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Agricultural Input Use and Sustainable Grain Production in China: Dynamic and Regional Evidence

Jin Wang[1], Wah June Leong [1], Yong Ge [1], Ying Huang [2] & Wendy Ling Shinyie [1]*
[1] Department of Mathematics and Statistics, Faculty of Science, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia.
[2] Department of Foundations of Education, Faculty of Educational Studies, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia.

Abstract: Stable grain production is central to food security, but the policy challenge is no longer only to expand agricultural inputs. It is also necessary to improve input efficiency and design region-specific production strategies. This study examines how major agricultural inputs affect grain output in China and evaluates whether these effects vary across dynamic, nonlinear, and regional dimensions. Using provincial panel data from 2000 to 2021, we estimate a two-way fixed-effects model as the baseline specification and extend the analysis with dynamic panel models, nonlinear specifications, and regional heterogeneity analysis for eastern, central, and western China. The results show that grain sown area has a stable and positive association with grain output, indicating that land protection remains a key condition for grain security. Grain output also shows strong persistence, suggesting that current production is closely related to previous production capacity and accumulated regional conditions. Pesticide use has a positive and significant effect, whereas fertilizer use has a weak and insignificant effect, indicating possible inefficiency in fertilizer application. The nonlinear results further suggest that the output effects of agricultural inputs do not follow a simple linear pattern. Regional estimates show clear differences across eastern, central, and western China, implying that uniform input policies may be less effective than region-specific strategies. Overall, the findings provide evidence for agricultural input policy and sustainable grain production in China. Policy should focus on protecting grain sown area, improving fertilizer-use efficiency, and designing differentiated input-management strategies according to regional production conditions.

Keywords: Grain Output, Agricultural Inputs, Dynamic Effects, Regional Heterogeneity

1. Introduction

Food security remains a central policy concern in China, and grain production is at the core of that concern. The stability of food production has always been a goal pursued by all countries (Gao et al., 2025). With technical progress, the overall agricultural total factor productivity (TFP) increased 4.3% during 1995-2014 (Diao et al., 2018). Recent research has confirmed that these inputs are closely related to agricultural economic performance in China, while also suggesting that their effects may differ across input categories and across time. In particular, Abate et al. emphasize that irrigation expansion and fertilizer use contribute significantly to agricultural economic growth, whereas the contribution of other inputs is less uniform, and that the roles of specific agricultural inputs should be examined separately rather than being absorbed into broad aggregate measures (Abate et al., 2025). Over the past few decades, research has shown that the interaction between agricultural inputs and climate fluctuations affects the stability of food production (Erokhin et al., 2022). Meanwhile, advancements in agricultural technology have also directly impacted food production. Irrigation technology helps alleviate water demand, and agricultural irrigation can also directly affect food security (Rosa, 2022). Nitrogen fertilizers are considered to enhance food yield potential and increase yields in the long term (Chandio et al., 2023). Therefore, agricultural production has been supported by a broad range of input resources, including irrigation, mechanization, chemical fertilizers, and cultivated land. Although the literature has made important progress, limitations remain. Much of the existing evidence focuses on single or two indicators to analyze the stability of grain output. However, focusing directly on whether there are interrelationships among these indicators and on differences in the marginal contributions of different types of input indicators is more policy-relevant to food security.

Many studies rely on national time-series evidence, making it difficult to identify regional heterogeneity in the input and output relationship. Huanhuan Heet et al. proposed that Gini coefficient (L-Gini) and exploratory spatial data analysis (ESDA) were used to study the spatial agglomeration characteristics of grain yield, and spatial regression methods (SRMs) were used to analyse the influencing factors by using Shandong Province panel data (He et al., 2022). Precipitation in China has a sharply uneven spatial-temporal distribution bu using statistic and K-means clustering methods (Jin et al., 2021). At the same time, heterogeneity exists between regions, with climate change results that significantly affects food security, bringing more uncertainty risks using using panel data (1984-2020) from 31 provinces and cities in China (Lee et al., 2024). Li et al. (2022) applied spatial autocorrelation analysis and geographically weighted regression, which have showed the spatial pattern of grain production exhibits a significant positive correlation. High yields are mainly concentrated in Shandong, Anhui, and Jilin provinces, and are shifting towards the Northeast region over time. Abate et al. (2025) explicitly note the need for more spatially disaggregated analysis and for closer attention to the differentiated effects of specific inputs. Wang et al. (2025) used panel data from 126 cities or autonomous regions in the Yangtze River Economic Belt from 2007 to 2021 and employed a geospatial detector method to determine the spatial heterogeneity of agricultural eco-efficiency. It was mainly influenced by planting structure, agricultural machinery input intensity, and urbanization level; the interaction among these factors exacerbated the spatial heterogeneity. Pan et al. (2020) assessed China’s grain yield (GY) form 2000 to 2014 and explored the potential drivers (PDFs) influencing the spatiotemporal dynamics of GY, including land, labor, capital, and the macroeconomic environment. The study shows that GY has significant spatiotemporal influences on the factors.This suggests that a provincial panel perspective may offer a more informative basis for understanding how agricultural inputs shape grain production in China over time.

From a methodological perspective, panel-data models provide a natural framework for studying this issue. Because it can not only control for unobserved province-specific factors but also common time shocks while tracing long-term structural relationships. The panel data commonly use Fixed Effects (FE) method, especially in agriculture field (Hu and McAleer, 2005). At the same time, using panel data from 30 Chinese provinces between 1991 and 1997 years, it also points out significant differences between provinces and estimates the productivity of China's agricultural sector. Felix et al. (2025) investigate the socioeconomic and environmental determinants of flood vulnerability in Indian states using a panel data approach. Drawing on state-level flood damage data from 1953 to 2020, also used FE and Random Effects (RE) models. Taken together, FE model is one-way fixed effects just to control for Province or State fixed effect. However, in the Chinese provincial context, both time invariant provincial heterogeneity and common year-specific shocks are likely to affect grain production. These insights suggest that The Two-Way Fixed Effects (TWFE) model is thus adopted to control for province effects and year effects simultaneously (Arkhangelsky et al., 2024). The panel data commonly use Fixed Effected (FE) method, especially, in agriculture field (Hu and McAleer, 2005).

To describe the temporal changes and regional disparities in agricultural inputs and grain output in China during 2000–2021. To estimate the direction, magnitude, and dynamic impact of major agricultural input variables on grain output. To test whether the relationships between agricultural inputs and grain output exhibit heterogeneous effects, nonlinear patterns, and diminishing marginal returns. To compare the regional differences in the effects of agricultural inputs on grain output among eastern, central, and western China. To address the four research objectives, this study investigates the dynamic effects of agricultural inputs on grain output in China using provincial panel data from 2000 to 2021. The analysis proceeds in stages. First, a two-way fixed effects model is employed as the baseline specification to estimate the average relationship between agricultural inputs and grain output while controlling for province and year effects. Second, the empirical framework is extended to dynamic panel models, nonlinear specifications, and heterogeneity analysis. To examine how past grain output affects current output, whether the effect of agricultural inputs becomes weaker at higher input levels, and how the input-output relationship varies across regions. In this way, the study aims to contribute to the literature in three respects: by shifting attention from aggregate agricultural growth to grain output, by using a provincial long panel to uncover dynamic and heterogeneous input effects, and by providing evidence on the nonlinear relationship between agricultural inputs and grain output in China.

The plan of the paper is as follows. The data and estimation framework are presented in Section 2. Section 3 describes the results. Section 4 discusses the empirical results. Some concluding remarks are given in Section 5.

2. The data and estimation framework

2.1 Data sources

In this study, we obtained agricultural data for 31 provincial administrative units across China from 1991 to 2020, excluding Hong Kong, Macao, and Taiwan. We examined the temporal grain production and agricultural inputs for up to 22 years. Because of the limited coverage of disaster-affected areas in Shanghai and Tianjin, and the relatively small amount of agricultural investment data in Tibet in the China Statistical Yearbook, we excluded data from these three locations. Therefore, the final dataset consisted of 6160, include 29 provinces, 9 agriculture inputs, and grain output. The final dataset contains grain output as the dependent variable and nine agricultural input indicators, namely the Total Grain Output(10,000 tons), Grain Sown Area (1,000 hectares), Agricultural Fertilizer Application (10,000 tons), Pesticide Use (tons), Agricultural Diesel Use (10,000 tons), Agricultural Plastic Film Use (tons), Total Power of Agricultural Machinery (10,000 kW), Disaster Affected Area (1,000 hectares), Agricultural Investment (100 million yuan), Rural Electricity Consumption (100 million kWh). Annual provincial data on grain output and agricultural inputs were extracted from the China Statistical Yearbook (2000-2021). The dependent variable in this study is grain output. The explanatory variables include grain sown area, fertilizer use, pesticide use, agricultural diesel consumption, agricultural film use, machinery power, disaster area, agricultural investment, and rural electricity consumption.

2.2 Data preprocessing

After collecting the provincial panel dataset, missing values were evaluated variable by variable. For a very small number of short gap missing observations in relatively smooth variables, such as fertilizer use and rural electricity consumption, within province linear interpolation was applied. By contrast, variables with stronger volatility, such as disaster-affected area, were not mechanically imputed in the baseline model and were only considered for limited imputation in robustness checks.

