

LAND USE AND LAND COVER PREDICTION AND ITS IMPACT ON SURFACE RUNOFF

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Abstract

Due to the rapid growth of Mahasarakham University (MSU), land use and land cover (LULC) change takes place on the campus and in its vicinity, and various types of environmental impacts occur in the area. The main objectives are to quantify the characteristics of the LULC change, to identify an optimum LULC change model for a LULC prediction, and to examine the effect of the LULC changes on the surface runoff at in Mueang Maha Sarakham and Kantharawichai districts of Maha Sarakham province. The 3 main components of the research methodology are the LULC assessment by visual interpretation, an optimum predictive LULC change model identification, and the impact of the LULC changes on surface runoff. The study revealed that the dominant LULC type during 2001-2011 was agricultural land, while the urban and built-up areas had been continuously increased by conversion of agricultural and forest lands. The overall accuracy and K hat coefficient for the LULC data in 2011 were 98.12% and 96.02%, respectively. It was found that an optimum predictive LULC change model was the CA-Markov model which provided higher accuracy than the Land Change Modeler. Also, most of the urban and built-up area sub-classes during 2001-2021 had continuously increased except for the dormitory sub-class, while the agricultural land, except the field crop, had continuously decreased. This study also demonstrated that there is strongly related the change of the urban area on has a strong effect on the surface runoff depth. Likewise, the level of urbanization is strongly associated with the mean surface runoff depth zonation. Evidence from the study suggests that the LULC changes have an effect on the surface runoff characteristics. In conclusion, it appears that geoinformatics technology and the LULC change model can be used as tools for a LULC change and environmental impact assessment.

Keywords: Land use and land cover prediction, surface runoff estimation, geoinformatics, CA-Markov model, Land Change Modeler

Introduction

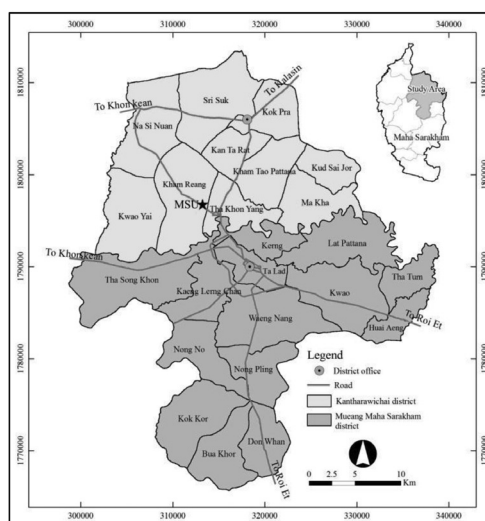
An understanding of land use and land cover (LULC) change, urbanization, and urban growth are critical to city planners and resource managers in any rapidly changing environments because changes in the LULC will cause changes in environmental conditions (Meyer and Turner,

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(2011); Jjumba and Dragičević (2012); Arsanjani *et al.* (2013); Zhang *et al.* (2013).

Therefore, geoinformatics technology with a LULC change model is here applied for a LULC change assessment and its impact on surface runoff. The specific objectives are to quantify the characteristics of the LULC changes, to identify an optimum LULC change model for LULC prediction, and to examine the LULC changes on the surface runoff.



In recent years, geoinformatics technology has become popular for land use and for urban planners and geographers as a geospatial simulation tool, and LULC change modeling and prediction have been emphasized in previous LULC change studies such as Landis (1995); Clarke and Gaydos (1998); Batty *et al.* (1999); Li and Yeh (2000); Wang and Zhang (2001); Weng (2001); Wu, (2002); Cheng and Masser (2003); Ayad (2005); Tang *et al.* (2005); Wu *et al.* (2006); Xiao *et al.* (2006); Liu *et al.* (2007); Shalaby and Tateishi (2007); Grêt-Regamey *et al.* (2008); Santé- Riveira *et al.* (2008); Kamusoko *et al.* (2009); Liu (2009); Verburg and Overmars (2009); Araya and Cabral (2010); Tudes and Yigiter (2010); Guan *et al.* (2011); Sang *et al.* (2011); Wilson and Weng,

Research Methodology

The research methodology framework of the study consisted of 3 main components: (1) a LULC assessment by visual interpretation, (2) an optimum LULC change model identification for LULC prediction, and (3) the impact of LULC changes on surface runoff (Figure 2). A summary of each main component is separately described as follows.

(1) LULC assessment by visual interpretation

Three remotely sensed datasets including color orthophotos in 2001, multispectral SPOT-5 imagery in 2006, and pan-sharpened THEOS imagery in 2011 were firstly visually interpreted based on the element of image interpretation (Jensen, 2007, Ongsomwang, 2011) (e.g., size,

shape, pattern, tone color, texture, site, situation, and association) by means of on-screen digitizing at the scale of 1:10000. The selected scale is based on the lowest spatial resolution of SPOT-5 at 10 m instead of color orthophotos at 1 m and pan-sharpened THEOS at 2 m. In this study the LULC classification system was modified from the standard land use classification of the Land Development Department (LDD), consisting of commercial, city and village, institution, dormitory, real estate, paddy field, field crop, perennial tree, orchard, secondary forest, eucalyptus plantation, development land, marsh land, and water body. In addition, an accuracy assessment for the interpreted LULC in 2011 was performed by a field survey in 2011/2012 for overall accuracy and K hat coefficient evaluation (Congalton and Green, 2008). Herein,

