

CROP PLANTING STRATEGY BASED ON DYNAMIC PLANTING SCHEME OPTIMIZATION MODEL

YiShuo Jing

College of Economics and Management, Tianjin University of Science and Technology, Tianjin 300222, China.
Corresponding Email: 19937983272@163.com

Abstract: As a key agricultural region in China, the development of organic farming in North China has a profound impact on promoting sustainable rural economic growth, enhancing farmers' quality of life, and advancing the construction of beautiful villages. This paper focuses on the application of dynamic programming models for the utilization strategies of arable land resources in the organic farming industry in North China. By using dynamic programming models, it provides tailored solutions to the specific conditions of rural areas, considering factors such as time, resources, and costs, to develop planting strategies that achieve optimal results under various conditions. During the model construction process, the climate characteristics of North China and the special requirements of organic farming are fully considered. Monte Carlo simulation algorithms are used for iterative screening, followed by adjustments based on elastic demand theory to select the best planting strategy. The application of this dynamic programming model not only enhances the production efficiency of organic farming but also reduces planting risks due to changes in climate and market conditions. It also promotes the rational allocation and efficient use of agricultural resources. By optimizing the utilization strategies of arable land resources, it lays a solid foundation for the sustainable development of the organic farming industry in North China's rural areas, contributing to the goals of rural revitalization and the construction of beautiful villages.

Keywords: Cultivated land resources; Organic farming; Dynamic planning; Sustainable development

1 INTRODUCTION

As China's rural revitalization strategy advances, the 'Comprehensive Rural Revitalization Plan (2024-2027)' emphasizes measures to boost farmers' income, accelerate agricultural and rural modernization, and promote comprehensive upgrades in agriculture, progress in rural areas, and all-around development of farmers. In the process of exploring sustainable development, rural areas are increasingly focusing on the rational allocation and efficient use of land resources. Organic farming, a key direction in modern agriculture, not only enhances the quality of agricultural products but also maintains soil health through ecological practices, promoting sustainable agricultural development. However, selecting suitable crop varieties and optimizing planting strategies based on local climate and soil conditions is crucial for the effective utilization of rural land resources and sustainable development.

The village under discussion is situated in North China, a typical cool region. The area has distinct climatic features, with consistently low temperatures throughout the year, which results in most farmlands being suitable for only one crop per year. This climate not only limits the growth cycle of crops but also introduces uncertainty into farmers' income. Selecting the right crops to plant within the limited growing season is crucial for optimizing planting strategies and enhancing agricultural productivity.

Studies on cultivated land use cover security dynamics, contradiction analysis, and efficiency evaluation. Huang et al. analyzed Hubei's cultivated land security, finding overall improvement 2010-2019 with declining quantity security and "west-high-east-low" spatial pattern [1]. Li et al. revealed a poverty contradiction in Heilongjiang's arable-rich regions, highlighting the importance of quality and location [2]. Zhu et al. proposed balancing economy and land protection in Huang-Huai-Hai Plain to reduce environmental pressure [3]. Zhang et al. found rising utilization efficiency in Henan 2000-2020, driven by population and economy [4]. Bogale et al. analyzed Ethiopian land use change, noting the need for policies to address farmland expansion and forest planting conflicts [5]. However, existing studies focus on single regions or dimensions, lacking cross-system dynamic synergy analysis.

Organic farming research focuses on system synergy and technological innovation. Csambalik et al. compared organic farming and plant factories, emphasizing regulatory and medium optimization [6]. Javed et al. noted that actinomycetes promote soil organic matter cycling via enzymatic reactions [7]. Hafez et al. confirmed that the combined use of spent grain and azospirillum improves soil fertility better than chemical fertilizers [8]. Nath et al. proposed lignin-derived carbon materials for pollutant degradation, aiding environmental remediation [9]. Sani et al. highlighted biostimulant synergy in enhancing organic crop yield and stress resistance [10]. However, few studies integrate the synergy of microorganisms, materials, and policies, with insufficient region-specific strategies.

