

An Economic-Ecological Modeling Framework for Agroecosystems: Integrating Dynamic Food Webs and Multi-Criteria Assessment

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Abstract: This paper proposes an intelligent algorithmic system for analyzing farmland ecosystems, focusing on computerized modeling and evaluation mechanisms that integrate multi-species interactions, agricultural intervention strategies, and system stability. First, an ecological computation pipeline centered on continuous-time dynamics is constructed. Producers, consumers, decomposers, and environmental factors are uniformly abstracted as computable state variables. Pulsed functions and decay mechanisms enable algorithmic representation of agricultural cycles and external inputs. Second, within this framework, multi-predator coordination and species recovery modules are introduced to conduct scenario simulations and comparative analyses of different regulatory strategies. Combined with a multi-indicator weighted algorithm, this enables automatic assessment of ecological status. Finally, ecological constraints are embedded into the profit optimization process, forming a decision support algorithm that balances system stability and output efficiency. This intelligent algorithmic system features a modular structure, excellent scalability, and scenario generalization capabilities. It can characterize complex ecological evolution processes with low computational complexity, providing an algorithmic paradigm with practical application value for intelligent agricultural management and ecological decision-making.

Keywords: Multi-Agent Systems; Computational Decision Support; Agroecosystem Modeling.

1. Introduction

This paper focuses on common challenges in intelligent modeling and algorithmic analysis of agricultural ecosystems, aiming to establish an algorithmic framework capable of uniformly describing multi-species dynamics, human interventions, and system evolution characteristics. As agricultural management grows increasingly complex, traditional empirical or single-factor analysis methods struggle to capture nonlinear coupling relationships among ecological elements and support stable, scalable computational decision-making. Existing research predominantly emphasizes static assessments or localized modeling, with insufficient holistic characterization of agricultural cyclical operations and hierarchical system structures.

Addressing these limitations, this paper adopts an algorithmic systems perspective, abstracting farmland ecological processes into computable dynamic state evolution flows. Through modular design, it integrates functional units such as population renewal, external perturbations, environmental feedback, and comprehensive evaluation into a unified computational pipeline. Methodologically, it combines continuous dynamics with event-driven mechanisms, enabling agricultural management actions to be embedded as algorithms within system operations. Simultaneously, multi-scenario configuration and indicator fusion achieve holistic assessment of system stability and operational status. Using farmland food web regulation as an application example, this paper validates the applicability and scalability of this algorithmic framework in complex ecological scenarios. Experimental results demonstrate that this method effectively characterizes system evolutionary trends and provides reliable computational support for

intelligent agriculture.

2. Agricultural Ecosystem Modeling System: Dynamic Food-Web Algorithms for Ecosystem Simulation

The farm food web model is divided into two main parts: the biological and the abiotic. The biological part comprises four submodels: the producer submodel $P(t)$, the herbivorous insect submodel $I(t)$, the bird submodel $B(t)$, and the decomposer submodel $D(t)$.

In this simple ecosystem, three levels of food web structure are defined: producers, first-level consumers, and second-level consumers. Decomposers are also present to break down plant and animal remains, using these materials to provide energy for their own population reproduction [1].

The model is mainly built in the form of differential equations, using auxiliary tools such as Dirac function and step function. The initial values are set to $P(0)$, $I(0)$, $B(0)$, $D(0)$, $SEI(0)$.

2.1. Farmland Food Web Model (FFWM) Tracking the Evolution of Various Components of The Farmland Ecosystem

(1) Producer Submodel (PS)

Producers are the cornerstone of agroecosystems. After considering herbicides, predators, and agricultural cycles, the producer sub-model is identified, and its explanation can be divided into three parts:

Regarding the plant growth model: The traditional logistic model did not take predatory behavior into account, and the Lotka-Volterra model could not further reflect the effect of resource constraints on biological growth. Thus, a

combination of the two is adopted, taking Lotka-Volterra as the main body and introducing the multiplier of the traditional logistic model $\frac{P(t)}{K}$ [2, 3].

$$\left. \begin{aligned} \frac{dP(t)}{dt} &= r_p P(t) \left(1 - \frac{P(t)}{K}\right) \\ \frac{dP(t)}{dt} &= P_{growth} - \alpha P(t)I(t) \end{aligned} \right\} \rightarrow \frac{dP(t)}{dt} = r_p P(t) \left(1 - \frac{P(t)}{K}\right) - \alpha P(t)I(t) \quad (1)$$

Where: the parameter r is the natural growth rate of the plant, K is the environmental accommodation of the producer, and α is the predation coefficient of herbivorous insects on the producer.

