Spatial and Efficiency Determinants of Grain Production in China: Evidence from Spatial Econometrics and Stochastic Frontier Analysis

Kaixuan Huang*

University of Tsukuba, School of Integrative and Global Majors, Tsukuba, Japan

Abstract. This study investigates the determinants of grain production and food security in China by integrating spatial econometric analysis and stochastic frontier analysis (SFA) using provincial panel data from 2000 to 2021. The spatial econometric framework examines per-unit yields of major crops—rice, wheat, maize, and sorghum—highlighting the roles of mechanization, irrigation, fertilizer use, rural income, and structural disparities. Results reveal limited spatial spillovers for staple grains, with only sorghum displaying marginal interprovincial dependence, while rice yield exhibits an inverted U-shaped relationship with rural income. Fertilizer use shows diminishing returns, and mechanization effects differ across crops due to institutional and ecological heterogeneity. Complementarily, the SFA model evaluates provincial-level technical efficiency, demonstrating that land, machinery power, and rural income significantly enhance grain output, whereas excess agricultural labor has little effect. Efficiency estimates suggest an average technical efficiency of 87.7 percents, with droughts significantly increasing inefficiency and floods occasionally yielding post-disaster recovery gains. By combining spatial and efficiency-based perspectives, this research underscores the dual importance of regional structures and environmental shocks in shaping China's food security. Policy implications include strengthening farmland protection, advancing precision and green technologies, improving rural income and labor transitions, and enhancing interregional as well as international cooperation to build a resilient food system.

1. Introduction

The central government of China has emphasized that "food security is a fundamental component of national security"[1]. Given China's vast territory and its enormous population base, securing adequate food for its 1.4 billion citizens has remained a paramount national task since the founding of the People's Republic. Through decades of self-reliant development, China has largely achieved basic food self-sufficiency and successfully transitioned from an era of widespread hunger to one of basic adequacy. More recently, the food system has been evolving toward diversified supply and industrial development[2].

China's grain output has steadily increased over the past years. Per capita grain availability has reached approximately 470–486 kg, consistently surpassing both the global average and the 400 kg threshold designated by the Food and Agriculture Organization (FAO) of the United Nations [3]. In 2022, China's total grain output reached 686.53 million tons, marking eight consecutive years since 2015 in which total production has remained above 650 million tons [4]. While China accounts for nearly one-fifth of the global population, it produces about one-quarter of the world's grain, feeding 20% of the world's people with only 9% of global arable land [5].

Nonetheless, China's food security is now facing a series of structural and emergent challenges. Dietary patterns are shifting with rising incomes and urbanization, leading to declining per capita consumption of staple grains and a surging demand for feed grains [6]. While domestic feed grain production, primarily corn and soybeans, remains constrained, the country has increasingly relied on imports to close the supply gap. In 2023, China imported 99.41 million tons of soybeans and 27.13 million tons of corn, together accounting for 78% of total grain imports—underscoring feed grain security as a critical vulnerability [7]. Wen Tiejun [8] has noted that despite continuous growth in overall grain production, China's grain self-sufficiency ratio has declined to around 88%, below the government's 95% security threshold. This paradox reflects an underlying structural imbalance: while staple food grains are largely self-sufficient, the country remains heavily dependent on external sources for oilseeds and feed grains.

Resource constraints further complicate food security. China has limited arable land per capita—only about 40% of the global average—and thus enforces the most stringent farmland protection policies in the world, including a red line of maintaining at least 120 million hectares of arable land under permanent protection. Yet, ongoing industrialization and urbanization exert

*Corresponding author's e-mail: s2319512@u.tsukuba.ac.jp

increasing pressure on high-quality farmland [9]. In addition, climate change–induced extreme weather events pose growing threats to stable food production. For instance, the 2022 summer drought in southern China adversely affected autumn grain harvests, which were only safeguarded through emergency drought relief and the expansion of high-standard farmland [5]. Long-term reliance on chemical fertilizers and pesticides has led to soil degradation and non-point source pollution [10]. Wen Tiejun [11], in his global analysis of agricultural crises, warned that the pursuit of high yields through industrialized farming has led to serious ecological consequences in countries such as the United States—most notably the Dust Bowl of the 1930s—offering a cautionary tale for China's own green transformation.

In this context, China's food security agenda has been elevated to a national strategic priority. The government has adopted a "new food security concept," emphasizing basic self-sufficiency in grains and absolute security in staple foods, grounded in domestic production, moderate imports, and technological support. Policy measures include safeguarding arable land, enhancing per-unit yields, improving grain reserves, and deploying market stabilization mechanisms [4]. In recent years, agricultural support policies have been strengthened—guaranteeing minimum procurement prices and subsidies to incentivize grain cultivation, expanding high-standard farmland, and promoting scientific and technological innovation. By the end of 2022, China had established approximately 66.67 million hectares of high-standard farmland, covering more than half of total arable land. These areas reported yield increases of approximately 1,500 kg per hectare, substantially enhancing national production capacity [5]. Through advances in mechanization, seed breeding, and technical extension, China's grain yields have steadily improved. In 2018, average grain yields reached 5,621 kg per hectare, over 25% higher than in 1996. Specifically, yields of wheat and rice increased by 46.8% and 11.3%, respectively—both significantly above global averages [12].

