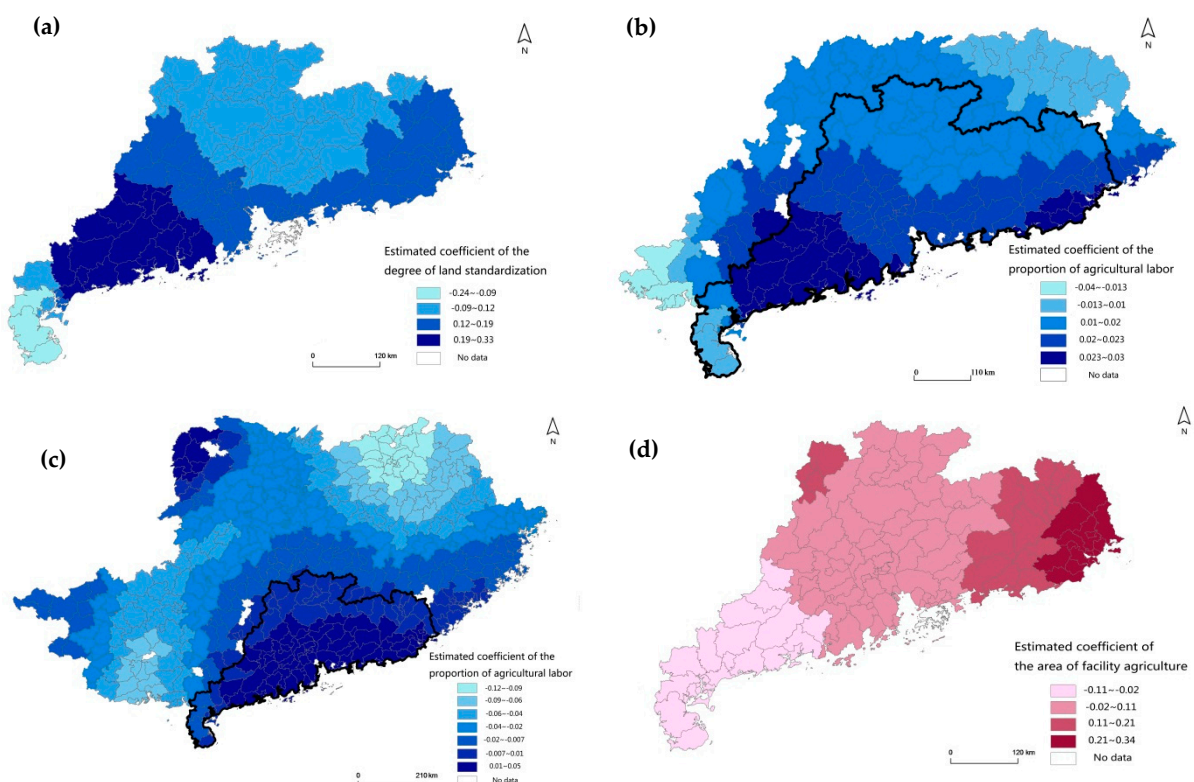


Figure 3. Effect of agricultural labor endowment on grain output; (a) Estimated coefficient of the proportion of agricultural labor under the R scale; (b) Estimated coefficient of the proportion of agricultural labor under the S scale; (c) Estimated coefficient of the proportion of agricultural labor under the L scale; (d) Estimated coefficient of the area of facility agriculture under the R scale.

Area of facility agriculture. Figure 3d presents the distribution of the estimated effect of the area of facility agriculture on the total grain output. The effect of the area of facility agriculture on the total grain output varies in signs and magnitudes across regions. In western Guangdong, the increase in the area of facility agriculture has a restraining effect on food production; that is, agricultural investment leads to land nongrainization. On the other hand, in eastern Guangdong, the opposite effect is observed. The increase

in the area of facility agriculture promotes grain production. The main reason for this heterogeneity is the difference in the return on capital of the industry. As mentioned above, the western Guangdong area is a small area in the province with high-yield grain production. The grain fields are relatively abundant, and the land is contiguous. The grain production is dominated by ordinary rice with small income elasticity of demand, while the agricultural production in the eastern Guangdong area includes mainly fine-grained, small-scale agricultural operations, with a low degree of specialization. Grain production is dominated by high-quality rice with strong income elasticity of demand. The yields of grain commercialization in the two places are different, resulting in diametrically opposite responses to economic development.

