

# Analysis of Precipitation and Streamflow Data for Drought Assessment in an Unregulated Watershed

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## ABSTRACT

Predicting drought occurrence accurately still remains a challenging task. To fill research gaps, this study identified and analysed meteorological and hydrological droughts using the Standardized Precipitation Index (SPI) and Streamflow Drought Index (SDI), respectively, in the upper Lam Pao watershed in Thailand. The study also focused on investigating the relationships between both droughts. The SPI and SDI were computed based on observed long-term precipitation and streamflow data during the period of 1988-2017. The drought analysis was carried out by using the R packages. The location, period and severity level of drought events were graphically presented. On the basis of trend analysis, the SPI series showed slightly increasing trends, whereas no trend was found for the SDI series. This implied that the hydrological drought was influenced by not only precipitation but also other factors. The key findings indicated that there was a positive relationship between meteorological and hydrological droughts. In addition, there was a specific lag time, which may depend on physical characteristics of a basin, in drought propagating from meteorological drought to hydrological drought. Overall, the drought indices can help to predict hydrological drought events, which could be valuable information for drought monitoring and early warning systems.

## 1. INTRODUCTION

Drought is a recurring natural and multifaceted phenomenon, which is significantly harmful to water-use sectors in all climatic zones (Mishra and Singh, 2010). Recently, a number of major droughts have resulted in great economical losses due to crop damage, destruction of infrastructure and human settlement, and also led to disputes amongst water users (Bachmair et al., 2016). Drought events are likely to increasingly occur based on climate change projections (Van Loon et al., 2016). According to several authors (Mishra and Singh, 2010), droughts can be clustered into different categories (e.g., meteorological, agricultural, hydrological, and socioeconomic) depending on their consequences, which lead to water shortages. Normally, the development of droughts occurs in the regions where climatic conditions (e.g., precipitation) are significantly below the normal or expected conditions over a period of time. At early stages, the droughts are usually referred to as meteorological

droughts. These meteorological droughts can develop into other droughts such as agricultural and hydrological droughts at a later stage (Barker et al., 2016).

One of the practical ways to assess drought events is through an index method. It derives drought indices from a variety of simple parameters to more complex functions (Mishra and Singh, 2010; Bachmair et al., 2016). Most indices for determining droughts, such as the Palmer drought severity index (Palmer, 1968) and the surface water supply index (Shafer and Dezman, 1982), in general, require a variety of data and an intensive computational effort (Van Loon, 2015; Bachmair et al., 2016). On the contrary, Standardized Precipitation Index (SPI) and Streamflow Drought Index (SDI) are simple and effective indices requiring very few input parameters and can be easily calculated. The SPI introduced by McKee et al. (1993) has been extensively used to characterise and monitor meteorological droughts

(Mishra and Singh, 2010). It can be used to measure the severity and occurrence of droughts, although only precipitation data is fed as input (Barker et al., 2016). The SDI developed by Nalbantis and Tsakiris (2009) is based on the SPI developing concepts and is usually applied to characterise hydrological droughts.

A large number of studies on meteorological and hydrological droughts in many regions have been carried out by applying either the SPI or SDI method (Nalbantis and Tsakiris, 2009). For example, meteorological drought studies were conducted using the SPI method in the UK (Barker et al., 2016), Ethiopia (Belayneh et al., 2014), and Greece (Karavitis et al., 2011) and hydrological drought studies were undertaken using the SDI method in the Tigris basin, Turkey (Ozkaya and Zerberg, 2019) and the upper Yangtze River Basin, China (Hong et al., 2015). However, few published studies have used standardised indicators to explain links between meteorological and hydrological droughts due to their complexity (Lorenzo-Lacruz et al., 2013).

Owing to the complexity between meteorological and hydrological droughts, it is necessary to improve the understanding of the hydrological response to climate variations at different timescales. Thus, the present study focused on characterising meteorological and hydrological droughts on the basis of climate and hydrological data recorded in the upper Lam Pao watershed from 1988 to 2017. This watershed is an unregulated basin, where there are neither large dams nor other man-made structures located. Therefore, its hydrological data (i.e., streamflow data) represents natural flows, which are generally a useful indicator of water availability in the basin. The aims of this study were: (1) to analyse meteorological and hydrological drought evolution by using the SPI and SDI methods; (2) to determine long-term trends in drought indices at different timescales by using Mann-Kendall and Sen's slope estimator methods; and (3) to investigate the relationships between meteorological and hydrological droughts over the study period.

## 2. METHODOLOGY

### 2.1 Study area and data

The upper Lam Pao watershed has an area of approximately 2,150 km<sup>2</sup> with its outlet at Ban Tha Hai, where the monitoring station E65 is placed (Figure 1). Geographically, the watershed extends

