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ORIGINAL PAPER

Towards a greater awareness for drought mitigation in China

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Abstract

Drought awareness promotes people to be more sensitive to water shortage and more likely to support water-saving policies. Studying the spatiotemporal patterns and determinants of drought awareness is necessary for developing drought-resistant measures that can adapt to regional social responses. This paper employs the Baidu Index and sc-PDSI, in conjunction with the Principal Component Analysis, to explore the spatiotemporal patterns and influencing factors of drought awareness in China. The results indicate that the first two principal component modes can explain 75% of the total variance of drought awareness in China. The drought awareness of the people is more sensitive to summer droughts and less to winter droughts. The population and education level are the two most important influencing factors at the current stage. It is found that people are most concerned about the drought in Northeast China, while people in central and eastern China are concerned about the drought events in local and other regions. The responses of drought awareness to actual meteorological drought events can be synchronous or asynchronous for different regions. The results demonstrate the usability of big data in drought awareness research and provide crucial insights for the formulation of drought mitigation policies in China.

Keywords Drought awareness (DA) · Baidu Index · Self-calibrated Palmer Drought Severity Index (sc-PDSI) · Principal Component Analysis (PCA) · China

1 Introduction

Drought is one of the most serious natural disasters, as it causes enormous economic and social losses every year due to its complex evolutionary mechanisms. Numerous studies have attempted to assess or predict the evolution and severity of droughts using hydrological models and climate data (Zhang et al., 2011,2017b; Niu et al., 2015; Ma et al., 2016; Sun et al., 2019; Valiya Veettil and Mishra 2020; Xing et al., 2020). Such studies have been able to understand the spatiotemporal dynamics of droughts and provide reasonably good predictions of droughts, thus allowing early warnings. However, tens of millions of people and livestock still suffer from the lack of water availability during drought periods, and droughts continue to cost huge economic losses. This situation may be due to the fact that drought research and relief policies are not sufficiently adapted to bring awareness to individuals on droughts, and so drought mitigation strategies cannot be effectively put into practice (Switzer and Vedlitz, 2017). Drought awareness can reflect the public concern on perception about water shortage and support for water-saving policies. A better understanding of drought awareness will promote drought monitoring and prediction and make drought relief measures to play a better social role. Thus, it is necessary to explore the determinants and effects of the public's drought awareness.

Traditional methods for drought awareness mainly include observation interviews, questionnaire surveys, and

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other field investigations (Wang and Wan, 2017). They use written records and data statistics to obtain an individual's degree of recognition of droughts and response actions in the context of meteorological and other environmental information (Su et al., 2012; Wheaton et al., 2016; Niu et al., 2019). However, it is important to note that people's judgement of drought relies on intuition and experience, which leads to different criteria to measure the extent of drought and increases the difficulty in quantifying drought awareness (Shi et al., 2008; Wang et al., 2012). In addition, traditional investigation has certain limitations, for instance, it costs a lot for field data collection, the sample size is limited, and the space–time scale is rough. The effectiveness of the sample is also affected by the memory of the interviewees, the sampling representativeness, the emphasis of the interviews, and other factors. All these limit the dynamic tracking and large-scale investigation of drought awareness.

During the past decade or so, the concept of Big Data Analysis has been gaining significant momentum. Internet search provides a large amount of social monitoring data, which has become a breakthrough data source for studying social responses in the light of its advantages of high resolution, large areal coverage, and real-time dynamics. At present, many studies use search data monitoring platforms, such as Google Trends, Baidu Index, and Aliyun, to analyze individual potential thoughts and consciousness. Search data has played a great role in unemployment prediction (Nagao et al., 2019), product pre-sale (Chumnumpan and Shi, 2019), disease outbreak (Boehm et al., 2019), tourism (He et al., 2017; Wu et al., 2018), and other hot social issues (Lee, 2020; Wang et al., 2019; Zhang et al., 2017a). Similarly, search data can be used to monitor public drought awareness and capture people's perception of drought. For instance, Gonzales and Ajami (2017) proposed to use the search data from Google Trends to verify the accuracy of the dynamic system model of people's water demand during the California drought from 2011 to 2017. The study by Kam et al. (2019) used the search data for "drought" to investigate potential triggers and dynamic patterns of public drought perception during the drought in California. It demonstrated that the search data can be a reliable source for quantifying and describing the public drought awareness. On this basis, Kim et al. (2019) first used the search data of Google Trends to quantify drought awareness in America and then obtained its spatiotemporal patterns, which played a positive role in understanding the social dynamics of drought awareness and its effect on drought relief programs.

In China, more than 80 percent of the Internet users use the Baidu search engine. The Baidu Inc. launched the Baidu Index, a data-sharing platform based on massive online behavior. The Baidu Index reflects the initiative search demand of netizens and is influenced by all the events that can affect netizens' search behavior. The disaster caused by drought and its negative impacts attracts public concerns and leads to significant public drought awareness, thus promoting drought search activities. Drought-related search behaviors show an increasing or declining trend with the development or mitigation of drought. With the support of big data, individual searching behavior of drought can be captured and counted, which can help better address the quantification of drought awareness. Therefore, in this paper, we aim to study the spatiotemporal patterns of drought awareness in China, on the basis of the Baidu Index in conjunction with self-calibrated Palmer Drought Severity Index, using Principal Component Analysis and Pearson correlation analysis. We analyze the correlations between the drought awareness and meteorological drought in space or at leading/lagged times, and further explore the effect of drought severity on drought awareness and the influencing factors of drought awareness. We consider the period 2011–2018 for analysis. The knowledge obtained from this study will be helpful for effective drought mitigation and building policy support, towards a greater and better drought awareness in China.

The rest of this paper is organized as follows. The Baidu search data and the methods used for analysis are described in Sect. 2. The analysis and results on the characteristics of drought awareness are presented in Sect. 3. A discussion of the results is provided in Sect. 4. Section 5 draws some major conclusions.

2 Data and methods

2.1 Data

The Baidu search index takes the keywords as the statistical object and is the weighted sum of search frequency of keywords in the Baidu webpage search. The data covers the search index of all administrative districts in China from 2011 to now. Thus, the search data of the Baidu index is used to quantify the drought awareness of people in China in this study. This study extracts and calculates the monthly search index of five keywords (i.e., "干旱" – drought, "旱灾" – drought disaster, "大旱" – great drought, "旱情" – drought situation, and "抗旱" – drought relief) in 31 administrative districts (including 22 provinces, 5 autonomous regions, and 4 municipalities directly under the central government), as shown in Fig. 1, except Hong Kong, Macao, and Taiwan, because of the lack of Baidu Index search data.

The quantification of meteorological drought depends on drought index, which is an important tool for drought monitoring (Shen et al., 2013). Many indexes have been

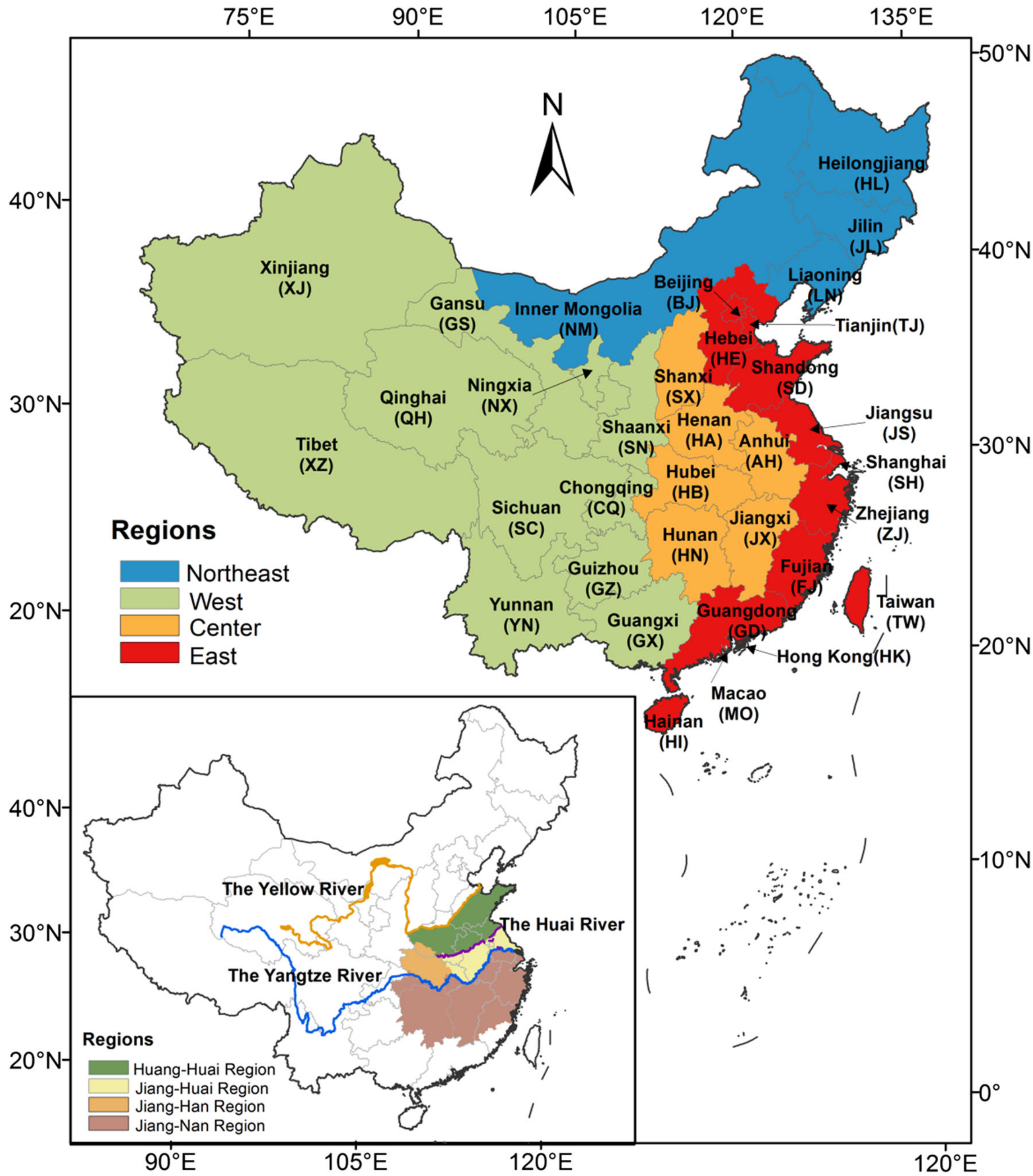

Fig. 1 Four major regions and the sub-regions mentioned in Table 1

used to measure drought events in China (Yang et al., 2017, 2019; Zhai et al., 2017). Among such, the Palmer Drought Severity Index (PDSI) considers the influence of both precipitation and temperature on soil moisture. It can effectively capture different degrees of drought events due to a high fitting degree with the actual regional drought in both arid and humid regions (Liu et al., 2018; Yang et al., 2018; Zhao, 2019). Therefore, in this study, the self-calibrated Palmer Drought Severity Index (sc-PDSI) is used to quantify the meteorological drought and the data set is the monthly time series at 0.5°spatial resolution. The monthly data was obtained from the KNMI Climate Explorer (http://climexp.knmi.nl/start.cgi) and was updated to 2018 when it was accessed for the investigation.

