A Multi-Scale ABM-SD Coupled Framework for Sustainable Agricultural Ecosystem Management: Modeling Bee Pollination and Invasive Ragweed Interactions

Xiaoyu Ao*, Shisun Qiu, Jiasen Cheng, Zhongmingyue Sun

College of Big Data and Information Engineering, Guizhou University, Guiyang, China, 550025

* Corresponding Author Email: Aoxiaoyu1028@163.com

Abstract. This study addresses the challenges of multi-scale interactions within agricultural ecosystems by developing a coupled Agent-Based Modeling (ABM) and System Dynamics (SD) framework. The framework aims to elucidate the dynamic interplay between micro-level behaviors and macro-level feedbacks, providing support for precision management. ABM quantifies individual decision-making and simulates biological interactions, while SD reveals the regulatory effects of agricultural interventions. A dynamic interface is designed to enable the flow of micro-level data to drive macro-parameter updates. Application validation demonstrates that the framework effectively synergizes yield, biodiversity, and stability, optimizing pesticide application strategies. The research quantifies the resilience effect of habitat maturity and uncovers the eco-economic synergy pathways of agricultural interventions, offering a theoretical reference for sustainable agriculture.

Keywords: Multi-Scale Modeling, Agricultural Ecosystem, Precision Management, Eco-Economic Synergy

1. Introduction

Agricultural ecosystems are complex, multi-scale systems shaped by interacting micro-level behaviors and macro-level feedbacks. Conventional agriculture, while increasing yields, often degrades soil and ecological functions, revealing limitations in single-dimensional management [1-2].

Current research struggles to capture feedback between micro-scale degradation and macro-scale succession, as well as key species interactions [3]. Thus, cross-scale modeling frameworks integrating individual behaviors and environmental feedbacks are urgently needed for sustainable management [4]. Agent-Based Modeling (ABM) and System Dynamics (SD) offer complementary tools. ABM simulates heterogeneity and its impact, while SD analyzes system dynamics. However, ABM lacks macro-feedback, and SD lacks micro-behavior detail. Cross-scale simulation quantifying agricultural impacts on food chains remains largely unexplored.

To address these challenges, this study offers innovative solutions:

(1) Methodological Level: An ABM-SD framework overcomes uni-directional analysis via bidirectional feedback between micro-behaviors and macro-feedbacks. ABM incorporates heterogeneity, while SD quantifies agricultural effects, forming a "micro-driven, macro-constrained" paradigm.

(2) Applicational Level: Multi-scale simulation reveals edge habitat restoration mechanisms. Restored habitats reduce pesticide risk and suppress invasive competition, sheltering crops. The model shows habitat maturity's non-linear gain on system stability.

(3) Strategic Level: A dynamic pesticide management model addresses ecological/production trade-offs. Optimized via yield, biodiversity, and residue constraints, it increases benefits and stability, achieving suppression through targeted application.

2. ABM-SD Coupled Dynamic Food Chain Model

We developed an ABM-SD coupled model to dissect multi-scale interactions in agricultural ecosystems. The ABM module focuses on individual heterogeneous behaviors driving population dynamics, while the SD module quantifies agricultural practices regulating macro-variables like soil quality and pesticide concentration. A dynamic data interface achieves real-time bidirectional feedback between ABM micro-simulation and SD macro-parameters [5], forming an adaptive closed-loop system to capture non-linear coupling. The model framework is shown in Figure 1. This dynamic model simulates interactions between micro-behaviors and macro-variables using seasonal cycles and feedback. The ABM meticulously characterizes micro-behaviors, and the SD regulates macro-dynamics, comprehensively simulating the agricultural ecosystem. The datasets employed in this modeling framework were primarily obtained from the National Earth System Science Data Center (http://www.geodata.cn), an authoritative platform integrating multi-domain agricultural and ecological datasets.

