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Original article

A comparative performance analysis of three standardized climatic drought indices in the Chi River basin, Thailand

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A B S T R A C T

Drought indices are generally used as a tool for monitoring changes in drought conditions. This paper evaluated the performance of three climatic drought indices to characterize drought trends in the Chi River basin in Northeast Thailand. Initially, the drought assessment was conducted using the Standardized Precipitation Index (SPI), a precipitation-based index, and the Standardized Precipitation Evapotranspiration Index (SPEI), an index taking into account the difference between precipitation and potential evapotranspiration (PET). Then, this study simply applied an index called the Standardized Precipitation Actual Evapotranspiration Index (SPAEI), similar to the commonly used SPEI, with the difference being in the use of actual evapotranspiration (AET) instead of PET. Time series of the three indices were compared with observed droughts. The results indicated that various indicators of different indices can have diverse effects on drought conditions. The simple SPI, considering only precipitation, can be used to identify characteristics of droughts with certain restrictions. Being multivariate indices, the SPEI and the SPAEI were able to clearly detect the temporal variability of droughts to a greater extent than the SPI index. Moreover, the different results derived from using P-AET instead of P-PET made a substantial difference to temporal drought severity. Thus, climatic water demand had important aspects in determining the drought conditions for this area.

Introduction

Drought is a recurring natural hazard characterized as having below normal precipitation over an extended period of time ranging from months to years (for example, Dai, 2011). Drought occurs as a result of numerous variables acting on multiple time scales and varies with spatial location and temporal season; thus, drought can have impacts on various sectors especially on agriculture and ecosystems (for example, Heim Jr., 2002; Hao and Singh, 2015). Due to its complex nature and widespread occurrence, it is difficult to define drought and to identify its characteristics. A drought initially occurs when there is a deficit of precipitation for a prolonged period and it may even lead to further deficiencies of other hydrological parameters depending on different time scales. Consequently, the impacts of drought can be categorized into four types—meteorological drought, agricultural drought, hydrological drought and socio-economic drought (for example, Wilhite and Glantz, 1985). Thus, the classifications of droughts may differ depending on perspectives and stakeholders (for example, Mo, 2008; Intergovernmental Panel on Climate Change, 2012).

Various types of data sources, including in-situ observations, land surface model simulations and remote sensing, can be used to characterize droughts. Generally, drought indices have been developed and used to capture a drought's physical characteristics such as its frequency, duration, severity and spatial extent (Wilhite and Glantz, 1985). In addition, the selection of drought indicators — a broad term for hydrological parameters (for example, precipitation, temperature, streamflow) — is an important factor in developing a drought index. Construction of drought indices can therefore be formed in several ways; for example, by using a single aspect, combining multiple variables or mixing drought indices (Hao and Singh, 2015). Examples of drought indices are often used, such as the Palmer Drought Severity Index (PDSI; Palmer, 1965), the standardized precipitation index (SPI; McKee et al., 1993) and the

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Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010). Recently, major drought indices were comprehensively reviewed and their different development methods together with limitations and strengths were also specified (Hao and Singh, 2015). Currently, there is no particular index that is capable of adequately characterizing drought conditions for every place and every time period (Svoboda et al., 2015). Thus, the selection of drought indices depends on the type(s) of droughts, region(s) of interest, objective(s) and information available to each drought user (Smakhtin and Schipper, 2008). Furthermore, the challenge of drought assessment lies in the selection of the proper indicators and index to quantify changes in drought conditions (Tsakiris and Vangelis, 2005).

Some drought indices have proven popular The SPI (McKee et al., 1993) is a precipitation-based drought index, so it is less complicated as it requires only simple inputs. This index keeps track of accumulative precipitation deficits which can be computed at various time scales and places. Such a method corresponds to the multi-scalar nature of droughts taking place across multiple temporal scales (Hou et al., 2007). However, apart from precipitation, other variables such as temperature (Sheffield and Wood, 2008), atmospheric demand (Vicente-Serrano et al., 2015) and heat waves (Beguería et al., 2014) may also increase the variability of droughts.

The SPEI (Vicente-Serrano et al., 2010) provides a further development of the drought index by taking into account monthly climatic water balances (P-PET). The SPEI is similar to and flexible like the SPI but it includes in addition, the PET demand, a key component of water cycle (Oki and Kanae, 2006). The original formulation of the SPEI employs the Thornthwaite (Th) equation (Thornthwaite, 1948) for PET calculation since it only requires temperature and latitudinal data. However, the use of Th equation leads to an underestimation of PET in arid and semiarid regions (Jensen et al., 1990), and an overestimation of PET in humid and tropical regions (Van der Schrier et al., 2011). The errors can be diminished by using the Penman Monteith equation (Allen et al., 1989) which accounts for additional climatic data. In addition, the issue of using actual evapotranspiration (AET) instead of PET has been evaluated and suggested for calculating drought indices (Joetzjer et al., 2013). There are still high uncertainties and much disagreement on global drought trends due to inconsistencies in the techniques and indicators used (for example, Seneviratne et al., 2012). Hence, more research is needed to bridge the gap, especially on local scales.

The objective of this paper was to evaluate the performance of three climatic drought indices to characterize the drought trends at the local scale. Focusing on a tropical monsoon climate, the Northeast Thailand was chosen as it is repeatedly subjected to drought events. In particular, the study considered temporal drought trends compared to observed droughts.

