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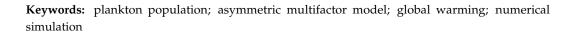


Quantifying the Effects of Global Warming on the Plankton Population: An Asymmetric Multifactor Mathematical Model-Based Approach

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Abstract: A nonlinear dynamical model for the plankton population in a fixed sea area under the influence of asymmetric multiple factors, including atmospheric CO_2 concentration, atmospheric temperature, nutrient concentration, seawater temperature, light intensity, and predator density is proposed to address the survival of the plankton population due to global warming. The model's accuracy is confirmed by comparison with actual data, and numerical simulations are carried out to justify the relevant findings. The results suggest that increasing plankton's ability to absorb atmospheric CO_2 or regulate atmospheric temperature can help to mitigate global warming. Furthermore, if the population density of fish, the primary predator of plankton, falls within a certain range, the increase in atmospheric temperature will be mitigated. Additionally, the stability conditions for the suggested model are obtained, along with the equilibrium point of the system. Overall, this paper considers the effects of asymmetric multifactor interaction on plankton population density and establishes a mathematical connection between environmental ecosystems and plankton that might aid in addressing the challenges posed by global warming and preserving the plankton population.



1. Introduction

1.1. Background

Plankton are the most crucial element in ensuring the stability of the marine ecological system, since they are the principal producer of the system, laying the groundwork for an aquatic food web, and they have a non-negligible impact on the system's energy flow, material cycle, and information transfer. Unfortunately, as industrialization has progressed, CO₂ emissions have risen dramatically. This not only destroys the bicarbonate buffer zone for plankton survival, but also causes the ocean's acidity to remain abnormally high [1]. It also exacerbates the rise in atmospheric temperature [2–5], which changes the growth cycle of the plankton population, disturbs their specific seasonal growth patterns, and ultimately poses a great threat to the survival of plankton [6,7]. At the same time, abiotic factors such as nutrient concentration in water and light intensity also affect the growth status of plankton [8–12]. For example, nutrient concentration, despite playing an indispensable role in the growth of plankton [13], will limit the growth of the plankton population after exceeding a certain range [14].

1.2. Related Work

Under the combined influence of the accelerating accumulation of CO_2 in the atmosphere and rising atmospheric temperatures, the living environment of plankton is facing a direct threat, which is undoubtedly a great challenge to the ecosphere.



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Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). First, the increase in CO_2 emissions is continuously destroying the living environment of marine life; Lüthi et al. [2] investigated the CO_2 concentration in the atmosphere, and found that it has been increasing since the Industrial Revolution. Capitani et al. [15] simulated food webs and analyzed changes in trophic level biomass in a tropical nearprimitive coral reef ecosystem. It was found that by the end of the century, the total available biomass would decrease by 1%, 8%, and 44% (from RCP2.6 to RCP8.5) under different ocean warming scenarios, which in turn would change the ecosystem structure and jeopardize biomass replenishment, leading to a decrease in ecosystem productivity.

At the same time, the increase in CO₂ concentration has led to an increase in ocean acidification. Bindoff et al. [4] and Leseurre et al. [16] studied the changes in seawater acidity caused by CO₂ accumulation, and found that CO₂ accumulation increases the absorption of CO_2 by seawater, thus making it more acidic, with a decrease in pH of 0.15 (-0.39, +0.001) at RCP8.5. Moreover, the intense acidification of the ocean in a short time can combine with other factors, such as ultraviolet light, to bring a serious crisis to the survival environment of the plankton. Jin et al. [17] conducted a quantitative meta-analysis based on published experimental assessments, and found that OA (ocean acidification) and UVR (ultraviolet light) act on some marine organisms as an additive emergency source interaction. It was found that those tropical primary producers are more susceptible to OA or UVR compared to conspecifics in other climatic regions. Kuroyanagi et al. [18] cultured bisexual reproductive specimens of large benthic foraminifera (a planktonic organism) under different pH conditions (pH 7.7~8.3, NBS scale), and confirmed that changes in seawater pH affect not only the amount of foraminiferal calcification (i.e., shell volume) but also shell mass (i.e., shell density), and predicted that under RCP 8.5, ocean acidification will have a dramatic impact on foraminiferal carbonate production in coral reefs by the end of the century.

In addition, the survival of plankton is threatened by the increase in atmospheric temperature. Bindoff et al. [4] predicted an increase in atmospheric temperature of more than 4 degrees Celsius in the short-term future in the context of the release of more CO₂ from human industrial activities. Moreover, Bhattacharyya et al. [19] and Sarker et al. [20] used the Rosenzweig–MacArthur predator–prey model and found that elevated atmospheric temperatures would significantly reduce the total plankton biomass and alter species turnover times, which would disrupt stable coexistence among plankton species. Alhakami et al. [21] used an RP-LMS neural network and obtained reference datasets for greenhouse gas emissions, ambient temperature, aquatic populations, and fishery populations, indicating that current global warming will continue unabated for the next 50 years.

In the meantime, elevated atmospheric temperatures often combine with nutrients to affect the survival status of planktonic organisms. By comparing the effects of elevated nutrients and temperature on three Caribbean corals—Acropora cervicornis, Orbicella faveolata, and Siderastrea siderea—Palacio-Castro et al. [22] found that addressing elevated temperature alone was not sufficient to ensure the presence of Caribbean corals and dinoflagellate algae. Noting that controlling nutrient inputs to coral reef areas is important for the survival of these coral species and dinoflagellate algae, the increase in CO₂ emissions will therefore cause significant harm to the plankton population, which needs to be fully appreciated and studied accordingly.

