Evaluating Spatiotemporal Patterns and Trends of Drought in Japan
Associated with Global Climatic Drivers

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Abstract: Drought disasters, such as water scarcity and wildfires, are serious natural disasters in Japan that are also affected by climate change. However, as drought generally has widespread impacts and the duration of drought can vary considerably, it is difficult to assess the spatiotemporal characteristics and the climatic causes of drought. Therefore, to identify the drought homogeneous regions and understand climatic causes of regional drought over Japan, this study provides a spatiotemporal analysis for historical drought patterns and teleconnections associated with global climatic drivers. The trends of meteorological elements, which are the basis of drought index calculation, was first assessed. Then, drought characterized by the Self-calibrating Palmer Drought Severity Index (scPDSI) was investigated. Trends and patterns of drought were identified through the trend-free pre-whitening Mann-Kendall test and distinct empirical orthogonal function. The continuous wavelet transform and cross wavelet transform together with wavelet coherence were utilized to depict the links between drought and global climatic drivers. The results are described as follows: (1) the trends of precipitation were insignificant. However, temperature and potential evapotranspiration increasing trends were detected over Japan; (2) the drought trend over Japan varied seasonally, increasing in spring and summer and decreasing in autumn and winter; (3) two major subregions of drought variability—the western Japan (W region) and most of the northernmost Japan near the Pacific (N region) were identified; (4) wildfires with large burned area were more likely to occur when the scPDSI was less than -1; and (5) the North Atlantic Index (NAOI) showed the strongest coherence connections with Distinguished Principle Components-1 among four...
climatic drivers. Additionally, Distinguished Principle Components-2 showed stronger coherence connections with NAOI and Arctic Oscillation Index. This study is the first to identify homogeneous regions with distinct drought characteristics over Japan and connect the drought in Japan with the global climatic drivers.

Key Words: Drought; scPDSI; DEOF; Spatiotemporal patterns; Wavelet analysis; Climatic causes.

1. Introduction

Under climate change conditions, especially direct and clear global warming (IPCC, 2014), drought has shown increasing trends in certain regions of the world (Cook et al., 2004; Dai, 2011, 2013; Kogan and Guo, 2016). Contrasted with permanent aridity in arid areas, drought is a temporary reduction in precipitation or water availability over an extended period (Hisdal, 2000) and can last for months or years. Considering the duration, intensity, geographical extent, and broad effects of droughts, it is difficult to determine drought occurrences and their effects (Asong et al., 2018). Additionally, drought is considered to be the most complex and impenetrable extreme climate event, affecting more people than any other natural hazard (Hagman, 1984). Droughts can have catastrophic impacts on the economy, society, and environment (Edwards et al., 2019; Wilhite et al., 2007). For example, droughts experienced in Africa, Asia, Australia, South America, and Europe have had devastating effects over large areas (Mishra and Singh, 2010). In particular, the deficit in precipitation combined with high evapotranspiration losses during a drought would increase the risk of other disasters such as wildfires (Sarris et al., 2014). The risk of water scarcity would be exacerbated by long-term drought, which poses challenges to water resources management (Iglesias et al., 2007).

The research on droughts over Japan has been receiving increasing attention. More than 70% of Japan is mountainous, causing rain to flow quickly to the ocean after falling. Historically, most areas of Japan have experienced droughts with varying duration, frequency, severity, and intensity. Particularly, long-lasting droughts occurred over a large part of Japan in 1967, 1973, 1978, 1984, 1985, and 1994 (Okada, 2016). In 1994, almost the whole of Japan experienced a particularly long-lasting drought and the drought caused an economic loss of approximately 1.3 billion dollars as a result of the decline in agricultural production (Lee et al., 2012). The number of areas affected by...
drought in Japan is decreasing but still exists every year (Okada, 2016). In 2007, due to the drought, the leaf necrotic area percentage of sampled dogwood trees was significantly severe in Yamaguchi, Japan (Wang et al., 2009). Also, due to climate change, the uncertainty of drought characterization in Japan would bring more challenges to water management.

Indeed, drought is generally driven by multiple global climatic drivers, which are forced by land-sea-atmosphere interactions (Sheffield et al., 2009). Therefore, to further understand the drought characteristics and predict drought events, it is necessary to consider the relationship between drought and global climate drivers (Asong et al., 2018). This type of research has been carried out in different regions. Rajagopalan et al. (2000) selected the Palmer Drought Severity Index (PDSI) to characterize drought and explored the impact of winter El Niño-Southern Oscillation (ENSO) and global sea surface temperatures (SSTs) on summer drought in the United States. Rangsiwanichpong et al. (2017) analysed the relationship between various ocean indices and precipitation in the Chao Phraya River Basin. Actually, the decrease in precipitation is often a cause of drought (Viste et al., 2013). Wang et al. (2015) explored the teleconnections of seven selected climatic drivers with drought in the arid region of China. Asong et al. (2018) used the Standardized Precipitation Evapotranspiration Index (SPEI) to identify drought patterns over Canada and analysed their teleconnections with global climatic drivers. Their researches have contributed to understanding the causes of drought across the region.

