EMPIRICAL ANALYSIS OF SMART AGRICULTURE'S IMPACT ON THE AGRICULTURAL ECONOMY BASED ON THE COBB-DOUGLAS PRODUCTION FUNCTION
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基于柯布-道格拉斯生产函数的智慧农业对农业经济影响实证分析

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ABSTRACT
This paper uses panel data from Sichuan Province and Shandong Province from 2012 to 2022 to build an evaluation index system for the development of smart agriculture. It systematically assesses the impact and internal mechanism of smart agriculture on regional agricultural economic growth. This assessment is based on the Cobb-Douglas production function and panel regression methods. The regression results show that for each unit increase in the level of smart agriculture development, the elasticity contribution to agricultural economic output is 0.42, which is significantly higher than that of capital (0.28) and labor (0.17). Provincial regressions reveal significant differences, with Sichuan showing an elasticity coefficient of 0.45 and Shandong 0.37. Smart agriculture plays a significant and positive role in promoting agricultural economic growth. Its effect surpasses that of traditional input factors. Moreover, the effect of smart agriculture varies across regions. The analysis of mediation effects further shows the role of technological progress. It serves as a key pathway through which smart agriculture influences agricultural economic growth. Robustness checks and extended analyses confirm the reliability of these findings. Finally, the paper puts forward policy recommendations focusing on strengthening technological innovation, improving infrastructure, and cultivating talent.

摘要
本文采用 2012 – 2022 年四川省和山东省的面板数据，构建智慧农业发展的评价指标体系。系统评估了智慧农业对区域农业经济增长的影响及其内在机制。这种评估是基于柯布-道格拉斯生产函数和面板回归方法。回归结果表明，智慧农业发展水平每提高一个单位，其对农业经济产出的弹性贡献为 0.42，显著高于资本（0.28）和劳动力（0.17）。各省回归显示出显著差异，四川的弹性系数为 0.45，山东为 0.37。智慧农业对促进农业经济增长具有重要而积极的作用。它的作用超过了传统的投入要素。此外，智能农业的效果因地区而异。对中介效应的分析进一步显示了技术进步的作用。它是智慧农业影响农业经济增长的关键途径。稳健性检查和扩展分析证实了这些发现的可靠性。最后，提出了加强技术创新、完善基础设施、培养人才的政策建议。

INTRODUCTION
Since the beginning of the 21st century, agricultural modernization has increasingly become a key strategy for enhancing agricultural competitiveness, ensuring food security, and promoting rural revitalization across countries. Smart agriculture integrates advanced technologies such as the Internet of Things, big data, and artificial intelligence. It enables intelligent, precise, and visualized agricultural production. It has become a major driving force in the transformation from traditional to modern agriculture (*Belay et al., 2024; Srinivasan and Yadav, 2024*). Most current studies on the impact of smart agriculture on agricultural economic growth focus on policy advocacy and technical pathways. However, they often lack solid empirical evidence at the regional level. This is especially true for quantifying economic contributions, clarifying underlying mechanisms, and identifying regional heterogeneity. In agricultural economic research, the Cobb-Douglas (CD) production function is widely used due to its simplicity and the strong interpretability of its elasticity parameters. It is commonly applied to identify influencing factors and analyze the contribution of different inputs (*Tabe-Ojong et al., 2024*).

For example, *Priyatna et al. (2025)* adopted a stochastic frontier version of the CD production function combined with maximum likelihood estimation to analyze data from 35 rice farmers. Their results show an average technical efficiency of 75%, suggesting that optimized resource allocation could increase output by 25%. Land, seeds, fertilizer, labor, and farming experience were identified as the main influencing factors. Similarly, *Opuala-Charles et al. (2025)* examined the applicability of the "sectoral big push" theory in Nigeria from 1985 to 2023. They proposed an empirical model based on the CD production function and an autoregressive distributed lag model. They analyzed government investment, income inequality, labor utilization, and technology across the service, agricultural, and industrial sectors. The results show that government investment significantly promotes economic growth in all three sectors, with the strongest response in services. However, most existing empirical studies remain at the macro level, leaving gaps in understanding regional differences, mechanisms of influence, and the construction of evaluation indicators. In response, this paper selects Sichuan and Shandong—two provinces with significantly different development foundations—as the focus of comparative analysis. Based on an extended CD production function model, it constructs a regional panel regression system. The model includes a composite input structure. This structure incorporates a systematically developed smart agriculture development index alongside traditional factors such as land, capital, and labor. The analysis introduces interaction terms and mediating variables to capture the indirect effects and regional characteristics of smart agriculture. The research aims to answer three main questions: What is the actual impact of smart agriculture on agricultural economic growth? What mechanism does smart agriculture follow in promoting economic development? And how does this effect vary across different regions? Therefore, this research aims to address the following research objectives: (1) Quantitatively assess the elasticity contribution of smart agriculture to agricultural economic growth in selected regions; (2) Identify the mediating role of technological progress in the influence path of smart agriculture; (3) Explore the regional heterogeneity in the effects of smart agriculture and derive differentiated policy implications. The innovation of this paper lies in building a comprehensive evaluation index system for smart agriculture and conducting a comparative analysis of regional differences.

