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SPATIO-TEMPORAL EVOLUTION OF RICE PRODUCTION IN CHINA IN THE REFORM AND OPENING-UP PERIOD (POST-1978) AND INFLUENCING FACTORS

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ABSTRACT

This study is based on panel data from 31 provincial-level administrative regions in China, analyzing the Spatio-temporal evolution and driving factors of rice production in China from the beginning of China's Reform and Opening-up in 1978 to 2022. The methods employed include the spatial Gini coefficient, industrial concentration index, center of gravity migration, and global Moran's index. The results show that China's rice yield has experienced fluctuating growth, with industrial concentration and the spatial Gini coefficient first decreasing and then increasing, reflecting enhanced regional concentration. Meanwhile, the primary concentration of rice production has moved to the northeastern area. indicating significant changes in spatial distribution. Additionally, rice production exhibits strong spatial dependence, with high-yield areas tending to cluster. Factors such as non-agricultural employment opportunities, comparative benefits, mechanization levels, and yield per unit area significantly impact the scale of rice production. Based on these findings, this study proposes policy recommendations, including adjusting the planting structure, improving mechanization, enhancing market competitiveness, paying attention to the impact of non-agricultural employment, strengthening regional planning coordination, and formulating strategies to cope with climate change. These suggestions offer a scientific foundation and actionable insights for optimizing rice production regions, shaping relevant policies, and ensuring sustainable rice cultivation in China. They boost the sustainable progress of the rice sector and provide a fresh viewpoint on regional shifts in rice production.

Key words: Rice production; Spatio-temporal evolution; Influencing factors; Spatial Durbin model

INTRODUCTION

Rice (*Oryza sativa* L.) is one of China's most important staple crops, plays a crucial role in national food security and sustainable agricultural development. China initiated its Reform and Opening-up policy in 1978 to address economic stagnation, inefficient agriculture, and food shortages under the planned economy system. The core strategy focused on economic development, with reforms continuing to this day. Key measures included implementing the Household Contract Responsibility System, raising agricultural product purchase prices, abolishing centralized procurement systems to introduce market mechanisms, and establishing special economic zones for openness (Zhang and Liu, 2009). In the rice sector, the reform empowered farmers through the Household Contract Responsibility System, complemented by hybrid rice research, agricultural mechanization, and upgraded water conservancy facilities to reduce costs and ensure production (Cheng *et al.*, 2007).

Following the inception of China's Reform and Opening-up policy, the rapid expansion of the national economy, the deepening of social transformation, and successive reforms in agricultural policy have jointly engendered pronounced Spatio-temporal reconfigurations in rice production. Numerous scholars have conducted extensive research on China's rice production, providing a rich theoretical foundation and empirical analysis. Through research on Henan and Heilongjiang provinces, it was found that the number of high-yield counties has significantly increased, and the spatial distribution of high-yield areas tends to be concentrated (Wang *et al.*, 2023a). At the same time, it was found that the focus of China's grain production is gradually shifting towards the north, and this trend is also reflected in rice production (Wang *et al.*, 2018). In addition, the GlobeLand30 dataset was used to study the changes in arable land in China from 2000 to 2020, and it was found that the eastern coastal areas experienced the most severe reduction in arable land, while the western regions saw a significant increase in arable land, which to some extent reflects the dynamic changes in rice planting areas (Zhang and Qie, 2024). From a time, series perspective, the overall rice yield in China shows an increasing trend, but the growth rate varies at different stages (Wang *et al.*, 2019). In addition, climate change has also had an impact on the time series of rice production, example, research has found that climate change has both short-term and long-term symmetrical and asymmetrical effects on rice production in Sri Lanka, Similar studies have also shown that rice yields in some regions of China are significantly affected by climate change (Samarasinghe *et al.*, 2025). The impact of climate factors on rice production is multifaceted. Research has found that the increase in nighttime temperatures caused by global warming can lead to a decrease in rice yield. Emphasis was placed on the importance of adaptation strategies (Peng *et al.*, 2004; Mei, 2024). The sensitivity of rice yield to climate change varies in different regions (Zhan *et al.*, 2023). Land use change has had a significant impact on rice production. The balance of land functions in the Central Plains region of China reveals a significant conflict between urbanization and agricultural production, with a large amount of arable land being occupied by urban expansion (Shi *et al.*, 2023).

The improvement of agricultural mechanization level has had a significant impact on rice production efficiency. The spatial spillover effect of agricultural mechanization level on the technical efficiency of grain production indicates that cross-regional operations of agricultural mechanization have a positive effect on improving grain production efficiency (Xie *et al.*, 2023). Another study verified the spatial spillover effect of agricultural mechanization on grain yield through the spatial Durbin model, and found that the improvement of mechanization level in a certain region will significantly promote the increase of grain production in surrounding areas through cross regional operation of agricultural machinery (Wu *et al.*, 2021). Outsourcing agricultural mechanization services can significantly improve farmers' production efficiency, especially in the case of labor transfer. The use of mechanization services can effectively compensate for the problem of labor shortage (Shen *et al.*, 2023). Research has found that the use of unmanned aerial vehicles for seeding and mechanized rice transplanting have significant advantages in energy efficiency and economic benefits in rice production (Yang *et al.*, 2023). With the improvement of people's living standards, the demand for high-quality rice continues to increase, which also promotes the development of rice planting structure towards higher quality and diversification (Krishnankutty *et al.*, 2025).

