Dependence of trends in and sensitivity of drought over China (1961–2013) on potential evaporation model

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Abstract The Palmer Drought Severity Index (PDSI) can lead to controversial results in assessing droughts responding to global warming. Here we assess recent changes in the droughts over China (1961–2013) using the PDSI with two different estimates, i.e., the Thornthwaite (PDSI_th) and Penman-Monteith (PDSI_pm) approaches. We found that droughts have become more severe in the PDSI_th but slightly lessened in the PDSI_pm estimate. To quantify and interpret the different responses in the PDSI_th and PDSI_pm, we designed numerical experiments and found that drying trend of the PDSI_th responding to the warming alone is 3.4 times higher than that of the PDSI_pm, and the latter was further compensated by decreases in wind speed and solar radiation causing the slightly wetting in the PDSI_pm. Interestingly, we found that interbasin difference in the PDSI_th and PDSI_pm responses to the warming alone tends to be larger in warmer basins, exponentially depending on mean temperature.

1. Introduction

Drought is a major natural hazard measured by water availability significantly below normal conditions for a region [Alley, 1984; Dai, 2011; Sheffield et al., 2012]. Because of great socioeconomic significance [Seneviratne et al., 2010; Greve and Seneviratne, 2015; Diffenbaugh et al., 2015], the occurrence of disastrous droughts has received enormous public attention and discussion including, for example, the recent prominent California droughts in 2011–2015 [Aghakouchak et al., 2015; Shukla et al., 2015; Diffenbaugh et al., 2015; Cheng et al., 2016] and the once-in-a-century droughts in southwest China (2009 continuing to now) [Qiu, 2010; Abbas et al., 2014; Zuo et al., 2015]. However, attribution of the recent droughts in California [Aghakouchak et al., 2015; Shukla et al., 2015] and in southwest China [Qiu, 2010; Abbas et al., 2014; Zuo et al., 2015] is controversial in terms of how much role the anthropogenic global warming was playing.

Generally, the expectation is that drought events (frequency and/or severity) would increase with global warming [Intergovernmental Panel on Climate Change, 2013]. However, that expected increase in droughts was not confirmed by a global assessment of droughts using observed precipitation [Sun et al., 2012] or simulated soil moisture from state-of-the-art land surface models [Sheffield et al., 2012; Greve and Seneviratne, 2015] for historical periods or climate model projections for future periods [Roderick et al., 2014]. Formal detection and attribution of regional droughts can be difficult [Cheng et al., 2016] for short instrumental records. In particular, assessment of droughts depends on the indices being chosen and the methods of estimating the potential evaporation with different climatic forcings [Hobbins et al., 2008; Sheffield et al., 2012; Yuan and Quiring, 2014]. For example, the Palmer Drought Severity Index (PDSI) [Palmer, 1965; Mishra and Singh, 2010] is among the most widely used indices in routinely monitoring and assessing droughts in the United States [Dai, 2011; Palmer, 1965; Hobbins et al., 2012] and also in the classification of meteorological drought category in China [China Meteorological Administration, 2006]. For the same PDSI index, very different, even opposite trends in droughts have been found when the potential evaporation was estimated in two different methods, i.e., the widely used Thornthwaite approach [Thornthwaite, 1948] and the Penman-Monteith approach [Allen et al., 1998] in Australia [Hobbins et al., 2008] and on the global average [Sheffield et al., 2012]. While the change of potential evaporation estimated by the Penman-Monteith method has better agreement with the pan measurement than the Thornthwaite method [Chen et al., 2005], assessment of droughts at global and/or regional scales is mostly based on the PDSI of using the traditional Thornthwaite approach which found increased drought frequency and severity in recent decades [Zou et al., 2005; Ma and Fu, 2006; Zhai et al., 2010; Dai, 2011].
In recognition of shortcomings in the Thornthwaite approach, this study aims at assessing and quantitatively interpreting recent changes of droughts over China using both the traditional Thornthwaite and the Penman-Monteith approaches.

