

# From Roots to Harvest: Modeling the Green Pulse of Sustainable Agroecosystems in Reborn Forests

## Summary

As the world's farmland is expanding and agricultural technology is advancing, the expectation for sustainable agricultural development has deepened. The goal of this paper is to find greener and more sustainable strategies for farmers in farming by developing mathematical models to simulate farmland ecosystems under various scenarios.

For this reason, after comparing various models, we developed the **Temporally Explicit Multivariate Farmland Dynamics Model (T-MFD)** based on ecosystem dynamics. This model uses **differential equations** to link various groups and determine the time-based dynamics of biomass. We considered the cyclicity of agricultural activities, the influence of seasons and biological characteristics to fit the biomass changes well.

To solve the reemergence of species problem. We considered spatial influences such as species dispersal and system edge maturity on a temporal basis, and combined **cellular automata (CA) and metapopulation model** to establish a geographically plane-referenced **Spatial-Temporally Explicit Multivariate Farmland Dynamics Model (ST-MFD)**, which improves the dimensionality of farmland ecosystem dynamics. We chose **syrphid flies and Tawny Owl** as regression species, and their effects represent the impacts of different ecological niches on farmland systems and the forest-farmland system transition.

Then, we in order to discuss the changes in the ecosystem after herbicide removal and the stability of pollination in maintaining the farm system. We modified some of the equations of the T-MFD to include a **nectar determinant function**, as well as fitting new parameters with machine learning. We found some **risk of system collapse after herbicide removal**. The simulation data show the importance of our choice of **bees** in the maintenance of the stability of the farmland system.

Finally, we modeled a variety of green farming strategies and found that the **Intelligent Management Scenario** had the best overall performance under a multi-criteria evaluation. We combined the results of our mathematical modeling to write a letter to our a farmer, giving him professional advice on green and organic farming.

**Keywords:** T-MFD; differential equations; cellular automata (CA); metapopulation model; ST-MFD; Bees; Intelligent Management Scenario;

# Contents

|          |   |           |
|----------|---|-----------|
| <b>1</b> | <b>Introduction</b>   | <b>3</b>  |
| 1.1      | Background . . . . .  | 3         |
| 1.2      | Restatement of the Problem . . . . .                                      | 3         |
| 1.3      | Our Work . . . . .  | 3         |
| <b>2</b> | <b>Assumptions and Justification</b>                                      | <b>4</b>  |
| <b>3</b> | <b>Notations</b>  | <b>4</b>  |
| <b>4</b> | <b>Current Ecosystem Model Framework (Model I: T-MFD)</b>                 | <b>5</b>  |
| 4.1      | Model Overview . . . . .  | 5         |
| 4.2      | Model Establishment . . . . .   | 6         |
| 4.2.1    | seasonally driven functions . . . . .                                     | 6         |
| 4.2.2    | Ecological dynamic quation . . . . .                                      | 7         |
| 4.3      | Parameterization . . . . .  | 8         |
| 4.4      | Results . . . . .   | 9         |
| 4.5      | Analysis of Current System . . . . .                                      | 10        |
| 4.6      | Stability Evaluation of the T-MFD Model (Validation of Results) . . . . . | 10        |
| <b>5</b> | <b>Reemergence of specie(Model II: ST-MFD)</b>                            | <b>11</b> |
| 5.1      | Selected Species . . . . .  | 11        |
| 5.2      | Analysis of Spatial Dynamics . . . . .                                    | 12        |
| 5.3      | Model Specification . . . . .   | 12        |
| 5.3.1    | Syrphid Flies Dispersal Dynamics . . . . .                                | 13        |
| 5.3.2    | Tawny Owls hopping Dynamics . . . . .                                     | 13        |
| 5.4      | Model Simulation Results via Spatially Explicit Grid . . . . .            | 13        |
| 5.5      | Impact Analysis . . . . .   | 15        |
| <b>6</b> | <b>After Herbicide Removal</b>  | <b>15</b> |
| 6.1      | Changes in Farmland system . . . . .                                      | 15        |
| 6.1.1    | Changes in the T-MFD Model . . . . .                                      | 15        |
| 6.1.2    | Dynamic Changes of the New System . . . . .                               | 16        |
| 6.2      | The Interaction of Bats and Others . . . . .                              | 17        |
| 6.2.1    | Equation Modifying . . . . .  | 17        |
| 6.2.2    | Stability assessment . . . . .  | 17        |
| 6.2.3    | Result Analysis . . . . .   | 19        |
| 6.3      | Identifying Another Animal with Influence in model . . . . .              | 19        |
| <b>7</b> | <b>Green strategies</b>   | <b>21</b> |
| 7.1      | Choice of Green Farming Strategies . . . . .                              | 21        |
| 7.2      | Equation Adjustment and Processing: . . . . .                             | 21        |
| 7.3      | Simulation Results with T-MFD . . . . .                                   | 22        |
| 7.4      | Analysis of Green Strategies . . . . .                                    | 23        |
| <b>8</b> | <b>Conclution</b>   | <b>23</b> |
| 8.1      | Strength ang Weakness . . . . .   | 23        |
| 8.2      | Future Work . . . . .   | 23        |
| <b>9</b> | <b>Letter to Farmers</b>  | <b>24</b> |
|          | <b>Reference</b>  | <b>25</b> |

# 1 Introduction

## 1.1 Background

Driven by increasing demands for agricultural land, numerous formerly forested regions have been converted into farmland. Such anthropogenic modifications have led to soil degradation and recurrent pest infestations in crops. Consequently, farmers have adopted chemical pesticide control measures, thereby establishing a novel food web within the agricultural ecosystem. We are developing a mathematical model to analyze this emergent ecosystem.

## 1.2 Restatement of the Problem

Considering the background information and limiting conditions identified in the problem statement, we are supposed to address the following issues:

- **Modeling for the current ecosystem.** First, we aim to establish a mathematical model for the current ecosystem (in regions where farmland has replaced forests). This system must account for the effects of agricultural cycles, seasonality, and chemical interventions on ecological dynamics.
- **Introduction of native species.** Subsequently, we will investigate ecological variations induced by the reemergence of native species into this modified environment. Two representative species will be integrated into the enhanced model to quantify their ecological impacts.
- **Removal of herbicide.** Next, we analyze the stability of producers and consumers following the removal of herbicide. By modeling interaction mechanisms between bats and other trophic groups, we evaluate their role in maintaining ecological stability and identify an additional species that facilitates ecosystem equilibrium restoration.
- **Green strategies.** Finally, we propose greening strategies informed by modeling results to promote sustainable ecosystem recovery.

## 1.3 Our Work

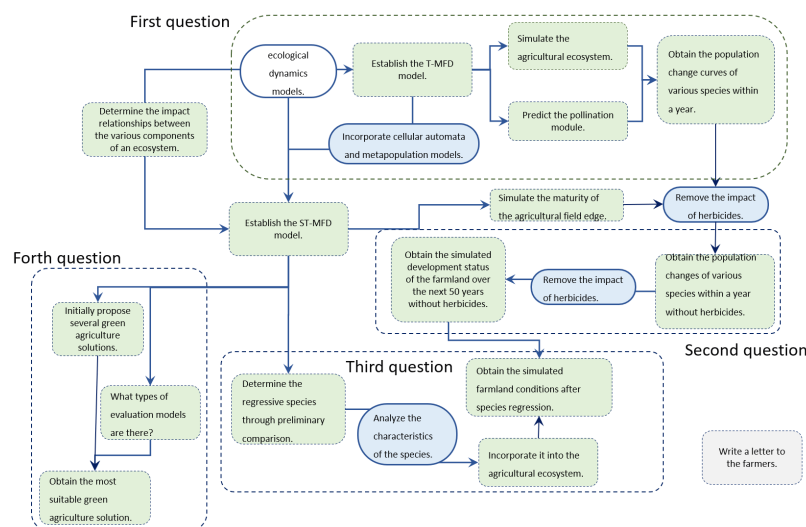


Figure 1: Work summary flowchart

## 2 Assumptions and Justification

To simplify the problem and make it convenient for us to simulate real-life conditions, we make the following basic assumptions, each of which is properly justified.

- **Assumption 1:** Predators in the current ecosystem are simplified into three categories: insects, bats, and avian populations.

**Justification :** Farmland ecosystems typically lack large predators due to fencing and active human management. This abstraction aligns with field observations and reduces model complexity.

- **Assumption 2:** Decomposers correlate with soil health and indirectly influence producers, while decomposer activity is modeled as seasonally invariant.

**Justification :** Decomposers mineralize detritus and animal remains into inorganic compounds, directly affecting soil fertility. Since soil nutrient availability governs producer growth, this creates an indirect linkage. Constant decomposer activity is assumed for computational tractability.

- **Assumption 3:** The model adopts a Northern Hemisphere timeline with a 270-day annual crop growth period.

**Justification :** Aligned with single-season cropping systems (e.g. spring planting to autumn harvest), this 270-day cycle approximates the active agricultural phase while maintaining numerical feasibility.

