Assessment of Forest Carbon Sink Function under the Influence of Compound Dry and Heat Events

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Abstract. With global warming, compound dry and heat events have attracted extensive attention due to their synergistic effects on ecosystems. The forest ecosystem is one of the largest carbon pools in terrestrial ecosystems, which means its carbon sink function is of great significance to maintain the global carbon cycle balance. Taking the unchanged forest in Enshi City of Hubei Province from 2000 to 2022 as the research object, it comprehensively used multi-source remote sensing data and identified compound dry and heat events by calculating SPI and STI, which means the standardized precipitation index and standardized temperature index. Next, the paper chose the improved Carnegie-Ames-Stanford Approach model (which is also called the CASA model) to estimate forest net primary productivity (NPP) to analyze the driving mechanism and lag response characteristics of compound dry and heat events on forest carbon sink changes with the help of the geographical detector (GD). The results showed that three compound dry and heat events in Enshi occurred in July 2011, October 2013, and August 2022, and the response time of forest carbon sequestration was about one month. The drought factor has a stronger effect on forest carbon sink change than the high temperature factor, and the interaction between them shows a significant nonlinear enhancement effect. The results will help to deeply understand how climate change makes impacts on mountain forest ecosystems, and provide a scientific basis for regional forest resource management.

Keywords: Compound dry and heat events, Forest carbon sink, CASA model, Enshi City.

1. Introduction

With the global temperature increasing, the awareness of environmental protection and the quality of remote sensing, climate, and other data have improved; research on small-scale target areas has become a hot topic in current research. At the same time, it should reveal the mechanism of driving factors, especially the dependence and interaction between factors [1]. The 2012 IPCC report pointed out that compound climate events are multiple climate drivers leading to social or environmental risks, and the harm caused by these events is often more severe and lasting than a single extreme climate event on a global scale, in which the frequency of occurrence in China has increased significantly[2,3]. Reading the bibliometric analysis of CiteSpace V, Mazdiyasni et al. summarized the current research focus and methods of compound dry and heat events, the results of which show that although China has a large number of papers, its influence needs to be improved [4]. The impact range of compound dry and heat events in forest areas is expanding because of the trend of global warming, and these events are becoming more and more frequent [5]. Therefore, the analysis of the current research progress of compound events has a guiding role for the future study of forest carbon sink function and coping with the disastrous impact of compound dry and heat events.

Facing the problem that field measurements are highly time-consuming and expensive, while ecological positioning research stations and flux observation towers are small and unevenly distributed, simulating models to estimate net primary productivity (NPP) has become a common method [6]. The CASA (Carnegie-Ames-Stanford Approach) model, as one of the representative process models in the existing NPP estimation models, is widely used to study how carbon cycles through the Earth's ecosystem and estimate the ecological process of vegetation. The key to the CASA model is to simulate the NPP and carbon cycle of vegetation under the combined action of several parameters, including solar radiation (SOL), the fraction of photosynthetically active radiation

(FPAR), water and temperature stress factors, and the maximum utilization rate of light energy [7]. However, the value of 0.389gc/(MJ) is not suitable for China [8].

Therefore, this project used the linear relationship between FPAR and NDVI to improve the accuracy of the CASA model, which can quantify the forest carbon sink function under the influence of compound dry and heat events on the basis of clarifying the distribution and net primary production during the time when drought and high temperature events happened. By comparing the actual impact of drought, high temperature, and their compound events on the forest carbon sink function and its temporal and spatial characteristics in Enshi City, Hubei Province, it aims to deepen the understanding of the climate response mechanism of the mountain forest ecosystem and provide a scientific basis for regional forest resource management.

2. Data and Methods

This study took the unchanged forest in Enshi City of Hubei Province from 2000 to 2022 as the research object, and integrated remote sensing data and climate data as well as land cover data to build a forest carbon sink assessment system.

