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Impacts of Climate Change on Forest Biodiversity Changes in Northeast China

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Abstract: Vegetation plays a vital role in connecting ecosystems and climate features. The biodiversity of vegetation is one of the most important features for evaluating ecosystems and it is becoming increasingly important with the threat of global warming. To clarify the effects of climate change on forest biodiversity in Northeast China, time-series NDVI data, meteorological data and land cover data from 2010 to 2021 were acquired, and the forest biodiversity of Northeast China was evaluated. The effect of climate change on forest biodiversity was analyzed, and the results indicated that the forest biodiversity features increased from west to east in Northeast China. There was also an increasing trend from 2010 to 2021, but the rate at which forest biodiversity was changing varied with different forest types of Northeast China, as different climatic factors had a different impact on forest biodiversity in different forest types. Average annual temperature, annual accumulated precipitation, CO_2 fertilization and solar radiation were the main factors affecting forest biodiversity changing trends. This research indicated the potential impact of climate change on forest ecosystems, as it emphasized with evidence that climate change has a catalytic effect on forest biodiversity in Northeast China.

Keywords: biodiversity; climate change; remote sensing; trend analysis; correlation analysis

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1. Introduction

Global warming has become a recognized reality and has a significant impact on the survival and development of human beings; it also has a significant impact on global ecosystems [1]. Forests are the most important terrestrial ecosystems, with tremendous influence on climate change, such as the survival of trees, growth, biodiversity and sustainability of forests [2–4]. The biodiversity of the forests is the physical and biological foundation of their life and reproduction of the forest ecosystem, as it is considered a measurement for evaluating the stability and function of an ecosystem [5]. Therefore, the biodiversity of forest ecosystems is often used to describe the characteristics and dynamics of the forest ecosystems in the background of climate change.

Currently, field surveys and remote sensing monitoring technology are the main methods and ways of forest biodiversity research [6]. Wang et al. assessed the β-diversity of soil bacteria in four different habitats in the arid zone of China and found that the environmental factor was the main controlled factor influencing the distance attenuation of diversity in alpine grassland habitats based on field measurements [7]. Parmengier et al. Compared the α-diversity index between the plots of the African rainforest and the Amazon rainforest and found that the value of the α-diversity in the Amazon was nearly three times that in Africa and concluded that the influence of the climate variables on the diversity in the two regions was very different [8]. Renato Valencia et al. carried out α diversity measurement in a one-hectare plot of tropical rainforest in Ecuador by using field survey methods. Although field measurement data always offers high accuracy, the cost of

labor and financial resources are also very huge [9]. Meanwhile, traditional biodiversity manual measurements are mainly used as they target species at a community level, but they are limited by the area of the research region; hence, it is difficult to perform biodiversity research on a large region scale [6,10,11].

The gap between knowledge about species and estimated species, which is also called the "Linnaean Shortfall", led to calls for the voices to use remote sensing technology for biodiversity monitoring [12,13]. Remote sensing technology has significant advantages in wide coverage, time series and repeatability and has become an important tool in monitoring, assessing and mapping the biodiversity of varied ecosystems on a large scale [14,15]. Remote sensing approaches were used for habitat assessment, to provide remotely detectable variables, to estimate the species richness or distribution patterns and for measurements of ecosystem function or community composition [16–18]. However, a global biodiversity monitoring system should be designed and the role of remote sensing should be clarified. Meanwhile, field measurements do not always match with remote sensing metrics [11]. Some scholars focus on research to make up for this shortcoming and push this technology of detection of biodiversity forward by using remote sensing technology [19–21].

Remote sensing technology has the ability for repeated observation, capture and measurement of diverse ecological habitats worldwide for terrestrial ecosystems [22]. Over the past few decades, a lot of excellent research is coming out. Some scholars established an estimating model between land patch data and remote sensing imagery for biodiversity research. The results offered a robust understanding of the disparities of forests, greatly aiding forest biodiversity research [23]. Meanwhile, it can offer unparalleled resolution and precision in data collection compared to visual human observations, especially when facing economic and technical obstacles during large-scale or global observations [24]. Therefore, most biodiversity-related research and monitoring primarily rely on satellite remote sensing technology, especially for large or global spatiotemporal scales [6].

Among those applications, imaging spectroscopy is considered the most promising remote sensing approach for mapping species distribution and functional diversity of plants [25]. Spectral diversity, which was calculated from remote sensing imagery, has been considered an indicator for vegetation biodiversity assessment [26–28]. As commonly used spectral diversity, spectral indices provide an accurate and sensitive changing imagery in plant growth and are the most commonly used indicators for determining the types and status of vegetation [29]. Anna et al. indicated that imaging spectroscopy technology can prove a reliable and effective method for assessing changes in species composition and plant diversity in terrestrial ecosystems [30]. It has become a more widely accepted method to use spectral diversity for determining plant diversity from image data [28,31].

Normalized Difference Vegetation Index (NDVI) is one of the most popular vegetation indexes; its time-series data have strong spatial and temporal distribution characteristics, which can reflect the spectral characteristics of vegetation, especially for the optical characteristics related to green vegetation [32]. In particular, NDVI can capture the changing trend of vegetation growth and quantify the impact of climate change on the ecosystem. Thereby, NDVI is an important tool for tracking the changes in forest biodiversity. Torresani et al. tested SVH (spectral variation hypothesis) using different spectral heterogeneity indices to estimate tree species diversity in alpine coniferous forests and compared the results with in situ measurements. Torresani et al. concluded that there is a significant correlation relationship between the measured Shannon index and the NDVI derived from multi-spectral satellite data [33]. Other researchers concluded that the variance characteristics of NDVI, such as standard deviation, variance and coefficient, can be used to predict the diversity of the tree species. In addition, NDVI has the capability to expose regional disparities in forest biodiversity [34]. Therefore, NDVI is always considered the main indicator to evaluate tree species diversity and it is widely regarded as an important tool for monitoring vegetation diversity and ecosystem health due to its ability to monitor and analyze vegetation characteristics accurately at multiple levels, large scales and time series [35].

Long-term monitoring and evaluation of biodiversity and ecosystem services and their state changes and trends always require high-quality patch data, land use type or land cover data to calculate the spectral diversity and evaluate the related biodiversity. However, remote sensing data products often suffer from missing data and inconsistent accuracy due to weather conditions, image quality, or data processing techniques. Therefore, more research work should be done to increase the accuracy of remote sensing techniques for biodiversity detection.

The forest is the biggest part of the terrestrial ecosystem and plays a crucial role in biodiversity and the global carbon cycle [36]. Northeastern China (NEC) owns about 37% of the forest land area of total China [37]. This region contains about 27.5% of the carbon stocks of the total forests of China [38]. Meanwhile, Northeast China, which is the most representative temperate monsoon climate zone, includes the humid, semi-humid and semi-arid regions from east to west and warm temperate, mesothermal temperate and cold temperate zones from southern to northern NEC. Therefore, the forest in NEC constitutes a temperate forest region and is one of the most biodiverse in the world [39]. In addition, NEC is an important ecological barrier for the country and plays a core role in ecological security [40]. Industrial emissions increase the amount of greenhouse gases in the atmosphere, exacerbating the greenhouse effect and creating certain risks and difficulties for the natural environment [41]. As a result, this region is sensitive and varied to climate change.

We aim to assess forest biodiversity changes in a long time series and clarify the impact of climate change on forest biodiversity in Northeast China. Land cover type data, MODIS NDVI data and meteorological data were collected and the five landscape pattern indices, which included the Patch Cohesion Index (COHESION), the number of patches (NP), the density of patches (PD), Shannon Diversity Index (SHDI) and splitting index (SPLIT) were selected and used to evaluate the forest biodiversity of NEC. Then, the spatial and temporal distribution characteristics and changing trend of the forest biodiversity were calculated and finally, the impact of climate change on forest diversity in NEC was analyzed. This study offers insights into the characteristics of landscape spatiotemporal changes and their climate response mechanisms in Northeast China. Additionally, it provides a theoretical foundation for the development of biodiversity conservation and sustainable development strategies in Northeast China.

