Enhanced Lotka-Volterra Equations: A Novel Approach to Investigate Plant Community Dynamics Under Varied Climatic Conditions

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Abstract. Amidst escalating climatic uncertainties, the adaptability of plant communities to varying drought frequencies and intensities emerges as a critical research domain. This study endeavors to decode the potential ramifications of such climatic extremities on plant community dynamics. By harnessing an augmented Lotka-Volterra model, we intricately weave in climatic variables, with a pronounced emphasis on drought indices, to forecast plant community trajectories. Our explorations divulged that specific drought scenarios significantly influence community resilience, with certain species compositions optimally enhancing community robustness. Moreover, through a judicious application of a genetic algorithm, we discerned an optimal species count that maximizes community biomass. This seminal work not only deepens our understanding of plant community dynamics under climatic vicissitudes but also paves the way for informed ecological and environmental policymaking.

Keywords: Plant Communities, Drought, Improved Lotka-Volterra Equations, SPEI.

1. Introduction

In an era where climate change transcends scientific discourse, becoming a global socio-economic and political quandary, the ramifications of escalating greenhouse gas emissions are palpable. The ensuing global warming, extreme weather fluctuations, and sea-level rise present formidable challenges to agriculture and ecosystems [1]. Yet, the topic remains contentious, mired in political debates and economic vested interests [2]. Concurrently, nations, with China at the forefront, are pioneering strategies for carbon neutrality and fortifying market-centric climate policies [4-5]. Such monumental global and national endeavors underscore the significance of understanding plant community adaptation strategies amidst climatic adversities, setting the stage for our research.

Amidst these global shifts, the stability and biodiversity of plant communities emerge as pivotal research domains. The escalating global temperatures, coupled with the surge in droughts, floods, and other climatic extremities, imperil not just plant growth but also global agricultural outputs and food security. The intricate ecological interplays and adaptive mechanisms within plant communities have thus garnered scientific attention, with species interactions and diversity being paramount [6]. The pressing questions revolve around the refinement of mathematical models to predict plant community dynamics under climatic vicissitudes and the role of species diversity in community adaptability.

In the intricate tapestry of plant community dynamics, a myriad of scholarly endeavors have sought to elucidate underlying patterns and interactions. Literature [7], in a nuanced exploration, delved into the microbial communities gracing plant leaf surfaces, harnessing experimental manipulations to unravel the profound influence of neighboring flora. Venturing into the realm of biodiversity, Literature [8] elegantly probed the correlation between species richness and territorial expansion, grounding their inquiry in a structuralist paradigm enriched by Mediterranean grassland observations. With a focus on the microbial realm, Literature [9] embarked on a meticulous examination of the symbiosis between plasmids and their microbial counterparts, leveraging a sophisticated competition experiment within a synthetically-stabilized milieu. In a bid to demystify the enigmatic time-storage effect underpinning species coexistence, Literature [10] juxtaposed contemporary coexistence theories against the tangible realities of ecosystems. Turning to agricultural interventions, Literature [11] embarked on a discerning inquiry into the multifaceted repercussions of fertilizer application on temperate grassland diversity, employing a rigorous experimental design to tease apart the nuances of interspecies competition. Literature [12], in a comprehensive synthesis, illuminated the ecological imprints left by the European elk sheep, gleaning insights from an exhaustive literary corpus. Venturing beneath the surface, Literature [13-14] meticulously dissected the intricate dance of interspecies dynamics among soil microfungi, wielding comparative culture methodologies. Concluding this scholarly tapestry. While these seminal works have cast light on previously shadowed corners, they simultaneously underscore the vast, uncharted territories that beckon further scholarly exploration.

In this study, we endeavor to bridge these gaps. We introduce a modified differential equation, inspired by the Lotka-Volterra model, encapsulating the inhibitory effects of climatic changes, environmental adaptability, and species interplay. By integrating weather as an abiotic influencer on species' intrinsic growth rates, we establish a growth rate function steered by a drought coefficient. Utilizing the 4th-5th order Runge-Kutta method, we predict plant community dynamics under erratic weather patterns.

Furthermore, we discern the optimal plant species count that augments community benefits. By categorizing species based on their drought resilience and employing a genetic algorithm, we ascertain the species proportion that maximizes community biomass. Through a trigonometric-based drought exponential function, we simulate varying drought conditions, exploring the interplay between species count and community magnitude under diverse drought frequencies. This research not only enriches our comprehension of plant community adaptability, ecosystem stability, and the nexus between biodiversity and ecological functions but also offers invaluable insights for future endeavors in ecology, climatology, and environmental science.

