ESTABLISHING SPATIAL DISTRIBUTIONS OF DROUGHT PHENOMENA ON CULTIVATION SEASONS USING THE SWAT MODEL

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ABSTRACT:
Due to global climate change, drought phenomena are becoming longer. As a result, water availability is insufficient to meet demand for agriculture during the cultivation seasons and many areas have affected by drought. These can cause difficulties in water resources management. The main objectives of this study were to establish the spatial distribution of drought phenomena at sub-basin scales in the Lam Khan Chu and Lam Nam Chi Part II watersheds, which is the major headwater of the Chi River Basin, Thailand. The Soil and Water Assessment Tool (SWAT) model was used to synthesize streamflow data at the sub-basins of the watersheds. To estimate drought severity, the Streamflow Drought Index (SDI) was computed from the time series of the synthesized streamflow data during 2008 to 2019. The simulated streamflow of the SWAT model was acceptable based on the R^2, Nash-Sutcliffe Efficiency (NSE) and Percent bias (PBIAS) reaching good levels in both calibration and verification. According to the SDI calculation, the most severe drought in the study period was in the year 2016. During January and April of 2016, the affected areas of about 3%, 30%, 14%, 30 and 23% of the study area were identified as none, mild, moderate, severe and extreme droughts, respectively. The integration of the hydrological model and drought index to monitor drought severity in space and time will be a useful tool for assessing drought severity. Moreover, the results can support managers for water resources management.

Key-words: *drought, Streamflow Drought Index, SWAT, Lam Khan Chu sub-watershed, Lam Nam Chi Part II sub-watershed.*

1. INTRODUCTION

Currently, our world is facing the challenge of climate change, which has become more intense. This challenge leads to water scarcity in many countries, and both rainfall and streamflow vary from normal value (Faiz et al., 2018; Irannezhad et al., 2020; Koo et al., 2020). The average rainfall in Thailand since the 2018 rainy season has been 5% lower than normal value. This circumstance is happening in many areas throughout the country, especially in northeastern Thailand (Rotjanakusol & Laosuwan, 2019). The Royal Irrigation Department is basically responsible for water management at regional level each year by considering seasonal related conditions based on meteorological conditions, streamflow in major rivers flowing into surface water resource, and reservoir operation rule (Llones et al., 2021; Wannasin et al., 2021). The core principle of operation is water allocation according to crop calendar both inside and outside the irrigation areas (Hussainzada & Lee, 2022). To allocate water for different activities through irrigation system, rainfall is the major source in the rainy season that people basically depend on while water stored in reservoir is the major source in the dry season (Takeda et al., 2015). However, measured by streamflow observed stations, the streamflow in rivers is mostly below the average, and water allocation does not go as planned. For this reason, many areas have to be declared as drought-affected, and agriculturists are able to plant only once a

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year or in the rainy season (Prabnakorn et al., 2019). On the other hand, growing crops with less water is needed during the dry season, or sometimes agriculturists are not able to grow their crops due to raw water shortage (Boonwichai et al., 2018).

According to the aforementioned problem, hydrological drought analysis is a way utilized for obtaining the results that are useful for prediction and decision support on water resource management planning in watershed areas. One of the universally used methods is hydrologic model for analyzing and predicting impacts in the past, present, and future situations (Kumar et al., 2022). The Soil and Water Assessment Tool (SWAT) is one of these commonly used because of its strong point in streamflow analysis, which is associated with size and extent classification of sub-watershed by physical evidence of the area and is able to calculate the streamflow with high reliability (Diriba, 2021; Prasanchum et al., 2020). In analyzing drought severity to integrate between the results obtained from hydrologic model and occurrence of drought, hydrological drought index called Streamflow Drought Index (SDI) was employed in this study. This index can also display severity levels of drought calculated from streamflow data, and it has been also used in many countries around the world (Brouziyne et al., 2020; Jahangir et al., 2020), Southeast Asia (Fung et al., 2019; Linh et al., 2021) including Thailand (Foyhirun & Promping, 2021; Lohpaisankrit & Techamahasaranont, 2021). The process of this study began with classifying the sub-watershed by using SWAT. Then the obtained analytical results of streamflow were measured for SDI value in order to eventually gain a spatial map displaying the severity levels according to the crop calendar of Thailand. For regional watersheds in Thailand, there have been a small number of studies applying SWAT to SDI and presenting spatial map. Therefore, this study has tried to assess the streamflow in watershed areas at the regional level, particularly in the major headwater areas that have been affected by drought. Hopefully, the results of this study will be beneficial to society. For instance, it will be helpful to the authorities concerned in improving their preventive measures in order to reduce any damage. Also, agriculturists will be able to plan for their cultivation in watershed areas and have more efficient way to manage water resources during a drought.