Variables with long structural missingness, such as agricultural investment in Tibet provinces, were not extensively imputed. Therefore, Shanghai, Tianjin, and Tibet are not included in the benchmark analysis. For provinces and years with missing values were imputed by Linear Interpolation and the following will explain in detail. To reduce heteroskedasticity and facilitate elasticity based interpretation, the main variables are transformed into natural logarithms. Let province be indexed by $i = 1,2,\dots,N$ and year by $t = 1,2,\dots,T$. The baseline variables are defined as follows.
Y_{it} denotes the grain output of province i in year t;
A_{it} denotes grain sown area;
F_{it} denotes fertilizer use;
P_{it} denotes pesticide use;
D_{it} denotes agricultural diesel consumption;
M_{it} denotes agricultural film use;
K_{it} denotes machinery power;
R_{it} denotes disaster area;
I_{it} denotes agricultural investment; and
E_{it} denotes rural electricity consumption.

Accordingly, the transformed variables used in the empirical models are defined as follows.
$lnY_{it} = \ln(grain\ output_{it})$;
$lnA_{it} = \ln(grain\ sown\ area_{it})$;
$lnF_{it} = \ln(fertilizer_{it})$;
$lnP_{it} = \ln(pesticide_{it})$;
$lnD_{it} = \ln(agricultural\ diesel_{it})$;
$lnM_{it} = \ln(agricultural\ film_{it})$;
$lnK_{it} = \ln(machinery\ power_{it})$;
$lnR_{it} = \ln(disasterarea_{it} + 1)$;
$lnI_{it} = \ln(agricultural\ investment_{it} + 1)$; and
$lnE_{it} = \ln(rural\ electricity_{it})$.

The variables disaster area and agricultural investment are transformed as $ln(x + 1)$ because they may contain zero values. This transformation preserves the observations while avoiding the undefined logarithm of zero. Under the log-log specification, the estimated coefficients can be interpreted approximately as elasticities, that is, the percentage change in grain output associated with a one-percent change in an explanatory variable, ceteris paribus.

2.3 Statistical analysis

Pearson correlation analysis is conducted to examine the pairwise associations among the study variables. The full-sample correlation matrix is defined as

$$\boldsymbol{\rho} = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1K} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{K1} & \rho_{K2} & \cdots & \rho_{KK} \end{bmatrix}$$

where ρ_{ab} denotes the Pearson correlation coefficient between variable a and variable b, and K denotes the total number of variables included in the correlation analysis.

For any two variables X and Z, the Pearson correlation coefficient is computed as

$$\rho_{XZ} = \frac{\sum_{j=1}^{n}(X_j - \bar{X})(Z_j - \bar{Z})}{\sqrt{\sum_{j=1}^{n}(X_j - \bar{X})^2}\sqrt{\sum_{j=1}^{n}(Z_j - \bar{Z})^2}}$$

where n is the number of observations, $\bar{X}$ is the sample mean of X, and $\bar{Z}$ is the sample mean of Z. In addition to the full-sample correlation matrix, province-specific correlation matrices are computed to provide a more detailed descriptive assessment of the association between grain output and agricultural input factors across provinces.

Third, temporal and regional descriptive visualizations are constructed. The national average of variable X in year t is defined as

$\bar{X}_t = \frac{1}{N_t}\sum_{i=1}^{N_t} X_{it},$

where $N_t$denotes the number of provinces observed in year t. This quantity is used to generate time-trend plots for grain output and agricultural input variables over the study period.

To examine regional differences, the sample is divided into eastern, central, and western China. The regional annual mean is given by

$$\bar{X}_{rt} = \frac{1}{N_{rt}}\sum_{i\in r} X_{it},$$

where $r \in$ (East, Central, West) and N_{rt} denotes the number of provinces in region r at year t. These regional means are used to compare the evolution of grain output and agricultural input variables across macro-regions. In addition, boxplots are employed to examine the distribution, dispersion, and outliers of the variables across regions.

Symbol definitions.
ρ_{ab}: Pearson correlation coefficient between variables a and b;
$\bar{X}$, $\bar{Z}$: sample means of variables X and Z;
n: number of observations used in the correlation calculation;
$\bar{X}_t$: national mean of variable X in year t;
$\bar{X}_{rt}$: regional mean of variable X for region r in year t;
N_t: number of provinces observed in year t;

N_{rt}: number of provinces in region r at year t.

2.4 Baseline econometric model

To identify the average effects of agricultural inputs on grain output, this study employs a two-way fixed effects (TWFE) panel model. The baseline specification is expressed as

$$lnY_it = \beta_0 + \beta_1 lnA_{it} + \beta_2 lnF_{it} + \beta_3 lnP_{it} + \beta_4 lnD_{it} + \beta_5 lnM_{it} + \beta_6 lnK_{\mathrm{it}} + \beta_7 lnR_{it} + \beta_8 lnI_{it} + \beta_9 lnE_{it} + \mathrm{\mu_i} + \lambda_t + \varepsilon_{it}.$$

In this model, $\mathrm{\mu_i}$ denotes province fixed effects, λ_t denotes year fixed effects, and ε_{it} is the idiosyncratic error term. The province fixed effects control for time-invariant unobserved provincial characteristics, such as geographic endowments, soil quality, climatic conditions, and long-run institutional factors. The year fixed effects capture common macroeconomic and policy shocks that affect all provinces in a given year. Accordingly, the TWFE estimator identifies the within-province effect of changes in agricultural inputs on changes in grain output over time after netting out province-specific and year-specific unobserved heterogeneity.

Because the model is estimated in logarithmic form, each coefficient β_k can be interpreted as an elasticity. For example, β_2 measures the percentage change in grain output associated with a one-percent increase in fertilizer use, holding all other factors constant.

Prior to model estimation, a multicollinearity diagnostic is performed using the variance inflation factor (VIF). For explanatory variable X_j, the VIF is defined as

$$\mathrm{VIF_j} = \frac{1}{1-\mathrm{R_j^2}},$$

where $\mathrm{R_j^2}$ is the coefficient of determination obtained from regressing X_j on all remaining explanatory variables. A larger VIF indicates a higher degree of multicollinearity.

Standard errors are clustered at the provincial level in all fixed effects estimations to account for heteroskedasticity and serial correlation within provinces over time.

2.5 Dynamic panel model

Grain production may exhibit temporal persistence because current output is likely to depend partly on past production conditions, accumulated agricultural capacity, and path dependent production decisions. To capture this dynamic characteristic, a lagged dependent variable is introduced into the fixed effects model. The dynamic panel specification is given by

$$\ln \mathrm{Y_{it}} = \alpha\, ln\mathrm{Y_{i,t-1}} + \beta_1 lnA_{it} + \beta_2 lnF_{it} + \beta_3 lnP_{it} + \beta_4 lnD_{it} + \beta_5 lnM_{it} + \beta_6 lnK_{\mathrm{it}} + \beta_7 lnR_{it} + \beta_8 lnI_{it} + \beta_9 lnE_{it} + \mathrm{\mu_i} + \lambda_t + \varepsilon_{it}\ .$$

where$ln\mathrm{Y}_{\mathrm{i,t-1}}$is the one period lag of the dependent variable, and α measures the persistence of grain output over time. A positive and statistically significant estimate of alpha indicates that grain production is path-dependent, such that higher output in the previous period is associated with higher output in the current period.

However, the inclusion of a lagged dependent variable in a fixed effects framework may induce endogeneity because$ln\mathrm{Y}_{\mathrm{i,t-1}}$can be correlated with the transformed error term. To complement the dynamic FE estimation, this study additionally estimates a generalized method of moments (GMM) model, in which deeper lags of grain output are used as instruments. The simplified GMM specification can be written as

$$\ln \mathrm{Y}_{\mathrm{it}} = \alpha\, ln\mathrm{Y}_{\mathrm{i,t-1}} + \gamma_1 lnA_{it} + \gamma_2 lnF_{it} + \gamma_3 lnP_{it} + \gamma_4 lnK_{\mathrm{it}} + \gamma_5 lnE_{it} + \eta_i + \nu_{it},$$

Where η_i denotes individual effects and ν_{it} denotes the error term.

The corresponding moment condition is

$$\mathbb{E}[Y_{i,t-s} \triangle \nu_{it}] = 0, s \geq 2,$$

which implies that lagged levels of grain output dated at least two periods earlier are valid instruments for the differenced lagged dependent variable, provided that they are uncorrelated with the current differenced disturbance term.

The dynamic FE model captures production persistence within provinces, whereas the GMM specification provides a complementary robustness-oriented treatment for the potential endogeneity of the lagged dependent variable.

Symbol definitions.
α: coefficient measuring the persistence of grain output;
$ln\mathrm{Y}_{\mathrm{i,t-1}}$: one-period lag of log grain output;
$\gamma_1, \ldots, \gamma_5$: slope coefficients in the GMM specification;
η_i: province-specific effect in the GMM model;
ν_{it}: error term in the GMM model;
$\triangle \nu_{it}$: first-differenced error term;
s: lag order used in the instrumental variable condition.

