A discrete wavelet spectrum approach for identifying non-monotonic trend patterns of hydroclimate data

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Abstract: The hydroclimatic process is changing non-monotonically and identifying its trend pattern is a great challenge. Building on the discrete wavelet transform theory, we developed a discrete wavelet spectrum (DWS) approach for identifying non-monotonic trend patterns in hydroclimate time series and evaluating their statistical significance. After validating the DWS approach using two typical synthetic time series, we examined annual temperature and potential evaporation over China from 1961-2013, and found that the DWS approach detected both the "warming" and the "warming hiatus" in temperature, and the reversed changes in potential evaporation. Further, the identified non-monotonic trend patterns showed stable significance when the time series was longer than 30 years or so (i.e., the widely defined "climate" timescale). The significance of trends in potential evaporation measured at 150 stations in China, with an obvious non-monotonic pattern, was underestimated and was not detected by the Mann-Kendall test. Comparatively, the DWS approach overcame the problem and detected those significant non-monotonic trends at 380 stations, which helped understand and interpret the spatiotemporal variability of the hydroclimatic process. Our results suggest that non-monotonic trend patterns of hydroclimate time series and their significance should be carefully identified, and the DWS approach proposed has the potential for wide use in hydrological and climate sciences.

Key words: trend identification; discrete wavelet spectrum; decadal variability; statistical significance; Mann-Kendall test

1. Introduction

Climate and hydrological processes are exhibiting great variability (Allen and Ingram, 2002; Trenberth et al., 2014). Quantitatively identifying changing signals in the hydroclimate process is of great socioeconomic significance (Diffenbaugh et al., 2008; IPCC, 2013) as an important basis for hydrological modelling, understanding the future hydroclimatic regimes, and water resources planning and management. However, it remains a challenge to both scientific and social communities. The simplest and the most straightforward way to identify changes in the hydroclimate process would be to fit a monotonic (e.g., linear) trend at a certain time period at which a significance level would be assigned by a statistical test. Among the methods used for the detection of trends, the Mann-Kendall non-parametric test is most widely used and has been successfully applied in studies on climate change and its impact, when the time series is almost monotonic as required and a statistical threshold of ±1.96 is set to judge the significance of trends at 95% confidence level (Burn and Hag Elnur, 2002; Yue et al., 2002). However, due to its nonlinear and nonstationary nature, the hydroclimate process is changing and developing in a more complicated way rather than a monotonic trend way at large time scales (Cohn and McMahon, 2005; Milly et al., 2008). For example, a debate on the recent change of global air temperature has been receiving enormous public and scientific attention that the global air temperature increased during 1980-1998 passing most statistical significance tests and has since stabilized till now, widely called "global warming hiatus" (Kosaka and Xie, 2013; Roberts et al., 2015; Medhaug et al., 2017). Another known example is "evaporation paradox" (Brutsaert and Parlange, 1998; Roderick and Farquhar, 2002) that potential evaporation has worldwide declined from the 1960s, again passing most statistical significance tests, but then reversed after the 1990s. In practice, for the hydroclimate time series, non-monotonicity is more the rule rather than the exception (Dixon et al., 2006; Adam and Lettenmaier, 2008; Gong et al., 2010). Therefore, identifying the non-monotonic trend pattern hidden in those hydroclimate time series and assessing its statistical significance present a significant research task for understanding hydroclimatic variability and changes at large time scales.

Among those methods presently used in time series analysis, the wavelet method, including both continuous and discrete wavelet transforms, has the superior capability of handling nonstationary characteristics of the time series at multi-time scales (Percival and Walden, 2000; Labat, 2005), so it may be more suitable for identifying non-monotonic trend patterns in hydroclimate time series at large time scales. In a seminal work, Torrence and Compo (1998) placed the continuous wavelet transform in the framework of statistical analysis by formulating a significance test. Since then, the continuous wavelet method has become more applicable and rapidly developed to estimate the significance of variability in climate and hydrological studies. Especially, the continuous wavelet spectrum (i.e., continuous wavelet variance) was established to detect those significant variabilities in the hydroclimate process (Labat et al., 2000). However, in the continuous wavelet results of a time series, a known technical issue is the “data redundancy” (Gaucherel, 2002; Nourani et al., 2014), which is the redundant information across timescales leading to more uncertainty.

On the contrary, the other type of wavelet transform, i.e., the discrete wavelet transform, has the potential to overcome that problem of data redundancy, in that those wavelets used for discrete wavelet transform must meet the orthogonal properties. Therefore, the discrete wavelet method can be more effective to identify and describe the non-monotonic trend pattern in a time series (Almasri et al., 2008; de Artigas et al., 2006; Kallache et al., 2005; Partal and Kucuk, 2006; Nalley et al., 2012). However, there lacked an effective discrete wavelet spectrum in the wavelet methodology without which uncertainty in the discrete wavelet-aided identification of a trend could not be accurately estimated, and the significance level of the identified trend could not be quantitatively evaluated either. For overcoming the problem, Sang et al. (2013) discussed the definition of trend, and proposed a discrete wavelet energy function-based method for the identification of trends, with the basic idea of comparing the difference of discrete wavelet results between hydrological data and noise. The method used a proper confidence interval to assess the statistical significance of the identified trend, in which the key equation for quantifying trend's significance was based on the concept of quadratic sum. However, computation of the quadratic sum disobeys the customary practice of computing variance in spectral analysis. By using the quadratic sum, the significance of a non-monotonic trend cannot be reasonably assessed, because it neglects the big influence of trend's mean value. For instance, for those trends with small variations but big mean values, the quadratic sums are big values, based on which the statistical significance of trends would inevitably be over-assessed. Therefore, evaluation of the statistical significance of a non-monotonic trend in a time series should be based on its own variability, and the influence of other factors should also be eliminated.