2. Materials and Methods

2.1. Study Area

The research region is in the northeast of China, which is located from 118°E to 135°E and 38°N to 55°N and it includes the Heilongjiang, Jilin and Liaoning provinces. This region is a temperate continental monsoon climate and exhibits pronounced seasonality and diverse climate patterns [42]. The study area encompasses both warm temperate, temperate and cold temperate zones [43]. The mean annual temperature ranges from 3.7 to 6.5 °C [37]. The average annual precipitation ranges from 550 to 950 mm and rainfall is mainly concentrated from June to September. This region is one of the largest temperate forest reserves in the world and the area of the forest in NEC is about 37% of the total forest area of the country [43]. The main forest types of NEC are broadleaf forests, coniferous forests and mixed coniferous broad-leaved forests. The broadleaf forests are widely distributed in this region. The coniferous forests are mainly distributed in The Daxing'anling region, while mixed forests dominate the Xiaoxing'anling and Changbai Mountain regions.

2.2. Materials

2.2.1. MODIS NDVI Data

The MODIS NDVI time-series data were used in this study. The MOD13Q1 NDVI time-series data were provided by NASA (National Aeronautics and Space Administration https://search.earthdata.nasa.gov, accessed on 28 October 2024) with a spatial resolution of 250 m. In this study, a total of 1380 NDVI images, which covered the research region by

the tiles of h25v03, h26v03, h26v04, h27v04 and h27v05, were collected and the period of the data is from 2010 to 2021. The prepossessing of NDVI data includes reprojection, merging, splicing and so on. The administrative boundary vector data were provided by the National Catalogue Service for Geographic Information of China (http://www.webmap.cn, accessed on 28 October 2024). The commercial software of ENVI 5.3 and ArcGIS 10.5 were used in this study.

2.2.2. Land Cover Data

Land cover data is a crucial parameter to distinguish different vegetation types and calculate forest diversity. In this study, GLC_FCS30 (Global 30 m Land Cover products with Fine Classification System) and FROM-GLC (Finer Resolution Observation and Monitoring of Global Land Cover) were used. GLC_FCS30 is a time-series global scale land cover dynamic monitoring product with a spatial resolution of 30 m and the products of GLC_FCS30 in 2010, 2015 and 2020 were used (https://data.casearth.cn, accessed on 30 October 2024). GLC_FCS30 is a global 30 m resolution land cover production developed by the research group of Pro. Liangyun Liu at Institute of Aerospace Information Innovation, Chinese Academy of Sciences [44]. FROM-GLC is a global 30 m resolution land cover production developed by the research group of Pro. Peng Gong at Tsinghua University. The products of FROM-GLC in 2017 were used in this study (https://data-starcloud.pcl.ac.cn/, accessed on 28 October 2024).

To study the impact of climate change on forest biodiversity in NEC, GLC_FCS30 and FROM-GLC data were reclassified into eight major categories: agricultural land, broadleaf evergreen forest, broad-leaved deciduous forest, evergreen coniferous forest, deciduous coniferous forest, mixed coniferous broad-leaved forest, grassland, moss and others. Then, reclassification data were resampled from the original 30 m spatial resolution to 250 m.

The map of the Vegetation Atlas of the People's Republic of China (1:1,000,000) provides the distribution of functional zones of vegetation in the northeast of China. The vegetation functional zones map was masked according to the vector boundary file of the research region (Figure 1). There are four vegetation functional zones: I. Cold temperate needle leaf forest region; II. Temperate needle leaf and broadleaf mixed forest region; III. Warm temperate broadleaf forest region; and IV. Temperate grassland region.

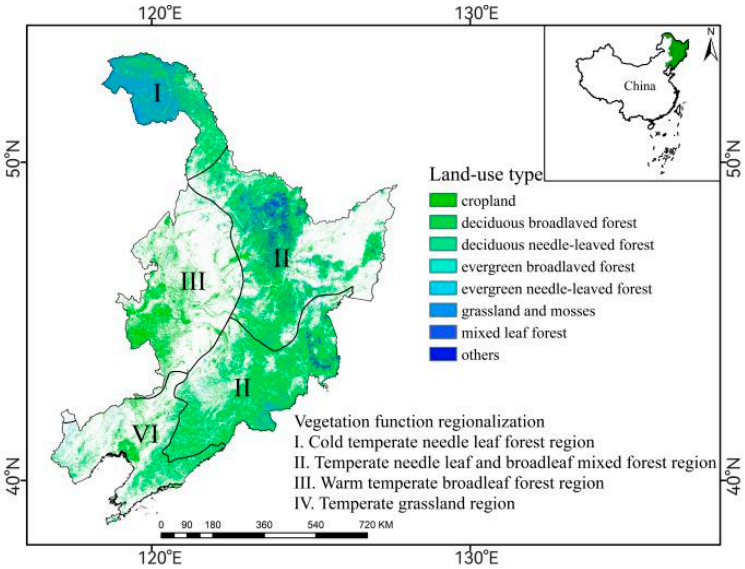


Figure 1. Land-use type and Vegetation function zones.

2.2.3. Climate Data

The U.S. National Oceanic and Atmospheric Administration (NOAA) provided the meteorological data as the source of the surface meteorological observations used in this

study. The average annual temperature, annual precipitation, annual radiation and carbon dioxide data were collected from 2010 to 2021 in Northeast China and surrounding areas (https://www.ncei.noaa.gov, accessed on 28 October 2024). To ensure data validity and continuity, 116 sites were selected. Finally, average annual temperature, annual precipitation, annual radiation and total CO_2 grid data were obtained using the Kriging interpolation method of the ArcGIS spatial analysis module [45].

2.3. Methodology

In this study, forest biodiversity and its influencing factors were analyzed by using NDVI, land cover data and meteorological data from 2010 to 2021. Five indicators of biodiversity were used in this study and the details can be found in Section 2.3.1 and Table S1. To access the forest biodiversity in NEC, the first important thing is to obtain continuous time-series diversity-indicator data, but there were only four periods of land cover data to calculate the indicators of biodiversity. However, land cover data for other years were missing and needed to be filled using remote sensing methods to ensure data continuity. Therefore, an estimation method of the five indicators of biodiversity was established using remote sensing variables. Then, a continuous time series of biodiversity indicators was calculated. Finally, the spatiotemporal variation characteristics of forest biodiversity in NEC were analyzed and the changing trend of forest biodiversity and the impact of climate change on it were summarized and concluded.

2.3.1. Choice and Introduction of Forest Biodiversity

There are a huge number of forest biodiversity indicators developed by researchers to study the biodiversity features of the terrestrial biosphere [46]. In this study, five indicators of biodiversity were selected and used. Patch Cohesion Index (COHESION) is usually used to describe the spatially aggregated features of different landscape types. The equation of COHESION is as follows [47]:

$$\text{COHESION} = [1 - \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} P_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{m} P_{ij}\sqrt{a_{ij}}}] \times \left[1 - \frac{1}{\sqrt{A}}\right]^{-1} \times 100 \quad (1)$$

In this equation, a_{ij} is defined as the area of the jth patch in the land cover type of ith, P_{ij} is defined as the perimeter of the jth patch in the ith land cover type and A is the total area of the landscape types.

The number of patches (NP) and the density of patches (PD) are key indicators for understanding the overall heterogeneity and fragmentation of the environment.

NP is the number of patches of the corresponding patch type or class. The equation of NP is as follows [48]:

$$\text{NP} = n_{\text{i}} \quad (2)$$

where, n_i is the number of patches in the landscape of patch type of class i.

PD represents the density of a certain patch in the landscape, which can reflect the overall heterogeneity and fragmentation of the landscape and the degree of fragmentation of a certain type and reflects the heterogeneity of the landscape per unit area. The equation of PD is as follows [43]:

$$\text{PD} = \frac{n_i}{A} \quad (3)$$

where n_i is the number of patches in the landscape of patch type of class I and A is the total landscape area (m^2).

The Shannon Diversity Index (SHDI) is the most widely used indicator which provides a measurement of landscape composition. The Shannon Diversity Index (SHDI) describes landscape diversity by considering the number of different landscape types and their proportion of the landscape area. It is more sensitive to the non-uniform distribution

condition of each patch type in the landscape. It is particularly vulnerable to changes in the distribution of patch types across the landscape [49]. The SHDI is defined as follows:

$$\mathrm{SHDI} = -\sum_{i=1}^{n}(P_i \times \ln P_i) \tag{4}$$

In this equation, P_i is the percentage of patches of type i in the landscape and can be calculated by N_i/N, N is the total number of patches and N_i is the number of patches belonging to patch type i.