2. STUDY AREA AND DATA COLLECTION

This study area was chosen because it is an upstream forest area in the western part of the Chi River, which is a main river of the northeastern region of Thailand. There are two watersheds selected for this study i.e. Lam Khan Chu and Lam Nam Chi Part II, which is a sub-watershed of the Chi River Basin (1 of 25 major watersheds in Thailand), with a catchment area of 1,733 and 3,795 square kilometers, respectively. In this area, there are the Lam Khan Chu River and the Chi River as the major river flowing from southwest to northeast. The average rainfall is 950 to 1,100 millimeters per year referred from data collected in 5 rainfall gauge stations. The average streamflow per year is between 620 to 1,078 million cubic meters referred from complete data collected from E21 observed station during 2008 to 2019. Moreover, further data also used in the study gathered from many institutes consist of Digital Elevation Model (DEM), river map, land use map, soil type map, meteorological data, and hydrological data, as shown in **Table 1** and **Fig. 1 (a)**, **(b)** and **(c)**, respectively.

Table 1.

Spatial data and hydrological data

Data type	Period	Scale	Source
Digital Elevation Model (DEM)	2018	30x30 m	Land Development Department
River map	2018	1:50,000	
Soil type map	2018	1:50,000	
Land use map	2018	1:50,000	
Climate and Rainfall data (5 stations)	2008-2019	Daily	Thai Meteorological Department
Observed streamflow data at E21	2008-2019	Monthly	Royal Irrigation Department

