Increasing Difference of China Summer Precipitation Statistics Between Percentage Anomaly and Probability Distribution Methods Due to Tropical Warming

Yayu Ma1, Liang Zhao‡, Jing-Song Wang‡, and Tao Yu‡

1Hubei Subsurface Multi-scale Imaging Key Laboratory, Institute of Geophysics and Geomatics, China University of Geosciences, Wuhan, China, ¨¨LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China, 3Key Laboratory of Space Weather, National Center for Space Weather, Beijing, China

Abstract  Precipitation anomaly grades are usually defined by the percentage anomaly (Pa) or probability distribution (Pd) methods. However, the difference between the two may lead to different estimates for the same events, creating difficulty in judging the severity of the events. Here, we quantify the difference in measuring precipitation variability in China between Pa and Pd methods and analyze physical meaning and influencing factors of the difference. The results show that Pa tends to underestimate the domain of wetness (e.g., it underestimated 7.67% in June 2018) and overestimate/underestimate the severity of extreme wetness/dryness compared to the Pd method. Because precipitation has a positive skewed distribution, and precipitation maximum values have a larger influence on Pa than on Pd. On the other hand, uniform Pa thresholds for classifying drought grades at all stations are unreasonable. Because of an asymmetrical range of actual Pa value, Pa fails to symmetrically reflect the degree of drought and flood. Spatially, the large difference usually appears in the areas with extreme precipitation. Therefore, the more extreme precipitation stations, the greater the spatial dispersion of precipitation and the greater the total difference between Pa and Pd in whole China. We further find that the Pa-Pd difference is significantly related to a concurrent warming of the tropical Indian Ocean and the tropical Pacific sea surface in spring. And the Pa-Pd difference is rising at 0.022σ/10a with the increase of extreme events associated with the ocean warming, which deserves attention from the decision-making departments.

Plain Language Summary

Frequent extreme weather events have brought huge disasters to human society. A reasonable description of the precipitation situation can help the decision-making department to reasonably evaluate the disaster levels and make reasonable response plans. There are many methods for evaluating precipitation status, among which percentage anomaly (Pa) and probability distribution (Pd) methods are commonly used. This article quantitatively compares the difference between Pa and Pd in describing the variability of precipitation. And what we find is that the Pa method underestimates the domain of wetness and overestimates the severity of extreme wetness compared to the Pd method. Besides, Pa cannot symmetrically reflect the degree of drought and flood. The same Pa value has different effects at different rainfall stations. Further, a large difference between the two methods usually appears in the areas with extreme precipitation. And the tropical ocean warming has resulted in a larger discrepancy in measuring China precipitation variability in recent years than before.

1. Introduction

Extreme precipitation has a great influence on the economy, agriculture, and the environment. Therefore, describing precipitation reasonably is particularly important (Huang & Zhou, 2002; Kharin et al., 2007; Park et al., 2001; Voss et al., 2002; Wehner, 2004). However, recently, regionally and temporally heterogeneous trends in extreme precipitation in China were reported (Sun & Zhang, 2017). And anthropogenic influence causes the variation in intensity and frequency of extreme precipitation events in China more complex (W. Li et al., 2018; Nanding et al., 2020). In this case, it is very necessary to deeply explore some reasonable methods and indices to characterize extreme precipitation (Li & Ma, 1998; Niemeyer, 2008; Tank et al., 2009).
The percentage anomaly (Pa) and probability distribution (Pd) methods for describing precipitation are widely used. In China, Pa is frequently applied in academic research, national climate operation platforms, and government documents from meteorological departments, governments, and hydrology and agriculture agencies because it is easy to understand (Zhai et al., 2005; Zou et al., 2019). However, in the context of climate change, more and more studies indicate that using Pa to characterize a climate anomaly is problematic. First, 30 years is usually considered the baseline period (e.g., 1961–1990) in the Pa method. However, precipitation does not strictly follow a 30-year cycle. Analyses of decadal precipitation time series from hundreds of stations in America, Asia, and Africa indicate that there are statistically significant precipitation changes in several different multidecadal and quasi-decadal precipitation cycles (Hu et al., 1998; Perry, 1980; Wang & Zhao, 2012). Several studies point out that almost 80, 12, 20, and 30–40-year cycles exist for the Asian monsoon or summer precipitation (e.g., Ding et al., 2008; Wang & Zhao, 2012). In America, different studies indicate that precipitation shows significant quasi-cycles with periods of approximately 2, 4–5, 6–8, and 16–22 years (e.g., Agosta & Compagnucci, 2012; Hu et al., 1998; Perry, 1980). For South African rainfall, 18.6-year lunar and 10–11-years solar cycle signals are detected (e.g., Currie, 1993). Besides, Africa rainfall is influenced by the multidecadal cycles of teleconnection patterns in the Indian Oceans, Pacific, and Atlantic oceans (Lüdecke et al., 2021). Therefore, taking a fixed period as the climatological mean state for precipitation lacks a sufficient scientific basis. Second, the Pa method depends strongly on the mean value according to its definition, which makes it difficult to establish a uniform criterion for describing precipitation grades and symmetrically reflecting the degree of drought and flood, especially in areas with less rainfall, where precipitation is unevenly spatially distributed (Han et al., 2009). For example, based on Pa, China National Standard Grades of meteorological drought define the levels of no drought (−40% < Pa), light drought (−60% < Pa ≤ −40%), moderate drought (−80% < Pa ≤ −60%), severe drought (−95% < Pa ≤ −80%), and special drought (Pa ≤ −95%). Yang and Li (2008) adopted Pa to define the same drought grades with different Pa (no drought: −15% < Pa, light drought: −30% < Pa ≤ −15%, moderate drought: −40% < Pa ≤ −30%), severe drought (−45% < Pa ≤ −40%), and special drought (Pa ≤ −45%). Some studies depict the flood using Pa but without uniform grades (Ma et al., 2018; Zhou et al., 2000). Zhan et al. (2019) indicated that Pa leads to a large fluctuation in precipitation that may amplify precipitation changes, especially in dry areas.

