Spatiotemporal Evaluation of Historical Drought in the Philippines

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ABSTRACT: Negative impacts of drought on agriculture and water resources vary according to different timescales and intensity. In this paper, the historical droughts in the Philippines were examined using the Standardized Precipitation Index (SPI) at different timescales (SPI-1, SPI-3, and SPI-12). SPI is derived from the monthly rainfall data of Tropical Rainfall Measuring Mission (TRMM) 3B43 v7 from 1998 to 2018. A total of 384 TRMM grids in the Philippines were used in the time series analysis to investigate the spatiotemporal dynamics of drought. Results showed that the Philippines was frequently hit by different types of drought. It also showed that the spatial distribution of the past drought events varied through timescales. Particularly, more variation was observed in the entire land area using the shorter SPI timescales, i.e. SPI-1 and SPI-3. With longer timescales, values tend to be more similar and closer to each other resulting in smoother trends. The affected areas in terms of percentage were also examined. Each drought event's severity, duration, and intensity for the areal average of the Philippines was also investigated. These results demonstrate the viability of satellite-derived SPI for drought evaluation at a national level, which is important in the decision-making for drought mitigation in the Philippines.

1. INTRODUCTION

Drought is a natural hazard and is caused by lower-than-normal precipitation with impacts varying across different sectors. This event is a normal feature of climate when precipitation reduction occurs over an extended period (Wilhite, 2000). It is said to be the most complex, the least understood, and the world's costliest natural disaster causing 6 to 8 billion dollars in damage annually. This climatic phenomenon affects more people than other natural hazards (Hagman *et al*., 1984; Wilhite, 2000).

Wilhite and Glantz (Wilhite And Glantz, 1985) categorized drought into four types. A meteorological drought occurs when there is a lower than normal precipitation for a month at a specific area. This meteorological drought, if it persists, can lead to an agricultural drought that impacts crops in a negative way. Hydrological drought occurs when an area experienced little-to-no precipitation for 6 to 24 months that significantly reduces water levels in reservoirs, lakes, and groundwater. The associated effect of drought to supply and demand of economic goods is called socioeconomic drought.

Drought indices are used to monitor the onset, severity, spatial extent, and termination of drought events. These indices are derived from a single or a combination of hydrometeorological variables like precipitation, temperature, and soil moisture (Svoboda *et al*., 2016). Although there is no single drought index that can precisely describe an event, an effective early-warning system must use several indices for characterizing drought. Among the most used drought index around the world were the Palmer Drought Severity Index (PDSI), Percent of Normal (PNP), Standardized Precipitation Evaporation Index (SPEI), Standardized Streamflow Index (SSI), and the Standardized Precipitation Index (SPI). PNP and SPEI is used for meteorological drought monitoring while PDSI is for monitoring agricultural drought. SSI is used for hydrological drought monitoring.

SPI has been recommended to be used by all National Meteorological and Hydrological Services (NMHS) via Lincoln Declaration on Drought Indices in characterizing meteorological drought (Svoboda *et al*., 2016). The main advantages of SPI are that it only requires precipitation data, and it is versatile that it allows SPI the capability to monitor meteorological, agricultural, and hydrological drought.

Numerous studies demonstrated the use of SPI in characterizing drought across different parts of the world. Hayes *et al*. (1999) test the capability of SPI to monitor the 1996 severe drought of the Great Plain and the southwestern United States using precipitation data from rain gauge stations. They were able to show that SPI detected the onset of the 1996 drought at least 1 month in advance compared to PDSI. Vicente-Serrano (2010) identified four homogenous drought regions in Iberian Peninsula by analyzing historical SPI values from rain gauge stations. Other studies evaluated the use of satellite data for monitoring and characterizing drought. Yan *et al*. (2018) evaluated the capability of Tropical Rainfall Measuring Mission (TRMM) rainfall product for drought monitoring in China. Results showed that SPI derived from TRMM was consistent with the SPI derived from rain gauge stations and that SPI derived from TRMM captures the development of drought. A study of Santos *et al*. (2017) utilized TRMM data for drought assessment of historical drought in the São Francisco River basin, Brazil. They were able to determine areas that were vulnerable to short-term, medium-term, and long-term drought together with the severity.

