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Research article

Future runoff projections based on land change using integrated Markov-Cellular Automata model and Soil Water Assessment Tool in Lam Pachi Basin, Thailand

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Abstract

Surface runoff is a key component of the hydrological cycle. Land use/land cover is a main factor affecting runoff processes. This research quantified the future changes in the runoff yield based on land use/land cover change (LULCC) using as a case study the Lam Pachi (LPC) Basin, a tropical watershed located in western Thailand. Future land change scenarios were projected using the integrated Markov model and cellular automata simulation (CA-Markov), and the impacts of LULCC on runoff yield were evaluated using the Soil and Water Assessment Tool (SWAT). The result revealed that more than half of the Lam Pachi Basin was covered by forest. From the CA-Markov simulation, approximately 7.6% of the LPC Basin would be converted from forest to agriculture in the next 35 yr. The simulation study using SWAT showed a minor increase in the water yield at a basin-wide level, while substantial changes were observed at the sub-watershed level. The increased water yield occurred in the watershed due to land conversion from forest to agriculture, particularly on steeper topography, whereas the same conversion in the flat lowlands resulted in reduced water yield.

Introduction

Surface runoff is a key component in complex hydrological process (Beven and Kirkby, 1979; Beven, 2011) and the quantification of runoff could indicate the availability of water resources in a basin and provides important information for water management (Kositsakulchai et al., 2018). Land-use/land-cover (LULC) is one of the main factors affecting runoff processes (Bruijnzeel, 2006; Burt and Slattery, 2006) as changes in LULC affect water circulation in the hydrological cycle; subsequently they induce variability and uncertainty on the state of water resources and complexity in water management.

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During the last decades, LULC in Thailand has substantially changed due to socio-economic development and population growth. The Lam Pachi (LPC) Basin, a sub-basin of the Mae Klong River Basin in west Thailand, is a watershed that reveals the impact of changes. Many areas in the Basin have been subjected to flooding during recent times, including, in 2005 and repetitive flooding from 2010 to 2013 in a particular area, with the recurrent flooding further inducing bank erosion and river sedimentation (Royal Irrigation Department, 2012) which increased the degree of flood hazard. Although many water agencies (Royal Irrigation Department, 2001; Department of Water Resources, 2004; Japan International Cooperation Agency and Royal Irrigation Department, 2005; Royal Irrigation Department, 2012) have conducted studies, particularly related to water resources management in the LPC Basin, only the current situation based on historical data was addressed. From the rapid development of information technology, the coupling of spatial satellite-derived data and a computer simulation tool now enable future projections of land and water scenarios.

Land use and land cover change (LULCC), also known as land change, is a general term for human modification of the Earth's surface (Ellis, 2013). Based on a highly uncertain future, multiple plausible futures need to be considered (Maier et al., 2016). The impacts of LULCC can be investigated by analyzing current trends and potential future scenarios (Krysanova and White, 2015). LULCC analysis using the Markov model has been reported in the literature since the 1970's (Bell, 1974), up until more recent times (Jahan, 1986; Muller and Middleton, 1994; Arsanjani et al., 2011; Ayana and Kositsakulchai, 2012; Kumar et al., 2014). Land change distribution has been simulated using cellular automata (CA) (Hyandye, 2015), a multi-agent system (Parker et al., 2003; Arsanjani, 2011) and from the integration of CA simulation and the Markov model (Arsanjani et al., 2011; Guan et al., 2011; Pandey and Khare, 2017).

For many years, uncertainty has been considered extensively in the context of environmental and hydrological models (Maier et al., 2016). Many models have been evaluated for their performance in assessing the impact of LULCC (Tegegne et al., 2017). The Soil and Water Tool (SWAT model; Arnold et al., 1998) has been applied worldwide to different watershed scales, climatic zones, environmental conditions and management systems (Krysanova and White, 2015). Examples of SWAT applications can be found in the literature (Gassman et al., 2007; Gassman et al., 2014), including the applications of SWAT for assessing the impacts of LULCC on the hydrological conditions of watersheds (Ayana et al., 2012; Baker and Miller, 2013; Ayana et al., 2014; Kositsakulchai et al., 2018).

The current work aimed to quantify the changes of runoff yield in the Lam Pachi Basin, based on LULCC. Future scenarios of LULCC were projected using the cellular automata and Markov models and the impacts of LULCC were evaluated using the SWAT model.

