Problem Chosen	2023	Team Control Number
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The Fitting Model Toward the Number of Plant Species and the Growth of Plants under the Drought Conditions

Summary

Drought is a natural disaster caused by abnormal temperatures and insufficient precipitation. Due to global warming and the influence of the greenhouse effect, the frequency and severity of drought have accelerated, causing irreversible damage to plants and even ecosystems. Therefore, it is necessary to study the impact of species numbers in plant communities on drought resistance and the ability of communities to withstand accelerating drought cycles. In this paper, a fitting prediction model based on quantitative drought evaluation index and plant growth is established to solve the current problem. Our model can be mainly divided into: Model I: Drought Evaluation Index using Principal Component Analysis. Model II: Vegetation Growth Prediction Model.

For Model I, we first identified SPI and T as the two main factors affecting the Drought Evaluation Index and introduced principal component analysis. After calculation, the contribution rates of the first principal component PC1 were 78.98%, 74.81% and 85.83%, respectively. The calculation results are greater than 70%, which verifies the feasibility of using PC1 as the principal component to represent DEI, and then we calculate the weights of SPI and T to PC1, which are 50% and 50%, respectively. Finally, the DEI value is obtained by normalization.

For model 2, firstly, based on historical meteorological data, near-infrared band and red light band remote sensing data, it is determined that temperature and precipitation are the main factors affecting the health status of plant communities. Subsequently, according to the formula (18) And (19) The monthly NDVI raster map and the monthly VCI raster map of the sample area were synthesized step by step using arcMAP, and the VCI mean of the sample area was used as an indicator to measure the health of the plant community. Based on the surface of temperature, precipitation and VCI fitting, the change direction of environmental variables on the health status of plant communities was determined.

Keywords: Principal Component Analysis; Drought Evaluation Index; Curve fitting

Contents

1 Introduction

1.1 Problem Background

In recent years, the world has experienced global warming and increased desertification of the land. Plants in some parts of the world have been plagued by drought and many fragile ecosystems have been devastated, while there are areas where plants have been able to withstand drought well.

Drought is a complex natural phenomenon usually caused by insufficient precipitation and high temperatures [1]. Droughts occur with irregular frequency and vary in severity. Plants are able to respond to external changes such as drought to better meet their survival needs due to characteristics such as stressfulness. Different plant responses for external stresses differently. In the process of fighting drought, communities with a variety of plants have shown greater resistance to drought. A variety of plants can influence each other. The effects of communities composed of different species of plants are different.

Meanwhile, many observations [2] prove that the number of different plant species has an important influence on the adaptation of plant communities to drought cycles over subsequent generations. For example, communities with four or more species of plants are usually better adapted to drought in subsequent generations than communities with only one species of plant. The background of the problem points us to the direction of research. Specific issues will be listed in the next section.

1.2 Restatement of the Problem

Based on the problem background and restricted conditions identified in the problem statement, we define the problems as below:

- Building a mathematical model to predict how plant communities change over time when exposed to various irregular weather cycles. Notably, we are supposed to consider the interactions between different species within the drought cycles.
- Illuerstrating how the type of species in a community affects the outcome of an experiment.
- Considering the frequency of drought cycles and the extent of drought damage on plant communities.

- Testing the accuracy of the model and predicting for certain specific drought events.
- Explaining the impact of other factors such as pollution and habitat reduction on model results.
- Proposing ecological recommendations to ensure the long-term viability of plant communities and the conservation of the wider environment.

1.3 Our Work

We were asked to build a mathematical model to predict the minimum number of species that a single plant can benefit from a plant community under drought conditions. Explore the impact of drought frequency on plant communities using quantitative criteria. Based on these, our work are as follows:

- First, based on a large number of literature reading, we identified the first drought assessment index model to be established, selected 1234 area as the study area, and took precipitation and temperature T as the main factors affecting drought.
- After that, we download precipitation and temperature information from various weather stations from databases such as NCEI and NESDC and process it into SPI and T.
- Combined with the data, the weights of precipitation and temperature in the drought assessment index were determined by principal component analysis, and the drought assessment index formula after data normalization was obtained.
- Combined with the NIR and R data of each weather station in the study area, we obtained NDVI through computational processing and calculated VCI, which was used as an index to evaluate plant growth, and at the same time, it could be used as an important index to test the rationality of the model.
- We will simplify the classification of the plants to be studied and determine the selected plant species.
- Using the resulting DEI data, the VCI index and the number of species fit curves, and an empirical formula between the three is obtained, which can be

used to predict the minimum number of species required for a single plant to benefit from the community.