The climate of the Philippines is highly influenced by El Niño Southern Oscillation (ENSO) (Hilario *et al*., 2009). The warm phase of ENSO is called El Niño wherein it affects rainfall distribution over the Philippines resulting in drier conditions. Studies in the Philippines shown that strong drought events were associated with El Niño (Hilario *et al*., 2009; Porio *et al*., 2019). This leads to loss in crop production, reduction of water supply, forest fires, and adverse human health impacts.

The Philippines' weather bureau, Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) uses SPI and PNP in monitoring drought. These indices were derived using rainfall data from synoptic stations. To date, there are 55 active synoptic stations around the country. Since they are sparsely distributed with some areas in the country not having a continuous rainfall measurements, characterizing drought at a national level is a challenge. This study will utilize freely available TRMM data in understanding the spatiotemporal dynamics of drought events that happened from 1998 to 2019 in the Philippines. Particularly, this study will assess the duration, severity, intensity, and spatial extent of historical droughts in the country. The results of this study could provide detailed information about the spatial and temporal distribution of drought in the Philippines and the possibility of using freely available satellite data for drought monitoring in the country. This can help the decision-making processes of government agencies toward drought preparedness and mitigation.

2. DATA AND METHODOLOGY

2.1 The study area

Philippines is an archipelagic country which consists of about 7,641 islands and has a total land area of 300,000 km^2. It is located between the South China Sea and the western part of the Pacific Ocean. The country experiences tropical and maritime climate which is characterized by relatively high temperature, high humidity, and has abundant rainfall. Spatial distribution of rainfall varies throughout the country from 645 to 4,064 millimeters (PAGASA) (Figure 1).

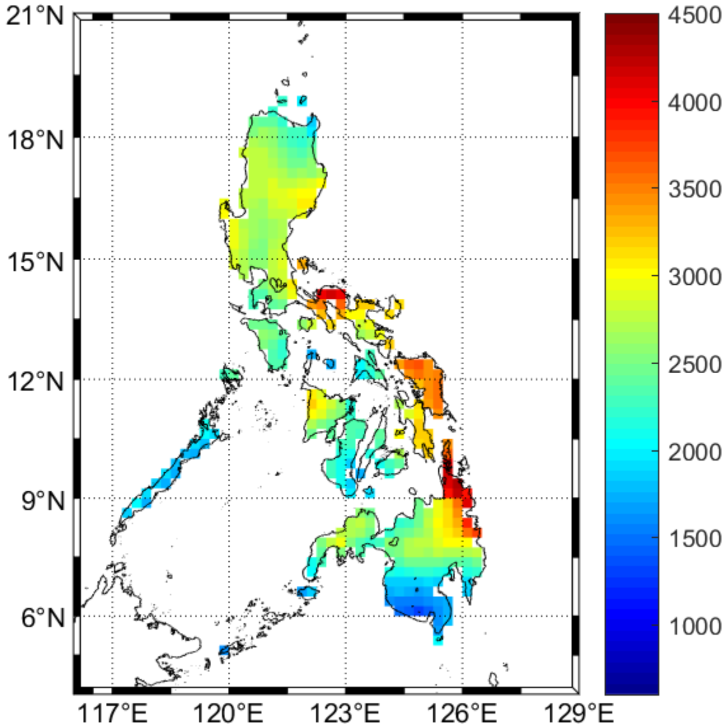

Figure 1. Annual rainfall (mm) of the Philippines derived from TRMM.

2.2 TRMM Precipitation data

The Tropical Rainfall Measuring Mission (TRMM) was a joint project by the National Aeronautics and Space Administration (NASA) of the United States and Japan Aerospace Exploration Agency (JAXA) of Japan. TRMM was launched in 1997 with the mission of monitoring tropical to sub-tropical precipitation from 50°S-50°N and 180°W-180°E. In this study, the TRMM Multisatellite Precipitation Analysis version 7 (TMPA 3B43 v7) was used which was downloaded from the NASA Goddard Space Flight Center website (https://mirador.gsfc.nasa.gov/). TMPA is a gridded monthly precipitation rate estimate with a spatial resolution of 0.25° x 0.25°. It was created by combining precipitation estimates from different satellites with rain gauge data (Huffman *et al*., 2007). A total of 21 years and 5 months of TMPA data, from January 1998 to May 2019, was used in this study. The downloaded dataset was clipped to consider only the land area of the Philippines. A total of 384 TRMM grids were used (Figure 1).