Materials and Methods

Study area

The Lam Pachi River (LPC; Fig. 1) is a tributary of the Mae Klong River, located in western Thailand. The tributary has a drainage area of 2,634 km² (representing approximately 8% of the Mae Klong River Basin) ranging from latitude 13°08'N to 13°55'N and longitude 99°10''E to 99°35'E. The main LPC course of 130 km runs northward from Ratchaburi province and joins the Khwae Noi River at the outlet of the Basin in Kanchanaburi province. The topography of the upstream basin is characterized by relatively high mountains and steep river valleys. The altitude ranges from 35 m above sea level (asl) at the LPC River outlet to 1,156 m asl at the Tanao Sri mountain range. The climate in the LPC Basin is influenced by the southwest monsoon from May to October and by tropical cyclones during the end of the rainy season from September to October (Biltonen et al., 2003). The total annual rainfall is 1,060 mm of which almost 85% falls during the rainy season from May to October. The temperature in the hottest month, April, reaches an average maximum of 37°C while January is the coldest month with an average minimum temperature of 17°C (Fig. 2).

Markov model and cellular automata simulation

The integrated Markov model and cellular automata (CA) simulation (the CA-Markov model) is composed of three processes: evaluation of the transition probability matrix of the Markov Chain, modeling of the transitional potential using logistic regression, and simulation of land change using CA. In this study, the Modules for Land Use Change Evaluation (MOLUSCE) was selected for the analysis and simulation of land change. MOLUSCE is a plug-in for the QGIS 2.x software package and was developed by Asia Air Survey and NEXTGIS (2014) for land change modeling and simulation. Inputs required by MOLUSCE are LULC maps from different time periods and axillary data. The axillary data can be biophysical or socio-economic driving-factor data such as the road network and topography.