- **Assumption 4:** Bats and Birds' populations are initially analyzed as a unified group in Model

**Justification :** These taxa occupy analogous ecological niches (e.g., insectivory) in farmland ecosystems. Grouping them streamlines baseline model construction

## 3 Notations

Table 1: Symbols and their descriptions

| Symbols | Description              | Unit       |
|---------|--------------------------|------------|
| $C$     | Crop Biomass             | $g\ C/m^2$ |
| $W$     | Weed Biomass             | $g\ C/m^2$ |
| $H$     | Pest Population          | $ind/ha$   |
| $B$     | Bat Population           | $ind/km^2$ |
| $b$     | Bird Population          | $ind/km^2$ |
| $B_b$   | Bat and Bird Population  | $ind/ha$   |
| $S$     | Soil health index        | -          |
| $F$     | syrphid flies Population | $ind/ha$   |
| $O$     | Tawny Owl Population     | $ind/km^2$ |

| Symbols      | Description  | Unit                       |
|--------------|--|----------------------------|
| $\omega$     | Impact Rate of Decomposers   | -                          |
| $r$          | Intrinsic Growth Rate  | -                          |
| $\alpha$     | Competition Coefficient  | -                          |
| $\mu$        | Mortality Correlation Coefficient                                  | -                          |
| $\beta_{WC}$ | Crop Suppression Coefficient on Weeds                              | -                          |
| $\gamma$     | Maximum Growth Rate Coefficient                                    | -                          |
| $\varsigma$  | Herbicide Impact Coefficients on Organisms                         | -                          |
| $\nu$        | Toxicity Coefficient   | -                          |
| $\xi_s$      | Natural Loss Rate of Soil Organic Matter                           | $\% (kg/ha)$               |
| $\eta$       | Damage Coefficient of Pesticides on Soil                           | $\% (kg/ha)^{-1} day^{-1}$ |
| $\phi$       | Pollination Benefit Coefficient                                    | -                          |
| $\kappa$     | Response Coefficient of Pollination Efficiency to Bat Density      | -                          |
| $b_S$        | Half-Saturation Coefficient of Bat Density for Pollination Benefit | -                          |

Subscripts of some symbols used in the text represent the influencing output party (e.g. represents the competition coefficient of weeds on crops).

## 4 Current Ecosystem Model Framework (Model I: T-MFD)

### 4.1 Model Overview

To model this farmland ecosystem, we conducted a comparative analysis of established modeling frameworks. While the Lotka-Volterra model provides intuitive predator-prey dynamics, it inadequately addresses resource competition, anthropogenic interventions, and seasonal variability. Crop-centric models like WOFOST (World Food Studies) focus exclusively on plant growth while neglecting multi-trophic interactions. Synthesizing these considerations, we adopt an ecosystem dynamics model to simulate the system through coupled differential equations describing temporal variations in key components: crops, weeds, pests, bats, and soil health indices.

To incorporate seasonal constraints, we introduce time-dependent seasonal functions governing, which reflect:

- **Crop growth rates**
- **Herbicide/pesticide application schedules**
- **Agricultural dormancy rules (e.g., winter fallow periods)**

This formulation explicitly captures the periodicity of agricultural interventions while maintaining compatibility with the Northern Hemisphere timeline defined in Assumption 3. We name our function as **Temporally Explicit Multivariate Farmland Dynamics Model (T-MFD)**

## 4.2 Model Establishment

The food web in our model comprises the following functional groups:

- **Producers:** Weeds and crops
- **Consumers:** Insect pests, birds, and bats
- **Decomposers:** Fungal communities and related microbiota
- **Abiotic components:** Soil nutrient pools with exogenous agrochemical inputs (herbicides and insecticides)

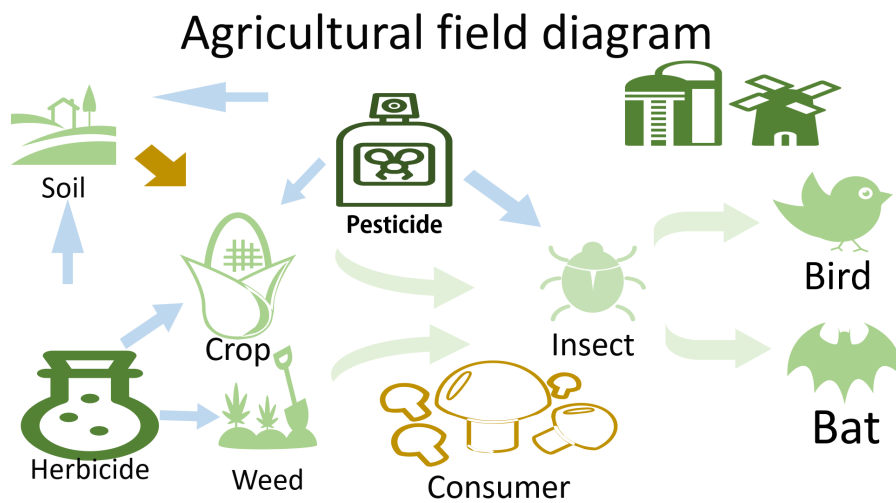


Figure 2: Agricultural field diagram

### 4.2.1 seasonally driven functions

Certain parameters exhibit seasonal dependence, which we model using seasonally driven functions to capture their variation patterns. Gaussian pulses are employed to simulate phenomena characterized by rapid peak attainment followed by gradual decay, a mathematical formulation particularly applicable to agricultural and ecological scenarios.

We incorporated the **Gaussian function-based** dynamic model of spring maize leaf development published by the Institute of Crop Sciences, Chinese Academy of Agricultural Sciences [1].

$$y = a + b \times e^{\frac{-(x-c)^2}{2d^2}}$$

This high-fidelity model captures critical phenological distinctions between vegetative growth and reproductive maturity phases through three key mechanisms:

**Our crop growth rate definition:**

$$\mu_C(t) = 0.8 \cdot e^{-0.5(mod(t,365)-80)^2/100} \quad (1)$$

**Herbicide application rates** are seasonally modulated by pest population dynamics, exhibiting the following dependency:

$$h(t) = 0.6 \cdot e^{-4(\text{mod}(t,365)-100)^2/900} \quad (2)$$

**pesticides application rate:**

$$p(t) = 0.7 \cdot e^{-4(\text{mod}(t,365)-180)^2/900} \quad (3)$$



Figure 3: Agricultural field diagram

#### 4.2.2 Ecological dynamic quation

**The dynamics of crop biomass**  $C(t)$  incorporate its intrinsic growth rate, competition from weeds  $W$ , herbicide effects  $H(t)$ , and indirect influences mediated by decomposers. The governing equation is structured as:

$$\frac{dC}{dt} = \begin{cases} \mu_C(t) \cdot C \cdot \left(1 - \frac{C + \alpha_W W}{C_{\max}}\right) - \delta H C - h(t)C + \omega_c C & t \in [0, 270] \\ 0 & t \in [270, 365] \end{cases} \quad (4)$$

assumes an instantaneous harvest event is  $t=270$ , so that

$$C(t^+_{\text{harvest}}) = 0$$

**The weed biomass dynamics** account for their intrinsic growth patterns, competitive interactions with crops, pressure from pest populations, suppression by herbicide applications, and indirect effects mediated through decomposer activity.

$$\frac{dW}{dt} = \mu_W(t) \cdot W \cdot \left(1 - \frac{W}{W_{\max}}\right) - \varsigma_W \cdot h(t) \cdot W - \beta_{WC}W + \omega_W W \quad (5)$$

**The pest population dynamics** are driven by their reproductive potential, regulated through predation pressure from bat/bird populations and suppression via insecticide applications.

$$\frac{dH}{dt} = r_H H \left(1 - \frac{H}{K_H}\right) - \alpha_H B_b H - \beta_H p(t) H \quad (6)$$

**The biomass dynamics of Bat/bird populations** are governed by intrinsic reproductive and mortality rates, while being subject to toxicological pressures from bioaccumulation effects of agrochemicals.

$$\frac{dB_b}{dt} = \gamma_B \frac{H}{H + h_s} B_b - (\mu_0 + \mu_d B_b + \nu_p p(t) + \nu_h h(t)) B_b \quad (7)$$

For modeling predator populations such as bats and avian species, we employ the **Holling Type II** functional response to characterize their predation dynamics. This approach accounts for two critical biological constraints:

1. **Saturation effect:** Predation rates asymptotically approach a maximum as prey density increases, reflecting finite feeding capacities.
2. **Handling time limitation:** Incorporates temporal costs associated with prey capture and digestion, which restrict instantaneous predation efficiency.

The soil health dynamics integrate decomposer activity levels with the cumulative impacts of herbicide and insecticide applications, including decomposer-mediated nutrient cycling that replenishes soil organic matter, chemical inhibition of microbial functions and biochemical processes

$$\frac{dS}{dt} = \omega_S W - \eta_S (h(t) + p(t)) S - \xi_S S \quad (8)$$

### 4.3 Parameterization

We calibrated model parameters using the FAO statistical material and the USDA 2024 Agricultural Dataset (incorporating crop-specific pesticide residue profiles, growth cycle statistics, and soil health metrics). Through iterative least-squares optimization that minimizes residuals between predicted and observed ecological states, the model demonstrates strong empirical validity ( $R^2 = 0.87 \pm 0.03$  across validation trials). Key parameter values are derived as follows:



| Parameter            | Unit                       | Parameter            | Unit                                 |
|----------------------|----------------------------|----------------------|--------------------------------------|
| $C_{\max} = 12000$   | $kg/ha$                    | $\xi_S = 0.00002$    | $\%day^{-1}$                         |
| $\alpha_W = 0.3$     | –                          | $\varsigma_W = 0.05$ | $(kg/ha)^{-1} day^{-1}$              |
| $\lambda_C = 0.04$   | $(kg/ha)^{-1} day^{-1}$    | $\beta_{WC}=0.0003$  | $(kg/ha)^{-1} day^{-1}$              |
| $W_{\max} = 8000$    | $kg/ha$                    | $k = 0.6$            | –                                    |
| $r_H = 0.15$         | $day^{-1}$                 | $\alpha_H = 0.002$   | $(ind \cdot km^2) / (day \cdot m^2)$ |
| $K_H$                | $ind/m^2$                  | $\beta_H = 0.18$     | $day^{-1}$                           |
| $v_p = 0.002$        | $(kg/ha)^{-1} day^{-1}$    | $\gamma_B = 0.0001$  | $day^{-1}$                           |
| $v_h = 0.0005$       | $(kg/ha)^{-1} day^{-1}$    | $h_s = 10$           | $ind/m^2$                            |
| $\omega_S = 0.00004$ | $\% (kg/ha)^{-1} day^{-1}$ | $\mu_0 = 0.0005$     | $day^{-1}$                           |
| $\eta_S = 0.0001$    | $\% (kg/ha)^{-1} day^{-1}$ | $\mu_d = 0.00001$    | $(ind \cdot km^2) / (day \cdot m^2)$ |