Table 1. Dataset and equipment

Dataset and equipment	Date	Resolution/Scale	Source
1. Remote sensing datasets			
1.1 Digital color orthophoto data	2001	1:4000	LDD
1.2 SPOT data	2006	10 × 10	GISTDA
1.3 THEOS pansharpened data	2011	2 × 2 m.	GISTDA
2. GIS datasets and documents data			
2.1 Soils series data	2002	1:100000	LDD
2.2 Digital Elevation Model (DEM) data	2009	30 × 30	NASA
2.3 Administrative boundary data	2000	1:50000	DOPA
2.3 Rainfall data	1981-2010	NA	TMD
2.4 Per capita income	2011	NA	CDD
2.5 Numbers of population	2011	NA	DOPA
3. Equipment			
3.1 Software			
3.1.1 ERDAS Imagine Version 8.7		Remote sensing, SUT	
3.1.2 Esri ArcGIS Version 9.3			
3.1.3 IDRISI Taiga			
3.2 Hardware			
3.2.1 GPS		Remote sensing, SUT, and personal	
3.2.2 Computer and Notebook			

Note: LDD = Land Development Department, GISTDA = Geo-Informatics and Space Technology Development Agency (Public Organization), TMD = Thai Meteorological Department, DOPA = Department of Provincial Administration, NASA = National Aeronautics and Space Administration, CCD = Community Development Department, SUT = Suranaree University of Technology, NA = Not Applicable.

sample size (N) derived from a multinomial distribution was determined based on the equation:

$$N = \frac{B\Pi_i(1-\Pi_i)}{b_i^2} \quad (1)$$

where Π_i is the portion of a population in the i^{th} class out of k classes that has the proportion closest to 50%;

b_i is the desired precision for the class;

B is the upper $(\alpha/k) \times 100$ percentile of the chi square distribution with 1 degree of freedom;

k is the number of classes.

In this study, the desired confidence level was 95% and the desired precision for the class was 5%, while the sampling scheme for the field survey was stratified random sampling.

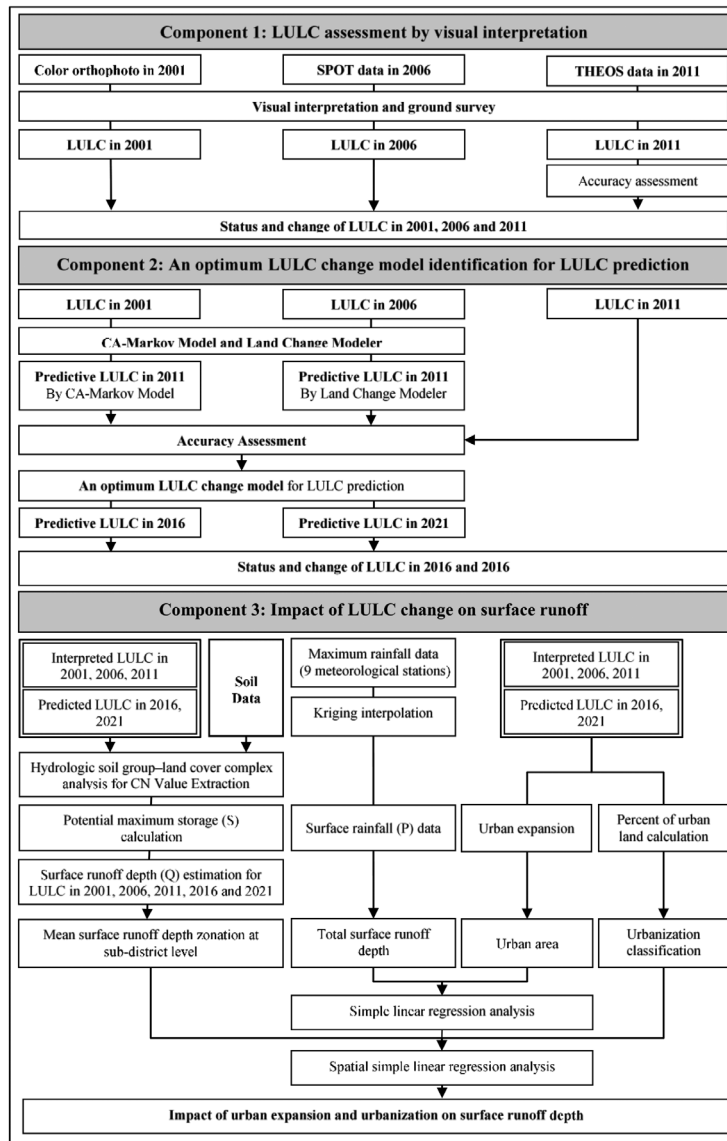


Figure 2. Work flow of research methodology

(2) An optimum LULC change model identification for LULC prediction

Two LULC change models, the CA-Markov model and the Land Change Modeler were here examined to identify an optimum LULC change model for LULC prediction in the future. The basic concept of each model can be separately reviewed as follows:

For the CA-Markov model, 2 basic processes are required include including the Markov process and Cellular automata (CA):

(i) Markov process. This process is considered in discrete time and characterized by variables that can be in 1 of N states from $S = \{S_1, S_2, \dots, S_N\}$. The set T of transition rules is substituted by a matrix of transition probabilities (P) and this is reflective of the stochastic nature of the process:

$$P = \begin{bmatrix} P_{1,1} & P_{1,2} & \dots & P_{1,N} \\ P_{2,1} & P_{2,2} & \dots & P_{2,N} \\ \dots & \dots & \dots & \dots \\ P_{N,1} & P_{N,2} & \dots & P_{N,N} \end{bmatrix} \quad (2)$$

where P_{ij} is the conditional probability that the state of a cell at moment $t + 1$ will be S_j , given it is S_i at moment t :

$$\text{Prob}(S_i \rightarrow S_j) = p_{ij} \quad (3)$$

The Markov process as a whole is given by a set of status S and a transition matrix P. By definition, in order to always be “in 1 of the states” for each i, the condition $\sum_j P_{ij} = 1$ should hold (Benenson and Torrens, 2004).

(ii) Cellular Automata (CA) Cellular automata are dynamic models being discrete in time, space, and state. A simple cellular automaton A is defined by a lattice (L), a state space (Q), a neighborhood template (δ), and a local transition function (f):

$$A = (L, Q, \delta, f) \quad (4)$$

Each cell of L can be in a discrete state out of Q. The cells can be linked in different ways. Cells can change their states in discrete time-steps. Usually cellular automata are synchronous, i.e. all cells change their states

simultaneously. The fate of a cell is dependent on its neighborhood and the corresponding transition function (Balzter *et al.*, 1998).