Materials and methods

Study area

Thailand, in Southeast Asia, is located close to the equatorial Indo-Pacific basins; thus monsoon precipitation has a strong correlation with the Southern Oscillation index (SOI), a sea level pressure-based El Niño-Southern Oscillation (ENSO) index (Singhrattna et al., 2005). This region is characterized by a monsoon tropical climate with distinctive dry and rainy seasons causing droughts and floods to repeat alternatively.

The Chi basin is located in the central part of Northeastern Thailand, within the range 15.3–17.3 °N and 101.3–104.3 °W. The total catchment area of the Chi basin is approximately 49,476 km^2, of which more than 60% is rain-fed agricultural area growing rice as the major crop. The basin is surrounded by mountains and high plateau ranges from the north to the west making the river basin of the lower part look like a flat bowl, as shown in Fig. 1. Deciduous and evergreen forests are the main forest types covering 20% of the entire area. The spatial dataset including a digital elevation map (DEM) and land use data were provided by the Land Development Department (LDD), Thailand. In terms of climate observation, the area is not greatly influenced by human activities (dams and irrigation) compared to the central region of Thailand (Kim et al., 2005).

Climatic datasets

The daily precipitation datasets used in this study were the V1003R1 datasets at 0.25° gridded data provided by the Asian Precipitation- Highly-Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE) project (Yatagai et al., 2009). The dataset of APHRODITE is freely available online (http://www.chikyu.ac.jp/precip/) in various formats. The daily, observed weather datasets consisting of the maximum and the minimum temperatures, relative humidity, wind speed and solar radiation were obtained from the Royal Irrigation Department (RID) of Thailand and the Thai Meteorological Department (TMD) for the period between January 1978 and December 2007.

The average annual precipitation over the Chi River basin is approximately 1150 mm per year, and the range in precipitation varies between 900 and 1700 mm. Fig. 2A shows a box plot for mean monthly precipitation for 30 year period. Fig. 2B shows a decreasing trend of annual precipitation which is consistent with Sheffield et al. (2012) who noted decreases in regional precipitation over Asia. The rainfall pattern in this area plays an important role in the occurrence of drought. The dry season always dries up the rivers causing serious problems for people during severe droughts. Fig. 2B shows an increasing trend of PET and evapotranspiration (ET) in the Chi River basin. There is evidence demonstrating that the frequency, severity and duration of droughts in the Northeastern region are higher than in other regions (Suwanabatr and Mekhora, 2002).

This study used the AET data obtained by the study conducted by Homdee et al. (2012) which used the Soil Water Assessment Tool (SWAT) model to simulate water balance. SWAT is a spatially distributed, hydrological model developed to mainly predict the impacts of land management practices on water balance (Arnold et al., 1998). Conceptually, the SWAT model overlays a DEM, land use and soil map and slope classes and further calculates the water balance for each subdivision. The Penman-Monteith method was used in the model to calculate the daily reference ET and the potential plant transpiration was calculated using the actual daily crop height and leaf area index. Potential soil evaporation is an exponential function of the reference ET and the soil cover, and is significantly reduced during periods with high plant water use. Actual soil evaporation is limited by the soil water content (θ) and is reduced exponentially when θ drops below field capacity. AET is the sum of interception, actual soil evaporation and actual plant transpiration.

AET is one of the standard outputs of the SWAT model which commonly generates daily stream flows during the period 19782007. Thus, this paper focused on changes in past drought events over the same period due to the limited, available AET data. Also, Thailand's monsoon rainfalls were more closely related to El Niño during 1980–1999 (Singhrattna et al., 2005); thus the observation of such drought variability over this period is valuable.

Climatic drought indices calculations

Standardized precipitation index

The Standardized Precipitation Index (SPI) (McKee et al., 1993) is an index based on probability of the long term precipitation

