

Article

## Dry/Wet Conditions Monitoring Based on TRMM Rainfall Data and Its Reliability Validation over Poyang Lake Basin, China

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**Abstract:** Local dry/wet conditions are of great concern in regional water resource and floods/droughts disaster risk management. Satellite-based precipitation products have greatly improved their accuracy and applicability and are expected to offer an alternative to ground rain gauges data. This paper investigated the capability of Tropical Rainfall Measuring Mission (TRMM) rainfall data for monitoring the temporal and spatial variation of dry/wet conditions in Poyang Lake basin during 1998–2010, and validated its reliability with rain gauges data from 14 national meteorological stations in the basin. The results show that: (1) the daily TRMM rainfall data does not describe the occurrence and contribution rates of precipitation accurately, but monthly TRMM data have a good linear relationship with rain gauges rainfall data; (2) both the *Z* index and Standardized Precipitation Index (SPI) based on monthly TRMM rainfall data oscillate around zero and show a consistent interannual variability as compared with rain gauges data; (3) the spatial pattern of moisture status, either in dry months or wet months, based on both the *Z* index and SPI using TRMM data, agree with the observed rainfall. In conclusion, the monthly TRMM rainfall data can be used for monitoring the variation and spatial distribution of dry/wet conditions in Poyang Lake basin.

**Keywords:** dry/wet monitoring; TRMM; *Z* index; SPI; Poyang Lake basin

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## 1. Introduction

Floods/droughts are one of the most common natural disasters in China and often cause severe economic losses and serious damage to towns and farms, or even human death [1,2]. Especially in Yangtze River basin, which is one of the most frequently areas affected by a variety of floods/droughts events almost every year [3,4]. Poyang Lake, located in the middle and lower reaches of the Yangtze River, as well as its surrounding catchments, have suffered from frequent floods and droughts which have caused huge damage to the environment and the agricultural economy during recent decades. Moreover, it has recently been shown that the frequency and severity of the floods and droughts in Poyang Lake basin have increased since 1990 [5]. Statistics indicate that there were four severe floods in the 1990s, *i.e.*, in 1992, 1995, 1996 and 1998, and thereafter droughts happened frequently, *e.g.*, in 2003, 2006 and 2007. The rise in frequency and severity of the floods and droughts could be attributable to the increased fluctuation of warm season rainfall in Poyang Lake basin since 1990 [6]. To better understand the recent climatic fluctuations, their manifestation in different sites, and to further monitor floods' and droughts' occurrence, it is worthwhile to investigate the spatiotemporal variability of local dry/wet conditions [7], and assess what has become an important prerequisite of floods/droughts disaster prevention and mitigation [8].

Several indices have been developed and widely used for monitoring the local dry/wet conditions and reflecting the status of water deficits in different drought types (meteorological, hydrological, agricultural and socioeconomic); such as, the Palmer Drought Severity index (PDSI) [9], Standardized Precipitation Index (SPI) [10], Standardized Runoff Index (SRI) [11], Multivariate Standardized Drought Index (MSDI) [12], Standardized Precipitation Evapotranspiration Index (SPEI) [13], and so on. Guttman [14] compared the PDSI and SPI in the United States and reported that the PDSI varied from site to site with complex structures, while the SPI performed well. Keyantash and Dracup [15] evaluated the most prominent indices for different forms of drought and showed that the SPI was suitable to monitor the meteorological drought [16]. At the same time, the SPI also has several advantages relative to other indices, including its simplicity and temporal flexibility that allow its application for drought monitoring on a wide spectrum of time scales [17]. So, it has already been widely used to characterize dry/wet conditions in many countries and regions. Moreover, in a recent meeting of the World Meteorological Organization (WMO), drought experts made a consensus agreement to recommend the SPI for the characterization of meteorological droughts [18], and the National Meteorological and Hydrological Services (NMHSs) has also been encouraged to use the SPI for meteorological drought analysis [18–20]. Another drought indicator extensively used in China, is *Z* index due to its robustness and convenience of use. The *Z* index has been used at a monthly time scale as the principal index to monitor drought and flood conditions in different regions of China.

In numerous researches, the SPI or *Z* index were calculated usually based on the long term ground rain gauges data [21,22]. However, the ground rain gauges data are either sparse in both time and space, or nonexistent in many regions of the world, especially in developing countries [23], and their limited sampling areas and problems inherent in point measurements, represent a substantial difficulty when dealing with effective spatial coverage of rainfall over a large area [24]. It is both economically and practically difficult to greatly increase the number of rain gauges for estimating the spatial distribution and intensity changes of rainfall [25]. Alternatively, satellite-based rainfall measurements

are widely accepted as promising strategies to address the above limitations [24], which can continuously monitor the precipitation over a large area and receive the rainfall data in near real-time. Particularly since the successful launch of the Tropical Rainfall Measuring Mission (TRMM) satellite, in November 1997, many algorithms have been developed to combine measurements of different spaceborne sensors and ground gauges data and improve the accuracy of satellite rainfall data. The TRMM rainfall data have been recommended for application in scientific researches and are also expected to offer an alternative to ground-based rainfall estimates in the present and the foreseeable future [26].

Numerous researchers have examined the quality of TRMM estimates compared with ground rain gauges data in various regions of the world [27]. For instance, Ward *et al.* [28] found that the daily TRMM 3B42 is unable to detect light rainfall amounts and underestimates rainfall in the dry season. Li *et al.* [29] believed that the daily TRMM rainfall data are better at determining rain occurrence and mean values than at determining the rainfall extremes. Narayanan *et al.* [30] validated TRMM 3B42 data with India Meteorological Department (IMD) rain gauges data and showed that the satellite algorithm does not pick up very high and very low daily rainfalls. Similar perspectives were also shown in research by Tian *et al.* [31], AghaKouchak *et al.* [32] and Sorooshian [33]. However, many researchers also show that the TRMM data performed perfectly at monthly or a longer time scale. For example, Nicholson *et al.* [34] found that TRMM data seems to be in excellent agreement with gauge data at monthly time steps: the root mean square error is of the order of 1 mm/day and there is no significant bias. Mehran *et al.* [35] believed that satellite data capture most observed precipitation at longer temporal accumulations. Su *et al.* [36] compared TRMM data with  $0.25^\circ \times 0.25^\circ$  gridded and interpolated gauge data in South America on daily and monthly scale and found the TRMM estimates performed significantly better on the monthly scale. These previous studies have concluded that TRMM rainfall data can correctly describe the spatiotemporal characteristics of rainfall at monthly or longer time scale, which indicated that TRMM data have good potential for useful application in dry/wet conditions analysis at monthly scale.