Despite the extensive research on rice production in China, key gaps remain in existing literature: overreliance on descriptive analyses, lack of rigorous empirical methods to explain the spatial dependence of production layout, neglect of dynamic spatial changes in production and inter-regional spillover effects, insufficient detailed analysis of effective climate change adaptation strategies, inadequate exploration of how regional characteristics influence production patterns, and absence of integrated studies on the combined effects of multiple factors. In order to address these gaps, this study uses provincial panel data from China's 31 provinces, municipalities, and autonomous regions. Employing methods such as the spatial Gini coefficient and industrial concentration index, it examines the Spatio-temporal changes in rice production, quantifies spatial dependence and spillover effects, assesses the effectiveness of climate adaptation strategies, and explores how regional differences in urbanization, agricultural policies, and other factors impact production patterns. Ultimately, it aims to put forward targeted recommendations to optimize production layout, improve agricultural policies, and promote the sustainable development of the rice industry.

MATERIALS AND METHODS

Data Sources: The study covers the period from 1978 to 2022, utilizing provincial-level panel data from 31 provinces, cities, and autonomous regions in China (excluding Hong Kong, Macau, and Taiwan). The data were sourced from the China Statistical Yearbook and the China Rural Statistical Yearbook. Before 1988, statistical data for Guangdong Province included Hainan Province, and before 1997, data for Sichuan Province included Chongqing Municipality. Considering the consistency of spatial units, Chongqing was merged into Sichuan, and Hainan was merged into Guangdong for the analysis. Data for the years before 1988 for Guangdong and Hainan, and before 1997 for Sichuan and Chongqing, were derived from the Statistical Compilation of 60 Years of New China and the Agricultural Statistical Compilation of 60 Years of New China. Missing data for individual years were interpolated linearly. In the empirical analysis, agricultural machinery total power was used as an indicator to reflect the level of mechanization in rice production. Specifically, the agricultural mechanization level was quantified by multiplying the total agricultural machinery power by the proportion of rice planting area to the total crop planting area. In the empirical analysis, some variables were presented as percentages, while rice yield, agricultural machinery total power, and rice average yield were represented in absolute values. To mitigate statistical issues such as heteroscedasticity, the study applied natural logarithmic transformation to rice yield, agricultural machinery total power, and rice yield per unit area.

Research Methods

Spatial Gini Coefficient: The Gini coefficient, originally employed to assess disparities in income distribution, has been applied to study industrial spatial agglomeration by some scholars (Song *et al.*, 2010). This research utilizes the spatial Gini coefficient to indicate the extent of spatial concentration of rice production in China. The formula for calculation is:

$$GINI = 1 - \frac{1}{n}\left(2\sum_{j=1}^{n-1} Y_j + 1\right) \qquad (1)$$

In Eq. (1), GINI represents the Gini coefficient; n denotes the number of provincial groups; Y_j represents the cumulative proportion of rice yield after sorting provinces by yield in ascending order; Y is the total national rice yield. When the spatial Gini coefficient (GINI) approaches 0, it indicates a more balanced spatial distribution of rice production. Conversely, when GINI approaches 1, it suggests a higher degree of spatial agglomeration.

Industrial Concentration Index: Although the spatial Gini coefficient plays an important role in measuring the balanced distribution of industries across regions, it has limitations in terms of industrial scale, geographical unit settings, and industrial classification. In comparison, the industrial concentration rate measures the proportion of the top few provinces (municipalities or regions) in the national total and can be used to reflect the agglomeration phenomenon of a specific industry in space (Duranton and Overman, 2005). The industrial concentration of rice production reflects the proportion of the total national output contributed by the top rice-producing provinces. The calculation formula is presented as follows:

$$CR_m = \frac{\sum_{i-1}^{m} Y_i}{\mathrm{Y}} \times 100\% \qquad (2)$$

In Eq. (2), CR represents the industrial concentration of the top m regions; m denotes the number of top provinces, which is generally taken as 1, 3, or 5. In this study, following the approach of Han *et al.* (2020), m was set to 5. $Y_i$is the rice yield of province i, and Y is the total national rice yield?

Center of Gravity Migration Trajectory: Any change in regional rice production will cause the national rice production center of gravity to shift (Chen and Zhao, 2019). Therefore, this study calculates the annual changes in the center of gravity of rice production among regions and plots the trajectory of the national rice production center of gravity using ArcGIS 10.2 software. The calculation formula is presented as follows:

$$X_t = \frac{\sum_{i=1}^{n} C_{it} X_i}{\sum_{i=1}^{n} C_{it}}, Y_t = \frac{\sum_{i=1}^{n} C_{it} Y_i}{\sum_{i=1}^{n} C_{it}} \qquad (3)$$

In Eq. (3), $X_t$and $Y_t$represent the longitude and latitude coordinates of the rice production center of gravity in year t, respectively. C_{it}it denotes the rice yield of province in year t, and $X_i$and Y_i are the coordinates of the centroid of province i. n is the number of provinces.