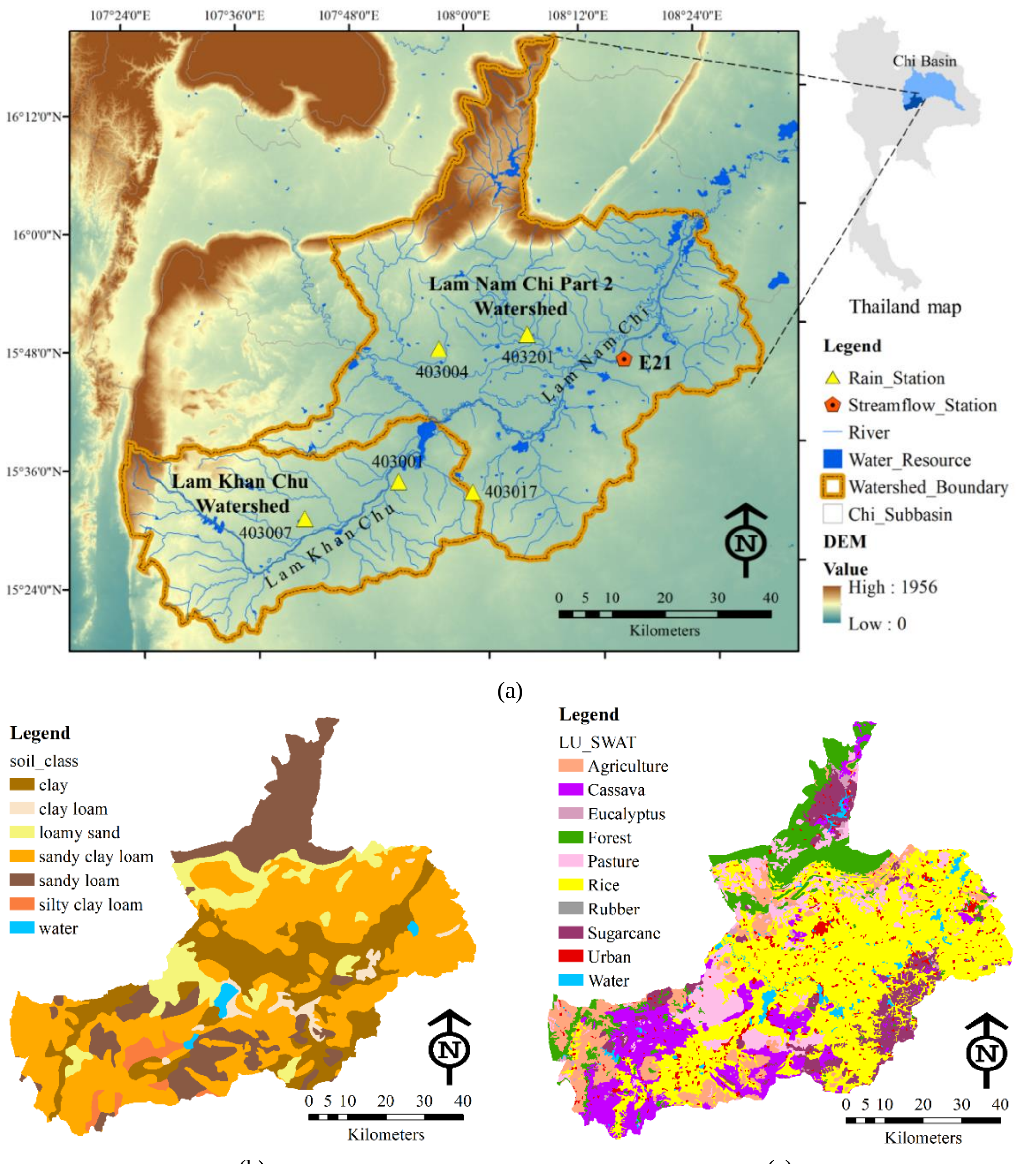

Fig. 1. Spatial data of the study area (a) Location of Lam Khan Chu and Lam Nam Chi Part II sub-watersheds, (b) Soil type map, and (c) Land use map.

3. METHOD

3.1. Streamflow simulation

3.1.1. SWAT Model

Soil and Water Assessment Tool (SWAT) is an open source model (Arnold et al., 1998) and also a semi-distributed hydrological model developed to analyze the streamflow (Koua et al. 2021), sediment, and water quality that are affected by climate and land use changes (Prasanchum & Kangrang, 2017). SWAT was applied to processing classification at many levels of river basin such as creation of sub-basins in a major basin as well as calculation to demonstrate outcome at daily level and long term. A water balance equation was then used for taking into account depending on hydrological process as Eq. (1):

$$SW_t = SW_o + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \tag{1}$$

where:

SW_t	-final soil water content (millimeter);
SW_0	-soil water content starting from day *i* (millimeter);
t	-time (day);
R_{day}	-rainfall amount of day *i* (millimeter);
Q_{surf}	-surface water amount of day *i* (millimeter);
E_a	-evapotranspiration amount of day *i* (millimeter);
W_{seep}	-the amount of water absorbed underground of day *i* (millimeter);
Q_{gw}	-the amount of underground water running into a river of day *i* (millimeter)

3.2.1. Model Accuracy Assessment

In assessing the accuracy of results from SWAT, data on monthly streamflow recorded at E21 station from 2008 to 2019 were equated and verified. The process began with sensitivity analysis of hydrological parameters that were related to streamflow defined by Hydrologic Response Unit (HRU), which was developed from the model (Khatun et al., 2018). This process of SWAT has been outstanding and widely accepted due to its efficiency and accuracy in calculation results compared to other semi-distributed models. In this study, a model called SWAT Calibration and Uncertainty Programs (SWAT-CUP) (Djebou, 2018; Faiza et al., 2018) through Sequential Uncertainty Fitting version 2 (SUFI-2) was utilized because it is a technique that requires the smallest number of sensitivity parameters, but it gives optimum outcomes (Malik et al., 2021). In goodness of fit test, calculation results obtained from SUFI-2 were compared to data collected from the measuring station by adjusting sensitivity parameters based on efficiency criteria i.e. Coefficient of Determination (R^2), Nash-Sutcliffe Efficiency (NSE), and Percent bias (PBIAS). The calculation can be done according to Eq. (2) to (4) below:

$$R^2 = \left[\frac{\sum_{i=1}^{n}[(Q_{obs}-\bar{Q}_{obs})(Q_{sim}-sim)]}{\sqrt{\sum_{i=1}^{n}(Q_{obs}-\bar{Q}_{obs})^2}\sqrt{\sum_{i=1}^{n}(Q_{sim}-\bar{Q}_{sim})^2}}\right] \tag{2}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{obs}-Q_{sim})^2}{\sum_{i=1}^{n}(Q_{obs}-\bar{Q}_{obs})^2} \tag{3}$$

$$PBIAS = \frac{\sum_{i=1}^{n}(Q_{obs}-Q_{sim})}{Q_{obs}} \times 100 \tag{4}$$

where:

i	-data order;
n	-total number of data;
Q_{obs}	-value obtained from observed;
$\bar{Q}_{obs}$	-average of total observed data;
Q_{sim}	-value obtained from model;
$\bar{Q}_{sim}$	-average of data obtained from all models;
SW_t	-final soil water content (millimeter)