MATERIALS AND METHODS

Theoretical foundation and research hypotheses

Theoretical analysis of the CD function and smart agriculture

The CD production function, first proposed by Charles Cobb and Paul Douglas in 1928, effectively measures the elasticity contribution of capital, labor, and smart agriculture to agricultural output. It is widely applied in empirical studies on agricultural economic growth and production efficiency (*Muhammad et al., 2023; López Santiago et al., 2023*). The general form is shown in Equation (1).

$$Y = AK^{\alpha} L^{\beta} \tag{1}$$

In Equation (1), Y represents output. K and L refer to capital input and labor input, respectively. A is the technological progress parameter, which captures all other factors affecting output beyond capital and labor. α and β represent the output elasticities of capital and labor. If $\alpha + \beta = 1$, it indicates constant returns to scale. If $\alpha + \beta > 1$, it indicates increasing returns to scale. If $\alpha + \beta < 1$, it indicates decreasing returns to scale.

Mechanisms and input structure through which smart agriculture affects the agricultural economy

Smart agriculture promotes improvements in production efficiency and optimization of resource allocation. It also upgrades the labor structure, enhances capital utilization efficiency, and refines industrial chains. These are concrete manifestations of endogenous technological progress, as emphasized by the new economic growth theory (*Ahmed et al., 2024*). The actual impact depends on regional infrastructure, talent availability, and the level of industrial promotion.

Formulation of research hypotheses

Based on the theoretical analysis above and the mechanisms through which smart agriculture affects agricultural economic growth, this study puts forward the following three research hypotheses: H1: The development level of smart agriculture has a significant positive effect on agricultural economic growth. After controlling for traditional input factors such as capital, labor, and land, improvements in smart agriculture can effectively increase agricultural output. H2: Compared with traditional input factors, smart agriculture plays a more significant role in promoting agricultural economic growth, indicating that it has become a key driver for the high-quality development of modern agriculture. H3: The impact of smart agriculture on agricultural economic growth varies across regions. Regions with different economic foundations and development stages show clear differences in marginal effects and operating mechanisms. This study constructs a multidimensional evaluation index system and a regression model. It conducts a systematic empirical test of the above hypotheses. The goal is to reveal the actual path and internal mechanisms through which smart agriculture promotes agricultural economic growth under different regional conditions.

Data and variable design

Data sources and processing

To provide a clearer understanding of the geographical features of the study areas, this study briefly analyzes the spatial location of Sichuan Province and Shandong Province. Their geographic distribution is shown in Figure 1.

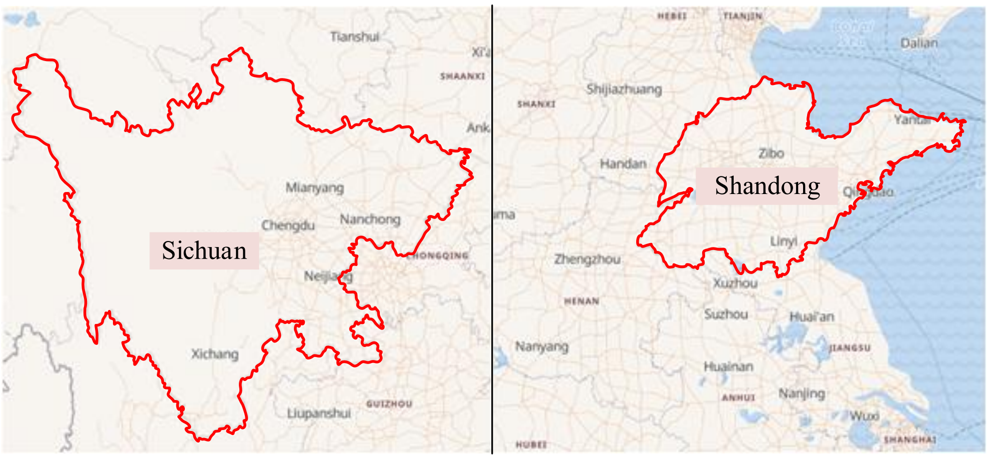


Fig. 1 - Schematic diagram of the geographical location of Sichuan Province and Shandong Province
(Source from: https://openmaptiles.org/languages/zh/#0.6/0/0)