Socioeconomic data used in this study to explore the influencing factors of drought awareness, including water resource per capita, population, GDP (Gross Domestic Product) per capita, and education level (expressed as the average number of college students per 100,000 population), are derived from the National Bureau of Statistics (http://www.stats.gov.cn).

Table 1 Drought descriptions across China from 2011 to 2018

Year	Drought description
2011	The rare drought in the middle and lower reaches of the Yangtze River (including Hubei, Jiangxi, Hunan, Jiangsu, Anhui, and Guizhou); summer droughts in northern Shaanxi, Gansu, Ningxia, Huang-Huai[1] and Jiang-Huai[2] regions
2012	The spring and winter droughts were severe in the southwest (especially in Sichuan and Yunnan); eastern Inner Mongolia and Northeast China were dry from spring to early autumn; but the national annual precipitation was heavy
2013	The summer droughts in the south of the Yangtze River, the autumn drought in East China and the continuous droughts in the north and southwest, Huang-Huai, Jiang-Huai and Jiang-Han[3] regions; but all 31 administrative districts suffered from floods and waterlogging with varying degrees
2014	North of the Yangtze River was seriously dry from spring to autumn; droughts in Jiang-Nan[4] region and southern China
2015	The severe summer droughts in the southwest; east of the northwest region was in severe drought, with drought occurring in more than 50% of the region
2016	The droughts occurred in East, Central, and West China; the flood disasters were serious, the rainfall was 15 percent more than that of the previous year, and the occurrence of catastrophic floods was more frequent
2017	North China and Northeast China experienced continuous droughts; spring and autumn droughts in Huang-Huai, Jiang-Nan regions; summer droughts in the middle and lower reaches of the Yangtze River
2018	Severe spring droughts in southern China and Jiang-Nan region; summer droughts in central and southern region; the natural disasters in that year were mainly floods and typhoons (especially in North and Northeast China)

[1]Huang-Huai region includes parts of Henan, Shandong, Anhui, and Jiangsu between the Yellow River and the Huaihe River

[2]Jiang-Huai region includes parts of Henan, Hubei, Anhui, and Jiangsu between the Huaihe River and the Yangtze River

[3]Jiang-Han region includes the rest of Henan and Hubei to the west of Jiang-Huai and Huang-Huai

[4]Jiang-Nan region includes Hunan, Jiangxi, Zhejiang, Shanghai, and parts of Anhui, Jiangsu, Hubei and Fujian between the Yangtze River and the Nanling Mountains

Considering the mutual limitations of data in time, we select January 2011 to December 2018 as the study period. The Baidu index of each district divided by the corresponding population (unit: million) to remove the influence of the population, and then obtain the relative drought search index which can represent the monthly time series of drought awareness, i.e., DA_i, where i is an administrative district. The monthly average PDSI in each administrative district represent the monthly meteorological drought, i.e., MD_i, where i is an administrative district.

2.2 Methods

In this study, the Principal Component Analysis (PCA) is employed. The PCA is a multivariate statistical analysis technique to select a few important variables through orthogonal linear transformation of multiple variables. As a result, the technique can effectively reduce the data dimension. The time series of drought awareness (DA_i) in 31 administrative districts for a period of 96 months (from 2011 to 2018) (represented as a 31×96 matrix) are projected onto the corresponding eigenvector to obtain the component scores of national drought awareness. The first and second principal components can explain more than 75% of the variance of drought awareness, while the variance explained by other components is limited (e.g., 3.5% for the third principal component) and not enough to represent the variation characteristics of national drought awareness. So we only select the first two principal components for analysis, represented as DA_{PC1} and $DA_{PC2.}$ Similarly, the first and second principal component mode scores ($MD_{i\text{-}PC1}$ and $MD_{i\text{-}PC2}$) of meteorological drought in 31 administrative districts are extracted from the monthly meteorological drought (MD_i) ($N_i \times 96$ matrix, where N_i is the number of sc-PDSI grids in a certain administrative district) from 2011 to 2018.

The principal component scores DA_{PC1}, DA_{PC2}, $MD_{i\text{-}PC1}$, and $MD_{i\text{-}PC2}$ are used to represent the two main trends of drought awareness (DA) in the country and meteorological drought (MD_i) in each district, respectively. The Pearson sample linear correlations of DA_{PC1} & DA_i, DA_{PC2} & DA_i, DA_{PC1} & $MD_{i\text{-}PC1}$, and DA_{PC2} & $MD_{i\text{-}PC2}$ in 31 administrative districts are computed. The correlations are converted to T-statistic and then are tested for significance at the 95% confidence level. With this, the relationship between the drought awareness and meteorological drought on a regional scale can be explored. For example, if DA_{PC1} is significantly correlated with DA_i of district i and the time correlation between $MD_{j\text{-}PC1}$ of district j and DA_{PC1} is positive (i and j represent two different administrative districts), then it may be speculated that the drought events in district j can be attributed to the development of drought awareness in district i. However, other natural phenomena, such as rainstorm and flood events that greatly offset the effects of droughts, and possible time-lag relations between the regional drought

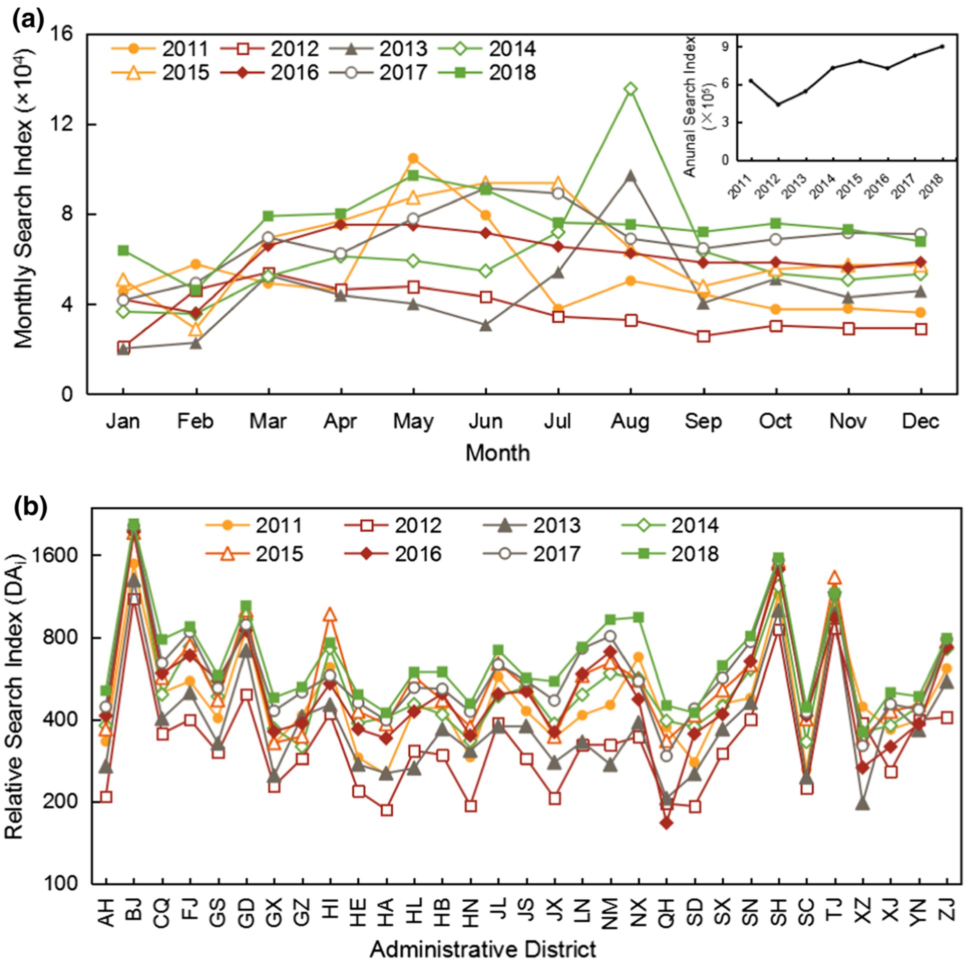

Fig. 2 **a** Annual and monthly drought search index in China for the period 2011–2018, and **b** the annual relative search index (i.e., the annual provincial drought awareness) in all administrative districts for the period 2011–2018

awareness and drought events may lead to a negative correlation or no correlation between the meteorological drought events and people's drought awareness.

In order to explore the response of each region to actual drought, this study also calculates the correlations at a lead/lagged time between DA_{PC1} & DA_i and between DA_{PC1} & $MD_{i\text{-}PC1}$. The calculation formula is as follows:

$$\rho(DA_{PC1}, DA_i, \lambda) = \frac{Cov[DA_{PC1_{(t+\lambda)}}, DA_{i(t)}]}{\sqrt{D[DA_{PC1(t+\lambda)}]}\cdot\sqrt{D[DA_{i(t)}]}} \quad (1)$$

$$\rho(DA_{PC1}, MD_{i-PC1}, \lambda) = \frac{Cov[DA_{PC1(t+\lambda)}, MD_{i-PC1(t)}]}{\sqrt{D[DA_{PC1(t+\lambda)}]}\cdot\sqrt{D[MD_{i-PC1(t)}]}} \quad (2)$$

where $\rho(DA_{PC1}, DA_i, \lambda)$ is the correlation between DA_{PC1} and DA_i at λ lead or lagged months (from 3 lead months (λ =-1,-2,-3) to 3 lagged months (λ=+1,+2,+3)); $\rho(DA_{PC1}, MD_{i\text{-}PC1}, \lambda)$ is the same as $\rho(DA_{PC1}, DA_i, \lambda)$, but for the correlation of DA_{PC1} and $MD_{i\text{-}PC1}$ in district i; t is the period from April 2011 to September 2018; $DA_{PC1(t+\lambda)}$ is the time series of DA_{PC1} during the period (t+λ); $DA_{i(t)}$ and $MD_{i\text{-}PC1(t)}$ is the time series of DA_i and $MD_{i\text{-}PC1}$ during the period t.