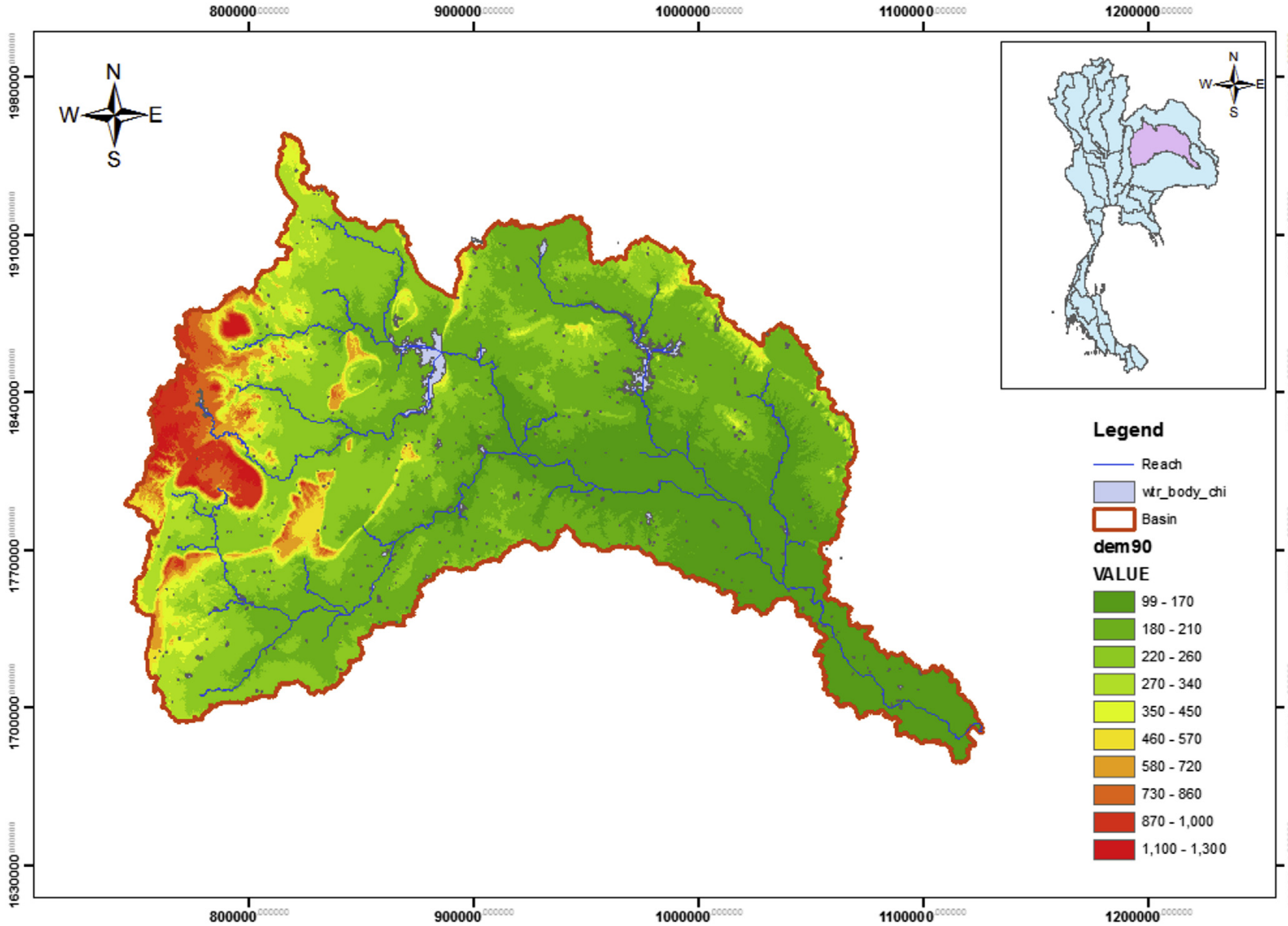

Fig. 1. Topography and river tributaries of the Chi River basin in Northeastern Thailand.

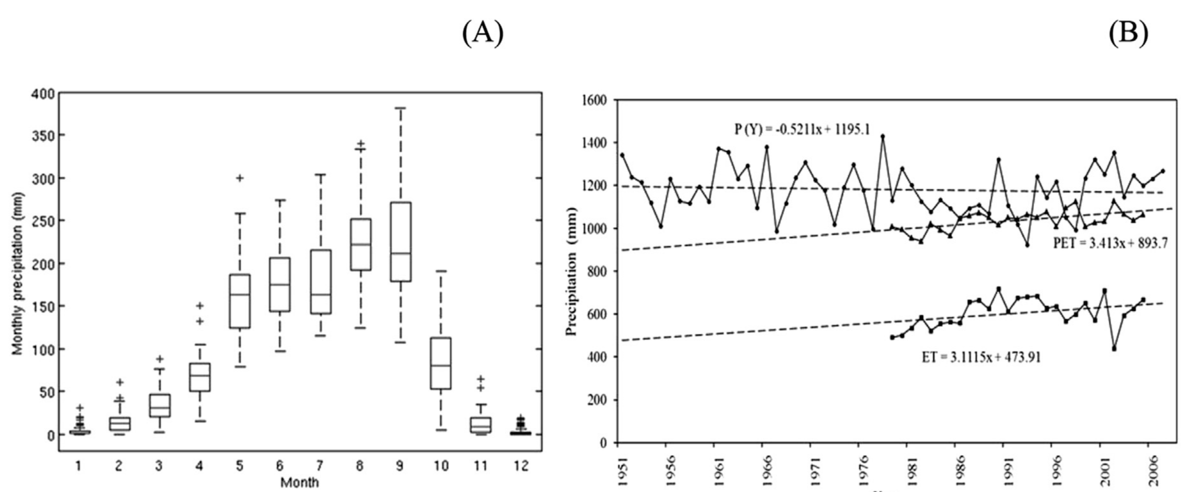

Fig. 2. Climatic data in the Chi river basin: (A) box plot for mean monthly precipitation; the solid line in the solid squares within the box plot depicts the mean monthly value of precipitation (B) time series of annual precipitation [P(Y)], potential evapotranspiration (PET) and evapotranspiration (ET).

representing either abnormal wetness or dryness conditions. The SPI was designed to quantify precipitation deficits for different time scales such as 3 mth, 6 mth, 9 mth, 12 mth or 24 mth of cumulative precipitation. This allows the SPI index to reflect impacts resulting from the availability of different hydrological parameters. The initial step for calculating the SPI is to fit long time series of monthly precipitation measurements to determine the cumulative probability density function (PDF). Then, the given PDF distribution of the observed precipitation is transformed into a normal distribution with a mean of zero and standard deviation of one. The original concept of the SPI applied the two-parameter gamma distribution. The complete calculation procedure for the SPI can be found in McKee et al. (1993), and some details are provided in Equation (1):

$$g(x) = \frac{1}{\beta^{\alpha}\,\tau\,(\alpha)} x^{\alpha-1} e^{\frac{-x}{\beta}} \tag{1}$$

where β is a scale parameter, α is a shape parameter, g(x) is the gamma probability density function, e is Euler's number for exponentiation and τ(α) is the ordinary gamma function of α. The estimation of β and α can be found in more detail in McKee et al. (1993).