While understanding the current situation, some scholars have more deeply explored the role of abiotic factors such as increased atmospheric CO₂ content, rising atmospheric temperature, and nutrients on plankton populations by building mathematical models and using various mathematical methods or computer tools. Mandal et al. [23] developed an environmental management model with time-varying parameters to explore the effects of rising atmospheric temperatures on marine ecosystems due to the rapid concentration

of CO₂ in the environment. Caperon [24] used the population–food velocity equation in conjunction with several assumptions:

$$\frac{db}{dt} = -k_1cb + k_2(c \cdot b)$$
$$\frac{d(c \cdot b)}{dt} = k_1cb - (k_2 + k_3)(c \cdot b)$$
$$\frac{dp}{dt} = k_3(c \cdot b)$$

Hysteresis-free hyperbolic equations for plankton populations and nutrient salinity were developed:

$$\frac{1}{n}\frac{dn}{dt} = \frac{rb}{b+A}$$

where c, b, p, and $c \cdot b$ denote the concentration of unoccupied sites, food, ingested food, and food adsorption site complexes, respectively, n is the population density; b is the food concentration; and both A and r are constants. This portrays the mathematical relationship between plankton populations and nutrient salts. Lehman et al. [25] used a computer simulation model to predict plankton growth dynamics and nutrient assimilation, which simulated the population dynamics and overall physiological characteristics of plankton. Bouterfas et al. [26] studied the effects of light and temperature on the growth of three freshwater green algae isolated from eutrophic lakes. These mathematical models and results reveal the intrinsic relationships between different environmental factors and plankton populations while illustrating the indispensable place of mathematical model applications in the future study of plankton population development.

1.3. Workflow of the Study

As seen above, research in the field of predicting the trend of several major indicators of the ocean by employing abiotic factors such as atmospheric CO_2 concentration, atmospheric temperature, and nutrients as single or double indicators, respectively, is widely used in the work of practical conservation.

However, changes in the plankton population frequently occur in the context of a combination of multiple key indicators, and discussing one of these indicators separately still makes it difficult to achieve an accurate description of reality. The plankton population is the most critical and vulnerable aspect for maintaining the stability of the marine ecological system. In the context of increasing CO₂ emissions, the survival of the plankton population has encountered unprecedented challenges. This poses new requirements for the study of how to protect the plankton population under the combined influence of multiple factors.

In general, there is still a lack of mathematical understanding of the influence of the combined effects of abiotic factors such as atmospheric CO_2 concentration, atmospheric temperature, and nutrients on the plankton population. So, we are committed to developing a mathematical model of marine ecology that can correlate several key indicators. This work focuses on the influence of the combined effects of atmospheric CO_2 concentration, atmospheric temperature, and nutrient concentration on the density of the plankton population.

The rest of the paper is organized as follows. In Section 2, we use different indices to portray different influencing factors separately and build a new multifactor nonlinear dynamical model. In Section 3, the model's accuracy is confirmed by comparison with actual data, and numerical simulations are carried out to justify the relevant findings. Further experiments with parameter variations are carried out to explore the findings and applications of the proposed model. In Section 4, the stability conditions for the suggested system are obtained, along with the equilibrium point of the system.

2. Asymmetric Multifactor Model

2.1. Problem Statement

The purpose of this study is to explore the effects of the combination of atmospheric CO_2 concentration, atmospheric temperature, and nutrient concentration on the density of the plankton population under the current situation of accelerating CO_2 emissions, as well as to predict the density of the plankton population as global warming continues. In this paper, we assume that the nutrients inflow and outflow in the study area are stable, the depth of the area is suitable to ensure access to sunlight, and the annual variation of water temperature in the area is stable. At the same time, the sea area studied in this paper refers to the general sea area under the conditions of the model assumptions and does not refer to a specific sea area, and the fixed sea area in this paper refers to the sea area.

The system is divided into four categories. The relationship between each parameter is displayed in Figure 1.

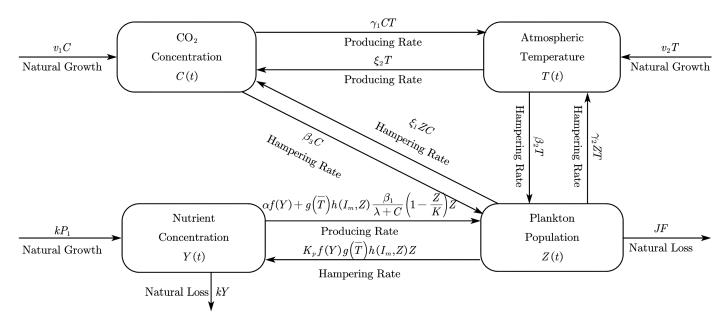


Figure 1. Relationship between parameters.

C(t) represents the concentration of CO₂ in the atmosphere at time *t*. Its concentration changes are influenced by various factors, the most significant of which is human activities [3–5,27]. T(t) denotes the atmospheric temperature. It depends on the atmospheric CO₂ concentration and the photosynthesis of plankton influence [23,28,29]. Y(t) denotes the nutrient concentration in the fixed sea area. Since the concentration of nutrients in the cell interior affects the growth rate of plankton, nutrient concentration plays a crucial role in the development of plankton population [11,14,30,31]. We assume that nutrients maintain a relative balance of inflow and outflow in this sea area. Z(t) is the density of the plankton population in the sea area, which is under great threat due to the combination of accelerated CO₂ emissions and fish predation [9,12,23,32–34].