3 Characteristics of national drought awareness

3.1 Annual and monthly changes

The annual search index for the period 2011–2018, in the top right panel of Fig. 2a, shows that the drought awareness in China has generally a steadily increasing trend. The annual search index value in 2011 is higher than that in 2012 and 2013, indicating that the rare drought in the middle and lower reaches of the Yangtze River in 2011 caused an abnormal outbreak of drought awareness in the whole country. It seriously threatened the regions with a well-developed industry and agriculture involving a large population. The monthly search index for the period 2011–2018 is mainly divided into three phases: the rising phase in spring (January–April), the outbreak phase in summer (May–August), and the flat stage in autumn and winter

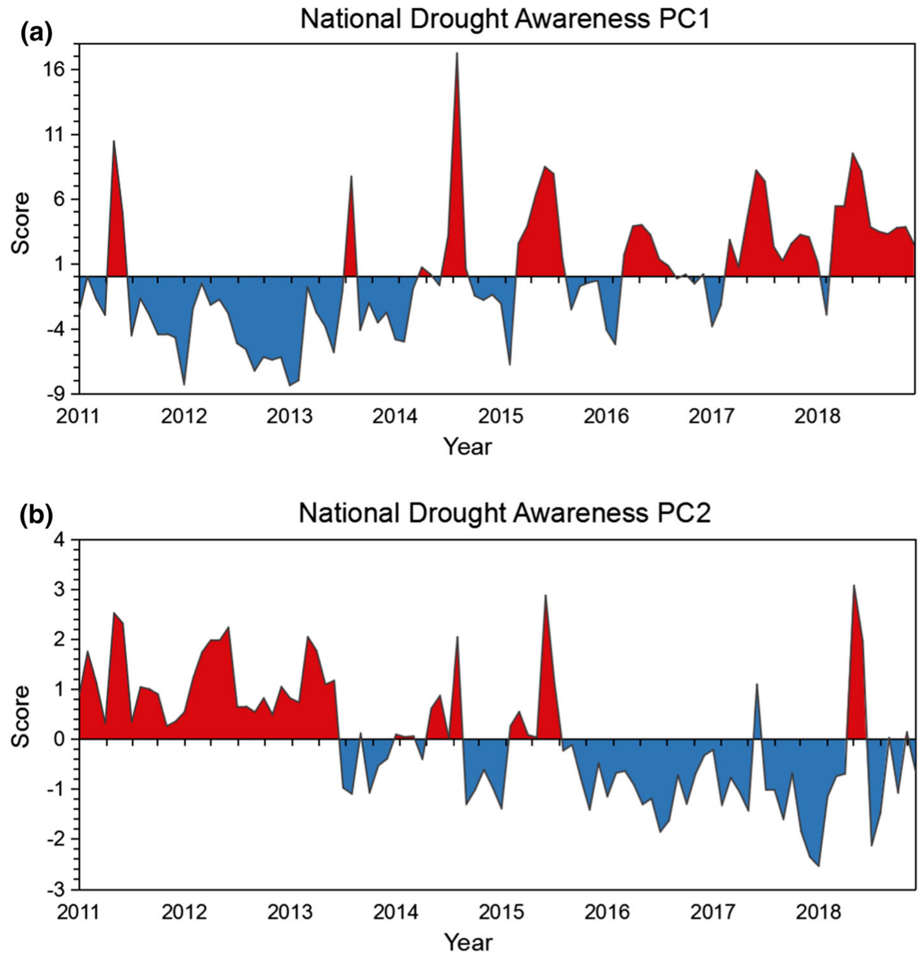

Fig. 3 The first **a** and second **b** principal component scores of national drought awareness

(September–December). The peak of drought awareness mostly occurs during May to August every year, which indicates that the drought awareness in China is mainly sensitive to the summer drought. The summer drought, caused by high temperature and less rain, often attracts people's attention, because it seriously affects the agricultural production and daily life. Drought in autumn and winter do not attract people's attention much, because the weather is generally dry and agricultural water requirement is greatly reduced.

It can be observed, from the relative search index in Fig. 2b, that Beijing (BJ), Shanghai (SH), and Tianjin (TJ) lie in the top three positions in terms of drought awareness. However, drought awareness has been low almost for the whole decade in Jiangxi (JX), Qinghai (QH), Shandong (SD), and Yunnan (YN) provinces, which often suffer from drought-related disasters. This may be particularly related to the local social and economic development, such as individual income and education level (Tan and Ma, 2014). The drought awareness in Hainan (HI), Guangdong (GD), Inner Mongolia (NM), Ningxia (NX), and other districts is also high, which are vulnerable to drought, and the government agencies, meteorological departments, and news media respond positively and frequently. Therefore, the public can maintain a relatively high drought awareness under the influence of the surrounding environment.

3.2 Results of principal component analysis

The first and second principal component (PC1 and PC2, respectively) scores of drought awareness (Fig. 3), i.e. DA_{PC1} and DA_{PC2}, can explain 70.31% and 4.97% of the total variance of drought awareness in China embedded in the search data, respectively. The first principal component accounts for more than 70% of the total variance, indicating that the drought awareness across China is in synchronicity, to a certain extent.

It can be observed from Table 1 and Fig. 3a that the positive peak of DA_{PC1} is closely related to the multiple drought events in the northeastern, southwestern, and east-central parts of China from 2011 to 2018. The drought that occurred in May 2011 in the middle and lower reaches of the Yangtze River was a once in a 60-year drought (Duan et al., 2012), which caused the first peak of drought

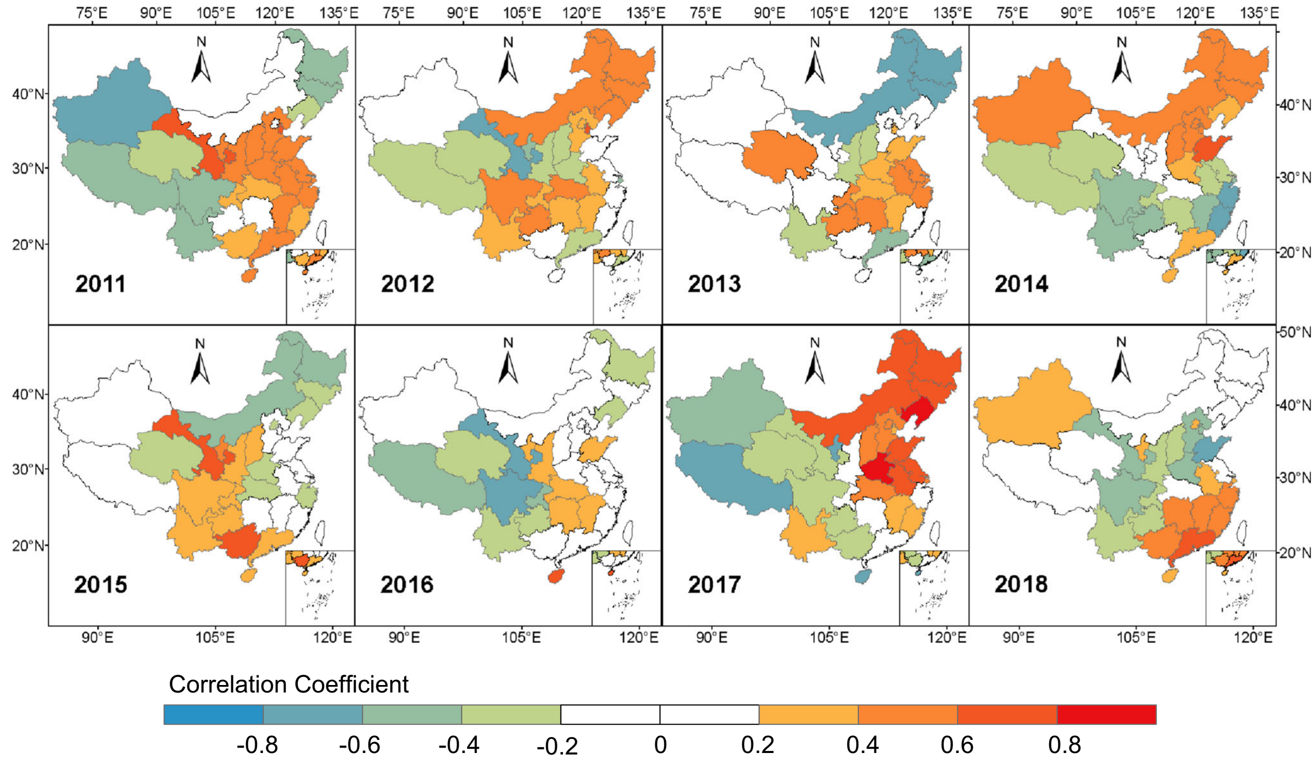

Fig. 4 Temporal correlations between the first principal component of national drought awareness (DA_{PC1}) and the first principal component of meteorological drought in each administrative district ($MD_{i\text{-}PC1}$) for each year during 2011–2018. White districts indicate non-significant correlation (α=0.05), the other pictures are the same

