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Future hydrological drought hazard assessment under climate and land use projections in Upper Nan River Basin, Thailand

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Abstract

Drought has extensively affected Thailand because agriculture is an important source of the country's income. Upper Nan River Basin (U-NRB) is an important basin for agriculture in Thailand. This research studies future drought hazard in U-NRB under climate and land use change projection by considering into three future period: 2020s (2011-2040), 2050s (2041-2070) and 2080s (2071-2100). This study analyzed the drought hazard under three parameters that are the standardized precipitation-evapotranspiration index (SPEI), Streamflow Drought Index (SDI), and ground water yield. The three Regional Climate Models (RCMs) are used to compute and figure out the SPEI under two Representative Concentration Pathway (RCP4.5 and 8.5). The SDI is calculated from future streamflow data which obtain from hydrological model. The weighting factors of each drought parameter are efined with Analytic Hierarchy Process (AHP). SPEI has more significant effect than SDI and ground water yield. Moreover, the drought period depends on standing shortage of rainfall at 1, 3, and 6 months. The future drought hazard maps are displayed as drought hazard levels which are very low, low, medium, and high. The results found that SPEI1 and SPEI3 under RCP4.5 and 8.5 change from very low to low, low to medium and medium to high but they do not change much in 2050s for RPC4.5. For SPEI6, the results show that drought hazard level has trended to decrease severity under RCP4.5 both in 2050s and 2080s but the drought hazard level under RCP8.5 has trended to increase severity as medium and high in 2050s and 2080s. Therefore, Most of the areas in U-NRB are low and medium hazard level in 2050s. Whereas, medium and high hazard levels are found in the U-NRB in 2080s.

Keywords: Analytic hierarchy process, Climate change projection, Drought hazard, Nan River Basin, SPEI

1. Introduction

The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) has given that the climate and land use change are factors that contribute to the changing hydrological cycle and probably to be severe in the future [1]. This is the cause of flood and drought disasters in many regions around the world [2, 3]. Currently, Thailand is a country experiencing increasing severity of flood and drought disasters every year and is expected to be more serve in the future. In the past five years, extreme drought disaster occurred in Thailand that has affected the agricultural production, which has lost billions bath. U-NRB is one the basin which is vulnerable drought problem in future.

There are many previous researches about climate change impact on water cycle under different greenhouse gas emission level [4, 5]. These studies found that rainfall and temperature were factors affecting streamflow in basin. In addition, the climate change of streamflow depends on the land use change [6, 7]. HEC-HMS is one the hydrological model which is widely used for studying climate change impact on streamflow [8, 9]. The streamflow is predicted under climate and land use change projections in U-NRB. For studying drought hazard, previous studies [10-13] indicated that the standardized precipitation evapotranspiration index (SPEI) is more able to reflect the impact of drought on agriculture and suitable for short- and long-term drought-monitoring. SPEI combines precipitation and potential evapotranspiration. Moreover, the Stream Drought Index (SDI) is widely used to study drought hazard [14, 15]. Therefore, this study objectives to study the climate and land use change for evaluating impacts on the hydrological drought hazard in U-NRB based on the rainfall and evapotranspiration under climate change condition (SPEI and SDI) and ground water yield.

2. Materials and methods

2.1 Study area

The U-NRB is one of sub-basins of the greater Chao Phraya basin. The U-NRB is located in Northern Thailand which covers latitude $17^{\circ}42'12''$-$19^{\circ}37'48''$ N and longitude $100^{\circ}06'30''$-$101^{\circ}21'48''$ E as shown in Figure 1. The elevation ranges between 7 to 2,061 meters above mean sea level. The lower part of U-NRB is Sirikit Dam with a capacity of 9,500 million cubic meters. The catchment area of U-NRB is 13,130 km^2 [16] that includes 65% of forest area, 31% of agricultural area and 4% of water body and built-up area. In this basin, field crops and rice are the dominant products in agriculture sector. The tropical climate of U-NRB has three seasons: a

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rainy season (Jun-Oct), a winter season (Nov-Feb) and a summer season (Mar-May). The average maximum, minimum temperatures and rainfall of U-NRB are 36.6℃, 15.3℃ and 1,371 mm, respectively.

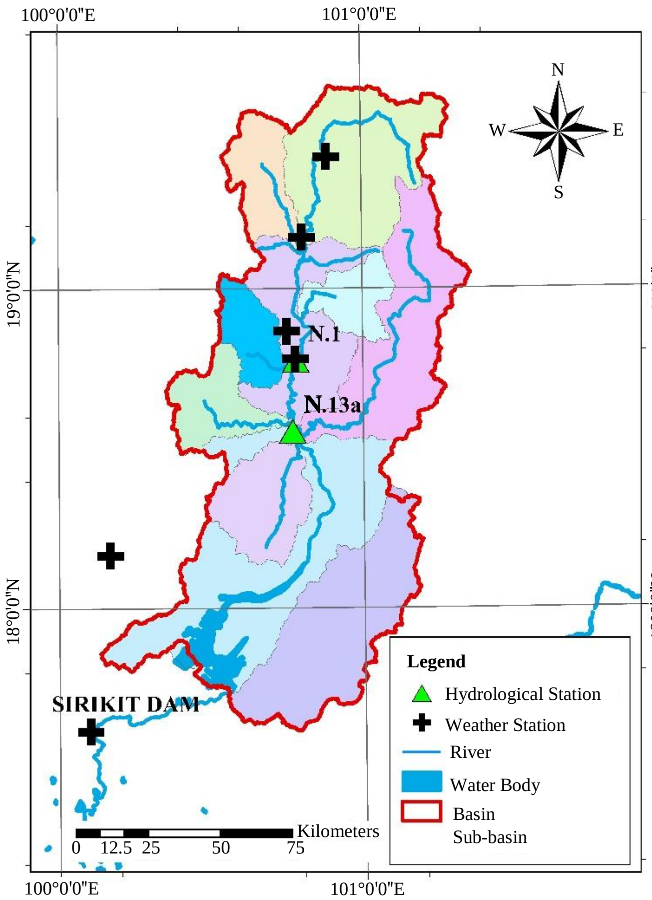


Figure 1 Location of study area in the Upper Nan River Basin (U-NRB), Thailand

2.2 Input data

The data of this study include the meteorological data and groundwater discharge data that obtained by Thai Methodological Department, Royal Irrigation Department, and Department of Groundwater Resources. The daily rainfall, minimum and maximum temperatures are the observed meteorological data for method of bias correction in order to consider standardized precipitation evapotranspiration index (SPEI). Whereas, groundwater discharge data were gauged by groundwater wells in this and surrounding basin. Moreover, ACCESS-CSRO-CCAM, CNRM-CM5-CSIRO-CCAM and MPI-ESM-CSIRO-CCAM under Representative Concentration Pathways (RCP4.5 and 8.5) are regional climate models which were used as data for future climate prediction.

