Drought severity and change in Xinjiang, China, over 1961–2013
Yi Li, Chunyan Chen and Changfeng Sun

ABSTRACT

Monthly climatic data from 53 sites across Xinjiang, China, were used to compare drought severity from the widely accepted Standardized Precipitation Index (SPI) with the recently proposed Standardized Precipitation Evapotranspiration Index (SPEI), as well as trends in the data from 1961 to 2013. Monthly Thornthwaite based (ETo.TW) and Penman-Monteith based reference evapotranspiration (ETo.PM) were computed and subsequently used to estimate SPEITW and SPEIPM, respectively. The indices’ sensitivity, spatiotemporal distributions and trends were analyzed. The results showed that the TW equation underestimated ETo, which affected the accuracy of the SPEI estimation. Greater consistency was found between SPI and SPEIPM than between SPI and SPEITW at different timescales. SPI and SPEIPM were sensitive to precipitation, but SPEITW and SPEIPM were insensitive to ETo. The scope of spatial SPEIPM was wider than that of SPI at the same timescale. Obvious differences in SPI, SPEITW and SPEIPM existed between northern and southern Xinjiang. SPEIPM was a better indicator of global warming than SPI. Both SPI and SPEIPM had increasing trends, which contradict previously reported trends in global drought. In conclusion, the decrease in drought severity observed over the last 53 years may indicate some relief in the water utilization crisis in Xinjiang, China.

Key words | drought severity, Standardized Precipitation Index, Standardized Precipitation Evapotranspiration Index, trend

INTRODUCTION

Global warming, as indicated by the reported increase in global surface temperature by 0.74 °C over the past 100 years, is now an accepted fact (IPCC 2007). Water- and climatic-related hazardous events have happened frequently over the past several decades, as have more extreme events. Drought is one of these extreme events and is harmful to agriculture, ecology, hydrology, economy and human life (Núñez et al. 2014). Under the global warming background, slight decreases in severity of drought were observed using the Palmer Drought Severity Index (PDSI) (Palmer 1965) and monthly precipitation (P) (Sheffield et al. 2012; Sun et al. 2012). By the end of the 21st century, 15–44% of the world is anticipated to be affected by drought (IPCC 2012). In China, the crop area affected by drought increased annually from an average 11.6 to 25.1 million hectares between the 1950s and early 2000s, which amounts to an increase of 116%; and the proportion of crop area impacted by drought increased from 8 to 16% (NBSC 2010; MWR 2010; Xu et al. 2014). Frequent severe droughts in many areas of northern China in 1997 and from 1999 to 2002 (Zhang 2003), as well as in southwestern China from 2009 to 2010 (Xu et al. 2014; Zhang et al. 2012a), caused huge economic and social losses. Drought severity has been quantified by different drought indices, such as the dryness index (DI) (Budyko 1974; Arora 2002), the PDSI (Palmer 1965) and the Standardized Precipitation Index (SPI) (McKee et al. 1993), the Crop Moisture Index (Palmer 1968), the Composite Index (CMA 2006), the Joint Deficit Index (Kao & Govindaraju 2010).
and so on. Among these, the SPI describes both short- and long-term drought impacts by taking into account $P$ anomalies at different timescales (Mirabbasi et al. 2015). The length of the $P$ record and the nature of probability distributions affect the estimation of SPI values (Mishra & Singh 2010). The SPI is a purely $P$-based index and does not consider the role of other climatic or hydrologic factors in the development of a drought event. This has led to the development of deuterogenic standardized drought indices, such as the Standardized Runoff Index (Shukla & Wood 2008), the Standardized Precipitation Evapotranspiration Index (SPEI) (Beguería et al. 2010; Vicente-Serrano et al. 2010), the Standardized Alternative to the PDSI (Sheffield et al. 2012), the Standardized Groundwater Index (Bloomfield & Marchant 2013), the Standardized Streamflow Index (Núñez et al. 2014), and the Standardized Snow Melt and Rain Index (Staudinger et al. 2014).

The SPEI, which is the standardized difference between cumulative $P$ and cumulative reference evapotranspiration ($ET_o$), is well suited to representing the effects of global warming on drought severity (Beguería et al. 2010). Besides being multiscale like the SPI, the SPEI is easy to calculate and is as sensitive as the PDSI in measuring evapotranspiration demand (Beguería et al. 2013). Although the SPEI is relatively new (developed in 2010), it has been applied in many research contexts, including studies of climate change, drought variability, drought reconstruction, drought atmospheric mechanisms, drought impacts and drought monitoring (Vicente-Serrano et al. 2010). With the increase in the applications of the SPEI, there has been considerable improvement in the methods used to compute it. One of the improvements requires calculating $ET_o$ using the Hargreaves equation (Hargreaves & Samani 1985) or the Penman-Monteith equation (Allen et al. 1998) recommended by the Food and Agriculture Organization (FAO) (Jensen et al. 1990), because there was bias toward the temperature of drought index (Zhang et al. 2016a), of which $ET_o$ was estimated using the Thornthwaite (1948) (TW) equation. By using observational and global gridded data, Beguería et al. (2013) highlighted three different $ET_o$ (or actual evapotranspiration) calculation methods and their effects on the resulting SPEI series. Based on this information, they recommended the most robust PM equation for estimating $ET_o$, provided the required climatic data are available.

In recent years, different drought indices, analysis technologies, study durations, and regions in Xinjiang have been investigated. First, the drought indices, i.e. SPI and SPEI, have been frequently utilized with the analysis of $T$ and $P$. Wang et al. (2013) reported that $P$ indices values significantly increased in Xinjiang from 1960 to 2009. Using the SPI, Zhang et al. (2012b) inferred that the severity and duration of droughts have decreased in northern Xinjiang (NX), but increased in the southern region of south Xinjiang (SX) and the center of eastern Xinjiang. Yang et al. (2011) conducted an analysis of spatiotemporal changes (1960–2100) in $T$ and $P$ extremes in the Tarim River Basin (located in the southeastern Xinjiang) over 1960–2009. Their results indicated a higher probability of flood occurrence in summer together with frequent occurrence of droughts. Wang et al. (2015) analyzed monthly SPEI during 1960 to 2010 and its teleconnection with atmospheric circulation patterns in northwestern China, including Xinjiang. Their results showed that step changes occurred in 1986, droughts occurred frequently before 1986, and wet periods prevailed after 1986. The periods of 1973–1983 and 1993–1998 showed the highest and lowest drought activity, respectively. Second, analysis technologies, such as tree ring or satellite data, were applied to overcome the limitations in observation data or in spatial scale (Chen et al. 2015; Xu et al. 2015). Cao et al. (2015) evaluated terrestrial water storage changes of Gravity Recovery and Climate Experiment satellite data, derived total deficit index to investigate drought dynamic over northwestern China, including Xinjiang, from 2003 to 2012. They concluded that the study region experienced a severe long-term drought from May 2008 to December 2009. Li & Zhou (2014) analyzed trends in $ET_o$, $P$ and an aridity index (DI) during 1960–2010 and found a general decline in drought severity in Xinjiang. Previous studies have contributed greatly to the assessments of drought severity, but regional drought severity research is still needed given the differences in the evolution, trends and spatiotemporal distribution of droughts in arid and semi-arid regions.

