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Study on Global Vegetation Dynamics Based on Remote Sensing Big Data

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Abstract: Vegetation is one of themostimportant factors in maintaining the Earth's ecological environment and has significant value of theecosystem. Vegetation monitoring is an important means of detecting dynamic changes in vegetation. The Remotely sensed NDVI (Normalized DifferenceVegetation Index) which isbased on the absorption of light by plants can respond well to changes in vegetation dynamics, thus becoming a commonly used indicator in large-scale monitoring. In this study, the global PKU GIMMS NDVI was used as the data source (two images per month, a total of 360 global images) for the period from 2001 to 2015. First, the global spatial distribution of vegetation NDVI was analyzed by averaging theNDVI over the fifteen-year period. Then the trend of vegetation NDVI was analyzed using a one-way linear regression model. The results of the study showed that vegetation NDVI was higher in regions such as Russia, South America, Central Africa and Southeast Asia. Regions with a significant increase in the rate of change of vegetation NDVI, such as Russia, the Czech Republic, China, the United States and Brazil, and regions with a significant decrease in the rate of change of vegetation NDVI, such as Kazakhstan, Nigeria, Canada and Argentina, were found.

Keywords: One-way linear regression, NDVI, global vegetation, remote sensing

I. INTRODUCTION

Vegetation, as a key component of the human living environment, plays a vital role in many aspects, and vegetation monitoring can play a key role in many aspects. Vegetation monitoring can detect changes in the type and distribution of vegetation in a timely manner, which is conducive to the protection and development of biodiversity. Vegetation monitoring can scientifically assess the effects and impacts of greening projects and provide a scientific basis for urban greening planning and management. Environmental protection is an important global issue, and vegetation monitoring, as one of the important means of environmental protection, is of great significance for the formulation of environmental protection policies and measures.

The rise of remote sensing technology and big data has promoted further research on vegetation monitoring. Researchers at home and abroad have begun to use remote sensing technology to calculate various vegetation index data, thus realizing long-term monitoring and research on vegetation information at a large scale. Monitoring using remote sensing technology has multiple advantages. Remote sensing monitoring methods can rapidly acquire vegetation information over a large area through remote sensing sensors carried on platforms such as satellites, aircraft or drones, and this large-scale acquisition makes remote sensing monitoring able to complete the collection and processing of a large amount of data in a short period of time, realizing the rapid monitoring and assessment of vegetation. In addition, remote sensing monitoring can monitor the same area several times at different times and from different angles, thus obtaining continuous and comparable vegetation information. This helps to analyze the change trend of vegetation information, and then try to explore the dynamic change law of vegetation.

In remote sensing applications, vegetation indices have been widely used to qualitatively and quantitatively evaluate vegetation cover and its growth vigor. Common vegetation indices include normalized vegetation index (NDVI), shaded vegetation index (SVI), difference vegetation index (DVI), ratio vegetation index (RVI), and enhanced vegetation index (EVI) . In this study, the global PKU GIMMS NDVI will be used as a data source for the period from 2001 to 2015 (two images per month for a total of 360 global images over 15 years). First, the vegetation NDVI was averaged over the fifteen-year period to analyze the spatial distribution of global vegetation NDVI. After that, the rate of change of vegetation NDVI and its significance were calculated using a one-way linear regression model to analyze the overall trend of vegetation NDVI.

II. DESCRIPTION OF DATA

The data used in this study were PKU GIMMS NDVI, (version 1.2), with a spatial coverage of 180ºW-180ºE, 63ºS-90ºN, 1/12° spatial resolution and 15-day temporal resolution, obtained as the global Normalized Vegetation Index (NDVI) for the years 2001-2015. The data we selected contain vegetation NDVI data twice a month every year, totaling 360 data frames. The vegetation NDVI data in this paper were obtained from PKU GIMMS, which is the Peking University Global Index of Land Surface Physical Climate and Vegetation data set. This data has the following advantages:

A. High data accuracy

The data utilizes information extracted from the GIMMS NDVI3g product and from 3.6 million high-quality Landsat NDVI samples around the world through the biome-specific BPNN model, and this processing method makes the PKU GIMMS data show high accuracy in assessing vegetation conditions.

