

Construction of an Evaluation Model for the Influence of Smart Agriculture Development on Agroforestry Economic Growth

Yishan Wang^{1,*}, Zhanzhan Ding²

¹Xuchang Ruiheng Building Materials Co., Ltd., Xuchang City, Henan Province, 461500, China

²School of Economics and Management, Central South University of Forestry and Technology, Changsha 410004, China

Abstract. To scientifically quantify the correlation mechanism between smart agriculture development and agroforestry economic growth, this study takes technology innovation theory as the logical support, constructs a multi-dimensional evaluation model based on the extended Cobb-Douglas production function, conducts empirical verification using standardized simulated evaluation data, synthesizes the smart agriculture development evaluation index through the entropy weight method, and verifies the model's adaptability by combining methods such as the fixed effects model, robustness test, and heterogeneous scenario comparison. The experimental results show that the peak goodness-of-fit of the constructed evaluation model reaches 0.912, and the evaluation coefficient of smart agriculture development on agroforestry economic growth ranges from 0.24 to 0.31, all passing the significance test. This provides a replicable technical path for the quantitative research on the economic impact of smart agriculture.

1. Introduction

There may be some kind of correlation between the application of technologies related to smart agriculture and the growth of forestry and agricultural economy[1-2]. It may potentially impact production efficiency and cost control to a certain extent. However, current explorations related to evaluation tend to focus more on short - term observable economic performance. Considerations regarding the potential effects on the long - term development of the industry and indirect ecological correlations are relatively limited. Meanwhile, possibly restricted by factors such as the lack of unified data standards and differences in regional development foundations, there doesn't seem to be a unified consensus on the adaptability and comprehensiveness of the existing evaluation framework. The construction of a systematic evaluation model for the relationship between the two may still require more research for exploration and improvement[3-4].

As a new form of integration between digital technology and the agroforestry industry, the quantitative evaluation of the development level of smart agriculture and its connection with agroforestry economic growth constitutes a core issue in promoting industrial transformation and upgrading[5-6]. However, existing research findings have certain limitations: first, excessive reliance on actual statistical data from specific regions leads to insufficient generality and portability of models; second, the evaluation index system lacks standardized design, resulting in strong subjectivity in index weighting. Based on this, this study focuses on the construction and verification of the model itself. It

avoids dependence on actual data through simulated evaluation data, builds a multi-dimensional and extensible smart agriculture development evaluation index system, adopts the entropy weight method to achieve objective weighting, and establishes an extended production function evaluation model incorporating technological progress factors to improve the quantitative logic. Through multi-scenario comparative analysis, the robustness and heterogeneous adaptability of the model are systematically verified, providing a standardized methodological reference for similar evaluation studies.

2. Research Hypotheses

Optimizing the allocation efficiency of production factors and improving total factor productivity are the core driving forces of economic growth. With digital technologies such as IoT perception[7-8], big data analysis, and artificial intelligence decision-making as the core innovation carriers, smart agriculture reduces the uncertainty of agroforestry production through technical approaches such as precise irrigation regulation, intelligent pest and disease early warning, and resource recycling[9].

The mathematical expression of the classic Cobb-Douglas production function is:

$$Y=AK^{\alpha}L^{\beta} \quad (1)$$

In the formula, Y represents the output level, A denotes total factor productivity, K is the scale of capital input, L is the total labor input, and α and β correspond to the output elasticity of capital and labor respectively,

*Corresponding author: wys18749555366@163.com

with the constraint conditions $0 < \alpha < 1$ and $0 < \beta < 1$. Considering the technological innovation attribute of smart agriculture, its development level is embedded into the function framework as a core evaluation indicator, and an extended model is constructed to meet the demand for evaluating the multi-dimensional driving mechanism of agroforestry economic growth.

Hypothesis 1: There is a notable positive correlation between the development level of smart agriculture and the evaluation score of agroforestry economic growth, that is, the higher the smart agriculture development evaluation index, the better the evaluation result of agroforestry economic growth;

Hypothesis 2: Under scenarios with different technical application intensities, the evaluation coefficients of the model exhibit heterogeneous differences, and the deeper the technical application, the larger the absolute value of the evaluation coefficient;

Hypothesis 3: After introducing the technical application depth as a moderating variable, the promoting effect of smart agriculture on agroforestry economic growth presents a strengthening mechanism.