By combining the advantages of discrete wavelet transform and successful practice in spectral analysis methods, this study aimed at developing a practical but reliable discrete wavelet spectrum approach for identifying non-monotonic trend patterns in hydroclimate time series and quantifying their statistical significance, and further improving the understanding of non-monotonic trends by investigating their variation with data length increase. To do that, Section 2 presents details of the newly developed approach building on the wavelet theory and spectrum analysis. In Section 3, we use both synthetic time series and annual time series of air temperature and potential evaporation over China as examples to investigate the applicability of the approach, which is followed by discussion and conclusion in the final section.

2. A discrete wavelet spectrum approach

Here we develop an approach, termed as "discrete wavelet spectrum approach," for identifying non-monotonic trend patterns in hydroclimate time series, in which the discrete wavelet transform (DWT) is used first to separate the trend pattern at large time scales, and its statistical significance is then evaluated by using the discrete wavelet spectrum, whose confidence interval is quantified and described through Monte-Carlo test.

Following the wavelet analysis theory (Percival and Walden, 2000), the discrete wavelet transform of a time series $f(t)$ with a time order t can be expressed as:

$$W_f(j,k) = \int_{-\infty}^{+\infty} f(t)\psi_{j,k}^*(t)dt \quad with \quad \psi_{j,k}(t) = a_0^{-j/2}\psi(a_0^{-j}t - b_0 k) \tag{1}$$

where $\psi^*(t)$ is the complex conjugate of the mother wavelet $\psi(t)$; a_0 and b_0 are constants, and integer k is a time translation factor; and $W_f(j,k)$ is the discrete wavelet coefficient under the decomposition level j (i.e., time scale a_0^j). In practice, the dyadic DWT is used widely by assigning a_0=2 and b_0=1:

$$W_f(j,k) = \int_{-\infty}^{+\infty} f(t)\psi_{j,k}^*(t)dt \quad with \quad \psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k) \tag{2}$$

The highest decomposition level M is determined by the length L of series $f(t)$, and can be calculated as $log_2(L)$ (Foufoula-Georgiou and Kumar, 2014). The sub-signal $f_j(t)$ in the original series $f(t)$ under each level j (j = 1, 2, …, M) can be reconstructed as:

$$f_j(t) = \sum_k W_f(j,k)\psi^*(2^{-j}t - k) \tag{3}$$

where the sub-signal $f_j(t)$ at the highest decomposition level (when j=M) defines and describes the non-monotonic trend pattern of the series $f(t)$, as generally understood. However, it should be noted that a meaningful trend closely depends on the time scale concerned. If the variability of series $f(t)$ on a certain smaller time scale K (K<L) is concerned, the proper decomposition level can be determined as $log_2(K)$, then the sum of all those sub-signals at the time scale equal to and bigger than K can be the non-monotonic trend pattern identified.

Sang (2012) discussed the influence of the choice of the mother wavelet and decomposition level, as well as noise types on the discrete wavelet decomposition of time series, and further proposed some methods to solve for them. By conducting Monte-Carlo experiments, he found that the seven wavelet families (126 mother wavelets) used for DWT can be divided into three types, and recommended the first type, by which wavelet energy functions of diverse types of noise data keep stable and thus have little influence on the wavelet decomposition of time series. Specifically, one chooses an appropriate wavelet, according to the relationship of statistical characteristics among the original series, de-noised series and removed noise, chooses a proper decomposition level by analyzing the difference between energy function of the analyzed series and that of noise, and then identifies the deterministic components (including trend) by conducting significance testing of DWT. These methods are closely built on the composition and variability of hydroclimate time series at different time scales. They were used here to accurately identify and describe the non-monotonic trend pattern in a time series, and assess its statistical significance.

Further, to establish a reliable discrete wavelet spectrum (DWS) of time series, we need to specify a spectrum value $E(j)$ for each sub-signal $f_j(t)$ (in Eq. 3), based on which we can quantitatively evaluate its importance and statistical significance. Following the general practice in conventional spectral analysis methods (Fourier transform, maximum entropy spectral analysis, *etc.*), here we define $E(j)$ at the jth level by taking the variance of $f_j(t)$:

$$E(j) = \mathrm{var}(f_j(t)) \tag{4}$$

It can accurately quantify the intensity of variation of sub-signals (including trend) by eliminating the influence of their mean values, which is different from the quadratic sum-based method proposed by Sang et al. (2013). For hydroclimate time series, both stochastic and deterministic components generally have distinctive characteristics from purely noise components (Sang et al., 2012; Rajaram et al., 2015). Due to the grid of dyadic DWT (Partal and Cigizoglu, 2008), discrete wavelet spectra $E_r(j)$ of various noise types strictly follow an exponentially decreasing rule with a base 2 (Sang 2012):

$$E_r(j) = 2^{-j} \tag{5}$$

The discrete wavelet spectra of deterministic components and that of noise are obviously different. Hence, we define the DWS of noise data as the "reference discrete wavelet spectrum (RDWS)", based on which we evaluate the statistical significance of the non-monotonic trend pattern of a time series.