B. Strong temporal consistency:

Compared with MODIS NDVI data, PKU GIMMS NDVI data embodies strong temporal consistency, so the dataset is able to continuously and stably monitor the changes in vegetation cover and provide reliable data support for long-term environmental studies.

C. Effective elimination of unfavorable effects:

Through innovative algorithms, the unfavorable effects of satellite orbital drift and sensor degradation are eliminated, and the reliability and accuracy of the data are improved.

III. METHODS

A large amount of NDVI data for the period from 2001 to 2015 was fitted by regression analysis to obtain vegetation NDVI as a function of time, which in turn was used to analyze and predict future trends in vegetation NDVI as well as to study ecosystem changes.

A. Data pre-processing

To ensure the quality of the data, outliers or errors that may affect the results of the analysis need to be identified and dealt with. For this purpose, we first performed data preprocessing to remove outliers and mean-integrate the data for each year.

1) Outlier handling

According to the information provided by the data source, the data for which no observations were obtained were assigned a padding value of 65535, indicating that the region has Non-veg or NDVI ≤ 0. After importing the data into MATLAB, we first identified all the data points that were assigned the value of 65535, which indicates that no observations were obtained. Because there are a total of 24 sets of measurements in a year, if a location is determined to have not acquired observations more than four times in a year, the point can be determined to be a marine area and assigned a value of NaN (Not a Number).

2) Mean value processing

We obtained the distribution of annual mean vegetation NDVI at each data point through the averaging process for subsequent analysis of the global cumulative mean annual trend of vegetation NDVI. The annual mean vegetation NDVI at the location was obtained by summing and averaging the valid data from the points detected in the outlier processing.

B. Trend analysis

We used one-way linear regression analysis to study the linear relationship between vegetation NDVI and time, and trend the methodology for the annual surface distribution of global vegetation NDVI from 2001 to 2015.

The one-way linear regression ultimately requires the equation: $y(x)=\beta_0+\beta_1 x$,which makes $y(x_i)\approx y_i$. Therefore, need to be determined β_0 and β_1, and the above equation shows that the difference between needs to be as small as possible, so that the mean square error is minimized: $y(x_i)$ and y_i

$$(\beta_0{}^*,\beta_1{}^*)=\underset{(\beta_0,\beta_1)}{\arg\min}\sum_{i=1}^{n}\left[y(x_i)-y_i\right]^2=\underset{(\beta_0,\beta_1)}{\arg\min}\sum_{i=1}^{n}(\beta_0+\beta_1 x_i-y_i)^2$$

where $\underset{(\beta_0,\beta_1)}{\arg\min}$ represents the mean square error ofvalues of . So solving β_0 and β_1 that correspond to the smallest $\sum_{i=1}^{n}\left[y(x_i)-y_i\right]^2$ for and β_0 β_1 means finding the functionwhen is minimized, a process known as least squares parameter estimation for least linear regression. To minimize a multivariate function, it is necessary to take the partial derivatives of each independent variable and make the partial derivatives zero, as follows: $F(\beta_0,\beta_1)=\sum_{i=1}^{n}(\beta_0+\beta_1 x_i-y_i)^2$

$$\frac{\partial F(\beta_0,\beta_1)}{\partial\beta_1}=\frac{\partial}{\partial\beta_1}\left[\sum_{i=1}^{n}(\beta_0+\beta_1 x_i-y_i)^2\right]=2\sum_{i=1}^{n}(\beta_0+\beta_1 x_i-y_i)x_i \tag{2}$$

$$\frac{\partial F(\beta_0,\beta_1)}{\partial\beta_0}=\frac{\partial}{\partial\beta_0}\left[\sum_{i=1}^{n}(\beta_0+\beta_1 x_i-y_i)^2\right]=2\sum_{i=1}^{n}(\beta_0+\beta_1 x_i-y_i) \tag{3}$$

Let respectively, $\frac{\partial F(\beta_0,\beta_1)}{\partial \beta_0}=0$, $\frac{\partial F(\beta_0,\beta_1)}{\partial \beta_1}=0$,and then solve to obtain:

$$\begin{cases} \beta_1 = \dfrac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \\ \beta_0 = \bar{y}-\beta_1\bar{x} \end{cases} \tag{4}$$

This means that the solution of the one-dimensional linear regression model is obtained. The above models were solved by MATLAB, and several resultant maps used to analyze the global spatial distribution of vegetation NDVI, the trend of change, and the characteristics of the distribution of the rate of change of vegetation NDVI were obtained.