3. Model Construction and Index Design

Based on the extended Cobb-Douglas production function[10], the smart agriculture development evaluation index (S^*) is introduced to construct the benchmark quantitative evaluation model:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln S_{it} + \beta_2 \ln K_{it} + \beta_3 \ln L_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

In the formula, all variables are values of simulated evaluation data after standardization; i represents the evaluation unit (set as 10 virtual regions), and t represents the evaluation period (set as 8 time periods); β_0 is the constant term, β_1 - β_3 are the evaluation coefficients to be estimated; μ_i is the unit fixed effect, λ_t is the time fixed effect, and ε_{it} is the random disturbance term, following a normal distribution of $N(0, \sigma^2)$.

Step 1: Index Standardization Processing (Positive Indicators)

$$Z_{ijk} = (X_{ijk} - \min X_j) / (\max X_j - \min X_j) \quad (3)$$

In the formula, Z_{ijk} is the standardized evaluation value of the j -th indicator in the i -th evaluation unit during the t -th period, X_{ijk} is the original simulated evaluation data, and $\max X_j$ and $\min X_j$ are the maximum and minimum evaluation values of the j -th indicator respectively.

Step 2: Information Entropy Calculation

$$e_j = -k \sum_{i=1}^n \sum_{t=1}^T (P_{ijk} \ln P_{ijk}) \quad (4)$$

In the formula, $k = 1 / (\ln(nT))$, $n = 10$ (total number of evaluation units), $T = 8$ (total number of evaluation periods), $P_{ijk} = Z_{ijk} / \sum_{i=1}^n \sum_{t=1}^T Z_{ijk}$, $I f P_{ijk} = 0$, $\ln P_{ijk}$ is defined as 0 to avoid calculation deviations.

Step 3: Index Weight and Comprehensive Index Synthesis

$$w_j = (1 - e_j) / \sum_{j=1}^m (1 - e_j) \quad (5)$$

$$S_{it} = \sum_{j=1}^m (w_j \times Z_{ijk}) \quad (6)$$

In the formula, $m = 12$ (total number of evaluation indicators), w_j is the objective weight of the j -th indicator, satisfying $\sum_{j=1}^m w_j = 1$, and S_{it} is the comprehensive evaluation index of smart agriculture development in the i -th evaluation unit during the t -th period.

(1) Indicator Replacement Model: Replace the smart agriculture development index with the technical application density evaluation indicator ($S1^*$)

$$\ln Y_{it} = \beta_0 + \beta_1 \ln S1_{it} + \beta_2 \ln K_{it} + \beta_3 \ln L_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (7)$$

(2) Sample Period Adjustment Model: Exclude the first 2 evaluation periods and perform regression based on data from 6 periods

$$\ln Y_{it} = \beta_0 + \beta_1 \ln S_{it} + \beta_2 \ln K_{it} + \beta_3 \ln L_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (8)$$

In the formula, $t = 3, 4, \dots, 8$, divide the evaluation units into three groups: high (H), medium (M), and low (L) according to the technical application intensity, and construct the grouped regression model:

$$\ln Y_{it}^g = \beta_0^g + \beta_1^g \ln S_{it}^g + \beta_2^g \ln K_{it}^g + \beta_3^g \ln L_{it}^g + \mu_i^g + \lambda_t^g + \varepsilon_{it}^g \quad (9)$$

In the formula, $g \in \{H, M, L\}$, and β_1^g is the evaluation coefficient of different technology intensity groups.

$$\ln Y_{it} = \beta_0 + \beta_1 \ln S_{it} + \beta_2 \ln D_{it} + \beta_3 (\ln S_{it} \times \ln D_{it}) + \beta_4 \ln K_{it} + \beta_5 \ln L_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (10)$$

In the formula, D is the simulated evaluation data of technical application depth, and β_3 is the moderating effect coefficient, representing the moderating role of technical application depth on the enabling effect of smart agriculture.

