

# Exploring the Gender Ratio of the Lamprey: The Mystery of Ecosystems

## Summary

Have you ever thought about how seemingly unremarkable creatures in nature might hold significant information? Take the lamprey, for instance. Despite not garnering much attention, it possesses valuable data. Uncovering and deciphering this data can enhance our understanding of natural laws.

We developed three models to explore the impacts of adaptive gender ratio variation in lampreys on the lampreys themselves, other species, and the ecosystem.

Here are the specific details:

Model I: To accurately assess the effects of adaptive gender ratio variation on lampreys, we analyzed their breeding patterns. We incorporated multiple parameters such as fecundity and survival rate, and adjusted **the growth rate of the logistic model** based on gender ratio. For sex ratio, we use **multiple regression analysis** to study the relationship between sex ratio and environmental factors. This enabled us to predict that the population fluctuation of lampreys follows **a periodic oscillatory curve**. Additionally, we simulated natural disasters to demonstrate their remarkable resilience to risks and enhanced **the genetic algorithm** into an evaluation algorithm to showcase **the evolutionary benefits of dynamic gender ratios**.

Model II: Recognizing the distinction between parasitism and predation, we referred to **the Nicholson-Bailey model** and made appropriate modifications to **the Lotka-Volterra model** that describes the two-population relationship, resulting in **a parasitic model**. We further extended this model to encompass multiple populations. Our findings indicate that lampreys can cause **more significant population fluctuations** in other species and may even lead to the **endangerment** of vulnerable species.

Model III: We identified three indicators: species evenness, oxygen consumption, and average body length and utilized a combination weight method to integrate **AHP** and **the entropy weight method**, thereby obtaining **a comprehensive evaluation model** of the ecosystem. By incorporating the results of Model II, we found that lampreys could **reduce species diversity** in the ecosystem and **decrease the complexity of the food chain**. However, they can also **reduce oxygen consumption and alleviate survival pressure** on species less connected to lampreys. Overall, the influence of lampreys on the stability of the ecosystem is negative.

Finally, we conducted sensitivity analysis on the models to confirm their stability and summarized the strengths and weaknesses of our models, along with all the conclusions derived from them.

**Keywords:** multivariate regression analysis; genetic algorithm; logistic model; Lotka-Volterra model; AHP; entropy weight method;

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# 1 Introduction

## 1.1 Background

The Fisherian sex allocation theory suggests that parents who can adjust the gender ratio of their offspring based on population gender biases will maximize their fitness compared to parents lacking this ability. There is ample evidence indicating that adaptive gender ratio adjustments occur in many natural populations [1].

The lamprey, referred to as a "living fossil," is a typical example of this phenomenon. Their gender ratio can vary based on external circumstances. The growth rate of marine lampreys during the larval stage determines whether they become male or female. The growth rate of these larvae is influenced by food availability. In cases of food scarcity, males dominate in numbers, while in times of abundant food, the gender ratio approaches 1:1.

Ecologically, lampreys are parasitic, feeding on other fish and invertebrates. However, to fishermen in the Great Lakes, lampreys are considered a serious pest as they cause a sharp decline in fish catches. Our task is to study this characteristic of lampreys, which allows them to alter their gender ratio based on resource availability, in order to gain a deeper understanding of interactions within the ecosystem.

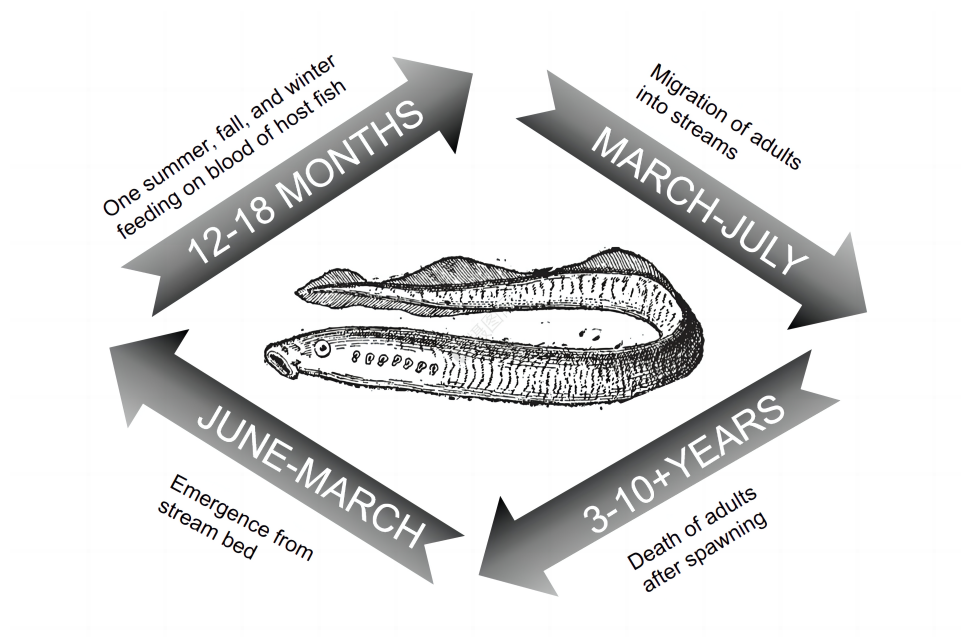


Figure 1: Life cycle of lampreys

## 1.2 Restatement of the Problem

Given the background information on the lamprey and the constraints outlined in the problem statement, we should address the following issues:

- What is the impact on the larger ecological system when the population of lampreys can alter its sex ratio?
- What are the advantages and disadvantages to the population of lampreys?

- What is the impact on the stability of the ecosystem given the changes in the sex ratios of lampreys?
- Can an ecosystem with variable sex ratios in the lamprey population offer advantages to others in the ecosystem, such as parasites?

### 1.3 Our Work and Model Overview

To further analyze the intrinsic connections within the research question, we have simplified the problem into three sub-questions. In essence, these involve investigating the impact of lamprey gender ratio variations on the lamprey population, other species, and the ecosystem. To address these questions, we have developed population models for lamprey, parasite models, and ecosystem assessment models.

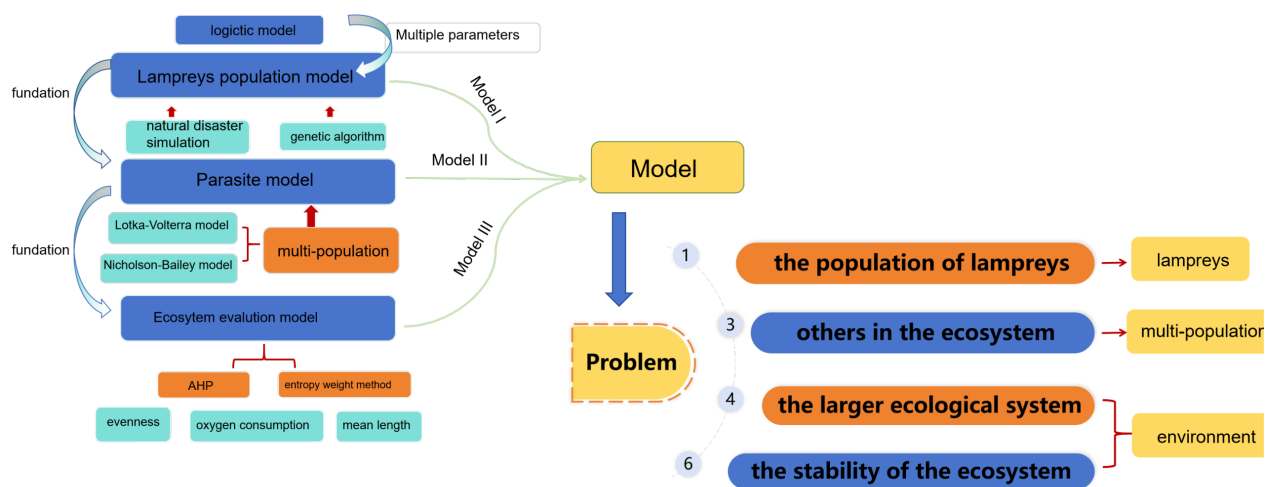


Figure 2: Overall flow chart

## 2 Model Assumptions and Justifications

To simplify the problem for simulation of real conditions, the following fundamental assumptions are proposed, each accompanied by a comprehensive justification.

- **Assumption 1:** The lamprey reproduces monogamously.  
 → **Justification:** The reproductive behavior of lamprey varies. According to Johnson et al. (2014), smaller lamprey tend towards group reproduction, while larger ones typically exhibit monogamous behavior. This study primarily focuses on larger lamprey. Additionally, it is widely accepted that lamprey typically die shortly after reproduction, favoring the conclusion of monogamy.
- **Assumption 2:** Human fishing impact on the lamprey population is not considered.  
 → **Justification:** This study primarily investigates the ecological impact of lamprey intrinsic characteristics. Human-induced impacts are variable and difficult to quantify, and hence not the primary focus of this study. To streamline the model, we choose to ignore the influence of human activities.