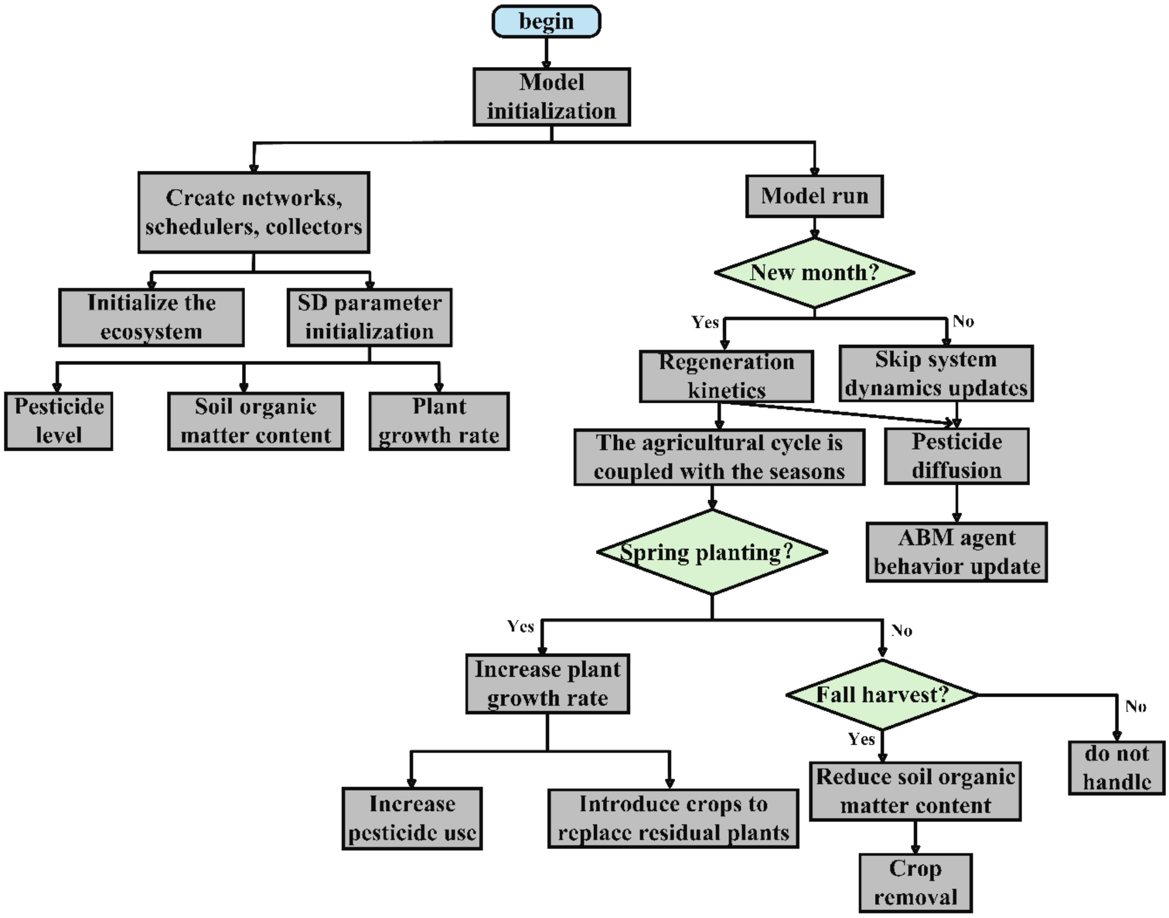

Figure 1. Theoretical Framework of the Model

The initialization phase of the model lays the foundation for subsequent dynamic processes. First, a spatial grid network is constructed to define spatial interaction relationships between agents, capturing neighborhood effects and resource competition characteristics [6]. Concurrently, a time scheduler is configured with a daily time step, arranging event triggering sequences on a monthly cycle to ensure orderly simulation progress. A data collector is also initialized during this phase to track key variables in real-time, providing data support for analysis. In setting ecosystem parameters, initial values of pesticide concentration are determined based on agricultural practice data, and initial values of soil organic matter content are estimated based on soil type and historical land use. Initial values of plant growth rates are determined by crop type and environmental conditions. The initial biomass of plant agents is set to a low value, simulating the natural state before planting; the initial density and location of pest agents are randomly distributed over the spatial grid or set based on field data. To support macro-level regulation by the SD module, a seasonal timetable is defined, and environmental variables are introduced to regulate plant growth and soil nutrient cycling. Specific parameter initializations include: initial pesticide concentration $C_p(0) = C_{p0}$, initial soil organic matter content $Q(0)=Q_0$, initial plant growth rate $r=r_0$, initial biomass of plant agents $P_i(0)=P_0$, and initial density and location of pest agents $C_{1,j}(0),\quad x_j(0)$.

The model iterates daily, updating SD macro-variables monthly. Each month, the ecosystem state is updated, with soil organic matter and pesticide dynamics described mathematically. Seasonal adjustments follow the agricultural cycle: spring sees increased plant growth/pesticide application, updating plant agent biomass based on resource limits and predation. Off-season, residual plants are replaced, and biomass is reset. Between monthly updates, ABM operations execute, simulating pesticide diffusion, plant biomass, and pest dynamics via equations. Autumn harvest reduces soil organic matter and adjusts plant biomass, modeling harvest effects. Specific dynamic equations include: Soil Organic Matter Dynamics:

$$\frac{dQ}{dt}=I_Q-\delta Q \tag{1}$$

where I_Q represents organic matter input (in kg/ha/month), and δ is the natural decay rate, with a value of 0.02 month^{-1}. Soil quality dynamics, specifically organic matter and nutrient levels, were parameterized based on the methods described in 'The role of soil organic matter in sustaining soil fertility' [7].

Pesticide Concentration Dynamics:

$$\frac{dC_p}{dt}=-kC_p \tag{2}$$

where k is the pesticide degradation rate, with a value of 0.05 day^{-1}. Pesticide concentration dynamics were parameterized using degradation rates and transport coefficients from the PRZM model [8].

Adjustment of Plant Growth Rate during Spring Planting Season:

$$r=r_{planting} \tag{3}$$

adjusted from 0.05 day^{-1} to 0.1 day^{-1}.

Increase of Pesticide Application Rate during Spring Planting Season:

$$C_p=C_p+\Delta C_p \tag{4}$$

where ΔC_p is 0.5 kg/ha.

Plant Agent Biomass Dynamics:

$$\frac{dP_i}{dt}=r_iP_i\left(1-\frac{P_i}{K_i}\right)-\beta_jC_{1,j}P_i \tag{5}$$

where P_i is the biomass of the i-th plant agent, K_i is the local carrying capacity, β_j is the pest predation efficiency (0.02 ha/individual/day), and $C_{1,j}$ is the pest density. Plant biomass dynamics, including growth rates, were parameterized using a crop growth model, informed by the plant-pest interaction approach developed by Zaffaroni et al. [9].

Resetting of Plant Biomass during Non-Planting Season:

$$P_i=P_{new} \tag{6}$$

with a value of 50 kg/ha.

Pesticide Spatial Diffusion:

$$\frac{\partial C_p}{\partial t}=D\nabla^2C_p \tag{7}$$

where D is the diffusion coefficient (0.01 m²/day), and ∇^2 represents the spatial second derivative.

Pest Agent Population Dynamics:

$$\frac{dC_{1,j}}{dt} = -\gamma_j C_{1,j} + \eta_j \beta_j C_{1,j} P_{local} - \mu_j C_p C_{1,j} \tag{8}$$

where γ_j is the natural mortality rate (0.03 day^{-1}), η_j is the conversion efficiency (0.1), P_{local} is the local plant biomass, and μ_j is the pesticide mortality rate (0.05 ha/kg). Pest population dynamics, including reproduction and mortality rates, were parameterized with reference to the ecological principles outlined by Putman and Wratten [10] and further informed by the modeling approaches in 'Coupled Information Diffusion–Pest Dynamics Models' [11].