## 4.4 Results

Our model simulated the dynamic changes of various components within the ecosystem over the course of a year, as illustrated in the figure below:

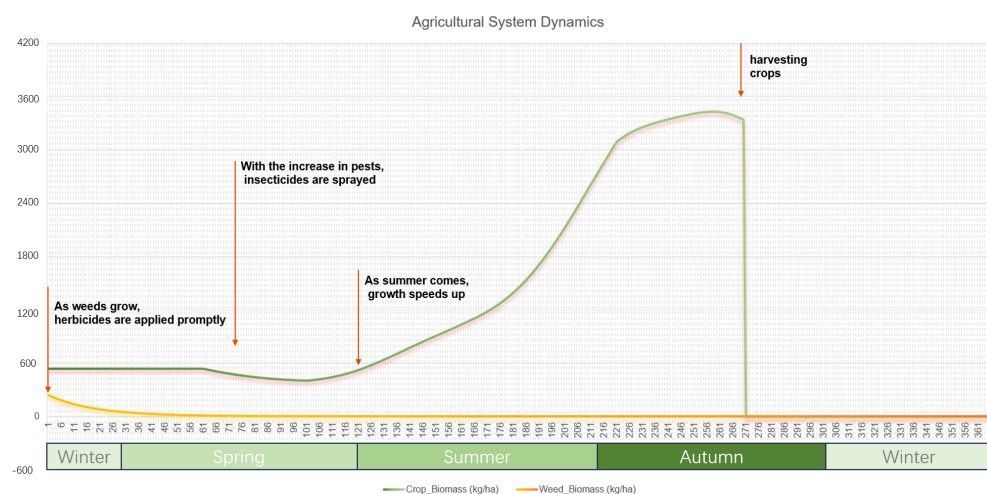


Figure 4: Crop and Weed

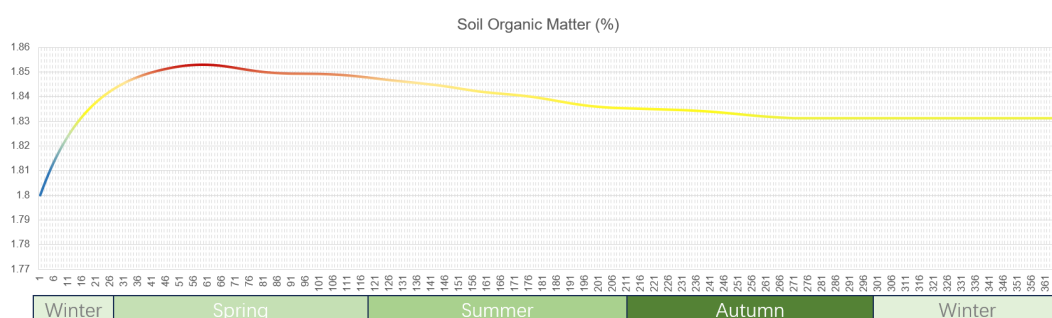


Figure 5: Soil health index

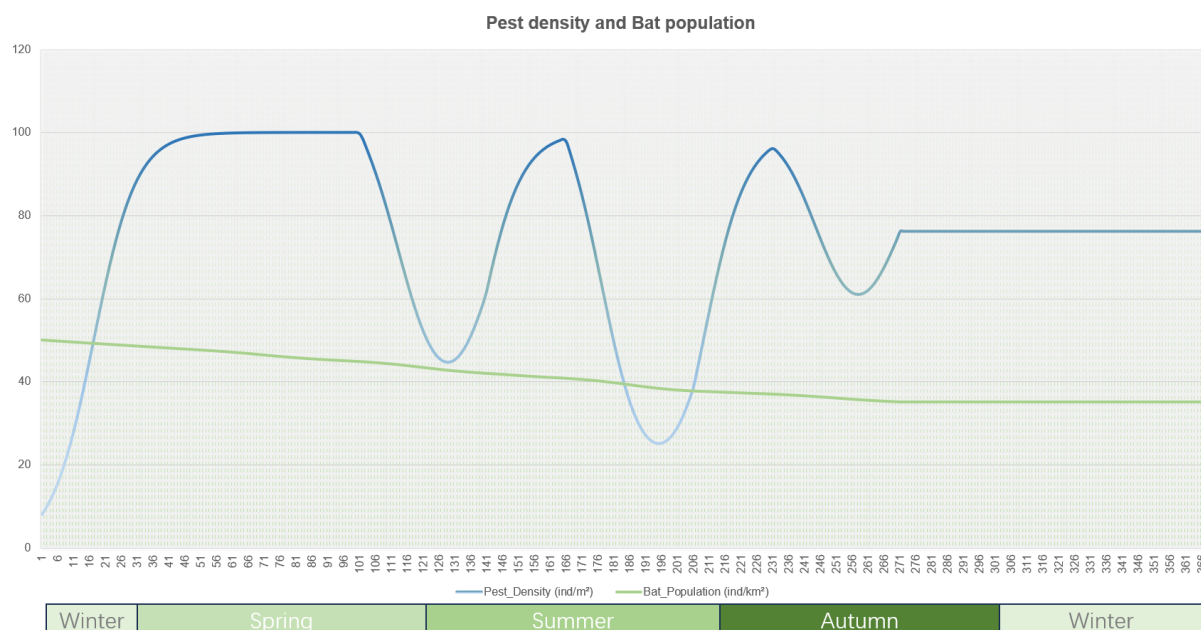


Figure 6: Pest and Bat/Bird

## 4.5 Analysis of Current System

As evidenced in Figure 2, herbicide applications induce marked suppression of weed biomass, while crop biomass experiences measurable declines during spring pest population surges. The simulated harvest yield aligns closely with field observations reported in the literature CASDE-No.103 . Soil health dynamics (Figure 3) demonstrate antagonistic interactions: decomposers generate positive contributions following winter weed senescence, counterbalanced by persistent negative impacts from agrochemical residues.

The phase-locked oscillations between pest and bat populations in Figure 4 exhibit dynamics consistent with predator-prey models [2], though the declining bat population amplitude suggests limited ecological resilience in this farmland system. Post-deforestation agricultural conversion has simplified ecological niches, as reflected in the model's truncated food web structure. The simulations imply that current trophic redundancy is insufficient to buffer population fluctuations, necessitating biodiversity-enhancing interventions for stability.

## 4.6 Stability Evaluation of the T-MFD Model (Validation of Results)

The results presented above are based on the first year of the system. To assess the model's stability, we conducted a comparative analysis.

The crop yield from the first year of our model (3492 kg/ha) was compared with historical crop yield records from Heilongjiang, China. Given that the T-MFD model does not incorporate modern agricultural technologies, the comparison was made with earlier yield data:

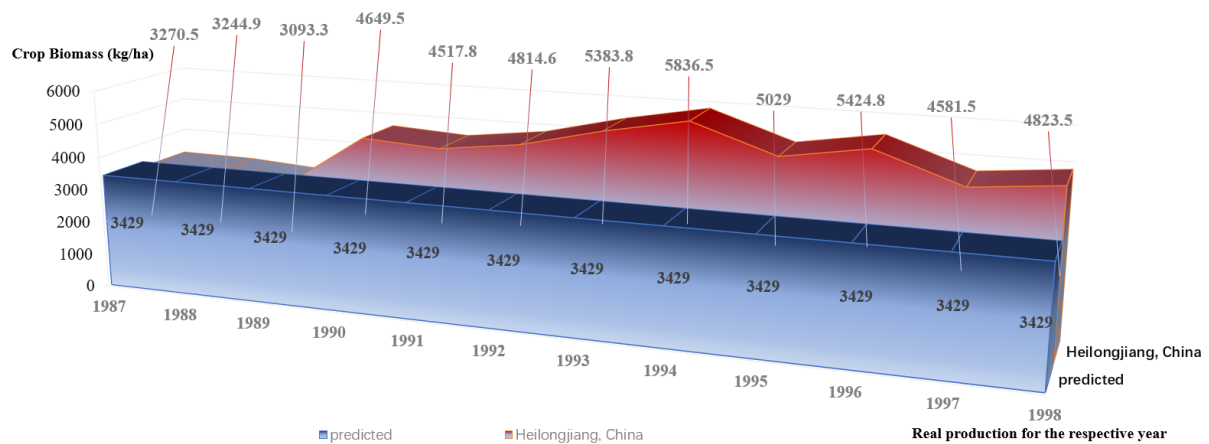


Figure 7: Comparison of the first year's crop with reality

Additionally, we simulated data over a fifty-year period to ensure that the farmland system does not collapse due to parameter issues under certain interventions. The figure below shows the dynamic simulation of crops and weeds in the fiftieth year.