3. Methodology

In this study, the methodology can be separated into five steps for drought hazard assessment in U-NRB. The first step is a bias correction and projection of daily rainfall, maximum and minimum temperatures by using linear regression method. The second step is the evaluation of land use change in the future under conservation and economic scenarios by using spatial dynamic modeling (FLUS model). The third step is a calibration and validation of hydrological model (HEC-HMS). Nash-Sutcliffe coefficient (NSE), the coefficient of determination (R^2), Normalized Root Mean Square Error (NRMSE) and Volume Ratio (V_r) are used as metrics for measuring the performance accuracy of this hydrological model. The fourth step is an analysis the drought index. Three drought indexes were analyzed, namely standardized precipitation-evapotranspiration index (SPEI), streamflow drought index (SDI) and ground water yield. The last step is the future drought hazard map prediction into three period: near future (2020s), mid future (2050s) and far future (2080s) under RCP4.5 and RCP8.5.

3.1 Bias correction for climate data projection

Bias correction method is a process of scaling climate data in order to improve these climate data matching with observed data. In this study, the linear scaling was selected to adjust the daily rainfall, maximum and minimum temperature between RCMs data and observed data, as this method is a perfect for increasing accuracy of simulated data from previous studies [17-19]. U-NRB covers 6 intersects which are inaccurate and insufficient for the simulated climate characteristics. The linear scaling equations (1) and (2) were used for adjustment and fitting of the historical and simulated rainfall data of RCMs with the observed rainfall data. For maximum and minimum temperature, data of RCMs were adjusted and fitted with observed temperature data by using the equations (3) and (4) [4, 5]. Moreover, the dispersion and central tendency were examined for accuracy of the data with SD and mean value.
Rainfall correction formulas:

$$P'_{his,d} = P_{his,d}\left[\frac{\mu_m \cdot P_{obs,d}}{\mu_m \cdot P_{his,d}}\right] \tag{1}$$

$$P'_{sim,d} = P_{sim,d}\left[\frac{\mu_m \cdot P_{obs,d}}{\mu_m \cdot P_{his,d}}\right] \tag{2}$$

Temperature correction formulas:

$$T'_{his,d} = T_{his,d} + \left[\mu_m \cdot T_{obs,d} - \mu_m \cdot T_{his,d}\right] \tag{3}$$

$$T'_{sim,d} = T_{sim,d} + \left[\mu_m \cdot T_{obs,d} - \mu_m \cdot T_{his,d}\right] \tag{4}$$

Where, P is rainfall, T is temperature, d is daily unit, μ_m is monthly unit, obs is observed data, his and sim are historical and simulated RCMs data respectively, and $'$ is corrected value.

3.2 Land use change model

The land use change model as mentioned in this study is Future Land Use Simulation model (FLUS), which is widely used for future land use projection [20-22] FLUS model is an integrated spatial model to simulate expected multiple land use scenarios under human activities and environment effect. The principle of FLUS model has two components that are multiple cellular automata (CA) allocation model and artificial neural network (ANN) algorithm [22]. The multiple CA allocation model is used for simulated future spatial land use pattern under various conditions. ANN algorithm is used to process the complex relationship of parameters that affect future land use types. The future land use map is simulated under conditions of economic and conservation pattern. In this study, the land use change projection from 2020-2100 was defined and evaluated from land use map in 2016 and 2019 of LDD by considering the land use types as agriculture, forest, miscellaneous, water body and built-up. The resolution of maps is 30x30 meter. While conservation scenario was estimated according to the Thailand Government Strategy on conserving and rehabilitating biological diversity to protect and increase forest area. The accuracy of model was assessed by Kappa statistical analysis (K) as shown in equation (5). The K has a value range 0 to 1 which 1 means the strong agreement between simulated and observed [5].

$$K = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \tag{5}$$

Where, Pr(a) is observed relative agreement amongst all raters and Pr(e) is the hypothetical probability of chance of agreement.

3.3 Hydrological model

HEC-HMS is hydrological model which is developed by US Army Corps of Engineering [16]. HEC-HMS is widely used because it can be simulated runoff both in short and longtime events and it uses common methods [23]. Therefore, HEC-HMS is applied to simulate runoff under different climate and land use scenarios in this study. The data and parameters for using the simulation in HEC-HMS was prepared through HEC-GeoHMS which is extension of HEC-HMS. Infiltration loss method was considered from SCS curve number and impervious percentage. Simple canopy and surface storage equations were used to define water detention and surface storage, respectively. The surface runoff simulation given time of concentration and storage coefficient computed by Clark unit hydrograph equation. The base flow method was defined from streamflow discharge data by using as constant monthly flow data. The weighting factor of each weather stations in sub-basin was computed by Thiessen polygon modification method. These method were used in HEC-GeoHMS to obtain input data in HEC-HMS. The results from HEC-HMS include daily streamflow discharge from daily rainfall data, maximum and minimum temperature. These results were compared with observed data from 1999-2007 for calibration and 2008-2017 for validation. Moreover, HEC-HMS were investigated performance by using standard statistical performance indices, namely, NSE, the R^2, NRMSE and Vr.

3.4 Drought indices

The Standardized precipitation-evapotranspiration index (SPEI) is an extension of the widely used Standardized Precipitation Index (SPI). The SPEI is based on the difference between precipitation and potential evapotranspiration (PET). The drought level was classified as five levels: no drought, light drought, moderate drought, severe drought, and extreme drought [13]. The SPEI was analyzed considering monthly precipitation during historical period (1950-2010) and three future periods (2020s, 205s0s, and 2080s). The Streamflow drought index (SDI) has the same concepts as the SPI, but unlike SPI, the SDI is computed from streamflow series. In this study, the streamflow, which is used to calculate SDI, was obtained from HES-HMS. The drought classification of SDI can be divided into five levels as well as SPEI. Moreover, the ground water yield was considered for analysis of drought hazard level with Analytical Hierarchy Process (AHP).