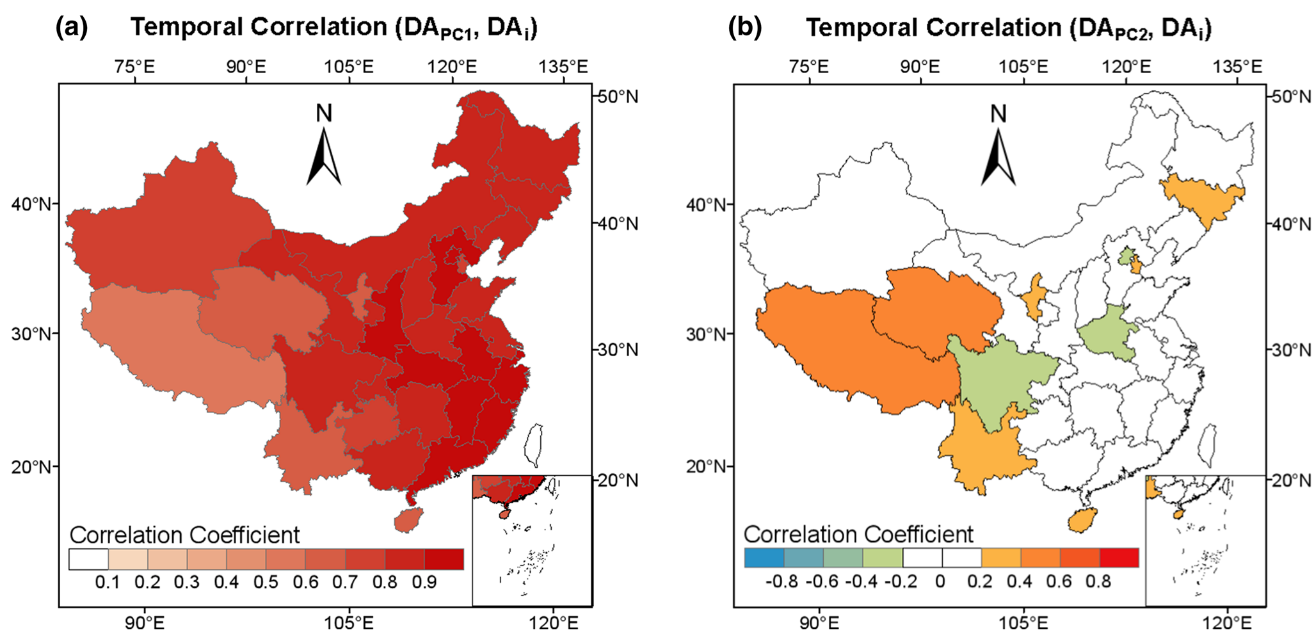

Fig. 5 **a** Temporal correlations between drought awareness principal component scores DA_{PC1} and DA_i for the period 2011–2018, **b** the same as (a), but for DA_{PC2} and DA_i

awareness; the summer drought in the northern and eastern parts of the Yangtze River in 2014 (Duan et al., 2015) led to the highest peak; and other severe drought events (Duan et al., 2013; Feng et al., 2014; Wang et al., 2016, 2017a, 2017b, 2017c; Zhang et al., 2017c, 2018a, 2018b, 2018c) made several peaks during

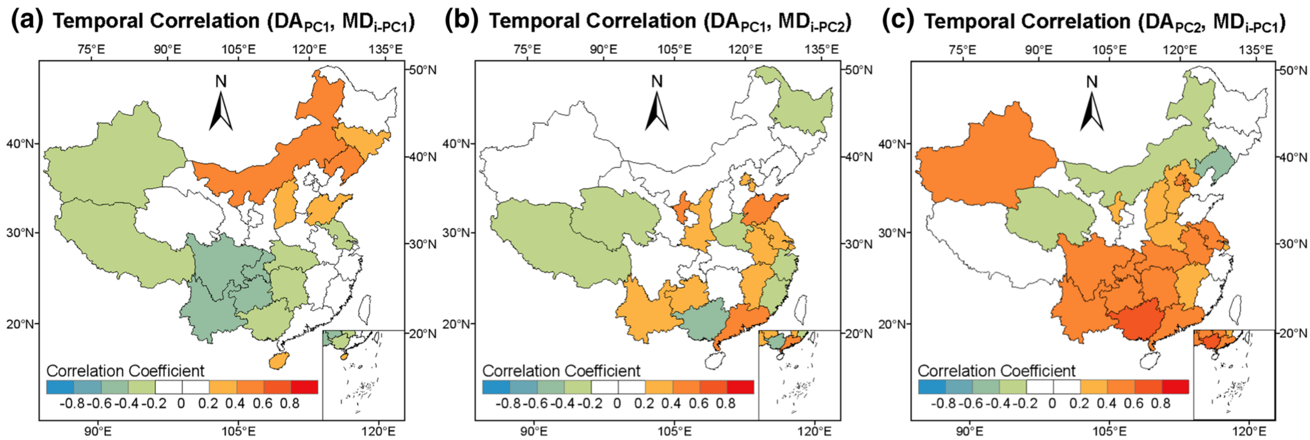

Fig. 6 Temporal correlations between DA_{PC1} and $MD_{i\text{-}PC1}$ **a**, DA_{PC1} and $MD_{i\text{-}PC2}$ **b**, DA_{PC2} and $MD_{i\text{-}PC1}$ **c** for the period 2011–2018

2013–2018. The change in the national drought awareness is basically consistent with that of the meteorological drought in recent years (shown in Fig. 4), and some abnormal trends are related to flood, typhoon, and other disasters. According to the annual disaster reports of China (Yan, 2013, 2014), precipitation in 2012 and 2013 was heavier than usual and severe flooding occurred in several basins, such as the Heilongjiang River Valley, Songhua River basin, and the Liao River basin of northeast China, which suffered severe flooding in recent decades, including in 2013. These led to the negative peaks in Fig. 3a and the negative correlations in northeast China in 2013, which is shown in Fig. 4.

As shown in Fig. 5a, DA_{PC1} has high positive correlations with DA_i. This national drought awareness trend is mainly caused by multiple droughts in the northeastern and northern parts of China, which is illustrated in Fig. 6a. As seen from Fig. 6a, DA_{PC1} is not highly correlated with $MD_{i\text{-}PC1}$ (the first principal component of meteorological drought during 2011–2018 in each administrative district) in Fujian, Hubei, Hebei, and other districts. However, it is also positively correlated with drought awareness in these districts, as can be seen in Fig. 5a. This suggests that even if there is no drought in these districts, the local people are aware of, and pay attention to, the droughts in other regions, especially the droughts in Northeast China. In some districts of western and central China, DA_{PC1} is negatively correlated with $MD_{i\text{-}PC1}$, indicating that the trends of drought awareness and local meteorological drought are opposite, which may be related to the frequent flood disasters in these regions in recent years. Considering that sometimes the drought events only occur on a small scale, $MD_{i\text{-}PC1}$ of each district cannot accurately express the evolution of drought in the whole district, so the correlation analyses of $MD_{i\text{-}PC2}$ (the second principal component of meteorological drought during 2011–2018 in each administrative district) and DA_{PC1} are also carried out. The results in Fig. 6b show favorable positive correlations in Guangdong, Jiangxi, Yunnan, Anhui, and Shandong, which indicate that people are also sensitive to the smaller range of drought events occurred in these districts. Meanwhile, because of the frequent and simultaneous occurrence of droughts and floods in the same area, drought is not always the dominant meteorological disaster, and there is no significant correlation between $MD_{i\text{-}PC1}$ and DA_{PC1}, as can be seen in Fig. 6a.

The second principal component score of national drought awareness, DA_{PC2}, explains about 5% of the trend of national drought awareness, which is associated with multiple droughts in the western, northeastern, and southern parts of China from 2011 to 2018 (see Fig. 15 of Appendix A), such as the summer drought in western China in 2015 and the summer drought in Guangdong, Guangxi, and Jiang-Nan region in 2018. As shown in Figs. 5b and Fig. 6c, the correlations of DA_{PC2} with DA_i and $MD_{i\text{-}PC1}$ in each district explain that the drought awareness in Yunnan, Tibet, and Qinghai is highly correlated with DA_{PC2}, and people in these regions are very sensitive to the droughts in most areas of the Yangtze River basin and the Pearl River basin.

3.3 Relationship between drought severity and drought awareness

In order to understand the role of drought severity in affecting the generation and spatial distribution of drought awareness, the correlations between DA_{PC1} and different levels of meteorological drought of the 31 administrative districts are calculated. To this end, drought severity is divided into four grades, according to the value of sc-PDSI. These are: weak drought (D1, the value of sc-PDSI is between − 0.5 and − 1.99); moderate drought (D2, the value of sc-PDSI is between − 2 and − 2.99); severe drought (D3, the value of sc-PDSI is between − 3 and −