On the other hand, the Pd method can be applied to describe the frequency distribution characteristics of different precipitation magnitude orders and has been widely adopted in the field of extreme precipitation (Cavanaugh et al., 2015; Guttman et al., 1993; Z. Li et al., 2014; Liang et al., 2012; Luo et al., 2016). It is a general statistical concept that can be easily understood by people from different disciplines. Applying the Pd-related percentile threshold method, the precipitation extremes in the return period can be extrapolated and be more convenient for a quantitative reference (Zhang et al., 2014). The Pd method helps researchers focus on the statistics of the frequency of extreme precipitation and the precipitation thresholds based on the particular return period. For example, J. Wang et al. (2019) adopted Pd to define the precipitation thresholds for the 1, 5, 10, 20, 30, 50, 100, 200, and 500-years return periods. And B. Wang et al. (2018) discussed the extreme precipitation with 50-year and 100-year return periods. And J. Li et al. (2011) explored the thresholds for the 10-years return period of precipitation at Xinjiang.

Although the Pa and Pd methods are frequently applied in academic research to evaluate the precipitation variability and situation, few articles discuss the differences between the two methods. Some studies tried to compare different defining methods or modified Pa method to solve its problems (e.g., Nazeri Tahroudi et al., 2020; Wei & Ma, 2003). However, previous studies have not quantitatively studied the difference between the two methods in detail and identified what physical factors are responsible for the difference. In the present study, the purpose is to quantitatively obtain the spatiotemporal discrepancies between Pd and Pa for summer precipitation in China, to evaluate which method optimizes the classification of meteorological drought and the waterlogging intensity threshold and to explore physical cause related to the discrepancies.

### 2. Materials and Methods

#### 2.1. Data

The monthly precipitation data set for 613 stations in China during 1951–2018 was provided by the China Meteorological Information Center. In this study, the data set from 1961 to 2018 was adopted based on the continuous record time length for most stations. Sea surface temperature (SST) from the NOAA Earth
System Research Laboratory Physical Sciences Division (ESRL/PSD) was adopted to explore the causes of the two methods’ discrepancies (Folland & Parker, 1995; Ishii et al., 2005; Japan Meteorological Agency, 2006). 26 monthly SST indices were provided by the National Climate Center, China Meteorological Administration (http://cmdp.ncc-cma.net/cn/download.htm). Among them, Niño-3 and Indian Ocean Basin-Wide (IOBW) index are mainly analyzed as they have fine coefficient correlations with SPa minus SPD. The former is the area averaged SST from 5°S–5°N to 150°W–90°W (Trenberth & Stepaniak, 2001). The latter is the area averaged SST from 20°S–20°N to 40°E–110°E (Yuan et al., 2008). Besides, we also used geopotential height, zonal wind ($u$), and meridional wind ($v$) of NCEP-NCAR reanalysis 1 data to analyze the physical mechanism which may lead to the difference between the two methods (Kalnay et al., 1996). They cover the period from 1948 to the present and is provided at a 2.5° resolution.

2.2. Percentage Anomaly Method

The precipitation anomaly percentage reflects the degree of deviation between the precipitation in a certain period ($P$) and the average historical precipitation in the same period ($\bar{P}$). The calculation formulas of $Pa$ and $\bar{P}$ for $N$ samples are as follows:

\[
Pa = \frac{P - \bar{P}}{\bar{P}} \times 100\%
\]

\[
\bar{P} = \frac{1}{N} \sum_{i=1}^{N} P_i
\]

2.3. Probability Distribution Method Based on the Generalized Extreme Value Distribution

The term “extreme climate events” usually refers to events represented by the probabilities at the tail of a probability distribution with extreme values in a random climate sequence. Many fitting models can be chosen to accurately describe the precipitation distribution pattern (Han et al., 2009; Z. Li et al., 2014; Liang et al., 2012). While, extreme value theory shows that most probability distributions’ tails can be approximated by the generalized extreme value (GEV) distribution, which is generally used in the study of periodic climate change factors. The GEV fit has been extensively used in extreme precipitation models (Fowler & Kilsby, 2003; Gilleland & Katz, 2006). Jenkinson (1955) proposed the GEV distribution based on the block maximum model. The estimated rate of return based on the maximum distribution of three random behaviors (Gumbel, Frechet, and Weibull) has great flexibility within the three extreme distributions (Fisher & Tippett, 1928). Therefore, GEV distribution is a relatively complete extreme value distribution system that can avoid the drawbacks of using a single distribution and has been widely applied in the study of hydrometeorological extreme events (Martins & Stedinger, 2000; Prescott & Walden, 1983). The distribution model originated from Fisher and Tippett’s extremum theory. The cumulative distribution function fitted by GEV for variable $x$ is as follow:

\[
Pd(x; \mu, \alpha, k) = \begin{cases} 
\exp \left( -\exp \left( \frac{x - \mu}{\alpha} \right) \right), & k = 0 \\
\exp \left( 1 + k \left( \frac{x - \mu}{\alpha} \right)^{\frac{1}{k}} \right), & k \neq 0, 1 + k \left( \frac{x - \mu}{\alpha} \right) > 0 
\end{cases}
\]

where $k \neq 0; k, \mu,$ and $\alpha$ are shape, location and scale parameters, respectively, and the scale parameter must be greater than zero ($\alpha > 0$). The maximum likelihood method and the L-moment method are normally used for parameter estimation in GEV. The L-moment method has obvious advantages in terms of computational efficiency and small-sample reliability (Coles & Dixon, 1999). However, there are many shortcomings for L-moment as the calculation is complicated, low precision leads to poor sensitivity, and parameter calculation may cause error accumulation (Jin, 2007). Thus, the maximum likelihood method is often used due to its invariance, asymptotic unbiasedness, and consistency. In this study, the maximum likelihood method is served to estimate the fitting parameters of the GEV distribution (Kharin et al., 2007). Return values as the
quantiles of a GEV distribution are used to define the threshold of precipitation with probability $p$ at every station point to samples of annual precipitation extremes. $T$-year return value means the threshold that an annual extreme exceeds with probability $p = 1/T$. The precipitation quantile of $p = 5\% / 95\%$ we mentioned in this study actually indicates the CDF quantile of GEV fit (Figure 1). The quantile function for a given probability $p$ is as follows (Kim et al., 2020):

$$X_p = \begin{cases} \mu - \alpha \ln \left( -\ln (p) \right), & k = 0 \\ \mu - \frac{\alpha}{k} \ln \left( 1 - (-\ln (p))^k \right), & k \neq 0 \end{cases}$$ (4)

2.4. Kolmogorov-Smirnov Test

The Kolmogorov-Smirnov (KS) test is based on the maximum difference between hypothetical ($P_d(x)$) distributions and empirical ($P_d(x)$) cumulative distributions (Stephens, 1970) and is routinely used for the GEV goodness-of-fit test.

$$D = \max \left| P_d(x_i) - P_d(x_i) \right|$$ (5)

Besides, this study uses root-mean-square deviation (RMSD) to evaluate the difference between the methods.