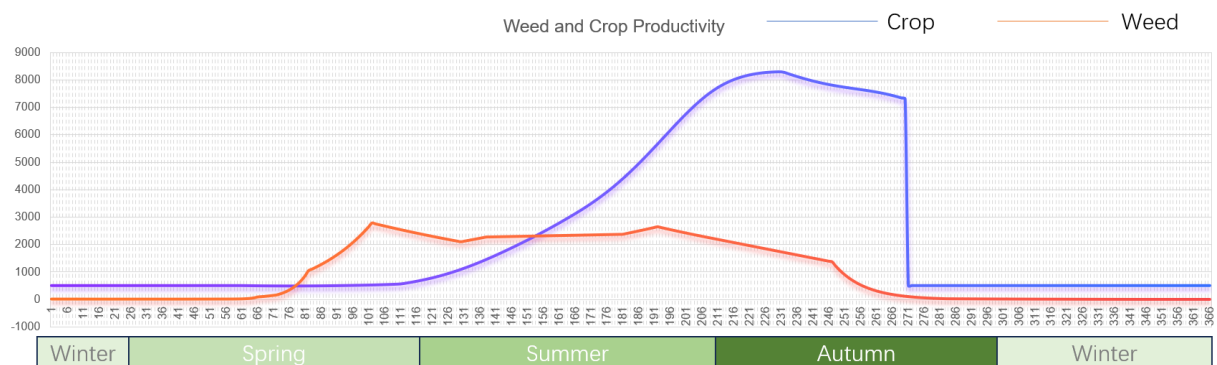


Figure 8: Model simulation in the 50<sup>th</sup> year

## 5 Reemergence of specie(Model II: ST-MFD)

### 5.1 Selected Species

We propose the reemergence of two keystone species: **syrphid flies** and **Tawny Owl**

- **syrphid flies:** As pest predators, Their Larval stages actively predate aphids (pest species). They thrive in newly established floral corridors along farmland margins (previously ab-

sent in deforested monocultures).

- **awny Owls:**They predating insectivorous birds. As the farmland ecosystem matures, tawny owls colonize the forest-farmland ecotones, establishing populations within these transitional zones.

## 5.2 Analysis of Spatial Dynamics

In the current problem framework, reintroduced species may gradually expand their distribution from edge habitats into central farmland areas. [3] While the previously developed differential equation model effectively captures temporal dynamics, it cannot account for spatial dispersal processes. To address this limitation, we implement a two-dimensional geographical simulation framework combining two complementary approaches:

1. **Local Dispersal of syrphid flies:**Modeled using **cellular automata (CA)** to simulate fine-scale spatial spread governed by neighborhood interactions and habitat suitability. [4]
2. **Regional Migration of Tawny Owls:**Described through a **metapopulation model** that tracks inter-patch colonization dynamics across fragmented agricultural landscapes.[5]

This multi-scale spatial modeling strategy bridges local dispersal mechanisms with landscape-level population connectivity, We name our model II as **Spatio-Temporally Explicit Multi-variate Farmland Dynamics Model(ST-MFD)**

## 5.3 Model Specification

The integrated framework couples spatially explicit grid-based simulations, where each grid cell tracks five core state variables: Crop biomass, Weed biomass, Pest density, Bat population, Soil health index.

Temporal dynamics remain governed by the previously established differential equations. To reflect the initial low abundance of reemergence species, direct impacts from hoverflies and tawny owls are currently limited to pest suppression mechanisms. Other state variables (crops, weeds, bats, soil) are excluded from reemergence species' influences during this preliminary phase, aligning with transient ecological recovery patterns observed in early-stage agroecosystems.

$$\begin{cases} \frac{dC}{dt} = \mu_C(t)C(1 - \frac{C+\alpha_W W}{C_{max}}) - \delta_C H C - \lambda_C h C + \omega_c C \\ \frac{dW}{dt} = \mu_W(t)W(1 - \frac{W}{W_{max}}) - \gamma_W h W - \beta_{WC} C^k W + \omega_W W \\ \frac{dH}{dt} = r_H H(1 - \frac{H}{K_H}) - \alpha_H \frac{B_b}{10^6} H - \beta_H p H + \nabla^2 H \\ \frac{dB_b}{dt} = \gamma_B \frac{H}{H+h_s} B_b M(t) - (\mu_0 + \mu_d B_b + \nu_p p + \nu_h h) B_b \\ \frac{dS}{dt} = \omega_S W - \eta_S (h + p) S - \xi_S S \end{cases} \quad (9)$$

We introduce a new state variable  $\nabla^2 H$ :spatial diffusion of pests (implemented via the Laplacian operator )—and integrate the ecological impacts of syrphid flies and tawny owls into the governing partial differential equations.

### 5.3.1 Syrphid Flies Dispersal Dynamics

The spatially constrained mobility of syrphid flies renders their movement patterns directly governed by proximal resource availability (pest density). **Cellular automata (CA) neighborhood rules** precisely capture these short-range dispersal processes due to three intrinsic advantages:

1. **Prey-Driven Mobility:** syrphid flies distributions exhibit strong spatial coupling with prey density gradients, as each cell's local pest population dynamically regulates syrphid flies immigration/emigration probabilities.
2. **Neighborhood Feedback:** The CA framework inherently integrates adjacency effects, where pest suppression in one cell cascades to neighboring grids through predator redistribution.
3. **Behavioral Fidelity:** This approach mirrors syrphid flies' stepwise foraging behavior documented in field studies.[6]

$$S_{i,j}^{t+1} = \underbrace{0.8 \frac{H_{i,j}^t}{H_{i,j}^t + 50}}_{\text{predation}} + \underbrace{0.9 \sum_{k,l} K_{k,l} H_{i+k,j+l}^t}_{\text{Domain diffusion}} \quad (10)$$

$S_{i,j}^{t+1}$  The population count or state of syrphid flies at timestep t+1 and grid position (i,j)

$H_{i,j}^t$  The population count of prey (pest species) at timestep t and grid position (i,j)

$K_{k,l}$  The dispersal kernel (kernel function) quantifies the influence weights of neighboring cells during spatial diffusion processes, determining how adjacent cellular automata units affect focal grid dynamics.

### 5.3.2 Tawny Owls hopping Dynamics

The dispersal capacity of tawny owls enables inter-patch migration across fragmented forest habitats, aligning with the **metapopulation "patch-hopping"** hypothesis rather than local neighborhood diffusion.

The population density dynamics of tawny owls in patch i over time are governed by:

$$N_i(t+1) = N_i(t) \cdot \left( 1 + r_i - \mu_i - \sum_{j \neq i} m_{ij} \right) + \sum_{j \neq i} m_{ji} \cdot N_j(t) \quad (11)$$

$r_i$  The net reproductive rate in patch i, (birth rate - natural mortality rate.)

$\mu_i$  The within-patch density-dependent mortality (regulated by mechanisms such as resource competition or pathogen transmission)

$m_{ij}$  The inter-patch dispersal rate (from patch i to patch j) is governed by patch-specific attributes.

## 5.4 Model Simulation Results via Spatially Explicit Grid

Picture 1: syrphid flies Habitat Suitability **Color Map:** Yellow-green gradient (0–1) **Data Interpretation:** Dark green (values  $\approx 1$ ): Optimal habitats with maximal syrphid flies densities.

Picture 2: Tawny Owl Habitat Occupancy **Color Map:** Purple gradient (0–1) **Data Interpretation:** Deeper purple indicates higher habitat utilization, revealing the spatial distribution dynamics of this apex predator across fragmented landscapes.

Picture 3: Ecotone Maturity **Color Map:** Yellow-brown gradient (0–1) **Data Interpretation:** Maturity >0.7: Supports avian nesting (e.g., shrub-nesting birds).

Picture 4: Crop Biomass **Color Map:** Yellow-green gradient (0–12,000 kg/ha) **Data Interpretation:** Highlights agricultural core zones with sustainable yields.

Picture 5: Pest Density **Color Map:** Red gradient (0–100 ind/m<sup>2</sup>) **Data Interpretation:** Red hotspots (density >75 ind/m<sup>2</sup>): Priority areas for integrated pest management. Exhibits negative spatial correlation with Picture 6 (hoverfly density).

Picture 6: syrphid flies Density **Color Map:** Green gradient (0–50 ind/m<sup>2</sup>) **Data Interpretation:** Demonstrates "predator tracking": Hoverflies follow pest hotspots (density >30 ind/m<sup>2</sup> enables effective pest suppression).