Spatial Autocorrelation Test: Regional economics posits that "almost all spatial data exhibit spatial dependence or spatial autocorrelation." The interconnections among regional systems are ubiquitous, especially when two systems are geographically adjacent or economically similar. Spatial autocorrelation is a method to test whether the observed values at a particular location are correlated with those at neighboring locations. If a high value at one location is accompanied by high values at nearby locations, it indicates positive spatial autocorrelation. Conversely, if a high value is surrounded by low values, it indicates negative spatial autocorrelation (Griffith, 2023). To test whether China's rice production exhibits spatial dependence, this study employs Moran's I index.

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

(4)

In Eq. (4), The element $w_{ij}$of the spatial weight matrix denotes the spatial weight coefficient between regions i and j. This study uses the most common 0-1 adjacency weight matrix and row-standardizes spatial weight matrix is employed to quantify spatial relationships. The Moran's I statistic, which ranges between -1 and 1, serves as a measure of spatial autocorrelation. A Moran's I value greater than zero signifies positive spatial autocorrelation, indicating that spatially proximate observations tend to exhibit similar values, such that high values are clustered with high values and low values with low values. Conversely, a Moran's I value less than zero denotes negative spatial autocorrelation, suggesting that high values are juxtaposed with low values. When Moran's I is near zero, it implies a spatially random distribution, with no discernible spatial autocorrelation present.

Spatial Panel Durbin Model: The data used in the empirical analysis of the Spatio-temporal changes in China's rice production are panel data. Standard panel econometric models, which ignore spatial effects, may lead to biased parameter estimates. Therefore, this study employs the spatial panel Durbin model, which not only optimizes omitted variable issues and corrects model uncertainty but also modifies the spatial econometric model to provide unbiased coefficient estimates (Lee and Yu, 2016). The general form of the spatial panel Durbin model is as follows:

$$\begin{aligned} y_{it} &= \rho w_i y_t + x_{it}\beta + w_i x_{it}\delta + \mu_i + v_t + \varphi_{it} \\ \varphi_{it} &= \lambda w_i \varphi_t + \varepsilon_{it} \end{aligned} \qquad (5)$$

In Eq. (5), y_{it} is the dependent variable, x_{it} is the vector of independent variables, w_i is the i-th row of the spatial weight matrix W, ρ is the spatial lag coefficient, The parameters β and δ represent the estimation coefficients associated with the independent variables and their respective spatial lag terms, respectively, μ_i is the individual effect, v_t is the time effect, λ is the spatial error coefficient, ε_{it} is the random error term satisfying the classical assumptions. Through corresponding tests, the rationality of the spatial panel Durbin model can be judged, i.e, whether it can be reduced to a spatial panel lag model or a spatial panel error model.

Construction of the Empirical Model and Variable Selection: The dependent variable in this study's empirical analysis is the scale of rice production, measured by rice yield. The following variables were selected to analyze the factors influencing the Spatio-temporal changes in China's rice production. The meanings, symbols, and expected effects of the variables are shown in Table 1. The variable settings and selection criteria are as follows:

Non-agricultural Employment Opportunities (X1): Measured by the proportion of GDP from the secondary and tertiary industries, it is expected to have a negative impact. This is because a higher proportion is more likely to attract labor transfer from rice cultivation, which may lead to a reduction in rice production (Shen *et al*., 2023).

Comparative Benefits of Rice Production (X2): Measured by the proportion of rice planting area to the total crop planting area, it is expected to have a positive impact. A higher proportion (i.e., a stronger "economic advantage" of rice in terms of planting area allocation) enhances farmers' willingness to grow rice and expands the production scale (Shen *et al*., 2023).

Level of Agricultural Mechanization (X3): Measured by the natural logarithm of "(total power of agricultural machinery × the proportion of rice planting area to total crop planting area)", it is expected to have a positive impact. Specifically, a higher level of mechanization (characterized by sufficient mechanical power and a reasonable proportion of rice planting area) is more conducive to the expansion of rice production and promotes the growth of the production scale (Ubabukoh and Imai, 2023).

Rice Yield per Unit Area (X4): Measured by the natural logarithm of rice yield per unit planting area, it is expected to have a positive impact. The core logic is that with the same (or expanded) planting area, a higher yield per unit area results in a higher total rice yield, which directly drives the expansion of the production scale (Matsubara *et al*., 2020).