Previous research has shown that the evolution and trends in drought characteristics in Xinjiang differ based on the drought indices used, and these apparent trends may even conflict with one another (Zhang et al. 2012b; Li & Zhou 2014). In recent years, the SPI and SPEI have
been applied widely to assess drought severity, but no comparisons related to the $ET_o$ estimation methods or their effects on SPEI at the site-scale have been conducted for arid and semiarid regions. This study aims to: (1) assess the differences between TW-based $ET_o$ and PM-based $ET_o$, as well as their effects on SPEI$_{TW}$ and SPEI$_{PM}$ estimates in the arid and semi-arid regions of Xinjiang; (2) compare the temporal evolution, trends and spatial distribution of SPEI$_{TW}$ and SPEI$_{PM}$ against the SPI at the one-, three-, six- and twelve-month timescales for different subregions; and (3) analyze the correlations between the three drought indices and assess their sensitivity to $P$ and $ET_o$. Given the extensive applications of the SPI and SPEI indices in drought analysis, the adaptability and utility of the SPEI in arid and semi-arid areas would be evaluated.

**METHODOLOGY**

**Study area and data sets**

The Xinjiang Uygur Autonomous Region is located in northwestern China, interior mainland central Asia. The region encompasses both arid and semi-arid zones. In general, the area is characterized by ‘three mountains and two basins.’ The ‘three mountains’ features include the Kunlun Mountains in the south, the Tianshan Mountains in central Xinjiang, and the Altai Mountains to the northeast. The ‘two basins’ refer to the Tarim Basin between the Tianshan and Kunlun mountains, and the Junggar Basin between the Altai and Tianshan mountains. The two basins both contain vast deserts, including the Takelamakan desert in the south, which is the largest desert in China. The region is thus divided into two (NX, which has 26 sites, and SX, which has 27 of the total 53 sites) by the Tianshan mountain range. The sites in SX and those close to the Taklamakan desert are extremely arid. Because wet marine air rarely reaches inland, the ecosystems in these regions are very fragile. The subsurface of the Gobi desert responds quickly to solar heating, resulting in major evaporation of ground moisture and thus increased drying (Zhang et al. 2012c). Xinjiang is also quite sensitive to global climate changes (Deng et al. 2014).

The 53 weather stations were selected in and around Xinjiang for this study (Figure 1). The elevations of these sites range between 30 and 3,095 m above sea level. The weather stations around the Taklamakan desert are very sparsely distributed. Climate data at the daily and monthly
timescales were collected from the Meteorological Data Sharing Service Network in China for the 1961 to 2013 period. These data have undergone quality control and are more than 99% complete. Missing data were replaced by the long-term averages for the relevant months.

Calculation of drought indices

Since McKee et al. (1995) first proposed the SPI as a meteorological drought index, this metric has been widely used to measure drought across different regions (Hayes et al. 1999; Bonaccorso et al. 2005; Tsakiris & Vangelis 2004; Paulo & Pereira 2007; Mishra & Singh 2010). To compute the SPI at different timescales using the P series in the present study, the procedure suggested by McKee et al. (1995) and Lloyd-Hughes & Saunders (2002) was followed. Drought levels were divided into five groups: extreme drought (SPI \( \leq -2.0 \)), heavy drought (\(-1.5 > \text{SPI} \geq -2.0 \)), moderate drought (\(-1.0 > \text{SPI} \geq -1.5 \)), mild drought (\(-0.5 > \text{SPI} \geq -1.0 \)) and normal conditions (\(0.5 > \text{SPI} \geq -0.5 \)).

The procedure for computing SPEI was developed by Vicente-Serrano et al. (2010). In order to compute this index, the following steps were followed: (1) estimate \( ET_o \) at the monthly timescale; (2) determine the accumulation of water deficit \( D_i \) (=P-\( ET_o \)) at the one-, three-, six- and twelve-month scales; and (3) normalize \( D_i \) as a log-logistic probability distribution and obtain the SPEI index. The plotting position method was used for the probability-weighted moments estimation, which were used for determining the scale, shape, and origin parameters of probability density function with a three-parameter log-logistic distribution. The drought level classifications for the SPEI are similar to those of the SPI. Because it is a component of the \( D_i \) calculation, the accuracy of the \( ET_o \) estimation affects the precision of the overall SPEI. Vicente-Serrano et al. (2010) estimated \( ET_o \) using the TW equation (\( ET_{o,TW} \) below). Other methods to calculate \( ET_o \) have also been used, including the FAO-56 PM equation (Allen et al. 1998; Li et al. 2010), the Blaney-Criddle (1950) equation, the Hargreaves-Samani (1985) equation, and the Priestley-Taylor (1972) equation. Of these, the FAO-56 PM equation is considered to be the standard and has been applied widely, including in studies of Xinjiang, China (Liao et al. 2012). The method is written as Equation (1) (Allen et al. 1998):

\[
ET_{o,PM} = \frac{0.408\Delta(R_n - G) + \gamma \ 900/T_a + 273u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.54u_2)}
\]

where \( ET_{o,PM} \) is the reference evapotranspiration (mm day\(^{-1}\)), \( G \) is soil heat flux (MJ m\(^{-2}\) day\(^{-1}\)), \( T_a \) is mean air temperature at 2 m (C), \( u_2 \) is wind speed at 2 m (m s\(^{-1}\)), \( e_s \) is saturation vapor pressure (kPa), \( e_a \) is actual vapor pressure (kPa), \( \Delta \) is the slope of the vapor pressure curve (kPa C\(^{-1}\)), \( \gamma \) is a psychrometric constant (kPa C\(^{-1}\)), and \( R_n \) is net radiation (MJ m\(^{-2}\) day\(^{-1}\)). \( R_n \) is the difference between incoming net shortwave radiation and outgoing net longwave radiation. Monthly \( G \) is estimated by:

\[
G_i = 0.07(T_{i+1} - T_{i-1})
\]

where \( i + 1 \), \( i \) and \( i - 1 \) are numbers of months, respectively. Here, \( ET_{o,PM} \) is assumed to be the closest value to true \( ET_o \). The difference between \( ET_{o,PM} \) and \( ET_{o,TW} \) is denoted as \( D_{ET} \):

\[
D_{ET} = ET_{o,PM} - ET_{o,TW}
\]

SPI and SPEI were calculated for each site. SPI and SPEI for SX, NX and EX were calculated using the averages of monthly climatic data at the 26, 27 and 53 sites, respectively.

