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Spatio-Temporal Analysis of Drought Indicated by SPEI over Northeastern China

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Abstract: Drought is a natural extreme climate event which occurs in most parts of the world. Northeastern China is one of the major agricultural production areas in China and also a typical vulnerable climate zone. To understand the spatio-temporal characteristics of drought over northeastern China, we first assessed the trends of precipitation and temperature. Drought events were then characterized by Standardized Precipitation Evapotranspiration Index over various temporal scales. The Trend Free Prewhitening Mann-Kendall test and distinct empirical orthogonal function, were used to investigate the trends and spatio-temporal patterns of droughts. The results indicate precipitation increasing trends are mostly detected in Heilongjiang and Jinling provinces, however, the majority of the trends are insignificant. Temperature increasing trends are detected over the entire northeastern China and most of them are significant. Decreasing drought trends are observed in Heilongjiang province and some bordering area in Jilin province, whereas increasing trends are noticed in Liaoning province and some bordering area in Jilin province. Two main sub-regions of drought variability-the Liaohe River Plain and the Second Songhua River basin (LS region), and the Songnen Plain and the Lesser Hinggan Mountains (SL region) are identified, and the detected droughts for the two sub-regions correspond well with recorded drought loss. The results will be beneficial for regional water resource management and planning, agriculture production, and ecosystem protection in northeastern China.

Keywords: climate change; DEOF; TFPW-MK; spatial patterns; SPEI; temporal variation; trends

1. Introduction

In response to the exacerbating climate change, particularly the successive and rapid global warming [1], a wealth of regional studies suggest an increasing trend in the intensity and frequency of droughts in many parts of the world [2–6]. Specifically, drought is a naturally recurring extreme climate event over land characterized by below-normal precipitation over a period of months to a few decades [7]. It occurs with spatio-temporal variation in frequency, severity, duration, and can have devastating impacts on regional water resources, agriculture, industry, and other social-ecological systems, with profound economic and societal impacts in an increasingly globalized and uncertain world [8,9]. In contrast to the permanent aridity in arid areas, drought is a temporary dry period occurs in most parts of the world, even in wet and humid regions.

Due to the wide range of sectors affected by droughts, their varied spatio-temporal variations, the interdependence across climatic, hydrologic, geologic, geomorphic, ecological, and societal variables,

and the demand placed on water supply by different users, it is very difficult to adopt a definition that fully describes the drought phenomena and the respective impacts [10–12]. Generally, based on the degree of water deficit, droughts are often classified into four types in practice: meteorological (lack of precipitation for a period of time), agricultural (lack of soil moisture for plant growth for a period of time without the effect of surface water), hydrological (lack of surface water for specific

water consumption from a water resource management system), and socioeconomic (system failure in supplying water demand for a good water economy) [13–15]. Among all types of droughts, meteorological drought normally triggers the other three drought types. A nice summary of drought classification and definition can be found in Reference [16].

Our particular interest is the spatio-temporal analysis of drought over northeastern China, a region known as China's granary, which is situated on one of the world's few fertile black earth belts and has the highest endowment of cropland per capita in China. Being a typical vulnerable climate zone in middle- and high-latitude, droughts in northeastern China are affected by both global climate change and site characteristics. The climate in northeastern China has recently become warmer and drier, evidenced by the increasing frequency and intensity of droughts since the 1990s, which has become a serious threat to food production and economic development in the region [17]. Yang et al. [18] analyzed the affected area and frequency of drought during 1950-2010 and found the increasing frequency and intensity of droughts in northeastern China. Shen et al. [19] used the Standardized Precipitation Evapotranspiration Index (SPEI) to analyze droughts in northeastern China. Ma et al. [20] analyzed the projections of the future drought under a moderate scenario for greenhouse gas emissions (SRES A1B) and concluded that the crop growing season in northeastern China will continue to be drier during 2011–2100. Liu et al. [21] investigated the spatial and temporal characteristics of precipitation in Jilin province and found that almost 90% of the stations showed decreasing trends in annual precipitation and evaporation. Yu et al. [22] analyzed drought risk in agricultural production season based on Standardized Precipitation Index (SPI) index, which showed that drought occurred more frequently and severely in 1996–2009 than in 1965–1983, especially in the western and northern regions where precipitation is scarce over northeastern China. Yang et al. [23] selected SPI and agricultural drought indicators to explore the causes of drought, which showed that spring drought was the most serious problem in northeastern China, while drought in winter chiefly occurred in Heilongjiang province and the northwest of Liaoning province. Yue et al. [24] analyzed the relationship between the reconnaissance drought index (RDI) and main large-scale atmospheric circulation patterns, which showed that droughts in northeastern China were less frequent, but had greater severity and duration, mainly in the western and southeastern part.

