

Article

Responses of Terrestrial GPP to Extreme Compound Heatwave and Drought Events of Different Intensities in the Yangtze River Basin

Jiawen Zhu ^{1,2}, Haokun Guo ¹ and Yankun Sun ^{1,*} 

¹ College of Resources and Environment, Northeast Agricultural University, Harbin 150030, China; zhujw@mail.iap.ac.cn (J.Z.)

² Key Laboratory of Earth System Numerical Modeling and Application, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China

* Correspondence: sunyankun@neau.edu.cn

Abstract: In 2022, a record-breaking extreme compound heatwave–drought (CHD) event occurred in China’s Yangtze River Basin (YRB), which significantly reduced terrestrial ecosystem Gross Primary Production (GPP), as many previous studies have shown. However, it remains uncertain how GPP responds to extreme CHD events of varying intensities, as well as the differences in GPP responses among different vegetation types in the YRB. This study used two independent GPP products (GPP_{GOSIF} and GPP_{FluxSat}) and Enhanced Vegetation Index (EVI_{MODIS}) data to investigate these uncertainties during three identified CHD years: 2003, 2013, and 2022. In 2022, when the CHD event intensity was the strongest, the YRB experienced the most significant GPP reductions, with amplitudes of $-0.37 \text{ gC m}^{-2} \text{ day}^{-1}$ (-3.05 standard deviation, hereafter STD) and $-0.57 \text{ gC m}^{-2} \text{ day}^{-1}$ (-5.97 STD) for GPP_{GOSIF} and GPP_{FluxSat}, respectively. In the less intense years, the year 2003 had less than one-third of GPP reductions in 2022, while the year 2013 even showed an overall slight GPP increase. Moreover, the year 2022 also showed the widest extent with significant GPP reductions exceeding one STD, which was more than twice the grid points in 2003 and 2013. This study also revealed significant differences in GPP responses across different vegetation types. In 2022, GPP reductions were the most pronounced in shrub-dominated areas, followed by evergreen forests, while deciduous forests and mixed forests experienced relatively smaller decreases. However, there were no significant differences among vegetation types in 2003 and 2013. These findings enhance our understanding of the variability in the GPP responses to extreme CHD events of varying intensities in the YRB terrestrial ecosystems, and this enhancement provides an important scientific basis for optimizing related vegetation and carbon cycle models.



Academic Editors: Xuejia Wang, Tinghai Ou and Wenxin Zhang

Received: 27 December 2024

Revised: 21 February 2025

Accepted: 26 February 2025

Published: 27 February 2025

Citation: Zhu, J.; Guo, H.; Sun, Y. Responses of Terrestrial GPP to Extreme Compound Heatwave and Drought Events of Different Intensities in the Yangtze River Basin. *Remote Sens.* **2025**, *17*, 848. <https://doi.org/10.3390/rs17050848>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: extreme compound climate event; terrestrial GPP; the Yangtze River Basin

1. Introduction

A compound heatwave–drought (CHD) event refers to the extreme climatic phenomenon when heatwaves and droughts occur simultaneously. Extreme CHD events have become increasingly frequent and severe with the global climate change [1,2], and this phenomenon is projected to continue in the future [3–5]. An extreme CHD event can cause greater damages than an individual extreme event does [6–8], leading to intensified effects on natural and socioeconomic systems [9–11]. For example, the risk of the reduction in terrestrial photosynthesis under CHD conditions can increase by 8–9% in comparison to individual dry conditions, and the risk is even enhanced by 25–42% compared to individual

hot conditions [8]. Gross primary production (GPP), the photosynthetic activity of terrestrial ecosystems, is a key component of the carbon cycle and is highly responsive to extreme climatic conditions [12–15]. Understanding how GPP responds to CHD events is crucial for assessing the resilience of terrestrial ecosystems to these intensifying climate challenges.

Numerous studies have investigated the effects of CHD events on GPP and explored the underlying mechanisms. In response to soil moisture deficit caused by drought, plants typically adopt a strategy of reducing stomatal conductance to minimize water loss [16]. However, this adaptive mechanism simultaneously inhibits carbon dioxide absorption, thereby weakening photosynthesis [17]. Prolonged drought can affect aboveground carbon allocation, such as reducing leaf area index, which further decreases GPP [18,19]. On the other hand, heatwaves not only can reduce photosynthetic capacity by directly damaging plant tissues but also can further suppress carbon fixation by significantly increasing evapotranspiration rates and exacerbating water stress [12,20]. Additionally, the simultaneous occurrence of high temperatures and droughts often leads to a significant increase in vapor pressure deficit (VPD) [21,22], which has been emphasized as the critical role in regulating GPP [23–25]. Overall, these studies indicate that extreme CHD events significantly reduce GPP in terrestrial ecosystems through multiple mechanisms and may have profound implications for the global carbon cycle.

However, not all extreme climate events result in significant damage to ecosystem productivity. Vegetation has notable adaptability and resistance to certain levels of climatic stress, and their responses depend on many key factors, such as event intensity and duration [26]. In response to moderate to extreme climate events, vegetation can reduce the decline in GPP by regulating stomatal conductance and other mechanisms [27]. However, there is still limited understanding and quantification of these adaptive mechanisms and how GPP responds to CHD events of different intensities. Addressing this limitation is essential for predicting future ecosystem responses under intensifying climate extremes and for developing targeted mitigation and adaptation strategies.

Moreover, different vegetation types show varying levels of resilience to extreme CHD events due to their differences in leaf characteristics, root systems, and canopy structures [28,29]. Generally, forests are more resistant than grasses or shrubs to short-term droughts due to their deeper root systems [30,31]. For forests specifically, evergreen forests and deciduous forests may also exhibit significant differences in GPP responses to extreme climate events. For instance, Han et al. (2024) analyzed tower observations and found that evergreen forests showed larger GPP reductions than deciduous forests in 2022 compared to 2021, with relative amplitudes of -21.0% and -3.4% , respectively [32]. However, the different GPP responses across vegetation types to CHD events of varying intensities remain insufficiently explored. This gap may hinder the efficient identification of terrestrial sensitivity to extreme events and limit our understanding of vegetation adaptation mechanisms.

The Yangtze River Basin (YRB) is an important ecological and economic region in China, which has experienced numerous CHD events over the past few decades [33]. In the summer of 2022, a record-breaking CHD event occurred across many regions of China, especially in the YRB, with abnormally high temperatures and prolonged drought conditions [34,35]. Some regions of the YRB experienced continuous high temperatures for 76 consecutive days, from June 16 to August 30, and experienced extremely low precipitation, with a reduction of over 80% [34]. Zhang et al. (2023) reported that the occurrence probability of the 2022 CHD event is approximately once in 152 years under the current climate conditions [36].

The CHD event in 2022 offers a valuable case to analyze how extreme compound climate events influence terrestrial carbon processes. Using different datasets, many pre-

vious studies have reported unprecedented GPP reductions in the YRB in response to the increased surface air temperature, vapor pressure deficit (VPD), and decreased soil moisture during the CHD event [37–39]. For example, Wang et al. (2023) analyzed FluxSat GPP product and reported that the extreme CHD event in 2022 led to a 7.46% reduction in GPP in the YRB compared to previous years, marking the largest decline since 2000 [37]. This significant decrease in GPP highlights the severe impact of extreme climate events on terrestrial ecosystem productivity and underscores the vulnerability of the YRB to such compound disturbances.

In this study, we investigated the responses of terrestrial GPP to three identified CHD events of different intensities in the YRB. The objective of this study is (1) to quantify differences in GPP responses to extreme CHD events of varying intensities, (2) to examine different GPP responses across vegetation types, and (3) to find potential new insights into the impacts of extreme climate events on terrestrial ecosystems. The results of this study are expected to contribute to a deeper understanding of vegetation–climate interactions and to offer valuable implications for optimizing carbon cycle models.

2. Materials and Methods

2.1. Study Area

This study focuses on the Yangtze River Basin (YRB), defined as the region spanning 25°N–33°N and 103°E–123°E (Figure 1). The climate in the YRB is predominantly characterized by a subtropical monsoon climate, featuring high temperatures and significant rainfall during the boreal summer months. The dominant vegetation types in YRB include evergreen forests (EF), deciduous forests (DF), mixed forests (MF), shrubs, and crops. In 2022, the YRB experienced a super-extreme compound heat and drought event during the boreal summer. This unprecedented event caused substantial impacts on both natural ecosystems and the local economy.

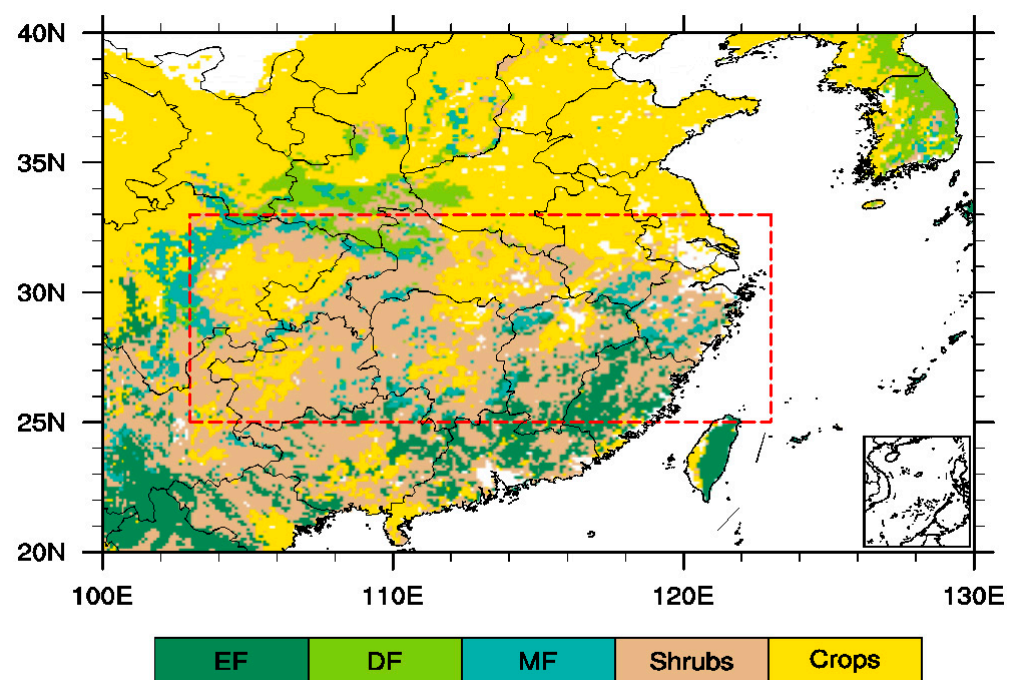


Figure 1. The spatial distribution of dominant vegetation types. The region marked within red dashed lines represents the Yangtze River Basin defined in this paper. The legends EF, DF, and MF represent evergreen forests, deciduous forests, and mixed forests, respectively.