- **Assumption 3:** The relationship between lamprey and other populations can be approximated as a predator-prey relationship.  
→**Justification:** As a parasite, the lamprey is positioned in the parasitic chain and has few natural predators. While the description of interspecies relationships can be compared to both predation and parasitism, we intend to find literature that supports this similarity.
- **Assumption 4:** All involved organisms are considered to be annual, completing one life cycle within a year.  
→**Justification:** Organisms have varying lifespans, and for our model to study population dynamics, iterations are based on the previous generation. Asynchronous time intervals in iterations would make comparisons between different species extremely difficult. The assumption of annual lifespan may reduce rigor in our results but greatly simplifies the problem.
- **Assumption 5:** The impact on other species and the ecosystem is only considered for populations directly related to the lamprey.  
→**Justification:** While gender ratio changes in lamprey may indirectly affect other species through ecological cascades, these effects diminish significantly as they propagate through successive levels. These indirect impacts are difficult to quantify. To simplify the model, we choose to directly ignore populations not directly related to the lamprey.
- **Assumption 6:** The length of the fish follows a normal distribution.  
→**Justification:** Although individual fish lengths may not adhere to a definite pattern, the law of large numbers suggests that the collective behavior of the population will eliminate unpredictable random factors. Moreover, according to the central limit theorem, when the sample size is sufficiently large, the distribution of sample mean approaches a normal distribution. Hence, we consider the assumption of length following a normal distribution to be reasonable.

### 3 Notation

In this work, we use the nomenclature in Table 1 in the model construction. Other nonefrequent-used symbols will be introduced once they are used.

Symbol	Description	Dimension
$F_W$	Net weight fertility	$1/g$
$F$	Number of eggs produced per female lamprey	-
$\bar{N}$	Total annual egg production of lamprey	-
$N_t$	Population of lamprey in year t	-
$\alpha(N)$	Proportion of female gender ratio changing with N	-
$D_a$	Population density	$1/m^2$
$D_r$	Relative population density	-

Table 1: Notation

## 4 Model I: Population Model for lamprey

The logistic hindered growth model is a typical model for describing changes in population size, with one of its key variables being the growth rate. We conducted a regression analysis to study the relationship between the proportion of females and the population size. By incorporating other important parameters specific to lamprey, such as fecundity, survival rate, and mortality rate, we obtained a modified expression for the growth rate tailored to the characteristics of lamprey. This modified growth rate expression was then incorporated into the logistic model to derive a more reliable population growth model.

Based on the characteristics reflected in the population growth model, we speculated on the effects of gender ratios on the total lamprey population from both short-term and long-term perspectives. We tested our ideas using risk resistance testing and genetic algorithm simulations.

Overall, the process of establishing the model is illustrated in Figure 3.

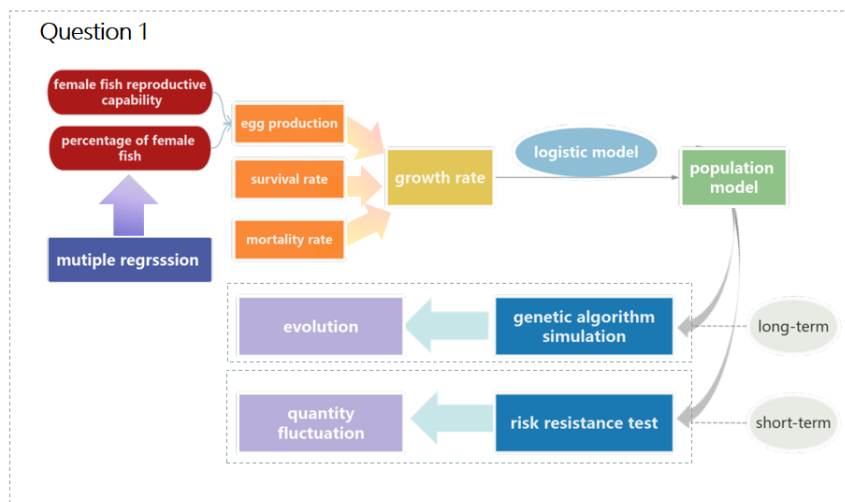


Figure 3: Flowchart of Model 1

### 4.1 Female Fish Reproductive Model

#### 4.1.1 Unit Reproductive Capacity of Female Fish

According to assumption 1, it can be inferred that when male lamprey dominate in numbers and adopt a monogamous reproductive strategy, the population size is mainly related to the female population. Furthermore, the reproductive capacity of the female lamprey is not constant. The number of eggs laid by a female lamprey can be calculated using the following formula (1):

$$F = F_W \times W \quad (1)$$

where:

- $F$  denotes the number of eggs produced by a female lamprey

- $F_W$  represents the fecundity of a female lamprey per unit net weight
- $W$  denotes the net weight after removing the viscera

Research has shown that both  $F_W$  and  $W$  can be approximated by a normal distribution [2], with significant levels of  $0.121 > 0.05$  and  $0.261 > 0.05$ , as confirmed by p-value tests. The fitted functions are as follows:

$$f_1(W) = \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(W-\mu_1)^2}{2\sigma_1^2}} \quad (2)$$

$$f_2(F_W) = \frac{1}{\sqrt{2\pi}\sigma_2} e^{-\frac{(F_W-\mu_2)^2}{2\sigma_2^2}} \quad (3)$$

where:

- $\mu_1 = 111.18$ ,  $\sigma_1 = 11.435$ , where  $f_1$  represents the frequency of  $W$ .
- $\mu_2 = 964.1$ ,  $\sigma_2 = 158.602$ , where  $f_2$  represents the frequency of  $F_W$ .

Equations 1, 2, and 3 indicate that the egg production increases with the increase in the reproductive capacity and weight of the female fish. To facilitate subsequent calculations, it is desirable to convert this to a constant value. Using the mean formula of the normal distribution probability density function, we calculated the average net weight and the average net weight egg production. Utilizing equation 4.1.1, we obtained an average egg production of 1,007,189 eggs for a female lamprey, which will serve as the basis for our subsequent calculations.

#### 4.1.2 Regression Analysis of Female Population

Field studies have shown that non-productive environments can lead to slow growth of lamprey, resulting in a skew towards males. In other words, the environment directly affects gender determination through growth rate, leading to differences in gender ratios [3]. Alternatively, this implies that gender ratio is highly correlated with population density. This is because in a resource-limited environment, the suitability for population growth is negatively correlated with population density. Therefore, as population density increases, the female ratio should decrease. We extracted relevant lamprey data provided by Margaret F. Docker et al. (1994), which was collected from 12 geographically different streams in the eastern United States. We will use this data to analyze the factors influencing the female ratio  $\alpha$ .

##### ● Step 1: Calculation of Regression Coefficients

We utilized correlation analysis to examine the relationships between relative density ( $Dr$ ), female ratio ( $\alpha$ ), pH, Total Hardness (Td), and Annual Thermal Units (At), using Pearson's correlation coefficient:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (4)$$

where  $x_i, y_i$  represent  $Dr, \alpha$ , and other variables and  $\bar{x}, \bar{y}$  denote the mean values of these variables.

The results of the correlation analysis are presented in Figure 4.

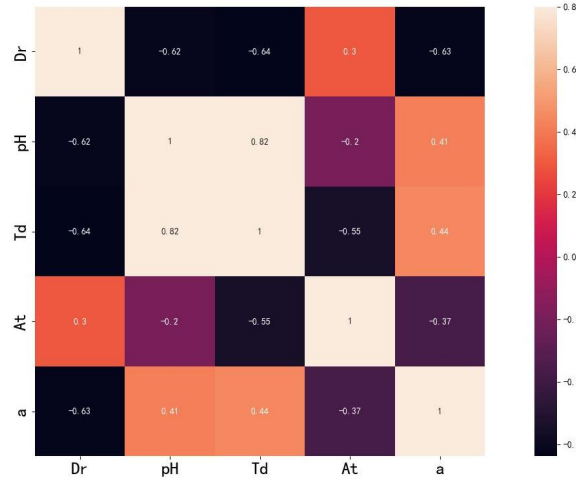


Figure 4: Heat map of the correlation coefficients

All variables passed the significance test. Our primary focus was on exploring the relationship between other variables and  $\alpha$ . From the graph, it can be observed that the relationship between  $Dr$  and  $\alpha$  is particularly prominent, displaying a relatively strong negative correlation. In contrast, pH and Td not only show no significant relationship with  $\alpha$ , but also exhibit linear correlation with  $Dr$ .

