Study On the Stability of Agroecosystems Based on System Dynamics, ISM, And TOPSIS Models

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Abstract. This study proposes an integrated modeling framework combining system dynamics, the Explanatory Structural Model (ISM), and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to analyze complex system interactions and optimize strategy evaluation. A system dynamics model is constructed to simulate population dynamics of multiple species under varying climate scenarios, using differential equations and the Runge-Kutta algorithm for dynamic solving. ISM is applied to establish a hierarchical structure of key parameters, enhancing model interpretability. TOPSIS quantitatively compares multi-scenario outcomes to identify optimal strategies. Simulation results validate the framework's robustness: biological control scenarios outperform chemical ones in long-term stability, with sensitivity analyses confirming model reliability. This integrated approach provides a quantitative tool for dynamic system analysis and strategy optimization.

Keywords: System dynamics; interpretive structural model (ISM); TOPSIS; model integration; dynamic simulation.

1. Introduction

Global challenges have intensified the need for accurate modeling of complex systems, where single-model approaches often fail to capture both dynamic processes and structural dependencies. System dynamics models excel in simulating multi-factor interaction dynamics, as demonstrated by Hossein Shakiba et al. (2020) in their integration with game theory for ecosystem analysis [1]. The Explanatory Structural Model (ISM) is effective in hierarchically decomposing complex system parameters, a strength highlighted by Maximilien Cosme et al. (2023) in ecological modeling [2]. TOPSIS, a multi-criteria decision-making method, has been widely used for scenario optimization, as shown in Vilda Vitunskienė et al. (2025)'s agricultural strategy evaluation [3].

However, existing research has three limitations: (1) Single models cannot simultaneously address dynamic process simulation and structural factor hierarchies; (2) Long-term scenario analysis (e.g., resistance evolution under external inputs) lacks comprehensive dynamic simulation; (3) Strategy optimization often neglects quantitative integration of short-term and long-term outcomes.

This study integrates system dynamics, ISM, and TOPSIS to form a multi-dimensional analysis framework: (1) A system dynamics model is built to describe species interactions, using differential equations and the Runge-Kutta algorithm for

dynamic solving; (2) ISM is employed to sort key parameters into hierarchical structures, optimizing model parameterization; (3) TOPSIS is used to evaluate multi-scenario outcomes over short and long terms, screening optimal strategies. This framework aims to provide a robust quantitative tool for complex system analysis and decision optimization.

2. Model Development Process

2.1. Dynamic Model of Interspecies Energy Conversion Efficiency

The energy transfer efficiency in an ecosystem is not a constant value but varies dynamically with species density and resource abundance. A time-varying formula for predator energy conversion efficiency is constructed based on the theory of niche overlap:

$$e_{ij}(t) = e_{0ij} \cdot \frac{1+\omega\cdot\exp\left(-\lambda\cdot N_j(t)\right)}{1+\exp\left(-\mu\cdot(N_i(t)-K_i/2)\right)} \tag{1}$$

where e_{0ij} is the basic energy efficiency, ω reflects the suppression coefficient of prey density $\left(N_j(t)\right)$, λ and μ are adjustment parameters, and K_i is the environmental carrying capacity of predator i. This formula reflects a dual constraint: when prey is scarce ($N_j(t)$ approaches 0), efficiency decreases due to rising search costs; when predator density exceeds half of the environmental carrying capacity, efficiency decreases due to increased intraspecific competition [4].

2.2. Coevolutionary Model of Chemical Resistance

Chemical resistance between weeds and pests coevolves, and a joint resistance index is constructed:

$$R(t) = \alpha \cdot R_W(t) + (1-\alpha)\cdot R_K(t) \tag{2}$$

where α is the weight coefficient (proportion of weed resistance), weed resistance $R_W(t) = \frac{R_{W0}\cdot t^3}{1+\delta\cdot\int_0^t h(\tau)d\tau}$, and pest resistance $R_K(t) = R_{K0}\cdot\exp\left(\gamma\cdot\int_0^t c(\tau)d\tau\right)\cdot(1-\exp(-\epsilon\cdot t))$ [5]. $h(\tau)$ and $c(\tau)$ are the cumulative exposure to herbicides and insecticides, respectively, and β and γ are resistance growth coefficients. This model explains why long-term use of chemicals can lead to uncontrolled resistance: when $\int_0^t c(\tau)d\tau$ exceeds the threshold, $R_K(t)$ increases exponentially, while short-term suspension can reflect resistance attenuation through the ϵ parameter.