2. Data and Methodology

2.1. Data and Control for Consistency

To estimate the PDSI and implement sensitivity analysis of the PDSI droughts to individual meteorological forcings, we use a daily meteorological data set that can drive the Penman-Monteith equation and the Thornthwaite equation. This daily meteorological data set is for the recent period of 1961–2013 and includes precipitation (denoted \( P \)), air temperature (mean, maximum, and minimum) (denoted \( T \)), wind speed (denoted \( W_s \)), sunshine duration (denoted \( S_d \)), relative humidity (denoted \( R_h \)), etc. That data set consisting of 756 stations is provided by the National Climate Center of the China Meteorological Administration and has been quality-controlled before being released to the scientific community (http://www.nmic.gov.cn/). The 756 stations are distributed in 10 large river basins covering China, as shown in Figure 1.

As the overall statistics over China are important, we conduct further temporal and spatial consistency control on the data based on the information of the length of available data (and the missing data) and density of stations, etc. First, we have done temporal consistency control using the information of data length and select 520, out of the 756, meteorological stations with continuing measurements. Then second, we conduct further control on the spatial inhomogeneity of station distribution. We select 210 grid boxes of 2° × 2° longitude by latitude, and each grid boxes should contain at least one station with continuing meteorological measurements. For any grid box containing more than one station, the average over those stations has been used to represent the results in that grid box. In doing that, we reduce possible influence from temporal and spatial inhomogeneities in the data and ensure that the overall statistics are robust.

2.2. The Thornthwaite and Penman-Monteith Methods in Estimating the PDSI

The PDSI is a simple water balance model originally designed by Palmer [Palmer, 1965] under the framework of balance between water supply and atmospheric evaporative demand. In brief, the PDSI drought is estimated under Climatically Appropriate For Existing Conditions (CAFEC) for each month. To estimate the required precipitation under CAFEC, potential evaporation is the important forcing.

In the original estimate of PDSI, the traditional Thornthwaite (denoted as \( PET_{th} \)) approach has been widely used,

\[
PET_{th} = 16(10T/l)^a
\]

where \( T \) is the monthly averaged air temperature and \( l \) is a heat index \( l = 12d \sum_{j=1}^{12} \left( \frac{T_j}{5} \right)^{1.514} \), in which \( d \) is a correction factor depending on latitude and month. And, \( a = 0.49 + 0.0179l - 0.000077l^2 + 0.000000675l^3 \).

In this study, we also use a Penman-type estimate of potential evaporation, i.e., the Food and Agricultural Organization (FAO) Penman–Monteith reference evaporation,

\[
PET_{pm} = \frac{0.408 \Delta (R_n - G) + \gamma 0.96 U_2 \left(1 - \frac{R_h}{100}\right)_{1275}}{\Delta + \gamma (1 + 0.34U_2)}
\]

where \( R_n \) is the net radiation (see the detailed calculation in section S1 in the supporting information), \( \Delta \) is the slope of the vapor pressure curve, \( G \) is the soil heat flux, \( U_2 \) is the wind speed (\( W_s \)) at 2 m height, \( \gamma \) is the psychrometric constant, \( e_c \) is the saturation vapor pressure at a given air temperature, \( R_h \) is the relative humidity (0–100), and \( e_c \times (1 - R_h/100) \) is the vapor pressure deficit. We apply the standard algorithm to estimate PET (denoted as \( PET_{pm} \)) as per recommended by the FAO [Allen et al., 1998].

2.3. Design of Numerical Experiments to Quantify the Sensitivity of Droughts

To disentangle different responses of the two estimated PDSI to meteorological forcings and then to quantify the sensitivity of droughts, we design a base case to examine the PDSI when all climatic forcings are free of any trends. Note that the trends in the PDSI and also in meteorological variables are calculated using the Sen’s slope in the nonparametric Mann–Kendall test [Mann, 1945; Kendall, 1975]. To do that, we apply a
detrending technique [Mao et al., 2015] that forms new climatic time series. The simplest and widely used detrending approach would be just eliminating the trend component from observed climatic time series to form new “detrended” time series. That detrending approach can apply to the air temperature. The complication is that other climatic variables are generally bounded by zero (e.g., precipitation, wind speed, sunshine duration, and relative humidity), and some are further bounded by one (e.g., relative humidity). For those meteorological variables, we apply the same detrending approach first to eliminate the trend component in climatic annual time series and then combine with relevant physical constraints (no less than zero and/or no larger than one) to avoid unphysical results (see the detail in section S2).