Recently, several attempts have been made to monitor the drought or wet conditions using satellite-based rainfall data. For example, Vernimmen *et al.* [37] evaluated and corrected the bias of satellite rainfall data for drought monitoring in Indonesia. Anderson *et al.* [38] analyzed droughts based on vegetation response using remote sensed precipitation data and concluded that satellite data can improve drought monitoring. Du *et al.* [39] adopted a synthesized drought index integrating MODIS and TRMM data to monitor the droughts in Shandong province, China. Rhee *et al.* [40] studied the suitability of a new remote sensing-based drought index for agricultural drought monitoring in both arid and humid regions. Feng *et al.* [41] validated the capability of TRMM data for capturing the drought severity in Poyang Lake basin. Naumann *et al.* [42] investigated the uncertainties of monitoring drought conditions using TRMM data in Africa. Moreover, AghaKouchak and Nakhjiri [20] combined TRMM data with long-term Global Precipitation Climatology Project (GPCP) observations for drought monitoring and analysis, which broke through the limitation of short records of TRMM data and could further expand the utilization of satellite data.

Poyang Lake basin, an important national rice-producing base in the middle and lower reaches of the Yangtze River, has received far less attention in dry/wet conditions monitoring using satellite-based rainfall measurements. The Poyang Lake plays a crucial role in water security and

ecosystem security for the lower reaches of the Yangtze River, and discharges from it into the Yangtze River are higher than the total runoff of Yellow River, Haihe River and Huaihe River [5]. To implement the flood protection and drought mitigation and regulation and ensure the water safety in areas around the Poyang Lake, it is necessary to identify the dry/wet conditions variation and their spatial distribution characteristics using satellite-based rainfall data. Therefore, the objectives of the study are designed to evaluate and compare the TRMM rainfall data with rain gauges data and investigate the usefulness of TRMM rainfall for monitoring the temporal and spatial distribution of dry/wet conditions by the SPI and Z index method in Poyang Lake basin. The study is expected to serve as a useful reference and afford valuable information for future study and application of TRMM rainfall in the Poyang Lake basin as well as in other regions.

The rest of this paper is organized as follows. In the next section, details of the study area, as well as the indices and methods used in the study, are described. The main results of this study are presented and discussed in Section 3, and Section 4 summarizes the conclusions.