2.2. Climate Datasets

This study used climatic variables including 2 m air temperature (T_{2m}), volumetric soil water in all the three layers (SM), vapor pressure deficit (VPD), and downward solar radiation (DSR). We directly downloaded the ERA5 (the fifth generation of the European Center for Medium-Range Weather Forecasts; [40]) land monthly averaged data for T_{2m}, SM, DSR, and dew-point temperature (T_d) from the Climate Data Store (<https://cds.climate.copernicus.eu>, accessed on 12 June 2024), while VPD was derived from T_{2m} and T_d following the equation in Section 2.5. All climatic variables have a horizontal resolution of 0.1° × 0.1° and cover the period from 2000 to 2022.

2.3. GPP Datasets

GPP refers to the total amount of carbon dioxide (CO₂) fixed from the atmosphere through photosynthesis and converted into organic matter by terrestrial ecosystems. It represents the upper limit of carbon input into the ecosystem and serves as a key indicator of vegetation productivity and the carbon cycle. Two GPP products are employed in this study. One is the GPP_{GOSIF} product (http://data.globalecology.unh.edu/data/GOSIF-GPP_v2/, accessed on 12 June 2024), which was derived from Solar-induced chlorophyll fluorescence (SIF) observed by the Orbiting Carbon Observatory-2 (OCO-2) [41]. The GPP_{GOSIF} product has been evaluated through comparisons with multiple tower observations and shows a good performance in producing global GPP estimations, both in terms of spatial distribution and seasonal cycle [42]. The other product is GPP_{FluxSat} (https://avdc.gsfc.nasa.gov/pub/tmp/FluxSat_GPP/, accessed on 12 June 2024), which was derived from the MODerate-resolution Imaging Spectroradiometer (MODIS) instruments on the NASA Terra and Aqua satellites [43]. This study used the latest version of GPP_{FluxSat} (V2.2), which employs machine learning with MODIS reflectance, trained on FLUXNET 2015 and OneFlux data. Both GPP_{GOSIF} and GPP_{FluxSat} are available at a 0.05° resolution for the period 2000-03-01 to the recent past. We employed the two GPP products for the July–August–September season (JAS) and interpolated them to a 0.1° resolution.

2.4. Vegetation Coverage and EVI

The fractional coverage of land plants is derived from MODIS MCD12C (<https://modis.gsfc.nasa.gov/data/dataproduct/mod12.php>, accessed on 12 June 2024) [44]. This product includes 17 land cover types based on the International Geosphere-Biosphere Programme (IGBP) classification system. The data provide annual updates on the vegetation coverage at a 0.05° resolution. For this study, we used vegetation coverage of the year 2022 and resampled it to a 0.1° horizontal resolution.

In addition to the two GPP products, we also downloaded the Enhanced Vegetation Index (EVI) from MODIS (EVI_{MODIS}; <https://modis.gsfc.nasa.gov/data/dataproduct/mod13.php>, accessed on 12 June 2024) [45]. EVI_{MODIS} is an improved vegetation index that reflects vegetation greenness and activity and is widely used for assessing the role of vegetation in the global carbon cycle. We used the EVI_{MODIS} at a 0.05° spatial and monthly temporal resolution from 2000 to 2022 and interpolated the EVI estimates into a 0.1° spatial resolution.

2.5. Methods

2.5.1. Calculation of VPD

Many previous studies have reported the key role of VPD in affecting terrestrial GPP during extreme climate events [37–39]. It is a pivotal indicator that helps to assess how air dryness influences terrestrial ecosystems. In this study, we calculated VPD as follows [46]:

$$\text{VPD} = 0.61078 \times \left(e^{\frac{17.27T_{2m}}{T_{2m} + 237.29}} - e^{\frac{17.27T_d}{T_d + 237.29}} \right)$$

where T2m and Td represent 2 m air temperature and dew-point temperature, which are downloaded from ERA5.

2.5.2. Calculation of Anomalies

This study focuses on the JAS season, when the intensity of the 2022 compound heatwave and drought event was extremely strong. Following Wang et al. (2023) [37], we first calculated absolute anomalies (ΔVar) in climatic and vegetation-related variables as:

$$\Delta\text{Var} = \text{Var} - \overline{\text{Var}}$$

where Var includes T2m, SM, VPD, DSR, GPP, and EVI, and $\overline{\text{Var}}$ represents the climatological mean of the period of 2000–2021. Considering the trending attribution of the CO₂ fertilization effect, we further removed the trend of the derived absolute anomalies based on the period of 2000–2021, as previous studies have performed [37,39]. By the two steps, we derived absolute anomalies in all variables, and the relative changes ΔVar_R in these variables are calculated as:

$$\Delta\text{Var}_R = \frac{\Delta\text{Var}}{\text{STD}}$$

where ΔVar represents absolute anomalies and STD is one standard deviation.

3. Results

3.1. Climate Anomalies

We first analyzed the temporal evolution of JAS climatic and vegetation-related anomalies from 2000 to 2022 (Figure 2). Based on the temporal series, this study defined a year as experiencing a CHD event if the T2m anomaly exceeded one standard deviation (STD) and, simultaneously, the magnitude of the negative SM anomaly also exceeded one STD. Using this definition, we identified three CHD years: 2003, 2013, and 2022 (Figure 2a). The magnitude of climatic and vegetation-related anomalies of the three CHD years are shown in Table 1.

Among the three CHD years, 2022 experienced the strongest CHD event, with an average positive T2m anomaly of 1.33 K and an average negative SM anomaly of $-0.05 \text{ m}^3 \text{ m}^{-3}$. The CHD events in 2003 and 2013 were weaker. The average positive T2m anomalies in 2003 and 2013 were 0.68 K and 0.61 K, respectively, and their average negative SM anomalies were about $-0.01 \text{ m}^3 \text{ m}^{-3}$ and $-0.02 \text{ m}^3 \text{ m}^{-3}$, respectively. These hot and dry conditions also resulted in positive anomalies in VPD, with 2022 being the strongest (3.84 hPa), followed by 2013 (1.96 hPa) and 2003 (0.83 hPa). Simultaneously, DSR showed positive anomalies in the years 2013 and 2022, with amplitudes of 13.38 W m^{-2} and 21.27 W m^{-2} , respectively, while the year 2003 showed a slightly negative anomaly in DSR (-1.02 W m^{-2}).

Figure 3 further shows the spatial distribution of climatic anomalies for the three CHD years. During the strongest CHD year of 2022, the entire YRB was concurrently characterized by very high T2m and notably low SM across all grid points. Additionally, relatively high VPD and DSR were also observed throughout the YRB. In 2003, the higher T2m anomalies were mainly concentrated in the coastal provinces of the YRB, and meanwhile, these provinces also had lower SM, higher VPD, and increased DSR. In 2013, the climate anomalies in the YRB were similar to those in 2022, but the intensity was weaker, especially with opposite signals observed in the western and southern grid points of the YRB. The different distributions of climate anomalies among these three CHD years may lead to varying responses in regional GPP.

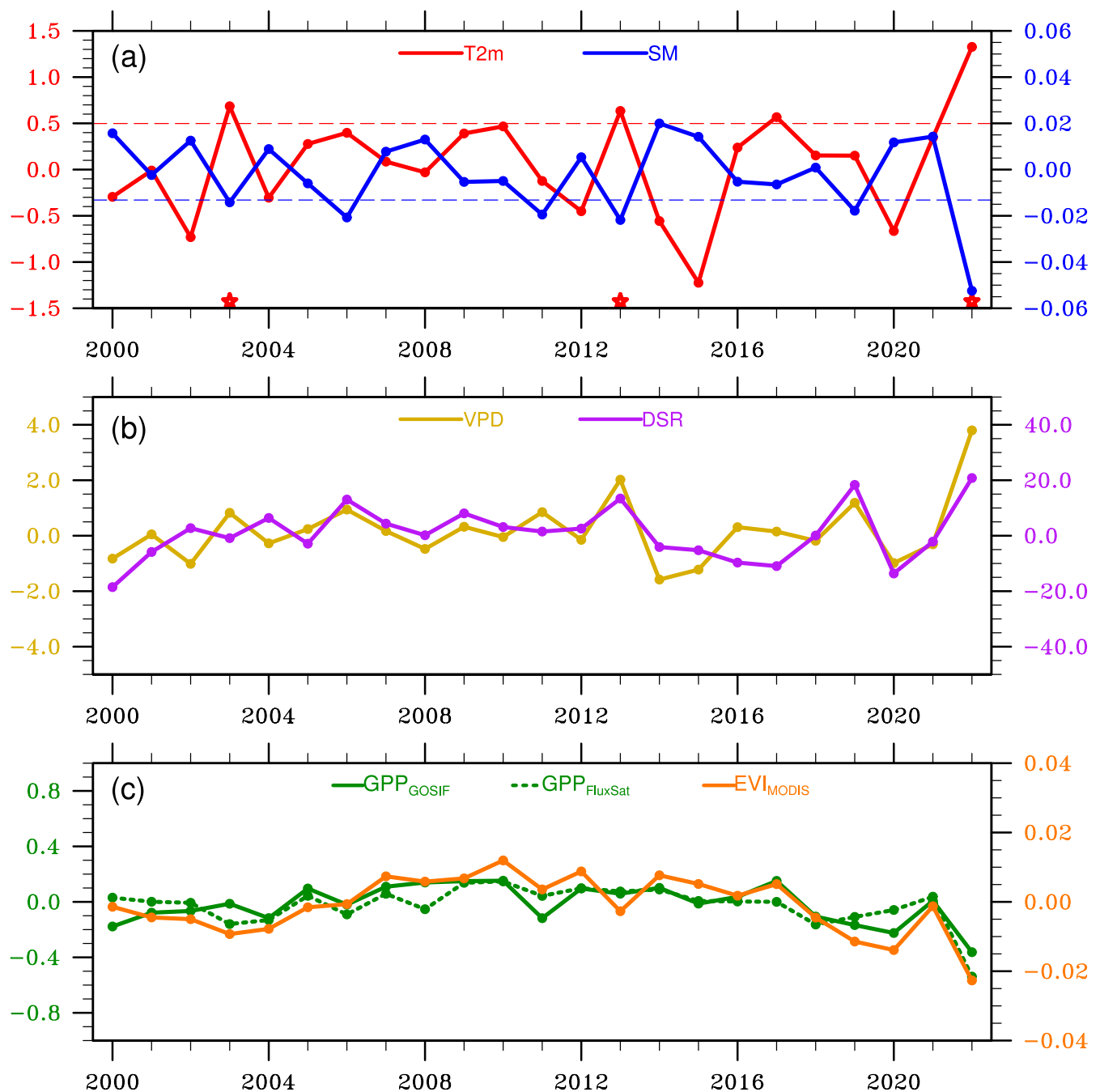


Figure 2. Temporal series of climatic and vegetation-related JAS anomalies from 2000 to 2022. Panel (a) is for 2 m air temperature (T2m, units: K) and soil moisture (SM, units: $\text{m}^{-3} \text{m}^{-3}$), and the red and blue dashed lines represent one standard deviation of T2m and SM, respectively. The stars in (a) represent the identified CHD years: 2003, 2013, and 2022. Panel (b) is for vapor pressure deficit (VPD, units: hPa) and downward solar radiation (DSR, units: W m^{-2}), and panel (c) is for the two GPP products (GPP_{GOSIF} and GPP_{FluxSat}, units: $\text{gC m}^{-2} \text{day}^{-1}$) and Enhanced Vegetation Index (EVI_{MODIS}, unitless).