As shown in Fig. 1, Sichuan Province is located in the southwest inland region of China. Its terrain mainly consists of basins and hills, with a mild climate and synchronized rainfall and heat, which makes it suitable for the cultivation of various crops. Its agriculture focuses on rice, rapeseed, and pig farming. In recent years, smart agriculture has been preliminarily promoted in areas such as the Chengdu Plain. Shandong Province, located along the eastern coast of China, features flat terrain and concentrated arable land. It is one of the country's major production bases for wheat, corn, peanuts, and fruits and vegetables. With a higher level of mechanization and informatization in agriculture, Shandong has a more solid foundation for the development of smart agriculture. The two provinces have different topography and resource endowments. As a result, their agricultural economic structures show distinct characteristics. These differences also provide a practical basis for region-specific development paths of smart agriculture.

Index system construction and evaluation method for smart agriculture

Based on the core concept of smart agriculture and actual conditions across different regions, this study builds an evaluation index system to measure the development level of smart agriculture in Sichuan and Shandong provinces from multiple dimensions. The smart agriculture development index considers several dimensions. These include IoT coverage, big data application, automation rate, and equipment penetration rate. The entropy method and Analytic Hierarchy Process (AHP) are used to assign weights. A linear weighted sum method is applied to calculate the composite score (*Uthaman and Raj 2024; Morkunas and Volkov, 2023*).

The specific calculation is shown in Equation (2).

$$SAI = \sum_{i=1}^{n} w_i \times X_i \tag{2}$$

In Equation (2), SAI represents the comprehensive smart agriculture development index. w_i denotes the weight of the i-th indicator, and X_i denotes the standardized value of the corresponding indicator.

Variable selection and explanation

Evaluating smart agriculture requires reflecting the level of technology application, infrastructure development, talent support, and industrial promotion. Based on the actual conditions of smart agriculture in China, this study establishes a smart agriculture development evaluation index system, which includes both primary and secondary indicators. The specific indicators are shown in Table 1.

Table 1

Indicators for the development level of smart agriculture

First-level indicator	Second-level indicator	Weight
Technological foundation	Internet of Things coverage rate	0.12
	Big data application intensity	0.10
	Automation control rate	0.10
Infrastructure development	Penetration rate of smart agricultural equipment	0.12
	Rural broadband access rate	0.10
Talent support	Proportion of smart agricultural professionals	0.10
	Coverage rate of smart agricultural training	0.08
Industrial promotion	Number of smart agricultural demonstration parks	0.10
	Proportion of area under smart agricultural use	0.10
	Number of smart agricultural enterprises	0.08

As shown in Table 1, in the dimension of technology infrastructure, both IoT coverage and automation control rate carry a weight of 0.10 or higher. The weight for the strength of big data application is 0.10, highlighting the importance of data-driven agricultural production. In the talent support dimension, the weight of smart agriculture professionals is 0.10, while the training coverage rate is slightly lower at 0.08, reflecting a policy focus on core human resources and a gap in training coverage. In the dimension of industrial promotion, the number of demonstration parks and the proportion of smart agriculture application area both carry weights of 0.10, emphasizing a balance between the breadth and depth of application. The number of smart agriculture enterprises is assigned a weight of 0.08, slightly lower, possibly indicating early-stage development or statistical difficulty in some regions.

Model construction and estimation methods

Basic CD model and extended specification

In practice, a log-linear transformation is usually applied to the model to facilitate regression analysis. The expression is shown in Equation (3).

$$\ln Y = \ln A + \alpha \ln K + \beta \ln L + \varepsilon \tag{3}$$

The study introduces the smart agriculture variable into the model in Equation (3). This allows further exploration of its effect on agricultural economic growth. Based on the classic CD production function, this study incorporates the smart agriculture development level into an extended production function model, as shown in Equation (4).

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} SA_{it}^{\gamma} e^{\varepsilon_{it}} \tag{4}$$

In Equation (4), Y_{it} represents the agricultural economic output of region i in year t. A_{it} denotes the rate of technological progress. SA_{it} represents the development level of smart agriculture, and γ is the output elasticity of smart agriculture. ε^{it} is the random error term, which follows a normal distribution. To facilitate linear regression analysis, a logarithmic transformation is applied to the production function, yielding the log-linear model shown in Equation (5).

$$\ln Y = \ln A_{it} + \alpha \ln K_{it} + \beta \ln L_{it} + \gamma \ln SA_{it} + \varepsilon_{it} \tag{5}$$

In Equation (5), ε_{it} represents the random error value. This study further introduces control variables to account for possible differences in policy environment and land resource scale in actual agricultural production. These variables include land area and policy environment. The final model is shown in Equation (6).

$$\ln Y_{it} = \beta_0 + \alpha \ln K_{it} + \beta \ln L_{it} + \gamma \ln SA_{it} + \delta_1 \ln Land_{it} + \delta_2 Policy_{it} + \varepsilon_{it} \tag{6}$$

In Equation (6), β_0 denotes the constant term. $Land_{it}$ represents the scale of land input in region i in year t. $Policy_{it}$ is the dummy variable for the smart agriculture policy environment. δ_1 and δ_2 are the coefficients representing the effects of land area and policy environment, respectively.