To be specific, we design a technical flowchart to show how we develop the DWS approach for identifying the non-monotonic trend pattern of time series, and also for evaluating the statistical significance of that trend pattern (see details in Figure 1):

(1) For the series $f(t)$ with length L to be analyzed, we normalize it, and decompose it using the DWT method in Eq. (2) and (3);

(2) We calculate the discrete wavelet spectrum of the series $f(t)$ by Eq. (4);

(3) For comparison, we then use the Monte-Carlo method to generate normalized noise data N with the same length as the series $f(t)$, and compute its RDWS by Eq. (4). Considering that discrete wavelet spectra of diverse types of noise data consistently follow Eq. (5), here we generate noise data following the standard normal probability distribution;

(4) We repeat the above step 5000 times, and calculate the mean value and variance of the spectrum values (in Eq. 4) of the normalized noise data N at each decomposition level j. Based on it, we estimate an appropriate confidence interval of RDWS at the concerned confidence level. In this study, we considered 95% confidence level;

(5) In comparing DWS of the series $f(t)$ and the confidence interval generated by that of noise (i.e., RDWS), we identified the deterministic components under the highest decomposition level as the non-monotonic trend pattern of the series, and judged whether it was significant. Specifically, if the spectrum value of the analyzed series' sub-signal under the highest level was above the confidence interval of RDWS, it was considered that the non-monotonic trend pattern was statistically significant; otherwise, if the spectrum value of the sub-signal under the highest level fell into the confidence interval of RDWS, it was not statistically significant;

(6) If a smaller time scale K is concerned, we can use the decomposition level $log_2(K)$, instead of M, and then repeat the steps (1-5) to identify the non-monotonic trend pattern at that time scale.

In the following section, we mainly investigate the applicability and reliability of the DWS approach for identifying the non-monotonic trend and assessing its significance, and further investigate the variation of non-monotonic trend with data length increase to improve our understanding of trend at large time scales.

< Figure 1>

3. Results

3.1 Synthetic series analysis

To test and verify the reliability of the developed discrete wavelet spectrum (DWS) approach for identifying the non-monotonic trend pattern of a time series, we considered the general hydrological situations and generated two synthetic series data, with known signals and noise a priori. For investigating the variation of non-monotonic trend with data length increase, we set the length of the two synthetic series as 200, and the noise in them followed a standard normal probability distribution. The first synthetic series S1 consisted of an exponentially increasing line and a periodic curve (with a periodicity of 200) with some noise content (Figure 2, left panel); and the second synthetic series S2 was generated by including a hemi-sine curve, a periodic curve (with a periodicity of 50) and some noise content (Figure 2, right panel). Using the MK test and considering monotonic trends, series S1 showed a significant increase but the trend of series S2 was not significant.

When using the DWS approach (Figure 1), we considered the time scale as data length, and used the Daubechies (db8) wavelet to decompose series S1 into seven (i.e., $<log_2 200$) sub-signals using Eq. (2) and Eq. (3). Then, we took the sub-signals under the seventh level as the defined non-monotonic trend pattern. As shown in Figure 2 (left panel), the identified non-monotonic trend pattern in series S1 was similar to the true trend pattern. However, the linear fitting curve (a monotonic curve) could not capture the detail of the non-monotonic trend pattern. The same approach applied to series S2 in Figure 2 (right panel) and the conclusion did not change. Moreover, for series S2 with large variability at large time scales, the linear fitting curve or other monotonic curves may not be physically meaningful.

< Figure 2>

We computed the discrete wavelet spectra of the two synthetic series using Eq. (4), and used the reference discrete wavelet spectrum with 95% confidence interval to evaluate the statistical significance of their non-monotonic trend patterns. That is, if the red point at a certain data length was above the 95% confidence bar, described by the blue line in Figure 3, it was considered that the trend pattern was significant at 95% confidence level. Using the DWS approach, the trend pattern of series S1, which was quasi-monotonic, was found significant (Figure 3a) as in the MK test (Figure 3c), but the non-monotonic series S2 showed a significant trend pattern (Figure 3b), which was greatly different from the MK test (Figure 3d).

In Figure 3, we also presented the significance of the identified trend patterns of the two series using both our DWS approach and the MK test, and we changed the data length to investigate the stability of the statistical significance of the non-monotonic trend pattern. Generally, it would have more uncertainty when evaluating the statistical significance of trend pattern with a shorter length, corresponding to a bigger 95% confidence interval. Using our DWS approach, the 95% confidence interval (i.e., the height of blue bars in Figure 3) for evaluating the statistical significance of trend pattern generally decreased with the increase of data length, as expected. However, in the MK test, the significance was always determined by the constant thresholds of +/-1.96, regardless of the data length.

In the DWS results in Figure 3, the significance levels of non-monotonic trend patterns did not consistently decrease with data length, but showed some fluctuation, as the proportions of different components (including trend) in the original series varied with data length. Furthermore, one would expect that if the trend pattern of a series at a certain length was identified statistically significant, the trend pattern would extend with the increase of data length, thus its significance may be more stable with a larger length of data considered. Using our DWS approach, the trend pattern of series S1 was significant when the data length was larger than 55 (Figure 3a), being similar to the result of the MK test (Figure 3c). The trend pattern of the series S2 was statistically significant when the data length was larger than 75 (Figure 3b). However, using the MK test, the monotonic trend of series S2 was significant only when the data length was between 40 and 185 (Figure 3d). In summary, the significance of trend pattern identified by our DWS approach was more stable than that detected by the MK test, demonstrating the advantage of the DWS approach in dealing with non-monotonic variation of hydroclimate time series.