2.3 The Standardized Precipitation Index (SPI)

SPI is utilized around the world as a drought monitoring tool. One advantage of SPI is that it allows the monitoring of different types of drought by using different SPI timescales. The shorter SPI timescales, 1-month SPI (SPI-1) and 3-month SPI (SPI-3), were used for meteorological and agricultural drought respectively. The longer SPI timescale, 6-month SPI (SPI-6), 12-month SPI (SPI-12), and 24-month SPI (SPI-24), were used for hydrological drought monitoring. McKee *et al*. (1993) recommend to have at least 30 years of monthly precipitation data for the calculation of SPI. In this paper, the spatiotemporal evaluation of different drought types was done through the use of SPI-1, SPI-3, and SPI-12 derived from 384 TRMM grids that represent the Philippine land area.

The SPI derivation was based on the methodology of Edwards and McKee (1997). Given a precipitation total for a specific location and timescale (1-month, 3-month, etc.) a gamma probability density function is fitted as:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \text{ for } x > 0 \qquad \text{(eq. 1)}$$

where:

$\alpha > 0$	α is the shape parameter
$\beta > 0$	β is the scale parameter
$x > 0$	x is the precipitation amount
$\Gamma(\alpha) = \int_0^{\infty} y^{\alpha-1} e^{-y}$	$\Gamma(\alpha)$ is the gamma function. (eq. 2)

The shape parameter α and scale parameter β of the probability density function for each location and time scale of interest is then calculated as:

$$\hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \qquad \text{(eq. 3)}$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{a}} \qquad \text{(eq. 4)}$$

where:

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \qquad \text{(eq. 5)}$$

n is the number of precipitation observations.

The cumulative probability of each observed precipitation event for the given month and time scale for a specific location is then computed using the estimated scale and shape parameters and is given by:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\Gamma(\hat{\alpha})} \int_0^x t^{\hat{\alpha}-1} e^{-1}\, dt \qquad \text{(eq. 6)}$$

where:

$$t = x/\hat{\beta}. \qquad \text{(eq. 7)}$$

Since gamma function is not valid when $x = 0$, but in reality, precipitation total can be zero. The cumulative probability is then expressed as:

$$H(x) = q + (1 - q)G(x) \qquad \text{(eq. 8)}$$

where:

$q = \frac{m}{n}$	q is the probability of zero precipitation (eq. 9)
m	is the number of zero precipitation in precipitation time series.

Finally, cumulative probability $H(x)$ can be transformed into the standard normal random variable Z using the equation:

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^2}\right) for\ 0 < H(x) \leq 0.5 \qquad \text{(eq. 10)}$$

$$Z = SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^2}\right) for\ 0.5 < H(x) < 1.0 \qquad \text{(eq. 11)}$$

where:

$$t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \qquad for\ 0 < H(x) \leq 0.5 \qquad \text{(eq. 12)}$$

$$t = \sqrt{\ln\left(\frac{1}{(1.0-H(x))^2}\right)} \qquad for\ 0.5 < H(x) < 1.0 \qquad \text{(eq. 13)}$$

$$\left.\begin{array}{l} c_0 = 2.515517 \\ c_1 = 0.802853 \\ c_2 = 0.010328 \\ d_1 = 1.432788 \\ d_2 = 0.189269 \\ d_3 = 0.001308. \end{array}\right\} \qquad \text{(eq. 14)}$$

The SPI is equivalent to *Z*-score with a mean of zero and standard deviation of one, which represents the number of standard deviations a precipitation total for a specific month, station, and timescale is above or below the mean.

SPI Values	Classification
2.00 and above	extremely wet
1.50 to 1.99	very wet
1.00 to 1.49	moderately wet
-0.99 to 0.99	near normal
-1.00 to -1.49	moderately dry
-1.50 to -1.99	severely dry
-2.00 and less	extremely dry

Table 1. Drought classification from SPI. (McKee *et al*., 1993)

2.4 Drought evaluation indicators

A drought event is defined as the period in which SPI is continuously negative and reaches a value of -1.0 or less (McKee *et al*., 1993). An event starts when the SPI first below zero and ends with a positive SPI value following an SPI of -1 or less. A drought event's duration, severity, and intensity were then calculated.