$$\text{RMSD} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( P_d(x_i) - P_a(x_i) \right)^2}$$ (6)
3. Results

3.1. Comparison of China Summer Precipitation Variability Based on the Probability Distribution and Percentage Anomaly Methods

3.1.1. Comparison at Baoshan Station, Shanghai

Precipitation in most areas of China is mainly concentrated in boreal summer (June, July, and August). The Meiuy season over the Yangtze River Basin (the Baiu season in Japan) is one of the typical summer monsoon precipitation, which begins in mid-June and ends in mid-July (Ding, 1992; Ding & Chan, 2005). Continuous precipitations during the Meiuy seasons often cause floods in the middle and lower reaches of the Yangtze River, which is the focus of East Asian meteorologists (Nanding et al., 2020). Shanghai is a megacity near to the estuary of the Yangtze River, typically affected by the Meiuy rainfall. Figure 1 shows the statistical characteristics of monthly precipitation at the Shanghai Baoshan station in June from 1961 to 2018 using the Pd method and the Pa method. Generalized extremum distribution integrating the three typical asymptotic distribution functions can describe the skewness characteristic of precipitation and has been applied to some extent in extreme climate studies, hydrology, and other fields (Gellens, 2002). In this study, considering the sample numbers (58 samples for each station) and the different precipitation thresholds at different rainfall stations, the value range of precipitation at each station is divided equally into 20 intervals. As shown in Figure 1a, the precipitation distribution at Baoshan station is skewed but can be reasonably fitted by GEV. The maximum monthly precipitation during the period is 570.9 mm (1999), while the minimum precipitation is 37.3 mm (2005). Figure 1b shows the empirical cumulative probability and its GEV distribution for precipitation in June at Shanghai Baoshan station. The 5%/95% extreme precipitation threshold fitted by GEV is 58.2 mm/363.0 mm, which is referred to as the extreme precipitation threshold of the 20-years return period. In 2018, June precipitation was 57.2 mm, and the corresponding cumulative probability was 4.74%, indicating that the precipitation at Baoshan station was very low in June 2018. Figure 1c shows the time series of precipitation represented by the Pa (blue curve) and Pd (red curve) methods for Shanghai Baoshan station during the period of 1961–2018. Figure 1d is the same as Figure 1c but for standardized Pa (SPA; blue curve) and standardized Pd (SPD; red curve). As shown in the graphs, after standardization, the overall variation trends in the precipitation time series as represented by the two methods are roughly the same. However, there are still large differences in some years, especially in extreme years. For example, in 1999 and 2015, the values of SPA are strikingly (about one standard deviation [σ]) larger than the values of SPD, resulting in different evaluations of the extreme events: extremely wet grade for Pa but very wet for Pd in 1999. The precipitation statistical characteristics for Beijing (North China) and Guangzhou (South China) are similar to the statistical characteristics of Shanghai, that is, the values of SPA are sometimes strikingly larger than those of SPD (Figures S1 and S2).

3.1.2. Comparison of Spatial Distribution

To investigate the spatial distribution of the differences between the Pd and Pa methods, the nearest interpolation was adopted to analyze the precipitation indicated by Pd and Pa at each rainfall station in China in the summer (June, July, and August) of 2018 (Figure 2). Incomplete data time series and the low rainfall make parts of the rainfall stations in Western China nonsignificant at the 5% level according to a KS test (Figures 2a, 2c and 2e). Besides, the GEV distribution has a high goodness-of-fit for the precipitation probability distribution at most rainfall stations in China. We defined the regions with Pd greater than 50% and Pa greater than 0% as wet areas, and regions with the inverse conditions were defined as dry areas. The wet areas defined by the Pd method are larger than the wet areas defined by the Pa method. The spatial patterns obtained by both methods are generally similar except for small differences in the western regions due to the uneven distribution of rainfall stations. Generally, in June 2018, Figures 2a and 2b show that there is more precipitation in the northwestern, southwestern, northeastern, and Yellow River basins of China than usual, while there is less precipitation in the middle and lower reaches of the Yangtze River in North China in July 2018 (Figures 2c and 2d). We find that the spatial patterns of wetness and dryness are generally similar for both methods, which is consistent with the conclusions of Wu and Chen (2019) and Wu et al. (2020). While in some dry-wet transition zones in South and East China, there are some differences. Some transition zones were classified as wet areas by the Pd method but as dry areas by the Pa method. In August, there were also some differences in the boundaries between the dry and wet conditions when Pa = 50% and Pd = 0%. Because of the skewed distribution of precipitation, the mean value of precipitation is greater than
the median value at most sites, which leads to the drought ranges defined by the limit of \( P_a = 0\% \) being greater than those defined by the limit of \( P_d = 50\% \). Here, we determined that the discrepancies in the dry and wet boundaries were caused by the difference between the mean and median precipitation.

Since the \( P_d \) and \( P_a \) methods have different variation ranges, their data cannot be quantitatively compared with each other. The spatial precipitation patterns in Figure 2 of \( P_d \) and \( P_a \) panels indicate that \( P_d \) is 50\% and \( P_a \) is 0\%, respectively, representing boundaries between dry and wet areas. The stations shown by the smaller/larger black dots in \( P_d \) are significant/non-significant at the 5\% level according to a KS test. KS, Kolmogorov-Smirnov.

![Figure 2. Spatial distribution of summer precipitation \( P_d \) (left, \%) and \( P_a \) (right, \%) for June (a), (b), July (c), (d) and August (e), (f) in 2018. The solid black contours in the \( P_d \) and \( P_a \) panels indicate that \( P_d \) is 50\% and \( P_a \) is 0\%, respectively, representing boundaries between dry and wet areas. The stations shown by the smaller/larger black dots in \( P_d \) are significant/non-significant at the 5\% level according to a KS test. KS, Kolmogorov-Smirnov.

3.1.3. Quantitative Comparison

To quantitatively compare the differences in dryness and wetness degrees between the two methods, we classified the rainfall stations based on their different standard deviations (\( \sigma \)) in the summer (June, July, and
August) of 2018 as determined by SPd and SPa and calculated the percentage of stations within each class (Table 1). We found some differences in the dryness and wetness grades between the two methods. First, except for the percentage of stations with the extreme wetness grade (>1.5σ), the percentages of stations based on SPd were usually greater than those of SPa, which means that SPd obtains a relatively wetter result than SPa when describing the wetness grades, except for the extreme wetness grade (>1.5σ). SPd obtains a relatively dryer result than SPa when describing the dryness grades (<–1.5σ and <–1.5σ). Second, for the dryness and wetness division, that is, the percentage of stations in the “>0” column, most (>50%) of the rainfall stations in China showed more precipitation in July and August of 2018 under SPa. While, SPd/SPa in June displayed a wetter/drier result (54.3%/46.7%), which means in June, SPa and SPd methods show different wet or dry conditions for June 2018 and may influence the decision-making of the government agencies. In total, SPa underestimates the domain of wetness (>0) in China for summer of 2018 by about 7.67% compared with SPd.