Landscape fragmentation (SPLIT) dispersed features of different landscape types. The SPLIT calculation formula is as follows [50]:

$$\mathrm{SPLIT} = \frac{A^2}{\sum_{i=1}^{m}\sum_{j=1}^{n} {a_{ij}}^2} \tag{5}$$

where, a_{ij} is the area of patch ij and the unit is m^2 and A is the total landscape area (m^2).

In the end, the forest diversity (FD) was evaluated using a linear model of those indices above. The formula of the forest diversity assessment is defined as follows:

$$\mathrm{FD} = a + b \times \mathrm{COHESION} + c \times \mathrm{NP} + d \times \mathrm{PD} + e \times \mathrm{SHDI} + f \times \mathrm{SPLIT} \tag{6}$$

FD represents the evaluation of forest diversity in the research region and a, b, c, d, e and f are the fitting parameters according to the least squares method [51].

2.3.2. Method of Time Series Forest Biodiversity Indicators Estimation

The forest biodiversity indicators introduced in Section 2.3.1 can be calculated using land use type data in Section 2.2.2 with the help of the Fragstats 4.0 software. However, the land use data were missing for some years. Normally, there are two ways to solve this problem: one is to produce a continuous year's land use data, and the other is to find a method to estimate the biodiversity indicators during missing years to make up for the lack of data. In this study, we chose the second way to generate a time-series forest biodiversity indicator.

Based on the research of Gustafson, E. J., fractional vegetation cover (FVC) has a significant linear relationship with forest biodiversity [52]. The forest biodiversity indicators can be described as a function of FVC; the least squares method of linear regression was used to develop a fitting model to establish the relationship between different biodiversity indicators and variables from remote sensing data. The fitted model is defined as follows [53]:

$$Y_t = a + b \times X_t + e \tag{7}$$

X_t is represented as a time-series FVC and Y_t is a time-series forest biodiversity indicator, the time-series starting value is defined as a, the time-series noise error is defined as e and the regression coefficient of the linear trend of forest biodiversity change is denoted as b. The parameters of a and b can be estimated using the least squares method from obtained forest biodiversity indicators and FVC was extracted from MODIS NDVI data.

The equation for calculating FVC is defined as follows:

$$\mathrm{FVC} = \frac{\mathrm{NDVI} - \mathrm{NDVI_{soil}}}{\mathrm{NDVI_{veg}} - \mathrm{NDVI_{soil}}} \tag{8}$$

where FVC is the fractional vegetation cover (FVC), $\mathrm{NDVI_{soil}}$ is the NDVI of bare soil and $\mathrm{NDVI_{veg}}$ is the NDVI of the vegetation in a pure pixel. The details about FVC estimation can be found in the research of Wu et al. [54].

When a time-series FVC was calculated, a time-series forest biodiversity indicator could be estimated using the model established above and time-series FVC calculated from MODIS NDVI. Then, the spatial and temporal distribution features could be analyzed and

the climate-responding mechanisms of forest biodiversity could also be revealed based on estimated time-series biodiversity indicators.

2.3.3. Trend Analysis

Trend analysis was performed using the slope of the linear best-fitting regression line, which is a widely used method for time-series data changing trend analysis [55]. The best-fitting linear regression model was fitted to annual summaries of the five biodiversity indices using the least squares method. The year was defined as the independent variable (X) and the biodiversity index as the dependent variable (Y). The inter-annual changing rate of forest diversity can be described by this slope of the fitting linear model [56].

The formula is as follows:

$$\text{Slope} = \frac{n\sum_{i=1}^{n} i \times Y_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} Y_i}{n\sum_{i=1}^{n} i^2 \sum_{i=1}^{n} i} \quad (9)$$

where Slope represents the slope of the best-fitting linear regression model between the time variable and forest biodiversity. The variable of time is defined by the variable "i" (an integer between 1 and n). Meanwhile, "n" represents the number of years of the study. Y_i is the forest biodiversity in the year i. Forest biodiversity showed a decreasing trend during the research period when the Slope was less than 0 and an increasing trend when the Slope was larger than 0. At the same time, a larger absolute value of Slope means a larger changing rate in forest biodiversity and vice versa.

2.3.4. Impact Analysis of Climate Factors on Forest Biodiversity

Correlation Analysis

A statistical method called partial correlation analysis was used to calculate the net correlation between individual components and the target factor while controlling the effects of other factors. The partial correlation coefficient is an important parameter that evaluates the importance of each factor, considering the influence of other factors and reducing their influence through mathematical methods [57]. Partial correlation analysis can more fully reveal potential influence than traditional one-way analysis of variance and simple linear correlation coefficient analysis [58].

Previous studies concluded that climate factors such as CO_2 levels, annual precipitation (P), solar radiation (SR) and average annual temperature (T) were the main factors influencing the growth of the plants in NEC and these would have a potential influence on forest biodiversity in this region [59]. Therefore, partial correlation analysis was used to evaluate the strength of the influence of different meteorological factors on forest biodiversity [60]. The formula for the partial correlation coefficient used in this study is defined as follows:

$$R_{xy,z} = \frac{R_{xy} - R_{xz}R_{yz}}{\sqrt{1 - {R_{xz}}^2}\sqrt{1 - {R_{yz}}^2}} \quad (10)$$

R_{xy}, R_{xz} and R_{yz} are the correlation coefficients of the simple linear regression, respectively. The significance of these correlation coefficients for this study was determined using the t-test with a 95% confidence interval.

Sensitivity Analysis

In this study, the multiple linear regression method was used to evaluate the sensitivity of biodiversity to climate change. A simple assumption of this method was that there was a linear relationship between the forest biodiversity (Y) and meteorological factors, such as CO_2 levels, annual precipitation (P), solar radiation (SR) and average annual temperature (T). The regression coefficients of multiple linear models can be used to indicate the sensitivity of forest biodiversity to CO_2, precipitation, solar radiation and temperature.

$$Y = a \times CO_2 + b \times P + c \times SR + d \times T \quad (11)$$

where Y is a biodiversity indicator, CO_2 is carbon dioxide concentration, P is annual precipitation, SR is solar radiation and T is the average annual temperature. The coefficient of the regression model determined the importance of the variable in the model and it represents the degree of importance and contribution rate of those climate variables to forest diversity [61,62].

3. Results

3.1. Estimating Forest Biodiversity Based on Vegetation Coverage

The forest biodiversity indicators were calculated from four different times of land cover data by using Fragstats software version 4.2. The synchronous FVC was extracted and a correlation between them was performed. The statistical results are shown in Figure 2.

The results showed that FVC was a very valuable variable in describing the changes in forest biodiversity, as shown in the scatter plot in Figure 2. There were significant linear relationships between FVC and COHESION, NP, PD, SHDI and SPLIT, respectively. There was a significant positive linear relationship between NP, PD, SHDI, SPLITI and FVC with coefficients of determination of 0.8746, 0.8626, 0.9964 and 0.9943, respectively. It was indicated that there would be higher forest biodiversity with the increase in FVC [63]. An increase in PD is beneficial to maintaining or enhancing the biodiversity of the forest ecosystem because the increasing numbers of patches provide more habitat types and increase the opportunities for species exchange. These results were consistent with Zhao and Gustafson, E. J.'s research [52]. For COHESION, there was a totally different result between COHESION and FVC. A negative linear relationship between COHESION and FVC was shown in Figure 2 with a coefficient of determination of 0.992. This indicated that the aggregation effect of the forest would be decreased with the increase in FVC. Although PD and SHDI both increased, COHESION decreased and indicated that the distance between patches did not increase. Biodiversity conservation needs to take into account not only the size and shape of patches but also their distribution and connectivity.

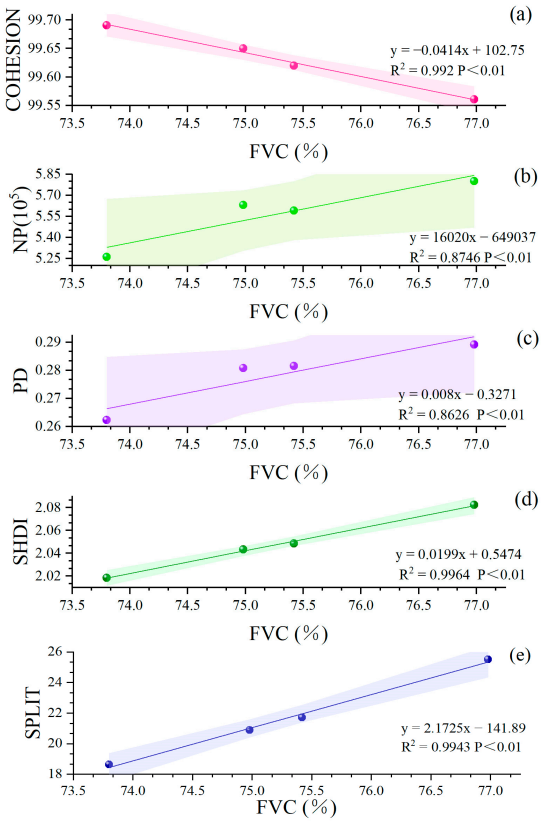


Figure 2. The scatter plots between FVC and forest biodiversity indicators. (**a**) COHESION; (**b**) NP; (**c**) PD; (**d**) SHDI and (**e**) SPLIT.