2.2. Asymmetric Multifactor Model

To investigate the variation pattern of the density of the plankton population in the fixed sea, we propose the following multifactor nonlinear dynamical model of the plankton population.

$$\begin{aligned} \frac{dC}{dt} &= v_1 C - \xi_1 Z C + \xi_2 T, \\ \frac{dT}{dt} &= v_2 T + \gamma_1 C T - \gamma_2 Z T, \\ \frac{dY}{dt} &= k P_1 - k Y - K_p f(Y) g(\overline{T}) h(I_m, Z) Z, \\ \frac{dZ}{dt} &= \alpha \frac{\beta_1}{\lambda + C} f(Y) g(\overline{T}) h(I_m, Z) \left(1 - \frac{Z}{K}\right) Z - \beta_2 T - \beta_3 C - J F. \end{aligned}$$
(1)

The derivation and the parameters of the above model are described below.

In nature, various biochemical reactions occur at all times, and new CO₂ is continuously produced [23,35,36], such as in forest fires and other natural disasters; here, we denote v_1 as the natural growth rate of CO₂. In addition, plankton perform photosynthesis, which can reduce the atmospheric CO₂ concentration by absorbing CO₂ [23,37], and the net CO₂ uptake by the plankton population (*Z*) is noted as $\xi_1 ZC$. However, frequent human industrial activities increase CO₂ emissions, especially the use of fuel [2], and the total amount of CO₂ produced from human industrial activities is noted as $\xi_2 T$.

Biochemical reactions occurring in nature also generate new heat to raise the atmospheric temperature (*T*), and we set v_2 as the natural growth rate of atmospheric temperature. Since atmospheric temperature usually has a positive correlation with CO₂ concentration [8,23,29], we note that $\gamma_1 CT$ denotes the increase in atmospheric temperature caused by the increase in CO₂. Moreover, plankton (*Z*) can absorb CO₂ through photosynthesis, so plankton can adjust the atmospheric temperature through photosynthesis [8,23,29,38], and the planktonic absorption of atmospheric temperature is noted as $\gamma_2 ZT$.

Under the action of seawater flow, the nutrient concentration (Y) in the fixed sea area will constantly change, and the nutrients in the sea area will not only have inflow and outflow, but will also be diluted by the seawater. Let *k* denote the dilution rate of nutrient by seawater flow and kP_1 and kY represent the total inflow and outflow of the nutrient after dilution in this sea area, respectively. Except for seawater flow, abiotic factors (mainly seawater temperature (\overline{T}) and light intensity (I_m)) also affect nutrient uptake by plankton [8–12], the functional response function f(Y) for nutrient uptake by plankton can better characterize the nutrient uptake capacity of the plankton population [39], which has the form

$$f(Y) = \frac{Y}{H_Y + Y}$$

The optimal exponential model $g(\overline{T})$ can depict the effect of seawater temperature on plankton growth more precisely [25,26]:

$$g(\overline{T}) = c_1 \exp\left(-c_2 |\overline{T} - T_{opt}|\right).$$

The following Steel model $h(I_m, Z)$ [26,39] is adopted to describe the effect of light intensity on plankton growth.

$$h(I_m, Z) = \frac{I_m}{I_{opt}} \exp\left(1 - \frac{I_m}{I_{opt}}\right)$$

This is also because the product accumulation method can more perfectly depict the effect on the density of the plankton population under the combined effect of multiple factors. Therefore, when considering the combined effects of the above abiotic factors,

Plankton (Z) have metabolic activities in the natural environment, where CO₂ concentration $\left(\frac{\beta_1}{\lambda+C}\right)$, nutrient concentration (f(Y)), sea temperature $(g(\overline{T}))$, and light intensity $(h(I_m, Z))$ all influence the metabolic activities of plankton population, and these factors at the right concentration can promote the growth of the density of the plankton population [8–11,32,37,40–42]. Under the influence of environmental and self-limitation, the plankton population has its life cycle; hence, we denote K, the carrying capacity of the plankton life cycle in the sea area. Moreover, because the product accumulation method can more perfectly portray the common effect on plankton under multiple factors, we note $\alpha \frac{\beta_1}{\lambda+C} f(Y) g(\overline{T}) h(I_m, Z) (1 - \frac{Z}{K}) Z$ as the effect on the density of the plankton population under the common effect of abiotic factors and metabolism. In addition, plankton themselves are very vulnerable, and both the increase in atmospheric temperature and ocean acidification reduces the density of the plankton population [8–11,23], denoting $\beta_2 T$ and $\beta_3 C$ for the amount of plankton loss due to the increase in atmospheric temperature and the amount of plankton loss due to ocean acidification, respectively. In addition, the density of the plankton population will decrease due to predator predation [33,34,43], so JF is the depletion of plankton due to predation by predators.

Based on the above assumptions and the principle of conservation laws, we establish the proposed mathematical model Equation (1). From the above analysis, it is clear that the impact of different factors on plankton is asymmetric, which means that each factor affects the plankton in different ways. For the details of the relevant parameters described above and their reference values, we refer to [23–26,39]. Here, we briefly list them in Table 1.

In this paper, the product accumulation method is used as the theoretical basis for modeling, and the common effects of the functional response function f(Y) [39], the optimal exponential model $g(\overline{T})$ [25,26] and the Steel model $h(I_m, Z)$ [26,39] on plankton are discussed.