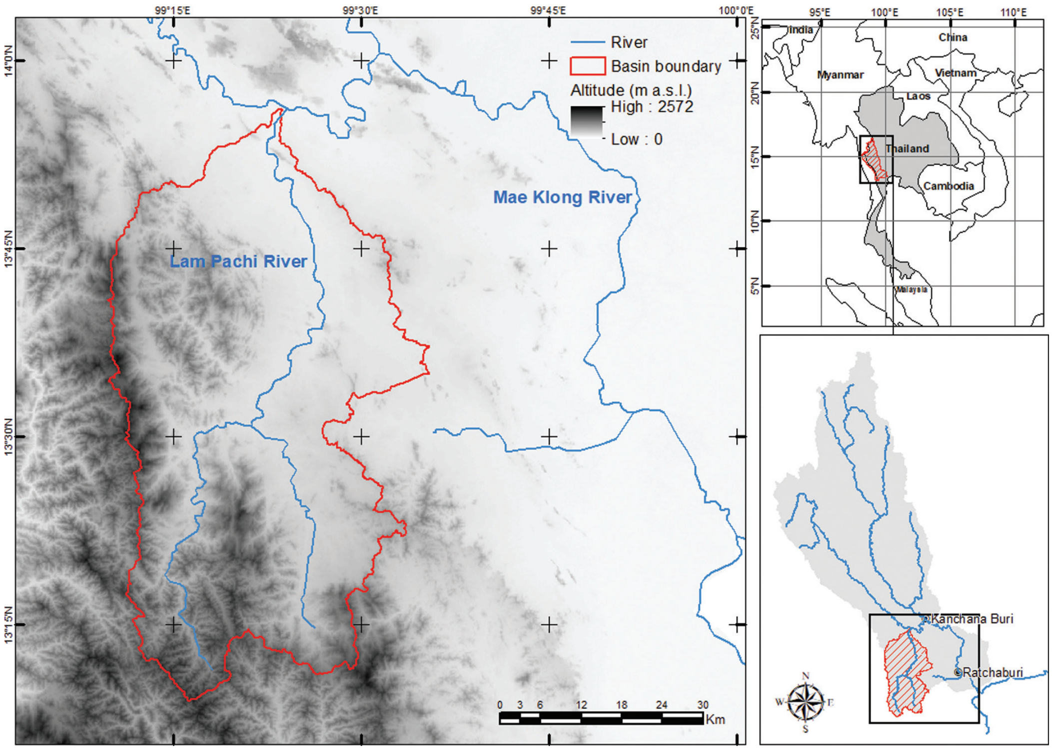

Fig. 1 Lam Pachi Basin, western Thailand

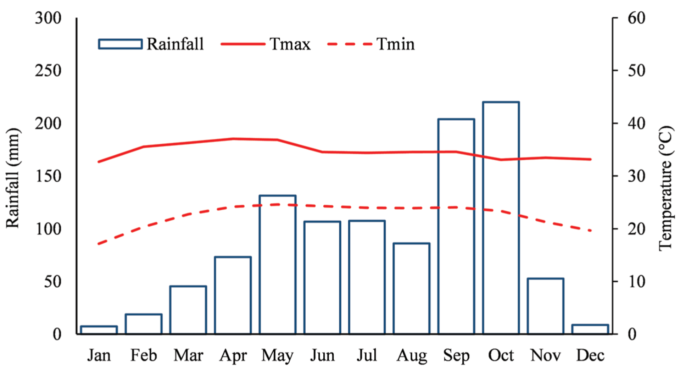

Fig. 2 Monthly rainfall and maximum (Tmax) and minimum (Tmin) temperatures in the Lam Pachi River Basin (2005–2015)

The Markov Chain determines the probability of change from one class to another class based on the so-called transition probability matrix (Equation 1) (Arsanjani et al., 2011):

$$P = (p_{ij}) = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nm} \end{pmatrix} \tag{1}$$

where p_{ij} is the transformation probability of the i^{th} land into the j^{th} land, n and m are the land use classes. Equation 1 must satisfy the conditions presented Equations 2 and 3:

$$0 \le p_{ij} \le 1 \ (i\,j=1,2,3,\ldots,n) \tag{2}$$

$$\textstyle\sum_{i=1}^{n} p_{ij} = 1 \ (i,j=1,2,3,\ldots,n) \tag{3}$$

The transitional potential of land was modeled using logistic regression. Land conversions occur at locations with the highest preference for the class of land at that time (Vrije University Amsterdam, 2015). The conversion preference of a location was calculated as a probability. The probability of land conversion (event y = 1) is defined by Equation 4:

$$P\,\{y = 1|x\} = f(z) \tag{4}$$

where $z = \beta^T x = \beta_0+\beta_1 x_1+\ldots+\beta_n x_n$, with x and β representing column vectors of values of independent variables 1, $x1,\ldots x_n$ and parameters (regression coefficients) $\beta_0, \beta_1,\ldots\beta_n$ respectively, and $f(z)$ is the logistic function defined by Equation 5:

$$f\,(z) = \frac{1}{1+e^{-z}} \tag{5}$$

As y takes only the values 0 and 1, the probability of accepting the value 0 is equal to P {y = 0 | x} = 1 - $f(z)$.

CA are dynamic models originally proposed by Ulam and Von Neumann in the 1940s (von Neumann and Burks, 1966). A CA model is defined as a 1- or 2-dimensional grid of identical automata cells (von Neumann, 1951). Each automata cell processes respective information, and proceeds in its actions based on data received from its environment, following rules that it stores or holds (Arsanjani et al., 2011). A basic CA model consists of five components: a grid space on which the model acts, cell states in the grid space, transition rules that determine the spatial dynamic process, a neighborhood that influences the central cell, and time steps (Moreno et al., 2009). Generally, a CA array is a 1- or 2-dimensional rectangular matrix of cells (Adamatzky, 2018). The most important concern in CA modeling is defining appropriate transition rules based on training data which control the model (Arsanjani et al., 2011).

Soil Water Assessment Tool model

SWAT is an eco-hydrological model at the basin scale (Arnold et al., 1995; Arnold et al., 1998; Arnold et al., 2012). The model was developed more than 30 yr ago at the US Department of Agriculture and Texas A&M University laboratories in Temple, Texas, USA (Krysanova and White, 2015). The SWAT model simulates the hydrological cycle based on the water balance Equation 6 (Neitsch et al., 2011):

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R - Q_{surf} - ET - W_{seap} - Q_{gw}\right) \tag{6}$$

where SW_t is the final soil water content, SW_0 is the initial soil water content on day i, R is the amount of precipitation on day i, Q_{surf} is the amount of surface runoff on day i, ET is the amount of evapotranspiration on day i, W_{seap} is the amount of water entering the vadose zone from the soil profile on day i and Q_{gw} is the amount of return flow on day i, with all parameters expressed in millimeters.