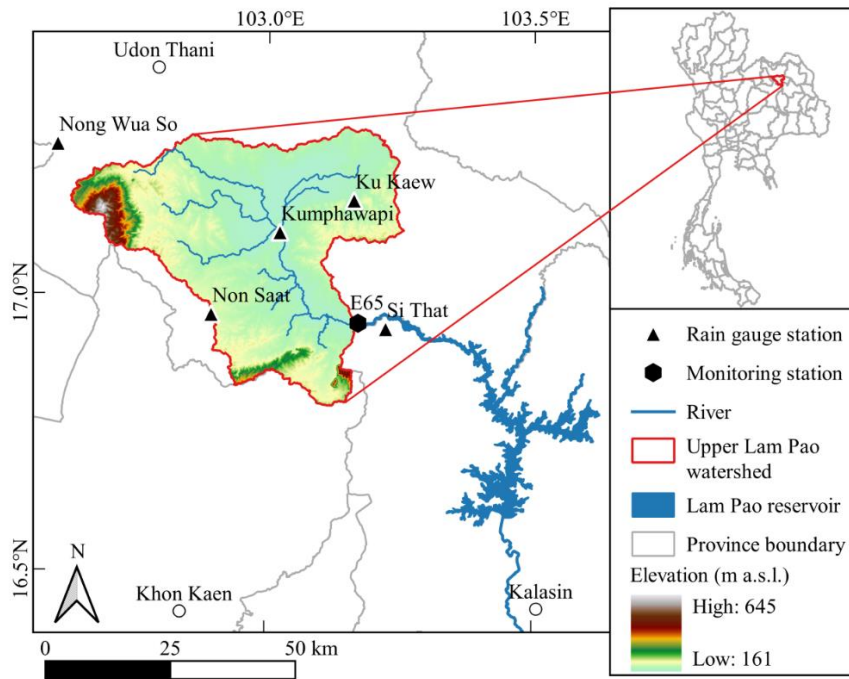
from latitude 16.8°N to 17.3°N and from longitude 102.6°E to 103.2°E. The Lam Pao River originates from mountainous areas in the Northwest and flows into the Lam Pao Reservoir in the Southeast. Its average annual streamflow is 749 MCM. The altitude ranges from 161 to 645 m.a.s.l. The upper Lam Pao watershed mainly covers Kumphawapi district and Nong Saeng district of Udon Thani Province, Northeastern Thailand. Average annual rainfall of the study area is 1,280 mm with mean daily temperatures ranging from 22 to 32°C. The rainy season begins in late May, lasting till October, whereas the dry season extends from November through mid-May.

Owing to being situated in a tropical monsoon climate, recurrent floods and droughts are considered to be major natural hazards. As is the case of water-use sectors, droughts have adverse impacts on water supply, agriculture, and the environment due to water shortages. Since droughts commonly occur in the watershed, it was chosen as the study area. In addition, most areas are used for rainfed crops, which are predominantly located in drought-prone areas. Therefore, the use of scientific insights can lead to better understand and predict drought because data available in the watershed meets the requirements of the index approach for drought analysis.

Meteorological data (rainfall) and hydrological data (streamflow) were collected in the period 1988-2017. Daily rainfall data of five rain gauge stations located inside and in the vicinity of the upper Lam Pao watershed were gathered from the Thai Meteorological Department (TMD). Moreover, daily water level data measured at the monitoring station E65 operated by the Royal Irrigation Department (RID) were used. Daily streamflow data were obtained from measurements of the daily water level by using local rating curves. Afterwards, both daily data were accumulated into monthly values in order to construct drought indices.

### 2.2 Drought indices

Studies of meteorological and hydrological droughts in the upper Lam Pao watershed were carried out by using an integrated index method for the long-term period 1988-2017. Drought indices were computed based on the monthly rainfall and streamflow data for cumulative periods of 6, 9, 12, and 18 months.



**Figure 1.** Map of study area with locations of rain gauge and streamflow monitoring stations.

SPI introduced by [McKee et al. \(1993\)](#) is a common indicator for monitoring and quantifying the intensity of meteorological drought events caused the shortage of rainfall or precipitation ([Belayneh et al., 2014](#)). This index was selected due to its simplicity and robustness ([Wilhite et al., 2005](#)), as previously mentioned. The SPI computation for any location begins by choosing a suitable probability distribution for long-term monthly precipitation data, typically a continuous period of at least 30 years. Subsequently, the cumulative probability distribution is converted into a normal distribution ([McKee et al., 1993](#)). In other words, the SPI represents a z-score variable of the standard normal distribution ([Karavitis et al., 2011](#)). The SPI can be computed as the ratio of the difference between the precipitation and the mean precipitation to the standard deviation as shown in equation (1):

$$SPI_i = \frac{x_i - \bar{x}_k}{\sigma_k} \quad (1)$$

Where;  $SPI_i$  is Standardized Precipitation Index for the  $i^{th}$  hydrological month,  $x_i$  is seasonal rainfall (mm),  $\bar{x}_k$  is long-term seasonal rainfall mean for the  $k^{th}$  reference timescale (mm), and  $\sigma_k$  is the standard deviation of the rainfall for the  $k^{th}$  reference timescale (mm).

SDI developed by [Nalbantis and Tsakiris \(2009\)](#) is a commonly used index for characterising

hydrological drought events. The SDI uses the same concept as the SPI but the SDI computation is performed by replacing rainfall by streamflow series. The formula for SDI can be expressed in equation (2).

$$SDI_i = \frac{Q_i - \bar{Q}_k}{\sigma_k} \quad (2)$$

Where;  $SDI_i$  is Streamflow Drought Index for the  $i^{th}$  hydrological month,  $Q_i$  is seasonal streamflow discharge ( $m^3/s$ ),  $\bar{Q}_k$  is long-term seasonal streamflow discharge mean for the  $k^{th}$  reference timescale ( $m^3/s$ ), and  $\sigma_k$  is the standard deviation of the streamflow discharge for the  $k^{th}$  reference timescale ( $m^3/s$ ).