3.2. The Spatial and Temporal Distribution Characteristics of Forest Biodiversity

The spatial and temporal distribution of forest biodiversity in NEC were mapped from 2010 to 2021 using time-series remote sensing data (Figure 3). Forest biodiversity is expressed by the correlation relationship of its basic index, shape index, spread index and diversity index [51,64]. Forest biodiversity was calculated using the method described in Section 2.3.2. The results showed that the distribution of forest biodiversity had a significant spatial heterogeneity in NEC. There was an increasing trend from west to east in NEC and higher biodiversity features in forest regions. Among them, the high-value biodiversity regions were mainly located in the Daxing'anling, Heihe City, Yichun City and Mudanjiang City regions of Heilongjiang Province. The functional type of vegetation is cold temperate coniferous forest areas. The high values of biodiversity in Jilin Province were mainly in temperate coniferous and broadleaf mixed forest areas, including Yanbian City and Changbai Mountain. The high values of biodiversity in Liaoning Province were mainly located in the eastern coastal areas of Liaoning Province, which are characterized by a warm temperate deciduous broad-leaved forest region.

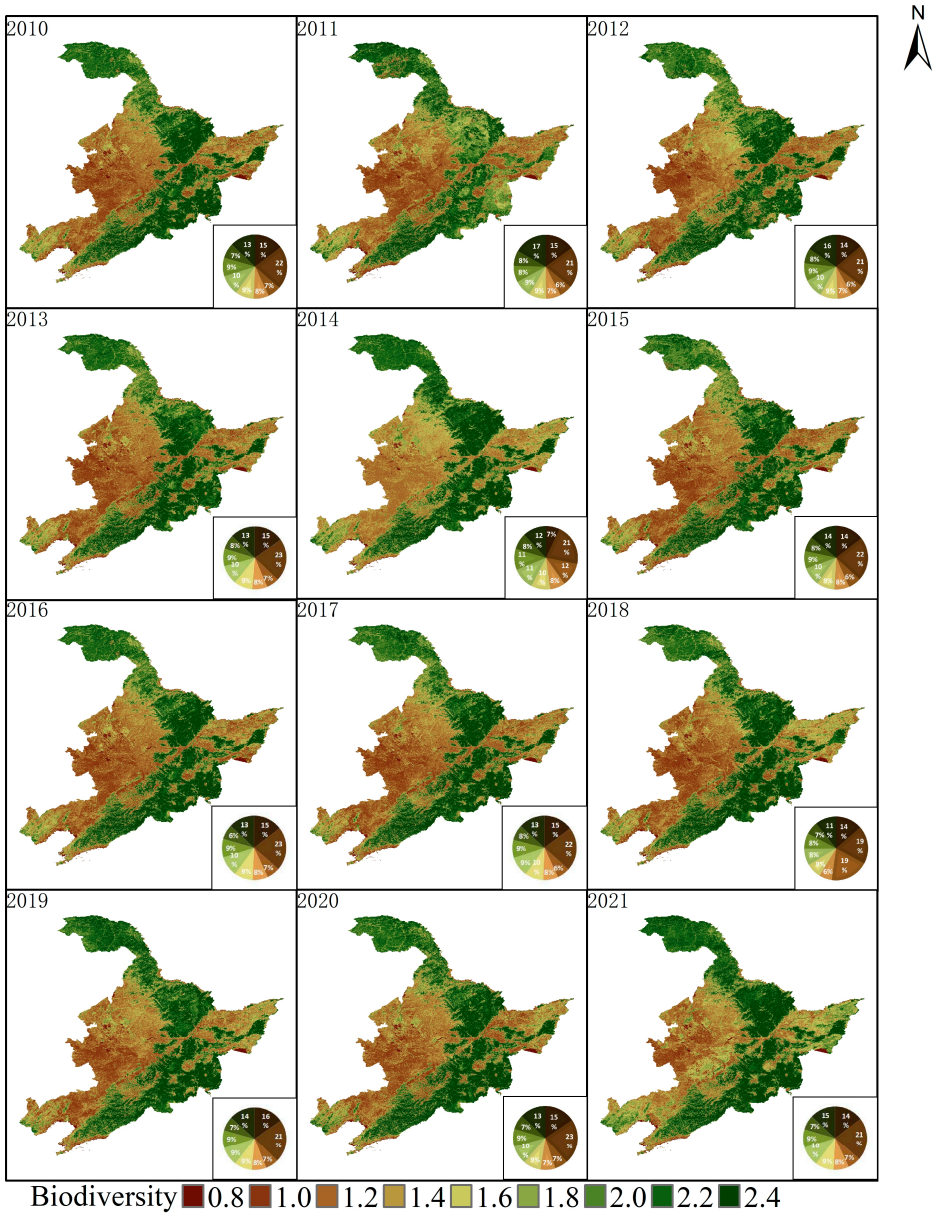


Figure 3. The spatial distribution feature of forest biodiversity in the Northeast region.

In this study, the temporal changing trends of forest biodiversity in NEC from 2010 to 2021 were statistically calculated. COHESION ranged from 99.56% to 99.77%. The range of NP was from 504,723 to 580,118. PD ranged from 0.25 to 0.29. SHDI changed from 1.98 to 2.08 and SPLIT changed from 14.57 to 25.52 during 2010 to 2021. The forest biodiversity in Northeast China showed a tendency for fluctuating growth from the statistical results. This increasing trend was not only related to climate change but also related to the forest protection policy. The Natural Forest Conservation Program was implemented in 1998. The annual harvest quota was 20.6% of the total harvest quota in China from 2001 through 2005. This value was reduced to 13.2% of the total harvest quota in the period of 2006–2010 [65]. The area of broad-leaved forest increased by about 0.11 million ha from 2000 to 2010 and then this value increased by a further 0.07 million ha from 2010 to 2015 [66]. Those events also contributed to the increase in forest biodiversity in Northeast China.

Then, the scatter plot of year-by-year changes of each forest biodiversity indicator was plotted in Figure 4, and the changing trend of each forest biodiversity indicator was calculated (Figure 4). For the COHESION indicator, there was a decreasing trend with a changing rate of −0.0118/a. There was a significant increasing trend for NP, PD, SHDI and SPLIT with a changing rate of 0.04664/a, 0.0023/a, 0.0056/a and 0.6125/a, respectively. These results indicated that there has been a significant increase in forest biodiversity in Northeast China. This implies that global warming favors the growth of forest vegetation in the region. Similar findings were found in other studies. For example, Keenan et al. found that global warming had a positive effect on vegetation growth in the Arctic and other boreal ecosystems [67]. Similar results were reported by Macias-Fauria et al. [68].

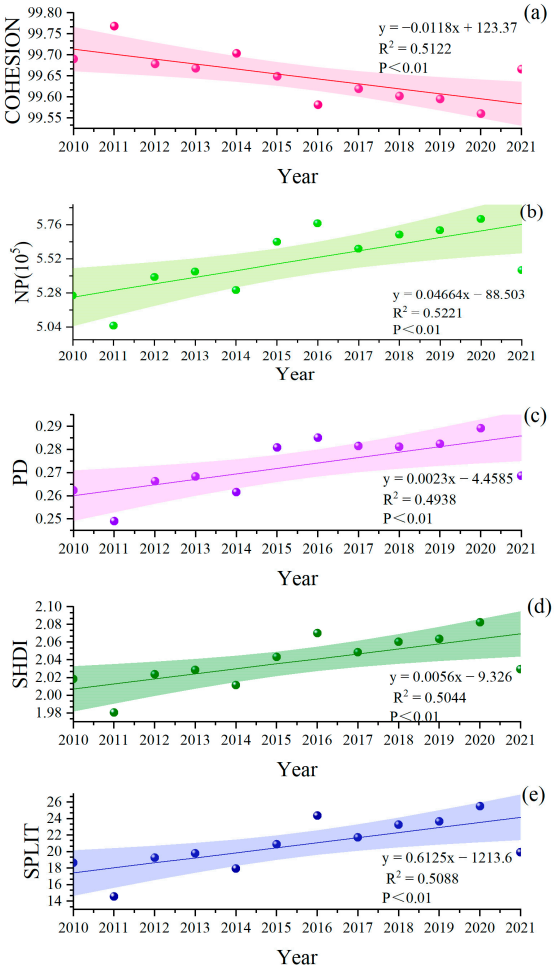


Figure 4. Inter-annual variations in forest biodiversity indicators in NEC from 2010 to 2021. (**a**) COHESION; (**b**) NP; (**c**) PD; (**d**) SHDI and (**e**) SPLIT.

