Dynamic Evolution of Agroecosystem Based on Improved Lotka-Volterra Model

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Abstract. With the global population growth and the rising demand for agricultural products, the impact of agricultural expansion on the ecosystem has attracted much attention, and how to balance the ecological benefits and economic benefits has become a concern. Therefore, we establish a mathematical model to study the dynamic evolution process of the agricultural ecosystem, aiming to analyze the influence of natural factors and human decision-making and provide a theoretical basis for farmers to adopt agricultural production strategies that combine both ecological and economic benefits. Based on the Logistic Growth model modified Lotka-Volterra model (LMLV), this study constructed a food web model of the agricultural ecosystem, simulating the influence of inter-species competition, agricultural cycle, persistence cycle, and chemical factors on the dynamic change of the ecosystem. In addition, we established the agroecological ecosystem stability index ($AESI$) to quantify ecosystem stability. Then we conducted numerical simulation of the model through the Runge-Kutta methods in MATLAB, and the results show that the improved LMLV model we constructed can effectively describe the dynamic evolution process of the agricultural ecosystem, which provides a scientific basis for optimizing the agricultural production strategies. This model not only contributes to understanding the complex interactions of ecosystems but also provides theoretical support for achieving sustainable agriculture.

Keywords: logistic growth, Lotka-Volterra, agroecological ecosystem stability, Runge-Kutta, sustainable agriculture

1. Introduction

The phenomenon of forests being converted into farmland has become increasingly common in recent years due to global population growth and rising agricultural demand. This large-scale deforestation has not only had a profound impact on ecosystems but also affects the sustainability of agricultural production. According to data from the Food and Agriculture Organization (FAO) [1], approximately 74 million hectares of forests are cleared annually worldwide, with some areas being transformed into agricultural land, particularly in tropical regions (FAO, 2020). This transformation has turned forests, once rich in biodiversity, into monoculture farming areas, leading to significant changes in the structure and function of ecosystems. However, agricultural expansion is not irreversible. With the growing awareness of ecological conservation, some regions have begun exploring more sustainable agricultural models, such as organic farming and edge habitat restoration strategies. Research has shown that species return plays a key role in restoring ecological balance while reducing chemical usage, which also helps improve the stability of agricultural ecosystems. Given this complex process of change, there is an urgent need for dynamic modeling to track the conversion process from forests to farmland, analyze the interaction between natural processes and human decisions, and provide a scientific basis for achieving a balance between agricultural production and ecological protection.

The Lotka-Volterra (LV) model is often used to construct the relevant mathematical model when constructing the ecosystem food web model. The LV model, introduced by Lotka in 1925 and later improved by Voltera, initially focused on simulating predator-prey relationships between species [2]. The model is applicable to problems such as competition between species, firms, coexistence, and ecosystem dynamics modeling, such as the study of species competition in ecosystems [3] and competition between firms or industries [4]. Over the past few decades, the LV model has been widely used in the field of ecosystem food web modeling due to its simplicity and intuitiveness. However, while traditional LV models are excellent at describing basic predator-prey relationships, they are limited in their ability to predict the dynamics of complex ecosystems. In particular, LV models generally assume that changes in population size are only influenced by interactions between a single predator and prey, ignoring other factors such as environmental changes, multi-species interactions, and human factors. Therefore, in recent years, researchers have begun to explore more complex models. For example, Huang et al simulated the impact of sex ratio on lampreys population and ecosystem stability through the LV model [5], Wang et al built three improved LV models and explored the ecosystem food web model under the multi-prey-multi-predator model [6]. Genda et al. investigated how periodical hunting and changes in food quantity affect the classic Hamiltonian LV model by modeling changes in the reproductive rate of prey with the coefficient of periodic changes [7]. Su et al. have intricately woven climate variables by using the enhanced LV model. The dynamics of plant communities under different climatic conditions were studied [8]. Davis et al. explored the method of quantifying the interaction between populations using the LV model [9].

However, for agroecosystems that are mainly affected by natural factors and human decisions, the above studies often do not fully consider the influence of human factors such as sowing, harvesting, weeding, insecticide, and seasonal changes of biological reproduction, which is not enough to build a reasonable and applicable agroecosystem food web model. Therefore, to address the limitations of traditional LV models in agricultural ecosystem applications, this study innovatively couples human decision variables (such as planting cycles and chemical agent application intensity) with natural ecological processes (species population dynamics and seasonal reproduction), constructing a dynamic model framework that integrates agricultural management cycles with ecological succession processes. Compared to the improvements made by Huang et al. [5] and Wang et al. [6] on biological intrinsic relationships, this study achieves the quantification of human intervention behaviors such as chemical agent application intensity and weeding through multi-parameter corrections to the growth rate. This innovation enables the model to capture the bidirectional feedback mechanism between "human selection and ecological response" that is unique to agricultural systems. Furthermore, the model structure creatively integrates the asymmetric competition mechanism from the Logistic Growth Model, solving the linear simplification problem of traditional LV models when describing multi-trophic level competition among crops, weeds, and pests. Compared to Su et al. [8] who embed climate variables, this study establishes a nonlinear relationship between pesticide concentration gradients and population growth rates, thereby more accurately depicting the cascading effects of pesticide use on food webs. Additionally, the model first dynamically matches the seasonal cycles of agricultural production with the human-intervened agricultural cycles, achieving a mathematical description of the alternating process of "cultivation window period - ecological recovery period" in tropical multi-cropping systems. This breakthrough provides a quantitative tool for evaluating the ecological carrying capacity under different agricultural practices. These theoretical innovations not only expand the application boundaries of LV models but also establish a computable analytical framework for formulating precise agricultural management strategies based on ecological thresholds. They are of significant methodological importance for achieving the synergistic advancement of the United Nations Sustainable Development Goals (SDGs) related to "zero hunger" and "terrestrial biodiversity."