Consideration of the agricultural cycle: Sowing and harvesting are key parts of the agricultural cycle. Given that the agroecosystem is overly homogeneous and environmental resistance stability is weak, the number of seeds sown by farmers decreases by 2% annually, while the harvest percentage increases by 2% annually. Harvest percentage as a function of time:

$$F(n) = f_0 \left(1 + \frac{n}{50}\right) \quad (2)$$

Where f_0 denotes the first-year harvest percentage.
Number of seeds sown as a function of time:

$$F_{harvest} = F(n)P(t) \sum_{n=0}^{\infty} \left[H\left(t - \left(n + \frac{3}{4}\right)T\right) - H\left(t - \left(n + \frac{3}{4} - \varepsilon\right)T\right) \right], n \in \mathbb{N} \quad (5)$$

Estimating the impact of herbicides on producers: Herbicides (intended for weeds) also affect agricultural producers, so their impact is incorporated into calculations. Accounting for herbicide impact and degradation on crops, and assuming farmers spray pesticides at the start of each agricultural cycle, the following equations are derived via the Dirac equation:

Herbicide concentration function:

$$C(t) = \sum_{n=1}^{\infty} u \delta(t - nT) e^{-b(t-nT)}, n \in \mathbb{N} \quad (6)$$

$$\frac{dP(t)}{dt} = r_p P(t) \left(1 - \frac{P(t)}{K}\right) - \alpha P(t)I(t) + S_{sow} - F_{harvest} - C_{impact} \quad (8)$$

(2) Herbivorous Insect Submodel (HIS)

Herbivorous insects (as primary consumers) participate in the ecosystem's material cycle and energy flow. The model's

$$I_{growth} = r_t I(t) f(P(t)), f(P(t)) = \frac{P(t)}{P(t) + k} I_{ingestion} = \alpha P(t)I(t) I_{eaten} = b_1 I(t) B(t) I_{death} = d_t I(t) \quad (9)$$

Where: r_t = natural mortality rate of herbivorous insects;
 k = half-saturation constant; b_1 = predation coefficient of

$$H(t) = \sum_{n=0}^{\infty} U \delta(t - nT) e^{-B(t-nT)}, n \in \mathbb{N}; I_{poisoned} = AH(t)I(t) \quad (10)$$

Where: U = concentration of insecticide per application;
 B = natural decline coefficient of the insecticide; A = effect coefficient of the insecticide on herbivorous insects.

Final Herbivorous Insect Submodel Equation

The plant growth model without considering human factors is as follows:

$$S(n) = S_0 \left(1 - \frac{n}{50}\right) \quad (3)$$

Where S_0 denotes the number of plants sown in the first year.

It is assumed that sowing occurs at 1/4 of each agricultural cycle, and harvesting occurs at 3/4 of the cycle. The Dirac function and Heaviside step function are used to implement seeding and proportional harvesting at specific moments:

Seeding function:

$$S_{sow} = S(n) \sum_{n=0}^{\infty} \delta\left(t - \left(n + \frac{1}{4}\right)T\right), n \in \mathbb{N} \quad (4)$$

Harvest function:

Herbicide impact on producers:

$$C_{impact} = aC(t)P(t) \quad (7)$$

Where: u = concentration of herbicide applied per spray;
 b = natural decline coefficient of the herbicide; a = inhibition coefficient of the herbicide on the producer.

Final Producer Submodel Equation

Combining the three components (plant growth, agricultural cycle, herbicide impact), the producer submodel equation is:

explanation for this submodel is divided into two parts:

Growth modeling of herbivorous insects:

birds on herbivorous insects.