The innovation of this paper lies in constructing a dynamic programming model that integrates "quantity-quality-ecology-economy" constraints of cultivated land, combining North China's climatic characteristics and organic farming technologies to achieve spatio-temporal optimization and dynamic risk control for cultivated land use in organic farming. As a multi-stage decision optimization method, dynamic programming has demonstrated remarkable problem-solving capabilities in various fields in recent years. Such models excel in their ability to integrate multiple factors

within rural organic farming, including soil quality, crop varieties, market demand, and environmental constraints—an integration that is crucial for formulating optimal strategies for arable land utilization in organic agriculture.

2 MODEL

2.1 Dynamic Programming Model

Located in the north of the mountainous area, the temperature is low all year round, and most farmland can only grow one crop per year. Let the crop number be i , and the name of the planting plot or greenhouse be j , $i = \{1, 2, 3, \dots, a\}$, $j = \{1, 2, 3, \dots, b\}$, $a = 41, b = 54$, the plots were numbered and divided into four types [G1, G2, G3, G4]. If the year is k and some cultivated land can plant two seasons of crops per year, then a certain plot of land can be planted with m seasons of crops per year, where i_a is the crop planted in the first season and i_b is the crop planted in the second season. The number of planting seasons per year for different types of land parcels, i.e. j and m , satisfies the relationship:

$$\begin{cases} m = 1, & j \in G_1 \\ m = 1 \text{ or } 2, & j \in G_2 \\ m = 2, & j \in G_3 \cup G_4 \end{cases} \quad (1)$$

The total planting area of the i -th crop in the k -th year is $X(k)$, and S is the total cultivated land area. If the area of the i -th crop planted on the j -th plot in the k -th year is $x(k)$, then there is.

$$\sum_{i=1}^a \sum_{j=1}^b x_{ij}(k) = \sum_{i=1}^a X_i(k) = S_t \quad (2)$$

According to seasonal requirements, ordinary greenhouses can grow two crops a year. The first season can be planted with a variety of vegetables, and the second season can only be planted with edible fungi. Cabbage, white radish and red radish can only be planted in the second season of irrigated land. The relationship between different plots of land j and crop i is as follows:

If $j \in G_1$, then $1 \leq i \leq 15$ for flat land, terraced land, and hillside land;

Watered land: If $j \in G_2$, then $m=1 \rightarrow i=16$ or $m=2 \rightarrow i_1 \in [17,34], i_2 \in [35,37]$;

Ordinary greenhouse: If $j \in G_3$, then $m=2 \rightarrow i_1 \in [17,34], i_2 \in [38,41]$

Smart greenhouse: If $j \in G_4$, then $m=2 \rightarrow i_1, i_2 \in [17,34]$.

The flowchart for selecting crop i suitable for plot type j in the main loop process is shown in Figure 1.