Considering that the drought over Japan has unique characteristics and may be different from other global arid land. Similar research on the causes of drought over Japan also needs to be carried out. The establishment of connection analysis between drought and global climatic drivers over Japan will also help to understand the potential links between different regions of drought. For Japan, choosing the appropriate global climatic drivers is first required. Previous studies have already analysed the relationship between global climatic drivers and hydroclimate in Japan. He et al. (2017) pointed out that the Arctic Oscillation (AO) affected freezing precipitation or snowfall events over East Asia. A statistically significant positive relationship between the North Atlantic Oscillation (NAO) and precipitation in the western region of Japan was also found (Aizen et al., 2001). Hu et al. (2005) analysed the connection between the ENSO and East Asian precipitation variations, which
showed that an ENSO generates stronger precipitation anomalies than a non-ENSO. Lee et al. (2012) pointed out that the Pacific Decadal Oscillation (PDO) has a certain impact on cyclone-induced precipitation over East Asia. These global climatic drivers have already been confirmed to have impacts on hydroclimate in Japan.

Overall, to further improve the capacity of early warning and risk assessment of drought at the regional level, it is necessary to identify the homogeneous regions with distinct drought characteristics over Japan and analyse the causes of drought. However, previous researches have mainly focused on the phenomenon of drought events. There is still a lack of understanding of the causes and specific consequences of the droughts in Japan. In other words, establishing the link between nationwide drought properties in Japan and global climatic drivers has not been addressed before. For this purpose, this study attempts to provide an in-depth analysis of historical droughts over Japan to fill these gaps. The drought events were characterized by Self-calibrating Palmer Drought Severity Index (scPDSI) using the most up-to-date data. Then trends in the meteorological elements (precipitation, near-surface temperature, potential evapotranspiration) and scPDSI were investigated by the trend-free pre-whitening Mann-Kendall (TFPW-MK) test. Major patterns of long-term trends in drought and periodicity were then identified using the distinct empirical orthogonal function (DEOF) and continuous wavelet transform, respectively. Additionally, the relationship between drought index and wildfire was analysed to identify the effects of the drought. Finally, the teleconnections between the major drought patterns and global climatic driving factors were analysed by cross wavelet transform together with wavelet coherence.

This paper is organized as follows: Section 2 describes the data of the study area and analytical methodology. In Section 3, the results and discussion are revealed. Finally, the summary and conclusions are given in Section 4.

2. Materials and Methodology

2.1 Study area

The study area comprises the whole of Japan, which is an area mostly characterized by steep mountainous terrain. Japan's total annual precipitation is approximately 1,719 mm, while the annual precipitation per capita is approximately 5,100 m³, which is only approximately 1/3 of the world
average of 16,800 m³ (MLIT, 2014). Moreover, water resources in Japan are significantly dependent on the weather. Precipitation is generally concentrated in the rainy, typhoon, and snowfall seasons. The country is so steep that most precipitation quickly runs off into the sea (Su et al., 2019).

2.2 Data

The 0.5° high-resolution gridded datasets of precipitation, near-surface temperature, potential evapotranspiration, and scPDSI were obtained from the Climatic Research Unit (CRU) at the University of East Anglia (Blunden et al., 2019; Harris et al., 2014; Van Der Schrier et al., 2013). The period of scPDSI from CRU is currently from 1901 to 2018. Since this paper is mainly dedicated to analysing the time trends and spatial homogeneity zone of drought, using data from the 1900s may leading the trend of drought to be exaggerated. Besides, at an early stage, there was a problem of sparse distribution of stations. Therefore, the time scale selected in this paper is from 1960 to 2018.

The scPDSI class is shown in Table 1 (Palmer, 1986). This scPDSI was presented by Wells et al. (2004), which was a variant of the original PDSI (Palmer, 1986) used to make the results from different climatic regimes more comparable. To better understand how scPDSI characterizes drought, the main calculation formulas of scPDSI are listed as follows:

\[
Z_i = K (P - (\alpha_i PE + \beta_i PR + \phi_i PRO - \delta_i PL))
\]  

(1)

The Z index can be used to show the dryness/wetness in month i. K is a climatic characteristic value that varies over both time and space to account for climate changes. \(\alpha_i, \beta_i, \phi_i, \delta_i\) are the weighted values according to the climate of the area. The \(P, PE, PR, PRO, PL\) represent precipitation, potential evapotranspiration, potential recharge, potential runoff, and potential loss, respectively. Through the Z index, the scPDSI value can be calculated for a given month using the following formula:

\[
scPDSI_t = \eta scPDSI_{t-1} + \rho Z_t
\]  

(2)

where \(\eta\) and \(\rho\) represent the sensitivity of the index to precipitation events. For specific values, see Van Der Schrier et al. (2013).