In the present study, the drought indices (i.e., SPI and SDI) were computed using the R package “preintcon” and were based on the monthly time-series of rainfall and streamflow data, respectively. These data were ordered according to the hydrological year, which is from April to March of the following year in Thailand. The series of cumulative sums of rainfall and streamflow for 6-, 9-, 12-, and 18-month timescales were used to compute SPI-6, SDI-6, SPI-9, SDI-9, SPI-12, SDI-12, SPI-18, and SDI-18, respectively. For example, SPI-6 and SDI-6 begin from April to September, while SPI-9 and SDI-9 begin from April to December. During the computation, the series were smoothed with a moving window of  $k$  months, where  $k$  indicates the reference timescale (e.g.,  $k=6, 9, 12, 18$  months, etc.). In addition, the

series were fitted to the Gamma probability distribution, which is often used by many researchers (Nalbantis and Tsakiris, 2009; Karavitis et al., 2011; Fischer et al., 2013; Boudad et al., 2018). Subsequently, the cumulative probability distribution of the series data was transformed into the normal distribution (Gumus and Algin, 2017).

The SPI values of each rain gauge station were computed over different timescales. Afterwards, the SPI values from all the five rain gauge stations were spatially averaged by using the Thiessen polygon method. These average SPI values were used to determine meteorological dry and wet periods of the study area. The SDI was obtained based on the monthly streamflow data recorded at the monitoring station E65. Since the SPI and SDI perform in a similar manner, drought classification of their results can be based on a similar criterion (Nalbantis and Tsakiris, 2009). According to McKee et al. (1993), thresholds used to categorise droughts are shown in Table 1.

**Table 1.** Drought classification

SPI and SDI range	Drought category
2.00 or more	Extremely wet
1.50 to 1.99	Very wet
1.00 to 1.49	Moderately wet
0.00 to 0.99	Slightly wet
-0.99 to 0.00	Mild drought
-1.49 to -1.00	Moderate drought
-1.99 to -1.50	Severe drought
-2.00 or less	Extreme drought

## 2.3 Trend analysis

To determine the overall direction of the SPI and SDI values at different timescales, we applied two statistical measures, namely, the Mann-Kendall test (Kendall, 1970) and the Sen's slope estimator method (Sen, 1968), which are frequently applied in environmental research (Boudad et al., 2018). In this study, the two statistical measures were calculated using the R package "trend".

### 2.3.1 Mann-Kendall test

The Mann-Kendall (M-K) test (Kendall, 1970) is a non-parametric statistic measure, which indicates variations of a time-series data and whether they are statistically significant. The M-K test statistic (S) and its standardised statistic ( $Z_{M-K}$ ) are computed as follows:

$$S = \sum_{q=1}^{n-1} \sum_{p=q+1}^n \text{sgn}(z_p - z_q) \quad (3)$$

$$Z_{M-K} = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, S > 0 \\ 0, S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, S < 0 \end{cases} \quad (4)$$

Where; n is the number of the data values,  $z_p$  and  $z_q$  are the data values in time series p and q, respectively, for which p is greater than q, sgn is the sign functions, and Var(S) is the variance of S. A positive sign of  $Z_{M-K}$  represents an increasing trend, whereas a negative sign of  $Z_{M-K}$  represents a decreasing trend. In addition, the values of  $Z_{M-K}$  are subjected to significance analysis. In this study, the significance level was set at  $\alpha=0.05$ . At the 5% significance level, if the absolute value of  $Z_{M-K}$  is greater than 1.96, the time-series data have a statistically significant trend.

### 2.3.2 Sen's slope estimator method

Similar to the M-K test, the Sen's slope estimator method developed by Sen (1968) is a non-parametric way to discover a trend in a time-series data. This method estimates the slope of a regression line that fits the time-series data on the basis of a least-squares estimate. The slope estimates of all data pairs are obtained from the following equation:

$$d_i = \frac{z_p - z_q}{p - q}, i = 1, 2, \dots, N \text{ and } p > q \quad (5)$$

Where;  $d_i$  is a slope estimate of the time-series data,  $z_p$  and  $z_q$  are the data values in time p and q, respectively, and N is all data pairs for which p is greater than q. Afterwards, the N values of  $d_i$  are ranked from the smallest to largest and the Sen's slope estimator (SSE), which is the median of  $d_i$ , is computed as follows:

$$\text{SSE} = \begin{cases} d_{(N+1)/2} & \text{if } N \text{ is odd} \\ \frac{1}{2} [d_{N/2} + d_{(N+2)/2}] & \text{if } N \text{ is even} \end{cases} \quad (6)$$

A positive value of SSE indicates an increasing trend, whereas a negative value represents a decreasing trend of the time-series data.

## 2.4 Cross-correlation analysis

In this study, cross-correlation analysis was performed using the R package "astsa" in order to evaluate the relations between meteorological and hydrological droughts, which were based on the cross-



correlations between the SPI and SDI values with varying a lag time between the two series. These cross-correlations were examined using the Pearson correlation coefficient ( $r$ ) (Hipel and McLeod, 1994). The estimate of this Pearson correlation coefficient can be obtained using the following equation:

$$r = \frac{n \sum X_i Y_i - \sum X_i \sum Y_i}{\sqrt{n \sum X_i^2 - (\sum X_i)^2} \sqrt{n \sum Y_i^2 - (\sum Y_i)^2}} \quad (7)$$

Where;  $r$  is the Pearson correlation coefficient,  $X_i$  and  $Y_i$  are SPI and SDI values at time  $i$ , respectively, and  $n$  is the number of paired values of  $X$  and  $Y$ .