Standardized precipitation evapotranspiration index

The Standardized Precipitation Evapotranspiration Index (SPEI) has been developed to measure drought conditions (Vicente-Serrano et al., 2010). This index is based on a monthly climatic water balance driven by precipitation and PET. The procedure of the SPEI computation relies on the original SPI calculation but uses the monthly difference between precipitation (P) and PET as shown in Equation (2):

$$D = P - PET \tag{2}$$

Here D provides a simple measurement of water deficits or surpluses aggregated at different time scales. The values are then fitted to several parametric statistical probability distributions to transform the original values to standardized units. Unlike Vicente-Serrano et al. (2010), the PET calculation in this paper used the Penman-Monteith (PM) equation (Allen et al., 1998) recommended by World Meteorological Organization (2009) which was confirmed as having the best performance over Northeastern Thailand (Haruethaithip, 2003).

Furthermore, this study applied the use of actual evapotranspiration (AET) instead of PET for the SPEI calculation and it was named the SPAEI index, where SPAEI stands for the Standardized Precipitation Actual Evapotranspiration Index. Similar to the SPEI method, the procedure for the SPAEI computation requires monthly differences between precipitations (P) and AET as shown in Equation (3):

$$D = P - AET \tag{3}$$

In order to measure the accuracy of the drought indices, distribution fitting was tested by applying various probability distributions such as gamma, log normal and normal distributions to fit a time series of accumulated precipitation. Based on validation for the distribution selection, the Kolmogorov–Smirnov (K–S) test is a test for the goodness of fit. The nonparametric test is calculated as the maximum difference between the empirical cumulative distribution of sampled points and the theoretical cumulative distribution. This paper used the Pearson r coefficient to measure the linear relationship between the time series of each index.

Results and discussion

Distribution fitting

The results of the K–S test (not displayed) illustrated that the two-parameter gamma distribution produced the best fit for all accumulation periods except for 1 mth SPI. This was consistent with some studies in India (Kumar et al., 2009) and the USA (McKee et al., 1993). However, it was less capable of fitting the data in isolated, coastal regions (Beguería et al., 2014). Apparently, the distribution function at the short timescale (1 mth SPI) does not quite fit with the empirical distribution compared to the longer timescale. This agreed with the findings by Vicente-Serrano et al. (2010). This may have been due to numerous zero values of precipitation in the short timescale of the SPI; hence, the evaluation of SPI can be misleading particularly in dry climates. Consequently, poorly fitting probability distributions have the potential to bias drought index values, either overstating or minimizing the perceived severity of the drought index (Beguería et al., 2014). Therefore, the proper selection of the probability distribution of precipitation over different timescales is necessary. With the SPEI distribution fitting, GEV distribution consistently performed the best goodness of fit across accumulation periods which was consistent with Stagge et al. (2015) reporting that the GEV distribution consistently produces the best goodness of fit, but which contrasts with (Vicente-Serrano et al., 2010).

Evaluation of climatic drought indices

The temporal variations of observed droughts were examined. Fig. 3 presents the time series of the SPI calculated for 1 mth, 3 mth, 6 mth, 9 mth, 12 mth and 24 mth, respectively. Drought events are defined whenever the SPI values are lower than −1, the threshold value. The degree of drought can be computed as a factor of the highlighted area size. The different timescales of the SPI demonstrated differences in magnitude and duration of droughts. Longer timescales showed a higher severity and longer duration of droughts than the short timescales. For long timescales (>6 mth SPI), water scarcity was less frequent, but lasted longer. Clearly, drought events were likely take place every year based on the 1-month timescale. This may have been due to the limitation of the probability distribution being fitted with zero values of precipitation causing the SPI to fail to detect drought conditions in the region with a distinct dry season, particularly at short timescales (Wu et al., 2007).

There is still no consensus on the most suitable techniques for the validation of the drought indices (Hao and Singh, 2015). Several studies confirmed a relationship between drought events and the ENSO variability. Their associations with El Niño conditions were also linked to the variability of monsoon precipitation causing drought variability in this region including India (Niranjan Kumar et al., 2013) and Thailand (for example, Buckley et al., 2007; Singhrattna et al., 2012). Moreover, many studies validated the performance of drought indices through drought events reported or compared with well-accepted drought indices (for example, Meza, 2013).

Fig. 4 illustrates evidence of El Niño years in Thailand conducted by anomalies of the 3-month moving average precipitation given by Thai Meteorological Department (2011). The figure demonstrates dry periods occurring many times during the 30 yr of this study scope. Mainly, droughts dominated during the early and late 1980s in 1982–1983 and 1986–1987; and were tended to be severe during 1991–1993, 1997–1998 and 2002–2003. A severe drought was experienced in 2004–2005. This was in accordance with the report by the National Weather Service (National Oceanic and Atmospheric Administration, 2015) as years of El Niño. Correspondingly, the annual observed precipitation shows a slightly decreasing trend (Fig. 2B) and rising temperature (not displayed) over the region which causes the increasing trend in PET (Fig. 2B). Singhrattna et al. (2005) also found an increasing drought trend since the 1980s as a result of a warmer climatic trend in Thailand. This was confirmed by Dai (2011) and Sheffield et al. (2012) that there had been increasing evaporation driven by warmer weather and decreased precipitation from 1950 to 2008.