Meanwhile, the Land Change Modeler, which additionally uses 3 driving forces for LULC change and 2 LULC datasets, operates under 3 modules: change analysis, transition potential, and change prediction (Eastman, 2007).

(i) Change analysis module. Two LULC datasets are used to calculate the transitional LULC change matrix for loss and gain evaluation and change map generation.

(ii) Transition potential module. The potential for transitional change between LULC types is firstly identified to generate variable transformation with a specific transformation type (e.g. evidence likelihood). Then, 3 dominant driving forces factors for LULC change are added to the transition sub-model for a multi-layer perceptrons neural network operation to generate a potential transition map for from-to change detection.

(iii) Change prediction module. The LULC is then predicted for a specific period using change demand modeling (Markov chain) and change allocation conditions.

In this study, the interpreted LULC data in 2001 and 2006 were used to predict the LULC data in 2011 by 2 LULC change models. Herein spatial multiple linear regression was also applied to identify the 3 most significant driving force factors for the LULC change for the Land Change Modeler. After that, the derived predictive LULC data in 2011 from both models were separately compared (pixel by pixel) with the visually interpreted LULC data in 2011 by an overlay operation to calculate the overall accuracy and K hat coefficient. The model which provides the higher overall accuracy and K hat coefficient values is chosen as the optimum LULC change model for the LULC prediction in 2016 and 2021.

(3) Impact of LULC changes on surface runoff

Under this component, the spatiotemporal surface runoff depth according to the LULC changes between 2001 and 2021 was firstly

estimated using the SCS-CN method (U.S. Department of Agriculture, 1986), and the impact of the LULC changes on the surface runoff depth was then examined using spatial and simple linear regression analyses.

(3.1) Surface runoff estimation by the SCS-CN method. The major steps of the surface runoff estimation, which was processed in raster format with a cell size of 30 m under the Model Builder application of ArcGIS (Esri, Redlands, CA, USA), are as follows.:

(i) Analysis of the hydrologic soil group–land cover complex. Soil and LULC data are used to create the hydrologic soil group–land cover complex for the runoff curve number (CN) extraction based on the standard SCS-CN value table. It shows the relationship between LULC types and hydrologic soil groups, which are the infiltration rates of soils by classifying soils into 4 groups: A - low runoff potential, B - moderately low runoff potential, C - moderately high

runoff potential, and D - high runoff potential, depending on their minimum infiltration rates for surface runoff estimation (U.S. Department of Agriculture, 1986). Table 2 demonstrates the CN based on the LULC types in 2011 and the hydrologic soil groups for the surface runoff estimation in this study.

(ii) Calculation of potential maximum storage. A potential maximum storage (S) is computed for each location (pixel) as:

$$S = 25.4 \times \frac{1000}{CN} - 10 \quad (5)$$

where S is the potential maximum storage in mm, and CN is the runoff curve number of the hydrologic soil group–land cover complex.

(iii) Surface rainfall interpolation. The maximum rainfall data from 30 years of climatological data of Thailand (1981-2010) from Kosum Pisai meteorological station and 8 neighboring stations are used to interpolate the

Table 2. The runoff curve number based on LULC types in 2011 and hydrologic soil group for surface runoff estimation

LULC type	Hydrology soil group			
	A	B	C	D
Commercial	89	92	94	95
City and village	89	92	94	95
Institution	89	92	94	95
Dormitory	89	92	94	95
Real estate	89	92	94	95
Paddy field	65	76	84	88
Field crop	72	81	88	91
Perennial tree	43	65	76	82
Orchard	43	65	76	82
Secondary forest	36	60	73	79
Eucalyptus plantation	45	66	77	83
Development land	77	86	91	94
Marsh land	98	98	98	98
Water body	98	98	98	98

Source: Modified from USDA (1986)

Note for Hydrologic soil group and soil texture:

- A Sand, loamy sand, or sandy loam
- B Silt loam or loam
- C Sandy clay loam
- D Clay loam, silty clay loam, sandy clay, silty clay, clay, silt

surface rainfall event using the kriging method.

(iv) Surface runoff estimation. The surface runoff depth (Q) is here generated using the SCS equation for storm runoff depth as:

$$Q = \frac{(P - 0.2S)^2}{(P + 0.8S)} \quad (6)$$

where Q is the direct runoff depth (mm), P is the rainfall (mm), and S is the potential maximum retention after runoff begins (mm).

(3.2) Impact of the LULC changes on the surface runoff depth

(i) Impact of urban expansion on total surface runoff depth. The relationship between the urban area and the total surface runoff depth changes in the study period was examined by simple linear regression analysis using Trend Analysis of Microsoft- Excel (Microsoft, Redmond, WA, USA).

(ii) Impact of urbanization on surface runoff depth. The Sspatial relationship between urbanization, which is measured as the urban land percentage (PU), and the mean surface runoff depth in each district was here examined by spatial simple linear regression analysis of IDRISI software (Clark Labs, Worcester, MA, USA) for describing its impact on the surface runoff depth. The derived correlation coefficient (R) and coefficient of determination (R^2) values of the regression analysis were also used to explain the spatiotemporal relationship between urbanization and the surface runoff depth. Herein, the urban land percentage (PU)

that describes the percentage of the urban areas of the total areas (Tian *et al.*, 2005) was calculated as:

$$PU = \frac{UL}{UT} \times 100 \quad (7)$$

where PU is the urban land percentage (%), UL is the urban land area (sq. km), and UT is the total land area (sq. km).

Results and Discussion

Visual Interpretation and LULC Assessment During 2001-2011

The LULC assessments in 2001, 2006, and 2011 were extracted from visual interpretation of remotely sensed data under the GIS environment. The distribution of the LULC pattern was presented in Figure 3 while the areas and percentages of the LULC types and theirs changes was are reported in Table 3.

