# Modeling Of Plant Population Community and Biodiversity Based On Differential Equation Model

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**Abstract.** Understanding the adaptive mechanisms of plant communities under drought conditions is crucial in the context of global climate changes. Drought resilience is intricately linked to the biodiversity within these communities, specifically, the number of species present. This research delves into how the diversity within plant communities influences their adaptation mechanisms when confronted with recurrent drought cycles over consecutive generations. To fathom the long-term dynamic interplay between plant communities and their environment, we devised a model. This model harnesses the power of genetic algorithms to optimize parameters, ensuring a comprehensive representation of ecological realities. Notably, it accounts for species migration, inter-species competition, and a myriad of other ecological factors. Consequently, our model can predict with commendable accuracy the evolutionary trajectory of plant communities when subjected to diverse and irregular weather patterns. Our findings not only shed light on the importance of biodiversity in ensuring ecological resilience but also provide invaluable insights for conservation strategies in the face of changing climate scenarios.

**Keywords:** Species competition model, Genetic algorithm, Plant species benefit model，Newton iteration method.

## 1. Introduction

As global climate patterns are altered, plant communities worldwide are faced with escalating challenges, notably drought, an imminent environmental stressor. Such changes not only disrupt the ecological balance but also influence myriad life forms dependent on these ecosystems [1]. Within this broader context, the pivotal role of species diversity in these communities has been highlighted. Communities endowed with a diverse spectrum of species are often observed to exhibit distinct adaptive strategies when subjected to consecutive drought cycles.

Studies indicate that the number and diversity of plant within a community play a crucial role in how well the community adapts to recurring drought events over multiple generations. Observations also reveal that communities with more than one plant species are better equipped to handle drought conditions than those with just those immature dying species.The intricate relationship between species diversity, environmental stressors, and community adaptation emphasizes the necessity for a sophisticated modeling mechanism. [2-5] While most existing research has been dedicated to individual facets such as species migration or inter-species competition, a holistic model encapsulating all these dynamics under diverse weather scenarios has yet to be developed. To address this void, a model based on genetic algorithms is introduced in this study, having been meticulously optimized to incorporate elements like species migration and competition. This model has been crafted with precision, having undergone rigorous optimization processes to effectively encompass pivotal factors such as species migration and the complex web of competition between species. Functioning as more than just a theoretical construct, this model serves as a predictive tool, offering foresights into the potential evolutionary pathways of plant communities. [6]

# 2. Preliminary

## 2.1. Symbols and Definitions

**Table 1** Symbols and Definitions

| Symbols | Definitions |
|---|---|
| $N_i\ (t)$ | Population i density of the first plant |
| $R(t)$ | Rainfall |
| $D(t)$ | Drought index |
| $a_{i,k}$ | Competition coefficient |
| $F_{i,k}$ | Responsiveness |
| $u_{i,j,k,l}$ | Species migration rate |
| $S(N)$ | Viability |
| $N*$ | Optimal number of species |

Table 1 shows the symbols and definitions to be used below.

# 3. Plant community prediction model based on differential equations

## 3.1. Establishment of a system of differential equations

Below is a mathematical model based on a system of differential equations to predict changes in plant communities during irregular weather cycles, taking into account the interactions between different species during dry cycles.

We can build the following systems of differential equations:

$$\frac{d_{Ni}}{dt} = N_i(t)[G_i(R(t), D(t), N_1(t), ..., N_n(t)) - M_i(R(t), D(t), N_1(t), ..., N_n(t))] \tag{1}$$

where $i = 1, . . ., n$ , $n$ is the number of species.