### ● Step 2: Regression Equation Estimation

We utilized a multiple regression model to analyze the impact of environmental factors on  $\alpha$ . The obtained regression equation is as shown in Eq. 5:

$$\alpha = 46.785 - 5.217Dr + 5.098pH - 0.41Td - 0.02At \quad (5)$$

The results indicate that among all environmental factors, population density and pH had the greatest impact on the female ratio. As population density increases and pH levels drop, the female ratio also decreases. This finding is consistent with the study by Hardisty, M. W. (1961), who suggested a positive correlation between abundance and gender ratio. In other words, as the population size increases, the proportion of females also increases. This supports the validity of the data used in this study.

### ● Step 3: Model Evaluation

The relevant parameters of the model are presented in Table 2. The tolerance and VIF (Variance Inflation Factor) are indicators of multicollinearity in the regression model. In general, if the tolerance is  $< 0.2$  or  $VIF > 10$ , it indicates an issue of multicollinearity among the independent variables. Both of these indicators for our model are excellent, indicating that multicollinearity among the independent variables in this study is not severe.



The coefficient of determination  $R^2$  is used to evaluate the explanatory power of the regression model on the observed data. It represents the proportion of the total variance in the dependent variable explained by the independent variables in the regression. The results indicate that approximately 40% of the variation in  $\alpha$  can be explained by our equation. While this value is not high, it is important to consider the complexity of biological models. It is possible that there are factors we have not taken into account.

	Tolerance	VIF	$R^2$
Dr	0.56	1.767	0.445
pH	0.220	4.548	
Td	0.161	6.225	
At	0.498	2.008	

Table 2: Assessment Parameters

### 4.1.3 Total Spawning

In section 4.1.1, we obtained the average number of eggs laid by a female fish. In section 4.1.2, we established the relationship between female ratio and relative population density. In this section, we will utilize these relationships to calculate the total spawning for the lamprey population annually. According to literature [4], lampreys die soon after reproduction, implying that only one reproductive event needs to be considered for each generation of lampreys. Therefore, we have the following equation (Eq. 6):

$$\bar{N} = F \cdot \alpha \cdot N_t \quad (6)$$

where:

- $N_t$  represents the population size of lampreys in year  $t$
- $F$  denotes the average number of eggs laid by each female fish
- $\bar{N}$  represents the total spawning for that year

## 4.2 Estimation of Growth Rate

The general growth rate is derived by subtracting the death rate from the birth rate. In this study, we have calculated the total spawning  $\bar{N}$  annually. For the death rate, we have used a different method. Fish mortality typically includes two types: natural mortality and fishing mortality [5]. Natural mortality encompasses death due to predation, competition, disease, etc. Based on assumption 2, we only consider natural mortality and do not account for human-induced impacts. Literature [6] provides a method for estimating the death rate based on virtual population analysis.

$$\begin{cases} M = 2 \ln \left( \frac{-C_t + \sqrt{C_t^2 + 4N_{t+1}N_t}}{2N_{t+1}} \right) \\ N_t = \frac{N_f}{N_f + M} N_t \left( 1 - e^{-(N_f + M)} \right) \end{cases} \quad (7)$$

where:

- $N_f$  represents the fishing mortality rate. Considering the actual situation, we set  $N_f = 0.4$ .
- $C_t$  denotes the annual catch in year  $t$ .
- $M$  stands for the natural mortality rate.

By solving the above system of equations, we can obtain the expression for  $M$ , which is calculated to be approximately 0.05. This value is understandable, for example, in the case of salmon, the general mortality rate is 5%-20%; and lampreys have very few natural predators, being considered an invasive species in the Great Lakes region, causing significant damage to the local fisheries.

We also considered the survival rate of fish eggs in order to adjust the growth rate and more accurately describe changes in population size. According to literature [7], the survival rate fluctuates widely, ranging from 20% to 80%, and is greatly influenced by the environment. Taking the average value, we set the survival rate of fish eggs  $\beta$  to be 50%. Thus, we obtained the expression for the growth rate  $r$ :

$$r = \frac{\alpha \cdot \bar{N} \cdot N_t \cdot (\beta - M)}{N_t} = \alpha \cdot \bar{N} \cdot (\beta - M) \quad (8)$$

### 4.3 The Logistic Growth Model

When considering an infinite space and natural resources, a population increases continuously with a fixed growth rate. The population quantity  $N_t$  should follow the following equation:

$$\frac{dN_t}{dt} = r \cdot N_t \quad (9)$$

Furthermore, taking into account the constraints imposed by finite resources and space in a realistic scenario, we introduce a limiting effect on the population growth. In this case, the population quantity should have a maximum value, denoted as  $K$  and referred to as the carrying capacity of the environment. Therefore, the population quantity is expected to satisfy the following equation:

$$\frac{dN_t}{dt} = r \cdot N_t \left(1 - \frac{N_t}{K}\right) \quad (10)$$

Thus, we obtain the Logistic growth model. The differential equation can be solved as:

$$N_t = \frac{K}{1 + \left(\frac{K}{N_0} - 1\right) \cdot e^{-rt}} \quad (11)$$

This equation describes the relationship between population quantity and time. It is worth noting that by substituting the results obtained prior to section 4.3 into the equation and using cubic spline interpolation for smoother results, we obtained the curve shown in figure 5. It is evident that the resulting curve represents fluctuating population quantity over time, in contrast to the typical population quantity curve without variations in the sex ratio ( $\alpha = \text{constant}$ ). We attribute these fluctuations to the

variability in the sex ratio as the fluctuations in the curve are brought about by the sex ratio variation, which leads to the growth rate no longer being constant.

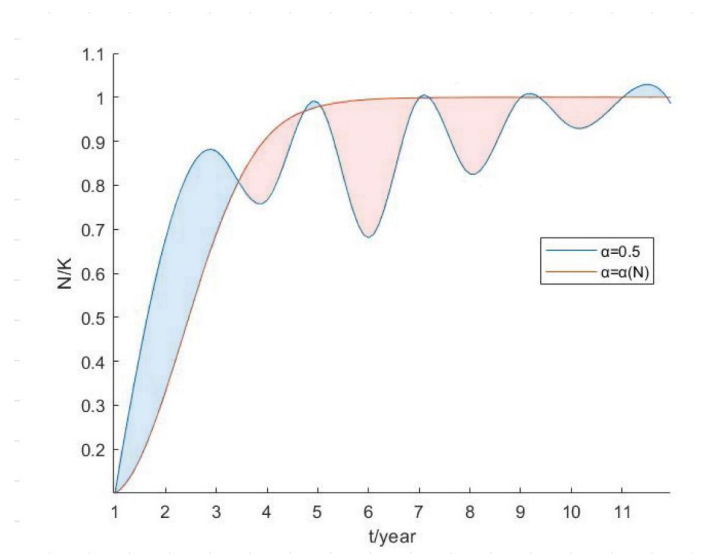


Figure 5: Comparison of Population Growth Curves

Upon analysis of the graph, it is evident that initially, the population with varying sex ratios (referred to as Population 2, with the other line representing Population 1) grows faster towards the carrying capacity of the environment. However, as the population density increases, the female sex ratio decreases, leading to a decline in the birth rate of Population 2 and a consequent temporary decrease in population quantity. As the quantity decreases to a certain level, the birth rate begins to rise again, and the population quantity gradually returns to its peak.

We also observed some fluctuations in the graph that show a tendency to gradually converge, indicating that there may still be some unaccounted factors in the model.

#### 4.4 Advantages and Disadvantages

Now that we have developed a comprehensive population growth model that considers multiple factors, we will conduct tests based on the characteristics reflected by this model. The results will serve as evidence to support our evaluation of its strengths and weaknesses. Subsection 1: Risk Resistance Test In evaluating the advantages and disadvantages of the flexible sex ratio in the lamprey population, we primarily focus on assessing its capacity to resist risks. Due to space limitations, the remaining aspects will be described in text. We subjected the population with normal growth, as illustrated in Figure 5, to a sudden shock that caused a  $0.3K$  decrease in population size, simulating the impact of uncontrollable random factors such as natural disasters. To ensure the reliability and rigor of our conclusions, we applied this intervention during both the upward and downward phases of Population 2. The results are presented in Figure 6 and Figure 7:

It is evident that Population 2, under intervention with a model random risk factor at any stage, can return to a normal state in a shorter time. This indicates a stronger capacity of Population 2 to resist risks. One possible explanation is that due to the fluctuating trend caused by changes in the sex ratio, Population 2 maintains a growth