The Soil Conservation Service (SCS) curve number equation (Soil Conservation Service, 1972; Mishra and Singh, 2003) was used to estimate surface runoff (Neitsch et al., 2011):

$$Q_{\mathrm{surf}} = \frac{(R - I_{\mathrm{a}})^2}{(R - I_{\mathrm{a}} + S)} \tag{7}$$

where Q_{surf} is the surface runoff or rainfall excess, R is the rainfall depth for the day, I_a is the initial abstraction which is generally approximated as 0.2S, where S is the retention parameter, with all parameters expressed in millimeters. S is defined as Equation 8:

$$S = 25.4\ (1{,}000 / CN - 10) \tag{8}$$

where CN is the SCS curve number for the day.

Model performance evaluation

The model performance in the hydrological simulation was evaluated using the Nash-Sutcliffe efficiency (NSE) and the coefficient of determination (R^2). The NSE is a normalized statistic that expresses the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information") (Nash and Sutcliffe, 1970). NSE can range between -∞ and 1.0, with NSE = 1.0 being the optimal value (Moriasi et al., 2007). The NSE is defined in Equation 9:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{9}$$

where O_i is the observed value, P_i is the predicted value, and $\bar{O}$ and $\bar{P}$ are the means of the observed and predicted values, respectively.

The coefficient of determination (R^2) describes the degree of collinearity between predicted and observed data, where the range of R^2 lies between 0 and 1 and describes how much of the observed dispersion is explained by the prediction (Krause et al., 2005). R^2 is defined in Equation 10:

$$R^2 = \left(\frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}}\right)^2 \tag{10}$$

where O_i is the observed value, P_i is the predicted value, and $\bar{O}$ and $\bar{P}$ are the means of the observed and predicted values, respectively.

Data

The SWAT model uses spatially-distributed topographic, land-use, soil and climate data as inputs (Krysanova and White, 2015). The CGIAR-CSI SRTM 90 m digital elevation model (DEM) downloaded from http://srtm.csi.cgiar.org, was used to delineate the boundary of the watershed and to analyze the drainage patterns.

The digital land use and soil maps were obtained from the Land Development Department (LDD) of Thailand. The physical properties of soil were compiled based on data from the LDD using the pedo-transfer functions (Schaap et al., 2001; Pachepsky and Rawls, 2004).

The climatic data (maximum and minimum temperature, sunshine duration, wind speed and relative humidity) covering a period of 11 yr (2005–2015) were obtained from the Thai Meteorological Department (TMD). The daily data were obtained from the two climatic stations, Kanchanaburi and Ratchaburi. The daily rainfall covering the period was obtained from six meteorological stations located in and nearby the study area.

The observed streamflow data, required for the model calibration and validation, were obtained from the Royal Irrigation Department (RID) of Thailand at the hydrometric stations of Ban Kha (K25A), Ban Bo (K17), Ban Thap Tako (K61) and Ban Nong Phai (K62).

Methodology

The methodology involved three main steps: (i) future land-use projection using the CA-Markov model, (ii) SWAT model set-up and (iii) simulation of the runoff response to the land change.

The future land-use projection started with data preparation. All vector maps were converted to raster format with a grid size of 60 m. The original LDD land-use maps were reclassified into five major classes (agriculture, forest, urban and built-up area, water body, miscellaneous). The transition probability matrix was evaluated using the Markov Chain model (Table 1). The land-use map in 2008 was the initial state, the map in 2015 was the final state (transition step of 7 yr). The land transitional potential was modeled using the logistic regression. Three driven forces were selected as independent variables, namely topography (slope), transportation (distance from road) and neighbor (distance from existing built-up area). The CA simulated a new land-use state from a base initial state using the transition probability matrix and the transitional potential. The land-use map in 2015 defined the base initial state for CA simulation. The projected land-use map in the next 35 yr (2050) was obtained after five iterative simulations and also for intermediate periods at 2022, 2029, 2036 and 2043.