3.5 Determination of drought weighting factors

In this study, three parameters (SPEI, SDI, and ground water yield) were computed to delineate drought hazard level in U-NRB. The SPEI and SDI values were classified into five levels. The ground water yield was separated into four levels. Analytical Hierarchy Process (AHP) was classified as five level drought hazard (very low, low, medium, high and very high) for calculating the drought weighting factors. For AHP, the rank factors from 1 to 9 levels are determined on relative significant scales. Comparison of two drought parameters was also shown by taking no. 1, 5, 7 and 9 which represent as equally, moderately, strongly, very strongly, and extremely preferred, respectively. The study found that SPEI has more effective than SDI and ground water yield. After that, the judgment matrix is created by using significant scales to weight each parameter. The AHP was determined for the computational weight weights accuracy of the drought parameters from using consistency parameters. The equations (6)-(8) show the equation of consistency parameters calculation. The equation (9) was used to calculate the drought hazard index.

$$\lambda_{\max} = \sum_{i=1}^{n}\left[\sum_{j=1}^{n} a_{ij} W_i\right] \tag{6}$$

$$CR = \left(\lambda_{\max} - n\right) / \left(n-1\right) \tag{7}$$

$$CI = CR / RI \tag{8}$$

Where *CI* is the consistency index, *CR* is the consistency ratio, *RI* is the random inconsistency index [24], λ_{max} is the Eigen value, a_{ij} is the judgment matrix data, W_i is the drought parameter weight i, n is the number of factors.

Hazard index = $c_1W_1 + c_2W_2 + c_3W_3$ (9)

Where c_i is the scores, and W_i is the weight (W_1+W_2+W_3=1). The ranges of score from 1-100% are defined in accordance with the ranges of drought hazard parameter. The values of W_1, W_2, and W_3 are determined according to the relative influence, which are achieved from survey and field data, among the SPEI, SDI, and ground water yield (as shown in Table 1).

Table 1 Weighting factor and coefficient of drought hazard factors

No (i)	Parameters	Drought Hazard Classification	Drought Hazard Level	c_i	W_i
1	SPEI	<-2	Extremely dry	1.00	0.63
		-1.50 to -1.99	Severely dry	0.80	
		-1.00 to -1.49	Moderately dry	0.60	
		-0.01 to -0.99	Near normal	0.40	
		>0	Wet	0.20	
2	SDI	<-2	Extremely dry	1.00	0.26
		-1.50 to -1.99	Severely dry	0.80	
		-1.00 to -1.49	Moderately dry	0.60	
		-0.01 to -0.99	Near normal	0.40	
		>0	Wet	0.20	
3	Ground water yield (m^3/hr)	<2	Very high	1.00	0.11
		2 to 10	high	0.75	
		10 to 20	Moderate	0.50	
		>20	Low	0.25	

4. Results and discussion

4.1 Climate bias correction and projection

In this study, the average daily rainfall, maximum and minimum temperatures from three RCMs, which are ACCESS, CNRM, and MPI, were projected the future climate under RCP4.5 and 8.5 in U-NRB. The six weather stations of TMD in U-NRB including 330201, 331201, 331301, 331401, 331402, and 351201 were used as baseline rainfall and temperatures to adjust in bias correction method (linear scaling). The mean and standard deviation (SD) were implemented to compare between simulated and observed climate characteristics as shown in Table 2. The mean and SD values were considered the dispersion measurement and central tendency of baseline and three RCMs. The results found that the rainfall data of CNRM has the higher accuracy and precision than ACCESS and MPI because the CNRM mean and SD values were relatively close to baseline values in almost all TMD stations. For the maximum and minimum temperatures, the mean and SD values of three RCMs were quite near the baseline values in all TMD stations. The input data of hydrological model for future streamflow projection was used as average daily rainfall, maximum and minimum temperatures from three corrected RCMs under RCP4.5 and 8.5. The data average method can increase the accuracy of predicted data and decrease the central tendency.

The results of future climate projection of station 331301 in U-NRB is discussed in this study. Table 3 shows the rainfall, maximum and minimum temperatures projection with different RCPs in near 2020s (2011-2040), mid 2050s (2041-2070), and far 2080s (2071-2100) future at Nan Agricultural Meteorological Station (331301). The results of projection indicated that the rainfall projection on

2020s, 2050s and 2080s under RCP4.5/8.5 have changed from 341-407 (increasing +19.35%) / 377-412 (+9.28%) mm (summer), 933-871 (decreasing -6.65%) / 982-833 (-15.17%) mm (rainy), 33-35 (+6.06%) / 28-41 (+46.43%) mm (winter), and 1,308-1,313 (+0.38%) / 1,387-1,286 (-7.28%) mm (annual), respectively. Moreover, the maximum and minimum temperatures projection of both RCPs showed a slight increase of about 2-3℃ from 31-32/31-34℃ and 20-21/20-23℃, respectively.

Table 2 Performance of bias correction method of three RCMs

Station ID	330201		331201		331301		331401		331402		351201	
	Mean (mm)	SD (mm)	Mean (mm)	SD (mm)	Mean (mm)	SD (mm)	Mean (mm)	SD (mm)	Mean (mm)	SD (mm)	Mean (mm)	SD (mm)
Rainfall												
Baseline	3.04	9.62	3.44	9.94	3.44	9.92	3.89	10.93	4.91	12.23	3.88	11.53
ACCESS	3.12	7.37	3.56	8.53	3.58	8.73	4.09	10.48	4.81	10.65	3.85	7.27
CNRM	3.02	7.70	3.72	9.94	3.95	9.63	4.10	12.53	4.50	11.78	4.06	10.06
MPI	3.13	6.80	3.42	9.17	3.69	9.18	3.81	10.51	4.58	12.26	3.90	8.84
Maximum temperatures												
Baseline	32.84	3.31	32.50	3.42	31.58	3.48	31.67	3.34	31.21	3.87	33.69	3.24
ACCESS	33.03	3.81	32.70	3.88	30.31	3.89	31.87	3.94	32.30	4.47	33.87	3.57
CNRM	33.01	3.78	32.68	3.86	30.25	3.87	31.84	3.91	31.36	3.87	33.87	3.52
MPI	33.04	3.61	32.70	3.83	30.29	3.80	31.86	3.88	31.32	3.69	33.88	3.66
Minimum temperatures												
Baseline	21.25	4.11	20.23	4.43	19.39	4.58	19.80	4.71	19.61	4.16	22.03	3.45
ACCESS	21.45	4.02	20.41	4.35	18.65	4.09	19.98	4.59	20.53	4.35	22.23	3.49
CNRM	21.45	4.03	20.41	4.37	18.62	4.13	19.98	4.61	19.69	4.37	22.23	3.50
MPI	21.45	4.02	20.40	4.39	18.63	4.12	19.97	4.63	20.00	4.17	22.22	3.58