< Figure 3>

3.2 Observed data analysis

We used the annual time series of air temperature (denoted as TEM) and potential evaporation (denoted as PET) over China to further verify the applicability of our developed DWS approach for identifying non-monotonic trend patterns of a time series. These time series were obtained from the hydroclimate data measured at 520 meteorological stations over China, with the same measurement years from 1961 to 2013. The data have been quality-checked to ensure their reliability for scientific research. The PET data were calculated from the Penman-Monteith approach (Chen et al., 2005).

The average time series of TEM and PET measured at 520 stations were first considered. Given the general nonstationary nature of observed hydroclimate time series, linear trends or more generally monotonic curves could not capture the trend pattern with large interdecadal variation and therefore were not particularly physically meaningful. In Figure 4 (left panel), we presented the average annual TEM time series visually showing nonstationary characteristics and non-monotonic variation. The TEM series decreased till the 1980s with fluctuations and then sharply rose till the 2000s, followed by a decreasing tendency. The large fluctuation of the average air temperature after the late 1990s is the well-known phenomenon of the “global warming hiatus” (Roberts et al., 2015). The linear fitting curve obviously missed out the more complicated trend pattern of the observed temperature time series. Using our DWS approach, we decomposed the TEM series into five (i.e., $<log_{2}53$) sub-signals using Eq. (2) and Eq. (3), and took the sub-signals under the fifth level as the trend pattern, which realistically presented the nonstationary variability of temperature at large time scales (Figure 4, left panel).

We also applied the DWS approach to the average annual PET time series. In the time series of PET (Figure 4, right panel), there was a decreasing trend for the period from 1961 to the 1990s, which is the well-known “evaporation paradox” leading to controversial interpretations continuing over the last decade of hydrological cycles (Brutsaert and Parlange, 1998; Roderick and Farquhar, 2002). That decreasing trend was then followed by an abrupt increase in around the 1990s, almost the same time when solar radiation was observed to be reversing its trend, widely termed as “global dimming to brightening” (Wild, 2009). Surprisingly, after the mid-2000s, PET started to decrease again (Figure 4, right panel). Sometimes, one would propose to fit linear curves for separate time periods. Again, linear curves could not capture the overall non-monotonic trend pattern of the PET series. Using the same DWS approach, we identified the non-monotonic trend pattern of the PET time series (Figure 4, right panel), which captured the two turning points of the changing trends in the 1990s and the 2000s.

< **Figure 4**>

The changes of trends in terms of magnitudes and signs for different periods led to the difficulty in assessing and interpreting the significance of trends. For example, the PET time series showed a significant decrease using the MK test (-3.76 < -1.96) during 1961-1992 (Figure 5d). At that moment before the reversed trend reported, the significant decrease could be literally interpreted, as that PET had significantly declined and might be declining in the future. However, the PET time series reversed after the 1990s and again in the 2000s, coming with an insignificant overall trend for the whole period of 1961-2013. For the more or less monotonic time series of the TEM series (1961-2013), the MK test detected a significant increase (6.00 > 1.96) (Figure 5c), which led to the surprise when air temperature was reported to have stopped increasing after the late 1990s. In summary, it becomes vital to develop an approach for testing the significance of trend pattern, which is suitable for non-monotonic time series, as it is an important basis and a prerequisite for hydrological simulation and prediction at decadal scales.

In this study, building on the discrete wavelet transform, we proposed an operational approach, i.e., DWS, for evaluating the significance of non-monotonic trend pattern in TEM (Figure 5a) and PET (Figure 5b) series. For comparison purposes, we also conducted the significance test for the two time series using the MK test (Figure 5c and 5d). Similar to Figure 3, we changed the data length to investigate the stability of statistical significance (Figure 5). Again, results indicated that the 95% confidence interval for evaluating the statistical significance of non-monotonic trend pattern generally decreased with data length, which was different from the constant thresholds +/-1.96 adopted in the MK test. The significance test using our DWS approach appeared to be more stable with data length than the MK test (Figure 5). Using our DWS approach, the trend pattern in the TEM series became significant when the data length increased to 30, and the significance was more stable when it was greater than 35 (Figure 5a). For the case of the PET series, the trend pattern became statistically significant when the data length was larger than 25 (Figure 5b). The findings here have important implications for non-monotonic hydroclimate time series analysis, in that the timescale of defining *climate* and *climate change* by the World Meteorological Organization is usually 30 years (Arguez and Vose, 2011) and in hydrological practice it is between 25-30 years.

For the whole time series investigated here, whose length was larger than 30 years, we were able to examine the significance using the developed DWS approach. Combining the trend pattern in Figure 4 (left panel) and the significance test in Figure 5a, we confirmed that the trend pattern of the TEM time series from 1961-2013 identified in this study was significant at

95% confidence interval. Similarly, the trend pattern in PET was also significant (Figure 4 right panel and Figure 5b). The significance test results suggested that the three main stages of the series (red lines, Figure 4) were detectable as the overall trend pattern from the variability of the series and were vital to understanding how the temperature and the PET series were changing at interdecadal scales. In particular, the reversed change in PET and its significance can be revealed by our DWS approach, which can provide more useful and physically meaningful information.