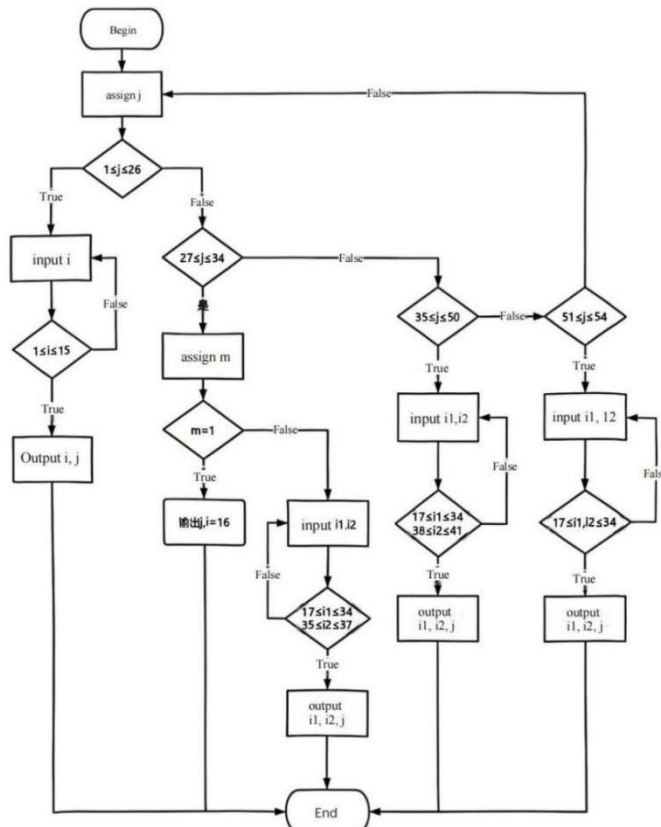


Figure 1 Flowchart for Selecting Crops Suitable for the Plot Type

According to the growth pattern of crops, each crop cannot be continuously planted in the same plot (including greenhouses), otherwise it will reduce the yield. Therefore, for crop i on the j -th plot in the $k+1$ th year:

$$i_{k+1}(j) \neq i_k(j) \quad (3)$$

Since soil containing leguminous crop rhizobia promotes the growth of other crops, starting from 2023, all land in each plot (including greenhouses) must be planted with legumes at least once within three years. By reviewing relevant data and predicting outcomes, the decision to plant legumes in each plot for the following year will determine whether the plot qualifies for mandatory legume cultivation under the "Strong Effectiveness" policy.

At the same time, the planting plan should also consider the convenience of farming operations and field management, so that the planting areas of each crop cannot be too scattered in each season. The planting area of each crop in a single plot (including greenhouses) should not be too small. For the convenience of management, it is assumed that the maximum number of different plots that can be planted with the same crop is 5, that is, $N_{ij} \leq \min N_j$. For the planting area of a single plot, the area outside the greenhouse should not be less than 0.1 mu, and the greenhouse should not be less than 0.01 mu. Namely:

$$\begin{cases} s_{ij} \geq \min s'_{ij}, j \in [1, 34] \\ s_{ij} \geq \min s''_{ij}, j \in [35, 41] \end{cases} \quad (4)$$

Introduce variables C_{ij} , P_{ij} , S_{ij} , W_{ij} , which satisfy the relation:

$$W_{ij} = S_{ij}P_{ij} - C_{ij} \quad (5)$$

where the C is the planting cost of planting crop i on the j -th plot, P represents the selling price per unit of planting crop i on the j -th plot, S represents the yield per mu of planting crop i on the j -th plot, and W represents the average profit of planting crop i on the j -th plot.

In order to solve the optimal planting scheme, it is necessary to maximize the efficiency of cultivated land use, that is, to maximize the total profit obtained from the crops planted in 2024 ~ 2030, which is:

$$\text{Max} \left\{ \sum_{k=2024}^{2030} \sum_{i=1}^a \sum_{j=1}^b W_{ij} x_{ij}(k) \right\} \quad (6)$$

The planting area of each crop in a single plot (including greenhouse) should not be too small. For the planting area of a single plot:

$$\begin{cases} s_{ij} \geq \min s'_{ij}, j \in G_1 \cup G_2 \\ s_{ij} \geq \min s''_{ij}, j \in G_3 \cup G_4 \end{cases} \quad (7)$$

where the s represents the planting area of a single plot.

Then, assume that the expected sales volume of wheat and corn will have an increasing trend in the future, with an average annual growth rate between 5% and 10%. The expected sales volume of other crops in the future will change by approximately $\pm 5\%$ compared to 2023. The yield per mu of crops is often affected by climate and other factors, with an annual variation of $\pm 10\%$. Due to market conditions, the average annual cost of crop cultivation increases by about 5%. The sales prices of grain crops are basically stable; The sales prices of vegetable crops have a growing trend, with an average annual increase of about 5%. The sales price of edible mushrooms has remained stable with a slight decrease of about 1% to 5% per year, especially the sales price of morel mushrooms has decreased by 5% per year. It is assumed that no crops planted on a given plot of land in the current year can be planted on the same plot of land in the next year, regardless of the size of the area; The annual planting cost will not be affected by the market, and will fluctuate with the development of science and technology and changes in agricultural policies.