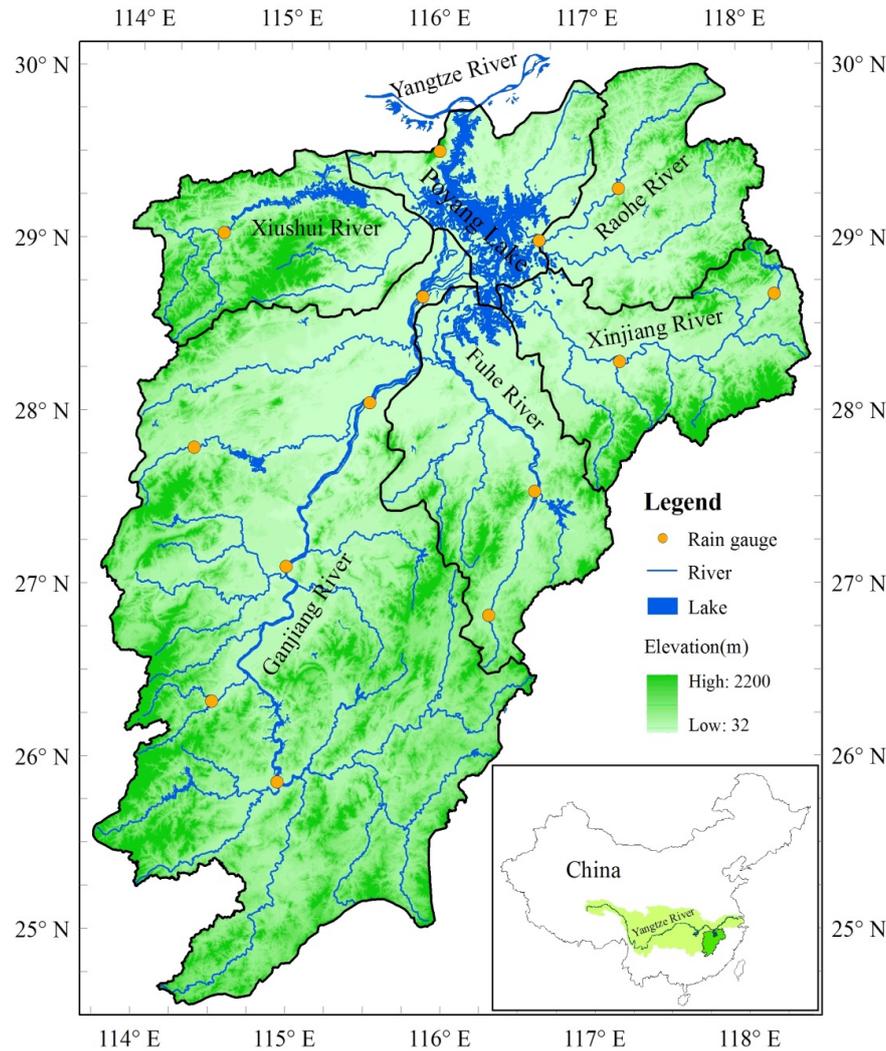
## 2. Study Area and Methods

### 2.1. Study Area and Data

Poyang Lake basin is located in the middle and lower reaches of the Yangtze River, China and the lake receives water flows mainly from five rivers: Xiushui River, Ganjiang River, Fuhe River, Xinjiang River and Raohe River and discharges into the Yangtze River (Figure 1). The total drainage area of the water systems is  $16.22 \times 10^4 \text{ km}^2$ , accounting for 9% of the drainage area of the Yangtze River basin. The topography in basin varies from highly mountainous and hilly areas to alluvial plains in the lower reaches of the primary watercourses. Poyang Lake basin has a subtropical wet climate characterized with a mean annual precipitation of 1680 mm for the period of 1960–2007 and annual mean temperature of 17.5 °C. Annual precipitation shows a wet and a dry season and a short transition period in between. In response to the annual cycle of precipitation, the floodplains are inundated and thus form a big lake with its inundation area reaching  $>3000 \text{ km}^2$  [43] and a volume of  $320 \times 10^8 \text{ m}^3$  in the wet season, but shrinks to  $<1000 \text{ km}^2$  to form a narrow meandering channel during the dry season and exposes extensive floodplains and wetland areas.

Daily rainfall data for 14 national meteorological stations in the Poyang Lake basin during the period 1998–2010 were collected from National Meteorological Information Center of China, and used to compare and evaluate the accuracy of TRMM rainfall data in the study. The distribution of rain gauges in the basin is shown in Figure 1. These data have been widely used for different studies previously and the quality has been proven to be reliable [5,6,44]. The spatial distribution of rainfall is estimated from the rain gauges data by the Inverse Distance Weighted (IDW) interpolation technique. The satellite-based rainfall data used in this study are daily TRMM 3B42 data at  $0.25^\circ \times 0.25^\circ$  grid resolution and the monthly TRMM data are aggregated from the daily rainfall data during the period from January 1998 to December 2010.

**Figure 1.** Location of Poyang Lake basin and the distribution of rain gauges.



2.2. Methods

2.2.1. Z index Method

Previous studies showed that the Z index method is more suitable for drought and wet monitoring in single rain gauge in China [45], and in the present study, the Z index is used to imply dry/wet conditions in the Poyang Lake basin. According to the treatments of Li *et al.* [46], each TRMM rainfall grid is regarded as a ground rain station, and the Z index is computed for each grid.

Daley [47] believed that the precipitation at a location for a specified time period usually does not have a normal distribution but obeys the Pearson type III distribution. The Z index method also assumes precipitation follows a Pearson type III distribution with the following probability density function:

$$f(x) = \frac{\beta}{\Gamma(\alpha)} (x - \alpha)^{\alpha-1} e^{-\beta(x-\alpha)}, (x > \alpha) \tag{1}$$

The probability density function of Pearson type III distribution can be converted to a standard normal distribution of variable Z [47] through the following conversion function:

$$Z_i = \frac{6}{C_s} \left( \frac{C_s}{2} \phi_i + 1 \right)^{1/3} - \frac{6}{C_s} + \frac{C_s}{6} \tag{2}$$

where,  $Z_i$  is the Z index for the precipitation in the  $i$ th month,  $C_s$  is the coefficient of skewness, and  $\phi_i$  is the standardized monthly precipitation. Both  $C_s$  and  $\phi_i$  can be calculated from the monthly precipitation of grids, *i.e.*,

$$C_s = \frac{\sum_{i=1}^n (P_i - \bar{P})^3}{n\sigma_3} \tag{3}$$

$$\phi_i = \frac{P_i - \bar{P}}{\sigma} \tag{4}$$

where,  $P_i$  is the precipitation (mm) in the  $I$  th month,  $n$  is the total month, and  $\sigma$  and  $\bar{P}$  are the standard error (mm) and mean (mm) of precipitation in all month, *i.e.*,

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - \bar{P})^2} \tag{5}$$

$$\bar{P} = \frac{1}{n} \sum_{i=1}^n P_i \tag{6}$$

According to previous studies [7,46], different wet and dry classes are defined based on the Z index value, including the severely wet, moderately wet, abnormally wet, normal, abnormally dry, moderately dry and severely dry. Table 1 shows the Z index value range for each class of wet/dry.

**Table 1.** Wet and dry classification based on the Z index and Standardized Precipitation Index (SPI) value.

Class	Type	Z value	SPI value
1	Severely wet	$Z > 1.96$	$SPI > 2.0$
2	Moderately wet	$1.44 < Z \leq 1.96$	$1.5 < SPI \leq 2.0$
3	Abnormally wet	$0.84 < Z \leq 1.44$	$1.0 < SPI \leq 1.5$
4	Normal	$-0.84 \leq Z \leq 0.84$	$-1.0 \leq SPI \leq 1.0$
5	Abnormally dry	$-1.44 \leq Z < -0.84$	$-1.5 \leq SPI < -1.0$
6	Moderately dry	$-1.96 \leq Z < -1.44$	$-2.0 \leq SPI < -1.5$
7	Severely dry	$Z < -1.96$	$SPI < -2.0$

### 2.2.2. SPI Method

The SPI was introduced by McKee *et al.* [10] as a measure of the precipitation deficit that is uniquely related to probability. It was based on an assumption that the gamma distribution fits well for precipitation at a location for a specified time period. The probability density function can be expressed as follows:

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}, (x > 0) \tag{7}$$

Then, the cumulative probability of precipitation for the given month and time scale for the considered station is computed as:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^x x^{\alpha-1} e^{-x/\beta} dx \quad (8)$$

For locations where observations of zero precipitation occur, the fitting of a gamma distribution becomes problematic since it is not defined for zero. In this case the cumulative probability  $H(x)$  becomes:

$$H(x) = q + (1 - q)G(x) \quad (9)$$

where,  $q$  is the probability of zero precipitation calculated from the frequency of observations of zero.