Table 1. Variable measurement and predicted impacts for identifying determinants of rice yield

Variable	Symbol	Measurement Method	Expected Effect
Rice Production Scale	Y	Natural logarithm of rice yield in each region	-
Non-agricultural Employment Opportunities	X1	Proportion of the value of secondary and tertiary industries in GDP	Negative
Comparative Benefits of Rice Production	X2	Proportion of rice planting area to total crop planting area	Positive
Level of Agricultural Mechanization	X3	Natural logarithm of (agricultural machinery total power × proportion of rice planting area to total crop planting area	Positive
Rice Yield per Unit Area	X4	Natural logarithm of rice yield per unit planting area	Positive

RESULTS

Fluctuating Growth in Rice Yield: Since the inception of the Reform and Opening-up policy, China's rice yield has undergone periods of fluctuation (Figure 1). From 1978 to 2022, rice yield increased from 136.93 million tons to 211.09 million tons, a growth of approximately 54.3%. The changes in rice yield can be divided into three stages: rapid growth from 1978 to 1997, decline from 1997 to 2003, and recovery from 2003 to 2022. The fluctuating trend in rice yield is consistent with the overall trend in national grain production. In 1996, China's total grain production reached its historical peak, one year ahead of the peak in rice yield. It then declined, reaching its nadir in 2003, before steadily recovering. The initial rapid growth in rice yield was closely related to the implementation of the household contract responsibility system and the reform of the grain circulation system, which provided institutional incentives. Subsequently, as the focus of economic system reform shifted to urban and industrial areas, and market sales difficulties arose due to the rapid increase in grain production, farmers' enthusiasm for growing grain was dampened, leading to the decline in rice yield from 1997 to 2003. In 2004, the central government issued the first "No. 1 Document" of the 21st century, focusing on agriculture, rural areas, and farmers, significantly enhancing national attention to "agriculture, rural areas, and farmers" issues and putting rice production back on a path of sustained growth.

Industrial Concentration of Rice Production First Decreases and Then Increases: As shown in Figure 2, from 1978 to 2022, both the industrial concentration and spatial Gini coefficient of China's rice production exhibited trajectories characterized by an initial decline followed by a subsequent increase. Specifically, the Gini coefficient exhibited a decline from 0.65 in 1978 to 0.55

in 1997, before rising to 0.75 in 2022, indicating an enhanced regional concentration of rice production. Additionally, the industrial concentration of rice production stabilized after 2007, reflecting that since the Reform and Opening-up, China's rice production has been increasingly concentrated in advantageous regions. After 2007, the regional layout adjustment of rice production was essentially completed. This trend can be attributed to multiple factors, including policy orientation, technological progress, and market demand. Since the initiation of the Reform and Opening-up policy, China's rice demand has shown a steady upward trend, with food consumption being the main source of demand. Simultaneously, the rise in rice yield per unit area and the substitution effect of feed have also exerted a certain influence on rice demand. National agricultural support policies have promoted the centralization of rice production, especially in the construction of infrastructure and technology promotion in major rice-producing areas. Meanwhile, with the continuous improvement of rice planting technology, production efficiency has been enhanced, further driving the development of advantageous regions.

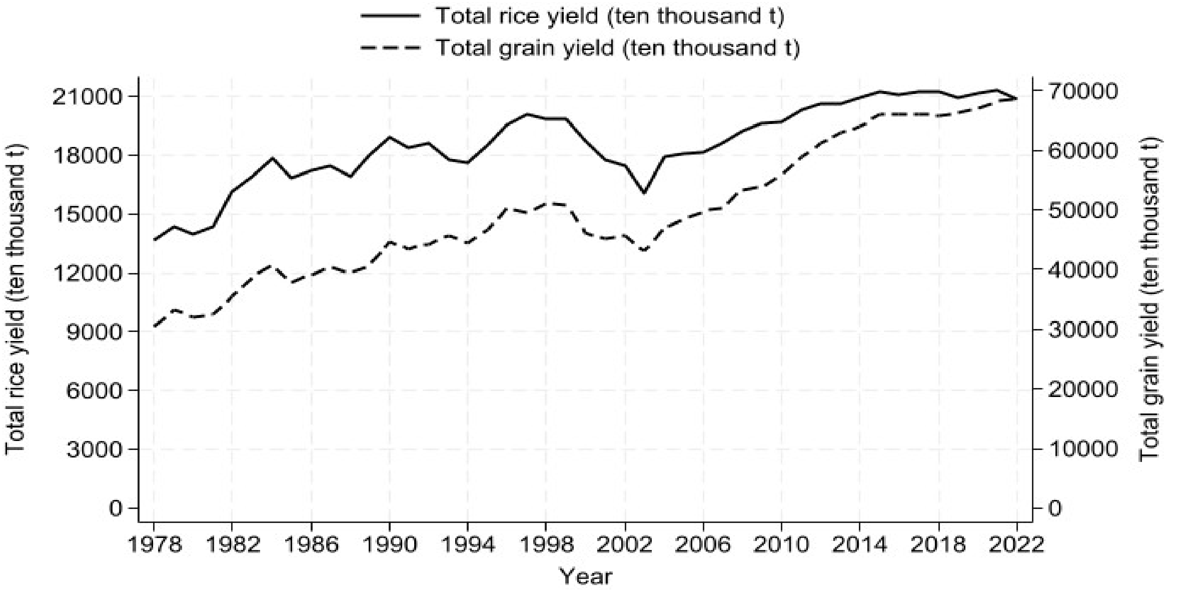

Figure 1. Dynamic changes of total rice yield and total grain yield in China under the background of Reform and Opening-up, 1978‑2022