Table 3 Rainfall, maximum and minimum temperatures projection under RCP4.5 and 8.5 in three period future at Nan Agricultural Meteorological Station (331301)

Season	2020s		2050s		2080s	
RCPs	4.5	8.5	4.5	8.5	4.5	8.5
Rainfall						
Summer	340.97	377.39	423.72	392.47	407.23	412.21
Rainy	933.34	981.80	885.73	913.19	871.28	832.72
Winter	33.33	28.30	28.97	28.22	34.81	41.27
Annual	1,307.63	1,387.49	1,338.42	1,333.88	1,313.31	1,286.20
Maximum temperatures						
Annual	31.35	31.41	31.81	32.62	32.41	34.15
Minimum temperatures						
Annual	19.59	19.73	20.16	20.89	20.66	22.53

4.2 Land use projection

The future land use projection in U-NRB was simulated under conditions of economic and conservation pattern. The last land use trend was considered from land use maps in 2016 and 2019. This study was projected the land use map in 2020 which was compared with observed land use based on Kappa statistical analysis (K). The K value is 0.92, which is very highly acceptable and sufficiently accurate for future land use projection. Figure 2 shows the projected land use maps in 2040, 2060, 2080, and 2100. The results indicated that the largest percentage changes are the forest and agricultural area. While, the built-up area has a very small percentage of change and the water body area was unchanged.

4.3 Hydrological model calibration and validation

The HEC-HMS model was used to simulate daily streamflow which was compared with observed data at stations N.1 and N.13a during 1999-2007 calibration period and 2008-2017 validation period. The location of stations N.1 and N.13a are in the middle and lower parts of U-NRB and upstream of inlet point to Sirikit reservoir. The reliability of this model was evaluated by statistical performance parameters, namely, R^2, NRMSE, NSE, and V_r. Table 4 shows values of statistical performance parameters during calibration and validation periods at N.1 and N.13. The R^2, NSE and V_r values should be close to 1 that means the model provides high performance. The NRMSE value should be less than 10%. The results show that the all statistical performance parameters during calibration period at both stations are satisfactory of value. Whereas, during validation period at both stations show a good agreement between simulated and observed data. Besides, Figure 3 displays graphs of comparison between observed and simulated daily streamflow at station N.1 and N.13a. These graphs show that the values simulated from HEC-HMS model are consistent with observed data during both calibration and validation periods. Therefore, this model can be used to predict future streamflow under different climate and land use change scenarios. These results, which are cumulative streamflow per monthly, are used to calculate as SDI value.

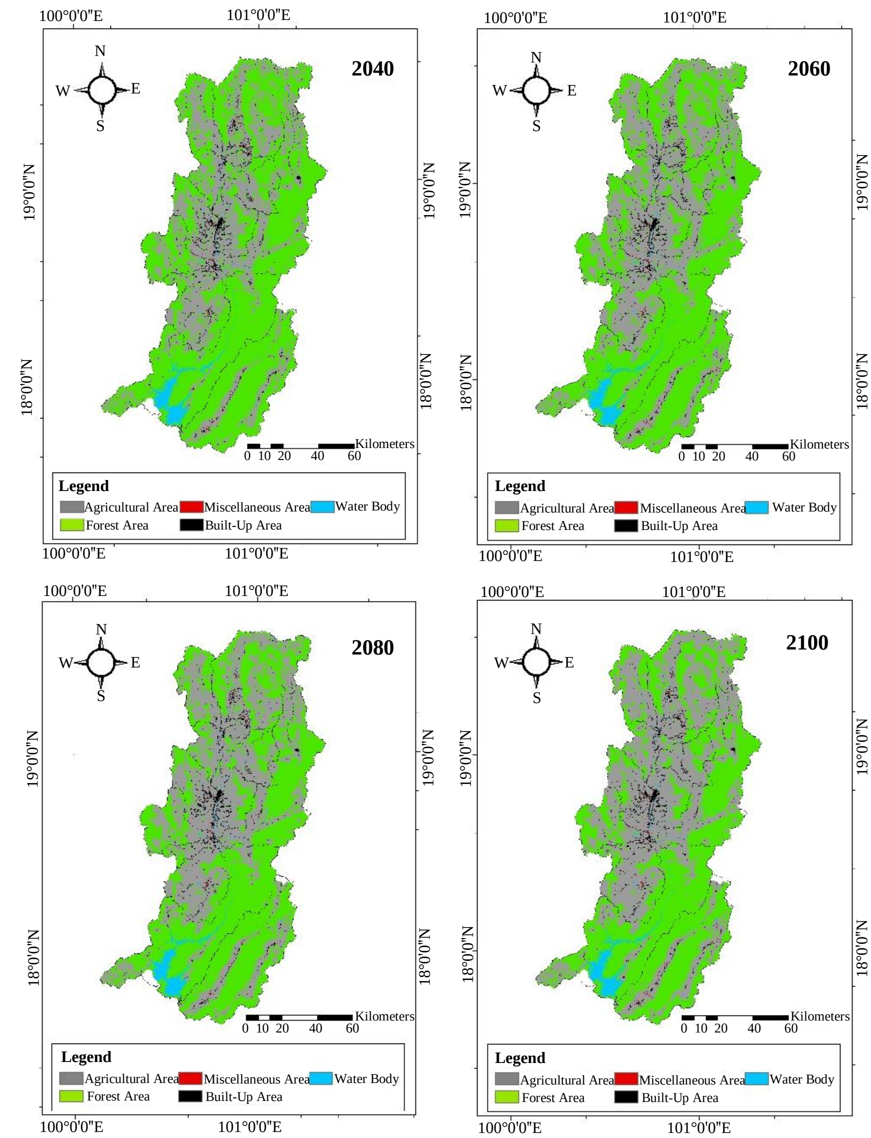


Figure 2 Projected land use maps in 2040, 2060, 2080, and 2100, respectively

Table 4 Performance of hydrological model (HEC-HMS)