2. Model Establishment: Improved Lotka-Volterra equations

In natural ecosystems, when multiple populations coexist, their interactions can be delineated into several categories: competition, mutualism, predation, or in some instances, a complete absence of any discernible relationship. To quantitatively capture the dynamics of these species'interactions, one can turn to the Lotka-Volterra equations. These mathematical models, introduced by scientists Alfred Lotka and Vito Volterra, serve as foundational tools in ecological studies, offering insights into the intricate interplay among biological populations [15], as represented in equation (1).

$$\frac{dx(t)}{dt} = rx\left(1 - \frac{x}{N}\right) \tag{1}$$

Herein, r represents the intrinsic growth rate of the species; x denotes the population size of the species; N signifies the environmental carrying capacity, which is the maximum population size the environment can sustain for a given species; and $\frac{dx(t)}{dt}$ illustrates the rate of change in species population over time.

When there are more than two species in the community, the effects between them are cumulative. When we consider abiotic factors such as climate, temperature, soil environment, light, etc., we can consider the intrinsic species growth rate as a function of these factors, i.e., abiotic factors are the independent variables and growth rate is the dependent variable. So, we can obtain this equation as follows.

$$\begin{cases} \dfrac{dx_1(t)}{dt} = r_1 x_1\left(1 - \dfrac{x_1}{N_1} - k\dfrac{x_2}{N_2}\right) \\ \dfrac{dx_2(t)}{dt} = r_2 x_2\left(1 - \dfrac{x_2}{N_2} - k\dfrac{x_1}{N_1}\right) \end{cases} \tag{2}$$

Within this context, $x_1(t)$ and $x_2(t)$ respectively denote the population sizes of the first and second species. The intrinsic growth rates of these species are represented by r_1 and r_2. N_1 and N_2 encapsulate the environmental carrying capacities for the respective species, indicating the maximum population size achievable when only that particular species is present. The competition coefficients, k_{12} and k_{21}, elucidate the extent to which one species impacts the other. For instance, k_{12} characterizes the competitive influence of species 2 on species 1.

This set of equations delineates the population dynamics of the two species as they vie for the same resource, with their dynamics being mutually influenced. Consequently, the overarching equation can be expressed as:

$$\frac{dx_i(t)}{dt} = r_i(t)x_i(t)\left(1 - \frac{x_i(t)}{N_i} - \sum_{j \neq i} k_{ij}\frac{x_j(t)}{N_j}\right) \quad (i,j = 1,2) \tag{3}$$

2.1. On the Resolution of $\mathbf{k_{ij}}$

In the intricate tapestry of ecological research, understanding interspecific interactions within communities stands as a cornerstone. The degree of connectivity and interdependence between species not only shapes the immediate dynamics of a community but also dictates its resilience, adaptability, and long-term evolution. Such interconnectivity, often nuanced and multifaceted, serves as a pivotal metric in discerning the underlying mechanisms that drive community dynamics.

Grounded in the principles of community classification, a meticulous approach is adopted wherein the significance values of species are harnessed. These values, often reflective of a species' role and prominence within the community, provide a quantitative lens through which interspecific interactions can be gauged [16].

From a theoretical perspective, both the association coefficient "V" and the competition coefficient k_{ij} serve as pivotal metrics, elucidating the intricate relational dynamics between two distinct entities. Within the ambit of association analysis, "V" adeptly captures the nuanced interplay between two arboreal species, a dynamic invariably shaped by their collective response to shared resource competition and other ecological determinants. Conversely, within the ecological modeling framework, k_{ij} offers a precise quantification of the competitive intensity between species, underscoring the profound conceptual congruence between these two metrics. To enhance the interpretative fidelity of "V" when cast in the role of k_{ij}, a normalization strategy is proposed, confining its value to the [0,1] interval. Here, a "V" value approaching 1 becomes emblematic of heightened interspecific competition, whereas a value nearing 0 suggests a subdued or virtually non-existent competitive dynamic. This normalization not only bolsters the interpretability of "V" but also accentuates its intuitive resonance in characterizing competitive dynamics. The associative gradient between arboreal entities, encapsulated by "V", can be construed as a mirror reflecting their competitive nuances over shared resources. Consequently, "V" emerges as a seminal parameter in the ecological modeling paradigm, delineating interspecific competitive intricacies. Based on these considerations, we further propose the following equation:

$$k = \frac{ad - bc}{\sqrt{(a+b)(a+c)(c+d)(b+d)}} \tag{4}$$

Within this framework, let a denote the number of quadrats where both species are present; b and c represent the number of quadrats where only one of the two species are observed, respectively; and d signifies the quadrats in which neither species appears.