2.6 Nonlinear specification

To examine whether the relationships between agricultural inputs and grain output are nonlinear and whether diminishing marginal returns exist, the baseline model is extended by including quadratic terms for selected agricultural inputs. Specifically, separate quadratic specifications are estimated for fertilizer, pesticide, agricultural diesel, agricultural film, and machinery power. The general nonlinear specification is

$$\ln \mathrm{Y}_{\mathrm{it}} = \beta_0 + \beta_1 lnX_{it} + \beta_2 (lnX_{it})^2 + Z'_{it}\gamma + \mu_{\mathrm{i}} + \lambda_t + \varepsilon_{it},$$

where X_{it} denotes one of the selected agricultural input variables, $(lnX_{it})^2$ is the

squared logarithmic term, and Z'_{it} is a vector of remaining control variables.
The marginal effect of input X_{it} on ln Y_{it} is therefore

$$\frac{\partial \ln Y_{it}}{\partial \ln X_{it}} = \beta_1 + 2\beta_2 \ln X_{it}$$

This expression shows that the effect of the input is no longer constant but varies with the level of input use. If β_1>0 and β_2<0, the relationship follows an inverted-U pattern, indicating diminishing marginal returns. That is, the contribution of the input to grain output remains positive at lower levels but gradually declines as input use increases.

The turning point is obtained by setting the marginal effect equal to zero:

$$\beta_1 + 2\beta_2 \ln X_{it} = 0.$$

Solving for the turning point yields

$$\ln X^* = -\frac{\beta_1}{2\beta_2},$$

and equivalently,

$$X^* = exp\left(-\frac{\beta_1}{2\beta_2}\right)$$

where X* denotes the threshold level beyond which the marginal effect of the input on grain output becomes zero. If observed input use exceeds this threshold, further increases may generate negligible or even adverse output effects.

Symbol definitions.
X_{it}: selected agricultural input variable entering the nonlinear model;
$(lnX_{it})^2$: squared logarithmic term of the selected input;
Z_{it}: vector of control variables;
γ: coefficient vector associated with Z_{it};
X*: turning point or threshold level of the selected input. itemize

2.7 Regional heterogeneity analysis

China exhibits substantial regional differences in agricultural resource endowments, production conditions, mechanization levels, infrastructure, and exposure to natural disasters. To examine whether the effects of agricultural inputs differ across regions, the sample is divided into eastern, central, and western China, and separate regressions are estimated for each region.

For region $r \in$ (East, Central, West), the regional TWFE model is specified as

$$lnY_{it}^{(r)} = \beta_0^{(r)} + \beta_1^{(r)} lnA_{it}^{(r)} + \beta_2^{(r)} lnF_{it}^{(r)} + \beta_3^{(r)} lnP_{it}^{(r)} + \beta_4^{(r)} lnD_{it}^{(r)} + \beta_5^{(r)} lnM_{it}^{(r)} + \beta_6^{(r)} lnK_{it}^{(r)} + \beta_7^{(r)} lnR_{it}^{(r)} + \beta_8^{(r)} lnI_{it}^{(r)} + \beta_9^{(r)} lnE_{it}^{(r)} + \mu_i^{(r)} + \lambda_t^{(r)} + \varepsilon_{it}^{(r)}.$$

Similarly, the regional dynamic model is written as

$$lnY_{it}^{(r)} = \alpha^{(r)} lnY_{i,t-1}^{(r)} + \beta_1^{(r)} lnA_{it}^{(r)} + \beta_2^{(r)} lnF_{it}^{(r)} + \beta_3^{(r)} lnP_{it}^{(r)} + \beta_4^{(r)} lnD_{it}^{(r)} + \beta_5^{(r)} lnM_{it}^{(r)} + \beta_6^{(r)} lnK_{it}^{(r)} + \beta_7^{(r)} lnR_{it}^{(r)} + \beta_8^{(r)} lnI_{it}^{(r)} + \beta_9^{(r)} lnE_{it}^{(r)} + \mu_i^{(r)} + \lambda_t^{(r)} + \varepsilon_{it}^{(r)}.$$

In these equations, the superscript (r) indicates that the model is estimated separately for each region. The coefficients $\beta_k^{(r)}$ measure the region-specific elasticities of grain output with respect to agricultural input factors, while $\alpha^{(r)}$measures region-specific production persistence. Comparing these coefficients across eastern, central, and western China allows the study to assess whether the productivity of agricultural inputs differs systematically across regions.

3. Results

3.1 Spatiotemporal dynamics of grain output and agricultural inputs

As shown in Figure Figure 1, clear temporal heterogeneity can be observed across agricultural inputs and grain output indicators over the study period. Grain output exhibited the most consistent upward trend, increasing steadily from approximately 1,600 in 2000 to around 2,400 by 2021, suggesting a persistent improvement in aggregate grain output capacity. Both grain sown area and machinery power showed a steady growth. Rural electricity consumption also expanded substantially, rising from below 100 at the beginning of the period to above 300 around 2017-2020, followed by a slight decline thereafter. In contrast, several agricultural input variables displayed a pronounced inverted U pattern over time, including agricultural diesel increased, agricultural film, fertilizer, and pesticide. Notably, agricultural investment displayed the strongest short term volatility. Overall, the results indicate that the temporal evolution of the variables was significant differentiated.

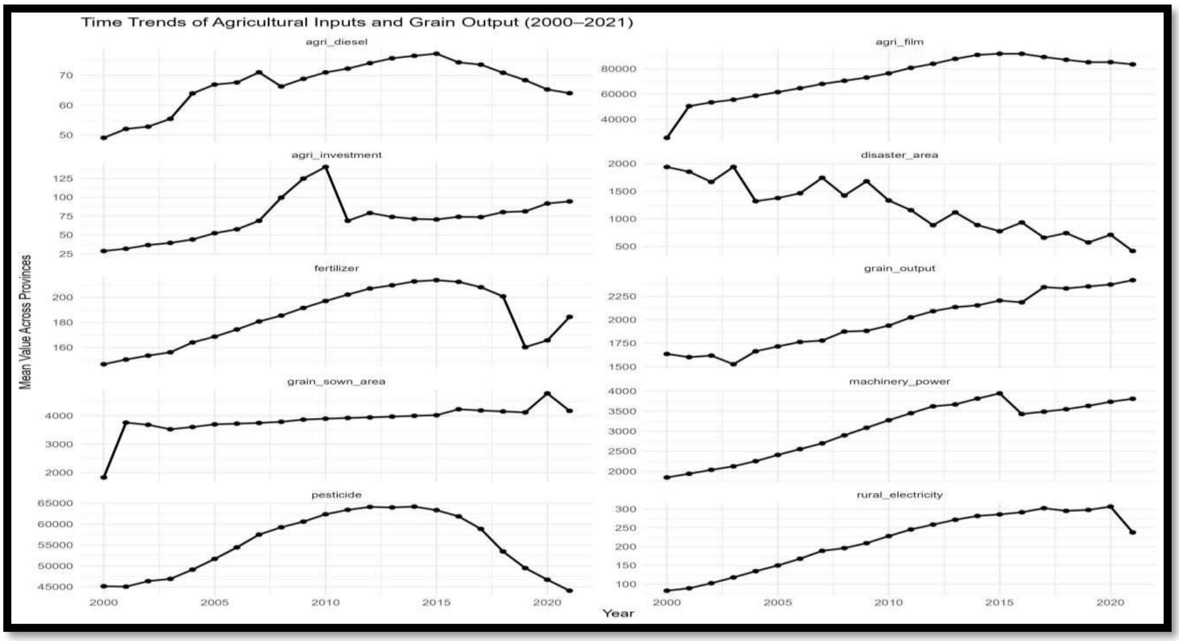

Figure 1. Time Trend of Agricultural Inputs and Grain Output (2000-2021).

To further verify the differences in agricultural inputs and grain output across different regions, we used regional mean maps to analyze all agricultural inputs and grain output over all time periods. Figure Figure 2 presents the temporal dynamics of agricultural inputs and grain output indicators across the three regions from 2000 to 2021. Overall, grain output showed a clear increasing trend in all regions, but the magnitude of growth differed substantially. The central region exhibited the highest grain output throughout the study period, rising from approximately 2300 in 2000 to nearly 4000 in 2021, an increase of about 74%. Meanwhile, the east region increased moderately from around 1600 to 2000. However, the west region only rose from about 1150 to 1600, indicating a relatively weaker improvement in grain output capacity.

Agricultural inputs also demonstrated region-specific patterns. Fertilizer application in the central region increased from approximately 190 in 2000 to a peak of nearly 300 around 2014-2015, followed by a sharp decline to about 190 in 2020 before rebounding to around 260 in 2021. This finding indicates that fertilizer use experienced both rapid expansion and subsequent adjustment. In contrast, fertilizer use in the east region remained relatively stable, fluctuating around 175-200 before declining slightly after 2016. The west region showed a gradual increase from about 90 to 165 before decreasing after 2017, suggesting a lower but rising input intensity. Similarly, pesticide use increased markedly before the mid-2010s, especially in the central region, rising from approximately 63,000 tons in 2000 to nearly 96,000 tons around 2013-2015, and then declining to about 67,000 tons by 2021. This decline was also observed in the east and west regions, indicating a general reduction in chemical input intensity in recent years.

Meanwhile, machinery power and agricultural film use increased substantially, indicating the strengthening of agricultural modernization. Machinery power in the central region increased from approximately 2200 in 2000 to more than 5400 in 2021, while the east and west regions rose from about 2600 to 3700 and from about 1000 to 2600, respectively. Agricultural film use also increased rapidly before 2015, particularly in the east region, which rose from about 25,000 to over 100,000, before declining slightly after 2016. These results suggest that technological and material inputs were positively associated with the improvement of grain output.

