Post-Imprint of China's GPP Changes During Typical Drought Years from 1982 to 2017

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Abstract

The reduction in Gross Primary Productivity (GPP) caused by drought has significant impacts on the terrestrial carbon sink. Based on the Standardized Precipitation Evapotranspiration Index (SPEI) calculated from monthly meteorological data at 618 stations nationwide and two publicly available GPP datasets (EC-LUE GPP and GLASS GPP), this study systematically analyzed the variations in GPP during typical drought years from 1982 to 2017 in China under different drought intensities across various temporal scales. The results indicate that: (1) Using five selected SPEI-based indicators, the typical drought years from 1982 to 2017 were identified as 2001 and 2011. (2) At annual and seasonal scales, regions where GPP was severely affected by drought in 2001 were mainly located in North China, Northeast China, and the northern parts of central-eastern regions, while in 2011 they were concentrated in the southeastern part of Southwest China and the central-eastern regions. At the monthly scale, GPP in May 2001 was most severely impacted by drought, primarily concentrated in most areas of North China and Northeast China. GPP in January 2011 was most severely affected by drought, mainly concentrated in most areas of the central-eastern regions. (3) Whether at annual, seasonal, or monthly scales, as drought severity increased, the decline rate of GPP became greater, with extreme drought having the greatest impact. From a seasonal perspective, extreme drought in summer 2001 caused GPP decline rates of 19.96% (EC-LUE GPP) and 15.57% (GLASS GPP), respectively; extreme drought in spring 2011 caused GPP decline rates of 14.32% (EC-LUE GPP) and 8.75% (GLASS GPP), respectively. The research findings can further enhance understanding of the impacts of different drought intensities on GPP across various temporal scales and are of significant importance for understanding carbon exchange between terrestrial ecosystems and the atmosphere under drought conditions.

Full Text

Changes in China's Gross Primary Productivity During Typical Drought Years from 1982 to 2017

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Abstract

Drought-induced reductions in gross primary productivity (GPP) can significantly impact the terrestrial carbon sink. Based on the Standardized Precipitation Evapotranspiration Index (SPEI) calculated from monthly meteorological data at 618 stations nationwide, and two publicly available GPP datasets (EC-LUE GPP and GLASS GPP), this study systematically analyzed changes in GPP affected by drought at different temporal scales during typical drought years from 1982 to 2017. The results revealed: (1) Based on five selected SPEI indicators, the years 2001 and 2011 were identified as typical drought years during the 1982–2017 period. (2) On annual and seasonal scales, drought-affected GPP in 2001 occurred mainly in North China, Northeast China, and the northern part of central-eastern China, while in 2011 it was concentrated in the southeastern part of Southwest China and central-eastern China. On the monthly scale, GPP in May 2001 was most severely affected by drought, concentrated primarily in most areas of North China and Northeast China; whereas in January 2011, severe impacts were concentrated in most areas of central-eastern China. (3) Regardless of whether examining annual, seasonal, or monthly scales, the decline rate of GPP increased with drought severity, with extreme drought having the greatest impact. For instance, on the seasonal scale, extreme drought in summer 2001 caused GPP declines of 19.96% (EC-LUE GPP) and 15.57% (GLASS GPP), while extreme drought in spring 2011 caused declines of 14.32% (EC-LUE GPP) and 8.75% (GLASS GPP). These findings deepen our understanding of how different drought intensities affect GPP across various temporal scales, which is crucial for comprehending carbon exchange between land and atmosphere under drought conditions.

Keywords: typical drought; standardized precipitation evapotranspiration index; gross primary productivity; China

Introduction

Drought is a weather-related natural phenomenon that can cause severe environmental, social, and economic consequences worldwide. It is also considered a potential natural disaster that ranks first among all natural disasters in terms of the number of people affected. Drought can strongly influence carbon exchange between land and atmosphere, as terrestrial ecosystems provide a substantial carbon sink that plays an irreplaceable role in mitigating increasing CO_2 concentrations and global warming. Climate change projections indicate that drought frequency and intensity will increase in the mid-to-late 21st century. Drought alters terrestrial carbon cycling by affecting ecosystem composition, structure, and function. Under extreme climate conditions, intensified drought and heatwaves may alter terrestrial ecosystem structure or function beyond typical or normal variability ranges. When plants' drought resistance measures (such as stomatal closure) are constrained by hydraulic limitations or further stress, ecosystem function loss caused by extreme drought may occur. During extreme drought, loss of ecosystem function can shift ecosystems from carbon sinks to carbon sources.

