

Article

Impacts of Drought and Heatwave on the Vegetation and Ecosystem in the Yangtze River Basin in 2022

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Abstract: In 2022, a severe drought and heatwave occurred in the middle and lower reaches of the Yangtze River Basin. Previous studies have highlighted the severity of this event, yet the relevance of soil moisture (SM), as well as vapor pressure deficit (VPD) and vegetation damage, remained unclear. Here, we utilized solar-induced chlorophyll fluorescence (SIF) and various flux data to monitor the impact of drought on vegetation and analyze the influence of different environmental factors. The results indicated a severe situation of drought and heatwave in the Yangtze River Basin in 2022 that significantly affected vegetation growth and the ecosystem carbon balance. SIF and NDVI have respective advantages in reflecting damage to vegetation under drought and heatwave conditions; SIF is more capable of capturing the weakening of vegetation photosynthesis, while NDVI can more rapidly indicate vegetation damage. Additionally, the correlation of SM and SIF are comparable to that of VPD and SIF. By contrast, the differentiation in the severity of vegetation damage among different types of vegetation is evident; cropland is more vulnerable compared to forest ecosystems and is more severely affected by drought and heatwave. These findings provided important insights for assessing the impact of compound drought and heatwave events on vegetation growth.

Keywords: drought and heatwave; Yangtze River Basin; vegetation; SIF; NDVI



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1. Introduction

Drought and heatwave are among the most common natural ecosystem disasters globally and are often associated with prolonged periods of abnormally low precipitation or exceptionally high temperatures lasting from several months to several years [1]. They can inflict severe damage upon terrestrial ecosystems [2], such as reducing vegetation productivity [3], thereby destroying the ecosystem carbon balance [4].

During the summer of 2022, many regions worldwide, including Europe and Asia, experienced extraordinarily high temperatures [5]. China was no exception, facing its most severe meteorological drought and heatwave event since comprehensive meteorological records began in 1961 [6]. Yuan's study indicated that cities along the Yangtze River Basin witnessed daytime maximum temperatures exceeding 42 °C, enduring over 40 consecutive days of heatwave conditions and more than 32 days of compounded hot weather [7]. As a result of the drought, the Yangtze River Basin experienced an unprecedented shortage of precipitation [8], significantly reducing hydroelectric power generation. Consequently, Sichuan Province encountered a substantial decline in its power supply capacity, greatly impacting the lives and productivity of the local residents [9].

The response of vegetation to drought and heatwave serves as a crucial indicator for assessing the health of terrestrial ecosystems [10]. Typically, during such periods, vegetation undergoes alterations in photosynthetic activity [11], consequently leading to a decline in productivity [12]. Vegetation indices (VIs) that measure greenness, such as the Normalized Difference Vegetation Index (NDVI), have been extensively used to evaluate the influence of water and heat stress on vegetation productivity during prolonged periods of drought and heatwave [13,14]. However, these conventional green VIs often only reflect the greenness of the vegetation canopy or chlorophyll content, solely pertaining to the potential photosynthetic activity of the vegetation, without considering the actual photosynthetic process [1,15]. Recent research has shown a growing consensus that solar-induced chlorophyll fluorescence (SIF) is an outcome of vegetation photosynthesis and is closely associated with gross primary production (GPP) [16–18]. Consequently, many scholars argue that SIF is more sensitive to environmental stressors compared to green-based VIs [19–21].

Under the combined conditions of high temperatures and reduced rainfall, vegetation responds to the increased vapor pressure deficit (VPD) by closing stomata to reduce water dissipation [22,23]. Consequently, soil moisture decreases, exacerbating vegetation water deficit, which further prompts plants to reduce stomatal aperture to mitigate water loss, thus adapting to the water-deficient conditions [24,25]. This, in turn, exacerbates vegetation damage [26,27]. Numerous academics argue that vegetation in arid regions at mid-latitudes exhibits heightened sensitivity to fluctuations in water availability [25,28]. They suggest that the atmosphere in arid regions is already very dry and hot, hence vegetation exhibits robust resistance to the rising levels of VPD. However, there are also dissenting opinions, with some scholars proposing that high VPD may have a greater impact on vegetation growth than low soil moisture. For instance, Wang, in analyzing drought and heatwave in both Yunnan and southern China, suggested that the correlation between VPD and SIF yield tends to be stronger at spatiotemporal scales [1].

Furthermore, different types of vegetation ecosystems exhibit varying responses to drought and heatwave [10,29–31]. For instance, some scholars suggest that the intensification of temperature exacerbates the degree of drought most significantly in temperate desert and grassland regions, while its effect is weakest in mixed coniferous–deciduous forest areas and cold temperate coniferous forest regions [32].

The recent compound drought and heatwave event in the Yangtze River Basin, China, which was characterized by its prolonged duration, wide coverage, high intensity, and extreme nature, presents an excellent opportunity for study. Therefore, we have chosen this drought and heatwave event in the Yangtze River Basin as our main research focus, aiming to explore its spatiotemporal dynamics and elucidate the strengths and weaknesses of NDVI and VIs in reflecting vegetation responses to extreme weather. Additionally, we will analyze whether SM or VPD predominates in driving vegetation damage during this event and examine the differences in responses among different vegetation types under drought and heatwave conditions. Our research findings will enhance current understanding of vegetation responses to drought and heatwave in the Yangtze River Basin.

2. Materials and Methods

2.1. Study Area

Our study area is the Yangtze River Basin in China. This region is primarily influenced by a monsoon climate, with an annual average temperature ranging from 16 to 18 °C. The hottest month is July, with precipitation concentrated in the summer; winters are relatively cold, with the least amount of precipitation throughout the year. The blowing of the monsoon brings significant seasonal climate changes, which have important impacts on local agricultural production and the ecological environment. As one of China's crucial agricultural regions, the Yangtze River Basin holds immense significance, with cropland extensively distributed in the plains and hilly areas, cultivating crops such as rice, wheat, rapeseed, and cotton. Its mountainous and hilly areas are largely covered with forests,

including fir, pine, and willow trees. Forests and cropland are the primary vegetation types in this region. During the summer of 2022, China faced unprecedented concurrent occurrences of drought and heatwave, resulting in severe soil water deficits that severely inhibited vegetation growth. Considering the vegetation's growing season, we consider the period from July to October as the occurrence time for this summer drought and heatwave event and will focus our analysis accordingly.

2.2. Meteorological Data and Environmental Data

Temperature and precipitation data are utilized in this study to characterize the severity of compound drought and heatwave. Monthly temperature and precipitation data are sourced from ERA5 (<https://cds.climate.copernicus.eu/>, accessed on 21 March 2024), with a spatial resolution of $0.25^\circ \times 0.25^\circ$. ERA5, generated by the ECMWF, is the fifth generation of the atmospheric reanalysis dataset covering global climate from January 1950 to the present day. These meteorological data have undergone quality control and are widely used in various studies of past climate events.

The soil moisture data used in this study also originate from the ERA5 reanalysis dataset. Due to variations in soil moisture infiltration rates at different depths, as well as differences in the impacts of evaporation, transpiration, and plant root distribution, soil moisture needs to be categorized into different layers to better understand the changes in soil moisture profiles. Therefore, we analyzed soil moisture data SM1–SM4 at four different depths (Layer 1: 0–7 cm, Layer 2: 7–28 cm, Layer 3: 28–100 cm, Layer 4: 100–289 cm). We utilized 2 m temperature data and 2 m dew point temperature data to calculate VPD. The resolution of both datasets is also $0.25^\circ \times 0.25^\circ$.

2.3. NDVI and SIF

We obtained the NDVI for the study area from The PKU GIMMS Normalized Difference Vegetation Index product (PKU GIMMS NDVI, version 1.2) via <https://zenodo.org/records/8253971> (accessed on 24 March 2024), which has a spatial resolution of $1/12^\circ$ and a temporal resolution of half a month. It is calculated based on satellite-measured surface reflectance data using NOAA's advanced very high-resolution radiometer (AVHRR) satellite data. The PKU GIMMS NDVI is based on a BPNN model specific to biomes, utilizing the GIMMS NDVI3g product and extracted from 3.6 million high-quality global NDVI samples. This approach effectively eliminates the effects of satellite orbit drift and sensor degradation. To expand the temporal coverage until 2022, it is then combined with MODIS NDVI (MOD13C1) through a pixel-level random forest fusion approach. To ensure consistency in analysis, we obtained monthly averages by taking the mean values and aggregated them at the monthly scale.

