Decline in net primary productivity caused by severe droughts: evidence from the Pearl River basin in China

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ABSTRACT

Understanding the spatiotemporal characteristics of drought events and their impacts on terrestrial net primary productivity (NPP) is crucial for drought mitigation and environmental protection. This study, by taking the Pearl River basin as the case region, investigated drought duration, severity, intensity, affected area, and centroids during 1960–2015 based on the Standardized Evapotranspiration Deficit Index and three-dimensional clustering algorithm and then revealed how these drought characteristics have affected NPP. Results showed that there were altogether 32 severe drought events lasting at least 3 months in the basin, with half lasting longer than 6 months. The total NPP loss significantly correlated with drought severity and intensity. Most drought events caused reduce in NPP across more than half of the drought-affected area; specifically, the February–December drought in 2011 has cut NPP by 31.85 Tg C, accounting for 11.7% of the regional annual mean NPP, while the September 2009–September 2010 drought caused a decrease of 20.26 Tg C in NPP. Our research improves the insight into the relationship between NPP and drought, which helps decision-makers manage droughts and provides guidance for drought-related studies across other regions.

Key words: drought events, net primary productivity, SEDI, spatiotemporal characteristics

HIGHLIGHTS

- Most drought events identified in the Pearl River basin from 1960 to 2015 lasted for more than 3 months.
- The total NPP loss significantly correlated with drought severity and intensity.
- The February–December 2011 drought in the PRB reduced NPP by 31.85 Tg C.
GRAPHICAL ABSTRACT

INTRODUCTION

Drought is considered as one of the most complex natural disasters with devastating impacts on agriculture, economy, water resources, and ecosystems (Zhao & Running 2010; Lesk et al. 2016; Li et al. 2021a, 2021b). During the past decades, frequent and long-lasting droughts occurred across many parts of the world, even in humid regions, leading to severe ecological environmental problems (Wu et al. 2017a; Tijdeman et al. 2020). Droughts in China are expected to increase particularly in south China due to global warming (Su et al. 2018; Li et al. 2021a, 2021b). Understanding the spatiotemporal characteristics of drought events and their impacts is of crucial importance for providing fundamental information on drought which in turn help prepare for the consequences.

To identify drought events and analyze their characteristics, several methods, including the run theory (Ayantobo et al. 2017), wavelet analysis (Zhang et al. 2016), principle component analysis and cluster analysis (Gocic & Trajkovic 2014), have been commonly used. Among the methods, the run theory and the threshold level are the robust ways toward analyzing droughts (Li et al. 2020a), while the wavelet analysis is widely utilized to analyze drought periodicity and teleconnections (Belayneh et al. 2014). These methods provided useful references for understanding droughts. However, they do not fully extract space–time drought structures; what they consider is the temporal evolution within a fixed area or the spatial pattern over fixed durations (Lloyd-Hughes 2012; Xu et al. 2015). Consequently, much of the spatiotemporal drought information is reduced to a lower subspace (one or two dimensions), and the real drought structures in space–time dimensions are discarded (Sheffield et al. 2009; Guo et al. 2018). In fact, drought is a three-dimensional phenomenon that simultaneously evolves in
both time and space (Li et al. 2020a). Until more recently, the three-dimensional clustering algorithm is applied to drought analysis at global and regional scales (Herrera-Estrada et al. 2017; Liu et al. 2019).

There is still few attention paying to the impacts of droughts on terrestrial ecosystems. As one of the major climatological disasters, drought can induce significant impacts on terrestrial ecosystems, especially for the terrestrial net primary productivity (NPP) (Anderegg et al. 2015). As the initial step in the terrestrial carbon cycle, NPP represents the amount of atmospheric carbon stored by plants and accumulated as biomass, which plays a key role in the global carbon cycle and climate change (Piao et al. 2009). NPP is also considered as a key variable for the evaluation of effects of drought events on ecosystem conditions due to its sensitivity to droughts (Zhao & Running 2010). Therefore, exploring the response of NPP to drought events is an essential way to understand the impact of climate change on the regional carbon cycle (Liang et al. 2015). Chen et al. (2013) analyzed the impact of drought on NPP globally and found a strong positive relationship between global average moisture availability and NPP. Castro et al. (2018) investigated the effect of drought on productivity in a Costa Rican tropical dry forest, pointing out that primary productivity was reduced by 13 and 42% during the drought seasons in 2014 and 2015, respectively. Several studies have discussed the impact of the increasing droughts on national and regional NPP variations across China, providing a key information on the potential biosphere feedback to drought risks (Sun et al. 2016). For example, Zhang et al. (2012) focused on the effect of the 2010 spring drought on NPP in Southwest China and reported that the drought has reduced NPP by 46 Tg C.