Empirical strategy and data analysis methods

This study uses fixed effects panel regression, Variance Inflation Factor (VIF) test, heteroskedasticity-robust standard errors, instrumental variable method, and Pearson correlation to conduct regression analysis. The research uses panel data from Sichuan and Shandong provinces from 2012 to 2022, which vary across time and regions. Therefore, panel data analysis is appropriate (*Ucan et al. 2024; Santalucia and Sibhatu, 2024*). Specifically, the Fixed Effects (FE) model is selected to capture unobserved regional heterogeneity. The general form of the fixed effects model is shown in Equation (7).

$$\ln Y_{it} = \beta_0 + \alpha \ln K_{it} + \beta \ln L_{it} + \gamma \ln SA_{it} + \delta_1 \ln Land_{it} + \delta_2 Policy_{it} + \mu_i + \varepsilon_{it} \tag{7}$$

In Equation (7), μ_i represents regional fixed effects used to control for unobservable heterogeneity caused by historical, cultural, and economic development differences. To verify the appropriateness of using the FE model, the Hausman test is conducted. The null hypothesis is that the Random Effects (RE) model is consistent. If the null hypothesis is rejected at the 5% significance level, the FE model is considered more suitable (*Al-Adamat et al., 2024*). The formula for the Hausman test statistic is shown in Equation (8).

$$H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})'[Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})]^{-1}(\hat{\beta}_{FE} - \hat{\beta}_{RE}) \tag{8}$$

In Equation (8), $\hat{\beta}_{FE}$ and $\hat{\beta}_{RE}$ represent the parameter vectors estimated by the FE and RE models, respectively. $Var(\hat{\beta})$ denotes the corresponding variance of the parameter estimates. To ensure the robustness of the empirical analysis, VIF test, endogeneity test, and heteroskedasticity test are further conducted (*Afouna and Ali 2024; Ekpa et al., 2023*). The VIF test examines multicollinearity among variables by calculating the variance inflation factor, as shown in Equation (9).

$$VIF_j = \frac{1}{1 - R_j^2} \tag{9}$$

In Equation (9), R_j^2 represents the coefficient of determination when the j-th independent variable is regressed on all other independent variables. In general, a VIF value less than 10 indicates no serious multicollinearity. For the endogeneity test, this study uses the instrumental variable method, with the one-period lag of the smart agriculture development level as the instrument. The first-stage regression is shown in Equation (10).

$$\ln SA_{it} = \pi_0 + \pi_1 \ln SA_{it-1} + \sum Controls_{it} + \mu_{it} + v_{it} \tag{10}$$

In Equation (10), the first-stage regression uses the instrumental variable to predict the smart agriculture variable. The second-stage regression substitutes the predicted value into the main equation, as shown in Equation (11).

$$\ln Y_{it} = \beta_0 + \alpha \ln K_{it} + \beta \ln L_{it} + \gamma \ln SA_{it,1} + \delta_1 \ln Land_{it} + \delta_2 Policy_{it} + \mu_i + \varepsilon_{it} \tag{11}$$

In Equation (11), $\ln SA_{it,1}$ represents the predicted value from the first-stage regression.

Mediation effect analysis and robustness testing methods

This study introduces the technological progress variable as a mediating variable to explore the mechanism through which smart agriculture promotes agricultural economic growth. The three-step mediation test is then applied. The equations are shown in Equation (12).

$$\begin{cases} \ln Y_{it} = c_0 + c_1 \ln SA_{it} + \sum Controls_{it} + \mu_i + \varepsilon_{it} \\ TFP_{it} = a_0 + a_1 \ln SA_{it} + \sum Controls_{it} + \mu_i + u_{it} \\ \ln Y_{it} = b_0 + b_1 \ln SA_{it} + b_2 TFP_{it} + \sum Controls_{it} + \mu_i + \varepsilon_{it} \end{cases} \tag{12}$$

In Equation (12), TFP is the technical efficiency index. The second step tests the impact of smart agriculture on technological progress. The third step examines the combined effect of smart agriculture and technological progress on agricultural output. In the heteroskedasticity robustness test, the White test is used to detect heteroskedasticity in the model, and the corrected standard errors are estimated using robust standard errors (*Zanré and Combary 2024*). To estimate the elasticity coefficients of each production factor in the CD production function, ordinary least squares regression is used to fit the log-linearized model, and heteroskedasticity-robust standard errors are used to reduce estimation bias. In addition, to address potential endogeneity, some models apply the instrumental variable method for robustness checks. The mediation analysis uses stepwise regression and effect decomposition to quantify the indirect effect of smart agriculture on output growth through technical efficiency.