3.2. Standard Drought Index (SDI)

SDI is counted as simple and efficient to drought analysis. It was developed by Nalbantis & Tsakiris (2009) to identify characteristics, analyze hydrological drought, and assess severity as well as causes of drought properly at all levels of area (Abbas & Kousar, 2021). In calculating, monthly data on streamflow volume from the observed station were used as input (Aghelpour et al., 2021). SDI has been widely used in studying and analyzing drought situations such as hydrological drought in river basin areas (Hong et al., 2015; Ozkaya & Zerberg, 2019), drought caused by climate change (Pandhumas et al., 2020), and drought in river basins without an observed station (Lohpaisankrit & Techamahasaranont, 2021). Negative results of SDI reflect hydrological drought with levels represented by number from 0 (mild drought) to -2 (extreme drought). In addition, positive results are also shown to indicate there is no situation of drought, as presented in **Table 2** (Hong et al., 2015; Niaz et al., 2021). In terms of calculating SDI, it was identified according to data on streamflow volume $V_{i,k}$ for each reference range of hydrological year i as seen in Eq. (5) below:

$$SDI_{i,k} = \frac{V_{i,k} = \bar{V}}{s_K} \qquad i = 1,2, \ldots\ldots k = 1, 2, 3, 4 \tag{5}$$

where;

V_k and s_k -mean and standard deviation, respectively, of accumulated streamflow of reference time k because these values have a long-term estimate. In this definition, reduction level was defined as V_k although other values could be used.

Table 2.

Drought classification for SDI

Description	**Class**
Extreme wet	SDI ≥ 2.00
Severe wet	1.50 ≤ SDI < 2.00
Moderate wet	1.00 ≤ SDI < 1.50
Mild wet	0.00 ≤ SDI < 1.00
Mild drought	-1.00 ≤ SDI < 0.00
Moderate drought	-1.50 ≤ SDI < -1.00
Severe drought	-2.00 ≤ SDI < -1.50
Extreme drought	SDI ≤ -2.00

3.3 Crop Calendar for Irrigation Area in the Northeast of Thailand

The Royal Irrigation Department (RID) of Thailand, determined a proper way of seasonal cultivation (Prabnakorn et al., 2018). In northeastern Thailand, crop calendar for dry-season farming was defined between January to April. Farmers are suggested to cultivate depending mainly on allocation water from a reservoir, and water distribution stops at the end of April in order that the farmers can harvest their crops. Nevertheless, water allocation during the dry season has its limitation, or it can be managed only in the irrigation area. When the rainy season arrives, between July and October, the farmers have to grow crops. In case that rainfall and streamflow in the reservoir are below the average, which affect water utilized for cultivation, the RID has to allocate water to be sufficient to farmer for their farming including other purposes of water use. However, to assure the risk of reservoir management, the RID needs to specify the end of November as the end of water allocation for growing crops in the rainy season in order that farmers can harvest their crops in December.

4. RESULTS AND DISSCUSSION

4.1 SWAT Accuracy Assessment

4.1.1 Parameter Sensitivity Analysis

The sensitivity analysis used 13 hydrological parameters related to streamflow by using SWAT-CUP for the purpose of optimization in order that the obtained results from the model could demonstrate value as close as possible to observed value. The analysis result has indicated the first five parameters influencing calculation: ALPHA_BF, CN2, ESCO, GW_DELAY, and CH_N2, respectively. These could be seen from statistics through creating a relation equation called "linear regression equation" depending on *t*-Stat and P-Value for the analysis. When P-Value becomes high (by not considering signs), it means that parameter is highly sensitive to objective function. When P-Value is close to zero, it means that parameter is sensitive to objective function with high significance. The details are shown in **Table 3**.

4.1.2 Model Calibration and Validation

In model calibration and validation, the SWAT-CUP was employed in specifying a cycle of calculation of 500 rounds to compare results to values recorded at E21 observed station from 2008 to 2019 as presented in **Fig. 2**. The calibration results by means of the calculation results from 2008 to 2015 (8 years) compared to observed values indicated R^2 = 0.86, NSE = 0.80, and PBIAS = -4.32% while the validation interval demonstrated R^2 = 0.87, NSE = 0.85, and PBIAS = -2.55%. According to the results, the calculation accuracy of streamflow is very good because R^2 and NSE are higher than 0.80, and PBIAS is lower than 10% (Prasanchum et al., 2021).

Table 3.