The variation parameter is defined as θ_d , where $d = \{1, 2, \dots, 7\}$. Since the uncertainty of the given variation parameter has a certain randomness, each parameter is determined by random sampling within the range to extract n values and finally determine the average.

$$Q_{i,j,k+1} = (1 + \theta_1)Q_{i,j,k}, \quad i = 6, 7 \quad (8)$$

where the Q is the expected sales volume.

The remaining d variables are shown above, and the ranges of decision variables i and j are clearly defined. Obtained: Objective function:

$$\left\{ \begin{array}{l} x_{ij}(k) \\ \text{Max} W = \text{Max} \left\{ \sum_{k=2024}^{2030} \sum_{i=1}^a \sum_{j=1}^b W_{ij} x_{ij}(k) \right\} \end{array} \right\} \quad (9)$$

Decision variables: i, j

Constraints:

$$\begin{cases}
j \in G_1, & 1 \leq i \leq 15 \\
j \in G_2, & m=1 \Rightarrow i=16 \text{ or } m=2 \Rightarrow i_1 \in [17,34], i_2 \in [35,37] \\
j \in G_3, & m=2 \Rightarrow i_1 \in [17,34], i_2 \in [38,41] \\
j \in G_4, & m=2 \Rightarrow i_1, i_2 \in [17,34] \\
i_{k+1}(j) \neq i_k(j) \\
N_{ij} \leq \min N_{ij} \\
i_{k-1} \text{ or } i_k \text{ or } i_{k+1} \in [1,5] \cup [17,19] \\
s_{ij} \geq \min s'_{ij}, j \in G_1 \cup G_2 \\
s_{ij} \geq \min s''_{ij}, j \in G_3 \cup G_4 \\
Q_{i,j,k+1} = (1 + \theta_1)Q_{i,j,k}, \quad i = 6, 7 \\
Q_{i,j,k+1} = (1 + \theta_2)Q_{i,j,k}, \quad i \neq 6, 7 \\
S_{i,j,k+1} = (1 + \theta_3)S_{i,j,k} \\
C_{i,j,k+1} = (1 + \theta_4)C_{i,j,k} \\
P_{i,j,k+1} = (1 + \theta_5)P_{i,j,k}, \quad i \in [17,37] \\
P_{i,j,k+1} = (1 + \theta_6)C_{i,j,k}, \quad i \in [38,40] \\
P_{i,j,k+1} = (1 + \theta_7)C_{i,j,k}, \quad i = 41
\end{cases} \quad (10)$$

2.2 Cross Elasticity of Demand

In economics, substitutability usually refers to the ability of consumers to choose one product to replace another when faced with multiple products that have similar functions or meet similar needs. And complementarity usually refers to the interdependence of two or more goods or services in consumption, that is, an increase in the consumption of one good or service will lead to a corresponding increase in the consumption of another good or service. There is also a certain correlation between expected sales volume, sales price, and planting cost. Based on the discussion and research, the main research objective is determined to be the impact of price fluctuations and cost changes on sales volume.

Use demand cross elasticity to describe these two concepts.

$$E_{AB} = \frac{\% \Delta Q_B}{\% \Delta P_A} = \frac{\Delta Q_B}{Q_B} \cdot \frac{P_A}{\Delta P_A} \quad (11)$$

Among them, ΔQ_B is the change in demand for product B, and ΔP_A is the change in price for product A.