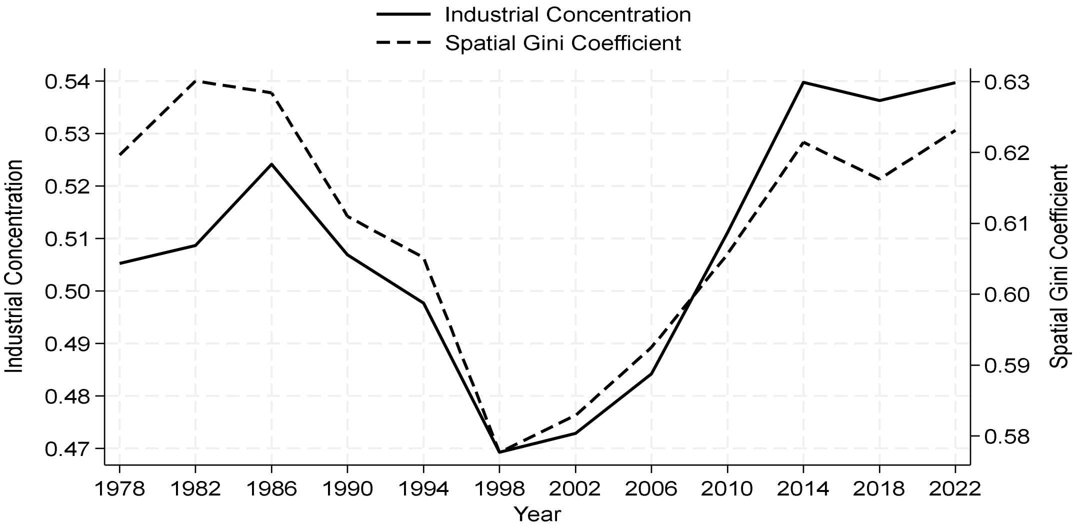

Figure 2. Evolution of industrial concentration (agglomeration degree) and spatial Gini coefficient (distribution difference) in China’ s rice production, 1978‑2022

The Center of Gravity of Rice Production Shifts Rapidly to the Northeast: As shown in Figure 3, centroid of China's rice production has exhibited a pronounced trend of northeastward migration from 1978 to 2022, The cumulative movement distance has reached about 380 kilometers. In 2004, the maximum distance of displacement of the center of gravity of rice production in China was 62.31 kilometers, and the direction of displacement conforms to the trend of southeast to northeast. This indicates that, since the Reform and Opening-up, the adjustment of the agricultural structure has led to a relative decline in the production contribution of major rice-producing provinces in the south and east has relatively declined, while that of the northeast has increased.