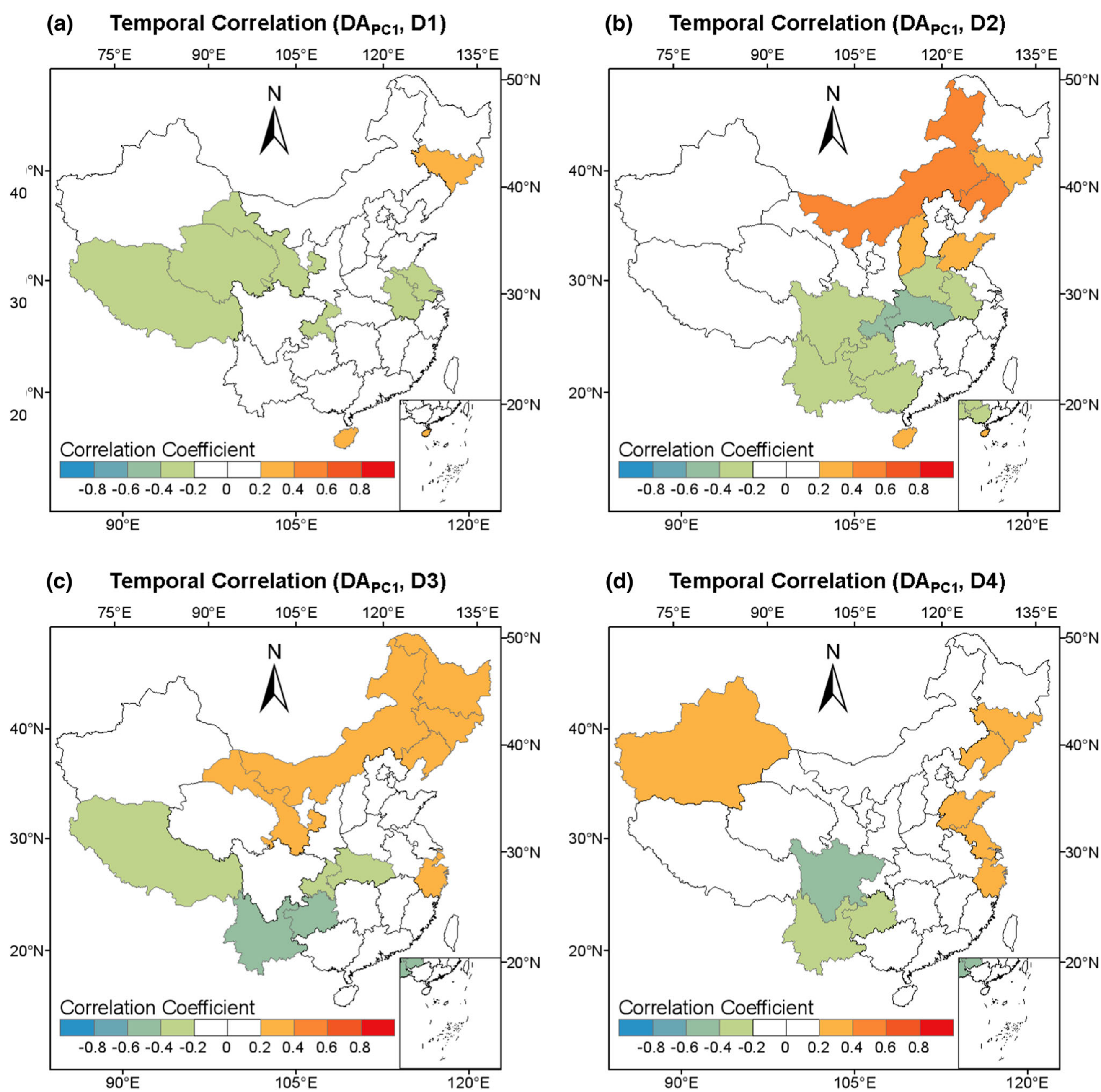

Fig. 7 Temporal correlations of DA_{PC1} and different drought severity for **a** DA_{PC1} and D1, **b** DA_{PC1} and D2, **c** DA_{PC1} and D3, **d** DA_{PC1} and D4 for the period 2011–2018

3.99); and extreme drought (D4, the value of sc-PDSI is below − 4). The monthly time series of a certain grade in an administrative district is derived from the number of grid cells with the grade in this district per month from 2011 to 2018. With this, the monthly time series of different drought severity of 31 administrative districts can be obtained to calculate their correlations with DA_{PC1}.

The results in Fig. 7a and b show that people's perception appears even if weak and moderate droughts occur in Jilin, Liaoning, Inner Mongolia, Shanxi, Shandong, and Hainan. This is mainly because of the frequent occurrences of droughts in these regions and the weak environmental anti-drought capacity. Therefore, once there are signs of droughts in these areas, the development of drought events will come into focus due to people's concerns about agricultural production and ecological changes there. However, in some inland areas (e.g., Gansu and Xinjiang) as well as coastal areas (e.g., Jiangsu and Zhejiang), drought draws people's attention only when it develops to a severe or even extreme drought, as shown in Fig. 7c and d. On one hand,

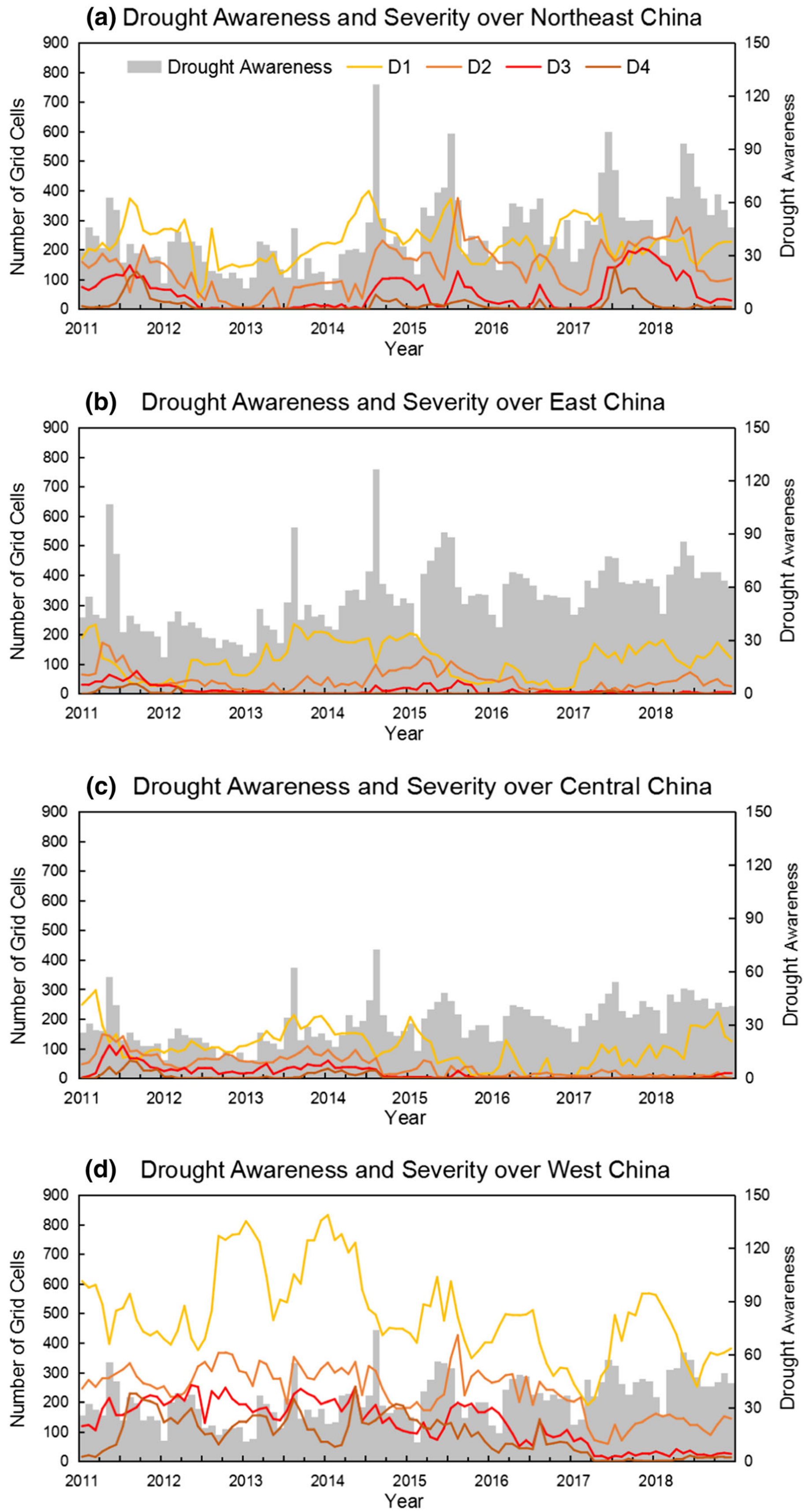

Fig. 8 Monthly time series of the regional drought awareness and different drought severity in four major regions in China for the period 2011–2018

the inland regions are in arid and semi-arid areas, and water shortage usually prevails. On the other hand, due to the small population, underdeveloped industry, and less agriculture in these regions, the drought damage is not overwhelming, leading to a loss of people's sensitivity to weak or even moderate drought. For the coastal areas with humid climate and abundant water storage, weak and moderate droughts are not enough to trigger the contradiction between supply and demand of water resources. Drought awareness will only break out only when drought reaches an extreme state that seriously affects people's daily life and causes irreparable disaster damage.

To further summarize the characteristics of drought awareness in the four major regions of China (i.e., northeast, east, central, and west), the regional drought awareness and the monthly time series of different drought severity (i.e., represented by the grid cells involved for D1, D2, D3, and D4 in the analyzed region) of the four major regions are calculated and analyzed. Figure 8 shows that several common peaks of drought awareness appeared in May 2011, August 2014, June and July 2015, June 2017, and May 2018, which are consistent with the peaks of meteorological drought in Northeast and West China. Although only a few and slight drought events occurred in eastern and central regions, their drought awareness is high and close to the development processes of droughts in Northeast China, indicating that people in these regions are acutely aware of droughts. Thus, their responses are not just limited to local drought events. The coverage and severity of droughts in West China are obviously the largest and heaviest in the country, but the tendency of drought awareness is not obviously consistent with the actual drought, especially for the grade of weak drought, illustrating that frequent drought events do not make people in this region to improve their awareness to droughts. Both the coverage and severity of drought in West China have been decreasing since 2015, but the drought awareness has not declined, showing that people there are gradually shifting their attention to droughts in this region to others.

3.4 Impact of lead and lagged times on the relation between drought awareness and meteorological drought

Figure 9 shows that DA_{PC1} has the strongest correlation with DA_i when the lead/lag is 0 month (i.e. no lead/lag); that is, drought awareness has widely spread across the country in the same month in which the drought awareness in the local area appears. The correlations between DA_{PC1} and $MD_{i\text{-}PC1}$ are obviously positive at the lead months in Northeast China and are strongest at the lagged months (actually 1 month) in the eastern and central regions, as shown in Fig. 10. However, for West China, the distribution of maximum correlation is irregular (Fig. 10c). Compared with meteorological drought, drought awareness in most administrative districts has no obvious lead or lagged times.