This formulation offers a quantifiable approach to assess the degree of association between two species. Such an assessment facilitates a deeper comprehension of interspecific interactions within the community, thereby laying the groundwork for constructing successional sequences in forest communities.

2.2. On the Resolution of $\mathbf{r_i(t)}$

For the sake of analytical convenience, it is posited that the intrinsic growth rate of a species correlates quadratically with the drought index. Historically, growth rate functions have been typically characterized by the Sigmoid function. However, a notable anomaly arises when soil moisture levels are exceedingly high. Under such conditions, rather than experiencing an uptick, the plant growth rate can decline, potentially leading to plant mortality. This suggests that heightened moisture levels do not invariably correspond to increased growth rates, highlighting a limitation in the application of the Sigmoid function. In our present study, we advocate for a more apt quasi-quadratic function to represent the growth rate, articulated as follows:

$$r_i(t) = p_i s^2(t) + q_i s(t) + h_i \tag{5}$$

$$s(t) = \frac{A}{2}[sin(\omega t) + 1] \tag{6}$$

Wherein, $r_i(t)$ denotes the growth rate at time t. The parameter p_i serves as the water utilization index, elucidating how a plant efficiently harnesses water to bolster its growth. A heightened value of p_i suggests the plant's adeptness in generating a more substantial biomass even under diminished water availability. The function $s(t)$ is the drought index function, delineating the temporal fluctuations of drought or moisture conditions. Given the periodic alterations in drought severity over time (seasonally) and the inherent disparities in drought conditions across various regions, we employ a trigonometric function to characterize the drought scenario at a specific locale and time t. Here, A represents the SPEI (Standardized Precipitation-Evapotranspiration Index), which amalgamates precipitation and evapotranspiration data. Its value can manifest as positive (indicating moist conditions) or negative (signifying drought conditions). The index q_i is the optimal growth point index, correlating with a distinct value of SPEI (elaborated in subsequent sections), signifying the conditions under which the plant achieves its maximal growth rate. Lastly, h_i is the intercept, representing the baseline growth rate in the absence of external influencing factors.

2.2.1 About SPEI

We designate the growth rate function as a quadratic function. In this model, we consider that the largest influence on the growth rate is the moisture factor. Therefore, we set the independent variable as the drought index, or SPEI [17-18].

We first collected and processed the month-by-month rainfall data. The month by-month potential evapotranspiration was solved by the Penman Monteith model method.

$$ET_0 = \frac{0.408\varDelta(R_n - G) + \gamma \frac{900}{T + 273} U_1(e_a - e_d)}{\varDelta + \gamma(1 + 0.34U_1)} \tag{7}$$

Wherein, ET_0 represents the potential evapotranspiration, signifying the cumulative amount of evaporation and plant transpiration that might occur on a sufficiently watered surface under stipulated climatic conditions. R_n stands for the net surface radiation, which is the differential between the solar radiation received by the Earth's surface and the long-wave radiation emitted from the same. The psychrometric constant denoted by γ is intrinsically tied to the humidity and temperature of the air. T is the temperature, while U_1 indicates the average wind speed. e_a and e_d are the saturated and actual vapor pressures, respectively. Lastly, Δ is the slope of the function relating saturated vapor pressure to temperature.

The parameters such as net surface radiation, mean wind speed and air pressure used to calculate the above evapotranspiration in this study were obtained from ECMWF Reanalysis v5, ERA5.

The difference of precipitation and evapotranspiration month by month is as follows

$$D_i = P_i - ET_0 \tag{8}$$

Wherein, P_i denotes the monthly precipitation, while D_i represents the monthly differential between precipitation and evapotranspiration.