3.3. Inter-Annual Variations of Climatic Factor

The scattering plot of inter-annual variations of climatic factors is shown in Figure 5. There was a significant increasing trend from 2010 to 2021. The increasing of carbon dioxide concentration in the atmosphere is a well-known fact and the changing trend from 2010 to 2021 was 2.3073 ppm/a. For annual accumulated precipitation, the minimum and maximum values of annual accumulated precipitation were 569 mm and 937 mm, which appeared in 2014 and 2016, respectively. The increasing trend of annual accumulated precipitation was 14.392 mm/a. Previous studies indicated that the precipitation and concentration of CO_2 were also two important variables that will affect vegetation growth [69]. Solar radiation also plays an important role in influencing changes in vegetation growth. The average solar radiation peaking value was 1405.07 kWh/m^2 in 2020 and the minimum of it was 1198.07 kWh/m^2 in 2013. The increasing trend rate was 8.56 kWh/m^2/a. For mean annual temperature, the lowest temperature appeared in 2013, with a mean annual temperature of 3.72 °C. The highest average temperature appeared in 2021, which was reached to 6.43 °C. At the same time, the annual mean temperature has a significantly increasing trend with a slope of 0.1324 °C per year in the northeast of China. As an indicator of the heat, change in the temperature has a close relationship with the growth of vegetation and the increase of the temperature from global warming promoted the growth of the vegetation in NEC [70].

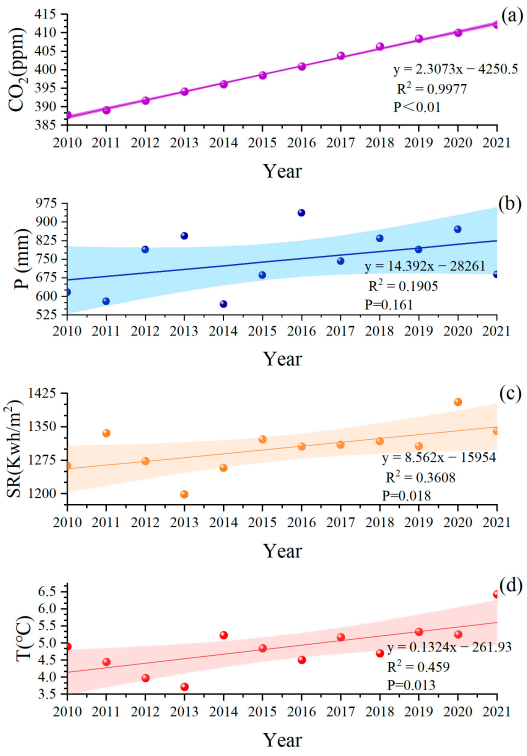


Figure 5. Inter-annual fluctuations of climatic factors. (**a**) concentration of CO_2 (CO_2); (**b**) precipitation (P); (**c**) solar radiation (SR); (**d**) temperature (T).

3.4. The Impact of Climate Change on Forest Biodiversity in NEC

3.4.1. The Impact of Climate Change on COHESION

The changing trend of COHESION with climate factors is shown in Figure 6. COHESION had a significantly decreasing trend with the concentrations of carbon dioxide and precipitation change. The changing rate between COHESION and the concentrations of carbon dioxide and precipitation was −0.0052/ppm and −0.0004/mm, respectively. Similar to other results above, the solar radiation and temperature had no significant effects on COHESION.

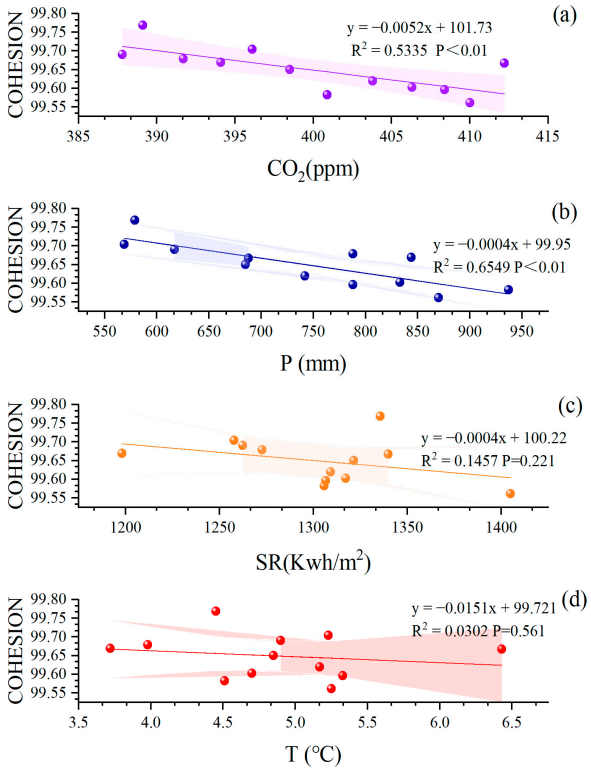


Figure 6. The response of COHESION to climate. (**a**) concentration of CO_2; (**b**) precipitation; (**c**) solar radiation; (**d**) temperature.

3.4.2. The Impact of Climate Change on NP and PD

The number of patches has an increasing trend with the increase of the climate factors (Figure 7). There was a statistically increasing trend for concentrations of carbon dioxide and amount of precipitation at a 95% confidence interval, respectively. The increasing rate of the number of patches with concentrations of carbon dioxide was 2042/ppm. Additionally, when precipitation increased by 1 mm, the number of patches would be increased by 154.34/mm. For solar radiation and temperature, Figure 7c,d showed a weak, increasing trend, but the results did not pass the significance test of statistics. Thus, those results were not statistically meaningful.

Similar results were observed regarding the density of the patches (Figure 8). The concentration of carbon dioxide and amount of precipitation show a significant linear relationship with the density of patches, and the R^2 of concentrations of carbon dioxide and precipitation were 0.5115 and 0.5621, respectively. The same trend occurred in concentrations of carbon dioxide with a slope of 0.001/ppm ($p < 0.01$). The rate of increase of the density of patches with the increase in precipitation was 8.0×10^{-5} per year ($p < 0.01$). However, the changing trends of solar radiation and temperature were not statistically meaningful in Figure 8.

3.4.3. The Impact of Climate Change on SHDI

There was an increased trend of SHDI with the increase of CO_2 (Figure 9). The changing rate of this trend was 0.0025/ppm ($p < 0.01$). The results also showed that an increase in precipitation caused an increase in SHDI with a slope of 0.0002/mm ($p < 0.01$). Although SHDI showed a weak, increasing trend with the increase of solar radiation and temperature, the *p*-value did not pass the significance test with values of 0.203 and 0.567, respectively.