The above study is based on a single summer. We further analyzed the scatter diagrams of SPd and SPa in the summer from 1961 to 2018 (Figure 4) to reveal some more stable features of the differences between the two methods. The results show that there are three inflection points at 1.5σ, –0.7σ, and –1.3σ for June, July, and August. Compared with SPd, SPa shows more extreme drought (<–1.3σ) and wetness (>1.5σ), but only a few data points show extreme drought compared to the number of points showing extreme waterlogging. Between –0.7σ and 1.5σ, SPd is wetter than SPa. For relatively dry conditions (–1.3σ to –0.7σ), the drought degree of SPd is greater than that of SPa. We also found that the values of SPd vary from –2 to 2, and the data range of SPa is from –2 to

Table 1

| Month | SPd | SPa | SPd | SPa | SPd | SPa | SPd | SPa |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|
| Jun   | 6.6 | 1.7 | 21.2| 14.2| 54.3| 46.7| 23.2| 16.1| 6.4 | 9.3 |
| Jul   | 3.4 | 1.5 | 14.0| 8.0 | 63.5| 54.7| 27.1| 21.3| 8.1 | 13.4|
| Aug   | 2.2 | 0.9 | 9.3 | 5.6 | 69.5| 62.9| 37.7| 29.8| 10.7| 18.4|

Abbreviations: SPa, standardized Pa; SPd, standardized Pd.
4; only a small number of stations had values less than −2. Due to the skewed distribution of precipitation, the ranges of positive and negative values are different, which indicates that the same SPa value leads to different dry and wet degrees in different regions. The dispersion of positive values also suggests that it is impossible to set uniform Pa thresholds for each station in China to define the dry/wet levels (Han et al., 2009), and the Pd method avoids this problem.

Figure 5 gives the spatial distributions of the RMSD between SPa and SPd for precipitation from 1961 to 2018. The RMSD spatial distribution shows the more stable spatial features of the differences between the two methods based on the longer data set. In general, except in western China, the regions with larger RMSD (e.g., >0.4 RMSD) are different among June, July, and August. In June, except in western China, there are large RMSD (>0.4) in the Hetao and Huanghuai regions (Figure 5a). In July, regions with larger RMSD (>0.4) appear in the middle and lower reaches of the Yangtze River and Southern China. In August, the discrepancies in Northeast China, the Huanghuai region, and the middle and lower reaches of the Yangtze River are obvious. Although the definitions of the two methods mathematically cause these discrepancies, the physical factors related to these differences are unclear. The differences in spatiotemporal distribution are likely related to the evolution of the monsoon and the rain band positions. In climatology, the rain band shifts northward with monsoon onset and development in June and July. We found that in the areas where the climatological rain bands are located, the RMSD was relatively small. The lower RMSD in these regions is likely because in the rainy season, the mean rainfall and frequency are usually larger than in other periods, and Pa tends to be fairly close to Pd. When an area is not in the rainy season, less extreme precipitation events tend to cause the average precipitation to be far from the median, resulting in a large difference between Pd and Pa. Therefore, extreme precipitation events, especially heavy rain, can have more influence on Pa but less influence on the value of Pd, especially in non-rainy seasons.
3.2. Threshold Definition of Extremes Based Pa and Pd Methods

Generally, in China, Pa is used to define the extent of drought. However, it is difficult to define a unified waterlogging standard by the Pa method due to the differences in Pa value ranges (e.g., the maximum Pa can be much larger than 200%) among the different stations. Using Pa (−95%) to define extreme drought thresholds seems unreasonable as well (Figures 6b, 6e, and 6h) (Han et al., 2009). The extreme dry thresholds for most stations are less than 10 mm. However, at some sites, especially in eastern China, these values have never appeared in historical observations since 1961. While, Pd can be used to define thresholds for both the dry and wet grades. The value ranges for the Pd method among different stations are the same, from 0% to 100%. The Pd method can be used to define thresholds of extreme dryness and wetness at different stations with a unified standard, for example, Pd of 5%/95% for extreme dryness/wetness thresholds (20-years return values) at different stations. Figure 6 shows the spatial distribution of extreme drought in China (left), of waterlogging thresholds expressed by the Pd method (right), and of drought thresholds defined by the Pa method (center). The spatial distribution of the precipitation thresholds of extreme drought in June shows (Figure 6a) that the thresholds differ greatly in the northwestern and southeastern regions. The thresholds in the northwestern region are less than 5 mm, while the thresholds in the middle and lower reaches of the Yangtze River and southern China are over 90 mm. The distribution patterns of drought thresholds increase stepwise from north to south with obvious growth rates. In July (Figure 6d), the drought thresholds are nearly the same in northeastern and central China and on the Tibetan Plateau. However, the precipitation thresholds in the southwestern region and parts of southern China are significantly higher than those in the above regions. For August (Figure 6g), the extreme drought thresholds in Southwest China are significantly higher than those in other areas. For extreme wet thresholds (the right panels), the wet thresholds vary greatly from near 0 to above 700 mm in each month. The thresholds in July and August in Northeast China
Earth and Space Science

and North China are higher than those in June, which is obviously related to rain band movement. For the wetness thresholds in August, there are small differences in Central and East China, and the thresholds are near 400 mm. For the Pd method, not only the thresholds of different stations but also the thresholds of different months can be compared with each other because they are based on the same standard.