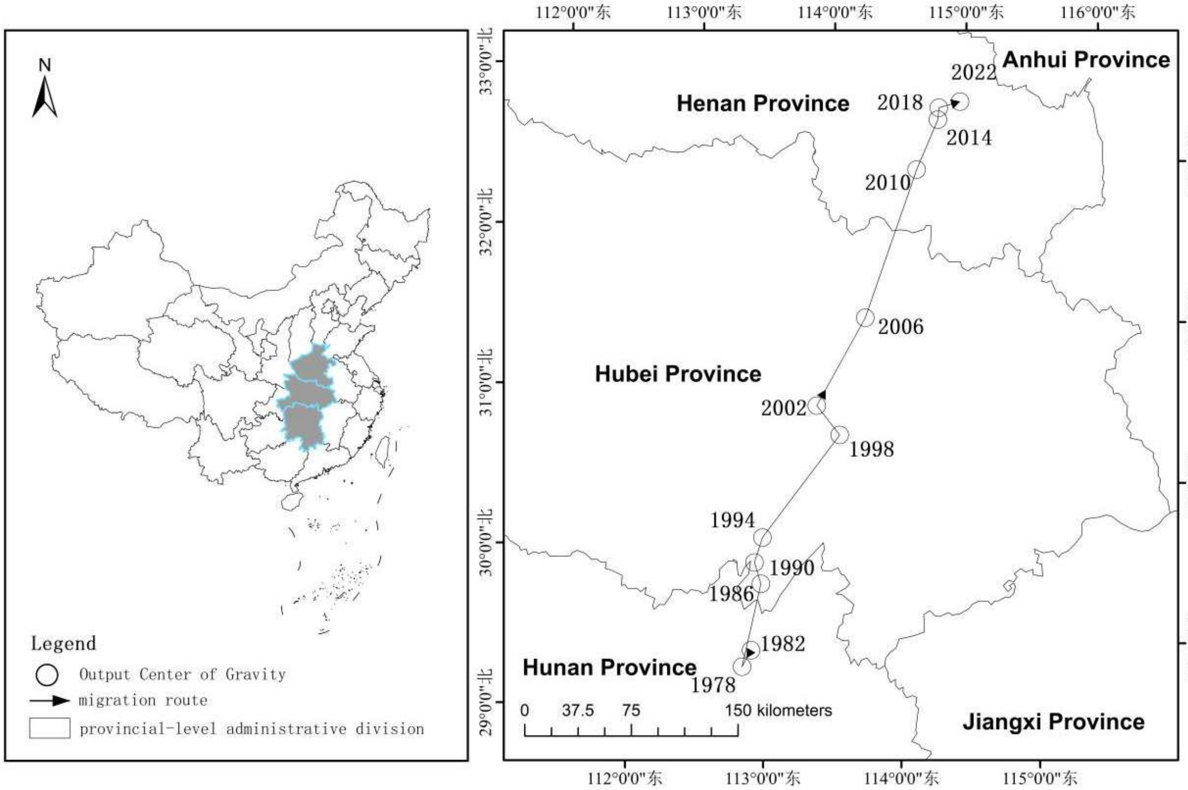

Figure 3. Migration route of China’s rice production gravity center, 1978-2022: Spatio - temporal evolution at the provincial administrative region scale (involving rice - growing regions of Henan, Hubei, and Hunan provinces)

Strong Spatial Dependence of Rice Production: As shown in Figure 4, the global Moran's I value fluctuated but remained relatively stable between 0.35 and 0.50 from 1978 to 2022, this finding suggests the existence of spatial dependence in rice production during this period. Moreover, Moran's I passed the 1% significance test in all years, meaning that high-yield regions tend to cluster together, as do low-yield regions. Therefore, in the process of studying the factors influencing the changes in the layout of rice production in various provinces and regions of China, the spatial effect cannot be ignored.

Estimation and Analysis of the Spatial Panel Durbin Model : The panel data were analyzed using Stata 18.0 software, and the Hausman test was performed. The Hausman test value was significantly different from zero, this finding suggests that the fixed-effects model is the appropriate choice. Subsequently, likelihood ratio (LR) and Wald tests were conducted to juxtapose the spatial lag model with the spatial Durbin model, as well as the spatial error model with the spatial Durbin model. The test outcomes uniformly rejected the null hypothesis, thereby corroborating the appropriateness of the spatial Durbin model. As evidenced by the estimation results (Table 2), the spatial regression coefficient attained statistical significance at the 1% level, thereby substantiating the existence of spatial spillover effects, which is congruent with the findings from the Moran's I test. Given that the estimation coefficients derived from the spatial Durbin model do not directly capture the relationship with the dependent variable, the model's estimation results were further decomposed into direct, indirect, and total effects (Table 3).

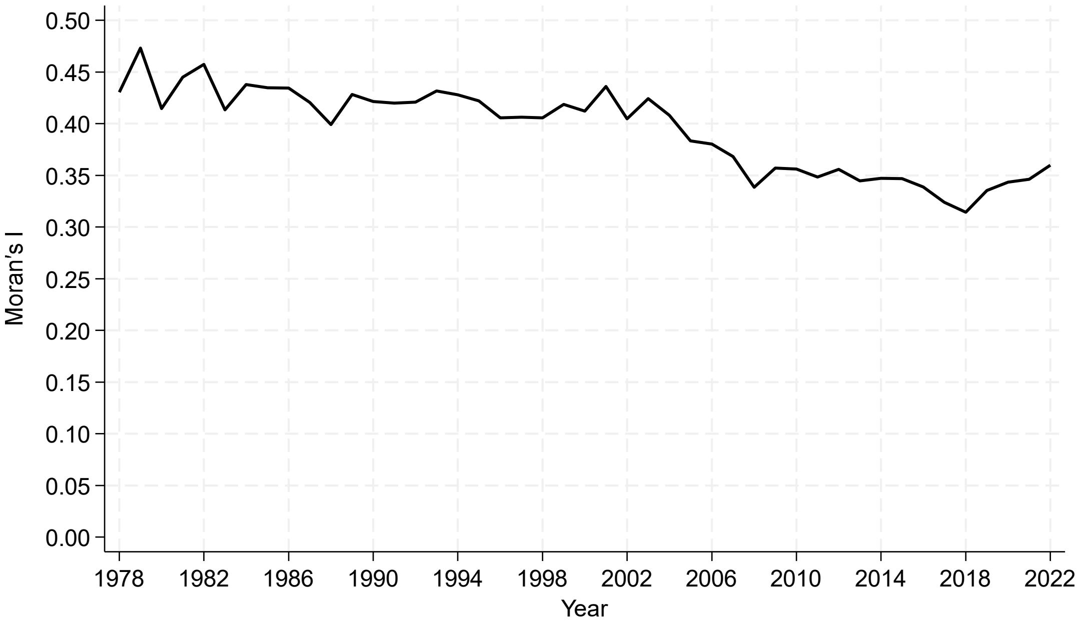

Figure 4. Spatial Autocorrelation Dynamics of China's Rice Yield (1978–2022): A Moran's I Perspective