Recent scholarship has further examined the key determinants of grain production, including mechanization levels, irrigation infrastructure, material inputs such as fertilizers, and rural economic development. Mechanization, in particular, is widely recognized as a cornerstone of modern agriculture, improving labor productivity and stabilizing output in the face of rural labor outflows [13]. However, its marginal contribution to yield growth may be diminishing. Cheng and Huang [14] found that although mechanization positively affects grain yields, the long-term causal effect appears limited, indicating that current mechanization primarily consolidates existing capacity rather than driving substantial future gains. Moreover, the traditional input-intensive model—heavily reliant on fertilizers and pesticides—has reached ecological and efficiency limits. In response, the government launched a "zero-growth action plan" in 2015 to curb excessive use of chemical inputs and promote precision agriculture. By 2020, fertilizer utilization rates for rice, wheat, and corn reached 40.2%, up 5 percentage points from 2015, signaling a shift toward more efficient and environmentally sustainable practices [10].

Meanwhile, an increasing number of studies and reports have highlighted the impact of climate variability and extreme weather events on agricultural stability, as well as the corresponding policy adjustments. According to a report by the European Parliament, droughts, floods, and extreme temperatures have led to substantial yield losses. For instance, in 2022 Europe experienced the most severe drought in decades, reducing maize, sunflower, and soybean yields by 20–30% [15]. Similarly, agriculture in China has been profoundly affected by extreme climatic events. Data from the China Meteorological Administration indicate that in 2022 the Yangtze River Basin experienced the most severe heatwave and drought in 60 years, resulting in a 5–10% reduction in rice and maize yields [16]. At the same time, northern and northeastern China suffered frequent floods, damaging croplands and infrastructure. Heatwaves also threatened livestock health in northern grassland pastoral areas, where forage production fell by about 30%, forcing herders to increase feed inputs [5].

Regarding key environmental variables, Wang et al. [17] found that precipitation, temperature, and solar radiation are critical drivers of wheat yield variation, with future climate scenarios projecting yield declines of 12–24%. Although optimized cultivars could increase yields, they would also raise nitrogen demand, greenhouse gas emissions, and reduce nitrogen-use efficiency, indicating significant environmental trade-offs. From the perspective of production processes, O. Halytsia [18] argued that while farms may appear efficient in terms of crop yields, an adjusted frontier function assessing environmental performance in Ukraine's agricultural system revealed an average environmental efficiency of 0.84. This implies that actual environmental performance in crop production is about 16% below the optimal level, with large-scale farms achieving slightly higher efficiency than small-scale farms due to the adoption of environmentally friendly technologies such as water-saving irrigation and precision fertilization. In terms of policy incentives, Will, Jager, and Müller [19] demonstrated that the design of agri-environmental schemes (AES) plays a much greater role in adoption rates than farmers' general openness: when expected payments decreased by 20%, adoption increased from 26.7% to 46.4%, whereas full openness raised it only to 37.6%. Moreover, increasing advisory coverage from 40% to 80% could raise adoption in certain contexts from 44% to 82%.

Against this backdrop, this study employs both spatial econometrics and stochastic frontier analysis to systematically examine the determinants of food security using comprehensive provincial-level panel data from China.On one hand, based on spatial econometric models, the study focuses on the total output and yield per unit area of major grain crops. It analyzes variables such as agricultural inputs, mechanization levels, irrigated land area, fertilizer and pesticide usage, and urban-rural income gaps. Particular attention is given to the spatial spillover effects of grain production across regions, revealing how structural factors and institutional conditions differentially impact grain output.On the other hand, the study combines stochastic frontier analysis to evaluate the relationship between provincial grain production efficiency and climate disasters. It finds that while cultivated land area, agricultural machinery power, and farmer income significantly boost output, extreme climate events still cause efficiency losses or even yield declines across different regions. Through this dual perspective, the study not only reveals the input-driven and spatially dependent mechanisms of China's food security but also emphasizes the importance of environmental risks and policy responses, thereby providing more empirically grounded references for optimizing food security policies.

It follows that research on the lightweight prefabricated composite floor needs to be further studied. Hence, the lightweight composite slab was put forward, which consists of H-type thin-walled steel beams and lightweight concrete including the precast panels and the post-pouring layer. The composite slabs also have advantages of no formwork support, being lighter weight and factory prefabrication, et al.