Growth rates and death rates can be modeled using the following functions:

$$\mathrm{G}_\mathrm{i}(R(t), D(t), N_1(t), ..., N_n(t)) = a_i R(t)^{Fi} f_i(D(t)) g_i(N_1(t), ..., N_n(t)) \tag{2}$$

$$M_i(R(t), D(t), N_1(t), ..., N_n(t)) = y_i R(t)^{6i} h_i(D(t)) p_i(N_1(t), ..., N_n(t)) \tag{3}$$

Among them, $a_i$, $F_i$, $y_i$, $6_i$ are the parameters:

$f_i\ (D(t))$, $g_i\ (N_1\ (t), . . . , N_n\ (t))$, $h_i\ (D(t))$, $p_i\ (N_1\ (t), . . . , N_n\ (t))$ are the drought response function and the density dependent function, which can be customized according to different species.

Drought Index $D(t)$ can be modeled using the following functions:

$$D(t) = \frac{R_0 - R(t)}{R_0} \tag{4}$$

Where $R_0$ is the drought threshold, which indicates that when rainfall falls below this value, a dry period will begin. When rainfall is above, $D(t)$ the value is negative.

Finally, we can use numerical methods to solve this system of differential equations and simulate changes in plant communities during irregular weather cycles. We can use the simulation results to predict the growth curve and species composition of plant community's res different dams in drastic cycles.

### 3.2. Long-term interactions between plant communities and the environment

Build a more detailed model to explore the long-term interaction between plant communities and the environment. The model will take into account factors, such as species migration, competition between species, environmental changes, and evolution.[7-8]

Assuming a plant community of nA species in a space divided into *M* grid cells, each hosting p individuals. *Ni,j,t* represents the count of the ith species in the 1st grid cell, *Pj* the total individuals in that cell, *Rj (t)* the resource availability, *Ei,j (t)* the species' competitive repulsion factor, and *s Mi,j,t* the mortality rate of the ith species over time t in the grid cell. Given species migration and growth rates, the species evolution equation can be described as:

$$\frac{\partial N_{i,j,t}}{\partial_t} = G_{i,j}(R_j(t), E_{i,j}(t))N_{i,j,t} - M_{i,j,t}N_{i,j,t} + u \overset{\mathrm{M}}{\underset{k=1}{\overset{M}{x}}} N_{i,k,t} - uN_{i,j,t} \tag{5}$$

Among them, *i = 1,2, . . . , n， j = 1,2, . . . , M,k=1.*

We assume that the competitive exclusion factor and mortality can be modeled in the following form:

$$E_{i,j}(t) = \underset{k=1,k\neq i}{\overset{n}{x}} a_{i,k} N_{k,j,t} \tag{6}$$

$$M_{i,j,t} = b_i + c_i R_i(t) \tag{7}$$

Among them, $a_{i,k}$ represents i the competition coefficient between the first $b_i$ species and the first species, *k* indicates *i* the natural mortality rate of the first species, $c_i$ and indicates i the relationship between the first species and the availability of environmental resources.

We can also assume that the competition coefficient and growth rate can be modeled in the form

$$a_{i,k} = a_{i,k}\sqrt{-F_{i,k}D_{j,t}} \tag{8}$$

$$G_{i,j}(R_j(t), E_{i,j}(t)) = T_i f(R_j(t)) \frac{1}{1 + \sum_{k=1,k\neq i}^{n} a_{i,k} N_{k,j,t}} \tag{9}$$

Among them, $a_{i,k}$ represents the ecological reciprocity coefficient between the i-th species and the k-th species, $F_{i,k}$ represents *i* the response degree of the ecological reciprocity coefficient between the i *f(Rj (t))*-th species and the k-th species to the drought index, and *k* represents *j* the resources in the grid unit can be the effect of utilization rate on growth rate $T_i$ represents *i* the maximum growth rate of the species.

Finally, we use methods such as genetic algorithm to optimize model parameters to obtain better prediction results.