< **Figure 5**>

We further detected and evaluated the significance of non-monotonic trends of the PET time series measured at 520 stations for investigating their spatial difference. Because the trends in the annual TEM time series were quasi-monotonic, and they were statistically significant at most of the stations, no matter using our DWS approach or the MK test, more details of TEM data were not repeated here. As for the trend patterns in the PET data, the results gotten from our DWS approach (Figure 6, left panel) and those in the MK test presented substantial differences. When conducting the statistical significance test using the MK test, the monotonic trends were detected as significant in those the annual PET time series measured at 230 stations. Significant downward monotonic trends were mainly found in the southern part of the Songliao River basin, the Haihe River basin, the Huaihe River basin, some regions in South China, and Northwest China. Significant upward monotonic trends were mainly found in the northern part of the Songliao River basin, the upper reach of the Yellow River basin, the southwest corner of China, and some regions in the Yangtze River Delta.

Comparatively, significant non-monotonic trends in the PET time series were detected at 380 stations throughout China. That means that those annual PET time series measured at 150 stations (28.8% of the total stations and mainly in the south part of China) mainly indicated non-monotonic variations rather than monotonic trends at interdecadal scales, with similar phenomena as shown in Figure 4 (right panel), and their significance was underestimated by the MK test, which can only handle monotonic trends. Previous studies (Zhang et al., 2016; Jiang et al., 2007) indicated that potential evaporation was influenced by more physical factors (precipitation, air temperature, wind speed, relative humidity, etc.) in the southern part of China rather than the northern part; thus, the potential evaporation process in South China presented a more complex variability and was more difficult to detect and attribute its physical causes. As a result, it is known here that the annual potential evaporation process in most parts of China indicated significance variability at interdecadal scales, but it was underestimated by the conventional MK test; moreover, only considering monotonic trends would cause a great difficulty in accurately understanding the temporal and spatial variability of potential evaporation and hydroclimate process in China, and also would be unfavorable for hydrological predictions at interdecadal scales. Our results suggest that the non-monotonic trend pattern of hydroclimate time series and its significance should be carefully identified and evaluated.

< Figure 6>

4. Summary and Conclusion

Climate and hydrological processes are changing non-monotonically. Identification of linear (or monotonic) trends in hydroclimate time series, as a common practice, cannot capture the detail of the non-monotonic trend pattern in the time series at large time scales, and then can lead to misinterpreting climatic and hydrological changes. Therefore, revealing the trend pattern of the time series and assessing its significance from the usually varying hydroclimate process remains a challenge. To that end, we develop the discrete wavelet spectrum (DWS) approach for identifying the non-monotonic trend in hydroclimate time series, in which the discrete wavelet transform is used first to separate the trend pattern, and its statistical significance is then evaluated by using the discrete wavelet spectrum (Figure 1). Using two typical synthetic time series, we examine the developed DWS approach, and find that it can precisely identify non-monotonic trend pattern in the synthetic time series (Figure 2) and has an advantage in significance testing (Figure 3).

Using our DWS approach, we identify the trend pattern in the annual time series of average temperature and potential evaporation over China from 1961-2013 (Figure 4). The identified non-monotonic trend patterns precisely describe how temperature and PET are changing at interdecadal scales. Of particularly interest here is that the DWS approach can help detect both the “warming” and the “warming hiatus” in the temperature time series, and reveal the reversed changes and the latest decrease in the PET time series. The DWS approach can provide other aspects of information on the trend pattern in the time series, i.e., the significance test. Results show that the trend pattern becomes more significant and the significance test becomes more stable when the time series is longer than a certain period like 30 years or so, the widely defined “climate” time scale (Figure 5). Using the DWS approach, in both time series of mean air temperature and potential evaporation, the identified trend patterns are found significant (Figure 5). Moreover, significance of trend patterns in the PET time series obtained from the DWS approach and the MK test has obviously different spatial distributions (Figure 6). The variability of hydroclimate process at large time scales, especially for non-monotonic trend patterns, would be underestimated by the MK test, which causes a great difficulty in understanding and interpreting the spatiotemporal variability of hydroclimate process. Comparatively, the developed DWS approach can quantitatively assess the statistical significance of non-monotonic trend pattern in the hydroclimate process, and so can meet practical needs much better.

In summary, our results suggest that the non-monotonic trend pattern of hydroclimate time series and its statistical significance should be carefully identified and evaluated, and the DWS approach developed in this study has the potential for wider use in hydrological and climate sciences.