Although many previous studies have investigated the duration, tendency, and frequency of droughts over northeastern China, their work mostly focuses on the temporal characteristics of droughts; even for few studies on spatial patterns of droughts, the results are quite contradicted and different. In addition, considering that agriculture is vital in northeastern China, drought analysis during crop growing season should be highlighted, which has not been the usual case used in previous studies, where monthly and annual were often studied. The drought characteristics in northeastern China remains uncertain and doubtful, which poses considerable challenges to water security and sustainable development, especially under changing climatic conditions.

Our primary objective is to provide a comprehensive spatio-temporal analysis of droughts over northeastern China using the most up-to-date data. Drought events are characterized by SPEI over various temporal scales including 1, 3, 6, and 12 consecutive months, and 5-month together from May to September, especially for crop growing season. First, the Trend Free Prewhitening Mann–Kendall (TFPW-MK) test are used to investigate the trends in the SPEI series. Major patterns of long-term change of drought events are then characterized using the Distinct Empirical Orthogonal Function (DEOF). Finally, the detected droughts are compared with the recorded historical drought in identified sub-regions.

To achieve this objective, the paper is structured as follows: Section 2 introduces the study area and the data used. Section 3 describes the methodology for analyzing drought characteristics. In Section 4, the results and discussion are revealed. Section 5 provides the summary and conclusions of the study.

2. Study Area and Data

Northeastern China ($38^{\circ}41'$ N $-53^{\circ}33'$ N, $118^{\circ}50'$ E $-135^{\circ}4'$ E) encompasses the three provinces of Liaoning, Jilin, and Heilongjiang, with a total area of 790,000 km² and a population of about 110 million. The northeast is China's most important source of soybeans, corn, and japonica rice, accounting for 41% of the country's soybean production, 34% of its corn output, and 30-50% percent of its japonica rice crop. The landscape is mostly characterized by plains and mountains with elevations from 3 to 1017 m. The high latitude makes northeast the coolest region in China with long durations of severely cold winters. The annual precipitation decreases from southeast (900 mm) to northwest (400 mm) as the distance from the sea increases, and the annual temperature varies from -4.2 to 10.9 °C, decreasing from south to north. The precipitation is generally concentrated in the summer and autumn, and it coincides with the crop growing season, in which the main crops are sowed at the beginning of May and harvested at the end of September.

The monthly ground-based meteorological datasets were obtained from China Meteorological Administration (CMA; http://www.cma.gov.cn/), including precipitation, average temperature, maximum and minimum temperature, relative humidity, sunshine hours, and wind speed. To analyze the most up-to-date drought characteristics over northeast China, the selected period ranges from 1960 to the newest 2017 altogether 696 months, before 1960 most of the meteorological stations had changed their observational instruments. There are 91 meteorological stations in northeastern China, however, 8 of 91 meteorological stations have insufficient record length, and 83 meteorological stations were finally selected across this region, with 22 stations in Liaoning province, 31 in Jilin province, and 30 in Heilongjiang province. Northeastern China and meteorological station locations are shown in Figure 1. Meteorological data from the CMA has been carefully assessed to ensure consistency, continuity, and quality by taking into account instrument location and relocation of the station when necessary, to mitigate the effects of changes in vegetation and urbanization [25]. It should be noted that there are only two meteorological stations in the north-west part of Heilongjiang province, therefore, the results and analyses regarding this area can be doubtful as interpolated values bring huge uncertainties.