Terrestrial gross primary productivity (GPP), defined as the total amount of carbon fixed by vegetation through photosynthesis, reflects the productivity level of terrestrial ecosystems and represents the starting point of carbon cycling. However, drought severity and frequency significantly affect GPP dynamics. In recent years, drought-induced declines in global terrestrial ecosystem productivity have become more frequent. For example, droughts in the Amazon region and Europe during 2005 and 2010 reduced global net primary productivity by 0.65 Pg C, and a severe heatwave and drought in Europe in 2003 reduced productivity across the continent. Therefore, quantitatively studying the impacts of major droughts on terrestrial ecosystems is essential for understanding carbon cycle dynamics.

Drought indices provide the most intuitive and straightforward metrics for drought assessment, converting data from one or several variables (such as temperature, precipitation, and potential evapotranspiration) into single values that describe drought severity, onset, and duration. Common indices include the Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI), and Standardized Precipitation Evapotranspiration Index (SPEI). PDSI depends heavily on soil water balance and may fail to capture monthly-scale drought due to its long-term memory of previous climate conditions, making it less sensitive to drought recovery. SPI is based solely on precipitation anomalies. SPEI, which incorporates relevant evapotranspiration variables, offers greater temporal flexibility and is therefore more widely used.

GPP estimation methods mainly include biomass surveys, eddy covariance techniques, and model simulations. Model simulation offers advantages for large-area, long-term GPP estimation. Numerous satellite-based models have been used to estimate regional and global GPP, primarily falling into three categories: light use efficiency models based on radiation transfer theory, machine learning models, and models based on vegetation photosynthesis biophysical processes. However, studies have found significant spatiotemporal differences among GPP datasets from different models due to variations in input data, model parameters, and structures. Among all model approaches, light use efficiency models show the most potential for adequately addressing GPP spatiotemporal dynamics. To avoid analytical discrepancies, many studies employ multiple GPP datasets for comparative analysis. For instance, Du et al. found that EC-LUE GPP and GLASS GPP showed consistent spatial distribution patterns of temporal trends in China from 1982 to 2017, while Tong et al. compared GPP assessed through different methods (EC-LUE, MODIS GPP, and ground measurements), revealing certain differences among approaches.

Based on this background, this study uses EC-LUE GPP and GLASS GPP datasets to quantitatively investigate changes in GPP affected by different drought grades across various temporal scales during typical drought years from 1982 to 2017.

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1. Data and Methods

1.1.1 GPP Data Two GPP datasets were used. The first is the EC-LUE GPP dataset simulated by a modified light use efficiency model, providing global GPP data from 1982 to 2017 at 0.05° resolution and multiple temporal scales. This dataset is available at https://doi.org/10.6084/m9.figshare.8942336.v3. The second is the GLASS GPP dataset generated using a Bayesian multi-algorithm ensemble method, sourced from the National Earth System Science Data Sharing Platform (http://www.geodata.cn) with 0.05° spatial resolution.

1.1.2 Drought Data Monthly meteorological data from 756 stations across China were collected from the National Climate Center, including precipitation, temperature, maximum and minimum temperatures, wind speed, relative humidity, and sunshine hours. To meet SPEI calculation requirements without missing data, 618 stations were selected to calculate and analyze SPEI values at different temporal scales (monthly, seasonal, and annual). Point data were converted to gridded data using inverse distance weighting interpolation. SPEI-1, SPEI-3, and SPEI-12 represent monthly, 3-month, and 12-month scales, respectively. Potential evapotranspiration was calculated using the Penman-Monteith model. The difference between monthly precipitation and potential evapotranspiration was computed to establish water balance accumulation sequences at different time scales. After standardizing the cumulative probability density using a probability distribution function, corresponding SPEI values were obtained. According to the "Meteorological Drought Grades" standard issued by the China Meteorological Administration, SPEI values were classified into different drought grades .

TABLE:1 Drought classification of SPEI

SPEI Value Range	Drought Grade
-0.5 to -1.0	Mild drought
-1.0 to -1.5	Moderate drought
-1.5 to -2.0	Severe drought
$\leq$ -2.0	Extreme drought

Note: SPEI is the Standardized Precipitation Evapotranspiration Index, with drought grades classified according to SPEI value ranges. The same applies below.