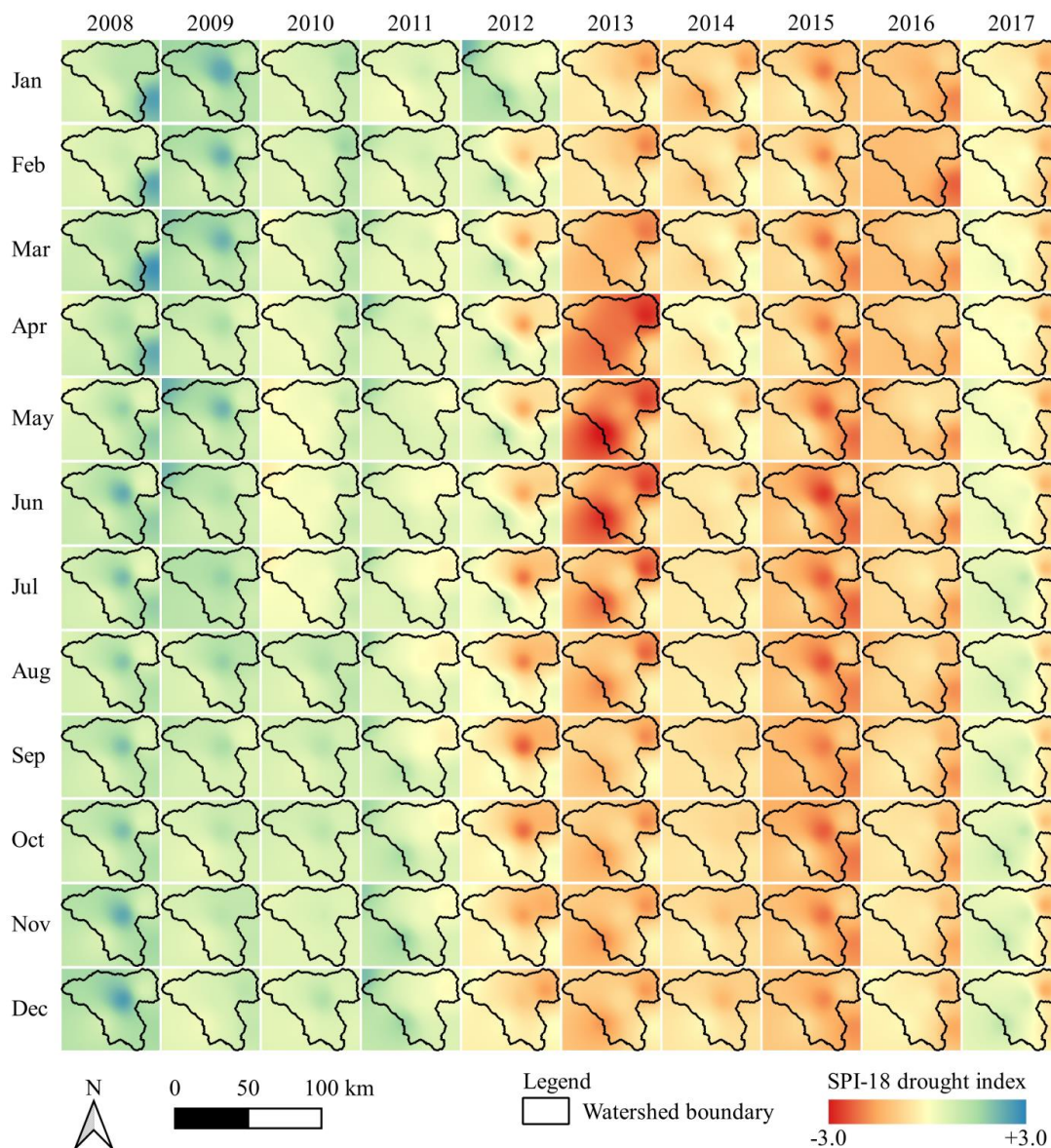
As previously mentioned, hydrological droughts usually develop from meteorological droughts. In order to analyse delay in drought propagation, the monthly SDI values at a given

timescale were lagged behind the SPI values in monthly increments from zero lag up to a 12-month lag. Afterwards, their cross-correlations ( $r$ -values) were computed by using the equation (7).

### 3. RESULTS AND DISCUSSION

#### 3.1 Meteorological and hydrological droughts

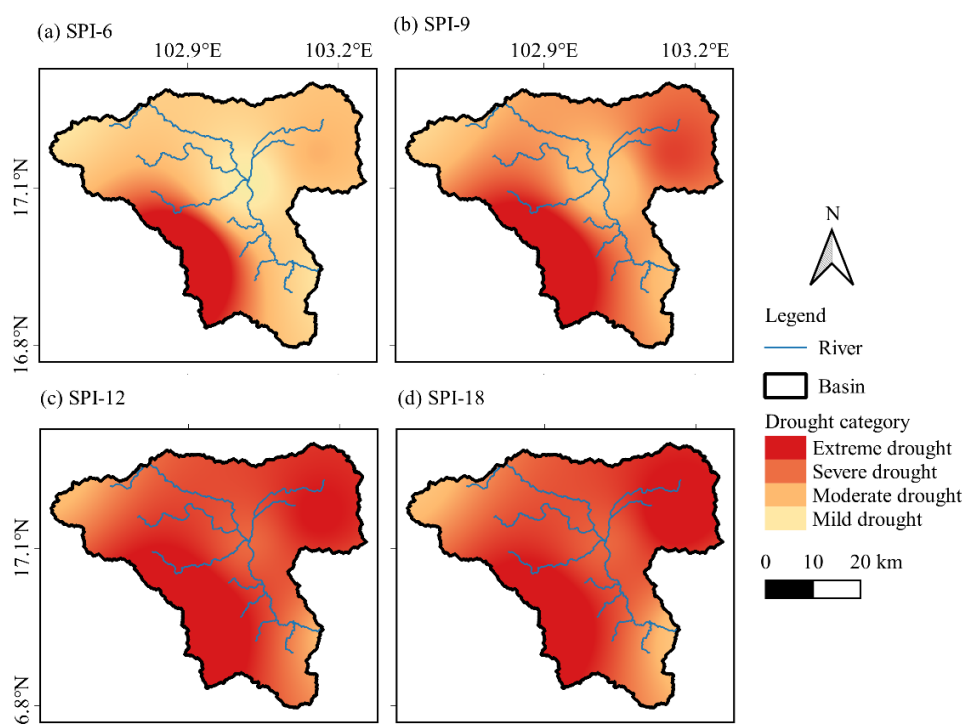
The spatial distribution maps of SPI values obtained by using the IDW method were based on rainfall data observed during the period of 30 years. Figure 2 shows, for instance, spatial-temporal variations from January 2008 to December 2017 on the basis of SPI-18 in the entire watershed and its surroundings. It can be seen from the figure that the year 2013 was the driest year in the watershed for the period of the analysis.