In contrast, disaster-affected area generally declined over time, especially in the east and west regions. The east region decreased from approximately 1500 in 2000 to less than 200 in 2021, while the west region declined from around 1500 to about 450. The central region showed stronger interannual fluctuation, decreasing from nearly 3000 in 2000 to about 700 in 2021, although several peaks occurred around 2003, 2008, and 2010. This finding indicates that natural disaster pressure weakened overall but remained unstable in some years.

Overall, the increase in grain output was accompanied by rising machinery power, agricultural film use, and relatively stable sown area, whereas the decline in disaster-affected area may have further supported production improvement. However, the sharp reductions in fertilizer and pesticide use after the mid\-2010s suggest that grain output growth was not solely dependent on continuous chemical input expansion, but was probably related to improved input efficiency, mechanization, and rural infrastructure development.

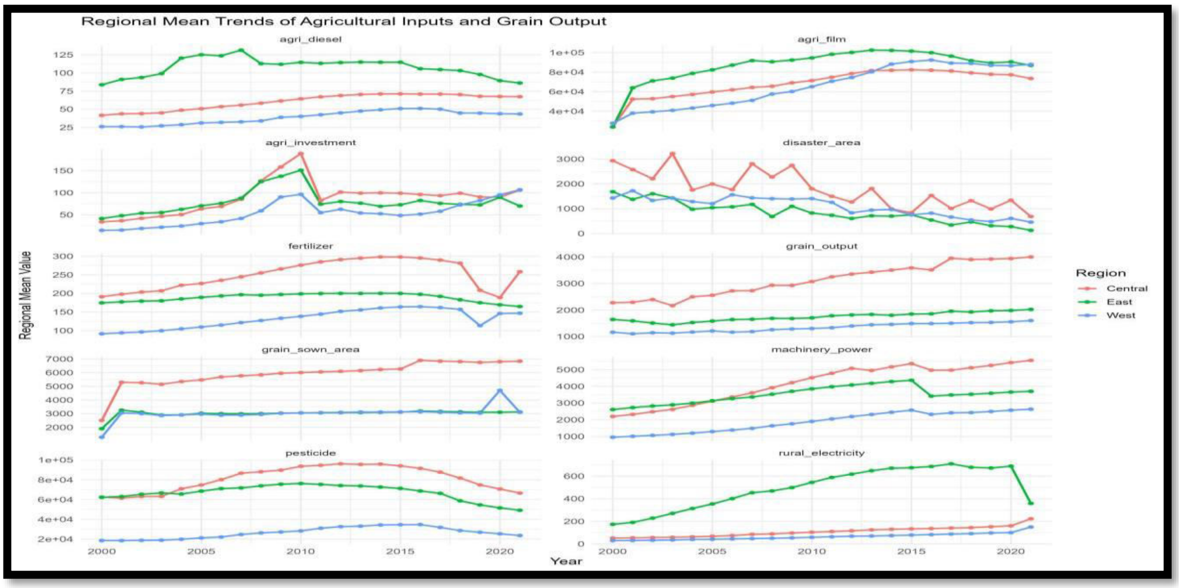

Figure 2. Reginal Mean Trends of Agricultural Inputs and Grain Output (2000-2021).

The Figure Figure 3 further show substantial dispersion and outliers in several variables, including pesticide use, agricultural plastic film use, agricultural investment, disaster-affected area, and machinery power. Clear regional differences were observed across most variables, indicating that grain production conditions and agricultural input structures varied substantially among regions. For agricultural diesel, the East region showed the highest median level, with a median of approximately 80-90 and an interquartile range of about 55-170. This was clearly higher than the Central region, whose median was around 50-60, and the West region, whose median was only about 30-40. In addition, the East region had several high-value outliers exceeding 430-490, indicating strong regional inequality in diesel consumption among eastern provinces. In addition, the East region had several high-value outliers exceeding 430-490, indicating strong regional inequality in diesel consumption among eastern provinces.

Agricultural investment demonstrated a different spatial pattern. The Central region had the highest median investment, approximately 80-90, followed by the East region at around 50-60 and the West region at about 35-45. Meanwhile, the Central region showed a broader upper distribution and several outliers above 250, with the maximum close to 500. This finding indicated that agricultural investment was not only higher on average in the Central region, but also more uneven across provinces. The East region also showed several outliers around 250-420, suggesting that some eastern provinces had relatively high investment intensity. In contrast, the West region presented a lower median and a narrower distribution, although several outliers above 180-250 were still observed. Overall, clear regional differences were observed across most variables, indicating that grain production conditions and agricultural input structures varied substantially among regions.

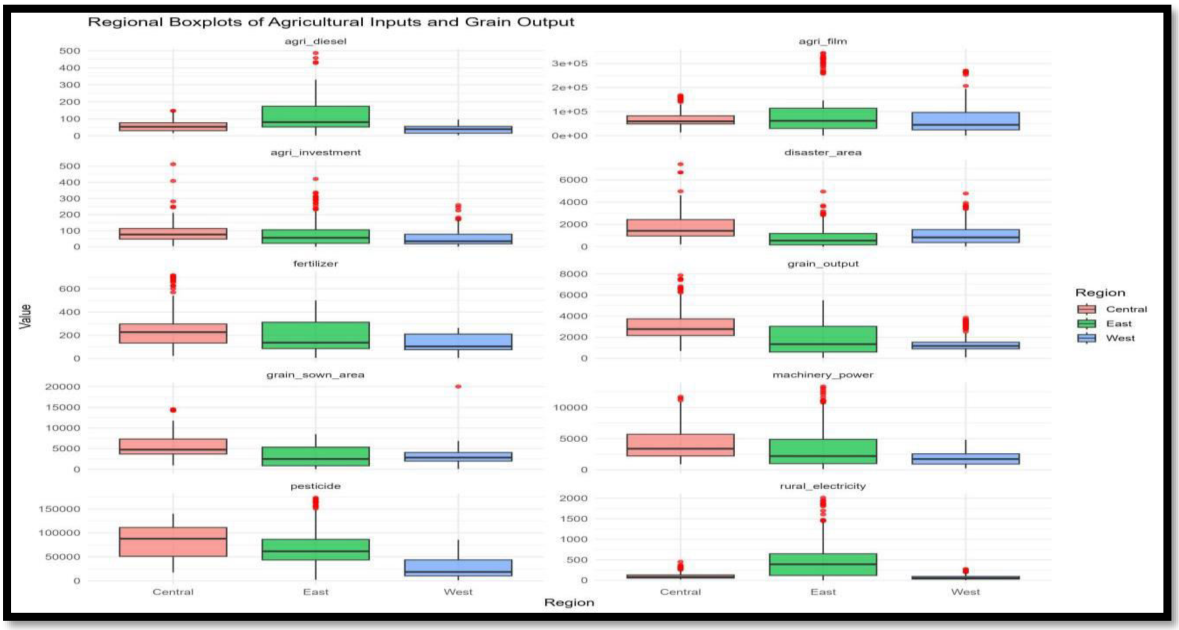

Figure 3. Reginal Boxplot of Agricultural Inputs and Grain Output (2000-2021).

The Figure Figure 3 results demonstrated pronounced regional heterogeneity in agricultural production conditions. The central region had the highest grain output, grain sown area, fertilizer use, pesticide use, machinery power, and disaster-affected area, suggesting that its high production capacity was supported by larger planting scale and stronger agricultural inputs, but was also accompanied by greater disaster exposure and chemical input pressure. Meanwhile, the east region showed higher agricultural diesel, agricultural film, and rural electricity, indicating stronger infrastructure and modernized input use, although its grain output was lower than that of the central region. In contrast, the west region generally showed lower levels of most agricultural inputs and grain output, suggesting relatively weaker production capacity. These findings indicate that regional differences in grain production were not only related to cultivated area and input intensity but also associated with infrastructure development, mechanization level, and exposure to natural disasters.

Beyond the above analysis, we investigated the interaction between grain output and agricultural input variables. We constructed a full sample correlation matrix to provide an initial assessment of the linear relationships between grain output and the selected agricultural input variables in Figure Figure 4. To preliminarily diagnose potential multicollinearity among variables, we use a correlation matrix as a diagnostic tool. It is also necessary to consider the close relationships between several agricultural inputs, including fertilizers, pesticides, diesel fuel use, and machinery power. As shown in Figure Figure 4, grain output was positively correlated with all explanatory variables, but the strength of association differed substantially across indicators. Mechanical power was also significantly positively correlated with grain output ($r = 0.81$), and fertilizer application was also highly correlated with grain output ($r = 0.80$), indicating that mechanization and the input of chemical nutrients are important supporting factors for improving grain production capacity. In contrast, rural electricity showed the weakest positive correlation with grain output ($r = 0.19$). This result suggested that rural electricity consumption may reflect broader rural infrastructure development rather than directly explaining changes in grain output. Surprisingly, the disaster affected area was also positively correlated with grain output ($r = 0.37$). This positive correlation probably reflected the fact that provinces with larger grain output scales and larger cultivated areas were also more likely to report larger absolute disaster-affected areas. Therefore, this coefficient should not be interpreted as a beneficial effect of disasters on grain output, but rather as a scale related association.