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Figures

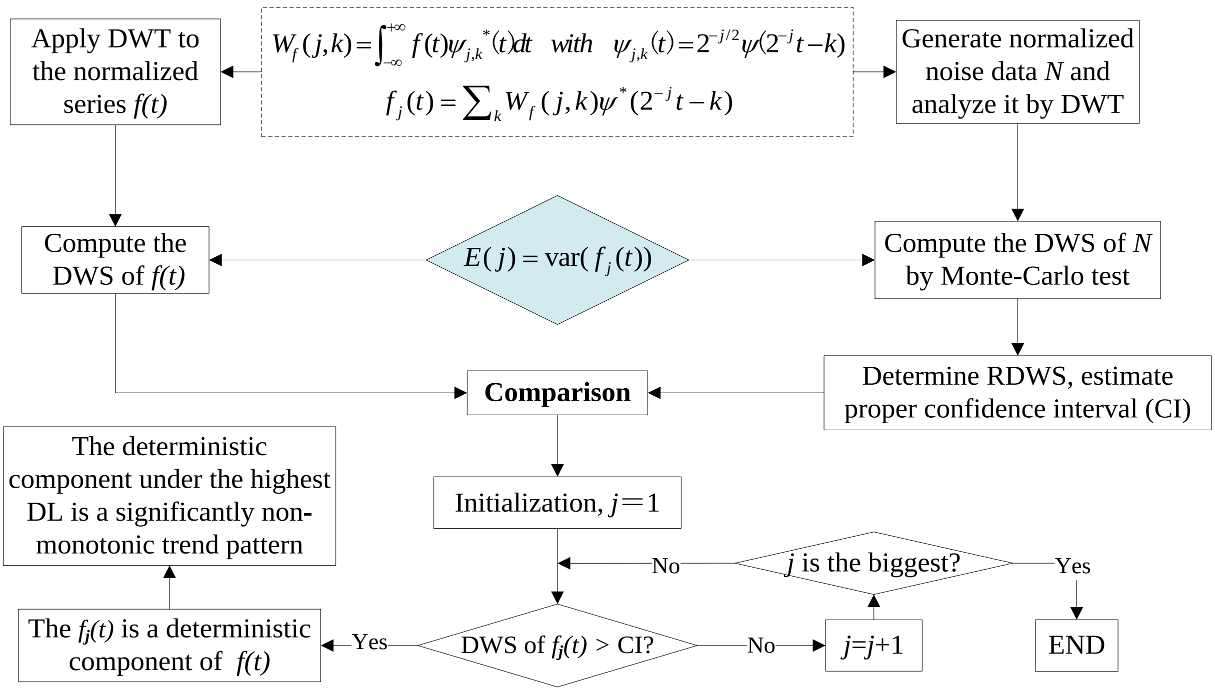

Figure 1. Technical flowchart for identification of the non-monotonic trend pattern in a time series using the discrete wavelet spectrum (DWS) approach developed, where the discrete wavelet transform (DWT) method was used to decompose the time series, and the reference discrete wavelet spectrum (RDWS) with certain confidence interval (CI) was used for the evaluation of significance.

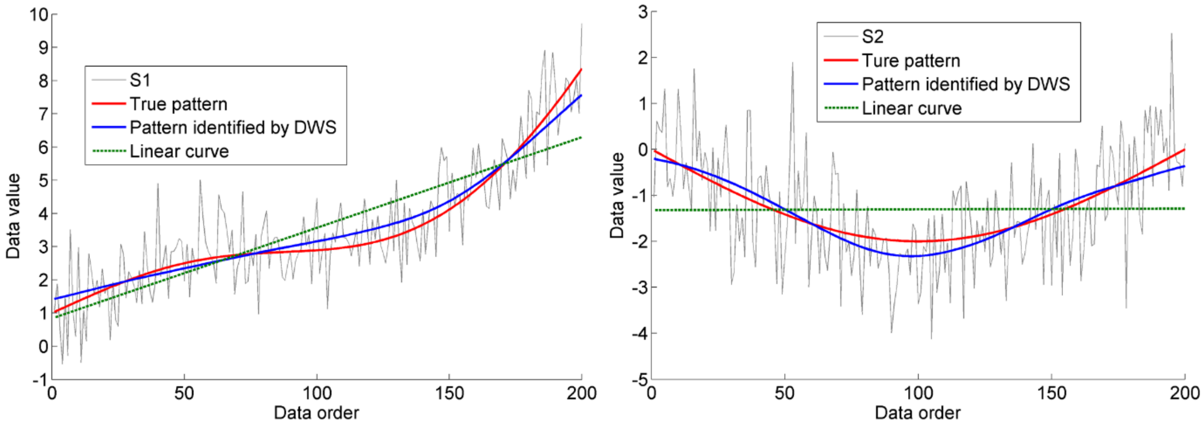

Figure 2. Non-monotonic trend patterns in the synthetic series S1 and S2 identified by the discrete wavelet spectrum (DWS) approach, and the linear trends in the two series. Synthetic series S1 is generated as: $S1=1.112^{0.1t}+0.8\times\sin(0.01\pi t)+\alpha$; and synthetic series S2 is generated as: $S2=\sin(0.04\pi t)+2\times\sin(\pi+0.005\pi t)+\alpha$, where α is a random process following the standard normal distribution.