The selection of data prices still adopts the method of random sampling. Unlike the second question, in this question, after preliminary selection of data, for the same type of product (such as wheat and corn, both of which are grain crops), if there is price fluctuation, for two similar products A and B, there are two situations where their demand cross elasticity values affect each other:

$E_{AB} > 0$, There is substitutability between two crops, and an increase in the price of product A will lead to an increase in demand for product B.

$E_{AB} < 0$, The two crops have a complementary relationship, and a decrease in the price of product B will lead to an increase in demand for product A.

3 RESULTS AND ANALYSIS

The relevant data were searched and analyzed to obtain the results. The data selected in this paper included 41 kinds of common crops. Data sources: https://www.mcm.edu.cn/html_cn/node/a0c1fb5c31d43551f08cd8ad16870444.html

To evaluate the correlation between expected sales volume, yield per mu, planting cost, and sales unit price, we can calculate the correlation matrix between these four factors to preliminarily determine the correlation. By using these models to evaluate the different influencing factors of crop planting economic benefits, data support can be provided for optimal planting strategies.

The heat map of the correlation matrix is shown in Figure 2.

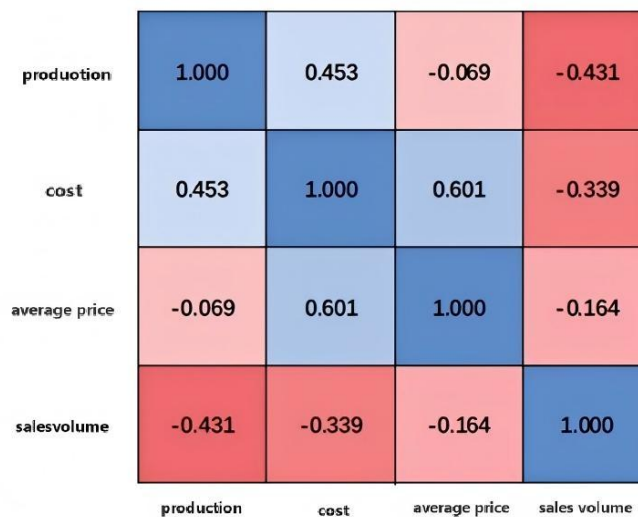


Figure 2 Heat Map of Correlation Matrix between Various Indicators

From the Figure 2, it is clear that price fluctuations and cost changes are negatively correlated with sales volume. By establishing a multiple regression equation to describe the specific correlation between the above variables, the polynomial regression curve of price fluctuation and cost change with sales volume is shown in Figure 3.

