1 **A discrete wavelet spectrum approach for identifying non-monotonic trend**

2 **patterns of hydroclimate data**

3 Yan-Fang Sang[1,2], Fubao Sun[1], Vijay P. Singh[3], Ping Xie[4], Jian Sun[1]

4 1. Key Laboratory of Water Cycle & Related Land Surface Processes, Institute of

5 Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences,

6 Beijing 100101, China;

7 2. Department of Atmospheric Sciences, University of Washington, Seattle 98195,

8 Washington, USA;

9 3. Department of Biological and Agricultural Engineering & Zachry Department of Civil

10 Engineering, Texas A and M University, 321 Scoates Hall, 2117 TAMU, College Station,

11 Texas 77843-2117, U.S.A.

12 4. State Key Laboratory of Water Resources and Hydropower Engineering Science, Wuhan

13 University, Wuhan 430072, China

15 **Corresponding author:**

16 Yan-Fang Sang: Tel/Fax: +86 10 6488 9310; E-Mail: sangyf@igsnrr.ac.cn,

17 sunsangyf@gmail.com

18 Fubao Sun: E-Mail: sunfb@igsnrr.ac.cn

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Abstract: The hydroclimate 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 is favorable for understanding and interpreting 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 those 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 hydroclimate regimes, and water resources planning and management. However, it remains a big 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 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 is receiving enormous public and scientific attention that the global air temperature increased during 1980-1998 passing most statistical significance tests and then stabilized afterwards 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

67   declined from the 1960s, again passing most statistical significance tests, but then reversed

68   after the 1990s. In practice, for the hydroclimate time series, the non-monotonicity is more the

69   rule rather than the exception (Dixon et al., 2006; Adam and Lettenmaier, 2008; Gong et al.,

70   2010). Therefore, identifying the non-monotonic trend pattern hidden in those hydroclimate

71   time series and assessing its statistical significance presents a significant research task for

72   understanding hydroclimatic variability and changes at large time scales.

73   Among those methods presently used in time series analysis, the wavelet method,

74   including both continuous and discrete wavelet transforms, has the superior capability of

75   handling the nonstationary characteristics of time series at multi-time scales (Percival and

76   Walden, 2000; Labat, 2005), so it may be more suitable for identifying non-monotonic trend

77   patterns in hydroclimate time series at large time scales. In a seminal work, Torrence and

78   Compo (1998) placed the continuous wavelet transform in the framework of statistical

79   analysis by formulating a significance test. Since then, the continuous wavelet method has

80   become more applicable and rapidly developed to estimate the significance of variability in

81   climate and hydrological studies. Especially, the continuous wavelet spectrum (i.e.,

82   continuous wavelet variance) was established to detect those significant variabilities in the

83   hydroclimate process (Labat et al., 2000). However, in the continuous wavelet results of a

84   time series, a known technical issue is the "data redundancy" (Gaucherel, 2002; Nourani et al.,

85   2014), which is the redundant information across timescales leading to more uncertainty.

86   On the contrary, the other type of wavelet transform, i.e., the discrete wavelet transform,

87   has the potential to overcome that problem of data redundancy, in that those wavelets used for

88   discrete wavelet transform must meet the orthogonal properties. Therefore, the discrete

89   wavelet method can be more effective to identify and describe the non-monotonic trend

90   pattern in a time series (Almasri et al., 2008; de Artigas et al., 2006; Kallache et al., 2005;

91   Partal and Kucuk, 2006; Nalley et al., 2012). However, there lacked an effective discrete

92   wavelet spectrum in the wavelet methodology without which uncertainty in the discrete

93   wavelet-aided identification of a trend cannot be accurately estimated, and the significance

94   level of the identified trend cannot be quantitatively evaluated either. For overcoming the

95   problem, Sang et al. (2013) discussed the definition of trend, and proposed a discrete wavelet

96   energy function-based method for the identification of trends, with the basic idea of

97   comparing the difference of discrete wavelet results between hydrological data and noise. The

98   method used a proper confidence interval to assess the statistical significance of the identified

99   trend, in which the key equation for quantifying trend's significance was based on the concept

100   of quadratic sum. However, the computation of quadratic sum disobeys the customary

101   practice of computing variance in spectral analysis. By using the quadratic sum, the

102   significance of a non-monotonic trend cannot be reasonably assessed, because it neglects the

103   big influence of trend's mean value. For instance, for those trends with small variations but

104   big mean values, the quadratic sums are big values, based on which the statistical significance

105   of trends would inevitably be over-assessed. Therefore, the evaluation of statistical

106   significance of a non-monotonic trend in a time series should be based on its own variability,

107   and the influence of other factors should also be eliminated.

108   By combining the advantages of discrete wavelet transform and successful practice in

109   spectral analysis methods, this study aimed at developing a practical but reliable discrete

110   wavelet spectrum approach for identifying non-monotonic trend patterns in hydroclimate time

111   series and quantifying their statistical significance, and further improving the understanding

112   of non-monotonic trends by investigating their variation with data length increase. To do that,

113   Section 2 presents details of the newly developed approach building on the wavelet theory

114   and spectrum analysis. In Section 3, we use both synthetic time series and annual time series

115   of air temperature and potential evaporation over China as examples to investigate the

116   applicability of the approach, which is followed by the discussion and conclusion in the final

117   section.

118   **2. A discrete wavelet spectrum approach**

119   Here we develop an approach, termed as "discrete wavelet spectrum approach," for

120   identifying non-monotonic trend patterns in hydroclimate time series, in which the discrete

121   wavelet transform (DWT) is used first to separate the trend pattern at large time scales, and its

122   statistical significance is then evaluated by using the discrete wavelet spectrum, whose

123   confidence interval is quantified and described through Monte-Carlo test.