### 3.3. Genetic Algorithm Solving Model Parameters

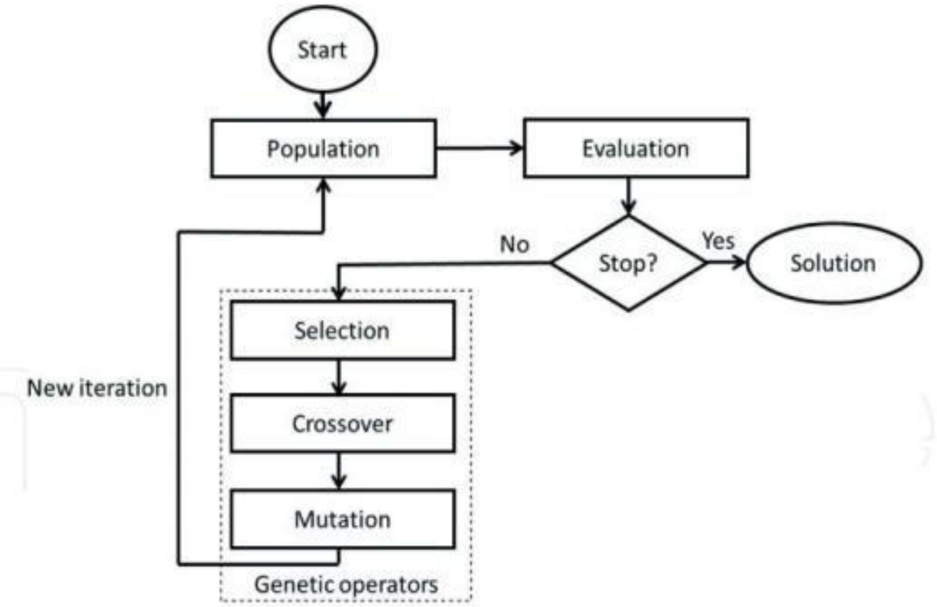


**Figure 1** - Genetic Algorithm Calculation Flowchart

Figure 1 shows that the Genetic Algorithm (*GA*) is a global search algorithm that simulates biological evolution to avoid local optima. Instead of directly dealing with the solution space, GA abstracts solution key points into a gene structure, seeking the optimal solution through genetic operations. Gene coding, crucial for aligning problems with algorithms, translates the solution space to the search space, with a chromosome set representing a feasible solution.

#### 3.3.1 Population initialization

For the genetic algorithm to function, it requires a population to perform operations like crossover and genetic variation.[9] The algorithm begins with an initial population, the quality of which impacts the solution's outcome and convergence rate. The initial population's criteria focus on diversity and empirical knowledge. There are two main generation rules:

1.Random generation ensures population richness but may compromise gene quality, slowing convergence and affecting the initial solution.

2.Empirical-based generation speeds up convergence, but with potential limited diversity, it might lead to local optima and uncertain optimization results.

In this paper, in order to ensure that the problem does not fall into the initial blind optimization process in the initial case, the homogeneous series ensures the diversity of the population, and the method of combining empirical and random initial population is considered, and the proportions are respectively 50%.

Random generation criterion: The chromosomal genes in the population are randomly sorted and generated by task numbers $\{1,2, \ldots, n\}$ .

#### 3.3.2 Cross operator

Cross-manipulation is the main method for generating new individuals and is the core operation in genetic algorithms. In the crossover operator, the algorithm randomly selects two chromosomes in the population to cross according to a certain crossover ratio to produce a new solution. commonly used decimal cross algorithms, there are multiple methods such as single-point crossing, two-point crossing, and multi-point crossing. In the application of the crossover strategy, multi-point crossover is less used, because there are too many intersections of multi-point crossing, and multi-point crossings cannot effectively preserve some important patterns in chromosomes. This paper adopts a combination of single-point intersection and two-point crossover.

### 3.3.3 Mutation operator

In genetic algorithms, chromosome crossover and selection drive solution evolution. Mutation, an auxiliary method, enhances the algorithm's local search ability. [10]When combined with crossover, variation facilitates a more directed global and local search, ensuring the algorithm effectively finds the optimal solution.