We acquired GOSIF data from <http://globalecology.unh.edu/data/GOSIF.html> (accessed on 24 March 2024). The GOSIF data are produced using the cubist machine learning method, incorporating MODIS EVI data and extensive reanalysis meteorological data. These datasets are available every 8 days, with a spatial resolution of 0.05° , spanning from the year 2000 to the present [33]. We used data from the period 2018 to 2022 in our study. In contrast to previous coarser resolution SIF data obtained directly from OCO-2 observations, GOSIF offers superior spatial resolution, global continuous coverage, and an extended historical record. We are confident that utilizing the GOSIF dataset can provide a more precise representation of vegetation photosynthetic activity in the research area. Similarly, to standardize the temporal resolution of this study to a monthly scale, we obtained monthly averages using the mean value method.

2.4. GPP and NEE

We obtained GPP derived from MODIS (MOD17A2H 006) for the years 2018 to 2022 from Google Earth Engine. This product utilizes MODIS land remote sensing data such as reflectance and chlorophyll indices, along with meteorological data like temperature and radiation, to estimate vegetation photosynthetic activity and productivity. It has temporal

and spatial resolutions of 8 days and 500 m, respectively, and we also aggregated it to a monthly scale [34]. GPP measures the rate at which plants convert solar energy into organic substances through photosynthesis, thereby indicating the overall efficiency of photosynthesis in plants. It can also be roughly understood as the total energy fixed by plants per unit area or unit time, serving as an important indicator of plant productivity.

We use the net ecosystem exchange (NEE) indicator to describe the carbon exchange between ecosystems and the atmosphere. This data originates from the SMAP L4 Global Daily 9 km EASE-Grid Carbon Net Ecosystem Exchange, Version 7 (<https://search.earthdata.nasa.gov/search>, accessed on 25 March 2024), a dataset provided by NASA's Soil Moisture Active Passive (SMAP) satellite. It employs the baseline algorithm, combining ground observations with satellite remote sensing data, such as SMAP's microwave observations and meteorological data, to estimate carbon fluxes in terrestrial ecosystems. This product provides daily NEE data globally, utilizing a 9 km resolution EASE-Grid. Like other datasets, we compute averages to obtain monthly scale data.

2.5. Land Cover Type Data

To distinguish vegetation types in our study area (Figure 1), we utilized the 2019 MODIS Land Cover Type (MCD12Q1) Version 6.1 data product based on the Annual International Geosphere-Biosphere Programme (IGBP) classification system. We obtained the map from <https://lpdaac.usgs.gov/products/mcd12q1v006/> (accessed on 14 July 2023) and the classification system from <https://climatedataguide.ucar.edu/climate-data/ceres-igbp-land-classification> (accessed on 25 July 2024). The spatial resolution of this dataset is 5600 m. The dataset is created by classifying MODIS Terra and Aqua reflectance data through supervised methods. After classification, additional processing integrates prior knowledge and supplementary information to enhance the accuracy of specific class distinctions. The specific classification scheme is delineated in Table 1.

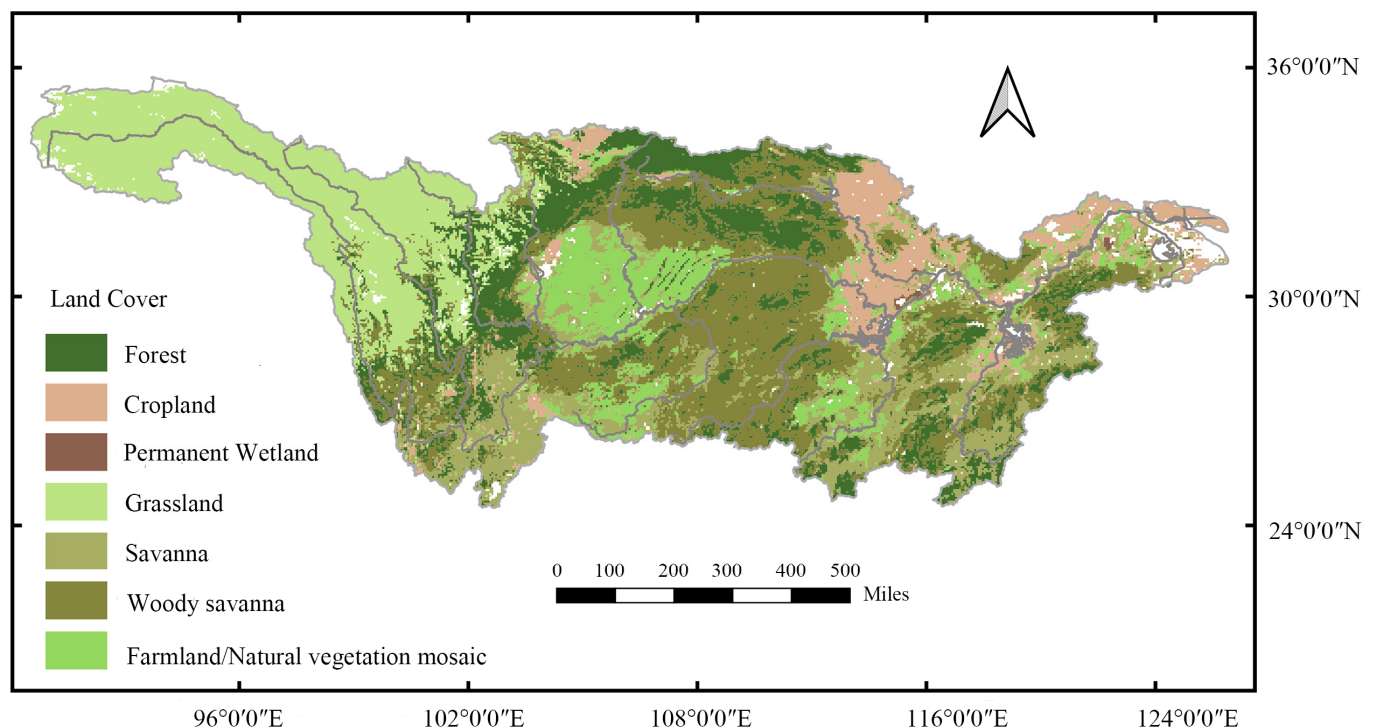


Figure 1. The Yangtze River Basin. The dark gray lines represent the primary and secondary water systems of the Yangtze River. The base map depicts the land cover type based on data processed from 2019 MCD12Q1 v006. Forest is a collective term encompassing evergreen coniferous forests, evergreen broad-leaved forests, deciduous broad-leaved forests, and mixed forests.

Table 1. IGBP global land cover classification system.

Code	Type	Details
1	Evergreen Needleleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 m. Almost all trees remain green all year. Canopy is never without green foliage.
2	Evergreen Broadleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 m. Almost all trees and shrubs remain green year-round. Canopy is never without green foliage.
3	Deciduous Needleleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 m. Consists of seasonal needleleaf tree communities with an annual cycle of leaf-on and leaf-off periods.
4	Deciduous Broadleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 m. Consists of broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods.
5	Mixed Forests	Lands dominated by trees with a percent cover >60% and height exceeding 2 m. Consists of tree communities with interspersed mixtures or mosaics of the other four forest types. None of the forest types exceeds 60% of the landscape.
6	Closed Shrublands	Lands with woody vegetation less than 2 m tall and with shrub canopy cover >60%. The shrub foliage can be either evergreen or deciduous.
7	Open Shrublands	Lands with woody vegetation less than 2 m tall and with shrub canopy cover between 10 and 60%. The shrub foliage can be either evergreen or deciduous.
8	Woody Savannas	Lands with herbaceous and other understory systems and forest canopy cover between 30 and 60%. The forest cover height exceeds 2 m.
9	Savannas	Lands with herbaceous and other understory systems and forest canopy cover between 10 and 30%. The forest cover height exceeds 2 m.
10	Grasslands	Lands with herbaceous types of cover. Tree and shrub cover is less than 10%. Permanent wetlands lands with a permanent mixture of water and herbaceous or woody vegetation. The vegetation can be present in either salt, brackish, or fresh water.
11	Permanent Wetlands	Lands with a permanent mixture of water and herbaceous or woody vegetation that cover extensive areas. The vegetation can be present in salt, brackish, or fresh water.
12	Croplands	Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems). Note that perennial woody crops will be classified as the appropriate forest or shrub land cover type.
13	Urban and Built-up Lands	Land covered by buildings and other man-made structures.
14	Cropland/Natural Vegetation Mosaics	Lands with a mosaic of croplands, forests, shrublands, and grasslands in which no one component comprises more than 60% of the landscape.
15	Snow and Ice	Lands under snow/ice cover most of the year.
16	Barren Sparse Vegetation	Lands with exposed soil, sand, or rocks and less than 10% vegetative cover during any time of the year.
17	Water Bodies	Oceans, lakes, reservoirs, and rivers, which can be freshwater or saline.