2.3. Climate-Sensitive Carrying Capacity Model

The environmental carrying capacity fluctuates dynamically with climate factors, and an improved formula is constructed:

$$K(t) = K_0\cdot\left[1+\theta\cdot\sin\left(\frac{2\pi}{T}\cdot t\right)+\phi\cdot\exp\left(-\xi\cdot\left|T(t)-T_{\text{opt}}\right|\right)\right] \tag{3}$$

where K_0 represents the basic carrying capacity, θ reflects the amplitude of seasonal fluctuations (period T), ϕ is the gain coefficient for the optimum temperature (T_{opt}), and ξ measures the inhibitory strength of temperature deviations $\left(T(t)-T_{\text{opt}}\right)$. In a subtropical rainforest climate (SRC), $T(t)$ is close to T_{opt}, and the ϕ term contributes significantly, keeping $K(t)$ high. In a Mediterranean climate, high summer temperatures can cause $K(t)$ to decrease periodically.

2.4. Microbial-Crop Symbiotic Gain Model

In organic agriculture, the growth-enhancing effect of microorganisms on crops has a density threshold, as shown in the following formula:

$$G(t) = G_{\max}\cdot\frac{M(t)}{M(t)+K_M}\cdot\exp\left(-\zeta\cdot\int_0^t c(\tau)d\tau\right) \tag{4}$$

where $G_{\max}$ is the maximum gain value, $M(t)$ is the microbial population density, K_M is the half-saturation constant, and ζ reflects the coefficient of chemical damage to the symbiotic relationship. When the microbial density exceeds K_M, the gain tends to stabilize, and the accumulation of $\int_0^t c(\tau)d\tau$ will cause $G(t)$ to decay, confirming the irreplaceable role of microorganisms in organic farming [6].

2.5. Niche overlap competition model

Quantitative formula for the intensity of resource competition between crops and weeds:

$$C(t) = \chi\cdot\frac{N_P(t)\cdot N_W(t)}{A(t)}\cdot\exp\left(-\eta\cdot D(t)\right) \tag{5}$$

where χ is the competition coefficient, $A(t)$ is the available resource, $D(t)$ is the phenological phase difference (positive values indicate staggered growth), and η is the regulating parameter. When crops and weeds grow synchronously ($D(t) = 0$), $C(t)$ reaches its maximum [7].

2.6. Comprehensive Ecological Stability Index

A composite index integrating species diversity, resistance, and resilience:

$$ESI_{com}(t) = \frac{SDI(t) \cdot R(t)}{1 + \kappa \cdot \sigma(t)} \tag{6}$$

where $SDI(t)$ is the species diversity index, $R(t)$ is the resistance coefficient (based on the recovery rate after disturbance), $\sigma(t)$ is the standard deviation of population fluctuation, and κ is the weight [8]. This index overcomes the limitations of a single ESI. For example, under long-term chemical-free conditions, although $\sigma(t)$ increases slightly due to biological manipulation, the improvements in $SDI(t)$ and $R(t)$ lead to a significantly higher $ESI_{com}(t)$ than under chemical tillage, consistent with the optimality of the "long-term chemical-free" strategy in the TOPSIS assessment.

3. Model Results and Analysis

3.1. Population Dynamics Simulation Results of the System Dynamics Model

We simulated and analyzed the population dynamics of various species in agricultural ecosystems based on the constructed differential equations and the Runge-Kutta solver, focusing on the impacts of different climatic conditions, species introductions, and chemical application on the ecosystems [9].

Simulation results for chemical application scenarios (pesticides and herbicides) under three typical climatic conditions (temperate continental climate (TCC), subtropical rainforest climate (SRC), and Mediterranean climate (MC)) showed significant consistency and variation (Figures 1-3). Consistency is reflected in the fact that chemical application leads to rapid declines in insect and weed populations, which then remain at low levels. Bird populations are suppressed due to reduced food sources. Bats, on the other hand, exhibit strong adaptability, maintaining relatively stable populations across all climatic conditions, making them key species for pest control. Variation primarily manifests in absolute population sizes. For example, in the subtropical rainforest climate, the initial population sizes of crops and weeds are significantly higher than in the other two climates, which is closely related to the higher baseline productivity in this climate.