124   Following the wavelet analysis theory (Percival and Walden, 2000), the discrete wavelet

125   transform of a time series $f(t)$ with a time order t can be expressed as:

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

127   where $\psi^{*}(t)$ is the complex conjugate of mother wavelet $\psi(t)$; a_0 and b_0 are constants, and

128   integer k is a time translation factor; $W_f(j,k)$ is the discrete wavelet coefficient under the

129   decomposition level j (i.e., time scale a_0^{j}). In practice, the dyadic DWT is used widely by

130   assigning $a_0=2$ and $b_0=1$:

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

132   The highest decomposition level M is determined by the length L of series $f(t)$, and can be

133   calculated as $log_2(L)$ (Foufoula-Georgiou and Kumar, 2014). The sub-signal $f_j(t)$ in the original

134   series $f(t)$ under each level j ($j = 1, 2, …, M$) can be reconstructed as:

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

136   where the sub-signal $f_j(t)$ at the highest decomposition level (when $j=M$) defines and describes

137   the non-monotonic trend pattern of the series $f(t)$, as generally understood. However, it should

138   be noted that a meaningful trend closely depends on the time scale concerned. If the

139   variability of series $f(t)$ on a certain smaller time scale K ($K<L$) is concerned, the proper

140   decomposition level can be determined as $log_2(K)$, then the sum of all those sub-signals at the

141   time scales equal to and bigger than K can be the non-monotonic trend pattern identified.

142   Sang (2012) discussed the influence of the choice of mother wavelet and decomposition

143   level, as well as noise types on the discrete wavelet decomposition of time series, and further

144   proposed some methods to solve them. By conducting Monte-Carlo experiments, he found

145   that the seven wavelet families (126 mother wavelets) used for DWT can be divided into three

146   types, and recommended the first type, by which wavelet energy functions of diverse types of

147   noise data keep stable and thus have little influence on the wavelet decomposition of time

148   series. Specifically, one chooses an appropriate wavelet, according to the relationship of

149   statistical characteristics among the original series, de-noised series and removed noise,

150   chooses a proper decomposition level by analyzing the difference between energy function of

151   the analyzed series and that of noise, and then identifies the deterministic components

152   (including trend) by conducting significance testing of DWT. These methods are closely built

153   on the composition and variability of hydroclimate time series at different time scales. They

154 were used here to accurately identify and describe the non-monotonic trend pattern in a time

155 series, and assess its statistical significance.

156 Further, to establish a reliable discrete wavelet spectrum (DWS) of time series, we need

157 to specify a spectrum value $E(j)$ for each sub-signal $f_j(t)$ (in Eq. 3), based on which we can

158 quantitatively evaluate its importance and statistical significance. Following the general

159 practice in conventional spectral analysis methods (Fourier transform, maximum entropy

160 spectral analysis, *etc.*), here we define $E(j)$ at the jth level by taking the variance of $f_j(t)$:

161
$$E(j) = \mathrm{var}(f_j(t)) \tag{4}$$

162 It can accurately quantify the intensity of variation of sub-signals (including trend) by

163 eliminating the influence of their mean values, which is different from the quadratic

164 sum-based method proposed by Sang et al. (2013). For hydroclimate time series, both

165 stochastic and deterministic components generally have distinctive characteristics from purely

166 noise components (Sang et al., 2012; Rajaram et al., 2015). Due to the grid of dyadic DWT

167 (Partal and Cigizoglu, 2008), discrete wavelet spectra $E_r(j)$ of various noise types strictly

168 follow an exponentially decreasing rule with a base 2 (Sang 2012):

169
$$E_r(j) = 2^{-j} \tag{5}$$

170 The discrete wavelet spectra of deterministic components and that of noise are obviously

171 different. Hence, we define the DWS of noise data as the "reference discrete wavelet

172 spectrum (RDWS)", based on which we evaluate the statistical significance of the

173 non-monotonic trend pattern of a time series.

174   To be specific, we design a technical flowchart to show how we develop the DWS

175   approach for identifying the non-monotonic trend pattern of time series, and also for

176   evaluating the statistical significance of that trend pattern (see the detail in Figure 1):

177   (1) For the series $f(t)$ with length L to be analyzed, we normalize it, and decompose it

178   using the DWT method in Eq. (2) and (3);

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

180   (3) For comparison, we then use the Monte-Carlo method to generate normalized noise

181   data N with the same length as the series $f(t)$, and compute its RDWS by Eq. (4).

182   Considering that discrete wavelet spectra of diverse types of noise data consistently

183   follow Eq. (5), here we generate noise data following the standard normal probability

184   distribution;

185   (4) We repeat the above step for 5000 times, and calculate the mean value and variance of

186   the spectrum values (in Eq. 4) of the normalized noise data N at each decomposition

187   level j. Based on it, we estimate an appropriate confidence interval of RDWS at the

188   concerned confidence level. In this study, we considered 95% confidence level;

189   (5) In comparing the DWS of the series $f(t)$ and the confidence interval generated by that

190   of noise (i.e., the RDWS), we identified the deterministic components under the

191   highest decomposition level as the non-monotonic trend pattern of the series, and

192   judged whether it was significant. Specifically, if the spectrum value of the analyzed

193   series' sub-signal under the highest level was above the confidence interval of RDWS,

194   it was considered that the non-monotonic trend pattern was statistically significant;

195   otherwise, if the spectrum value of the sub-signal under the highest level fill into the

196   confidence interval of RDWS, it was not statistically significant;

197   (6) If a smaller time scale K is concerned, we can use the decomposition level $log_2(K)$,

198   instead of M, and then repeat the steps (1-5) to identify the non-monotonic trend

199   pattern at that time scale.

200   In the following section, we mainly investigate the applicability and reliability of the

201 DWS approach for identifying the non-monotonic trend and assessing its significance, and

202 further investigate the variation of the non-monotonic trend with data length increase to

203 improve our understanding of trend at large time scales.