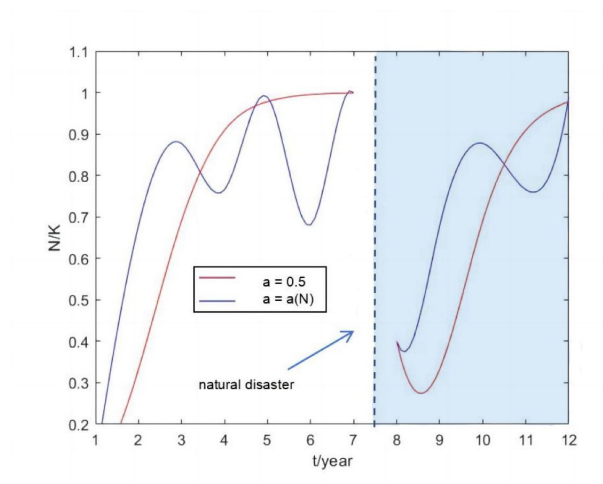


Figure 6: Intervention during the growth phase of Population 2

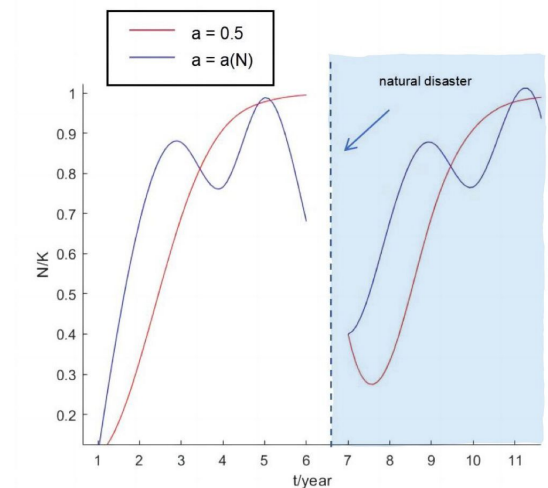


Figure 7: Intervention during the decline phase of Population 2

rate at a relatively high level for a significant amount of time. This enables it to quickly adapt to external changes by relying on this high growth rate when facing dangerous situations.

In comparison, Population 1, although capable of maintaining a stable state, generally exhibits a moderate growth rate, barely keeping up with the death rate. When facing dangerous situations, it requires more time to adapt to such changes.

#### 4.4.1 Test 2: Genetic Algorithm Simulation

We believe that the dynamic changes in sex ratio of the lamprey population can provide an evolutionary advantage and we aim to simulate the evolutionary process using a genetic algorithm. Genetic algorithms draw inspiration from the principles of biological evolution, simulating natural selection and genetic mechanisms, typically used to solve complex optimization problems. We have made certain improvements to enable its use in comparing the evolutionary speeds of different populations. The basic principles are as shown in the schematic diagram in Figure 8.

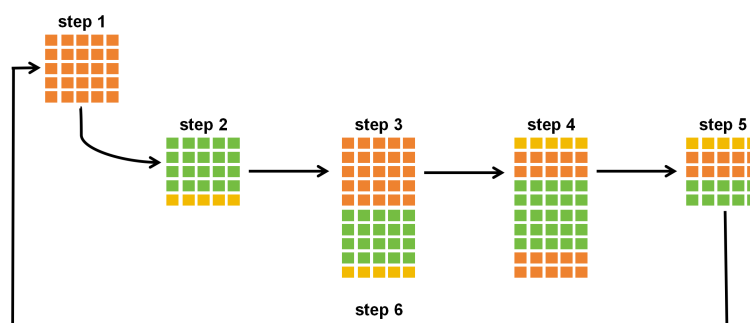


Figure 8: Schematic diagram

● **Step 1: Define Ancestry** In the initial stage, we randomly generate  $n$  individuals as a population, each with five randomly generated values to measure characteristics

such as body size, speed, strength, and other indicators. We also randomly define the current environment's optimal solution, i.e., the best values for the five indicators, along with the corresponding fitness function. Deviations from the optimal values lead to a decrease in evaluation.

● **Step 2: Generate New Individuals** The generation of new individuals is achieved through the interchange and mutation of indicator values, which is complex and not our focus. In simple terms, it involves using the genetic pool of the ancestor population to produce new combinations of indicator values.

● **Step 3: New and Old Individuals Merge** The new individuals and the parent population are examined together.

● **Step 4: Fitness Value Sorting** All individuals are evaluated and ranked. The higher the score, the higher the adaptability to the environment.

● **Step 5: Selection of Dominant Individuals** The individuals with the highest fitness values,  $m$  groups in total, are selected as the winners of this evolution and are used to replace the ancestors.

● **Step 6: Loop** Repeat the above steps.

We have made improvements to the genetic algorithm to consider the impact of dynamic changes in sex ratios on evolution and to compare evolutionary speeds by comparing the number of iterations, improving the optimization algorithm thereby evolving it into an evaluation algorithm.

Our improvements are as follows:

(1) **Defined Two Populations:** Their initial parameters vary, with Population 1 having a quantity and sex ratio of 1000 and 1, respectively, while Population 2 fluctuates in quantity from 1000 to 700 and in sex ratio from 7:3 to 1, while keeping the other parameters consistent.

(2) **Considered the Influence of Sex:** Utilized a sampling method to ensure that individuals are selected from the population based on sex ratio for crossover and mutation, effectively controlling the participation of individuals of different sexes in the population.

(3) **Established Evaluation System:** Set the maximum iteration count to 200, and used a termination condition of the population's average score reaching 120% of the initial population's average score, recorded the number of iterations, and conducted 100 genetic algorithm simulations to gather and analyze the results. Fewer iterations indicate faster evolutionary speed. Based on the further amendments to the code by OpenAI ChatGPT (see 10.0.3, 10.0.5, 10.0.7), we have derived Figure 9. The results indicate that changes in sex ratio can indeed bring about evolutionary advantages. Population 2, which experiences dynamic changes in sex ratio, generally had fewer iterations in each simulation compared to Population 1. The statistics in Table 3 show that the evolutionary speed is approximately 15% faster.

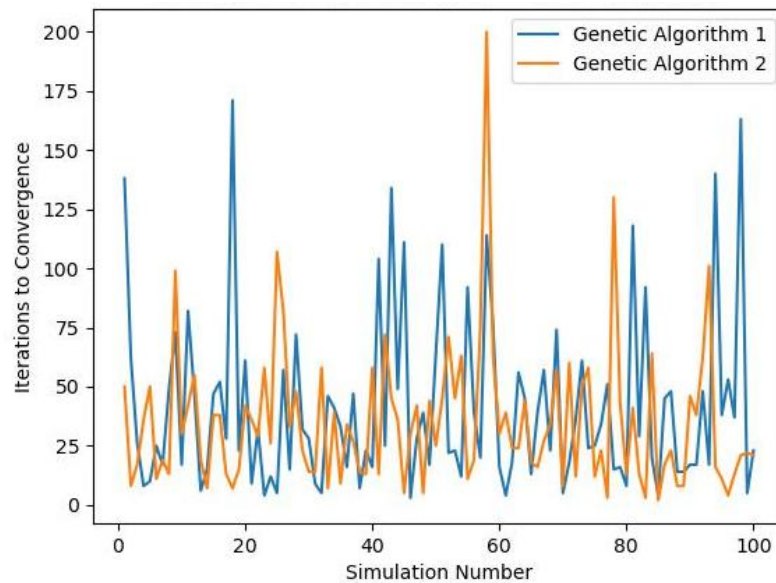


Figure 9: Iterations in 100 simulations using genetic algorithms

Population	Average Iterations
Population 1	41.28
Population 2	35.05

Table 3: Iteration Statistics

#### 4.4.2 Conclusion

In summary, we have identified the following advantages and disadvantages:

##### ● Advantages

- Strong resistance to risks  
→ **Reason:** The population spends a significant amount of time with a high growth rate, enabling it to rapidly adapt to external changes.
- Prevention of over-exploitation of host species by lampreys  
→ **Reason:** Indirectly controlling the population size through sex ratio adjustment ensures that resources always remain above basic needs. Although there is spontaneous regulation in the food chain (which is also why populations without sex ratio changes can survive for long periods), adjusting the population size due to sex ratio changes is certainly faster than this natural regulation process.
- Faster evolutionary speed  
→ **Reason:** A higher male ratio intensifies intraspecific competition and selects for stronger male genes. At the same time, the adjustment in sex ratio provides a buffer period for the population to avoid excessive competition. We have verified this using genetic algorithms. The fact that lampreys, as "living fossils" from the dinosaur era, have survived until today also supports this point.

##### ● Disadvantages

- **Reduced Genetic Diversity**  
 → **Reason:** The low number of females, and the high reproductive output of each female, may lead to a higher likelihood of interbreeding among the offspring, resulting in reduced genetic diversity. This point has not been verified and is only a reasonable speculation based on biological theories.

## 5 Model II: Parasite Model

A well-known biological model describing interspecies relationships is the Lotka-Volterra model; however, it was originally designed to analyze predator-prey relationships. While we believe this model can be used to approximate parasitic relationships based on assumption 2, for the sake of rigor, we have adjusted the predator model  $\implies$  to a parasite model, taking into account the results of our previous research.