2. Data and Methodology

This study employs panel data from 31 provincial-level administrative units in mainland China covering the period 2000–2021. The dataset is primarily drawn from the China Statistical Yearbook, the China Agricultural Statistical Yearbook, and annual reports published by the Ministry of Agriculture and Rural Affairs [5]. Key variables include grain output and per-hectare yields disaggregated by major crops, along with explanatory indicators such as rural income, mechanization power, irrigation coverage, fertilizer and pesticide use, and the agricultural share of regional GDP. After removing missing values, the dataset forms a balanced provincial panel suitable for capturing spatial heterogeneity and spillover effects in grain production.

In parallel, the analysis also utilizes a panel dataset for the period 2004–2021 that integrates agricultural production, rural socioeconomic indicators, and environmental disaster information. Table 2 reports summary statistics for the main variables used in the stochastic frontier analysis. Agricultural variables such as sown area, labor allocation, rural income, and machinery power are sourced from the China Rural Statistical Yearbook, while disaster data—including droughts, floods, hailstorms, and cold or snow events—are obtained from the China Environmental Statistical Yearbook. After excluding observations with incomplete records, 179 complete province-year observations remain, with 119 used for estimation once regression-relevant variables are considered. This dataset supports the stochastic frontier framework, enabling the evaluation of technical efficiency and the impact of climate shocks on grain production.The integration of spatial econometric data with stochastic frontier information provides complementary insights, capturing both interregional spillover effects and efficiency losses induced by environmental shocks.

Table 1 presents the descriptive statistics of the main variables used in the spatial econometric analysis. For the spatial econometric part, first, the share of primary industry in regional GDP (agri_gdp_ratio) is used to indicate the relative importance of agriculture in local economies [36]. A higher proportion generally suggests stronger policy support and resource allocation, which may help stabilize grain output. Relatedly, rural per capita disposable income (rural_income) reflects both the purchasing power and investment capacity of farm households. On the one hand, higher income may boost input use and production incentives; on the other hand, sustained income growth may trigger labor outmigration and declining planting willingness, forming an inverted-U effect [14]. The urban-rural income ratio (income_ratio) measures development disparities. A higher value typically indicates the relative weakening of rural areas in policy and resource allocation, leading to further labor loss and reduced land use stability in agriculture.

Given the high dependence of modern agriculture on mechanization, we include total agricultural machinery power (farm_mech_power) and mechanization intensity per unit of arable land (agri_mechanization) to capture its role in substituting labor and improving efficiency. Effective irrigated area (irrigated_area) serves as a proxy for water security capacity, especially relevant for water-intensive crops like rice and wheat [57]. For instance, the extreme drought in southern China during the summer of 2022 significantly impacted autumn grain production, underscoring the critical role of irrigation [5]. Fertilizer use (fertilizer_use), once a traditional yield driver, has transitioned toward efficiency-first under the "zero-growth" policy, making it important for understanding the elasticity of inputs versus output [38].

In addition, agricultural intermediate inputs (agri_intermediate_input), including seeds, pesticides, and fuel, reflect the degree of materialization and intensification of agricultural production. Empirical studies suggest that while moderate input levels are positively correlated with grain output, excessive input can increase costs and reduce farmers' willingness to cultivate [20]. To improve variable comparability and interpretability, some indicators are log-transformed or normalized by arable land or agricultural population, capturing both intensity and efficiency of input use.

We control for region-specific and time-specific effects using two-way fixed effects to address unobserved heterogeneity across geography and time [10]. To systematically assess the role of economic, resource, and input factors, as well as identify potential regional linkages, we apply spatial econometric models within a panel data regression framework. Given the significant geographic concentration and externalities of grain production, especially among major grain-producing provinces, spatial spillover effects may emerge in agricultural policy, factor allocation, and technology diffusion [21,22]. To enhance explanatory power, a spatial lag structure is incorporated on top of the classical fixed effects panel model.

The baseline model adopts a linear fixed effects panel specification with both region and year controls, expressed as:

$$Y_{it} = \alpha + X_{it}\beta + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where Y_{it} denotes the grain output of province i in year t; X_{it} is the matrix of explanatory variables including economic structure, rural income, mechanization, irrigation, and input use; μ_i and λ_t represent region and year fixed effects, and ε_{it} is the error term. The fixed effects structure is supported by Hausman tests to control for time-invariant structural factors [23].

To account for spatial interactions in agricultural development, we further extend the model into a Spatial Lag Model (SLM), defined as:

$$Y_{it} = \rho W Y_{it} + X_{it}\beta + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where WY_{it} denotes the spatially lagged dependent variable; W is a spatial weights matrix defined by Rook contiguity, row-standardized to represent the weighted average grain output of neighboring provinces. The spatial autoregressive coefficient ρ captures the influence of neighboring regions' grain output on local performance. A significantly positive ρ indicates spatial spillovers [22,24], which are critical for understanding coordinated mechanisms in regional food security.