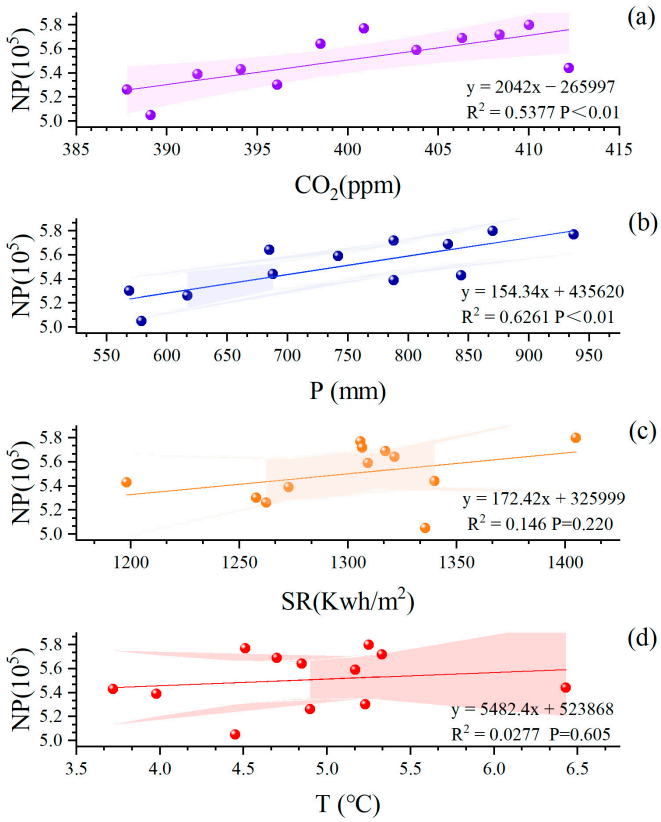


Figure 7. The response of NP to climate factors. (**a**) concentration of CO_2; (**b**) precipitation; (**c**) solar radiation; (**d**) temperature.

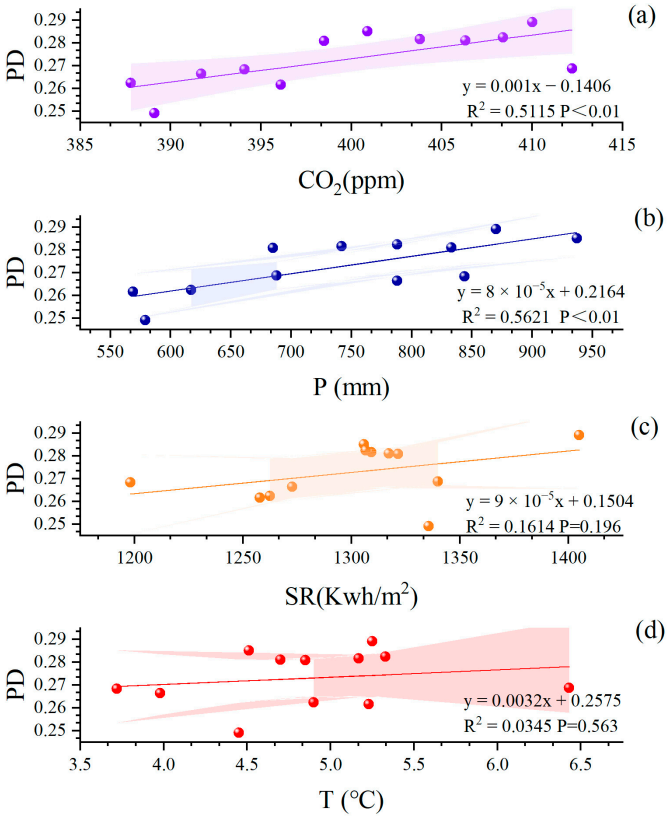


Figure 8. The response of PD to climate factors. (**a**) concentration of CO_2; (**b**) precipitation; (**c**) Solar radiation; (**d**) temperature.

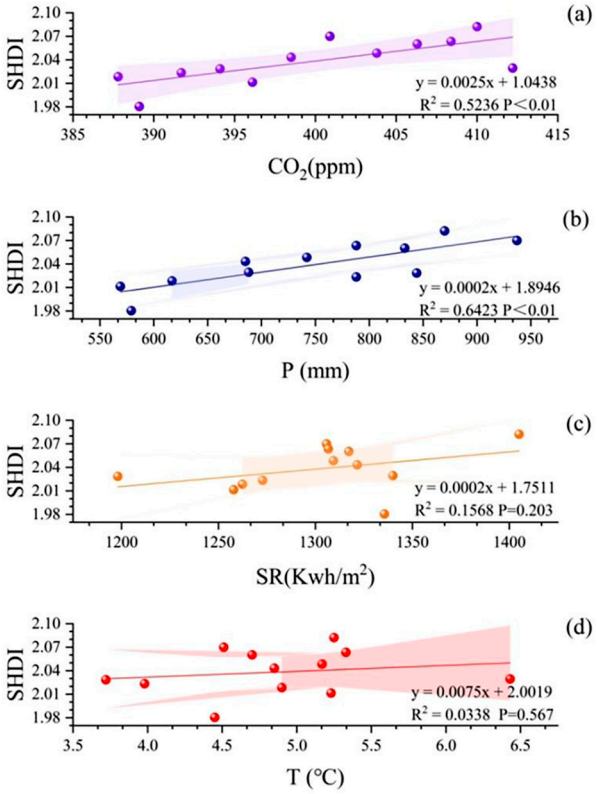


Figure 9. The response of SHDI to climate factors. (**a**) concentration of CO_2; (**b**) precipitation; (**c**) solar radiation; (**d**) temperature.

3.4.4. The Impact of Climate Change on SPLIT

The splitting index is defined as the number of patches in a grid when the total region is divided into parts of equal size [71]. SPLIT can be interpreted as an effective mesh number of a constant mesh size. Based on the scatter plot between SPLIT and climate factors in Figure 10, there was a significant linear relationship between SPLIT and concentrations of carbon dioxide and the amount of precipitation. When concentrations of carbon dioxide in the atmosphere increase by 1 ppm, the SPLIT will increase by 0.2702. The rate of SPLIT changes was 0.0212/mm with the increase in precipitation. However, the changes in the solar radiation and temperature had no statistical effect on the SPLIT.

3.4.5. Partial Correlation Analysis Between Climate Factors and Forest Biodiversity

To clarify the effect of each climate factor on forest biodiversity changes, the partial correlation coefficients were calculated and the results can be found in Table 1. The results indicate that there is a significant relationship between CO_2 concentration, precipitation, solar radiation and average annual temperature and forest biodiversity indices in NEC; precipitation was the first important variable that affected changes in the forest biodiversity, and this result was similar to some previous studies on the impact of climate change on forest ecology. Liu et al. found that there was a significant positive correlation between summer precipitation and forest ecological functions in Northeast China, but the correlation relationship between air temperature and forest service functions is low [72]. Moreover, Ji et al. found that the forest ecosystem is significantly affected by precipitation, followed by solar radiation and temperature; the research also indicated that the influence of meteorological conditions on the ecological characteristics and functions of forests was complicated in Northeast China [73]. CO_2 concentration was the second important meteorological factor that had a significant effect on forest biodiversity. Zhu et al. concluded that the contribution of CO_2 concentration to vegetation growth trend is more significant because the water and heat resources in most forest areas tend to be better and the increase of CO_2

concentration benefited vegetation growth [74]. The effect of solar radiation was located in the third position, and the effect of temperature on forest biodiversity had the minimum influence on forest biodiversity. The rise of temperature promoted the growth of plants in a certain period, but the obvious increase in temperature increases the transpiration and evaporation of water in the forest and affects the growth of vegetation in those forest regions [73]. In general, meteorological conditions have a significant impact on forest ecology in Northeast China, and precipitation is the most important factor, followed by CO_2 concentration, which affects the change in the ecological service function of forests in summer in Northeast China.

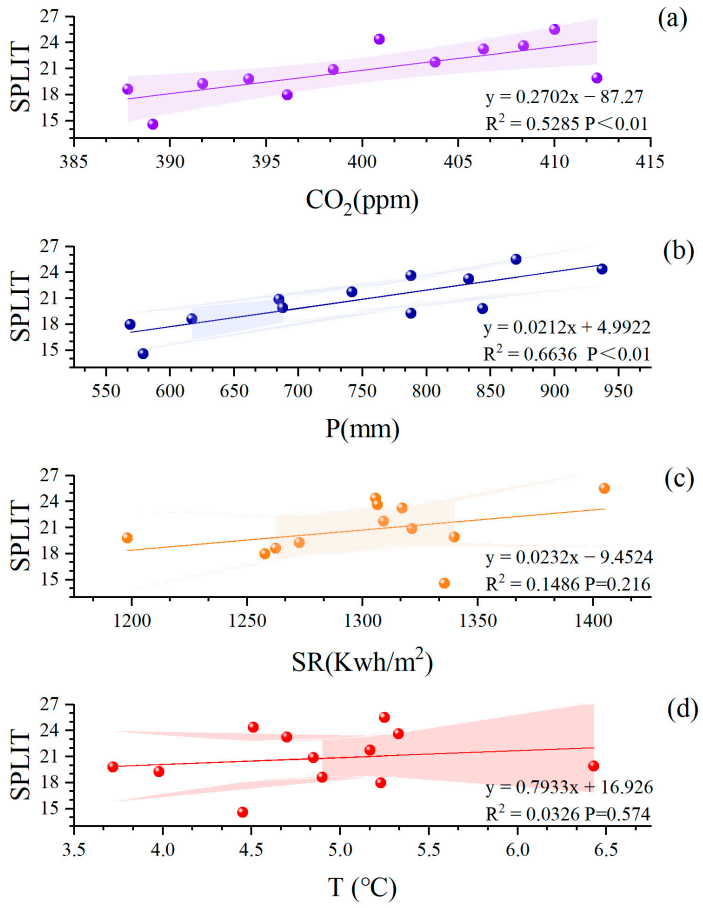


Figure 10. The response of SPLIT to climate factors. (**a**) concentration of CO_2; (**b**) precipitation; (**c**) solar radiation; (**d**) temperature.