Figure 1. Locations of northeastern China as well as meteorological stations.

3. Methodology

3.1. Standardized Precipitation Evapotranspiration Index (SPEI)

Drought indices are quantitative measures of drought level by assimilating single or multiple atmosphere variables (e.g., precipitation and temperature) into a single numerical value, which prove to be more useful than the original variables [26]. Based on the analysis of the advantages and disadvantages of Palmer Drought Severity Index (PDSI) [27] and Standardized Precipitation Index (SPI) [28], Vicente-Serrano et al. [29] proposed a new drought index, Standardized Precipitation Evapotranspiration Index (SPEI). This index takes both precipitation and temperature into account, it combines the response of drought to evapotranspiration which PDSI pays attention to and the advantages of simple calculation and multi-time scale of SPI. SPEI has been successfully used and validated to analyze the spatial and temporal characteristics of drought in many parts of China [30–32].

The SPEI calculation in this paper adopted the SPEIcalc, an SPEI calculator from Consejo Superior de Investigaciones Científicas (CSIC; http://spei.csic.es/index.html) [29]. SPEI is very easy to calculate, which is based on the monthly difference between precipitation and potential evapotranspiration (*PET*), at different time scales of interest. The SPEI at different time scales can represent different climatic water balances. Vicente-Serrano et al. [29] applied the Thornthwaite procedure [33] to estimate the *PET*, which only requires monthly mean temperature and latitude of the site. With a value for *PET*, the difference between the precipitation *P* and *PET* for the month *i* can be calculated as follows:

$$D_i = P_i - PET_i \tag{1}$$

The calculated D_i values are aggregated at different time scales. The difference in a given month j and year i depends on the chosen timescale k. For example, the accumulated difference for one month in a particular year i with a 12-month timescale can be calculated as follows [29]:

$$X_{i,j}^{k} = \begin{cases} \sum_{l=13-k+j}^{12} D_{i-1,l} + \sum_{l=1}^{j} D_{i,l}, \ j < k \\ \sum_{l=j-k}^{j} D_{i,l}, \ j \ge k \end{cases}$$
(2)

where $D_{i,l}$ is the *P* – *PET* difference in the *l* month of year *i*.

Based on the behavior at the most extreme values, the log-logistic distribution adapts very well to standardize the *D* series to obtain the SPEI [29]. The probability density function of a three-parameter log-logistic distributed variable is expressed as:

$$f(x) = \frac{\beta}{\alpha} \left(\frac{x-\gamma}{\alpha}\right)^{\beta-1} \left[1 + \left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right]^{-2}$$
(3)

where α , β , and γ are scale, shape, and origin parameters, respectively, for *D* values in the range ($\gamma > D < \infty$).

According to Ahmad et al. [34], the L-moment procedure is the most robust and easy approach to estimate the parameters of the Log-logistic distribution. When L-moments are calculated, the parameters of the Pearson III distribution can be obtained following Singh et al. [35]:

$$\beta = \frac{2w_1 - w_0}{6w_1 - w_0 - 6w_2} \tag{4}$$

$$\alpha = \frac{(w_0 - 2w_1)\beta}{\Gamma(1 + 1/\beta)\Gamma(1 - 1/\beta)}$$
(5)

$$\gamma = w_0 - \alpha \Gamma (1 + \frac{1}{\beta}) \Gamma (1 - \frac{1}{\beta})$$
(6)

where the *k*-th probability-weighted moment can be estimated as

$$w_k = \frac{1}{n} \sum_{i=1}^n x_i \left(1 - \frac{i - 0.35}{n}\right)^k, k = 0, 1, 2, \dots$$
(7)

where x_i is an ordered random sample $x_1 \le x_2 \le x_n$, and *n* is the sample size.