The cumulative probability density function  $H(x)$  can be converted to a standard normal distribution through the following conversion function:

$$H(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-t^2/2} dt \quad (10)$$

Further solving the equation, provides:

For  $0 < H(x) \leq 0.5$ ,

$$SPI = - \left( t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} \right) \quad (11)$$

$$t = \sqrt{\ln \left( \frac{1}{(H(x))^2} \right)} \quad (12)$$

For  $0.5 < H(x) \leq 1$ ,

$$SPI = t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} \quad (13)$$

$$t = \sqrt{\ln \left( \frac{1}{(1 - H(x))^2} \right)} \quad (14)$$

where,  $c_0$ ,  $c_1$ ,  $c_2$ ,  $d_1$ ,  $d_2$  and  $d_3$  are the following constants,  $c_0 = 2.515517$ ,  $c_1 = 0.802853$ ,  $c_2 = 0.010328$ ,  $d_1 = 1.432788$ ,  $d_2 = 0.189269$ ,  $d_3 = 0.001308$ .

Similarly, the wet and dry classes are also defined based on SPI values according to the literature and as shown in Table 1. Moreover, the SPI can be calculated for any accumulation time scale (such as, 1, 3, 6, 9, 12 month) when wet or dry phenomena occur and, because of its standardization, is particularly suited to compare wet or dry conditions among different time periods and regions, with different climatic conditions [48]. Generally, the soil moisture conditions respond to precipitation anomalies on a relatively short timescale, while streamflow and reservoir storage reflect the longer-term precipitation anomalies. So, the 1 to 3 month scale SPI are used mainly for the meteorological drought, the 3 to 6 month scale SPI for agricultural drought, and 6 up to 12 months SPI or more are mainly used for hydrological drought analyses and applications.

### 3. Results and Discussion

#### 3.1. Validation of TRMM Rainfall with Rain Gauges Data

For the comparison between TRMM and gauging rainfall data, we firstly analyzed several statistical indices, such as areal average rainfall, maximal daily rainfall, maximal 5 day rainfall and average annual rainfall. The comparison was made for five sub-basins (namely Xiushui, Ganjiang, Fuhe, Xinjiang and Raohe) and the results are shown in Table 2. It can be seen that the areal average rainfall estimated from rain gauges data, using the Thiessen polygon interpolation method, were 6.14–10.03 mm/d in 1998–2007 and 5.04–8.72 mm/d for TRMM data in the same period. The differences are small and to an acceptable degree, although the TRMM rainfall is less than the gauge rainfall. The maximal daily rainfall from TRMM data are 152.9, 92.9, 113.4, 157.5 and 143.1 mm respectively, for five sub-basins, while they are 157.2, 68.8, 99.5, 145.1 and 134.1 mm respectively, for rain gauges data. It is shown that the TRMM rainfall data had difficulty estimating the extreme precipitation accurately in Poyang Lake basin. Similar situations were observed further in the comparison of maximal 5 day rainfall. As for the annual rainfall totals, the TRMM data are equivalent to rain gauge data, except in Xiushui and Raohe sub-basins.

**Table 2.** Comparison of statistical indices between averaged Tropical Rainfall Measuring Mission (TRMM) and rain gauges rainfall.

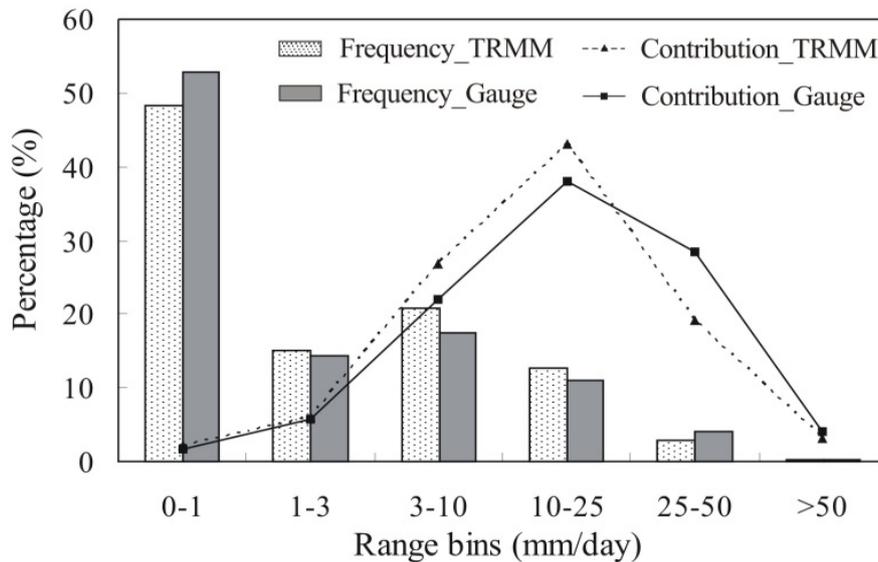
Sub-basin	Areal average		Max. daily rainfall		Max. 5-day rainfall		Annual rainfall	
	(mm/day)		(mm/day)		(mm/5day)		(mm/year)	
	Gauge	TRMM	Gauge	TRMM	Gauge	TRMM	Gauge	TRMM
Xiushui	8.75	7.55	157.2	152.9	289.2	280.5	1642	1762
Ganjiang	6.14	5.04	68.8	92.9	155.2	171.4	1631	1642
Fuhe	8.43	6.67	99.5	113.4	300.5	268.7	1793	1770
Xinjiang	8.99	7.67	145.1	157.5	453.7	320.8	1901	1880
Raohe	10.03	8.72	134.1	143.1	371.6	320.7	1747	1894

Figure 2 shows the distribution of daily rainfall intensity in different intensity ranges and their contributions to the total rainfall. It can be seen that non-rain and light rain (<1 mm/day) were most frequent, occurring on almost 50% of the total days, in all data sets. The difference between TRMM rainfall and rain gauges data is also quite small. The occurrence of the light rainfall ranges (1 mm/day < rainfall ≤ 3 mm/day) from TRMM is generally equivalent to those from rain gauge data. It can also be seen that although the occurrences of the first two classes, *i.e.*, non-rain and light rain classes, accounted for as high as 65%–70% of the total days, their contributions to the total rainfall was very small. The occurrence of the middle class rainfall ranges (3 mm/day < rainfall ≤ 25 mm/day) estimated by TRMM are higher than that of the rain gauge, also with higher contribution rates to the total rainfall. Additionally, it is important to note that the high rainfall ranges (>25 mm/day) play a significant role in contributing rain amount to the total rainfall. Although the high rainfall classes accounted for only about 6% of the total days, their contribution to the total rainfall are as high as 30% and 22% respectively for rain gauge data and TRMM data. It is seen that TRMM performed perfectly for both occurrence and contribution rates in the >50 mm/day class and the statistics matched well with their