Following the same logic as herbicides, the insecticide impact is modeled as:

$$\frac{dI(t)}{dt} = I_{growth} + I_{ingestion} - I_{eaten} - I_{poisoned} \quad (11)$$

(3) Bird Submodel (BS)

As top predators, birds regulate herbivorous insect

populations and maintain ecosystem stability. The submodel incorporating predation and natural death, referencing insect submodel and logistic model is:

$$\frac{dB(t)}{dt} = b_1 I(t) B(t) - B_{death}, B_{death} = d_2 B(t) \left(1 - \frac{B(t)}{K}\right) \quad (12)$$

Where: d_2 = natural mortality rate of birds; b_1 =

$$R_{harvest} = R_0 \sum_{n=0}^{\infty} \delta(t - nT) + R_0 \sum_{n=0}^{\infty} [\theta(t - nT) - \theta(t - (n+1)T)] e^{-\lambda(t-nT)} - R_0 \sum_{n=0}^{\infty} \delta(t - (n+1)T), n \in \mathbb{N} \quad (13)$$

Where R_0 = fixed amount of plant residue per harvest.

$$\frac{dD(t)}{dt} = r_d D(t) \times \eta (R(t) + R_{harvest}(t)) - D_{death}, D_{death} = d_3 D(t) \quad (14)$$

Where: r_d = natural growth rate of decomposers; η = decomposers energy acquisition efficiency from decomposition; d_3 = natural mortality rate of decomposers.

(5) Soil Fertility Submodel (SFS)

As a key abiotic factor in agroecosystems, soil fertility provides essential elements for producer growth and reflects ecosystem stability. The Soil Fertility Index (SFI) model accounts for regular fertilizer application and fertility decline, with the equation:

predation coefficient of birds on herbivorous insects.

(4) Decomposer Submodel (DS)

The submodel accounts for natural growth, natural mortality, and harvesting effects on plant residues, divided into two parts:

Plant residues from harvesting: Harvesting (once per agricultural cycle) generates large plant residues. The residue model using Dirac function summation describes residue production and decay:

Incorporating natural growth and mortality of decomposers, the decomposer submodel equation:

$$SFI(t) = SFI(0) + M \times C \times \eta_2 \times E^{-V(t-t_0)} \quad (15)$$

2.2. Interpretation of Results

Calculation results from the Figure 1 show: Producers, consumers, and decomposers exhibit periodic fluctuations initially, but eventually tend to stabilize. After initial fluctuations, the ecosystem trends toward stability. The strongest correlation is observed between the number of herbivorous insects and producers.

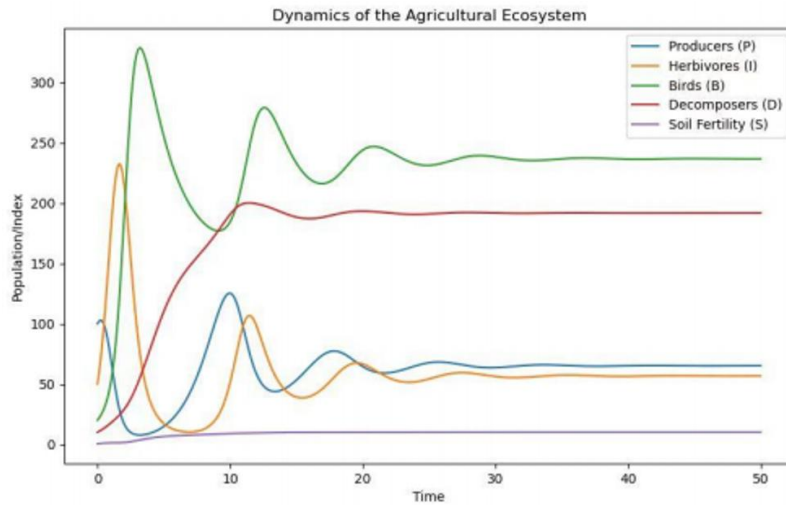


Figure 1. Dynamics of the agricultural ecosystem

2.3. Incorporate Bats into The Food Web and Remove Herbicide Effects

Bat incorporation in food web modeling: Bats are modeled as predators at the same level as birds (based on the original framework), with interspecific competition between bats and birds considered. The competition coefficient γ_T is set, and $\Delta T_{rival} = \gamma_T T(t) B(t)$ represents the competition effect on bat population. The bat submodel equation is:

$$\frac{dT(t)}{dt} = b_T T(t) I_{all}(t) \left(1 - \frac{T(t)}{K_T}\right) - \Delta T_{rival} - T_{death}(t), \quad T_{death} = d_T T(t) \quad (16)$$

Where: b_T = predation coefficient of bats on herbivorous insects; $I_{all}(t)$ = total number of insects in the ecosystem.