Table 1. Anomalies in climatic and vegetation-related variables for the three CHD years: 2003, 2013, and 2022. The climatic variables include 2 m air temperature (T2m, units: K), soil moisture (SM, units: $10^{-2} \text{ m}^{-3} \text{ m}^{-3}$), vapor pressure deficit (VPD, units: hPa), and downward solar radiation (DSR, units: W m^{-2}), while vegetation-related variables include GPP (units: $10^{-1} \text{ gC m}^{-2} \text{ day}^{-1}$) and EVI (units: 10^{-2}). The numbers before the solidus are the absolute anomalies and the numbers after the solidus are the relative changes in units of one standard deviation.

Variables	Year	All	EF	DF	MF	Shrubs	Crops
T2m	2003	0.68/1.37	1.47/2.30	0.07/0.19	0.72/1.52	0.82/1.56	0.23/0.46
	2013	0.61/1.23	0.06/0.10	0.60/1.49	0.50/1.05	0.56/1.07	0.89/1.77
	2022	1.33/2.69	1.11/1.73	1.08/2.69	1.20/2.51	1.32/2.51	1.49/2.96
SM	2003	−1.39/−1.05	−4.51/−2.58	1.12/1.03	−1.52/−1.57	−1.99/−1.49	0.40/0.20
	2013	−2.10/−1.59	−0.72/−0.41	−0.42/−0.39	−1.86/−1.93	−2.09/−1.57	−2.78/−1.39
	2022	−5.26/−3.98	−4.82/−2.77	−3.53/−3.27	−4.31/−4.47	−5.04/−3.77	−6.30/−3.15
VPD	2003	0.83/0.98	3.20/2.65	−0.67/−1.34	0.79/1.25	1.15/1.25	−0.26/−0.26
	2013	1.96/2.30	1.05/0.87	0.64/1.29	1.45/2.30	2.03/2.21	2.40/2.37
	2022	3.84/4.50	3.92/3.24	1.85/3.74	2.84/4.52	3.81/4.15	4.40/4.33
DSR	2003	−1.02/−0.11	11.27/0.84	−12.02/−1.03	−1.19/−0.14	1.29/0.14	−7.65/−0.78
	2013	13.38/1.49	9.30/0.69	20.70/1.78	14.82/1.69	12.63/1.35	14.68/1.50
	2022	21.27/2.37	27.74/2.07	11.30/0.97	20.12/2.29	22.67/2.43	18.17/1.86
GPP _{GOSIF}	2003	−0.09/−0.07	1.43/1.01	0.11/0.04	0.82/0.65	0.17/0.14	−1.3/−0.75
	2013	0.67/0.55	1.62/1.14	−0.21/−0.08	0.80/0.64	0.46/0.37	0.88/0.50
	2022	−3.71/−3.05	−2.96/−2.09	−3.31/−1.28	−1.07/−0.85	−4.07/−3.26	−4.08/−2.30
GPP _{FluxSat}	2003	−1.58/−1.67	−1.58/−1.22	−0.01/−0.01	−0.55/−0.52	−1.02/−0.88	−3.17/−2.10
	2013	0.86/0.91	−0.12/0.09	1.60/0.98	0.15/0.14	0.55/0.47	1.87/1.24
	2022	−5.66/−5.97	−6.64/−5.14	−2.50/−1.53	−4.95/−4.74	−6.33/−5.41	−4.66/−3.09
EVI _{MODIS}	2003	−0.88/−1.20	−0.09/−0.11	−0.68/−0.63	0.32/0.39	−0.75/−1.00	−1.76/−1.72
	2013	−0.19/−0.26	−0.40/−0.46	0.43/0.40	−0.16/−0.20	−0.30/−0.40	0.00/0.00
	2022	−2.42/−3.30	−3.16/−3.57	−1.67/−1.55	−0.80/−0.97	−2.49/−3.35	−2.67/−2.60

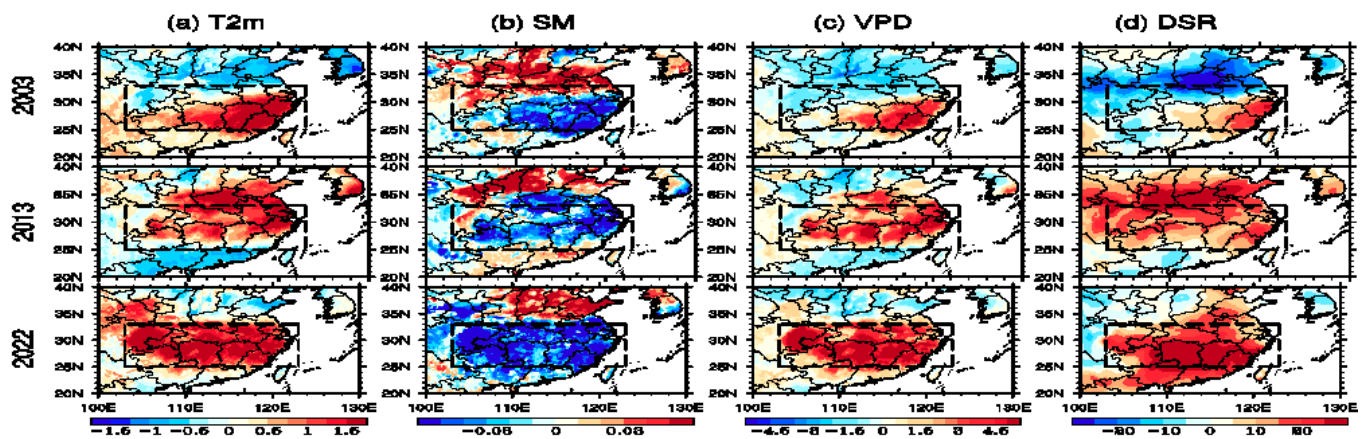


Figure 3. The spatial distributions of (a) 2 m air temperature (T2m, units: K), (b) soil moisture (SM, units: $\text{m}^{-3} \text{ m}^{-3}$), (c) vapor pressure deficit (VPD, units: hPa), and (d) downward solar radiation (DSR, units: W m^{-2}) for the three CHD years.

3.2. Responses of GPP to the CHD Events

Figure 2c shows the anomalies in average GPP during the JAS period in the YRB from 2000 to 2022. In 2022, when the most intense extreme drought and heatwave occurred, the reduction in GPP was the most intensified, with amplitudes of $-0.37 \text{ gC m}^{-2} \text{ day}^{-1}$ and $-0.57 \text{ gC m}^{-2} \text{ day}^{-1}$ for GPP_{GOSIF} and GPP_{FluxSat}, respectively. In 2003, the reduction in GPP was much smaller compared to 2022, with values of $-0.01 \text{ gC m}^{-2} \text{ day}^{-1}$ and $-0.16 \text{ gC m}^{-2} \text{ day}^{-1}$ for GPP_{GOSIF} and GPP_{FluxSat}, respectively. In contrast, the GPP in 2013 showed an opposite signal, with a slight increase of $0.07 \text{ gC m}^{-2} \text{ day}^{-1}$ and

$0.09 \text{ gC m}^{-2} \text{ day}^{-1}$ for $\text{GPP}_{\text{GOSIF}}$ and $\text{GPP}_{\text{FluxSat}}$, respectively. The $\text{EVI}_{\text{MODIS}}$ showed consistent results with the two GPP products, with the largest reduction occurring in 2022 (-0.024), followed by 2003 (-0.009), and the smallest reduction in 2013 (-0.002). These results provide important evidence that the responses of GPP to CHD events can vary significantly due to the difference in the intensity of CHD events.

The spatial distribution of GPP anomalies further shows the differences in GPP responses to the three CHD years (Figure 4). In 2022, when the reduction in GPP was most severe, both $\text{GPP}_{\text{GOSIF}}$ and $\text{GPP}_{\text{FluxSat}}$ showed negative anomalies across most grid points in the YRB, with proportions reaching 76.20% and 85.05%, respectively. The regions with the largest negative GPP anomalies were concentrated in the provinces of Jiangxi, Hunan, Guizhou, and Chongqing.