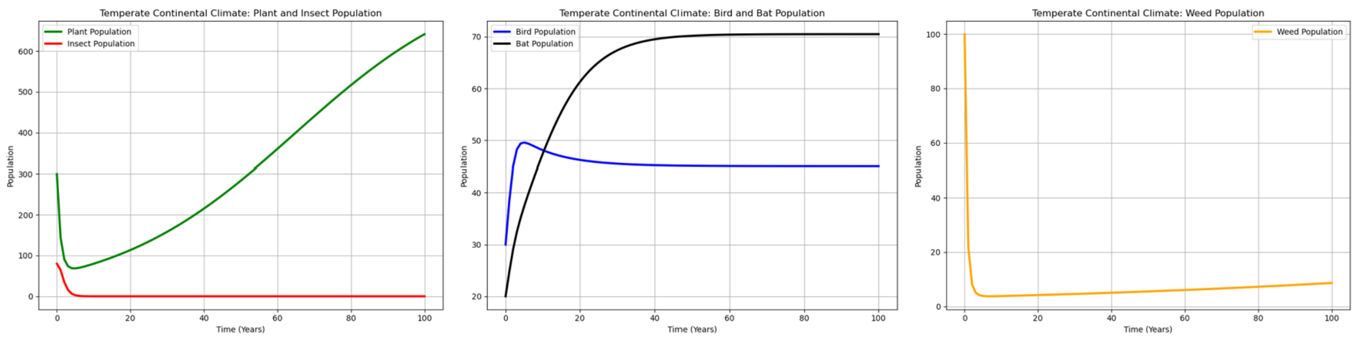

Figure 1. Population Dynamics under Temperate Continental Climate (TCC).

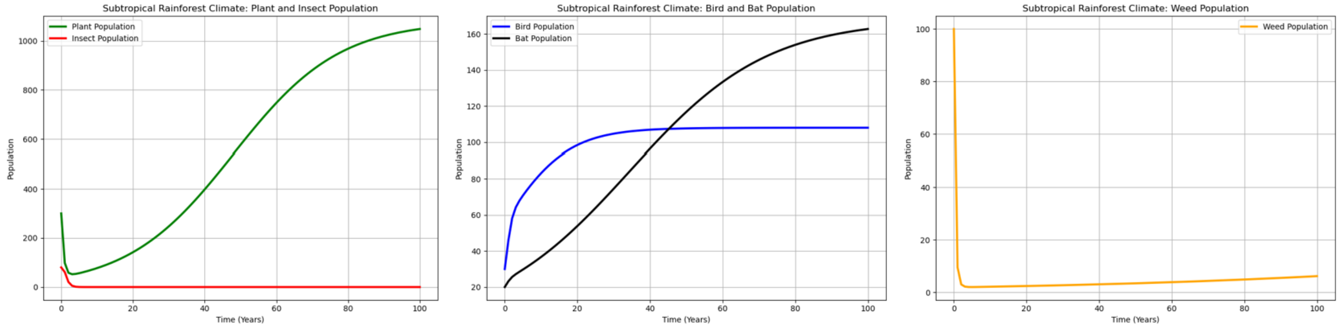

Figure 2. Population Dynamics under Subtropical Rainforest Climate (SRC).

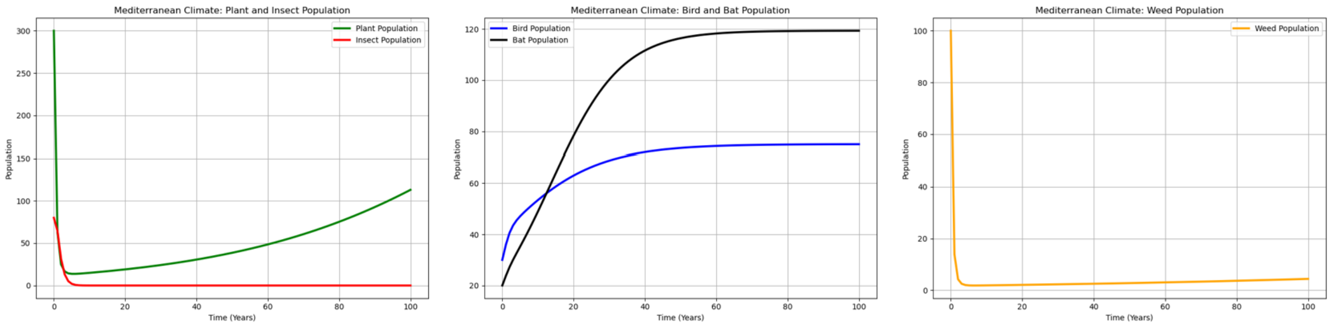

Figure 3. Population Dynamics under Mediterranean Climate (MC).