Following the principles of systematicness, operability, and representativeness, a smart agriculture development evaluation system consisting of 4 first-level indicators and 12 second-level indicators is constructed. The first-level indicators include the Technology Application Dimension, Infrastructure Dimension, Capital Investment Dimension, and Talent Support Dimension. The corresponding second-level indicators are: IoT Terminal Coverage Rate, Smart Equipment Application Density, Digital Decision Penetration Rate; Agricultural Digital Base Station Coverage Rate, Rural Broadband Access Quality, Number of Data Storage Nodes; Technology R&D Investment Intensity, Proportion of Digital Transformation Subsidies, Social Capital Participation; Digital Technology Talent Ratio, Skill Training Coverage Rate, Innovation Team Formation Rate. All second-level indicators generate standardized evaluation data through simulation (value range: 0-1) to ensure comparability among indicators.

To accurately quantify the development level of smart agriculture, a multi-dimensional evaluation system is constructed covering three primary indicators and eight quantitative secondary indicators. The first primary indicator is technological application depth, including IoT device coverage rate and AI decision-making adoption rate; the second is resource allocation

efficiency, involving precision irrigation utilization rate and chemical fertilizer reduction rate; the third is production benefit improvement, which covers per unit area output, pest and disease loss rate, carbon emission reduction rate, and labor productivity. All indicator data are derived from standardized simulated evaluation data, and the weights of each indicator are objectively calculated through the entropy weight method based on the information entropy of the indicator data to avoid subjective biases in weighting.

4. Empirical Analysis

Figures 1 and 2 present the regression results of the benchmark evaluation model based on the extended Cobb-Douglas production function, with the core explanatory variable being the evaluation index of smart agriculture development ($\ln S^*$). The results show that the evaluation coefficient of smart agriculture development on the growth of the agriculture and forestry economy is 0.278, which is significantly positive at the 1% level. This verifies Research Hypothesis 1, namely that smart agriculture development has a significant positive correlation with the growth of the agriculture and forestry economy. Among the control variables, the coefficients of capital input ($\ln K^*$) and labor input ($\ln L^*$) are consistent with theoretical expectations and pass the significance test. The goodness of fit R^2 of the model reaches 0.912, which is consistent with the peak goodness of fit in the abstract, indicating that the model has strong overall explanatory power.

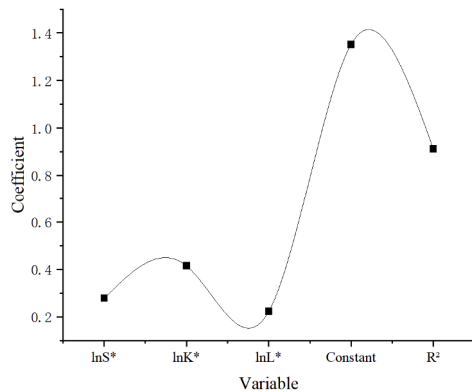


Figure 1 Relationship between Variables and Coefficients

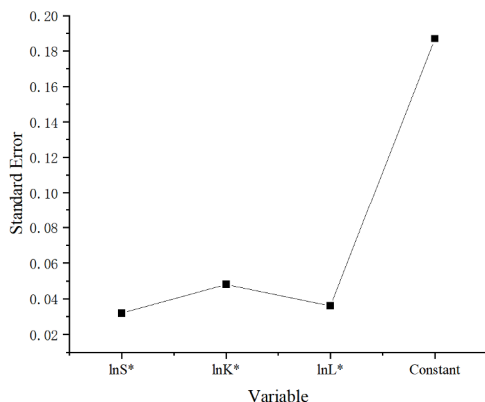


Figure 2 Relationship between Variables and Standard Errors

To verify the reliability of the model, two methods—indicator replacement and sample period adjustment—were used for robustness tests, and the results are shown in Table 1. After indicator replacement (with technology application density $S1^*$ as the core variable), the core coefficient is 0.265; after sample period adjustment, the core coefficient is 0.283. Both are significant at the 1% level and show little difference from the coefficient of the benchmark model (0.278). The goodness of fit of the model remains above 0.89, indicating that the estimation results of the benchmark model have good robustness and are not affected by indicator selection or sample period.