The probability distribution function of the *D* series, according to the log-logistic distribution, is given by

$$F(x) = \left[1 + \left(\frac{\alpha}{x - \gamma}\right)^{\beta}\right]^{-1}$$
(8)

The SPEI can be easily obtained as the standardized values of F(x) [36].

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}$$
(9)

where

$$W = \sqrt{-2\ln(P)}, \quad P \le 0.5$$
 (10)

and *P* is the probability of exceeding a determined *D* value, P = 1 - F(x). If P > 0.5, then *P* is replaced by 1 - P and the sign of the resultant SPEI is reversed. The constants are: $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$.

The SPEI of one month usually represents meteorological drought, while the timescale of 3–6 months is considered as agricultural drought index. Longer scales, such as 6 months and 12 months, are used to indicate hydrological drought and to monitor surface water resources [37,38]. In addition to the consecutive 1, 3, 6, and 12 consecutive months, and 5-month together from May to September is also selected to analyze the drought characteristic for crop growing season. The SPEI class is shown in Table 1.

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

Categories	SPEI Values
Extremely wet	[2.0, +∞)
Severely wet	[1.5, 2.0)
Moderately wet	[1.0, 1.5)
Slightly wet	[0.5, 1.0)
Near normal	(-0.5, 0.5)
Slightly dry	(-1.0, -0.5]
Moderately dry	(-1.5, -1.0]
Severely dry	(-2.0, -1.5]
Extremely dry	(−∞, −2.0]

3.2. Trend Free Prewhitening Mann-Kendall Nonparametric Test

The Mann–Kendall (MK) nonparametric test, proposed by Mann [39] and then modified by Kendall [40], is based on the correlation between the ranks of a time series and their chronological order. This method is often used to analyze the trend change of hydro-meteorological time series such as precipitation, runoff, temperature, drought index, etc. [41–44]. The test has the advantage of being rarely disturbed by outliers, it is easy to calculate, and it does not assume any special form for the probability distribution function of the data [45].

However, some hydrological time series may usually have serial correlation, which will increase the probability that the MK test detects a significant trend, leading to a disproportionate rejection

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paper. The specific steps are as follows:

Step 1. The slope b of a trend in time series X_t is estimated by the Theil-Sen approach (TSA) [50]. If the slope is almost equal to zero, then it is unnecessary to continue to conduct trend analysis. If it differs from zero, then it is assumed to be linear, and the time series are detrended by:

(TFPW-MK) [46], which detrends and prewhitens the time series before MK test, is adopted in this

$$X'_t = X_t - T_t = X_t - bt \tag{11}$$

Step 2. The lag-1 serial correlation coefficient r_1 of the detrended series X'_t is computed using Equation (11) and then the Auto Regression Model (1) is removed from the X'_t by Equation (12).

$$r_{k} = \frac{\frac{1}{n-k} \sum_{t=1}^{n-k} [X_{t} - E(X_{t})] [X_{t+k} - E(X_{t})]}{\frac{1}{n} \sum_{t=1}^{n} [X_{t} - E(X_{t})]^{2}}$$
(12)

$$Y'_t = X'_t - r_1 X'_{t-1} \tag{13}$$

This pre-whitening procedure after detrending the series is referred to as the TFPW procedure. The residual series after applying the TFPW procedure should be an independent series.

Step 3. The identified trend T_t and the residual Y'_t are blended by

$$Y_t = Y'_t + T_t \tag{14}$$

Step 4. The MK test is applied to the blended series to assess the significance of the trend.