Period	Station N.1		Station N.13a	
	Calibration	**Validation**	**Calibration**	**Validation**
R^2	0.85	0.79	0.80	0.77
NRSE	3.29	5.30	6.16	6.85
NSE	0.78	0.68	0.75	0.67
V_r	1.12	1.05	1.17	1.22

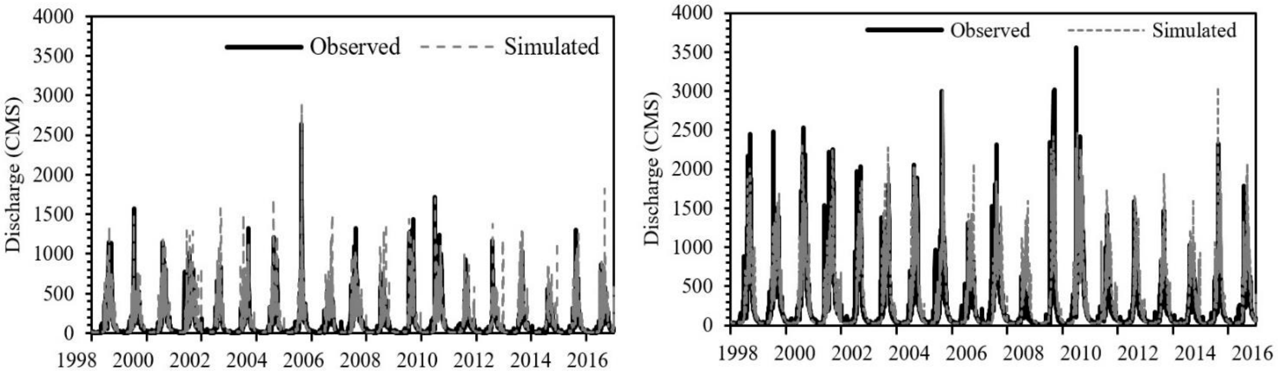


Figure 3 Comparison between observed and simulated streamflow with calibration (1999-2007) and validation (2008-2017) periods at station N.1 and N.13a, respectively.

4.4 Drought hazard assessment

4.4.1 Drought indices determination

The estimation of SPEI and SDI values are mentioned in this section. This study considered a drought period depending on standing shortage of rainfall. The paddy field (rice) can rainfall stand shortage not more than one month. The field crops (cassava, sugarcane, and corn) can rainfall stand shortage more than 1-3 months. For fruit crops, they can rainfall stand shortage more than 1-6 months. Therefore, SPEI and SDI were evaluated as SPEI1/SDI1, SPEI3/SDI3, and SPEI6/SDI6. The six meteorological stations were applied to calculate SPEI and SDI all three scenarios during 1970-2010. Normally, the values of SPEI and SDI range between -3 and 3 [25]. This result shows only SPEI1, SPEI3, and SPEI6 values with three time scales which are 2020s, 2050s, and 2080s under RCP4.5 and 8.5 as shown in Table 5. The SPEI values in 2020s and 2050s are near zero which means near drought condition. Whereas, in 2020s, 2050s, and 2080s have the negative value which means drought condition. The results of SDI were similar to those of SPEI (show the same +/- value).

Table 5 The SPEI1, 3, and 6 values in three future period at six meteorological stations

Station ID	2020s		2050s		2080s	
	4.5	8.5	4.5	8.5	4.5	8.5
SPEI1						
330201	0.09	0.21	0.04	-0.04	-0.09	-0.15
331201	0.05	0.20	0.05	0.02	-0.06	-0.20
331301	0.06	0.20	0.04	0.02	-0.06	-0.19
331401	0.08	0.30	0.01	0.07	-0.07	-0.34
331402	0.05	0.18	0.01	0.05	-0.04	-0.22
351201	0.06	0.18	0.04	-0.03	-0.07	-0.13
SPEI3						
330201	0.12	0.27	0.03	-0.08	-0.09	-0.18
331201	0.02	0.25	0.06	0.02	-0.02	-0.27
331301	0.04	0.26	0.05	0.01	-0.04	-0.26
331401	0.04	0.36	0.02	0.11	-0.03	-0.47
331402	0.00	0.19	0.01	0.10	0.02	-0.31
351201	0.07	0.25	0.05	-0.05	-0.09	-0.20
SPEI6						
330201	0.13	0.33	0.08	-0.12	-0.13	-0.20
331201	-0.03	0.31	0.10	0.04	0.02	-0.35
331301	0.01	0.34	0.10	0.03	-0.02	-0.36
331401	-0.01	0.42	0.04	0.15	0.03	-0.58
331402	-0.07	0.19	0.03	0.16	0.10	-0.39
351201	0.10	0.33	0.10	-0.08	-0.15	-0.27

4.4.2 Weighting factor determination

The weights of SPEI, SDI, and ground water yield were computed with AHP by using questionnaire surveying of U-NRB and meteorological stations data. These results found that the drought duration SPEI is the most effective against the rice in drought duration. Moreover, SPEI has more significant effect than SDI and ground water yield. Table 6 shows the pairwise comparison matrix which is normalized weight by setting the sum of each column equal 1 [26, 27]. The weight of SPEI, SDI, and ground water yield are 0.63, 0.26, and 0.11 respectively as shown in Table 7. The weight can be verified by summation of weight as 1. Besides, the consistency parameters, which are Eigen value, consistency ratio and consistency index, used to verify the weighting. The Eigen value must be equal to the number of all drought parameters. Whereas, the consistency ratio and consistency index must be close to zero. This study shown that Eigen value has equal the number of hazard parameter, which is 3, and the consistency ratio and consistency index are very close zero.