Compared with the time series of 3 mth SPI, drought events could be detected and they conformed to El Niño years. Moreover, the results were compared with the recorded natural disasters in Thailand provided by the Center for Research on the Epidemiology of Disaster (Guha-Sapir et al., 2011). The recorded droughts sorted

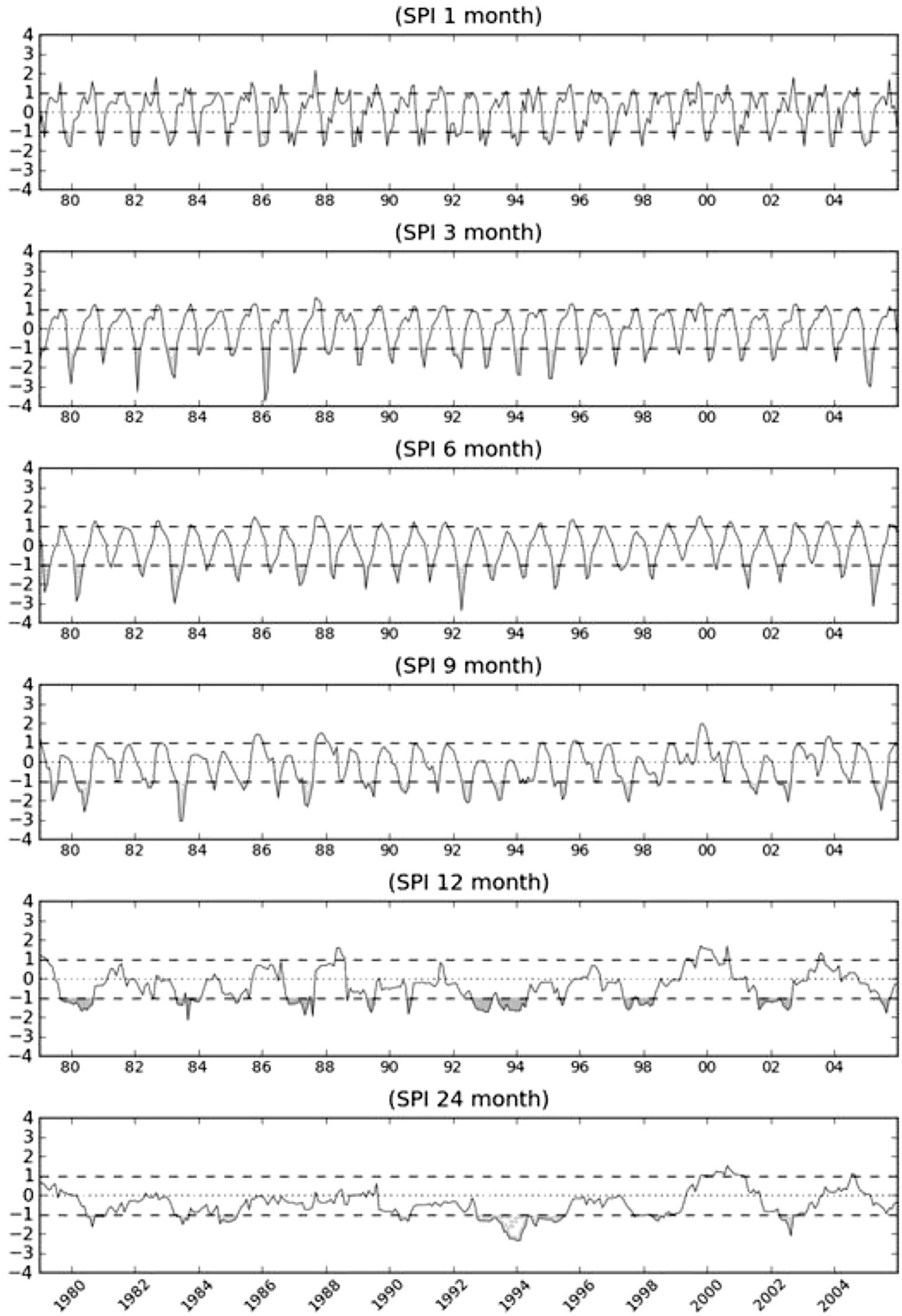

Fig. 3. Evaluation of different months of the Standardized Precipitation Index (SPI). The gray shaded areas mean duration and magnitude of drought defined by its beginning and end. Drought events (gray shaded areas) occur any time an SPI value reaches an intensity of −1 or less.

by total number of affected people are rather similar to the number of drought episodes compared to the SPI time series. However, the index is unsuitable to be used to quantify drought severity based on the original criteria of the SPI calculation. For example, McKee et al. (1993) defined the category moderately to severely dry when the SPI values were found in the range− 1 to −1.99 for the period of 1–3 mth SPI. In fact this was simply dry spells in the summer monsoon season in this region which may not cause damage to agricultural fields. However, longer timescales of the SPI (>12 mth SPI) are able to broadly identify the characteristics of drought durations with the exception of their intensity level. This corresponded to an earlier study that analyzed the spatial patterns of droughts using remote sensing data in Northeastern Thailand which found that the worst dry years in 1979, 1981, 1997–1998, 2001 and 2003 affected widespread areas for 6–12 mth SPI (Wattanakij et al., 2006). However, the interpretation and utilization of the SPI over the tropical monsoon region with distinct seasonal precipitation should be carefully carried out to avoid any