A drought duration is the number of months from the start (included) and end (not included) of a drought event. Drought severity is the absolute sum of all SPI values throughout a drought event. Drought intensity is the severity divided by the duration of a drought event. Drought grid proportion is the ratio of the number of grids with SPI<-1 to the total grids used in this study.

3. RESULTS AND DISCUSSION

Figure 2 shows the SPI values from different SPI timescales. The red lines show the average SPI values from the 384 grids representing the Philippines. The grey lines were the SPI values for each TRMM grid within the Philippine land area. It appears that there are several instances where drought is felt across different areas in the country, as shown by SPI values less than zero. For shorter SPI timescales, SPI-1 and SPI-3, there is a stronger temporal variability and wider spread in SPI values. While there were grids experiencing drought, the others experiences wet conditions at the same time. This implies that meteorological and agricultural drought varies spatially throughout the Philippines. On the longer SPI timescales, SPI-12, the values tend to be similar and closer to each other resulting in a smoother time series. Figure 3 shows the percentage of affected area while Table 2 summarizes the observed drought events according to duration, severity and intensity, taken from the national average of SPI values. There was a total of 8 meteorological drought events (SPI-1), 6 agricultural drought event (SPI-3), and 3 hydrological drought events (SPI-12) observed within the study period.

The 1998 drought coincided with the 1997-1998 El Niño event, one of the strongest El Niño events in the century, which had a severe impact on society (Hilario *et al.,* 2009). A strong El Niño event led to 50% reduction in monthly rainfall during its peak in the Philippines. This was reflected on both SPI-1 and SPI-3. On a meteorological drought perspective, at most 75% of the Philippines were affected by this drought event with severity and intensity of 8.34 and 0.93, respectively. While at most 92% of the Philippines were affected by agricultural drought (SPI-3) with severity of 9.92 and intensity of 1.24. It was also reported by Jose *et al*. (2002) that in this drought event, 292,000 hectares of rice and corn area were completely damaged.