204 **< Figure 1>**

205 **3. Results**

206 **3.1 Synthetic series analysis**

207   To test and verify the reliability of the developed discrete wavelet spectrum (DWS)

208 approach for identifying the non-monotonic trend pattern of a time series, we considered the

209 general hydrological situations and generated two synthetic series data, with known signals

210 and noise a priori. For investigating the variation of non-monotonic trend with data length

211 increase, we set the length of the two synthetic series as 200, and the noise in them followed a

212 standard normal probability distribution. The first synthetic series S1 consisted of an

213 exponentially increasing line and a periodic curve (with a periodicity of 200) with some noise

214 content (Figure 2, left panel); and the second synthetic series S2 was generated by including a

215 hemi-sine curve, a periodic curve (with a periodicity of 50) and some noise content (Figure 2,

216 right panel). Using the MK test and considering monotonic trends, series S1 showed a

217 significant increase but the trend of series S2 was not significant.

218   When using the DWS approach (Figure 1), we concerned the time scale as data length,

219 and used the Daubechies (db8) wavelet to decompose series S1 into seven (i.e., $<log_2 200$)

220 sub-signals using Eq. (2) and Eq. (3). Then, we took the sub-signals under the seventh level as

221 the defined non-monotonic trend pattern. As shown in Figure 2 (left panel), the identified

222 non-monotonic trend pattern in series S1 was similar to the true trend pattern. However, the

223 linear fitting curve (a monotonic curve) could not capture the detail of the non-monotonic

224 trend pattern. The same approach applied to series S2 in Figure 2 (right panel) and the

225 conclusion did not change. Moreover, for series S2 with large variability at large time scales,

226 the linear fitting curve or other monotonic curves may not be physically meaningful.

227 **< Figure 2>**

228   We computed the discrete wavelet spectra of the two synthetic series using Eq. (4), and

229 used the reference discrete wavelet spectrum with 95% confidence interval to evaluate the

230 statistical significance of their non-monotonic trend patterns. That is, if the red point at a

231 certain data length was above the 95% confidence bar, described by the blue line in Figure 3,

232 it was considered that the trend pattern was significant at 95% confidence level. Using the

233 DWS approach, the trend pattern of series S1, which was quasi-monotonic, was found

234 significant (Figure 3a) as in the MK test (Figure 3c), but the non-monotonic series S2 showed

235 a significant trend pattern (Figure 3b), which was greatly different from the MK test (Figure

236 3d).

237   In Figure 3, we also presented the significance of the identified trend patterns of the two

238   series using both our DWS approach and the MK test, and we changed the data length to

239   investigate the stability of the statistical significance of the non-monotonic trend pattern.

240   Generally, it would have more uncertainty when evaluating the statistical significance of trend

241   pattern with a shorter length, corresponding to a bigger 95% confidence interval. Using our

242   DWS approach, the 95% confidence interval (i.e., the height of blue bars in Figure 3) for

243   evaluating the statistical significance of trend pattern generally decreased with the increase of

244   data length, as expected. However, in the MK test, the significance was always determined by

245   the constant thresholds of +/-1.96, regardless of the data length.

246   In the DWS results in Figure 3, the significance levels of the non-monotonic trend

247   patterns did not consistently decrease with data length, but showed some fluctuation, as the

248   proportions of different components (including trend) in the original series varied with data

249   length. Furthermore, one would expect that if the trend pattern of a series at a certain length

250   was identified statistically significant, the trend pattern would extend with the increase of data

251   length, thus its significance may be more stable with a larger length of data considered. Using

252   our DWS approach, the trend pattern of series S1 was significant when the data length was

253   larger than 55 (Figure 3a), being similar to the result of the MK test (Figure 3c). The trend

254   pattern of the series S2 was statistically significant when the data length was larger than 75

255   (Figure 3b). However, using the MK test, the monotonic trend of series S2 was significant

256   only when the data length was between 40 and 185 (Figure 3d). In summary, the significance

257   of trend pattern identified by our DWS approach was more stable than that detected by the

258 MK test, demonstrating the advantage of the DWS approach in dealing with non-monotonic

259 variation of hydroclimate time series.

260 **< Figure 3>**

261 **3.2 Observed data analysis**

262   We used the annual time series of air temperature (denoted as TEM) and potential

263 evaporation (denoted as PET) over China to further verify the applicability of our developed

264 DWS approach for identifying non-monotonic trend patterns of a time series. These time

265 series were obtained from the hydroclimate data measured at 520 meteorological stations over

266 China, with the same measurement years from 1961 to 2013. The data have been

267 quality-checked to ensure their reliability for scientific research. The PET data were

268 calculated from the Penman-Monteith approach (Chen et al., 2005).

269   The average time series of TEM and PET measured at 520 stations were first considered.

270 Given the general nonstationary nature of observed hydroclimate time series, linear trends or

271 more generally monotonic curves could not capture the trend pattern with large interdecadal

272 variation and therefore were not particularly physically meaningful. In Figure 4 (left panel),

273 we presented the average annual TEM time series visually showing nonstationary

274 characteristics and non-monotonic variation. The TEM series decreased till the 1980s with

275 fluctuations and then sharply rose till the 2000s, followed by a decreasing tendency. The large

276 fluctuation of the average air temperature after the late 1990s is the well-known phenomenon

277 of the "global warming hiatus" (Roberts et al., 2015). The linear fitting curve obviously

278 missed out the more complicated trend pattern of the observed temperature time series. Using

279 our DWS approach, we decomposed the TEM series into five (i.e., $<log_2 53$) sub-signals using

280   Eq. (2) and Eq. (3), and took the sub-signals under the fifth level as the trend pattern, which

281   realistically presented the nonstationary variability of temperature at large time scales (Figure

282   4, left panel).