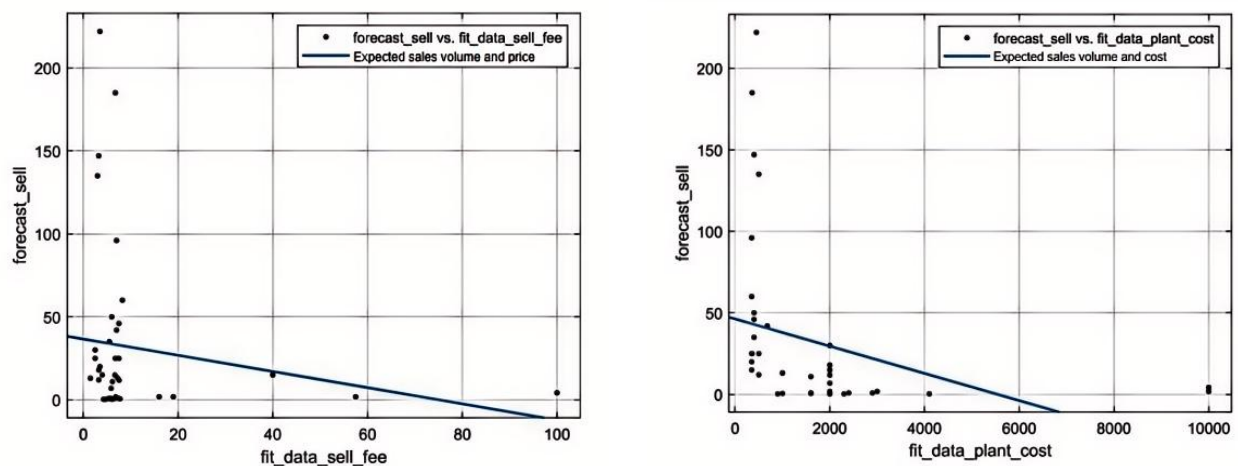


Figure 3 Polynomial Regression Curve

The exponential regression curve of price fluctuation and cost with sales volume is shown in Figure 4.

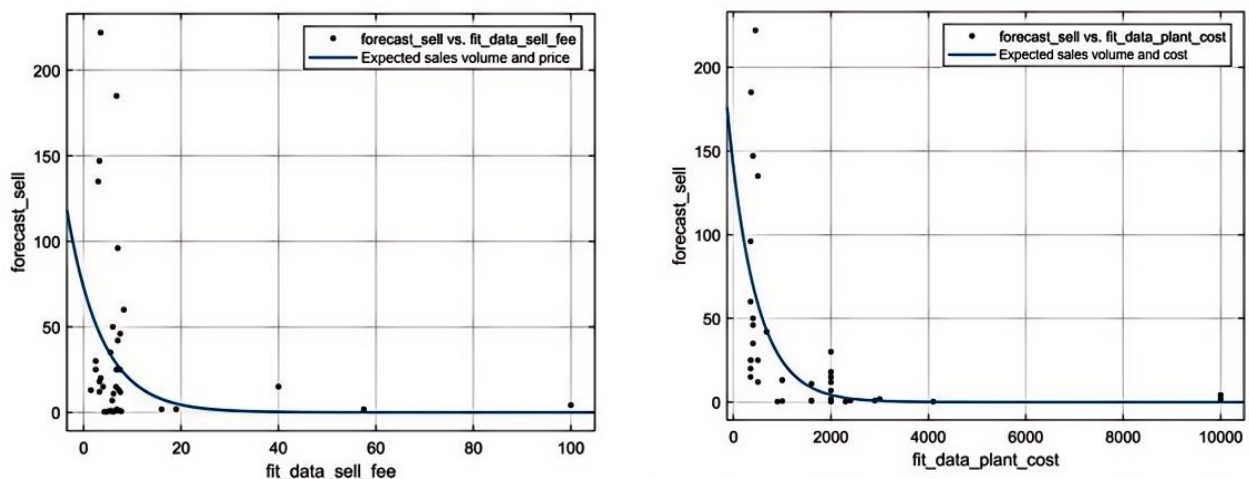


Figure 4 Exponential Regression Curve

Regression fitting is performed on the above variables, and the exponential regression curve has a better fitting effect, satisfying the above relationship when making decisions on product prices, costs, and sales volume. On the basis of satisfying the substitutability and correlation mentioned above, solve the model.

In the previous assumption, the location of when to plant legumes on a certain plot has already been determined. Therefore, based on this, the Monte Carlo simulation algorithm is used to traverse and determine the crop i and its planting area s on plot j . Through this method, a large number of results are randomly sampled and compared to select the optimal solution as the initial value.

The total profit obtained by solving under the above constraints is 3.4351×10^7 . From practical life experience, when the price of a crop increases, its sales volume in the market will decrease. Compared to traditional farming methods, it enhances the efficiency of farmland utilization. Simultaneously, it integrates organic farming standards into the model, maintains soil health through legume crop rotation, balances short-term economic benefits with long-term ecological sustainability, and effectively mitigates planting risks posed by climate fluctuations, market price variations, and other factors. At the same time, the sales volume of products that are replaceable with it will increase, resulting in a decrease in the expected sales volume of the product in the following year. The expected sales volume of alternative products will increase, leading to a decrease in the total output of the agricultural product and an increase in the total output of alternative products. When the total output decreases to a specific value, its market sales price will increase, and the market sales price of alternative products will decrease. This will once again lead to a decrease in the total output of alternative products in the following year ... From this cycle, the total annual profit will eventually stabilize, but due to social and economic development, inflation, and other factors, the total annual profit will gradually increase, but the fluctuation is not significant.