In order to assess additional information on drought conditions, the ratios of \( P \) to \( ET_{o,PM} \) and \( ET_{o,TW} \), denoted as \( DI_{TW} \) and \( DI_{PM} \), i.e., \( DI_{TW} = P/ET_{o,TW} \) and \( DI_{PM} = P/ET_{o,PM} \), were also computed. In these equations, dryness increases as \( DI \) decreases. The UNEP (1995) defines \( DI \) values in the ranges of \([0.05, 0.2] \), \([0.2, 0.5] \), \([0.5, 0.65] \), and \([0.65, 0.8] \) as arid, semi-arid, dry sub-humid, and semi-humid climate types, respectively.

Trend analysis

The modified Mann-Kendall (MMK) method (Yue & Wang 2002) based on a non-parametric analysis (Mann 1945; Kendall 1975) was applied in this study to robustly test trends in the time series \( x_i \) (\( L = 1, 2, ..., n \), where \( n \) is the total number of years). The MMK test considers the effects
of self-correlation on the $x_{ij}$ statistic ($Z$) tested using the original Mann-Kendall method to obtain a modified statistic $Z_m$ using a correction factor – $n^*$, written as follows:

$$Z_M = Z / \sqrt{n^*},$$

where

$$n^* = \begin{cases} 1 + \frac{2}{n} \sum_{j=1}^{n-1} (n - 1) r_j & \text{for } j > 1 \\ 1 + \frac{2}{n} \sum_{j=1}^{n-1} m_j^2 + (n - 1) r_j & \text{for } j = 1 \end{cases}$$

where $r_j$ is the self-correlation coefficient of $x_{ij}$ given a lag time $j$. The sample auto-correlation coefficient $r_j$ is estimated by (Kotegoda 1980; Topaloglu 2006)

$$r_j = \frac{1}{\bar{x}} \sum_{i=1}^{n} (x_i - \bar{x})(x_{i+j} - \bar{x})$$

where $\bar{x}$ is the average of all $x_i$ in the data set. The lower and upper limits of $r_j$ at 95% confidence level are estimated as follows (FAO 1973; Kotegoda 1980):

$$CL(r_j)(\alpha = 0.05) = -\frac{1}{n-j} \pm \frac{1.96}{n-j} \sqrt{\frac{n}{2(n-j)}}$$

If $r_j$ falls inside the confidence limits, the hypothesis that $r_j$ is zero is accepted using a two-tailed test and a maximal lag $j$ with temporal-dependence in $x_L$, i.e. $j_{TD}$, is determined.

Both $Z$ and $Z_m$ follow a standard normal distribution under the null hypothesis that there is no trend in $x_L$. The null hypothesis is rejected if $|Z|$ and $|Z_m|$ are both larger than 1.96 at the 0.05 confidence level. If $Z$ (or $Z_m$) is positive (negative), $x_L$ has an upward (downward) trend. When $j_{TD} = 0$, the value of $Z$ can reliably be used to determine the significance of a trend; when $j_{TD} \geq 0$, the value of $Z_m$ is computed to detect the significance of the trend (Li et al. 2010). The magnitude of the trend (b) was robustly estimated by Sen (1968) and can be calculated as follows:

$$b = Median\left(\frac{x_k - x_m}{k - m}\right)$$

where $x_m$ and $x_k$ are the values in the $m$th and $k$th year, respectively.

## RESULTS

### Spatial distribution of $ET_o$, $P$, $D_{ET}$ and $D_i$

Xinjiang, China has a temperate continental climate. The average winter temperature ($T_a$) is always below zero. Thus, when using the TW and PM equations for $T_a < 0$, $ET_{o,TW}$ equals 0 mm but $ET_{o,PM}$ is positive. $D_{ET}$ also varies depending on the site, resulting in spatially different $D_{i,TW}$ and $D_{i,PM}$. Figure 2 shows the spatial distribution of annual mean monthly $ET_{o,TW}$, $ET_{o,PM}$, $D_{ET}$, $P$, $D_{i,TW}$ and $D_{i,PM}$ across Xinjiang. The values were divided geographically by the Tianshan Mountain range. Li & Zhou (2014) examined the spatial distribution of monthly climatic variables and found higher insolation and temperature values in SX than in NX. Hence, large differences in index values for climatic variables can be expected between NX and SX. There were larger $ET_{o,TW}$, $ET_{o,PM}$ and $D_{ET}$ values but smaller $P$, $D_{i,TW}$ and $D_{i,PM}$ values in SX than in NX, which is reasonable given the ‘three mountains and two basins’ landscape of Xinjiang. Although $ET_{o,TW}$ and $ET_{o,PM}$ had similar spatial distributions (Figure 2(a) and 2(b)), $ET_{o,TW}$ underestimated $ET_o$ when compared to $ET_{o,PM}$ at all 53 sites. $D_{ET}$ values ranged from 4 to 48 mm for the various sites (Figure 2(c)), and $P$ ranged from 1 to 42 mm (Figure 2(d)). $D_{ET}$ was large in Xinjiang, which was not unexpected. Jensen et al. (1990) also reported that the TW equation underestimated $ET_o$ in arid and semiarid regions. Zhang et al. (2016a) recommended using the more robust PM equation to estimate $ET_o$ and the PDSI to account for this variation. The present results also indicate that the PM equation is a more reliable estimate of $ET_o$ in Xinjiang than the TW equation because $D_{ET}$ is large and should not be neglected in this area. As a result, $D_{i,TW}$ and $D_{i,PM}$ varied among the sites and had different ranges (Figure 2(e) and 2(f)), which accounted for the corresponding differences between SPEI$_{TW}$ and SPEI$_{PM}$ values in NX and SX.

