International Scientific Technical and Economic Research | ISSN: 2959-1309 | Vol.3, No.4, 2025
www.istaer.online——Research Article

Study on the Agricultural System in a Certain Region Based on the LSTM Model and Genetic Algorithms

*Yangyun Wang, Yan Qian, Shangyang Zou, Dongping Sheng**

Changzhou Institute of Technology, Jiangsu, China

Received: 25 Sep 2025
Revised: 28 Sep 2025
Accepted: 01 Oct 2025
Published: 03 Oct 2025

Abstract: In response to the two core demands in agricultural production, namely "precision irrigation" and "sustainable transformation", this study conducts two key research tasks: First, it predicts the crop irrigation demand based on meteorological data. Initially, the 3σ principle is adopted to identify and label outliers—isolated outliers are filled using linear interpolation, while consecutive outliers are filled with average value. Subsequently, two types of models are constructed: on the one hand, three evapotranspiration formulas (Hargreaves, Priestley-Taylor, and Makkink) are integrated, and the evapotranspiration (ET) amount is calculated through weighted fusion to establish the ET formula; on the other hand, a Long Short-Term Memory (LSTM) model is built via a two-layer architecture. These two models are then compared. Second, it carries out research on the transformation of organic agriculture based on farm economic and environmental data. First, farms are classified into geographical types (Plain, hilly, and mountainous). Then, a multi-objective optimization model is constructed with the goals of "maximizing economic benefits" and "maximizing environmental benefits". Combined with constraints on transformation ratio and annual transformation, the genetic algorithm is used to solve the model.

Keywords: 3σ Principle; LSTM Model; ET Formula; Multi-Objective Optimization; Genetic Algorithm

1 INTRODUCTION

It can be known by referring to journal [1], in recent years, with the accelerated advancement of agricultural modernization, "efficient resource utilization" and "ecological environment protection" have become core issues in the sustainable development of agriculture. On the one hand, the accurate prediction of crop irrigation demand is crucial for avoiding water resource waste and improving irrigation efficiency. However, outliers in meteorological data tend to interfere with prediction accuracy, and traditional ET models have limited adaptability to complex meteorological conditions. On the other hand, the transformation to organic agriculture serves as a vital approach to reducing agricultural carbon emissions and improving soil quality. Nevertheless, issues such as "high initial investment" and "uncertain short-term returns" during the transformation process have restricted its promotion, making it necessary to balance economic and environmental benefits.

To address the issues, this study focuses on two core research tasks: First, regarding irrigation demand forecasting, systematic preprocessing of meteorological data is conducted initially, followed by the construction of an ET fusion model and an LSTM model. The superiority of the LSTM model is verified through error comparison. Second, for the transformation to organic agriculture, farms are first classified into geographical types and the characteristics of data distribution are analyzed; subsequently, a multi-objective optimization model is established, and a genetic algorithm is employed to solve the optimal transformation strategy. Through the integration of these two research tasks, an integrated solution can be provided for the "precision" and "greening" of agricultural production, thereby contributing to the sustainable development of agriculture.

2 RELATED WORK

Based on the meteorological data collected by the research team, an irrigation demand prediction system for crops is constructed. Firstly, the 3σ principle is adopted to identify and label outliers in the meteorological data—isolated outliers are filled using the linear interpolation method, while consecutive outliers are filled with the average value method to ensure data quality. Subsequently, two types of prediction models are developed separately: an ET fusion model that integrates three classic evapotranspiration formulas (Hargreaves, Priestley-Taylor, and Makkink), and an LSTM model based on a two-layer architecture. The applicability of different models in crop irrigation demand prediction is verified through error comparison, ultimately providing technical support for precision irrigation decision-making.

Combined with farm economic and environmental data, research on the transformation to organic agriculture is conducted. First, farms are classified into three geographical types (Plain, hilly, and mountainous) according to topographic features, and differences in transformation costs, profit potential, and environmental carrying capacity among different types of farms are analyzed. Then, a multi-objective optimization model with "maximizing economic benefits" and "maximizing environmental benefits" as dual objectives is established, incorporating constraints on transformation ratio (The total number of transformed farms shall not exceed 80% of the total number of farms) and annual transformation (The proportion of farms transformed each year shall not exceed 25%). The genetic algorithm is used to solve the optimal transformation strategy, providing a quantitative scheme for the promotion of organic agriculture.