4. Discussions

To reasonably apply the two methods, it is very necessary to understand the physical causes of the differences. The spatial average of the precipitation anomaly percentage at all stations in a region can be used to evaluate the mean state (i.e., the overall conditions) of precipitation for the region (Li & Ma, 1998; Zou et al., 2019). Here, we use spatial averaged SPA and SPD to define the mean state of precipitation variability in China. Figure 7 shows the spatial averaged time series of SPA and SPD at all stations in China in summer. We found that all the correlation coefficients of the spatial average for SPA and SPD were 0.97 (June, July, August, and JJA), and the RMSD for both methods was relatively small. This indicates that the gaps between the two methods are small when assessing the mean state. However, in some years, there are obvious gaps between SPA and SPD, such as in June 1971 and July 1993, when the results of the SPA method are obviously higher than those of the SPD method. To explore the factor that leads to this difference, we compared the time series of the difference between SPA and SPD (SPA minus SPD) with the standardized spatial variance of precipitation. We found that in July and summer, the difference series correlated well with the spatial variance of the national precipitation (r = 0.4, p = 0.002 and r = 0.24, p = 0.08, respectively) (Table 2). In general, the larger the variance is, the stronger the regional drought and waterlogging are and the more unbalanced the distribution is. A larger variance may be accompanied by a higher extreme value of precipitation, which leads to a higher SPA while SPD is relatively stable. This situation leads to a positive correlation between the national precipitation variance and the difference between SPA and SPD.
The correlation coefficients of SPa minus SPd in summer (JJA) with 26 monthly SST indices ahead of precipitation 6–1 month were explored. We found that the correlation coefficient between the SPa minus SPd and the Niño-3 SST anomaly index in May was 0.32 ($p < 0.02$) (Table 2). This indicates that in El Niño-Southern Oscillation (ENSO) years, for example, Niño-3 index $>0.5$, the difference between SPa and SPd tends to be larger. This likely results from the uneven spatial distribution of precipitation and the larger extreme precipitation values in ENSO years, having a larger influence on Pa values than Pd. This is consistent with previous studies showing that if El Niño occurred in the preceding season, the following summer in China was prone to regional floods and uneven rainfall distribution (Chen, 2002; Huang & Zhou, 2002; L. Zhao et al., 2006, 2007).

Indian Ocean supplies an amount of water moistures and plays an essential role in the precipitation evolution to China (Li & Zhao, 2019; Tan et al., 2004; Yang & Ding, 2007; S. S. Zhao et al., 2011). The correlation coefficients between the SPa minus SPd and IOBW index in March, April, and May were 0.26, 0.25, and 0.29 ($p < 0.05$). This denotes that a positive IOBW index usually leads to a larger difference between the two methods. Figure 8a showed the correlation maps between SPa minus SPd and China summer precipitation. It illustrated a correlation distribution with flooding in South and drought in North China except Xinjiang region, which denotes extreme events that easily occur in the summer with an anomaly difference value between SPa and SPd. We found that correlation maps of summer precipitation in China with the summer precipitation spatial variance in China, May Niño-3 index, and average IOBW index from March to May (Figures 8b–8d) are similar to Figure 8a, especially with more precipitation in the Yangtze River basin. This suggests that the SST anomaly patterns in the tropical Indian and Pacific oceans

### Table 2

| Indices                     | SPa minus SPd |
|-----------------------------|---------------|
| **Precipitation spatial variance** |               |
| Jun                         | $-0.23^*$ (June) |
| Jul                         | 0.40* (July)   |
| Aug                         | 0.14 (August)  |
| Summer                     | 0.24* (Summer)  |
| Mar                         | 0.14 (Summer)  |
| Apr                         | 0.25* (Summer)  |
| May                         | 0.32* (Summer)  |
| **Niño-3**                  |               |
| Mar                         | 0.26* (Summer)  |
| Apr                         | 0.25* (Summer)  |
| May                         | 0.29* (Summer)  |
| **IOBW**                    |               |

Note. The values significant at 90% confidence level are denoted by stars. IOBW, Indian Ocean Basin-Wide; SPa, standardized Pa; SPd, standardized Pd.

![Figure 8](image-url)
are important factors leading to the difference between following summer SPa and SPd and a large precipitation spatial variation in China.

To identify the relationship among them, Figure 9 shows the time series of the indices from 1961 to 2018 and the correlation maps of SPa minus SPd in summer (JJA) and global SST from March to May. The Spa-SPd difference is increasing at 0.022σ/10a with the tropical ocean warming. And the significant correlation coefficients increase in the tropical Indian Ocean and the tropical Pacific Ocean from March to May (Figures 9a–9c). And the advance and retreat of the subtropical high have an important effect on the summer precipitation in China (e.g., Sha et al., 2009). Figure 10 showed Eurasia summer mean 500 hPa geopotential height field, 700 hPa wind vector composition of zonal wind (u), and meridional wind (v) obtained by regression with the standardized four time series in Figure 9. All the geopotential height fields presented an anticyclone over the north China, leading to drought in the north China because of the descending motion anomaly generated by the high-pressure anomaly. In the wind vector regression maps, the northerlies and the southwestlies at the western edge of the west Pacific subtropical high converged over the middle and lower reaches of the Yangtze River, resulting in cyclonic shear, which favors extreme precipitation. The maps displayed by regressing the detrended wind vector and geopotential height field onto the detrended indices showed similar results (Figure 11). Furthermore, here, we selected the years with the absolute value of the standardized indices greater than one σ and performed the composite analysis on the geopotential height field of the corresponding years. In the years with larger values of SPa minus SPd (Figure 10a), the subtropical high system (denoted by 5,880 gpm) was strong and westward, leading to the prevailing southwesterly flow, in favor of frequently extreme precipitation in middle and lower reaches of Yangtze River. The strengthening subtropical high is likely induced by the tropical SST anomaly pattern (ENSO and

---

**Figure 9.** (left panel) Correlation maps between the summer SPa minus SPd and the sea surface temperature in (a) March, (b) April, and (c) May. Grid points that are statistically significant at the 95% confidence level are denoted by small crosses. (right panel) Standardized time series of (d) summer SPa minus SPd (green curve), (e) summer precipitation spatial variance (blue curve), (f) Niño-3 index in May (pink curve), and (g) mean Indian Ocean Basin-Wide (IOBW) index in March, April, and May (purple curve) from 1961 to 2018. The linear trend of the time series (green dotted line) is also plotted in (d). SPa, standardized Pa; SPd, standardized Pd.
IOBW). ENSO can cause rainfall anomalies over East Asia through the Pacific-East Asian teleconnection, in which an anomalous anticyclone over the northwestern Pacific near the Philippine sea is forced by El Niño (B. Wang et al., 2000). And the IOBW can also lead to anomalous descending motion over this region and the strengthening of the subtropical high through inducing an anomalous reversed Walker circulation (Yuan et al., 2008). Therefore, the anomaly circulation pattern associated with tropical ocean warming may explain the anomaly values of SPa minus SPd with more extreme precipitation and drought in China in summers.

5. Conclusions

This study compared the temporal and spatial distributions of monthly precipitation data as represented by the Pd method and Pa method and discussed their advantages and disadvantages when used to express the extent and distribution of dryness and wetness. The possible causes and physical meanings of the differences between both methods were also analyzed.