In particular, the potential evapotranspiration was calculated through the Penman-Monteith equation rather than the Thornthwaite equation, which can more realistically estimate potential evapotranspiration. The specific formula is listed as follows:
where \( R_n \) is the net radiation at the crop surface, \( G \) is the soil heat flux density, \( T \) is the air temperature at the 2 m height, \( U_2 \) is the wind speed at the 2 m height, \( e_s \) is the vapour pressure of the air at saturation, \( e_a \) is the actual vapour pressure, \( \Delta \) is the slope of the vapour pressure curve and \( \gamma \) is the psychrometric constant (Allen et al., 1998).

Additionally, scPDSI can deal with snow by adding a simple snowmelt and accumulation process, which other drought indices, such as the Standardized Precipitation Index (SPI), Effective Drought Index (EDI), and SPEI could not consider. Snowmelt was treated using the following simple formula:

\[
M = \beta T_{pdd}
\]

where \( \beta \) is the degree-day factor and \( T_{pdd} \) is the sum of all positive daily mean temperatures during the entire research period. For specific values, see Van Der Schrier et al. (2013)

The snow accumulation was estimated for each month from monthly mean temperature and monthly precipitation as follows (Blunden et al., 2019; Harris et al., 2014; Van Der Schrier et al., 2013):

\[
f = \frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{T_r} e^{-(T-T_m)^2/2\sigma^2} dT
\]

where \( T_r \) is the rain/snow threshold temperature and \( T_m \) is the monthly mean temperature. \( \sigma \) is the standard deviation of daily temperatures.

Table 1 Categories of dryness/wetness degree according to the scPDSI values

| Categories          | scPDSI values |
|---------------------|---------------|
| Extremely wet       | [4.0, +∞)     |
| Severely wet        | [3.0, 4.0)     |
| Moderately wet      | [2.0, 3.0)     |
| Mid wet             | [1.0, 2.0)     |
| Incipient wet       | [0.5, 1.0)     |
| Normal              | (-0.5, 0.5)    |
To analyse the key global climatic drivers of drought events over Japan, the following four global climatic indices were investigated. The Arctic Oscillation Index (AOI) (Li et al., 2003) and North Atlantic Oscillation Index (NAOI) (Li et al., 2003) are employed to describe the abnormal conditions of the AO and NAO, respectively. These indices are sourced from https://ljp.gecss.cn/dct/page/1 (last access: 10 March 2020). The Pacific Decadal Oscillation Index (PDOI) (Mantua et al., 2002) and Oceanic Niño Index (ONI) (Bamston et al., 1997) respond to the abnormalities of PDO and ENSO, which are sourced from https://www.esrl.noaa.gov/psd/ (last access: 10 March 2020).

### 2.3 Trend-Free Pre-whitening Mann-Kendall test

The Mann-Kendall (MK) test, which was proposed by Mann (Mann, 1945) and modified by Kendall (Giglio et al., 2015), is widely used for analysing the change trends in hydrometeorological time series (Liu et al., 2015; Yue et al., 2003a, 2003b). The advantage of the MK test is that the time series does not require any special form for the probability distribution function, which means it is less sensitive to potential interference from outliers in the data (Serrano et al., 1999). However, this test requires that the data should be independent. Some hydrometeorological time series may usually display serial correlation. This will increase the probability that the MK test detects a significant trend, altering the magnitude estimate of serial correlation (Yue et al., 2002). To efficiently eliminate the effect of the serial correlation on the MK trend test, Yue et al. (2002) proposed the trend-free pre-whitening MK (TFPW-MK) test. Before the MK test, the time series is first detrended and pre-whitened. In this paper, we adopted TFPW-MK to analyse the time series trends. The specific details of TFPW-MK can be found in Yue et al. (2002). The main steps are listed as follows:

1. Using the Theil-Sen approach (Sen, 1968) estimates the slope $b$ of the trend in the time series. If the slope is equal to zero, then it is unnecessary to continue conducting the trend analysis.
If the slope differs from zero, then it is assumed to be linear, and the time series are detrended by the following equation:

$$X'_i = X_i - T_i = X_i - bt$$  \hfill (6)  

Step 2. The lag-k serial correlation coefficient $r_k$ of the detrended series $X'_i$ is computed using Equation (7), and then, Autoregressive (k) (AR) is removed from $X'_i$ by Equation (8).

$$r_k = \frac{1}{n-k} \sum_{t=k+1}^{n} [X_t - E(X_t)] [X_{t+k} - E(X_{t+k})] \hfill (7)$$

$$Y'_i = X'_i - r_k X'_{i-k}$$  \hfill (8)  

This pre-whitening procedure after detrending the series is referred to as the TFPW procedure.

After applying the TFPW procedure, the time series should be independent.

