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Key Points:

- Droughts have become more severe in the *PDSI_{th}* but slightly lessened in the *PDSI_{pm}* estimate
- Drought responding to warming was compensated by decreases in wind speed and solar radiation
- *PDSI_{th}* responds much more strongly to global warming than *PDSI_{pm}*

Supporting Information:

- Supporting Information S1

Correspondence to:

F. Sun,
sunfb@igsnrr.ac.cn

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

Jie Zhang^{1,2}, Fubao Sun², Jijun Xu³, Yaning Chen⁴, Yan-Fang Sang², and Changming Liu²
¹College of Water Sciences, Beijing Normal University, Beijing, China, ²Key Laboratory of Water Cycle and Related Land Surface Processes, Institute of Geographic Science and Natural Resources Research, Chinese Academy of Sciences, Beijing, China, ³Yangtze River Scientific Research Institute, Wuhan City, China, ⁴State Key Laboratory of Desert and Oasis Ecology, Xinjiang, Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi, China

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 Ws), sunshine duration (denoted Sd), relative humidity (denoted Rh), 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 $2^\circ \times 2^\circ$ 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 by the difference between the observed monthly precipitation and required “precipitation” that 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,

$$PET_{th} = 16(10T/l)^a \quad (1)$$

where T is the monthly averaged air temperature and l is a heat index $l = 12d \sum_{i=1}^{12} \left(\frac{T_i}{5}\right)^{1.514}$, 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,

$$PET_{pm} = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} U_2 e_s (1 - Rh/100)}{\Delta + \gamma(1 + 0.34U_2)} \quad (2)$$

where R_n is the net radiation (see the detailed calculation in section S1 in the supporting information), Δ is the slope of the vapor pressure curve, G is the soil heat flux, U_2 is the wind speed (Ws) at 2 m height, γ is the psychrometric constant, e_s is the saturation vapor pressure at a given air temperature, Rh is the relative humidity (0–100), and $e_s \times (1 - Rh/100)$ 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

Figure 1. The study area covering 10 large river basins (regions). No. 1, the SongHua River; no. 2, the Liao River; no. 3, Northwestern Rivers; no. 4, the Hai River; no. 5, the Yellow River; no. 6, the Yangtze River; no. 7, the Huai River; no. 8, Southeastern Rivers; no. 9, Southwestern Rivers; and no. 10, Pearl River. In this study area, 210 ($2^\circ \times 2^\circ$) grid boxes (color: cyan) were identified containing at least one station with continuous instrumental meteorological records. In total, 520 meteorological stations (purple dots) were used.

“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 $\pm$ 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

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 $\sigma/\sqrt{n}$.

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 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 μ and standard deviation σ) 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 (W_s only) case, (e) the sunshine duration (S_d 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.

Table 1. Summary of the Changes in the Two PDSI Estimates in Numerical Experiments ($\Delta PDSI_{pm}$ and $\Delta PDSI_{th}$)^a

	<i>P</i> (only)	<i>T</i> (Only)	<i>Ws</i> (Only)	<i>Rh</i> (Only)	<i>Sd</i> (Only)	Observed
$\Delta PDSI_{pm}$	0.10	−0.23	0.19	−0.10	0.11	0.14
$\Delta PDSI_{th}$	0.14	−0.78				−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).

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 decline 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 $\left(\left(\frac{\partial PDSI_{th}}{\partial T} \right) / \left(\frac{\partial PDSI_{pm}}{\partial T} \right) \right)$ 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

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 $\left(\frac{\partial PDSI_{th}}{\partial T} / \frac{\partial PDSI_{pm}}{\partial T}\right)$ as the function of the mean temperature in each basin (region).

210 grid boxes examined, the $\left(\frac{\partial PDSI_{th}}{\partial T} / \frac{\partial PDSI_{pm}}{\partial T}\right)$ and the $\left(\frac{\partial PDSI_{pm}}{\partial T} / \frac{\partial PDSI_{th}}{\partial T}\right)$ are always for the same sign, which leads to positive values of the PDSI ratio. By plotting the PDSI ratio against the mean air temperature in each basin, we can fit an exponential curve ($PDSI \text{ ratio} = 2.16 e^{0.06 T}$, the determination coefficient: 0.77; Figure 4). Interestingly, the PDSI ratio (≈ 3.4) and the mean air temperature ($\approx 9.8^\circ\text{C}$) over China can be plotted very closely to the exponential curve (Figure 4). The result is somewhat counterintuitive and indicates that for a basin (or a region) with high temperature, the drought measured by the $PDSI_{th}$ can respond more strongly by an order of magnitude than the $PDSI_{pm}$ to the warming, and thus, the PDSI ratio $\left(\frac{\partial PDSI_{th}}{\partial T} / \frac{\partial PDSI_{pm}}{\partial T}\right)$ depends exponentially on the mean state of the air temperature over the basin.