Symbol	Description	Values	Unit
α	Maximum growth rate of plankton population	3	day ⁻¹
\overline{T}	Ocean temperature	20	°C
I_m	Illumination intensity	5000	Lx
k	Dilution ratio	0.8	day^{-1}
P_1	Nutrient input rate	0.1	$mg \cdot mL^{-1}$
λ	Saturation constant	0.01	day^{-1}
β_1	Phytoplankton population growth rate induced by CO ₂	0.00108	km^{-3}
β_2	Phytoplankton population loss rate caused by rising atmospheric temperature	0.001	km ⁻³
β_3	Phytoplankton population loss rate caused by changes of seawater pH	0.21	km^{-3}
J	Predation rate of fish on plankton	0.0002	km^{-3}
F	Density of the plankton population	99.81	_
K_p	Maximum uptake rate of nutrients by plankton	0.05	mL·(num·day) ⁻¹
v_1	Natural growth rate of atmosphere carbon dioxide concentration	0.0395	kg⋅km ⁻²
v_2	Natural temperature growth rate	0.099	°C
ξ_1	Net absorption rate of CO ₂ by plankton population	0.00191	kg∙km ^{−2}
ξ2	CO ₂ production rate from industrialization by plankton population	0.003	$kg\cdot km^{-2}$
γ_1	Rise in atmospheric temperature due to carbon dioxide emissions	0.00025	°C
γ_2	Absorption rate of plankton to temperature	0.00565	°C
c_1	Temperature parameters	1.57	-
<i>c</i> ₂	Temperature parameters	0.24	_

Table 1. Parameters collection.

Symbol	Description	Values	Unit
T _{opt}	Optimum temperature for plankton growth	35	°C
H_{Y}	Semisaturated parameters of nutrient uptake by plankton	0.35	$mg \cdot mL^{-1}$
Iopt	Optimal light intensity	10,000	Lx
Ŕ	Phytoplankton environmental carrying capacity	100,000	_

Table 1. Cont.

3. Stability Analysis

Stable and reasonable mathematical models play an important role in environmental prediction, risk assessment, and practical protection when considering the hazards facing the plankton population. For a class of nonlinear systems composed of differential equations, studying the stability properties of multiple possible equilibrium points can effectively reveal the system's dynamical behavior. This section is dedicated to the system's equilibrium point and the analysis of the stability conditions of these points.

Some researchers have explored the effects of abiotic factors such as increased atmospheric CO₂ content, rising atmospheric temperature, and nutrients on the planktonic population by building mathematical models, and have made constructive suggestions. Bouterfas et al. [26] used an optimal exponential model to characterize the effect of seawater temperature on the growth of plankton and studied the effect of light and temperature on the growth of three freshwater green algae isolated from a eutrophic lake under nontrophic limited conditions, respectively. Zheng et al. [44] considered a mathematical system consisting of plankton and fish, investigated sufficient conditions for the equilibrium of the system to be asymptotically stable on a global scale, and demonstrated that the equilibrium is equiprobably stable under relatively weak conditions. Premakumari et al. [45] analyzed a model of plankton–fish dynamics containing toxicity, joint fishing, and other factors by considering Holling-II functional response; examined the interdependent evolutionary forms of three aspects of phytoplankton, zooplankton, and fish populations under Caputo fractional derivatives; and theoretically investigated the conditions for the stability of each equilibrium point.

This article solves the general equilibrium point of the model and carries out a study on the eigenvalues of the Jacobi matrix of the system, through which the stability of the equilibrium point is judged and the conditions for the stability of the equilibrium point are discussed comprehensively [23].

Recalling the multifactor nonlinear dynamical model Equation (1), we denote the equilibrium point of the system by (C^*, T^*, Y^*, Z^*) . Let the terms on the right side of the system vanish; the equilibrium point is obtained, which is given by

$$\begin{cases} C^* = \frac{v_1 \gamma_2 + \xi_1 \gamma_1 - v_1 \gamma_1}{\xi_1 \gamma_1}, \\ T^* = \frac{[v_2 \xi_1 + \gamma_1 (\xi_1 - v_1)][v_1 \gamma_2 + \gamma_1 (\xi_1 - v_1)]}{\xi_1 \xi_2 \gamma_1 \gamma_2}, \\ Y^* = \frac{H_Y}{\frac{H_Y}{(\beta_2 T^* + \beta_3 C^* + JF)(\lambda + C^*)}}, \\ Z^* = \frac{\xi_1 (v_2 + \gamma_1) + v_1 (\gamma_2 - \gamma_1)}{\xi_1 \gamma_2}. \end{cases}$$
(2)

The Jacobi matrix of the system and the corresponding characteristic polynomial can be calculated in the following form. For convenience, let

$$\begin{cases}
A = K_p g(\overline{T}) h(I_m, Z) \frac{H_Y Z}{(H_Y + Y)^2} + k, \\
B = K_p g(\overline{T}) h(I_m, Z) \frac{Y}{H_Y + Y}, \\
D = -\alpha g(\overline{T}) h(I_m, Z) \frac{\beta_1 H_Y \left(1 - \frac{Z}{K}\right) Z}{(H_Y + Y)^2 (\lambda + C)}, \\
E = \alpha g(\overline{T}) h(I_m, Z) \frac{\beta_1 \left(1 - \frac{2Z}{K}\right) Y}{(H_Y + Y) (\lambda + C)}.
\end{cases}$$
(3)

Hence, the Jacobi matrix of Equation (1) has the form

$$M = \begin{pmatrix} v_1 - \xi_1 Z & \xi_2 & 0 & -\xi_1 C \\ \gamma_1 T & v_2 + \gamma_1 C - \gamma_2 Z & 0 & -\gamma_2 T \\ 0 & 0 & -A & -B \\ -\alpha g(\overline{T})h(I_m, Z) \frac{\beta_1(1 - \frac{Z}{K})YZ}{(H_Y + Y)(\lambda + C)^2} - \beta_3 & -\beta_2 & -D & E \end{pmatrix}.$$