Herbicide effect removal: With herbicide effects excluded,

producer population is no longer suppressed by herbicide concentration, leading to the updated producer equation:

$$\frac{dP(t)}{dt} = r_p P(t) \left(1 - \frac{P(t)}{K}\right) - \alpha P(t) I(t) + S_{sow} - F_{harvest} \quad (17)$$

2.4. Consider Returning Species

Regression plant modeling:

In the absence of natural enemies, regression plants grow under resource-limited conditions, modeled as:

$$\frac{dP_B(t)}{dt} = r_B P_B(t) \left(1 - \frac{P_B(t)}{K_B}\right) \quad (18)$$

Regression Insects Modeling:

Based on the original herbivorous insect submodel, the

regression insect model incorporates bat predation effects:

$$\frac{dI_B}{dt} = r_{IB}I_B(t)f(P(t)) + I_{\text{ingestion}} - I_{\text{death}} - I_{\text{eaten}} \quad (19)$$

$$I_{\text{ingestion}} = \beta P(t)I_B(t), I_{\text{eaten}} = b_1I_B(t)B(t) + b_TI_B(t)T(t), I_{\text{death}} = d_4I_B(t) \quad (20)$$

Where: r_{IB} = natural growth rate of regression insects; β = feeding coefficient of regression insects on plants; d_4 = mortality rate of regression insects.

3. Multi-criteria Evaluation Framework for Agroecosystem Stability Using Algorithmic Weighting

This model evaluates agroecosystem stability under different scenarios.

3.1. Indicator Weight Determination

The AHP method (with Saaty 9-scale) is used to weight indicators:

First-level indicators: Biotic factors, abiotic factors;

Second-level indicators: C1–C6. The relative importance of indicator C_i vs. C_j is reflected by the weight ratio w_i/w_j . The process starts with constructing a comparison matrix [4-6].

$$A = \begin{pmatrix} \frac{w_1}{w_1} & \dots & \frac{w_n}{w_1} \\ \frac{w_1}{w_1} & & \frac{w_n}{w_1} \\ \vdots & & \vdots \\ \frac{w_1}{w_n} & \dots & \frac{w_n}{w_n} \\ \frac{w_n}{w_n} & \dots & \frac{w_n}{w_n} \end{pmatrix} = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nn} \end{pmatrix} \quad (21)$$

Where the element a_{ij} (representing the relative importance of indicator C_j to C_i) is defined as:

$$a_{ij} = \frac{w_j}{w_i} \quad (22)$$

w_i denotes the weight of the i -th indicator C_i ; $w = (w_1 \ w_2 \ \dots \ w_n)^T$ is the weight vector, as shown in the Table 1.

Table 1. Indicator Weights (FIEM)

Level 1 Indicators	Weights	Secondary Indicators	Weights
biological factor	0.89	species type	0.28
		Number of producers	0.23
		Number of primary consumers	0.19
		Number of secondary consumers	0.16
		Number of decomposers	0.14
abiotic factor	0.11	soil fertility	1

3.2. Ecosystem Stability Analysis by AHP

Based on the indicator weights obtained earlier, an agroecosystem stability evaluation formula is proposed (the specific formula content is not fully presented in this fragment).

$$f_i = \sum_{j=1}^n w_j^i y_j^i \quad (23)$$

Where w_j^i is the weight of indicator j at moment i , and y_j^i is the value of indicator j at moment i .

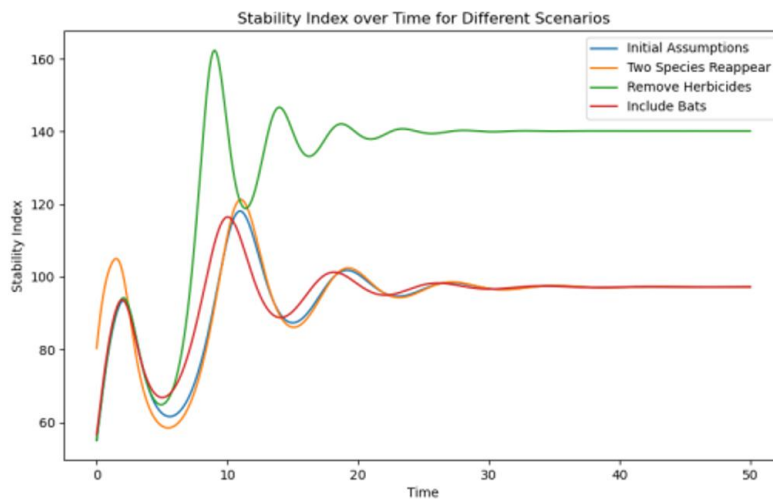


Figure 2. Stability index over time for different scenarios

From the data images shown in Figure 2, it can be observed that agricultural ecosystems in all scenarios tend toward long-term stability.