Step 3. The identified trend $T_i$ and the residual $Y'_i$ are blended by the following equation:

$$Y_i = Y'_i + T_i$$  \hfill (9)  

Step 4. The MK test is applied to the blended series to assess the significance of the trend. We can obtain the statistic $Z$ through the calculation of the TFPW-MK test and measure the degree to which a trend is consistently decreasing or increasing. In the bilateral trend test, if $|Z| > Z_{1-\alpha/2}$ is at a desired confidence level $\alpha$, the original hypothesis is unacceptable; that is, the time series trend is not statistically significant at the 1-$\alpha$ confidence level. The confidence levels of 0.05 and 0.1 are equal to the $Z$ values of 1.96 and 1.64, respectively. Thus, the trend can be classified according to the $Z$ value (Table 2) (Wang et al., 2014).

| Categories                        | Z values       |
|-----------------------------------|----------------|
| Significant increasing trend      | [1.96, +∞)     |
| Weak increasing trend             | [1.64, 1.96)   |
| No significant increasing trend   | [0, 1.64)      |
| No significant decreasing trend   | (-1.64, 0)     |
| Weak decreasing trend             | (-1.96, -1.64] |
| Significant decreasing trend      | (-∞, -1.96)    |
2.4 Distinct Empirical Orthogonal Function

The empirical orthogonal function (EOF), which deals with temporal and spatial functions, is used to extract the spatiotemporal modes based on the data variance representations. The EOF was introduced into meteorology and climate research by Lorenz (1956) in the 1950s and has already been widely applied in other fields, such as geoscience and hydrology. The EOF analysis method can decompose the time-varying variable fields into the space function part (EOFs) that does not change with time and the time function part (principal components, PCs) that depends only on time. The distinct EOF (DEOF) analysis was subsequently introduced to overcome problems in the EOF analysis (Dommenget, 2007). In the DEOF, a continuous spectrum of spatial patterns resulting from a stochastic process can be represented by EOF modes, where some spatial structures will be more dominant than others. Based on the isotropic diffusion null hypothesis, the DEOF modes (DEOFs) can be found by rotating the leading DEOF modes, corresponding to the distinguished principal components (DPCs) (Ye et al., 2019b). These DPCs take up a large part of the total variance in all the variables in the original field, which is equivalent to the main information of the original field concentrated on a few main components. The higher the eigenvalues, the more typical the corresponding modes, and the greater the contribution to the total variance. The details about DEOF can be found in Dommenget (2007).

2.5 Wavelet analysis

The continuous wavelet transform (CWT) (Torrence et al., 1998) is widely used for analysing the frequency domain of hydrometeorological time series (Fang et al., 2018; Li et al., 2020). The spectral and temporal features of the time series can be projected onto a time-frequency plane by CWT, where the dominant cycle period and its duration can be identified (Grinsted et al., 2004). The square modulus of the CWT defines the wavelet power spectrum (WPS) (Jiang et al., 2014), which represents the signal energy at a specific scale (period) and time (Asong et al., 2018). In this paper, the time-frequency domain of DPCs was analysed by CWT. The specific calculation process for CWT can be found in Torrence et al. (1998). Notably, the CWT brings about a cone of influence (COI) that delimits a region of the WPS beyond which the edge effects become significant and the power could be suppressed (Torrence et al., 1998).
Also, the cross wavelet transform (XWT) (Torrence et al., 1998) and wavelet coherence (WCO) (Torrence et al., 1999) can examine the relationship between the DPCs and the global climatic driving factor. WCO reveals local similarities between two time series and may be found to be a local correlation coefficient in the time-frequency plane; that is, their possible teleconnection can be identified by WCO (Asong et al., 2018). Similar to the CWT, the parts outside of the COI should also be interpreted with caution. The specific XWT and WCO analysis methods can also be found in Torrence et al. (1998;1999).

3. Results and Discussion

3.1 Variation characteristics of meteorological elements

To better understand the drought trends in Japan, the variation characteristics of meteorological elements (precipitation, temperature, and potential evapotranspiration) were first analysed by anomaly curves. Figure 1 shows the anomaly curves of precipitation, temperature, and potential evapotranspiration, which reflects the difference between the annual value of meteorological elements and the overall mean over Japan. For precipitation, there was a weak increasing trend. Moreover, the years with the least precipitation were 1978, 1984, and 1994. The annual scale deviations were -414.91 mm, -411.48 mm, and -339.88 mm respectively.

For temperature and potential evapotranspiration, it could be interpreted that these two meteorological elements have similar obvious increasing trends, especially after the late 1970s. Most annual values of temperature and potential evapotranspiration were greater than the overall mean after 1990. In particular, most anomaly values of temperature and potential evapotranspiration appeared in 2004 (0.99 °C) and 1994 (2.42 mm), respectively.