We can get the statistic *Z* through the calculation of TFPW-MK test. The time series shows an increasing trend when *Z* is greater than 0, while the trend is decreasing when *Z* is less than 0, and the greater the absolute value of *Z*, the more obvious the trend of increase or decrease. Thus, in the bilateral trend test, if $|Z| \ge Z_{1-\alpha/2}$ at a given α confidence level, the original hypothesis is unacceptable. That is to say, at the $1 - \alpha$ confidence level, the time series has a distinct upward or downward trend. The *Z* values of ±1.96, and ±1.64 are equal to the confidence levels of 0.05, and 0.1, respectively. Based on these confidence levels, the detected trend could be classified into six zones according to *Z* value [42]: (1) *Z* < -1.96, indicating significant decreasing trend; (2) *Z* ∈ [-1.96 to -1.64), indicating weak decreasing trend; (3) *Z* ∈ [-1.654 to 0), indicating no significant decreasing trend; (4) *Z* ∈ (0 to 1.64], indicating no significant increasing trend; (5) *Z* ∈ (1.64 to 1.96], indicating weak increasing trend; and (6) *Z* > 1.96, indicating the significant increasing trend.

3.3. Distinct Empirical Orthogonal Function

The analysis presented in this paper adopt the Distinct Empirical Orthogonal Function (DEOF) [51], which has proved to obtain better results in studies of spatial variability patterns identification. The DEOF method is based on normal EOF method, and is then compared against a fitted isotropic diffusion process [52]. In DEOF, the EOF-modes are considered as a representation of a continuous spectrum of spatial patterns resulting from a stochastic process. In the spatial structure, some spatial structures will be more dominant than others. The most distinguished EOF-modes (DEOFs) from the isotropic diffusion null hypothesis can be found by rotating the leading EOF-modes. The time series of

the DEOFs are referred to as the distinguished principle components (DPCs). The details about the method can be found in http://users.monash.edu.au/~{}dietmard/deof-analysis.html.

4. Results and Discussion

4.1. Variation Characteristics of Precipitation and Temperature

To better understand the drought patterns over northeastern China, the variation characteristics of the two elements in SPEI, precipitation, temperature are analyzed first. TFPW-MK trend test was applied to the 83 annual precipitation and temperature series from 1960 to 2017 at each meteorological station, and then, the *Z* values were interpolated over northeast China, as shown in Figure 2. It can be seen that more than half of northeastern China has increasing trends in precipitation and the regions with increasing trends are mostly located in Heilongjiang and Jilin provinces. However, most increasing trends are insignificant. Most of the Liaoning province and regions around the north of Lesser Hinggan Mountains in Heilongjiang province present decreasing trends; however, the decreasing trends are insignificant, either.



Figure 2. Trends of precipitation and temperature over northeastern China. (The *Z* values of ± 1.64 , ± 1.96 and ± 2.58 are equal to the confidence levels of 0.1, 0.05 and 0.01, respectively.).

For temperature, it is more straightforward that the entire northeastern China shows increasing trends and the majority of them are significant. The strong increasing trends of temperature is consistent with [8], which reports each of the past three decades has been warmer than all preceding decades since 1850 and the period from 1983–2012 was "likely" the warmest 30-year period of the past 1400 years in the Northern Hemisphere.

The areal average precipitation and temperature anomaly curves relative to the average of entire study period at annual and crop growing seasonal scales are presented in Figures 3 and 4. Northeastern China experienced dry periods in two separate decades, at both annual and crop growing seasonal scales, during the 1970s and years after 2000. The annual scale deviations are -23.9 mm and -5.3 mm for the two periods, respectively. The dry period presence is much stronger for the crop growing season, where the seasonal deviations are -49.0 mm and -42.5 mm, respectively. These analyses indicate that the amplitude of variation for precipitation at crop growing season is larger, which means even a mild water shortage year could still have a severe water shortage during crop growing shortage, consistent with Yu et al. [22].



Figure 3. Areal average precipitation anomaly curves. (**a**) Annual. (**b**) Crop growing season. (The dotted lines represent the decadal averages).