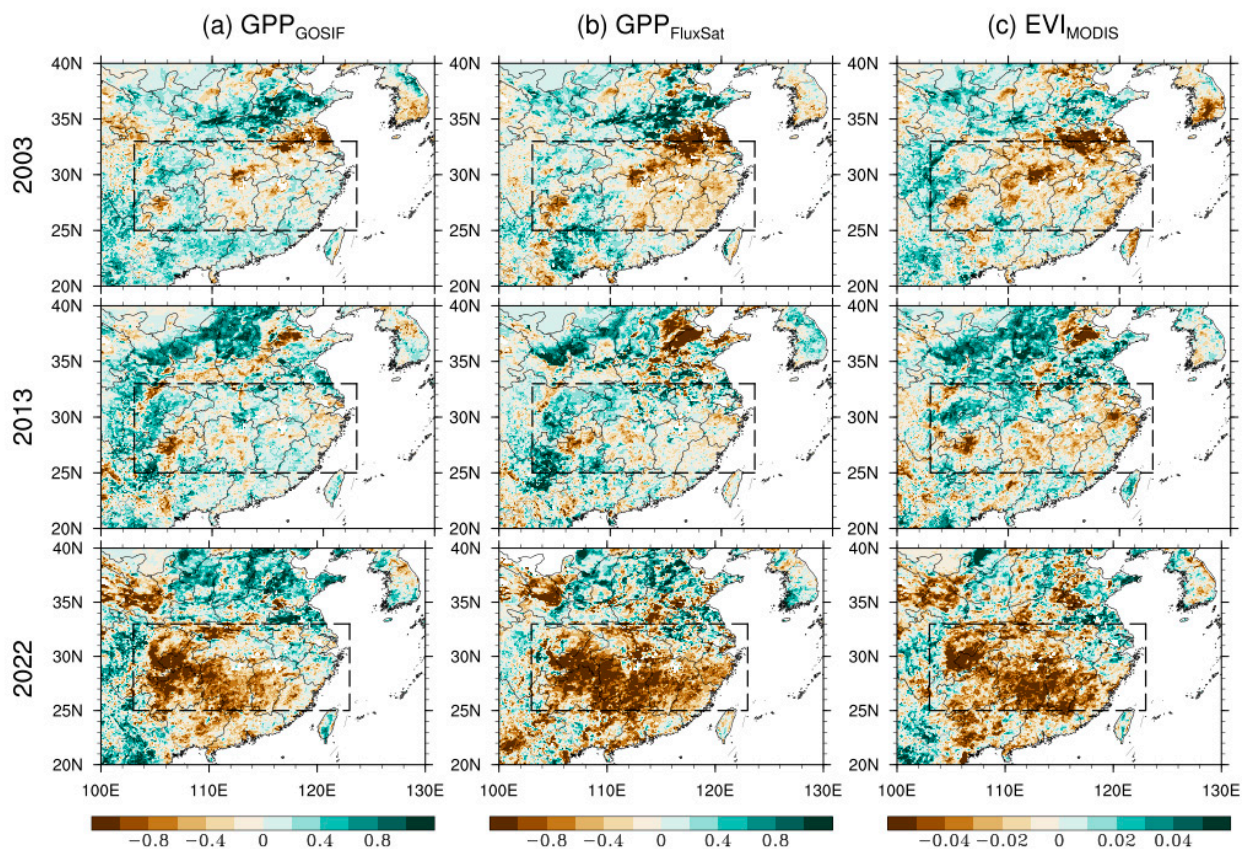


Figure 4. The spatial distribution of vegetation-related anomalies for the three CHD years, 2003, 2013, and 2022. The panels (a), (b), and (c) are for products $\text{GPP}_{\text{GOSIF}}$, $\text{GPP}_{\text{FluxSat}}$ (units: $\text{gC m}^{-2} \text{ day}^{-1}$), and $\text{EVI}_{\text{MODIS}}$ (unitless), respectively.

In 2003, fewer grid points showed negative GPP anomalies, with proportions of 47.26% for $\text{GPP}_{\text{GOSIF}}$ and 66.02% for $\text{GPP}_{\text{FluxSat}}$, and the magnitude of GPP reduction was also smaller. In 2013, the magnitude of both positive and negative GPP anomalies was relatively small, but there were more positive anomaly grid points than negative ones, ultimately leading to a slight increase in the average GPP in the YRB. The spatial distribution of EVI anomalies is consistent with the two GPP products, particularly $\text{GPP}_{\text{FluxSat}}$, further confirming the GPP response patterns to the three CHD years.

Considering the differences in vegetation characteristics, their responses to extreme events can vary significantly. We further classified the grid points in the YRB into five categories based on their dominant vegetation types: evergreen forests (EF), deciduous forests (DF), mixed forests (MF), shrubs, and crops. Figure 5 and Table 1 show the response of these five vegetation types to the CHD events during the three years.

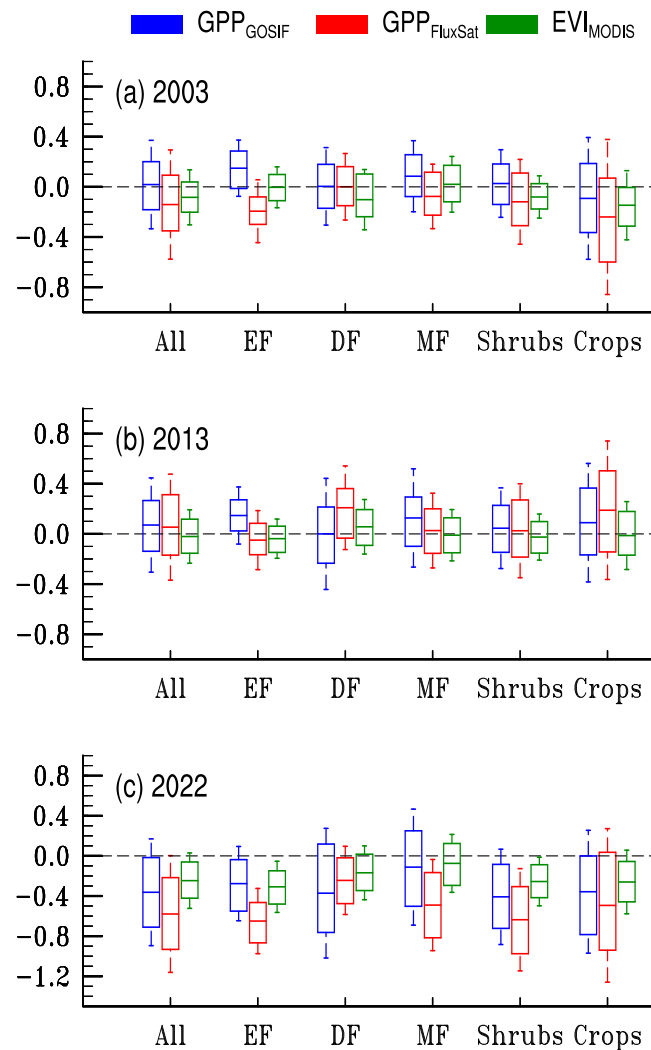


Figure 5. The box plots of vegetation-related anomalies across the corresponding grid points. The boxes indicate the 25th and 75th percentiles with the median between. The error bars indicate one standard deviation. The units for GPP are $gC\ m^{-2}\ day^{-1}$, and for EVI are 10^{-1} .

In 2022, GPP_{GOSIF} , $GPP_{FluxSat}$, and EVI_{MODIS} overall indicate that the GPP reduction was most significant for shrubs, with median values of $-0.41\ gC\ m^{-2}\ day^{-1}$, $-0.64\ gC\ m^{-2}\ day^{-1}$, and -0.03 , respectively. Among the three types of forests, deciduous and mixed forests showed a smaller GPP decrease, even a GPP increase in many grid points, while evergreen forests showed the largest GPP reduction. For crops, the overall GPP reduction was also quite significant, with strong variations between different grid points.

For the years 2003 and 2013, the responses of the five vegetation types showed no significant differences, with both negative and positive anomalies, and the medians were near the zero line. Additionally, some discrepancies were observed between the two GPP products, highlighting the inherent uncertainties in the GPP products, which will be discussed further in the following section.

3.3. Different Responses of Vegetation to CHD Events of Varying Intensities

The above analysis indicates that GPP exhibits significant differences in response to extreme climate events of varying intensities. Suitable temperature, moisture, and light conditions can promote an increase in GPP, whereas extreme temperatures and drought conditions can lead to a marked reduction in vegetation GPP. Particularly during the severe CHD event in 2022, vegetation in the YRB faced far greater stress than in the

years 2003 and 2013, resulting in a substantial decline in GPP. In the following sections, we will focus on discussing these differences in GPP responses to the extreme CHD events of varying intensities in these three years. To unify the contributions of different variables, all climatic and vegetation-related variables were standardized using their standard deviations (STD). Figure 6 and Table 1 show the analyzed results for the whole YRB and five vegetation-dominated regions, while Figures 7–9 are the results based on grid points.

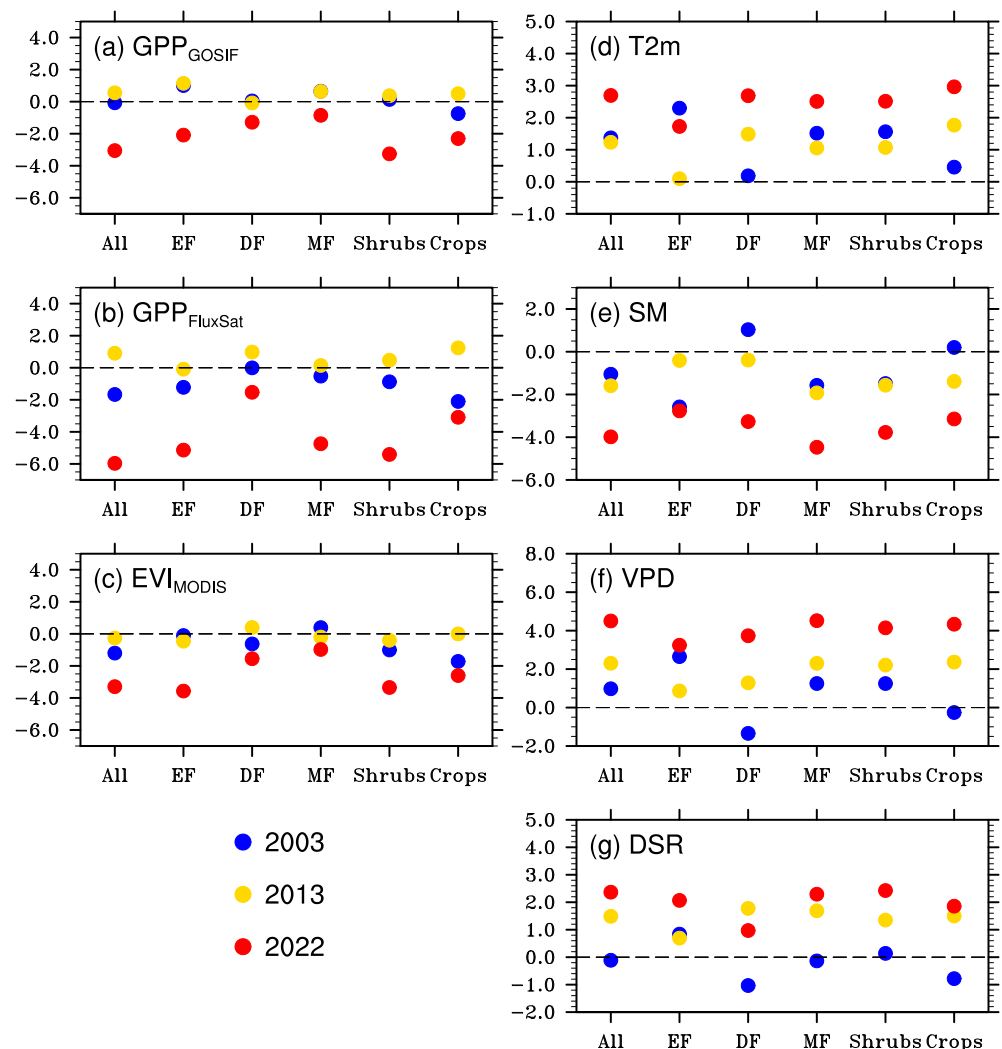


Figure 6. The average anomalies in climatic and vegetation-related anomalies over the corresponding grid points. The blue, yellow, and red dots represent the CHD years 2003, 2013, and 2022, respectively. Panels (a–g) represent variables GPP_{GOSIF} , $GPP_{FluxSat}$, EVI_{MODIS} , 2 m air temperature (T2m), soil moisture (SM), vapor pressure deficit (VPD), and downward solar radiation (DSR), respectively. All units are standard deviation.