It's noteworthy that the values of D_i do not inherently exhibit the characteristics of a normal distribution. Assuming the precipitation follows a Γ distribution, we reflect upon the trend of precipitation through the probabilities of the Γ distribution. Subsequently, after normalizing this trend, the drought levels are discerned based on the cumulative frequency of D_i.The table below shows the SPEI and its corresponding drought and flood levels, as is shown in Table 1:

Table 1: SPEI index and drought/flood level

$\boldsymbol{SPEI}$	$\boldsymbol{Drought/Flood\ Level}$
$2.00 \le SPEI$	$Extremely\ Flooding$
$1.50 \le SPEI \le 1.99$	$Severe\ Flooding$
$1.00 \le SPEI \le 1.49$	$Moderate\ Flooding$
$0.10 \le SPEI \le 0.99$	$Light\ Flooding$
$-0.99 \le SPEI \le 0$	$Light\ Drought$
$-1.49 \le SPEI \le -1.00$	$Moderate\ Flooding$
$-1.99 \le SPEI \le -1.50$	$Severe\ Drought$
$-2.00 \ge SPEI$	$Extremely\ Drought$

2.2.2 About $\mathbf{p_i}$

It is well-established that an optimal moisture level exists, at which the intrinsic growth rate of a species peaks. Deviations from this optimal moisture, either in excess or deficit, invariably lead to a decline in the growth rate. Consequently, the growth rate function we delineate is a downward-opening quadratic function.

Referring to the aforementioned table, it becomes evident that within the range $\mathbf{0 < SPEI < 0.1}$, the balance between drought and inundation is most conducive. Thus, we postulate that plants attain their maximal growth rate when $\mathrm{SPEI} = 0.05$, signifying the midpoint abscissa of the quadratic function as $s(t) = 0.05$.

The term p_i in equation (5) is designated as the water response coefficient. Intriguingly, a plant's drought resilience is directly proportional to its Water Use Efficiency (WUE). This is underscored by the observation that a larger coefficient for the quadratic term in the function broadens its opening, suggesting a steeper variation. To ensure a positive growth across an expansive SPEI range when enhancing drought tolerance - that is, when WUE is elevated - it becomes imperative to configure p_i in inverse proportion to the species' WUE.

The Water Use Efficiency (WUE) of plants can vary widely depending on the species, environmental conditions, and other factors. Generally speaking, plants with a high WUE are able to produce a greater amount of biomass for a given amount of water, while plants with a low WUE may require more water to produce the same amount of biomass.

Some studies have estimated the average WUE for different types of plants, although these values can vary depending on the specific plant species and growing conditions. Here are some general ranges of WUE for different types of plants:

- C3 plants (which include most trees, shrubs, and cool-season grasses) typically have a WUE of around 3-6 grams of dry matter per kilogram of water ($g\ DM/kg\ H_2O$).
- C4 plants (which include most warm-season grasses and some crops such as maize and sorghum) typically have a WUE of around 5-10 $g\ DM/kg\ H_2O$.
- Succulent plants (such as cacti and other desert plants) typically have a very high WUE, ranging from 10-50 $g\ DM/kg\ H_2O$ or more.

3. Results

3.1. Model Solving

3.1.1 Numerical Approach to Differential Equations

To address the intricacies of the differential equations presented in our model, we employed the 4th-5th order Runge-Kutta algorithm, a widely recognized and robust method for solving ordinary differential equations. This method, known for its accuracy and efficiency, was implemented using MATLAB.

3.1.2 Initial Conditions and Assumptions

The initial population capacities for species a, b, and c were set at 80, 100, and 100, respectively. These values were chosen based on preliminary observations and are representative of the starting conditions in our simulated environment.

Recognizing the constraints of the natural environment, particularly the limited availability of resources, it is inevitable that species within a plant community will engage in competitive interactions. Such interactions are pivotal in shaping community dynamics and determining species dominance or coexistence.

3.1.3 Competition Coefficients

Competition, a fundamental ecological interaction, is often quantified using competition coefficients. These coefficients provide insights into the intensity and direction of competitive interactions between species. In our model, due to the inherent competitive nature of the species in the given environment, we opted for positive values for these coefficients. This decision was grounded in the understanding that positive competition coefficients typically signify interspecific competition, where an increase in one species results in a decrease in another.

The specific competition indices for our species are as follows:

$$\begin{pmatrix} 1 & 0.4 & 0.6 \\ 0.3 & 1 & 0.3 \\ 0.5 & 0.2 & 1 \end{pmatrix} \tag{9}$$

And the figures are based on different SPEI. SPEI=[-2,-1,0,1,2].