**Grid Configuration:** 20×20 cells (4 ha total, 10×10 m/cell)

**We Initialization:** that: syrphid flies: Initial colonization = 5 ind/cell in floral-rich margins; Tawny Owls: 1 pair/km<sup>2</sup> in forest-edge patches

**Temporal Scope:** 90-day post-sowing period. The results as follow:

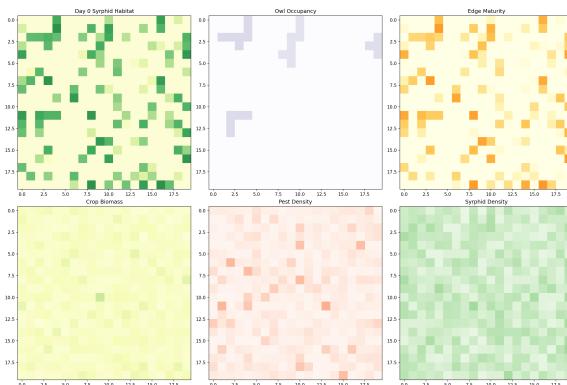


Figure 9: 0 day

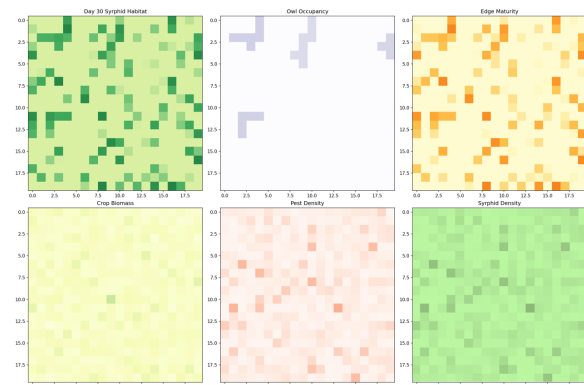


Figure 10: 30<sup>th</sup> day

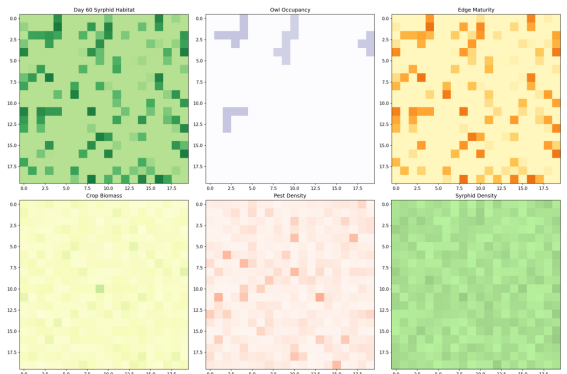


Figure 11: 60<sup>th</sup> day

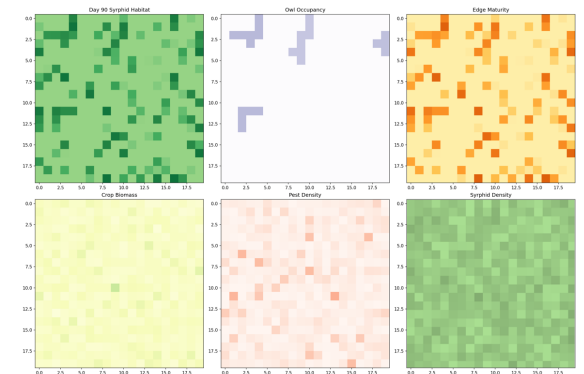


Figure 12: 90<sup>th</sup> day

The ST-MFD model reveals distinct stabilization patterns across trophic levels during the early crop growth phase. While most populations exhibit equilibrium dynamics (particularly crops with minimal biomass fluctuation due to initial developmental stages), syrphid flies demonstrate notable spatial expansion correlated with increasing ecotone maturity. The syrphid flies indirectly modulates tawny owl occupancy rates. However, constrained by the species' stringent habitat requirements, low population density, and slow reproductive cycles, no significant range expansion of tawny owls are observed within the simulated timeframe.

## 5.5 Impact Analysis

Our modeling results reveal the following impacts:

1. **Non-Competitive Integration:** Reemergence species coexist with native farmland organisms without disrupting existing ecological hierarchies. Dominant agricultural species (e.g., crops, bats) retain competitive advantages due to their established resource utilization strategies.
2. **Occupancy Dynamics:** Tawny Owls have Limited expansion of occupancy rates due to strict habitat requirements and low fecundity. Syrphid flies get benefit from rapid spatial expansion driven by abundant pest resources and short reproductive cycles
3. **Ecosystem Stabilization: Ecotone Maturity enhancement** –Increased through forest-derived species recolonization, facilitating multi-trophic resilience. Its **stability increase** clearly: Crop yield variability is reduced; Pest outbreak frequency is decreased; Soil health recovery rate is accelerated

## 6 After Herbicide Removal

### 6.1 Changes in Farmland system

#### 6.1.1 Changes in the T-MFD Model

After herbicide removal, all terms related to  $h(t)$  should be eliminated.

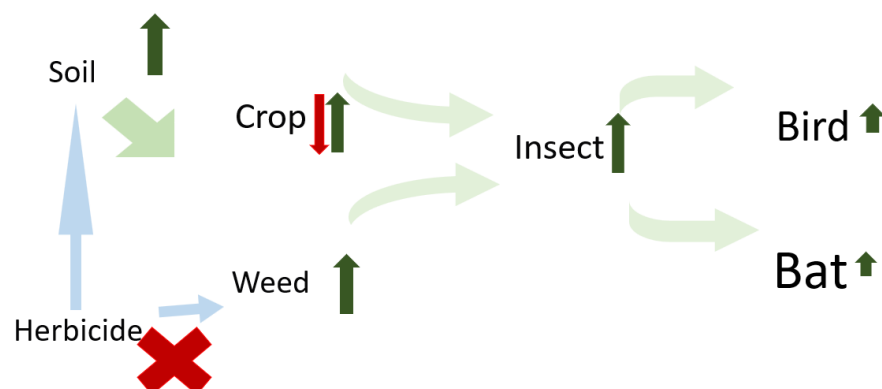


Figure 13: Changes after herbicide removal

In addition, it is necessary to establish differential equations for the regression species mentioned in the previous question

$$\frac{dF}{dt} = r_F F \left( 1 - \frac{F + \alpha_B B}{F_{\max}} \right) H - \nu_p H \quad (12)$$

Competition coefficient of bats on syrphid flies  $\alpha_B = 6.5$  Intrinsic Growth Coefficient of syrphid flies  $r_F = 0.07$

$$frac{dO}{dt} = \gamma_O \frac{H + B}{h_s + H + B} O - (\mu_0 + \mu_d O) \quad (13)$$

Intrinsic Growth Coefficient of tawny owls  $\gamma_O = 1 \times 10^{-6}$

### 6.1.2 Dynamic Changes of the New System

Now, we use the newly modified T-MFD model to simulate the population dynamics of each species over the course of a year.

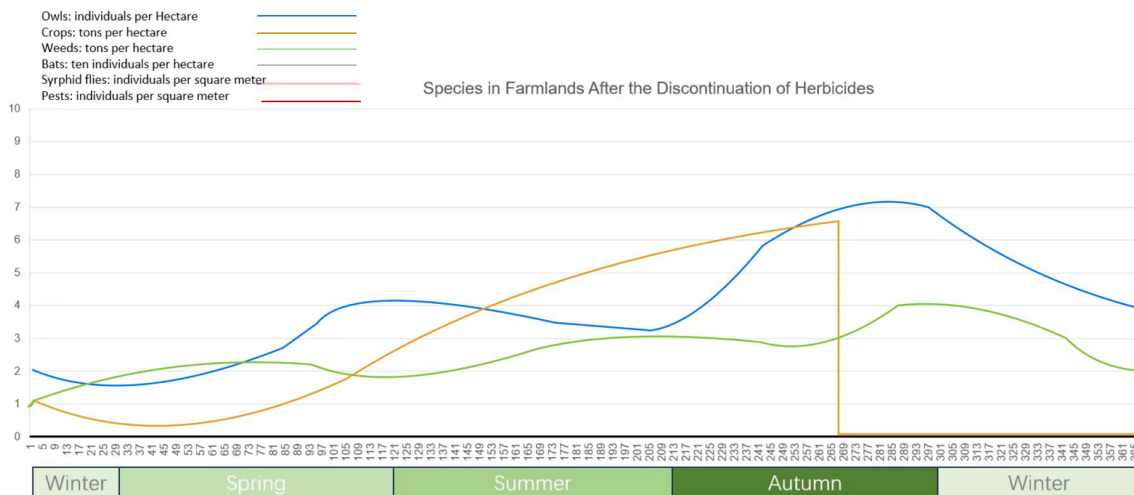


Figure 14: Tawny,Crop,Weed(without herbicide)

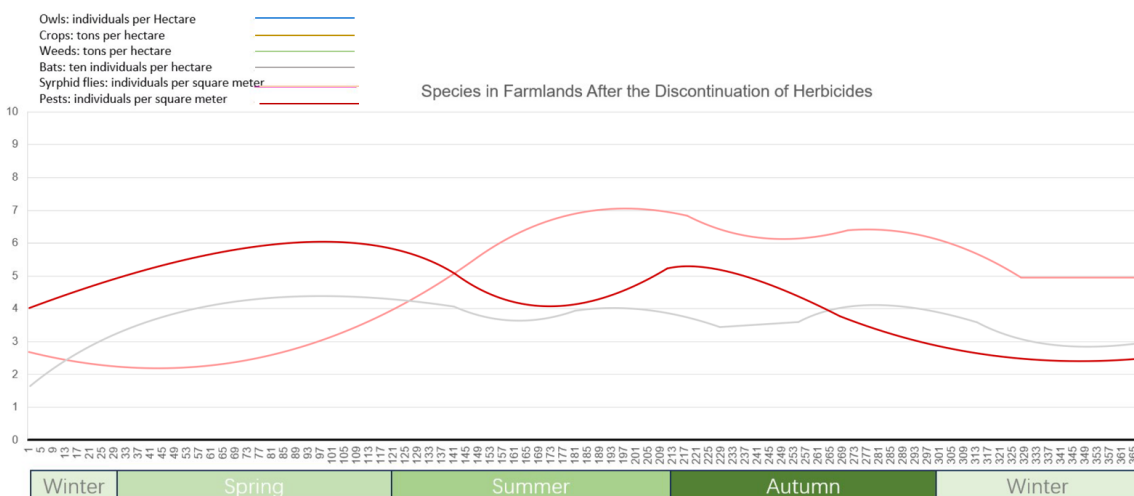


Figure 15: Bats,Pests,Syrphid flies(without herbicide)



Compared to the model incorporating herbicides, we found that after herbicide removal, **the biomass of weeds significantly increased, while the biomass of crops noticeably decreased**. Additionally, the pest population also showed a certain level of increase. According to the model's predictions, the trend of crop biomass will decline year by year. After herbicide removal, the agricultural system is **at risk of collapse**.