4. Conclusion and Summary

The PDSI with different estimates of the potential evaporation can lead to con-

troversial results in assessing droughts responding to global warming. That controversy leads to assessing changes in droughts remaining a challenge. To help address the controversy, we selected China as the study area and then assess and interpret recent changes in the droughts over China using the PDSI but with both the Thornthwaite and Penman-Monteith approaches. Using 520 meteorological stations with continuous 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 $PDSI_{pm}$, which is with the Penman-Monteith approach, are for slightly 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 stilling," 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 $\left(\frac{\partial PDSI_{th}}{\partial T} / \frac{\partial PDSI_{pm}}{\partial T}\right)$) 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

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 $PDSI_{pm}$ 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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References

- Abbas, S., J. E. Nichol, F. M. Qamer, and J. Xu (2014), Characterization of drought development through remote sensing: A case study in Central Yunnan, China, *Remote Sens.*, 6(6), 4998–5018, doi:10.3390/rs6064998.
- Aghakouchak, A., L. Cheng, O. Mazdiyasi, and A. Farahmand (2015), Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought, *Geophys. Res. Lett.*, 41, 8847–8852, doi:10.1002/2014GL062308.
- Allen, R., L. Pereira, D. Raes, and M. Smith (1998), Crop evapotranspiration guidelines for computing crop water requirements, FAO Irrig. Drain. Pap. 56, Food and Agric. Organ. of the U. N., Rome.
- Alley, W. M. (1984), The Palmer Drought Severity Index: Limitations and assumptions, *J. Clim. Appl. Meteorol.*, 23(7), 1100–1109, doi:10.1175/1520-0450(1984)023<1100:TPDSIL>2.0.CO;2.
- Chen, D., G. Gao, C.-Y. Xu, J. Guo, and G. Ren (2005), Comparison of the Thornthwaite method and pan data with the standard Penman-Monteith estimates of reference evapotranspiration in China, *Clim. Res.*, 28, 123–132, doi:10.3354/cr028123.
- Cheng, L., M. Hoerling, A. Aghakouchak, B. Livneh, X. W. Quan, and J. Eischeid (2016), How has human-induced climate change affected California drought risk?, *J. Clim.*, 29, 111–120, doi:10.1175/JCLI-D-15-0260.1.
- China Meteorological Administration (2006), *Classification of Meteorological Drought, GB/T 20481-2006* [in Chinese], China Meteorol. Press, Beijing.
- Dai, A. (2011), Characteristics and trends in various forms of the Palmer Drought Severity Index during 1900–2008, *J. Geophys. Res.*, 116, D12115, doi:10.1029/2010JD015541.
- Diffenbaugh, N. S., D. L. Swain, and D. Touma (2015), Anthropogenic warming has increased drought risk in California, *Proc. Natl. Acad. Sci. U.S.A.*, 112(13), 3931–3936, doi:10.1073/pnas.1422385112.
- Greve, P., and S. I. Seneviratne (2015), Assessment of future changes in water availability and aridity, *Geophys. Res. Lett.*, 42, 5493–5499, doi:10.1002/2015GL064127.
- Hobbins, M., A. Wood, D. Streubel, and K. Werner (2012), What drives the variability of evaporative demand across the conterminous United States?, *J. Hydrometeorol.*, 13(4), 1195–1214.
- Hobbins, M. T., A. Dai, M. L. Roderick, and G. D. Farquhar (2008), Revisiting the parameterization of potential evaporation as a driver of long-term water balance trends, *Geophys. Res. Lett.*, 35, L12403, doi:10.1029/2008GL033840.
- IPCC (2013), *Climate Change 2013: The Physical Science Basis, Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge Univ. Press, Cambridge, U. K.
- Kendall, M. G. (1975), *Rank Correlation Methods*, 202 pp., Oxford Univ. Press, New York.