3.2. Analysis and Evaluation of results

According to the trend of the curves in each of the above graphs, it can be obtained that: when SPEI=-2, extreme drought conditions, the species quickly go to death; when SPEI=-1, mild drought, the species with strong drought resistance survive and the species with weak drought resistance go to death; when SPEI=0, the moisture conditions are better and all three species grow rapidly; when SPEI=1, mild flooding, the community biomass still grows; when SPEI=2, extreme flooding, the three species also quickly go to extinction.

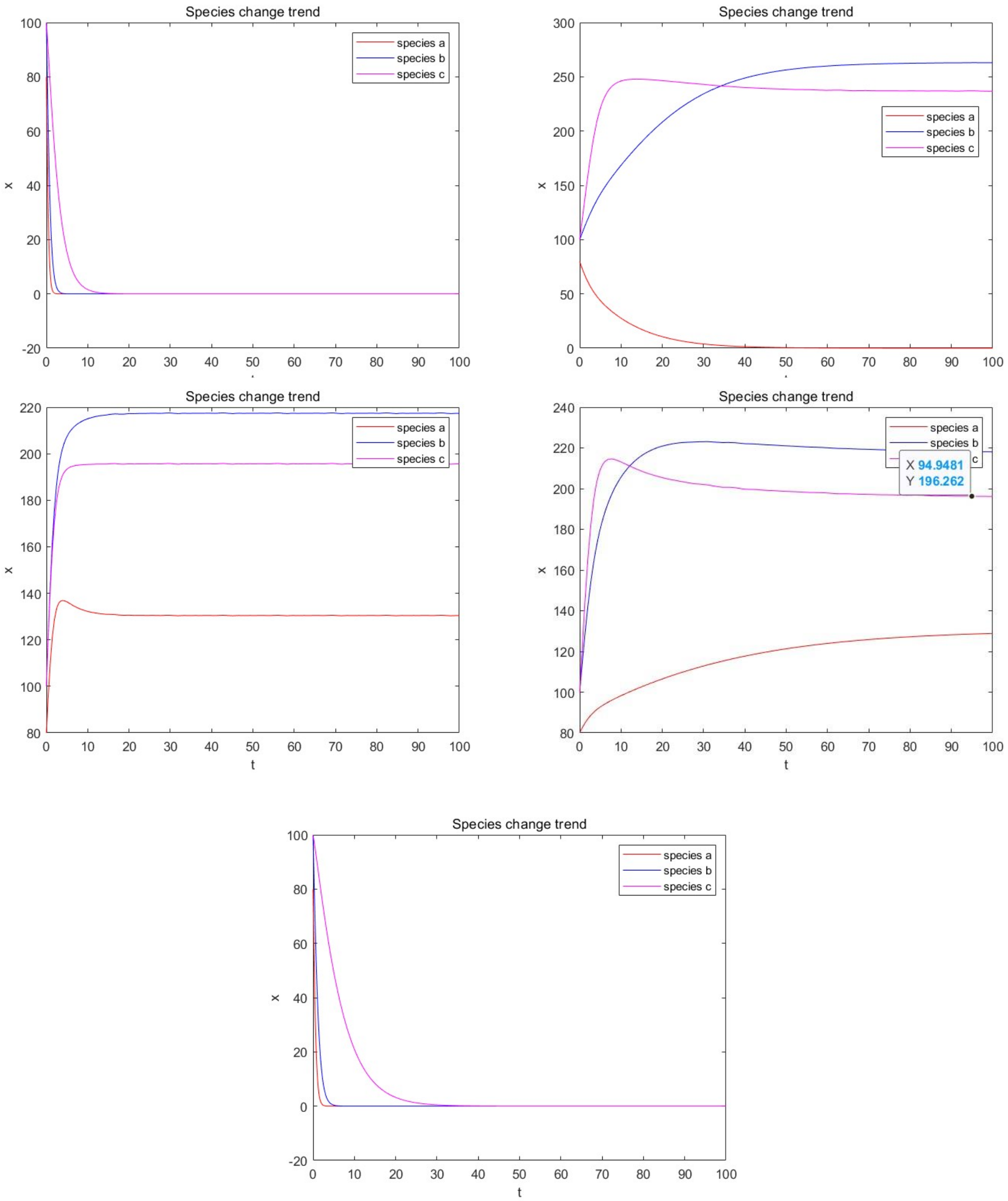

Figure 1: Changes in plant exposure to different weather conditions

From Figure 1 we can see that when plant communities are exposed to various irregular weather cycles, species with some drought tolerance possess the ability to regulate the effects of environmental changes, allowing them to adapt to drought and flood conditions. And when climatic conditions are extreme, drought-resistant plant communities will also go to death.