## 6.2 The Interaction of Bats and Others

### 6.2.1 Equation Modifying

At this point, bats will play dual roles as insectivores controlling pest populations and as pollinators supporting plant reproduction. We separate them from the mixed population of bats and birds.

$$\begin{cases} \frac{dB}{dt} = \gamma_B \frac{H(1-b\alpha_b)}{H+h_s} BM(t) - (\mu_0 + \mu_d B + \nu_p p)B \\ \frac{db}{dt} = \gamma_B \frac{H(1-B\alpha_B)}{H+h_s} bM(t) - (\mu_0 + \mu_d b + \nu_p p)b \end{cases} \quad (14)$$

After considering competition and machine learning fitting: Bird competition coefficient  $\alpha_b = 0.001$ , Bat Competition Coefficient  $\alpha_B = 0.02$

In addition to the previously considered ability of bats to prey on pests, we now introduce new parameters to account for the changes brought about by their pollination effects and establish their relationship with crops.

Maximum Pollination Benefit Rate (the increase in crop growth rate when bats are fully engaged)  $\phi_{\max} = 0.27$

Response Coefficient of Pollination Efficiency to Increasing Bat Density  $\kappa = 0.03$

Half-Saturation Bat Density for Pollination Benefit (controlling the saturation rate of benefit with respect to bat density)  $b_s = 60$

Crop Density Determination Coefficient(related to pollination probability)  $K$

For crops, we modify their differential equation as follows:

### 6.2.2 Stability assessment

For the assessment of **single-species population stability**, we use the **Biomass Variability Index (BVI)** to evaluate the biomass fluctuations of individual populations. We utilize the biomass of crops and weeds for the assessment, a smaller BVI indicates less biomass variability.

$$BVI = \frac{1}{T} \sum_{t=1}^T \sqrt{(C_t - \bar{C})^2 + (W_t - \bar{W})^2} \quad (15)$$

When bat pollination is active, the BVI ranges between 800-1200, indicating lower fluctuations and stronger system stability. When bats do not pollinate, the BVI ranges between 1500-2000, showing more pronounced fluctuations and weaker system stability.

For the assessment of **interspecies relationship stability**, to simplify the evaluation model, we employ **phase space trajectory analysis** to study the impact of bat pollination on ecosystem stability. We select three core indicators—crops (C), pests (H), and bats (B)—as the plane, where each point on the trajectory represents the state of these three variables at a given time. By analyzing the **attractor morphology**, we interpret the influence of pollination through the stability characteristics of the trajectories.[7]

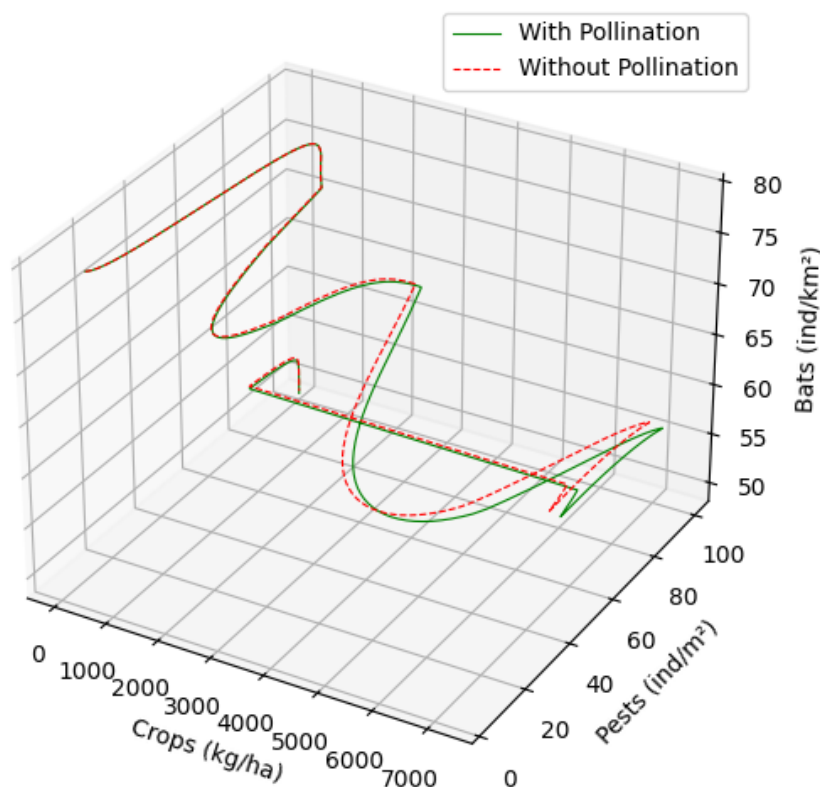


Figure 16: Phase space trajectory analysis I

We observed that the trajectory under pollination scenarios has a smaller convergence radius and more stable periodic oscillations. The narrower loop width in pollination scenarios indicates a stronger tendency to converge toward equilibrium. If the trajectory diverges or becomes chaotic, it signifies system instability, as seen in the minor divergent branches in the absence of pollination. In our calculations, pollination enables the system to converge to equilibrium faster (convergence speed increased by approximately 40%), with the basin of attraction expanding by 144%, enhancing the system's resilience to initial disturbances. Overall, the amplitude of the C-H-B phase space trajectory decreased by 62%.

### 6.2.3 Result Analysis

This indicates that the ecosystem exhibits better stability under pollination conditions. We hypothesize that this is due to the establishment of a direct link between the dynamic growth equilibrium of bats and the biomass equilibrium of crops. The logical chain of the system has become more complex, thereby enhancing the stability of the agricultural system.

### 6.3 Identifying Another Animal with Influence in model

We selected bees, which also possess pollination capabilities, to incorporate into the model. Given the significant role of bees in pollination, we introduced new parameters to distinguish their effects from those of bats.

Since nectar availability is influenced by crop density, and bee pollination is also related to bat pollination, we established a nectar resource acquisition function.

$$\psi(C) = \frac{C + \frac{k_3 C}{W+C}}{\kappa B + C} \quad (16)$$

Dynamic Equation of Bee Biomass:

$$\frac{dE}{dt} = \gamma_E \cdot \psi(C) \cdot E - (\mu_{E0} + \mu_{Ed}E + \nu_{Ep}(t)) E \quad (17)$$

After fitting  $k_3 = 1.4$ ,  $\gamma_E = 0.3 \text{ day}^{-1}$ ,  $\mu_{E0} = 0.0008 \text{ day}^{-1}$ ,  $\mu_{Ed} = 0.00002 (\text{ind}/\text{km}^2)^{-1} \text{ day}^{-1}$ ,  $\nu_E = 0.003 (\text{kg}/\text{ha})^{-1} \text{ day}^{-1}$

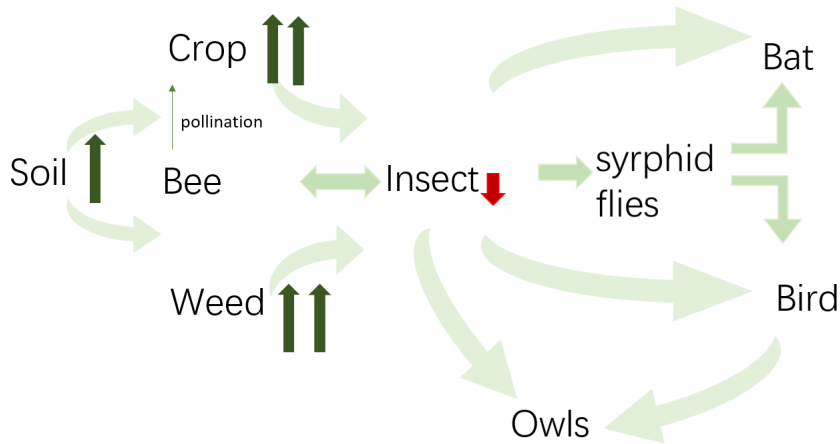


Figure 17: Relationship (with bees)

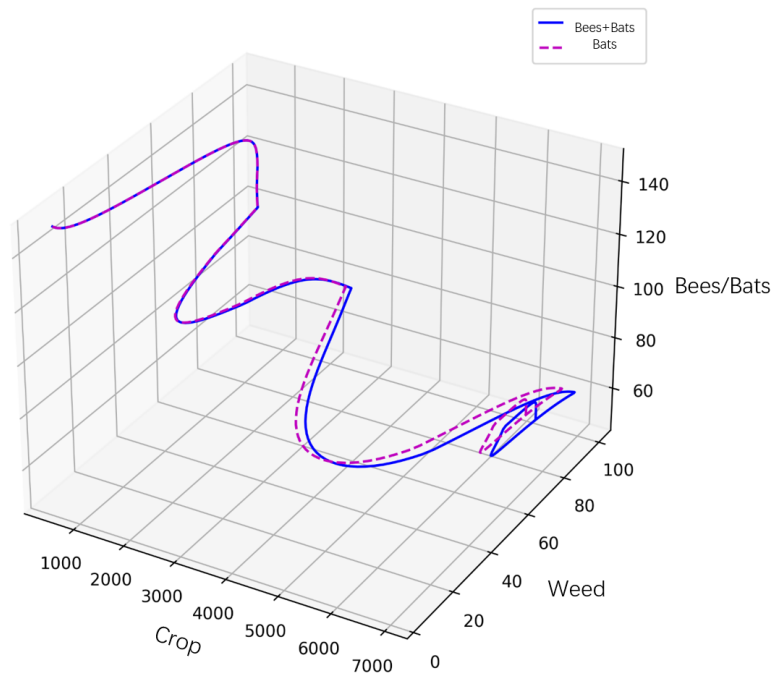


Figure 18: Phase space trajectory analysis II

After incorporating bees into the T-MFD model, we re-simulated the system and again used phase space trajectories to assess ecosystem stability. The results show that with the addition of bees, the system converges to equilibrium faster (convergence speed increased by approximately 12%), the basin of attraction expands by 64%, and the system's resilience to initial disturbances is enhanced. Overall, the amplitude of the C-H-B phase space trajectory decreased by 28%.