Sensitivity parameters and fitted values using SUFI-2 from SWAT-CUP

Ranks	Parameter	Description	Fitted value	*t*-stat	P-value
1	ALPHA_BF	Baseflow alpha factor	0.218	-31.69	0
2	CN2	SCS runoff curve number	0.108	-21.12	0
3	ESCO	Soil evaporation compensation factor	0.649	11.43	0
4	GW_DELAY	Groundwater delay	5.300	-6.09	0.000000002
5	CH_N2	Channel Manning's coefficient	0.0200	5.76	0.000000015
6	CH_K2	Effective hydraulic conductivity in main channel alluvium	120.508	5.08	0.000000545
7	GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur	248.500	-5.07	0.000000559
8	REVAPMN	Threshold depth of water in the shallow aquifer for "revap "to occur	466.500	4.32	0.000019147
9	SOL_AWC	Available water capacity of the soil layer	0.661	4.17	0.000035378
10	GW_REVAP	Groundwater "revap "coefficient	0.136	-3.86	0.000127172
11	RCHRG_DP	Deep aquifer percolation fraction	0.623	-3.23	0.001292101
12	LAT_TTIME	Lateral flow travel time	104.580	2.80	0.005379043
13	SLSOIL	Slope length for lateral subsurface flow	63.450	-2.16	0.031036977

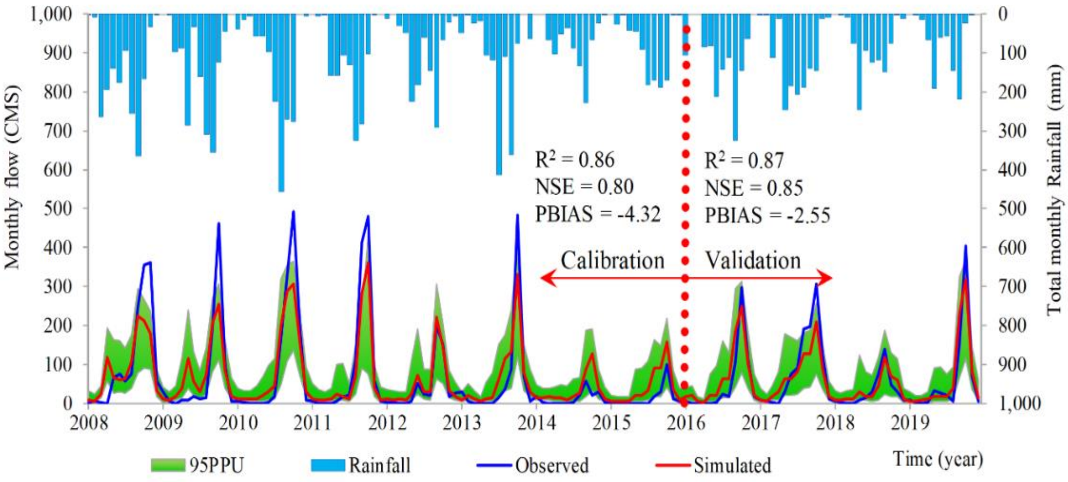

Fig. 2. Calibration and validation of the SWAT-CUP model.

4.2 Monthly SDI from Streamflow Simulation

Drought situations at sub-basin scales in the Lam Khan Chu and Lam Nam Chi Part II watersheds have been monitored based on SDI. To visualize the spatial distribution of SDI, the first step is to simulate the appropriate sub-watershed boundary in the Lam Khan Chu and Lam Nam Chi Part II sub-watersheds based on the DEM data. **Fig. 3** shows 25 sub-watersheds of the study area resulted from watershed delineation techniques of the SWAT model. Then, SWAT calculated monthly streamflow from 2008 to 2019 and yielded results at all 25 sub-watershed levels (the sensitivity parameters were adjusted and fixed to achieve the highest accuracy results as detailed in the previous section). Subsequently, monthly streamflow in each sub-watershed were calculated as monthly SDI and integrated into the GIS model to provide a map of the spatial distribution of drought phenomena in the study area.

Fig. 4 illustrates the results of a 1-month SDI in 25 sub-watersheds during 2008 to 2019. SDI results of SB-7, SB-11 and SB-16 basins were described as examples of the change in time series and position of different areas. The SB-7 basin is located along the main river, whereas the SB-11 and SB-16 basins are located along the Lam Khan Chu River and the Chi River, respectively. SDI values provide information on historical drought events. As shown in the figure, temporal characteristics of drought events among the basins were quite dissimilar. In the SB-7 basin, five months and fourteen months were classified as severe and moderate drought months, respectively. The period of three months between February and April of 2010 was the longest duration of the severe drought event in the basin. The worst drought event in the SB-11 between March and April of 2016 and the SDI values were below -2.0, which were classified as an extreme drought. In the SB-16 basin, it is found that the longest period of drought event was between September, 2014 and April, 2015 and was classified as severe to extreme drought months. The result shows that drought conditions in sub-basins located beside of and far away from the river are different. Drought conditions in basins located far away from the river may mainly rely on precipitation. This finding is consistent with that of Shen et al. (2017) and Peña-Gallardo et al., (2019) who noted that drought is significantly influenced by meteorological factors. Meanwhile, droughts conditions in basins located beside of the river may be influenced by precipitation (Yang et al., 2020) and hydrological conditions (Zhao et al., 2019) of upstream basins.