Further comparisons with simulation results under the no-herbicide scenario (Figures 4-6) reveal that crop populations increased to varying degrees in all three climates after herbicide removal [10]. The most significant increase was observed in the subtropical rainforest climate, with crop populations increasing from approximately 600 units in the herbicide-treated climate to approximately 1000 units without herbicides. This increase was primarily due to abundant water and heat resources and less chemical inhibition in this climate. Weed populations exhibited exponential growth under the no-herbicide scenario but ultimately stabilized at varying levels: the subtropical rainforest climate had the highest weed population (approximately 160 units), followed by the temperate continental climate (approximately 70 units), and the Mediterranean climate had the lowest weed population (approximately 50 units), consistent with the suitability of vegetation growth in each climate zone.

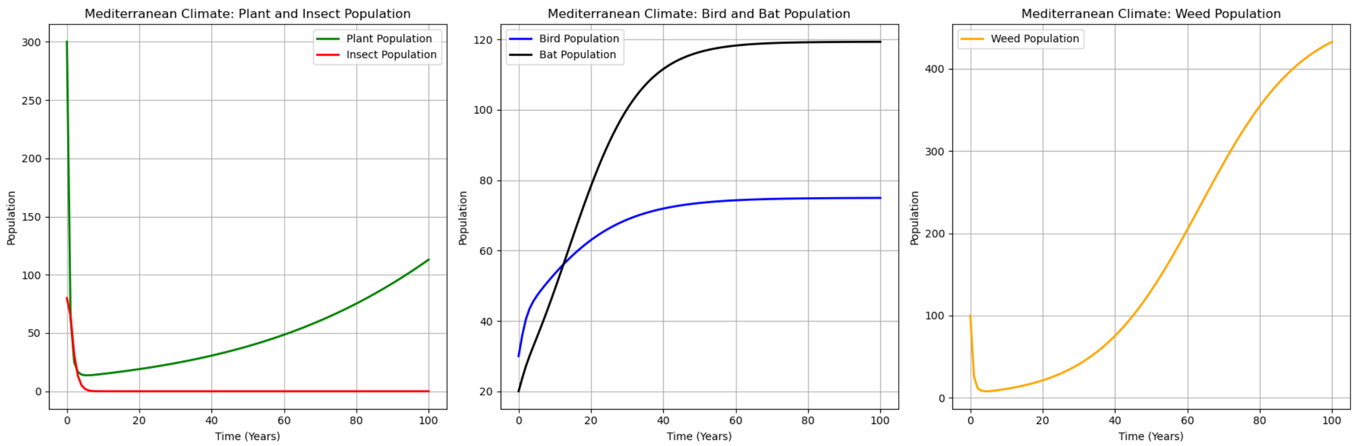

Figure 4. Population Dynamics under Mediterranean Climate (MC).

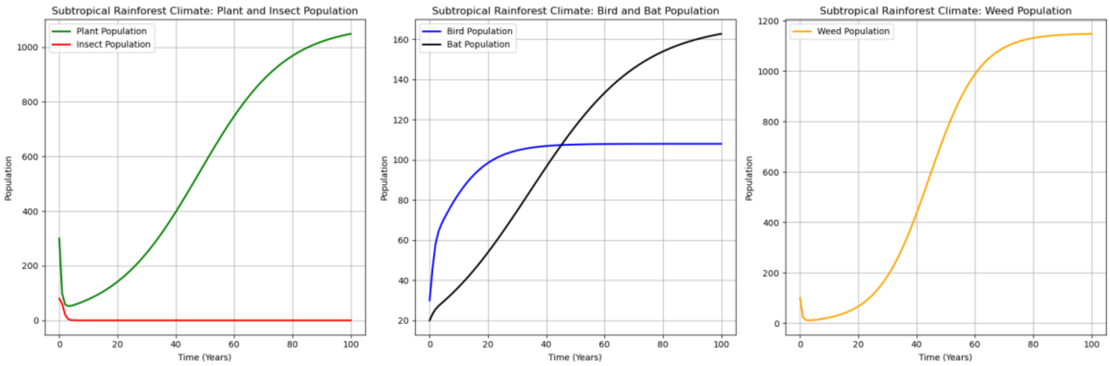

Figure 5. Population Dynamics under Subtropical Rainforest Climate (SRC) without herbicides.