As shown in the results, the dominant LULC types in 2001, 2006, and 2011 were agricultural land including paddy field, field crops, perennial trees, and orchards. Meanwhile, urban and built-up areas including commercial, city and village, institution, dormitory, and real estate had been continuously increased in these periods. Here, the percentage of change for dormitory and real estate was about 789% and 200%, respectively, between 2001 and 2006 and was about 140% and 222%, respectively, between 2006 and 2011 (Figure 4(a)). These

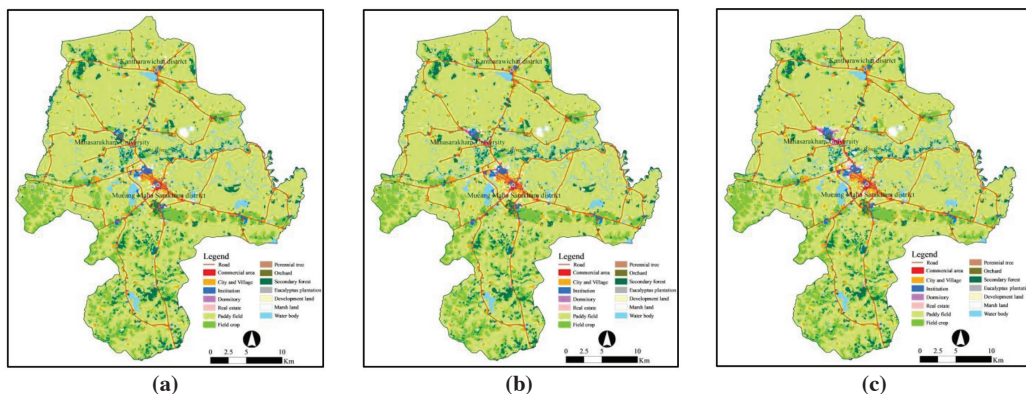


Figure 3. Distribution of the interpreted LULC pattern: (a) in 2001, (b) in 2006, and (c) in 2011

phenomena correspond to the increase in the number of registered students at MSU. In fact, the number of MSU students was increased from 12658 in 2001 to 46273 in 2011 (Mahasarakham University, 2011).

In addition, most of the urban and built-up areas in 2006 and 2011 were converted from agricultural and forest lands. The annual increasing rates of the commercial, city and village, institution, dormitory, and real estate areas during 2001-2006 were about 0.16, 0.16,

0.10, 0.14, and 0.05 sq. km, respectively, and were 0.20, 0.90, 0.06, 0.22, and 0.16 sq. km, respectively, during 2006-2011. This reveals that most of the urban and built-up area sub-classes continuously increased except the institution area (Figure 4(b)).

Accuracy Assessment for Visual Interpretation of LULC in 2011

In the study, 692 randomly stratified sampling points based on the multinomial

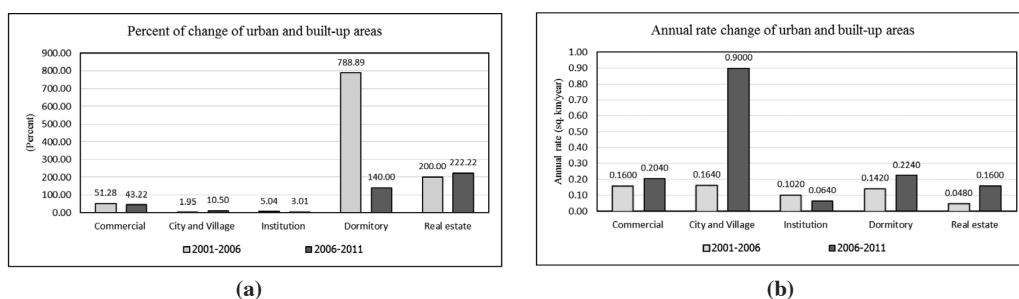


Figure 4. Comparison of urban and built-up area sub-classes between 2001-2006 and 2006-2011:(a) percent of change and (b) annual increasing rate

Table 3. Areas and percentages of LULC types in 2001, 2006, and 2011 and theirs changes

LULC	2001		2006		2011		Change 2001-2006			Change 2006-2011		
	sq. km	%	sq. km	%	sq. km	%	sq. km	% of change	Annual rate	sq. km	% of change	Annual rate
Urban and built-up areas												
Commercial	1.56	0.16	2.36	0.24	3.38	0.34	0.80	51.28	0.1600	1.02	43.22	0.2040
City and village	42.02	4.30	42.84	4.38	47.34	4.84	0.82	1.95	0.1640	4.50	10.50	0.9000
Institution	10.11	1.04	10.62	1.09	10.94	1.12	0.51	5.04	0.1020	0.32	3.01	0.0640
Dormitory	0.09	0.01	0.80	0.08	1.92	0.20	0.71	788.89	0.1420	1.12	140.00	0.2240
Real estate	0.12	0.01	0.36	0.04	1.16	0.12	0.24	200.00	0.0480	0.80	222.22	0.1600
Agricultural land												
Paddy field	704.74	72.12	703.23	71.97	699.90	71.62	-1.51	-0.21	-0.3020	-3.33	-0.47	-0.6660
Field crop	80.36	8.22	81.41	8.33	79.69	8.16	1.05	1.31	0.2100	-1.72	-2.11	-0.3440
Perennial tree	0.57	0.06	0.52	0.05	0.57	0.06	-0.05	-8.77	-0.0100	0.05	9.62	0.0100
Orchard	7.92	0.81	7.76	0.79	7.18	0.73	-0.16	-2.02	-0.0320	-0.58	-7.47	-0.1160
Forest land												
Secondary forest	63.39	6.49	60.66	6.21	54.90	5.62	-2.73	-4.31	-0.5460	-5.76	-9.50	-1.1520
Eucalyptus plantation	12.24	1.25	12.09	1.24	14.33	1.47	-0.15	-1.23	-0.0300	2.24	18.53	0.4480
Miscellaneous land												
Development land	12.09	1.24	12.69	1.30	12.38	1.27	0.60	4.96	0.1200	-0.31	-2.44	-0.0620
Marsh land	3.45	0.35	3.06	0.31	4.86	0.50	-0.39	-11.30	-0.0780	1.80	58.82	0.3600
Water body	38.50	3.94	38.76	3.97	38.61	3.95	0.26	0.68	0.0520	-0.15	-0.39	-0.0300
Total	977.16	100	977.16	100	977.16	100						