The relationship among agricultural inputs also showed clear clustering patterns. For example, fertilizer application was strongly correlated with machinery power ($r = 0.84$) and pesticide use ($r = 0.78$), indicating that fertilizer-intensive areas were usually also characterized by stronger mechanization and higher pesticide input. Notably, the disaster-affected area was negatively correlated with rural electricity ($r = -0.15$), suggesting that areas with higher rural electricity consumption may have slightly lower disaster-affected areas, probably reflecting better infrastructure, disaster prevention capacity, or regional development conditions. In general, the magnitude of this negative correlation was small. These findings suggest that grain output differences were mainly driven by planting scale and agricultural input intensity, especially mechanization and fertilizer use. However, the strong correlations among fertilizer, pesticide, machinery power, and sown area also indicate potential multicollinearity among agricultural input variables. Therefore, we will use the variance inflation factors (VIFs) derived from a pooled OLS specification to estimate the multicollinearity among the variables.

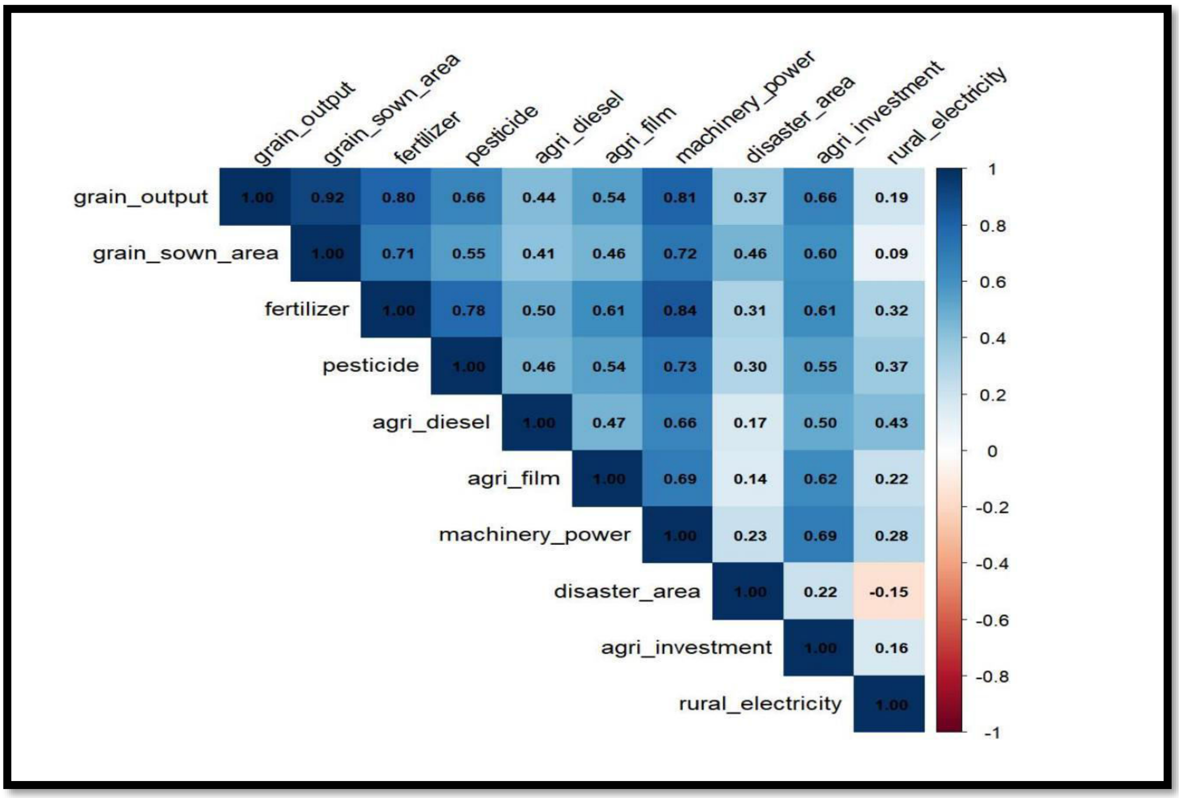

Figure 4. Heatmap of Agricultural Inputs and Grain Output (2000-2021).

Table Table 1 shows the multicollinearity among the agriculture inputs. The estimated VIF values range from 1.542 to 7.027, which are all below the conventional critical threshold of 10. The highest VIF is observed for total power of agricultural machinery (7.027), followed by fertilizer application (4.888) and grain sown area (3.010), whereas the remaining regressors exhibit comparatively low values. This evidence indicates that multicollinearity is present only at a moderate level and does not appear to pose a serious threat to model estimation.

Table 1. Descriptive VIF values.

grain_sown_area	fertilizer	pesticide
3.010217	4.887755	2.977808
agri_diesel	**agri_film**	**machinery_power**
2.267829	2.143732	7.026557
disaster_area	**agri_investment**	**rural_electricity**
1.542291	2.264625	1.576746

Table Table 2 presents the Two-Way Fixed-Effects (TWFE) model, which examines the relationship between agricultural inputs and grain output. Grain sown area was significantly and positively associated with grain output, with a coefficient of 0.592 and significance at the 1% level (p = 0.0097). This result indicated that, after controlling for province and year fixed effects, cultivated area remained the most important factor explaining changes in grain output. Specifically, a 1% increase in grain sown area was associated with an approximately 0.59% increase in grain output. Meanwhile, pesticide use was also significantly and positively related to grain output, with a coefficient of 0.147 (p = 0.0365), suggesting that pesticide input contributed to maintaining or improving grain production. In contrast, fertilizer, agricultural diesel, agricultural film, machinery power, disaster-affected area, agricultural investment, and rural electricity did not show significant direct effects. Among them, agricultural diesel, agricultural film, disaster affected area, and rural electricity had negative coefficients, but none passed the significance test, indicating that their direct effects were not statistically stable. Therefore, this result suggests that the impact of agricultural inputs may be heterogeneous, nonlinear, or partially lagged. We will conduct dynamic, nonlinear, and regional heterogeneity analyses.

Table 2. Baseline TWFE estimation results for grain output.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
ln_grain_sown_area	0.592334	0.212833	2.783092	0.0097088 **
ln_fertilizer	0.063145	0.037339	1.691140	0.1023233
ln_pesticide	0.147399	0.066979	2.200680	0.0364935 *
ln_agri_diesel	-0.018340	0.059506	-0.308202	0.7602941
ln_agri_film	-0.014166	0.033443	-0.423582	0.6752264
ln_machinery_power	0.037027	0.069014	0.536519	0.5959934
ln_disaster_area	-0.001796	0.013294	-0.135078	0.8935519
ln_agri_investment	0.041068	0.025684	1.598935	0.1214732
ln_rural_electricity	-0.032193	0.031703	-1.015462	0.3188994

Observations	616
Fixed effects	Province and year
Standard errors	Clustered by province
RMSE	0.098778
Adjusted R^2	0.990962
Within R^2	0.672703

Dependent variable is ln_grain_output. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.

In the dynamic fixed-effects model, grain output showed strong path dependence (Table Table 3). The coefficient of lagged grain output was 0.712, which was significant at the 0.1% level ($p < 0.001$), indicating that grain production in the previous period had a strong persistent effect on current grain output. Meanwhile, pesticide use remained significantly and positively associated with grain output, with a coefficient of 0.049 ($p = 0.0022$). This finding suggested that even after accounting for the lagged effect of grain output, pesticide input still had a significant positive relationship with grain output. Notably, disaster-affected area showed a significant negative effect in the dynamic model, with a coefficient of -0.019 ($p = 0.0004$). This result indicated that natural disasters suppressed grain output more clearly when production inertia was considered. Therefore, the negative effect of disaster exposure may not be fully captured in the contemporaneous fixed-effects model, but became more evident in the dynamic specification.

Table 3. Dynamic fixed-effects estimation results for grain output.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
lag_ln_grain_output	0.711617	0.104518	6.808577	2.5913e-07 ***
ln_grain_sown_area	0.218470	0.144357	1.513399	1.4180e-01
ln_fertilizer	0.012684	0.009625	1.317801	1.9864e-01
ln_pesticide	0.049183	0.014539	3.382741	2.2053e-03 **
ln_agri_diesel	-0.006159	0.018313	-0.336307	7.3924e-01
ln_agri_film	-0.005914	0.009511	-0.621764	5.3931e-01
ln_machinery_power	-0.015234	0.019356	-0.787022	4.3812e-01
ln_disaster_area	-0.019105	0.004732	-4.037455	4.0079e-04 ***
ln_agri_investment	0.015950	0.010156	1.570489	1.2795e-01
ln_rural_electricity	0.000678	0.010251	0.066100	9.4779e-01
Observations	588			
Fixed effects	Province and year			
Standard errors	Clustered by province			
RMSE	0.059196			
Adjusted R^2	0.996770			
Within R^2	0.869515			

Furthermore, we tested the nonlinear relationships between major agricultural inputs and grain output by adding quadratic terms. The results showed that the quadratic terms of fertilizer, pesticide, agricultural diesel, and machinery power were not statistically significant. Specifically, the coefficient of the fertilizer squared term was -0.027 (p = 0.385) in Table Table 4, the pesticide squared term was -0.029 (p = 0.246) in Table Table 5, the agricultural diesel squared term was -0.0005 (p = 0.985) in Table Table 7, and the machinery power squared term was 0.030 (p = 0.333) in Table Table 7. These findings indicated that there was no stable inverted U-shaped or U-shaped relationship between these inputs and grain output in the current sample. In other words, although the marginal effects of fertilizer, pesticide, diesel, and machinery power may vary across regions or years, their nonlinear patterns were not statistically supported by the regression results. However, agricultural film exhibited a significant nonlinear relationship with grain output. After including both the linear and squared terms, the coefficient of agricultural film was -0.298, significant at the 1% level (p = 0.0035), while the coefficient of the squared term was 0.018, significant at the 5% level (p = 0.0161) in Table Table 8 . This finding suggested that the impact of agricultural film on grain output is not a linear relationship., but depended on the intensity of film use.