### 5.1 Additional Assumptions

The following assumptions are necessary for this particular model to be reasonable. They are not essential for other models, and in order to avoid interference with other models, we only consider them effective in this section:

- Consideration of a parasitic chain relationship involving only salmon, lampreys, and nematodes, as demonstrated in the figure below. (Figure to be included)

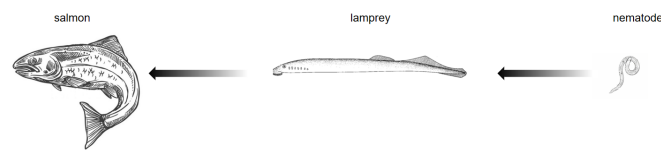


Figure 10: Ecosystem Ratings

- The increase in parasites depends on the number of hosts, and the decrease in hosts depends on the number of parasites (for the parasitic chain, this refers to the host and the parasite).
- All three populations are assumed to always exist, with changes only in quantity, i.e., they will not go extinct [8].

### 5.2 Predator Model

We will use the example of mice and snakes. Let the quantities of mice and snakes at time  $t$  be denoted as  $x(t)$  and  $y(t)$  respectively. When living independently, they both exhibit exponential growth, with a growth rate of  $r$ . However, the presence of snakes reduces the growth rate of mice. According to the assumption, the rate of reduction is proportional to the number of snakes, thus  $x(t)$  satisfies the equation:

$$\frac{dx}{dt} = r_1x - axy = x(r_1 - ay) \quad (12)$$

The coefficient  $a$  represents the snake's ability to prey on mice. If the snake were to live independently, its death rate would be  $-r$ . However, the existence of mice provides food for the snake, effectively lowering its death rate and promoting its growth. According to the assumption, the growth rate is proportional to the number of mice, with the coefficient  $b$  reflecting the nourishment capacity of prey for predators. Thus,  $y(t)$  satisfies:

$$\frac{dy}{dt} = -r_2y + bxy = y(-r_2 + bx) \quad (13)$$

Equations 11 and 12 represent the Lotka-Volterra predation model [9].

### 5.3 Parasite Model

In contrast to the predator model, the impact of parasitism on the host is given in a probabilistic form. The Nicholson-Bailey model is a model that describes parasitism, and we will adopt a similar approach to describe parasitism. We assume that parasites randomly search for hosts based on a probability  $p$ , which is a constant that varies with the host. We can then provide the parasite model and expand it into the form of three populations.

$$\begin{cases} \frac{dN_t^1}{dt} = r_1N_t^1 - p_1N_t^1N_t^2 = N_t^1(r_1 - p_1N_t^2) \\ \frac{dN_t^2}{dt} = -r_2N_t^2 + b_1N_t^1N_t^2 = N_t^2(-r_2 + b_1N_t^1 - p_2N_t^3) \\ \frac{dN_t^3}{dt} = -r_3N_t^3 + b_2N_t^2N_t^3 = N_t^3(-r_3 + b_2N_t^2 - p_3N_t^3) \end{cases} \quad (14)$$

In the current context,  $N_t^i (i = 1, 2, 3)$  represent the population numbers of salmon, lampreys, and nematodes in year  $t$ , and  $b_i (i = 1, 2, )$  represent the nourishment capacity of the  $i$ -th population to the subsequent population. We apply the results obtained from the first model to simulate the dynamic change of sex ratio by substituting them into  $r_2$ , with an initial population size of  $N_0=(0.4,0.8,2)$ . The resulting comparison is shown in Figure 12, while Figure 11 serves as the control group with a constant sex ratio.

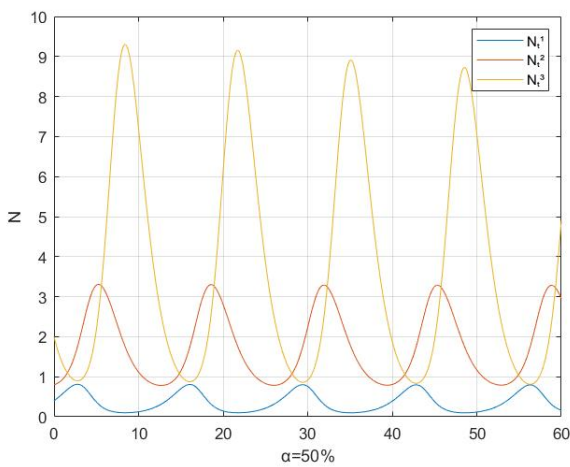


Figure 11: Control Group

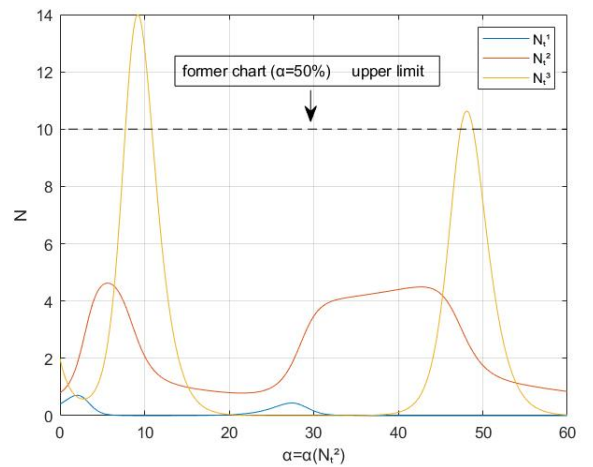


Figure 12: Parasite Chain Population Changes



## 5.4 Results Analysis

In the model with a constant  $\alpha$ , it can be observed that the three populations exhibit lagging fluctuations in the order of the parasitic chain, resembling the situation in predator-prey models. However, when the sex ratio changes, the population of salmon undergoes significant fluctuations, indicating a pattern that suggests a stage of near-extinction. Similarly, the fluctuation in the nematode population is more severe compared to the control group, also experiencing a near-extinction stage. On the other hand, the fluctuation in the lamprey population is relatively gradual, indicating strong resistance.

The explanation for these observations lies in the fact that, compared to salmon, the changing sex ratio of lampreys intensifies the original fluctuations. However, for salmon, its growth speed and adaptability are not as strong as the lamprey's (a characteristic we have previously demonstrated in Section 4), and its stability is insufficient to withstand significant fluctuations. In fact, considering a more realistic scenario, lampreys have a broader ecological niche and higher stability compared to salmon. However, in the case of nematodes, while increased fluctuations are understandable, there should not be a near-extinction stage, as their food source from the lamprey is relatively stable. We believe this is an effect that the model has failed to consider.

In summary, we believe that lampreys may exacerbate the fluctuations and even lead to extinction of the host, and it is clear that for parasites, it will lead to even more severe population fluctuations.

## 6 Model III: Ecosystem Evaluation Model

This model is based on the parasitic model, utilizing the obtained data. Due to the focus on the impact of sex ratios, according to assumption 5, we still only consider the parasitic chain consisting of three species and regard it as forming an ecosystem. The conclusions drawn from this assumption can also be applied to other species directly related to the lamprey.

### 6.1 Determination of Indicators

#### 1) Species Evenness ( $E$ )

Species evenness is an important indicator for measuring species diversity. In ecology, higher evenness is generally considered better. High evenness indicates a relative balance in the abundance of different species in the ecosystem, without any one species being overly dominant. This balanced coexistence of different species promotes interdependence, aiding in maintaining the stability and ecological functions of the ecosystem. It is calculated using the formula:

$$H = - \sum_{i=1}^s (P_i \ln P_i) \quad (15)$$

$$E = \frac{H}{H_{\max}} = \frac{H}{\ln S} \quad (16)$$

Where  $S$  is the total number of species in the community, and  $P_i$  is the proportion of the  $i$ -th species among all species. Based on the data from the parasitic model, we obtained the following results:

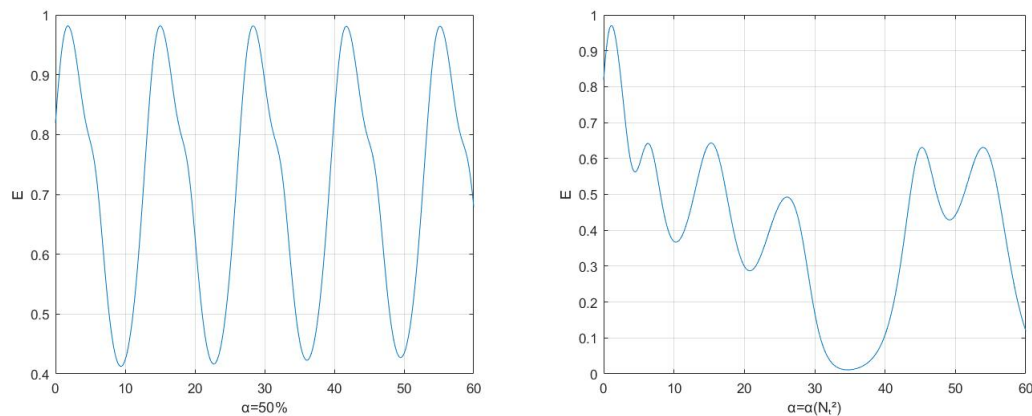


Figure 13: Evenness Over Time

By comparing the two figures, it can be concluded that the change in sex ratio of lampreys is detrimental to species evenness, leading to a decrease in species richness. It should be noted here whether the expression needs to be strengthened.