The next step set up the SWAT model for the LPC Basin. The DEM with a mask (in raster format) was loaded to extract the area of interest, delineate the watershed boundary and digitize the stream networks. In this study, the minimum threshold area to delineate a sub-watershed was 2,500 ha. The land use and soil maps (in raster format) were imported into the model and overlaid. Multiple hydrologic response units (HRU) with 5% land use, 25% soil and 25% slope thresholds were used in this study. Daily rainfall and daily climatic data were prepared in the appropriate format and imported into the model. Parameter calibration for the model was performed using SWAT-CUP (Abbaspour, 2015). The data from January 2010 to December 2015 on a monthly basis were used in the calibration. The remaining data (2005–2009) were reserved for validation. The more recent data were selected for calibration so that the model parameters would more closely reflect the current actual conditions of the basin. Three parameters that affected the runoff were selected based on guidance from previous studies (Kimala and Kositsakulchai, 2012; Ayana et al., 2014; Kositsakulchai et al., 2018): 1) CN2.mgt was the initial SCS runoff curve number for moisture condition II; 2) GWQMN.gw was the threshold water level in the shallow aquifer for base flow (measured in millimeters); and 3) SOL_AWC.sol was the available water content of the soil layer (measured in millimeters H2O per millimeter of soil depth). The initial values of the parameters were first matched with the default values in the SWAT database. The model parameters were calibrated sequentially until the average simulated and measured values were in close agreement.

Table 1 Transition probability matrix of land use in Lam Pachi Basin from 2008 to 2015

		2015				
	Land use	Agriculture	Forest	Misc.	Built-up	Water
2008	Agriculture	91.50%	1.06%	2.19%	4.95%	0.31%
	Forest	3.82%	95.74%	0.11%	0.29%	0.04%
	Misc.	30.82%	1.66%	63.53%	1.98%	2.01%
	Built-up	14.39%	0.80%	1.79%	82.92%	0.10%
	Water	5.81%	1.09%	1.31%	0.76%	91.03%

Finally, the runoff responses to the land change were simulated using the SWAT model set up for the LPC Basin. All simulations used the climate and rainfall data from 2010 to 2015. The LDD land-use map in 2015 (LU2015) represented actual conditions (reference scenario), while the simulated land-use maps using the CA-Markov model with the 7 yr transition steps (LU2022, LU2029, LU2036, LU2043, LU2050) represented future land conditions.

Results and Discussion

Future land use projection

Table 2 shows the main land-use classes from 2015 to 2050. Land use classes in 2015 were derived from the LDD data, while those in 2022, 2029, 2036, 2043 and 2050 were simulated using the integrated CA-Markov models. Forest land represented the largest coverage in the LPC Basin, followed by agricultural land. Fig. 3 shows the LDD land-use map in 2015 (Fig. 3A) and the projected land-use for the next 35 yr (2050; Fig. 3B). The projected land-use (from 2015 to 2050) shows a decreased forest area of 19,573 ha (-7.6%), whereas agricultural land increases by the same proportion. In addition, the built-up area and water bodies will increase by approximately 667 ha (0.26%).

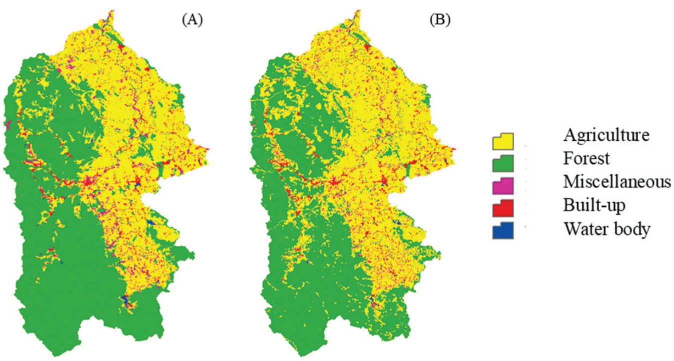

Fig. 3 Land use in Lam Pachi Basin: (A) Land Development Department data in 2015; (B) future projection for next 35 yr (2050)

Estimation of Soil Water Assessment Tool model parameters

Estimation of the SWAT model parameters for the LPC Basin used the climate and streamflow data from 2010 to 2015 as the calibration dataset and from 2005 to 2009 as the validation dataset. Table 3 shows the ranges of the calibrated parameters and fitted values of the selected parameters (curve number, CN2.mg; aquifer threshold, GWQMN.gw; available soil water, SOL_AWC.sol).

The model performance indicators during the parameter estimation (calibration) and the results (validation) are shown in Table 4. The hydrometric stations in the LPC River (K25A, K17, K61, K62) were located from upstream to downstream, respectively. Fig. 4 shows the comparison of the observed and predicted values of mean monthly stream flows at the hydrometric stations K25A and K17. Figs. 4A and 4B present the periods during validation (2005–2009) and calibration (2010–2015), respectively, of K25A, while Figs. 4C and 4D are the equivalent ones for K17.