We further conduct a series of numerical experiments where the observed trend in a meteorological variable used in the PDSI estimates is kept while the rest are detrended. Note that keeping one variable and detrending the rest may affect the interdependencies of the underlying meteorological variables. Nevertheless, the numerical experiments here offer a way to synthetic analysis of one variable at the time. For example, the precipitation (only) case is the numerical experiment where all meteorological variables, except for the precipitation, are detrended. The same terminology also applies to the temperature (only) case, the wind speed (only) case, the sunshine duration (only) case, and the relative humidity (only) case. At last, we keep the observed trends in all meteorological variables and denote this numerical experiment as the historical observed case (all).

3. Results

3.1. Recent Changes in Droughts Over China
To describe the overall statistics of recent changes in droughts over China, we first prepare a plot of the time series of the PDSI (mean ± standard error) with the two different estimates of the potential evaporation, i.e., the Thornthwaite and Penman-Monteith approaches, denoted as $PDSI_{th}$ and $PDSI_{pm}$, respectively (Figure 2a). The overall statistics are based on the 210 grid boxes instead of 520 stations to reduce potential
influence of different spatial station densities as discussed in section 2.1. As shown in Figure 2a, the PDSI_th has almost remained at the normal level with almost zero trend before early 1990s and gradually declines (declining means drying) afterward, generally following the dramatic increase in air temperature (Figure 2a). The overall trend in the PDSI_th is for dramatically drying (−0.73), when integrated over the whole period of 1961–2013. Note that in classifying droughts [Palmer, 1965], the change of −0.73 in the PDSI formally leads to a higher level of drought severity.

The time series of the PDSI_pm behaves differently from that of the PDSI_th (Figure 2a), and the overall trend in the PDSI_pm is for slightly wetting (+0.09) over the same entire period. The PDSI_th responds more strongly to the increase in air temperature than the PDSI_pm as one can track the possible source from the different estimates of potential evaporation (Figure 2b). It is interesting to note that there is strong correspondence in the variations of the PDSI between the two approaches (interannual correlation = 0.73 in Figure 2a and monthly correlation = 0.78 in Figure S1 in the supporting information), while the overall trends in the PDSI can be opposite (Figure 2a). That interesting phenomenon leads to the recent debate on how much difference the estimates of potential evaporation can make in assessing droughts when using PDSI [Dai, 2011; Sheffield et al., 2012; Yuan and Quiring, 2014].

3.2. Quantifying the Sensitivity of the PDSI Droughts

We conduct a series of numerical experiments to quantify the sensitivity of the PDSI droughts. We summarize the probability density function (hereafter, PDF) of the trend in the PDSI from the grid box level (Figure 3 and Table 1) and display detailed maps in Figure S2. For the base case designed in section 2.3, all meteorological variables are detrended. In this base case, one would expect that the mean trend in the PDSI approaches to zero, if the sample size is large enough. Using the above detrended meteorological time series, which are of minimum trend for the period of 1961–2013, the trend in the PDSI_pm is roughly normally distributed (Figure 3a). The overall mean trend in the PDSI_pm in the base case is for +0.05, which is integrated over the whole period, with the standard deviation of 0.33. Similarly, the mean trend of the PDSI_th is for +0.08 with the standard deviation of 0.40 (Figure 3a). The results confirm that the new detrended time series can be practically regarded as the base case to be compared against in the following numerical experiments.

Figure 2. Changes in the recent droughts over China: 1961–2013. (a) Time series of the two different PDSI estimates forced with the Thornthwaite method (denoted as PDSI_th) and with the Penman-Monteith (denoted as PDSI_pm), against the temperature anomaly. (b) Time series of the two different estimates of potential evaporation anomaly using the two approaches (denoted as PET_th and PET_pm). The shaded range in both plots is estimated using $\sigma/\sqrt{n}$. 