2.6. Methods

2.6.1. Spatiotemporal Evolution Analysis

To determine the occurrence and severity of the 2022 drought and heatwave in the study area, we obtained temperature, precipitation, SM, and VDP data within the Yangtze River Basin using provincial boundary lines. Subsequently, we calculated their monthly averages for both reference years (2018–2021) and the extreme climate year (2022). Meanwhile, to monitor changes in vegetation productivity under extreme climate conditions and the response of ecosystem carbon balance, we also calculated the monthly averages of NDVI, SIF, GPP, and NEE for the reference years and 2022 in the region. Additionally, we calculated the change percentages of all indices for the year 2022 compared to the average values from 2018 to 2021.

2.6.2. Analysis of Anomalies

The standardized anomalies of all variables (including temperature, precipitation, VPD, SM, NDVI, SIF, GPP, and NEE) are computed to facilitate the study of the spatiotemporal variations of these variables during droughts and heatwaves. We calculate the standardized anomalies for each variable at the pixel level. These anomalies represent how each pixel deviates from the average conditions over multiple years, adjusted for the standard deviation between 2018 and 2021. The specific formula is as follows:

$$Y(i,j,t)' = \frac{(Y(i,j,t) - \bar{Y}(i,j))}{\text{std}(Y(i,j,t))} \quad (1)$$

where $Y(i,j,t)'$ represents the normalized index anomaly of pixel (i,j) at time (t) ; $Y(i,j,t)$ denotes the original values of the index for pixel (i,j) at time (t) ; $\bar{Y}(i,j)$ is the mean data for pixel (i,j) during the period 2018–2021; and $\text{std}(Y(i,j,t))$ is the standard deviation for pixel (i,j) from the years 2018 to 2021.

The anomaly calculation formula (Formula (1)) is based on the robust satellite techniques (RST) approach. The RST approach is a widely used approach for analyzing multi-temporal satellite data that is primarily aimed at detecting anomalies in the spatiotemporal domain to monitor environmental changes. The core idea of this method is to establish a baseline normal state based on years of satellite observations, typically represented by the temporal mean and standard deviation of signals over specific time periods. By comparing current observed signals with this baseline normal state, anomalies can be identified [35]. The RST method has been successfully applied across various fields, including monitoring changes in soil moisture and dynamic monitoring of landslides using NDVI [36,37].

2.6.3. Correlation Analysis

In conducting the correlation analysis of SIF, SM, and VPD anomalies for July, August, September, and October 2022, we selected the anomalies of Layer 1's soil moisture (SM1) as representative of soil moisture anomalies. The computation not only required temporal consistency across the indices but also spatial consistency. Therefore, we performed bilinear interpolation resampling on SM anomaly and VPD anomaly data to adjust their original resolutions to match the resolution of the SIF images. Specifically, for each pixel position in the target image, we identified its four nearest neighboring pixels in the original image. Firstly, we linearly interpolated between two adjacent pixels horizontally to obtain two temporary values. Then, we linearly interpolated vertically between these two temporary values to obtain the final target pixel value.

Upon achieving uniform spatial resolution across these three datasets, we proceeded to calculate Pearson correlation coefficients between SIF anomalies and anomalies of SM and VPD values. This analysis aimed to assess the interdependencies among these variables and provide insights into their relationships over the specified months of July, August, September, and October 2022.

2.6.4. Methods for Distinguishing Vegetation Types

Based on the land cover type map of MCD12Q1 (Figure 1) and the IGBP classification data (Table 1), we roughly divided the vegetation types in the Yangtze River Basin into the following two categories: forests and croplands (type_12). In this study, we investigated all types of forests found within the area, such as evergreen needleleaf forest (type_1), evergreen broadleaf forest (type_2), deciduous broadleaf forest (type_4), and mixed forest (type_5), collectively "forests". This categorization facilitates the examination of how various vegetation types respond to the intricate drought and heatwave events of 2022, as well as the alterations in ecosystem carbon balance (we did not include grassland in the forest category). We also conducted a detailed analysis of the monthly average changes in the major vegetation indices for these two primary vegetation types for both reference years and 2022 to gain a more intuitive understanding.

3. Results

3.1. Spatiotemporal Dynamics of the 2022 Drought and Heatwave in the Yangtze River Basin

The compound drought and heatwave in the Yangtze River Basin in 2022 was record-breaking, consistent with previous research findings [38]. In the research area, the global temperatures showed positive anomalies in both July and August (Figure 2a,b); in September and October, the central and southern regions maintained negative anomalies, albeit with a decreasing intensity, while the western and easternmost regions experienced negative anomalies (Figure 2c,d). In contrast, precipitation anomalies appeared more consistent, with predominantly negative anomalies throughout July to October, and a tendency toward southward movement of the anomaly center (Figure 2e–h). Figure 2i,j showed that the VPD in July and August mostly exhibited positive anomalies, with the anomaly center shifting from the west to the southeast. However, Figure 2k,l indicated that in the later period (September–October), the southwestern region showed opposite negative anomalies, consistent with the spatial-temporal distribution of temperature anomalies.

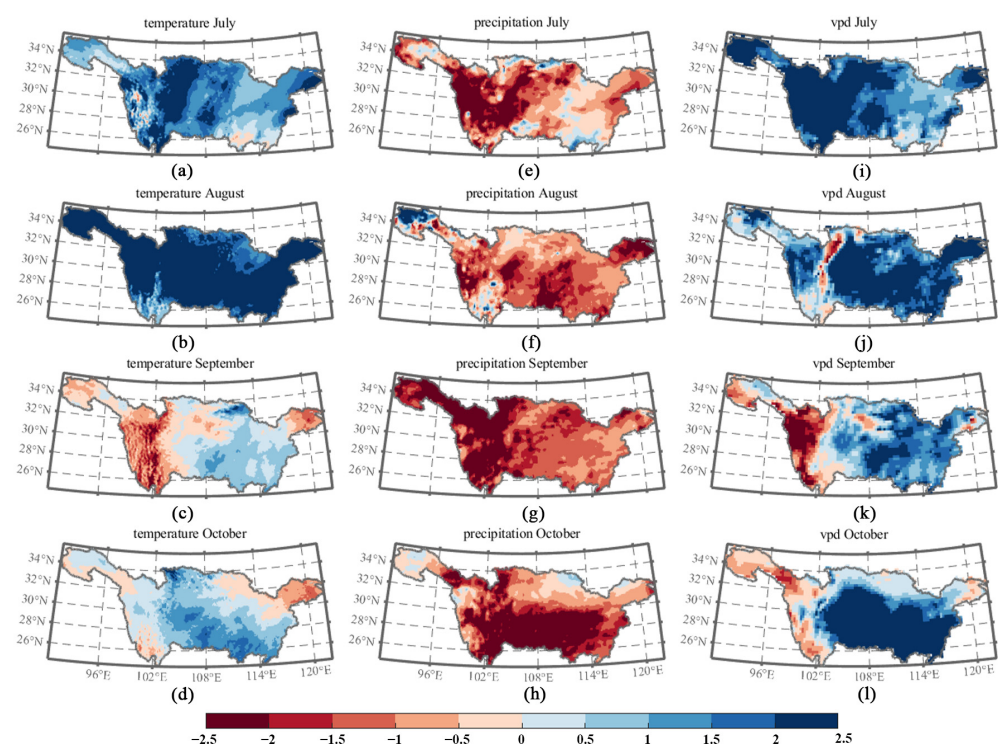


Figure 2. Spatial distributions of temperature, precipitation, and VPD anomalies in the Yangtze River Basin during July ((a,e,i) in 1st row), August ((b,f,j) in 2nd row), September ((c,g,k) in 3rd row), and October ((d,h,l) in 4th row) in 2022.