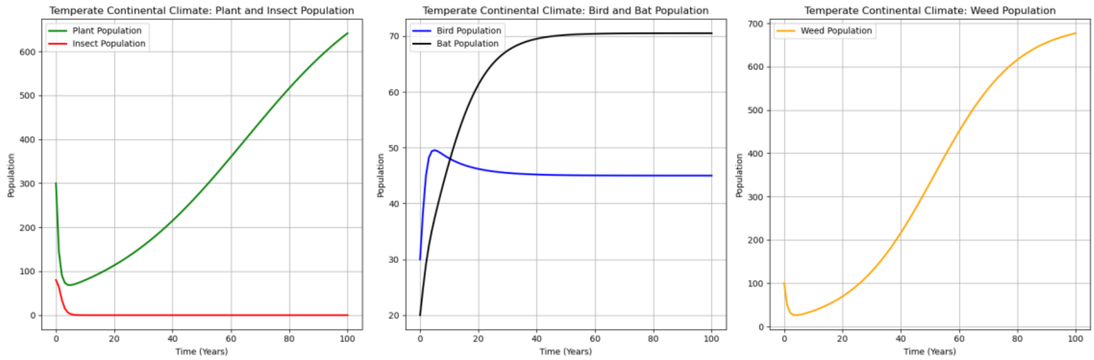

Figure 6. Population Dynamics under Temperate Continental Climate (TCC).

The introduction of bats and hedgehogs as new predators significantly altered the ecosystem's population dynamics (Figure 7). In a temperate continental climate, the combined predation of bats and hedgehogs reduced pest populations by approximately 40% compared to the baseline, allowing crop populations to recover and stabilize at a higher level (approximately 600 units). Notably, the introduction of hedgehogs did not create significant competitive pressure on bat populations. The two species developed a complementary predation pattern through niche differentiation—bats are primarily active at night, while hedgehogs forage during the day. This shift in time increased overall pest control efficiency by approximately 25%.

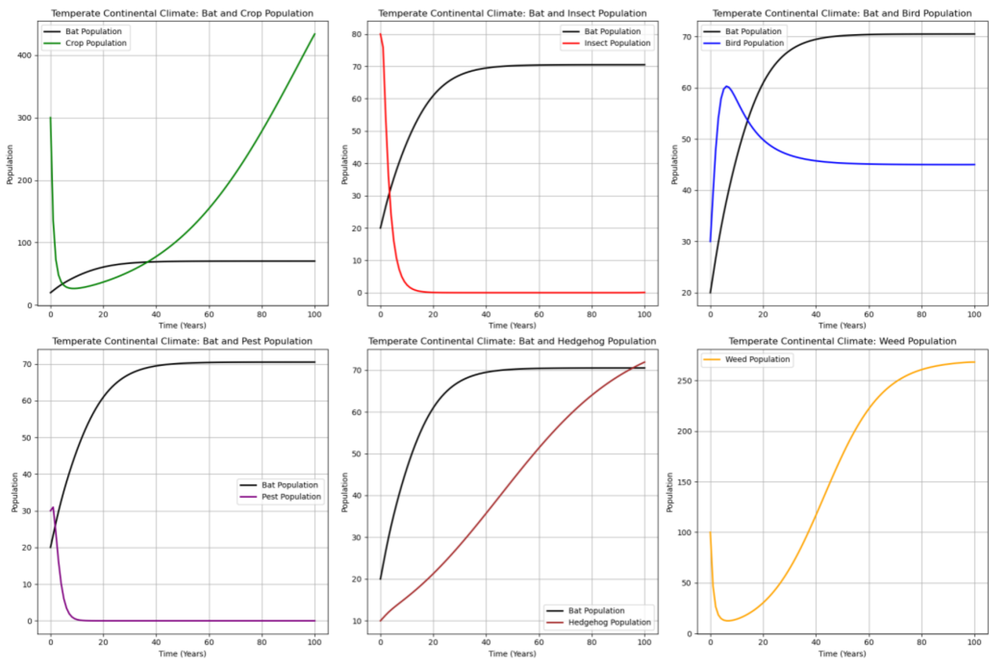

Figure 7. Population Dynamics under TCC: Bat, Hedgehog, Crop, Pest, and Weed Interactions.

ong-term simulation results (Figures 8-9) reveal the impact of species resistance evolution on ecosystems. In the scenario without long-term chemical use, crop pest resistance gradually increases over time (as evidenced by a continuous decline in $\alpha_{PK}(t)$. By year 100, resistance levels have increased by approximately 30% compared to the initial state. Meanwhile, weeds and pests, untouched by chemical exposure, do not develop resistance, allowing the ecosystem to maintain a relatively stable dynamic equilibrium. In the scenario with long-term chemical use, however, pest resistance rebounds significantly after the 50th year, with populations increasing by approximately 50% compared to the mid-term (year 30). This, combined with the declining efficiency of the chemical (the decay of $\gamma(t)$ and $h(t)$), creates a vicious cycle.