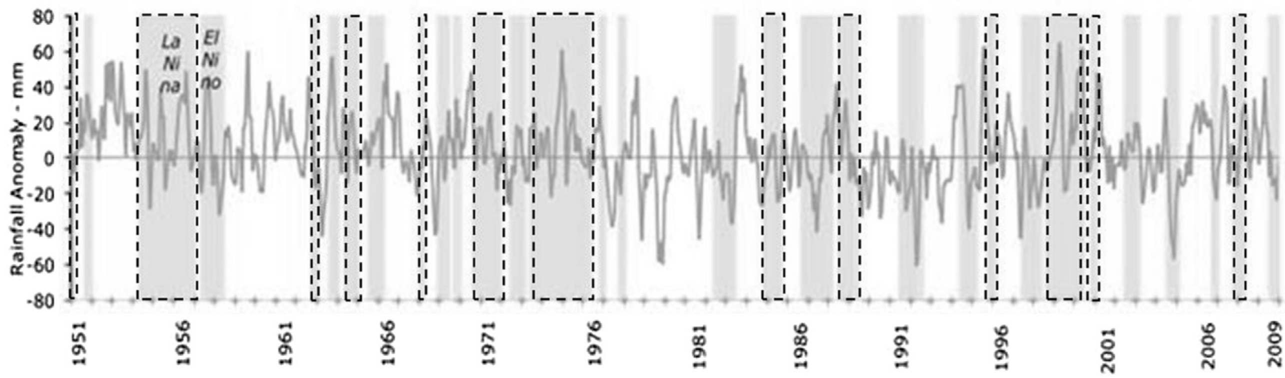

Fig. 4. Anomaly of 3-mth moving average precipitation (base period 1971–2000) in Thailand. El Niño (shaded with no outline) and La Niña (shaded with dashed outline) events are an El Niño-Southern Oscillation index based on the SST anomalies in the Niño 3.4 region at 120°W–170°W and 5°S–5°N (Thai Meteorological Department, 2011).

misleading interpretations when being applied to the short timescale.

Fig. 5A and B show the performance of multivariate indices of the SPEI (P-PET) and the SPAEI (P-AET) at multiple timescales (1–24 mth). Both indices indicated extreme drought severity in the early 20th century. The drying values fluctuated between +2 and −2 at short timescales (3–6 mth) except for the period of 1 mth. There was a downward trend toward the value of −4 at longer timescales (9–24 mth) which indicates a severe dry period in this region. However, slight problems of overstating the frequency of droughts at the 1-mth timescale still appear as it still uses the SPI index. The performances of both climatic indices seem to be able to capture the main characteristics of drought conditions. Both indices recognized significant severe droughts (12 mth period) in 1986–1987 and 1993–1994, especially the worst droughts in 1997–1998 and 2003–2004. More consecutive episodes of droughts and higher intensity of multi-year droughts (12–24 mth) were observed since the early 1990s. The findings are consistent with Guha-Sapir et al. (2011) who recorded natural disasters in Thailand confirming that the years mentioned earlier experienced extreme droughts. These prolonged droughts had adverse effects on the agricultural and water resource sectors across the country. Moreover, dry spells and droughts have threatened widespread areas of crops. For example, after the spring season in 1997, drought brought disaster to the farm sector and cost an estimated USD 290 million loss in farm income through the crop year 1998–1999. In addition, these drought episodes were the most spatially extensive covering more than 8 million km^2 from eastern China to central Asia (Sheffield and Wood, 2008).

Similarly, the SPEI and the SPAEI showed substantial higher severity and longer durations of droughts than the SPI. This may have been due to the temperature rise which was conducive to an increase in the water demand of PET and AET that triggered the severity of droughts especially on longer timescales. This has been supported by McCarthy (2001) who found that temperatures measured in Thailand in the spring during 1976–1999 displayed an increasing trend, and thereby, the rainfall showed a decreasing trend. Moreover, both indices clearly detected notable drought episodes during 2003–2004 consistent with El Niño years (Thai Meteorological Department, 2011). The serious, strong drought episodes resulting in a scarcity of water for consumption and agricultural use continued to the following year. Several provinces experienced serious droughts and were declared as drought–-stricken areas. During 2004, the Department of Disaster Prevention and Mitigation of Thailand declared serious water shortages in major dams which lasted until 2005. Thus, these droughts can be referred to as agricultural and hydrological droughts in this region.

However, the SPI could not clearly identify the episode of drought severity. Therefore, both indices detected agricultural drought better than the SPI; and appeared to be more suitable to capture characteristics of droughts—specifically the degree of drought.