- We also test the stability of our model by changing the frequency of droughts and make assessments.
- Finally, we also make recommendations to the relevant governments based on the results of our model.

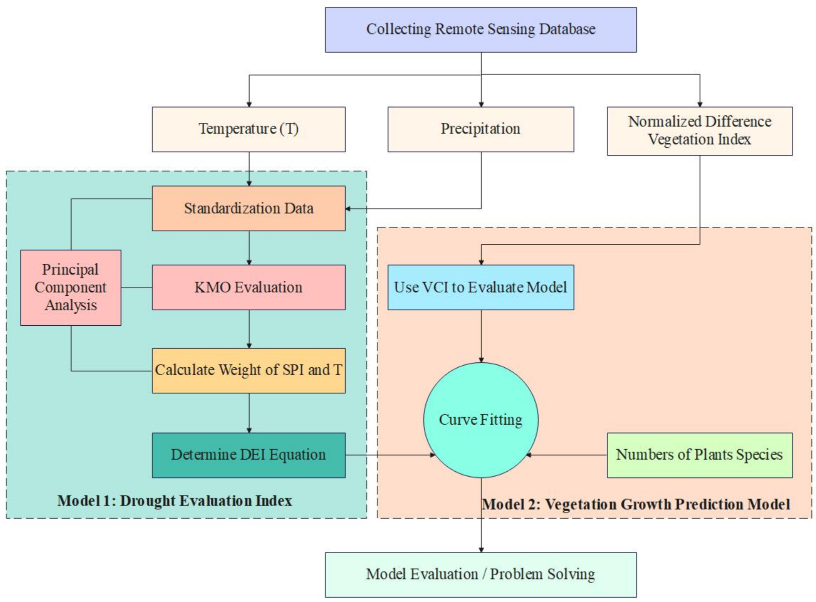

Figure 1: Thinking and Modeling Process

2 Assumptions and Justifications

To simplify the model of plant communities affected by irregular drought events and reduce the variables of input. We make the following basic assumptions and explain why they exist.

- **Assumption 1:** The drought stress studied in this paper is caused by only two factors: excessive temperature and insufficient precipitation, ignoring other factors.
- **Justification:** Environmental variables such as solar irradiance and illumination hours in the same region are relatively fixed every year, they have little impact on the long-term analysis of the model. Therefore, the influence of other factors is ignored in this article.
- **Assumption 2:** The plants in this paper are all major native species and are fully adapted to local regular weather fluctuations.
- **Justification:** That is, plants can exist and reproduce for a long time under mild environmental conditions and will not die rapidly at the same time when subjected to a certain degree of drought stress, but gradually reduce the biomass of each individual plant as drought continues. The decay rate of the biomass of the community is expressed by the change of normalized differential vegetation index (NDVI), which has a certain correlation with the degree of drought stress.
- **Assumption 3:** This paper does not consider the complex classification of plant species, but only classifies plants according to biological characteristics: lichen plants, herbs, shrubs, trees [3]. The special parasitic and symbiotic relationships between specific species are not considered, and individual plant communities are regarded as a unified whole.
- **Justification:** Because plants with the same biological characteristics in the same community tend to have similar canopy structure parameters and resistance to drought stress [4].
- **Assumption 4:** For our model, we do not consider disturbances from random non-meteorological extra community factors, including but not limited to: invasive alien species, organized human activities, and non-meteorological natural disasters.

3 Notations

Table 1: Notations

Symbol	Description	Unit
X1	Standardized Precipitation Index	N.A
X2	Temperature	°C
Yi	A set of SPI and T data	N.A
Z	SPI Value	N.A
G(X)	Cumulative Probability Function of Precipitation x>0	N.A
H(X)	Actual precipitation accumulation probability function	N.A
x	Precipitation Amount	inch
B	Principal Component	N.A
R	Correlation coefficient Matrix	N.A
D	Normalized Matrix	N.A

4 Model Preparation

4.1 Data Collection

We found and selected three study areas with distinctive characteristics (Northeast China, Inner Mongolia and Southridge) from Google Earth Engine (GEE). From the National Oceanic and Atmospheric Administration (NOAA), we obtained 561,600 daily precipitation and temperature data on the study area. This data will be used to calculate the Standardized Precipitation Index (SPI) and Temperature (T). From the National Economic and Social Development Council (NESDC) and the Land Processes Distributed Active Archive Center (LPDAAC), we collected Near Infrared Spectrum (NIR) and Infrared Spectrum (R) and finally processed it to obtain 119 NDVI data.