In the genetic algorithm encoded by a decimal positive integer, the principle of variation is position mutation, and the rule is to exchange the task sequence number of two random positions in the chromosome, resulting in a new chromosome individual.

The mutation operation, triggered by a certain probability, ensures effective gene transmission. In the algorithm's early stages, mutation probability shouldn't be too high. As the genetic algorithm progresses and population diversity decreases, this paper sets an adaptive mutation probability to maintain optimization performance and enhance diversity, as indicated in the subsequent formula.

$$p_m = \begin{cases} p_m C, nC > \frac{1}{3}, NC and f(nC) = f(nC-20) \\ p_m, else \end{cases} \tag{10}$$

Leading to the best optima because they stop as soon as a local optimum is found. In order not to get stuck on this local optimum, there are various strategies which allow the search to continue after having found an optimum. One strategy to over- come the abrupt stopping of the search for a local optimum is to iterate the descent method. The following steps are carried out from the found optimum:

• Apply a perturbation on the current solution,
• Apply a descent method on that solution.
• Determine if the new optimum should replace the current solution based on an acceptance criterion and repeat until a stop criterion is met. Stop criteria include execution time, iteration count, and total evaluations. Disturbances can be a random solution, one distant from or similar to the optimum. Heuristic Iterative Local Search uses a concept where, rather than starting from random solutions, a perturbation is applied to the current local optimum for the next iteration. This disturbance aims to find a better local optimum.

The disruption mechanism is crucial in *GA*. An acceptance criterion determines when a new local optimum can replace the current one. Together, they balance intensification and diversification. Various acceptance criteria can achieve this balance.

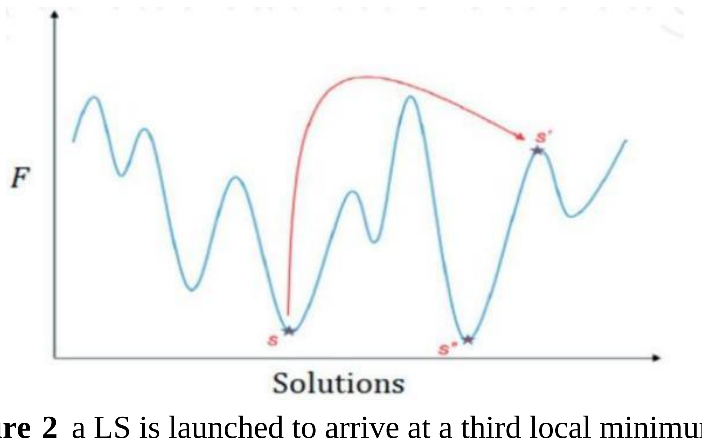


**Figure 2** a LS is launched to arrive at a third local minimum s'

Figure 2 shows that from a local minimum s, a disturbance of the latter generates a minimum s' from which a LS is launched to arrive at a third local minimum s” potentially better than s.

By substitution, the following conclusions can be drawn:

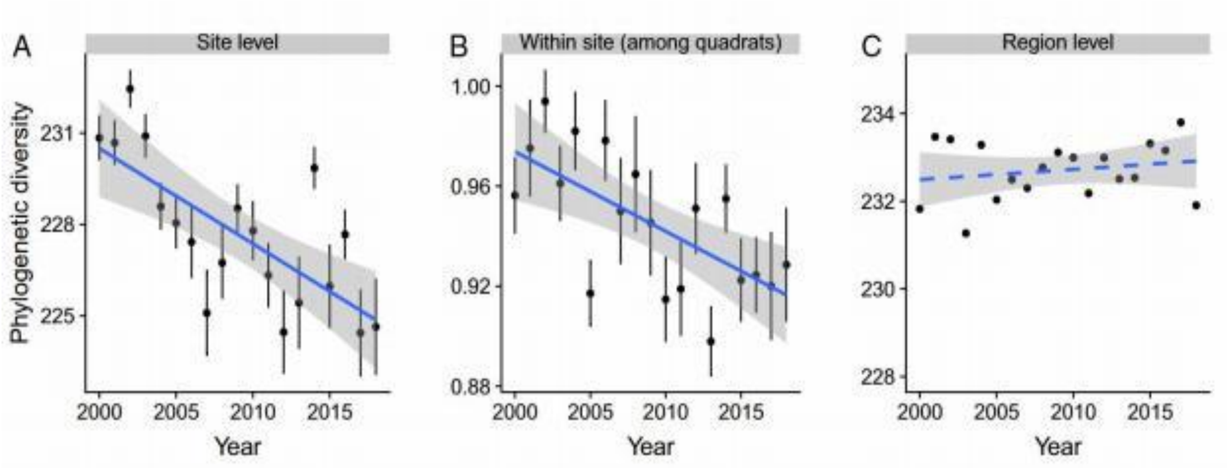


**Figure 3** -*SE* of phylogenetic diversity across all sites

Figure 3 shows that solid lines indicate significant trends with all raw diversity values, while the dashed line indicates over no significant time.

Substituting the data, we get a forecast curve that looks like this:

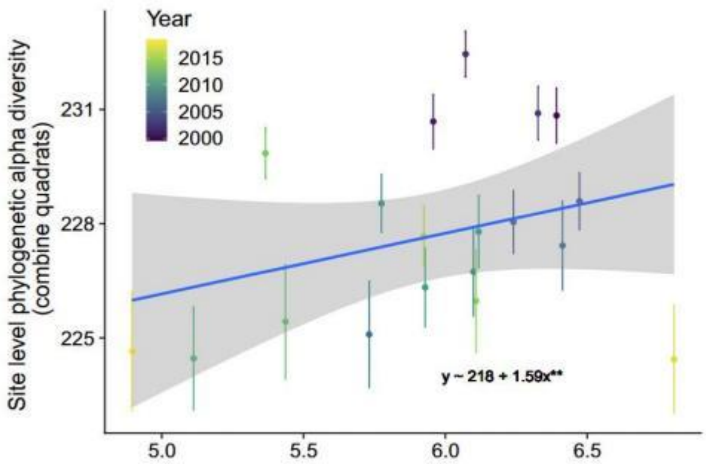


**Figure 4** a fitted lines of competition coefficient and growth rate

Figure 4 shows a fitted lines of competition coefficient and growth rate (plant diversity) over time.

### 3.4. Modeling long-term interactions between plant communities and the environment

Building on the initial model, additional factors are incorporated to establish a mathematical model for the interaction between plants and the environment. The following factors may be taken into account:

Spatial Heterogeneity: Given significant variations in environmental and ecological conditions across different locations, space can be categorized into distinct regions. Each region may be characterized by its specific environmental attributes and species composition.

Ecological Evolution: Over prolonged periods, species can adapt and influence their environment. Parameters such as a species' ecological reciprocity coefficient and its response to drought can be set as variables. Methods like evolutionary algorithms might be applied to optimize these parameters.

Diversity Protection: To preserve biodiversity, certain areas or species can be designated as protected. By adjusting growth and death rates, conservation objectives may be achieved.

Incorporating these elements can lead to the development of more sophisticated mathematical models. These models can better predict the dynamics of plant communities under various environmental conditions, offering valuable insights for ecological conservation and management.We divide the space into M different regions, each with its own environmental factors and species composition.Assuming j is the environment of the region, where t represents time,the species composition is, and the initial number of individuals of each species