## 2) Oxygen Consumption (O)

Dissolved oxygen is essential for many organisms in marine ecosystems, including marine flora, fauna, and microorganisms. It is generally assumed that the concentration of dissolved oxygen remains relatively constant. Therefore, it can be inferred that an increase in oxygen consumption will increase the survival pressure on other populations. As shown in Figure 14, using the average oxygen consumption per gram for different fish provided in the literature [10], we calculated an average value. Nematodes consume almost no oxygen and are not included in our calculation. By utilizing the data from the parasitic model, we obtained a graph showing the average oxygen consumption (avg) over time ( $t$ ). It is evident that lampreys lead to a decrease in the ecosystem's oxygen consumption, thereby reducing the survival pressure on other species. We speculate that this is caused by a significant decrease in the population directly associated with lampreys. From this perspective, lampreys are able to provide a more favorable environment for species that are more distantly related in terms of food chains.

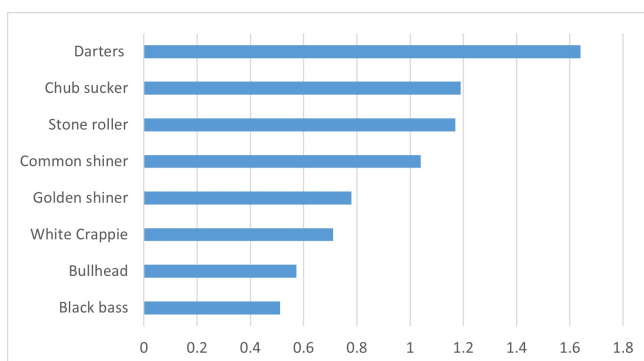


Figure 14: Oxygen Consumption Statistics

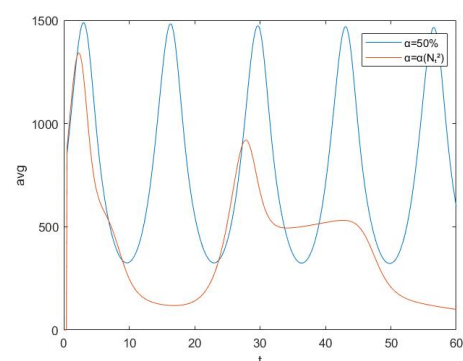


Figure 15: Average Oxygen Consumption

## 3) Average Length (L)

The average length is considered an important indicator for evaluating marine ecosystems in the literature [11]. On one hand, the average body length of fish can reflect the growth status of fish in the marine ecosystem. A larger value indicates a higher number of mature individuals. On the other hand, the length of fish is positively correlated with trophic levels, a conclusion that has been strongly supported in the literature [12] with a fitted linear regression of  $r^2 = 0.194$ ,  $P < 0.001$ . A higher trophic level indicates more energy flow pathways and richer ecological diversity in the ecosystem, thereby better maintaining ecological balance and stability.

According to assumption 6, we establish a Gaussian distribution model based on the average length of the fish. It is also noted that the lamprey has a higher parasitic preference for longer fish [13]. This implies that we need to consider the impact of lampreys on the length distribution of salmon. In the parasitic model, the parasitic probability  $P$  is a constant. However, in this section, we will make adjustments to this. The shorter the fish, the lower the parasitic probability, and conversely, the longer the fish, the higher the parasitic probability. For lampreys, the impact of preference should not be linear. We introduce the sigmoid function and define the formula for the parasitic probability  $p$  as it changes with length:

$$P = \frac{1}{1 + e^{\frac{(-L+90)2\ln 3}{30}}} \quad (17)$$

We obtained the corrected distribution of salmon quantities with respect to length, as shown in Figure 16.

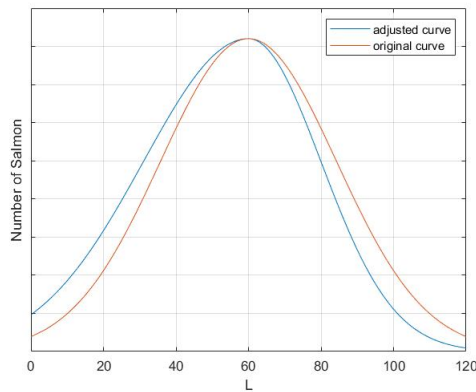


Figure 16: Distribution of salmon quantities with respect to length

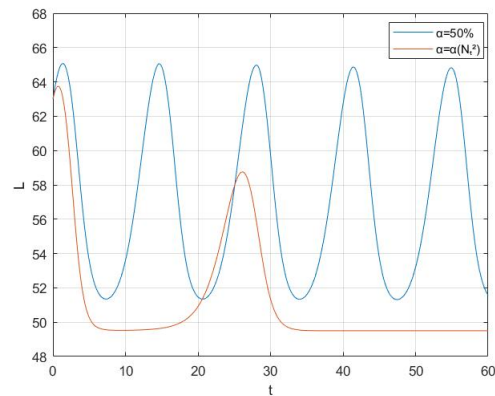


Figure 17: Average body length

Figure 17 illustrates the change in the average length of the ecosystem defined under varying and constant gender ratios over time. By comparing the curves, we observe that lampreys lead to a decrease in the average length of the ecosystem. This implies a reduction in species at higher trophic levels, rendering the food chain of the ecosystem more fragile. Our explanation is that as parasitic fish, lampreys typically prefer to parasitize larger fish and exhibit a preference for longer lengths within the same population. The advantage brought by the changing gender ratio makes it easier for it to parasitize longer fish.

## 6.2 Determination of Weights Composite Weighting Method

The Analytic Hierarchy Process obtains the relative weights between various factors through pairwise comparisons, effectively addressing qualitatively challenging issues and enhancing the objectivity and scientific nature of decisions. However, the Analytic Hierarchy Process involves subjective weighting, and the preferences of the decision-maker can significantly influence the results. Therefore, we combined the entropy weighting method from objective weighting techniques to control the subjective randomness within a certain range and achieve a balance between subjective and objective weighting.

### 6.2.1 Subjective Weighting

#### Step 1: Constructing the judgment matrix

According to the principle of comparing indicators with each other, we obtain the judgment matrix

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \\ = \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{3} \\ \frac{1}{2} & 1 & \frac{1}{4} \\ 3 & 4 & 1 \end{bmatrix}$$

#### Step 2 Consistency Check

Subjective pairwise weighting can lead to inconsistencies, so we need to use a consistency check to verify that there are no contradictions. We calculate the maximum eigenvalue  $\lambda_{max}$  of the judgment matrix and use equations 18 and 21 to calculate the consistency index (CI = 0.0091) and consistency ratio (CR = 0.0176, which is less than 0.01, thus the consistency is acceptable).

$$CI = \frac{\lambda - n}{n - 1} \quad (18)$$

$$CR = \frac{CI}{RI} \quad (19)$$

#### Step 3 Weight Calculation

Multiply the elements of matrix A by row to obtain a new column vector, take the n-th root of each component of the new vector, then normalize the column vector to obtain the weight vector.

### 6.2.2 Objective Weighting Method Correction

The calculation formula for entropy weighting is complex and is no longer fully introduced. In simple terms, information entropy describes the amount of data information, with smaller information entropy indicating greater dispersion of the indicator. The calculation formula for entropy weighting, as in equation 20, indicates that the impact (i.e., weight) of the indicator on the comprehensive evaluation is greater when the information entropy value is smaller.

$$H(X) = - \sum_{i=1}^q p(x_i) \log(p(x_i)) \quad (20)$$

where:  $H$  is the information entropy,  $q$  is the number of messages from the information source, and  $p(x_i)$  is the probability of message  $x_i$  occurring.

By combining the weights obtained from both methods, we can obtain the combined subjective and objective weights  $\omega_j$ :

$$\omega_j = \frac{\alpha_j \beta_j}{\sum_{j=1}^n \alpha_j \beta_j} \quad (21)$$

where:  $\alpha_j$  represents the weight obtained from the Analytic Hierarchy Process, and  $\beta_j$  represents the weight obtained from the entropy method.