In addition, with the increase in temperature and decrease in precipitation, soil moisture and air humidity also undergo changes. Apart from a special situation showed in Figure 3m, the spatial distributions of soil moisture anomalies across four different layers were generally consistent, characterized by predominantly negative anomalies, with a trend of the anomaly center shifting from the northwest to the central-eastern region (Figure 3). However, the deeper the layer, the lighter the anomaly intensity. SM1–SM3 also exhibited opposite positive anomalies in the southwestern region from September to October compared to other regions (Figure 3c,d,g,h,l), which is consistent with the peculiar phenomena observed in temperature and VPD.

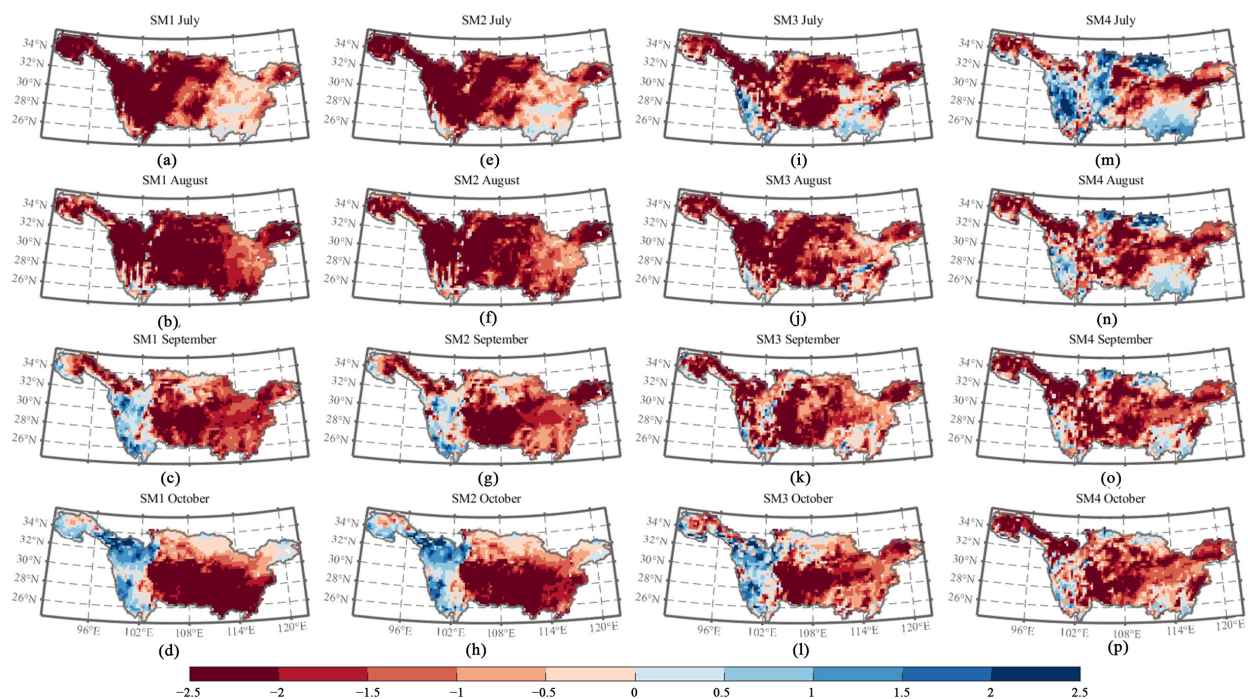


Figure 3. Spatial distributions of SM1, SM2, SM3, and SM4 anomalies in the Yangtze River Basin during July ((a,e,i,m) in 1st row), August ((b,f,j,n) in 2nd row), September ((c,g,k,o) in 3rd row), and October ((d,h,l,p) in 4th row) in 2022.

The monthly averages of all environmental indices for the year 2022, along with their change percentages, are listed in Tables 2 and 3. An overall analysis reveals that the temperature and VPD columns from July to October in both tables are predominantly in red, while the remaining columns are mostly in blue. This indicates that during the summer of 2022, temperatures and VPD were significantly higher than usual, while precipitation and soil moisture content were notably lower than usual, which suggests a pronounced drought and heatwave event.

Table 2. Monthly average environmental indices for the year 2022. Red indicates an increase in the monthly average compared to the mean for the base years (2018–2021), while blue indicates a decrease.

Month	Temperature	Precipitation	VPD	SM1	SM2	SM3	SM4
January	273.1416	61.50192	1.50065	0.37011	0.36771	0.36318	0.39969
February	272.55076	59.88396	1.78544	0.37913	0.38209	0.38263	0.40034
March	282.0996	109.97059	4.27324	0.37094	0.37013	0.37371	0.40142
April	284.37078	141.87742	4.92106	0.38383	0.38629	0.38301	0.4045
May	287.71506	153.96961	4.94959	0.385	0.38607	0.38705	0.40828
June	292.55077	213.31838	6.113	0.39408	0.39336	0.38498	0.41264
July	295.16993	140.01088	8.87914	0.35136	0.35281	0.35186	0.40851
August	296.51411	92.07134	11.40851	0.28761	0.29172	0.30846	0.39665
September	290.9224	52.59121	7.65444	0.3291	0.3274	0.3183	0.38783
October	285.35649	38.47303	5.28278	0.33866	0.33989	0.33847	0.38678
November	281.78179	33.20679	3.33306	0.34682	0.34157	0.33459	0.38434
December	274.39817	11.53739	2.57534	0.34734	0.35417	0.34788	0.38213

In this table, the unit for temperature is κ , the unit for precipitation is mm, the unit for VPD is hPa, and SM1–SM4 are unitless.

Table 3. The change percentages of all environmental indices for the year 2022 compared to the average values from 2018 to 2021. Positive values are shown in red, indicating an increase in the monthly average for that index in 2022 compared to the average of base years. Negative values are shown in blue, indicating a decrease.

Month	Δ Temperature	Δ Precipitation	Δ VPD	Δ SM1	Δ SM2	Δ SM3	Δ SM4
January	0.06185	20.84159	−23.98909	0.53817	−0.36934	−1.52415	0.56513
February	−1.25051	10.63857	−31.36631	2.76613	3.88524	3.52919	0.89134
March	0.63128	21.81804	23.08826	−2.04043	−1.48528	0.31253	0.878
April	0.03043	36.95338	5.30185	2.64044	3.664	3.22362	1.34068
May	−0.40948	−6.13164	−12.95424	1.75255	2.43307	4.98721	2.08927
June	0.06897	0.05786	4.03657	0.6669	1.02995	2.73307	2.60974
July	0.38508	−39.68248	44.26614	−11.71673	−11.72808	−10.25374	−0.19815
August	0.78578	−47.18728	59.76322	−22.60341	−21.04353	−16.17213	−2.98858
September	0.06414	−63.55857	37.59321	−13.06911	−13.03871	−13.49273	−4.75427
October	0.20108	−54.758	42.21785	−10.25648	−10.33978	−10.45781	−4.98396
November	0.82659	−32.15983	11.78168	−5.07065	−7.43555	−10.00847	−4.9414
December	0.06544	−67.41344	21.05722	−3.86582	−2.82911	−5.42747	−4.66375

In this table, the unit for all numbers is %.

To be more specific, in 2022, temperatures stayed above average from June to December (Figure 4a), peaking in August at 23.35 °C, compared to the usual peak of 21 °C (Table 2). Precipitation peaked unusually early in June at 213.31 mm, differing from previous years, in which the peak was in July at 232.12 mm (Figure 3c and Table 2). Also, VPD levels exceeded normal from June, peaking in August before gradually returning to normal (Figure 4e,f).