The results show that the Pa method tends to underestimate/overestimate the wetness/dryness domains compared with the Pd method. In fact, the boundary between dryness and wetness defined by the Pd method is mainly affected by the median precipitation, while for the Pa method, it is related to the mean precipitation. Due to the skewed distribution of precipitation, the mean value is normally greater than the median,
which causes the areas of dryness/wetness defined by the Pa method to be usually larger/smaller than the areas defined by the Pd method. In addition, using the Pd method to express the difference in precipitation can prevent the influence from the nonlinearity of Pa and the effect of the mean value variation on the extreme frequency, which is more in line with the general statistical significance. Moreover, the Pa method may overestimate/underestimate the severity of extreme wetness/dryness because of the skewed precipitation distribution. Facing frequent extreme climate events in the future (Easterling et al., 2000), the Pa method may exaggerate the actual impact of extreme weather events. Moreover, it is somewhat challenging to establish a unified standard to describe the degrees of drought or flooding with the Pa method. For the different rainfall stations, due to their various ranges of Pa, it is unreasonable to use a unified anomaly percentage standard (especially an extreme flood threshold) to classify their dryness/wetness levels. For each rainfall station, the nonlinearity and skewed distribution of precipitation make the positive and negative value ranges of Pa asymmetrical, which leads to a different dryness/wetness extent based on the same absolute value of Pa. Further studies have revealed that ENSO events and Indian Ocean SST variation, which usually lead to regional drought or wetness, may result in large discrepancies when both methods are used to define extreme events and the degrees of drought and flood. The characteristics of southern flood and northern drought in the summer are more obvious in the years with high value of SPa minus SPd. This is due to the synergistic effect of the simultaneous warming of the tropical Indian Ocean and the tropical Pacific SST in spring, which makes a more obvious evolution of west Pacific subtropical high in summer. Cyclonic shear on the west of the subtropical high finally leads to more precipitation in the middle and lower reaches of the Yangtze River.

Several articles have pointed out the problems of the Pa method when it is used to describe precipitation (Han et al., 2009; Zhan et al., 2019). Notably, in this article, we identified the differences between the Pa and Pd methods using specific spatial distributions, indicated the discrepancies when they were used to describe the drought and flood degree within determined threshold ranges, and finally explored the physical reasons...
for the differences. Our results show that the Pd method more reasonably and symmetrically represents the degrees of dryness and wetness under the climate conditions of frequent extreme precipitation events than the Pa method.

Nevertheless, using the Pd method to describe precipitation is limited by the number of samples and the fitting method. More samples and better fitting methods will make the advantages of the probability distribution method more prominent. In addition, the distribution of precipitation is only one of the methods of demonstrating the drought and flood situation. To reflect the real dryness and wetness conditions, evaporation, runoff, and groundwater recharge should also be included (Hunter et al., 2015; Trenberth, 1999; Walsh et al., 1998). Further research in this field that considers the rationality of threshold definitions and their application’s effects is needed.

Data Availability Statement

The precipitation data are provided by the China Meteorological Information Center from their website at https://www.nmic.cn/site/index/index.html. Sea surface temperature indices can be found at https://cmdp.ncc-cma.net/monitoring/cn_index_130.php and are provided by the National Climate Center, China Meteorological Administration. The authors also use the sea surface temperature (version 2), provided by the NOAA Earth System Research Laboratory Physical Sciences Division (ESRL/PSD) (https://psl.noaa.gov/data/gridded/data.cobe.html). Geopotential height field, zonal wind, and meridional wind could be accessed at http://www.psl.noaa.gov/data/gridded/data.ncep.reanalysis.derived.html.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant Nos. 41774195 and 42075040) and the National Thousand Talents Program in China (Grant No. 412481).

References

Agosta, E. A., & Compagnucci, R. H. (2012). Central-West Argentina summer precipitation variability and atmospheric teleconnections. Journal of Climate, 25(3), 1657–1677. https://doi.org/10.1175/JCLI-D-11-00206.1

Cavagnaro, N. R., Gershunov, A., Panorska, A. K., & Kozubowski, T. J. (2015). The probability distribution of intense daily precipitation. Geophysical Research Letters, 42(5), 1560–1567. https://doi.org/10.1002/2015GL063238

Chen, W. (2002). Impacts of El Niño and La Niña on the cycle of the East Asian winter and summer monsoon. Chinese Journal of Atmospheric Sciences, 26(5), 595–610. https://doi.org/10.1002/mop.10502

Coles, S. & Dixon, M. (1999). Likelihood-based inference for extreme value models. Extremes, 2(1), 5–23. https://doi.org/10.1023/A:1009905522644

Currie, R. G. (1993). Luni-solar 18.6- and 10–11-year solar cycle signals in South African rainfall. International Journal of Climatology, 13(3), 237–256. https://doi.org/10.1002/joc.3370130302

Ding, Y. H. (1992). Summer monsoon rainfall in China. Journal of the Meteorological Society of Japan. Series II, 70(1B), 373–396. https://doi.org/10.2151/jmsj1965.70.1B_373

Ding, Y. H., & Chan, J. C. L. (2005). The East Asian summer monsoon: An overview. Meteorology and Atmospheric Physics, 91(1–4), 117–142. https://doi.org/10.1007/s00703-005-0125-z

Ding, Y. H., Wang, Z., & Sun, Y. (2008). Inter-decadal variation of the summer precipitation in East China and its association with decreasing Asian summer monsoon. Part I: Observed evidences. International Journal of Climatology, 28(9), 1139–1161. https://doi.org/10.1002/joc.1615

Easterling, D. R., Evans, J. L., Groisman, P. Y., Karl, T. R., Kunkel, K. E., & Ambenje, P. (2000). Observed variability and trends in extreme climate events: A brief review. Bulletin of the American Meteorological Society, 81(3), 417–425. https://doi.org/10.1175/1520-0477(2000)081<0417:OVATIE>2.0.CO;2

Fisher, R. A., & Tippett, L. H. C. (1928). Limiting forms of the frequency distribution of the largest or smallest member of a sample. Mathematical Proceedings of the Cambridge Philosophical Society, 24(2), 180–190. https://doi.org/10.1017/S0305004100015681

Folland, C. K., & Parker, D. E. (1995). Correction of instrumental biases in historical sea surface temperature data. Quarterly Journal of the Royal Meteorological Society, 121, 319–367. https://doi.org/10.1002/qj.49712152206