2. Model

2.1. The logistic Growth model modified the Lotka-Volterra model.

The Lotka-Volterra Mode is a classical mathematical model that describes the interaction between two species and is commonly used in ecology to study the relationship between predator and prey. The model consists of two equations that describe how predator and prey populations change over time. The logistic Growth model is a mathematical model that describes the change of biological population over time. This model takes into account the fact that the population growth rate decreases as the population size increases, because of limited resources and the growth rate decreases significantly as the population size approaches the maximum that the environment can support (called the environmental capacity). Here, we adopt the Logistic Growth model modified Lotka-Volterra (LMLV) model as the basic model to describe the dynamic changes of the agroecosystem.

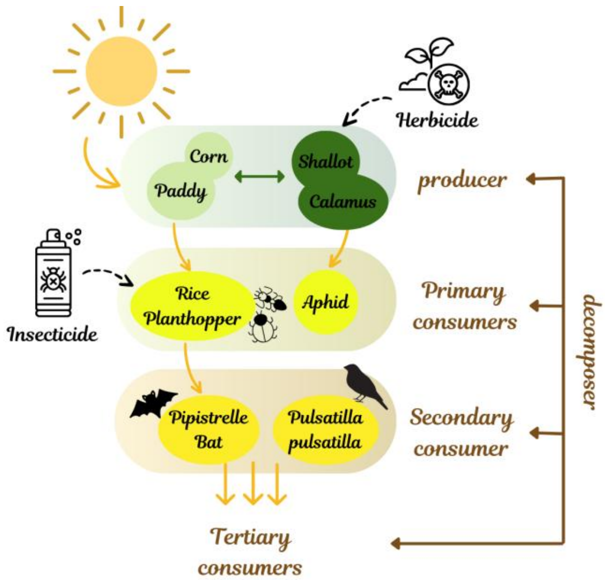

Fig. 1 The Food Web Models for Agroecosystems

To implement this model, we first constructed a basic food web model of an agro-ecosystem as shown in Figure 1. There are five levels of this food web: producers (crops, weeds), primary consumers, secondary consumers (bats, birds), tertiary consumers, and decomposers. Then the following kinetic equation is established. (Third, consumers and decomposers have less influence on this ecosystem, so we ignore the impact of these two organisms on the model.)

(1) The equation for producers (mainly crops and herbaceous plants).

Crops:

$$\frac{dP_a}{dt} = r_a P_a (1 - \frac{P_a}{K_a}) - \alpha_{ca} C \frac{P_a}{P_a + 1} \tag{1}$$

Herbaceous plants :

$$\frac{dP_o}{dt} = r_o P_o (1 - \frac{P_o}{K_o}) - \alpha_{co} C \frac{P_o}{P_o + 1} \tag{2}$$

where P_a and P_o C represent the population density of crops and herbs and primary consumers respectively, r_a and r_o represent the natural growth rate of crops and herbs, K_a and K_o represent the environmental capacity of crops and herbs, α_{ca} and α_{co} represent the predation rate of crops and herbs by primary consumers. $\frac{1}{1+P_a}$ And $\frac{1}{1+P_o}$ represents the functional response function between primary consumers, crops, and herbs, and represents the amount of prey consumed per unit of time.

(2) The equation for primary consumers (mainly insects).

$$\frac{dC}{dt}=(\delta_c+\frac{P_a+P_o}{K_a+K_o})r_cC(1-\frac{C}{K_c})-\alpha_{HC}H\frac{C}{1+C}-\mu_cC \tag{3}$$

where H is the population density of secondary consumers, K_c is the environmental capacity of primary consumers, r_c is the natural growth rate of primary consumers, α_{HC} is the predation rate of secondary consumers on primary consumers, and μ_c represents the natural mortality rate of primary consumers. $\frac{1}{1+C}$ Represents the functional response function between secondary consumers and primary consumers. $\delta_c+\frac{P_a+P_o}{K_a+K_o}$ Reflects the effect of the number of primary producers on the growth rate of primary consumers, based on the principle that the population density of primary producers affects the predation rate of primary consumers, and δ_c is a constant.

(3) The equation for secondary consumers (mainly birds and bats).

$$\frac{dH}{dt}=(\delta_H+\frac{C}{K_c})r_HH(1-\frac{H}{K_H})-\mu_HH \tag{4}$$

where r_H is the natural growth rate of secondary consumers, K_H is the environmental capacity of secondary consumers, μ_H is the natural death rate of secondary consumers, $\delta_H+\frac{C}{K_C}$ reflects the impact of the number of primary consumers on the growth rate of secondary consumers, δ_H is a constant.

2.2. Competition model modification

During ecosystem modeling, the original LMLV model describes the interactions between predators and prey. In the real world, however, competition for resources is not limited to predator-prey relationships but also includes competition for resources between species. In agroecosystems, the main producers are herbs and crops, which have a clear competitive relationship. Therefore, we further modified the LMLV model to take into account competition between crops and herbs. By introducing the effects of resource constraints and inter-species competition, the model can more accurately reflect the complex interactions between species in an ecosystem. We believe that crop growth is not only limited by environmental carrying capacity and predators but also by competition with herbaceous species. The specific dynamic equation is as follows:

Crops:

$$\frac{dP_a}{dt}=r_aP_a(1-\frac{P_a}{K_a})-\alpha_{ca}C\frac{P_a}{P_a+1}-\lambda_{oa}P_o\frac{P_a}{K_a} \tag{5}$$

Herbaceous plants :

$$\frac{dP_o}{dt}=r_oP_o(1-\frac{P_o}{K_o})-\alpha_{co}C\frac{P_o}{P_o+1}-\lambda_{ao}P_a\frac{P_o}{K_o} \tag{6}$$

where λ_{oa} represents the competition inhibition rate of herbaceous plants on crop growth, and λ_{ao} represents the competition inhibition rate of crops on herbaceous plant growth.

2.3. Agricultural cycle model modification

The influence of the agricultural activity cycle on ecosystem population dynamics is particularly significant. In order to more accurately describe the dynamic changes of the population in the agricultural cycle, we modified the model by referring to the typical characteristics of the rice planting cycle and formed a dynamic correction model combining the temporal characteristics and ecological relations. The modified model not only describes the interactions between producers (crops), consumers (pests, natural enemies), and the environment but also reflects the disturbing effects of agricultural interventions (e.g., fertilization, pest control, etc.) on ecosystems. First, we construct a timeline model that intuitively shows human intervention in agroecosystems throughout the agricultural cycle.