For the whole YRB (Figure 6), climate factors such as T2m, SM, VPD, and DSR showed extreme anomalies in 2022, with averaged T2m and SM anomalies reaching 2.69 STD and -3.98 STD, respectively. These extreme high temperature and drought conditions intensified vegetation water loss, leading to a significant GPP decline, with negative GPP anomalies ranging from -3.05 STD to -5.97 STD. In contrast, during 2003 and 2013, although temperature and soil moisture also showed average anomalies exceeding one STD, the decrease in GPP was not apparent, and even a positive anomaly was observed in 2013. This suggests that only when climate anomalies reach a certain intensity do they have a substantial negative impact on GPP.

Furthermore, Figure 6 also illustrates that different vegetation types responded differently to extreme CHD events of similar intensity. In 2022, although the intensity of climate anomalies was not significantly different across the five dominant vegetation zones, the reduction in GPP showed noticeable differences. Among them, the negative impact on photosynthesis was smaller for deciduous forests and mixed forests, with a decline of GPP less than -2.0 STD, while shrubs experienced the most severe decrease in GPP, ranging from -3.26 STD to -5.41 STD. Evergreen forests also showed a marked decline similar to that of shrubs, with a significant drop in GPP even under relatively moderate climate anomalies. This indicates that even under similar climatic conditions, different vegetation types exhibit distinct tolerance levels and responses to extreme climate events.

In 2003 and 2013, the intensity of extreme climate events was lower, and the differences in GPP responses among vegetation types were also smaller. For example, GPP_{FluxSat} data show that in 2022, the difference in GPP reductions between deciduous forests and shrubs was 3.88 STD, whereas in 2003 and 2013, this difference decreased to 0.87 and 0.51 STD, respectively (Table 1). This suggests that as the intensity of extreme climate events decreases, differences in the response among vegetation types also narrow.

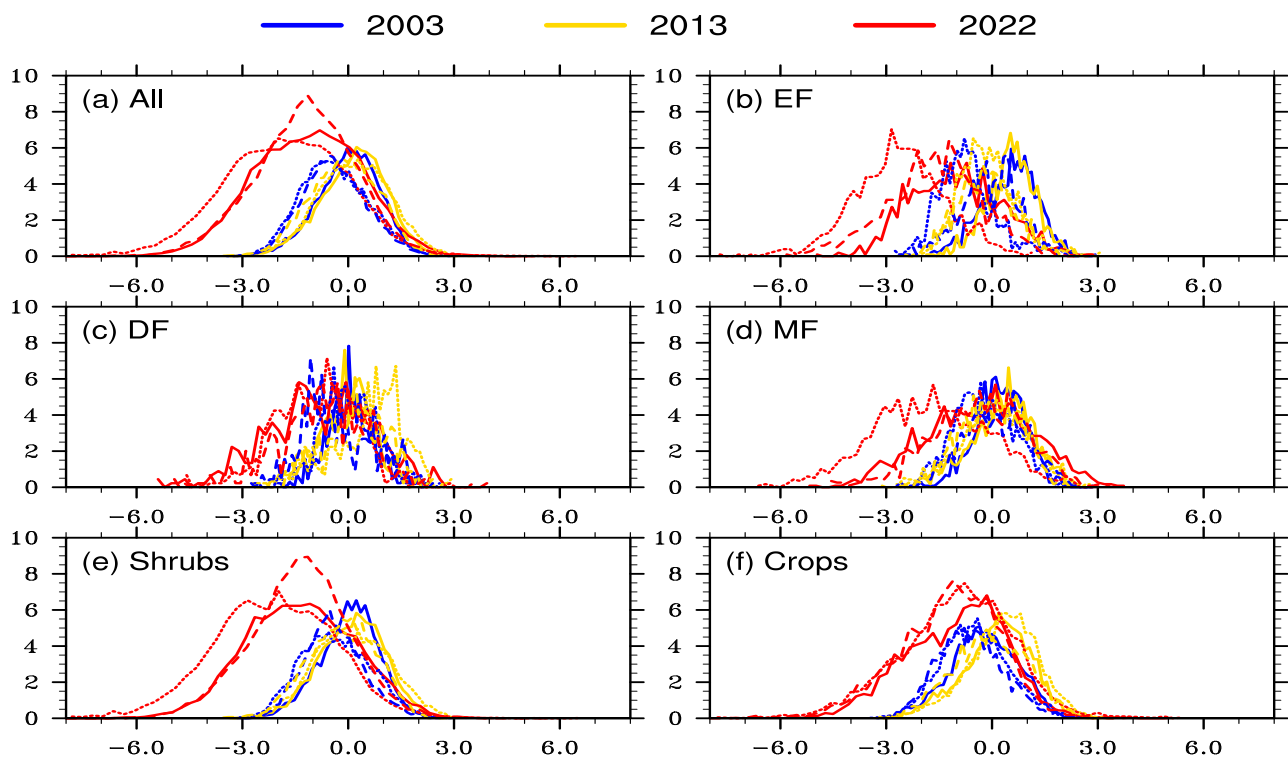


Figure 7. The probability density distribution (PDF) of vegetation-related anomalies (units: %). The blue, yellow, and red lines represent the CHD years 2003, 2013, and 2022, respectively. The solid lines and short- or long-dashed lines represent products GPP_{GOSIF}, GPP_{FluxSat}, and EVI_{MODIS}, respectively. Panels represent regions of (a) the entire defined YRB and grid points dominated by (b) evergreen forests (EF), (c) deciduous forests (DF), (d) mixed forests (MF), (e) shrubs, and (f) crops, respectively.

To validate the above conclusions, we further analyzed the probability density distribution (PDF) of climatic and vegetation-related anomalies in the YRB (Figure 8), and the results further support our findings. During the extreme CHD event in 2022, positive T2m anomalies concentrated around 2.0 STD, and the maximum anomalies can exceed 4.0 STD. At the same time, negative SM anomalies mainly centered around -2.0 STD, with extreme values exceeding -6.0 STD. Correspondingly, GPP showed negative anomalies over most grid points, with extreme values reaching over -6.0 STD (Figure 7a). In contrast, in 2003

and 2013, the positive temperature anomalies and negative soil moisture anomalies were more evenly distributed, and the intensity of extreme values was much lower than those in 2022. Therefore, in the two years, GPP anomalies were mainly concentrated around zero, and extreme values were around -3.0 STD, which is half of that in 2022 (Figure 7a).

Additionally, the PDF analysis also clearly reflects the different responses of the five vegetation types to the extreme CHD events. In 2022, the greatest differences in GPP responses were observed between deciduous forests and shrubs, and their PDF profiles differed significantly. For example, compared to deciduous forests, shrubs had a higher proportion and greater intensity of negative GPP anomalies (Figure 7). However, for climate anomalies, there was no obvious difference in the PDF profiles between deciduous forests and shrubs in 2022 (Figure 8). Their positive T2m anomalies and negative SM anomalies were both centered around 2.0 STD and -2.0 STD, with extreme values reaching 4.0 STD and -6.0 STD, respectively. Additionally, the comparison between deciduous forests and evergreen forests shows an opposite phenomenon. For T2m, most evergreen forest-dominated grid points showed weaker positive anomalies than deciduous forest-dominated grid points (Figure 8a). Nevertheless, the intensity and proportion of negative GPP anomalies for evergreen forests were still higher than those for deciduous forests. These differences illustrate that other climatic variables may be key factors causing the different responses between evergreen forests and deciduous forests. In comparison, although there were slight differences in climate anomalies among the five vegetation-dominated areas in 2003 and 2013, their GPP response differences were not particularly significant between the two years.