Compared with conventional OLS or fixed effect panel models, spatial lag models better capture interregional linkages, policy externalities, and geographic dependencies in grain production. In recent years, spatial panel approaches have been widely applied to studies of agricultural efficiency, food security, and input allocation [25,26], offering empirical support for designing coordinated regional strategies.

Following the spatial econometric analysis, this study further employs a Stochastic Frontier Analysis (SFA) to evaluate provincial-level technical efficiency and its environmental constraints. The SFA framework, originally developed by Aigner, Lovell, and Schmidt [27] and later extended by Battese and Coelli [62], decomposes the deviation of observed output from the production frontier into two components: random noise and technical inefficiency. The production function is specified as:

$$ln(Y_{it}) = \beta_0 + \beta_1 ln(Labor_{it}) + \beta_2 ln(Machinery_{it}) + \beta_3 ln(Sown_{it}) + \beta_4 ln(Income_{it}) + v_{it} - u_{it}$$

where Y_{it} denotes the grain output (10,000 tons) of province i in year t. The explanatory variables include $Labor_{it}$, the share of employment in the primary sector, which reflects agricultural labor input but is often associated with "hidden unemployment" in China; $Machinery_{it}$, total agricultural machinery power (10,000 kW), representing mechanization that plays an increasingly important role in sustaining yields under rural labor outflows; $Sown_{it}$, the grain sown area (1,000 ha), the most critical land input, with elasticity estimates often close to unity, underscoring agriculture's strong dependence on arable land [48]; and $Income_{it}$, rural per capita disposable income, which captures household economic capacity and directly influences production decisions and technology adoption. The two-sided error term v_{it} is assumed to follow $N(0, \sigma_v^2)$ and reflects uncontrollable exogenous shocks (e.g., weather variability and measurement error), while the non-negative inefficiency term u_{it} measures the deviation from the optimal frontier.

To incorporate environmental stressors, the model assumes that u_{it} is a function of exogenous climatic variables, specified as:

$$u_{it} = \delta_0 + \delta_1 ln(Drought_{it} + 1) + \delta_2 ln(Flood_{it} + 1)$$
$$+\delta_3 ln(Hail_{it} + 1) + \delta_4 ln(Cold_{it} + 1) + w_{it}$$

where $Drought_{it}$, $Flood_{it}$, $Hail_{it}$, and $Cold_{it}$ denote the crop area (1,000 ha) affected by droughts, floods and geological disasters, hailstorms, and low-temperature or snow-related events, respectively. The logarithmic transformation (with a constant added) mitigates skewness and ensures feasibility when zero values occur. The residual w_{it} follows a truncated-normal distribution, ensuring $u_{it} \geq 0$. Empirical evidence suggests that droughts significantly increase inefficiency, floods may have more complex impacts due to policy interventions [28], while spring droughts and cold spells have caused substantial yield losses in northern China [29]. Including these natural disaster variables in the inefficiency equation thus allows the model to capture the adverse impacts of climate shocks on agricultural efficiency.

The model is estimated using maximum likelihood techniques. Due to the limitations of the standard sfa() function in the frontier package in R, which does not directly support inefficiency-effect models, a two-step approach is adopted. First, the standard stochastic frontier model is estimated to derive provincial-level technical efficiency scores. Second, these scores are converted into inefficiency measures and regressed on disaster-related variables using a truncated regression (Tobit) model. This procedure quantifies the marginal effects of different types of natural disasters on production efficiency and provides insights into the vulnerability of China's agricultural system under climate shocks.

Table 1. Descriptive Statistics of Variables for Spatial Econometric Analysis.

Variable	Unit	Obs	Mean	Std. Dev.	Min	P25	Median	P75	Max
rice_yield_per_area	Rice yield per hectare (kg/ha)	155	6803.18	1289.23	1228.10	5940.60	6814.70	7673.00	9019.90

wheat_yield_per_area	Wheat yield per hectare (kg/ha)	155	3806.90	1409.88	952.20	2918.40	3473.20	5118.00	6011.00
maize_yield_per_area	Maize yield per hectare (kg/ha)	155	5448.20	978.29	3093.60	4675.70	5401.10	6297.10	7462.80
sorghum_yield_per_area	Sorghum yield per hectare (kg/ha)	155	3264.43	1534.33	478.30	2500.00	3125.00	3899.50	7111.40
agri_gdp_ratio	Agriculture share of GDP (%)	155	11.07	4.65	0.80	8.90	11.70	14.20	20.30
rural_income	Rural per capita income (CNY)	155	6115.41	2702.84	2723.80	4506.70	5523.70	7119.70	16475.70
income_ratio	Urban-rural income ratio	155	3.06	0.60	2.06	2.58	2.94	3.51	4.28
agri_mechanization	Agri mechanization level ($10{,}000kW$)	155	98.56	181.01	0.70	4.50	23.40	95.10	818.60
agri_output	Agri value-added (100 million CNY)	155	838.69	605.93	59.00	463.00	676.20	1150.20	2329.90
farm_mech_power	Total mech. power(10,000kW)	155	3746.57	3422.10	241.10	1822.70	2399.90	3401.30	12419.90
irrigated_area	Effective irrigated area(1,000ha)	155	2334.94	1554.29	154.70	1274.20	1654.10	3721.60	5150.40
fertilizer_use	Fertilizer used (10,000 tons)	155	211.16	157.84	13.60	110.40	176.90	240.30	684.40
agri_intermediate_input	Agri intermediate input (100 million CNY)	155	501.07	397.46	56.00	257.00	369.30	573.00	1643.10