1.2 Research Methods The quantitative method for assessing drought impact on GPP involves comparing long-term average GPP in normal years with GPP in drought years to evaluate drought effects:

$$\Delta GPP = GPP_{dmod} - GPP_{amod} = GPP_{dmod} - \frac{1}{n}\sum_{i=1}^{n} GPP_i$$

where ΔGPP represents the GPP anomaly caused by drought (which can be positive or negative), GPP_{amod} is the multi-year average simulated GPP for normal years, GPP_{dmod} is the simulated GPP for drought years, GPP_i is the simulated GPP for the i-th normal year, and n is the number of normal years.

2. Results

2.1 Temporal Variation Characteristics of SPEI in China Based on the five selected indicators (percentage of stations experiencing drought, etc.), the typical drought years during 1982–2017 were identified as 2001 and 2011. As shown in , analysis of SPEI values calculated from 618 stations revealed that the years with the maximum percentage of drought-affected stations were 2001 (47.4%) and 2011 (47.7%). The percentage of stations experiencing mild drought exceeded 40% in 2001 (48.9%) and 2011 (48.1%). Only 2001 had moderate drought affecting over 20% of stations (20.6%). Years with severe drought affecting over 10% of stations were 2001 (10.8%) and 2011 (13.3%). These indicator-based results demonstrate that 2001 and 2011 were the primary typical drought years.

TABLE:2 Results of years with more severe drought selected from 1982 to 2017

Indicator	2001	2011
Maximum percentage of stations with drought	47.4%	47.7%

Indicator	2001	2011
Percentage of stations with mild drought >40%	48.9%	48.1%
Percentage of stations with moderate drought >20%	20.6%	-
Percentage of stations with severe drought >10%	10.8%	13.3%
Percentage of stations with extreme drought >5%	10.0%	10.0%

2.2 Quantitative Assessment of Drought Impact on Annual GPP Using EC-LUE GPP and GLASS GPP datasets, we analyzed the spatial distribution of different drought grades in typical drought years (2001 and 2011) at the annual scale [Figure 2: see original paper]. In 2001, drought occurred mainly in North China, Northeast China, and the northern part of central-eastern China. Areas where GLASS GPP decreased were primarily located in North China, Northeast China, and the northern part of central-eastern China. In 2011, drought occurred mainly in the southeastern part of Southwest China and central-eastern China. Areas where GLASS GPP decreased appeared mainly in the southeastern part of Southwest China and central-eastern China.

FIGURE:2 Spatial distributions of different levels of drought in typical drought years based on SPEI

The spatial distribution of annual GPP changes affected by drought in typical drought years is shown in [Figure 3: see original paper]. presents the proportion of annual GPP affected by different drought grades. Both datasets show that extreme drought caused the largest GPP loss, followed by severe drought, moderate drought, and mild drought, indicating that GPP damage increases with drought intensity.

FIGURE:3 Distributions of annual GPP changes affected by drought in typical drought years

TABLE:3 Proportion of the annual GPP affected by different levels of drought in the typical drought years

Drought Grade	EC-LUE GPP Loss	GLASS GPP Loss
Mild drought	7.09%	6.87%
Moderate drought	10.12%	7.00%
Severe drought	14.04%	7.33%
Extreme drought	21.77%	9.69%

2.3 Quantitative Assessment of Drought Impact on Seasonal GPP Using EC-LUE GPP and GLASS GPP datasets, we compared the impacts of different seasonal drought grades in typical drought years (2001 and 2011) on corresponding seasonal GPP [FIGURE:4-7]. In 2001, spring drought occurred mainly in central-southern North China, southwestern Northeast China, and central-eastern China. Areas where GLASS GPP decreased appeared mainly in northern China. Summer drought occurred primarily in North China, central-northern Northeast China, northern central-eastern China, and central-eastern Northwest China, with GPP decreases mainly in North China, Northeast China, and northern central-eastern China. Autumn drought occurred mainly in central-eastern North China, Northeast China, and north-central central-eastern China, with GPP decreases primarily in North China, Northeast China, and central-eastern China.

FIGURE:4 Spatial distributions of different levels of seasonal drought in typical drought years based on SPEI (2001)

FIGURE:5 Distributions of seasonal GPP changes affected by drought in 2001

As shown in , different drought grades caused greater proportional losses to summer GPP. In 2001, mild, moderate, severe, and extreme drought caused GLASS GPP losses of 10.17%, 13.47%, 18.61%, and 19.96%, respectively, and EC-LUE GPP losses of 10.15%, 11.89%, 12.66%, and 15.57%, respectively. Both datasets indicate that the 2001 drought caused the most severe GPP losses in summer, followed by autumn and then spring, suggesting that northern regions experienced greater drought impacts during summer.