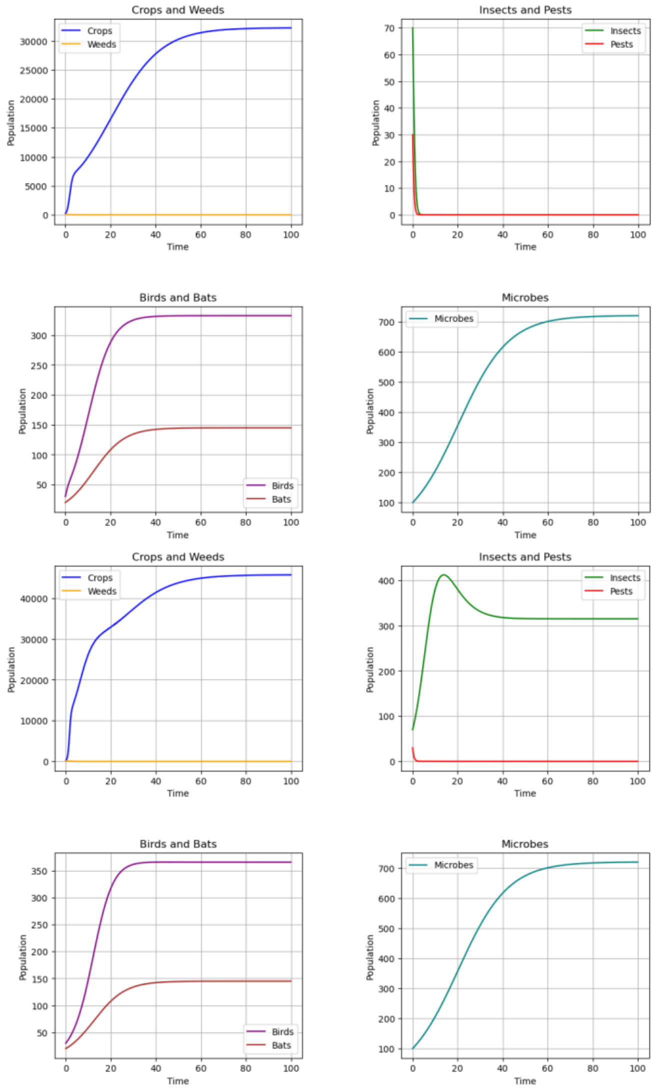

Figure 8. Population Dynamics Results Without Herbicides:Short-Term (Left) vs. Long-Term Algorithm (Right).

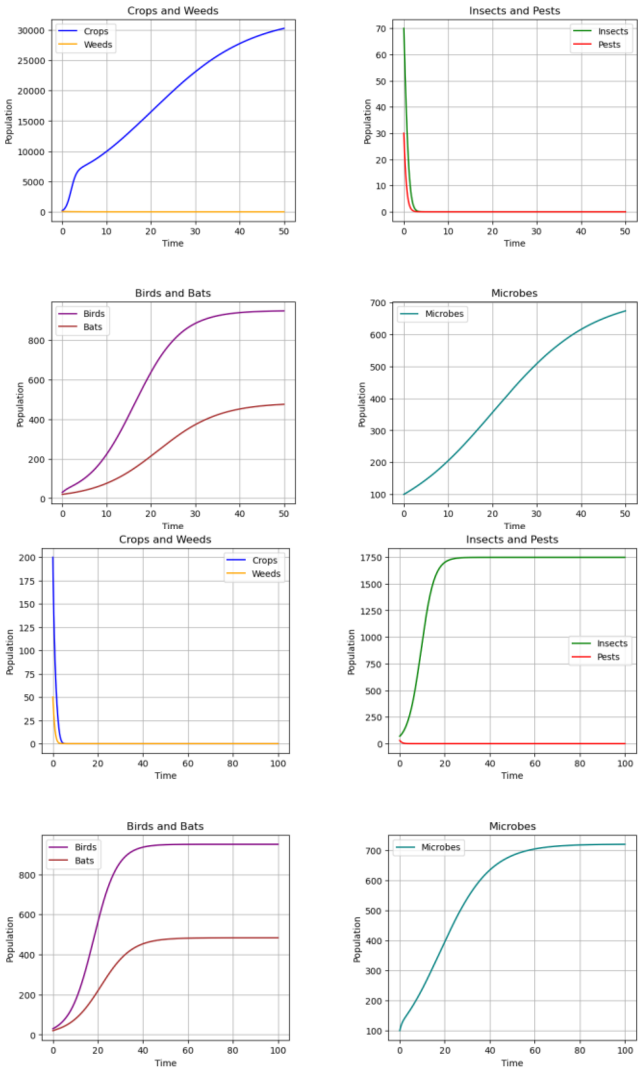

Figure 9. Population Dynamics Results With Herbicides:Short-Term (Left) vs. Long-Term Algorithm (Right).