IV. RESULTS AND DISCUSSION

A. Global spatial distribution of vegetation NDVI

We started with one year of data based on the following: if a location did not acquire observations more than four times in a year, we determined the point to be an oceanic area and assigned the value of NaN to determine the oceanic point location, and summed the 24 sets of data from the non-oceanic point location in that year to obtain a plot of the global vegetation NDVI mean for that year.

Then the data of each image element for fifteen years were averaged to get the global vegetation NDVI from 2001-2015average map , as shown in Figure 2. From the 2001-2015 global vegetation NDVI average data, the global vegetation mainly covers the regions of South America, Central Africa and Southeast Asia.

Figure 1 Map of global vegetation NDVI averages, 2001-2015

According to this multi-year global vegetation NDVI average map, we can analyze that the global vegetation mainly covers Russia, Central Africa, South America and Southeast Asia.

According to the statistical map of vegetation NDVI of each continent, the average vegetation NDVI of the Americas is about 0.497, ranking the first; the average vegetation NDVI of Africa is about 0.424; the average vegetation NDVI of Europe is about 0.423; the average vegetation NDVI of Asia is about 0.363; and the average vegetation NDVI of Oceania is the lowest among all the continents (except for Antarctica), about 0.306.

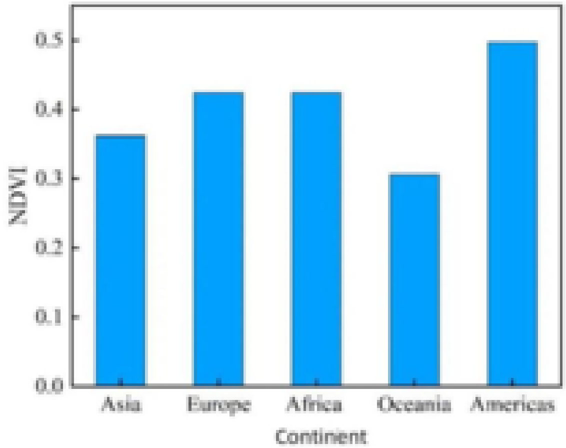

Figure 2 Vegetation NDVI statistics by continent.

V. ANALYSIS OF RESULTS

A. Trend analysis of vegetation indices

We used MATLAB to take 24 remote sensing image data in the same year as input data, and then traversed each image element in the image one by one. The time series of each image element is taken as input and the fitting function corresponding to the position of each image element is calculated using linear regression method. Output the calculated values into a raster image. Finally we can get a raster image containing the slope significance of all image elements.

The p-value distribution of global vegetation NDVI rates of change from 2001-2015 is plotted below:

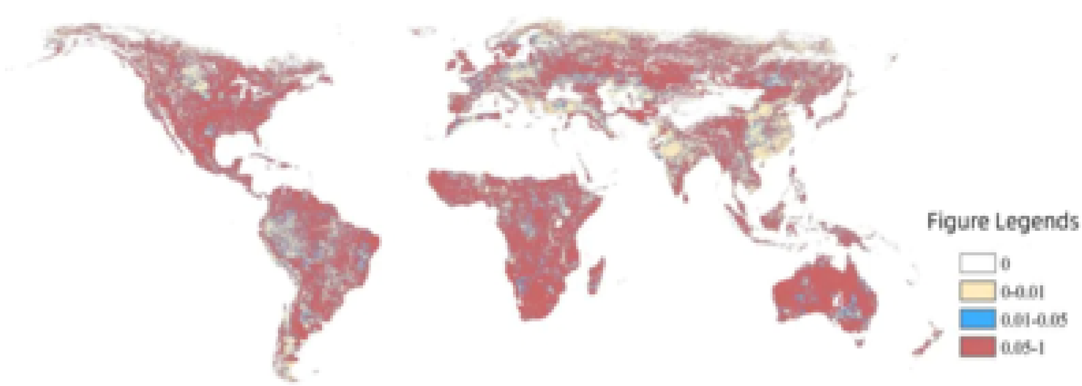

Figure 3 Distribution of p-values of global vegetation NDVI rates of change, 2001-2015

The p-value change in the rate of change is shown in Table 1.