Thus, the eigenpolynomial $|\mu I - M|$ takes the form

$$|\mu I - M| = a_4 \mu^4 + a_3 \mu^3 + a_2 \mu^2 + a_1 \mu + a_0 = 0,$$

where

$$\begin{split} a_4 &= 1, \\ a_3 &= (A - E) - [(v_1 - \xi_1 Z) + (v_2 + \gamma_1 C - \gamma_2 Z)], \\ a_2 &= - [(v_1 - \xi_1 Z) + (v_2 + \gamma_1 C - \gamma_2 Z)](A - E) - (EA + BD) \\ &- [\xi_1 CF + \beta_2 \gamma_2 T + \xi_2 \gamma_1 T - (v_1 - \xi_1 Z) * (v_2 + \gamma_1 C - \gamma_2 Z)], \\ a_1 &= [(v_1 - \xi_1 Z) * (v_2 + \gamma_1 C - \gamma_2 Z) - \xi_1 CF - \beta_2 \gamma_2 T - \xi_2 \gamma_1 T]A + \\ &[(v_1 - \xi_1 Z) + (v_2 + \gamma_1 C - \gamma_2 Z)](EA + BD) + \\ &[(v_2 + \gamma_1 C - \gamma_2 Z)\xi_1 CF + (v_1 - \xi_1 Z)\beta_2 \gamma_2 T - \xi_2 \gamma_2 TF - \beta_2 \xi_1 \gamma_1 TC] + \\ &[\xi_2 \gamma_1 T - (v_1 - \xi_1 Z)(v_2 + \gamma_1 C - \gamma_2 Z)]E, \\ a_0 &= [(v_1 - \xi_1 Z)\beta_2 \gamma_2 T + (v_2 + \gamma_1 C - \gamma_2 Z)\xi_1 CF - \xi_2 \gamma_2 TF - \beta_2 \xi_1 \gamma_1 TC]A + \\ &[\xi_2 \gamma_1 T - (v_1 - \xi_1 Z)(v_2 + \gamma_1 C - \gamma_2 Z)](EA + BD). \end{split}$$

Hence, the eigenvalues of the system can be determined by the above eigenpolynomial. To further simplify the form of each coefficient, we let

$$\begin{split} \eta &= v_1 - \xi_1 Z, \qquad \beta = v_2 + \gamma_1 C - \gamma_2 Z, \qquad \delta = \beta_2 \xi_1 \gamma_1 T C, \\ x &= \xi_1 C F, \qquad y = \beta_2 \gamma_2 T, \qquad z = \xi_2 \gamma_1 T. \end{split}$$

It easily yields $\xi_2 \gamma_2 TF = \frac{xyz}{\delta}$, so the coefficients of the eigenpolynomial can be simplified to the following form:

$$\begin{aligned} a_4 &= 1, \\ a_3 &= (A - E) - (\eta + \beta), \\ a_2 &= -(\eta + \beta)(A - E) - (EA + BD) - (x + y + z - \eta\beta), \\ a_1 &= (\eta\beta - x - y - z)A + (\eta + \beta)(EA + BD) + \left(\eta y + \beta x - \frac{xyz}{\delta} - \delta\right) + (z - \eta\beta)E, \\ a_0 &= \left(\eta y + \beta x - \frac{xyz}{\delta} - \delta\right)A + (z - \eta\beta)(EA + BD). \end{aligned}$$

Now, we are in the position to state our main result on the stability of the equilibrium point:

Theorem 1. The equilibrium point (C^*, T^*, Y^*, Z^*) of Equation (1) is stable if the system satisfies: 1. $\eta y + \beta x - \frac{xyz}{\delta} - \delta > 0$,

- $2. \qquad z-\eta\beta>0, \qquad o$
- 3. $(\eta + \beta)(EA + BD) > (x + y + z \eta\beta)A$,
- 4. $a_2a_1 > a_0a_3$.

Proof. We provide proof via the Routh–Hurwitz criterion. The Routh table for characteristic polynomials has the form

$$\begin{aligned} S^{4} & a_{0} & a_{2} & a_{4} \\ S^{3} & a_{1} & a_{3} \\ S^{2} & b_{1} & b_{2} \\ S^{1} & c_{1} \\ S^{0} & d_{1} \end{aligned}$$
Here, $b_{1} = -\frac{1}{a_{1}} \begin{vmatrix} a_{0} & a_{2} \\ a_{1} & a_{3} \end{vmatrix} , b_{2} = -\frac{1}{a_{1}} \begin{vmatrix} a_{0} & a_{4} \\ a_{1} & 0 \end{vmatrix} , c_{1} = -\frac{1}{b_{1}} \begin{vmatrix} a_{1} & a_{3} \\ b_{1} & b_{2} \end{vmatrix} ,$

$$d_{1} = -\frac{1}{c_{1}} \begin{vmatrix} b_{1} & b_{2} \\ c_{1} & 0 \end{vmatrix} .$$