The trend analysis of three meteorological elements during different seasons from 1960 to 2018 was calculated (see Figure 1). Except for summer, precipitation values have shown an increasing trend in the other three seasons, although these trends were not significant. The temperature and potential evapotranspiration showed a consistent trend in different seasons. The increasing trend was most obvious in spring, while the increasing trend in winter was weakest when compared to other seasons.
Figure 1. Average meteorological element anomaly curves and Z value of different seasons over Japan from 1960 to 2018. (a) Precipitation. (b) Temperature. (c) Potential evapotranspiration

Next, the TFPW-MK trend test results were calculated and then interpolated over Japan by inverse distance weighted (IDW) (see Figure 2). For precipitation, except for some parts of the northernmost region, Japan showed increasing trends. However, all the precipitation trends were insignificant. For temperature, the whole of Japan showed strong increasing trends. The trends in northeast Japan was most significant. For potential evapotranspiration, the trends of potential evapotranspiration were similar to that of temperature. It was evident that almost all of Japan showed increasing trends in potential evapotranspiration, except for several parts of the northernmost region. The trends of potential evapotranspiration in most of eastern Japan were insignificant and only
several coastal areas in southwestern Japan showed significant trends. Also, the increased temperature and evapotranspiration could cause the acceleration of soil moisture evaporation loss, which would increase the risk of drought.
3.2 Variation characteristics of drought

For drought, the average scPDSI series of Japan from 1960 to 2018 is shown in Figure 3. A drought month event is defined to occur when the scPDSI is less than -1 (Ye et al., 2019a). The results indicated that the two driest periods occurred in 1983–1988 and 1994–1997. In these two periods, the minimal values of scPDSI were -3.80 and -3.42, which both reached the level of severely dry, as shown in Table 1. To better analyse the size and influence of droughts, the proportions of monthly drought grid points were calculated. The number of grid points where scPDSI ≤ -1 is divided by the total number of grid points. These proportions could indirectly reflect the severity of the droughts, as shown in Figure 4. Specifically, there were 193 months out of the 708 months from 1960 to 2018 when the drought grid point proportions were ≥50%. In this case, the situation of the drought grid point proportions of ≥90% occurred in 22 months, which meant that drought occurred over almost all of Japan during this several month periods. The range of drought grid point proportions was 0.97 to 0.99 from September 1984 to January 1985 when the maximal value appeared.
Figure 4. The drought grid point proportions of the scPDSI over Japan from 1960 to 2018.

Also, the number of drought month occurrences in different seasons of each year was counted throughout 1960–2018 (Figure 5). There were 10.1 drought month occurrences on average in 1985 with more than two droughts month occurring each season. Indeed, different seasons showed different trends. Figure 6 shows the number of drought month occurrences in different seasons. The percentage of drought month occurrences in spring and summer were observed to be increasing, while the percentage of drought month occurrences in autumn and winter were decreasing. In other words, spring and summer became drier and autumn and winter became wetter in Japan.

Figure 5. The number of scPDSI≤-1 event for different seasons over Japan from 1960 to 2018.
Figure 6. The drought seasonal proportions according to the scPDSI over Japan from 1960 to 2018. (a) Spring. (b) Summer. (c) Autumn. (d) Winter.

Figure 7a shows the Z values of the scPDSI series at each grid point calculated by the TFPW-MK trend test. Significantly increasing drought trends (decrease in scPDSI) were observed in some western regions. Decreasing trends were found in the northwestern region, the western part of the central region, the partial area of the northeast region, and most of the northernmost region. And when the precipitation and the scPDSI trend analysis results were compared one mesh by one mesh (Figure 7b–c), the trend analysis results of scPDSI varied with the change of precipitation trend.
Figure 7. (a) TFPW-MK trend analysis results over Japan (The blue contour indicates that Z value is less than -1.64; the red contour indicates that Z value is greater than 1.64). (b)–(c) Comparison of the trends of each mesh between precipitation and scPDSI.

Besides, the comparison of trend analysis results of scPDSI based on different datasets was also applied (As shown in the Appendix II), which proved the robustness of the results.

3.3 Spatial and temporal variabilities in drought using DEOF

The DEOF calculation used the scPDSI time series of each grid point on the monthly scale. Figure 8a–b displays the spatial partitioning results of the first two DEOFs. The explained variances in the first two DEOFs were 46.85% and 20.55% respectively, which meant that the DEOFs could explain approximately 67.40% of the total spatial wet/dry characteristics of Japan from 1960 to 2018.

The first two had sufficiently explained variances to represent most of the wet/dry conditions in Japan. The explained variances in DEOF3 and DEOF4 were only 8.0% and 4.2% respectively. The explained variance in the remaining DEOF values would become much smaller and not considered in this research.