- Ma, Z. G., and C. B. Fu (2006), Some evidences of drying trend over north China from 1951 to 2004, *Chin. Sci. Bull.*, 51(23), 2913–2925, doi:10.1007/s11434-006-2159-0.
- Mann, H. B. (1945), Non-parametric test against trend, *Econometrika*, 13, 245–259.
- Mao, Y., B. Nijssen, and D. P. Lettenmaier (2015), Is climate change implicated in the 2013–2014 California drought? A hydrologic perspective, *Geophys. Res. Lett.*, 42, 2805–2813, doi:10.1002/2015GL063456.
- McVicar, T. R., et al. (2012), Global review and synthesis of trends in observed terrestrial near-surface wind speeds: Implications for evaporation, *J. Hydrol.*, 416(1), 182–205, doi:10.1016/j.jhydrol.2011.10.024.
- Mishra, A. K., and V. P. Singh (2010), A review of drought concepts, *J. Hydrol.*, 391(1–2), 202–216, doi:10.1016/j.jhydrol.2010.07.012.
- Palmer, W. C. (1965), *Meteorological Drought*, U.S. Dep. of Commer., Weather Bur., Washington, D. C.
- Qiu, J. (2010), China drought highlights future climate threats, *Nature*, 465, 142–143, doi:10.1038/465142a.
- Roderick, M. L., L. D. Rotsteyn, G. D. Farquhar, and M. T. Hobbins (2007), On the attribution of changing pan evaporation, *Geophys. Res. Lett.*, 34, L17403, doi:10.1029/2007GL031166.
- Roderick, M. L., F. Sun, W. H. Lim, and G. D. Farquhar (2014), A general framework for understanding the response of the water cycle to global warming over land and ocean, *Hydrol. Earth Syst. Sci.*, 18(5), 1575–1589, doi:10.5194/hess-18-1575-2014.
- Seneviratne, S. I., T. Corti, E. L. Davin, M. Hirschi, E. B. Jaeger, I. Lehner, B. Orlowsky, and A. J. Teuling (2010), Investigating soil moisture-climate interactions in a changing climate: A review, *Earth Sci. Rev.*, 99(3–4), 125–161, doi:10.1016/j.earscirev.2010.02.004.
- Sheffield, J., E. F. Wood, and M. L. Roderick (2012), Little change in global drought over the past 60 years, *Nature*, 491, 435–438, doi:10.1038/nature11575.
- Shukla, S., M. Safeeq, A. Aghakouchak, K. Guan, and C. Funk (2015), Temperature impacts on the water year 2014 drought in California, *Geophys. Res. Lett.*, 42, 4384–4393, doi:10.1002/2015GL063666.
- Sun, F. B., M. L. Roderick, and G. D. Farquhar (2012), Changes in the variability of global land precipitation, *Geophys. Res. Lett.*, 39, L19402, doi:10.1029/2012GL053369.
- Thornthwaite, C. W. (1948), An approach toward a rational classification of climate, *Geogr. Rev.*, 38(1), 55–94, doi:10.2307/210739.
- Wang, K. C., Q. Ma, Z. J. Li, and J. K. Wang (2015), Decadal variability of surface incident solar radiation over China: Observations, satellite retrievals, and reanalyses, *J. Geophys. Res. Atmos.*, 120, 6500–6514, doi:10.1002/2015JD023420.
- Wild, M. (2009), Global dimming and brightening: A review, *J. Geophys. Res.*, 114, D00D16, doi:10.1029/2008JD011470.
- Yuan, S., and S. M. Quiring (2014), Drought in the US Great Plains (1980–2012): A sensitivity study using different methods for estimating potential evapotranspiration in the Palmer Drought Severity Index, *J. Geophys. Res. Atmos.*, 119, 10,996–11,010, doi:10.1002/2014JD021970.
- Zhai, J. Q., B. D. Su, and V. Krysanova (2010), Spatial variation and trends in PDSI and SPI indices and their relation to streamflow in 10 large regions of China, *J. Clim.*, 23, 649–663, doi:10.1175/2009JCLI2968.1.
- Zou, X., P. Zhai, and Q. Zhang (2005), Variations in droughts over China: 1951–2003, *Geophys. Res. Lett.*, 32, L04707, doi:10.1029/2004GL021853.
- Zuo, D. D., W. Hou, and W. X. Wang (2015), Sensitivity analysis of sample number on the drought descriptive model built by Copula function in southwest China, *Acta Phys. Sin.*, doi:10.7498/aps.64.100203.