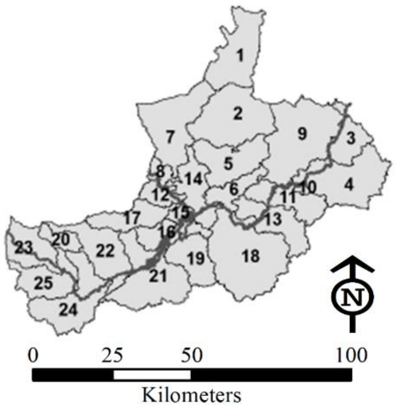

Fig. 3. 25 sub-watersheds of the study area divided from SWAT.

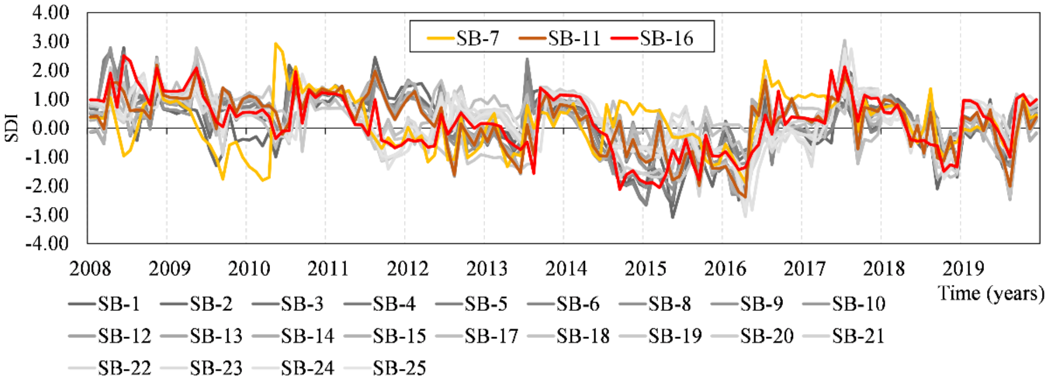

Fig. 4. 1-month SDI in 25 sub-watersheds during 2008-2019.

4.3 Spatial Distribution Area of SDI on Cultivation Seasons

To make an easily understandable presentation on drought severity in the Lam Khan Chu and Lam Nam Chi Part II watersheds, maps of SDI distributions were produced. The SDI was used to determine drought severity conditions on the basis of streamflow deficits. **Fig. 5** presents the spatial distribution of drought phenomena in the dry season between 2008 to 2019 at sub-watershed scales. The results of drought analysis based on SDI show that the drought phenomenon in the year 2016 was the most severe drought event. The SDI values of seven sub-watersheds, namely SB-8, SB-11, SB-12, SB-13, SB-14, SB-15 and SB-18 were found to be ranged from -2.17 to -2.01 during the month of January and April, 2016 indicating the presence of extreme drought. The seven sub-watersheds covered an area of 1,247 square kilometers (23% of the watershed area) as shown in **Table 4**. These results are likely to be related to observed streamflow data at E21 observed station (**Fig. 2**). Since the streamflow for the years 2015 and 2016 was below average during 2008 to 2019 at the station E21, low streamflow conditions in the year 2015 may result in a potential drought situation for the early period of the following year. **Fig. 6** shows the spatial distribution of drought phenomena in the rainy season between 2008 and 2019 in the study area. For example, the 18 sub-watersheds (66% of the watershed area) indicated with the SDI values ranging from -1.79 to -1.05 were determined as moderate to severe droughts in the year 2018 (**Table 4**). The results have pointed out that drought events can occur throughout the year for all regions.