Pest Movement Behavior:

$$x_j(t+1) = x_j(t) + v_j \tag{9}$$

where $v_j = \alpha \nabla P_{local}$, α is 0.1 m/day.

Decrease of Soil Organic Matter during Autumn Harvest Season:

$$Q = Q - \Delta Q \tag{10}$$

where ΔQ is 10% of Q.

Adjustment of Plant Biomass during Autumn Harvest Season:

$$P_i = P_{post\text{-}harvest} \tag{11}$$

with a value of 5 kg/ha.

Harvesting Process:

$$P_i(t^+) = P_i(t^-) \cdot (1 - H) \tag{12}$$

where H is 0.9.

The ABM and SD modules achieve data interaction through dynamic coupling mechanisms, ensuring the co-evolution of micro and macro levels. Micro-data generated by the ABM module is fed back to the SD module, influencing the updating of soil organic matter input and pesticide concentration; macro-variables of the SD module, in turn, regulate ABM agent behaviors, forming a two-way interaction. This mechanism enhances the model's ability to simulate complex dynamics. The formulas used are based on ecological and environmental science theories, ensuring scientific validity and verifiability.

Through the above design, the modeling process clearly reflects the interaction logic of micro-level behaviors and macro-level dynamics in the agricultural ecosystem. From initialization to execution, the model integrates spatial grids, time scheduling, agent behaviors, and system feedbacks. Incorporating agricultural cycle characteristics, it comprehensively simulates plant growth, pest dynamics, pesticide diffusion, and soil quality evolution processes. The integration of ABM and SD achieves multi-scale synergy through detailed micro-equations and macro-level regulation, laying the foundation for parameter analysis and agricultural practice optimization.

3. Expanding the Model: Dynamic Interactions between Native and Invasive Species

Building upon the ABM-SD coupled framework constructed in the previous section, this study further incorporates the dynamic interactions between the Western honeybee (Apis mellifera) and the invasive species common ragweed (Ambrosia artemisiifolia) into a unified modeling system. By deepening the bidirectional coupling mechanism between agent attributes and system dynamics variables, a cross-species, cross-scale co-evolution model is established, achieving closed-loop feedback from micro-behavioral decision-making to macro-ecological effects.

In the spatially heterogeneous grid environment, the movement behavior of individual honeybees inherits the grid network initialized in the second part, with their spatial coordinates (x_i, y_i) being dynamically updated. To represent the combined effects of pesticide exposure on bee populations, a function for the decline in individual pollination efficiency is introduced: $\omega_{B,i}(t) = \omega_{B0} \cdot e^{-\gamma_C C_{local}(x_i, y_i, t)}$. In this function, the local pesticide concentration C_{local} is obtained by reading the global variable $C(t)$ in the SD module in real-time and is calculated based on grid edge correction rules [12]. This design enables the pollination service capacity of honeybees to dynamically respond to changes in agricultural management practices.

The population-scale honeybee density evolution equation is established by aggregating individual agent states:

$$\frac{dA}{dt} = \left[r_A \cdot \frac{1}{N} \sum_{i=1}^{N} \omega_{B,i}(t) \right] A \left(1 - \frac{A}{K_A} \right) - \beta_A \cdot \left(\frac{1}{N} \sum_{i=1}^{N} C_{local}(x_i, y_i, t) \right) A \tag{13}$$

This equation achieves deep coupling between ABM and SD: $\sum \omega_{B,i} / N$ in the first term within the parentheses reflects the group average of individual efficiency, while the spatially averaged concentration $\sum C_{local} / N$ in the second term quantifies the cumulative effects of pesticide exposure. The above cross-scale parameter transfer mechanism inherits and extends the data interface design from the previous section, enabling honeybee population dynamics to respond simultaneously to micro-behavioral heterogeneity and macro-environmental fluctuations.