283   We also applied the DWS approach to the average annual PET time series. In the time

284   series of PET (Figure 4, right panel), there was a decreasing trend for the period from 1961 to

285   the 1990s, which is the well-known "evaporation paradox" leading to controversial

286   interpretations continuing over the last decade of hydrological cycles (Brutsaert and Parlange,

287   1998; Roderick and Farquhar, 2002). That decreasing trend was then followed by an abrupt

288   increase in around the 1990s, almost the same time when solar radiation was observed to be

289   reversing its trend, widely termed as "global dimming to brightening" (Wild, 2009).

290   Surprisingly, after the mid-2000s, PET started to decrease again (Figure 4, right panel).

291   Sometimes, one would propose to fit linear curves for separate time periods. Again, linear

292   curves could not capture the overall non-monotonic trend pattern of the PET series. Using the

293   same DWS approach, we identified the non-monotonic trend pattern of the PET time series

294   (Figure 4, right panel), which captured the two turning points of the changing trends in the

295   1990s and the 2000s.

296   **< Figure 4>**

297   The changes of trends in terms of magnitudes and signs for different periods led to the

298   difficulty in assessing and interpreting the significance of trends. For example, the PET time

299   series showed a significant decrease using the MK test ($-3.76 < -1.96$) during 1961-1992

300   (Figure 5d). At that moment before the reversed trend reported, the significant decrease could

301   be literally interpreted as that PET had significantly declined and might be declining in the

302 future. However, the PET time series reversed after the 1990s and again in the 2000s, coming

303 with an insignificant overall trend for the whole period of 1961-2013. For the more or less

304 monotonic time series of the TEM series (1961-2013), the MK test detected a significant

305 increase (6.00 > 1.96) (Figure 5c), which led to the surprise when air temperature was

306 reported to have stopped increasing after late the 1990s. In summary, it becomes vital to

307 develop an approach for testing the significance of trend pattern, which is suitable for

308 non-monotonic time series, as it is an important basis and prerequisite for hydrological

309 simulation and prediction at decadal scales.

310   In this study, building on the discrete wavelet transform, we proposed an operational

311 approach, i.e., the DWS, for evaluating the significance of non-monotonic trend pattern in the

312 TEM (Figure 5a) and PET (Figure 5b) series. For comparison purpose, we also conducted the

313 significance test for the two time series using the MK test (Figure 5c and 5d). Similar to

314 Figure 3, we changed the data length to investigate the stability of statistical significance

315 (Figure 5). Again, the result indicated that the 95% confidence interval for evaluating the

316 statistical significance of non-monotonic trend pattern generally decreased with data length,

317 which was different from the constant thresholds +/-1.96 adopted in the MK test. The

318 significance test using our DWS approach appeared to be more stable with data length than

319 the MK test (Figure 5). Using our DWS approach, the trend pattern in the TEM series became

320 significant when the data length increased to 30 and the significance was more stable when it

321 was greater than 35 (Figure 5a). For the case of the PET series, the trend pattern became

322 statistically significant when the data length was larger than 25 (Figure 5b). The findings here

323 have important implications for non-monotonic hydroclimate time series analysis, in that the

324   timescale of defining *climate* and *climate change* by the World Meteorological Organization

325   is usually 30 years (Arguez and Vose, 2011) and in hydrological practice it is between 25-30

326   years.

327   For the whole time series investigated here, whose length was larger than 30 years, we

328   were able to examine the significance using the developed DWS approach. Combining the

329   trend pattern in Figure 4 (left panel) and the significance test in Figure 5a, we confirmed that

330   the trend pattern of the TEM time series from 1961-2013 identified in this study was

331   significant at 95% confidence interval. Similarly, the trend pattern in PET was also significant

332   (Figure 4 right panel and Figure 5b). The significance test results suggested that the three

333   main stages of the series (red lines, Figure 4) were detectable as the overall trend pattern from

334   the variability of the series and were vital to understanding how the temperature and the PET

335   series were changing at interdecadal scales. In particular, the reversed change in PET and its

336   significance can be revealed by our DWS approach, which can provide more useful and

337   physically meaningful information.

338   **< Figure 5>**

339   We further detected and evaluated the significance of non-monotonic trends of the PET

340   time series measured at 520 stations for investigating their spatial difference. Because the

341   trends in annual TEM time series were quasi-monotonic, and they were statistically

342   significant at most of the stations, no matter using our DWS approach or the MK test, more

343   details of TEM data were not repeated here. As for the trend patterns in the PET data, the

344   results gotten from our DWS approach (Figure 6, left panel) and those in the MK test

345   presented substantial differences. When conducting the statistical significance test using the

346   MK test, the monotonic trends were detected as significant in those annual PET time series

347   measured at 230 stations. Significant downward monotonic trends were mainly found in the

348   southern part of the Songliao River basin, the Haihe River basin, the Huaihe River basin,

349   some regions in South China, and Northwest China. Significant upward monotonic trends

350   were mainly found in the northern part of the Songliao River basin, the upper reach of the

351   Yellow River basin, the southwest corner of China, and some regions in the Yangtze River

352   Delta.

353   Comparatively, significant non-monotonic trends in the PET time series were detected at

354   380 stations throughout China. That means that those annual PET time series measured at 150

355   stations (28.8% of the total stations and mainly in the south part of China) mainly indicated

356   non-monotonic variations rather than monotonic trends at interdecadal scales, with similar

357   phenomena as shown in Figure 4 (right panel), and their significance was underestimated by

358   the MK test, which can only handle monotonic trends. Previous studies (Zhang et al., 2016;

359   Jiang et al., 2007) indicated that potential evaporation was influenced by more physical

360   factors (precipitation, air temperature, wind speed, relative humidity, etc.) in the southern part

361   of China rather than the northern part; thus, potential evaporation process in South China

362   presented a more complex variability and was more difficult to detect and attribute its

363   physical causes. As a result, it is known here that annual potential evaporation process in most

364   part of China indicated significance variability at interdecadal scales, but it was

365   underestimated by the conventional MK test; moreover, only considering monotonic trends

366   would cause a great difficulty in accurately understanding the temporal and spatial variability

367   of potential evaporation and hydroclimate process in China, and also would be unfavorable

368   for hydrological prediction at interdecadal scales. Our results suggest that the non-monotonic

369   trend pattern of hydroclimate time series and its significance should be carefully identified

370   and evaluated.