3. Results

3.1. Results of Spatial Econometric Analysis

This study employs spatial lag fixed-effects models to examine the drivers of per-unit yields of maize, rice, wheat, and sorghum, with a focus on the role of agricultural inputs, rural economic development, and spatial spillover effects. Table 3 presents the estimated coefficients of spatial econometric models for maize, rice, wheat, and sorghum, while Table 4 shows the spatial lag coefficients (λ) and their significance for each crop, highlighting significant heterogeneity among crops as revealed by the regression results. Notably, only sorghum's spatial lag coefficient is marginally significant at the 10% level ($\lambda = 0.2192$, $p = 0.0644$), while models for maize, rice, and wheat show no significant spatial autocorrelation. This suggests that for major staple crops in China, per-unit yields do not exhibit strong spatial dependence across provinces, a result that contradicts conventional spatial economic theory [21,22] but aligns with China's institutional reality. Agricultural policy implementation is largely bounded within administrative jurisdictions, limiting the cross-regional flow of agricultural resources and technologies [30]. Moreover, land fragmentation and local government competition reinforce "self-sufficient" production incentives over regional collaboration [31].

The marginally significant spatial effect observed in the sorghum model may reflect ecological clustering in regions like Northwest and Northeast China, where similar agro-ecological conditions and cultivation systems exist [32]. Conversely, for nationally distributed staple crops such as rice, maize, and wheat, the absence of significant spatial transmission is attributable to vast ecological differences and decentralized policy execution.

Among the explanatory variables, rural per capita disposable income exhibits a pronounced inverted-U relationship with rice yield: the income linear term is negative and highly significant. This supports the hypothesis that income growth initially facilitates agricultural investment in inputs like fertilizer and irrigation but, beyond a threshold, induces labor and capital shifts toward non-agricultural sectors or higher-value crops [33]. This aligns with the "agrarian dilemma" articulated by Wen Tiejun, wherein profit-maximizing farmers withdraw from low-efficiency staple grain cultivation [34,40]. Given declining rice prices and rising land costs, farmers increasingly abandon labor-intensive rice farming [5]. In contrast, no such nonlinear trend is observed for maize or wheat, possibly because these crops remain dominant income sources in many rural regions.

Table 2. Summary Statistics of Main Variables for Stochastic Frontier Analysis (2004-2021).

Variable	Mean	Std. Dev.	Min	25%	Median	75%	Max
Grain Output (10,000 tons)	1890.05	1635.34	28.80	639.40	1383.45	2935.98	7867.70
Primary Sector Labor Share (%)	40.33	14.35	3.90	33.30	43.90	50.70	70.50
Agricultural Machinery Power (10,000 kW)	3011.72	2800.27	94.00	1081.45	2331.55	3804.55	13353.00
Grain Sown Area (1,000 ha)	3596.15	2938.69	46.50	1198.53	3094.75	5270.78	14551.30
Rural Per Capita Disposable Income (Yuan)	9806.16	6418.85	1721.55	4661.03	8601.00	13327.68	38520.70
Drought Area (1,000 ha)	351.91	557.93	0.00	3.15	102.10	442.10	2922.10
Flood Area (1,000 ha)	151.96	173.99	0.00	12.10	87.70	228.00	838.70
Hailstorm Area (1,000 ha)	93.56	132.60	0.00	3.15	42.60	115.30	666.80
Cold/Snow Disaster Area (1,000 ha)	16.67	24.99	0.00	1.10	8.80	21.20	149.10

Fertilizer use is significantly positive only in the maize model at the 5% level, suggesting diminishing marginal returns to fertilizer application in other crops. This is consistent with findings on fertilizer saturation and environmental degradation in intensive farming areas [35]. Especially in rice paddies, excessive fertilizer is inefficiently absorbed and may cause pollution and health risks, such as cadmium contamination [5].

Agricultural mechanization exhibits divergent effects. It positively impacts sorghum yields, suggesting that mechanization remains in its growth phase in sorghum regions, improving labor substitution and operational efficiency [37]. Conversely, the coefficient is significantly negative for wheat, possibly reflecting inefficiencies from "mechanical oversupply" in fragmented landscapes like the Huang-Huai-Hai plain [38,39]. As highlighted by the research of sustainable development, mechanization's effects are conditional on institutional support and land consolidation.