In summary, the modeling framework consists of three main steps: First, the baseline CD production function is established using traditional inputs (capital and labor). Second, the smart agriculture index is integrated into the extended CD model to assess its direct contribution. Third, a mediation analysis is performed by introducing technical efficiency as an intermediate variable. Finally, robustness tests are conducted to validate the stability of the estimated effects. The definitions of all variables used in the regression models are summarized in Table 2 for clarity.

Table 2

Definitions of Key Variables

Variable	Symbol	Definition
Agricultural output	Y	Logarithm of regional agricultural GDP
Capital input	K	Logarithm of fixed asset investment in agriculture
Labor input	L	Logarithm of number of rural laborers in agriculture
Smart agriculture	SA	Composite index calculated using entropy-AHP method
Land input	$Land$	Logarithm of cultivated land area
Policy environment	$Policy$	Dummy variable (1 = policy implemented, 0 = otherwise)
Technological progress	TFP	Technical efficiency index (used in mediation model)

RESULTS

Descriptive statistics and correlation analysis

The study first conducted descriptive statistics of the main variables to reflect the basic distribution characteristics of smart agriculture, agricultural output, and related input factors in Sichuan and Shandong. The statistical results are shown in Table 3.

Table 3

Descriptive statistics results

Variable	Count	Mean	Standard deviation	Minimum	1st	Median	3st	Maximum
Y	22	59.21	7.82	44.69	55.58	58.16	64.25	72.63
SA	22	0.580	0.096	0.394	0.506	0.588	0.631	0.814
K	22	545.85	45.520	461.85	514.54	537.63	588.12	617.81
L	22	181.09	20.710	127.61	170.98	181.79	194.14	211.29
$Land$	22	556.36	29.220	501.46	543.46	555.29	570.41	635.45

As shown in Table 3 the mean value of Y was 59.21, with a standard deviation of 7.82. The minimum and maximum values were 44.69 and 72.63, respectively, indicating a certain degree of dispersion. SA showed that most samples were already within the high-level range. Capital input exhibited relatively large fluctuations, with a standard deviation of 45.52 and a maximum value as high as 617.81, suggesting significant differences in fixed asset investment across regions. Regarding L, the interquartile range was from 170.98 to 194.14, showing that the distribution of labor resources was relatively balanced and the overall quantity was not low. The median value of $Land$ was 555.29, with a maximum of 635.45 and a standard deviation of 29.22, indicating a moderate range of variation in arable land area distribution. To further reveal the direction and strength of the relationships between variables, the study conducted a correlation analysis of the main variables. The results are presented in Table 4.

Table 4

Correlation coefficients among main variables

/	Y	SA	K	L	$Land$	$Policy$
Y	1.000	0.218	0.217	0.316	-0.010	-0.486
SA	0.218	1.000	-0.173	0.030	0.238	-0.086
K	0.217	-0.173	1.000	0.021	-0.001	0.123
L	0.316	0.030	0.021	1.000	-0.303	-0.159
$Land$	-0.010	0.238	-0.001	-0.303	1.000	0.035
$Policy$	-0.486	-0.086	0.123	-0.159	0.035	1.000

In Table 4, the correlation coefficient between Y and L was 0.316, indicating a moderate positive correlation. The coefficient between Y and the SA index was 0.218, suggesting a positive relationship between smart agriculture and agricultural output, though its elasticity was slightly lower than that of labor input. $Land$ and L showed a weak negative correlation, indicating that the expansion of arable land did not significantly boost output during the sample period. Notably, the correlation coefficient between the $Policy$ variable and agricultural output was -0.486, indicating a significant negative correlation.

Regression analysis and interpretation of main results

Based on the analysis of basic data characteristics and correlations, the study employed a panel data model to examine the impact of smart agriculture and traditional input factors on agricultural output. The regression results and significance tests are shown in Table 5.