Table 4. Error matrix and accuracy assessment of LULC in 2011

LULC in 2011	Ground truth data														Total	User's accuracy (%)
	U1	U2	U3	U4	U5	A1	A2	A3	A4	F1	F2	M1	M2	W		
Commercial (U1)	2														2	100.00
City and village (U2)		34													34	100.00
Institution (U3)			8												8	100.00
Dormitory (U4)				1											1	100.00
Real estate (U5)					1										1	100.00
Paddy field (A1)						492	3		1						496	99.19
Field crop (A2)						3	52				1				56	92.86
Perennial tree (A3)								1							1	100.00
Orchard (A4)							1		4						5	80.00
Secondary forest (F1)										39					39	100.00
Eucalyptus plantation (F2)											8	2			10	80.00
Development land (M1)											1	7			9	77.78
Marsh land (M2)						1							3		3	100.00
Water (W)															27	100.00
Total	2	34	8	1	1	496	56	1	5	39	10	9	3	27	692	
Producer's accuracy (%)	100.00	100.00	100.00	100.00	100.00	99.19	92.86	100.00	80.00	100.00	80.00	77.78	100.00	100.00	692	
Overall accuracy (%)	= 98.12															
K hat coefficient (%)	= 96.02															

distribution theory (Equation 1) with the desired levels of confidence at 95% and precision at 5% were used for the accuracy assessment. The overall accuracy and K hat coefficient for the visually interpreted LULC in 2011 was 98.12% and 96.02%, respectively (Table 4). According to Landis and Koch (1977), a K hat coefficient more than 80% represents strong agreement or accuracy between the classification map and the ground reference information.

An Optimum LULC Change Model Identification for LULC Prediction

Two LULC change models:, the CA-Markov model and the Land Change Modeler, were here examined for an optimum predictive LULC change model identification using the IDRISI software. For the CA-Markov model, the interpreted LULC data in 2001 and 2006 were used to generate a transition probability matrix with a transition area matrix which was then applied to predict the LULC in 2011 with the cellular automata model. Similarly, the Land Change Modeler also used both LULC data for the prediction of the LULC in 2011 but it required 3 more three dominant driving forces for the LULC change prediction. In this study, the most dominant factors for the urban and built-up areas expansion were per capita income, population density, and slope, according to the coefficient values from spatial multiple

linear regression analysis of the relevant data in 2011 as:

$$\begin{aligned} UNU2011 = & 0.367 + 3.0930*INCOME \\ & + 0.7897*MSU + 0.6045* \\ & DISTU + 0.4746*ROAD + \\ & 1.6858*SLOPE - 1.6877*POP \end{aligned}$$

where *UNU2011* is the urban area and non-urban area (sq.km), *INCOME* is the per capita income in each sub-district (baht), *MSU* is the distance to MSU's new location (m), *DISTU* is the distance to the existing urban area (m), *SLOPE* is the slope percentage, and *POP* is the population density in each sub-district (person).

It was found that the CA-Markov model provided an overall accuracy and K hat coefficient with values of 96.84% and 93.27%, respectively, which were higher than the Land Change Modeler with values of 96.04% and 91.60%, respectively. Therefore, the CA-Markov model was here chosen as an optimum LULC change model for LULC prediction in 2016 and 2021 (Figure 5). This finding is similar to the previous work of Ongsomwang and Suravisutra (2011) which identified the CA-Markov model as an optimum predictive model for future urban growth prediction. Furthermore, the derived K hat coefficient of the CA-Markov model, which was higher than 80%, is acceptable and suitable for LULC change prediction according to the suggestion of Subedi *et al.* (2013).

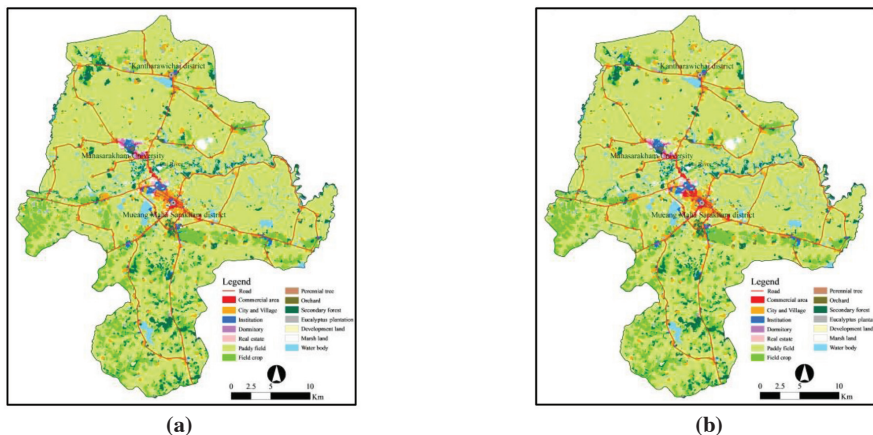


Figure 5. Distribution of predictive LULC pattern: (a) in 2016 and (b) in 2021

LULC Development in the Past and Future

According to the LULC assessment in the past, during 2001-2011, by visual interpretation and in the future, during 2016 and 2021, by an optimum predictive LULC change model, it was found that most of the urban and built-up area sub-classes continuously increased during 2001-2021, except the dormitory. On the contrary, most of the sub-classes of agricultural land, except the field crop and secondary forest, continuously decreased in these periods. Meanwhile, the marsh land had a decreasing trended but development land had an increasing trended to increase in the future. At the same times, the water body was unpredictable. The area of the LULC change in terms of gain (+) and loss (-) for each LULC type in the 4 different periods is summarized in Table 5.