Table 4. Quadratic fertilizer model estimation results for grain output.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
ln_grain_sown_area	0.579569	0.210744	2.750113	0.010501 *
ln_fertilizer	0.312948	0.289418	1.081300	0.289128
ln_fertilizer_sq	-0.027173	0.030797	-0.882334	0.385385
ln_pesticide	0.157093	0.067310	2.333875	0.027293 *
ln_agri_diesel	-0.031504	0.060056	-0.524570	0.604163
ln_agri_film	-0.029560	0.030976	-0.954285	0.348406
ln_machinery_power	0.036087	0.068553	0.526407	0.602903
ln_disaster_area	-0.001748	0.013401	-0.130438	0.897187
ln_agri_investment	0.041662	0.025469	1.635826	0.113482
ln_rural_electricity	-0.023940	0.029720	-0.805509	0.427564
Observations	616			
Fixed effects	Province and year			
Standard errors	Clustered by province			
RMSE	0.098271			
Adjusted R^2	0.991038			
Within R^2	0.676054			

*Dependent variable is ln_grain_output. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.*

Table 5. Quadratic pesticide model estimation results for grain output.

Variable	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
ln_grain_sown_area	0.580618	0.212369	2.734011	0.010909 *
ln_fertilizer	0.058162	0.034958	1.663755	0.107727
ln_pesticide	0.754762	0.528537	1.428020	0.164752
ln_pesticide_sq	-0.029229	0.024655	-1.185498	0.246150
ln_agri_diesel	-0.036700	0.057578	-0.637399	0.529233
ln_agri_film	-0.023223	0.032665	-0.710946	0.483215
ln_machinery_power	0.038887	0.070422	0.552202	0.585352
ln_disaster_area	-0.003151	0.012347	-0.255191	0.800509
ln_agri_investment	0.042567	0.025518	1.668104	0.106853
ln_rural_electricity	-0.022393	0.029474	-0.759761	0.453981
Observations	616			
Fixed effects	Province and year			
Standard errors	Clustered by province			
RMSE	0.098091			
Adjusted R^2	0.991071			
Within R^2	0.677234			

*Dependent variable is ln_grain_output. Significance levels: *** $p<0.001$, ** $p<0.01$, * $p<0.05$, . $p<0.1$.*

Table 6. Quadratic diesel model estimation results for grain output.

Variable	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
ln_grain_sown_area	0.591963	0.217894	2.716746	0.011364 *
ln_fertilizer	0.063204	0.037640	1.679157	0.104659
ln_pesticide	0.147606	0.066231	2.228655	0.034356 *
ln_agri_diesel	-0.014978	0.203355	-0.073655	0.941828
ln_agri_diesel_sq	-0.000495	0.026273	-0.018834	0.985112
ln_agri_film	-0.014432	0.035526	-0.406223	0.687781
ln_machinery_power	0.036612	0.070845	0.516793	0.609508
ln_disaster_area	-0.001811	0.012976	-0.139576	0.890031
ln_agri_investment	0.041090	0.025917	1.585445	0.124509
ln_rural_electricity	-0.032096	0.031898	-1.006204	0.323251
Observations	616			
Fixed effects	Province and year			
Standard errors	Clustered by province			
RMSE	0.098777			
Adjusted R^2	0.990946			
Within R^2	0.672706			

*Dependent variable is ln_grain_output. Significance levels: *** $p<0.001$, ** $p<0.01$, * $p<0.05$, . $p<0.1$.*

Table 7. Quadratic machinery power model estimation results for grain output.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
ln_grain_sown_area	0.601151	0.215946	2.783798	0.0096925 **
ln_fertilizer	0.067699	0.037552	1.802812	0.0825912 .
ln_pesticide	0.143923	0.063474	2.267432	0.0315806 *
ln_agri_diesel	-0.005095	0.060851	-0.083723	0.9338947
ln_agri_film	0.019686	0.035062	0.561455	0.5791185
ln_machinery_power	-0.407326	0.447039	-0.911165	0.3702723
ln_machinery_power_sq	0.029705	0.030151	0.985191	0.3332769
ln_disaster_area	-0.002300	0.012769	-0.180164	0.8583691
ln_agri_investment	0.041309	0.026600	1.552952	0.1320790
ln_rural_electricity	-0.033365	0.031673	-1.053411	0.3014891
Observations	616			
Fixed effects	Province and year			
Standard errors	Clustered by province			
RMSE	0.098066			
Adjusted R^2	0.991076			
Within R^2	0.677404			

*Dependent variable is ln_grain_output. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.*

Table 8. Quadratic agricultural film model estimation results for grain output.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
ln_grain_sown_area	0.601276	0.215308	2.792637	0.0094902 **
ln_fertilizer	0.062996	0.036771	1.713199	0.0981377 .
ln_pesticide	0.115490	0.073099	1.579915	0.1257717
ln_agri_diesel	-0.043972	0.060769	-0.723598	0.4755357
ln_agri_film	-0.297692	0.093069	-3.198607	0.0035118 **
ln_agri_film_sq	0.018144	0.007063	2.568769	0.0160521 *
ln_machinery_power	0.046462	0.070303	0.660878	0.5142907
ln_disaster_area	-0.001361	0.013400	-0.101569	0.9198491
ln_agri_investment	0.038875	0.025647	1.515757	0.1412019
ln_rural_electricity	-0.055910	0.030826	-1.813716	0.0808515 .
Observations	616			
Fixed effects	Province and year			
Standard errors	Clustered by province			
RMSE	0.097407			
Adjusted R^2	0.991195			
Within R^2	0.681723			

*Dependent variable is ln_grain_output. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.*

3.2 Regional heterogeneity results

The regional estimations reveal substantial heterogeneity in the effects of agricultural inputs on grain output across east, central, and west China. In the east region, grain sown area is the most dominant determinant of grain output (Table Table 9). In the baseline TWFE model, the coefficient on reaches 0.911 and is highly significant at the 1% level, while in the dynamic FE model it remains strongly positive at 0.696 (Table Table 10), also significant at the 1% level. By contrast, agricultural diesel use is significantly negative in both specifications, with coefficients of -0.149 in the TWFE model (Table Table 9) and -0.110 in the dynamic FE model (Table Table 10). These results suggest that the east region is best characterized as a scale-dominated production system, where expansion or maintenance of grain sown area plays the most important role. In addition, diesel input appears to be associated with lower production efficiency.

Table 9. Baseline TWFE estimation results for the eastern region.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
ln_grain_sown_area	0.911028	0.066457	13.708504	7.7285e-07 ***
ln_fertilizer	0.171202	0.162872	1.051142	3.2391e-01
ln_pesticide	-0.031215	0.060431	-0.516537	6.1945e-01
ln_agri_diesel	-0.149408	0.026413	-5.656566	4.7777e-04 ***
ln_agri_film	-0.027455	0.034421	-0.797610	4.4812e-01
ln_machinery_power	0.121727	0.073534	1.655385	1.3644e-01
ln_disaster_area	-0.006902	0.009870	-0.699281	5.0420e-01
ln_agri_investment	0.004763	0.018755	0.253984	8.0591e-01
ln_rural_electricity	-0.006130	0.014719	-0.416455	6.8803e-01
Observations	198			
Fixed effects	Province and year			
Standard errors	Clustered by province			
RMSE	0.057172			
Adjusted R^2	0.997690			
Within R^2	0.923475			

Dependent variable is ln_grain_output. Significance levels: *** $p<0.001$, ** $p<0.01$, * $p<0.05$, . $p<0.1$.

Table 10. Dynamic fixed-effects estimation results for the eastern region.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
lag_ln_grain_output	0.287333	0.089972	3.193583	0.01273459 *
ln_grain_sown_area	0.696104	0.098000	7.103116	0.00010168 ***
ln_fertilizer	0.123838	0.083583	1.481615	0.17672135
ln_pesticide	0.001178	0.031350	0.037576	0.97094631
ln_agri_diesel	-0.110225	0.031503	-3.498861	0.00809258 **

ln_agri_film	0.004336	0.019161	0.226304	0.82664025
ln_machinery_power	0.021915	0.048984	0.447380	0.66646589
ln_disaster_area	-0.009938	0.007562	-1.314246	0.22519253
ln_agri_investment	0.010388	0.012235	0.849034	0.42054103
ln_rural_electricity	0.013041	0.016541	0.788396	0.45319172
Observations	189			
Fixed effects	Province and year			
Standard errors	Clustered by province			
RMSE	0.048388			
Adjusted R^2	0.998351			
Within R^2	0.940133			

*Dependent variable is ln_grain_output. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.*

In the central region, the production structure is more complex in Table. Grain sown area remains strongly significant in both models, with coefficients of 0.634 in the TWFE specification (Table Table 11) and 0.528 in the dynamic FE specification (Table Table 12). Pesticide use is significantly positive in the static model, with a coefficient of 0.230 (Table Table 11). The disaster-affected area is significantly negative at -0.055. After controlling for output lagged effect, the central dynamic FE model still shows a strong lag effect (0.592, 1% level), and the negative effect of disaster remains robust at -0.050. In addition, agricultural diesel use is significantly negative in both models, with coefficients of -0.212 in the TWFE model (Table Table 11) and -0.141 in the dynamic FE model (Table Table 12), whereas agricultural film use becomes significantly positive in the dynamic specification at 0.125. Therefore, the central region is not only scale-dependent, but also highly sensitive to both protective inputs and adverse shocks. This pattern indicates that grain production in the Center is shaped by the joint interaction of scale, input intensity, and disaster vulnerability.