Level of agricultural informatization. Figure 4a–d shows the distribution of the estimated effects of agricultural informatization on the total grain output. This indicator has a negative impact on the total grain output in the main sales area in southern China, and the magnitude varies across areas. Within the sampling ranges of R and S, the inhibitory effect of agricultural informatization on grain production is increased from the central to the east and west. When the sampling range is expanded to M and L, this inhibition is weakened in the southern main sales area, but the sign is still negative. This shows that the more developed the informatization in an area, the more pressure grain production is under and the greater the probability that local farmers will produce nongrain crops. For example, in Guangdong, the process of agricultural informatization has a less restraining effect on grain production, especially in the Pearl River Delta region, indicating that the stimulus effect of informatization in developed regions is weaker than that in less developed regions, and it has a weaker crowding out effect on grain production. The effect of agricultural informatization level on grain production is inconsistent among regions, which is related to the differences in local capital rates of return. This evidence is in line with proposition 3.

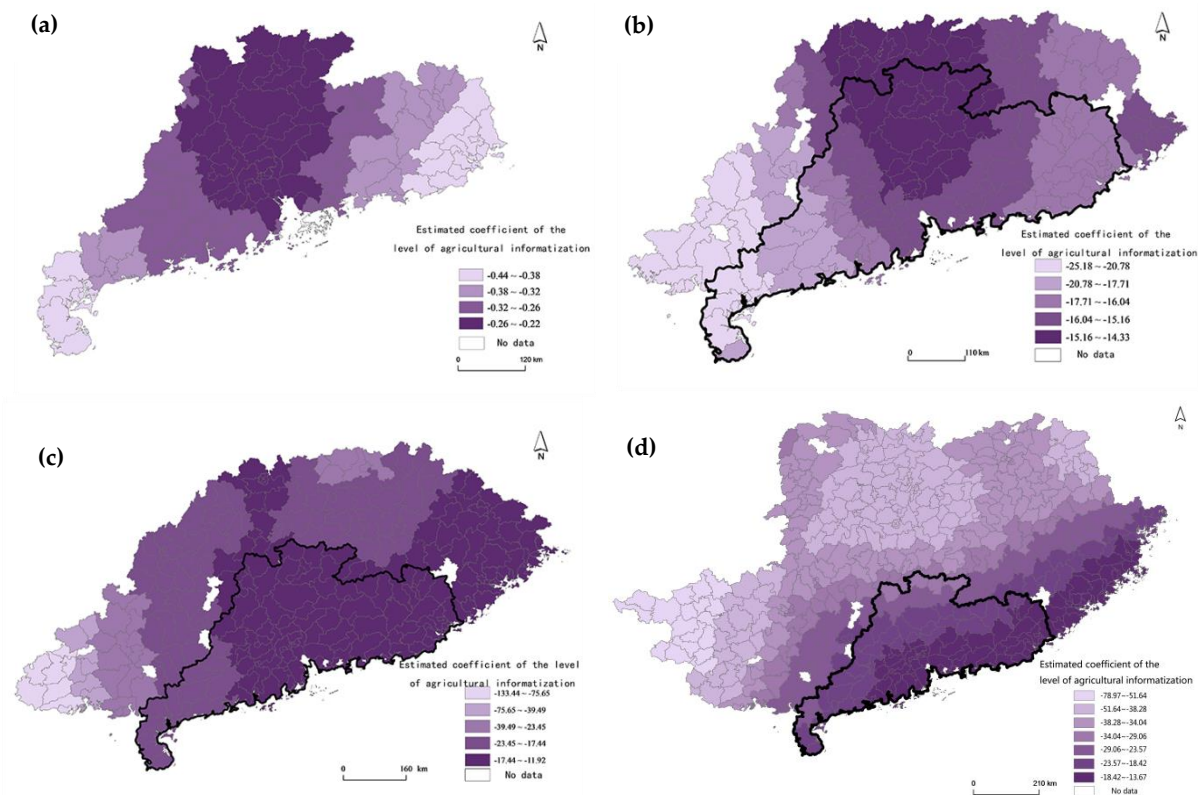


Figure 4. Effect of agricultural technology endowment on grain output; (a) Estimated coefficient of the level of agricultural informatization under the R scale; (b) Estimated coefficient of the level of agricultural informatization under the S scale; (c) Estimated coefficient of the level of agricultural informatization under the M scale; (d) Estimated coefficient of the level of agricultural informatization under the L scale.

4. Discussion

In light of the above analysis, it is evident that the spatial heterogeneity in the effect of land, labor, and technology in the main grain sales areas of southern China on grain production is significant, and hence, the policies for stabilizing grain production in various regions should also vary under specific circumstances.