4.2 Data Sources

Table 2: Data Source Collection

Database Names	Database Websites Data	Type
GEE	https://code.earthengine.google.com/	Remote Sensing
NOAA	https://www.ncei.noaa.gov/	Meteorology
NESDC	http://www.nesdc.org.cn/	Remote Sensing
LPDAAC	https://lpdaac.usgs.gov/	Remote Sensing

5 Model I: Drought Evaluation Index

The drought stress suffered by terrestrial plants is mainly caused by abnormal temperatures and insufficient precipitation. There is a correlation between temperature and precipitation in the same area. In order to simplify and quantitatively describe the drought situation in different regions, principal component analysis is used to determine the weighted shares of the two variables. This allows the degree of drought to be accurately expressed in terms of Drought Evaluation Index (DEI).

We introduce the Standardized Precipitation Index (SPI) and Temperature (T) as the independent variables of the model, denoted by X_1 and X_2, respectively.

Applying principal component analysis, we determine a quantified DEI index obtained by linearly combination of two variables, SPI and temperature T. In the end, we will give evaluation criteria.

5.1 Calculation of Evaluation Index

5.1.1 Standardized Precipitation Index (SPI)

The standard precipitation index(SPI) is an indicator used to assess the frequency of droughts, mainly by converting long-term precipitation into a standard normal distribution function. We refer to the gamma functions and approximation theory of Thom (1966) and Abramowitz and Stegun (1965) to build the computational model of SPI [5].

We collect years of precipitation, convert it into a precipitation frequency gamma distribution, and then transform the gamma distribution into a standard normal distribution to obtain SPI.

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad \text{for } x > 0 \tag{1}$$

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}^{\hat{\alpha}}\Gamma(\hat{\alpha})} \int_0^x x^{\hat{\alpha}-1} e^{-x/\hat{\beta}} dx \tag{2}$$

Let t = x/β , then we can derive:

$$G(x) = \frac{1}{\Gamma(\hat{\alpha})} \int_0^x t^{\hat{\alpha}-1} e^{-t} dt \tag{3}$$

Considering that the actual precipitation may be zero, we construct the distribution function H(x) of the actual precipitation. q is the probability that precipitation will be zero.

$$H(x) = q + (1-q)G(x) \tag{4}$$

By transforming the normal distribution of H(x), we can obtain the relationship between SPI and precipitation, so that SPI can be calculated from the precipitation data.

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad \text{for } 0 < H(x) \leq 0.5 \tag{5}$$

$$Z = SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad \text{for } 0.5 < H(x) < 1.0 \tag{6}$$

where:

$$\begin{array}{ll} \alpha > 0 & \alpha \text{ is a shape parameter} \\ \beta > 0 & \beta \text{ is a scale parameter} \\ x > 0 & x \text{ is the precipitation amount} \\ \Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy & \Gamma(\alpha) \text{ is the gamma function} \end{array}$$

$$\hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right)$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{\alpha}}$$

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n}$$

n = number of precipitation observations

$$t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \quad \text{for } 0 < H(x) \leq 0.5$$

$$t = \sqrt{\ln\left(\frac{1}{(1.0 - H(x))^2}\right)} \quad \text{for } 0.5 < H(x) < 1.0$$

$$c_0 = 2.515517, c_1 = 0.802853, c_2 = 0.010328$$

$$d_1 = 1.432788, d_2 = 0.189269, d_3 = 0.001308$$

The evaluation criteria for the standard precipitation index are shown in the table below, covering climate conditions ranging from extreme drought to extreme humidity.

Table 3: Relationship between SPI and the Drought Level [6]

SPI Value Range	Drought Level
>2.0	Extremely Wet
1.5 - 1.99	Very Wet
1.0 - 1.49	Mean Wet
-0.99 - 0.99	Normal
-1.0 - 1.49	Mean Drought
-1.5 - 1.99	Very Drought
<-2.0	Extremely Drought

5.1.2 Temperature (T)

Drought is mainly affected by temperature and precipitation [7]. Geographically, altitude affects air temperature. At the same location, the temperature decreases with altitude. In order to eliminate the temperature difference due to altitude between different regions, the study areas selected were all 800m-1400m above sea level.