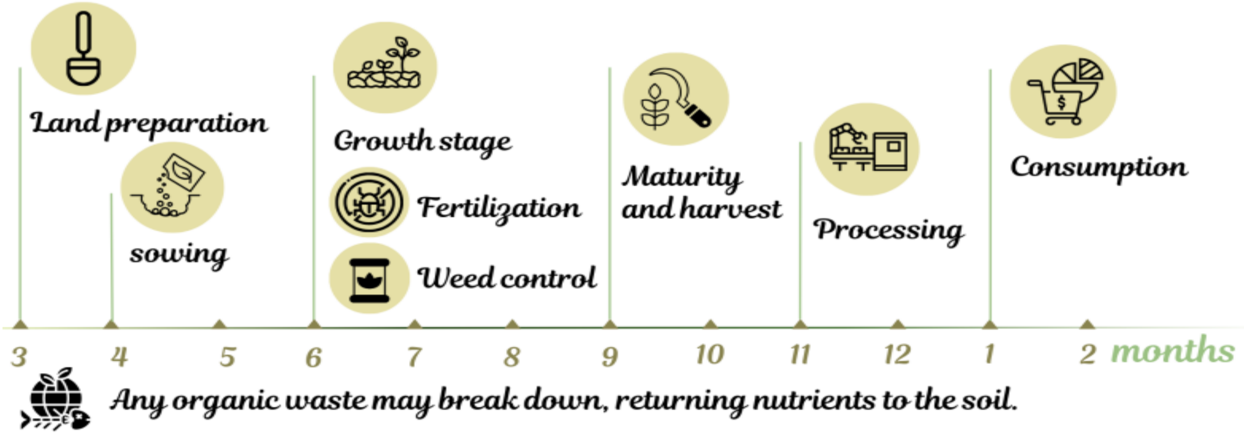

Fig. 2 Activities of the Agricultural Cycle

As shown in Figure 2, land preparation and weeding are carried out in February, sowing occurs in March, fertilization and herbicide application take place from April to July, harvesting happens in August, and from August to the following February, the focus is mainly on agricultural product processing and sales, with agricultural products temporarily leaving the agricultural ecosystem. (Maintain pest control throughout the year)

Based on this, we can establish the following piecewise function model:

$$\begin{cases} P_o(t) = P_{of} \\ P_a(t) = P_{af} \\ \begin{cases} r_a' = (1+\eta) r_a \\ \dfrac{dC}{dt} = f(\beta) \end{cases} \\ P_a(t) = 0 \end{cases} \tag{7}$$

where, P_{of} represents the initial density of herbaceous plants in the agro-ecosystem, i.e. the density of herbaceous plants after weeding. P_{af} Represents the initial amount of crops in an agro-ecosystem, that is, the amount of crops grown in the ecosystem at each seeding. η Shows how efficiently the fertilizer promotes crop growth, and β shows how much the pesticide inhibits insect growth.

The above formulas represent the effects of agricultural activities on the model from top to bottom, weeding in February, sowing in March, fertilizing and using herbicides to weed in April to August, and harvesting in September.

2.4. Seasonal growth model modification

The seasonal growth correction reflects the impact of seasons on the growth rate, improving the model's dynamic changes across different seasons. Seasonal factors (such as temperature and precipitation) will influence the model from both the plant growth cycle and the insect reproduction cycle. Therefore, the growth rate parameters of producers and consumers need to be modified accordingly.

The correction for the growth rate of producers:

$$\begin{cases} r_a(t) = r_a(1 + A_1 \sin(\dfrac{2\pi t}{T_1} + \vartheta_1)) \\ r_o(t) = r_o(1 + A_2 \sin(\dfrac{2\pi t}{T_2} + \vartheta_2)) \end{cases} \tag{8}$$

where A_1 and A_2 represent the degree of seasonal variation in the growth of herbaceous plants and crops. T_1 And T_2 denote the growth cycles of herbaceous plants and crops, typically lasting one year. ϑ_1 And ϑ_2 are phase shifts are used to adjust the functions, ensuring that the periodic functions accurately reflect the seasonal growth rate variations of herbaceous plants and crops.

The correction for the growth rate of primary consumers:

$$r_c(t) = r_c(1 + B\sin(\frac{2\pi t}{T_c} + \vartheta_c)) \tag{9}$$

where B represents the degree of seasonal variation in the reproduction of primary consumers, T_c represents the reproductive cycle of primary consumers, typically lasting one year, and ϑ_c is the phase shift used to adjust the function, ensuring that the periodic function reflects the seasonal growth rate variations of primary consumers.

The correction of the growth rate of secondary consumers:

$$r_H(t) = r_H(1 + C\sin(\frac{2\pi t}{T_H} + \vartheta_H)) \tag{10}$$

where C represents the degree of seasonal variation in the reproduction of secondary consumers, T_H represents the reproductive cycle of secondary consumers, typically lasting one year, and ϑ_H is the phase shift used to adjust the function, ensuring that the periodic function reflects the seasonal growth rate variations of secondary consumers.

2.5. Chemical model modification

In agricultural ecosystems, pesticides are often used to control pests, and herbicides are used to suppress the growth of herbaceous plants in order to increase crop yield. Therefore, we have designed a modified model to simulate the effects of chemicals such as herbicides and pesticides on the ecosystem.

Considering the impact of herbicides on plant health:

Crops:

$$\frac{dP_a}{dt} = r_a P_a(1 - \frac{P_a}{K_a}) - \alpha_{ca} C \frac{P_a}{P_a + 1} - \lambda_{oa} P_o \frac{P_a}{K_a} - \theta_a P_a \tag{11}$$

Herbaceous plants

$$\frac{dP_o}{dt} = r_o P_o(1 - \frac{P_o}{K_o}) - \alpha_{co} C \frac{P_o}{P_o + 1} - \lambda_{ao} P_a \frac{P_o}{K_o} - \theta_o P_o \tag{12}$$

where θ_a and θ_o represent the inhibition rates of herbicides on the growth of crops and herbaceous plants, respectively.