For maize, the results reflect policy shifts since the removal of temporary reserve policies in 2016. Farmers in Northeast China have diversified into soybean and wheat, while industrial and feed demand for maize continues to grow [48]. This has led to increased imports from countries like Ukraine, the U.S., and France, and deeper agricultural cooperation with Russia [41]. Climate change-induced arable land expansion in Russia's Far East also offers a strategic grain buffer [42,43].

Overall, the findings reveal strong crop-specific and institution-dependent mechanisms in grain yield determination. Spatial spillovers are limited in core staples, while rural income, fertilizer use, and mechanization have nonlinear and region-specific effects. Policy design must shift from "universal incentives" to "structural matching" and "crop-adaptive optimization" to secure food security amid complex internal and external challenges.

Table 3. Regression Coefficients for Four Grain Crops (with Significance).

Variable	Maize	Rice	Wheat	Sorghum
agri_gdp_ratio	126.56	587.58***	36.56	105.71
rural_income	0.276	-0.6818***	-0.0136	-0.0951
income_ratio	1159.09	3689.4**	-137.42	36.41
agri_mechanization	4.58	-1.686	-4.98*	17.81*
agri_output	2.86	-2.04	1.39	-0.54
farm_mech_power	0.15	0.0928	0.188	-0.098
irrigated_area	-0.754	-0.0018	0.056	-1.23
fertilizer_use	13.35*	11.25	4.21	-6.92

Variable	Maize	Rice	Wheat	Sorghum
agri_intermediate_input	-4.95	1.28	-2.51	-0.32

Table 4. Estimated Spatial Lag Coefficients (λ) and Significance.

Crop	λ	p-value	Significance
Maize	0.0074	0.9515	
Rice	-0.0318	0.7493	
Wheat	-0.0599	0.6212	
Sorghum	0.2192	0.0644	*

3.2. Results of Stochastic Frontier Analysis

The estimation results of the SFA model indicate that grain sown area, total agricultural machinery power, and rural per capita disposable income all exert significant positive effects on grain output. Table 5 presents the estimation results of the stochastic frontier production function. Among these, the elasticity of sown area is the largest ($\beta = 0.955, p < 0.001$), suggesting that land remains the most critical production factor in China's agricultural system. This finding implies that China continues to operate within a land-intensive, subsistence-oriented agricultural framework, rather than resembling the technologically advanced agricultural systems of developed countries where land is relatively abundant and labor less central. This phenomenon aligns with Huang's classical study [28] on China's peasant economy and land–labor relations, in which the theory of "involution" is used to illustrate how, under demographic pressure, Chinese agriculture historically maximized output on limited land by infinitely intensifying labor inputs, resulting in a land-centered, highly labor-intensive but low labor productivity production model. Furthermore, the elasticity of rural per capita income is positive and significant ($\beta = 0.185$, $p < 0.01$), indicating that improvements in household economic conditions facilitate greater input use and higher output. From a microeconomic perspective, this suggests that higher rural incomes allow households not only to secure basic living needs but also to reinvest surplus resources into production, such as purchasing superior inputs, improving labor quality, or adopting new technologies and improved varieties [44].

The positive coefficient for agricultural machinery power ($\beta = 0.084, p < 0.05$) further corroborates the argument that upgrading production inputs enhances agricultural efficiency. Mechanization substitutes for human and animal labor, greatly increasing operational speed and precision, reducing production costs and harvest losses, and promoting large-scale, standardized production. In turn, this fosters land transfer and intensive farming, thereby providing the material foundation for the construction of a modern agricultural industrial system [45]. In contrast, the coefficient for the share of labor employed in the primary sector is negative ($\beta = -0.177$) and statistically insignificant, suggesting that China's current production structure cannot effectively absorb such a large agricultural labor force. Historically, rural areas have functioned as a "stabilizer" and "reservoir" by providing resources for industrialization and absorbing economic shocks [46]. Due to the household registration (hukou) system, rural agriculture often served as the ultimate safety net: during economic downturns, large numbers of migrant workers returned to farming, effectively transforming urban open unemployment into rural hidden underemployment.

The efficiency estimates show that the sample average technical efficiency reaches 87.7%, indicating that overall grain production efficiency in China is relatively high, though significant inter-provincial disparities exist. While the inefficiency component accounts for 56.3% of the total residual variance ($\gamma = 0.563$) but does not reach statistical significance, this still suggests that nearly half of the observed output differences can be attributed to non-random variations in production efficiency.

Table 5. Stochastic Frontier Analysis Results.