4 CONCLUSIONS AND OUTLOOKS

The article takes the climatic characteristics of North China as an example to explore the application of dynamic programming models in the utilization strategy of farmland resources for the organic farming industry. Specifically, the strategy can be implemented by optimizing crop rotation structure and crop configuration, constructing a dynamic risk response mechanism, promoting facility upgrades and technology integration, and strengthening policy guidance and market collaboration. To improve the planning effectiveness of the algorithm, comprehensive constraints are imposed on various aspects. Subsequently, based on the actual situation of rural areas, limited farmland resources can be fully utilized to develop the organic farming industry according to local conditions, which has important practical significance for the sustainable development of rural economy. Through the systematic integration of the above strategies, optimal planting strategies that are tailored to the actual situation of North China can be formulated, effectively improving production efficiency and reducing planting risks that may be caused by various uncertainties. This provides a theoretical basis for promoting agricultural economic development, improving farmers' living standards, and promoting the construction of beautiful villages.

In terms of improvement, a more concise solution method can be adopted to shorten computation time, while also requiring the satisfaction of more and more realistic constraints to enhance the practicality of the model. This provides a theoretical basis for promoting agricultural economic development, improving farmers' quality of life, and facilitating the construction of beautiful villages.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

- [1] Huang L, Feng Y, Zhang B, et al. Spatio-temporal characteristics and obstacle factors of cultivated land resources security. *Sustainability*, 2021, 13(15): 8498.
- [2] Li D, Yang Y, Du G, et al. Understanding the contradiction between rural poverty and rich cultivated land resources: A case study of Heilongjiang Province in Northeast China. *Land Use Policy*, 2021, 108: 105673.
- [3] Zhu Y, Zhang Y, Ma L, et al. Simulating the dynamics of cultivated land use in the farming regions of China: A social-economic-ecological system perspective. *Journal of Cleaner Production*, 2024, 478: 143907.
- [4] Zhang H, Zhu C, Jiao T, et al. Analysis of the trends and driving factors of cultivated land utilization efficiency in Henan Province from 2000 to 2020. *Land*, 2024, 13(12): 2109.
- [5] Bogale T, Damene S, Seyoum A, et al. Land use land cover change intensity analysis for sustainable natural resources management: The case of northwestern highlands of Ethiopia. *Remote Sensing Applications: Society and Environment*, 2024, 34: 101170.
- [6] Csambalik L, Divéky-Ertsey A, Gál I, et al. Sustainability perspectives of organic farming and plant factory systems—From divergences towards synergies. *Horticulturae*, 2023, 9(8): 895.
- [7] Javed Z, Tripathi G D, Mishra M, et al. Actinomycetes—the microbial machinery for the organic-cycling, plant growth, and sustainable soil health. *Biocatalysis and Agricultural Biotechnology*, 2021, 31: 101893.
- [8] Hafez M, Popov A I, Rashad M. Integrated use of bio-organic fertilizers for enhancing soil fertility—plant nutrition, germination status and initial growth of corn (*Zea mays* L.). *Environmental Technology & Innovation*, 2021, 21: 101329.

- [9] Nath S, Naha A, Saikia K, et al. Degradation of organic pollutants using lignin-derived carbon materials as a sustainable approach to environmental remediation. *Biotechnology for Sustainable Materials*, 2025, 2(1): 11.
- [10] Sani M N H, Yong J W H. Harnessing synergistic biostimulatory processes: A plausible approach for enhanced crop growth and resilience in organic farming. *Biology*, 2021, 11(1): 41.