371   **< Figure 6>**

372   **4. Summary and Conclusion**

373   Climate and hydrological processes are changing non-monotonically. Identification of

374   linear (or monotonic) trends in hydroclimate time series, as a common practice, cannot

375   capture the detail of the non-monotonic trend pattern in the time series at large time scales,

376   and then can lead to misinterpreting climatic and hydrological changes. Therefore, revealing

377   the trend pattern of the time series and assessing its significance from the usually varying

378   hydroclimate process remains a challenge. To that end, we develop the discrete wavelet

379   spectrum (DWS) approach for identifying the non-monotonic trend in hydroclimate time

380   series, in which the discrete wavelet transform is used first to separate the trend pattern, and

381   its statistical significance is then evaluated by using the discrete wavelet spectrum (Figure 1).

382   Using two typical synthetic time series, we examine the developed DWS approach, and find

383   that it can precisely identify non-monotonic trend pattern in the synthetic time series (Figure 2)

384   and has an advantage in significance testing (Figure 3).

385   Using our DWS approach, we identify the trend pattern in the annual time series of

386   average temperature and potential evaporation over China from 1961-2013 (Figure 4). The

387   identified non-monotonic trend patterns precisely describe how temperature and PET are

388   changing at interdecadal scales. Of particularly interest here is that the DWS approach can

389   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). 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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References

Adam, J. C., and Lettenmaier, D. P.: Application of new precipitation and reconstructed streamflow products to streamflow trend attribution in northern Eurasia. J. Clim., 21, 1807-1828, 2008.

Allen, M. R., and Ingram, W. J.: Constraints on future changes in climate and the hydrologic cycle. Nature, 419, 224-232, 2002.

Almasri, A., Locking, H., and Shukar, G.: Testing for climate warming in Sweden during 1850-1999 using wavelet analysis. J. Appl. Statis., 35, 431-443, 2008.

Arguez, A., and Vose, R. S.: The definition of the standard WMO climate normal: The key to deriving alternative climate normal. Bull. Am. Meteorol. Soc., 92, 699-704, 2011.

Brutsaert, W., and Parlange, M. B.: Hydrologic cycle explains the evaporation paradox. Nature, 396, 30, 1998.

Burn, D. H., and Hag Elnur, M. A.: Detection of hydrologic trends and variability. J. Hydrol., 255, 107-122, 2002.

Chen, D., Gao, G., Xu, C. Y., Guo, J., and Ren G.: Comparison of the Thornthwaite method and pan data with the standard Penman-Monteith estimates of reference evapotranspiration in China. Clim. Res., 28, 123-132, 2005.

433   Cohn, T. A., and McMahon, H. F.: Nature's style: naturally trendy. Geophys. Res. Lett., 32,

434   L23402, 2005.

435   Diffenbaugh, N. S., Giorgi, F., and Pal, J. S.: Climate change hotspots in the United States.

436   Geophys. Res. Lett., 35, L16709, 2008.

437   de Artigas, M., Elias, A., and de Campra, P.: Discrete wavelet analysis to assess long-term

438   trends in geomagnetic activity. Phys. Chem. Earth, 31, 77-80, 2006.

439   Dixon, H., Lawler, D. M., and Shamseldin, A. Y.: Streamflow trends in western Britain.

440   Geophys. Res. Lett., 32, L19406, 2006.

441   Foufoula-Georgiou, E., and Kumar, P. (Eds.). Wavelets in geophysics (Vol. 4). Academic

442   Press, 2014.

443   Gaucherel, C.: Use of wavelet transform for temporal characteristics of remote watersheds. J.

444   Hydrol., 269, 101-121, 2002.

445   Gong, S. L., Zhao, T. L., Sharma, S., Toom-Sauntry, D., Lavoue, D., Zhang, X. B., Leaitch,

446   W. R., and Barrie, A.: Identification of trends and interannual variability of sulfate and

447   black carbon in the Canadian High Arctic: 1981-2007. J. Geophys. Res.-Atmos., 115,

448   D07305, 2010.

449   Hamed, K. H.: Trend detection in hydrologic data: The Mann-Kendall trend test under the

450   scaling hypothesis. J. Hydrol., 349, 350-363, 2008.

451   IPCC: Climate Change 2013: The Physical Science Basis, Contribution of Working Group I

452   to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change,

453   Cambridge Univ. Press, Cambridge, UK, 2013.

454 Jiang, T., Chen, Y.D., Xu, C.Y., Chen, X., Chen, X. and Singh, V.P.: Comparison of
455   hydrological impacts of climate change simulated by six hydrological models in the
456   Dongjiang Basin, South China. Journal of hydrology, 336(3), 316-333, 2007.

457 Kallache, M., Rust, H. W., and Kropp, J.: Trend assessment: applications for hydrology and
458   climate research. Nonlinear Proc. Geoph., 12, 2001-2210, 2005.

459 Kosaka, Y., and Xie, S. P.: Recent global-warming hiatus tied to equatorial Pacific surface
460   cooling. Nature, 501, 403-407, 2013.

461 Labat, D.: Recent advances in wavelet analyses: Part 1. A review of concepts. J. Hydrol., 314,
462   275-288, 2005.

463 Labat, D., Ababou, R., Mangin, A.: Rainfall-runoff relations for karstic springs. Part II:
464   continuous wavelet and discrete orthogonal multiresolution analyses. Journal of hydrology,
465   238(3):149-78, 2000.

466 Medhaug, I., Stolpe, M. B., Fischer, E. M., and Knutti, R.: Reconciling controversies about
467   the 'global warming hiatus'. Nature, 545(7652), 41-47, 2017.