### 6.3 Comprehensive Evaluation

The data from Section 6.1 is normalized for comparative purposes within the same framework and then inserted into our comprehensive evaluation formula (Eq. 22):

$$Grades = \omega_1 E' + \omega_2 O' + \omega_3 L' = 0.6609E' + 0.3135O' + 0.0256L' \quad (22)$$

Here, "Grades" represents the stability rating of the ecosystem, and Figure 18 displays the variation of Grades over the years.

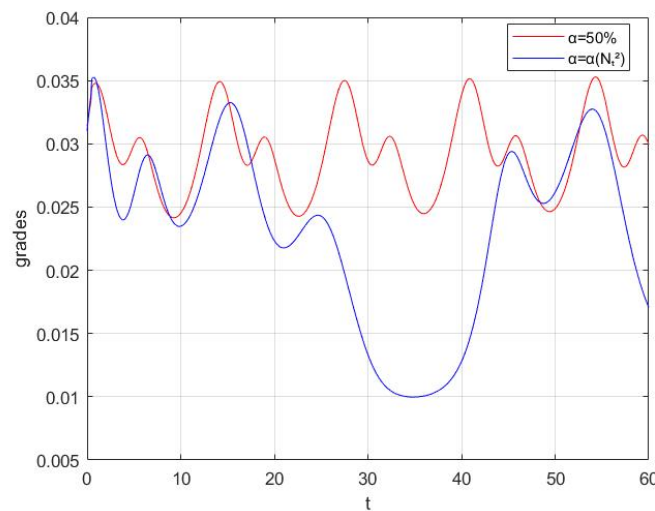


Figure 18: Ecosystem Ratings

Analysis reveals that compared to populations with no dynamic changes in gender ratios, the ecosystem of populations like lampreys shows an overall declining trend in stability. Contrary to the parasitic model results, stability significantly decreases in years close to the extinction of the salmon population.

It is noteworthy that:

- The weight of the average body length indicator is relatively low, possibly due to the limited consideration of fish species and minimal variation in body length, resulting in a low weight from the entropy method.
- In individual years, lampreys contribute to stability improvements, which could be attributed to beneficial aspects within the ecosystem, such as a reduction in dissolved oxygen, potentially balancing the harm they cause.

## 7 Sensitivity Analysis

In Sec.5, we established a parasitic model that forms the basis of the model in Sec.6, including various parameters, most of which are referenced from literature. However, the initial population numbers are self-determined. In this section, we examine the impact of different initial numbers of three species on the model results.

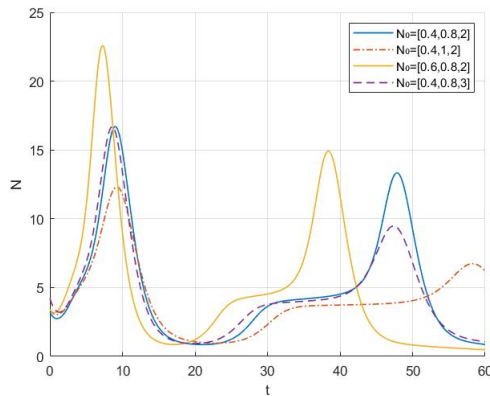


Figure 19: Total Number

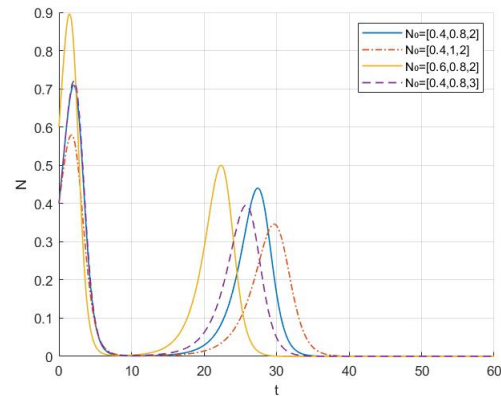


Figure 20: Salmon

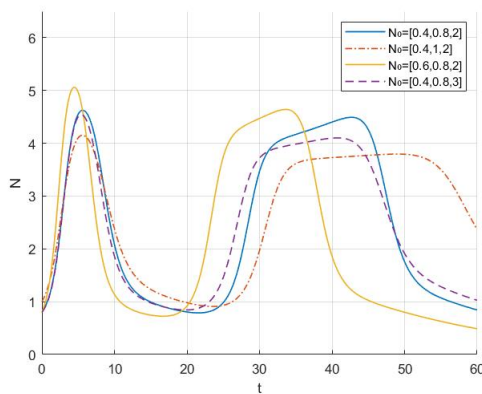


Figure 21: Lampreys

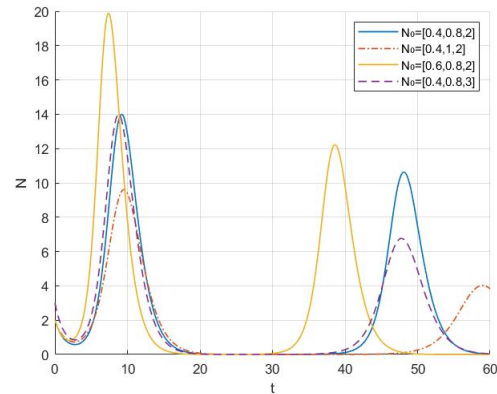


Figure 22: Nematodes

It can be seen that our model performs well in sensitivity analysis. As the populations reproduce generation after generation, the impact of parameter fluctuations on the results is relatively minor, and the trend in population changes remains stable. This indicates that our model exhibits good long-term stability.

## 8 Advantages and Limitations

### 8.1 Advantages

- **Authoritativeness:** The model is substantiated by extensive literature references, and important biological viewpoints, if not derived, are supported by citations.
- **Clear structure and rigorous logic:** The three models are logically connected in a cascading manner, with each subsequent model serving as the basis for the following one, which in turn corrects the former model.
- **Stability demonstrated through sensitivity analysis:** Our model exhibits good long-term stability through successive generations.
- **Time-dependent modeling:** Our models are time-dependent, allowing for predictions of the impact of lampreys at any given time under our specified conditions.
- **Use of a combined subjective and objective evaluation method** reduces the negative impact of single evaluation and enhances the rigor of the results.

### 8.2 Limitations

- **Limited species consideration:** The natural food chain is complex and diverse, yet our model only considers the food relationships of three species, thus limiting its universality.
- **Weak correlation of two indicators in Model 3** with nematodes focuses the study primarily on the impact of lamprey parasitism, while the effects of parasitic lampreys are underemphasized.
- **The premise conditions for simulating evolution** are overly simplistic, potentially leading to oversight of certain factors and resulting in biased outcomes.

## 9 Conclusion

The following summarizes the impact of the dynamic change in gender ratio of lampreys, consolidating the conclusions obtained from all the models.

### ● On Its Own

In the short term, changes in gender ratio lead to a mostly high population growth rate for lampreys, enhancing their ability to adapt quickly to external changes and strengthening their resilience to risks. It can also indirectly control the population size, preventing overexploitation of hosts by lampreys. In the long term, a higher male ratio intensifies intraspecific competition, enhancing evolutionary speed. The gender ratio regression provides the population with a buffer period, preventing excessive competition. However, it also brings drawbacks, such as a decrease in genetic diversity due to low female numbers leading to inbreeding.

### ● On Other Species

Changes in gender ratio result in amplified population fluctuations in lampreys, transmitting these fluctuations up and downstream along the parasitic chain, thereby increasing the population of other species. For the parasitic lamprey population, the impact mainly exacerbates the original population fluctuations, as their food source remains relatively stable. However, for the hosts of lampreys, the intensified fluctuation without other forms of compensation and their weaker resilience may lead them towards extinction.

### ● On the Ecosystem

Specifically, lampreys reduce the oxygen consumption of the ecosystem, alleviating the survival pressure on other species. We hypothesize that this is due to a substantial decrease in populations directly associated with lampreys. From this perspective, lampreys can provide a more favorable living environment for species that are distantly related in terms of food chains. Lampreys contribute to a decline in the average length of the ecosystem, reducing the species at higher trophic levels and making the food chain more fragile. Overall, although lampreys bring some benefits to the ecosystem, they tend to decrease its stability.



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## 10 AI Utilization Report

Our utilization of AI primarily focused on code modification. Apart from inquiries regarding genetic algorithms, the rest is not directly relevant to the paper and is difficult to cite. Regarding the effectiveness of AI responses, since the questions were concentrated on the programming aspect, we have verified that all code can run, hence the responses are deemed effective.

### 10.0.1 OpenAI ChatGPT (November 30, 2022 version, ChatGPT-3.5)

#### 10.0.2 Query 1:

<The range of all five indicators is 1-10, and each indicator has a randomly generated optimal solution. The fitness function fits a linear function based on this optimal solution, with a maximum value of 1.>

#### 10.0.3 Output:

<Understood. You want to define a fitness function and fit a linear function based on the randomly generated optimal solutions for five indicators, such that the highest fitness for an optimal solution is 1. We can first generate five random optimal solutions as per your request and then define the fitness function based on these solutions.