The spatial distribution of DEOF1 illustrated that a high positive loading occurred in the western region at approximately 35°N (W region). This finding meant that the W region had similar drought characteristics from 1960 to 2018. Similarly, the spatial distribution of DEOF2 illustrated
the common positive spatial behaviour of drought in most of the northernmost region near the Pacific (N region). However, the central region, western region, and most parts of the northwestern region showed common negative spatial behaviour, indicating that these regions showed the opposite drought characteristics as the N region. Notably, the two DEOFs were unable to represent all drought characteristics across the whole of Japan. However, according to their loadings, the whole region could be divided into two drought subregions, the W and N regions, which had different spatial variabilities in drought.

For the corresponding drought temporal characteristics, the DPC scores are displayed in Figure 9. The DPC1 scores showed a decreasing trend, which meant that the W region became drier. However, the N region was getting wetter. The trends in the DPC scores were consistent with the TFPW-MK trend results in Figure 7. In addition, the drought characteristics in different seasons were analysed. Figures 10–11 show the number and proportion of drought occurrences of DPCs in different seasons. From 1960 to 2018, the number of drought events in the DPC1 scores was highest in spring, accounting for 31%. For the DPC2 scores, the maximal value, 28% of drought occurrences, appeared in autumn.
Figure 8. Patterns of the first two DEOFs for scPDSI (a) scPDSI DEOF1, (b) scPDSI DEOF2, and (c) One-point correlation based on Pearson correlation coefficient.
Figure 9. DPC scores of the first two DEOFs for scPDSI. (a) DPC1. (b) DPC2.

Figure 10. The number (a) and percentage (b) of drought occurrences in different seasons of DPC1 from 1960 to 2018.

Figure 11. The number (a) and percentage (b) of drought occurrences in different seasons of the DPC2 from 1960 to 2018.

3.4 Comparison between spatial patterns of dryness wildfires
Drought is a factor influencing wildfire occurrence. Considering that drought would cause a decrease in duff moisture and soil moisture, forest fuels (such as grass fallen leaves and branches) become drier and more ignitable, contributing to fire ignition and the subsequent outcomes. Indeed, there have been various studies on the relationship between scPDSI and wildfires. The wildfires in the southern and mountainous ecoregions of the United States showed significant increasing trends, coinciding with trends toward increased drought characterized by scPDSI (Dennison1 et al., 2014). Mongolia experienced a dry period after the 1500s, which coincided with more fires and shorter fire return intervals (Hessl et al., 2016). By comparing various drought indices (PDSI, Drought Index (DI), Monthly Drought Code (MDC), and SPI), the scPDSI was considered to be the best predictor of burned forest area in southern Sweden over 1942-1975 (Drobyshev et al., 2012).

Considering the ability of scPDSI to adequately represent the water balance, the analysis of combining drought with wildfires would further enhance the understanding of drought-induced natural disasters. In Japan, the most of wildfires occur in spring, especially in March to May (Suzuki et al., 2009). Therefore, the comparison between the annual burned forest area in spring (March to May) with DPCs was extracted, as shown in Figure 12. The burned area data come from fire reports provided by the Fire and Disaster Management Agency, Government of Japan. The burned area data of the W region included the Ishikawa prefecture, Fukui prefecture, Gifu prefecture, Aichi prefecture, Shiga prefecture, Kyoto prefecture, Osaka prefecture, Hyogo prefecture, Nara prefecture, Wakayama prefecture, Tottori prefecture, Okayama prefecture, and Mie prefecture. The burned area data of the N region included the Hokkaido prefecture.

In a wet spring, when the scPDSI was positive, the burned area of western Japan was less than 100 ha. The three springs with severe wildfires, when the burned area was larger than 300 ha, were accompanied by drought events in which the scPDSI was less than -1. Although there were fewer wildfire occurrences in the N region than in the W region, these two regions followed a similar pattern. A total of six wildfires with burned areas of over 60 ha occurred in the N region. The scPDSI values corresponding to these six wildfires were all negative, and four of them experienced drought (scPDSI ≤ -1). When the scPDSI was more than 1, there were only six wildfire occurrences in the N region, and the burned area was less than 60 ha.
Whether in the W or N region, there was, to a certain extent, a relationship between the wildfire burned area and drought. Indeed, the drought did not necessarily lead to large wildfires, but a lack of soil moisture could increase the risk of severe wildfires. Understanding the effects of drought on other natural disasters could encourage scholars to pay more attention to drought research in Japan.

(a) DPC1 VS Burned Area in W region

(b) DPC2 VS Burned Area in N region

Figure 12. Comparison of DPCs for annual burned forest area in spring (a) DPC1. (b) DPC2.

3.5 Links between drought and global climatic drivers

Due to the complexity in the causes of drought, the relationship between drought and global climatic drivers needs to be discussed. Figure 13 shows the WPS results of the DPCs of the scPDSI time series. The dominant frequencies of drought were identified. For DPC1 (W region), the significant interannual variability over approximately 44 to 60 months was obvious during the period from 1975 to 1982. Also, a strong dominant frequency band was found to be centred at...
approximately 48 to 128 months during the mid-1980s to mid-2000s. In the N region (DPC2), a major periodicity of approximately 20 to 56 months was observed in the 1970s. During the 1990s, there was a dominant frequency band of approximately 42 to 58 months. Overall, the frequencies of drought were not strong in DPC1 or DPC2.