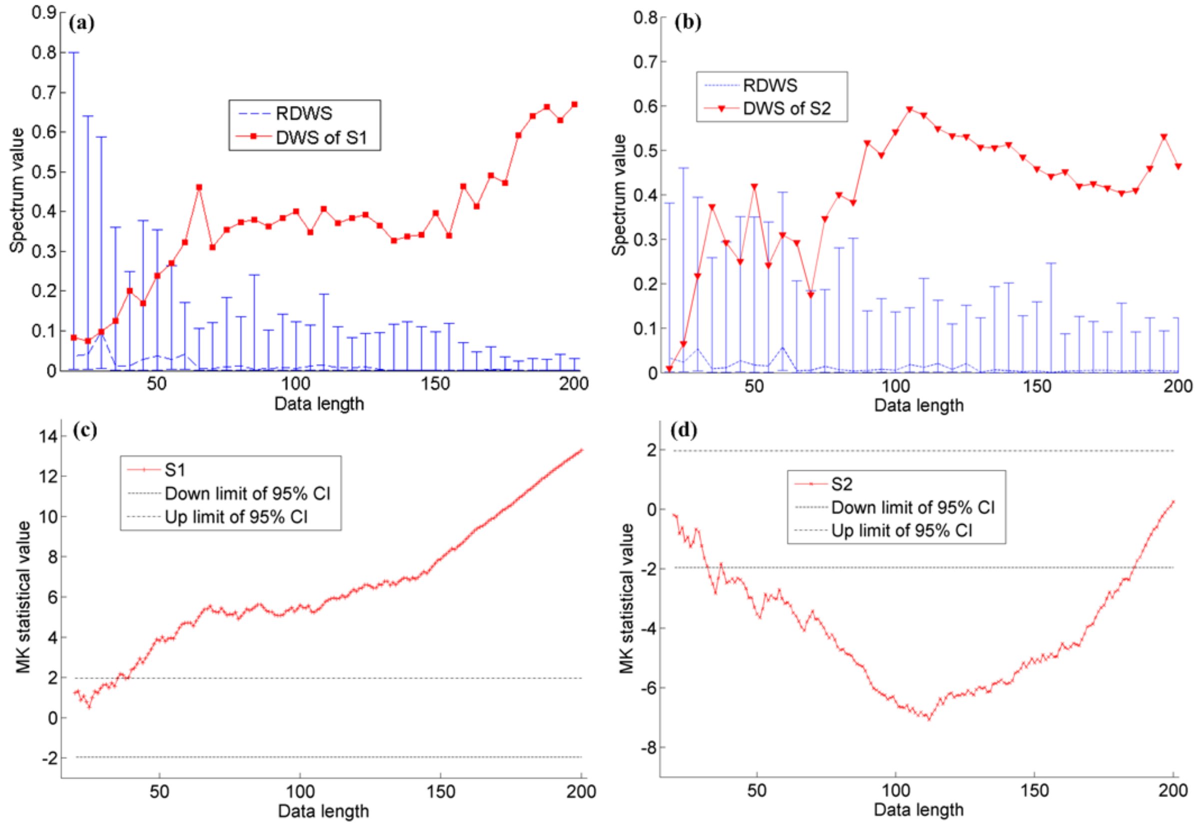

Figure 3. Evaluation of statistical significance of non-monotonic trend patterns in the synthetic series S1 (a) and S2 (b) with different data length by the discrete wavelet spectrum (DWS) approach, and the results by the Mann-Kendall (MK) test (c and d). In figure a and b, the blue line is the reference discrete wavelet spectrum (RDWS) with 95% confidence interval under each data length; if the red point at certain data length is above the blue bar, it is thought that the trend pattern is significant at 95% confidence level. In figure c and d, the two black dash lines indicate 95% confidence interval (CI) with the thresholds of +/- 1.96 in the MK test.

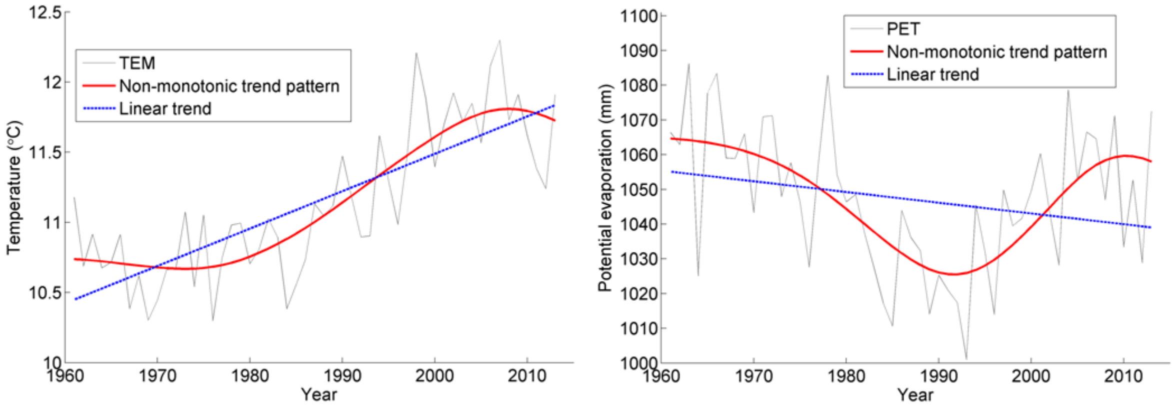

Figure 4. Non-monotonic trend patterns in the annual time series of the mean air temperature (TEM) and the potential evaporation (PET) over China from 1961-2013 identified by the discrete wavelet spectrum (DWS) approach, and the linear trends in the two series.