Interestingly, the SPEI failed to represent extreme droughts during 1993–1994 where it only showed a slightly laggard dry period, while the SPAEI based on P-AET clearly identified an intensification of drought related to observed droughts. Furthermore, Joetzjer et al. (2013) confirmed that the use of P-AET shows higher consistency with the hydrological drought index. In contrast to our study, Beguería et al. (2014) preferred to use P-PET as evidenced by the detection of a strong heat wave in Central Europe and Russia. Nevertheless, the inclusion of precipitation and PET or AET contains diverse substantial variability of drought severities in this study. This supports the finding of previous studies indicating that PET plays an important role in the hydrological cycle in Thailand (for example, Kanae et al., 2001); and its variation is primarily affected by precipitation, land use and land cover change (Kim et al., 2014).

Fig. 6 shows differences in the Pearson r coefficient of the three indices for 1–24 months. The correlation between the SPI and the SPEI was relatively close at shorter timescales (1–6 mth) and dramatically decreased at longer timescales (9–24 mth). The correlation between the SPI and the SPAEI also followed a similar pattern with a slightly lower correlation than the former. These indicate that precipitation is a dominant aspect driven by drought conditions conforming to the characteristics of a seasonal monsoon climate in this region.

Undoubtedly, the correlation between the SPEI and the SPAEI was expected to give a high degree of similarity through all time series due to the use of rather similar variables. The differences were very close with the maximum correlation value of 0.98 at 6 mth timescales. The consistent pattern implied a robust relationship between PET and AET which can be generally found in monsoon periods. These results emphasized that changes in precipitation were not the only dominant driver causing the long term drought variations but that rising temperature in terms of PET and AET was also responsible for the drought severities. However, Ma et al. (2014) argued that no consistent association between the SPEI and PET in humid areas existed.

There are many factors leading to the diverse performances of P-PET and P-AET, especially in land use and land cover in agricultural areas. Correspondingly the recent study by Kim et al. (2014) noted that the variation of ET in Thailand was the result of precipitation variation and adverse land change. Moreover, differences in AET and PET are derived not only from the process of transpiration of land cover, but are also attributable to the fact that AET was

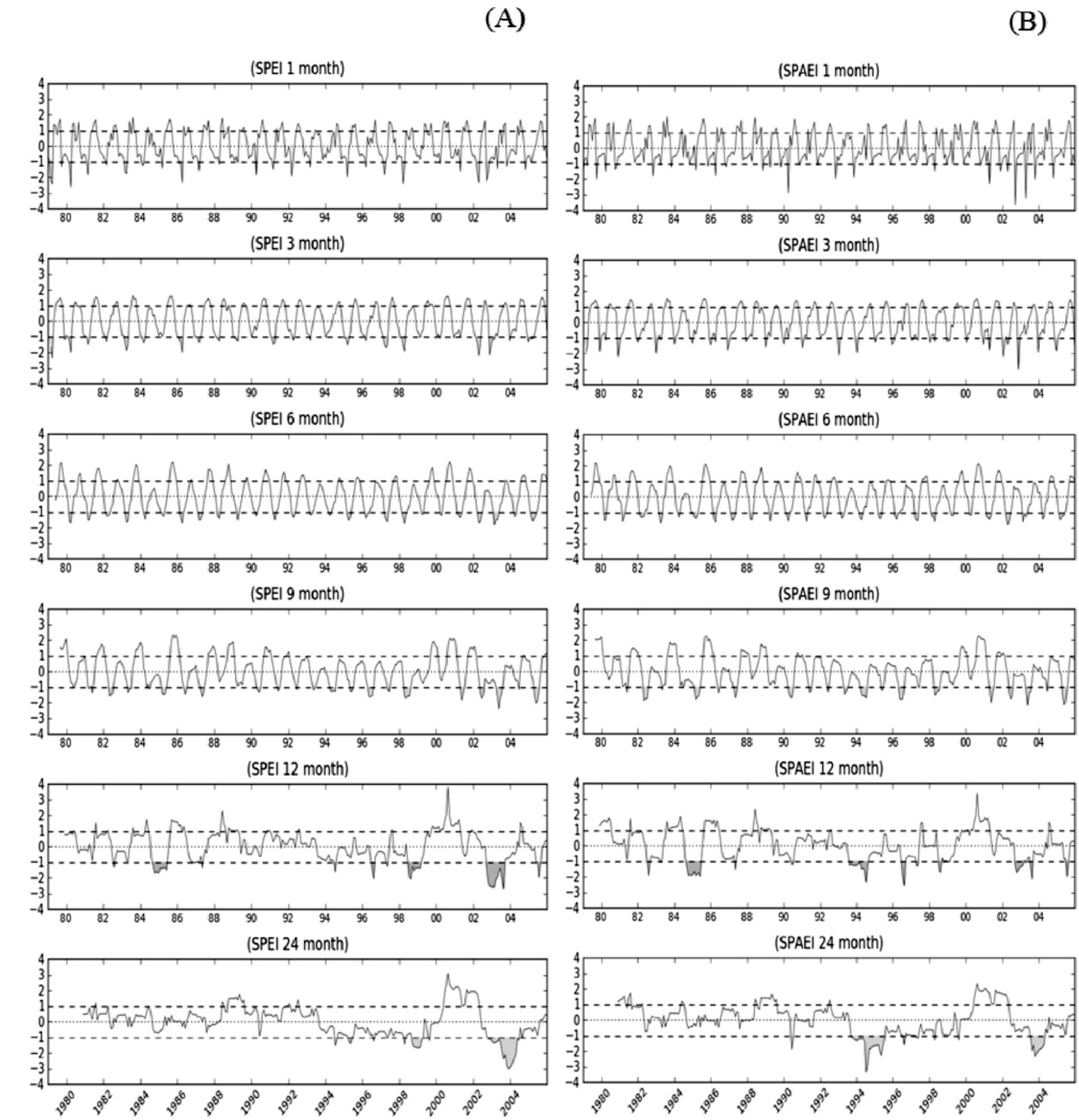

Fig. 5. Comparison of climatic drought indices for varying monthly periods: (A) Standardized Precipitation Evapotranspiration Index (SPEI); (B) Standardized Precipitation Actual Evapotranspiration Index (SPAEI). Drought events (gray shaded areas) occur any time an SPEI/SPAEI value reaches an intensity of −1 or less.