Fowler, H. J., & Kilsby, C. G. (2003). A regional frequency analysis of United Kingdom extreme rainfall from 1961 to 2000. International Journal of Climatology, 23(11), 1313–1334. https://doi.org/10.1002/joc.943

Gellens, D. (2002). Combining regional approach and data extension procedure for assessing GEV distribution of extreme precipitation in Belgium. Journal of Hydrology, 268(1–4), 113–126. https://doi.org/10.1016/S0022-1694(02)00160-9

Gilleland, E., & Katz, R. W. (2006). Analyzing seasonal to interannual extreme weather and climate variability with the extremes toolkit. Journal of Climate, 25(5), 1650–1657. https://doi.org/10.1002/joc.1615

Guttman, N. B., Hosking, J. R. M., & Wallis, J. R. (1993). Regional precipitation quantile values for the continental United States computed from L-moments. Journal of Climate, 6(12), 2326–2340. https://doi.org/10.1175/1520-0442(1993)006<2326:RPQV>2.0.CO;2

Han, H., Hu, W., Chen, X., Wang, N., & Li, G. (2009). Application and comparison of three meteorological drought indices. Applied Meteorology, 20(1), 157–165. https://doi.org/10.1007/s13145-009-0003-y

Huang, R., & Zhou, L. (2002). Research on the characteristics, formation mechanism and prediction of severe climatic disasters in China. Journal of Natural Disasters, 11(1), 1–9. https://doi.org/10.13577/j.jnd.2002.0101

Huang, R., & Zhou, L. (2002). Research on the characteristics, formation mechanism and prediction of severe climatic disasters in China. Journal of Natural Disasters, 11(1), 1–9. https://doi.org/10.13577/j.jnd.2002.0101
Hunter, T. S., Crites, A. H., Campbell, K. B., & Gronewold, A. D. (2015). Development and application of a North American Great Lakes hydrometeorological database—Part I: Precipitation, evaporation, runoff, and air temperature. Journal of Great Lakes Research, 41(1), 65–77. https://doi.org/10.1016/j.jglr.2014.12.006

Ishii, M., Shouji, A., Sugimoto, S., & Matsumoto, T. (2005). Objective analyses of sea-surface temperature and marine meteorological variables for the 20th century using ICOADS and the Kobe collection. International Journal of Climatology, 25, 865–879. https://doi.org/10.1002/joc.1169

Japan Meteorological Agency. (2006). Characteristics of global sea surface temperature analysis data (COBE-SST) for climate use. Monthly Report on Climate System Separated, 12, 116.

Jenkinson, A. F. (1955). The frequency distribution of the annual maximum (or minimum) values of meteorological elements. Quarterly Journal of the Royal Meteorological Society, 81(348), 158–171. https://doi.org/10.1002/qj.49708134804

Jin, G. Y. (2007). Characteristics and application of linear moment method. Journal of China Hydrology, 27(6), 16–21. https://doi.org/10.1007/s10642-007-0106-6

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., et al. (1996). The NCEP/NCAR 40-year reanalysis project. Bulletin of the American Meteorological Society, 77, 437–471. https://doi.org/10.1175/1520-0477(1996)077<0437:tnyrp>2.0.co;2

Kharin, V. V., Zwiers, F. W., Zhang, X., & Hegerl, G. C. (2007). Changes in temperature and precipitation extremes in the IPCC ensemble of coupled model simulations. Journal of Climate, 20(8), 1419–1444. https://doi.org/10.1175/JCLI4066.1

Kim, Y., Min, S., Zhang, X., Sillmann, J., & Sandstad, M. (2020). Evaluation of the CMIP6 multi-model ensemble for climate extreme indices. Weather and Climate Extremes, 29, 100269. https://doi.org/10.1016/j.wace.2020.100269

Li, C. & Zhao, T. (2019). Seasonal responses of precipitation in China to El Niño and positive Indian Ocean dipole modes. Atmosphere, 10(7), 372. https://doi.org/10.3390/atmos10070372

Li, J., Zhang, Q., Zhang, X., & Bai, Y. (2011). Spatial-temporal evolution pattern of probability distribution characteristics of extreme precipitation in Xinjiang autonomous region 2011. Journal of Climatology, 28(2), 11–17. https://doi.org/10.3969/j.issn.1000-811X.2011.02.003

Li, W., Jiang, Z., Zhang, X., & Li, L. (2018). On the emergence of anthropogenic signal in extreme precipitation change over China. Geophysical Research Letters, 45(17), 9179–9185. https://doi.org/10.1029/2018GL079133

Li, Z., Brissette, F., & Chen, J. (2014). Assessing the applicability of six precipitation probability distribution models on the Loess Plateau of China. Journal of Hydrology: Regional Studies, 1, 72–77.

Li, C., & Zhao, T. (2019). Seasonal responses of precipitation in China to El Niño and positive Indian Ocean dipole modes. Atmosphere, 10(7), 372. https://doi.org/10.3390/atmos10070372

Li, J., Zhang, Q., Zhang, X., & Bai, Y. (2011). Spatial-temporal evolution pattern of probability distribution characteristics of extreme precipitation in Xinjiang autonomous region 2011. Journal of Climatology, 28(2), 11–17. https://doi.org/10.3969/j.issn.1000-811X.2011.02.003

Li, W., Jiang, Z., Zhang, X., & Li, L. (2018). On the emergence of anthropogenic signal in extreme precipitation change over China. Geophysical Research Letters, 45(17), 9179–9185. https://doi.org/10.1029/2018GL079133

Li, Z., Brissette, F., & Chen, J. (2014). Assessing the applicability of six precipitation probability distribution models on the Loess Plateau of China. Journal of Hydrology: Regional Studies, 1, 72–77.

Li, C., & Zhao, T. (2019). Seasonal responses of precipitation in China to El Niño and positive Indian Ocean dipole modes. Atmosphere, 10(7), 372. https://doi.org/10.3390/atmos10070372

Li, J., Zhang, Q., Zhang, X., & Bai, Y. (2011). Spatial-temporal evolution pattern of probability distribution characteristics of extreme precipitation in Xinjiang autonomous region 2011. Journal of Climatology, 28(2), 11–17. https://doi.org/10.3969/j.issn.1000-811X.2011.02.003

Li, W., Jiang, Z., Zhang, X., & Li, L. (2018). On the emergence of anthropogenic signal in extreme precipitation change over China. Geophysical Research Letters, 45(17), 9179–9185. https://doi.org/10.1029/2018GL079133

Li, Z., Brissette, F., & Chen, J. (2014). Assessing the applicability of six precipitation probability distribution models on the Loess Plateau of China. Journal of Hydrology: Regional Studies, 1, 72–77.