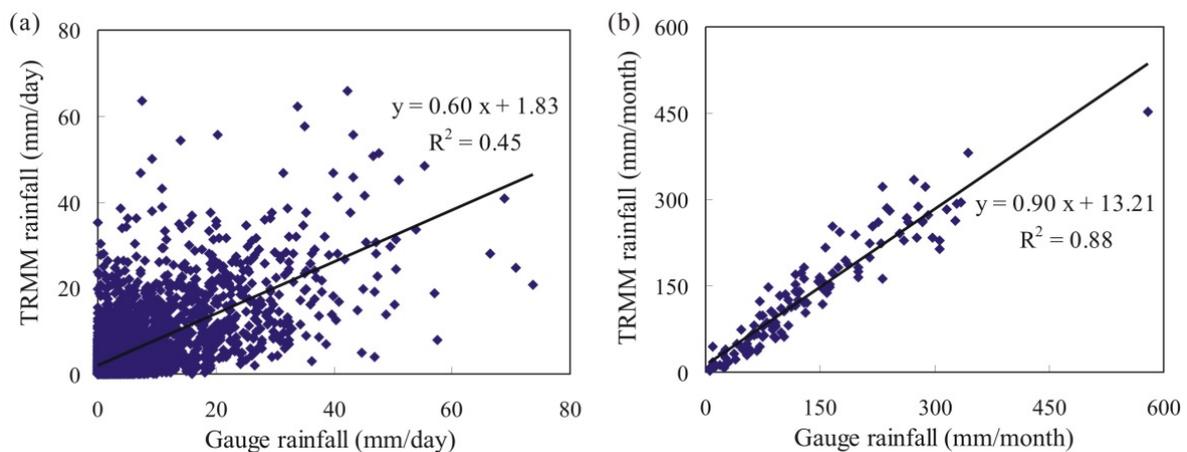
counterparts. However, in the 25–50 mm/day class, rainfall occurrence and contribution rates are lower than that of observation data. On the whole, TRMM rainfall data can describe the intensity distributions of precipitation with small errors in terms of occurrence and contribution rates.

In order to evaluate the correlation of the two data sets, the scatter plots of TRMM rainfall against rain gauges rainfall data at daily and monthly scale are shown in Figure 3. It can be seen that a bad linear relationships between the TRMM data and rain gauges data is presented at daily scale, the relative low value of determination coefficient ( $R^2 = 0.45$ ) further indicates the daily TRMM rainfall data have large errors in depicting the actual rainfall amount. While at monthly scale, there is a good linear relationship with a high  $R^2$  value of 0.88 and a slope of near 1.0. These values indicate that the monthly TRMM rainfall data captures the signal of rainfall well, in comparison with the rainfall measurement from the manual rain gauges situated in different locations of the Poyang Lake basin.

**Figure 2.** Distribution of daily rainfall intensity in different intensity ranges and their contributions to the total rainfall based on TRMM and rain gauges data.



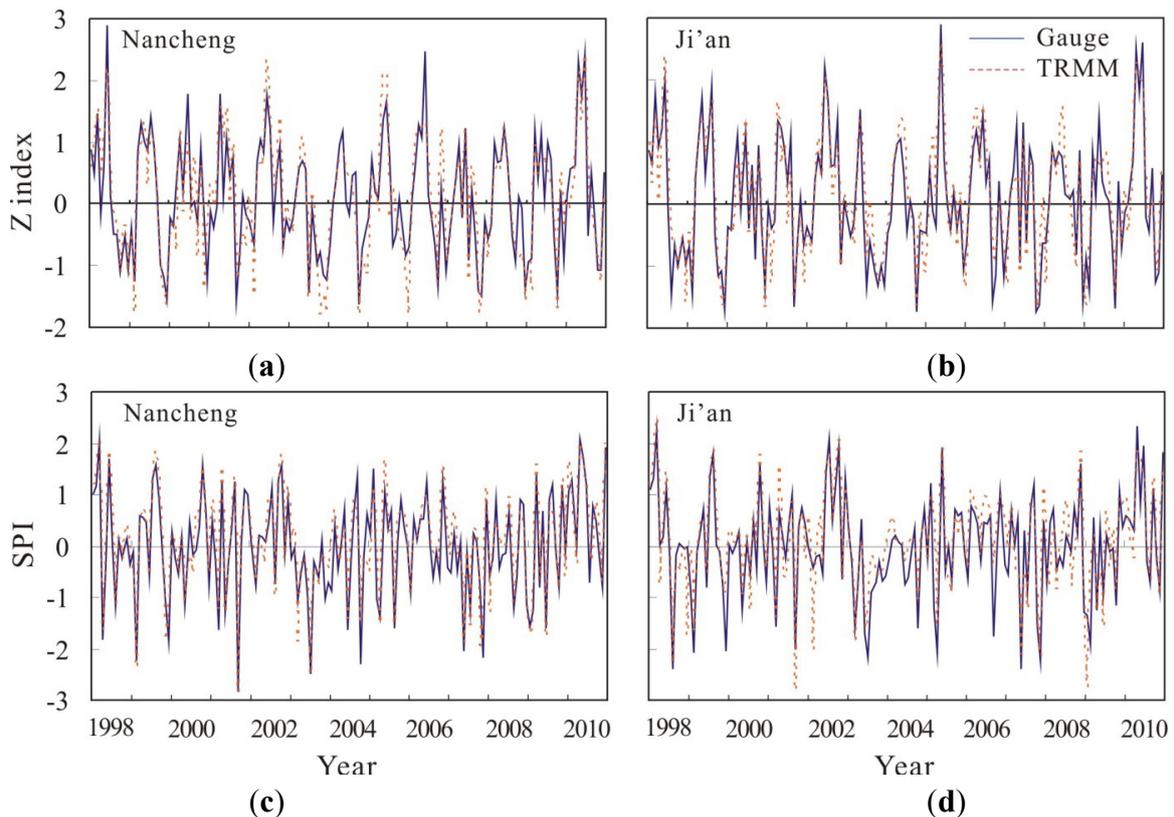
**Figure 3.** Scatter plots of areal average rainfall from rain gauges data and TRMM data at (a) daily; and (b) monthly scale.