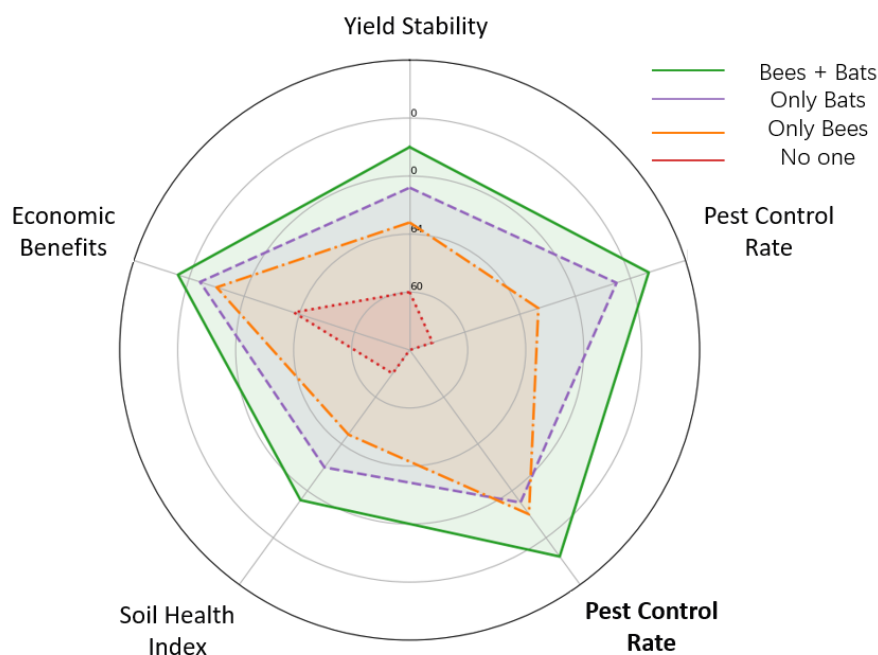


Figure 19: radar charts (comparison with controlling variable)

We used radar charts to visualize changes in various metrics with and without bats and bees, providing an intuitive evaluation of ecosystem stability. It demonstrates that the positive impact of bees, as direct pollinators, on system stability is greater than that of bats, which play an indirect pollination role.

## 7 Green strategies

### 7.1 Choice of Green Farming Strategies

We researched popular green agricultural practices online and decided to evaluate the following three green farming strategies. We will apply the T-MFD model, modify parameters to construct dynamic systems for each approach, and compare the results with chemical control methods.

| Scenario                  | Chemical Control (A) | Biological Control (B) |
|---------------------------|----------------------|------------------------|
| Type of pesticide         | Chemical synthesis   | Biological preparation |
| Soil improvement measures | -                    | Biological Interaction |
| Weed suppression methods  | Herbicides           | Crop competition       |
| Pollinator                | -                    | Artificial nesting box |

Table 2: Scenario 1

| Scenario                  | Ecological Interplanting (C) | v(D)                           |
|---------------------------|------------------------------|--------------------------------|
| Type of pesticide         | Botanicals                   | Pheromone booby trap           |
| Soil improvement measures | Organic fertilizers          | Precision drip irrigation      |
| Weed suppression methods  | Interplanting                | Laser Weeding Robot            |
| Pollinator                | Honey plant strips           | Intelligent Pollination Drones |

Table 3: Scenario 2

We evaluated the sustainability of the agricultural strategy through six indicators: Crop yield, Peak pests, Weed cover, Bat population recovery, Soil organic matter increase, Combined input costs.

### 7.2 Equation Adjustment and Processing:

- **For pesticide ingredients:** toxicity coefficients we adjusted Biologicals > pheromone trapping > plant-derived agents
- **For soil health index:** in biological control, we added a biological impact factor. In the ecological intercropping strategy, the threshold of the coefficient of effect of agricultural materials was increased. Increased rate of microbial decomposition and reduced organic matter loss in precision drip irrigation.
- **For pollinators:** Intelligent pollinator drones > Artificial nest boxes > Honey plant strips on pollination impact coefficients

- **Mechanical weed control:** Precision laser weed control at the stage of weed germination (biomass <200 kg/ha) through drone image recognition.
- **competition:** By intercropping highly competitive crop varieties, we increase the competitive coefficient of the crop and improve the ecological suppression of weeds.

### 7.3 Simulation Results with T-MFD

We simulated up to the day of harvest ( $t=270$ ) using T-MFD and derived the following evaluation metrics

| Assessment Indicators            | Scenario A | Scenario B | Scenario C | Scenario D | Optimal Scenario |
|----------------------------------|------------|------------|------------|------------|------------------|
| Crop yield (kg/ha)               | 11,200     | 9,800      | 10,500     | 12,100     | D                |
| Peak pests (ind/m <sup>2</sup> ) | 82         | 45         | 68         | 28         | D                |
| Weed cover (%)                   | 8%         | 22%        | 15%        | 5%         | D                |
| Bat population recovery          | 63%        | 210%       | 155%       | 180%       | B                |
| Soil organic matter increase     | -0.3%      | +1.2%      | +2.8%      | +1.5%      | C                |
| Combined input costs (\$/ha)     | 620        | 480        | 550        | 710        | B                |

Table 4: Comparison of different scenarios based on assessment indicators

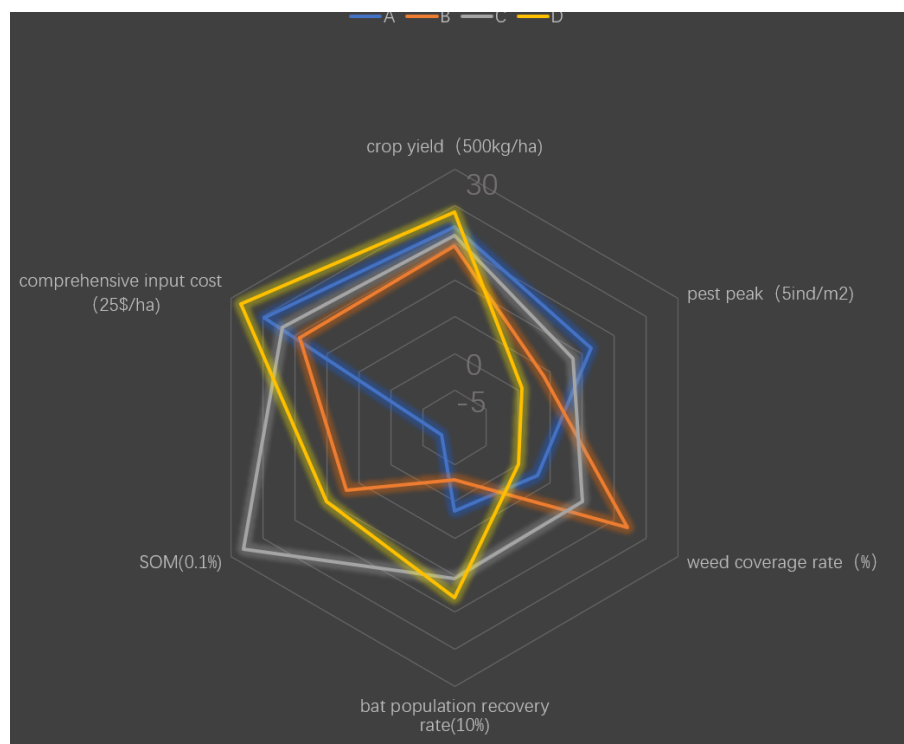


Figure 20: Indicator radar charts

In T-MFD, we simulated up to the day of harvest ( $t=270$ ) and came up with the following evaluation metrics. We found that the best overall evaluated green farming method was **Intelligent Management (D)**. Then Ecological Interplanting (C) and Biological Control (B) which have their own advantages. In the evaluation of sustainability and benefits, Chemical Control ranked last.

## 7.4 Analysis of Green Strategies

Of course, we can make trade-offs among the models to arrive at an optimal green agriculture strategy. For example, the use of highly intelligent agricultural machinery to assist in biological control, combined with intercropping to maximize the amount of crops harvested.

# 8 Conclusion

## 8.1 Strength and Weakness

- **Strength:** Our model incorporates both spatial and temporal relationships. On the temporal scale, it includes factors such as crop growth cycles, farmer planting cycles, and seasonal variations. On the spatial scale, it considers edge habitat suitability and species dispersal rates, ensuring a comprehensive scenario analysis.
- **Weakness:** Our model includes a limited number of species, focusing only on a few representative ones, and the food web is far less complex than in reality. Moreover, with the advancement of modern agricultural technologies, the best agricultural system management strategies cannot be inferred solely based on interspecies relationships.

## 8.2 Future Work

In the future, we will incorporate additional factors into the model, such as randomly introducing disaster scenarios to test environmental balance stability.