### Monthly variations in $ET_{o,TW}$ and $ET_{o,PM}$, $P$ and $D_{ET}$

Figure 3 shows the temporal variations in $D_{ET}$ at the monthly and yearly scales for the period 1961–2013 in NX, SX and the entirety of Xinjiang (EX). The trend test results using the MMK method are given in Table 1. For the mean monthly values (Figure 3(a)–3(c)), $ET_{o,TW}$ were lower than $ET_{o,PM}$
for every month, and $D_{ET}$ was greatest in April (57, 65 and 62 mm in NX, SX and EX, respectively). The $ET_{o,TW}$, $ET_{o,PM}$ and $P$ values were greatest in July (summer) and extremely small in January and December (winter). $P$ values in July equaled 31.9, 14.5 and 25.1 mm while $ET_{o,PM}$ values equaled 174, 168, and 176 mm in NX, SX and EX, respectively. For the annual values (Figure 3(d)–3(f)), $ET_{o,TW}$ were 608, 669 and 644 mm while $ET_{o,PM}$ were 993, 1,095 and 1,075 mm in NX, SX and EX, respectively. Similar to the monthly variations, there were obvious differences in annual $ET_{o}$ and $P$ between NX and SX (see Li & Zhou 2014). Annual mean $D_{ET}$ values in NX, SX and EX reached as high as 386, 426 and 450 mm, respectively. Our annual $ET_{o,PM}$ results for EX were similar to those for $ET_{o,PM}$ values reported for certain stations throughout Xinjiang. Additionally, variations in annual $ET_{o,TW}$, $ET_{o,PM}$, $P$ and $D_{ET}$ were also shown (Figure 3(d)–3(f)). By combining with the results from Table 2, it was shown that annual $P$ increased significantly in NX, SX, and EX with $j$ values all being larger than 12, showing strong temporal dependence. Annual $ET_{o,TW}$ for EX increased insignificantly with a value $b$ equal to 0.85, while annual $ET_{o,PM}$ in EX decreased significantly with a value $b$ equal to -1.04 for the study period. Both $ET_{o,TW}$ and $ET_{o,PM}$ had strong temporal dependence with all $j_{TD}$
values >3. There were also trends differences in NX and SX with different \( j_{TD} \) values. Opposite temporal trends for \( ET_{o, TW} \) and \( ET_{o, PM} \) resulted in decreasing \( D_{ET} \) values, which were insignificant in all of NX, SX and EX. Although \( ET_{o, TW} \) varied similarly with \( ET_{o, PM} \) for different months and at the annual scale, the TW equation underestimated \( ET_{o} \) in NX, SX, and EX. Therefore, the TW equation proved unsuitable for estimating \( ET_{o} \) in Xinjiang.

Figure 4 demonstrates the temporal variations of \( D_{i,TW} \) and \( D_{i,PM} \) at the monthly and annual scales during 1961–2013 in NX, SX and EX. The trend test results are also given in Table 1. The mean monthly \( D_{i,TW} \) values were all larger than \( D_{i,PM} \) for every month, and only small differences between NX, SX and EX were seen (Figure 4(a)–4(c)). Annual \( D_{i,TW} \) was also larger than \( D_{i,PM} \) in NX, SX and EX (Figure 4(d)–4(f)). In general, the large differences between \( D_{i,TW} \)
Table 1 | Trend test results for \( P, ET_o, PM, ET_o, TW, D_{ET}, D_{PM} \) and \( D_{ET} \) in different sub-regions

<table>
<thead>
<tr>
<th>Region</th>
<th>Item/Statistic (mm)</th>
<th>NX</th>
<th>SX</th>
<th>EX</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( j_{TD} )</td>
<td>( Z_m )</td>
<td>( b )</td>
<td>( j_{TD} )</td>
</tr>
<tr>
<td>( P )</td>
<td>12</td>
<td>3.63*</td>
<td>0.11</td>
<td>11</td>
</tr>
<tr>
<td>( ET_o PM )</td>
<td>3</td>
<td>-1.76</td>
<td>-0.73</td>
<td>9</td>
</tr>
<tr>
<td>( ET_o TW )</td>
<td>6</td>
<td>2.22*</td>
<td>0.84</td>
<td>9</td>
</tr>
<tr>
<td>( D_{ET} )</td>
<td>9</td>
<td>-1.60</td>
<td>-1.51</td>
<td>11</td>
</tr>
<tr>
<td>( D_{PM} )</td>
<td>0</td>
<td>1.93</td>
<td>1.94</td>
<td>8</td>
</tr>
<tr>
<td>( D_{ET} )</td>
<td>0</td>
<td>1.13</td>
<td>0.42</td>
<td>0</td>
</tr>
</tbody>
</table>

\( j_{TD} \) = maximal lag with temporal-dependence in series \( x \), \( b \) = Sen’s slope.  
* = significant trend.

and \( D_{ET} \) for the various months and at the annual scale were caused by how \( ET_o \) was estimated (i.e., using the TW or PM equations). This also resulted in different variances and trends in the annual \( D_{ET} \) and \( D_{PM} \) series. Annual \( D_{PM} \) in SX increased insignificantly, but significantly in NX and EX with \( j_{TD} \) = 0, 7 and 8, respectively. The \( b \) values of annual \( D_{PM} \) in NX, SX and EX were 1.94, 2.00 and 1.86, respectively. Annual \( D_{ET} \) in NX, SX and EX increased insignificantly with serial independence (\( j_{TD} = 0 \)), the \( b \) values in NX, SX and EX were 0.42, -0.26 and 0.06, respectively, which were much smaller in absolute values of trends for annual \( D_{ET} \) than annual \( D_{PM} \). The linear trends in annual \( D_{ET} \) did not reflect the actual variation in drought severity, considering that \( P \) increased and \( ET_o \) decreased simultaneously in Xinjiang. The tested trends in annual \( D_{PM} \) did reflect drought severity in Xinjiang very well.

The observed \( D_{ET} \) in Xinjiang resulted to different \( D \) values for different months and at the annual scale (see Table 2; certain high \( DI_{ET} \) values for the months of February, March and November should be omitted because they were overestimated as a result of very low \( ET_o, TW \) values). Because the \( ET_o, TW \) values were lower than the \( ET_o, PM \) values, higher \( DI_{ET} \) values than \( DI_{PM} \) values were obtained for each respective month. The \( DI_{ET} \) implied a wetter climate in Xinjiang than the \( DI_{PM} \) did, resulting in a ‘semi-arid’ climate classification for EX rather than ‘arid’. This also showed the deviation of \( ET_o, TW \) from \( ET_o, PM \) and that of \( DI_{ET} \) from \( DI_{PM} \). Using \( DI_{ET} \) resulted in an unreasonable climate type classification for Xinjiang.