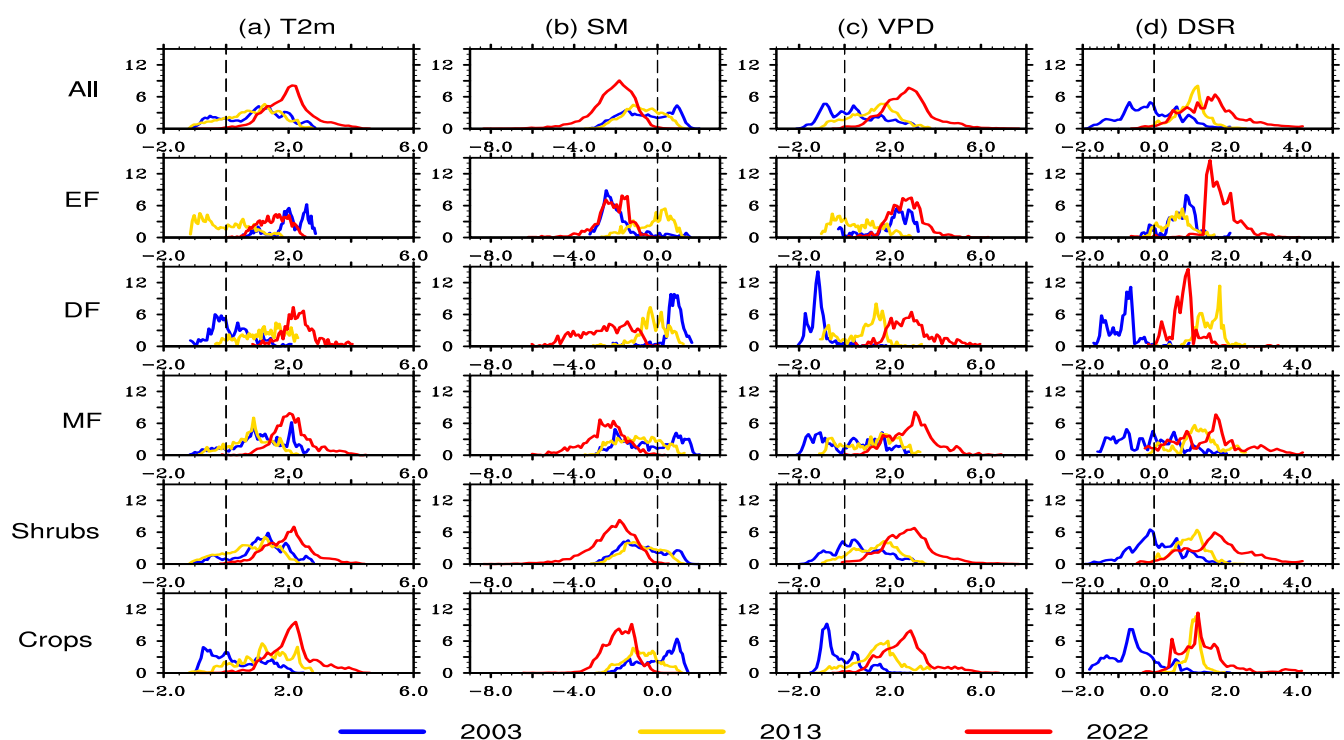


Figure 8. The probability density distribution (PDF) of climatic anomalies (units: %). The blue, yellow, and red lines represent the CHD years 2003, 2013, and 2022, respectively. Panels (a–d) represent variables 2 m air temperature (T2m), soil moisture (SM), vapor pressure deficit (VPD), and downward solar radiation (DSR), respectively, for the whole defined YRB (All) and grid points dominated by evergreen forests (EF), deciduous forests (DF), mixed forests (MF), shrubs, and crops.

Figure 9 shows the analysis of climatic and vegetation-related anomalies exceeding one STD, which are considered significant changes. The results clearly indicate that the extent

of significant climate anomalies in 2022 was much broader compared to 2003 and 2013. Over 90% of the grid points in the whole YRB experienced anomalies in T2m, SM, and VPD exceeding one STD in 2022 (Figure 9c). In contrast, the proportion of grid points with significant anomalies in 2003 and 2013 was around 50%. Correspondingly, the proportion of grid points showing significant negative anomalies in GPP and EVI in 2022 exceeded 50%, which was more than twice the proportions in 2003 and 2013.

For different vegetation types, evergreen trees and shrubs, showing the strongest GPP reductions in 2022, are also characterized by higher grid point proportions with significant GPP decrease, reaching 89.37% and 72.98%, respectively, according to GPP_{FluxSat} data. In comparison, deciduous forests and mixed forests, which had weaker GPP responses, showed lower proportions of significant grid points at 44.97% and 34.97%, according to GPP_{GOSIF} data. However, in 2003 and 2013, the differences in the proportions of significant GPP changes among different vegetation types were also relatively small.

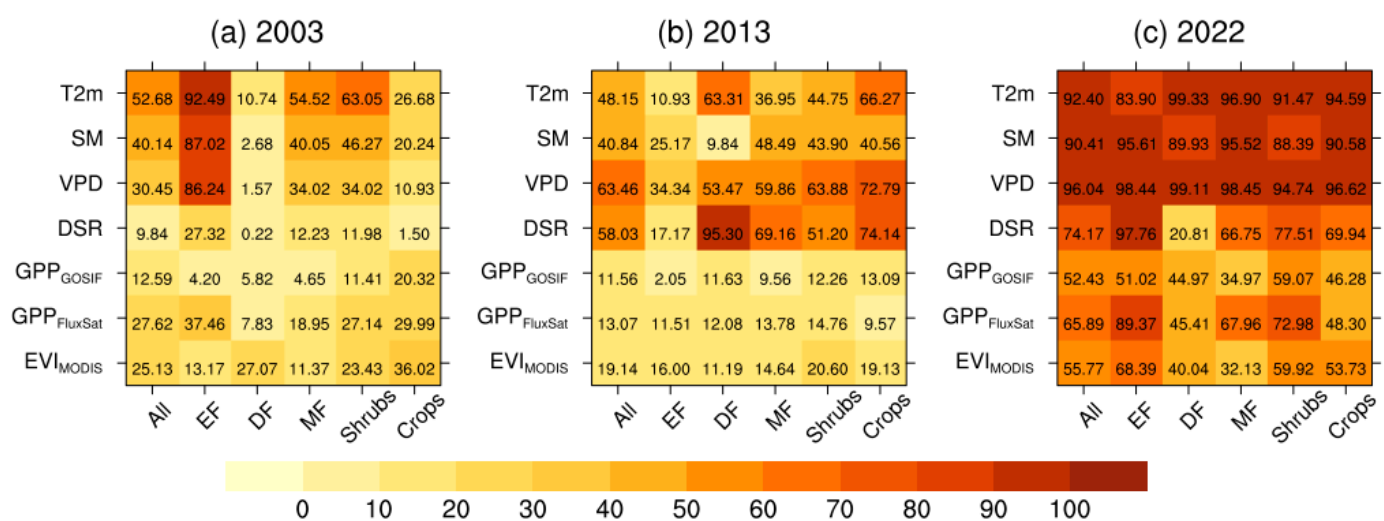


Figure 9. The percentage (%) of grid points with significant changes exceeding one standard deviation for the CHD years (a) 2003, (b) 2013, and (c) 2022, respectively. Here, significant positive anomalies were counted for 2 m air temperature (T2m), vapor pressure deficit (VPD), and downward solar radiation (DSR), while significant negative anomalies were counted for soil moisture (SM), GPP, and EVI.

In summary, these results indicate that different intensities of extreme CHD events have different impacts on vegetation photosynthesis, and different vegetation types exhibit distinct response intensities and patterns to extreme climate events. This variation is crucial for understanding and predicting the adaptive capacity of different ecosystems to future climate changes.

4. Discussion

4.1. Uncertainties Between the Two GPP Products

This study utilized two commonly used GPP products, GPP_{GOSIF} and GPP_{FluxSat}, to analyze the response of terrestrial ecosystem photosynthesis to extreme CHD events. Overall, the two datasets demonstrated consistent responses but also exhibited some differences. For example, compared to the GPP_{GOSIF}, the GPP_{FluxSat} product showed stronger negative GPP anomalies (Figure 4) and greater differences in GPP anomalies among the five vegetation types (Figure 6) in 2022. These differences highlight the inherent uncertainties of the data products, which may be related to differences in data algorithmic processing.

Despite the uncertainties, the overall consistency in responses between the two GPP products is evident, especially in 2022. Figure 10 presents the scatterplot of GPP anomalies from GPP_{GOSIF} and $GPP_{FluxSat}$. It clearly shows that the GPP anomalies of each vegetation type for each year are significantly correlated between the two GPP products, particularly for shrubs, with correlation coefficients exceeding 0.60. This indicates that the response behaviors of GPP anomalies reflected by the two GPP products are highly consistent, providing a reliable depiction of how terrestrial ecosystem photosynthesis responds to extreme compound drought and heatwave events.

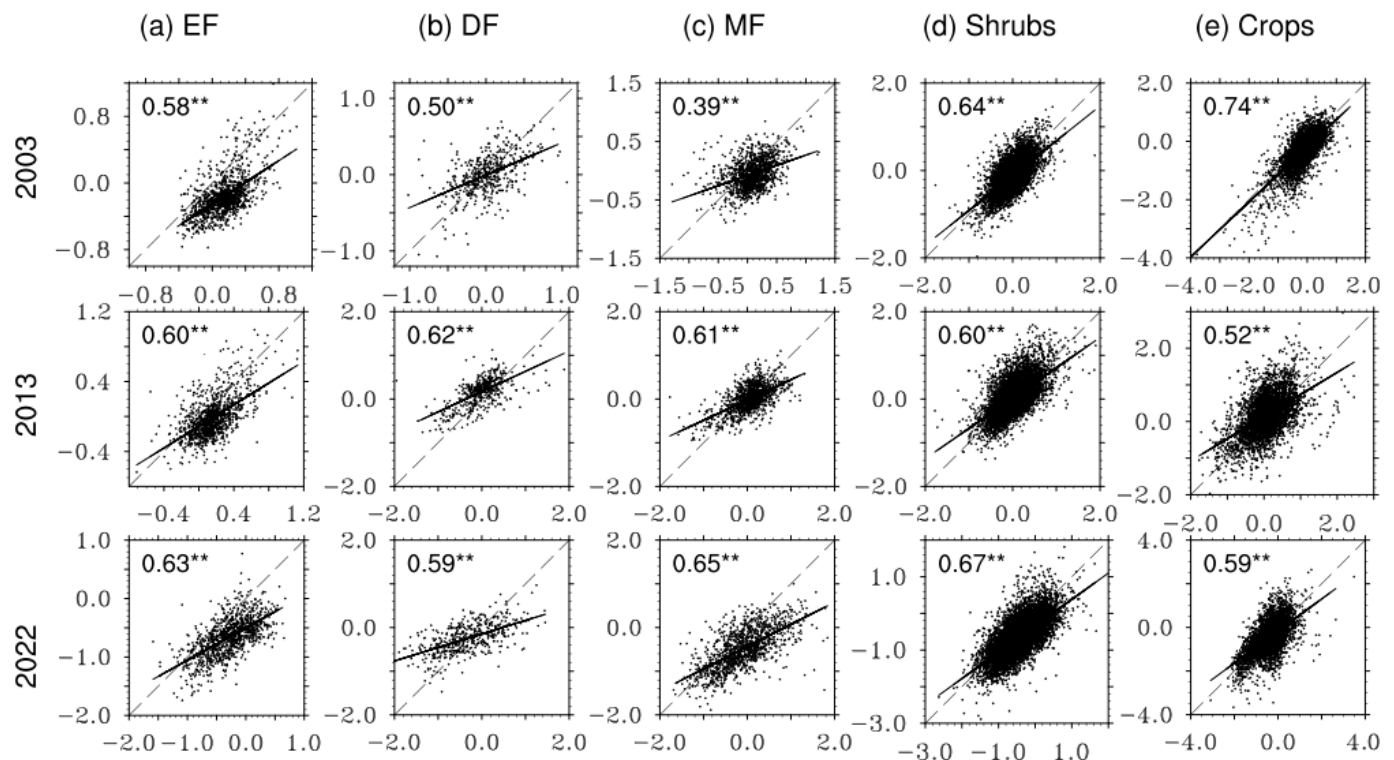


Figure 10. The scatterplot of the relationship between anomalies in GPP_{GOSIF} (X-axis) and $GPP_{FluxSat}$ (Y-axis) for the three CHD years. Panels correspond grid points dominated by (a) evergreen forests (EF), (b) deciduous forests (DF), (c) mixed forests (MF), (d) shrubs, and (e) crops, respectively. The numbers represent the correlation coefficients between the two GPP products, and the two asterisks indicate a significant correlation ($p < 0.01$).