468 Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W.,
469   Lettenmaier, D. P., and Stouffer, R. J.: Stationarity is dead: whither water management?
470   Science, 319, 573-574, 2008.

471 Nalley, D., Adamowski, J., and Khalil, B.: Using discrete wavelet transforms to analyze
472   trends in streamflow and precipitation in Quebec and Ontario (1954–2008). J.
473   Hydrol., 475, 204-228, 2012.

474   Nourani, V., Baghanam, A. H., Adamowski, J., and Kisi, O.: Applications of hybrid

475   wavelet-artificial Intelligence models in hydrology: A review. J. Hydrol., 514, 358-377,

476   2014.

477   Partal, T., and Kucuk, M.: Long term trend analysis using discrete wavelet components of

478   annual precipitation measurements in Marmara region (Turkey). Phys. Chem. Earth, 31,

479   1189-1200, 2006.

480   Partal, T., and Cigizoglu, H. K.: Estimation and forecasting of daily suspended sediment data

481   using wavelet-neural networks. J. Hydrol., 358, 317-331, 2008.

482   Percival, D. B., and Walden, A. T.: Wavelet Methods for Time Series Analysis, Cambridge

483   University Press, Cambridge, UK, 2000.

484   Roberts, C. D., Palmer, M. D., McNeall, D., and Collins, M.: Quantifying the likelihood of a

485   continued hiatus in global warming. Nature Clim. Change, 5, 337-342, 2015.

486   Sang, Y. F., Wang, Z., and Liu, C.: Period identification in hydrologic time series using

487   empirical mode decomposition and maximum entropy spectral analysis. J. Hydrol., 424,

488   154-164, 2012.

489   Sang, Y. F.: A practical guide to discrete wavelet decomposition of hydrologic time series.

490   Water Resour. Manage., 26, 3345-3365, 2012.

491   Sang, Y. F., Wang, Z., and Liu, C.: Discrete wavelet-based trend identification in hydrologic

492   time series. Hydrol. Process., 27, 2021-2031, 2013.

493   Rajaram, H., Bahr, J. M., BlH, G., Cai, J. X., Scott Mackay, D., Michalak, A. M., Montanari,

494   A., Sanchez-Villa, X., and Sander, G.: A reflection on the first 50 years of Water

495   Resources Research. Water Resour. Res., 51, 7829-7837, 2015.

496   Renard, B., Lang, M., Bois, P., Mestre, O., Niel, H., Sauquet, E., Prudhomme, C., Parey, S.,

497   Paquet, E., Neppel, L., and Gailhard, J.: Regional methods for trend detection: Assessing

498   field significance and regional consistency. Water Resour. Res., 44, W08419, 2008.

499   Roderick, M. L., and Farquhar, G. D.: The cause of decreased pan evaporation over the past

500   50 years. Science, 298, 1410-1411, 2002.

501   Torrence, C., and Compo, G. P.: A practical guide to wavelet analysis. B. Am. Meteorol. Soc.,

502   79: 61-78, 1998.

503   Trenberth, K. E., Dai, A., der Schrier, G., Jones, P. D., Barichivich, J., Briffa, K. R., and

504   Sheffield, J.: Global warming and changes in drought. Nature Clim. Change, 4, 17-22,

505   2014.

506   Wild, M.: Global dimming and brightening: A review. J. Geophys. Res., 114, D00D16, 2009.

507   Yue, S., Pilon, P., and Cavadias, G.: Power of the Mann-Kendall and Spearman's rho tests for

508   detecting monotonic trends in hydrological series. J. Hydrol., 259, 254-271, 2002.

509   Zhang, J., Sun, F., Xu, J., Chen, Y., Sang, Y.F., Liu, C.: Dependence of trends in and

510   sensitivity of drought over China (1961–2013) on potential evaporation model.

511   Geophysical Research Letters, 43(1): 206-213, 2016.

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518 **Figures**

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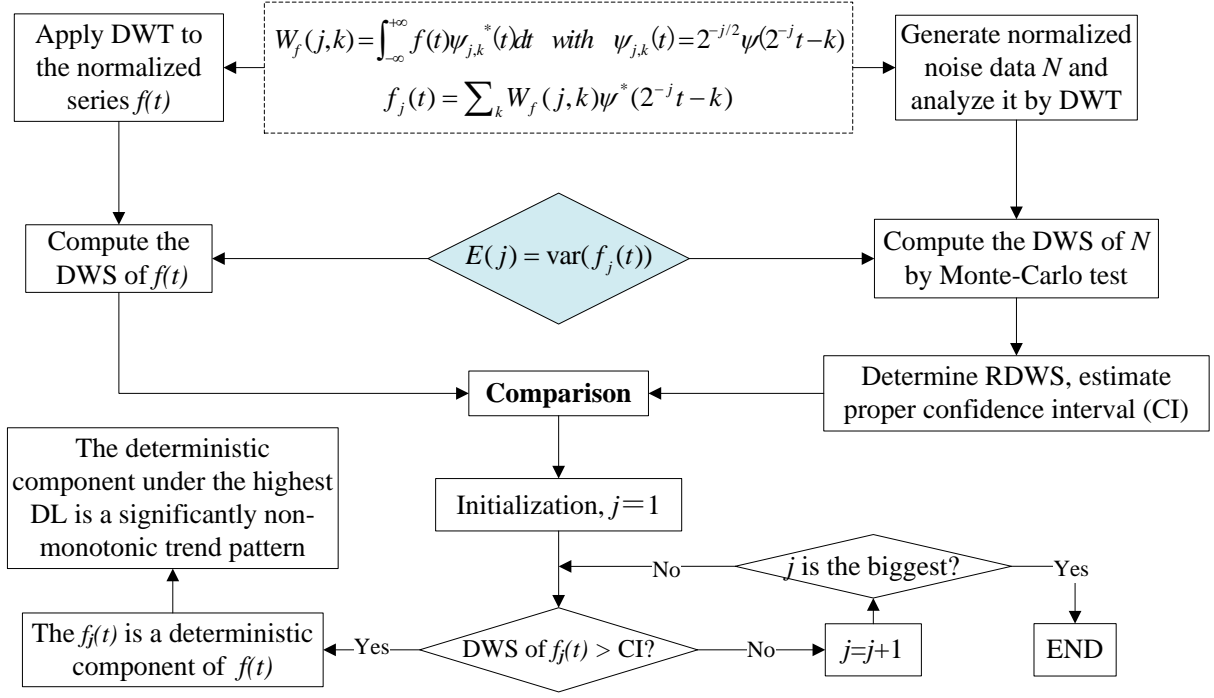
523 **Figure 1.** Technical flowchart for identification of the non-monotonic trend pattern in a time