For the modeling of the invasive species common ragweed, this study extends competition attributes based on the original crop agent class. The spatial diffusion of ragweed follows improved cellular automaton rules, with its diffusion probability D_W being negatively correlated with the soil organic matter content $S_{OM}(t)$ from the SD module ($D_W = D_{W0} \cdot [1 - S_{OM}(t) / S_{\max}]$), a relationship that directly references the output variables of the soil degradation model [13]. The population dynamics equation for ragweed embeds a non-linear competition term into the ABM-SD coupled framework:

$$\frac{dW}{dt} = r_W W \left(1 - \frac{W}{K_W(t)} \right) - \alpha \cdot \frac{W^2}{W^2 + \left[K_W(t) \right]^2} \cdot \left(\frac{1}{M} \sum_{j=1}^{M} p_j(t) \right) \tag{14}$$

where $K_W(t) = K_{W0} \cdot [1 + \eta \cdot S_{OM}(t)]$ represents the regulatory effect of soil conditions on the invasive species, and $\sum p_j / M$ is the mean of gridded crop density statistically derived from the ABM module. The Allee effect term ($\frac{W^2}{W^2 + \left[K_W(t) \right]^2}$) introduced in the equation is dynamically bound to the agricultural planting cycle via the threshold parameter $K_W(t)$, causing the ragweed outbreak period and the crop growing season to form spatiotemporal coupling [14].

Dynamic pesticide management strategies achieve closed-loop optimization by fusing ABM-SD dual-source data in real-time:

$$I_{pesticide}(t) = k_p \left(1 - \frac{Y(t)}{Y_{target}} \right) + k_w \cdot \frac{1}{L} \sum_{l=1}^{L} W_l(t) \tag{15}$$

where the calculation of crop yield $Y(t)$ integrates the contribution of bee pollination ($\sum \omega_{B,i} / N$) from the ABM module and the loss due to ragweed competition ($\sum W_l / L$), while Y_{target} is dynamically corrected by the economic model from the SD module.

The final multi-objective optimization function balances ecological and economic indicators through the entropy method:

$$J(t) = \lambda \cdot Y(t) + (1-\lambda) \cdot \left(-\sum_{k=1}^{K} \frac{N_k(t)}{N_{total}} \ln \frac{N_k(t)}{N_{total}} \right) \tag{16}$$

In this equation, the Shannon diversity index $H'(t)$ directly depends on the number of individuals of each species $N_k(t)$ statistically derived from the ABM, while the calculation of *Y(t)* integrates the yield accumulation model from the SD module. This cross-module indicator fusion mechanism can simultaneously reflect the ecological thresholds of species interactions and the economic constraints of pesticide regulation, providing a quantitative decision-making basis for sustainable agricultural management.

4. Simulation Validation and Results Analysis

4.1. Pareto Frontier Analysis of Eco-Economic Trade-offs

The multi-objective optimization model based on the entropy method reveals the non-linear trade-offs between ecological conservation and agricultural production in agricultural ecosystems. As shown in Figure 2, the simulation results indicate that the synergistic effects of dynamic pesticide application strategies and edge habitat restoration significantly enhance the overall system benefits. When the ecological index (biodiversity conservation) reaches 0.9 and the economic index (agricultural production efficiency) is 0.86, the entropy score of the overall system benefits reaches a peak of 0.77, indicating that this equilibrium point can balance both ecological and economic benefits. Further analysis reveals that the ecological index and the economic index are negatively correlated; however, the non-linear characteristics suggest that by optimizing the spatiotemporal heterogeneity configuration of pesticide dosage and timing, biodiversity can be enhanced without significantly sacrificing yield. This conclusion validates the effectiveness of the dynamic data interface and cross-scale feedback mechanisms in the model, providing theoretical support for the precise regulation of agricultural management strategies.