Table 2. Results of Likelihood Ratio (LR) and Wald Tests for Hypothesis Validation

Statistical Test	Statistical Value	P-value	Result
LR Test	81.42	Prob>chi2=0.0000	Reject null hypothesis
Wald Test	46.97	Prob>chi2=0.0000	Reject null hypothesis

Table 3. Estimation Results of Spatial Durbin Model and Decomposition of Direct, Indirect, and Total Effects

Variable	Coefficient	Direct Effect	Indirect Effect	Total Effect
X1	-0.004	0.003	0.185***	0.189***
	(-0.27)	(0.25)	(6.07)	(5.01)
X2	3.982***	4.006***	1.015*	5.020***
	(12.82)	(13.83)	(1.88)	(10.36)
X3	0.136***	0.139***	0.059***	0.198***
	(17.60)	(18.34)	(3.32)	(9.29)
X4	1.212***	1.213***	0.036	1.249***
	(23.71)	(24.34)	(0.27)	(8.32)
rho	0.172***			
	(4.72)			
sigma2_e	0.131***			
	(26.33)			
R-squared	0.382			

Note: ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively. Numbers in parentheses are Z-values. X1: Non-agricultural Employment Opportunities; X2: Comparative Benefits of Rice Production; X3: Level of Agricultural Mechanization; X4: Rice Yield per Unit Area

DISCUSSION

China's rice production shows a significant spatial agglomeration trend: the industrial concentration index and spatial Gini coefficient declined from 1978 to 1997, then rose from 1997 to 2022, with regional concentration strengthened and layout adjustment stabilized since 2007. This aligns with the general trend of agricultural specialization and comparative advantage-driven spatial clustering in China's agriculture identified in relevant studies. Chen and Zhao (2019) studying efficiency differences between major and non-major grain-producing areas, noted agricultural production concentrates in regions with superior resource endowments and policy support, as technological spillovers and infrastructure investment amplify agglomeration effects. Their finding that major grain-producing areas contributed over 70% of national grain output by 2018 directly supports this study's rice agglomeration observation. Han *et al.* (2020) investigating herbivorous animal husbandry, also found an "initial decline then increases" in industrial concentration, attributing it to pre-2000 policy-driven balance and post-2000 market-driven specialization. This cross-sector consistency confirms China's rice production, like other agriculture, has shifted from "balanced distribution" to "advantage-based agglomeration" amid reforms, verifying this study's generalizability. Notably, this study extends prior research with a 44-year time series and dual metrics (spatial Gini coefficient + industrial concentration index) to quantify agglomeration dynamics. Unlike Wang *et al.* (2019) who only analyzed county-level rice changes up to 2018, it shows rice agglomeration stabilized after 2007—consistent with China's major agricultural policy adjustments (e.g., food security "No. 1 Central Document") and mature regional comparative advantages (Zhang and Qie, 2024). In addition, it was further pointed out that urbanization and the expansion in the Northeast region have led to the loss of cultivated land in the eastern coastal areas (traditional rice-growing regions), directly promoting the transfer of rice to advantageous areas.

From 1978 to 2022, China's rice production centroid shifted significantly northeastward, peaking at 62.31 km annual displacement in 2004. This fills gaps in prior studies: Wang *et al.* (2018) focused on short-term grain centroid shifts without specifying rice also first identified national grain centroid northward shift, but this study confirms it is more pronounced for rice, driven by two interrelated factors: First, climate adaptability: Zhan *et al.* (2023) simulated 5–10% northeast rice yield growth by 2050 (extended growing seasons, less heat stress) and 3–7% southern decline (extreme heat/floods). Mei (2024) added nighttime temperature rise— a key yield threat (Peng *et al.*, 2004)—is 1.2°C lower in the northeast, making it more suitable for high-yield rice. Second, land use optimization: Zhang and Qie (2024) pointed out that from 2000 to 2020, the arable land in the Northeast increased by 8.2% (from 28.5 million hectares to 30.9 million hectares) thanks to the "Grain for Green" policy adjustments. In contrast, the arable land in the South decreased by 6.1% due to urbanization. This change enabled a 40% expansion in rice planting in the Northeast. Although southern China still holds a dominant position, the Northeast's share of national output has risen from 5.3% in 1978 to 18.7% in 2022. This is consistent with Wang *et al.* (2023a) reported a The growth rate of the proportion of countrywide grain yield in Heilongjiang was greater than that in Henan between 2000 and 2021, thus confirming a structural change rather than mere short-term fluctuations.