Therefore, we found temperature data from National Oceanic and Atmospheric Administration(NOAA) for the selected areas from 2010 to 2019, and calculated the relevant monthly mean temperature.

5.2 Principal Component Analysis

5.2.1 Kaiser-Meyer-Olkin (KMO)

KMO is a standard that tests the relative magnitude of the simple and partial correlation coefficients between the original variables [8]. It can be used as a basis for whether the model is suitable for principal component analysis. The KMO equation is as follow:

$$\mathrm{KMO} = \frac{\sum\sum_{\mathrm{i}\neq\mathrm{j}} \mathrm{r}_{\mathrm{j}}^2}{\sum\sum_{\mathrm{i}\neq\mathrm{j}} \mathrm{r}_{\mathrm{ij}}^2 + \sum\sum_{\mathrm{i}\neq\mathrm{j}} \alpha_{\mathrm{ij}}^2} \tag{7}$$

Here r_{ij} represents the simple correlation coefficient, $\alpha^2_{\mathrm{ij}.1,2,3,\cdots\mathrm{k}}$ indicates the biased correlation coefficient[1]. The value of KMO is between 0 and 1. The larger the calculated KMO value, the more suitable the model is for principal component analysis, and the comparison standard table is as follows:

Table 4: Relationship between KMO and Fitness of the Variable

KMO Range	**Fitness of the Variable**
>0.9	Perfect Fit
0.8 - 0.9	Well Fit
0.7 - 0.8	Fit
0.6 - 0.7	Barely Fits
0.5 - 0.6	Bad
<0.5	Very Bad

5.2.2 Data Standardization

The Drought Evaluation Index (DEI) proposed in this paper is determined by two main factors: the Standardized Precipitation Index (SPI) and temperature (T). Therefore, DEI will be represented as a new composite variable (principal component) in B. The relationship between principal components and raw variables can be expressed as:

$$\begin{cases} B_1 = a_{11}X_1 + a_{12}X_2 \\ B_2 = a_{21}X_1 + a_{22}X_2 \\ \quad\vdots \\ B_n = a_{n1}X_1 + a_{n2}X_2 \end{cases}, \quad \mathrm{n} > 2 \tag{8}$$

a_{ij} is the coefficient of linear correlation between the ith principal component and the original jth variable X_j. We want to preserve the information of the original variable as much as possible, while making the independence between the principal components B_i as great as possible.

Before data standardization, in order to facilitate data processing, we first organize the input data of X_1 and X_2 into sets of matrices[2]:

[1] The calculation equation of the simple correlation coefficient r_{ij} and biased correlation coefficient $\alpha^2_{\mathrm{ij}.1,2,3,\cdots\mathrm{k}}$ are omited, because the result is easy to calculate from X_1 and X_2.

[2] X_1 and X_2 represent data sets of SPI and T separately, Y_i and represent a SPI and T combination data

$$Y=\left(Y_{1}, \cdots, Y_{p}\right)^{\tau} \tag{9}$$

$$Y_{i}=\left(y_{i 1}, y_{i 2}, \cdots, y_{i p}\right), \quad i=1,2, \cdots, \mathrm{n} \tag{10}$$

p represents the dimension of the original indicator data, in this model p = 2, n is the number of samples, in this model n = 2. Then, construct the sample matrix as follows:

$$\mathrm{Y}=\left[\begin{array}{cccc}
y_{11} & y_{12} & \cdots & y_{1 p} \\
y_{21} & y_{22} & \cdots & y_{2 p} \\
\vdots & \vdots & \ddots & \vdots \\
y_{n 1} & y_{n 2} & \cdots & y_{n p}
\end{array}\right] \tag{11}$$

Perform the following data standardization transformations on the sample elements:

$$D_{i j}=\frac{y_{i j}-\bar{y}_{j}}{s_{j}}, i=1,2, \ldots, n ; j=1,2, \ldots, p \tag{12}$$

which $\bar{y}_{j}=\frac{\sum_{i=1}^{n} y_{i j}}{n}, s_{j}^{2}=\frac{\sum_{i=1}^{n}\left(y_{i j}-\bar{y}_{j}\right)^{2}}{n-1}$.