Considering the impact of pesticides on primary consumers (mainly insects) populations:

$$\frac{dC}{dt} = (\delta_c + \frac{P_a + P_o}{K_a + K_o}) r_c C(1 - \frac{C}{K_c}) - \alpha_{HC} H \frac{C}{1 + C} - \mu_c C - \beta C \tag{13}$$

where β represents the inhibition rate of pesticides on insect growth.

Considering the impact of chemical use on the stability of the ecological environment:

Firstly, according to the dynamic factor-based farmland ecosystem stability evaluation method proposed by Zhao et al. [10], the Agricultural Ecosystem Stability Indicator ($AESI$) was defined. Farmland ecosystem stability refers to the dynamic process in which the system structure remains relatively reasonable, the material circulation and energy flow in the system remain relatively balanced, and the system output fluctuates around a certain value under continuous natural and human interference. This value can be increased as technology advances, but there is also a ceiling.

The stability of farmland ecosystem refers to a dynamic process in which the structure of the system is more reasonable, the material circulation and energy flow of the system can maintain a relative balance, and the output of the system fluctuates around a certain quantity value under the uninterrupted interference of nature and man. This amount can be increased as technology advances, but there is an upper limit. The stability evaluation of farmland ecosystem takes regional farmland ecosystem stability evaluation as the target layer, and its characterization indexes are divided into regional ecological environment quality (C_1), artificial input process (C_2), yield formation process (C_3), and economic and social process (C_4) 4 broad categories of classification indicators, which represent aspects that affect the overall stability of agroecosystems.

Zhao et al. used principal component analysis (PCA) to determine the weights of the components of the $AESI$. The consistency ratio (CR) of the $AESI$ indicator weights was found to be 0.06036, which is less than 0.1, indicating that the weight matrix passes the consistency test and is reasonable.

The resulting $AESI$ calculation formula is as follows:

$$AESI = 0.177 \cdot C_1 + 0.233 \cdot C_2 + 0.314 \cdot C_3 + 0.276 \cdot C_4 \tag{14}$$

In this model, it is assumed that economic benefits do not influence the measures taken by humans in the ecosystem. In other words, humans in this ecosystem do not consider economic benefits when making decisions. Therefore, we set $C_3 = C_4 = 1$.

Since the environmental stability of an ecosystem is typically related to fluctuations in population density, a stable ecosystem should be able to resist external disturbances (such as pesticide use) and maintain a relatively stable population size. We can use the following formula to calculate the environmental stability index (ESI)of the ecosystem(C_1):

$$ESI = \frac{1}{M}\sum_{i=1}^{N}\left(1 - \frac{|N_i - N|}{N_{\max} - N_{\min}}\right) \tag{15}$$

where N_i is the population density of each species, M is the number of each species, $N_{\max}$ is the maximum population density of the species, and $N_{\min}$ is the minimum population density of the species.

The human input process, namely the human impact on ecosystem stability index $HESS$ (Human Ecosystem Stability Index), can be measured by the degree of damage to the environment caused by human use of chemical products. This model $HESS$ only considers the degree of damage to the environment caused by the human use of herbicides and pesticides of different concentrations. The $HESS$ (C_2) formula is calculated as follows:

$$HESS = 1 - \beta - \theta \tag{16}$$

Considering the impact of ecosystem environmental stability on the species growth rate, the following feedback model is established. For all organisms in this ecological environment, we have an environmental carrying capacity K that satisfies:

$$K'(AESI) = K \cdot AESI \tag{17}$$

where K is the carrying capacity of the natural environment and K' is the carrying capacity of the environment dynamically regulated by the $AESI$ factor? This model can explain how chemicals affect quantitative changes in individual components of an ecosystem by destabilizing it.

3. Results and analysis

Since the model we establish is a nonlinear ODE system, it contains multiple variables and complex interactions. Solving such systems analytically is often impossible, so numerical methods are necessary. Our model takes into account seasonal variations and agricultural cycles, which means that the solution will change significantly over time. Numerical methods are able to capture these dynamic behaviors.

3.1. Solution scheme for the ODE system based on the Runge-Kutta algorithm

We solve this ODE system using the Runge-Kutta method, which is a very popular numerical integration method used to solve $ODEs$ .Runge-Kutta methods are a class of implicit and explicit iterative methods for solving initial value problems. The central idea of these methods is to more accurately estimate the change in solution by evaluating the slope of the function at multiple points. The 4th-order Runge-Kutta method (i.e., the method used by $ode45$), involves the following steps:

(1) Initialization: setting the initial conditions and the time step.

(2) Slope Evaluation: Evaluate the slope of the function at four different locations at the current time point.

(3) Update Solution: Use the weighted average of these four slopes to update the solution.

(4) Time advancement: Advance the time by one step and repeat steps (2) and (3) until the desired final time is reached.

The key to this method is that it provides higher accuracy than the simple Eulerian method while maintaining a relatively simple and efficient computational process.

Combining all the above correction methods, we have established a comprehensive ODE system for agroecosystems. We solved this ODE system using the built-in $ode45$ solver based on the Runge-Kutta method MATLAB. The data we used during the experiment as well as the initial values are shown in Table 1.

Table 1. Initial values and variables

Symbol	Numerical	Unit	Symbol	Numerical	Unit
$P_a(0)$	1000	Plants/ha	δ_C	0.8	/
$P_o(0)$	500	Plants/ha	r_H	0.03	/
$C(0)$	15000	Per/ha	μ_H	0.02	/
$H(0)$	50	Per/ha	K_H	100	Per/ha
r_a	0.07	/	δ_H	0.8	/
r_o	0.15	/	λ_{ao}	0.002	/
K_a	8000	Plants/ha	λ_{oa}	0.005	/
K_o	10000	Plants/ha	θ_a	0.05	/
α_{ca}	0.0015	/	θ_o	0.05	%
α_{co}	0.001	/	β	0.01	/
μ_C	0.01	/	r_C	0.05	/
K_C	20000	Per/ha	α_{HC}	0.2	/

We used this model to simulate the dynamic change of population density of each component of the agroecosystem over a period of two years and the dynamic change $AESI$ over time under the action of agricultural cycles. Further, we explored the effects of insecticide and herbicide intensity on various components of the agroecosystem $AESI$.