Figure 4. Areal average temperature anomaly curves. (**a**) Annual. (**b**) Crop growing season. (The dotted lines represent the decadal averages).

It is apparent from Figure 4 that the warming trends are quite obvious at both annual and crop growing seasonal scales, with almost strictly monotone increasing at decade level. The climate (or temperature) in northeastern China can be divided into a warm and a cold period at 1990. For annual temperature, the increases for the 1990s and the years after 2000 are almost identical; while the increase in years after 2000 is stronger than in the 1990s for temperature during crop growing season.

4.2. Results and Uncertainty of SPEI

SPEI was calculated for 83 meteorological stations to analyze the regional conditions of drought at various time scales. The areal average SPEI series of northeastern China at different time scales are shown in Figure 5. At areal average, SPEI1 and SPEI3 have increasing trend and SPEI6_{May-Sep} has decreasing trend. While for SPEI6 and SPEI12, the changing trends are not very obvious.



Figure 5. Areal average SPEI series over different time scales.

Since all the analyses in this paper are based on the SPEI results, it is very necessary to study the uncertainty regarding SPEI calculation. The accuracy and reliability of SPEI calculation basically depend on the observed data, especially on the length of the sample. Similar to Hu et al. [53] about SPI sampling uncertainty, the uncertainty of SPEI caused by sampling uncertainty is calculated as follows: (1) Resampling technology is used to extract a certain number of samples from the original sample (the precipitation and temperature data), which allows repeated sampling. (2) Calculate the SPEI according to the extracted samples. (3) Repeat the above 1000 times, and thus get 1000 samples of SPEI. (4) Calculate the sample variance of the above 1000 samples of SPEI, and get the variance of the statistic [53]. The expected estimation of SPEI is the average value of the 1000 sets of SPEI_j, j = 1, 2, ..., 999, 1000, and the lower bound (LB = SPEI₅₁) and upper bound (UB = SPEI₉₅₀) of the 90% confidence interval (CI) estimation are calculated, accordingly.

Taking SPEI6_{May–Sep} as an example, Figure 6 shows the results of uncertainty of SPEI6_{May–Sep} due to sampling in three typical meteorological stations. It can be seen that the 90% CI is very narrow compared to the expected value, which means sampling uncertainty is small in our paper. Therefore, the SPEI results are directly used for further analyses.



Figure 6. Estimations of the SPEI6_{May-Sep} considering the sampling uncertainty.

4.3. Spatial Patterns of Temporal Trends in Drought

TFPW-MK trend test was then applied to the SPEI series at each meteorological station and the *Z* values were interpolated over northeastern China. Figure 7 depicts the spatial structure of long-term SPEI trends. Decreasing drought trends (i.e., increase of SPEI) are observed in Heilongjiang province and some bordering area in Jilin province, whereas increasing trends are noticed in Liaoning province and some bordering area in Jilin province. The situation of long-term drought trends is quite different at different timescales. As can be seen from Figure 7, the decreasing drought trends are observed in majority of northeastern China at 1- and 3-month timescales, while with the increasing of timescale, the increasing trends of drought have also been noticed in more and more regions of northeastern China. Specifically, the increasing trends of drought are dominant at 12-month timescale. Overall, the significant increase in drought severity mostly occurs in the coastal region of Liaodong Gulf, southeastern Liaodong Peninsula, and the downstream region of Hunhe River Basin, while the significant decrease is mostly observed in regions such as the northwest corner of Heilongjiang province, the southeast of Lesser Hinggan Mountains and the northeast of Changbai Mountains.



Figure 7. Spatial structure of long-term SPEI trends at various timescales. (The *Z* values of ± 1.64 , ± 1.96 and ± 2.58 are equal to the confidence levels of 0.1, 0.05 and 0.01, respectively.).