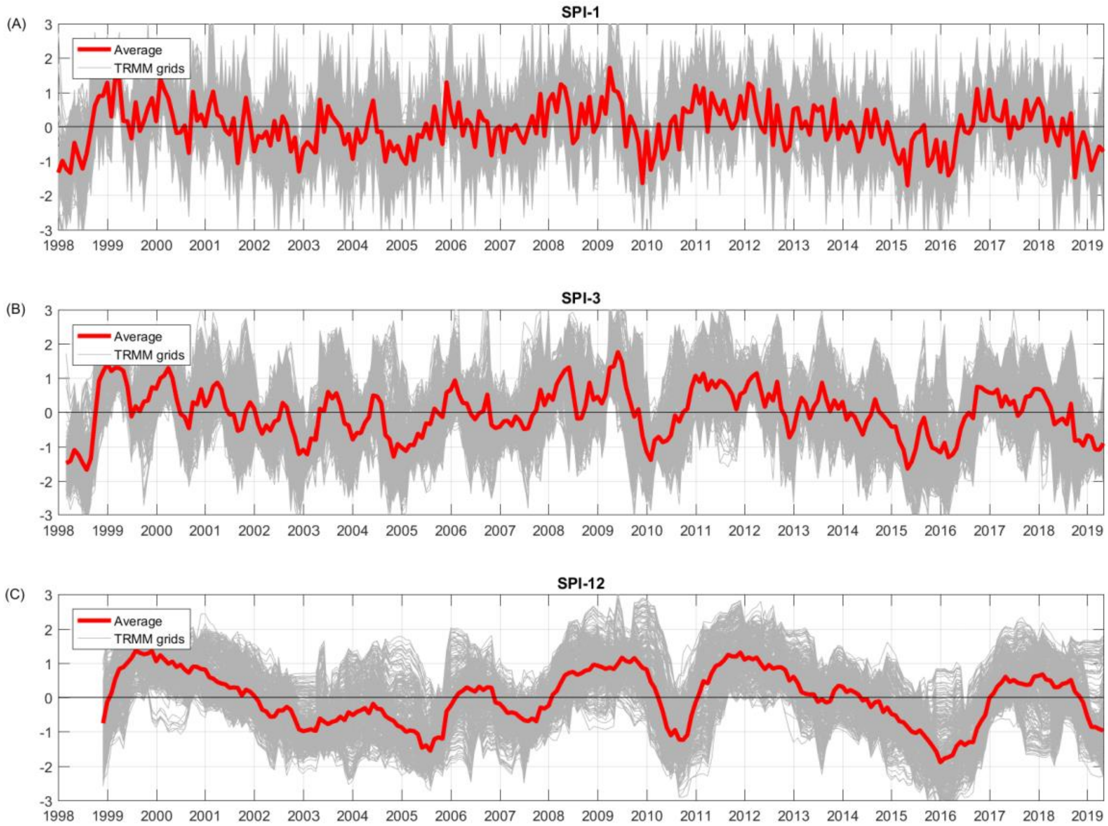

Figure 1. Historical SPI of the Philippines. (A) SPI-1, (B) SPI-6 and (C) SPI-12 values

Other meteorological droughts that affect more area were the September to October 2001 event, the October 2002 to April 2003 event, the July 2004 to June 2005 event which lasts for a year, the November 2009-March 2010 event, the January to August 2015 event wherein at most 85% were affected. It was followed by the October 2015 to May 2016 event. The latest being the October 2018 to May 2019 event. It was found that the longest meteorological drought observed from the study timespan was the July 2004 to June 2005 event.

Some notable agricultural drought was the October 2002 to April 2003 event, the September 2004 to August 2005 event that lasted for a year, and the December 2009 to September 10 event. The longest event lasted almost for two years happened from November 2014 to September 2016 with severity of 17.07 and intensity of 0.74. The last event is the October 2018 to May 2019 (Table 2).

A four-year hydrological drought happened from February 2002 to April 2006 were at most 83% of the area was affected. This event has a severity of 33.22 and an intensity of 0.68. This event was followed by a 10-month drought that occurred from April 2010 to January 2011. Another hydrological drought from June 2014 to July 2017 happened. This drought event has an intensity of 0.91 which was the strongest among the three events. Interestingly, the 2002 to 2006 period had three El Niño episodes with severity ranging from weak to moderate, while another moderate El Niño was recorded in 2009-2010 and a very strong El Niño episode in 2015-2016.

Finally, the percentage of the affected areas were also investigated. From SPI-1 the most areas affected by drought were the 2015-2016 event wherein at most 85% of area were affected. From an agricultural perspective, the 1998 drought event was the worst in terms of percentage as it affects at most 92% of the area observed by SPI-3. From SPI-12, the worst hydrological drought was the 2002-2006 event as it affects at most 95% of the Philippines.

4. CONCLUSIONS

The study analyzed the spatiotemporal drought occurrences in the Philippines using the TRMM-derived SPI. Results showed that the Philippines was frequently hit by different drought types mostly coinciding with El Niño events. There is a large spatiotemporal variability observed in the SPI-1 and SPI-3 values, implying that different areas in the country experience varying degree of meteorological and agricultural drought. On the other hand, at longer time scale, SPI-12 values are more coherent, showing a large proportion of the country experiencing hydrological drought. From the average values of SPI from all the TRMM grids that represent the Philippines, the number of drought events and their corresponding duration, severity, and intensity were calculated. This process is an initial step in examining the spatiotemporal characteristic of drought in the Philippines by utilizing freely available satellite data, which can be helpful in drought preparedness and mitigation.