The sufficient and necessary condition for the stability of the equilibrium point is that the first column elements of the Routh table are all positive. In this case, all the eigenvalues are located on the left half complex plane. Hence, the system is stable under the following conditions:

$$\begin{cases} a_{0} = \left(\eta y + \beta x - \frac{xyz}{\delta} - \delta\right) A + (z - \eta\beta)(EA + BD) > 0 \\ a_{1} = (\eta\beta - x - y - z)A + (\eta + \beta)(EA + BD) + (\eta y + \beta x - \frac{xyz}{\delta} - \delta) + (z - \eta\beta)E > 0 \\ b_{1} = -\frac{1}{a_{1}} \begin{vmatrix} a_{0} & a_{2} \\ a_{1} & a_{3} \end{vmatrix} = \frac{a_{2}a_{1} - a_{0}a_{3}}{a_{1}} > 0 \\ b_{1} = -\frac{1}{b_{1}} \begin{vmatrix} a_{1} & a_{3} \\ b_{1} & b_{2} \end{vmatrix} = \frac{a_{3}b_{1} - a_{1}b_{2}}{b_{1}} > 0 \\ d_{1} = -\frac{1}{c_{1}} \begin{vmatrix} b_{1} & b_{2} \\ c_{1} & 0 \end{vmatrix} = b_{2} > 0 \end{cases}$$

$$(4)$$

Now, we check the above criterion with the aid of the conditions given in the theorem. From Condition (2), we can obtain that $x + y + z - \eta\beta > 0$. Combining Condition (3) and $A = K_{pg}(\overline{T})h(I_m, Z)\frac{H_YZ}{(H_Y + Y)^2} + k > 0$, we have $EA + BD > \frac{x + y + z - \eta\beta}{\eta + \beta}A > 0$. From Conditions (1) and (2), then we obtain $a_0 > 0$. Since K >> Z, it can be obtained that $1 - \frac{2Z}{K} > 0$, so $E = \eta g(\overline{T})h(I_m, Z)\frac{\beta_1(1 - \frac{2Z}{K})Y}{(H_Y + Y)(\lambda + C)} > 0$. Then, we have $a_1 > 0$. Condition (4) yields that $b_1 = \frac{a_2a_1 - a_0a_3}{a_1} > 0$.

Next, we examine c_1 . It is obvious that $c_1 > 0$ is equivalent to $b_1 > \frac{a_1}{a_3}$. Assuming $a_3 \ge 0$, we can obtain $A - E > \eta + \beta > 0$, so $a_2 = -(\eta + \beta)(A - E) - (EA + BD) - (x + y + z - \eta\beta) < 0$. However, $a_2 > \frac{a_0a_3}{a_1} \ge 0$, which contradicts Condition (4), so $a_3 < 0$, $b_1 > 0 > \frac{a_1}{a_3}$, Hence, we obtain $c_1 > 0$. For d_1 , since $b_2 = -\frac{1}{a_1} \begin{vmatrix} a_0 & u_4 \\ a_1 & 0 \end{vmatrix} = a_4 = 1 > 0$, we have $d_1 = b_2 > 0$.

In summary, the conditions in Equation (4) are satisfied. Using the Routh–Hurwitz criterion, we conclude that the equilibrium point (C^*, T^*, Y^*, Z^*) of the system is stable. This ends the proof. \Box

4. Numerical Analysis

4.1. Model Validation

To verify the validity of the model, the actual data from 2012~2017 reported in [46] are adopted. We use ode45 solver in MATLAB to numerically simulate the nonlinear dynamical Equation (1) to predict the temperature and plankton population density, and the results are shown in Figure 2. It can be seen that the model established in this paper is effective.

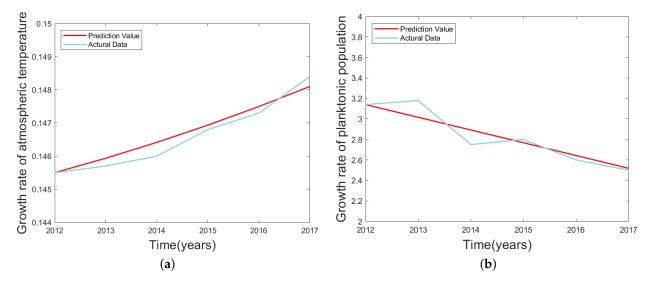


Figure 2. Comparison of model prediction and actual data: (**a**) atmospheric temperature; (**b**) plankton population density.

4.2. Numerical Simulation

In this subsection, in order to better illustrate the variation trend of the density of the plankton population under the effect of multiple influencing factors, numerical simulations are performed for the above-established plankton population autonomous nonlinear dynamics model. Based on the parameter values set in Table 1, the initial values of the model are set to $C_0 = 0.04$, $T_0 = 0.07$, $Y_0 = 0.092$, and $Z_0 = 17.5$. The numerical simulation effect diagrams are shown in Figure 3.

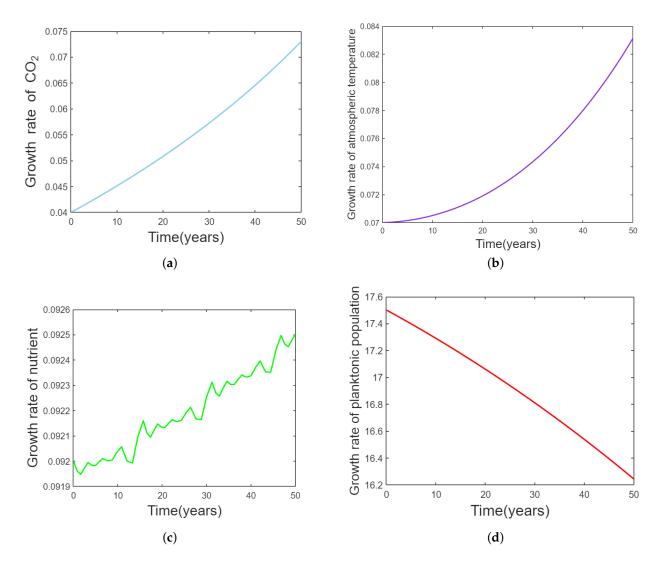


Figure 3. Simulation results of the nonlinear dynamics model for the plankton population. (a) The growth rate of atmospheric CO_2 concentration over time. (b) The growth rate of atmospheric temperature over time. (c) The growth rate of nutrient concentration in the sea over time. (d) The growth rate of the density of the plankton population over time.