Table 5

Regression results and significance tests

Variable	Coefficient	Standard error	t-value	p-value
$\ln K$	0.280	0.050	5.600	0.0003
$\ln L$	0.170	0.070	2.428	0.0228
$\ln SA$	0.420	0.060	7.000	0.0000
$\ln Land$	0.150	0.040	3.750	0.0012
$Policy$	0.080	0.030	2.667	0.0154

In Table 5, the regression coefficient of $\ln SA$ was 0.420, with a t-value of 7.000 and a *p*-value less than 0.0001, indicating that smart agriculture had a significant and stable positive effect on agricultural output. Its output elasticity surpassed that of all traditional input factors, making it a key driver of current agricultural economic growth. The coefficients and *p*-values of $\ln K$ also suggested that fixed assets remained a core resource for agricultural development. Labor input had a relatively small but still notable marginal contribution. The coefficient of $\ln Land$ was 0.150, with a *p*-value of 0.0012, indicating a significant positive effect of arable land on output improvement. To intuitively present the confidence intervals of the regression coefficients, model fit, and error distribution, the study produced the results shown in Fig. 2.

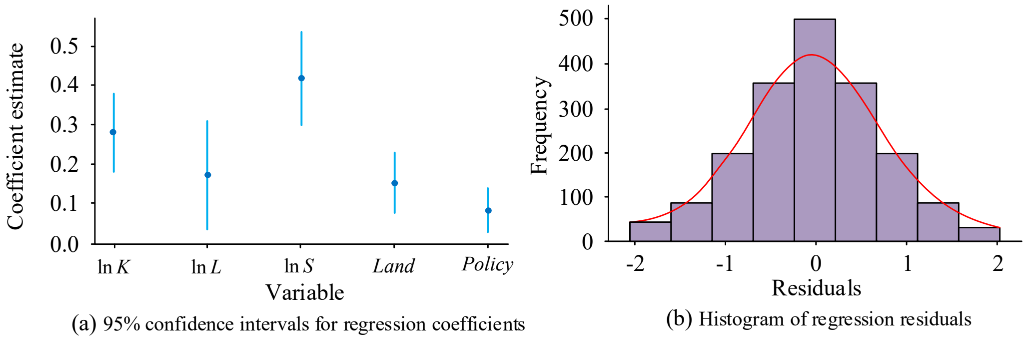
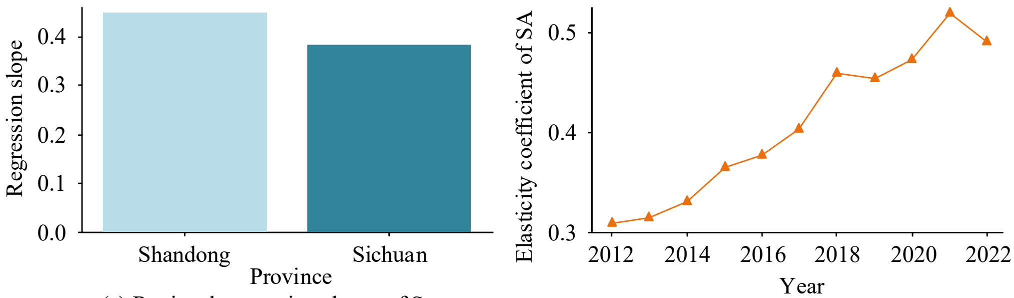


Fig. 2 - Model estimation accuracy and error distribution (Source from: author self-drawn)

In Fig. 2(a), the point estimate of $\ln S$ was the highest, at 0.42, indicating a strong and stable positive effect on agricultural output. The confidence intervals of $\ln L$ and $\ln Land$ were slightly wider but remained within the positive range, fluctuating around 0.27 and 0.15, respectively. $Policy$ had the lowest estimate, at 0.08, and its confidence interval was close to the zero axis. In Fig. 2(b), the residuals displayed an approximate normal distribution, with the peak concentrated around 0 and the highest frequency nearing 500. This indicated that the prediction errors of most observations were small and that the regression model had a good fit. The residual distribution was symmetrical with no significant skewness. The left tail extended to approximately -2, and the right tail to about 2, with few extreme residuals. No obvious heavy-tailed or skewed patterns were observed, supporting the basic assumption of normality in the error term.

Heterogeneity analysis

The study used regression slope plots to analyze regional differences in economic growth driven by smart agriculture. It also illustrated the evolution of its effects over time by visually comparing the marginal effects on agricultural output across different regions. It also examined the elasticity changes from 2012 to 2022. The results are shown in Fig. 3.