The large \( D_{ET} \) values found resulted from the use of different equations to estimate \( ET_o \) values. The TW equation only considers air temperature-related climatic variables; therefore, increasing air temperature (\( T \)) should result in increased \( ET_o \). On the other hand, the PM equation considers \( T \) as well as \( u_2 \), relative humidity and sunshine hour, and the estimated \( ET_o, PM \) values reflect the comprehensive interactions between these factors. Therefore, \( ET_o, PM \) values are thought to better characterize atmospheric evaporation ability in Xinjiang. Beguería et al. (2013) emphasized the more important role of using proper \( ET_o \) equations in moisture-limited areas than in high-\( P \) areas. As with the \( DI_{ET} \) versus \( DI_{PM} \) variations, the variations in \( D_{ET} \) likely contribute to corresponding differences between the subsequent estimates of SPEI{\( ET_{TW} \)} and SPEI{\( ET_{PM} \)} values in Xinjiang.

Table 2 | Multi-year mean monthly and annual \( DI_{ET} \) and \( DI_{PM} \) in NX, SX, and EX

<table>
<thead>
<tr>
<th>Month/Annual</th>
<th>NX</th>
<th>SX</th>
<th>EX</th>
<th>NX</th>
<th>SX</th>
<th>EX</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.89</td>
<td>0.13</td>
<td>0.37</td>
</tr>
<tr>
<td>February</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.45</td>
<td>0.07</td>
<td>0.19</td>
</tr>
<tr>
<td>March</td>
<td>9.2</td>
<td>0.14</td>
<td>0.97</td>
<td>0.24</td>
<td>0.04</td>
<td>0.10</td>
</tr>
<tr>
<td>April</td>
<td>0.41</td>
<td>0.07</td>
<td>0.20</td>
<td>0.17</td>
<td>0.03</td>
<td>0.09</td>
</tr>
<tr>
<td>May</td>
<td>0.26</td>
<td>0.08</td>
<td>0.17</td>
<td>0.16</td>
<td>0.05</td>
<td>0.10</td>
</tr>
<tr>
<td>June</td>
<td>0.22</td>
<td>0.10</td>
<td>0.16</td>
<td>0.16</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>July</td>
<td>0.23</td>
<td>0.11</td>
<td>0.17</td>
<td>0.18</td>
<td>0.09</td>
<td>0.13</td>
</tr>
<tr>
<td>August</td>
<td>0.20</td>
<td>0.09</td>
<td>0.14</td>
<td>0.15</td>
<td>0.07</td>
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<tr>
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<td>–</td>
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<td>December</td>
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<td>–</td>
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<td>0.20</td>
<td>0.06</td>
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Temporal variations in SPI, SPEITW and SPEIPM

We have shown the computed SPI, SPEITW and SPEIPM for all studied sites, but detailed results have not been shown due to limited space. Temporal changes of SPI, SPEITW and SPEIPM in EX from 1961 to 2013 at the one-, three-, six- and twelve-month scales are illustrated in Figure 5. SPI values ranged from 3.5 to 3.2, 2.9 to 4.0, -2.6 to 3.2, and -2.9 to 3.7, respectively. SPEITW values ranged from -2.9 to 3.7, -3.9 to 3.9, -3.2 to 2.9 and -3.6 to 2.5, respectively; and SPEIPM values fluctuated between -5.5 and 2.5, -2.8 and 2.6, -2.5 and 2.5, and -2.6 and 2.2, respectively. Both the SPI and the SPEIPM indicated less severe droughts than the SPEITW at different timescales, especially in the most recent 20 years. This suggests that SPEITW does not reflect actual changes in drought conditions in Xinjiang very well, particularly given the general increase in DI over the last 50 years (Li & Zhou 2014).

Further comparisons of temporal changes in the twelve-month SPI, SPEITW and SPEIPM values in NX, SX and EX
(Figure 6) showed the following. (1) Both the twelve-month SPI and SPEIPM were generally consistent in their variation patterns from 1961–2013, and both indicated some discrepancy between the drought severity levels in NX and SX, especially from 1969–1973 and 1989–1992. For the most severe drought recorded (1974–1981) (Wen & Shi 2006), the peak values and durations of both the SPI and SPEIPM were consistent at the twelve-month scale when briefly compared. (2) Drought conditions reflected by the twelve-month SPEITW partly agreed with those reflected by the twelve-month SPI and SPEIPM; discrepancies were more frequent between the NX and SX regions, which is unusual for adjacent regions, particularly given that NX is semi-arid and SX is arid according to their respective DI values. Absolute values of the twelve-month SPEITW were larger than those of the twelve-month SPI and SPEIPM and indicated more extreme drought or waterlogged conditions, especially in SX. The twelve-month SPEITW was less satisfactory in denoting the most severe drought over the period 1974–1981 in Xinjiang because it showed short persistence and higher agreement between NX and SX. These phenomena indicate that the PM equation is better than the TW equation at supporting accurate SPEI estimates in Xinjiang. Beguería et al. (2015) noted that accurate index estimations are vital to realistic drought severity assessments in moisture-limited areas; and our results support this conclusion. (3) A comparison of the SPEITW and SPEIPM with SPI, indicated that both SPEIs had larger, more frequent peak values than SPI for a given period, i.e., 1967, 1970, 1979, 1983 and 2007–2010. This suggests that different drought severity implications are deduced by the SPEIs compared to the SPI. Both the SPEITW and SPEIPM reinforced drought severity over the SPI, although values varied for SPEITW and SPEIPM, and the former consistently indicated even shorter drought durations and larger peak values. These trends were especially evident during the most severe drought event in Xinjiang (1974–1981). Vicente-Serrano et al. (2010) concluded that if $T$
increased progressively by 2 or 4°C, the reinforcement of drought severity associated with higher water demands prompted by $ETo$ was readily identified by SPEI. Therefore, the SPEI can better reflect the effects of increased $T$ on droughts when compared to the SPI. (4) Although only the twelve-month comparison between SPI, SPEITW, and SPEIPM is shown here, similar conclusions were drawn for the other timescales. Therefore, the PM equation should be used to estimate $ETo$ in Xinjiang over the TW equation. However, in data scarce regions, the TW equation may still be used because $T$-related data are easy to obtain in most regions of the world.

**Correlations between SPI, SPEITW and SPEIPM**

Correlation scatter plots for each SPI, SPEITW, and SPEIPM pairing at different timescales across the region (EX) are shown in Figure 7 ($R^2$ is determination coefficient). Relatively good correlations were found between SPI and SPEIPM at all four temporal scales across Xinjiang ($0.66 < R^2 < 0.76$), while the correlations between SPI and SPEITW ($0.47 < R^2 < 0.64$) and between SPEITW and SPEIPM ($0.54 < R^2 < 0.64$) were less notable (Figure 7). These relationships were also revealed by the concentration of data-points along the 1:1 line. The linear-trend lines relating SPI to SPEIPM at the four timescales were close to the 1:1 lines, and the linear slope and $R^2$ values both increased with the timescale analyzed. On the other hand, the trend lines for the SPI-SPEITW pairing and the SPEITW-SPEIPM pairing were not as close to their respective 1:1 lines, and their linear slope and $R^2$ values generally decreased with the timescale analyzed. SPEITW did not agree with SPI very well, but SPEIPM did at the EX scale.