3.2. Temporal Variation of Dry/wet Conditions Based on TRMM Rainfall

The Z index as well as SPI values is computed for each grid ( $0.25^\circ \times 0.25^\circ$ ) in Poyang Lake basin using the monthly TRMM rainfall data from January 1998 to December 2010. At the same time, as a comparison, the rain gauges data from 14 national meteorological stations in the basin are also used to calculate the Z index and SPI. Wherein, the positive Z index or SPI indicates that the rainfall over that period is higher than the mean rainfall for the whole time series, while the negative Z index or SPI shows that the rainfall is lower than the mean, and the larger the absolute value, means the dryer or wetter conditions in the basin [10,46]. Subsequently, the dry/wet classes are determined according to the Z index and SPI value ranges as shown in Table 1 respectively. Considering the relative location of rain gauges in the grid and the spatial distribution in the basin, the two grids are selected for the comparison between satellite pixel ( $0.25^\circ \times 0.25^\circ$  grid) and the gauging stations inside the grids (namely Nancheng and Ji'an) and the results are shown in Figure 4. It can be seen that both the Z index and SPI based on monthly TRMM rainfall data oscillate around zero, and their interannual variability generally match well with the results from rain gauge data; although it slightly over-predicts some peak values when using TRMM rainfall data. At the same time, it can also be seen that little change has been observed in droughts over the past 13 years, which are consistent with the results of Sheffield *et al.* [49] and Damberg and AghaKouchak [50]. From the results of Figure 4, we believed that it is feasible to use monthly TRMM rainfall data to monitor the variation of dry/wet conditions in Poyang Lake basin.

**Figure 4.** Comparison of (a, b) Z index; and (c, d) SPI based on TRMM data and rain gauging data at (a, c) Nancheng; and (b, d) Ji'an station.



In addition, the SPI is also calculated at 3, 6, 9 and 12 month scale respectively using TRMM rainfall and gauge rainfall data. Figure 5 shows the interannual variability of SPI based on TRMM and rain gauge data at different time scale at Nancheng station. It can be seen that the curve of SPI becomes smoother when the time scale extends from 3 to 12 months, and the severity of dry and wet conditions in some months also become palliative, *i.e.*, the SPI value decreases from 2.90 at 3 month scale to 2.31 at 12 month scale in 2010 and increases from  $-1.32$  at 3 month scale to  $-0.68$  at 12 month scale in 1999. Also, it is obvious from Figure 5 that the curve of SPI from TRMM rainfall data demonstrates a closer agreement with that from rain gauges data with the increase in the time period. This further validates that the TRMM rainfall data has potential to be a suitable data source for the dry/wet conditions monitoring in Poyang Lake basin.

**Figure 5.** Comparison of SPI based on TRMM and rain gauges data at (a) 3 month; (b) 6 month; (c) 9 month; and (d) 12 month scale.