The simulation results using the calibrated parameters showed good agreement with the observed values of monthly streamflow (NSE values from 0.65 to 0.86 and R^2 values from 0.82 to 0.94). Although some peak flows at the most upstream station (K25A) were not well captured (resulting in the lowest performance indicators [NSE = 0.647, R^2 = 0.82]), the downstream stations (K17, K61, K62) satisfactorily simulated streamflow. During the validation, there was close agreement between the observed and simulated monthly streamflow (NSE values from 0.50 to 0.71 and R^2 values from 0.82 to 0.85). In general, model simulation for streamflow can be judged as satisfactory if NSE > 0.5 (Moriasi et al., 2007), and typically values of R^2 > 0.50 are considered acceptable (Moriasi et al., 2007).

Table 2 Land use classes in 2015 derived from Land Development Department data and for future projections (2022–2050) simulated using CA-Markov model

Year	Land use (ha)				
	Agriculture	Forest	Miscellaneous	Built-up	Water body
2015	101,409	139,909	6,825	6,843	2,451
2022	107,583	135,866	4,917	7,023	2,048
2029	110,676	133,524	4,895	7,091	1,251
2036	112,124	130,873	4,721	6,920	2,799
2043	108,222	131,976	8,158	6,932	2,148
2050	121,083	120,336	6,057	7,175	2,785
2015–2050	19,674 (+7.6%)	-19,573 (-7.6%)	-768 (-0.3%)	333 (+0.1%)	334 (+0.1%)

Table 3 Model parameters selected for calibration

Parameter	Unit	Method	Initial value	Range	Fitted value
CN2.mgt	-	Relative	Varied	-10–+10%	-9.55%
GWQMN.gw	mm	Absolute	1000	+0–+4000	+3582
SOL_AWC.sol	mmH2O/mm soil	Absolute	Varied	+0–+0.4	+0.1455

CN2.mgt = initial SCS runoff curve number for moisture condition II; GWQMN.gw = threshold water level in shallow aquifer for base flow; SOL_AWC.sol = available water content of soil layer

Table 4 Model performance indicators during parameter calibration and result validation

Hydrometric	Calibration (2010–2015)		Validation (2005–2009)	
Station	R^2	NSE	R^2	NSE
K25A	0.818	0.647	0.821	0.504
K17	0.880	0.772	0.846	0.711
K61	0.894	0.792	N/A	N/A
K62	0.936	0.863	N/A	N/A

NSE = Nash-Sutcliffe efficiency; R^2 = coefficient of determination; N/A = Observed data not available