In terms of data sources, the meteorological data (Average temperature, solar radiation, precipitation, etc.), farm economic data (Transformation costs, product premium, government subsidies, etc.), and environmental benefit data (Carbon emission reduction, water saving volume, soil quality indicators, etc.) required for the study are all obtained through field surveys, statistical reports from agricultural departments, and regional agricultural ecological databases. This ensures the authenticity and timeliness of the data.

3 MODEL ESTABLISHMENT AND SOLUTION

3.1 MODEL ESTABLISHMENT

3.1.1 ET Formula

For the ET model (A computational model for crop evapotranspiration), it is known from consulting relevant journals [2] and [3] that in practical work, meteorological stations in different regions all have missing data for the above-mentioned parameters, which poses

Wang et.al., ISTAER. 2548 (2025)., 03 Oct 2025 https://doi.org/10.71451/ISTAER2548

certain difficulties for accurate calculation of evapotranspiration. Meanwhile, it is precisely to address this problem that the research and development of approximate estimation methods have been promoted, such as classic models including Hargreaves, Priestley-Taylor, and Makkink. In the following, these three models will be combined to calculate the crop irrigation demand.

First, key parameters are derived based on the weather_data dataset, including average temperature (T_m), temperature (ΔT), saturated water vapor pressure ($e_{s,max}$ and $e_{s,min}$) and slope of saturated water vapor pressure(δ).

(1)Hargreaves Model:

The evapotranspiration (ET) calculated by this model is more sensitive to temperature fluctuations. By reviewing relevant journals [3] and considering the actual data conditions, the formula for calculating crop evapotranspiration based on temperature and solar radiation data is as follows:

$$ET_{0,H} = 0.023 \times (T_m + 17.8) \times \sqrt{|\Delta T|} \times (R_s \times 0.408) \quad (1)$$

Where: R_s is solar radiation(MJ/(m²·d))

(2)Priestley-Taylor Model:

The evapotranspiration (ET) calculated by this model is more consistent with the law of energy balance, but it exhibits lower sensitivity to extreme temperatures. As indicated in the literature [4] and [5], the formula for calculating crop evapotranspiration with consideration of energy balance is as follows:

$$ET_{0,PT} = \alpha \times \left(\frac{\delta}{\delta+\gamma}\right) \times \left(\frac{R_S}{\lambda_v}\right) \quad (2)$$

Where: γ is the psychrometric constant, and λ_v is the latent heat of vaporization.

(3) Makkink Model:

The reference crop evapotranspiration (ET_0) calculated by this model can maintain high accuracy even in more simplified calculation processes. As indicated in Journal [6], the formula for calculating the reference crop evapotranspiration (ET_0) is as follows:

$$ET_{0,M} = 0.61 \times \left(\frac{\delta}{\delta+\gamma}\right) \times \left(\frac{R_S}{\lambda_v}\right) - 0.12 \quad (3)$$

After calculating the reference crop evapotranspiration (ET_0)using the three models, reasonable weight allocation is conducted. Subsequently, a weighted fusion strategy is adopted to synthesize the integrated reference crop evapotranspiration (ET_0), and its expression is as follows:

$$ET_{0,,ens} = 0.4 \times ET_{0,H} + 0.4 \times ET_{0,PT} + 0.2 \times ET_{0,M} \quad (4)$$

Finally, based on the aforementioned reference crop evapotranspiration (ET_0), the target variable is defined for the irrigation requirement (IR) to be predicted, and its expression is as follows:

$$IR = max\,(0, ET_{0,,ens} \times k_c - P_{eff}) \quad (5)$$

Where:P_{eff} denotes the effective precipitation, and k_c denotes the crop coefficient.

3.1.2 LSTM Model

Compared with the ET formulas, the LSTM model possesses a certain ability to capture complex nonlinear relationships and temporal dynamic characteristics, as indicated in the literature [7].

In the construction of the LSTM model, feature input and sequence construction are first performed. Subsequently, the dataset is divided into an 80% training set, a 10% validation set, and a 10% test set using the stratified sampling method. After that, the RobustScaler transformation method is adopted to standardize the input feature sets and target variables in the model, which facilitates subsequent model training and calculation.