The Pearl River basin, as the second-largest drainage basin in China, is economically developed and is of great importance to the socioeconomic development of China (Wu et al. 2017b). With the recent economic boom, the basin has become the major carbon dioxide emitter in China (Zhang et al. 2015). As a typical humid region, the basin has an abundant number of vegetative ecosystems, providing great potential for local biological carbon sequestration to partially offset fossil fuel emissions. However, this region has suffered from frequent and severe droughts in recent decades (Deng et al. 2018); these disturbances may cause large impacts on vegetative productivity and thus weaken the carbon sequestration of vegetation. Although the variations in droughts over this region have received increasing attention (Xiao et al. 2016; Deng et al. 2018), few studies have specifically focused on the impact of long-lasting and severe droughts on NPP.

To reveal how drought events have affected NPP, this study took the Pearl River basin as the case region, attempting to map the spatiotemporal characteristics of drought events from 1960 to 2015, and subsequently exploring the relationships between drought characteristics (e.g. severity and intensity) and NPP. Drought events were identified using the Standardized Evapotranspiration Deficit Index (SEDI) and the three-dimensional clustering algorithm (Lloyd-Hughes 2012; Xu et al. 2015), and the characteristics of drought events, including duration, severity, intensity, centroid, and affected areas, were investigated afterward. Finally, the impacts of droughts on NPP were assessed. We devoted to providing detailed information on drought evolution and an insight into the variations in terrestrial ecosystems caused by drought disturbance as well as the biosphere feedback to drought risks.

**STUDY AREA AND DATA**

**Study area**

The Pearl River basin (102°14′–115°53′E, 21°31′–26°49′N) (Figure 1) is the second-largest basin in China. It covers a total drainage area of 455,690 km² with three main tributaries including the West River, the East River, and the North River. The basin is dominated by a tropical and sub-tropical climate. Rainfall in this basin is unevenly distributed in time with precipitation during March–October accounting for about 90% of the total annual (Wu et al. 2018). In recent decades, droughts in the basin exhibit a spreading trend. For example, the upstream has experienced severe drought during September 2009 and May 2010 (Zhang et al. 2016). Moreover, due to rapid urban expansion and the population explosion, the basin suffers from increasing water use stress (Deng et al. 2018). A comprehensive understanding of the drought conditions is of great importance to deal with the potential and enormous threats caused by droughts.

**Data**

Daily meteorological datasets from 1960 to 2015 were collected from 91 observational stations within and surrounding the basin (Figure 1). The datasets include precipitation, maximum air temperature, mean air temperature, minimum air temperature, air pressure, wind speed, relative humidity, and sunshine duration. They were provided by the China Meteorological Administration (http://www.cma.gov.cn/en2014/) and the Resources and Environmental Science Data Center, Chinese Academy of Sciences (http://www.resdc.cn/default.aspx). The temporal coverage exceeds 99.7%, and the missing data
were filled in with the average value of the neighboring days. The datasets were interpolated into a 0.1° spatial resolution using the kriging method.

Monthly streamflow observation data at the Gaoyao, Shijiao, and Boluo hydrological stations during 1960–2000 were collected to calibrate and validate the VIC model for the West, North, and East River sub-basins, respectively. All streamflow data were provided by the Hydrological Bureau of Guangdong Province. The elevation data with a spatial resolution of 90 × 90 m were downloaded from the International Scientific and Technical Data Mirror Site. The FAO’s Harmonized World Soil Database with a 1 km spatial resolution was used for soil parameter specification in the VIC model (FAO 2009). The hydrological attributes required by the VIC model were obtained using formulas developed by Saxton & Rawls (2006). To match the spatial scale, the soil data and elevation data were resampled to a 0.1° spatial resolution.

NPP datasets with a spatial resolution of 8 × 8 km from 1982 to 2015 were calculated from the Carnegie Ames Stanford Application Model by using the monthly normalized difference vegetation index (NDVI) and the meteorological data. The study of Lai et al. (2018), which used the NPP datasets, demonstrates that NPP data simulated by this model are satisfactory. The original NPP datasets were resampled to a 0.1° spatial resolution.