Beguería *et al.* (2015) verified that the equations used to calculate $ETo$ could potentially influence long-term trends in SPEI series and that the magnitude of the SPEI trend increased as the timescale studied increased (i.e., from months to years). Our results confirmed their conclusions to a large extent. However, the results of Beguería *et al.* (2015) were based on global gridded data, which is useful for drought severity monitoring at the global scale but lacks the resolution necessary to support a regional analysis such as Xinjiang. This emphasizes the importance and necessity of the present research once again.

There are also differences between the Pearson’s correlation coefficient ($r$) in the NX, SX and EX regions. The values of $r_1$ for SPI vs SPEITW, $r_2$ for SPEITW vs SPEIPM, and $r_3$ for SPEITW vs SPEIPM for the four studied timescales in NX, SX, and EX are compared in Figure 8. An acceptably high correlation ($r > 0.5$) between the SPI, SPEITW, and SPEIPM series was found. As the timescale assessed increased, the $r_1$ and $r_3$ values generally decreased, while the $r_2$ value increased. The $r_2$ curves were generally higher than the $r_1$ and $r_3$ curves for NX, SX, and EX. Values of $r_1$ and $r_2$ exhibited the following regional pattern: NX > EX > SX. Values for $r_3$ followed the opposite trend. The largest difference in $r_3$ values existed between NX, SX and EX compared to $r_1$ and $r_2$ ranges. In general, the correlations between the SPI and SPEIPM were better than between...
Figure 7 | Correlations between SPI, SPEI<sub>Tw</sub> and SPEI<sub>PM</sub> at the (a)–(c) one-month, (d)–(f) three-month, (g)–(i) six-month, and (j)–(l) twelve-month timescales in EX. \( R^2 \) is the coefficient of determination.
SPI and SPEITW or between SPEITW and SPEIPM, and all correlations between the three drought indices showed large differences between the NX and SX regions.

The $r$ values of the three drought indices for different timescales were much smaller and more variable than the $r$ values found in Beguería et al. (2013). The $r$ values in their study were greater than 0.93 for three different $ET_o$ equation-based SPEI series and 13 sites in the Netherlands and Spain. This indicates that the performance of different $ET_o$ equations affects SPEI more in Xinjiang, China, than in the Netherlands or Spain. This is likely because Xinjiang is located in an arid and semi-arid region and there are over three months when $T$ is below zero there, which results in large $D_{ET}$ values. On the other hand, negative $T$ values have less impact on $D_{ET}$ in the Netherlands and Spain because these countries belong to different (wetter and warmer) climate types than Xinjiang. Therefore, it is not surprising that larger deviations between SPEITW and SPEIPM were found in Xinjiang than in the Netherlands and Spain. This emphasizes the importance of choosing a proper $ET_o$ equation when calculating SPEI.

### Influence of $P$ and $ET_o$ on SPI, SPEITW and SPEIPM

Correlations between the drought indices (SPI, SPEITW and SPEIPM) and related climatic variables ($P$ and $ET_o$) reflect the influence of climatic variables on these indices. Higher (positive or negative) $r$ values mean greater (positive or negative) sensitivity of the drought index to $P$ or $ET_o$ (Vicente-Serrano et al. 2015). The $r$ values for SPI vs $P$, $r_5$ for SPEITW vs $P$, $r_6$ for SPEIPM vs $P$, $r_7$ for SPEITW vs $ET_o$, and $r_8$ for SPEIPM vs $ET_o$ at the various timescales within NX, SX and EX are illustrated in Figure 9. $r$ values were largest compared to the other four $r$ values, followed by $r_6$, $r_5$, $r_8$ and $r_7$ for the same region. $r_4$, $r_5$ and $r_6$ values were positive, but $r_7$ and $r_8$ values were negative; as a result, the sensitivity of the drought indices to $P$ was much higher than their sensitivity to $ET_o$.

Sensitivities were ranked as follows: SPI vs $P$ $>$ SPEIPM vs $P$ $>$ SPEITW vs $P$ $>$ SPEITW vs $ET_o$ $>$ SPEIPM vs $ET_o$ $>$ SPEITW vs $ET_o$. The sensitivity of the SPEITW to $P$ or $ET_o$ was generally lower than the sensitivity of SPEIPW to $P$ or $ET_o$ in NX, SX and EX. Additionally, all absolute values for $r_4$, $r_5$, $r_6$, $r_7$ and $r_8$ decreased as the timescale analyzed increased. In terms of the different regions, the sensitivity of the various drought indices to the related climatic variables in NX (wetter and cooler) was stronger than that in SX and EX (drier and warmer).

Values of $r$ for SPEI vs $P$ and for SPEI vs $ET_o$ in this study were generally lower than $r$ values found in Vicente-Serrano et al. (2015), where 21 series of $P$ and $ET_o$ were generated following a Monte Carlo simulation and then applied to calculate four standardized drought indices, including SPEI. In their study, SPEI was equally sensitive to $P$ and $ET_o$; the correlation between SPEI and $P$ increased nonlinearly as average $P$ increased, and the correlation between SPEI and $ET_o$ increased linearly as average $P$ increased (see Figure 10(a) in Vicente-Serrano et al. 2015). However, it should be noted that the stations they selected were mostly coastal or near coastal regions; only two out of 34 sites were located inland. On the other hand, all
studied sites in the present research were located inland and were far from any seas. Therefore, the results of these two studies may differ because there is unavoidable spatiotemporal variability in $P$ and $T$ for different regions.

Trends in the SPI and SPEIs

The Sen’s slope ($10^3b$) and MMK statistic ($Z_m$) values were compared for the SPI, SPEI$_{TW}$ and SPEI$_{PM}$ over twelve months at the one-, three-, six- and twelve-month timescales (Figure 10). Figure 10 shows the following.

1) Values of $b$ and $Z_m$ for both SPI and SPEI$_{PM}$ in different months were generally positive regardless of the temporal scale. This indicates that drought severity for each month in Xinjiang generally decreased from 1961 to 2013 according to the SPI and SPEI$_{PM}$, although seasonality was a factor. However, there were negative $Z_m$ values for SPEI$_{TW}$ at months 4, 6, 4 and 2 given the one-, three-, six- and twelve-month scales, respectively. Additional negative values were found for the SPEI$_{TW}$ $b$ value. Trends in SPEI$_{TW}$ varied alternately between increasing and decreasing, revealing the complicated nature of drought severity. These results indicate that droughts in Xinjiang were alternately lighter or harsher over the period 1961–2013 according to the SPEI$_{TW}$.