4.2. Limitations and Perspective

Although this study enhances our understanding of the impact of extreme CHD events of varying intensities on GPP, several limitations remain and should be addressed in future research. First, due to the limited availability of data, this study only analyzed three extreme CHD events in the YRB, which may constrain the representativeness and generalizability of the findings. Second, the lack of continuous observational data prevented us from incorporating site-level measurements for validation. Third, further model validation and a more precise quantification of the contributions of different influencing factors are crucial aspects that need to be refined in future studies.

These limitations also highlight key directions for future research. First, the study of tipping points in GPP responses to extreme CHD events remains an area in urgent need of further exploration. Existing studies have shown that GPP responses to extreme CHD events exhibit significant regional differences on a global scale. For example, in mid-latitude regions such as Europe and North America, CHD events (e.g., the 2003 European heatwave) have led to substantial GPP reductions [12], while the responses of high-latitude boreal

forests are more complex—warming may extend the growing season but can also exacerbate water stress [47]. Therefore, future research should incorporate a broader selection of extreme CHD events of varying intensities across different regions worldwide. A systematic investigation of the diverse GPP response characteristics, particularly the identification and mechanistic understanding of GPP tipping points, will be a crucial direction for future studies. Second, establishing a long-term, continuous site observation system on a global scale is essential. This would not only enhance our understanding of key processes and factors influencing terrestrial ecosystem carbon cycling but also provide reliable data support for model validation. Future efforts should focus on expanding global terrestrial ecosystem observation networks, particularly in data-scarce regions such as the tropics and high-latitude areas [17,48]. Third, developing terrestrial ecosystem models that accurately capture the responses of the land carbon cycle to extreme CHD events is another crucial research priority. This requires integrating multi-source observational data and improving model parameterization schemes, particularly by enhancing the representation of key processes such as plant physiological responses, soil moisture dynamics, and ecosystem resilience [49,50]. Furthermore, incorporating emerging technologies such as machine learning into model development should be considered to improve both prediction accuracy and interpretability [51].

5. Conclusions

This study focuses on the Yangtze River Basin and investigates the responses of terrestrial GPP to extreme compound heatwave and drought events of varying intensities. Using two independent GPP products and EVI data, we found that during the strongest extreme compound heatwave and drought event in 2022, GPP exhibited the largest decrease in magnitude and the widest spatial extent. During the less intense events in 2003 and 2013, the magnitude and extent of GPP reduction were significantly smaller than those in 2022. Notably, in 2013, the overall GPP even showed a slight increase. Our study also revealed significant differences in GPP responses across regions dominated by different vegetation types. During the most intense event of 2022, GPP reductions were most pronounced in shrub-dominated areas, followed by evergreen forests, while deciduous forests and mixed forests experienced relatively smaller decreases. However, during the weaker events of 2003 and 2013, these differences among vegetation types were less pronounced, with responses across vegetation types being more similar.

These different responses of GPP in the whole Yangtze River Basin indicate that terrestrial ecosystems possess a certain degree of adaptability to mild and moderate extreme climate events. However, when the intensity of such events surpasses a certain threshold, this adaptability diminishes, highlighting the existence of a resilience tipping point in ecosystems. Our reported differences in the responses among vegetation types further enhance our understanding of the adaptive mechanisms of various vegetation types and help to identify vulnerable areas within ecosystems that are prone to disturbance. This enhancement provides an important scientific basis for developing more targeted ecological protection strategies and improving ecosystem resilience. This study emphasizes the variability in the responses of photosynthesis in the Yangtze River Basin's terrestrial ecosystems to extreme compound heatwave and drought events. These findings are of great significance for advancing the understanding of vegetation–climate coupling and for optimizing related vegetation and carbon cycle models.

Author Contributions: Methodology, J.Z.; Formal analysis, H.G.; Data curation, H.G.; Writing—original draft, J.Z.; Writing—review & editing, J.Z.; Supervision, Y.S.; Funding acquisition, J.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Strategic Priority Research Program of the Chinese Academy of Sciences (XDB0500303), the Youth Innovation Promotion Association of the Chinese Academy of Sciences (2022076), and the National large Scientific and Technological Infrastructure “Earth System Numerical Simulation Facility”.

Data Availability Statement: Data available in a publicly accessible repository (accessed on 12 June 2024): ERA5 is openly available in <https://cds.climate.copernicus.eu> [40]; GOSIF GPP is in http://data.globalecology.unh.edu/data/GOSIF-GPP_v2/ [41]; FluxSat GPP is in https://avdc.gsfc.nasa.gov/pub/tmp/FluxSat_GPP/ [43]; MODIS fractional coverage of land plants is in <https://modis.gsfc.nasa.gov/data/dataproduct/mod12.php> [44]; MODIS EVI is in <https://modis.gsfc.nasa.gov/data/dataproduct/mod13.php> [45].

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Masson-Delmotte, V.P.; Zhai, A.; Pirani, S.L.; Connors, C.; Péan, S.; Berger, N.; Caud, Y.; Chen, L.; Goldfarb, M.I.; Gomis, M.; et al. (Eds.) IPCC, 2021: Summary for Policymakers. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. In *Climate Change 2021: The Physical Science Basis*; Cambridge University Press: Cambridge, UK.
2. Zhou, S.; Yu, B.F.; Zhang, Y. Global concurrent climate extremes exacerbated by anthropogenic climate change. *Sci. Adv.* **2023**, *9*, eabo1638. [CrossRef] [PubMed]
3. Zhou, S.; Zhang, Y.; Williams, A.P.; Gentile, P. Projected increases in intensity, frequency, and terrestrial carbon costs of compound drought and aridity events. *Sci. Adv.* **2019**, *5*, eaau5740. [CrossRef] [PubMed]
4. Zhang, Q.; She, D.X.; Zhang, L.P.; Wang, G.S.; Chen, J.; Hao, Z.C. High Sensitivity of Compound Drought and Heatwave Events to Global Warming in the Future. *Earths Future* **2022**, *10*, e2022EF002833. [CrossRef]
5. De Luca, P.; Donat, M.G. Projected Changes in Hot, Dry, and Compound Hot-Dry Extremes Over Global Land Regions. *Geophys. Res. Lett.* **2023**, *50*, e2022GL102493. [CrossRef]
6. Dannenberg, M.P.; Yan, D.; Barnes, M.L.; Smith, W.K.; Johnston, M.R.; Scott, R.L.; Biederman, J.A.; Knowles, J.F.; Wang, X.; Duman, T.; et al. Exceptional heat and atmospheric dryness amplified losses of primary production during the 2020 US Southwest hot drought. *Glob. Chang. Biol.* **2022**, *28*, 4794–4806. [CrossRef]
7. Hao, Y.; Hao, Z.C.; Fu, Y.S.; Feng, S.F.; Zhang, X.; Wu, X.Y.; Hao, F.H. Probabilistic assessments of the impacts of compound dry and hot events on global vegetation during growing seasons. *Environ. Res. Lett.* **2021**, *16*, 074055. [CrossRef]
8. Wu, X.Y.; Jiang, D.B. Probabilistic impacts of compound dry and hot events on global gross primary production. *Environ. Res. Lett.* **2022**, *17*, 034049. [CrossRef]
9. Tabari, H.; Willems, P. Global risk assessment of compound hot-dry events in the context of future climate change and socioeconomic factors. *Npj Clim. Atmos. Sci.* **2023**, *6*, 74. [CrossRef]
10. Zhang, Y.T.; Hao, Z.C.; Zhang, Y. Agricultural risk assessment of compound dry and hot events in China. *Agric. Water Manag.* **2023**, *277*, 108128. [CrossRef]
11. Liu, J.D.; Qi, J.L.; Yin, P.; Liu, W.; He, C.; Gao, Y.; Zhou, L.; Zhu, Y.X.; Kan, H.D.; Chen, R.J.; et al. Rising cause-specific mortality risk and burden of compound heatwaves amid climate change. *Nat. Clim. Chang.* **2024**, *14*, 1201–1209. [CrossRef]
12. Ciais, P.; Reichstein, M.; Viovy, N.; Granier, A.; Ogée, J.; Allard, V.; Aubinet, M.; Buchmann, N.; Bernhofer, C.; Carrara, A.; et al. Europe-wide reduction in primary productivity caused by the heat and drought in 2003. *Nature* **2005**, *437*, 529–533. [CrossRef] [PubMed]
13. Liao, Z.Z.; Zhou, B.H.; Zhu, J.Y.; Jia, H.Y.; Fei, X.H. A critical review of methods, principles and progress for estimating the gross primary productivity of terrestrial ecosystems. *Front. Environ. Sci.* **2023**, *11*, 1093095. [CrossRef]
14. Wei, Y.C.; Yu, M.; Wei, J.F.; Zhou, B.T. Impacts of Extreme Climates on Vegetation at Middle-to-High Latitudes in Asia. *Remote Sens.* **2023**, *15*, 1251. [CrossRef]
15. Kang, J.; Yu, M.; Xia, Y.; Sun, S.L.; Zhou, B.T. Impacts of Compound Hot-Dry Events on Vegetation Productivity over Northern East Asia. *Forests* **2024**, *15*, 549. [CrossRef]
16. Chaves, M.M.; Flexas, J.; Pinheiro, C. Photosynthesis under drought and salt stress: Regulation mechanisms from whole plant to cell. *Ann. Bot.* **2009**, *103*, 551–560. [CrossRef]
17. Reichstein, M.; Bahn, M.; Ciais, P.; Frank, D.; Mahecha, M.D.; Seneviratne, S.I.; Zscheischler, J.; Beer, C.; Buchmann, N.; Frank, D.C.; et al. Climate extremes and the carbon cycle. *Nature* **2013**, *500*, 287–295. [CrossRef]
18. Zhao, M.S.; Running, S.W. Drought-Induced Reduction in Global Terrestrial Net Primary Production from 2000 Through 2009. *Science* **2010**, *329*, 940–943. [CrossRef]