Table 1 Global vegetation NDVI rate of change p-values

	0-0.01	0.01-0.05	0.05-1
Raster number	274647	193095	920973
Proportions	19.78%	13.91%	66.31%

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In Fig. 3, the yellow part is the region of very high significance of the rate of change of $0<p<0.\ 01$, and the red part of the figure is the region of significance of $0.01<p<0.05$. The analysis obtained that the regions with the most significant and concentrated rate of change are Europe, East Asia, North America and India. vegetation in these regions The rate of change of showed a clear trend, and a variety of factors such as climate, human activities and land use may cause such changes.

C. Analysis of the rate of change of vegetation NDVI

The rate of change in the time series of each image is represented by the slope obtained from a one-way linear regression, i.e., the trend of change of that image over time. The slope measures the rate and direction of change of the image over time, with larger values indicating a faster rate of change and positive and negative values indicating the direction of change. Positive slope values indicate an upward or increasing trend, while negative slope values indicate a downward or decreasing trend. We consider slope>0 and $0.01<p<0.05$ to be the area where the rate of change is significantly increasing, and slope>0 and $p<0.01$ to be the area where the rate of change is very significantly increasing; and we consider slope<0 and $0.01<p<0.05$ to be the area where the rate of change is significantly decreasing, and slope<0 and $p<0.01$ to be the area where the rate of change is very significantly decreasing.

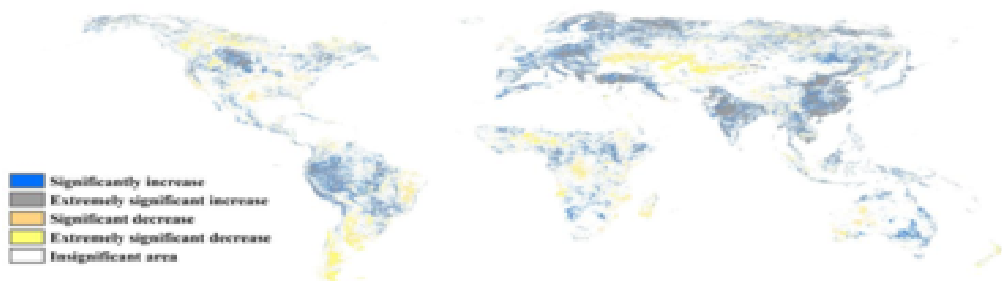

Figure 4 Distribution of significant rates of change in NDVI for global vegetation,2001-2015 Table 2 Significance of changes in NDVI

	Increasesignificantly	Increase extremely significant	Decline significant	Decline extremely significant	Non-significant areas
Rasternumber	137940	215738	55155	58909	425867
Proportions	15.44%	24.14%	6.17%	6.59%	47.66%

Figure 4 shows that there are obvious regional differences in the distribution of global vegetation NDVI rate of change, analyzed by geographical location, the vegetation NDVI rate of change in Europe, America and Southeast Asia and other regions is >0, which represents that the vegetation NDVI rate in this region shows a significant upward trend, in which Russia, Czech Republic, Turkey, China, the United States, Brazil and other regions show a very significant increase in the rate of change in the vegetation NDVI rate of change characteristics. The rate of change of vegetation NDVI in Kazakhstan, Africa, and the Americas is <0, which means that the rate of change of vegetation NDVI in this region for fifteen years has shown a decreasing trend, in which the regions of Kazakhstan, Nigeria, Canada, and Argentina have shown a very significant decreasing trend in the rate of change of vegetation NDVI.

VI. CONCLUSION

In this study, based on the PKU GIMMS NDVI dataset for all seasons of the year from the widely distributed vegetation biomes on a global scale, we analyzed the vegetation cover on a global scale during the period of 2001-2015 to study the trend of global ecosystem change. By analyzing the results of the calculations of the univariate linear regression model, based on the results of the rate of change of the vegetation NDVI, from the global geographic location, the rate of change of the vegetation NDVI in the regions of Europe, America and Southeast Asia shows a significant upward trend, and the rate of change of the vegetation NDVI in Kazakhstan, Africa and America shows a downward trend.