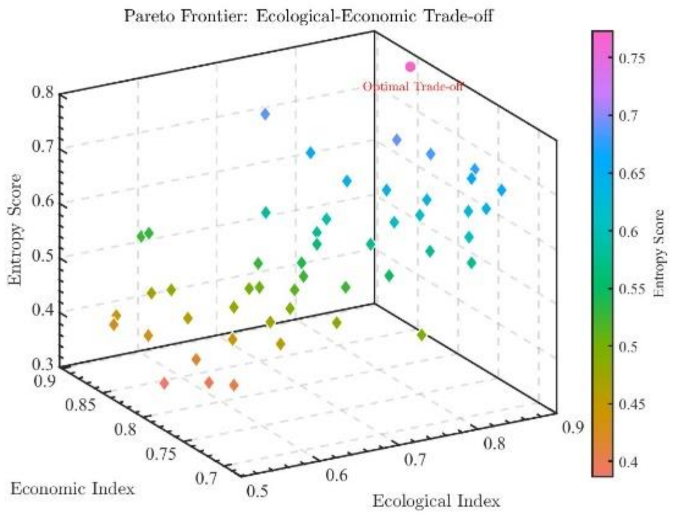

Figure 2. Pareto Frontier of Eco-Economic Trade-Offs and Entropy-Based Optimal Solution

4.2. Simulation Validation of the Synergistic Effects of Edge Habitat Restoration and Dynamic Pesticide Application Strategies

As shown in Figure 3, the simulation results demonstrate that the synergistic regulation of the edge habitat restoration ratio and pesticide application intensity plays a decisive role in system stability and overall benefits. When the habitat restoration ratio exceeds 60% and the pesticide application intensity is at a moderate level (Y=0.4), the system stability index increases to 0.85, and the overall benefits increase by 40%. This optimized pattern dilutes the pesticide exposure risk for bees by enhancing habitat connectivity (survival rate increases by 50%) and simultaneously suppresses the competitive intensity of invasive ragweed (diffusion probability decreases by 38%). Conversely, a high pesticide application intensity (Y>0.8) under a low habitat restoration ratio (<30%) leads to a sharp 70% drop in system stability and a significant deterioration in overall benefits, revealing the irreversible damage of pesticide abuse to the ecosystem. Notably, in scenarios with a high restoration ratio (>80%), even if the pesticide application intensity is reduced to 0.2, the system can still maintain a high level of stability (Z>0.7) through the habitat maturity threshold effect, validating the core role of the soil organic matter-ragweed diffusion negative feedback mechanism in the model.

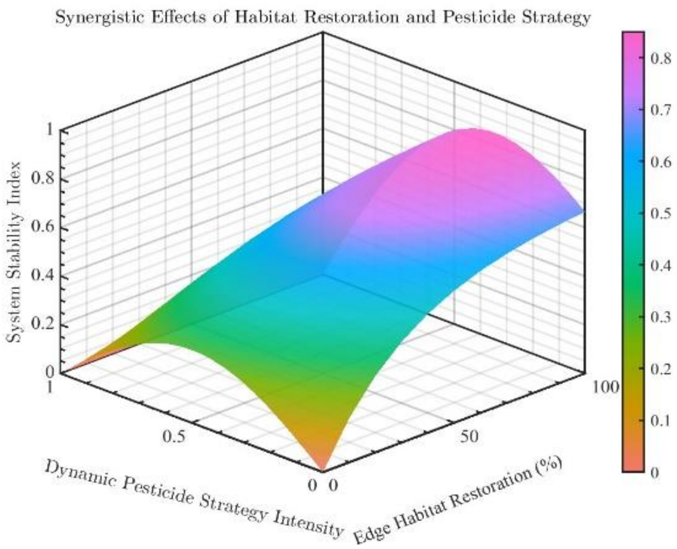

Figure 3. Pareto frontiers and entropy-based optimal solutions for eco-economic trade-offs