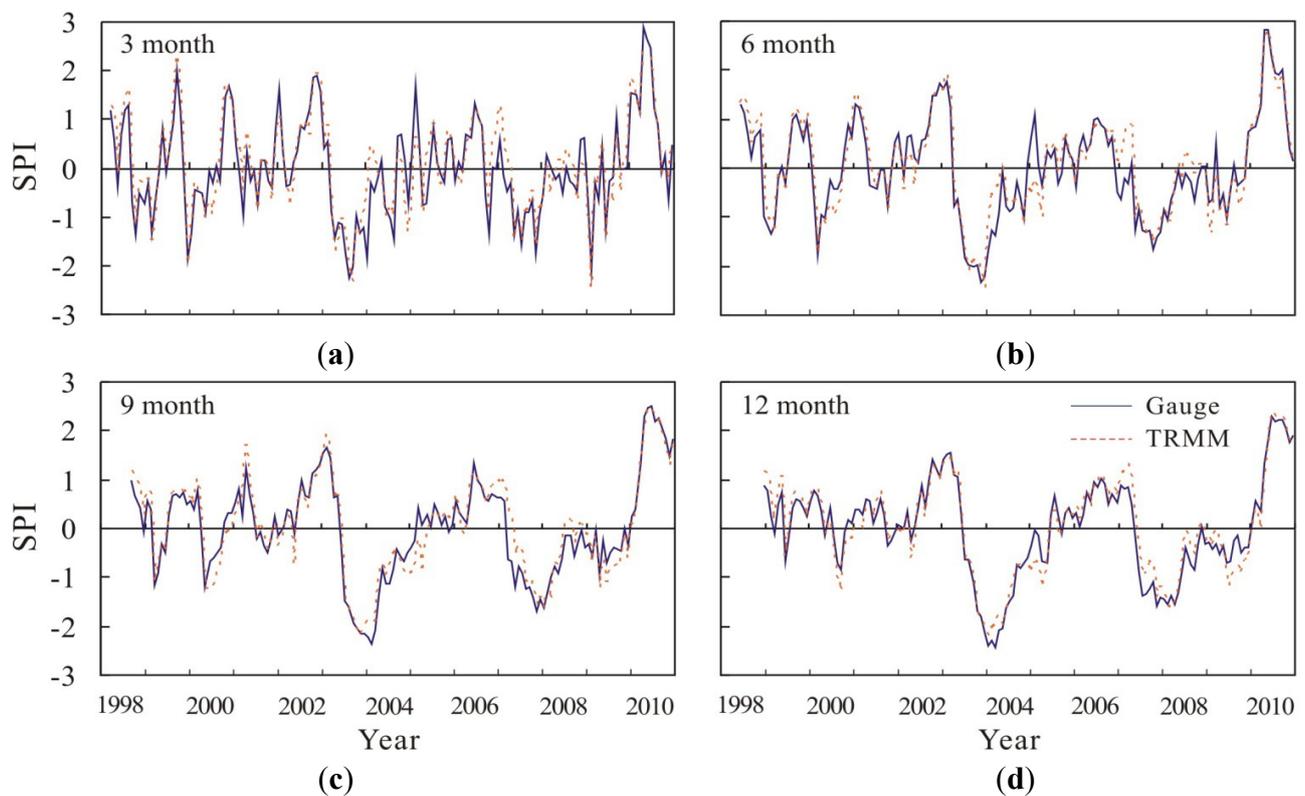
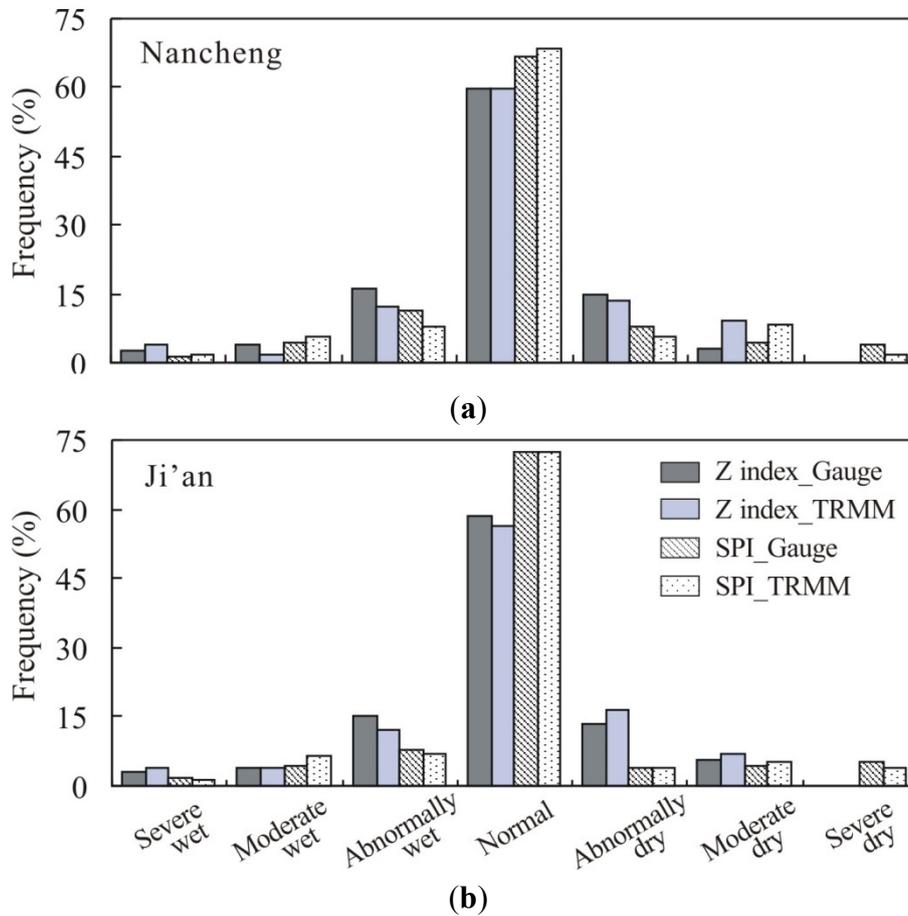


Figure 6 shows the comparison of frequency in each dry/wet class using TRMM and gauge rainfall data at the Nancheng and Ji'an stations. It can be seen that the normal class, either based on  $Z$  index or SPI, has the largest occurrence, occupying about 60%–70%, and the severe dry and wet classes have the lowest frequency, occupying less than 5%. The occurrence frequency of other classes, including moderate dry and wet, and abnormally dry and wet, vary from 5% to about 15%. Moreover, it is obvious that the occurrence frequency of different classes, based on both the  $Z$  index and SPI, using TRMM data are very close to that from rain gauges data. From the similar frequency of different classes we believed further that TRMM rainfall data can be used to determine the dry/wet classification in the basin and accurately reflect the actual regional drought or wet severity.

**Figure 6.** The comparison of frequency in each dry/wet class based on Z index and SPI using TRMM and rain gauges data at (a) Nancheng; and (b) Ji'an station.