19. Poorter, H.; Niklas, K.J.; Reich, P.B.; Oleksyn, J.; Poot, P.; Mommer, L. Biomass allocation to leaves, stems and roots: Meta-analyses of interspecific variation and environmental control. *New Phytol.* **2012**, *193*, 30–50. [\[CrossRef\]](#)
20. Wahid, A.; Gelani, S.; Ashraf, M.; Foolad, M.R. Heat tolerance in plants: An overview. *Environ. Exp. Bot.* **2007**, *61*, 199–223. [\[CrossRef\]](#)
21. Seneviratne, S.I.; Corti, T.; Davin, E.L.; Hirschi, M.; Jaeger, E.B.; Lehner, I.; Orlowsky, B.; Teuling, A.J. Investigating soil moisture-climate interactions in a changing climate: A review. *Earth Sci. Rev.* **2010**, *99*, 125–161. [\[CrossRef\]](#)
22. Miralles, D.G.; Gentile, P.; Seneviratne, S.I.; Teuling, A.J. Land-atmospheric feedbacks during droughts and heatwaves: State of the science and current challenges. *Ann. N. Y. Acad. Sci.* **2019**, *1436*, 19–35. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Doughty, C.E.; Metcalfe, D.B.; Girardin, C.A.J.; Amézquita, F.F.; Cabrera, D.G.; Huasco, W.H.; Silva-Espejo, J.E.; Araujo-Murakami, A.; da Costa, M.C.; Rocha, W.; et al. Drought impact on forest carbon dynamics and fluxes in Amazonia. *Nature* **2015**, *519*, 78–82. [\[CrossRef\]](#) [\[PubMed\]](#)
24. Teskey, R.; Wertin, T.; Bauweraerts, I.; Ameye, M.; McGuire, M.A.; Steppe, K. Responses of tree species to heat waves and extreme heat events. *Plant Cell Environ.* **2015**, *38*, 1699–1712. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Grossiord, C.; Buckley, T.N.; Cernusak, L.A.; Novick, K.A.; Poulter, B.; Siegwolf, R.T.W.; Sperry, J.S.; McDowell, N.G. Plant responses to rising vapor pressure deficit. *New Phytol.* **2020**, *226*, 1550–1566. [\[CrossRef\]](#) [\[PubMed\]](#)
26. Fang, O.Y.; Zhang, Q.B. Tree resilience to drought increases in the Tibetan Plateau. *Glob. Chang. Biol.* **2019**, *25*, 245–253. [\[CrossRef\]](#)
27. Flach, M.; Brenning, A.; Gans, F.; Reichstein, M.; Sippel, S.; Mahecha, M.D. Vegetation modulates the impact of climate extremes on gross primary production. *Biogeosciences* **2021**, *18*, 39–53. [\[CrossRef\]](#)
28. Papagiannopoulou, C.; Miralles, D.G.; Dorigo, W.A.; Verhoest, N.E.C.; Depoorter, M.; Waegeman, W. Vegetation anomalies caused by antecedent precipitation in most of the world. *Environ. Res. Lett.* **2017**, *12*, 074016. [\[CrossRef\]](#)
29. Tschumi, E.; Lienert, S.; van der Wiel, K.; Joos, F.; Zscheischler, J. The effects of varying drought-heat signatures on terrestrial carbon dynamics and vegetation composition. *Biogeosciences* **2022**, *19*, 1979–1993. [\[CrossRef\]](#)
30. Anderegg, W.R.L.; Schwalm, C.; Biondi, F.; Camarero, J.J.; Koch, G.; Litvak, M.; Ogle, K.; Shaw, J.D.; Shevliakova, E.; Williams, A.P.; et al. Pervasive drought legacies in forest ecosystems and their implications for carbon cycle models. *Science* **2015**, *349*, 528–532. [\[CrossRef\]](#)
31. Zhu, J.W.; Zhang, M.H.; Zhang, Y.; Zeng, X.D.; Xiao, X.M. Response of Tropical Terrestrial Gross Primary Production to the Super El Nino Event in 2015. *J. Geophys. Res. -Biogeosci.* **2018**, *123*, 3193–3203. [\[CrossRef\]](#)
32. Han, L.; Chen, Y.N.; Wang, Y.; Sun, Y.; Ding, Z.; Zhang, H.S.; Tang, X.G. Divergent responses of subtropical evergreen and deciduous forest carbon cycles to the summer 2022 drought. *Environ. Res. Lett.* **2024**, *19*, 054043. [\[CrossRef\]](#)
33. Peng, T.T.; Zhao, L.; Zhang, L.; Shen, X.Y.; Ding, Y.H.; Wang, J.S.; Li, Q.Q.; Liu, Y.J.; Hu, Y.M.; Ling, J.; et al. Changes in Temperature-Precipitation Compound Extreme Events in China During the Past 119 Years. *Earth Space Sci.* **2023**, *10*, e2022EA002777. [\[CrossRef\]](#)
34. Lin, S.; Li, H.Y.; Huang, P.C.; Duan, X.Y. Characteristics of high temperature, drought and circulation situation in summer 2022 in China. *J. Arid Meteorol.* **2022**, *40*, 748–763. [\[CrossRef\]](#)
35. Xu, W.F.; Yuan, W.P.; Wu, D.H.; Zhang, Y.; Shen, R.Q.; Xia, X.S.; Ciais, P.; Liu, J.X. Impacts of record-breaking compound heatwave and drought events in 2022 China on vegetation growth. *Agric. For. Meteorol.* **2024**, *344*, 109799. [\[CrossRef\]](#)
36. Zhang, L.; Yu, X.; Zhou, T.; Zhang, W.; Hu, S.; Clark, R. Understanding and Attribution of Extreme Heat and Drought Events in 2022: Current Situation and Future Challenges. *Adv. Atmos. Sci.* **2023**, *40*, 1941–1951. [\[CrossRef\]](#)
37. Wang, J.; Yan, R.; Wu, G.X.; Liu, Y.M.; Wang, M.R.; Zeng, N.; Jiang, F.; Wang, H.M.; He, W.; Wu, M.S.; et al. Unprecedented decline in photosynthesis caused by summer 2022 record-breaking compound drought-heatwave over Yangtze River Basin. *Sci. Bull.* **2023**, *68*, 2160–2163. [\[CrossRef\]](#)
38. Chen, S.Y.; Qiu, R.N.; Chen, Y.M.; Gong, W.; Han, G. Impacts of Drought and Heatwave on the Vegetation and Ecosystem in the Yangtze River Basin in 2022. *Remote Sens.* **2024**, *16*, 2889. [\[CrossRef\]](#)
39. Li, T.Y.; Wang, S.Q.; Chen, B.; Wang, Y.P.; Chen, S.L.; Chen, J.H.; Xiao, Y.H.; Xia, Y.; Zhao, Z.Q.; Chen, X.; et al. Widespread reduction in gross primary productivity caused by the compound heat and drought in Yangtze River Basin in 2022. *Environ. Res. Lett.* **2024**, *19*, 034048. [\[CrossRef\]](#)
40. Muñoz-Sabater, J.; Dutra, E.; Agustí-Panareda, A.; Albergel, C.; Arduini, G.; Balsamo, G.; Boussetta, S.; Choulga, M.; Harrigan, S.; Hersbach, H.; et al. ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth Syst. Sci. Data* **2021**, *13*, 4349–4383. [\[CrossRef\]](#)
41. Li, X.; Xiao, J. A Global, 0.05-Degree Product of Solar-Induced Chlorophyll Fluorescence Derived from OCO-2, MODIS, and Reanalysis Data. *Remote Sens.* **2019**, *11*, 517. [\[CrossRef\]](#)
42. Li, X.; Xiao, J.F. Mapping Photosynthesis Solely from Solar-Induced Chlorophyll Fluorescence: A Global, Fine-Resolution Dataset of Gross Primary Production Derived from OCO-2. *Remote Sens.* **2019**, *11*, 2563. [\[CrossRef\]](#)
43. Joiner, J.; Yoshida, Y. Satellite-based reflectances capture large fraction of variability in global gross primary production (GPP) at weekly time scales. *Agric. For. Meteorol.* **2020**, *291*, 108092. [\[CrossRef\]](#)

44. Friedl, M.; Sulla-Menashe, D. MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 0.05Deg CMG V061. 2022, Distributed by NASA EOSDIS Land Processes Distributed Active Archive Center. 2022. Available online: <https://lpdaac.usgs.gov/products/mcd12c1v061/> (accessed on 12 June 2024).
45. Didan, K. MODIS/Terra Vegetation Indices Monthly L3 Global 0.05Deg CMG V061. Distributed by NASA EOSDIS Land Processes Distributed Active Archive Center. 2021. Available online: <https://lpdaac.usgs.gov/products/mod13c2v061/> (accessed on 12 June 2024).
46. Monteith, J.L.; Unsworth, M.H. *Principles of Environmental Physics*, 3rd ed.; Academic Press: Cambridge, MA, USA, 2007.
47. Buermann, W.; Parida, B.; Jung, M.; MacDonald, G.M.; Tucker, C.J.; Reichstein, M. Recent shift in Eurasian boreal forest greening response may be associated with warmer and drier summers. *Geophys. Res. Lett.* **2014**, *41*, 1995–2002. [[CrossRef](#)]
48. Baldocchi, D.; Falge, E.; Gu, L.H.; Olson, R.; Hollinger, D.; Running, S.; Anthoni, P.; Bernhofer, C.; Davis, K.; Evans, R.; et al. FLUXNET: A new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities. *Bull. Am. Meteorol. Soc.* **2001**, *82*, 2415–2434. [[CrossRef](#)]
49. Fisher, J.B.; Huntzinger, D.N.; Schwalm, C.R.; Sitch, S. Modeling the Terrestrial Biosphere. *Annu. Rev. Environ. Resour.* **2014**, *39*, 91–123. [[CrossRef](#)]
50. McDowell, N.; Pockman, W.T.; Allen, C.D.; Breshears, D.D.; Cobb, N.; Kolb, T.; Plaut, J.; Sperry, J.; West, A.; Williams, D.G.; et al. Mechanisms of plant survival and mortality during drought: Why do some plants survive while others succumb to drought? *New Phytol.* **2008**, *178*, 719–739. [[CrossRef](#)]
51. Reichstein, M.; Camps-Valls, G.; Stevens, B.; Jung, M.; Denzler, J.; Carvalhais, N.; Prabhat. Deep learning and process understanding for data-driven Earth system science. *Nature* **2019**, *566*, 195–204. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.