Furthermore, the future trends of the sub-classes of the urban and built-up areas were examined using various regression types including exponential, linear, logarithmic, polynomial, power, and moving average types using Trend Analysis of Microsoft-Excel, as summarized in Table 6 and Figure 6. As a results, it was found that the best fit for the commercial,

city and village, institution, and real estate areas was the linear regression type, while the best fit for the dormitory was the logarithmic regression type. The R^2 of the regression analysis varies between 90.51-98.70%. These results show a nearly perfect explanation of time to the areas of urban and built-up area sub-classes. The predictive area of the urban and built-up area sub-classes until 2046, with 5 yearly intervals, was also reported in Table 7. It was found that the highest percentage of change of the urban and built-up area sub-classes between 2011 (at the present) and 2046 (in the future) was the real estate (240.52%) while the lowest percentage of change was the institution (19.01%). These results indicate that urban expansion will continuously increase in the study area in the near future.

Spatiotemporal Surface Runoff Depth Estimation Using SCS-CN Method

The spatiotemporal surface runoff depth estimation by the SCS-CN method was implemented based on the LULC change during 2001-2021 with a presumable permanent soil texture and the interpolated maximum rainfall

Table 5. Development of LULC area during 2001 to 2021

LULC types	Change in terms of gain and loss (sq.km)			
	2001-2006	2006-2011	2011-2016	2016-2021
Commercial	0.80	1.02	0.41	0.83
City and Vvillage	0.82	4.50	2.42	1.32
Institution	0.51	0.32	0.01	0.56
Dormitory	0.71	1.12	0.31	-0.25
Real estate	0.24	0.80	0.43	0.04
Paddy field	-1.51	-3.33	2.30	-1.72
Field crop	1.05	-1.72	-1.41	1.03
Perennial tree	-0.05	0.05	0.00	-0.01
Orchard	-0.16	-0.58	-0.52	-0.09
Secondary forest	-2.73	-5.76	-4.44	-1.93
Eucalyptus plantation	-0.15	2.24	2.15	-0.59
Development land	0.60	-0.31	-1.84	1.2
Marsh land	-0.39	1.80	0.24	-0.42
Water body	0.26	-0.15	-0.06	0.03

during 1981–2010 using ModelBuilder of the ArcGIS software (Figure 7). The distribution of the spatiotemporal surface runoff depth estimation in the study period is displayed in Figure 8 while the statistic of the minimum,

mean, and maximum values and total surface runoff depth by summation of the surface runoff depth from all cells (1085733 pixels) is presented in Table 8.

It was found that the characteristics of

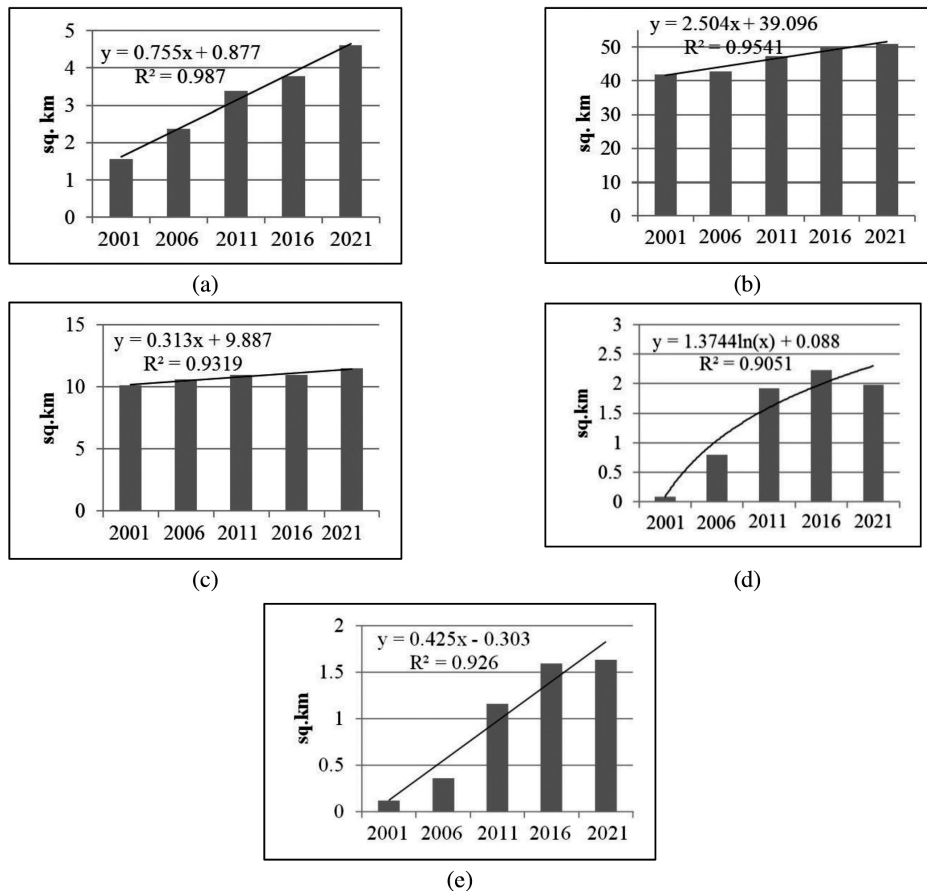


Figure 6. Trend analysis of urban and built-up areas sub-classes: (a) commercial, (b) city and village, (c) institution, (d) dormitory, and (e) real estate

Table 6. Predicted model for sub-classes of the urban and built-up areas by Trend Analysis