Upon completion of the above work, to realize end-to-end prediction of irrigation requirements, the construction of a two-layer LSTM architecture is initiated for model training. The construction process of the LSTM model is illustrated in Figure 1:

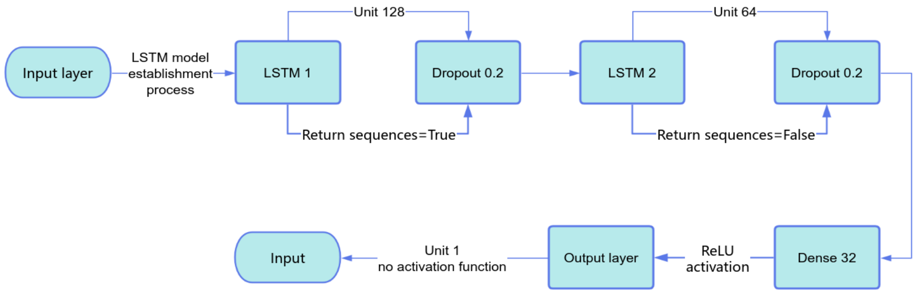

Fig. 1: Flowchart of LSTM Model Construction.

3.1.3 Multi-Objective Optimization Model

The decision-making for the transformation to organic farming in this study is a typical NP-hard problem, as it involves both economic benefit and environmental benefit objectives. Therefore, a multi-objective genetic algorithm optimization model is adopted to solve this problem

First, the decision variable $x_i = (1,2,\cdots,n)$, with n representing the total number of farms.

In accordance with the requirements of this problem, the following two objective functions are constructed based on practical conditions:

(1) Economic Benefit Objective Function

$$max\ \ f_1(x) = \frac{1}{E_{max}} \sum_{i=1}^{n} x_i \cdot [G - L - K + B] \tag{6}$$

Where: G represents the price premium benefit, L represents the transformation cost, B represents the constant of government subsidies, and Emax (the normalization constant for economic benefits) is equal to 30% of the total profit.

(2) Environmental Benefit Objective Function

$$max\ \ f_2(x) = \frac{1}{V_{max}} \sum_{i=1}^{n} x_i \cdot [C_r + W_s \times \delta] \tag{7}$$

Where:$C_r$represents the carbon emission reduction,$W_s$epresents the water saving volume, and V_{max} the normalization constant for environmental benefits) is equal to 40% of the total carbon footprint.

Finally, to ensure the rationality of the output results, transformation proportion constraints and annual transformation constraints are established as follows:

①Transformation proportion constraint: $\sum_{i=1}^{n} x_i \leq 0.8n$.The total number of transformed farms shall not exceed 80% of the total number of farms.

② Annual transformation constraint: $\sum_{i \in Y_k} x_i \leq 0.25n$, $\forall k = 1,2,\ldots,5$. The proportion of farms transformed each year shall not exceed 25%.

Where: Y_k denotes the set of farms planned to be transformed in the k-th year.

3.2 Model Solution

3.2.1 Irrigation Demand Prediction

Based on the LSTM model established above, the variation of the model's training loss and validation loss with the number of iterations during the training process can be obtained. Its visualization is shown in Figure 2:

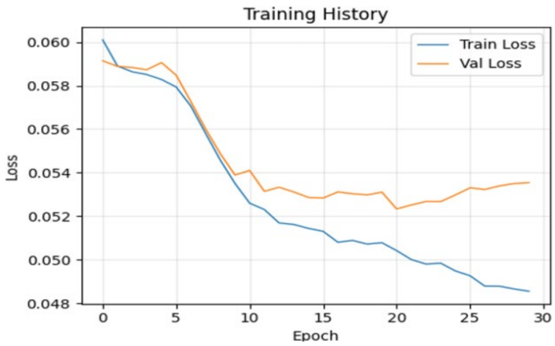

Fig. 2: Variation of Loss During the Training Process of the LSTM Model.

As can be observed from the figure, in the early stage of model training, both metrics decrease rapidly, which reflects the model's fast learning ability. With the progress of model training, the training loss shows a continuous downward trend, while the validation loss, despite some fluctuations, gradually stabilizes overall—indicating that the model has basically converged.