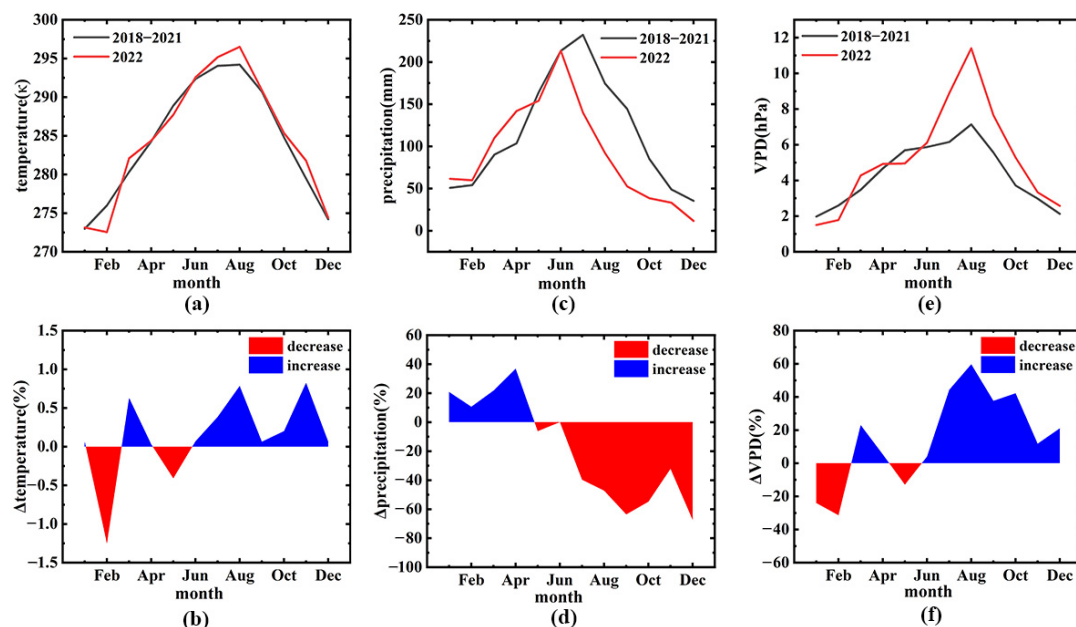


Figure 4. The seasonal cycles of different environmental metrics: (a) temperature (°C), (c) precipitation (mm), and (e) VPD (hPa). The corresponding change percentages for the year 2022 compared to the average values from 2018 to 2021 are shown in (b) temperature, (d) precipitation, and (f) VPD. In (a,c,e), the black line represents the monthly average for 2022, and the red line represents the monthly average value from 2018 to 2021. In (b,d,f) the blue part represents the proportion of value in 2022 that exceeds the average from 2018 to 2021, while the red part represents the proportion of value in 2022 that falls below the average from 2018 to 2021.

Figure 5, combined with Tables 2 and 3, showed that SM1–SM4 from July to October were all below the annual average. From Figure 5a,c,e and Figure 5b,d,f, it is evident that the trends of SM1–SM3 are highly similar, all reaching their lowest values of the year in August, with the most significant deviation from previous years occurring in the same

month. In contrast, the decrease in SM4 was relatively smooth (Figure 5g,h). Additionally, as soil depth increased, the decrease in SM gradually diminished, with the maximum decrease decreasing from 22.6% in Layer 1 to 4.9% in Layer 4.

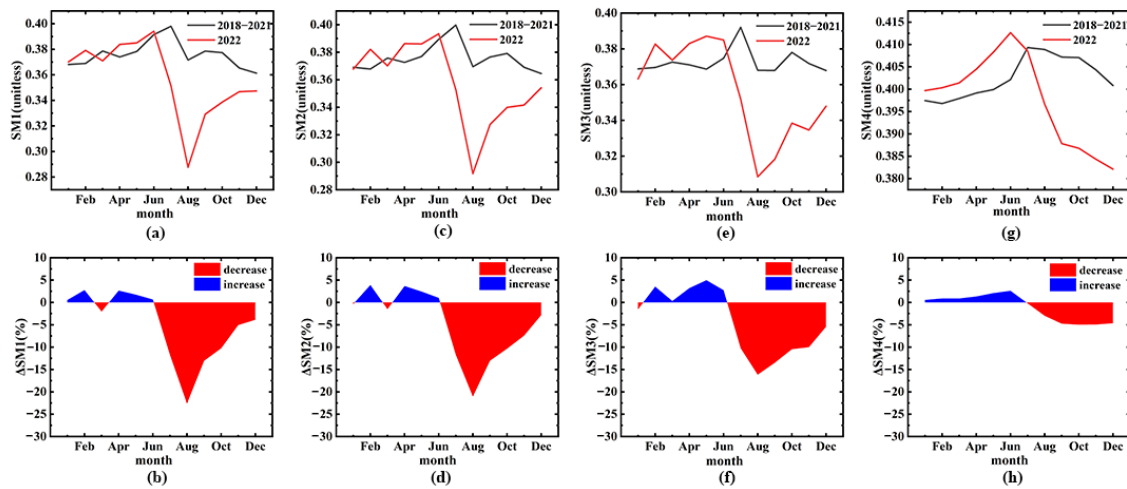


Figure 5. The seasonal cycles of different soil moisture metrics: (a) SM1 (unitless), (c) SM2 (unitless), (e) SM3 (unitless), and (g) SM4 (unitless). The corresponding change percentages for the year 2022 compared to the average values from 2018 to 2021 are shown in (b) SM1 (unitless), (d) SM2 (unitless), (f) SM3 (unitless), and (h) SM4 (unitless). In (a,c,e,g), the black line represents the monthly average for 2022, and the red line represents the monthly average value from 2018 to 2021. In (b,d,f,h), the blue part represents the proportion of value in 2022 that exceeds the average from 2018 to 2021, while the red part represents the proportion of value in 2022 that falls below the average from 2018 to 2021.

3.2. The Response of Vegetation and Ecosystem to the 2022 Drought and Heatwave

Our study indicates that the summer drought and heatwave in 2022 had a negative impact on vegetation productivity and ecosystem carbon balance. Ana Bastos has also explored this issue and arrived at similar conclusions [39]. Tables 4 and 5 present the estimated monthly averages of various productivity metrics for the year 2022, along with their change percentages relative to the reference year. The overall analysis shows that in both tables, most cell values from July to October, except for the last column, are predominantly blue, especially in August and September. The change percentages of the last column, NEE, are red from May to August and blue from September to October. This indicates that vegetation growth conditions were reduced from their usual levels in the summer of 2022, with negative impacts on the carbon cycling system, as well.

Table 4. Monthly average data of NDVI, SIF, GPP, and NEE for the year 2022. Red indicates an increase in the monthly average compared to the mean for the base years (2018–2021), while blue indicates a decrease.

Month	NDVI	SIF	GPP	NEE
January	0.4551	0.02598	1.71776	0.71092
February	0.42272	0.03172	2.70615	0.64699
March	0.45195	0.06879	6.23024	1.30209
April	0.52012	0.14856	9.16238	0.66888
May	0.59753	0.24623	8.6162	0.51057
June	0.66165	0.31369	9.98955	−0.14165
July	0.71436	0.35914	13.45568	−1.7425
August	0.69438	0.3142	11.39368	−1.4031
September	0.65029	0.21294	8.41859	−0.22193
October	0.5891	0.12502	4.55401	0.30409
November	0.52874	0.06758	4.79452	0.65478
December	0.46464	0.03045	1.8233	0.38198

In this table, the unit for GPP and NEE is $\text{gC m}^{-2} \text{d}^{-1}$, and NDVI and SIF are unitless.

Table 5. The change percentages of NDVI, SIF, GPP, and NEE for the year 2022 compared to the average values from 2018 to 2021. Red indicates an increase in the monthly average compared to the mean for the base years (2018–2021), while blue indicates a decrease.

Month	Δ NDVI	Δ SIF	Δ GPP	Δ NEE
January	5.552	12.19048	−2.03061	20.7616
February	−1.41054	−4.51962	−14.14507	−23.81739
March	1.88785	19.41702	24.68247	7.75961
April	1.26141	11.02048	5.93509	−17.01419
May	1.47964	6.63404	−4.70174	75.78726
June	0.65554	3.84533	−1.02022	1.71822
July	−0.58247	4.13018	24.58137	71.41891
August	−4.16176	−2.17843	−2.39262	1.40614
September	−4.35804	−8.66621	−4.01513	−45.23306
October	−2.46817	0.86978	−17.39621	−3.3217
November	1.47221	12.20108	10.10721	53.46793
December	−0.84992	−1.02301	−4.70653	−21.94149

In this table, the units of all numbers are %.