The findings imply that CO_2 concentration in the atmosphere will steadily increase over the next 50 years, with a linear growth rate. The growth rate of atmospheric temperature will be exponential, and the greenhouse effect will further intensify. The growth rate of nutrient concentration in this sea area generally shows a steady growth of waves, because the increase in atmospheric CO_2 concentration aggravates ocean acidification and deteriorates the growth environment of plankton population. Meanwhile, rising air temperatures have a deleterious impact on plankton's capacity to absorb nutrients. For plankton, the growth rate of their population density shows an approximately linear decrease. The above results are consistent with the findings of numerous scholars [23,25–29,39].

4.3. Parameter Sensitivity Analysis

4.3.1. Experiment 1

This experiment explores the dynamics of the model as the net absorption rate ξ_1 of atmospheric CO₂ by plankton population changes.

It can be observed from Figure 4a that when ξ_1 increases, the growth rate of atmospheric CO₂ concentration decreases significantly, indicating that the plankton population plays a crucial role in regulating the atmospheric CO₂ concentration. At the same time, there is a positive correlation between atmospheric temperature and atmospheric CO₂ concentration, so as ξ_1 increases, the growth rate of atmospheric temperature also decreases; thus, the greenhouse effect is mitigated, as shown in Figure 4b. Figure 4c illustrates that as ξ_1 increases, the uptake of nutrients by plankton is promoted, which causes its growth rate to decrease. According to Figure 4d, the growth rate of the density of the plankton population will increase when ξ_1 increases and before the absorption of CO₂ does not reach saturation concentration.

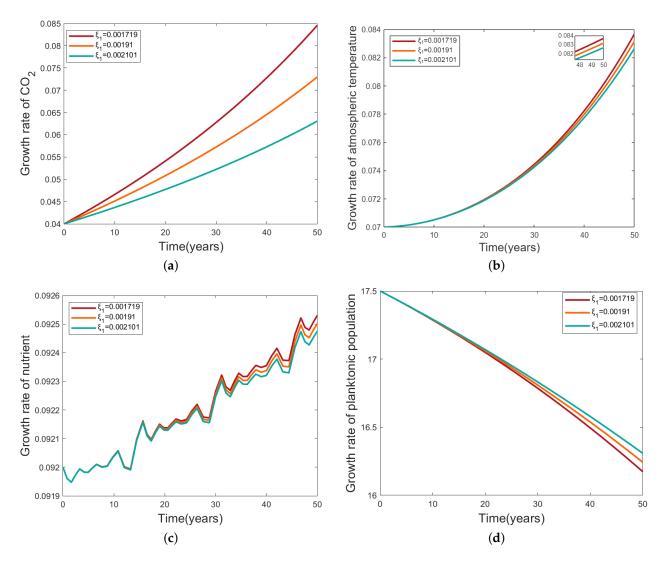


Figure 4. The dynamics of the autonomous nonlinear dynamics model of the plankton population due to the increase in ξ_1 . (a) The growth rate of atmospheric CO₂ concentration over time due to the increase in ξ_1 . (b) The growth rate of atmospheric temperature over time due to the increase in ξ_1 . (c) The growth rate of nutrient concentration in the sea over time due to the increase in ξ_1 . (d) The growth rate of the density of the plankton population over time due to the increase in ξ_1 .

As a result, the above numerical simulation results show that as ξ_1 increases, the growth rate of CO₂ concentration in the atmosphere decreases significantly, as does the growth rate of atmospheric temperature, alleviating the greenhouse effect while decreasing the growth rate of nutrient concentration in the sea area. Moreover, the density of the plankton population is increasing at a faster rate [47]. The aforementioned experimental findings are congruent with academic studies by [23,25–29,39].

4.3.2. Experiment 2

The next experiment explores the dynamics of the model as the absorption rate γ_2 of atmospheric temperature by plankton population changes.

As depicted in Figure 5a, as γ_2 increases, the growth rate of atmospheric CO₂ concentration slows, although only slightly. Figure 5b indicates that the growth rate of atmospheric temperature is reduced significantly. However, the change in γ_2 has little effect on the growth rate of nutrient concentration and the density of the plankton population in this sea area, as illustrated in Figure 5c,d. The results of the experiment are consistent with the academic research by [23,25–29,39,48].