LULC type	Model Type	Equation	R ²
Commercial areas	Linear regression	$y = 0.755x + 0.877$	98.70
City and village areas	Linear regression	$y = 2.504x + 39.096$	95.41
Institution areas	Linear regression	$y = 0.313x + 9.887$	93.19
Dormitory	Logarithmic regression	$y = 1.3744\ln(x) + 0.088$	90.51
Real estate	Linear regression	$y = 0.425x - 0.303$	92.60

Note: y is a dependent variable which represents the area of the urban and built-up area sub-classes in sq.km
x is an independent variable which represents as 5- yearly interval such as 1 for year 2001, 2 for year 2006, 3 for year 2011, and so on.

the minimum and maximum values of the surface runoff depth in 2001 and 2006 and in 2016 and 2021 were similar while the minimum and maximum values of the surface runoff depth in 2011 were dissimilar from the others years. However, the mean values and total surface runoff depth were different from each other in these periods. They continuously increased during 2001 to 2021. These phenomena correspond to the LULC change in this period. Especially, the increase of the urban and built-up areas, which consist of impervious surfaces, is a major cause of the increased surface runoff depth in the study area.

Impact of Urban Expansion on Total Surface Runoff Depth

The changes of the urban area and total surface

runoff depth in the study period are presented in Table 9. It was found that both changes were continuous increases. Meanwhile, the relationship between the urban area and total surface runoff depth during 2001 to 2021 is a linear regression by Trend Analysis of Microsoft-Excel, as presented in Figure 9. The simple linear equation between the urban area and total surface runoff depth showed shows a positive relationship with R^2 at 98.30% as:

$$y = 0.01111x + 10^8$$

where y is the total surface runoff depth in mm and x is the urban area in sq. m in the study period. This equation implies that when the urban area increases then the total surface runoff depth increases. Meanwhile, the derived



Figure 7. Schematic diagram of Esri's ModelBuilder Builder of ESRI ArcGIS for spatiotemporal surface runoff depth estimation

Table 7. Predictive area of sub-classes of urban and built-up areas in 2046

Sub-classes of urban and built-up areas	Area in sq. km in Yyear				
	2026	2031	2036	2041	2046
Commercial	5.41	6.16	6.92	7.67	8.43
City and Vvillage	54.12	56.62	59.13	61.63	64.14
Institution	11.77	12.08	12.39	12.70	13.02
Dormitory	2.55	2.76	2.95	3.11	3.25
Real estate	2.25	2.67	3.10	3.52	3.95

R^2 , which is the percentage of the response variable variation that is explained by a linear model, indicated that expansion of the urban area regulates the total surface runoff depth in the study area. It should be here noted that the total surface runoff depth basically derives from all the various LULC types based on the variation of the CN of the hydrologic soil group–

land cover complex. However, the CN values of the urban and built-up areas are relatively higher than those of others LULC types, except the marsh land and water body. These phenomena agreed with the finding of Wilson and Weng, (2010) which stated that surface runoff volume is mostly related to changes in the spatial extent of each land cover over the study period.

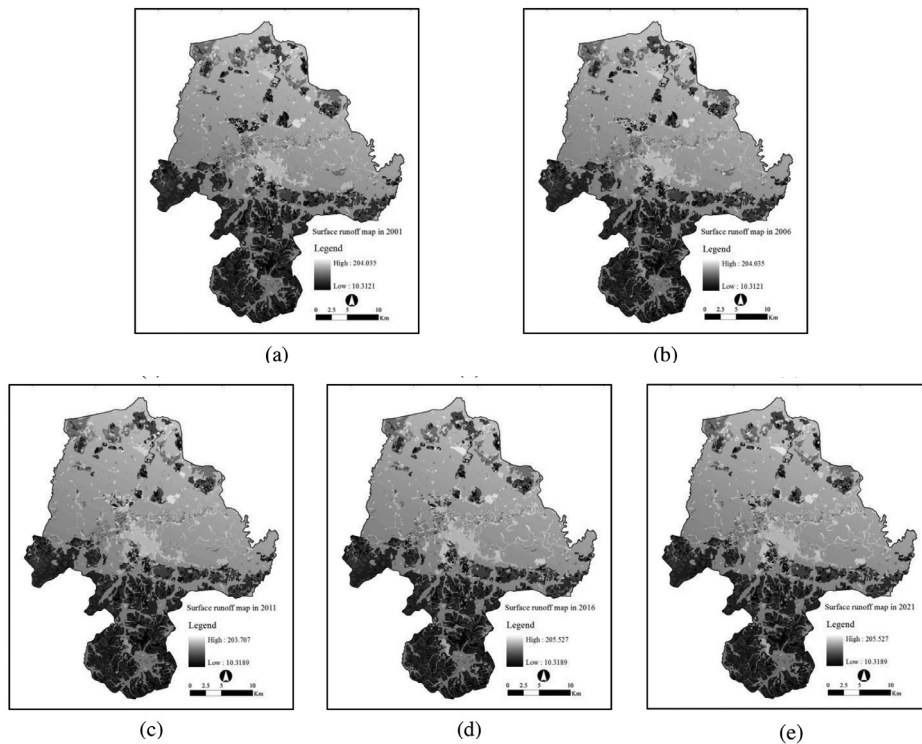


Figure 8. Distribution of the spatiotemporal surface runoff depth estimation: (a) in 2001, (b) in 2006, (c) in 2011, (d) in 2016, and (e) in 2021

Table 8. Statistics of surface runoff depth estimation by cell (minimum, mean, and maximum value) and its total values during 2001 to 2021

Year	Surface runoff depth in mm.			
	Minimum value	Maximum value	Mean value	Total
2001	10.312	204.035	127.721	138670420
2006	10.312	204.035	128.073	139052900
2011	10.319	203.707	128.645	139674640
2016	10.319	205.527	129.252	140334100
2021	10.319	205.527	129.481	140581730

Impact of Urbanization on Surface Runoff Depth

The spatial simple linear regression analysis between the (PU) (Equation 6) as the urbanization level (Figure 10) and mean surface runoff depth zonation by sub-district (Figure 11) during 2001-2016 were examined to describe the impact of urbanization on the surface runoff depth.