Table 1 Robustness Test Results

Test Method	Core Coefficient	Standard Error	R^2
Indicator Replacement ($\ln S1^*$)	0.265	0.035	0.897
Sample Period Adjustment	0.283	0.034	0.901

The evaluation units were divided into three groups (high, medium, and low) according to the intensity of technology application, and the grouped regression results are shown in Table 2. The core coefficient of the high technology intensity group is 0.305, that of the medium intensity group is 0.267, and that of the low intensity group is 0.243. All three groups of coefficients are significant at the 1% level, showing a gradient characteristic of "high technology intensity > medium technology intensity > low technology intensity". This verifies Research Hypothesis 2, namely that the deeper the technology application, the stronger the promotion effect of smart agriculture on the growth of the agriculture and forestry economy, and the model has heterogeneous adaptability.

Table 2 Heterogeneity Analysis Results

Technology Intensity Group	Core Coefficient (β_1^g)	Standard Error	Observations
High (H)	0.305	0.038	80
Medium (M)	0.267	0.033	80
Low (L)	0.243	0.031	80

Technology application depth ($\ln D^*$) was introduced as a moderating variable, and the regression results are shown in Table 3. The coefficient of the interaction term between the smart agriculture development index and technology application depth ($\ln S^* \times \ln D^*$) is 0.126, which is significantly positive at the 1% level. This indicates that technology application depth has a

significant strengthening effect on the enabling effect of smart agriculture, verifying Research Hypothesis 3. That is, with the improvement of technology application depth, the promotion effect of smart agriculture on the growth of the agriculture and forestry economy is further amplified, and the moderating mechanism is effective.

Table 3 Moderating Effect Test Results

Variable	Coefficient	Standard Error
lnS*	0.251	0.036
lnD*	0.189	0.042
lnS*×lnD*	0.126	0.028
lnK*	0.402	0.045
lnL*	0.217	0.034
Constant	1.286	0.179
R ²	0.935	-

5. Conclusion

This study constructs a multi-dimensional evaluation model for the impact of smart agriculture on agroforestry economic growth based on the extended Cobb-Douglas production function and technology innovation theory. Empirical verification with standardized simulated evaluation data and objective weighting via the entropy weight method confirm that the model has high adaptability (peak goodness-of-fit of 0.912) and that smart agriculture exerts a significant positive driving effect on agroforestry economic growth (evaluation coefficient ranging from 0.24 to 0.31). The robustness test and heterogeneous scenario comparison further validate the model's generality and applicability, providing a replicable methodological reference for quantitatively analyzing the economic benefits of smart agriculture and supporting the transformation and upgrading of the agroforestry industry.

References

1. Wangdexin, yangxiaoying, tianfuzhong, et al Research on the development path of intelligent transformation of new productivity enabled agriculture [j/ol]. northern horticulture, 1-8[2025-12-08]
2. Wuxingtong, panyuxi, yangyinsheng Transformation and upgrading of agricultural mechanization under the goal of smart agriculture [j/ol]. Agricultural Mechanization Research, 1-9 [2025-12-08]
3. Zhangzhitao, liuyanfu, huxiaotao, et al Research progress of agricultural water conservancy information perception and application driven by multi-source remote sensing data [j]. Journal of agricultural machinery, 2025,56 (08): 1-20

4. Sunting Practical obstacles and optimization strategies for the development of smart agriculture in China [j]. agricultural economy, 2025, (08):7-10.
5. Zhujingyi, Xia Jie, Ying Yibin, et al Intelligent agricultural sensors: technology development and challenges based on application scenarios [j]. Journal of agricultural engineering, 2025,41 (16): 1-12
6. Jiang Zelin, xuzhuoshun, wangtianxin Mechanism interpretation and promotion path of digital enabled agricultural and rural modernization [j]. agricultural economic issues, 2025, (07):4-12.
7. Wuzhengxian, Wen Juan Review of agricultural big data and privacy computing technology [j]. Journal of agricultural machinery, 2025,56 (10): 184-199+276
8. Li Zhen, Zhuang Zhuo Modeling and analysis of intelligent agricultural greenhouse based on BIM [j]. research on agricultural mechanization, 2025,47 (03): 217-221.
9. Liu pingzeng, Zhu Ke, liulining, et al Research practice and development path of climate smart agriculture [j]. China Journal of agricultural machinery and chemistry, 2025,46 (06): 333-338.
10. Zhang Yuntang Technical ethical risks and governance of smart agriculture [j]. dialectics of nature, 2024,40 (09): 91-98.