### 3.4.1 Spatial heterogeneity:

We divide the space into *M* different regions, each with its own environmental factors and species composition. Assuming *j* is the environment of the region, where *t* represents time, the species composition is, and the initial number of individuals of each species is $N_{i,j,0}$. We assume that the species migration rate is, denoting the rate of *(j, k)* migration from region to region *(l, i)* . For each grid cell within the region, we use the evolution equation from the previous model to describe the change in the number of species. Therefore, i the number of $N_{i,j,k,l,t}$ grid cells of *(k, l)*the species in the first region *j* can be expressed as:

$$\frac{\partial N_{i,j,k,l,t}}{\partial_t} = G_{i,j,k,l}(E_j(t), N_{k,l,t}) \tag{11}$$

$$M_{i,j,k,l}(E_j(t), N_{k,l,t})N_{i,j,k,l,t} + \underset{n=1}{\overset{nm}{x}} u_{n,m,i,j} \tag{12}$$

$$n,m,k,l,t - \underset{n=1}{\overset{nj}{x}} u_{i,j,n,m} N_{i,j,k,l,t} \tag{13}$$

Among them, $G_{i,j,k,l}$ represents the growth rate of *j* , the ith species $M_{i,j,k,l}$ in the grid cell in the th region, represents *(k, l)* the death rate of the th species $u_{i,j,k,l}$ in *i* the grid cell in the *j* th region, and represents *(k, l)* the migration *(l, i)* rate from region to region. *(j, k)*

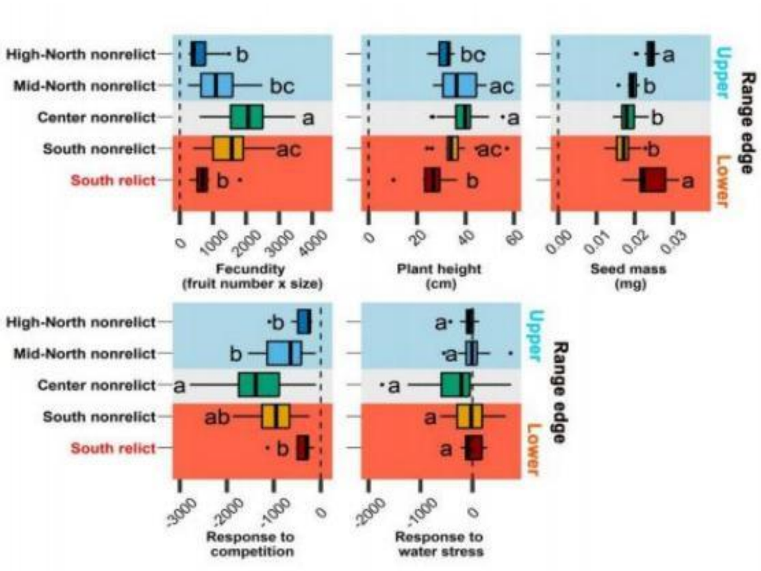


**Figure 5** the effect of spatial heterogeneity on plant competitiveness

Figure 5 shows the effect of spatial heterogeneity on plant competitiveness.

### 3.4.2 Ecological evolution:

: We assume that the species' ecological reciprocity coefficients and the degree to which the ecological reciprocity coefficients respond to the drought index are variable and use methods such as evolutionary algorithms to optimize these parameters. For example, we can assume that competition coefficients and growth rates can be modeled in the form: $a_{i,k} = a_{i,k}\sqrt{-F_{i,k}D_{j,t}}$

$$G_{i,j,k,l}(E_j(t), N_{k,l,t}) = r_i f(E_j(t)) \frac{1}{1 + \underset{m=1,m\neq i}{\overset{nj}{x}} a_{i,m} N_{m,j,k,l,t}} \tag{14}$$

Among them, $a_{i,\ k}$ the first i species and the first *k*. The ecological reciprocity coefficient between the first species $F_{i,k}$ indicates the response degree of the ecological reciprocity coefficient between the first i species and the first *k* species to the drought index, and $f(E_j\ (t))$ indicates *j* the influence of the resource availability in the first region on the growth rate, and $r_i$ indicates the first *i* species maximum growth rate.