The correlation coefficient matrix R is obtained from the normalized matrix D:

$$R=\left[r_{i j}\right]_{p} x p=\frac{D^{T} D}{n-1} \tag{13}$$

We already know that R is a 2×2 square matrix (n=2), assuming that the R matrix has eigenvalues, it can be obtained by the eigenvalue calculation method:

$$|\lambda \mathbf{E}-\mathbf{R}|=\left|\begin{array}{cccc}
\lambda-\mathbf{r}_{11} & -\mathbf{r}_{12} & \cdots & -\mathbf{r}_{1 n} \\
-\mathbf{r}_{21} & \lambda-\mathbf{r}_{22} & \cdots & -\mathbf{r}_{2 n} \\
\cdots & \cdots & \cdots & \cdots \\
-\mathbf{r}_{n 1} & -\mathbf{r}_{n 2} & \cdots & \lambda-\mathbf{r}_{n n}
\end{array}\right|=0 \tag{14}$$

If $\frac{\sum_{j=1}^{m} \lambda_{j}}{\sum_{j=1}^{p} \lambda_{j}} \geq 0.85$, we can get m. Then we calculate unit feature vector b_j for every $\lambda_j, j = 1, 2, \ldots$, m by solve the equation Rb=$\lambda_j b_j^o$

By calculating what we get:

The correlation coefficient matrix R is mathematically the covariance matrix of the matrix after being normalized to the original data [3]. By finding the eigenvalues of the covariance matrix, the correlation of different variables can be reflected. The variance contribution rate refers to the proportion of variance that can be explained by a principal component to all variance, and the variance contribution rate is formulated as follow:

$$\frac{\lambda_i}{\sum_{k=1}^{p} \lambda_k}(i = 1, 2, \dots p) \tag{15}$$

A larger variance means a higher dispersion of the data points and a greater dispersion along the line. At the same time, the more information it contains, the more weight it occupies.

The Calculation results of eigenvalaue and contribution rate are as follow:

Table 5: Statistical Table of Principal Component Analysis Results

Area	**Principal Component**	PC1	PC2
Southridge	Eigenvalue	1.57979935	0.420201
	Contribution Rate/%	78.9899676	21.01003
Inner Mongolia	Eigenvalue	1.49632669	0.503673
	Contribution Rate/%	74.8163347	25.18367
Northeast	Eigenvalue	1.71671344	0.283287
	Contribution Rate/%	85.835672	14.16433

According to the calculation results, the variance contribution rate of PC1 are all $>$ 70%, It is explained that the first principal component obtained after the principal component transformation can concentrate on expressing most of the information of drought conditions in the studied area. Therefore, we chose PC1 as the first principal component. Studying the contribution of SPI and temperature T in PC1 can help us better quantify DEI. The contribution rates of SPI and temperature T in PC1 are shown in the following table:

[3] Covariance Matrix Formula: $Conv = \frac{1}{n-1}XX^T$, X is the standardized data matrix.

Table 6: Statistical Table of Contribution Rate of Each Index of Principal Component Analysis

Area	**Index**	PC1	PC2
Southridge	Temperature (T)	0.707107	0.707107
	SPI	-0.707107	0.707107
Inner Mongolia	Temperature (T)	0.707107	0.707107
	SPI	-0.707107	0.707107
Northeast	Temperature (T)	0.707107	0.707107
	SPI	-0.707107	0.707107

From the data in the table, we can obtain that the characteristic contribution rate of Temperature (T) in the first principal component PC1 in each study area is positive. It is explained that T contributes to the growth of the drought index, that is, the degree of drought in the study area is exacerbated. The characteristic contribution rate of Standard Precipitation Index (SPI) was negative, indicating that SPI was negatively correlated with drought degree, and SPI had a negative effect on the increase of drought degree. In reality, the more precipitation, the less drought. The higher the temperature, the relative severity of drought. Therefore, it is feasible to construct Drought Evaluation Index (DEI) with the first principal component.

Here we use I to represent the original evaluation data of the drought index. Based on the above, SPI and T are given with an accurate weight of 0.5, respectively. The formula is as follows:

$$I = 0.5T - 0.5SPI \tag{16}$$

Normalizing the contribution rates of the two factors of SPI and T in Table 6, we finally obtain the evaluation formula of DEI:

$$\text{DEI} = \frac{I - I_{\text{min}}}{I_{\text{max}} - I_{\text{min}}} \tag{17}$$

I_{min} represents the minimum value of I over a period of time. I_{max} represents the maximum value of I over a period of time. I is the value determined by SPI and T at a certain point in the selected time interval.