524 series using the discrete wavelet spectrum approach developed. In the figure, "DWT" is

525 the discrete wavelet transform, "DWS" is the discrete wavelet spectrum, "RDWS" is the

526 reference discrete wavelet spectrum, "DL" is the decomposition level, and "CI" is the

527 confidence interval.

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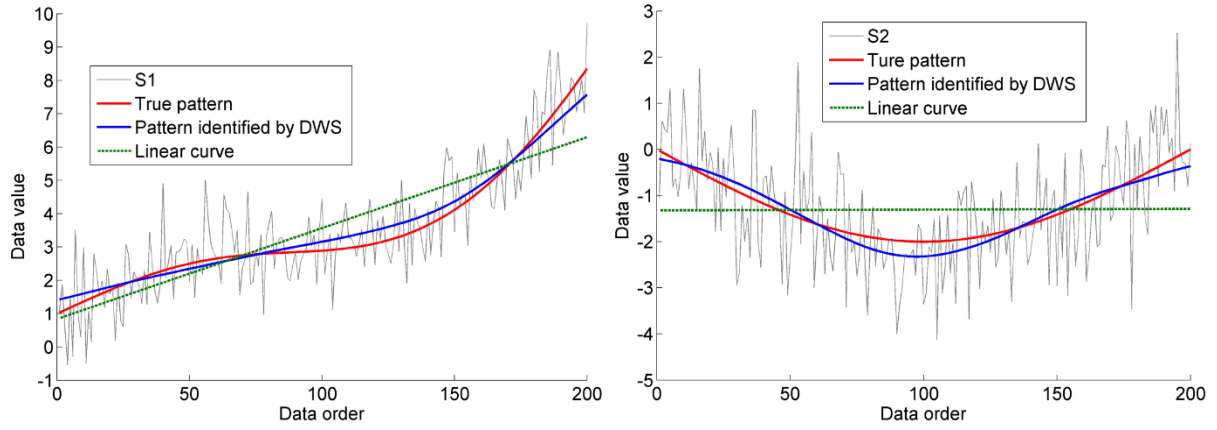
Figure 2. Non-monotonic trend patterns in the synthetic series S1 and S2 identified by the discrete wavelet spectrum (DWS) approach, and the linear trends in the two series. Synthetic series S1 is generated as: $S1=1.112^{0.1t}+0.8\times\sin(0.01\pi t)+\alpha$; and synthetic series S2 is generated as: $S2=\sin(0.04\pi t)+2\times\sin(\pi+0.005\pi t)+\alpha$, where α is a random process following the standard normal distribution.
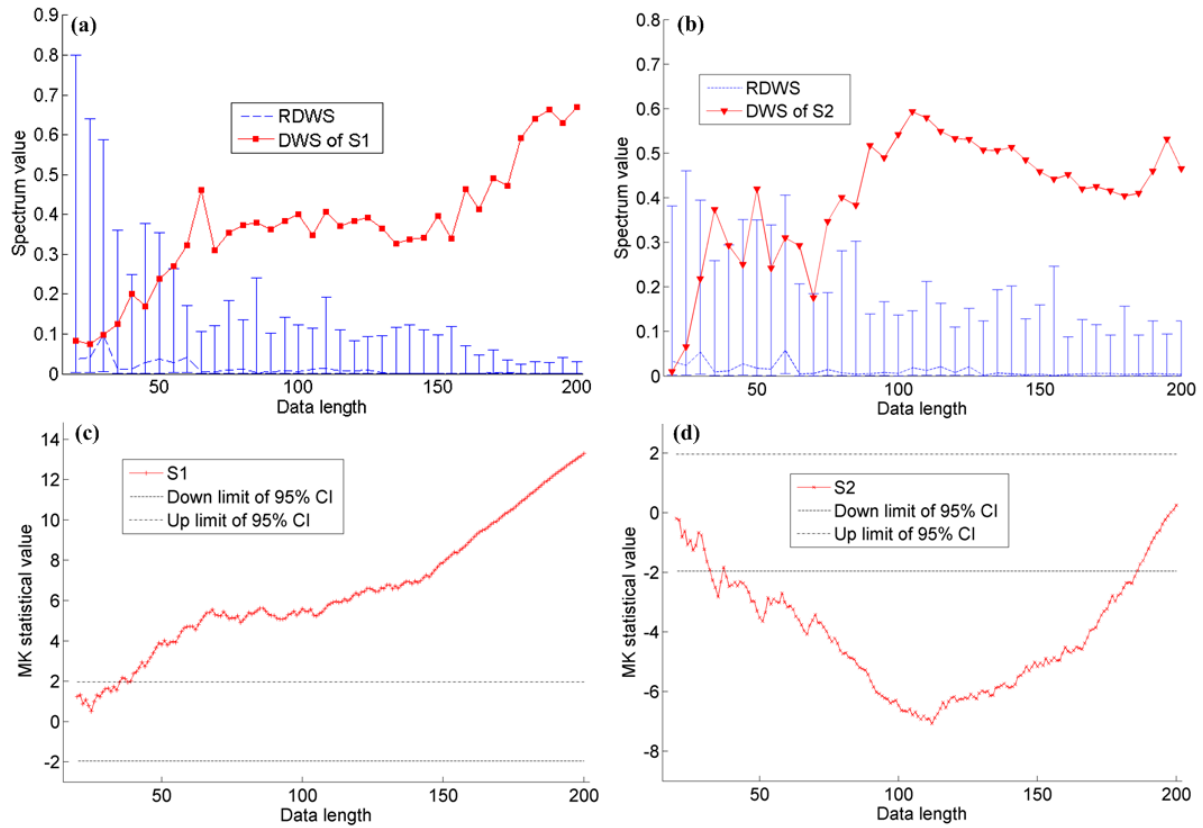
Figure 3. Evaluation of statistical significance of non-monotonic trend patterns in the synthetic series S1 (a) and S2 (b) with different data length by the discrete wavelet spectrum (DWS) approach, and the results by the Mann-Kendall (MK) test (c and d). In figure a and b, the blue line is the reference 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.