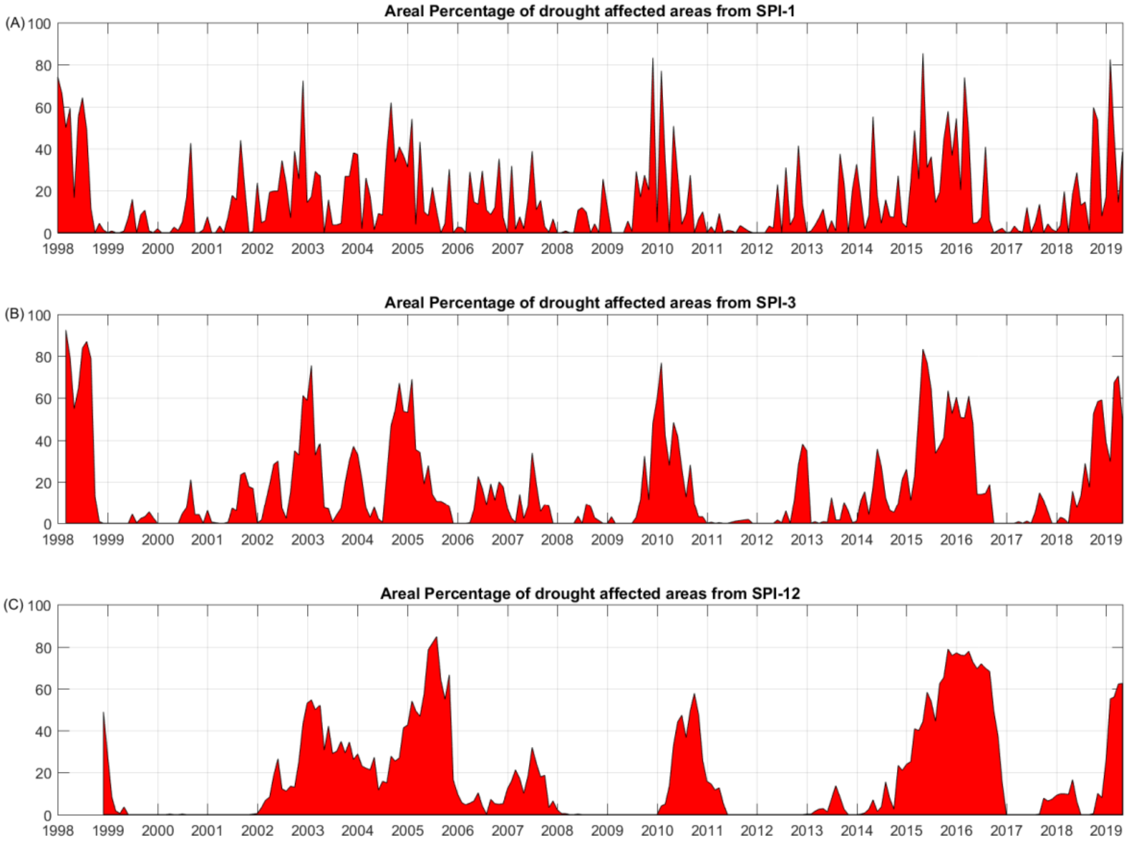

Figure 2. Percentage of affected areas. (A) SPI-1, (B) SPI-6 and (C) SPI-12 values

SPI	DURATION	SEVERITY	INTENSITY	START	END
SPI-1	9	8.34	0.93	Jan-1998	Sep-1998
	2	1.13	0.57	Sep-2001	Oct-2001
	7	4.77	0.68	Oct-2002	Apr-2003
	12	6.83	0.57	Jul-2004	Jun-2005
	5	4.35	0.87	Nov-2009	Mar-2010
	8	5.35	0.67	Jan-2015	Aug-2015
	8	7.1	0.89	Oct-2015	May-2016
	8	6.25	0.78	Oct-2018	May-2019
TOTAL = 8 events					
SPI-3	8	9.92	1.24	Mar-1998	Oct-1998
	7	6.14	0.88	Oct-2002	Apr-2003
	12	9.76	0.81	Sep-2004	Aug-2005
	10	7.49	0.75	Dec-2009	Sep-2010
	23	17.07	0.74	Nov-2014	Sep-2016
	8	7.08	0.89	Oct-2018	May-2019
TOTAL =6 events					
SPI-12	49	33.22	0.68	Feb-2002	Feb-2006
	10	7.64	0.76	Apr-2010	Jan-2011
	32	28.97	0.91	Jun-2014	Jan-2017
TOTAL = 3 events					

Table 2. Summary of drought events based on different SPI timescales from the average of TRMM grids.

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