6 Model II: Vegetation Growth Prediction Model

6.1 Vegetation Condition Index (VCI)

The Vegetation Condition Index (VCI) reflects the growth of plants on the ground [9], so we use it as a measure of plant growth. In the field of remote sensing, VCI is calculated from the NDVI. NDVI can be obtained from Near Infrared Spectrum (NIR) and Infrared Spectrum (R). NDVI and VCI are calculated as follows:

$$NDVI = \frac{NIR - R}{NIR + R} \tag{18}$$

$$\text{VCI} = \frac{NDVI_i - NDVI_{\text{min}}}{NDVI_{\text{max}} - NDVI_{\text{min}}} \tag{19}$$

where $NDVI_i$ is the NDVI value of the ith period of a year; $NDVI_{\text{max}}$ is the historical maximum NDVI; $NDVI_{\text{min}}$ is the historical minimum NDVI.

Using ArcGIS software, we calculate NDVI by processing R and NIR and finally get VCI data.

6.2 Curve Fitting

The determination of the study area means that the number of plant species in the area is also determined. Based on this, we used Matlab software to fit the data for DEI, VCI, and time t in the three study regions, and established a functional relationship between the three quantities. The fitting results are as follows:

Inner Mongolia (Number of Plant Species = 2):

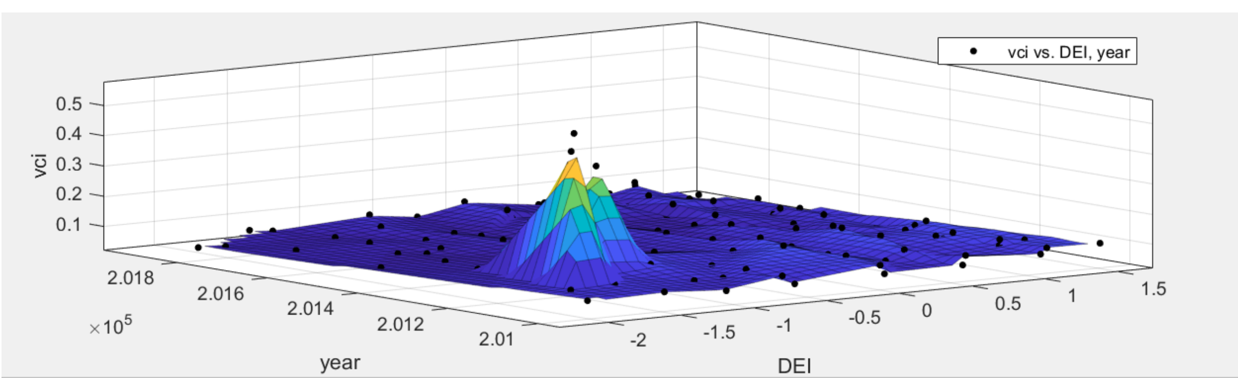

Figure 2: Curve Fitting of Inner Mongolia

Northeast (Number of Plant Species = 3):

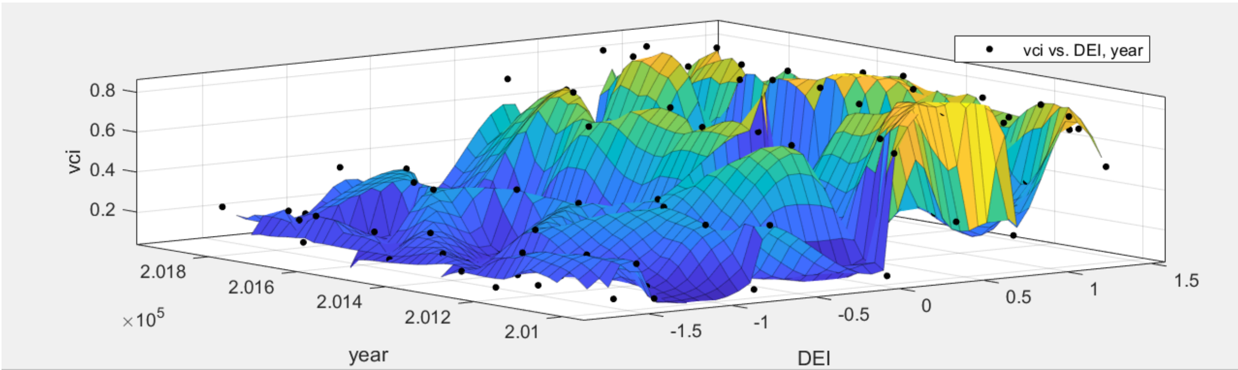

Figure 3: Curve Fitting of Northeast

Southridge (Number of Plant Species = 4):