Variable	Estimate	Std. Error	Significance
Intercept	-1.784	0.824	*
$log(labor\_ratio)$	-0.177	0.115	
$log(machinery\_power)$	0.084	0.042	*
$log(sown\_area)$	0.955	0.043	***
$log(income)$	0.185	0.066	**
σ^2	0.0515	0.0238	*
γ	0.563	0.425	
Log Likelihood = 34.38			
Observations = 119			
Mean Technical Efficiency = 0.877			

Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

In the second-stage truncated regression analysis, technical inefficiency is used as the dependent variable to investigate its association with four major types of natural disasters. The findings indicate that droughts significantly contribute to an increase in technical inefficiency. $(\delta = 0.0228, p < 0.001)$The results of the second-stage truncated regression on technical inefficiency, which are consistent with the mainstream agricultural economics literature, are reported in Table 6. Droughts affect key components of agricultural systems, including soil moisture, water availability, sowing timing, and irrigation planning, and thus impose systemic and persistent threats [47,48]. This effect is especially severe in arid and semi-arid northern China, where water scarcity is chronic and springtime aridification has intensified in recent years, severely limiting stable agricultural production [49]. Moreover, droughts exhibit significant spatiotemporal heterogeneity. For instance, Xinjiang has the highest probability of drought occurrence among all meteorological hazards [50]. In Northeast China, spring and summer droughts dominate, with the latter being more intense and destructive, leading to significant yield declines.

Floods and geological disasters are associated with significantly lower inefficiency $(\delta = -0.0174, p < 0.001)$, suggesting improved efficiency. Although counterintuitive, this can be explained through the lens of state-led policy responses. Post-disaster periods typically see financial subsidies, irrigation infrastructure repairs, and technological interventions, contributing to faster recovery and even efficiency gains [41]. For instance, after Typhoon Butterfly in 2025, China's Ministry of Finance and Ministry of Emergency Management allocated 40 million yuan to support emergency relief and disaster mitigation efforts in Hainan, Guangdong, and Guangxi. These "anti-fragility" effects are consistent with the findings of Huang [61], emphasizing long-term infrastructure improvements and resource reallocation benefits.

Cold spells and snow disasters also exhibit significant negative effects on agricultural efficiency $(\delta = 0.009, p < 0.05)$. These cold events lead to direct freezing injury, slowed growth, and physiological dehydration, all of which disrupt photosynthesis and crop development [51].

In contrast, the coefficient for hailstorms is statistically insignificant, likely due to their spatially scattered and short-term nature. While local studies highlight potential crop destruction during flowering or grain-filling phases [52], the national data does not show a consistent impact, possibly due to insufficient long-term infrastructure or disaster response.

Table 6. Stochastic Frontier Analysis Results.

Variable	Estimate	Std. Error	Significance
Intercept	0.0718	0.0166	***
$log(drought + 1)$	0.0228	0.0047	***
$log(flood + 1)$	-0.0174	0.0043	***
$log(hail + 1)$	-0.0025	0.0057	
$log(cold + 1)$	0.0090	0.0045	*
σ	0.0513	0.0037	***
Log Likelihood = 190.34			
Observations = 119			

Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

To verify the appropriateness of the SFA model, a likelihood ratio (LR) test was conducted. The null hypothesis is that technical inefficiency is absent $(\sigma_u^2 = 0)$. The LR statistic is calculated as:

$$LR = 2 \times (logL_{SFA} - logL_{OLS}) = 2 \times (34.38 - 0.53) = 67.71 \quad (3)$$

This value follows a chi-squared distribution with 1 degree of freedom. The resulting p-value is far below 0.001, indicating strong rejection of the null hypothesis. Therefore, the SFA model significantly outperforms the OLS model, confirming the relevance of the inefficiency component in explaining agricultural production outcomes.

4. Policy Implications

Based on the empirical results above, this study offers the following policy recommendations to improve grain production capacity and optimize resource allocation efficiency.

First, the promotion of agricultural scale and specialization is essential to address the observed "inverted U-shaped" relationship between rural income and grain yield. To this end, land resources should be reallocated toward m 。 ore productive agricultural entities, such as family farms, professional farming enterprises, and county-level government-led cooperatives [53,54]. Supporting policies should include transaction information services, land transfer subsidies, and mechanisms that raise land transfer prices and reduce the fixed costs of scaled operations. Local initiatives, such as allowing rural residents to participate as shareholders in agricultural ventures, can further attract social capital and professional farmers into staple grain production. Meanwhile, optimizing the spatial layout of grain production is also crucial: high-yield staple crops such as rice and corn should be concentrated in core production zones, while marginal areas may transition toward feed grains or higher-value economic crops to enhance interregional specialization and land use efficiency [55].

Second, as the results indicate diminishing marginal returns of fertilizer use and increasing environmental pressures, a strategic shift from yield maximization to quality and efficiency is urgently needed. Resource-use efficiency should be prioritized by curbing fertilizer overuse and promoting site-specific nutrient management, organic substitution, and precision fertilization technologies such as drip irrigation [56]. Mechanization should be enhanced through better integration of equipment and agronomic practices, especially via centrally coordinated pilot programs led by national agricultural research institutes and key universities. These programs should promote intelligent and small-scale machinery adapted to smallholders [57]. At the same time, socialized agricultural machinery services—such as cooperative or third-party contracting for tilling, planting, and harvesting—should be scaled up to reduce transaction costs. Continued investment in irrigation and farmland infrastructure, including the construction of high-standard farmland and adoption of water-saving technologies, is also key to improving per-hectare yields and production resilience.