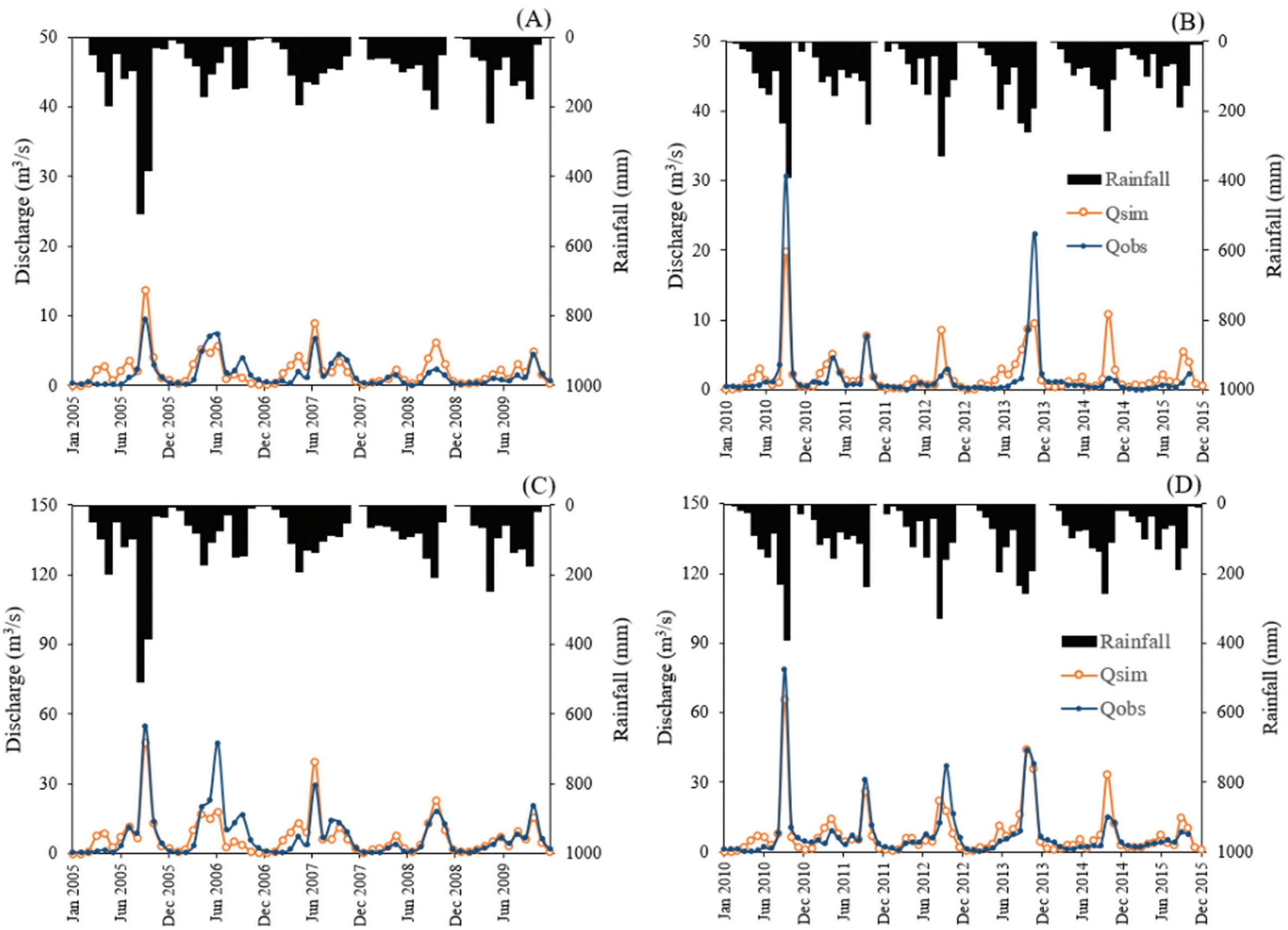

Fig. 4 Comparison between observed (Qobs) and simulated (Qsim) values of mean monthly streamflow at Station K25A for periods: (A) 2005–2009; (B) 2010–2015 and at station K17 for periods: (C) 2005–2009; (D) 2010–2015

Projection of future runoff in Lam Pachi Basin

The water yield (WY) of a watershed represents the total runoff, which is the sum of surface runoff (direct runoff), interflow and groundwater flow (base flow). Table 5 shows the values for the monthly and annual water yields in the LPC Basin from 2015 to 2050. SWAT was used to simulate the water yields using different land-use scenarios derived from the CA-Markov model. The LU2015 scenario was the base scenario using the LDD land-use map. The LU2020, LU2029, LU2036, LU2043 and LU2050 scenarios were projected based on the 7 yr transitional probability.

The annual water yield of the LPC Basin slightly increased from 174.4 mm in 2015 to 179.8 mm in 2050 (Table 5). Fig. 5A shows the annual water yield at the sub-watershed level in 2015 (WY2015) and Fig. 5B shows it in 2050 (WY2050). The annual water yield at the sub-watershed level ranged from 94 mm to 284 mm in 2015 and from 94 mm to 324 mm in 2050. The high WY areas were in the central basin (watershed numbers 18, 19, 28, 35, 37) and in the southeastern basin (watershed numbers 44, 45, 47, 52). The low WY areas were the northern plain of the basin near the river outlet (watershed numbers 1, 2, 5, 6, 7, 8, 10) and the upstream part in the southern basin (watershed numbers 48, 53, 59, 61, 62). The high WY watershed was mainly characterized by sloping land dominated by forest, whereas the low WY watershed was on the plain and dominated by agriculture.

The changes in WY were indicated using the ratio of WY2050 to WY2015 (Fig. 6), where ratio values greater than 1 represented an increased WY, while those less than 1 indicated a decreased WY. Substantial changes were observed at the sub-watershed level. From Fig. 6, there were increased yields in the central basin (watershed numbers 13, 22, 25, 30), while decreased yields occurred on the eastern plain of the basin (watershed numbers 12, 14, 18, 21, 26, 34, 37, 44, 47). Increased water yield was associated with watersheds where there was land conversion from forest to agriculture, particularly on steeper topography, with the exception of watershed number 30 where there was an expansion in the built-up area.