2.1. Data Sources

The data sources mainly include MODIS MOD13Q1 vegetation index data set and ERA5-LAND surface solar radiation (SSRD) data set, which are downloaded in batches through JavaScript script through Google Earth Engine (GEE) platform, which selected the series of long time data describing normalized difference vegetation index (NDVI) from 2000 to 2022, and constructed the monthly scale NDVI Series in the form of monthly maximum synthesis, which was used to characterize the energy input of vegetation photosynthesis [9]. In addition, China's 1 km monthly precipitation data set and monthly average temperature data set (1901-2024) and China's 30 m annual land cover data set (CLCD) released by the National Qinghai-Tibet Plateau Scientific Data Center are used to identify extreme climate events and extract unchanged forest areas that maintain forest attributes from 2000 to 2022 [10-12].

2.2. Data Preprocessing

In order to convert the original data into a standard format that can be directly input into the NPP calculation model, the ArcGIS ModelBuilder is used to complete the grid clipping, projection conversion, and mask extraction. All kinds of data are unified into the Albert cone equal area projection coordinate system and WGS84 geographical coordinate system, and the nearest neighbor method and bilinear interpolation method are used to resample to 30 m spatial resolution; Then, the modeler and band math tools of ENVI platform are used to unify the data format, row and column numbers and units, in which the units of temperature and precipitation are respectively 1 ℃ and 1 mm. Aiming at the problem of data missing and noise in the MOD13Q1 time series, gap filling (GF) and Savitzky – Golay (SG) filtering methods are used in order to reconstruct the series of long-time NDVI data [13]. In view of the problem that the MOD13Q1 data started in February 2000 and the quality of Landsat and other remote sensing data in January of that year is poor, the MOD13Q1 data in January 2001 is used to replace it, which is based on the seasonality and similarity of the data to ensure the integrity of the data [14].

2.3. Data Processing

In the stage of carbon sink dynamic analysis, extreme drought, high temperature, and compound events were identified by the standardized precipitation index and standardized temperature index; it can call them SPI and STI. The area is defined as the place where the extreme drought events occurred when the value of SPI is under or equal to -1.5 while the area with the value of STI above or equal to 1.5 is defined as the occurrence zone of extreme high temperature events, and the intersection of the

two is taken to determine the space-time interval of compound events (specific to the month), as shown in formula (1) (2) [15].

$$SPI=\frac{X_{pre}-\mu_{pre}}{\sigma_{pre}}. \quad (1)$$

$$STI=\frac{X_{tem}-\mu_{tem}}{\sigma_{tem}}. \quad (2)$$

Where, X_{pre} means the precipitation of the current month, μ_{pre} and σ_{pre} respectively mean the average precipitation and the standard deviation of precipitation of the station. X_{tem} is the average temperature of the current month; μ_{tem} and σ_{tem} respectively mean the average temperature and the standard deviation of the average temperature of the station.

At the same time, the CASA model is used to simulate the monthly net primary productivity (NPP), the vegetation NPP software module V1.0 developed under the IDL software platform was used to process the data, and the Forest NPP was extracted using the unchanged forest screened by CLCD as the mask, as formula (3) [16].

$$NPP(x,t)=APAR(x,t)\times\varepsilon(x,t). \quad (3)$$

The absorbed photosynthetically active radiation (APAR, mj/m2/t) is calculated from the total solar radiation per unit pixel (sol, mj/m ²/t) and the photosynthetically active radiation absorption ratio (FPAR), as in formulas (4) and (5) [17].

$$APAR(x,t)=SOL(x,t)\times FPAR(x,t)\times 0.5 \quad (4)$$

$$\varepsilon(x,t)=\varepsilon_{max}\times T_{scalar}(x,t)\times W_{scalar}(x,t) \quad (5)$$

Where 0.5 is a coefficient, indicating how much effective solar radiation is available to vegetation. The light energy use efficiency (ε) is corrected by high temperature stress (T_{scalar}) and water stress (W_{scalar}), ε_{max} is the maximum efficiency of vegetation using light energy.