Table 11. Baseline TWFE estimation results for the central region.

Variable	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
ln_grain_sown_area	0.633866	0.109125	5.808643	0.00065771 ***
ln_fertilizer	0.032305	0.024567	1.314954	0.22996310
ln_pesticide	0.230482	0.068292	3.374926	0.01184040 *
ln_agri_diesel	-0.212293	0.088858	-2.389129	0.04823048 *
ln_agri_film	0.230342	0.117502	1.960313	0.09077782 .
ln_machinery_power	0.064357	0.071895	0.895154	0.40043706
ln_disaster_area	-0.054953	0.011758	-4.673712	0.00227756 **
ln_agri_investment	0.031810	0.022758	1.397770	0.20488165
ln_rural_electricity	0.054897	0.041304	1.329104	0.22549586
Observations	176			
Fixed effects	Province and year			

Standard errors	Clustered by province
RMSE	0.062769
Adjusted R^2	0.980355
Within R^2	0.651182

Dependent variable is ln_grain_output. Significance levels: *** *p<0.001,* ** *p<0.01,* * *p<0.05, . p<0.1.*

Table 12. Dynamic fixed-effects estimation results for the central region.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
lag_ln_grain_output	0.591982	0.102856	5.755422	0.00069454 ***
ln_grain_sown_area	0.528071	0.097573	5.412071	0.00099552 ***
ln_fertilizer	0.003202	0.007102	0.450804	0.66576359
ln_pesticide	0.035266	0.038326	0.920158	0.38810010
ln_agri_diesel	-0.140847	0.033287	-4.231249	0.00388212 **
ln_agri_film	0.124680	0.043539	2.863637	0.02421130 *
ln_machinery_power	-0.001686	0.023804	-0.070833	0.94551193
ln_disaster_area	-0.050302	0.012486	-4.028780	0.00500354 **
ln_agri_investment	0.013028	0.009110	1.430074	0.19577528
ln_rural_electricity	0.033644	0.020580	1.634770	0.14611303
Observations	168			
Fixed effects	Province and year			
Standard errors	Clustered by province			
RMSE	0.039545			
Adjusted R^2	0.992069			
Within R^2	0.840833			

Dependent variable is ln_grain_output. Significance levels: *** *p<0.001,* ** *p<0.01,* * *p<0.05, . p<0.1.*

The west region exhibits a markedly different pattern. In the static TWFE model, grain sown area is not significant, with a coefficient of only 0.166, whereas pesticide use is significantly positive at 0.242, and fertilizer is only marginally significant at 0.170 (Table Table 13). However, once output is introduced, the most striking feature is the very large coefficient on the lagged dependent variable, which reaches 0.798 and is highly significant. This is the largest coefficient among all three regions, far above the East (0.287) and the Center (0.592). By contrast, most contemporaneous inputs lose significance in the western dynamic FE model, and pesticide remains only weakly significant at 0.056 (10% level) in Table Table 14. These results imply that western grain production is much more strongly influenced by historical output conditions and structural inertia than by immediate changes in current agricultural inputs. In other words, the West appears to be the region with the strongest path dependence and the weakest short-run responsiveness to input variation.

Table 13. Baseline TWFE estimation results for the western region.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
ln_grain_sown_area	0.166369	0.162260	1.025324	0.329373
ln_fertilizer	0.169638	0.077653	2.184563	0.053829 .
ln_pesticide	0.241530	0.082690	2.920912	0.015277 *
ln_agri_diesel	-0.002361	0.091185	-0.025890	0.979855
ln_agri_film	0.035600	0.038728	0.919225	0.379617
ln_machinery_power	-0.054649	0.083357	-0.655596	0.526879
ln_disaster_area	0.019962	0.024324	0.820678	0.430958
ln_agri_investment	-0.003228	0.027416	-0.117739	0.908606
ln_rural_electricity	0.033401	0.092332	0.361745	0.725069
Observations	242			
Fixed effects	Province and year			
Standard errors	Clustered by province			
RMSE	0.083445			
Adjusted R^2	0.990133			
Within R^2	0.516725			

*Dependent variable is ln_grain_output. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.*

Table 14. Dynamic fixed-effects estimation results for the western region.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
lag_ln_grain_output	0.797736	0.053560	14.894375	3.7419e-08 ***
ln_grain_sown_area	0.052639	0.054206	0.971090	3.5441e-01
ln_fertilizer	0.033072	0.018583	1.779721	1.0547e-01
ln_pesticide	0.056284	0.028672	1.963069	7.8038e-02 .
ln_agri_diesel	-0.013463	0.020696	-0.650509	5.3002e-01
ln_agri_film	-0.011541	0.019399	-0.594963	5.6509e-01
ln_machinery_power	-0.010257	0.023854	-0.430003	6.7631e-01
ln_disaster_area	-0.011010	0.010862	-1.013587	3.3468e-01
ln_agri_investment	-0.008787	0.010466	-0.839511	4.2080e-01
ln_rural_electricity	0.028058	0.027128	1.034284	3.2537e-01
Observations	231			
Fixed effects	Province and year			
Standard errors	Clustered by province			
RMSE	0.047779			
Adjusted R^2	0.996720			
Within R^2	0.826330			

*Dependent variable is ln_grain_output. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.*

A direct comparison across regions further highlights the heterogeneity of production mechanisms. First, the elasticity of grain sown area declines sharply from 0.911 in the East to 0.634 in the Center and becomes insignificant in the West in the static models. A similar ranking is observed in the dynamic specifications (0.696, 0.528, and 0.053, respectively). Second, the lagged effect of grain output rises monotonically from East to Center to West, with lag coefficients of 0.287, 0.592, and 0.798. Third, agricultural diesel use is significantly negative in the East and Center but insignificant in the West, suggesting that diesel-based input may already have low or even adverse marginal productivity in the more intensively cultivated eastern and central regions. Finally, disaster-affected area is only robustly significant in the Center, where its coefficients are -0.055 in the static model and -0.050 in the dynamic model, indicating that the central grain belt is the most vulnerable to disaster-related output losses. Taken together, these findings provide strong evidence that the effects of agricultural inputs on grain output are region-specific rather than homogeneous, implying that differentiated regional policies are more appropriate than a uniform national input strategy.

4. Discussion

4.1 Temporal pattern and regional heterogeneity of agricultural inputs and grain output

During the study period, China’s Grain output increased annually, while these changes were not spatially uniform across provinces. There are significant differences between the eastern, central, and western regions in terms of agricultural input levels, resource endowments, mechanization levels, irrigation conditions, and grain production capacity. According to Figures Figure 1-4, the eastern region may have higher levels of technology and agriculture investment, but its grain output space is constrained by urbanization and arable land. The coefficient of agricultural diesel is significantly negative, which may reflect the possibility that diesel use is associated with higher production costs, inefficient energy use, or structural changes in agricultural production. The machinery variable is positive but not significant, suggesting that machinery power alone may not be sufficient to increase grain output in the eastern region. Land fragmentation and non-agricultural land pressure may limit the effectiveness of mechanization. The central region is typically a major grain output area with strong land resources and a solid foundation for grain output. Pesticide use has a positive and significant effect, indicating that pest control is particularly relevant for maintaining grain output in central provinces. Agricultural diesel is significantly negative, and disaster area is also significantly negative. These results suggest that grain production in the central region is sensitive to both energy related input efficiency and natural disaster shocks. The positive effect of agricultural film at the 10% significance level may indicate that film use contributes to output under certain crop or climate conditions, although this effect is weaker than that of land and pesticide input. The western region may be limited by water resources, topography, and infrastructure, and the mechanism by which agricultural inputs affect grain output differs. The grain sown area is not statistically significant, while fertilizer and pesticide show positive effects.The pesticide being statistically significant and fertilizer marginally significant. This suggests that in western provinces, land expansion alone may not be the main driver of grain output. Instead, chemical and biological input management may play a relatively stronger role. The weaker role of sown area also suggests that improving land quality and input efficiency may be more important than expanding cultivated area in this region. It is well known that there are significant differences among Chinese provinces in terms of agricultural resources, production conditions, and economic development levels. Using only national-level data is insufficient to reveal the spatial differences in the impact of agricultural inputs on grain output (Wang Hao et al., 2025). Therefore, this paper uses provincial panel data to more precisely identify the relationship between agricultural inputs and food output in different regions. This allows the analysis to control for province-specific characteristics and common year shocks, and to further examine regional heterogeneity in the input-output relationship.