Third, promoting regional coordination and establishing benefit-sharing mechanisms between grain-producing and grain-consuming regions is essential. Our results suggest that spatial spillover effects still influence certain crops at the margin, particularly in regions where major producing provinces bear the burden of national food security but face fiscal constraints and rising labor outmigration. In such cases, consumption-heavy provinces like Henan should channel fiscal transfers to support grain-producing counties, ideally through flexible, non-capped matching subsidies [58]. For crops like sorghum that exhibit significant spatial dependence, adjacent regions should foster collaborative innovation and technology diffusion. Interprovincial agricultural alliances, led by local agricultural departments and top agricultural universities, could serve as platforms for sharing improved seed varieties, agronomic techniques, and mechanization models [59]. Grain support policies should also be differentiated across regions by tailoring direct subsidies, minimum purchase prices, and crop insurance support to local needs. For instance, wealthier eastern provinces could support central and western production areas via industrial partnerships and human capital assistance—creating long-term mechanisms for rural-urban and industrial-agricultural integration. In this process, "amber box" and "blue box" subsidies under WTO frameworks can be flexibly used to both protect farm incomes and guide green transitions and capacity restructuring.

Fourth, policy should simultaneously promote rural income growth and optimize the agricultural labor structure. Pomeranz [60] argues that although China—particularly the Jiangnan region—once held a leading position in market development and agricultural techniques, the absence of external resource inflows comparable to North America and the lack of revolutionary financial innovations meant that capital was largely consumed in sustaining a massive population or allocated to land transactions and usury rather than productive investment. In the contemporary context, this implies that China should strengthen rural financial services, develop rural industrial chains, and provide income subsidies to enhance farmers' disposable income and reinvestment capacity, thereby increasing agricultural inputs and facilitating technology adoption. At the same time, rural labor should be encouraged to transition in an orderly manner toward the secondary and tertiary sectors, mitigating the problem of "hidden unemployment" in agriculture. Through vocational training and skill enhancement, the remaining workforce can be guided toward modern agriculture, mechanization services, and agricultural processing, improving both efficiency and farmers' welfare.

Fifth, with respect to land and natural constraints, farmland protection and the construction of high-standard farmland should be reinforced, while agricultural risk management systems must be improved at both institutional and international levels. Strict enforcement of the "red line" for farmland protection is essential to prevent the conversion of prime cropland to non-agricultural or non-grain uses. At the same time, efforts should be made to enhance soil quality, adopt integrated water–fertilizer management, and promote soil improvement practices to maximize yields on limited land resources. Additional infrastructure investment should be directed to central, western, and disaster-prone regions, advancing the construction of drought- and flood-resilient farmland and the adoption of water-saving technologies to enhance resilience and resource-use efficiency. Furthermore, international cooperation should be leveraged to diversify grain import sources and reduce dependence on any single country or climatic condition. Establishing strategic agricultural partnerships with Russia and Southeast Asian countries could expand import channels for key crops such as corn, sorghum, and soybeans [59]. Climate change is expanding arable land in regions such as Russia's black soil zone, offering China new opportunities to build a more resilient and strategically buffered food system.

5. Conclusion

This study provides new empirical insights into China's food security by linking spatial heterogeneity in crop yields with efficiency constraints shaped by environmental stressors. Spatial econometric results highlight the institutional and structural mechanisms that govern interregional grain production, with rural income, mechanization, and fertilizer use exerting crop-specific and nonlinear effects. Meanwhile, stochastic frontier analysis reveals that although China's overall production efficiency is relatively high, it remains vulnerable to climatic shocks, particularly droughts and cold events. Together, these findings suggest that policy design must move beyond input intensification and uniform subsidies toward regionally adaptive, efficiency-oriented, and environmentally sustainable strategies. Ensuring food security requires integrated measures: protecting arable land, promoting technological innovation and mechanization suited to smallholders, guiding labor transitions, and strengthening disaster risk management. Moreover, interregional benefit-sharing and international partnerships will be crucial for building resilience against both structural and environmental challenges. Nevertheless, certain methodological and data-related limitations should be acknowledged: the specification of spatial weight matrices and inefficiency effects involves subjective choices that may influence robustness, while the reliance on provincial-level panel data constrains the ability to capture farm-level heterogeneity and plotspecific environmental differences, particularly in relation to the micro-level interactions among technology adoption, institutional incentives, and climatic shocks; future research should therefore integrate remote sensing, household survey data, and dynamic climate scenario simulations within multi-level spatial–efficiency models to provide a more comprehensive assessment of adaptation pathways and policy effectiveness under resource constraints and environmental risks.

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