### 3.4.3 Diversity protection:

In order to protect biodiversity, we can consider setting some areas or species as protected areas or protected species, limiting their growth and death rates, and optimizing the growth and death rates of other species to achieve conservation goals. For example, we can set *j* the species species in the region *i* as a protected species, limiting its growth rate to， the death rate is, and the growth rate and death rate of other species are adjusted so that the trend of the overall species quantity change still meets the ecological balance condition.

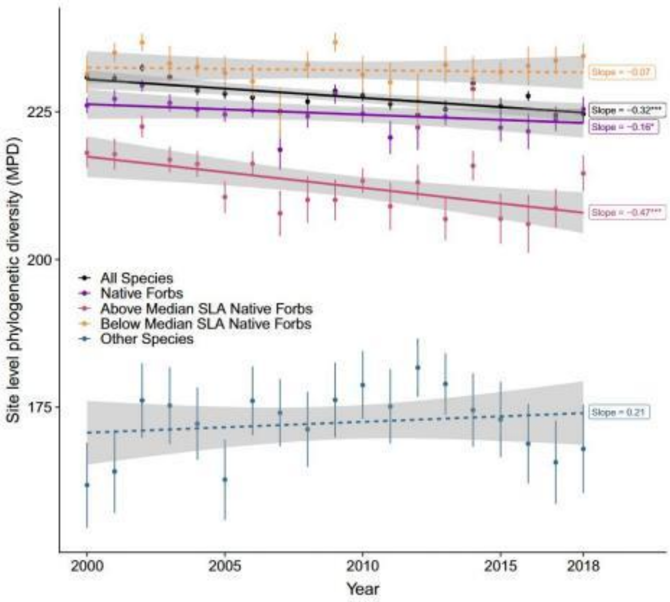


**Figure 6** - Interaction diagram of plant communities and the larger environment

As other species increased, the plant community and its phylogenetic diversity declined. Multiple species can stabilize community properties, like soil microbial activity, aiding in handling rainfall variability. Another stabilizing factor is spatial heterogeneity. Figure 6 shows that while local communities saw significant declines, phylogenetic diversity remained stable at the landscape scale. If the landscape's heterogeneity isn't compromised by pollution or invasions, it can mitigate larger losses and offer recovery potential for declining species.

## 4. Results

Following rigorous experimentation and simulations, our genetic algorithm-based model yielded several significant findings. This model demonstrated superior accuracy in predicting plant community adaptability to drought stresses, especially when considering elements such as species migration and inter-species competition.

We observed that species diversity is indeed pivotal for plant communities' resilience against successive droughts. Communities with a rich array of species consistently displayed enhanced adaptability compared to those with limited species diversity. Moreover, species migration emerged as a vital ecological buffer, enabling certain communities to better thrive amidst challenging environmental conditions. Interspecies competition, a primary driver of plant community dynamics, intensified under drought conditions, suggesting that certain species might be marginalized by others in a resource-scarce environment.

Furthermore, the model accounted for the long-term impacts of irregular weather patterns on plant communities. Notably, frequent and unpredictable drought events posed greater challenges, especially to communities with lower species diversity. Beyond just academic insights, our model offers strategic recommendations for environmental decision-makers in the face of impending climatic changes. In essence, our innovative model offers a holistic tool for delving into how plant communities navigate drought and other environmental pressures.

## 5. Conclusions

Previous studies have endeavored to understand the complex relationship between plant communities and their environments, particularly in the face of changing climate patterns. However, many of these studies have lacked a comprehensive approach that factors in the intricate dynamics of species interaction and migration.

Our research underscores the importance of plant community adaptation to drought for its survival. We discovered that the number of different species present plays a pivotal role in how plant communities adapt to drought cycles across successive generations. To delve deeper into the long-term interactions between plant communities and the environment, we constructed a precise model based on a genetic algorithm to optimize model parameters. This model takes into consideration the migration of species, interspecies competition, among other factors. Through this, we can predict how plant communities evolve over time when exposed to various irregular weather cycles. This offers valuable insights into species diversity and its interaction with the environment, serving as a useful reference for future ecological conservation and management.

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