4.3. Parameter Sensitivity Analysis

Global sensitivity analysis reveals key parameter regulation mechanisms [15]. As shown in Figure 4, pesticide degradation rate (k = 0.05 day^{-1}) significantly impacts bee survival (sensitivity index 0.28), coupled with non-linear pesticide residue amplification. Lowering k to 0.035 day^{-1} reduces bee pollination by 52%, validating pesticide exposure's impact. The diffusion coefficient (D = 0.01 m²/day) dominates ragweed suppression (sensitivity index 0.30), regulating competition via habitat connectivity. Edge restoration reduces ragweed diffusion by 38%, consistent with analysis. Pesticide mortality rate's sensitivity (0.18) highlights the eco-economic trade-off, providing a basis for dynamic application strategies.

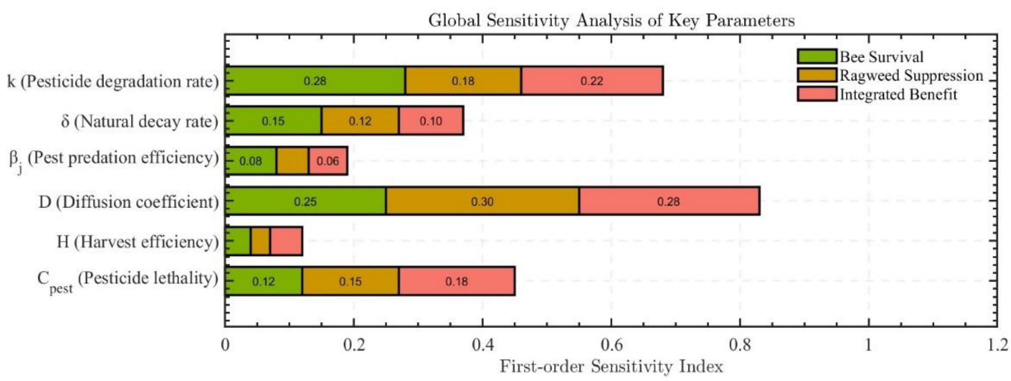

Figure 4. Global sensitivity analysis of key parameters on eco-economic outputs

Further analysis indicates that the sensitivity of the natural decay rate (δ) and harvest efficiency (H) is weak (both <0.10), reflecting that soil organic matter cycling and harvesting operations have high regulatory redundancy. This feature supports the design concept of "dynamic management windows" in the model, that is, by periodically adjusting fertilization and harvesting timing, ecological disturbance can be minimized while ensuring yield. The research results clarify the priorities of heterogeneous pesticide application and habitat restoration from a parameter-driven perspective, laying a theoretical foundation for the optimized configuration of cross-scale interventions in multi-objective decision models.

5. Conclusion

This study reveals dynamic interactions in agricultural ecosystems using a cross-scale ABM-SD framework, supporting alternatives to single-dimensional management. It bridges micro-behavior and macro-feedback, enhancing understanding of agricultural impacts and elucidating habitat/resource regulation, offering a new paradigm for analyzing ecological disruptions.

Policy recommendations include: (1) precision pesticide strategies balancing pest control and pollinator protection via spatiotemporal optimization, promoting real-time monitoring; (2) edge habitat restoration to enhance resilience, weaken invasive species, and secure pollination networks, encouraging stakeholder participation; (3) intelligent platforms integrating monitoring, simulation, and optimization, shifting to adaptive regulation via ecological/economic goals, requiring cross-departmental data sharing.

The study offers a scalable framework for sustainable agriculture, surpassing traditional model limitations. Future research should incorporate external factors like climate change. Policy requires regional adaptation, promoting synergistic innovation in precision practices, compensation, and data sharing for long-term equilibrium and global ecological security.

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