This trend may be influenced by climatic factors, human activities and ecological protection policies. Climate change is usually an influencing vegetation NDVIimportant factor the trend of change, warming climate and increased precipitation help vegetation growth, while drought and extreme weather will lead to vegetation reduction.

VII. ACKNOWLEDGEMENTS

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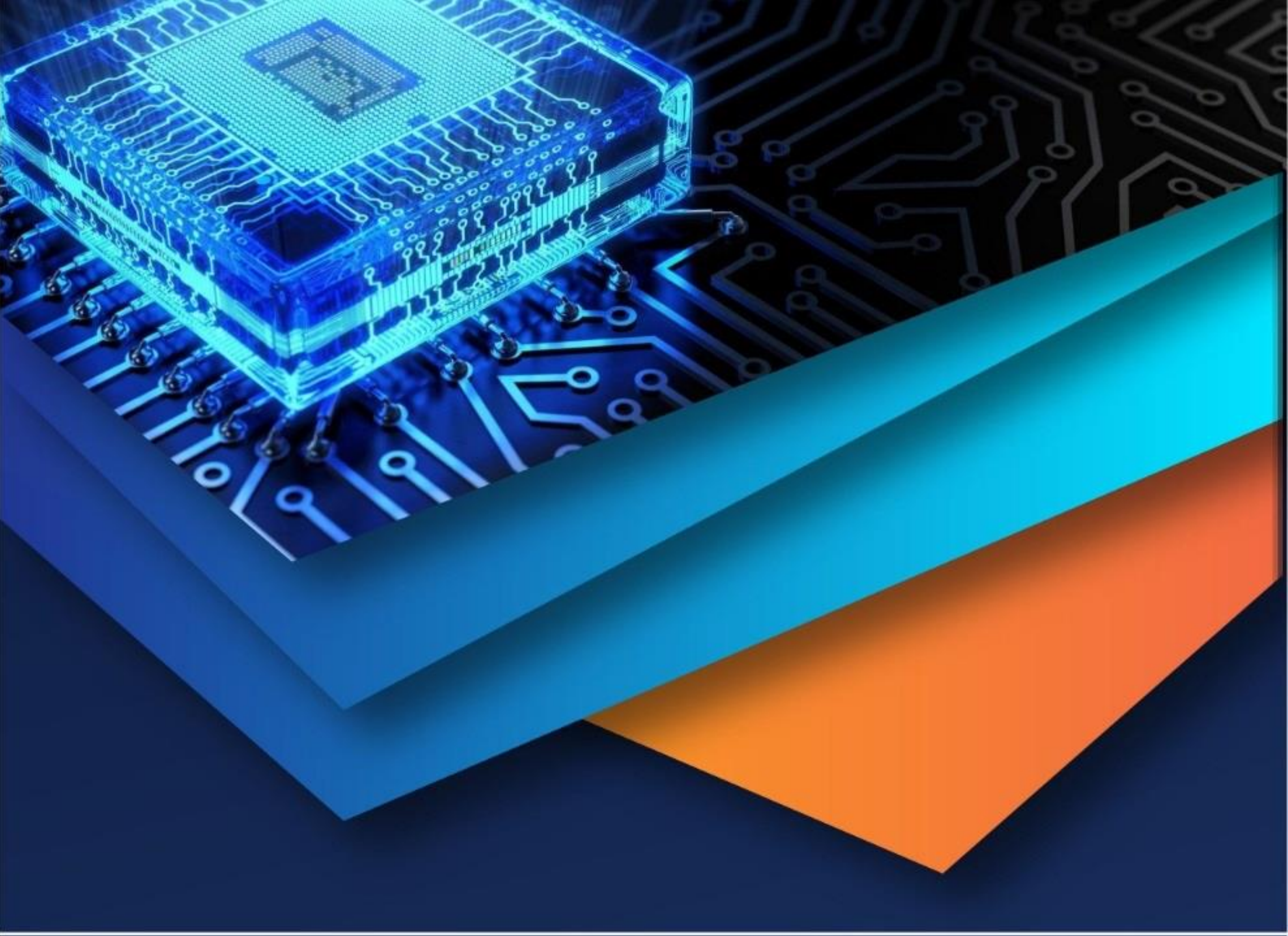

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