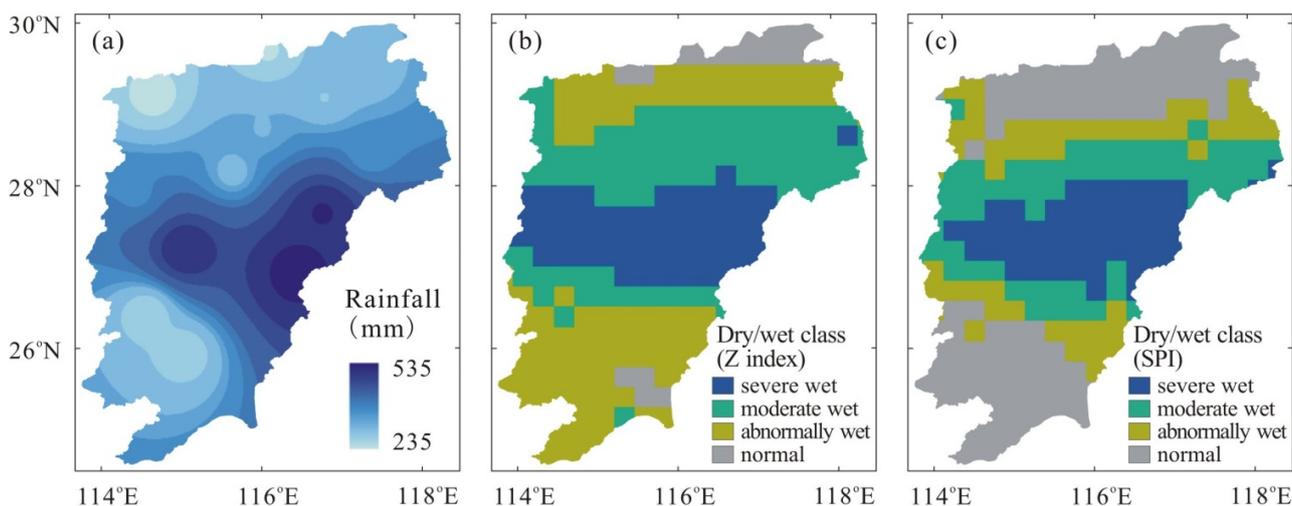


### 3.3. Spatial Distribution of Dry/wet Conditions Based on TRMM Rainfall

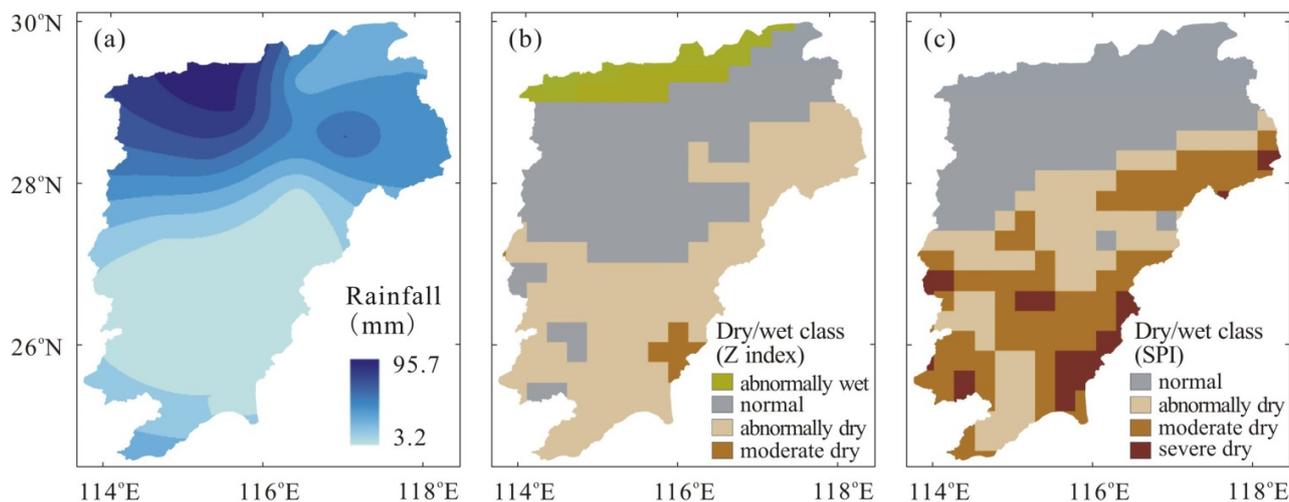
Compared with ground rain gauging data, the TRMM rainfall data are available over a large area and can reflect the spatial distribution of dry/wet conditions. Therefore, the presented research is also extended to examine and compare the spatial accuracy of dry/wet conditions. Figures 7 and 8 show the spatial distribution of dry/wet classes based on the Z index and SPI values from TRMM rainfall data in April 2010 and July 2003 respectively. As a comparison, the spatial distribution of monthly rainfall in the same period are interpolated from rain gauges data using the IDW technique with a power of 2. It can be seen from Figure 7a that heavy rainfall occurred in April 2010 with strong spatial differences. The largest monthly rainfall occurred in the middle area of Poyang lake basin, traversing from east to west with a monthly rainfall as high as 530 mm, and the lowest was observed in the southern and northern parts (about 240 mm). Accordingly, it is obvious from Figure 7 that the spatial pattern of dry/wet classes, either based on the Z index or SPI, have good agreement with the spatial distribution of monthly gauges rainfall. Both the Z index and SPI showed a high flood risk in the middle parts of the basin rather than in southern and northern areas, although the normal range from SPI data covered a larger area than that from the Z index. Also, Figure 8 shows that the overall rainfall is low (<96 mm) in July 2003 and mainly occurred in the northwest area of the basin; a similar spatial pattern was presented by the Z index as well as SPI which indicated the drought occurred in the south due to the

moisture deficit. Figures 7 and 8 suggest that the spatial pattern of moisture status, based on both the Z index and SPI using TRMM rainfall data are in agreement with that of observed rainfall, and TRMM rainfall data can be used for monitoring the spatial distribution of dry/wet conditions in Poyang Lake basin.

**Figure 7.** The spatial distribution of (a) rainfall and dry/wet classification, based on (b) Z index; and (c) SPI in April 2010.



**Figure 8.** The spatial distribution of (a) rainfall and dry/wet classification, based on (b) Z index; and (c) SPI in July 2003.



#### 4. Conclusions

This paper evaluated and compared satellite-based rainfall data (*i.e.*, TRMM) with rain gauge data in Poyang Lake basin and investigated the usefulness of the TRMM rainfall data for monitoring the variation and spatial distribution of dry/wet conditions. The results revealed that: (1) the daily TRMM rainfall data has difficulty in describing the occurrence and contribution rates of precipitation accurately, but at a monthly scale, there is a good linear relationships between TRMM and rain gauges rainfall data, with high  $R^2$  values; (2) both the Z index and SPI based on monthly TRMM rainfall data

oscillate around zero and show a consistent interannual variability as compared with rain gauges data; (3) the spatial pattern of moisture status, either in dry or wet months, based on both the *Z* index and SPI using TRMM rainfall data are in agreement with observed rainfall. That is to say, the monthly TRMM rainfall data can successfully be used for monitoring the variation and spatial distribution of dry/wet conditions in the Poyang Lake basin.

It is acknowledged that there are several flaws in the study: Firstly, considering the large biases in the real-time TRMM rainfall data, as previous researchers noted [23–28], the TRMM 3B42 was used in the study, which has several weeks delay in availability which may limit its application for dry/wet conditions monitoring in real-time; secondly, the TRMM rainfall data may not provide the significant statistical characteristics due to its short time records, which demand continuous progress in combining the TRMM rainfall data with other data sources, such as GPCP, to prolong the data series (*i.e.*, reference [20]). Moreover, efforts to improve algorithms and techniques in real-time satellite-based rainfall estimation need to continue to increase the data accuracy, and further advance its utilization in real-time droughts monitoring and other applications in large-scale watersheds.

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### Conflicts of Interest

The authors declare no conflict of interest.

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