Species re-emergence: Has dual effects—improves stability to some extent but introduces uncertainty.

Herbicide removal: Short-term (5-6 years): Stability is similar to other scenarios.

Long-term: Stability rises sharply, with an average 40% higher stability than other scenarios.

Overall trend: Species return has the greatest short-term impact on stability; herbicide removal drives a qualitative leap in long-term stability.

4. Economic Optimization in Agroecosystems: Algorithmic Decision Support for Sustainable Farming

4.1. Model Establishment

The model introduces ladybug beetles (as biological pest control) to optimize pest population management. The goal is to determine the appropriate number of ladybugs to maximize economic benefits, with the ladybug population function defined as $L(t)$.

Income Function: Farmer's income derived solely from agricultural products is modeled as:

$$G(t) = P_{sell} \times H(n)P(t)W \quad (24)$$

Where: $H(n)$ represents the harvesting ratio function.

Cost Function: Farmer's costs primarily stem from pesticides, herbicides, and fertilizers, modeled as:

$$X = C_h + C_r + C_F \quad (25)$$

Where: C_h = cost of herbicides; C_r = cost of pesticides; C_F = cost of fertilizers.

Objective Function: To balance economic benefits and environmental factors (supporting sustainable development while accounting for all ecosystem components), the objective function is set to maximize net profit:

$$\text{Max}(G(t) - X) \quad (26)$$

4.2. Constraint Conditions

Crop Growth Rate Constraints:

The nonlinear relationship between crop growth rate and soil fertility is modeled as:

$$r(P, SEI) = r_0 \left(1 - \frac{P}{K_P} \right) \left(1 - \frac{SEI}{SEI_{\text{Max}}} \right) \quad (27)$$

Where r_0 = maximum crop growth rate. Constraint: $0.1 < r(P, SEI) < 0.2$.

Bird/Bat Predation Rate Constraints:

The predation rate (related to herbivorous insect population and seasonal variations) is:

$$b_1 = b_0 \left(1 - \frac{I}{I_{\text{Max}}} \right) \quad (28)$$

Where b_0 = maximum bird/bat predation rate. Constraint: $0.005 < b_1 < 0.01$.

Ladybug Predation Rate Constraints:

The ladybug predation rate (related to herbivorous insect population) follows a similar form:

$$b_L = B_0 \left(1 - \frac{I}{I_{\text{Max}}} \right) \quad (29)$$

Where B_0 = maximum ladybug predation rate on

herbivorous insects.

Species Population Range Constraints:

For a stable ecosystem, the population of each species is constrained by the integrated environmental carrying capacity K .

Shannon-Weiner Index Constraint:

To further ensure ecosystem stability, the Shannon-Weiner index (a measure of species diversity) is added as a constraint:

$$H' = -\sum_i p_i \ln p_i \quad (30)$$

Where p_i = proportion of species i in the ecosystem.

Constraint range: $1.0 < H' < 2.0$.

4.3. Organic Farming Model Solution

Calculations yield the optimal introduction range for ladybug beetles. Comparisons show:

In the long term, appropriate ladybug introduction can replace insecticides.

This introduction also improves agroecosystem stability.

5. Conclusions

This paper proposes an intelligent algorithmic model for analyzing and managing farmland ecosystems. By systematizing and computationalizing ecological processes, it provides a unified tool for evaluating and optimizing complex agricultural systems. First, the model integrates producers, consumers, decomposers, and environmental factors through a modular algorithmic structure. This enables a holistic characterization of multi-level interactions within farmland ecosystems and reflects the system's evolution from initial fluctuations toward long-term stability. Second, after incorporating biological regulation and management strategies, the model quantifies ecological stability through integrated evaluation methods. Results indicate that long-term system stability can be enhanced by approximately 40% under certain scenarios, demonstrating the model's practical value for agricultural management and policy assessment. Finally, by integrating ecological constraints into economic benefit calculations, the model achieves coordination between ecological conservation and agricultural profitability, providing a feasible pathway for sustainable agricultural decision-making. Overall, this model offers clear structure, strong adaptability, and good scalability. Future research could further expand its capabilities in data integration and regional-scale applications.

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