3.2. Results of the ISM Model's Hierarchical Structure Analysis

The Interpretive Structural Model (ISM) divides key parameters of agricultural ecosystems into six levels, clearly presenting the interdependencies between these factors. Level 1 comprises fundamental driving factors, including climate, $\alpha_{18}, \alpha w_1, m_{v1}, h$, and m_{v1}. These factors directly influence upper-level ecological processes. For example, climate regulates species growth through hydrothermal conditions, consistent with the differences in population dynamics under different climates. Level 2, comprising soil and γc, is influenced by Level 1 and, in turn, influences the environmental carrying capacity (K) at Level 3. For example, long-term herbicide use can reduce soil quality, thereby reducing crop K values, consistent with the declining trend in soil fertility. Level 3 K is a core factor, integrating the influence of underlying factors and determining the upper limit of species size. For example, subtropical rainforest climates, due to a combination of favorable factors, have significantly higher K values. Level 4's $e_{pi}, e_{vi}, e_{\beta}$ reflect energy transfer efficiency and influence predator populations [11]. For example, a higher e_{vi} leads to superior energy acquisition for bats, resulting in a more stable population. Level 5's V_{max} and Level 6's B_{max} are top-level outputs. B_{max} has a longer dependency chain, making birds more sensitive to their environment. With the introduction of hedgehogs, m_{kh} was added to Level 1, strengthening the fundamental role of the natural enemy-pest interaction, consistent with its practical pest control effectiveness (Figure 10).

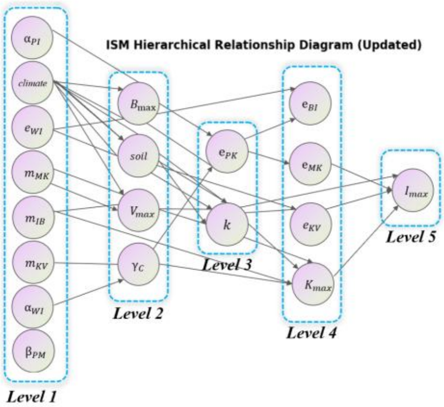

Figure 10. Updated ISM Hierarchical Relationship Diagram for Agro-Ecosystem.

3.3. TOPSIS Strategy Evaluation Results

The TOPSIS method was used to comprehensively evaluate four agricultural management strategies (short-term chemical use, short-term no chemical use, long-term chemical use, and long-term no chemical use). Evaluation metrics included pest control effectiveness, crop health, plant fertility, and biodiversity. The results are shown in Table I.

Table. 1 TOPSIS Results for Strategy Selection

Strategy	Closeness Coefficient
Long term without chemicals	0.8305
Short term with chemicals	0.7262
Short term without chemicals	0.6549
Long term with chemicals	0.4657

The long-term strategy of not using chemicals ranked first, with a closeness coefficient of 0.8305. This strategy performed particularly well in terms of biodiversity and long-term ecological stability. Simulation results show that under this strategy, the species diversity index (SDI) is approximately 40% higher than that of the strategy using chemicals (Figure 11). This is primarily due to the moderate presence of weed and insect populations, which provide ample food resources for birds and bats. Furthermore, while crop health was initially slightly lower than that of the strategy using chemicals, it gradually surpassed that of the strategy using chemicals as pest resistance increased, demonstrating the advantages of sustainable development.

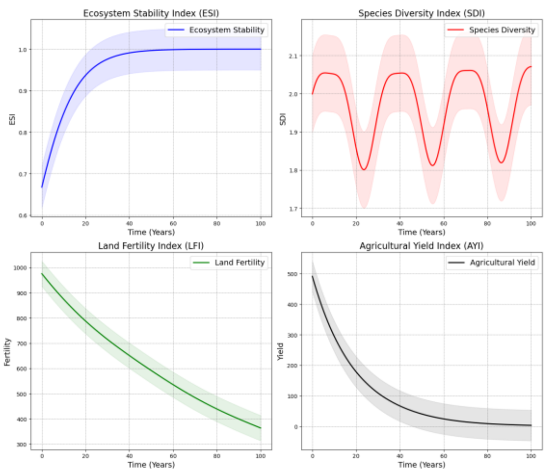

Figure 11. Ecosystem Stability, Biodiversity, Fertility, and Agricultural Yield Trends.