METHODS

VIC model

The VIC model was employed to compute evapotranspiration (ETa). It has been widely used to simulate soil moisture and evapotranspiration, and many studies have demonstrated that the VIC-based output such as soil moisture, streamflow, and evapotranspiration are reliable (Xia et al. 2014; Zhou et al. 2016). The model has been successfully applied in the Pearl River basin for soil moisture and streamflow simulations (Niu 2013; Wu et al. 2014). The simulated soil moisture and evapotranspiration are capable of capturing the variation of dry and wet conditions over the basin (Niu & Chen 2016). In this study, the VIC model was verified through a comparison between the simulated stream flows and the observations. The Nash-Sutcliffe efficiency (NSE), relative error (Bias), and determination coefficient ($R^2$) were used for the evaluation of model accuracy (Zhou et al. 2019, 2020; Kao et al. 2020; Lin et al. 2020). A significant coincidence rate with $P < 0.05$ was detected in both the calibration and validation (Figure 2), demonstrating that the VIC-based ETa is adaptable and rational for the subsequent drought analysis. More details on the calibration and validation can be found in Li et al. (2020b).
Figure 2 | Calibration and validation of the VIC model through comparison between the observed and simulated stream flows at the Gaoyao (a), Shijiao (b), and Boluo (c) hydrological stations during 1960–2000.
Drought index
Currently, the Standardized Precipitation Index (SPI) (McKee et al. 1993) and the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2010) are commonly applied to exploring the response of ecosystems to droughts. However, compared with precipitation-dependent indices, evapotranspiration-based drought indices may be more appropriate for the identification of ecosystem droughts (Vicente-Serrano et al. 2018). Therefore, the SEDI was developed (Vicente-Serrano et al. 2018) which is determined by the standardization of the evaporation deficit (ED) defined as the difference between ETa and atmospheric evaporative demand (AED). Vegetation activity is greatly influenced by ED, whereby high ED leads to stomatal closure reducing photosynthetic activity, carbohydrate accumulation, and NPP (Vicente-Serrano et al. 2015). If ED keeps increasing, the wilting point is reached leading to vegetation mortality due to excessive depletion of plant available water and carbohydrates (Anderegg et al. 2015). The SEDI considers plant growth and responding mechanisms and therefore is more suitable for studying the effect of droughts on vegetation productivity (Vicente-Serrano et al. 2018). To validate the SEDI, it is appropriate to compare it with other drought indices. In this study, we not only compared it with SPEI, but also compared it with another widely used drought index, i.e. self-calibrating Palmer Drought Severity Index (scPDSI).

As stated above, we used the ETa calculated from the VIC model because in situ ETa measurement is usually unavailable. There are different ways to determine AED, including using pan evaporation or potential evapotranspiration (PET). In this study, AED was represented by PET. The Thornthwaite and Penman–Monteith equations are the two popular methods to calculate PET. However, the Thornthwaite equation tends to underestimate evapotranspiration, as it only considers temperature without considering other climate factors. Therefore, the Penman–Monteith equation was adopted in our study.

Drought event identification
In this study, SEDI was used to identify drought events. The identification is based on the three-dimensional clustering method (Lloyd-Hughes 2012). The three-dimensional space, including the longitude, latitude, and time, is built by stacking spatial SEDI maps over the basin from 1960 to 2015. Detailed steps are as follows.

First, drought patches were identified for each month. Drought condition was identified when its SEDI value was less than –1 at a grid cell. The density-based spatial clustering of application with noise clustering algorithm (Sander et al. 1998) was used to extract the drought patches, and the small and discontinuous patches were filtered out.

Secondly, a drought patch with an area greater than a prescribed threshold was selected. Drought clusters having small areas can persist for many years through tenuous spatial connectivity, and thus prolong drought duration (Sheffield et al. 2009). Previous studies suggest that a threshold of 1.6% of the total area of region of interest is suitable for drought identification (Xu et al. 2015; Guo et al. 2018). Therefore, we used the threshold of 7,259 km² (1.6% of the total area of Pearl River basin).

Thirdly, the overlap area between patches was calculated for two consecutive months. Two drought patches are considered to belong to a same event if the overlapping area is larger than the specified threshold (i.e. 7,259 km²); otherwise, they are considered two independent events.