**Figure 2.** Spatial-temporal variations of SPI-18 drought index between 2008 and 2017.

The SPI values were classified according to McKee et al. (1993) into different levels of drought severity. Figure 3 shows an example of drought map of the upper Lam Pao watershed for the month of May 2013, which had the most critical drought condition in the entire period of the analysis. Figures 3(a) and (b) show that extreme drought events were observed in the

southwest of the watershed for SPI-6 and SPI-9, respectively. In spite of that, Figures 3(c) and (d) demonstrate that extreme drought events were encountered in the southwest and northeast parts of the watershed for SPI-12 and SPI-18, respectively, with around 20% of the area affected by such events.



**Figure 3.** Spatial variations of drought based on SPI for May 2013.

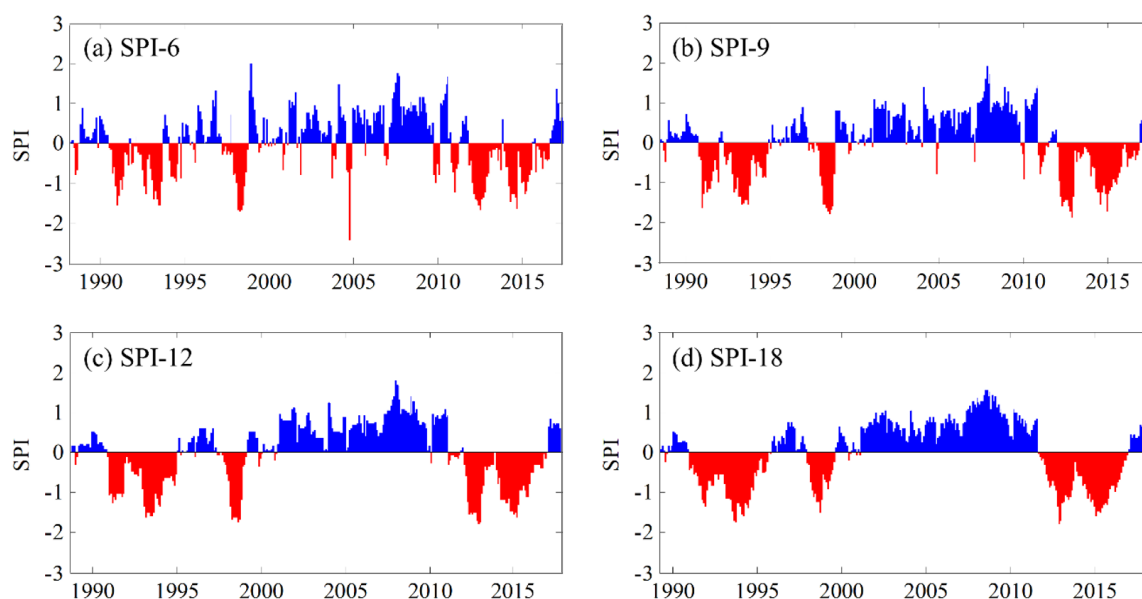
The evolution of the average SPI and SDI series for each reference timescale is separately shown in Figure 4 and Figure 5, respectively. On the basis of the average SPI and SDI series, fluctuations of their values represent dry and wet periods. In a short timescale (e.g., 6 months), the average SPI and SDI series resemble tropical monsoon seasonal variations of the study watershed as shown in the figures. In the medium and long timescales (i.e., 9, 12, and 18 months), severe consecutive droughts during 1992-1994 and extreme consecutive droughts during 2012-2013 were identified by both the SPI and SDI. For example, the driest conditions occurred in the year 2013 determined with an average SPI-12 value of -1.78 for May 2013 and an SDI-12 value of -2.87 for June 2013.