Figure 13. WPS of the DPC time series. The black contour designates the 95% confidence level against red noise, and the COI, where edge effects might distort the picture, is shown as a lighter, paler shade.

To identify the coherence between drought subregions and climatic causes, the WCO method was used to analyse the covarying occurrence in the dominant frequency bands and time intervals. Figures 14 show the results of the WCO coefficients between the DPCs and climatic driving factors (AOI, NAOI, PDOI, and ONI). In these figures, the level of the coherence and timescale variability between the two time series is represented by different colours corresponding to values that range from 0 to 1. Also, the information inside the thick black lines indicated statistical significance. The arrows illustrate the phase difference between the two time series. If the arrow points to the right (left), then the two time series are in-phase (antiphase). That is, there is a positive correlation (negative correlation). When the arrow points up (down), then the independent variables lead the dependent variables in phase by 3/4 (1/4) of a period. Similarly, if the arrow points to the lower right, lower left, upper right or upper left by 45°, the leading frequency would be 1/8, 3/8, 5/8 or 7/8 of a period, respectively. In this case, because this paper focuses on the impacts of climatic causes on drought, the DPCs were considered to be dependent variables, while the global climatic drivers were considered to be independent variables.
For the W region, Figure 14a–b shows that sporadic but significant coherence was found between DPC1 with AOI, NAOI, PDOI, and ONI. For AOI (as shown in Figure 14a), a positive correlation occurred between approximately 96 and 128 months from the 1970s to the mid-1990s, while a temporary negative correlation was found during 1992–2000 in the range of 20 to 32 months. The coherence between DPC1 and NAOI is shown in Figure 14b. It was obvious that the NAOI led the DPC1 in phase by approximately 84 to 112 months from the 1980s to 2000s. However, over the 1995–2010 period, DPC1 lagged the NAOI, ranging from 36 to 72 months. In Figure 14c, the directions of the arrows were somewhat messy, meaning that the coherence between PDOI and DPC1 was slightly difficult to determine. But a relatively obvious relationship was that DPC1 lagged PDOI by approximately 8 to 16 months from 1992 to 2005. Also, three strong coherence bands were observed in Figure 14d, one of which was nearly a positive correlation between the DPC1 and ONI in the 1970s. And the ONI led the DPC1 by approximately 12 to 16 months in the 1998–2010 period. From 1998 to 2000, the coherence band was mainly concentrated over 140–168 months.

The coherence was stronger in DPC2 than in DPC1. As shown in Figure 14e, a band of approximately 112–128 months of high energy was observed during the period of the mid-1970s to mid-2000s, while the regions beyond the COI were ignored due to edge effects. In this period, the coherence was initially unstable, but after 1985, the relationship between the DPC2 and AOI gradually showed positive correlations. The NAOI (Figure 14f) led the DPC2 by 63–105 months and 84–168 months over the periods of 1970–1980 and 1980–2005, respectively. In Figure 14g, from 1992 to 2002, the PDOI led the DPC2 by 8 to 16 months, which was similar to the relationship between PDOI and DPC2 during the same period. Besides, the leading relationship of time-frequency became 14–20 months between 2002 and 2010. The correlation between ONI and drought was relatively weak compared with the other three climatic factors. The results indicated that the ONI (Figure 14h) led the DPC2 by 14–18 months from 1995 to 2010.
Figure 14. Squared wavelet coherence between the global climatic driving factors and the temporal patterns in the W region and N region. (a) AOI-DPC1. (b) NAOI-DPC1. (c) PDOI-DPC1. (d) ONI-DPC1. (e) AOI-DPC2. (f) NAOI-DPC2. (g) PDOI-DPC2. (h) ONI-DPC2. The black contour designates the 95% confidence level against red noise, and the COI, where edge effects might distort the picture, is shown as a lighter, paler shade.
The foregoing analysis has shown the teleconnection between drought over Japan and global climatic drivers. This paper mainly focused on qualitative analyses to determine the climatic driving factors that have the most obvious impact on drought rather than focusing on quantitative analyses. For DPC1, the most significant coherence between DPC1 and NAOI occurred from the 1980s to 2000s, and the dominant frequency of DPC1 appeared in 1985~2005, which suggested that the periodic features of drought in the W region were likely to be affected by the NAO. For the N region, the significant coherence between drought with the AO and NAO appeared throughout the research period, but because of the edge effects, the coherence analysis mainly revolves around the parts in the COI. This finding also showed that the complexity in the cause of the drought was affected by more than one climatic driving factor. The CWT and WTC analysed the relationship between drought and global climatic driving factors from only a statistical point of view, so the underlying physical process was not the target of this research. However, this paper would be meaningful for determining the climatic driving factors that affect the occurrence of drought, and in-depth research on predicting droughts through climatic driving factors is required.