Based on the predictions of the ET model and LSTM model, the final prediction comparison chart can be visualized, as shown in Figure 3:

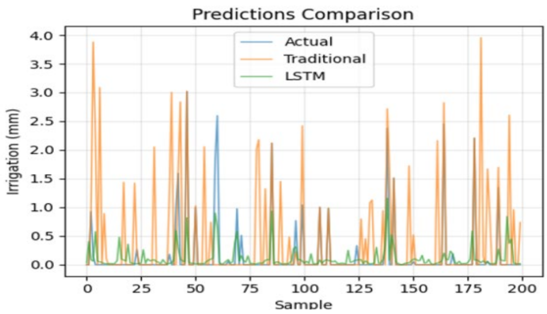

Fig. 3: Prediction Comparison Chart.

In this figure, the blue line represents the actual irrigation demand (With peaks indicating the corresponding crop water requirement periods), the orange line represents the predicted values of the traditional LH model, and the green line represents the predicted values of the LSTM model. Based on the above analysis and in combination with the journal [8], it can be observed that the predicted values of the traditional LH model fluctuate significantly, indicating that this method tends to cause overprediction; in contrast, the predicted values of the LSTM model are closer to the actual irrigation demand, demonstrating that the LSTM model has a better fitting effect.

Wang et.al., ISTAER. 2548 (2025)., 03 Oct 2025 https://doi.org/10.71451/ISTAER2548

The corresponding error metrics calculated based on the above models yield the results shown in Table 1:

Table. 1: Model Error Metrics.

Type	RMSE	MAE
LH	0.698	0.271
LSTM	0.413	0.192

It can be seen from these results that the LSTM model has lower errors and a better fitting effect.

To summarize, in the irrigation demand prediction, when comparing the LSTM model with the LH model, the former exhibits superior fitting performance, with a more stable convergence during the training process and smaller errors. Therefore, the LSTM model achieves better performance in the task of predicting irrigation demand.

3.2.2 Impact of Organic Agriculture Transition

Based on the multi-objective optimization model constructed above, the genetic algorithm (GA) is adopted to solve the problem. It is known from consulting relevant journal [9], the steps include population initialization and genetic operations such as selection, crossover, and mutation, with the specific algorithm flow chart shown in Figure 4:

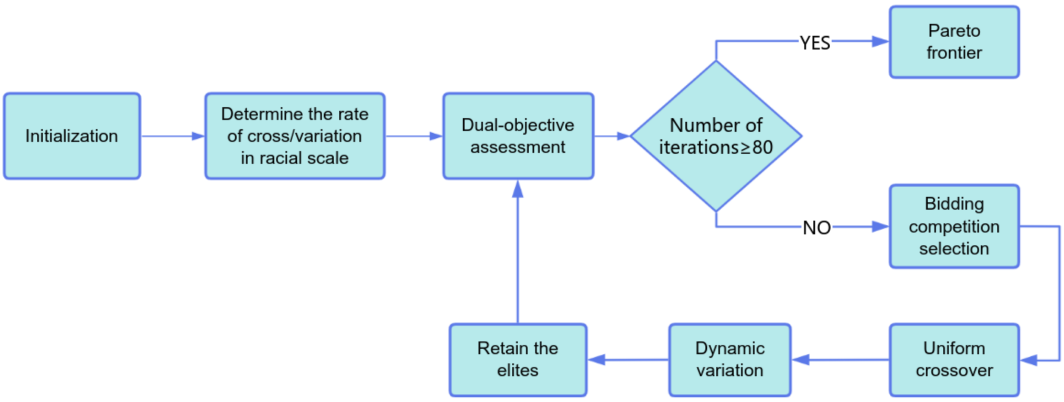

Fig. 4: Flowchart of the Genetic Algorithm.

After solving the model using the aforementioned method, the visualization of the comparative evaluation of comprehensive benefits before and after the organic agriculture transition can be conducted, as shown in Figure 5:

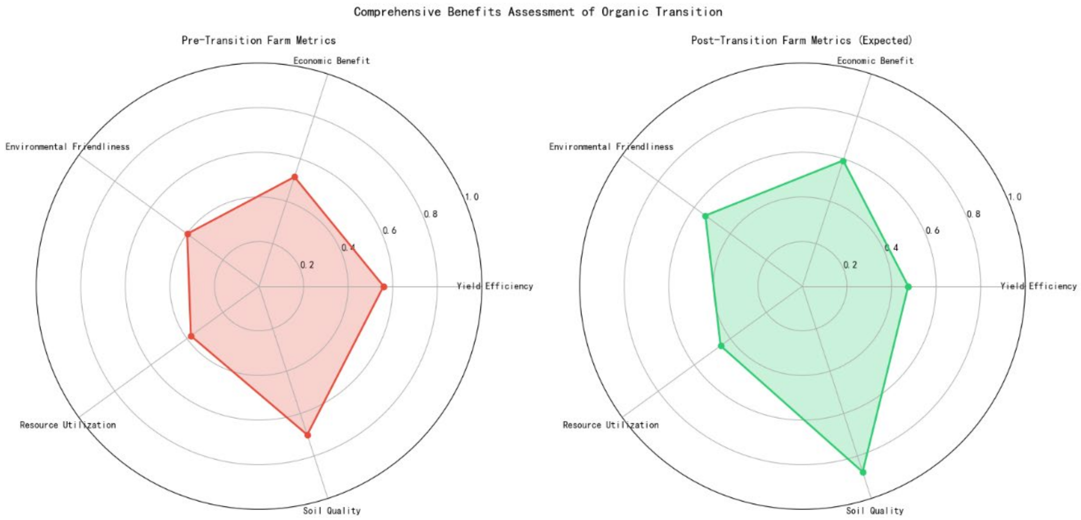

Fig. 5: Comparative Evaluation of Comprehensive Benefits.

From the left graph (Before the organic agriculture transition), it can be observed that although its yield efficiency is relatively prominent, its environmental friendliness is poor, and on the contrary, its economic benefits do not show a significant performance. From the right graph (After the organic agriculture transition), it can be seen that except for the relatively weak yield efficiency, other indicators have improved significantly, with soil quality showing the most notable improvement. Overall, organic agriculture after the transition is a healthier and more excellent agricultural development model.

After analyzing the overall situation, combining the content of the journal [10], the following will separately analyze the evaluation results of the impact of organic agriculture transition on two aspects: economic benefits and carbon emissions.

3.2.2.1 Evaluation of the Impact on Economic Benefits

From the output results, it can be intuitively observed that when the number of farms transitioning to organic agriculture reaches 377, an initial investment of approximately 105.4 million yuan is required, with an expected annual revenue growth of about 25.47 million yuan and an investment payback period of 3 to 4 years.

For a more in-depth analysis, the visualization of the investment payback period analysis is provided in Figure 6：

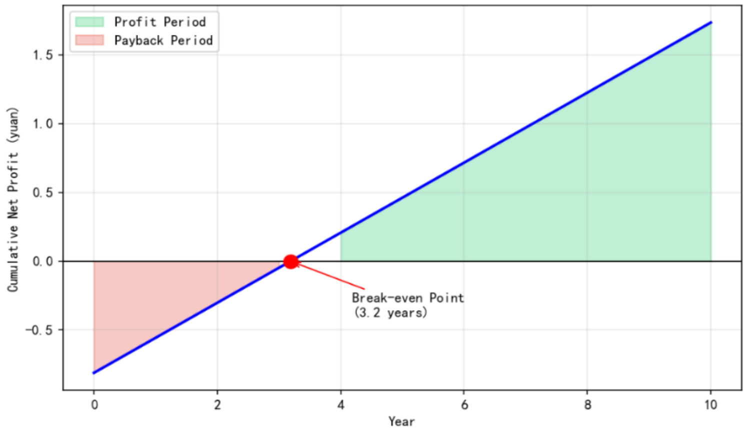

Fig. 6: Schematic Diagram of Investment Payback Period Analysis.

As can be seen from the figure, the 3.2-year mark of the investment corresponds to the break-even point. This indicates that while the initial investment required for the organic agriculture transition is relatively large, the economic benefits it brings are quite significant in the long run.

3.2.2.2 Carbon Emission Impact Assessment

From the output results, it can be intuitively observed that after transitioning to organic agriculture, the annual carbon emission reduction amounts to 3,966 kg CO_2, while soil quality is projected to improve by 25% within three years. The visualization of the comprehensive environmental quality score and soil health recovery curve is presented in Fig. 7 as follows:

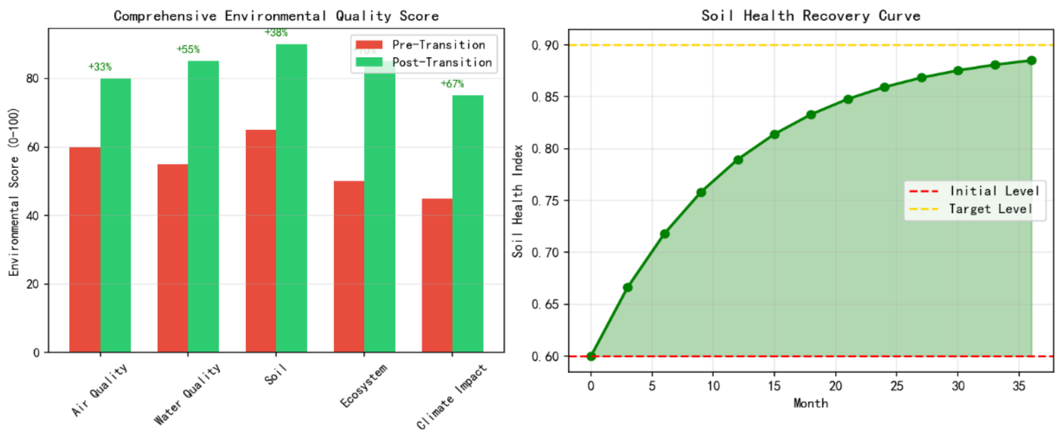

Fig. 7: Schematic Diagram of Carbon Emission Impacts Before and After Organic Agriculture Transition.

As can be observed from the figures, after the transition to organic agriculture, all indicators of environmental quality have shown significant improvement. The soil health recovery curve is gradually approaching the target level, with the degree of soil health continuously improving.

Therefore, the impacts brought about by the transition to organic agriculture involve optimization and enhancement across multiple dimensions. Based on the above analysis and in combination with the literatures [11] and [12], except for the slightly weaker yield efficiency, other aspects—including economic benefits, environmental friendliness, resource utilization, and soil quality—have all achieved significant improvement after the transition to organic agriculture, making it a healthier and more excellent agricultural development model.

To achieve the ecological goal of harmonious coexistence between agriculture and the natural ecosystem, targeted planning for agricultural transition can be carried out based on the visualization of "Farm Geographic Distribution and Transition Strategies," as specifically shown in Figure 8:

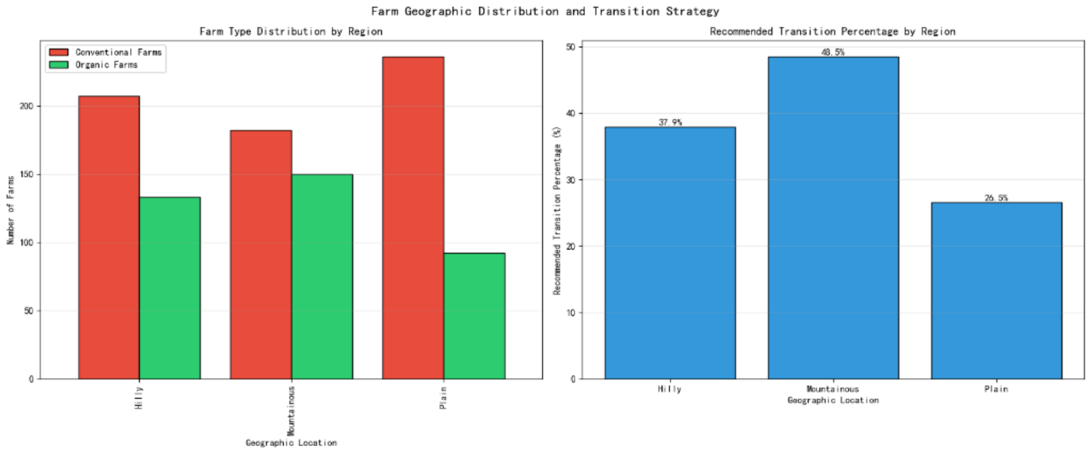

Fig. 8: Schematic Diagram of Farm Geographic Distribution and Transition Strategies.

As can be seen from the figure, traditional farms dominate in all regions, while the number of organic farms is generally small. Among the recommended transition ratios across regions, mountainous areas account for 48.5%; planning for organic agriculture transition can be carried out based on the priority of these transition ratios.

4 CONCLUSIONS

Based on this study on irrigation demand prediction and organic agriculture transition, the following conclusions are drawn:

By constructing the above models and conducting a comparison, it is found that the LSTM model has a better fitting effect, with RMSE = 0.413 and MAE = 0.192—errors that are significantly lower than those of the ET model. The results after agricultural transition show that the initial investment for organic agriculture transition is approximately 105.4 million yuan, with an investment payback period of 3 to 4 years; in the long term, the annual revenue growth is about 25.47 million yuan, the annual carbon emission reduction reaches 3,966 kg CO_2, and soil quality is expected to improve by 25% within 3 years.