Finally, drought events were characterized by five parameters, including drought duration (DD), drought severity (DS), drought intensity (DI), drought area (DA), and drought centroid (DC). To analyze drought evolution, monthly severity (MS), intensity (MI), affected area (MA), and centroid (MC) during a drought event were also calculated. More details about this method can be found in Xu et al. (2015).

Detection of NPP responses to drought event
To assess NPP responses to large-scale and severe drought events, we focused on the NPP variation across the drought-affected area. The three-dimensional cluster of NPP was extracted with the same spatiotemporal dimensions of the drought events that occurred during 1982–2015. We analyzed NPP anomalies at each grid during a drought event. NPP anomaly caused by a drought event at each grid is calculated by the following equation:

\[ \Delta \text{NPP}(i, j, k) = \text{NPP}(i, j, k) - \bar{\text{NPP}}(i, j, k) \]  \hspace{1cm} (1)

where \( \Delta \text{NPP}(i, j, k) \) is referred to the monthly NPP anomaly within a grid during a drought event (g cm\(^{-2}\)); \( i \) and \( j \) indicate the grid location; \( k \) is the time (month); \( \text{NPP}(i, j, k) \) represents NPP for the \( k \)th month at the grid\((i, j)\); \( \bar{\text{NPP}} \) is the mean NPP at the grid\((i, j)\) for the \( k \)th month during the reference period of 1982–2015; positive/negative \( \Delta \text{NPP}(i, j, k) \) indicates change in NPP...
at grid\((i,j)\) for the \(k\)th month. Afterward, we calculated the total NPP anomaly (Tg C) (defined as the cumulative NPP anomaly for all grids during a drought event), and the positive/negative total NPP anomaly indicates increase/decrease in NPP. The total NPP anomaly during the \(n\)th drought event is defined as follows:

\[
TNA_n = \sum_i \sum_j \sum_k (\Delta NPP(i, j, k) \times \text{area}(i, j, k))
\]  

\(2\)

**RESULTS**

**Validation of SEDI**

A comparison between the SEDI and the multi-time scale SPEI and monthly scPDSI was carried out and shown in Figure 3. The SEDI series generally exhibited significant correlations \((P < 0.05)\) with the short time scale SPEI; the correlations were greater than 0.4 for the 1- and 3-month SPEI across almost the entire region; however, the statistical significance of the correlations gradually decrease for longer time scales. A significant correlation between SEDI and scPDSI was also found for most regions. To further validate SEDI, soil moisture was employed to verify the identified drought events, given that soil moisture generally decreases during severe droughts (Xu et al. 2015; Guo et al. 2018). The three layers of soil moisture were used to verify droughts by fully considering the capability of SEDI to reflect soil moisture. Soil moisture standardized anomaly (SSMA) was first obtained for each grid using the z-score standardized method (Wu et al. 2001) to reduce the effects of seasonality and to facilitate the comparison (Guo et al. 2018). Using the three-dimensional clustering algorithm and the monthly SEDI time series from 1960 to 2015, the drought events were discerned and drought severities were computed. The corresponding drought events were also achieved based on the SSMA time series. Each SSMA cluster had the same

![Figure 3 | Spatial distribution of coefficient correlation between SEDI and multi-time scale SPEI and monthly scPDSI.](https://example.com/image.png)
spatiotemporal dimension with the drought event identified by SEDI to ensure that they had the same duration and affected area. The corresponding drought severities were calculated based on the SSMA clusters.

Figure 4 shows the comparison between drought severities calculated from SSMA and SEDI. The SEDI and the SSMA drought severities were highly correlated ($P < 0.01$); $R^2$ values were greater than 0.93, indicating that soil moisture in all three layers is sensitive to large-scale and severe drought events identified by SEDI. Despite the abundant soil moisture in humid areas, evapotranspiration was strong with lack of precipitation during drought periods, which has led to decrease in soil moisture. In addition, humid regions such as southern China generally cover dense vegetation which would pump more water from the deep soil during severe droughts, resulting in a decrease in soil moisture (Wang et al. 2016). Overall, these analyses indicate that the SEDI can be used to identify drought events.