TABLE:4 Proportion of the seasonal GPP affected by different levels of drought in the typical drought years

Season	Drought Grade	EC-LUE GPP Loss	GLASS GPP Loss
Spring 2001	Extreme drought	14.32%	8.75%
Summer 2001	Extreme drought	15.57%	19.96%
Autumn 2001	Extreme drought	9.25%	7.25%
Spring 2011	Extreme drought	13.23%	8.28%
Summer 2011	Extreme drought	8.98%	7.16%
Autumn 2011	Extreme drought	8.75%	6.72%

In 2011, spring drought occurred mainly in the eastern part of Southwest China and central-eastern China, with GPP decreases appearing in these same regions. Summer drought occurred in central-eastern Southwest China and central-eastern China, with GPP decreases in the northern part of North China and southern China. Autumn drought occurred in central Southwest China, eastern North China, and Northeast China, with GPP decreases in eastern Southwest China and central-eastern China. Different drought grades caused greater proportional losses to spring GPP. In 2011, mild, moderate, severe, and extreme drought caused EC-LUE GPP losses of 12.31%, 13.23%, 14.32%, and 9.41%, respectively, and GLASS GPP losses of 7.25%, 8.98%, 8.28%, and 8.75%, respectively. The 2011 drought caused the most severe GPP losses in spring, followed by summer and then autumn, indicating that southern regions experienced greater drought impacts during spring.

FIGURE:6 Spatial distributions of different levels of seasonal drought in typical drought years based on SPEI (2011)

FIGURE:7 Distributions of seasonal GPP changes affected by drought in 2011

2.4 Quantitative Assessment of Drought Impact on Monthly GPP

Using EC-LUE GPP and GLASS GPP datasets, we compared monthly drought grades in typical drought years (2001 and 2011) with corresponding monthly GPP impacts. In 2001, monthly drought was not obvious from January to March. The drought area expanded in April, mainly in western North China. GPP decline occurred mainly in April in central-southern and eastern China, and in May in Northeast and Northwest China. The drought in May affected an extremely wide area with mostly severe drought, involving North China, Northeast China, Northwest China, and central-eastern China. GPP decline occurred mainly in May in Northeast and North China, while Southwest China was minimally affected. The timing and regions of drought occurrence were basically consistent with GPP decline patterns.

FIGURE:8 Spatial distributions of different levels of monthly drought based on SPEI-1 in 2001

FIGURE:9 Average changes in GPP affected by drought in different regions in each month of 2001

As shown in , different drought grades had the greatest impact on GPP mainly from May to July 2001. In these months, mild, moderate, severe, and extreme drought all caused GPP reductions. The most severe impact occurred in May, when mild, moderate, severe, and extreme drought caused GLASS GPP losses of 18.80%, 22.54%, 22.91%, and 22.74%, respectively, and EC-LUE GPP losses of 15.63%, 15.17%, 22.10%, and 15.43%, respectively. The most severely affected regions were mainly most parts of North China and Northeast China.

TABLE:5 Proportion of the monthly GPP affected by different levels of drought in 2001

Month	Drought Grade	EC-LUE GPP Loss	GLASS GPP Loss
May	Mild drought	15.63%	18.80%
May	Moderate drought	15.17%	22.54%
May	Severe drought	22.10%	22.91%
May	Extreme drought	15.43%	22.74%

In 2011, severe drought began appearing in southern North China and northern central-eastern China in January. February drought occurred mainly in central-eastern China, with some alleviation in March, though drought remained in central-eastern China in April. From May to July, drought spread to other regions, gradually shifting to central-southern Southwest China with decreasing intensity. During this period, the May drought affected an extremely wide area with severe intensity. [Figure 10: see original paper] shows that GPP decline in Northeast China occurred in May, while Northwest China experienced decline in June, and central-southern and eastern China in July. Southwest China showed minimal impact. The timing and regions of drought were consistent with GPP decline patterns.

FIGURE:10 Spatial distributions of different levels of monthly drought based on SPEI-1 in 2011

FIGURE:11 Average changes in GPP affected by drought in different regions in each month of 2011

As shown in , different drought grades had the greatest impact on GPP mainly from May to July 2011. In these months, all drought grades caused GPP reductions. The most severe impact occurred in May, when mild, moderate, severe, and extreme drought caused GLASS GPP losses of 48.46%, 86.29%, 86.68%, and 97.91%, respectively, and EC-LUE GPP losses of 51.16%, 91.99%, 91.86%, and 97.89%, respectively. The most severely affected regions were mainly most parts of central-eastern China.