(a) Regional regression slopes of Smart agriculture development on agricultural output (b) Changes in smart agriculture elasticity from 2012 to 2022

Fig. 3 - Regional regression slopes and changes in smart agriculture elasticity (Source from: author self-drawn)

As shown in Fig. 3(a), the regression coefficient for Shandong was slightly higher than that for Sichuan, at 0.45 and 0.38, respectively. This indicated that with each one-unit increase in the smart agriculture index, agricultural output in Shandong grew at a slightly higher rate than in Sichuan. As shown in Fig. 3(b), the elasticity coefficient showed a steady upward trend overall. It started at 0.31 in 2012, exceeded 0.40 in 2017, and peaked at 0.52 in 2021, marking the highest point over the decade. It then slightly declined to 0.49 in 2022. However, the overall elasticity remained at a relatively high level.

Mediation mechanism and robustness analysis

To investigate the transmission mechanism of smart agriculture, the study applied a mediation effect model and analyzed the trends in technical efficiency from 2012 to 2022. The results are presented in Fig. 4.

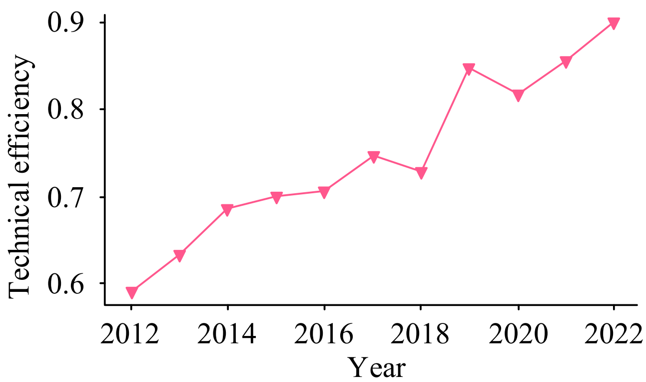


Fig. 4 - Trends in technical efficiency from 2012 to 2022 (Source from: author self-drawn)

As shown in Fig. 4, the initial value of technical efficiency was only 0.59 in 2012. It then increased to 0.68 by 2014. From 2016 to 2018, it remained stable at 0.73. Starting in 2019, efficiency began to rise significantly again, surpassing 0.82 in 2020 and reaching 0.89 in 2022. The regression results under alternative variable specifications are shown in Fig. 5.

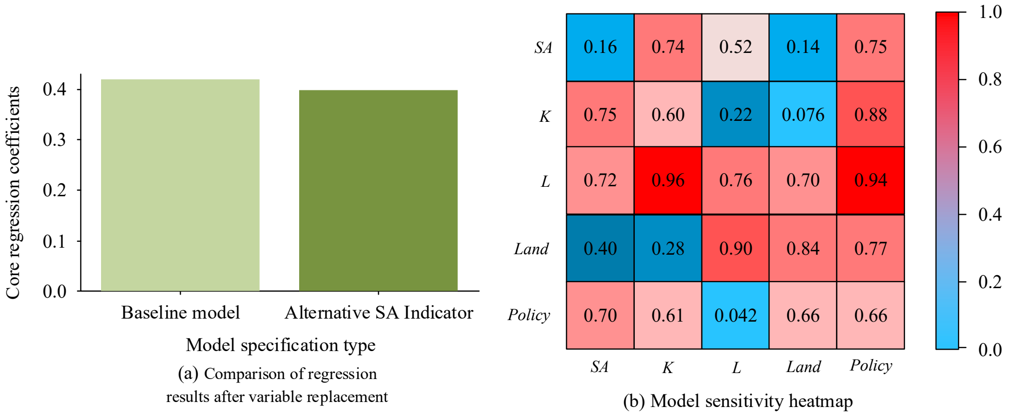


Fig. 5 - Robustness and multicollinearity sensitivity tests (Source from: author self-drawn)

In Fig. 5(a), the coefficient of the core variable under the baseline model was 0.42. After replacing variables, the coefficient became 0.39. The difference from the baseline was only 0.03. As shown in Fig. 5(b), most variables were highly correlated. The correlation coefficient between K and L reached 0.96, and that between K and $Policy$ was 0.88, both of which were close to perfect correlation, suggesting a serious multicollinearity issue between these variables. In comparison, the $Land$ variable showed relatively low correlation with other factors, indicating a more independent structure. Notably, the correlation coefficient between SA and $Policy$ was 0.75, suggesting that policy support had a strong positive influence on the development of smart agriculture.