3.3. The population yields maximum biomass.

3.3.1 Model Establishment: Genetic Algorithm

Genetic algorithm is a search algorithm based on natural selection and population inheritance mechanism, which simulates the reproduction, hybridization and mutation phenomena in the process of natural selection and natural inheritance. When a genetic algorithm is used to solve a problem, each possible solution to the problem is encoded as a "chromosome", i.e. an individual, and several individuals make up the population (all possible solutions). At the beginning of the genetic algorithm, some individuals are randomly generated (i.e., the initial solution), and each individual is evaluated according to a predetermined objective function, which gives a fitness value. Based on which, some individuals are selected to generate the next generation. The "good" individuals are used to generate the next generation, and the "bad" individuals are eliminated. Then, the selected individuals are recombined by crossover and variation operators to generate a new generation, which inherits some good traits from the previous generation and thus outperforms the previous generation. The genetic algorithm can be seen as a process of initial evolution of a population of feasible solutions.

Upon thorough examination of pertinent literature, it has been discerned that a community manifests optimal benefits when comprised of 8 distinct species. As the number of species escalates, interspecific competition within the community might intensify, potentially leading to a decline in the community's overall biomass. Consequently, we postulate that the number of distinct species within a community does not exceed 12. With this constraint in mind, we formulated an objective function. The optimal number of species that maximizes community benefit was then ascertained using a genetic algorithm.

3.3.2 Model Solving

The flow chart of the genetic algorithm is shown below:

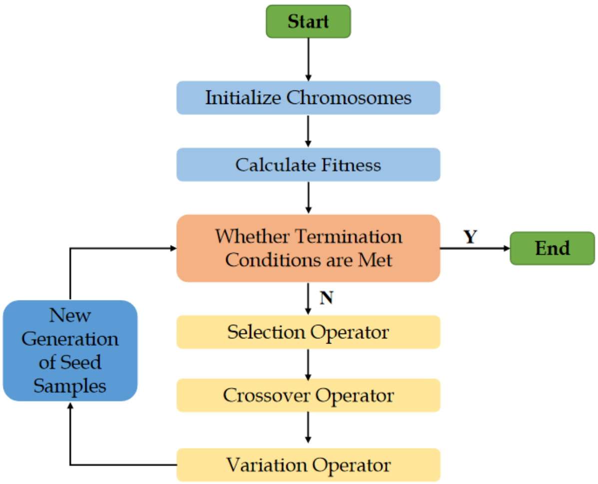

Figure 2: Genetic Algorithm

Objective function:

$$\omega = ai \sum_{n} x_i(t)\,, n < 13 \tag{10}$$

Let ω represent the total biomass within the community. For the i species category, a_i denotes the corresponding species count, while $x_i(t)$ signifies the biomass of the species. The flowchart is shown in Figure 2.

3.3.3 Analysis and Evaluation of results

Upon computation, the total biomass in the community is maximized when the number of different species is eight, which can be interpreted as benefiting the community. As the number of species continues to increase, the biomass of the community tends to stabilize.

3.4. Effects of changes in drought frequency and intensity on overall plant communities

We know that droughts occur with different frequencies in different regions, so our work explores trends in the growth of plant species under different drought frequencies. In this experiment, we designated species A as having low inter-specific competitive ability but high Water Use Efficiency (WUE), while species B was the opposite, having high competitive ability but low WUE. From the experimental results, it is evident that these two species exhibited contrasting growth patterns under different drought conditions ($\omega = 0.01{,}10$). Therefore, we can conclude that when drought occurs frequently, species with high WUE, or stronger drought resistance, have a competitive advantage in the community. However, when the frequency of drought is low, the competitive advantage depends on the inter-specific competition coefficient. Consequently, it is clear that drought frequency has a significant impact on species growth within the community. The experimental results are shown in Figure 3.