By observing the differences in NDVI, SIF, and GPP during the seasons of 2022 compared to the reference year (Figure 6, Tables 4 and 5), we found that NDVI exhibited the earliest response and the longest duration, remaining below the annual average throughout July to October (Figure 6b). Although its peak values in previous years occurred in August (0.72), in 2022, it reached a relatively smaller peak value in July (0.71) (Figure 6a). In comparison, SIF and GPP were significantly higher than the annual average in July, reaching their peaks in 2022 (SIF: 0.40, GPP: 13.46), exceeding their usual peak values (SIF: 0.34, GPP: 11.67). It was not until August that SIF and GPP began to decrease below normal values, followed by a trend of returning to the reference year's levels (Figure 6c–f). However, despite SIF and GPP showing relatively delayed responses compared to NDVI during the drought and heatwave event, the severity of their damage (GPP: 17.4%, SIF: 8.7%) was significantly higher than NDVI (4.4%), which is consistent with previous research findings. Therefore, we can evaluate the advantages of SIF and NDVI in reflecting the impact of drought and heatwave on vegetation from different perspectives. As an indicator of vegetation photosynthetic rates, SIF better reflects changes in GPP compared to NDVI in terms of both the degree of response and temporal alignment. This can partly explain the conclusion that SIF is more capable of capturing vegetation photosynthesis compared to NDVI. However, in terms of the timing and duration of response, NDVI is more agile in capturing the onset and duration of extreme environmental conditions compared to SIF.

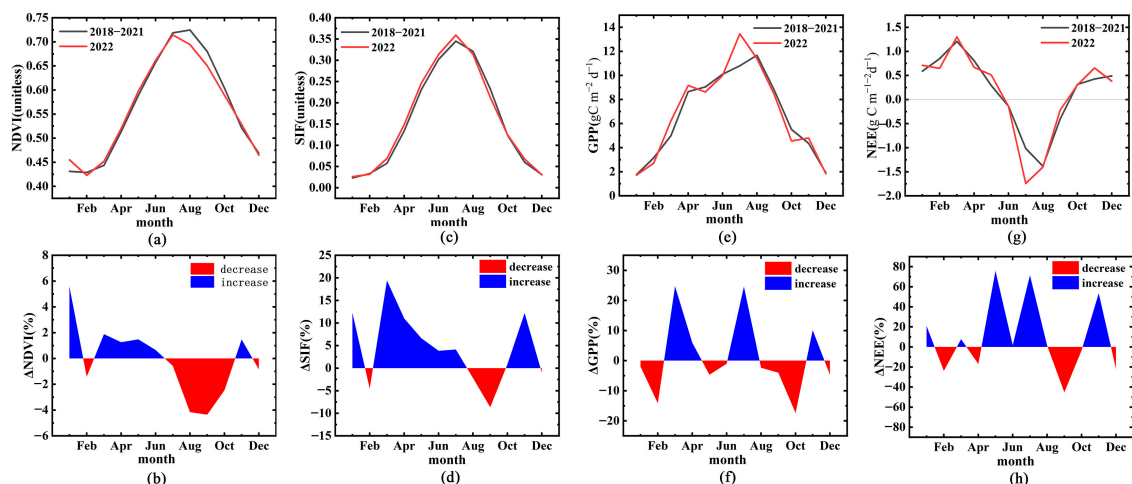


Figure 6. The seasonal cycles of different soil moisture metrics: (a) NDVI (unitless), (c) SIF (unitless), (e) GPP ($\text{gC m}^{-2} \text{d}^{-1}$), and (g) NEE ($\text{gC m}^{-2} \text{d}^{-1}$). The corresponding change percentages for the

year 2022 compared to the average values from 2018 to 2021 are shown in (b) NDVI (unitless), (d) SIF (unitless), (f) GPP ($\text{gC m}^{-2} \text{d}^{-1}$), and (h) NEE ($\text{gC m}^{-2} \text{d}^{-1}$). In (a,c,e,g), the black line represents the monthly average for 2022, and the red line represents the monthly average value from 2018 to 2021. In (b,d,f,h), the blue part represents the proportion of value in 2022 that exceeds the average from 2018 to 2021, while the red part represents the proportion of value in 2022 that falls below the average from 2018 to 2021.

Figure 6g showed that in a typical year, the NEE value reached its lowest point in August (-1.38), but in 2022, it started to significantly decrease below the average level of the reference year from June, reaching its lowest point in July (-1.74) (Table 4). However, there was a notable increase in NEE during the midterm of the drought and heatwave period in August and September, reversing from negative to positive and showing an increase compared to the typical year (Figure 6h). Despite the significant decrease in NEE values compared to the average of the reference year during the early stage of the drought and heatwave, the NEE value in 2022 turned positive earlier, even exceeding that of the reference year. This clearly indicated that the ecosystem carbon balance has been affected by the drought and heatwave.

Figure 7a–h depicted similar spatial distributions of NDVI and SIF anomalies, with prominent negative anomalies concentrated in the southeastern region, particularly in August and September. While widespread negative anomalies in SIF occurred relatively late, manifesting in a large-scale pattern in the central and eastern regions by October (Figure 7g), NDVI had already established this pattern as early as August and sustained it through September (Figure 7b,c). In comparison, the abnormal distribution of GPP appeared relatively independent, with a global positive anomaly prevailing in July (Figure 7i). Negative anomalies began to emerge in the northeast in August (Figure 7j), gradually spreading southwestward, culminating in widespread negative anomalies by October (Figure 7l). Additionally, there were some notable phenomena, in which the negative anomalies of NDVI and SIF in the western region from September to October significantly weakened, contrary to the overall trend. We attribute this phenomenon to the early recovery of normal temperature, VPD, and soil moisture levels in the western Yangtze River Basin region.

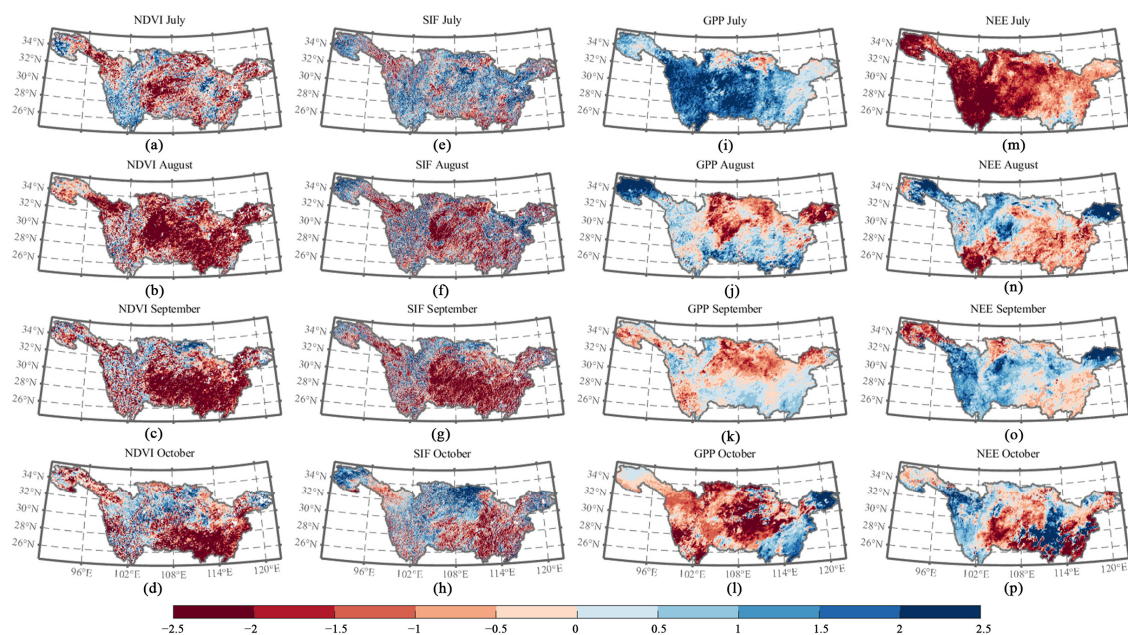


Figure 7. Spatial distributions of NDVI, SIF, and GPP anomalies in the Yangtze River Basin during July ((a,e,i,m) in 1st row), August ((b,f,j,n) in 2nd row), September ((c,g,k,o) in 3rd row), and October ((d,h,l,p) in 4th row) in 2022.