**Spatiotemporal variation in drought events**

A total of 32 prolonged and severe drought events lasting for at least 3 months were identified. All drought events (ranked by their severity) and their characteristics are shown in Table 1. Most of the drought events lasted for 3–6 months. Droughts lasting longer than 9 months occurred several times and only one lasted longer than 1 year. In addition, prolonged droughts mainly occurred during the past two decades. More specifically, the 1962–1963 drought event was the most severe one during the past 56 years; it persisted for 11 months from December 1962 to October 1963, with a severity of $4.4 \times 10^6$ km²-month, while the most prolonged drought lasted for 13 months from September 2009 to September 2010, ranking second in the list. Two drought events affected almost the whole basin, the drought area of which was larger than 400,000 km². Moreover, drought events with the same duration could have quite different drought-affected areas and severities. For example, although there were three drought events lasting for 11 months, the severity of the 2006–2007 event (the 9th event) was completely different from that of the one occurring during 1962–1963 (the 1st event) and that in 2011 (the 3rd event) due to different drought intensities and affected areas; its severity was relatively low, i.e. $1.72 \times 10^6$ km²-month. Also, despite the similar severities, the duration and intensity can differ, as is seen in the 12th and 13th events; the 12th event had a relatively small region with low intensity but had a long duration, whereas the 13th event affected a larger area with a shorter duration and a higher intensity. On the other hand, the 6th drought event lasted for only 6 months but the severity was relatively high due to the high intensity and large affected area. On the whole, longer duration drought events had higher severities and larger affected areas, but droughts having short durations may have high severity.

Figure 5 shows the spatial distribution of the centroids for all drought events. The centroids of the prolonged and severe drought events were mainly detected in the upper and middle reaches. The drought events in the eastern part of the basin were generally with shorter duration and were less severe. The temporal distribution of the characteristics of the drought events is shown in Figure 6. It can be seen that drought events did not overlap before 2000, indicating that the drought events occurred separately over time. The basin experienced fewer severe droughts during the 1970 and 1980s compared
to other periods, and the droughts during this period were less intense with shorter durations and smaller affected areas. After 2000, the basin experienced frequent large-scale droughts with higher severity and larger drought-affected areas. The time intervals between droughts were short, and almost all drought events had multiple peaks for both severity and affected area. Furthermore, the basin suffered from more droughts during spring and summer than the other two seasons.

Major drought events
The spatial pattern and temporal evolution characteristics of the top five drought events were analyzed to further reveal the characteristics of severe drought events. The spatial pattern of the accumulated SEDI and the corresponding temporal evolution of the monthly characteristics (i.e. MS, MI, and MA) are shown in Figure 7. The track of the most severe drought (December 1962–October 1963) stretched across the entire basin. It emerged in the western part of the basin, then moved eastward, and finally wandered in the central part for 7 months until October 1963. The monthly affected area during the event varied considerably; the largest area
**Figure 5** Drought centroids, durations (month), and severities \((10^5 \text{ km}^2 \cdot \text{month})\) during 1960–2015.

**Figure 6** Temporal variations of drought severity, affected area, and intensity for the total lifetime (i.e. DS, DA, and DI) and each monthly step (i.e. MS, MA, and MI). The black lines represent DS, DA, and DI, and the MS, MA, and MI are shown by the orange pillars. Please refer to the online version of this paper to see this figure in colour: doi:10.2166/nh.2021.061.
Figure 7 | Spatial distribution of the cumulated SEDI and temporal evolution of monthly characteristics for the top five drought events. (a–e) represent the drought periods of December 1962-October 1963, September 2009–September 2010, February 2011–December 2011, September 1998–June 1999, and November 2003–August 2004, respectively. The black dots indicate centroids of the drought cluster in each month, and the black lines between centroids reveal the drought paths with red arrow pointing to the destination.
affected occurred in May 1963, reaching up to $3.84 \times 10^5$ km$^2$ accounting for 84.6% of the basin. The evolutions of severity and intensity were also complex with multiple peaks. The drought from September 2009 to September 2010 was mainly concentrated on the eastern part of the basin with a circular track. It originated in the central part, wandered into the western part for 11 months, and disappeared in the westernmost part. The affected area suffered from extremely dry conditions from April to June 2010 with the largest value in June 2010, i.e. $3.15 \times 10^5$ km$^2$. For the February 2011–December 2011 drought event, it spread throughout the study region with an ambiguous track (Figure 7(c)). The drought originated in the mid-northern part, shifting to the eastern part afterward and back to the central part later on, and then moved to the western part, ending in the eastern part. Although it lasted for 11 months with the largest monthly drought area of $3.87 \times 10^5$ km$^2$, only one peak of drought severity and intensity was detected. As for the 4th drought event, it was mainly concentrated in the central part, originating from the eastern part and moving into the central region. The drought lasted for 10 months from September 1998 to June 1999. According to the drought centroid, the pattern of the last drought event consisted of two sub-patterns, i.e. the central region (from November 2003 to June 2004) and the western region (July and August 2004). The drought path wandered in the central region and then moved westward. The monthly drought severity and area reached the maximum in the second month since its onset.