3.2. The dynamic change of the model over time

Under the initial value conditions and data in Table 1, MATLAB was used to solve the model, and the curve of herb and crop population density changed over time, the curve of primary and secondary consumer population density changed over time and the curve of $AESI$ overtime was drawn in the two agricultural cycles, as shown in Figure 3, 4 and 5.

Figure 3 shows trends in herbaceous and crop population density over time. The population density of both herbaceous plants and crops showed obvious cyclical fluctuations. In an agricultural cycle, crops grow rapidly after sowing, but the growth rate gradually slows down and eventually tends to stabilize. In the field preparation stage, the density of herbaceous plants decreased sharply due to physical weed control. In the sowing stage, because of the low population density and weak interspecific competition, herbaceous plants grow rapidly. In the growth stage of crops, the population density of herbaceous plants decreased significantly due to herbicide intervention and crop competition inhibition. During the harvest period, due to the temporary removal of the agroecosystem and the artificial stop of herbicide use, the interspecific competition between crops and herbs and the inhibition effect of human factors on herbs were weakened, and the population density of herbs began to rise. Due to the strong reproductive ability of herbs, the population density quickly rose, and soon reached the highest value. And gradually leveling off. These cyclical changes indicate that cyclical agricultural activities have a significant impact on the structure of vegetation in agro-ecosystems, where interventions such as fertilizers, herbicides, and pesticides can optimize crop yields in the short term, but at the same time can lead to ecosystem fluctuations such as sharp declines in herb population densities.

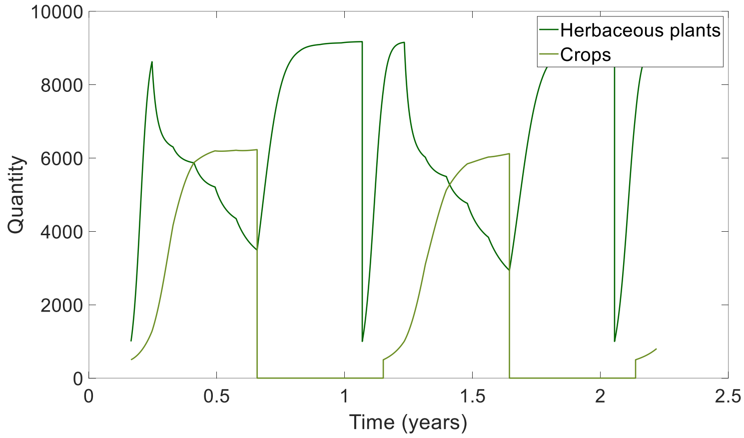

Fig. 3 Trends in herbaceous and crop population density over time

Figure 4 shows the dynamics of population density over time among primary consumers (mainly insects) and secondary consumers (mainly birds and bats). The population density of primary consumers showed a periodic peak, which was directly affected by the use of pesticides in the agricultural cycle. After the application of pesticides, the population of primary consumers declined rapidly. However, with the arrival of the harvest season, the use of pesticides was stopped, the ecosystem gradually recovered, and the population of primary consumers gradually increased and returned to a stable state. The change in secondary consumer population density lags behind that of the primary consumer population, reflecting the dependence of secondary consumers on the change in primary consumer population density. The decrease in the number of secondary consumers indicates that there is a certain predation pressure in the ecosystem, and the number of secondary consumers increases after the number of primary consumers recovers. This dynamic reveals the complex interactions between predators and prey in agro-ecosystems, and the use of pesticides has a significant impact on this balance, potentially controlling pests in the short term, but potentially disrupting natural control mechanisms by affecting populations of natural predators such as birds in the long term.

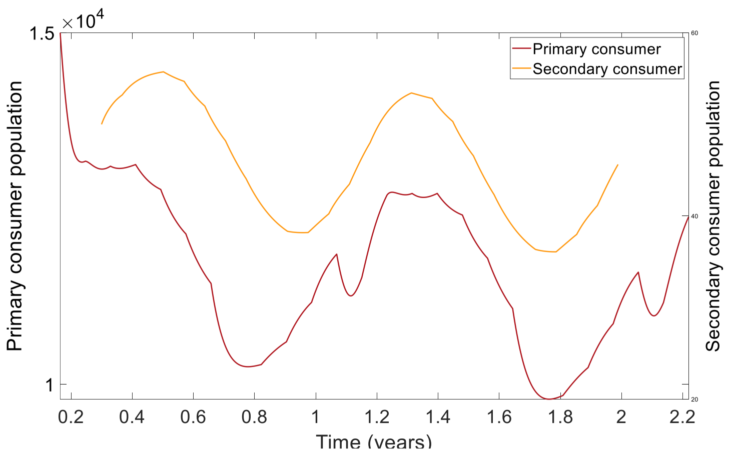

Fig. 4 Trends of population density of primary and secondary consumers over time

By comparing Figure 3 and Figure 4, we can see that the reproduction of primary and secondary consumer groups is affected by seasonal changes, showing an obvious seasonal change trend. In the peak period of their growth cycle, the population density increases rapidly, while in the off-season, the natural population growth rate decreases and remains unchanged under the influence of predation and natural death. The population density tends to decrease. On the other hand, crops and herbs are also affected by seasonality, but because the agricultural cycle is significantly more important than the seasonal impact on vegetation structure, their population density is mainly represented by agricultural cyclical changes.