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Figure 3. Quantifying the sensitivity of the recent changes in droughts over China using a series of numerical experiments. (a) The base case: the PDF (and the mean $\mu$ and standard deviation $\sigma$) of changes in the two different estimates of the PDSI after applying the “detrending” technique to all meteorological variables. (b) The temperature ($T$ only) case: detrending all variables except for the temperature, (c) the precipitation ($P$ only) case, (d) the wind speed ($Ws$ only) case, (e) the sunshine duration ($Sd$ only) case, (f) the relative humidity ($Rh$ only) case, (g) the historical observed case (all): keeping the trends in all meteorological variables, and (h) the summary of the contributions from different meteorological variables to the PDSI droughts.
In the first numerical experiment, we then just release the observed trend in the air temperature and keep the warming signal alone (Figure 3b), i.e., the temperature (only) case. The PDF of the PDSI_pm moves to the left by, on average, −0.23 with little change in the standard deviation. For the PDSI_th, the PDF moves further to the left by, on average, −0.78 with a slightly broader distribution. The results show that the response of the PDSI drought to the warming by the Thornthwaite approach is triple higher than that with the Penman-Monteith estimate.

The other climatic variable, commonly used in both the PDSI estimates, is precipitation. Thus, the succeeding numerical experiment is to keep the observed trend in precipitation alone (Figure 3c). Different from the trend in the air temperature, the precipitation change is generally less uniform spatially. As it turns out, the PDF of the PDSI in both approaches is broadened by around 2.5 times when the trend in precipitation is included. The averaged trend in the PDSI of both approaches is for slightly wetting but very small compared with the large variation. In fact, the responses of the PDSI drought intensity to the precipitation alone in the two estimates are very similar (Figures 3c and S2f and S2g) and are highly related (interception: 0 and correlation coefficient: 0.98). The interesting point here is that the precipitation trend principally determines the similar spatial pattern in the changes of the PDSI drought using the two approaches (Figures 3c and S2f and S2g) but has very little contribution to the difference in the overall averaged trend in the droughts over China.

Hence, to interpret the large difference in the PDSI by the two approaches (Figures 2 and S2a and S2b), we need to further investigate other meteorological variables individually that are absent in the PDSI_th estimate and only relevant to the PDSI_pm (Figures 3d, 3e, and 3f and S2e, S2h, and S2k). By releasing the observed trend in the wind speed, the PDSI_pm is for a positive (wetting) trend (=0.19), on average, with a slightly larger standard deviation (Figures 3d and S2k). Adding to that, when the observed trend in the sunshine duration is included, which is the surrogate shortwave radiation [Wang et al., 2015] in the potential evaporation estimate recommended by the FAO [Allen et al., 1998], the change in the PDSI_pm is for a further slightly positive (wetting) trend (=0.11) (Figures 3f and S2h). A slight decrease of relative humidity can enlarge vapor pressure deficit and then lead to a slightly negative (drying) trend in the PDSI_pm (=−0.10). Note that the change in wind speed (now termed as “global stilling” [Roderick et al., 2007; Mcvicar et al., 2012] and the decline in solar radiation (termed as “global dimming” [Wild, 2009; Wang et al., 2015]) have been observed worldwide. The combination of the decline in the wind speed and the solar radiation reported here can effectively lead to less atmospheric evaporative demand and hence less droughts. With the compensation from the effect of the warming and slightly decreasing relative humidity, the PDSI_pm is for, if any, a slightly wetting trend (+0.14) in the droughts over China on average (Figures 3g and S2b). (The PDFs of trends in all relevant meteorological variables are summarized in Figures S4–S8.) In fact, the averaged change in the drought is very small, compared with large spatial variation in the PDSI trend, that mainly arises from the spatial variation of the precipitation trend (Figures 3b, 3f, and 3h).

3.3. Interbasin Difference of the Response of PDSI Droughts to the Warming

The same framework and numerical experiments for quantifying the sensitivity of droughts can also apply to the 10 large river basins covering the whole China. The sensitivity results of the PDSI droughts are shown in Figure S3. There are large interbasin differences in the response of the two PDSI estimates of droughts to individual meteorological variables (Figure S3). Of interest in this study is the interbasin difference in the PDSI response to the warming. For simplicity, we define a PDSI ratio \( \left( \frac{\Delta \text{PDSI}_{\text{th}}}{\Delta T} \right) \) by taking the scaling ratio between the different responses of the PDSI_th and PDSI_pm to the warming (only). We found that the PDSI ratio is not a constant and can be as small as 2.8 in a cold basin like the Songhua River basin but can be as large as 10.1 in a warm basin like the Pearl River basin. Literally taken, the response of the PDSI_th can be 10 times stronger than that of the PDSI_pm to the warming in the Pearl River basin (Figure 4). Note that over the