### 3.2 Analysis of drought trends

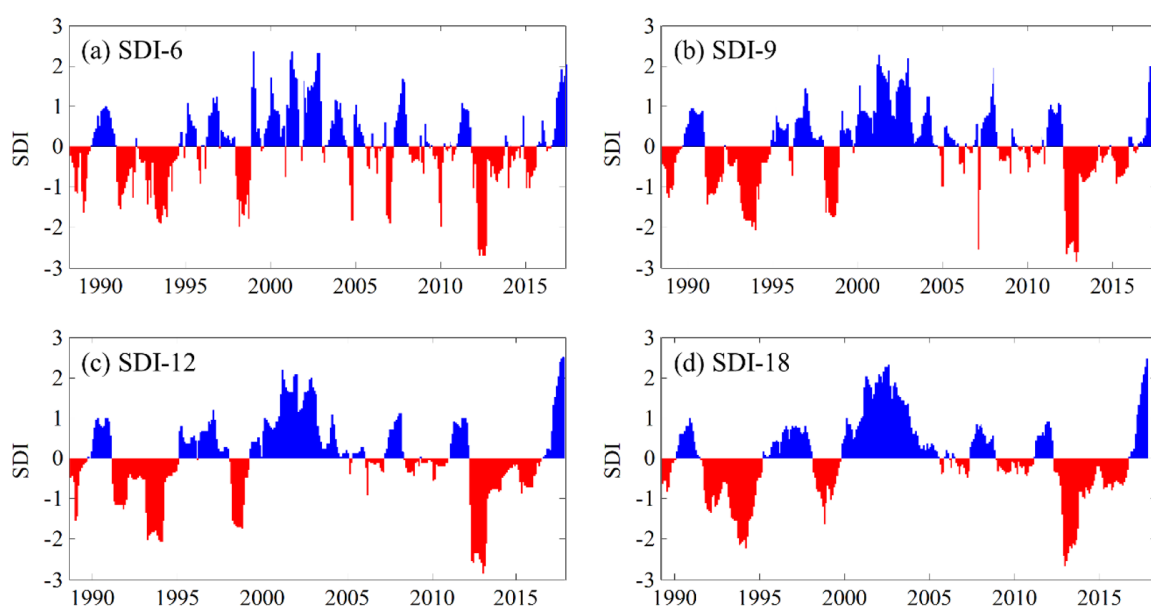
The Z statistics of the Mann-Kendall test ( $Z_{M-K}$ ) for the SPI and SDI series as well as their values of SSE are presented in Table 2. According to the Mann-Kendall (M-K) test at the 5% significance level, a

trend in a time-series is accepted when the absolute value of  $Z_{M-K}$  is greater than 1.96. There were significantly increasing trends for the SPI-9, SPI-12, and SPI-18 series. In contrast, no significant trend of the SDI series was recognized by the M-K test.

Moreover, trend slopes were evaluated by using the Sen's slope estimator (SSE) method. This method produced positive values of SSE for all the SPI series, which indicated upward trends (Table 2). This result suggested that there has been no tendency for increasing meteorological droughts in recent years. The values of SSE for the SDI-6, SDI-9, and SDI-12 series showed slightly increasing trends. However, the SDI-18 series was found to have a slightly declining trend. The present study found that hydrological droughts were influenced by not only precipitation but also other factors. This finding is consistent with that of Van Loon et al. (2016), who stated that factors such as soil type, geology, and land cover can modify the hydrological response to climate variability.



**Figure 4.** Temporal evolution of the average SPI of the five rain gauge stations in the accumulation periods of (a) 6, (b) 9, (c) 12, and (d) 18 months



**Figure 5.** Temporal evolution of the SDI at the monitoring station E65 in the accumulation periods of (a) 6, (b) 9, (c) 12, and (d) 18 months.

**Table 2.** Z values of the M-K test ( $Z_{M-K}$ ) and the Sen's slope estimator (SSE) of SPI and SDI series during the 1988-2017 (values in bold represent statistically significant trends at the 5% significance level).

Test	SPI-6	SPI-9	SPI-12	SPI-18	SDI-6	SDI-9	SDI-12	SDI-18
$Z_{M-K}$	1.507	<b>2.602</b>	<b>3.336</b>	<b>3.534</b>	1.801	0.739	0.150	-0.440
SSE	0.0007	0.0013	0.0016	0.0018	0.0009	0.0004	0.0001	-0.0003

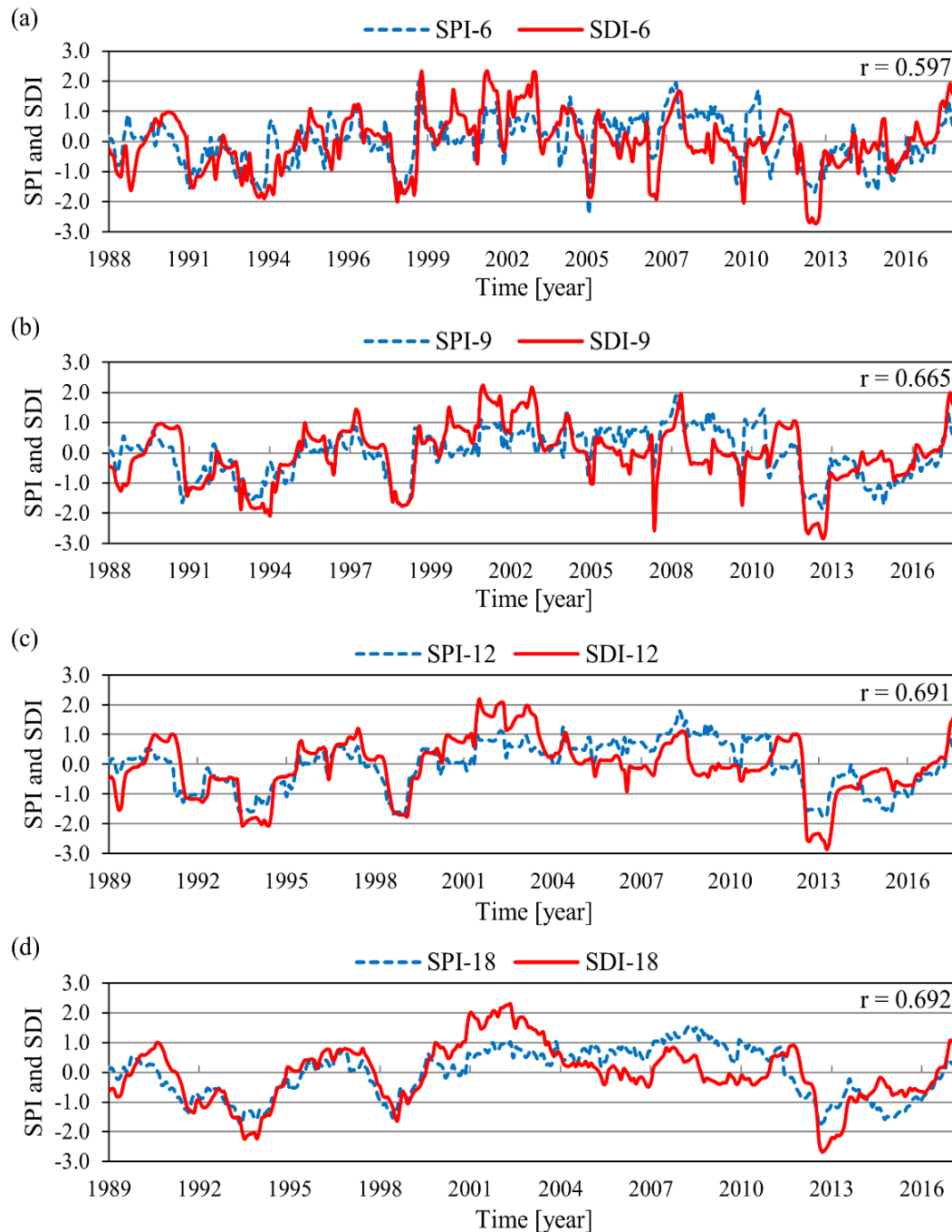
### 3.3 Correlation between meteorological and hydrological droughts