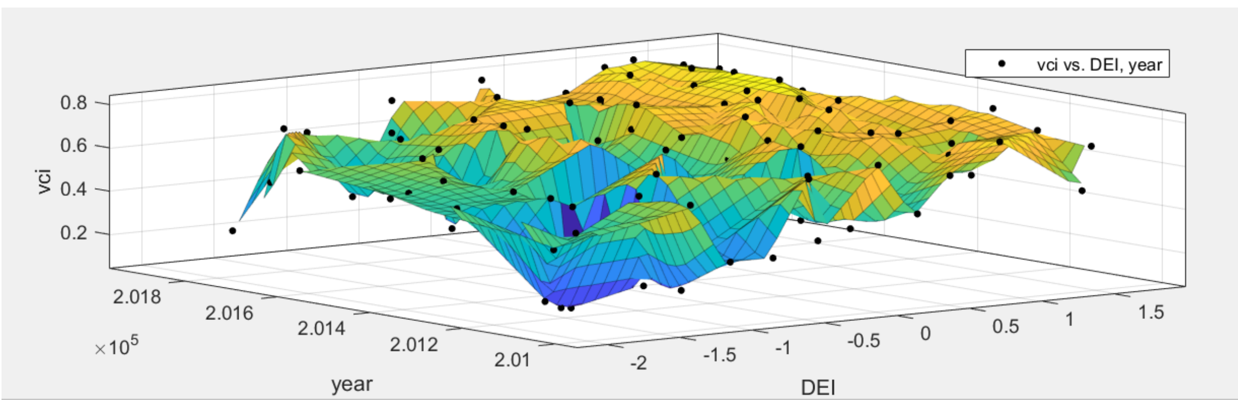

Figure 4: Curve fitting of Southridge

7 Model Testing (Sensitivity Analysis)

Sensitivity analysis is a technique for examining and analyzing how sensitive changes in a system's state or output are to adjustments made to the system's parameters or the environment. The sensitivity analysis formula is as follows:

$$\begin{aligned}\frac{\partial \eta}{\partial r} &\approx \frac{\eta(r+\Delta r)-\eta(r)}{\Delta r} \\ \frac{\partial \eta}{\partial L} &\approx \frac{\eta(r+\Delta L)-\eta(L)}{\Delta L}\end{aligned} \tag{20}$$

According to the stability analysis formula and images, it can be seen that the fluctuation range of Northeast and South Ridge has been small and the stability is better for many years. However, the western region of Inner Mongolia was affected by a strong cold wave from November to December 2012, with strong fluctuations and poor stability.