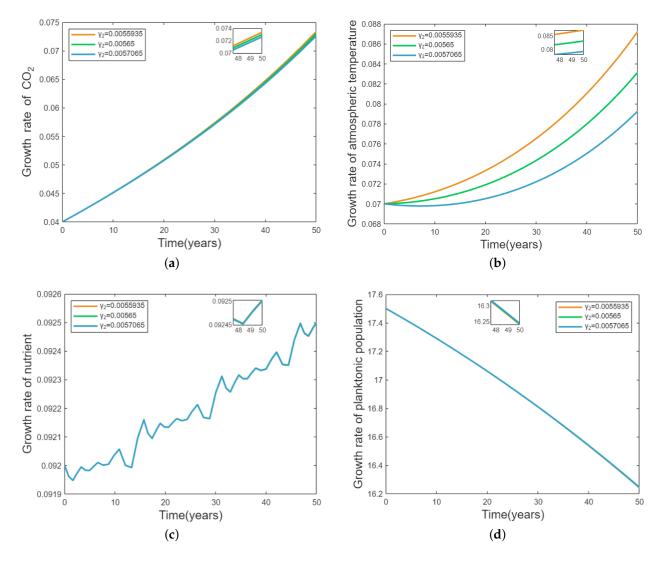


Figure 5. The dynamics of the autonomous nonlinear dynamics model for plankton population due to the increase in γ_2 . (a) The growth rate of atmospheric temperature over time due to the increase in γ_2 . (b) The growth rate of atmospheric temperature over time due to the increase in γ_2 . (c) The growth rate of nutrient concentration in the sea over time due to the increase in γ_2 . (d) The growth rate of the density of the plankton population over time due to the increase in γ_2 .

4.3.3. Experiment 3

The last experiment explores the dynamics of the model as the predator population density *F* changes.

It can be observed from Figure 6a that when F decreases, the density of the plankton population grows, increasing the total absorption of atmospheric CO₂ and causing the growth rate of atmospheric CO₂ concentration to decrease. Figure 6b shows that when the

rate of rise in CO_2 concentration in the atmosphere slows, so does the rate of growth of atmospheric temperature. As *F* declines and the density of the plankton population grows, total nutrient absorption increases, and therefore, the growth rate of nutrient concentration in the marine area reduces, as illustrated in Figure 6c. Figure 6d illustrates that when *F* declines, the growth rate of the plankton population increases. The experimental results are in good agreement with academic studies by [23,25–29,39,48].

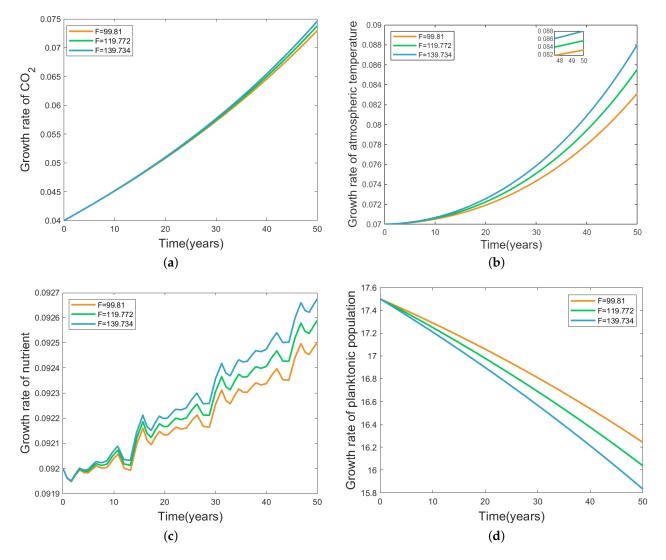


Figure 6. The dynamics of the autonomous nonlinear dynamics model of the plankton population due to the decrease in *F*. (**a**) The growth rate of atmospheric CO_2 concentration over time due to the decrease in *F*. (**b**) The growth rate of atmospheric temperature over time due to the decrease in *F*. (**c**) The growth rate of nutrient concentration in the sea over time due to the decrease in *F*. (**d**) The growth rate of the plankton population over time due to the decrease in *F*.

Consequently, the preceding numerical simulation demonstrates that when F declines, the density of the plankton population rises. The rate of increase in atmospheric CO₂ concentration slows as more CO₂ is taken up by the plankton population. Another factor that considerably lessens the impact of the high temperatures brought on by the greenhouse effect is the increasing rate of atmospheric temperature. At the same time, the growth rate of nutrient concentration in this sea area will decrease and the growth rate of the density of the plankton population will increase. Additionally, the plankton population's density will rise more quickly.

5. Conclusions

In this paper, a nonlinear dynamics model for the plankton population is established that integrates the effects of multiple asymmetric factors. The validity of the model is verified by comparing the predicted values with the real data. Furthermore, the model investigates the effects on the density of the plankton population under the combined effects of abiotic factors such as atmospheric CO₂ concentration, atmospheric temperature, and nutrient concentration. The relevant results are obtained by numerical simulation experiments and analyzed. The paper compares the effects on the density of the plankton population when the net absorption rate of atmospheric CO_2 by the plankton population, the absorption rate of atmospheric temperature by the plankton population, and the density of the predator population are varied. The results show that the plankton population can effectively mitigate global warming because plankton can absorb CO₂ through photosynthesis, and there is a positive correlation between atmospheric temperature and CO_2 concentration, so it can mitigate the increase in atmospheric CO_2 concentration and the rise in atmospheric temperature. In addition, predator density is inversely correlated with plankton density, and its effect on the decrease in the rate of increase in atmospheric temperature is greater than its effect on the decrease in the rate of increase in atmospheric CO_2 . This suggests that global warming can also be mitigated by controlling predator density. From the above analysis, we conclude that the impact of different factors on plankton is asymmetric.

In this study, the mathematical equation between plankton and the environment is established based on the actual situation in a fixed sea area. The results of this study may also change if the factors related to it change. Future research work can focus on trying to weaken the assumptions of the model to make it more general. For example, we can try to introduce a relationship function between light intensity and sea depth to further address the effect of the variation of light intensity with depth on the model. The differential equations are established based on the relationships between variables, so the parameters are selected in the sea environment under the assumption of constraints.

The results of this comprehensive study show that the harm caused by global warming can be effectively mitigated by improving the living environment of the plankton population and maintaining reasonable control of the predator population while ensuring the stability of the ecosystem.

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