4.2 Influences of agriculture inputs and grain output

The baseline TWFE results indicate that grain sown area is the most stable and important determinant of grain output (Zeng et al., 2022). The coefficient of grain sown area is positive and statistically significant, suggesting that land devoted to grain output remains a fundamental factor in maintaining grain output (Cao et al., 2023). Specifically, a 1% increase in grain sown area is associated with an increase of approximately 0.592% in grain output. The dynamic fixed-effects model provides strong evidence that grain output is persistent over time. The coefficient of lagged grain output is positive and highly significant, with a value of approximately 0.712. This indicates that current grain output is strongly influenced by previous grain output.

Several factors can explain this lagged effect. First, grain output depends on accumulated production capacity, including farmland quality, irrigation systems, machinery availability, and local agricultural infrastructure. These factors do not change rapidly from year to year. Second, farmers' planting decisions and regional crop structures tend to be stable over time, especially in major grain output provinces. Third, agricultural policies and local production targets may also create continuity in grain output. Therefore, the significant lagged dependent variable suggests that policies aimed at improving grain production may have cumulative and long-term effects.

The pesticide variable also shows a positive and statistically significant effect in the baseline model (Sharma et al., 2019). This suggests that pesticide use may contribute to grain output by reducing crop losses from pests and diseases. In grain output, pest control can be particularly important because pest outbreaks directly reduce yield stability and output quantity (Malalgoda and Simsek, 2021). However, Figure Figure 2 clearly shows that pesticide use is gradually decreasing in all regions, possibly due to national policies emphasizing safe, efficient, and environmentally sustainable pesticide use. The pesticide variable remains positive and significant in the dynamic model, indicating that pest control continues to play an important role even after accounting. This suggests that pesticide use may have a relatively direct short-term effect on grain output by protecting crops during the production cycle. Meanwhile, disaster area becomes significantly negative in the dynamic model. This result is intuitive because natural disasters can reduce grain output through drought, flood, pests, storms, or other adverse shocks. The significant negative effect of disaster area also shows that grain production is sensitive to environmental and climate related risks. The fertilizer coefficient is positive but not statistically significant in the baseline model (Gao et al., 2025). This suggests that fertilizer use may contribute to grain output, but its effect is weaker or less stable after controlling for province and year fixed effects and other inputs. Over the past three decades in China, the use of chemical fertilizers has tripled and yet the efficiencies grew only 32%, compared to the global average of 55% (Van Wesenbeeck et al., 2021) The more fertilizer is applied to increase agricultural production, thus finally leading towards more severe soil nutrition loss (Dom\'nguez-Garc\'a et al., 2019). This degradation makes grain output more vulnerable to impacts. This is consistent with the idea of diminishing marginal returns in agricultural input use.

Other variables, including agricultural diesel, agricultural film, machinery power, agricultural investment, disaster area, and rural electricity, are not statistically significant in the baseline specification. This does not necessarily mean that these variables are unimportant. Rather, their effects may depend on regional conditions, input efficiency, farm structure, or dynamic adjustment processes. For example, machinery power may not directly increase grain output if land is fragmented or if machinery services are not efficiently matched with local production needs.

4.3 Nonlinear effects and diminishing marginal returns

The nonlinear specifications provide further insight into whether agricultural inputs have diminishing marginal effects on grain output. The squared terms for fertilizer, pesticide, diesel, and machinery power are not statistically significant, suggesting that strong nonlinear effects are not consistently observed for these inputs in the full sample. For fertilizer, the squared term is negative but statistically insignificant. This weakly suggests the possibility of diminishing marginal returns, although the evidence is not strong enough to confirm a significant inverted-U relationship.

The agricultural film model shows a different pattern. The linear term is negative and significant, while the squared term is positive and significant. This suggests a possible U-shaped relationship rather than a diminishing marginal effect. One possible explanation is that agricultural film may have different effects depending on the level of use and local production conditions. At lower or moderate levels, film use may reflect fragmented or inefficient input use, while at higher levels it may be associated with more specialized or technologically supported production systems.

Overall, the nonlinear results suggest that the input-output relationship in grain output is not purely linear. Some inputs may generate stronger effects at certain levels, while others may show limited marginal contribution after reaching a threshold. These findings support the broader argument that China's grain output policy should shift from input expansion to input efficiency. Increasing agricultural inputs alone may not guarantee sustainable growth in grain output. Instead, improving the efficiency, coordination, and environmental sustainability of input use is more important.

4.4 Policy implications

We provided certain recommendations to eventually facilitate China's grain output and ensure grain security while maintaining a sustainable agricultural environment. The following section provides detailed recommendations. First, protecting grain sown area remains essential for maintaining grain output, particularly in eastern and central regions where its effect is strong and significant. The TERMCN-Land model was used to evaluate the fallow system, and the results showed that the rational use of existing arable land stabilized China's agricultural output (Wang et al., 2019). Previous studies show that the conversion of cropland to non-grain use can weaken grain production and increase food security risks (Li and Wu, 2025). Land policies should therefore focus not only on preserving cultivated land quantity but also on improving land quality, soil fertility, and land-use efficiency. China has tightened farmland transfer policies through a compensation-based approach to land acquisition, prioritizing the development of high-quality land for grain production (Zhong et al., 2022; Shi et al., 2025). However, only a few provinces have achieved sustained growth. Traditional major grain-producing areas such as Heilongjiang, Inner Mongolia, Henan, and Shandong have maintained their advantages. In the Northeast (e.g., Jilin and Heilongjiang), fertile black soil, mechanization, and investment in high-standard farmland have increased yields (Chen et al., 2022). In the central and western regions (e.g., Xinjiang, Jiangxi, and Hunan), farmland restoration, supplementary cultivation, and ecological agriculture have improved land quality (Xie et al., 2018). In addition, China has responded with strict land protection policies, including the farmland red line and high-standard farmland programs, to ensure stable grain supply.

Second, agricultural policy should shift from simple input expansion to input-use efficiency. The fertilizer results indicate that additional fertilizer use may not always generate significant output gains, suggesting the need for precision fertilization, soil testing, organic fertilizer substitution, and balanced nutrient management. Now, China has promoted the Zero Growth of Fertilizer Use Action Plan and soil testing programs to improve fertilizer efficiency. These policies focus on reducing fertilizer application (37.2%) while maintaining production through technological improvements (Cheng et al., 2025). However, previous studies show that long-term fertilizer subsidies and policy support have contributed to overuse and environmental pollution, suggesting that improving efficiency is more important than increasing input (Li et al., 2013). These policies focus on reducing fertilizer application while maintaining production through technological improvement. Similarly, the positive role of pesticide use highlights the importance of effective pest control, but pesticide policy should emphasize safe application, integrated pest management, and environmental risk reduction. Currently, China is widely promoting precision agriculture technologies. For example drone-based monitoring and spraying systems, which can significantly improve input efficiency and crop management levels, thereby enhancing agricultural productivity (Hafeez et al., 2023).

In addition, disaster prevention, climate resilience, and region-specific mechanization policies are important for sustaining grain production. The significant negative effect of the disaster area, especially in the central region, indicates the need for investment in irrigation, drainage, early-warning systems, agricultural insurance, and climate-resilient technologies. The insignificant effect of machinery power in the full sample suggests that mechanization policy should focus on improving machinery-use efficiency rather than simply increasing machinery input. Promoting drone-based pesticide spraying can serve as an effective policy tool to increase agricultural productivity while reducing pesticide overuse, especially in ecologically fragile areas and regions facing labor shortages. To accelerate this transition, the Chinese government provides targeted subsidies, technical training, and institutional support (such as drone service providers and rural infrastructure), particularly for smallholder farmers, to ensure widespread and equitable access to precision agriculture technologies (Li et al., 2025). Overall, agricultural inputs remain important for China's grain output, but their effects are dynamic, nonlinear, and regionally heterogeneous. Therefore, differentiated regional policies are needed: eastern regions should emphasize land protection under urbanization pressure, central regions should strengthen stable grain production and disaster prevention, and western regions should improve input efficiency, infrastructure, and land productivity.

5. Conclusions

Considering provincial panel data from China from 2000 to 2021, this study examines the effects of agricultural inputs on grain output from dynamic, nonlinear, and regional perspectives. The findings show that agricultural inputs remain important determinants of grain output, but their effects differ across input types and regions. Grain sown area plays a fundamental role in maintaining grain output, particularly in eastern and central China. Pesticide use also shows a positive effect in several model specifications, indicating that effective pest control contributes to grain production.

The dynamic results reveal strong lagged effect in grain output. There are suggestions that current grain output is closely related to previous production capacity, accumulated agricultural infrastructure, and stable regional production systems. The nonlinear analysis further indicates that the relationship between agricultural inputs and grain output is not purely linear, and that simply increasing input quantity may not always generate proportional output gains. In addition, the heterogeneity results confirm that the effects of agricultural inputs vary across eastern, central, and western regions. Overall, this study provides provincial-level evidence that China's grain output is shaped by dynamic adjustment, nonlinear input effects, and regional heterogeneity.

Availability of data and materials

The data used in this study are publicly available from the China Statistical Yearbook published by the National Bureau of Statistics of China: www.stats.gov.cn. The code used in this study is not publicly available, but may be made available by the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no competing interests.

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