To specifically explore the regional characteristics, Year 2014 is considered as an example for analysis. As can be seen from Fig. 11, drought in Northeast China attracts high attention at three months lead. Even before the peak of the meteorological drought, the shortage of water resources had already had an impact on local agriculture, industry, and domestic water consumption, thus causing a series of social concerns. In central China (e.g., Henan, Anhui, Hubei, and other provinces), drought awareness peaks within 1–2 months after the occurrence of drought. The drought effects in such area, which drive the development of drought awareness, lags behind the meteorological drought, so there is a certain delay in drought awareness. In the western region, and especially for the southwest region, the correlations increased significantly at three months lag. There is generally a longer delay in drought awareness to meteorological drought, which is partly related to the long rainy season and humid climate in the southwest part of

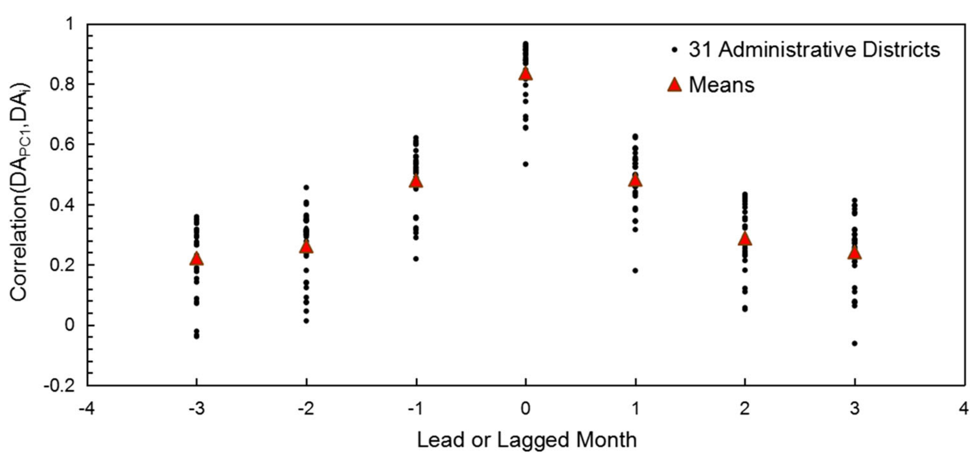

Fig. 9 Lead and lagged correlations between DA_{PC1} and DA_i

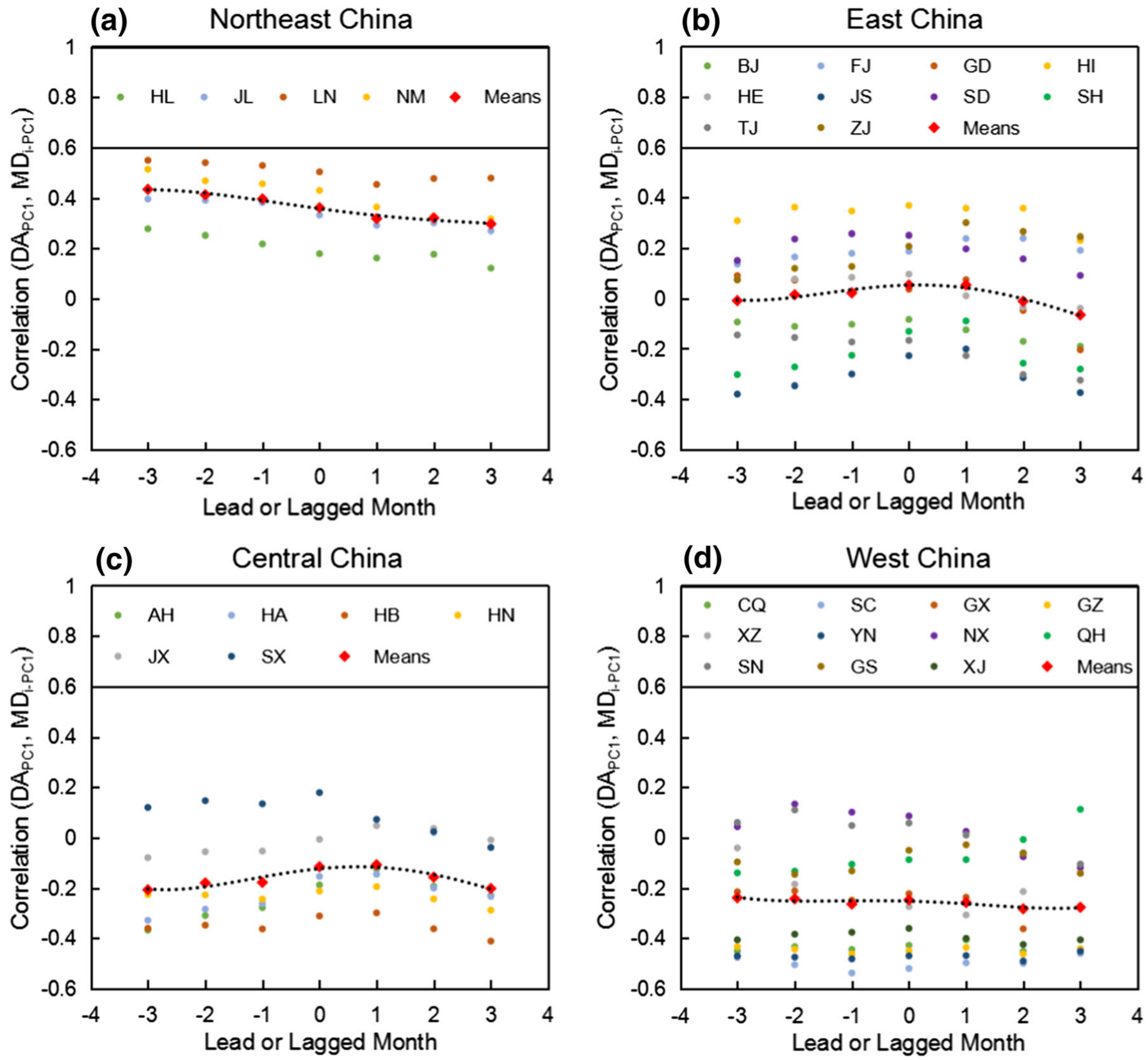

Fig. 10 Lead and lagged correlations between DA_{PC1} and $MD_{i\text{-}PC1}$ in four major regions in China

China. For example, according to meteorological records, Jiang-Nan region and southern China suffered from a severe drought in the autumn of 2014. However, people's drought awareness did not increase along with it; instead, it was mainly negatively correlated. This may be due to the fact that drought awareness was low for a long time after the more severe summer floods of the same year and people lost their sensitivity to the forthcoming drought. This seems to indicate that people who experience a major disaster (e.g., flood) are likely to overlook other natural disasters (e.g. drought) that may follow (Wheaton et al., 2016).

3.5 Regional correlation analysis between drought awareness and meteorological drought

To study the linkages between drought awareness and meteorological drought among the administrative districts, the correlations of DA_i and $MD_{i\text{-}PC1}$ among the 31 administrative districts are calculated. The right triangle in Fig. 12 shows that within the same region (except in West China), the correlations of $MD_{i\text{-}PC1}$ among the districts are significantly positive. This seems to indicate that the scope of drought in China is usually the whole region (spanning several administrative districts). However, due to the obvious differences in climatic conditions between the northwest and southwest parts of China, there is no correlation or negative correlation for many districts in the western region. The left triangle in Fig. 12 shows that DA_i in most of the central and eastern districts (except for Hainan and Tianjin) is positively correlated with that in the other regions. This indicates that the high drought awareness in these regions may play a leading role in the whole country. Since the eastern and central regions occupy an important position in economic and technological development, and rapid development of media information and

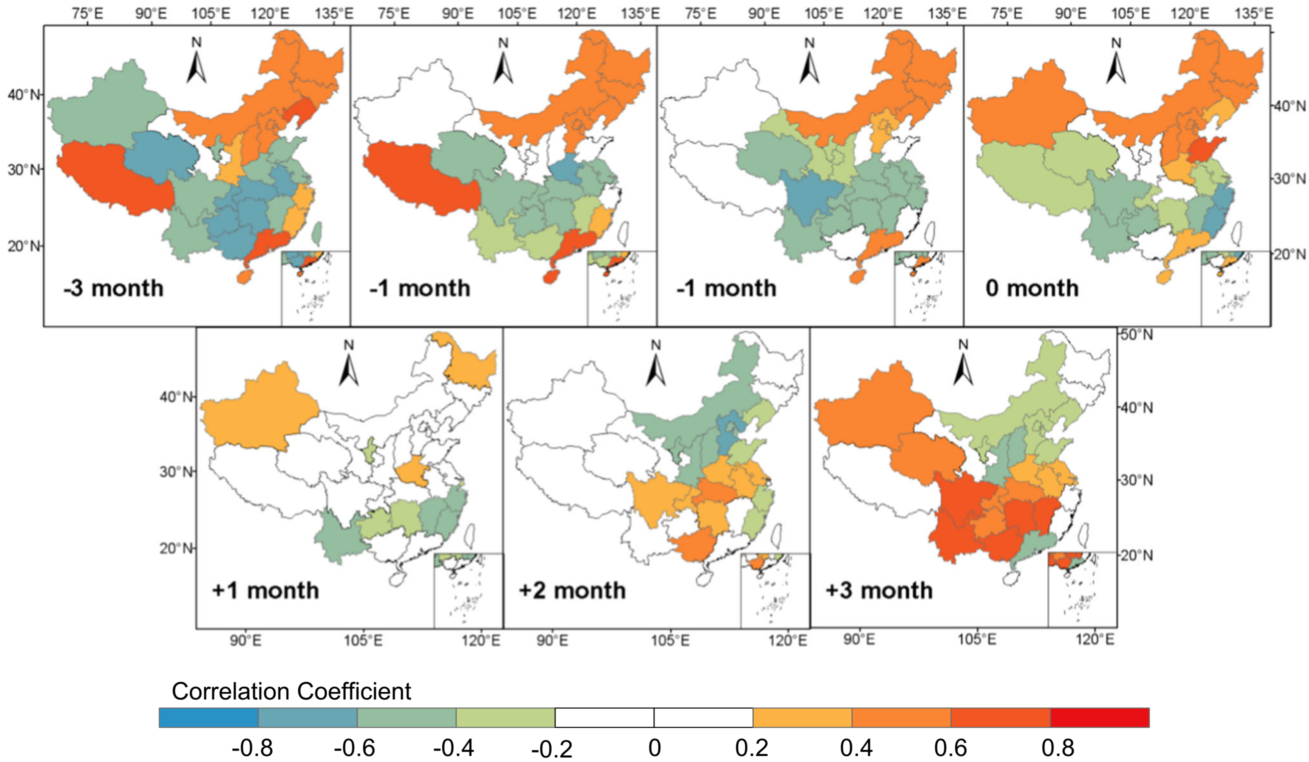

Fig. 11 Lead and lagged correlations between DA_{PC1} and $MD_{i\text{-}PC1}$ in 2014