The monthly vegetation NPP change (VNPP) was further calculated as an indicator of forest carbon sink change, and the attribute values of SPI, STI, and VNPP were extracted from 750 m grid samples. The explanatory power of SPI and STI on VNPP (q value, value range from 0 to 1; greater explanatory power means a larger q value, which indicates the impact is stronger) and interaction were quantitatively analyzed by the geographical detector(GD), as formulas (6), (7), and (8) [18].

$$VNPP_0=NPP_i-NPP_{i-1} \quad (6)$$

$$VNPP_m=NPP_{i+m}-NPP_i \quad (7)$$

$$NPP_C=\sum_{A=i}^{i+n} NPP_A - \sum_{B=i}^{i+n} NPP_B \quad (8)$$

3. Results and Discussion

3.1. Characteristics of Compound Dry and Heat Events

As shown in Fig. 1, 30956 effective analysis grids were obtained in the unchanged forest area of Enshi from 12000 to 2022, accounting for a high proportion of the area.

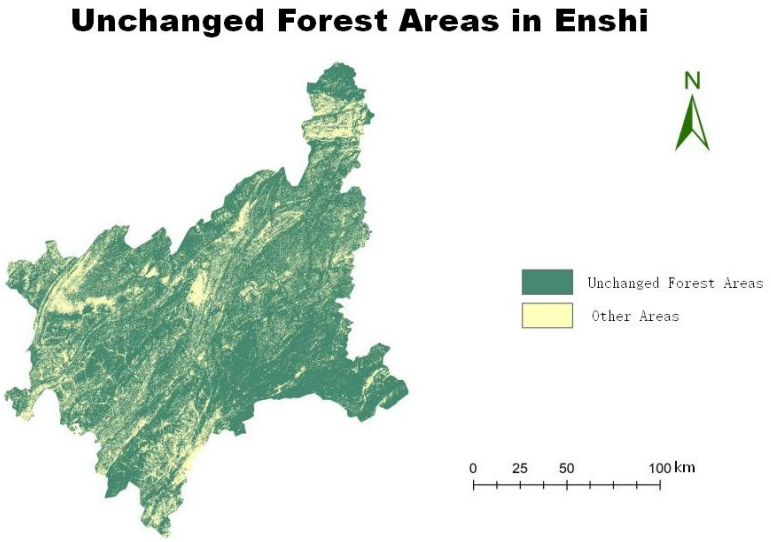


Fig. 1 The structure of unchanged forest areas in Enshi City, Hubei Province (Photo credit: Original)

Based on the joint identification results of SPI and STI, three typical compound dry and heat events were detected, which occurred in July 2011, October 2013, and August 2022, respectively. As shown in Fig. 2, roughly according to the conclusion of research on the increase in extreme high-temperature events, the compound dry and heat events are intermittent, but recently the frequency and intensity of occurrence have increased, generally speaking.

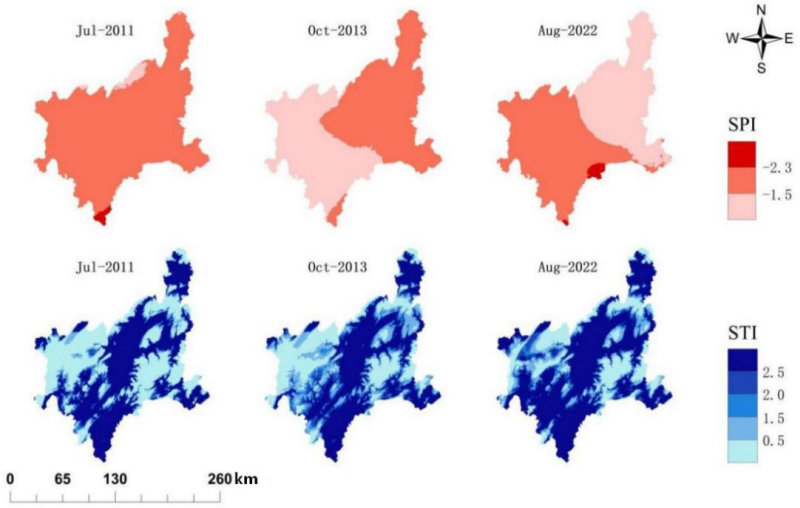


Fig. 2 The structure of time periods of compound dry and heat events in Enshi city from 2000 to 2022 (Photo credit: Original)

3.2. Response Characteristics of Forest Carbon Sink

The results of NPP change analysis showed that the forest carbon sink in Enshi had obvious lag response characteristics to the compound dry heat event. The geographical detector analysis shows that, according to Table 1, the q value of the compound events on forest carbon sink changes reaches the maximum value (q=0.300) one month after the occurrence of the compound dry heat event. This phenomenon shows that the forest ecosystem has a certain buffer capacity, and the extreme climate impact often needs to go through the vegetation physiological process and ecological feedback process before it can be fully revealed.