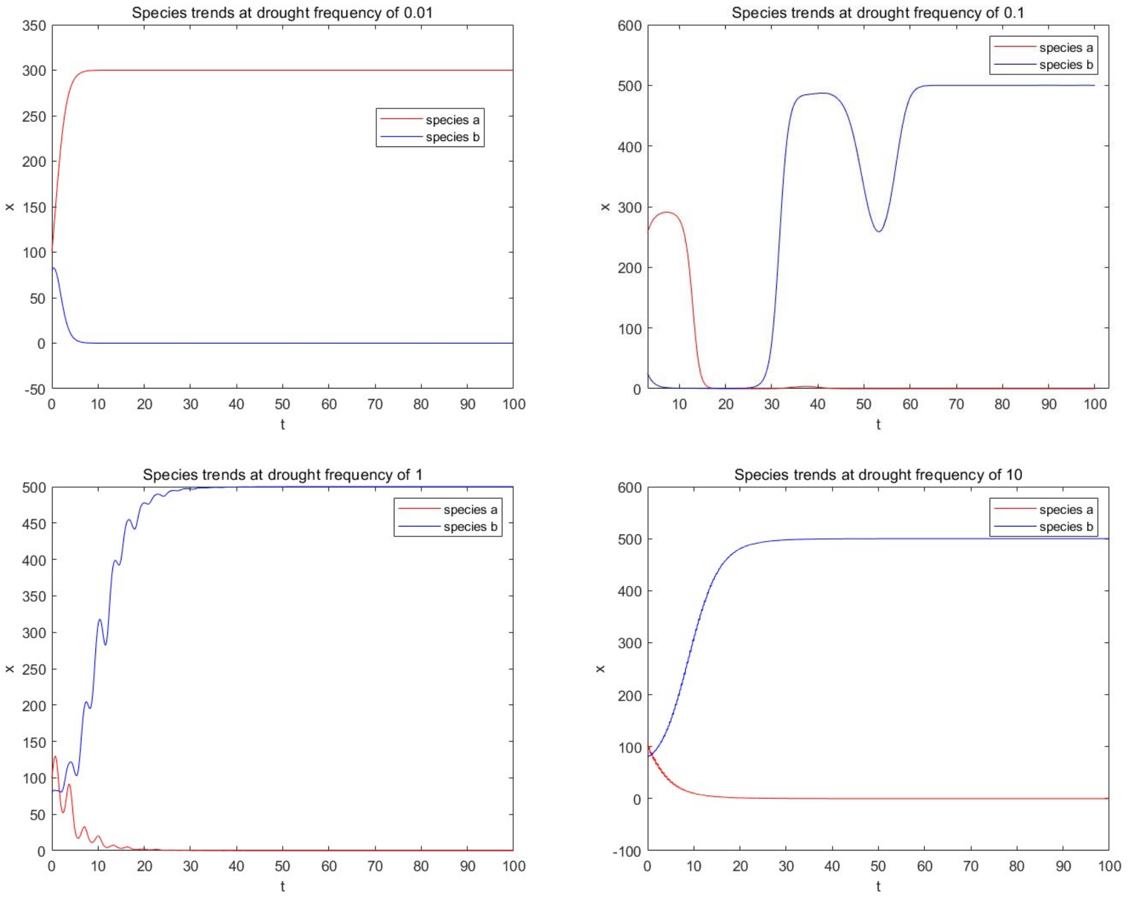

Figure 3: Changes in species under different drought frequencies

4. Conclusion

In an era marked by climatic upheavals, our research offers a deep dive into the adaptability and dynamics of plant communities amidst these challenges. Utilizing a modified Lotka-Volterra model, we've illuminated the nuanced effects of climatic shifts on environmental adaptability and species interplay. Our findings underscore the pivotal role of drought coefficients in shaping species' growth rates and the broader community dynamics.

Furthermore, our exploration into the optimal plant species count has revealed key insights into maximizing community benefits. By leveraging drought resilience categorizations and a genetic algorithm, we've mapped out the species proportions that optimize community biomass in varying drought conditions.

In essence, our study bridges critical knowledge gaps in plant community dynamics, offering invaluable insights for the broader realms of ecology and environmental science. As the global narrative on climate change intensifies, our research underscores the resilience and adaptability of plant communities, providing a roadmap for future ecological endeavors.

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