**Drought impacts on NPP**

The spatial distribution of correlation coefficients between NPP and SEDI during the four seasons of 1982–2015 was analyzed, and the results are shown in Figure 8. Overall, most of the basin was dominated by weak correlations in spring and summer, while significant positive correlations were detected in most of the basin during winter. According to the NPP cluster, the ratios in percentages between the grids with negative $\Delta$NPP and total grids for 1982–2015 were calculated and are shown in Figure 9. In general, more than 50% of the drought region suffered from NPP losses during the 1982–2015 drought events. A loss of NPP was detected for nearly the entire drought region during two events (October 2004–January 2005 and February 2011–December 2011). For the total NPP loss, notably, the value was the largest during the February 2011–December 2011 drought, which reached to 31.85 Tg C accounting for 11.7% of the regional annual mean NPP. The drought from September 2009 to September 2010 also caused large NPP loss up to 20.26 Tg C, accounting for 7.4% of the annual mean. Figure 10 further shows the temporal variations of drought severity, intensity, affected area, and total NPP loss during the drought events from 1982 to 2015. The total NPP loss showed significant correlations ($P < 0.05$) with drought severity and intensity, with correlation coefficients of 0.72 and 0.42, respectively.

Subsequently, the top two drought events with large NPP losses were selected to analyze the variations in NPP under severe drought events. The spatial pattern of cumulative NPP and the temporal evolution of monthly cumulative NPP, along with the correlations between the cumulative SEDI and NPP during the two drought events, are shown in Figure 11. A significant correlation ($P < 0.05$) was detected between cumulative SEDI and NPP for the two drought events. During the February 2011–December 2011 drought, a decrease in NPP was detected across nearly the entire basin. NPP showed a large

**Figure 8** | Spatial distribution of correlation coefficient between SEDI and normalized NPP at four seasons from 1982 to 2015. Values larger than 0.33 or smaller than −0.33 indicate statistically significant correlations.
reduction across the region with low SEDI, indicating that persistent drought severely affected NPP. The temporal variation of monthly cumulative NPP was generally consistent with monthly drought severity evolution; the NPP loss increased with higher drought severity. The September 2009–September 2010 drought caused a large decrease in NPP over the western part of the basin.

**DISCUSSION**

Variations in drought are affected by multiple factors, such as climate change, atmospheric circulation, and local geological conditions. Climate change has profound impacts on drought variation by changing climatic water supply and demand. A
trend analysis of monthly SEDI from 1960 to 2015 was carried out to reveal the change in drought; variations in monthly precipitation, PET, and ETa were also analyzed, and the results are shown in Figure 12. A significant drying trend ($P < 0.05$) was found across most of the basins particularly for the upper reach. Precipitation tended to decrease, while PET and ETa generally increased significantly in the upper reach, which may largely contribute to the drying trend. Also, the droughts in the upstream may be partly affected by local complex topography. The upstream is characterized by karst topography which can trigger severe droughts (Guo et al. 2013). Hydrological characteristics over the karst region are found eventually altered by rocky desertification, particularly the rainfall–runoff process (Zhou 2020a). Rocky desertification features with little vegetation and soil breakage increase infiltration to subsurface systems reducing flow storage capacity and residence time and decreasing the resistance to overland flow, causing frequent drought and flood events in karst regions (Jiang et al. 2014; Yan & Cai 2015). Additionally, rainfall erosivity in some regions also shows an upward trend that the probability of water and soil erosion is increasing correspondingly (Peng & Wang 2012; Wang et al. 2013), which further exacerbates drought conditions in the upstream. On the other hand, because the basin is located in the monsoon region, where climate is strongly influenced by global circulation patterns, such as the El Nino-Southern Oscillation (ENSO) (Deng et al. 2018). Large-scale atmospheric circulation can induce drought changes, as it alters the amount of water vapor available for precipitation and could affect the key components of the hydrologic cycle, such as soil moisture and ETa (Liu et al. 2013). The severe 2009–2010 drought over the upper reach was largely attributed to the concurrent distinctive warm pool El Niño that generated a strong anomalous cyclone over the northwestern Pacific and led to a serious reduction in rainfall over this region (Zhang et al. 2013). A study by Niu (2013) also shows a significant correlation between ENSO and precipitation variation in the eastern part of the Pearl River basin. By affecting precipitation patterns, the drought duration exhibited different patterns in different parts of the basin during warm/cool ENSO phases (Xiao et al. 2016).