Additionally, this paper identified the two global climatic drivers, AO and NAO, which had the most significant effects on drought over Japan. But the effects of these two global climatic drivers on regional climate is not limited to Japan. Actually, in the Korean Peninsula across the sea from Japan, the spring drought events in this region have also been confirmed to be affected by the NAO (Kim et al., 2017). Also, the majority of UK recorded droughts in recent history showed a clear relationship with NAO (Rust et al., 2019). Even in the northeastern United States, drought prediction was performed based on NAO (Berton et al., 2017). The AO had significantly affected the extreme drought event over southwestern China (Yang et al., 2012), hydrological drought over Turkey and northern Iran (Vazifehkhah et al., 2018), and climatological drought over Finland (Irannezhad et al., 2017). Global climatic drivers such as NAO and AO had vast and far-reaching effects on the different regional hydroclimate. This paper is the first to connect the drought over Japan with NAO and AO. The discovery of regional droughts with similar climatic causes would also provide the basis for conducting further research on different drought teleconnection analysis in different regions.
4. Summary and Conclusions

Investigation of the coherence connections between drought and global climatic driving factors is significant for a better understanding of drought. This paper focused on Japan, which has less available drought-related research, as the research area and provided a comprehensive analysis of drought patterns over Japan during the period from 1960 to 2018 using the scPDSI drought index. The relationship between wildfire burned area and the scPDSI was analysed. Wavelet analysis was applied to detect the climatic driving factors that had the strongest relationship with drought, which overcame the insufficiency of classical drought analysis in determining the cause of the drought.

The main conclusions obtained from this paper are summarized as follows: (1) The potential evapotranspiration and temperature showed increasing trends throughout almost all of Japan, while the changing trend in precipitation was not significant. The changes in potential evapotranspiration and precipitation were most obvious in summer, whereas there was little difference in the temperature in different seasons. (2) On average, 1983~1988 and 1994~1997 were the two driest periods in Japan. Also, the droughts were greater in spring and summer and weaker in autumn and winter. (3) DEOF was used to identify two major subregions of drought variability—the western region (W region) and most of the northernmost region near the Pacific (N region). The corresponding scores of DPC1 and DPC2 showed a trend of decreasing (increasing in drought) and increasing (decreasing in drought), respectively. (4) When scPDSI was less than -1, wildfires with larger burned areas were more likely to occur. (5) The global climatic driving factors that showed the strongest cross-correlation with DPC1 and DPC2 were the NAOI and AOI together with the NAOI, respectively, and their corresponding coherence times were 1980~2010 and 1975~2005, respectively.

The outputs of the paper provide a reference for the future study of drought prediction in Japan. Through the identification of drought subregions with similar drought spatiotemporal characteristics, it can be helpful for drought risk management at the regional scale over Japan. The analysis of the climatic causes of drought in these subregions can be useful for choosing suitable impact factors for drought predictions.

5. Appendices
Appendix I: To analyze the robustness of trend results, the precipitation and temperature data from the Automated Meteorological Data Acquisition System (AMeDAS) of Japan Meteorological Agency and the radiation, wind speed and dew point temperature from Dynamical Regional Downscaling Using Japanese 55-year Reanalysis Data (DSJRA55) (Kayaba et al., 2016) were selected. Due to the time scale of DSJRA55 data is only available from 1958–2012, this paper only compared the consistency of the data from 1958 to 2012. The specific results are shown in the Figure A1–A3. Although the results of the two datasets were a little different, the trend analysis results in most areas were consistent.

Figure A1. TFPW-MK trend analysis results of precipitation based on different datasets from 1960–2012 (Display of Significant area).

Figure A2. TFPW-MK trend analysis results of temperature based on different datasets from 1960–2012 (Display of Significant area).
Figure A3. TFPW-MK trend analysis results of potential evapotranspiration based on different datasets from 1960~2012 (Display of Significant area).

Appendix II: Based on the data mentioned in Appendix I, the scPDSI based on the different datasets were also compared during the period of 1958~2012 (As shown in Figure A4).

Figure A4. Trend analysis results of scPDSI based on different datasets from 1960~2012. (The blue contour indicates that Z value is less than -1.64; the red contour indicates that Z value is greater than 1.64)

Data availability
All datasets utilized to perform this study are freely available on the internet. For further information, please contact the corresponding author.

Author contributions
Ke Shi: Methodology, Software, Formal analysis, Original Draft; Yoshiya Touge: Data Curation, Review & Editing, Project administration, Funding acquisition. So Kazama: Supervision, Project administration, Funding acquisition.

Competing Interest

The authors declare no conflicts of interest.

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