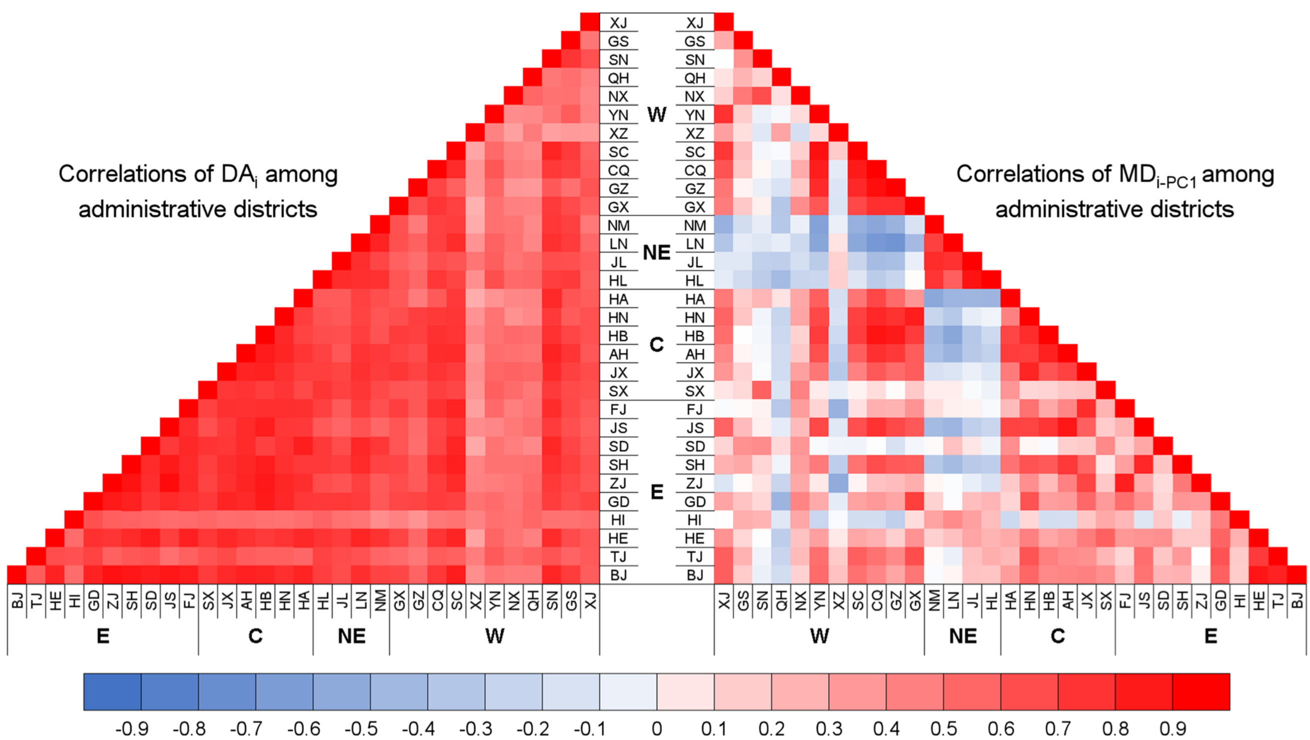

Fig. 12 Temporal correlation color block map of regional DA_i and $MD_{i\text{-}PC1}$ for the period 2011–2018 (the abbreviations in the figure represent the following regions: E-East China, C-Central China, NE-Northeast China, and W-West China)

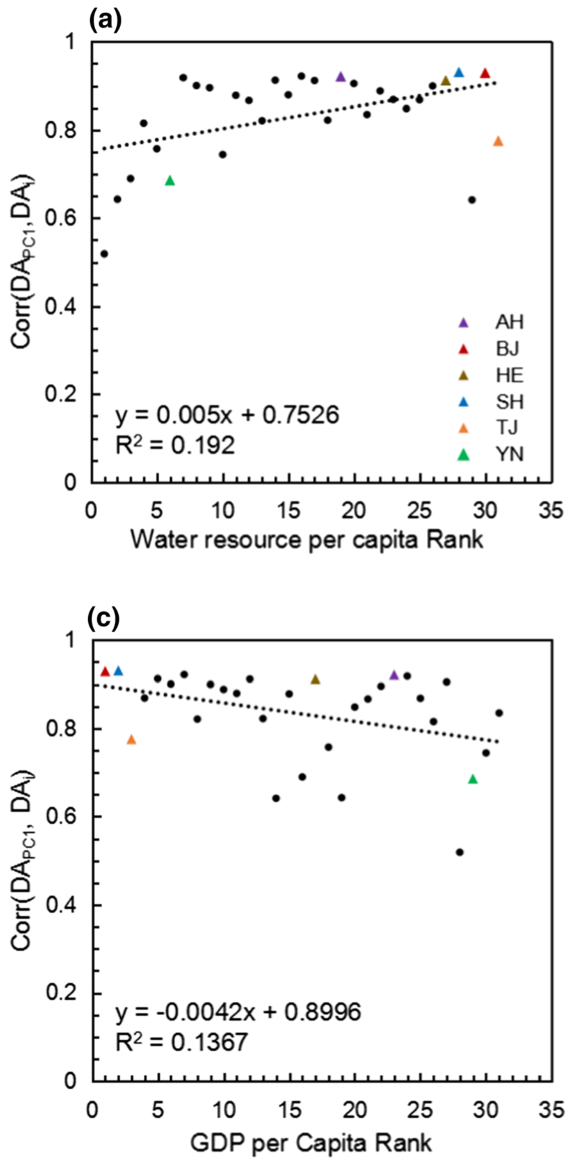

Fig. 13 Linear regression analysis diagram of the temporal correlations between DA_{PC1} and DA_i under the influence of social factors. The colored triangles represent districts of AH, BJ, HE, SH, TJ, YN, and the black dots represent the other districts. The X-axis corresponds to the ranking of water resource per capita **a**, population **b**, GDP per capita **c**, and education level **d** in each administrative district. The smaller the X-axis value is, the higher the ranking of the region is. The Y-axis corresponds to the correlation between DA_{PC1} and DA_i in each administrative district

network, it may be construed that the eastern and central regions are the spread bridge of drought awareness in China.

3.6 Influencing factors of drought awareness

The correlations between DA_{PC1} and DA_i may be related to socio-economic structure and natural factors. They are examined here by plotting them collectively in Fig. 13. In these plots, the X-axis is the factor ranking in each district from the highest to the lowest, and the Y-axis corresponds to the correlations between DA_{PC1} and DA_i in the 31 administrative districts. The higher the ranking, the more water resource per capita, the larger the population, the higher the level of economy and education (see Table 2 in the Appendix A for the detailed ranking).

A simple linear regression analysis is used to evaluate the influence of water resource per capita, population, economy, and education factors on the correlations between DA_{PC1} and DA_i. As shown in Fig. 13, water resource per capita explains 19.2% of the total variance, and GDP per capita also has little effect on the correlations, explaining 13.7% of the variance. Population and education level are important social factors that influence the

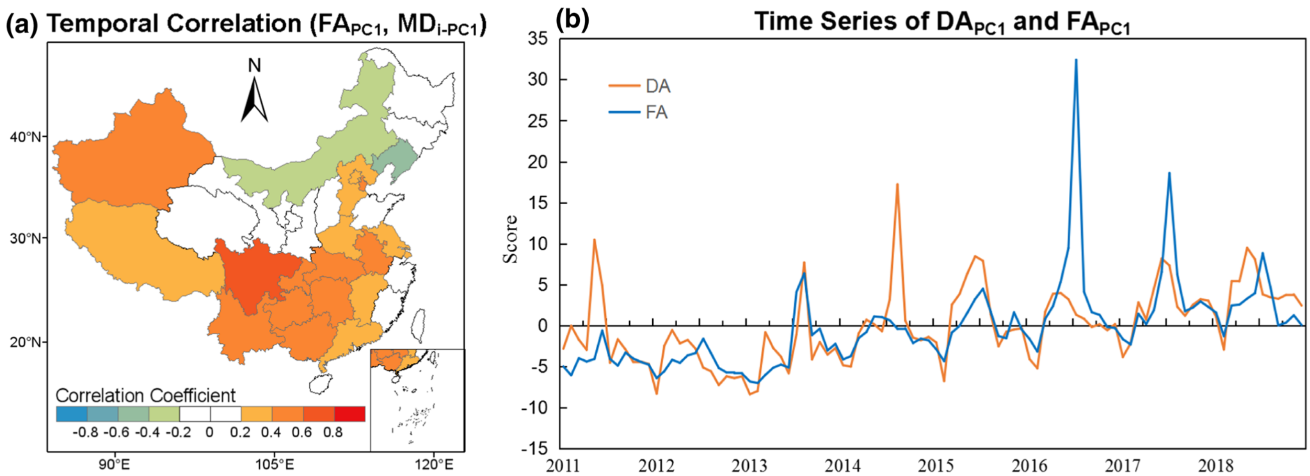

Fig. 14 **a** Temporal correlations of FA_{PC1} (first principal component of national flood awareness) and $MD_{i\text{-}PC1}$ in each administrative district, and **b** the first principal component scores of flood and drought awareness for the period 2011–2018

correlations between DA_{PC1} and DA_i, with the total variance of 38.5% and 36.8%, respectively. This observation can be used to explain why the eastern and central regions are able to become a bridge for the transmission of drought awareness, which benefits from the high population density and population mobility, while the improvement of education and economic level is favorable to the generation and development of drought awareness.

In addition, flood awareness (FA) is introduced here to analyze the effects of natural factors. In Fig. 14a, there are significant positive correlations between FA_{PC1} (the first principal component score of the national flood awareness during 2011–2018; its calculation procedure is the same as that of DA_{PC1}) and $MD_{i\text{-}PC1}$ of each administrative district in the western and central regions. However, as can be seen from Fig. 6a, there is no positive correlation in these regions, indicating that frequent floods or the high-speed transition between drought and flood will make people pay more attention to the occurrence of flood disasters. Figure 14b explains the variation of 70.3% of drought awareness and 87.3% of flood awareness in China, respectively. It can be observed that the peaks of drought and flood awareness are often synchronous, and the development of drought awareness is suppressed when both peaks appear simultaneously. Therefore, the occurrence of other natural disasters will also affect the development of drought awareness. For example, the natural disasters that reduce drought risk will hinder the development of drought awareness, while disasters that increase drought risk, such as wildfires and greenhouse effect, may promote the growth of drought awareness.

4 Discussion

4.1 Explanation for the difference in spatiotemporal patterns of drought awareness

Northeast China is the main producing area of grain and industry of China, but there is a serious imbalance between supply and demand of water resources. Drought can easily affect agricultural production and industrial development, causing losses to national grain reserves, steel manufacturing, and other sectors. Thus, individuals are extremely sensitive to the droughts in Northeast China, and their drought awareness often reaches its peak even before the outbreak of drought events. However, Northeast China still suffers from enormous damages during the development of drought, suggesting that other factors may affect the drought evolution. For example, the drought measures are single and water conservancy facilities are weak, resulting in poor performance of drought mitigation. In the western region of China, the negative effects of drought events are not that significant, which is difficult to stimulate the generation of drought awareness. People in the eastern and central regions attach great importance to education, and GDP per capita is also high in these regions. According to Maslow's hierarchy of needs (Maslow, 1943), people in these regions have more resources to pursue more socially meaningful needs, such as environmental requirements. As a result, they will not only pay attention to drought events in their own region, but also search for drought information in other regions, and perhaps even know about the drought events abroad. The same result can be found in the northeastern and western United States because of large population, high GDP per capita and high percentage of the population with bachelor degree (Kim et al., 2019).