The spatial distribution of NEE anomalies also exhibited a relatively delayed response akin to GPP. In July, NEE remained globally negative, with the western region particularly affected (Figure 7m). Positive anomalies began to emerge in the northwest in August (Figure 7n), spreading subsequently to the central and eastern regions (Figure 7o). However, by October, some positive anomalies replaced negative ones, leaving only the western and central-eastern regions as negative anomalies (Figure 7p).

3.3. The Impacts of SM and VPD on SIF

This section delves into the correlation between vegetation growth (measured by SIF) and VPD and SM. In Figure 8, red indicates a positive correlation between two variables. This means that as one variable increases, the other variable also increases. The deeper the red, the stronger the positive correlation; conversely, lighter shades of red indicate a weaker positive correlation. On the other hand, blue represents a negative correlation between two variables. This implies that as one variable increases, the other variable decreases. Deeper shades of blue indicate a stronger negative correlation, while lighter shades indicate a weaker negative correlation. We found that except for certain areas in the southwest and a few eastern regions where the opposite occurs, overall anomalies in SIF show a positive correlation with anomalies in SM and a negative correlation with anomalies in VPD. This indicates that in most regions, a decrease in SIF accompanies a decrease in SM and an increase in VPD. Excluding the inconsistencies in the southwest, it can be concluded that the correlation of SM with SIF ($R = 0.30$) and VPD with SIF ($R = -0.28$) are roughly equivalent. This suggests that during compound dry-hot periods, the correlations of SIF with SM changes and SIF with VPD changes are consistent. Although the correlation with SM changes is slightly higher, it does not demonstrate a significant advantage over VPD changes.

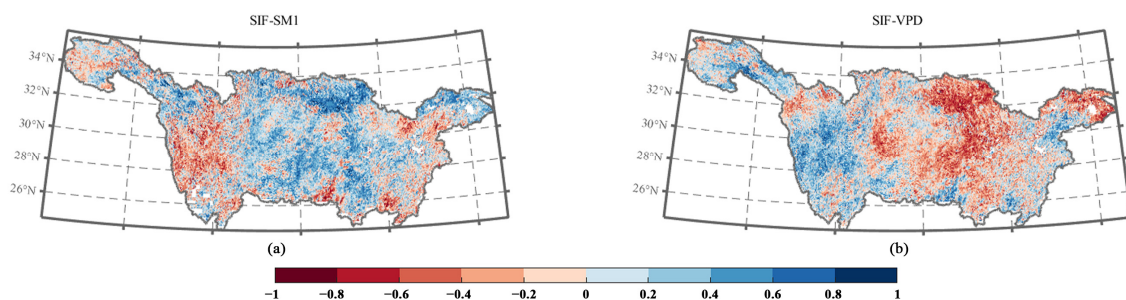


Figure 8. Spatial distribution of partial correlations between July and October 2022: (a) correlations between SM1 anomalies and SIF anomalies, (b) correlations between VPD anomalies and SIF anomalies. The blue part represents a positive correlation, while the red part represents a negative correlation.

3.4. Response of Different Types of Vegetation during Drought and Heatwave

As previously mentioned, based on the land cover types delineated by MODIS in the Yangtze River Basin, we selected the following two representative vegetation types: forest and cropland. In Figure 9, the forest is represented by green, while cropland is represented by purple. During the 2022 drought and heatwave period, the variation in temperature (Figure 9a) between forest and cropland ecosystems was not significantly different, indicating a similar severity of the heatwave. Regarding precipitation, except for a significant decrease in cropland compared to forest from May to June, resulting in cropland SM1 and SM2 being lower than forest during almost the same period, the precipitation patterns between forest and cropland within the study period (July–October) were almost identical (Figure 9b). Therefore, we believe that the severity of the drought and heatwave in the forest and cropland ecosystems is also similar. Under such temperature and precipitation conditions, the soil moisture values of the four layers in cropland were consistently lower than those in the forest from July to October (Figure 9c–f).

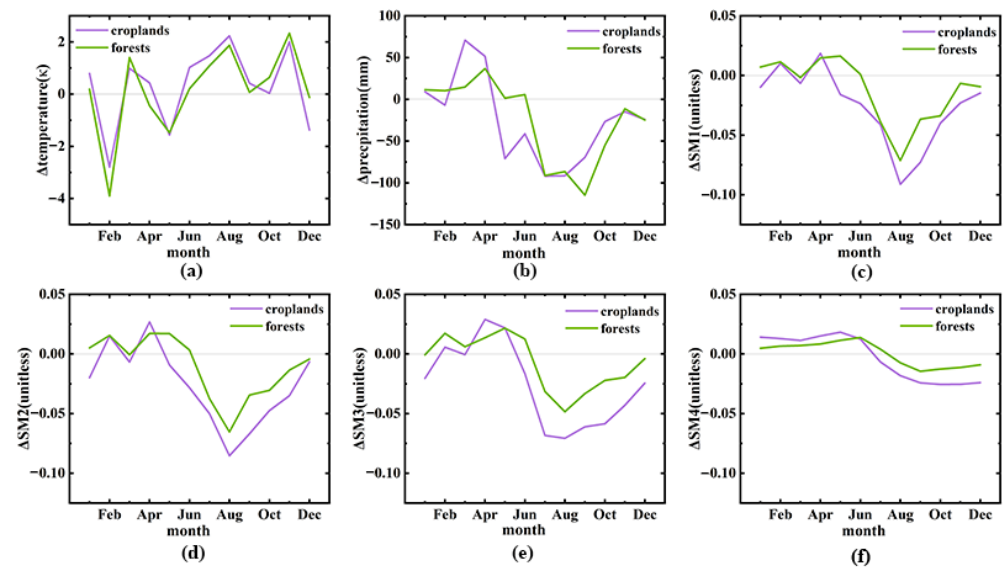


Figure 9. The differential values of the seasonal cycles for the year 2022 compared to the average values from 2018 to 2021: (a) temperature(K), (b) precipitation(mm), and (c–f) SM1–SM4 (unitless). The green line represents forest while the purple line represents cropland.

For vegetation indices, during the same period (August–October), the reduction in NDVI, SIF, and GPP in cropland was significantly higher than in forest (Figure 10). This indicates that the growth status (greenness) of the forest was superior to cropland in the later stages of the drought and heatwave, suggesting that forests have a stronger self-protection ability when facing extreme climatic conditions. This is consistent with the performance of soil moisture, indicating the mutual influence between them; vegetation growth is influenced by the water absorbed from the soil by roots, and the maintenance of soil moisture also requires the stability of vegetation roots.

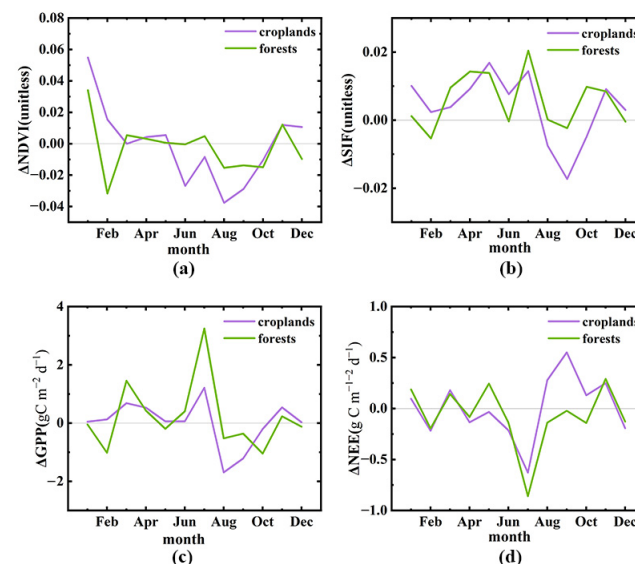


Figure 10. The differential values of the seasonal cycles for the year 2022 compared to the average values from 2018 to 2021: (a) NDVI (unitless), (b) SIF (unitless), (c) GPP ($\text{gC m}^{-2} \text{d}^{-1}$), and (d) NEE ($\text{gC m}^{-2} \text{d}^{-1}$). The green line represents forest, while the purple line represents cropland.