Table 1. The partial correlation coefficient between biodiversity indicators and climate factors.

	CO_2	P	SR	T
COHESION	−0.73	−0.809	−0.382	−0.187
NP	0.733	0.791	0.382	0.167
PD	0.715	0.75	0.402	0.186
SHDI	0.724	0.801	0.396	0.184
SPLIT	0.727	0.815	0.385	0.181

Then, a multiple linear regression calculation was performed, and the coefficients of the multiple linear regression coefficients were used to evaluate the sensitivity and contribution of each climate factor on forest biodiversity changes. The value of the coefficient represents the rate of change of the forest biodiversity index under the influence of climatic variables. The results of the study are shown in Figure 11. For CO_2 concentration, the COHESION will decrease by 0.119, NP will increase by 0.399, PD will increase by 0.328, SHDI will

increase by 0.116 and SPLIT will increase by 0.101 when the concentration of CO_2 increases by 1 ppm. If precipitation changes by 1 mm, COHESION will decrease by 0.836, NP will increase by 0.618, PD will increase by 0.617, SHDI will increase by 0.821 and SPLIT will increase by 0.850. When solar radiation increases by 1 Kwh/m^2, COHESION will decrease by 0.053, NP will increase by 0.058, PD will increase by 0.094, SHDI will increase by 0.082 and SPLIT will increase by 0.064. When the temperature increases by 1 °C in NEC, the COHESION will decrease by 0.301, NP will increase by 0.038, PD will increase by 0.085, SHDI will increase by 0.290 and SPLIT will increase by 0.314.

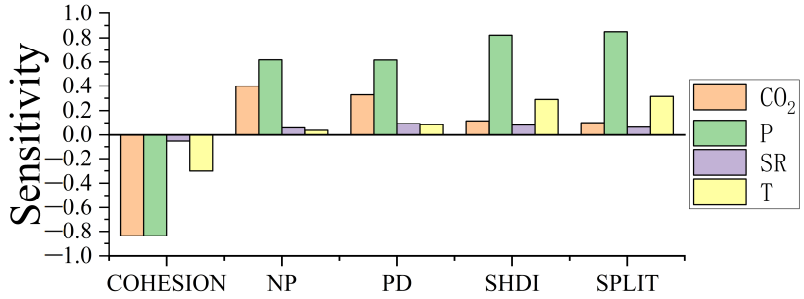


Figure 11. The sensitivity of forest biodiversity in the northeast region to climate change.

3.5. The Response of Biodiversity of Different Forest Types to Climate Change

To reveal the degree of climate change effects on different forest types, the partial correlation coefficients between biodiversity indices of different forest types and climate factors were calculated. In this study, the partial correlation coefficients of three forest types, which were boreal-temperate coniferous forest, temperate coniferous and broad-leaved mixed forest and warm temperate broad-leaved forest, were calculated, and the results can be found in Figure 12.

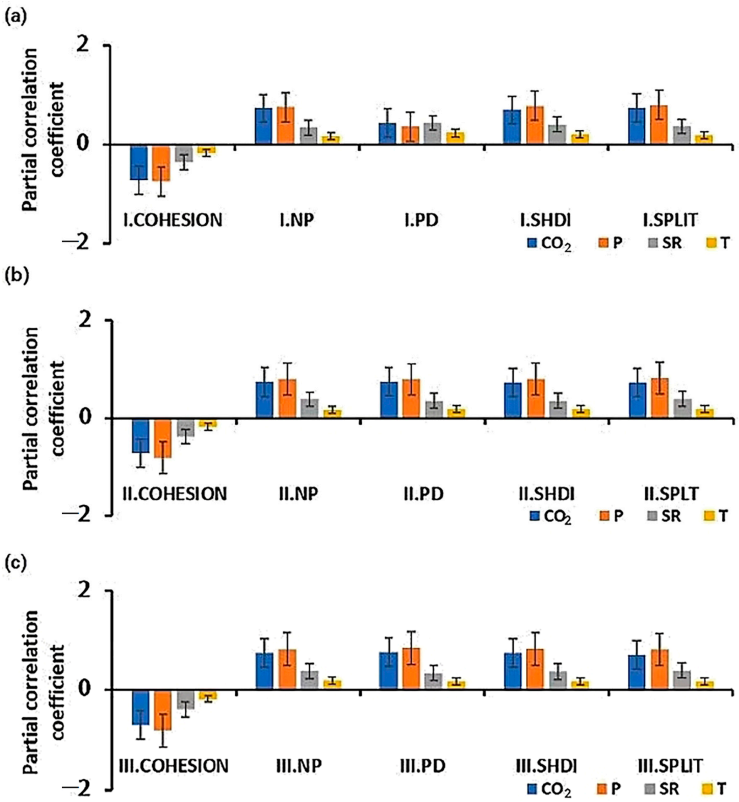


Figure 12. The partial correlation coefficients between biodiversity indicators of different forest types and climate factors (**a**) boreal-temperate coniferous forest (I); (**b**) temperate coniferous and broad-leaved mixed forest (II); (**c**) warm temperate broad-leaved forest (III).

For the boreal-temperate coniferous forest region, the climate factors had a positive effect on NP, PD, SHDI and SPLIT (Figure 12a), as they increased with the increase of climatic factors (Table S2). However, the changes in climate factors had a negative effect on COHESION. Precipitation was the most significant climate factor, followed by CO_2 concentration. Solar radiation and temperature were also important factors. However, an exception here was the index of patch density for the boreal-temperate coniferous forest region, where the first important climate was solar radiation, followed by precipitation, concentration of CO_2 and temperature. Keenan et al. found that climate change promotes vegetation growth in Arctic and boreal forests, which is similar to this research [67].

For temperate coniferous and broad-leaved mixed forest and warm temperate broad-leaved forest regions, the effect of climate factors on forest biodiversity was similar (Figure 12b,c). The climate factors had a positive effect on NP, PD, SHDI and SPLIT, which increased with the increase of climatic factors (Table S3), while there was a negative effect on COHESION (Table S4). The first important climate factor was precipitation, followed by concentration of CO_2, solar radiation and temperature.

The partial correlation coefficient between the forest biodiversity index of different forest types and climate factors is shown in Figure 13. For the boreal-temperate coniferous forest region, the concentration of CO_2 was the first important climate factor and played the most important role in biodiversity. This was followed by solar radiation, precipitation and temperature. For the temperate coniferous and broad-leaved mixed forest and warm temperate broad-leaved forest regions, the most important climate factor was precipitation. The second important climate factor was the concentration of CO_2. Solar radiation and temperature were the third and fourth most important factors.

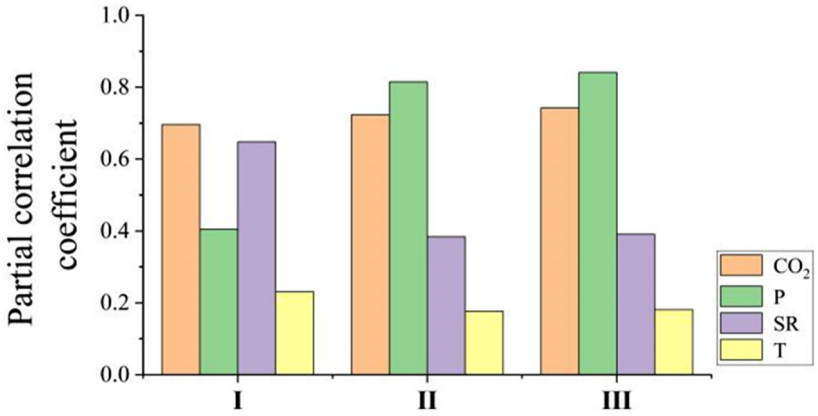


Figure 13. The biodiversity indicators of different vegetation functional types show a partial correlation with concentration of CO_2, precipitation, solar radiation and temperature. I. Cold temperate needle leaf forest region; II. Temperate needle leaf and broad-leaved mixed forest region; III. Warm temperate broad-leaved forest region.