4.2 Analysis of outliers in socio-economic influence

In Fig. 13b, there is an ultra-low outlier, namely Yunnan Province (YN); its expected correlation with the generated linear equation is 0.86 but the true correlation is 0.69. However, the correlation value of YN fits well in the Fig. 13c and d. According to the data in Table 2 (of Appendix A), the GDP per capita and education level of Yunnan ranks 29th and 27th, respectively. Therefore, though it has a large population and has advantages in the spreading of drought awareness, the economic and educational level of Yunnan hinders the generation and development of drought awareness. On the contrary, Beijing (BJ) and Shanghai (SH), as high outliers in Fig. 13b, rank low in population but fit nicely in Fig. 13a, c, and d. Obviously, the water shortage and high level of social development spawned the drought awareness.

There are also several obvious outliers in Fig. 13c–d, such as Anhui (AH), which is ranked 21st in education and 23rd in GDP per capita (shown in Table A1), but the correlation coefficient reaches 0.92, much higher than the expected value (0.80) in Fig. 13d. The high correlation may be related to the frequent occurrence of droughts there, as the frequency of drought has significant effects on drought awareness (Switzer and Vedlitz, 2017). It will promote local people with more experience in drought relief and to sense the drought evolution in time. The same is true of Hebei (HE). Tianjin (TJ) ranks second in education level and third in GDP per capita, its relative search index ranks third in Fig. 2b. However, the correlation coefficient of Tianjin is only 0.78, lower than the expectation (0.93) in Fig. 13d. Based on the information that Tianjin ranks last in water resource per capita, it may be inferred that the drought awareness of Tianjin residents has been maintained at a high level for a long term and does not fluctuate with specific drought events. Regardless of when and where drought occurs, the Tianjin residents have a strong awareness of water conservation and drought relief. This analysis is similar to the conclusion proposed by Li et al. (2013) that Tianjin citizens have a strong sense of water resource shortage and have water-saving habits. Such awareness is driven by the serious imbalance between the supply and demand of water resources in Tianjin and ensured by high education and economic level.

4.3 Limitations

Although this study successfully uses social monitoring data to explore the national drought awareness in China, it still possesses some limitations. One such limitation is the possibility of accidental errors due to the short time period considered for study (2011–2018) and the fact that the search data is easy to be disturbed or misled by public opinion and noise words. Additionally, people's drought awareness is multifaceted, but the current research is limited to search behavior, which is not comprehensive enough. Meanwhile, there is a lack of drought awareness research on other social subjects (such as government agencies, news media, etc.). In the future, comprehensive qualitative and quantitative research can further help determine the mechanism of drought awareness generation, diffusion, and transfer, as well as the form of interaction with actual drought, so that one can make full use of people's drought awareness for proposing and undertaking drought relief plans.

5 Conclusions

This study used the Baidu index search data to quantify drought awareness in China. The spatiotemporal patterns of drought awareness were investigated, including the distribution characteristics of the correlations between the drought awareness and meteorological drought in space or time, the effect of drought severity, and socioeconomic factors on drought awareness. The major findings from this study are as follows.

Drought awareness in China is sensitive to summer droughts, and people generally pay less attention to drought in winter.

People in the eastern or central regions (e.g., Fujian, Hebei, Zhejiang, and Hubei) pay attention to the droughts not only in their own regions, but also in others (especially in Northeast China). Therefore, one can start from the eastern and central regions to publicize the drought relief plans and take the northeast as a pilot to implement anti-drought or drought mitigation measures, which can quickly make the whole country be aware of and understand the drought relief work.

The severity of drought does not directly affect the drought awareness, and only when it causes damage can it trigger the enhancement of drought awareness. Therefore, there is a time difference between meteorological drought and drought awareness. As a result, droughts in the regions with underdeveloped economy, industry, and agriculture (such as Yunnan, Guizhou, Guangxi, Qinghai, Xinjiang Uygur, etc.) have a relatively small impact, making it difficult to facilitate drought awareness. It is only when drought is extremely severe that it attracts the attention of the whole country. The drought awareness is displayed and overall it is lagging behind the actual drought event. In regions with developed agriculture, industry, and high social development (such as Inner Mongolia, Liaoning, Guangdong, etc.), weak drought events will also attract attention, or the embodiment of drought awareness is ahead of meteorological drought. In this study, four social factors that may affect drought awareness were examined and their effects were quantified. The results show that the influence of these four factors, ranking from large to small, are population, education level, water resource per capita, and GDP per capita. Furthermore, the occurrence of floods and other natural factors will indirectly affect the forming of drought awareness. These factors collectively affect drought awareness directly or indirectly and eventually make people in areas with a large population or developed society or water shortage (such as Beijing, Tianjin, Shanghai, Guangdong) to have relatively active and long-term drought awareness.

Appendix A

See Fig. 15 and Table 2.

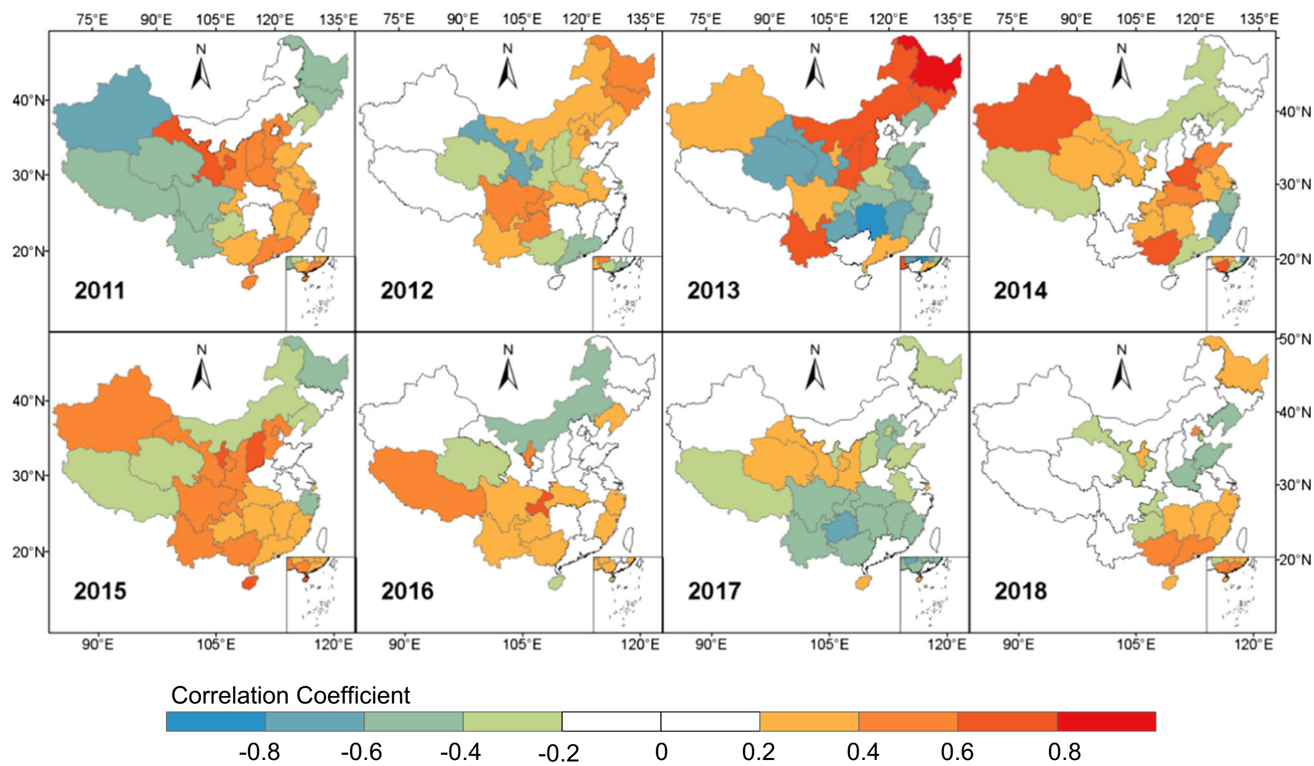

Fig. 15. Temporal correlations between the second principal component of national drought awareness (DA_{PC2}) and the first principal component of meteorological drought in each administrative district ($MD_{i\text{-}PC1}$) for each year during 2011–2018

Table 2 Ranking of five major influential factors in each administrative district

Region	Water resource per capita	Population	GDP per capita	Education level	Correlation between DA_{PC1} & DA_i
Anhui	19	8	23	21	4
Beijing	30	26	1	1	2
Chongqing	15	20	11	7	14
Fujian	8	15	6	14	10
Gansu	21	22	31	23	20
Guangdong	16	1	7	16	3
Guangxi	4	11	26	25	23
Guizhou	10	19	30	28	26
Hainan	3	28	16	18	27
Hebei	27	6	17	24	7
Heilongjiang	12	16	21	11	18
Henan	24	3	20	17	19
Hubei	17	9	12	5	8
Hunan	11	7	15	19	15
Inner Mongolia	13	23	8	26	22
Jiangsu	23	5	4	8	16
Jiangxi	7	13	24	10	5
Jilin	18	21	13	6	21
Liaoning	22	14	10	9	13
Ningxia	29	29	14	22	30
Qinghai	2	30	19	31	29
Shaanxi	20	17	27	3	9
Shandong	26	2	9	12	11
Shanghai	28	24	2	4	1
Shanxi	25	18	25	13	17
Sichuan	9	4	22	20	12
Tianjin	31	27	3	2	24
Tibet	1	31	28	30	31
Xinjiang	5	25	18	29	25
Yunnan	6	12	29	27	28
Zhejiang	14	10	5	15	6

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Authors' contributions Conceptualization: JN; Methodology: ZW; Formal analysis and investigation: ZW, WZ; Writing—original draft preparation: ZW; Writing—review and editing: JN, BS, JC; Funding acquisition: JN, TD; Resources: ZW, JN; Supervision: JN.

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