We found that the most persistent drought events have occurred over the last decades in the basin. These drought events have visible impacts on agriculture, water resources, and ecosystems. The 2009–2010 drought with a duration of 13 months

Figure 11 | Spatial distribution of cumulated NPP anomaly, temporal evolution of monthly drought characteristics (normalized MS, MI, and MA), and scatterplot between cumulated NPP and SEDI for the drought period of (a) February 2011–December 2011 and (b) September 2009–September 2010.
nearly affected the entire basin, particularly the upper reach (Guangxi and south of Guizhou Province). It had large and destructive effects on agricultural production and the drinking water supply to residents (Barriopedro et al. 2012). During the drought period, numerous small and medium-sized rivers and reservoirs dried up in Guangxi and Guizhou (Lin et al. 2015). The drought has damaged winter wheat, causing a 30% reduction in production resulting in a temporary impact on local grain supply-demand balance (Li et al. 2010; Zhang et al. 2013). The freshwater supply of the Pearl River Delta, which is one of the most highly urbanized regions in the world, is facing an increasing risk in recent decades (Liu et al. 2014). The East River is one of the most important water supply resources for major cities in the Pearl River Delta such as Hong Kong, Guangzhou, Shenzhen, Dongguan, and Huizhou. However, the water supply is at an increasing risk because it suffers from more frequent dry seasons along with serious saltwater intrusion (Liu et al. 2016). To alleviate water supply pressure and ensure water security, water was delivered from the West River to the Pearl River Delta in recent years. Therefore, the increasingly frequent and severe drought events have caused far-reaching impacts on regional development, and more attention should be paid to drought risk over the basin in future.

Our study demonstrates that prolonged and severe drought events largely decreased regional NPP. For example, the 2009–2010 drought reduced NPP by 31.85 Tg C across the whole basin, accounting for 11.7% of the regional annual mean NPP. The occurrence of long-lasting and severe droughts could cause serious disturbances in the biochemical and physiological processes of ecosystems such as photosynthesis, respiration, and nitrogen and protein metabolism (Kurz et al. 2008; Zhang et al. 2012; Anderegg et al. 2013). Long-term dry conditions also influence ecosystem productivity by increasing pest and disease infestation. It is therefore necessary to manage water resources at the long-term time scale, such as monthly and seasonal reservoir storage management and water allocation (Zhou 2020b). While a prolonged and severe drought can lead to increasingly large NPP losses, drought events with short durations and low severities generally have less impact on NPP. Generally, the resilience and restorability of vegetation to drought stress is strong in humid regions. Most of the vegetation in humid regions possesses residual water and deep root systems that reduce the impact of short-term water shortages on plant productivity. In addition, the increase in radiation during drought periods can cause a decline in cloud cover and an increase in plant productivity (Saleska et al. 2007; Wang et al. 2015). These may explain the relatively less NPP loss during moderate drought events in the basin.

CONCLUSIONS

In this study, the Pearl River basin was taken as the case region where severe drought events and their characteristics from 1960 to 2015 were analyzed using SEDI and the three-dimensional clustering algorithm. In addition, the impact of severe drought events on NPP was assessed.
droughts on NPP was evaluated. It is shown that SEDI has the potential to identify drought events, and the basin experienced frequent extensive and severe drought events during the past two decades. About half of the drought events persisted for 6 months or longer, and some lasted for more than 9 months, which generally occurred in the upper and middle reaches. Results also indicate that drought events generally caused a reduction in NPP for more than half of the drought-affected area. The total NPP loss significantly correlated with drought severity and intensity. Typical examples further show that the total loss of NPP during the 2011 drought has reached 31.85 Tg C accounting for 11.7% of the annual mean, while the drought from September 2009 to September 2010 caused an NPP loss of 20.26 Tg C accounting for 7.4% of the annual mean.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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