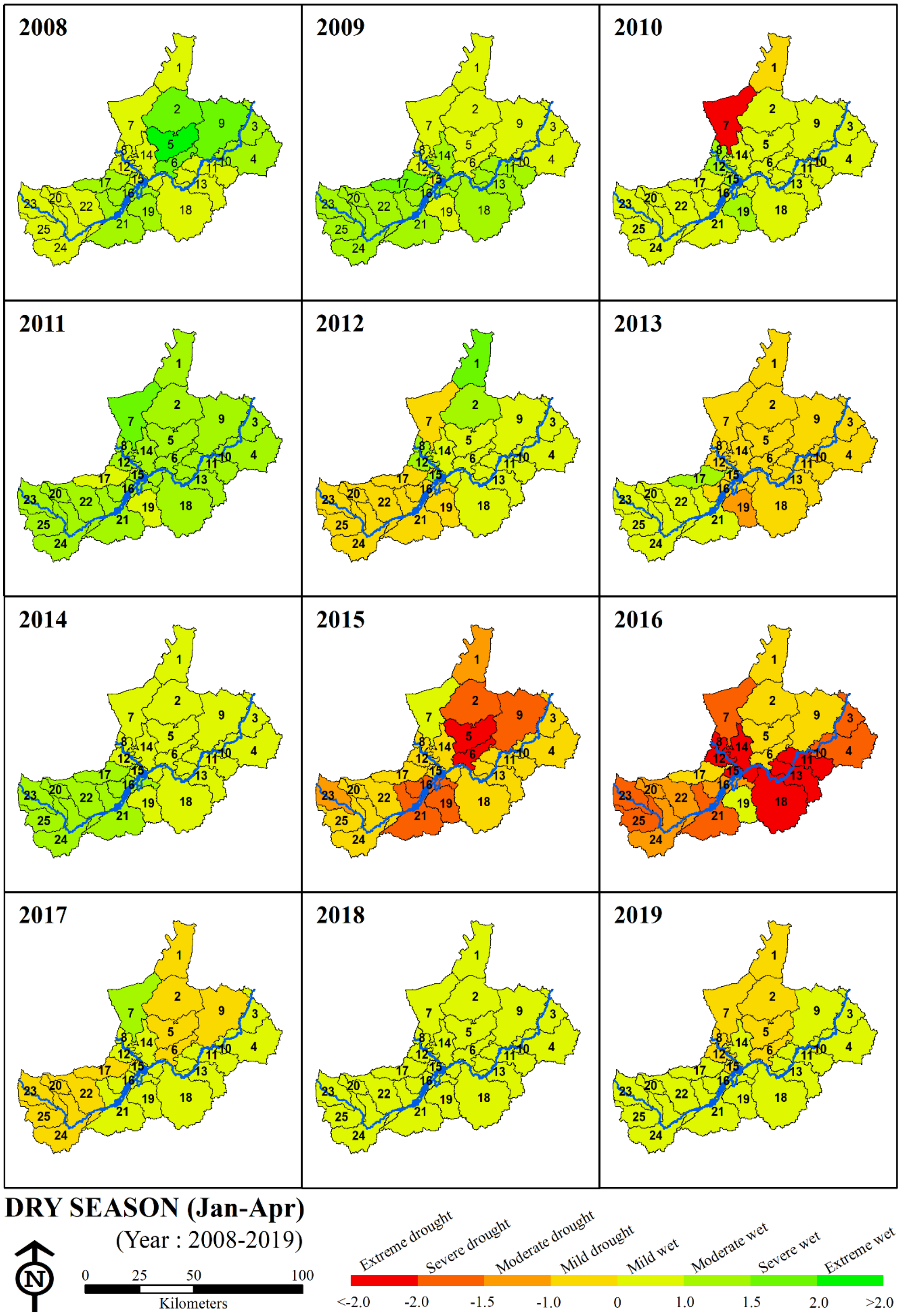

Fig. 5 Spatial distribution of drought phenomena in dry season (January to April) during 2008 to 2019.