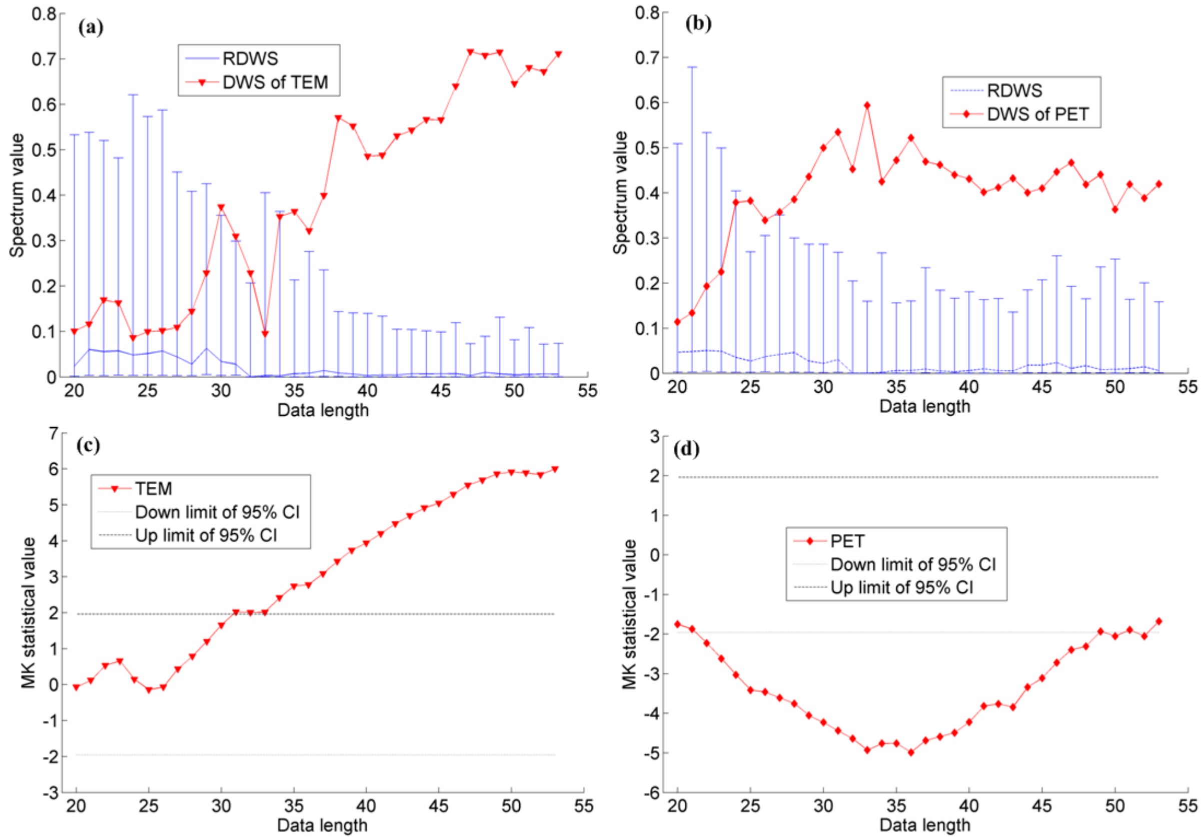

Figure 5. Evaluation of statistical significance of non-monotonic trend patterns in the annual time series of the mean air temperature (TEM, a) and the potential evaporation (PET, b) over China with different data length by the discrete wavelet spectrum (DWS) approach, and the results by the Mann-Kendall (MK) test (c and d). In figure a and b, The blue line is the reference discrete wavelet spectrum (RDWS) with 95% confidence interval under each data length; and in figure c and d, the two black dash lines indicate 95% confidence interval (CI) with the thresholds of +/- 1.96 in the MK test.

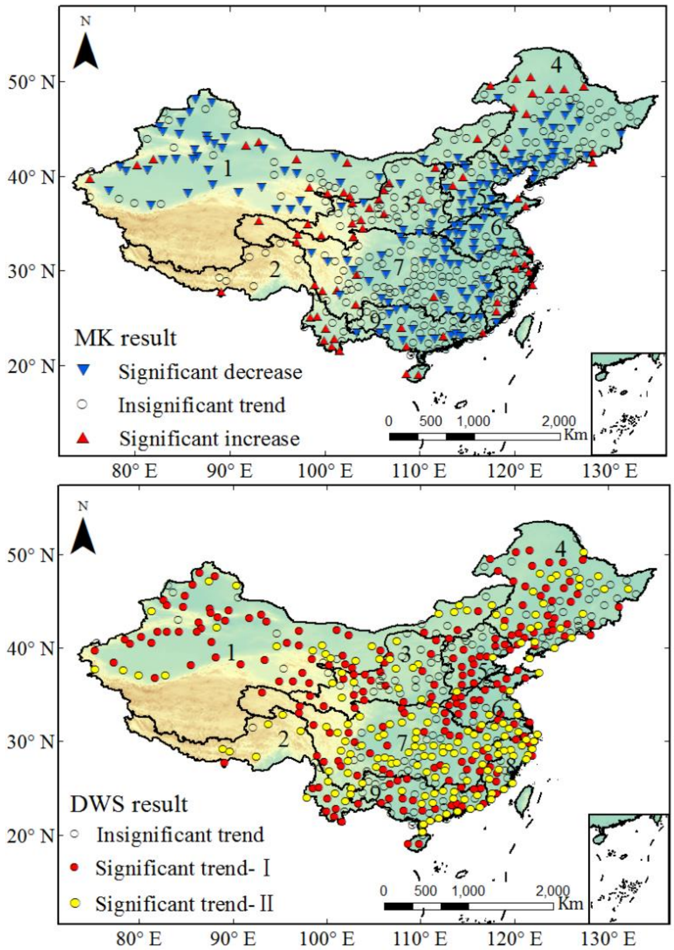

Figure 6. Spatial distribution of the significance of trends in the annual potential evaporation data during 1961-2013 and measured at 520 weather stations over China. The result above was gotten from the Mann-Kendall (MK) test. The result below was gotten from the discrete wavelet spectrum (DWS) approach developed, in which significant trend-I means those significant trends (at 230 stations) can be identified by both the DWS approach and the MK test, but significant trend-II means those significant trends (at 150 stations) can only be identified by the DWS approach but not the MK test. 1, the Northwest Inland River basin; 2, the Southwest River basin; 3, the Yellow River basin; 4, the Songliao River basin; 5, the Haihe River basin; 6, the Huaihe River basin; 7, the Yangtze River basin; 8, the Southeast River basin; and 9, the Pearl River basin.