From the simulation results, land conversion from forest to agriculture increased the water yield in the LPC Basin. This finding was supported by various studies (Hibbert, 1967; Bosch and Hewlett, 1982; Costa et al., 2003). However, the land conversion from forest to agriculture could also result in a decreased water yield. Based on Hibbert's review, the establishment of forest cover on sparsely vegetated land decreases water yield (Hibbert, 1967; Bosch and Hewlett, 1982). As the sub-watershed responses were varied, there were only slight increases in the water yield for the whole LPC Basin.

In summary, the results of the CA-Markov modeling indicated that approximately 7.6% of the land in the LPC Basin would be converted from forest to agriculture in the next 35 yr. The built-up area and water bodies would increase to some extent. At the basin-wide level, these land changes would result in a minor increase in the water yield, while substantial changes were observed at the sub-watershed level. The increased water yield was predicted in watersheds where there was land conversion from forest to agriculture, particularly in on steeper topography, whereas the same conversion in flat lowland areas resulted in a reduced water yield.

Table 5 Future projection of mean monthly water yield of Lam Pachi Basin from 2015 to 2050

Month	Mean monthly water yield based on future land use (mm)					
	2015	2022	2029	2036	2043	2050
January	5.8	5.7	5.7	5.7	5.7	5.6
February	3.6	3.6	3.6	3.6	3.6	3.5
March	3.5	3.5	3.5	3.5	3.5	3.5
April	4.9	5.0	5.1	5.1	5.1	5.3
May	5.7	5.7	5.8	5.7	5.8	5.9
June	6.8	6.8	6.9	6.8	6.9	7.0
July	7.3	7.4	7.4	7.3	7.4	7.4
August	7.7	7.7	7.8	7.7	7.8	7.8
September	30.6	31.0	31.3	31.3	31.2	32.2
October	61.5	62.2	62.6	62.7	62.3	64.0
November	27.0	27.2	27.3	27.3	27.3	27.8
December	9.9	9.9	9.9	9.8	9.9	9.8
Annual	174.4	175.8	176.8	176.5	176.3	179.8

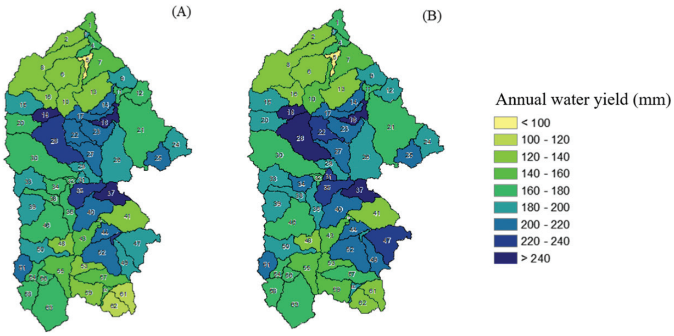

Fig. 5 Annual water yield of Lam Pachi Basin simulated using Soil Water Assessment Tool based on land conditions: (A) in 2015; (B) in 2050, where polygon numbers indicate catchment identification

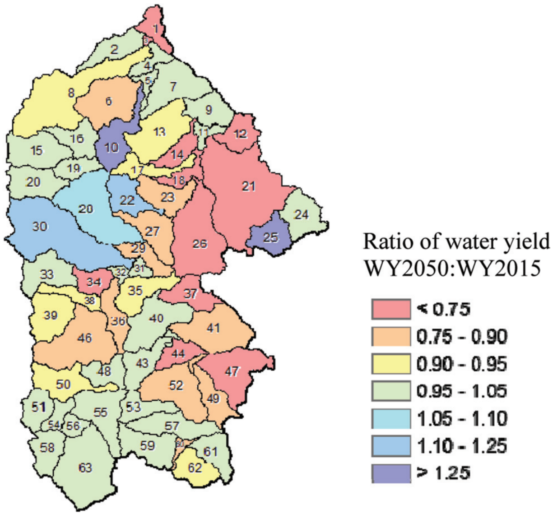

Fig. 6 Ratio of annual water yield in 2050 to 2015 (WY2050:WY2015) of Lam Pachi Basin, where polygon numbers indicate catchment identification

Conflict of Interests

The authors declare that there are no conflicts of interests.

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