TABLE:6 Proportion of the monthly GPP affected by different levels of drought in 2011

Month	Drought Grade	EC-LUE GPP Loss	GLASS GPP Loss
May	Mild drought	51.16%	48.46%
May	Moderate drought	91.99%	86.29%
May	Severe drought	91.86%	86.68%
May	Extreme drought	97.89%	97.91%

3. Discussion

This study aimed to use different GPP datasets to investigate drought impacts on GPP. The results show that drought damage to GPP becomes increasingly severe with drought intensity. Studies on drought impacts on grassland net primary productivity also indicate that GPP decreases significantly with increasing drought intensity. However, GPP does not always decrease under drought across different years and temporal scales, possibly due to simulation errors in GPP models and differences in vegetation drought resistance across regions where different drought grades occur. Research shows that different vegetation types have varying drought resistance capacities. For example, North China belongs to semi-arid regions with certain drought tolerance, while Northeast China shows lagged responses to climate change, resulting in delayed drought impacts.

The most severely affected season was summer (July) in 2001, with extreme drought impacts concentrated in the northern part of central-eastern China, most of North China, and parts of Northeast China. In contrast, the most severely affected season was spring (May) in 2011, with impacts concentrated in most areas of central-eastern China. This may be because central-eastern China belongs to subtropical regions with evergreen vegetation, diverse plant types, and good growing conditions that are vulnerable under extreme conditions. The poor growing environment in winter makes vegetation more susceptible to damage when climate changes dramatically, resulting in greater losses in May.

This study only considered drought as a single factor without examining interactions between drought and other factors or their combined effects on GPP. However, in nature, many abiotic and biotic factors modify drought-ecosystem relationships through complex mechanisms. For example, air temperature changes and land use alterations can enhance or reduce GPP responses in different vegetation types. Different climate conditions, vegetation types, and phenological stages across regions create uncertainties in GPP data simulation results.

Both GPP datasets are simulated by light use efficiency models. While our results show consistent basic patterns between the two datasets, substantial differences remain in spatial distribution and magnitude. This may result from different model selections, parameter variations, and errors from multiple algorithms. The GLASS GPP simulation integrates widely used light use efficiency models and multiple algorithms to reduce uncertainty from single algorithms and ensure product accuracy and quality. However, this simulation uses remote sensing and meteorological data alongside eddy covariance flux station data, and ground-based and satellite data have spatial scale differences. For instance, C4 crops have stronger photosynthetic capacity than C3 crops, but the algorithm does not differentiate their potential photosynthesis, and mixed-pixel problems can bias GLASS GPP estimates. These factors contribute to GPP simulation uncertainties.

Due to drought complexity, no single index can describe all spatiotemporal characteristics of different drought types applicable to all regions and impact assessments. Different indices may produce different results for the same drought event. This study used only SPEI to characterize drought, though multiple indices exist with respective advantages and disadvantages. Using multiple indices could reduce drought assessment uncertainties. For example, Zhang et al. found that SPEI and PDSI showed consistent drying trends across China, except in the Tibetan Plateau alpine vegetation region, though they differed in distribution areas and extent. Lei et al. used four drought indices to study global GPP responses, finding significant regional differences in responses. Therefore, using multiple drought indices could provide more comprehensive understanding.

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4. Conclusions

1) On annual and seasonal scales, drought-affected GPP in 2001 occurred mainly in North China, Northeast China, and the northern part of central-

eastern China, while in 2011 it was concentrated in the southeastern part of Southwest China and central-eastern China. On the monthly scale, GPP in May 2001 was most severely affected, concentrated in most areas of North China and Northeast China, whereas in January 2011, impacts were concentrated in most areas of central-eastern China.

2) Regardless of annual, seasonal, or monthly scales, the GPP decline rate increased with drought severity, with extreme drought having the greatest impact. On the seasonal scale, extreme drought in summer 2001 caused GPP declines of 19.96% (EC-LUE GPP) and 15.57% (GLASS GPP), while extreme drought in spring 2011 caused declines of 14.32% (EC-LUE GPP) and 8.75% (GLASS GPP).

3) The results deepen understanding of how different drought grades affect GPP across various temporal scales, which is crucial for comprehending carbon exchange between land and atmosphere under drought conditions.

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Note: Figure translations are in progress. See original paper for figures.