By comparing the $b$ and $Z_m$ values for the SPI, SPEI$_{TW}$ and SPEI$_{PM}$, we were able to identify great consistency between the SPI and SPEI$_{PM}$ trends but little consistency between the SPI-SPEI$_{TW}$ and SPEI$_{TW}$-SPEI$_{PM}$ trends.

2) The differences in $b$ values over twelve months decreased consistently as the timescale increased for each index. The $j_{TD}$ values of SPI in 2, 4, 6 and 12 months were larger than 0, the $j_{TD}$ values of SPEI$_{TW}$ in 3, 2, 0 and 0 months were larger than 0, and the $j_{TD}$ values of SPEI$_{PM}$ in 7, 8, 8 and 12 months were larger than 0. The $j_{TD}$ values of SPI from one- to twelve-month timescale increased from 1 and 8 to 11 and 12, respectively. The $j_{TD}$ values of SPEI$_{TW}$ were generally smaller than 8, indicating temporal-independence of SPEI$_{TW}$. The $j_{TD}$ values of SPEI$_{PM}$ ranged between 1 and 12 and become more and more close for each month as the timescale increased to 12-month. The general increase in $j_{TD}$ values at the
The changes, correlations and trends in SPEITW did not agree well with those of SPI at the four studied timescales, but those of SPEIPM did. Beguería et al. (2013) reported that the magnitude of a trend increased with the timescale for SPI but declined at the global scale, i.e., drought severity was increasing worldwide. In spite of their conclusion, local and regional drought severity and trends may differ from our results. Given that SPI has been accepted worldwide as a spatiotemporal drought index (Guttman 1998; Hayes et al. 1999), SPEIPM is a more acceptable and applicable index than SPEITW in Xinjiang because of its high consistency with SPI at different timescales. Therefore, the following section will compare SPI and SPEIPM but not SPEITW.

Figure 11 shows the spatial distributions of Sen’s slope ($10^3b$) and the significance of the trends in annual mean SPI and SPEIPM at the one-, three-, six- and twelve-month timescales for the 1961–2013 period in Xinjiang. The number of sites at which different SPI and SPEIPM trends were noted and series with serial self-correlation structures ($j_{TD} \geq 1$) were found are also given in Table 3. At 51 of 53 sites, there were upward trends in SPI for all timescales. Only two sites, i.e., Tienganlike and Qijiaojing, both of which were located in eastern Xinjiang, exhibited downward trends in SPI at the four timescales. The number of sites with significant upward trends in SPI generally increased as the timescale assessed increased because there were an increasing number of sites at which the SPI series had self correlations. Fewer sites exhibited significant upward trends in SPEIPM than in SPI. A greater number of sites showed insignificant (upward or downward) trends in SPEIPM than in SPI. No site exhibited a significant upward trend in SPEIPM. The spatial distribution of SPI in Xinjiang was close for different timescales and was similar to that for SPEIPM. However, the spatial distributions of SPI and SPEIPM generally differed greatly at the same timescale. The SPI series at 21, 26, 29 and 49 sites had serial self correlations at the one-, three-, six- and twelve-month timescales, respectively, while the SPEIPM series at 40, 41, 45 and 53 sites had serial self-correlations at the one-, three-, six- and twelve-month timescales, respectively. Therefore, the greater the number of sites at which the SPEIPM (or SPI) series had self-correlations, the greater the number of sites with significant trends in SPEIPM (or SPI); this is because serial self-correlations always change the significance of the trends from being significant to insignificant. Generally, there were more sites that had significant trends in SPEI or SPEIPM in NX than in SX. The differences in the trends across these two regions were more evident in the SPI values than in the SPEIPM values at the different temporal scales. Ranges of $b$ for the SPI shifted from $-4.2 \times 10^{-3}$–$1.62 \times 10^{-3}$ at the one-month timescale to $-1.87 \times 10^{-2}$–$3.66 \times 10^{-2}$ at the twelve-month timescale; and ranges of $b$ for SPEIPM shifted from $-3.73 \times 10^{-2}$–$-3.92 \times 10^{-2}$ at the one-month timescale to $-4.19 \times 10^{-2}$–$-5.91 \times 10^{-2}$ at the twelve-month timescale. Whether using SPI or SPEIPM, many more sites indicated upward trends than downward trends, which highlighted the general decrease in drought severity throughout Xinjiang. These results agreed well with Li et al. (2014), who inferred general increasing trends in $P$ throughout Xinjiang, as well as with Li & Zhou (2014), who also showed a historical decrease in drought through their analysis of spatiotemporal variations in DI from 1961 to 2010 in Xinjiang.

On the one hand, $ET_0$ began increasing in the early 1990s in northwestern China, including Xinjiang (Li et al. 2014), which has resulted in increased drought risks because of higher atmospheric evaporative demand. However, on the other hand, the increase in mean annual $P$ in Xinjiang (Wang et al. 2015) has resulted in upward trends for both the SPI and SPEI indices in recent decades. The increasing trend of SPI in Xinjiang or northwestern China is mainly due to $P$ increase. This result has been reported by other studies (Zhang et al. 2012b; Wang et al. 2013; Chen et al. 2015; Xu et al. 2015), also shown in this research in Tables 1 and 3. Correspondingly, the weather in Xinjiang has become slightly wetter than before, despite the occurrence of major droughts from 1974 to 1981 and 2009 to 2010.
DISCUSSION

There were many studies on the evolutions, spatial-temporal distributions, and frequencies of drought in Xinjiang. Many applied observed data and calculated some drought indices, such as SPI (Zhang et al. 2012b), evaporative wet index (Zhang et al. 2016b), $T$ and $P$ extremes (Yang et al. 2011), and SPEI (Wang et al. 2015). Other studies also applied tree-ring or satellites technologies, and the deduced data were further used for estimating some drought indices (Cao et al. 2015; Chen et al. 2015; Xu et al. 2015; Zhang et al. 2016b). This study used the observation data at 53...
sites in EX over 1961–2013. In general, there is some consistency between this and other studies, i.e., both revealed decreasing trends of drought, but differ in some severe drought period during the study period. For example, the drought period was 1973–1983 during the whole period of 1960–2010 from Wang et al. (2015), but was 1974–1981 from Wen & Shi (2006) and this research. The differences in the results existed because of many factors. These factors include the following. (i) The drought indices were estimated using different mathematic methods. The proposed indices were used for different goals, e.g., the $T$ and $P$ extremes focused on extreme drought events, SPI and SPEI revealed multi-scalar drought evolutions, and $DI$ denoted the ratio of $P$ to $ET_o$. (ii) The tree ring sampling revealed a long history of droughts, but at a small spatial scale at single or a few sites. The satellite data provided drought distribution information in a larger spatial scale, but with a shorter duration.