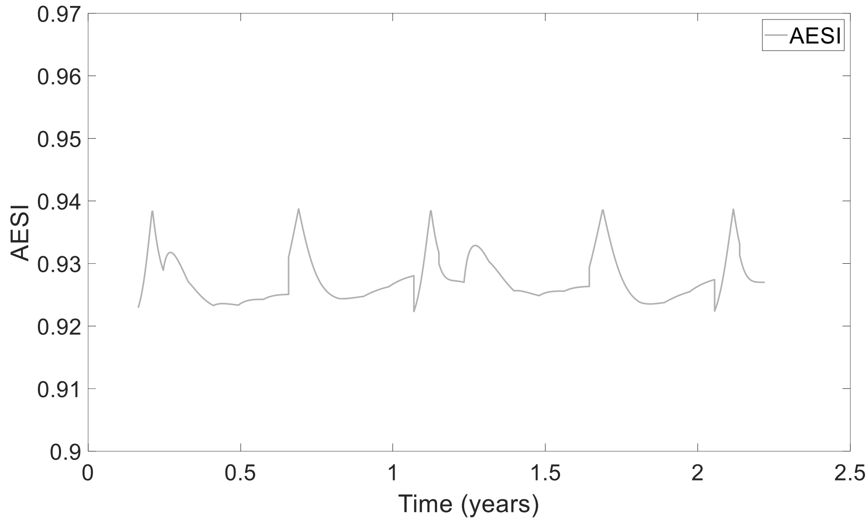

Fig. 5 The trend of AESI over time

The change in the agroecosystem Stability Index ($AESI$) over time is shown in Figure 5. The fluctuation of AESI in the time dimension is small, and the overall level remains high (about 0.9), indicating that the current agroecosystem has a certain self-regulation ability. However, $AESI$ declines briefly after agricultural interventions such as pesticides and harvesting, suggesting that these anthropogenic measures interfere with the short-term stability of the ecosystem. Over time and with the temporary removal of human intervention, $AESI$ will gradually rebound, indicating that this agroecosystem has some resilience and stability, but if the intervention is frequent or too intense, it may lead to a decline in the overall stability of the ecosystem. Therefore, sound agricultural management practices, such as reducing the frequency of pesticide use and adopting biological control, can reduce the impact on ecosystems while maintaining yields.

In conclusion, the model fits well with the predator-competition relationship, agricultural cycle, seasonal breeding activities, and the effects of chemical use on ecosystem stability and dynamics.

3.3. The dynamic change of the model with the use intensity of chemical products

Under the model established in part B, we changed the use intensity $\theta\beta$ of chemical products, solved the model again, and observed the dynamic changes of the model in the process of changing the use intensity of chemical products. The dynamic change curves of various components of the agricultural ecosystem with fixed θ of 0.05 and β varying between 0 and 0.08 are drawn over time, as shown in Figure 6; the dynamic change curves of various components of the agricultural ecosystem with fixed β of 0.01 and θ varying between 0 and 0.08 are shown in Figure 7.

Figure 6 shows the dynamic changes of agroecosystem components over time under different pesticide intensities (β). Figure 6.(a) shows that, as the β increased, the number of herbaceous plants decreased slightly, indicating that the use of pesticides had less effect on the herbaceous plants. Figure 6.(b) shows a slight increase in crop numbers with increased β, suggesting that pesticides have an inhibitory effect on primary consumers (mainly insects), affecting the number of insects' prey crops through the food chain. Figure 6.(c) shows that with the increase β, the number of insects eaten by primary consumers decreases significantly, and is close to zero when $\beta = 0.08$, indicating that the effect of insecticides on insects is strong at this time, exceeding the adaptive range of insect populations, and insects are going to extinction. Figure 6.(d) shows the decrease of secondary consumers (mainly birds and bats) as β increases, especially when $\beta = 0.08$. The trend in the number of secondary consumers reflects the trend in the number of primary consumers, the food chain effect, which reflects the indirect effects of pesticides on secondary consumers, as the reduction in the number of primary consumers limits the food supply of secondary consumers.

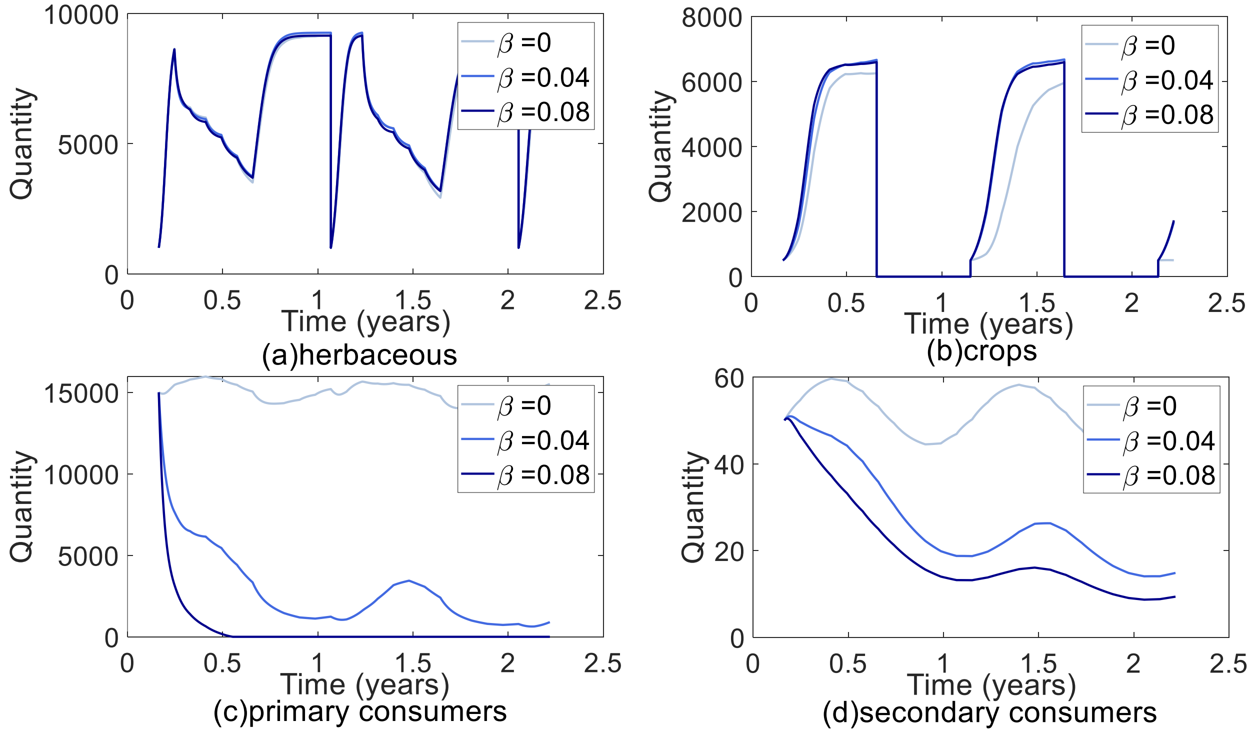

Fig. 6 Dynamic changes of ecosystem components over time with different insecticide intensity