8 Conclusions

8.1 Summary of Results

8.1.1 Result of Problem 1

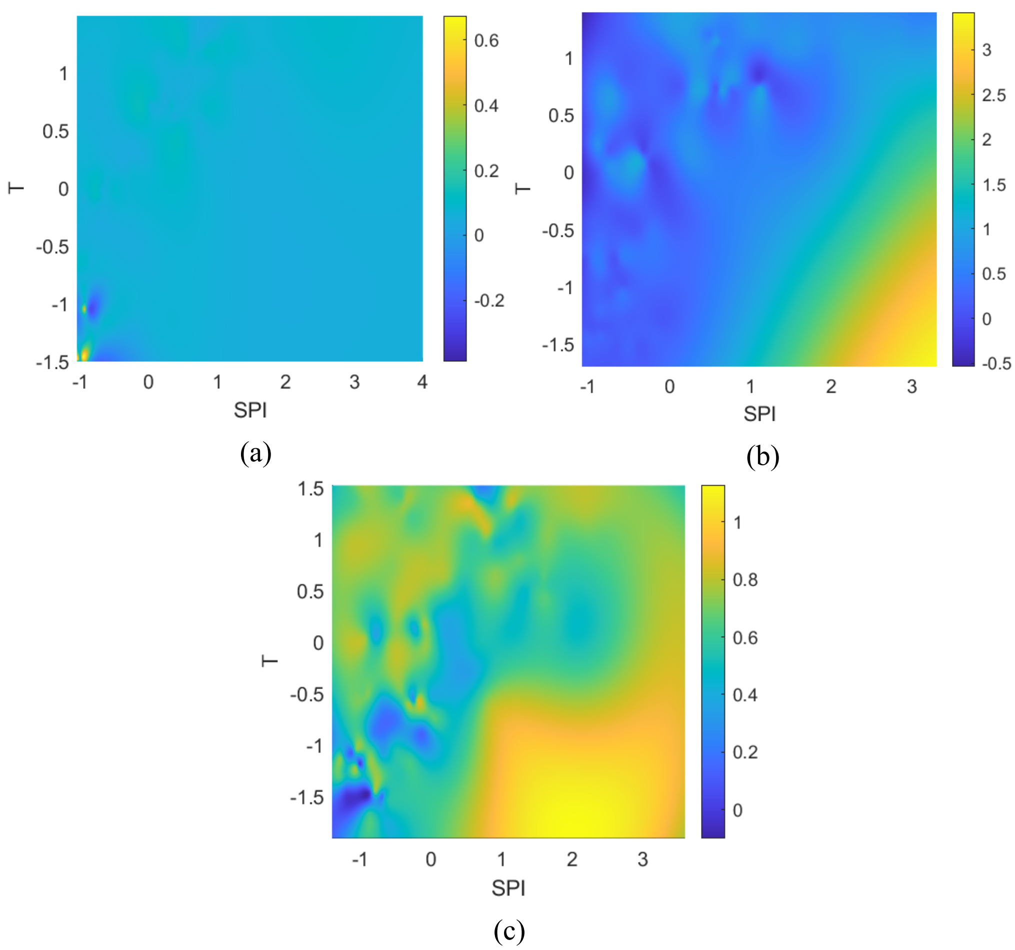

Figure 5: NDVI values of the same species that in response to different meteorological conditions (a). NDVI value of Inner Mongolia (2 species) (b). NDVI value of Northeast (3 species) (c). NDVI value of Southridge (4 species)

Temperature and SPI are both normalized indicators.

Since Inner Mongolia, which has two species, shows extremely rapid changes in the face of drought stress, that is, the image shows spike-like changes. Compared with Inner Mongolia with species number 2, the data in Northeast China with species number 3 changed relatively slowly, showing a slow change trend. The model maintained this slow change when the number of species further increased to four, so we thought that when the number of species ≥ 3, a single plant could benefit from the community.

Our sample size is large enough to avoid the impact of local climatic anomalies on the statistical results. The table below shows the latitude and longitude range of our selected study area:

Table 7: The Latitude and Longitude of the Selected Study Area

Area	Longitude	Latitude
Inner Mongolia	East longitude 98-104	36-42 North latitude
Northeast	East longitude 116-141	47-55 North latitude
Southridge	East longitude 108-112.5	25-30 North latitude

8.1.2 Result of Problem 2

The three regions represent different numbers and types of species, so for the three regions, species types and numbers mean:

Inner Mongolia: Combined with specific weather events, we speculate that communities with two species equal to two are not sufficiently resistant to environmental change when the number of species equals two.

Northeast: greater seasonal variation, more significant monsoon characteristics, and greater seasonal variation in precipitation and temperature.

Southrige: After the drought, Nanling has less fluctuations and shows better stability. An atypical depression appears in the middle of the figure, indicating an extreme weather event. If the remote sensing data values have not changed much, it indicates that the community in the region has a good resistance to drought.

8.1.3 Result of Problem 3

Using the curves and equations obtained in Model II, a surface with respect to temperature and river water is fitted, the derivatives of NDVI with respect to SPI and T are obtained, and SPI and T are integrated during the change. Finally, a model was obtained to evaluate the survival status of plant populations under irregular dry weather.

8.2 Strengths

- A large number of real and reliable statistics are used for indicator calculations and model building. The selection of the three study areas was typical.
- The construction of the DEI model is scientific and accurate, which can be well used in the assessment of drought degree of SPI and temperature.
- The use of principal component analysis method accurately and effectively gives the evaluation criteria of drought degree.
- Fitted images visualize our data to visually spot patterns and solve problems.

8.3 Possible Improvements

- We can use raw precipitation and temperature data for more precise calculations and analysis.
- The amount of data for the same region at the same time can be increased, making the definition of DEI more independent and independent of time.

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