(1) Policies that improve land infrastructure are applicable in more than half of the counties. The elasticity in the coefficient of the degree of land standardization shows the change in the level of grain production when the sample counties' land endowment increases. It can be seen that when the quantity or quality of cultivated land increases, more than half of the sample counties experience an increase in grain output, with the most obvious effect in western Guangdong. This result is consistent with the conclusions in the existing literature that the increase in arable land areas [46–49], the improvement in the quality of arable land [50], and the increase in arable land per capita [51] will improve the grain production level. This shows that the problems of land fragmentation, slow circulation, and land abandonment have always been an unavoidable setback in grain production in the low hilly areas in the south. It is most beneficial to facilitate policies such as high-standard basic farmland, large-scale planting bonuses, and land transfer market construction in these areas. However, these areas generally have a lower level of economic development. Take Guangdong province as an example. The land promotion policies are not conducive to increasing grain production in the Pearl River Delta region, sometimes even having a counterproductive effect in western and eastern Guangdong, leading to a reduction in production level. There should be appropriate adjustments in policies in these areas.

(2) Labor promotion policies are applicable to most counties. The results show that the continuous decrease in the proportion of agricultural labor force is detrimental to the level of food production in most areas, and the impact is relatively evenly distributed geographically, indicating that the southern main sales area is facing a major issue of “who will farm the land.” The existing literature has contradictory empirical results on the effect of labor endowment on grain production. Some studies show that the labor movement in the rural areas raises productivity and grain output because the loss of agricultural labor will motivate the production process to shift from labor intensive to capital intensive. This structural transformation also manifests itself in the adjustment in plantation structure [52,53]. There are also studies that test the complementary relationship between nonagricultural employment and grain output [31,54,55]. However, the effect of rural labor outflow on grain output exhibits significant spatial heterogeneity. Wang (2013) argues that the outflow of rural labor has no significant impact in the major sales area but has a positive effect in the major production area [56]. Cheng (2015), however, indicates the opposite [57]. Moreover, the substitutability of labor in grain production also affects grain production [58,59]. The empirical evidence of this paper indicates that the substitutability from labor to capital or machines is low in the sampling regions and, therefore, imposing a negative effect on the grain output.

(3) The facility upgrading policy is applicable to the more developed areas along the southern coast. The elasticity of the effect of the area of facility agriculture depicts the changes in the level of grain production when the comparative benefits of planting grain crops in the sample counties decrease. Compared with economically developed regions, the improvement of the level of facilities in the economically underdeveloped regions will introduce the issue of nongrainization. This is less of an issue in regions with faster economic development. The potential mechanism could be the costs of facility upgrading. Nevertheless, most studies argue that the application of high-quality facilities and automation could improve the grain output [60,61]. However, if the costs of facilities are taken into consideration, the facility upgrading would be inapplicable in less developed regions and, in turn, reduce the grain production or hinder these areas from transforming into growing high-value-added crops. This is consistent with the conclusion of Yang et al. (2018) [62].

(4) The improvement of agricultural informatization has brought a negative impact on the stability of food production. The elasticity of the effect of the level of agricultural informatization shows that while the informatization level of the sample counties continues to improve, it has a negative impact on the grain production in all counties, especially in the western region. The coastal areas experience a relatively smaller effect, while the inland areas experience a relatively larger effect. This can be explained by the fact that the implementation of agricultural informatization requires the basic support of local informatization. The implementation of digital agriculture in underdeveloped areas (currently, many agricultural projects use this as a gimmick) can easily lead to reduced food production and dampen local agricultural output. Therefore, the promotion of agricultural informatization in the southern main sales area needs to cooperate with other food stabilization policies to ensure the stability of food production.

5. Conclusions

This study discussed the regional differences in the factors affecting the level of grain production in the main sales area, as well as the magnitude and patterns of these differences. Through analyzing the regression results of the GWR model under different sampling ranges, it is found that, first, in the main grain sales area, the impact of agricultural land endowment on county grain production levels is uncertain. The empirical results of the major sales areas in the south indicate that the effect of the degree of land standardization on grain production shows a pattern of “high in the west and low in the east.” The effect of the total area of arable land on grain output is not sensitive. There is even a negative feedback phenomenon in the southern coastal areas. This is related to the difference in the structure of agricultural production in different locations. Second, the impact of agricultural labor endowment on the level of food production has regional differences. Under a large sample, the level of grain production in the main sales districts and counties of the south is not sensitive to changes in the proportion of agricultural labor, which is related to the excessively high labor price and the lagging of the agricultural production service market. Finally, the magnitudes and signs in the effect of technological progress on the level of food production show regional heterogeneity. The impact of agricultural informatization on the total grain output shows a pattern of “high in the east and low in the west.” Take Guangdong province as an example. The negative impact of the level of agricultural informatization on the total grain output has weakened from the Pearl River Delta to the surrounding areas. This is potentially related to the regional differences in the return to capital.

However, there are still caveats in this study. Due to the limitation of data, there are many explanatory variables that are not related to grains specifically. This is because the data on factors for grain production are not collected from the national statistical yearbook. Therefore, the data on land, labor, and technology endowment are for agricultural production in general. This may cause biased results and requires careful interpretation. The future work on this topic will benefit from more precise data.

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