This study found that all the average SPI series were correlated to the SDI series at the same timescale

as shown in Figure 6. These results agree with the findings of other studies (Nalbantis and Tsakiris, 2009; Boudad et al., 2018), in which strong relationships between the SPI and SDI series were

reported. Here, the greatest correlation was found between the SPI-18 and SDI-18 series with a correlation coefficient of about 0.692. These results need to be interpreted with caution because the average SPI series were based on available rainfall data from the five rain gauge stations located inside and outside of the study area. Figure 6(d) exhibits a good relationship between SPI-18 and SDI-18 series. However, their trend directions were found to be

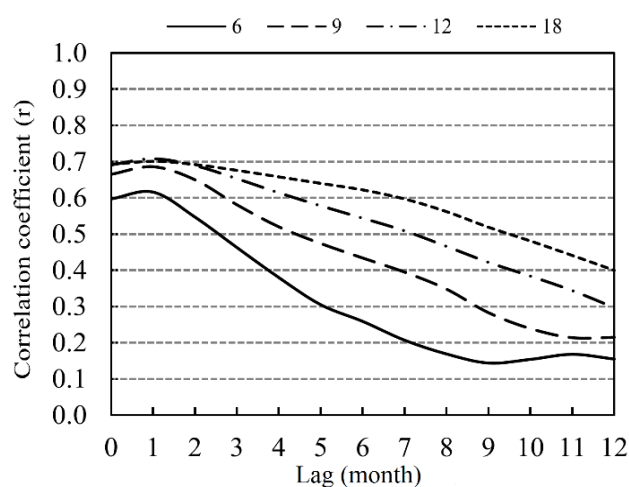
different. Several factors could explain these observations. Firstly, potential evaporation may be an important factor, which has an influence on drought conditions. Another possible factor is the lag time between rainfall and runoff, which can delay in drought propagating from meteorological drought to hydrological drought. The observations are in agreement with those obtained by [Lorenzo-Lacruz et al. \(2013\)](#) and [Barker et al. \(2016\)](#).



**Figure 6.** Average SPI values of the upper Lam Pao watershed and SDI values for the monitoring station E65 for reference timescales (6, 9, 12, 18 months). (a) SPI-6 and SDI-6 series; (b) SPI-9 and SDI-9 series; (c) SPI-12 and SDI-12 series; and (d) SPI-18 and SDI-18 series.



Furthermore, the cross-correlation test revealed that the SPI series can be used to predict hydrological drought events. Figure 7 shows the changes in the linear correlation coefficients (r-values) between the SPI series and corresponding SDI series, which were shifted after the SPI series in monthly increments from zero lag up to a 12-month lag. The peak r-values were obtained from a one-month lag between the SPI and SDI series for all the reference timescales. These results reflect those of Blagojević et al. (2013), who also found that the correlation improved as the SPI series was compared with the SDI series of the following month. Nalbantis and Tsakiris (2009) showed that a delay of one month between the two drought indices was too large for their test basin, an area of about 350 km<sup>2</sup>. However, the 1-month lag was too small for the Seyhan-Ceyhan River basins with a total area of approximately 43,840 km<sup>2</sup> (Gumus and Algin, 2017). These results are likely to be related to the physical properties of the drainage basins. The finding is in line with that of previous studies (Lorenzo-Lacruz et al., 2013; Van Loon, 2015).



**Figure 7.** Correlation coefficients between SPI and SDI series at different time lags from zero up to 12 months.

In general, it seems that monitoring of meteorological and hydrological droughts can be carried out by using several drought indices (e.g., SPI and SDI). The results are suggestive of links between meteorological and hydrological droughts based on the use of the SPI and SDI. For example, the lag time between the SPI and SDI series can be useful information for improving drought monitoring and early warning systems. However, hydrological droughts may not be fully explained just by the meteorological drought indices (Van Loon, 2015). Indeed, there are other variables such as physical

characteristics of the basin, soil moisture, land use as well as the relations between streamflow and groundwater that have resulted in the hydrological drought (Barker et al., 2016). In further investigations, it might be possible to use a different drought index and to establish a more complete hydrological drought index for improving drought monitoring and prediction.