Although the changing trends are insignificant over northeastern China at crop growing seasonal scale, the vast majority of the area experiences insignificant or weak increasing trends, except the very

northwest corner of Heilongjiang province, the northeast of Changbai Mountains and the central part of Songnen Plain have observed insignificant decreasing drought trends. This is not surprising given the fact that the situation of precipitation and temperature are more adverse during the crop growing season. From the analyses above, we could conclude that the drought situation may be even worse during crop growing season as the vast majority of northeastern China has an increasing drought trend.

4.4. Spatial Variability of Drought Using DEOF

Table 2 displays percentages of variance explained by the first two DEOFs relative to the considered timescales. The first two DEOFs are able to explain about 54.1 to 58.6% of the total explained temporal variances of drought depending on the timescale, with the maximum and minimum variances observed for SPEI1 and SPEI12, respectively.

Categories	Explained Variance	
	DEOF1 (%)	DEOF2 (%)
SPEI1	45.2	13.4
SPEI3	44.6	13.6
SPEI6	43.3	13.7
SPEI12	40.2	13.9
SPEI6 _{May-Sep}	42.5	14.1

Table 2. Percentage of variance explained by the first two DEOFs of the SPEI at various timescales.

The patterns of the leading two DEOFs for SPEI time series were computed for 83 meteorological stations and interpolated over northeastern China, shown in Figure 8. The congruence coefficient proposed in Richman and Lamb [54] was used to check whether the patterns represented potential physical modes of SPEI variability, or were only an artifact of the DEOF analysis. The congruence coefficient ranges from 0.81 to 0.91 within the regions enclosed by the contour in Figure 8, which indicates the identified variability modes are acceptable as described in in Richman and Lamb [54]. For all SPEI series, the loading patterns of the first DEOF (DEOF1) with a maximum explained the temporal variance of 45.2% and 40.2% are relative to SPEI1 and SPEI12, respectively. The DEOF1 values are all positive and the spatial distribution of the DEOF1 indicates the high positive loading in the Liaohe River Plain and the Second Songhua River basin (LS region). This shows that the LS region has a similar temporal distribution of drought as that detected under various time series. This region is the main channel for tropical cyclone and other southern cyclone systems to penetrate northeastern China. These cyclones usually make landfall from the west of Liaoning province, bringing abundant water vapour and thus making this region wet. Droughts often occur in the years without cyclone. Besides, LS region has many similar hilly and mountainous terrains, which is another reason for the similar drought characteristics in this region. The unique natural weather and land surface conditions are the main reasons for the similarity of drought characteristics in this region.

The DEOF2s explain a maximum variance of around 14.1% in the case of SPEI6_{May-Sep} and 13.4% for SPEI1, respectively. The spatial distribution of DEOF2 indicates the high positive spatial behavior of drought in the Songnen Plain and the Lesser Hinggan Mountains (SL region). The SL region belongs to the cold temperate zone where the climate characteristics are significantly affected by the Lesser Hinggan Mountains, while Liaohe River Plain and area surrounding its east are near the ocean which mainly receive the influence of seawater vapor. In addition, this region is also affected by the air currents of the Sea of Japan and the Sea of Okhotsk. Although two DEOFs are unable to extract the full temporal variation of drought across the region, their loadings seem to divide the whole region into two sub-regions that is LS and SL regions, characterized by different drought variabilities.



Figure 8. Cont.



Figure 8. Patterns of the first two DEOFs for SPEI at various timescales.

The two drought sub-regions DEOF1 and DEOF2 coincide basically with the drought-prone Heilongjiang and northwest Liaoning described by Yu et al. [22] and Yang et al. [23], which also show the importance of dividing the drought sub-regions for research. Therefore, by studying the changes of drought in DEOF1 and DEOF2 over time, we can understand the main drought evolutions in northeastern China.