As can be seen from Figure 7.(a), at the time of annual application of herbicides (i.e., from April to August each year), the number of herbaceous plants decreased significantly with the increase of herbicide intensity, and after the application of herbicides was stopped, the population density of herbaceous plants began to quickly recover to a stable point. Higher herbicide concentrations inhibit the growth of herbs and reduce their competition with crops. However, in the case of low herbicide dosage, the growth of herbaceous plants was not significantly affected, and the value remained high, indicating that the herbicide dosage was too small and the effect was not good. As can be seen from Figure 7.(b), herbicide intensity has little effect on crop quantity. Crop yields increase rapidly after sowing, decline at harvest, and increase slightly with increased herbicide use. Proper use of herbicides can reduce herb competition and benefit crop growth, while excessive use can damage soil and crop growth. Figure 7.(c) shows a gradual decrease in insect populations as herbicide use increases, indicating an indirect effect on insects through reduced food sources (herbs). As can be seen from Figure 7.(d), the number of birds did not change much with the increase of herbicide use, but the number of birds also decreased with the decrease of insect numbers. This highlights food chain effects: overuse of herbicides can disrupt birds' food sources and affect the stability of their populations.

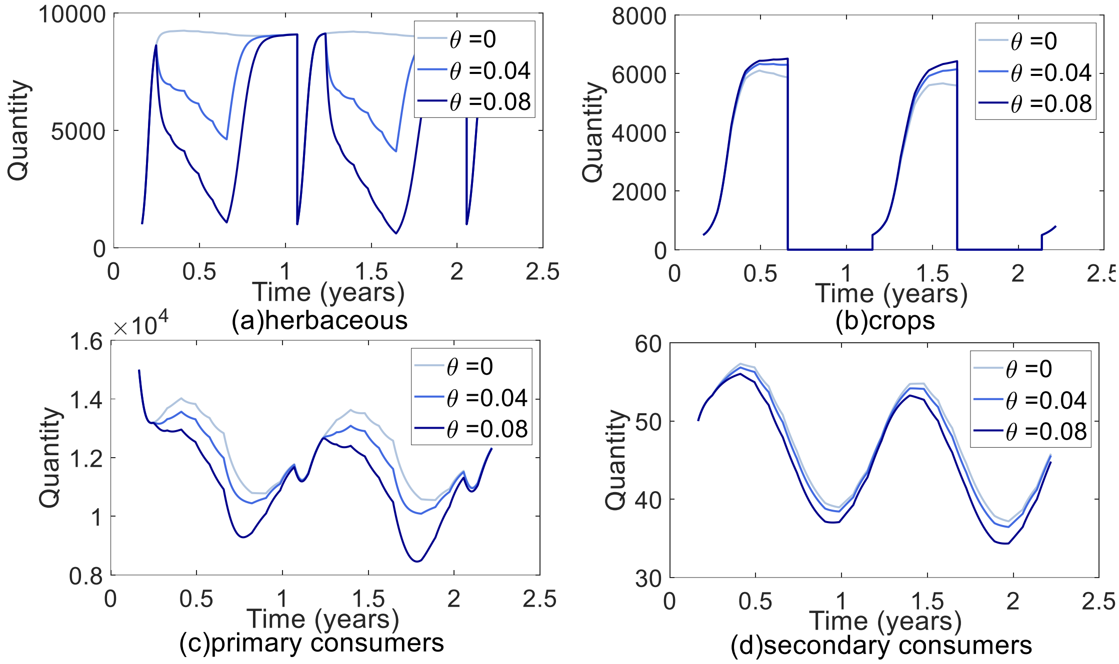

Fig. 7 Dynamic changes of ecosystem components over time with different herbicide intensity

We calculated the *AESI* agroecosystems on the day before harvest each year under different herbicide or insecticide action intensities and obtained two sets of curves as shown in Figure 8.

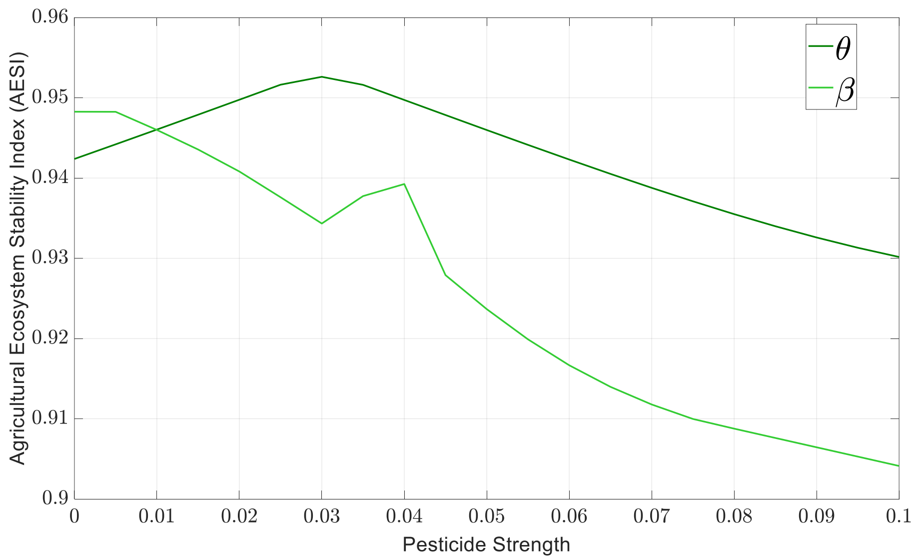

Fig. 8 The curve of *AESI* with θ and β the day before harvest

Figure 8 shows the effect of different chemical inhibition intensities on *AESI* the agricultural Ecosystem Stability Indicator). The increase of herbicide intensity (θ), *AESI* initially increased and then decreased, indicating that appropriate use of herbicides can improve the stability of the ecosystem, while excessive use will cause harm to the environment and destroy the stability of the agricultural ecosystem. It was also observed that with the increase of insecticide intensity (β), *AESI* initially decreased and then began to rise, reaching a maximum value at $\beta = 0.04$, and then rapidly decreasing. The analysis is that since the main consumers of this ecosystem are insects, the impact of pesticides leads to ecological imbalance at this level. Therefore, *AESI* should be significantly reduced as the strength of the insecticide increases. However, the density of each population in the ecosystem also affects the stability of the ecosystem. When β is near 0.03 to 0.04, the influence of population density (ESI) on $AESI$ briefly exceeds that of $HESS$. Therefore, at this time, $AESI$ tends to rise with the increase β. Then $AESI$ continues to decline significantly.