Furthermore, from July to October, the NEE value of forest was consistently lower than that of cropland. This indicates that the forest ecosystem has a stronger carbon sequestration capacity during this period, while the carbon fixation capacity of cropland is relatively

weaker. Combined with the analysis of the changes in NDVI, SIF, and GPP discussed earlier, it can be inferred that cropland is more susceptible to the impacts of drought and heatwave events, while forests exhibit stronger self-regulation abilities (i.e., lower sensitivity to compound drought and heatwave events).

4. Discussion

4.1. The Potentials and Limitations of Spatial Anomaly Analysis

Through the study of the spatiotemporal anomaly distribution of various indices during this drought and heatwave period, we believe that the significant weakening of negative anomalies in NDVI and SIF in the western region from September to October is associated with the early recovery of normal temperature, VPD, and soil moisture levels in the western Yangtze River Basin region. After all, these two indicators are highly sensitive to climate and environmental changes [25]. The unique temperature, VPD, and soil moisture anomalies in this region may be related to local climate circulation and topographical conditions. Furthermore, there is strong consistency in the spatial distribution and evolution of NEE and GPP anomalies, which is determined by the relationship between GPP and NEE. GPP determines the total photosynthetic rate of ecosystems, i.e., the ability of plants in the ecosystem to fix carbon dioxide [40]. Therefore, ecosystems with low GPP due to summer droughts and heatwaves often exhibit poorer potential carbon uptake capacity, potentially resulting in NEE values close to zero or even positive, indicating less carbon absorption by the ecosystem. This can have significant implications for the carbon balance of ecosystems [41,42].

Formula (1) established based on the RST approach does not require any specific assumptions about the data and exhibits inherent robustness. Moreover, calculating anomalies pixel-by-pixel based on differences from observed values and mean, as well as standard deviation, allows for more intuitive comparisons of data changes across different times and locations, aiding in the discovery of potential patterns and trends. However, the RST method necessitates a significant amount of historical data to establish reference fields. In this study, the historical data span is insufficient, which may impact the statistical correlation of observed anomalies with historical data. Additionally, the lack of preprocessing for observational conditions (such as satellite viewing angles, solar angles, etc.) and cloud cover could potentially have adverse effects on the statistical correlation of anomaly calculation results [35].

Furthermore, we condensed the data spanning a long period (over 100 days from July to October) into four-month averages for spatial anomaly analysis. This approach may smooth over some small yet significant features within this time span. This could potentially lead to the omission of important information, an increase in monthly average deviations, and a weakening of spatiotemporal sequence correlations. However, many scholars conducting similar studies have also used spatialized monthly averages and have identified reliable phenomena [10,21]. Therefore, in our study, the negative impacts of this issue may be negligible.

4.2. The Response of Different Vegetation Indices to Drought and Heatwave

Our results indicate that SIF is more effective than MODIS vegetation indices in monitoring vegetation photosynthetic responses to drought heatwaves over corresponding timescales. This finding aligns with previous studies, such as that of Yang, Burling, and Ni, who consider SIF a robust indicator for assessing the impacts of droughts and heatwaves on vegetation growth [43–45]. SIF refers to the phenomenon in which vegetation re-emits absorbed solar energy as fluorescence during photosynthesis [46]. Due to its physiological relevance [47], SIF directly measures photosynthetic processes, providing a more direct and sensitive reflection of vegetation responses to drought heatwaves compared to traditional vegetation indices, which only describe potential photosynthetic activity without direct correlation to actual processes [48–50].

Additionally, we argue that NDVI responds earlier to drought–heatwave events compared to SIF. This contradicts some previous studies, such as those by Shekhar et al., examining droughts and heatwaves in Europe in 2018 [51]. This discrepancy may be due to vegetation’s physiological adaptations under drought–heatwave conditions [52], prioritizing photosynthesis to maintain necessary energy for growth and survival. Such adaptations may result in reduced NDVI due to drought effects, yet enhanced photosynthetic efficiency is reflected in increased SIF and GPP. For instance, plants under drought conditions may adjust water use efficiency to optimize photosynthesis with limited water resources [53]. Moreover, under high temperatures, plants may exhibit heat stress responses, including adjustments in photosynthesis and the protection of chlorophyll and other physiological processes. These factors explain why NDVI metrics in 2022 could anticipate extreme climate conditions earlier.

4.3. Correlations between Vegetation Indices and Environmental Factors

We found that the correlation strength between SIF anomalies and anomalies in VPD and SM are comparable. The influence of extreme climates on vegetation cannot be decisively attributed to either low SM dominance or high VPD dominance. This contrasts with some previous studies advocating for either SM dominance [38] or VPD dominance [54,55]. On one hand, during drought and heatwave, the decrease in soil moisture imposes severe water limitations on vegetation, leading to the partial closure of plant stomata to prevent hydraulic conductivity loss [56]. On the other hand, under drought and heatwave conditions, atmospheric evaporative demand (VPD) may increase sharply, prompting vegetation to increase transpiration to cope with environmental water stress. As the rate of water evaporation increases, vegetation tends to reduce stomatal conductance and water loss, resulting in decreased photosynthetic activity and consequently reduced intensity of vegetation photosynthetic products and SIF signals.

4.4. Differences in Response of Different Vegetation Types to Drought and Heatwave

The response of vegetation growth in different ecosystems to drought and heatwave varies. Overall, our study results indicate that forests are less sensitive to drought compared to agricultural ecosystems. Xiao utilized three different proxies for vegetation conditions, also demonstrating that regions with a higher proportion of forests exhibit stronger ecosystem resilience to extreme drought than agricultural fields [57]. This discrepancy may be attributed to several mechanisms. Forests typically possess deeper and wider root systems [58], enabling them to better access soil moisture and maintain relatively stable water levels during drought periods [59]. In contrast, many crops in agricultural ecosystems may have shallower root systems, relying primarily on shallow soil water, which evaporates rapidly during drought and heatwave without timely replenishment from precipitation. Additionally, trees in forests generally have larger leaf areas, implying higher transpiration rates. While this may lead to water loss, it also aids in reducing ambient temperatures through the transpiration process and maintaining a certain level of humidity, thus alleviating the impacts of drought and heatwaves. Furthermore, forests possess climate-regulating capabilities, as they can decrease surface temperatures and create relatively cooler microclimates in the surrounding environment. In contrast, agricultural ecosystems may be more susceptible to high temperatures due to their typically sparse tree canopy and lack of microclimate regulation.

5. Conclusions

We used environmental data, multiple vegetation productivity indices, and ecosystem data to investigate the impacts of the 2022 summer compound drought–heatwave on vegetation growth and ecosystem carbon balance in the Yangtze River Basin. The research indicates that this extreme climate event has caused significant damage to vegetation growth and ecosystem carbon balance. We also found that NDVI responds faster to damaged vegetation than SIF, while SIF better captures the intensity of vegetation damage. Further-

more, the degree of vegetation damage correlates closely with anomalies in soil moisture and vapor pressure deficit. Additionally, forest ecosystems exhibit stronger self-protection mechanisms and are slightly less affected by the compound drought–heatwave compared to croplands. This study enhances our understanding of vegetation and ecosystem responses under heatwave drought conditions. In the future, if similar extreme climate events occur more frequently, our research will help researchers select appropriate indicators to assess vegetation responses and accurately predict their correlation with environmental factors.

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Data Availability Statement: The data that support our findings are openly available. The ERA5 monthly climate dataset is available at <https://cds.climate.copernicus.eu/> (accessed on 21 March 2024); the MODIS vegetation indices (NDVI) is available at <https://zenodo.org/records/8253971/> (accessed on 24 March 2024); the GOSIF dataset is available through http://data.globalecology.unh.edu/data/GOSIF_v2/ (accessed on 24 March 2024); the GPP dataset is available at Google Earth Engine; and the NEE dataset is provided at <https://search.earthdata.nasa.gov/> (accessed on 25 March 2024).

Conflicts of Interest: I affirm that this paper contains original and unpublished content not currently under review for publication elsewhere. All listed authors have endorsed the enclosed manuscript. We confirm that there are no financial or personal relationships with individuals or organizations that could unduly influence our work. Furthermore, we have no professional or personal interests in any product, service, or company that could bias the position put forth in the manuscript titled “Impacts of drought and heatwave on vegetation and ecosystem in the Yangtze River Basin in 2022”.

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