The DPC scores are also investigated to characterize the temporal variability of drought severity. Figure 9 presents DPC1 and DPC2 scores for the value of SPEI6_{May-Sep}, since crop growing season is our primary concern. Figure 9a reveals that the LS region (DPC1) experienced severe drought in years 1982 and 1999 to 2001, which is consistent with Yue et al. [24] describing that drought hot spots mainly occur in the western part of the study area in 2000–2004. These detected droughts correspond well with the China's Drought Statistics Yearbook, which recorded that northeastern China suffered from severe drought in 1982. Especially in the Liaohe River Plain and the Second Songhua River basin, most of the moisture was merely 5–10% for 50-cm deep surface soil. It also recorded that 3-year consecutive drought has occurred in Liaoning province during 1999–2001, with 90% rivers were witnessed cutoff. For the SL region (DPC2), the only year extreme drought was observed in 1995 with DPC score less than –2.5. In 1995, nine counties and cities in Heilongjiang province were recorded suffering from extreme drought, and more than half of the agricultural areas were in a drought state. The rest 1964, 2001, 2004, 2007, and 2010 years detected as severe dry were all recorded severe drought in the LS region.



Figure 9. DPC scores of the first two DEOFs for SPEI at crop growing seasonal scale.

5. Summary and Conclusions

This paper provides a comprehensive analysis of spatio-temporal patterns over northeastern China during the period 1960–2017. The widely used SPEI drought index is selected to evaluate drought characteristics at various timescales, especially the crop growing season from May to September. The results are based on long-term meteorological datasets and widely used methods, and are consistent with previous studies and observed drought statistics. Therefore, the results are credible to some degree and can be used to assist with drought mitigation. The main conclusions are summarized as follows.

- (1) The annual precipitation changing trends increase from south to north, with decreasing trends in nearly the entire Liaoning province, and increasing trends in Heilongjiang and Jilin provinces. However, the majority of the trends are insignificant. The warming trends are more obvious and straightforward, as increasing trends are detected over entire northeastern China.
- (2) TFPW-MK test detects the changing trends of SPEI at various timescales. Overall, significant increasing drought trends are observed in the coastal region of Liaodong Gulf, southeastern Liaodong Peninsula, and the downstream region of Hunhe River Basin, while significant decreasing trends are noticed in the northwest corner of Heilongjiang province, the southeast of Lesser Hinggan Mountains and the northeast of Changbai Mountains. Further, drought increasing trends are more dominant at crop growing seasonal scale, thus the drought situation may be even worse during crop growing season than the rest of the year.
- (3) DEOF is used to identify two main sub-regions of drought variability—the Liaohe River Plain and the Second Songhua River basin (LS region), and the Songnen Plain and the Lesser Hinggan Mountains (SL region). Based on the crop growing seasonal DPC scores, the LS region experienced severe droughts in the years 1982 and 1999 to 2001. In the SL region, severe to extreme droughts were observed in 1964, 1995, 2001, 2004, 2007, and 2010.

The detected drought trend in this paper is very important as it provides reference for the future study of drought prediction in northeastern China. Special attention should be paid to the obvious growth of temperature, which can produce positive interaction and feedback that intensify drought. The identification of these sub-regions with similar drought variability and characteristics can be useful for drought risk management at a regional scale in northeastern China. Especially for management departments, drought resistance strategy and irrigation schemes can be formulated purposefully according to drought sub-regions.

Like any natural phenomena, drought is very difficult to characterize. Although various drought indices have been proposed to monitor drought, this paper only adopted the widely used SPEI index

because the present analyses are already very complicated with the temporal trends and spatial variability of drought over various temporal scales. The SPEI index is merely an index belongs to meteorological drought, so the comparable studies of multi drought indices in the future would provide more comprehensive analysis of drought. It also should be noted that there is only two meteorological station in the north-west part of Heilongjiang province, therefore, the results and analyses regarding this area can be very doubtful as interpolated values will bring huge uncertainties. If gridded data can be obtained for drought analysis, the reliability of the results will be greatly improved. Another factor contributing to the uncertainty is that, although our results are consistent with the measured data, there is no quantitative relationship between the degree of loss and SPEI.

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