In the aspect of single-factor effect, the average explanatory power of the drought factor is 0.151, which is higher than that of the high temperature factor (0.072), indicating that water condition is the key factor limiting the function of forest carbon sink in Enshi City. Enshi has a large topographic relief, a thin soil layer in some areas, and limited water storage capacity. When the precipitation

continues to decrease, the water absorption capacity of vegetation roots decreases, leading to the weakening of photosynthesis and the decline of NPP.

Table 1. Optimal response time of Enshi compound dry and heat event from 2000 to 2022

q	No lag	lag 1 month	lag 2 months	Lag 3 months
$q_{drought}$	0.151	0.130	0.138	0.167
q_{heat}	0.072	0.162	0.102	0.094
$q_{drought \cap heat}$	0.242	0.300	0.276	0.279

3.3. Interaction Analysis of Compound Dry and Heat Events

Interactive detection showed the result that the q value, which means explanatory power, of drought and high temperature interaction reached 0.242. It was significantly higher than that of single-factor interaction. As shown in Table 2, the three typical events in 2011, 2013 and 2022 showed a nonlinear enhancement effect, and the interaction intensity reached 0.233, 0.207 and 0.382, respectively.

This nonlinear enhancement mechanism shows that high temperature not only directly affects the physiological activities of vegetation, but also further aggravates the degree of drought by enhancing transpiration and soil evaporation, thereby amplifying the stress effect on the ecosystem. When soil water content continued to decrease, vegetation stomata closed, photosynthesis was inhibited, leading to a significant decline in carbon fixation capacity. Therefore, the impact of combined dry heat events on forest carbon sink function is far greater than that of single drought or high temperature events.

Table 2. Compound dry and heat events' interaction law on carbon dynamics in Enshi

Year/month	2011/04	2013/10	2022/08
Interaction strength	0.233	0.207	0.382
Interactive mode: D∩H (D—Dry H—Heat)		presentation: nonlinear enhancement	

3.4. Research Deficiencies and Prospects

This study based on Remote Sensing Inversion and meteorological data analysis, can better reveal the regional-scale forest carbon sink change law, but there are still some limitations. The parameters of the CASA model have certain regional adaptability differences, and this study mainly considers the factors of temperature and precipitation, and has not yet taken into account potential factors such as soil moisture, evapotranspiration, and topographic factors, which may lead to some mistakes when estimating NPP [19]. In addition, the model results still need to be further verified because long-term field observation data remain required and need to be further developed. Future research can combine high-resolution remote sensing data, flux observation tower data, and machine learning methods to improve the accuracy of forest carbon sink assessment, and further explore the response differences of different forest types to compound extreme climate events [20].

4. Conclusion

Based on data of multi-source remote sensing and meteorological data from 2000 to 2022, this study evaluated the response characteristics of unchanged forest carbon sink function to extreme drought, high temperature, and compound events of them in Enshi City, Hubei Province, by using standardized index, improved CASA model, and geographical detector (GD). During the study period, three typical compound dry and heat events (occurred in July 2011, October 2013, and August 2022) were identified. The events occurred intermittently but with an increasing frequency, which was consistent with the frequent occurrence of extreme high temperatures under the background of global warming. The response of the forest carbon sink to the compound dry heat event has a significant lag effect. The geographical detector (GD) shows that one month after the event, the explanatory power of drought as well as high temperature factors on the change of forest net primary productivity (NPP) reaches the peak (q=0.300), indicating that the optimal lag response time is about one month, which

reflects that the forest ecosystem has a certain buffer capacity, and the extreme climate impact needs to be fully reflected through the process of vegetation physiological and ecological feedback.

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