This suggests that human interventions, such as the use of pesticides or herbicides, need to balance ecological benefits with economic benefits to minimize negative impacts on non-target species and ensure the sustainability of agroecosystems.

4. Conclusions And Outlooks

4.1. Conclusions

In this paper, we construct an agroecosystem food web model based on the Logistic Growth model modified Lotka-Volterra model (LMLV). The effects of species competition, agricultural cycle, seasonal change, and chemical factors on the dynamic change of agroecosystem were analyzed by numerical simulation.We also introduced the Agroecosystem Stability Index ($AESI$) to quantify ecosystem stability and investigated the effects of chemical interventions on ecosystem dynamics and stability by simulating ecosystem dynamics at different herbicide and pesticide intensities.

We first improved the traditional Logistic Growth model and Lotka-Volterra model to construct an LMLV model that can more accurately reflect the dynamic changes of the agro-ecosystem. The model combines the effects of human interventions (such as herbicide and pesticide use) and natural factors (such as seasonal changes) on ecosystems. Through numerical simulations, we found that agricultural activities (such as seeding, fertilization, weeding, harvesting, etc.) have a significant impact on the structure and function of ecosystems: they can optimize crop yields in the short term, but can negatively impact ecosystem stability in the long term. In addition, we introduced the Agricultural Ecosystem Stability Indicator ($AESI$), which is used to quantify the stability of the ecosystem, and found that moderate chemical intervention can improve the stability of the ecosystem by simulating the dynamic changes of the ecosystem under different herbicides and pesticide application intensities, while excessive use can disrupt the ecological balance and lead to the decline of the ecosystem stability.

The improved LMLV model established in this study can effectively describe the dynamic evolution process of agricultural ecosystems and reveal the relationship between agricultural activities and ecosystem stability. By simulating ecosystem responses under different management practices, the model provides a scientific basis for developing sustainable agricultural management strategies. Specifically, the results of this study highlight the importance of balancing ecological and economic benefits in agricultural production, and recommend the adoption of more sustainable agricultural management measures, such as reducing the frequency of chemical use and introducing biological control, to maintain the long-term stability of ecosystems. These conclusions have important reference value for guiding practical agricultural production practice and promoting sustainable agricultural development.

4.2. Outlooks

Although this study has made some achievements in the dynamic modeling of agro-ecosystems, there are still some aspects worth further exploration and improvement:

Model expansion and optimization: While current models focus on the interactions between crops, herbs, primary consumers (insects), and secondary consumers (birds and bats), future models can be further expanded to include more ecological components (such as soil microorganisms, disintegrators, etc.) to more fully reflect the complexity of agroecosystems. In addition, the effects of chemical products and fertilization on soil quality and the time attenuation effect of their effects were not considered in this model, so it can be considered to continue to optimize and complicate the model in these aspects to obtain a more realistic mathematical model of agro-ecosystem.

Multi-factor coupling analysis: This study mainly considers the impact of chemical factors (herbicides and pesticides) on the ecosystem, and further studies can be made on the comprehensive impact of other factors (such as climate change, land use change, water resources management, etc.) on the agro-ecosystem, especially the coupling effect between these factors.

In conclusion, this study provides theoretical support for understanding the dynamic evolution process of agro-ecosystem and provides a scientific basis for realizing sustainable agricultural development. Future research can be further deepened and expanded on this basis to address the challenges posed by global climate change and population growth and promote the healthy and sustainable development of agro-ecosystems.

References

[1] Zhou, T., Chen, B., Liao, H., et al. Integrative Development and Trends in Restoration Ecology. Scientia Sinica Vitae, 2024, 54(09): 1614-1625.

[2] Lotka A J. Elements of physical biology[J]. Williams and Wilkins, 1925.

[3] Huang B, Yang Y, Peng L. Modeling and analysis of ecosystem dynamics based on the Lotka-Volterra model[J]. Highlights in Science, Engineering and Technology, 2024, 94: 653-660.

[4] Lei Yu, Shuai Bin. Research on the competitive cooperation relationship between high-speed rail and air Express transportation based on Lotka-Volterra model [J]. Railway transportation and economy, 2022, 44 (03) : 73-78 + 91.

[5] Huang Q, Huang J. An Ecological Network Analysis Based on The Lotka-Volterra Model[J]. Highlights in Science, Engineering and Technology, 2024, 101: 340-347.

[6] Wang X, Zhou T, Wang Y. Ecosystem Stability Analysis and Numerical Simulation via Three Improved Lotka-Volterra Models[M]//Fuzzy Systems and Data Mining IX. IOS Press, 2023: 121-132.

[7] Genda A, Fidlin A, Lenci S, et al. Effects of seasonal hunting and food quantity variations on the Lotka-Volterra model[J]. Nonlinear Dynamics, 2024: 1-19.

[8] Su Y, Deng Z. Enhanced Lotka-Volterra Equations: A Novel Approach to Investigate Plant Community Dynamics Under Varied Climatic Conditions[J]. Highlights in Science, Engineering and Technology, 2023, 69: 583-592.

[9] Davis J D, Olivença D V, Brown S P, et al. Methods of quantifying interactions among populations using Lotka-Volterra models[J]. Frontiers in Systems Biology, 2022, 2: 1021897.

[10] Zhao Zhixuan, Jin Xin, Wang Linghe, et al. Evaluation of farmland ecosystem stability based on dynamic factors [J]. Journal of South China Agricultural University,2010,31(04):22-26.