Table 6 Pairwise comparison matrix of SPEI, SDI and ground water yield

Drought parameters	SPEI value	SDI value	Ground water yield
SPEI value	1	3	5
SDI value	1/3	1	3
Ground water yield	1/5	1/3	1

Table 7 The normalized weight of SPEI, SDI and ground water yield

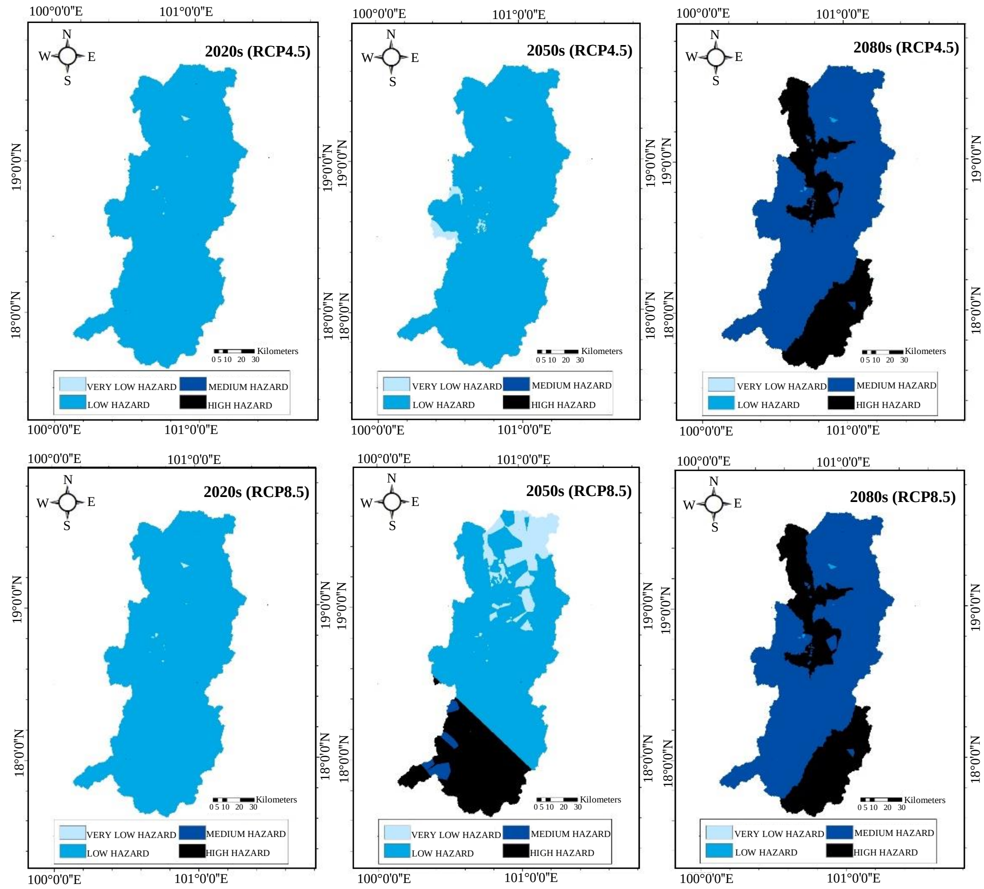
Drought parameters	SPEI value	SDI value	Ground water yield	Weight (W_i)
SPEI value	15/23	9/13	5/9	0.63
SDI value	5/23	3/13	3/9	0.26
Ground water yield	3/23	1/13	1/9	0.11
Summation	1.00	1.00	1.00	1.00

4.4.3 Drought hazard level prediction

The drought hazard index was computed to create the drought hazard map in U-NRB as shown in Figure 4. The maximum and minimum drought hazard indices are 21-48. Therefore, the drought hazard levels can be separated into four levels which are very low (21-27), low (28-34), medium (35-41), and high (42-48). Figure 4(a) shows the paddy field of future drought hazard maps with SPEI1 under different RCPs (4.5 and 8.5) in 2020s-2080s. It indicated that hazard levels in 2020s for RCP4.5 has changed from very low (0.1%) and low (99.9%) hazard level to medium (70%) and high (30%) hazard level in 2080s but it has not change in 2050s. For RCP8.5, the very low (0.1%) and low (99.9%) change to medium (70%) and high (30%) respectively during 2020s-2080s. Figure 4(b) shows the field crop of future drought hazard maps with SPEI3 under different RCPs (4.5 and 8.5) in 2020s-2080s. This result found that the drought hazard map in 2020s under RCP4.5 has changed hazard level from very low (0.1%) and low (99.9%) to very low (19%) in 2050s but it has changed as medium (66%) and high (18%) in 2080s. For RCP8.5, the very low and low changed to medium (73%) and high (27%) respectively in 2050s and 2080s. Figure 4(c) shows of the fruit crops future drought hazard maps with SPEI6 under different RCPs (4.5 and 8.5) in 2020s-2080s. The result showed that drought hazard level has tended to decrease severity under RCP4.5 both in 2050s and 2080s. Whereas, the drought hazard level under RCP8.5 has trended to increase severity as medium and high in 2050s and 2080s. Especially in 2080s, the map was the high hazard level. Therefore, the drought under different RCPs (4.5 and 8.5) are more significant in U-NRB in 2020s-2080s for every crops.