FUNDING

This work is supported by ministry of education industry-university cooperative education project (Grant No.: 231106441092432), the research and practice of integrating "curriculum thought and politics" into the whole process of graduation design of Mechanical engineering major: (Grant. No.: 30120300100-23-yb-jgkt03), Theoretical and Practical Exploration of a New Teaching Model for Mechanical Manufacturing Equipment Design

Empowered by Artificial Intelligence (Grant. No.: JGKT202525).

REFERENCES

[1] Song, J., Yang, D., E, D. J., Song, T. T., & Han, S. (2025). Carbon emission research based on the Tapio-LMDI-LEAP model. Global Energy Interconnection, 8(05), 580-593. DOI: https://doi.org/10.19705/j.cnki.issn2096-5125.20240349

[2] Feng, K. P., & Tian, J. C. (2014). Study on calculating reference crop evapotranspiration in Ningxia region using Hargreaves equation. Journal of Arid Land Resources and Environment, 28(9), 100-105. DOI: https://doi.org/10.13448/j.cnki.jalre.2014.09.026

[3] Baber, S., & Ullah, K. (2024). Short-term forecasting of daily reference crop evapotranspiration based on calibrated Hargreaves–Samani equation at regional scale. Earth System and Environment, 8, 1077–1097. DOI: https://doi.org/10.1007/s41748-024-00373-5

[4] Bottazzi, M., Bancheri, M., Mobilia, M., Bertoldi, G., Longobardi, A., & Rigon, R. (2021). Comparing Evapotranspiration Estimates from the GEOframe-Prospero Model with Penman–Monteith and Priestley-Taylor Approaches under Different Climate Conditions. Water, 13(9), 1221. DOI: https://doi.org/10.3390/w13091221

[5] Li, F. F., Rao, L. Y., Lü, K. L., & Others. (2013). Parameter modification of the Priestley-Taylor model and its application in evapotranspiration estimation. Journal of Zhejiang A & F University, 30(5), 748-754. DOI: https://doi.org/10.11833/j.issn.2095-0756.2013.05.018

[6] Nagai, A. (1993). Estimation of pan evaporation by Makkink equation. Journal of Japan Society of Hydrology and Water Resources, 6(3), 238–243. DOI: https://doi.org/10.3178/jjshwr.6.3_238

[7] Liu, Y. F., Liu, S. F., & Zhang, Z. R. (2025). Yield prediction of maize based on StaMaLSTM and multi-source data. Chinese Journal of Agricultural Machinery, 46(09), 81-90. DOI: https://doi.org/10.13733/j.jcam.issn.2095-5553.2025.09.011

[8] Yu, X. Y., Pan, H., & Wang, G. G. (2024). Decomposition and prediction model of power carbon emissions based on improved LSTM. Electronic Design Engineering, 32(23), 12-16. DOI: https://doi.org/10.14022/j.issn1674-6236.2024.23.003

[9] Niu, Q., Fu, Y., & Dong, X. (2024). Omnidirectional AGV Path Planning Based on Improved Genetic Algorithm. World Electric Vehicle Journal, 15(4), 166. DOI: https://doi.org/10.3390/wevj15040166

[10] Yu, X., Wang, Q., Tian, M., & Ji, A. (2024). Exploring the Impact of Cultivated Land Utilization Green Transformation on Agricultural Economic Growth: Evidence from Jiangsu Province in China. Sustainability, 16(16), 7032. DOI: https://doi.org/10.3390/su16167032

[11] Lala M, Sallu SM, Lyimo F, Moore E, Shirima DD, Nnyiti P, Mwanga L and Pfeifer M (2023) Revealing diversity among narratives of agricultural transformation: insights from smallholder farmers in the Northern Kilombero Valley, Tanzania. Front. Sustain. Food Syst. 7:1148928. DOI: https://doi.org/10.3389/fsufs.2023.1148928

[12] Li, P. J. (2025). A study on the influencing factors of rural industrial development in Tibet [Doctoral dissertation, Tibet University]. DOI: https://doi.org/10.27735/d.cnki.gxzdx.2025.000179