We can also mix multiple green strategies to fit an optimal green farming model, which in turn helps farmers improve their farming systems to be more sustainable.

We aim to use our model to predict the best approaches for farmers to manage agricultural systems sustainably, contributing our part to global green development.

## 9 Letter to Farmers

Dear Partner in  
Agriculture,

Konwing that you are considering the path to switching to organic farming. As a team of professionals, we've combined the results of our mathematical modeling simulations to provide you with some practical advice

**Firstly, building a resilient ecology from the land.** When you decide to reduce or discontinue the use of chemicals, your farmland will go through a brief “pain period”. The return of weeds and fluctuations in pests may worry you.. In our model (T-MFD) simulations, discontinuing the use of herbicides temporarily unbalances the ecosystem. It may be worthwhile to try a phased transition: keep a small amount of chemical intervention as a buffer initially, and gradually introduce biological controls. At the same time, inter-planting nitrogen-fixing crops such as legumes or cover plants (e.g., clover) not only inhibits weed growth, but also replenishes the soil with natural nutrients and reduces fertilizer inputs.

**Tn addition, using intelligent technology for cost optimization.** Complete reliance on manual weed ing or conventional organic methods may increase labor costs. In our simula tions, we found that smart agriculture is more sustainable and effective. We sug gest exploring the integration of “precision management” with natural forces.

**What's more, leveraging policy dividends to develop green markets.** As consumer demand for healthy food continues to grow, you have the oppor tunity to earn a higher price for your products by participating in community supported agriculture (CSA) or green branding partnerships.

**A call to drive change in the industry.** We call on the government to set up a special fund to support small farmers in purchasing biological agents and smart equipment; advocate the establishment of a transparent organic certification system to prevent inferior products from dis rupting the market;

Switching to organic farming is a journey to reconnect with nature. We would like to walk side by side with you, provide technical advice with mathematical modeling, and work together to draw a blueprint for agricultural and ecological co-prosperity.

Sincerely yours,

Your friends



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# Report on Use of AI

## 1. OpenAI ChatGPT (Nov 5, 2023 version, ChatGPT-o1,)

**Query1:** <What models are available to simulate spatial problems in ecological dynamics>

**Output:** <There are several models available to simulate spatial problems in ecological dynamics, depending on the complexity of the system and the scale of the study. Some of the commonly used models include:

1. **Individual-Based Models (IBMs):** - These models simulate the behaviors and interactions of individual organisms within a population, considering their spatial distribution. - They are particularly useful in studying complex ecological processes like predation, competition, and dispersal. - Example: **NetLogo** is a widely used platform for creating IBMs.
2. **Agent-Based Models (ABMs):** - Similar to IBMs, ABMs focus on simulating the actions and interactions of autonomous agents within a spatial environment. - They are often used for modeling the spread of diseases, animal movement, or plant growth across a landscape. - Example: **Repast** is a popular platform for agent-based simulations.
3. **Cellular Automata (CA):** - Cellular automata use a grid-based system to represent space, with each cell evolving over time based on specific rules related to its neighbors. - They are particularly useful in simulating land-use changes, habitat fragmentation, and vegetation dynamics. - Example: **GAMA** is a modeling platform that can incorporate cellular automata.
4. **Metapopulation Models:** - These models simulate the dynamics of populations distributed across fragmented habitats, where interactions between subpopulations (e.g., migration, extinction) are essential. - They are widely used to study species conservation, landscape connectivity, and habitat corridors. - Example: **RAMAS Metapop** is a model for studying metapopulations.
5. **Landscape Models:** - These models are designed to simulate ecological processes across spatial landscapes, considering factors like habitat quality, fragmentation, and movement corridors. - They often incorporate spatial patterns and habitat heterogeneity to predict biodiversity outcomes. - Example: **Landis-II** is a forest

landscape modeling tool.

6. **Spatially Explicit Population Models (SEPMs)** - These models combine population dynamics with spatial structures to examine how environmental heterogeneity affects species' growth and dispersal. - SEPMs are useful for predicting species persistence in varying environmental conditions. - Example: **VORTEX** is a software for population viability analysis with spatial components.

7. **Reaction-Diffusion Models** - These models describe the movement and spread of species, diseases, or pollutants through space, often using differential equations. - They are effective for simulating spatial patterns like species invasion, disease spread, or pollutant dispersion. - Example: **EcoSim** is an example of using reaction-diffusion equations in ecological simulations.

8. **Spatially Explicit Lotka-Volterra Models** - These models extend the classic Lotka-Volterra equations for predator-prey dynamics by including spatial heterogeneity in the form of local interactions between populations. - They are commonly used to study spatially structured communities.

Each model is suited to different types of ecological problems, and often, models can be integrated or hybridized to address more complex spatial dynamics.>

## 2. OpenAI Ernie (Jan 26, 2025 version, ChatGPT-4o)

**Query1:** <Could you please describe a few green farming options?>

**Output:** <Certainly! Here are a few green farming options that focus on sustainability and environmental preservation:

1. **Organic Farming**: This method avoids synthetic fertilizers and pesticides, focusing on natural processes like crop rotation, composting, and using organic inputs to maintain soil health. It promotes biodiversity and reduces the environmental impact of farming.

2. **Agroforestry**: Integrating trees and shrubs into agricultural systems can help improve soil fertility, reduce erosion, increase biodiversity, and provide additional sources of income through timber or fruit production. Trees can also act as carbon sinks, absorbing CO<sub>2</sub> from the atmosphere.

3. **Permaculture**: This system designs agricultural ecosystems that mimic natural ecosystems, focusing on sustainability, resilience, and minimal waste. It involves using renewable resources, efficient

water management, and diverse crop systems to minimize environmental harm.

4. **\*\*Hydroponics and Aquaponics\*\***: These methods grow plants without soil, typically using water-based solutions enriched with nutrients. Aquaponics combines hydroponics with fish farming, creating a symbiotic environment where the fish waste fertilizes the plants, and the plants help filter the water for the fish. These methods use less water and can be practiced in urban areas.

5. **\*\*Conservation Tillage\*\***: This farming practice minimizes soil disturbance by reducing plowing. It helps prevent soil erosion, maintains soil moisture, and supports carbon sequestration in the soil.

6. **\*\*Cover Cropping\*\***: Growing specific crops, like legumes or grasses, during the off-season can help prevent soil erosion, improve soil fertility, and reduce the need for chemical fertilizers. These crops also provide habitat for pollinators and other beneficial insects.

7. **\*\*Integrated Pest Management (IPM)\*\***: This approach reduces reliance on chemical pesticides by combining biological, cultural, and mechanical practices to control pests. It involves careful monitoring, natural predators, crop rotation, and selecting resistant plant varieties. Each of these methods helps reduce the environmental footprint of farming while maintaining productivity and resilience in the face of climate change.>

**Query2:** <What factors need to be considered for the greening of agroecology?>

**Output:** <The greening of agroecology involves transforming agricultural systems to be more sustainable, resilient, and environmentally friendly. Several factors need to be considered in this process:

1. **\*\*Biodiversity Conservation:\*\*** - Promoting biodiversity at both the farm and landscape levels is essential for ecological resilience, pest control, and ecosystem services. - Encourage the use of polycultures, agroforestry, and the preservation of natural habitats.

2. **\*\*Soil Health and Fertility:\*\*** - Practices that enhance soil fertility, such as crop rotation, composting, and the use of organic fertilizers, are crucial. - Reducing soil erosion and improving water retention through agroecological techniques is also important.

3. **\*\*Water Management:\*\*** - Efficient use of water through techniques like rainwater harvesting, drip irrigation, and soil moisture con-

servation helps in managing limited water resources. - Reducing water pollution and maintaining healthy water cycles are key aspects.

4. **\*\*Climate Change Mitigation and Adaptation:\*\*** - Agroecology must focus on reducing greenhouse gas emissions through practices like reduced tillage, agroforestry, and cover cropping. - Adaptation strategies to cope with climate variability include diversifying crops and improving the resilience of farming systems.

5. **\*\*Agroecological Knowledge and Innovation:\*\*** - Promoting the exchange of local knowledge, traditional practices, and scientific research is vital. - Support for training farmers on agroecological principles and sustainable practices ensures long-term success.

6. **\*\*Sustainable Pest and Disease Management:\*\*** - Integrated pest management (IPM) should be emphasized over chemical pesticides, using biological control, crop rotation, and natural predators. - Reducing the use of chemical inputs enhances biodiversity and ecosystem health.

7. **\*\*Circular Economy in Agriculture:\*\*** - Agroecology should integrate practices that close nutrient and material loops, such as recycling organic waste, composting, and using renewable energy. - Waste reduction in food production, processing, and consumption is essential for sustainability.

8. **\*\*Fair and Equitable Access to Resources:\*\*** - The greening of agroecology should prioritize social equity, ensuring that smallholder farmers, women, and marginalized groups have access to resources and decision-making power. - Land tenure security, fair trade practices, and market access are critical for equitable food systems.

9. **\*\*Policy and Institutional Support:\*\*** - Governments and institutions need to provide policies, incentives, and support that promote sustainable agricultural practices and green technologies. - Adequate subsidies for sustainable practices, research funding, and infrastructure development are necessary.

10. **\*\*Local and Global Food Systems Integration:\*\*** - Agroecology must consider the broader food system, linking local production with regional and global markets. - Supporting local food networks, direct-to-consumer sales, and sustainable supply chains reduces the carbon footprint and promotes food sovereignty.

By considering these factors, the greening of agroecology can create more resilient, sustainable, and productive agricultural systems that

work in harmony with nature.>