The global Moran's I index of rice yield stayed 0.35–0.50 (1978–2022), all passing 1% significance tests, indicating strong positive spatial dependence (high-yield clustering). This aligns with regional economics spatial autocorrelation theory (Griffith, 2023) and recent agricultural technological spillover studies. Griffith (2023) emphasized agricultural spatial autocorrelation stems from "proximity-induced knowledge sharing," where neighboring farmers adopt successful technologies (e.g., high-quality seeds). This study quantifies this via the Spatial Panel Durbin Model, supported by two studies: Xie *et al.* (2023) found cross-regional machinery operations boost neighboring grain efficiency by 12–15% via technology demonstration, explaining positive Moran's I. Notably, Wu *et al.* (2021) found grain yield Moran's I at 0.28–0.42, lower than rice's 0.35–0.50—due to rice's greater reliance on region-specific technologies than other grains, deepening understanding of agricultural spatial dependence.

Non-agricultural employment shows -0.004 direct effect but 0.189 total effect. Although initially expected to be negative, the positive total effect arises because labor loss is offset−and outweighed−by cross-regional mechanization spillovers. Shen *et al.* (2023) found 10% non-agricultural income growth raises mechanized service spending by 8.5%, with "labor substitution" offsetting labor loss—matching 0.185 indirect effect (mechanization spillovers) outweighing direct negatives. Zhang and Xu (2023) added non-agricultural income reinvestment in agriculture creates "income feedback." The 0.189 total effect captures both mechanisms, refuting "labor transfer harms agriculture."

Comparative Benefits of Rice Production shows 4.006 direct and 1.015 indirect positive effects. Wang *et al.* (2023b) found The promotion of hybrid rice varieties will significantly improve the yield and production efficiency of rice per unit area. The logic of "technology investment leading to increased rice production capacity" is essentially a positive benefit brought by the improvement and diffusion of rice varieties.

Level of Agricultural Mechanization shows 0.139 direct and 0.059 indirect positive effects. Yang *et al.* (2023) found Mechanization indirectly enhances the comprehensive capacity of grain production, reduces production costs, and increases output per unit area by driving the collaborative input of production factors such as high-quality seeds and fertilizers. Liu and Li (2023) conclude that agricultural production mechanization can effectively promote the improvement in grain production capacity and efficiency and promote the process of agricultural modernization. Ubabukoh and Imai (2023) added mechanization impacts labor-intensive rice more than sorghum.

Rice Yield per Unit Area shows 1.213 direct but 0.036 indirect effect. Wang *et al.* (2023b) notedthe results showed possible spillover and crowding effects of hybrid rice adoption across provinces. In particular, the development of hybrid rice varieties in Hunan province has had a significant influence on changes in rice yield and the distribution of rice areas in other regions. Samarasinghe *et al.* (2025) added rice is more microclimate/soil-sensitive. This study confirms region-specific policies (e.g., high-yield breeding) for yield improvement.

Based on the findings, this paper advocates a holistic, science-based restructuring of China's rice sector integrating Spatio-temporal dynamics, inter-regional synergy, risk governance, and benefit sharing: public investment should first upgrade irrigation, storage, and drying infrastructure in resource-rich high-density rice regions, while prioritizing water-saving systems and drought-resistant cultivars in the northeast; targeted subsidies and concessional loans should accelerate full-mechanization in major rice belts to cut unit costs and boost economies of scale; high-yield, high-quality, climate-adaptable varieties, conservation tillage, and integrated rice–aquaculture models should be promoted to lift output, quality, and market competitiveness, and turn green premiums into long-term grower incentives; a "rice-retention subsidy + socialized service vouchers" scheme should offset off-farm employment-driven opportunity costs, guaranteeing basic incomes and technical support for remaining farmers; remote-sensing and meteorological early-warning platforms should build a basin-scale, cross-administrative risk framework, popularizing heat-tolerant cultivars and ecological farming in flood-retention zones of disaster-prone areas; the ultimate goal is a resilient, sustainable rice industry with complementary regional functions, smooth factor mobility, better disaster resistance, and stable farmer welfare.

Conclusion: This study examines the factors influencing China's rice production and the trajectory of the production center's shift from 1978 to 2022. It was found that the production center shifted 380 kilometers to the northeast, with output increasing by 54.3%. This change was shaped by the combined effects of policy, mechanization levels, and non-agricultural employment opportunities, rather than the linear accumulation of output. Notably, the impact of long-term policy fluctuations was greater than that of technological progress, indicating that policy variables should be prioritized in food security analysis models. Additionally, the Northeast region became the sole marginal supply increase area, with the national system exhibiting path dependence on it. If the comparative advantage of this region is not addressed, it may transform into systemic risk. Meanwhile, the Moran's I index indicated an increase in spatial agglomeration, which may weaken future adaptive capacity. Moreover, the Spatial Durbin Model revealed that non-agricultural employment initially reduced labor input but ultimately increased output through mechanical spillover effects and structural optimization. This suggests that labor loss can be compensated by mechanization and organizational spillover effects, implying that China's food security may have shifted from reliance on labor retention to capital maintenance and institutional coordination. Overall, these findings provide important references for ensuring food security, promoting sustainable rice industry development, and optimizing production layout, suggesting a shift from the production function paradigm to a human-land coupling system framework in food security analysis. However, the study also has limitations, such as reliance on provincial data and the lack of county-level indicators for climate and policy, which provide directions for future fine-grained and multi-factor studies.

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