| Table 1. Summary of the Changes in the Two PDSI Estimates in Numerical Experiments (\( \Delta \text{PDSI}_{\text{pm}} \) and \( \Delta \text{PDSI}_{\text{th}} \))
| \( P \) (only) | \( T \) (Only) | \( Ws \) (Only) | \( Rh \) (Only) | \( Sd \) (Only) | Observed |
|----------------|----------------|----------------|----------------|----------------|-----------|
| \( \Delta \text{PDSI}_{\text{pm}} \) | 0.10 | −0.23 | 0.19 | −0.10 | 0.11 | 0.14 |
| \( \Delta \text{PDSI}_{\text{th}} \) | 0.14 | −0.78 | 0.19 | −0.10 | 0.11 | −0.65 |

*aNote that each column (denoted as \( P \) (only), \( T \) (only), \( Ws \) (only), \( Rh \) (only), \( Sd \) (only), and observed) represents the contribution from each meteorological variable by taking the difference between each case and the base case in the relevant numerical experiment.*
which indicates that the instrumental records (1961–2013), we found that on average the droughts have dramatically become more severe (−0.73) in the PDSI_th with the warming, which is forced by the Thornthwaite estimate of the potential evaporation, but the changes in droughts in the PDSI_pm in the response to the warming (only) has then been compensated by the decreasing wind speed (+0.19), i.e., "global dimming," and decreasing solar radiation (+0.11), i.e., "global dimming," and therefore, the overall averaged trend in the PDSI_pm is for slight wetting (+0.09) over the same period (Figure 2).

To quantitatively interpret the different responses in droughts, we designed a series of numerical experiments considering the base case with all meteorological variables free of trends, the historically observed case with all meteorological variables' trends included, and additional five separate cases to include the observed trend in meteorological variable individually (Figures 3 and S2). We found that the warming alone leads to a dramatic drying trend in the PDSI_th by −0.78 but only induces a small drying trend in the PDSI_pm by −0.23. That small drying trend (−0.23) of the PDSI_pm in the response to the warming (only) has then been compensated by the decreasing wind speed (+0.19), i.e., "global dimming," and decreasing solar radiation (+0.11), i.e., "global dimming," and therefore, the overall averaged trend in the PDSI_pm is for slight wetting (Table 1). Surprisingly, while the precipitation trend at the grid box level basically determines the similarity of the spatial pattern in the PDSI_th and PDSI_pm (correlation = 0.98; Figures 3c and S2f and S2g), the contribution of the precipitation trend to the overall averaged PDSI trend is very small (Table 1).

We also apply the same framework for quantifying the sensitivity of droughts developed in this study at the basin (regional) scale (Figure S3). We found that the difference in the drought response to the warming between the PDSI_th and PDSI_pm tends to be larger in warm basins (regions) and tends to be smaller in cold basins (regions). The PDSI ratio (defined as \( \frac{\frac{\partial \text{PDSI} \text{th}}{\partial T}}{\frac{\partial \text{PDSI} \text{pm}}{\partial T}} \)) can be 10.1 in the Pearl River basin, which indicates that the PDSI_th drought can respond by an order of magnitude more strongly than the PDSI_pm to the warming in very warm regions. Of great interest here, we further found that the PDSI ratio

![Figure 4](image_url)

**Figure 4.** Interbasin (region) difference in the sensitivity of the two PDSI estimates responding to the warming. The scaling ratio of the sensitivity between the two PDSI estimates responding to the warming \( \left( \frac{\frac{\partial \text{PDSI} \text{th}}{\partial T}}{\frac{\partial \text{PDSI} \text{pm}}{\partial T}} \right) \) as the function of the mean temperature in each basin (region).
depends exponentially on the mean state of air temperature in each basin (region) (PDSI ratio = 2.16 e^{0.06 T}; Figure 4) and that relationship can precisely determine the PDSI ratio to be 3.4 for China. Overall, we suggest to use the PDSI_prm instead of the PDSI_th in assessing drought severity or trend because of the bias toward temperature of the PDSI_th.

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