#### 4. CONCLUSIONS

This study set out to investigate meteorological and hydrological droughts in the upper Lam Pao watershed of Thailand and to explore their relations. Analysis of both droughts was performed based on the monthly values of the SPI and SDI in the period 1988-2017. The use of the SPI and SDI together with their classifications is considered a reliable tool in the assessment of meteorological and hydrological drought evolution in space and time. The Mann-Kendall test suggested that the occurrence of meteorological drought would not probably increase in recent years. However, the Sen's slope estimator method suggested an increase in the long-term hydrological drought because a slightly negative trend of SDI-18 was detected. The investigation of the relationships between meteorological and hydrological droughts presented new findings, which indicated a time lag between both droughts. The time lag may vary depending on physical characteristics of a basin. This time lag can be useful information for determining future potential hydrological droughts when rainfall data are available. In conclusion, the present study has offered a framework for the exploration of meteorological and hydrological droughts. Future studies should attempt to identify the relationships between droughts using different climatic and geophysical variables.

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#### REFERENCES

- Bachmair S, Stahl K, Collins K, Hannaford J, Acreman M, Svoboda M, et al. Drought indicators revisited. Wiley Interdisciplinary Reviews: Water 2016;3(4):516-36.

- Barker LJ, Hannaford J, Chiverton A, Svensson C. From meteorological to hydrological drought using standardised indicators. *Hydrology and Earth System Sciences* 2016;20(6):2483-505.
- Belayneh A, Adamowski J, Khalil B, Ozga-Zielinski B. Long-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet neural network and wavelet support vector regression models. *Journal of Hydrology* 2014;508:418-29.
- Blagojević B, Mihailović V, Gocić M, Trajković S. Streamflow drought index modelling through standard precipitation index assisted by service-oriented paradigm. In: Lamaddalena N, Todorovic M, Pereira LS, editors. *Water, Environment and Agriculture*. Valenzano, Italy: CIHEAM-IAMB; 2013. p. S9-2.
- Boudad B, Sahbi H, Mansouri I. Analysis of meteorological and hydrological drought based in SPI and SDI index in the Inaouen Basin (Northern Morocco). *Journal of Materials and Environmental Science* 2018;9(1):219-27.
- Fischer T, Gemmer M, Su B, Scholten T. Hydrological long-term dry and wet periods in the Xijiang River Basin, South China. *Hydrology and Earth System Sciences* 2013;17(1):135-48.
- Gumus V, Algin HM. Meteorological and hydrological drought analysis of the Seyhan-Ceyhan River Basins, Turkey. *Meteorological Applications* 2017;24(1):62-73.
- Hipel KW, McLeod AI. *Time Series Modelling of Water Resources and Environmental Systems*. Amsterdam, London, UK: Elsevier; 1994.
- Hong X, Guo S, Zhou Y, Xiong L. Uncertainties in assessing hydrological drought using streamflow drought index for the upper Yangtze River Basin. *Stochastic Environmental Research and Risk Assessment* 2015;29(4):1235-47.
- Karavitis CA, Alexandris S, Tsesmelis DE, Athanasopoulos G. Application of the Standardized Precipitation Index (SPI) in Greece. *Water* 2011;3(3):787-805.
- Kendall MG. *Rank Correlation Methods*. London, UK: Griffin, 1970.
- Lorenzo-Lacruz J, Vicente-Serrano SM, González-Hidalgo JC, López-Moreno JJ, Cortesi N. Hydrological drought response to meteorological drought in the Iberian Peninsula. *Climate Research* 2013;58(2):117-31.
- McKee TB, Doesken NJ, Kleist J. The relationship of drought frequency and duration to time scales. *Proceedings of the 8<sup>th</sup> Conference on Applied Climatology*; 1993 Jan 17-22; Anaheim: USA; 1993. p. 179-84.
- Mishra AK, Singh VP. A review of drought concepts. *Journal of Hydrology* 2010;391(1-2):202-16.
- Nalbantis I, Tsakiris G. Assessment of hydrological drought Revisited. *Water Resources Management* 2009;23(5):881-97.
- Ozkaya A, Zerberg Y. A 40-Year Analysis of the Hydrological Drought Index for the Tigris Basin, Turkey. *Water* 2019; 11(4):657.
- Palmer WC. Keeping track of crop moisture conditions, nationwide. *Weatherwise* 1968;21(4):156-61.
- Sen PK. Estimates of the regression coefficient based on Kendall's Tau. *Journal of the American Statistical Association* 1968;63(324):1379.
- Shafer BA, Dezman LE. Development of a surface water supply index (SWSI) to assess the severity of drought conditions in snowpack runoff areas. *Proceedings of the 50<sup>th</sup> Annual Western Snow Conference*; 1982 Apr 19-23; Reno: USA; 1982. p. 164-175.
- Van Loon AF. Hydrological drought explained. *Wiley Interdisciplinary Reviews: Water* 2015;2(4):359-92.
- Van Loon AF, Stahl K, Di Baldassarre G, Clark J, Rangelcroft S, Wanders N, et al. Drought in a human-modified world. *Hydrology and Earth System Sciences* 2016;20(9):3631-50.
- Wilhite DA, Svoboda MD, Hayes MJ. Monitoring drought in the United States. In: Boken VK, Cracknell AP, Heathcote RL, editors. *Monitoring and Predicting Agricultural Drought*. Oxford, USA: Oxford University Press; 2005. p. 121-31.