obtained from a hydrological simulation model which included direct evaporation from large reservoirs that may play an important role in the available water cycle. There are complex interactions among precipitation, soil moisture and evapotranspiration by vegetation (Intergovernmental Panel on Climate Change, 2012); for example, dry weather in summer certainly increases the amount of soil water available for evapotranspiration. Thus, land use and land cover change may have substantial influences on drought trends.

The study aimed to analyze the temporal drying trends using three climatic drought indices and to provide useful insights on how different drought indices can be effectively used. The various indicators of different indices can have diverse effects on drought conditions. The simple SPI (considering only precipitation) can be used to identify characteristics of droughts with certain restrictions. Even though the SPI has been put forward by the World Meteorological Organization (2009) as a universal index, a single indicator may not be sufficient to characterize a complicated drought (for example, Hao and Singh, 2015).

Similar to the procedure for the SPI calculation, the SPEI considers the difference between P and PET, while the SPAEI takes into

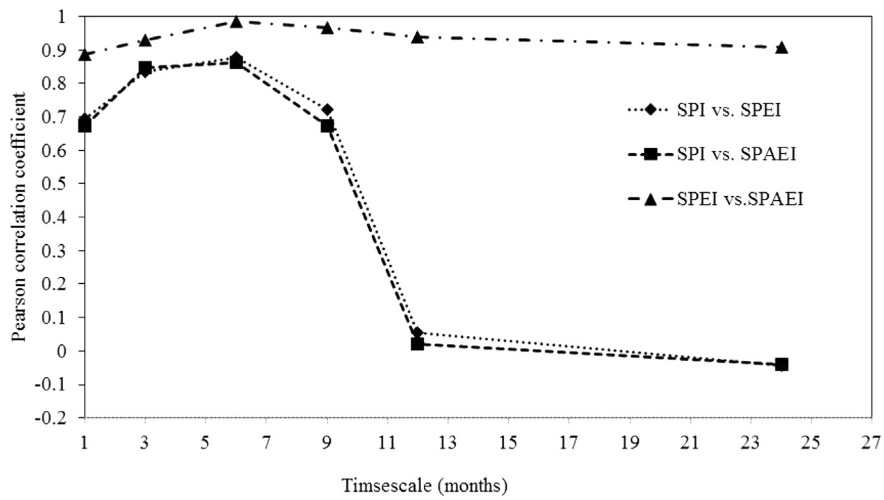

Fig. 6. Pearson correlation between the 1–24 mth of Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI) and Standardized Precipitation Actual Evapotranspiration Index (SPAEI).

account the difference of P-AET. Certainly, the use of multivariate indices is more effective in terms of detecting temporal changes in drought conditions than using the stand-alone indicator, the SPI. The results suggested that although precipitation had a key role in explaining the temporal variability of droughts, increasing temperature also had a crucial influence on water stress in the region, especially over the longer timescales. Moreover, different aspects also affect diverse drying such as the replacement of PET with AET produces a substantially different result when capturing the durations and magnitudes of the droughts that occurred in 1993. Thus, the use of AET may be a useful parameter for better understanding drought trends in that kind of basin. The indicator not only explicitly considers the actual effects of vegetation changes that substantially influence evaporation, but also includes alteration of land atmosphere feedback processed through simulation of the hydrological model.

Thailand is an agricultural country; hence, metrological and agricultural drought indices are important. The Thai Meteorological Department is the national weather agency carrying out the operational monitoring of drought conditions using the Generalized Monsoon Index (GMI) that considers only monsoon precipitation in rainy season (Thai Meteorological Department, 2014). However, monsoon precipitation varies, and the factors affecting its variations differ in different seasons and regions. For example, precipitation in the southern region is slightly influenced by ENSO but it correlated well with local wind (Tsai et al., 2015). Therefore, these present a big challenge to the prediction of monsoon droughts on seasonal-to-decadal timescales (for example, Niranjan Kumar et al., 2013). Thus, the use of the GMI index is difficult to connect to other parameters since it only considers monsoon precipitation in the rainy season, unlike SPEI's long time series which can be directly used to account for the inter-annual variability of annual stream flow (Joetzjer et al., 2013).

Even though drought episodes cannot be immediately detected like floods, their consequences are somehow greater than the damages caused by floods. Thus, effective monitoring of drought conditions needs to be implemented in order to mitigate drought impacts. There is still no consensus on global drought trends, thus more research is strongly encouraged, especially at local and regional scales (for example, Sheffield et al., 2012). In addition, drought experts should play an important role in providing information using several different indices at multiple time steps that are most suitable for their respective application (for example, Svoboda et al., 2015).

Conflict of interest

The authors declare that there are no conflicts of interest.

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