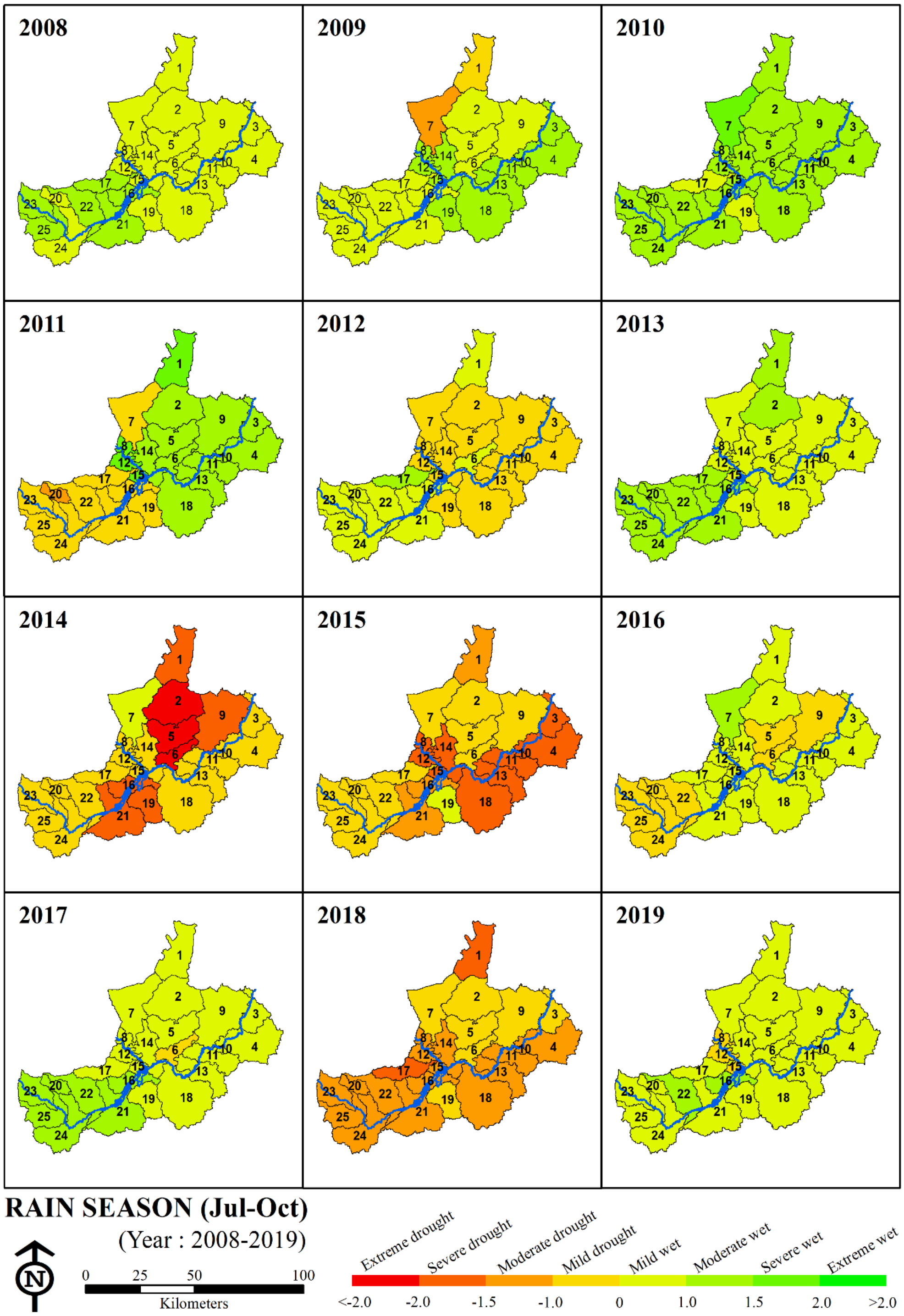

Fig. 6 Spatial distribution of drought phenomena in rainy season (July to October) during 2008 to 2019.

Table 4.

The quantity of area during the year affected by the continuous drought phenomena divided by the SDI level

SDI level		2014		2015		2016		2017		2018	
		Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Dry season	Moderate wet	1,653	30.6	0	0.0	0	0.0	343	6.4	0	0.0
	Mild wet	3,741	69.4	343	6.4	170	3.2	2,436	45.2	5,394	100
	Mild drought	0	0.0	2,726	50.5	1,625	30.1	2,615	48.5	0	0.0
	Moderate drought	0	0.0	472	8.8	757	14.0	0	0.0	0	0.0
	Severe drought	0	0.0	1,505	27.9	1,595	29.6	0	0.0	0	0.0
	Extreme drought	0	0.0	348	6.5	1,247	23.1	0	0.0	0	0.0
Rainy season	Moderate wet	0	0.0	0	0.0	343	6.4	1,496	27.7	0	0.0
	Mild wet	343	6.4	170	3.2	3,257	60.4	3,791	70.3	0	0.0
	Mild drought	2,907	53.9	2,667	49.4	1,794	33.3	107	2.0	1,834	34.0
	Moderate drought	0	0.0	797	14.8	0	0.0	0	0.0	3,112	57.7
	Severe drought	1,423	26.4	1,760	32.6	0	0.0	0	0.0	448	8.3
	Extreme drought	721	13.4	0	0.0	0	0.0	0	0.0	0	0.0

6. CONCLUSIONS

The current study established the spatial distribution of drought phenomena at sub-watershed scales in the Lam Khan Chu and Lam Nam Chi Part II watersheds using SDI for the historical period (2008-2019). The SDI was computed based on streamflow information simulated using the SWAT model. According to the simulated results of the SWAT model in the calibration and validation processes, the model can provide reasonable streamflow data based on R^2, NSE and PBIAS. Simulated monthly streamflow data obtained from the SWAT model for each sub-watershed outlet was used to compute SDI. In this study, the drought analysis based on SDI was performed in dry and rainy seasons. This SDI was found to be suitable for drought monitoring. Drought events indicated by the SDI seem to be consistent with observed streamflow in the main river. Moreover, the spatial distributions of SDI over the watershed can identify areas, prone to droughts. Further work is required to integrate results of SDI with additional indices related to meteorological and agricultural droughts. The integration can provide useful support for long-term drought mitigation and management.

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