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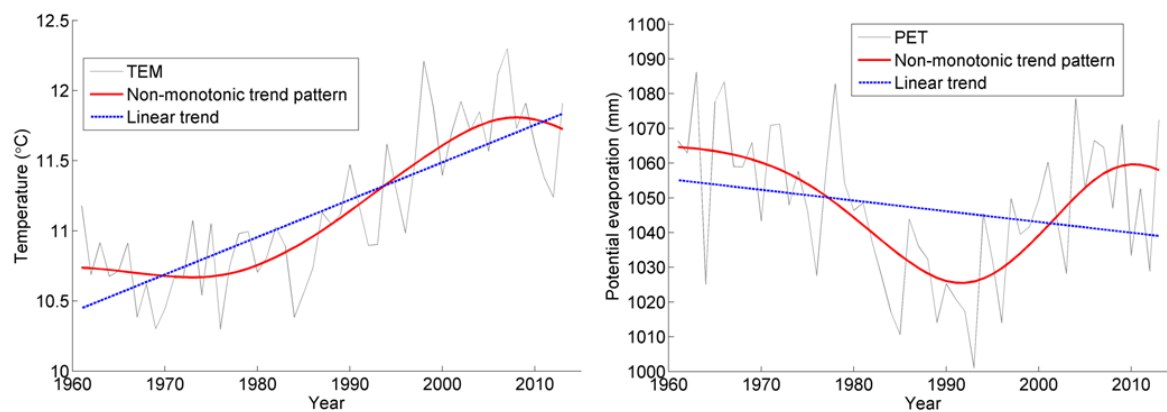
551 **Figure 4.** Non-monotonic trend patterns in the annual time series of the mean air temperature

552 (TEM) and the potential evaporation (PET) over China from 1961-2013 identified by the

553 discrete wavelet spectrum (DWS) approach, and the linear trends in the two series.

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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.

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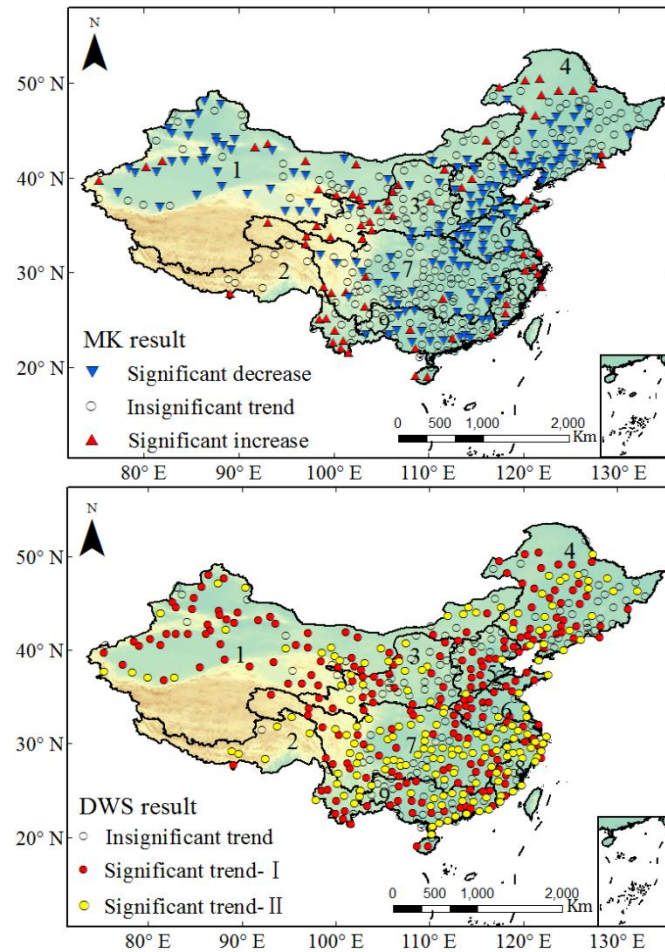
573 **Figure 6.** Spatial distribution of the significance of trends in the annual potential evaporation

574 data during 1961-2013 and measured at 520 weather stations over China. The result

575 above was gotten from the Mann-Kendall (MK) test. The result below was gotten from

576 the discrete wavelet spectrum (DWS) approach developed, in which significant trend-I

577 means those significant trends (at 230 stations) can be identified by both the DWS

578 approach and the MK test, but significant trend-II means those significant trends (at 150

579 stations) can only be identified by the DWS approach but not the MK test. 1, the

580 Northwest Inland River basin; 2, the Southwest River basin; 3, the Yellow River basin; 4,

581 the Songliao River basin; 5, the Haihe River basin; 6, the Huaihe River basin; 7, the

582 Yangtze River basin; 8, the Southeast River basin; and 9, the Pearl River basin.