4. Discussion

4.1. The Spatiotemporal Distribution of Forest Biodiversity

In this study, the forest biodiversity in NEC from 2010 to 2021 was calculated and its spatiotemporal distribution features were analyzed using trend analysis. The results showed that the distribution of forest biodiversity in Northeastern China had significant spatial heterogeneity with a gradual increase in biodiversity from west to east. These results were similar to Wang et al. [75]. The main reason may be the spatial heterogeneity of precipitation and temperature. Since precipitation and temperature have a significant effect on the ecological function distribution, they will also affect the vegetation distribution at horizontal and vertical scales. Liang et al. found that there was a significant positive correlation between precipitation and forest ecological functions in Northeast China [76], and the precipitation varied from east to west. Compared to the western part of the research region, the precipitation increased significantly in the Greater and Lesser Xing'an

Mountains in Inner Mongolia and east of Heilongjiang [77]. It is very helpful to vegetation growth. At the same time, compared to the Heilongjiang province, Jilin and Liaoning are significantly warmer. These variations in precipitation and temperature from west to east also promote changes in forest biodiversity. This may account for the gradual increase in biodiversity from west to east.

According to the results of this study, there was an overall increase in forest biodiversity in Northeast China from 2010 to 2021. Compared to the climate factors in those years, it also showed an increasing trend due to climate change. The increase in the climate factors makes vegetation grow fast. Similar results can be found in Lan's research. They found that climate change promoted the growth of mixed forest flora and increased soil microbial abundance and soil nutrients [78]. The improvement of soil condition and increase in its nutrients is also beneficial to vegetation growth. This also contributed to the growth of the vegetation and increase in biodiversity. Sun et al. found that the function of soil and water conservation of the forest region in Northeast China has steadily improved since 2000 and meteorological conditions were important factors affecting the growth of forest vegetation and its service function [79]. The increase in precipitation and temperature increases the versatility of ecosystem service functions such as water conservation, soil conservation, carbon storage, stand productivity and soil fertility maintenance and increase forest biodiversity in Jilin Province, Northeast China [80]. Hence, climate change is a significant driver of increasing forest biodiversity [81]. In addition to these natural reasons, social and economic factors were also contributors to forest growth. As a social and economic factor, the Natural Forest Protection Project and policies related to the conservation of natural resources also played a very important role in contributing to the growth of forests. The forest growth will lead to an increase in forest biodiversity [82]. Meanwhile, biodiversity showed an increasing trend year by year. However, the changing trends of biodiversity varied by the different forest types. One possible reason was that the effect of environmental conditions on the morphology and characteristics of leaves in different forest types were different [83]. The growing rate varied from species to species and the forest biodiversity changing rate also varied.

Meanwhile, the increase in forest biodiversity will have a potential ecological implication. Gao et al. found that increasing biodiversity could enhance the productivity and the spatial stability of the ecosystem simultaneously [84]. The dominant species in the herb layer will increase due to the increasing biodiversity. Additionally, related forest structures, tree diversity, herb richness and evenness for diversity traits will also be altered [85]. Changes in these characteristics will have a profound impact on the regional ecosystem and contribute to the Convention on Biological Diversity (CBD).

4.2. The Climate Response Mechanisms of Forest Biodiversity

Responses of forest biodiversity in NEC to climate change were summarized by using partial correlation coefficient analysis among different forest types. The results indicated that the increase in forest biodiversity benefited from increases in temperature, precipitation, carbon dioxide concentration and solar radiation. Similar results were found by Gao et al. [86]. Because of global climate change, vegetation can grow in cold and humid climates [87]. In the cold temperate zone, the heat was not high and the increase in solar radiation had a significant impact on vegetation growth [67,68]. Furthermore, the fertilization effect of carbon dioxide has a significant impact on the growth of vegetation [73]. In temperate and warm temperate zones, where there are better water and heat resources in forest areas, the growth of forests will be limited by the variation of precipitation and CO_2 concentration in Northeast China. Meanwhile, the increase in temperature and solar radiation will increase water consumption and affect the nutrient production of vegetation [74]. Therefore, there will be different effects of climate factors in different vegetation functional regions. At the same time, the changes in climate factors contributed not only to prolonged vegetation growth but also accelerated soil organic matter decomposition and nutrient release, which will promote the increase of forest biodiversity [88].

In addition, this research indicated that the climatic factors affecting forest biodiversity varied with different forest types. Precipitation and CO_2 concentration were the main drivers of vegetation diversity in the study area, with different effects on different vegetation types. Precipitation and CO_2 concentration were the most important factors with the most significant contribution to forest biodiversity. Zhu et al. found that vegetation growth was sensitive to precipitation in the southwestern United States, southern South American countries and Mongolia [74]. Compared with precipitation and CO_2 concentration, temperature and solar radiation had less contribution to forest biodiversity. For temperate mixed coniferous and broadleaf forest regions and warm temperate broadleaf forest regions, precipitation and CO_2 concentration were the two most important factors affecting forest biodiversity. These results indicated that precipitation was the main factor affecting plant growth [89,90]. In the boreal-temperate coniferous forest region, the concentration of CO_2 was the most important climate factor. The cold temperate coniferous forest region is located at high latitudes and it has a lower temperature condition. The different climate regions showed different forest biodiversity changing trends. This is clear evidence to show the impact of climate factors on forest biodiversity changes. However, global warming promotes vegetation growth and the increase of the concentration of CO_2 has a CO_2 fertilization effect that promotes plant growth [91,92]. Meanwhile, the changes in the climate conditions extend and lengthen the growing season in NEC [93]. Zhu et al.'s results indicated that CO_2 fertilization played a major role in the contribution of the changing trend global leaf area index and suggested that the structure and functioning of forest ecosystems may be more affected by future climate change [74].

4.3. Limitations

In this study, there are still some limitations. First, the meteorological factor only focuses on the temperature, precipitation, concentration of CO_2 and solar radiation in a year's time scale. There is a significant difference in the growth of plants in different months. Besides this, it ignored the impact of extreme climatic events and their delayed effects on vegetation growth. Secondly, the impact of human activities on vegetation has not been considered in this study. This means that further research is needed to add more factors about human activities to clarify the effect on forest biodiversity.

5. Conclusions

In this study, the forest biodiversity distribution in NEC from 2010 to 2021 was mapped and its spatiotemporal distribution features were analyzed using trend analysis. Then, the changing trend of forest biodiversity and its mechanism response to climate change were analyzed. The results showed that forest biodiversity in Northeast China had significant spatial heterogeneity with a gradual increase from west to east. And there was an overall increase in forest biodiversity in Northeast China between 2010 and 2021. But this increasing trend varied with different forest types. The main factors affecting biodiversity were CO_2 concentration and precipitation. The role of climate change in influencing forest biodiversity in Northeast China varies with different forest types. This research indicated that the potential impact of climate change on forest ecosystems was emphasized. It also provided compelling evidence that climate change has a catalytic effect on forest biodiversity in Northeast China.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs16214058/s1, Table S1. The correlation analysis of landscape indices. Table S2. Climate response trend of diversity index of Cold temperate needle leaf forest region. Table S3. Climate response trend of diversity index of Temperate needle leaf and broadleaf mixed forest region. Table S4. Climate response trend of diversity index of Warm temperate broadleaf forest region.

Author Contributions: X.Y. conceived and designed the experiments; L.Y. performed the experiments and analyzed the data; X.Y. and L.Y. wrote the paper; X.Y., Y.M., Y.Y. and Z.W. reviewed and edited the paper. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The MODIS NDVI, Climate data and Land cover data used during this study are openly available from NASA's website (https://search.earthdata.nasa.gov, accessed on 28 October 2024), the U.S. National Oceanic and Atmospheric Administration (NOAA) (https://www.ncei.noaa.gov, accessed on 28 October 2024), respectively, and GLC_FCS30 (http://data.casearth.cn/sdo/detail, accessed on 28 October 2024) and FROM-GLC (https://data-starcloud.pcl.ac.cn/, accessed on 28 October 2024), respectively.

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