DISCUSSION

This study provides robust empirical evidence on the impact of smart agriculture on agricultural economic growth based on an extended Cobb-Douglas production framework. The main findings reveal that smart agriculture exhibits the highest elasticity coefficient (0.42) among all input variables, outperforming capital (0.28) and labor (0.17). This confirms the growing dominance of digital agricultural inputs in enhancing productivity, and aligns with the global transformation toward technologically integrated agriculture. A notable insight from the regression analysis is the regional heterogeneity in the marginal effects of smart agriculture. Sichuan Province—despite having a lower average smart agriculture index (mean = 0.548)—shows a higher elasticity (0.45) than Shandong Province (0.37). This supports the "technology-gap" theory proposed by *Fujiwara and Matsuyama* (2024), which suggests that underdeveloped regions often experience stronger marginal gains when adopting frontier technologies. It also aligns with *Li and Ito*'s (2024) research on rural Gansu, which emphasizes the role of agricultural cooperatives in enhancing technical efficiency through smart agricultural inputs.

The temporal dynamics further highlight the progressive role of smart agriculture. The elasticity of smart agriculture rose from 0.31 in 2012 to a peak of 0.52 in 2021. It then slightly declined in 2022. Simultaneously, the technical efficiency index improved steadily, from 0.59 to 0.89. These trends reflect a staged development process. First, there is initial technology diffusion and infrastructure buildup. This is followed by systemic efficiency gains. This is consistent with *Li* et al. (2023), who observed similar trends in large-scale Japanese rice farming, noting an early plateau before a second wave of gains from system-level restructuring. The mediation analysis confirms that 26% of the total effect of smart agriculture is transmitted through technological progress, reinforcing its role not just as a production input but also as a channel for productivity enhancement. This indirect effect is especially strong in Sichuan, indicating that regions with greater absorption capacity for innovation benefit more from smart technology deployment.

However, the relatively lower elasticity observed in Shandong may be attributed to behavioral or institutional frictions. *Harmak and El*'s study on Morocco highlights that low farmer acceptance is a key constraint in technology adoption. Similarly, Li et al. (2023) found that policy incentives were not always aligned with farmer behavior. This misalignment could limit the return on investment in digital systems. These constraints may help explain diminishing marginal effects in Shandong. *Nguyen* et al. *(2024)* further emphasize that the success of smart agriculture depends on more than just technology provision—it also hinges on social influence, perceived performance, and organizational support. Their study on rice farmers in Vietnam demonstrates that cooperatives and leading enterprises function as key intermediaries in the diffusion process, which is especially relevant in contexts where individual farmers lack digital literacy or access to technical resources. Statistical diagnostics support the reliability of these findings. The model residuals exhibit near-normal distribution with low skewness, indicating that the assumptions of the regression framework hold. Additionally, capital input shows high variability across provinces, suggesting uneven investment behavior. The weak negative correlation between land and labor inputs implies that simple land expansion does not automatically translate into higher output, likely due to quality constraints or inefficient usage.

Despite these strengths, this study is not without limitations. First, the dataset includes only two provinces, limiting the generalizability of the findings. Second, the model does not account for dynamic or lagged effects, which may be important in capturing long-term technology adoption. Third, the lack of micro-level behavioral data prevents exploration of gendered responses, household-level decision-making, or social learning mechanisms.

Overall, the evidence confirms that smart agriculture is a pivotal driver of modern agricultural transformation, particularly in regions with low initial technological endowments. Its successful implementation, however, requires a coordinated strategy. This strategy should combine infrastructure investment, institutional adaptation, cooperative governance, and capacity building to fully unleash its potential.

CONCLUSIONS

This study empirically analyzed the impact of smart agriculture on agricultural economic growth based on the extended Cobb-Douglas production function model. It also examined the underlying mechanism. The results showed that the development level of smart agriculture significantly increased agricultural output, with an elasticity coefficient of 0.42—substantially higher than that of capital and labor. These effects also varied across provinces. In particular, the standard deviation of the smart agriculture index in Sichuan (0.15) was nearly twice that of Shandong (0.08), indicating a larger development gap. However, Sichuan exhibited a higher elasticity coefficient, suggesting that smart agriculture has stronger marginal productivity in less developed regions. The mediation analysis further revealed that improvements in technical efficiency accounted for 26% of the total effect, highlighting the indirect role of technology diffusion in enhancing output. Residual diagnostics confirmed that the model assumptions were satisfied, with residuals approximately normally distributed ($p > 0.1$), thereby supporting the validity of the estimation results. These findings imply that smart agriculture, when supported by effective policies and infrastructure investment, can serve as a strategic lever for bridging regional development gaps. Policymakers should prioritize tailored technological deployment, enhance cooperative governance, and invest in rural human capital to maximize smart agriculture's potential in driving sustainable agricultural modernization. Despite its contributions, this study has certain limitations, including restricted data access, static model assumptions, and limited regional coverage. Future research could incorporate time-varying coefficient models, expand geographic scope, and integrate high-frequency and behavioral data to better capture dynamic patterns and provide more targeted support for policy and regional strategy design.

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