This work is an important contribution to the understanding of the spatiotemporal variations in drought severity within arid and semi-arid regions. The SPI, SPEITW and SPEIPM must be selectively applied based on regional conditions. The SPI is applicable when the region’s water balance is not a contributing factor to drought. The SPEI accounts for the possible effects of temperature variability and temperature extremes beyond the context of global warming (Vicente-Serrano et al. 2010), but this index requires more climate data than the SPI to be reliable. The SPEIPM performed better than the SPEITW when compared to the SPI, indicating that the PM equation is a better estimation of $ET_o$. Therefore, the SPEIPM is the most preferred index for denoting drought severity in Xinjiang when climatic data are available. SPEITW is applicable when only temperature data are available. Of the three drought indices, SPEIPM was selected as the best index for denoting drought severity in Xinjiang, China.

Although there were deviations for $ET_o,TW$ when compared to $ET_o,PM$ in this research, and the TW method has several well documented limitations and biases (e.g., Jensen 1973; Amatya et al. 1995), the method has been extensively applied (Beguería et al. 2013; Yu et al. 2014), because it requires only temperature-related climatic variables, and is more accurate in the regions with positive temperature in most days of a year. Mavromatis (2007) showed that the PM equation is not necessarily superior to the TW when used in a drought index. Yu et al. (2014) computed SPEITW for the whole China and revealed that severe and extreme droughts have become more serious since the late 1990s for all of China. $ET_o,TW$ were also applied in drought evaluation of other regions (such as California drought) with the index PDSI (Robeson 2015). SPEITW and SPI were effective to monitor the effects of rapid onset of drought at Mead, in the north eastern United States (Hunt et al. 2014). Except for the TW and PM equations, other methods were used, such as Haude (1992) formula and Hargreaves (Hg) equation (Hargreaves & Samani 1985) for estimating SPEI in the Czech Republic (Potop et al. 2012) and global droughts (Beguería et al. 2013), respectively. Estimation of $ET_o$ could be conducted with different methods, considering the user’s objectives, the studied regions, and the efficacy that could be achieved.

<table>
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<th>Timescale (months)</th>
<th>SI</th>
<th>II</th>
<th>SD</th>
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$SI$, significant increase; $II$, insignificant increase; $SD$, significant decrease; $ID$, insignificant decrease; $SN_{TD,1}$ means site number in the total 53 sites with $TD_o \geq 1$.

ETo values in Xinjiang differed depending on whether they were estimated by the TW or PM equation. Positive $D_{ET} (-ET_o,PM-ET_o,TW)$ values occurred either for different months or at inter-annual scales. Annual $D_{ET}$ values in EX reached 430 mm. Under the circumstances, the TW equation proved unsuitable for estimating ETo. Generally large $D_{ET}$ values resulted in correspondingly different $D_{ET,TW}$ and $D_{ET,PM}$ values, as well as different SPEITW and SPEIPM values. The PM equation was more reliable than
the TW equation in accurately estimating $ET_o$ and subsequent SPEI in Xinjiang. The computed SPEI$_{TW}$ was more consistent with the SPEI$_{PM}$ but less consistent with the widely-accepted SPI at the four studied timescales, not only based on the $r$ values at the different indices, i.e., SPI, SPEI$_{TW}$ and SPEI$_{PM}$, but also based on their appropriateness in denoting the historically severe drought from 1974–1981. Moreover, correlations between the three types of drought indices and their related climatic variables ($P$, $ET_o$,$TW$, or $ET_o$,$PM$) showed that both the SPI and SPEI$_{PM}$ were highly sensitive to $P$, but the SPEI$_{PM}$ and SPEI$_{TW}$ were not very sensitive to $ET_o$.

Using the MMK method, increasing trends in SPI and SPEI$_{PM}$ were detected for different months, although seasonality was a factor. There were much more downward trends in SPEI$_{TW}$ which were largely inconsistent with the upward trends in SPI and SPEI$_{PM}$. Trends in the SPI and SPEI$_{PM}$ for different timescales increased at most sites, although the number of sites with insignificant trends increased as the timescale assessed increased. A greater number of sites had insignificant SPEI$_{PM}$ trends than SPI trends at the same timescales because the SPEI$_{PM}$ series had stronger self-correlations than the SPI series. The generally increasing trends in the drought indices implied a decrease in drought severity across the arid and semi-arid regions of Xinjiang. The drought evolution patterns in Xinjiang contradicted those at the global scale, as noted in Beguería et al. (2013).

In the meantime, regional differences were also shown between NX and SX through a comparison of different $D_{ET}$ ranges, different correlations between the three drought indices or drought indices vs climatic variables, different trends and significances, and different spatial distributions. The overall comparison between the three different drought indices indicated that the SPI and SPEI$_{PM}$ were both applicable in Xinjiang; however, the SPEI$_{PM}$ better denotes drought severity in Xinjiang in the context of climate change.

Overall, there were three important points from this research which demonstrated new insights. First, this study clearly quantified the relative accuracy difference between $ET_o$,$TW$ and the $ET_o$,$PM$ in time and space for different sub-regions of Xinjiang, China. This knowledge may serve as a reference for the other arid regions. Second, our results revealed how the SPEI changed when $ET_o$ was estimated by two different methods, i.e., the Thornthwaite (1948) and the FAO56 Penman-Monteith equation. The performances of the drought indices, i.e., SPI, SPEI$_{TW}$ & SPEI$_{PM}$, may change in different climate regimes, e.g., humid or tropical conditions, but the results from this study are particularly useful for arid or semi-arid regions. Third, this study determined and ranked the sensitivities of the drought indices to different climatic variables over Xinjiang. It also examined drought severity, evolution, distribution, and trend over the two sub-regions, i.e., NX and SX. This knowledge is critical for regional and local water resource management.

Drought is a complex phenomenon and difficult to pinpoint in time and space (Vicente-Serrano et al. 2011). This research provides a detailed comparison between three drought indices and their applications in Xinjiang. The outcome of this investigation, particularly new information of regional drought evolution, is essential for disaster prevention and management.

**ACKNOWLEDGEMENTS**

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