Li, J., Zhang, Q., Zhang, X., & Bai, Y. (2011). Spatial-temporal evolution pattern of probability distribution characteristics of extreme precipitation in Xinjiang autonomous region 2011. Journal of Climatology, 28(2), 11–17. https://doi.org/10.3969/j.issn.1000-811X.2011.02.003

Li, W., Jiang, Z., Zhang, X., & Li, L. (2018). On the emergence of anthropogenic signal in extreme precipitation change over China. Geophysical Research Letters, 45(17), 9179–9185. https://doi.org/10.1029/2018GL079133

Li, Z., Brissette, F., & Chen, J. (2014). Assessing the applicability of six precipitation probability distribution models on the Loess Plateau of China. Journal of Hydrology: Regional Studies, 1, 72–77.

Li, J., Zhang, Q., Zhang, X., & Bai, Y. (2011). Spatial-temporal evolution pattern of probability distribution characteristics of extreme precipitation in Xinjiang autonomous region 2011. Journal of Climatology, 28(2), 11–17. https://doi.org/10.3969/j.issn.1000-811X.2011.02.003

Li, W., Jiang, Z., Zhang, X., & Li, L. (2018). On the emergence of anthropogenic signal in extreme precipitation change over China. Geophysical Research Letters, 45(17), 9179–9185. https://doi.org/10.1029/2018GL079133

Li, Z., Brissette, F., & Chen, J. (2014). Assessing the applicability of six precipitation probability distribution models on the Loess Plateau of China. Journal of Hydrology: Regional Studies, 1, 72–77.
Walsh, J. E., Kattsov, V., Portis, D., & Meleshko, V. (1998). Arctic precipitation and evaporation: Model results and observational estimates. *Journal of Climate, 11*(1), 72–87. https://doi.org/10.1175/1520-0442(1998)011<0072:APAEMR>2.0.CO;2

Wang, B., Wu, R., & Fu, X. (2000). Pacific-East Asian teleconnection: How does ENSO affect East Asian climate? *Journal of Climate, 13*(9), 1517–1536. https://doi.org/10.1175/1520-0442(2000)013<1517:PEATHD>2.0.CO;2

Wang, B., Zhao, L., Xu, H., & Liu, Y. (2018). Probability distribution and partition of hourly rainfall during the rainy season over Sichuan Province. *Torrential Rain and Disasters, 37*(2), 115–123.

Wang, J., Tao, P., & Qing, W. (2019). Spatial and temporal distributions of extreme precipitation in the Wujiang River valley and reproducibility analysis. *Torrential Rain and Disasters, 38*(3), 267–275.

Wang, J., & Zhao, L. (2012). Statistical tests for a correlation between decadal variation in June precipitation in China and sunspot number. *Journal of Geophysical Research, 117*, D23117. https://doi.org/10.1029/2012JD018074

Wehner, M. F. (2004). Predicted twenty-first-century changes in seasonal extreme precipitation events in the parallel climate model. *Journal of Climate, 17*(21), 4281–4290. https://doi.org/10.1175/JCLI3197.1

We, J., & Ma, Z. (2003). Comparison of palmer drought severity index, percentage of precipitation anomaly and surface humid index. *Acta Geographica Sinica, 58*, 117–124.

Wei, J., & Ma, Z. (2003). Comparison of palmer drought severity index, percentage of precipitation anomaly and surface humid index. *Acta Geographica Sinica, 58*, 117–124.

Wu, J., Tan, X., Chen, X., & Lin, K. (2020). Dynamic changes of the dryness/wetness characteristics in the largest river basin of South China and their possible climate driving factors. *Atmospheric Research, 233*, 104865. https://doi.org/10.1016/j.atmosres.2019.104865

Yang, M. Z., & Ding, Y. H. (2007). A study of the impact of south Indian Ocean dipole on the summer rainfall in China. *Chinese Journal of Atmospheric Sciences, 31*(4), 685–694.

Yang, X., & Li, D. L. (2008). Precipitation variation characteristics and arid climate division in China. *Journal of Arid Meteorology, 26*(2), 17–24.

Yuan, Y., Zhou, W., Chan, J. C. L., & Li, C. (2008). Impacts of the basin-wide Indian Ocean SSTAs on the South China Sea summer monsoon onset. *International Journal of Climatology, 28*(12), 1579–1587. https://doi.org/10.1002/joc.1671

Zhai, P., Zhang, X., Wan, H., & Pan, X. (2005). Trends in total precipitation and frequency of daily precipitation extremes over China. *Journal of Climate, 18*(7), 1096–1108. https://doi.org/10.1175/JCLI-3318.1

Zhang, Z., Gao, C., Liu, Q., Zhai, J., Wang, Y., Su, B., & Tian, H. (2014). Risk assessment on storm flood disasters of different return periods in Huaihe River basin. *Geographical Research, 33*(7), 1361–1372. https://doi.org/10.11821/dlyj201407015

Zhao, L., Zhou, L., Wang, E., & Yin, H. (2006). Impacts of the East Asian summer monsoon anomaly during the ENSO event period on the seasonal precipitation in the lower-middle reaches of the Yangtze river and Huahe river valley. *Journal of Tropical Meteorology, 22*(4), 360–366. https://doi.org/10.16032/jissn.1004-4965.2006.04.007

Zhou, L., Zhou, L., & Wang, E. (2007). Study on causes of drought and flood over the Huahe and mid-lower Yangtze valleys during the summers with and without ENSO. *Scientia Meteorologica Sinica, 27*(06), 618–625. https://doi.org/10.3969/j.issn.1009-0827.2007.06.005

Zha, S. S., Zhou, T. J., Yang, X. Q., Zhu, Y. M., Tan, Y. K., & Sun, X. G. (2011). Interdecadal change of the relationship between the tropical Indian ocean dipole mode and the summer climate anomaly in China. *Journal of Meteorological Research, 25*(2), 129–141. https://doi.org/10.1007/s13351-011-0021-z

Zhou, Z., Song, L., & Li, X. (2000). Analysis of precipitation during the 1998 catastrophic deluge in the Changjiang river basin. *Journal of Applied Meteorological Science, 11*(3), 287–296.

Zou, Y., Wu, H., Lin, X., & Wang, Y. (2019). A quantitative method for the assessment of annual state of climate. *Acta Meteorologica Sinica, 77*(6), 1124–1133. https://doi.org/10.11676/qxxb2019.067