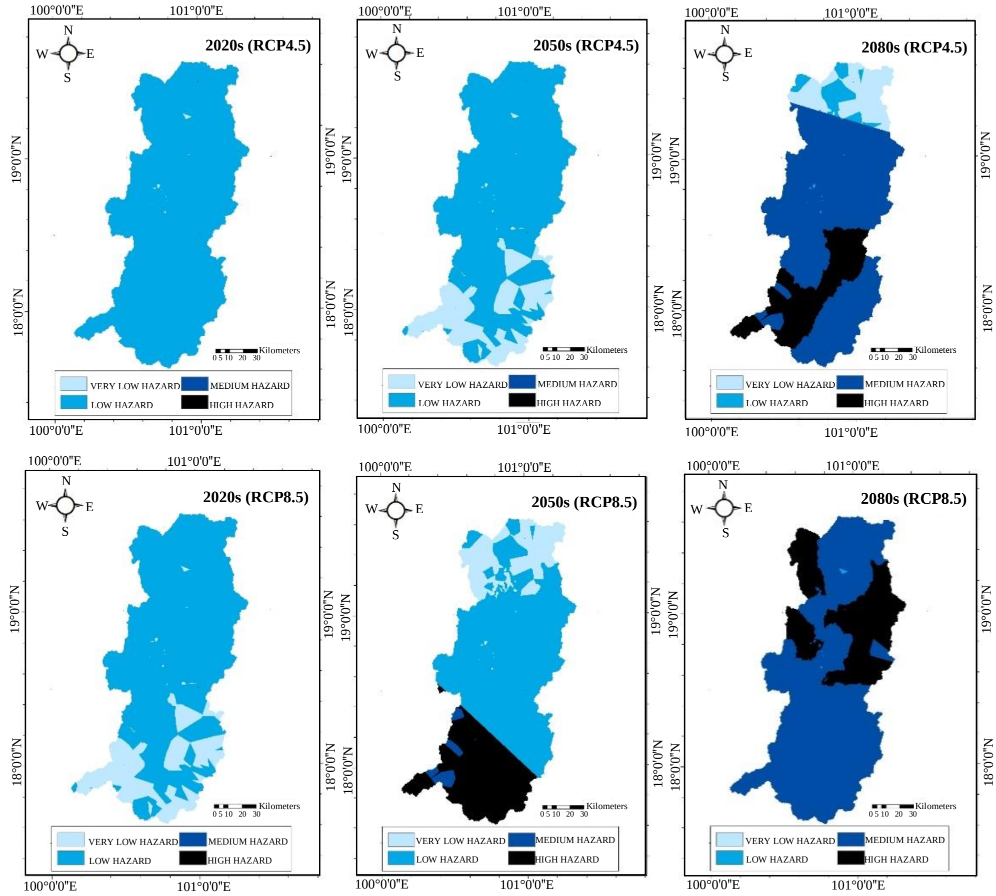
5. Conclusions and discussions

The U-NRB future drought hazard assessment was studied for 2020s-2080s. The three RCMs (ACCESS, CNRM, and MPI) were biased and used to project the future climate under RCP4.5 and 8.5. The projected future annual precipitation increased 0.38% and decreased 7.28% for RCP4.5 and 8.5, respectively. The drought hazard was analyzed under three parameters which are the SPEI, SDI, and ground water yield. The SPEI values depend on the cumulative month precipitation under different greenhouse gas emission levels which data obtained from results of predicted future climate. While, the SDI values depend on the cumulative streamflow per monthly under different greenhouse gas emission levels which obtained from the results HEC-HMS. The SPEI has more significant effect than SDI and ground water yield. The drought period depends on standing shortage of rainfall at 1 month for rice, 3 months for field crop, and 6 months for fruit crops. The SPEI were evaluated as SPEI1, SPEI3, and SPIE6. The future drought hazard maps were displayed as drought hazard levels which are very low, low, medium, and high in 2020s, 2050s, and 2080s under RCP4.5 and 8.5. The SPEI1 and SPEI3 under RCP4.5 and 8.5 changed from very low to low, low to medium and medium to high but they do not change much in 2050s for RPC4.5. For SPEI6, the results showed that drought hazard level has trended to decrease severity under RCP4.5 both in 2050s and 2080s but the drought hazard level under RCP8.5 has trended to increase severity as medium and high in 2050s and 2080s. The most of areas in U-NRB are low and medium hazard level in 2050s. Whereas, medium and high hazard level are found areas of U-NRB in 2080s. Therefore, the future drought hazard under RCP4.5 and RCP8.5 are more significant in U-NRB in 2020s-2080s for every crops. Moreover, this study did not consider the impact of future climate and land use change to groundwater yield.