Firstly, we can use Python to generate random optimal solutions and calculate the fitness function. The code is as follows: `python import random`

```
# Generate random optimal solutions for five indicators
optimal_solutions = [random.uniform(1, 10) for i in range(5)]
```

```
# Define the fitness function
def fitnessfunction(solution):
    # Calculate the slope of the fitted linear function
    slope = 1 / sum(optimal_solutions)
    # Calculate fitness
    fitness = 1 - abs(sum(solution) * slope - 1)
    return fitness
```

```
# Test the fitness function
testsolution = [7, 8, 9, 10, 6]
fitnessscore = fitnessfunction(testsolution)
print("Fitness score for the test solution:", fitnessscore)
```

In this code snippet, we first generate five random optimal solutions and then define the fitness function `fitnessfunction`. This function calculates the slope of the fitted linear function and computes the fitness score based on the input solution. Finally, we use a test solution to verify the calculation of the fitness function. You can run this code to verify the functionality of the fitness function and modify it as needed. If you have any specific requirements for the definition of the fitness function, please let me know.

#### 10.0.4 Query 2:

<I mean each metric has its own fitness function, and this fitness function is linearly fitted based on the optimal solution. Deviating below or above this optimal solution will result in a decrease in score.>

#### 10.0.5 Output:

<Understood. You want to define a fitness function for each metric, such that the fitness function is linearly fitted based on the optimal solution for each metric, and deviating below or above the optimal solution will result in a decrease in the fitness function score. In this case, we can define five fitness functions, each corresponding to

a metric, and linearly fit them based on the optimal solution for each metric. Below is an example code in Python implementing this:

```

“python import random

# Generate random optimal solutions for five metrics optimal_solutions = [ran-
dom.uniform(1, 10) for _ in range(5)]

# Define the fitness function def fitness_function(index, value): # Calculate the
slope of the fitted linear function slope = 1 / optimal_solutions[index] # Calculate
fitness fitness = max(0, 1 - abs(value * slope - 1)) return fitness

# Test the fitness function test_values = [7, 8, 9, 10, 6] fitness_scores = [fitness_function(i,
test_values[i]) for i in range(5)] print("Fitness scores for the test values:", fitness_scores)

```

In this code snippet, we first generate five random optimal solutions and then define the fitness function `fitness_function`. This function takes two parameters, the index of the metric and its corresponding value. It linearly fits the function based on the optimal solution and calculates the fitness score. Finally, we use a test values array to test the calculation results of the fitness functions for each metric.

You can run this code to verify the functionality of the fitness functions and modify them as needed. If you have any other questions or if you require more details on improving the genetic algorithm, feel free to let me know.>

### 10.0.6 Query 3:

<This is my current code:

```

“python import random

# Randomly generate optimal solutions for five metrics optimal_solutions = [ran-
dom.uniform(1, 100) for _ in range(5)] print(optimal_solutions)

# Define the fitness function # Suppose we have five metrics  $x_1, x_2, x_3, x_4, x_5$ , and
their optimal solutions are  $a_1, a_2, a_3, a_4, a_5$ . # The fitness functions for linear fitting
can be expressed as follows: # For metric  $x_1$ , the fitness function  $f_1(x_1)$  can be ex-
pressed as:  $f_1(x_1) = \max(0, 1 - |b_1x_1 - 1|)$  # For metric  $x_2$ , the fitness function  $f_2(x_2)$ 
can be expressed as:  $f_2(x_2) = \max(0, 1 - |b_2x_2 - 1|)$  # For metric  $x_3$ , the fitness func-
tion  $f_3(x_3)$  can be expressed as:  $f_3(x_3) = \max(0, 1 - |b_3x_3 - 1|)$  # For metric  $x_4$ , the
fitness function  $f_4(x_4)$  can be expressed as:  $f_4(x_4) = \max(0, 1 - |b_4x_4 - 1|)$  # For met-
ric  $x_5$ , the fitness function  $f_5(x_5)$  can be expressed as:  $f_5(x_5) = \max(0, 1 - |b_5x_5 - 1|)$ 
def fitness_function(index, value): # Calculate the slope of the fitted linear function
slope = 1 / optimal_solutions[index] print(slope) # Calculate fitness fitness = max(0, 1
- abs(value * slope - 1)) return fitness

# Calculate the fitness scores for each metric test_values = [7, 8, 9, 10, 6] fitness_scores
= [fitness_function(i, test_values[i]) for i in range(5)]

# Weight for each metric weight = 1/5

# Sum to get the total score total_score = sum(fitness_scores) * weight

print("Total fitness score:", total_score)

# Initialize population size and iterations population_size = 1000 iterations = 10

```

```
for i in range(iterations): # Alternate population size setting in each iteration if
i population_size = 1000 else: population_size = 700 # Set population size to 700 in
odd iterations # Output population size in the current iteration print("Iteration:", i + 1,
"Population size:", population_size)>
```

#### 10.0.7 Output:

```
< Error displayed: Package biblatex Error: File 'CHinese Vversion.bbl' not created by
biblatex. >
```

#### 10.0.8 Query 4:

```
<Please complete my probability settings.>
```

#### 10.0.9 Output:

<To introduce probability parameters for the genetic algorithm, we need to add settings for crossover probability and mutation probability, and apply these probabilities in each iteration. Based on the mutation probability of 0.005 and crossover probability of 0.5 you provided earlier, we can make the following modifications:

First, we will add settings for mutation probability and crossover probability: `mutation_rate = 0.005` # Mutation probability is 0.005 `crossover_rate = 0.5` # Crossover probability is 0.5

Next, in each iteration, we need to use these probability parameters for crossover and mutation operations. In your current code, you set the population size to 1000 in even iterations and 700 in odd iterations. We need to use these probability parameters in each iteration, so we can pass these probability parameters to the genetic algorithm function called in each iteration. Here is a sample code snippet showing how to apply the genetic algorithm function and use mutation probability and crossover probability in each iteration: `for i in range(iterations): if i population_size = 1000 else: population_size = 700 print("Iteration:", i + 1, "Population size:", population_size)`

```
# Call the genetic algorithm function and pass mutation probability and crossover
probability best_solution = genetic_algorithm(population_size, mutation_rate, crossover_rate)
print("Best solution in iteration", i + 1, ":", best_solution)
```

In this sample code, we call the `genetic_algorithm` function, passing population size, mutation probability, and crossover probability as parameters. This way, in each iteration, we use new population size and probability parameters to execute the genetic algorithm. Doing this ensures that we use the specified probability parameters in each iteration. I hope this helps. If you have any other questions or need further assistance, feel free to let me know.

In your usage example, you can use the modified `initialize_population` function to initialize the population and run the genetic algorithm. The logic of the algorithm does not need to be changed.

```
# Assuming your usage example population_size = 800 # Population size is set to
800 male_ratio = 0.5 # Gender ratio is set to 0.5 mutation_rate = 0.005 crossover_rate =
0.5 max_iterations = 20
```

```
best_solution = genetic_algorithm(population_size, male_ratio, mutation_rate, crossover_rate,
max_iterations) print("Best solution:", best_solution.features)
```

With the above modifications, your population will be fixed at 800 individuals, and the gender ratio will be 0.5. If you have any questions or need further assistance, feel free to let me know.>

#### 10.0.10 Query 5:

<

#### 10.0.11 Query 1:

<Insert the exact wording of the subsequent input into the AI tool>

#### 10.0.12 Output:

<Understood. If you only want to modify the attributes of the original population, fixing the population size at 800 and the male-female ratio at 0.5, you can adjust the 'initialize\_population' function as follows:

```
""python def initialize_population(population_size, male_ratio): # Determine the
number of males and females male_count = int(population_size * male_ratio) female_count
= population_size - male_count # Create the population, distributing genders accord-
ing to the specified ratio population = [Individual([random.uniform(1, 100) for _ in
range(5)], 'male' if i < male_count else 'female') for i in range(population_size)] return
population ""
```

If you have any further requests or questions, please let me know.>

#### 10.0.13 Query 6:

```
<syms K N0=0.1*K ; chl=0.05; M=0.00495; ct=0.04; x=zeros(1,21); x(1)=0.1 for i=1:20>
```

#### 10.0.14 Output:

```
<# Assuming your usage example population_size = 800 # Population size is set to 800
male_ratio = 0.5 # Gender ratio is set to 0.5 mutation_rate = 0.005 crossover_rate = 0.5
max_iterations = 20
```

```
best_solution = genetic_algorithm(population_size, male_ratio, mutation_rate, crossover_rate,
max_iterations) print("Best solution:", best_solution.features)>
```