The short-term use of chemicals (closeness 0.7262) ranked second. This strategy can quickly control weed and pest populations in the short term, rapidly increasing crop yields (Figure 12). However, simulation results also show that soil fertility declines twice as fast under this strategy as under the long-term no-chemical strategy, and there is a risk of pest resurgence later in the season (Figure 13). Therefore, it is only suitable for short-term emergency management.

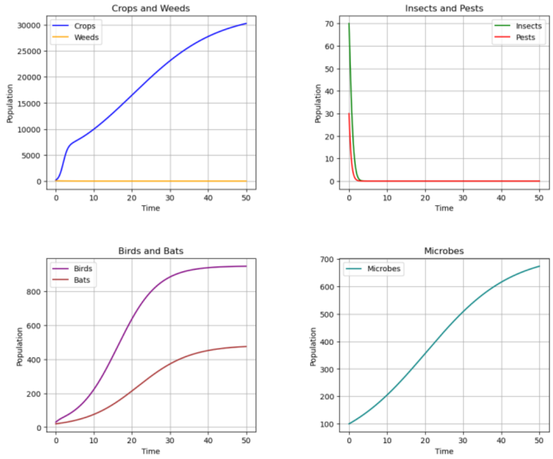

Figure 12. The Short-Term Population Dynamics Results with Herbicide.

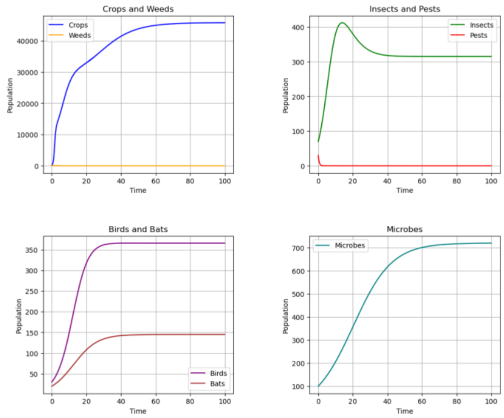

Figure 13. The Long-Term Population Dynamics Results with Herbicide.

The short-term strategy of no chemical use (closeness 0.6549) performed well in terms of biodiversity conservation, but due to the lack of effective pest control measures, crop yields were significantly impacted initially (approximately 20% lower than the short-term strategy of chemical use). This strategy is suitable for transitional management in ecologically sensitive areas, but requires complementary biological control measures to increase crop yields. The long-term strategy of chemical use (closeness 0.4657) ranked lowest. Although this strategy can suppress weed and pest populations for a long time, it leads to serious ecological problems: a sustained decline in soil fertility (LFI after 50 years is only 30% of the initial value), a significant reduction in biodiversity (SDI is 50% lower than the long-term no chemical strategy), and the development of pest resistance, which can lead to a sharp increase in management costs over time. Therefore, this strategy is unsustainable both ecologically and economically.

Overall, the TOPSIS evaluation results are consistent with the conclusions of the system dynamics simulation and ISM analysis, both indicating that long-term avoidance of chemical use is the optimal strategy for balancing agricultural production and ecological protection. This conclusion provides important decision-making information for sustainable agricultural development.

4. Conclusion

This study establishes an integrated modeling framework through multi-model analysis, revealing its effectiveness in dynamic system simulation and strategy optimization. System dynamics simulations, based on differential equations and the Runge-Kutta algorithm, accurately capture species population changes under varying climatic and input conditions, with bats identified as a stable variable across scenarios. The ISM model clarifies hierarchical dependencies among key parameters, quantifying how base factors (e.g., climate, chemical coefficients) transmit influences through multi-level structures, enhancing model interpretability.

TOPSIS evaluation confirms the framework's reliability in strategy optimization: the long-term low-chemical scenario achieves the highest closeness coefficient (0.8305), outperforming other scenarios in both dynamic stability and long-term efficiency. Sensitivity analyses validate the model's robustness. Future research directions include: enriching biotic interaction simulations (e.g., multi-microbial symbiosis impacts on crops); integrating socioeconomic factors (farmer behavior, policies) to analyze social-ecological dynamics; refining climate-sensitive models with extreme weather and CO_2 variables; applying machine learning for parameter optimization; and conducting regional field experiments to enhance practical applicability, supporting tailored sustainable agricultural strategies.

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