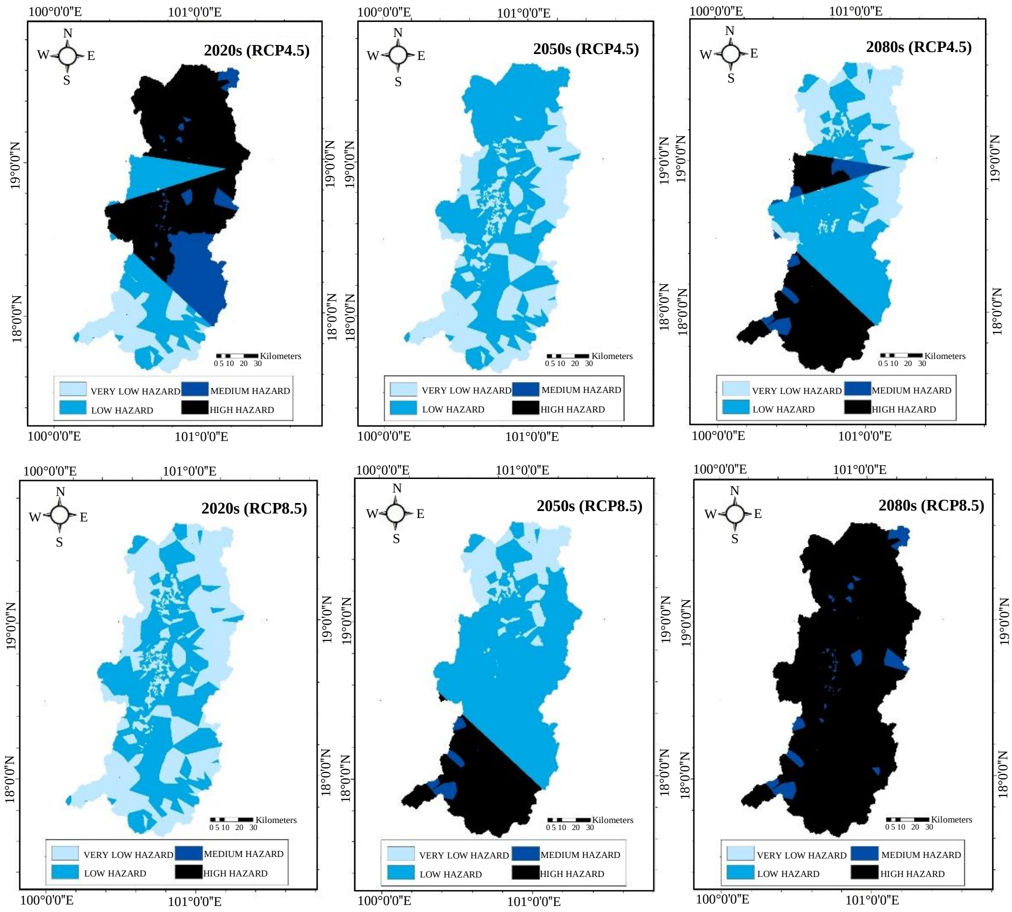


(a) Paddy field of future drought hazard maps (SPEI1) under RCP4.5 and RCP8.5

Figure 4 U-NRB Future drought hazard maps for three future periods



(b) Field crops of future drought hazard maps (SPEI3) under RCP4.5 and RCP8.5



(c) Fruit crops of future drought hazard maps (SPEI6) under RCP4.5 and RCP8.5

Figure 4 (continued) U-NRB Future drought hazard maps for three future periods

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7. References

[1] IPCC. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press; 2013.
[2] Wei W, Yan Z, Jones PD. A decision-tree approach to seasonal prediction of extreme precipitation in eastern China. Int J Climatol. 2020;40(1):255-72.
[3] Janes T, McGrath F, Macadam I, Jones R. High-resolution climate projections for South Asia to inform climate impacts and adaptation studies in the Ganges-Brahmaputra-Meghna and Mahanadi deltas. Sci Total Environ. 2019;650:1499-520.
[4] Shrestha S. Climate change impact on reservoir inflows of Ubolratana dam in Thailand. In: Shrestha S, editor. Climate change impacts and adaptation in water resources and water use sectors. New York: Springer; 2014. p. 25-41.
[5] Shrestha S, Bhatta B, Shrestha M, Shrestha PK. Integrated assessment of the climate and landuse change impact on hydrology and water quality in the Songkhram River Basin, Thailand. Sci Total Environ. 2018;643:1610-22.
[6] Al-Safi HI, Sarukkalige P. Evaluation of the impacts of future hydrological changes on the sustainable water resources management of the Richmond River catchment. J Water Clim Change. 2018;9:137-55.
[7] de Salis HHC, da Costa AM, Vianna JHM, Schuler A, Kunne A, Fernandes LFS, et al. Hydrologic modeling for sustainable water resources management in urbanized karst areas. Int J Environ Res Public Health. 2019;16(4):2542.
[8] Chu X, Steinman A. Event and continuous hydrologic modelling with HEC-HMS. J Irrigat Drain Eng. 2009;135(1):119-24.
[9] Sharma D, Gupta A, Babel M. Spatial disaggregation of bias-corrected GCM precipitation for improved hydrologic simulation: Ping River Basin, Thailand. Hydrol Earth Syst Sci. 2007;11:1373-90.
[10] Zhao H, Gao G, An W, Zou X, Li H, Hou M. Timescale differences between SC-PDSI and SPEI for drought monitoring in China. Phys Chem Earth A B C. 2017;102:48-58.
[11] Li WG, Yi X, Hou M, Chen HL, Chen ZL. Standardized precipitation evapotranspiration index shows drought trends in China. Chin J Eco-Agr. 2012;20(5):643-9.
[12] Begueria S, Vicente-Serrano SM, Reig F, Latorre B. Standardized precipitation evaporation index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. Int J Climatol. 2014;34(10):3887.
[13] Yang M, Yan D, Yu Y, Yang Z. SPEI-based spatiotemporal analysis of drought in Haihe River Basin from 1961 to 2010. Adv Meteorol. 2016;2016(1):1-10.
[14] Nalbantis I, Tsakiris G. Assessment of a hydrological drought revisited. Water Resour Manag. 2009;23(5):881-97.
[15] Pandhumas T, Kuntiyawichai K, Jothityangkoon C, Suryadi FX. Assessment of climate change impacts on drought severity using SPI and SDI over the Lower Nam Phong River Basin, Thailand. Eng Appl Sci Res. 2020;47(3):326-38.
[16] Babur M, Babel MS, Shrestha S, Kawasaki A, Tripathi NK. The impact of climate change on reservoir inflows using multi climate-model under RCPS' including extreme events-a case of mangle dam in Pakistan. Water. 2016;8(9):389.
[17] Lee JK, Hamlet AF, Grossman EE. Climate change impacts of climate change on regulated streamflow, hydrologic extremes, hydropower production, and sediment discharge in the Skagit River Basin. NW Sci. 2016;90(1):23-43.
[18] Manee D, Tachikawa Y, Yorozu K. Analysis of hydrologic variable changes related to large scale reservoir operation in Thailand. J Jpn Soc Civ Eng Ser B1. 2015;71(4):61-6.
[19] Nyunt CT, Kawahara Y. Assessment of reservoir inflow and operating rule under climate change. J Jpn Soc Civ Eng Ser B1. 2017;73(4):91-6.
[20] Liang X, Liu X, Li X, Chen Y, Tian H, Yao Y. Delineating multi-scenario urban growth boundaries with a CA-based flus model and morphological method. Landsc Urban Plann. 2008;177:47-63.
[21] Liang X, Liu X, Chen G, Leng J, Wen Y, Chen G. Coupling fuzzy clustering and cellular automata based on local maxima of development potential to model urban emergence and expansion in economic development zones. Int J Geogr Inform Sci. 2020;34(10):1930-52.
[22] Liu X, Liang X, Li X, Xu X, Ou J, Chen Y, et al. A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. Landsc Urban Plann. 2007;168:94-116.
[23] Halwatura D, Najim M. Application of the HEC-HMS model for runoff simulation in a tropical catchment. Environ Model Software. 2013;46:155-62.
[24] Ahmad I, Verma MK. Application of analytic hierarchy process in water resources planning: a GIS based approach in the identification of suitable site for water storage. Water Resour Manag. 2018;32:5093-114.
[25] Vicente-Serrano Sergio M. The climate data guide: standardized precipitation evapotranspiration index (SPEI) [Internet]. Boulder: National Center for Atmospheric Research; 2020 [cited 2021 Jan]. Avaiable from https://climatedataguide.ucar.edu/climate-data/standarized-precipitation-evapotranspiration-index-spei.
[26] Saaty RW. The analytic hierarchy process-what it is and how it is used. Math Model. 1987;9(3-5):161-76.
[27] Vaidya OS, Kumer S. Analytic hierarchy process: an overview of application. Eur J Oper Res. 2006;169(1):1-29.