It was found that the urbanization level strongly correlated with the mean surface runoff depth zonation by sub-district because the spatial pattern between the urbanization level, which describes the percentage of urban areas in a sub-district, and the mean surface runoff depth zonation, which is created by the mean surface runoff depth value in each sub-district, are similar. Herewith, the highest

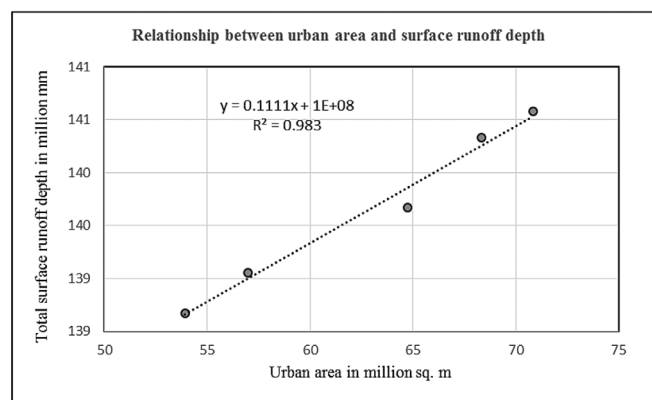


Figure 9. Simple linear regression analysis between urban area and surface runoff depth

Table 9. Surface runoff depth and urban area during 2001-2021

Year	Urban and built-up areas in sq. m	Total Surface runoff depth in mm
2001	53910000	138670420
2006	56980000	139052900
2011	64730000	139674640
2016	68320000	140334100
2021	70820000	140581730

Table 10. Summary of spatial simple linear regression model between urbanization and mean surface runoff depth zonation

Year	Model	Correlation Coefficient (R) (%)	Coefficient of determination (R ²) (%)
2001	$Y = 0.036044 + 0.908790X$	84.98	72.21
2006	$Y = 0.035703 + 0.858506X$	85.85	73.70
2011	$Y = 0.062702 + 0.854680X$	85.47	73.05
2016	$Y = 0.025225 + 0.907646X$	87.80	77.09
2021	$Y = 0.031557 + 0.882305X$	86.90	75.51

Note: X = Urbanization (PU), Y= Mean surface runoff zonation

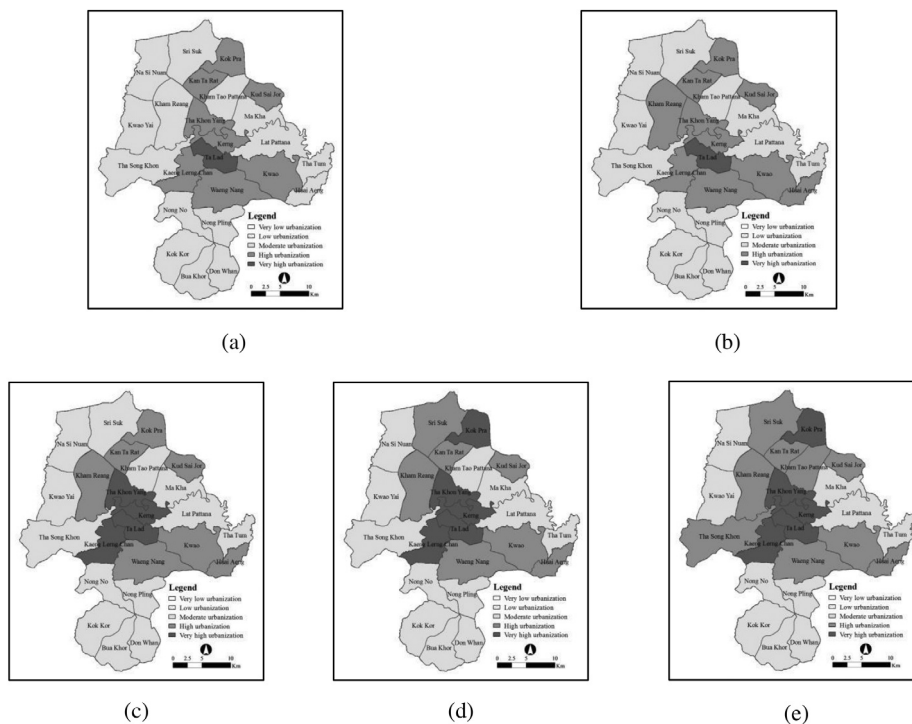
values of R and R^2 were 87.80% and 77.09%, respectively, in year 2016 while the lowest values of R and R^2 were 84.98% and 72.21%, respectively, in year 2001 (Table 10). This result implies that when urbanization takes place in each sub-district, then the surface runoff depth increases in each sub-district. Likewise, urbanization has a considerable environmental impact on surface runoff in the study area.

Conclusions

An optimum LULC change model can provide a good baseline of LULC data which is the one of the required datasets for a variety of applications and modellings. This study applied

geoinformatics technology (remote sensing and GIS) and a LULC change model as basic tools to assess the LULC and its impact on surface runoff. The study demonstrates that the dominant LULC type in 2001, 2006, and 2011, from a visual interpretation of remotely sensed data, was agricultural land. At the same time, the urban and built-up areas had continuously increased by conversion of agricultural and forest lands. In addition, the accuracy assessment of the interpreted LULC data in 2011, as a baseline data for an optimum LULC change model identification, showed that the overall accuracy and K hat coefficient were 98.09% and 95.95%, respectively.

This study has revealed that an optimum



Classification of urbanization

Bbased on urban land percentage (PU)

Very low urbanization	=	$PU < 0.001\%$
Low urbanization	=	$0.001\% \leq PU < 1\%$
Moderate urbanization	=	$1\% \leq PU < 5\%$
High urbanization	=	$5\% \leq PU < 10\%$
Very high urbanization	=	$10\% \leq PU$

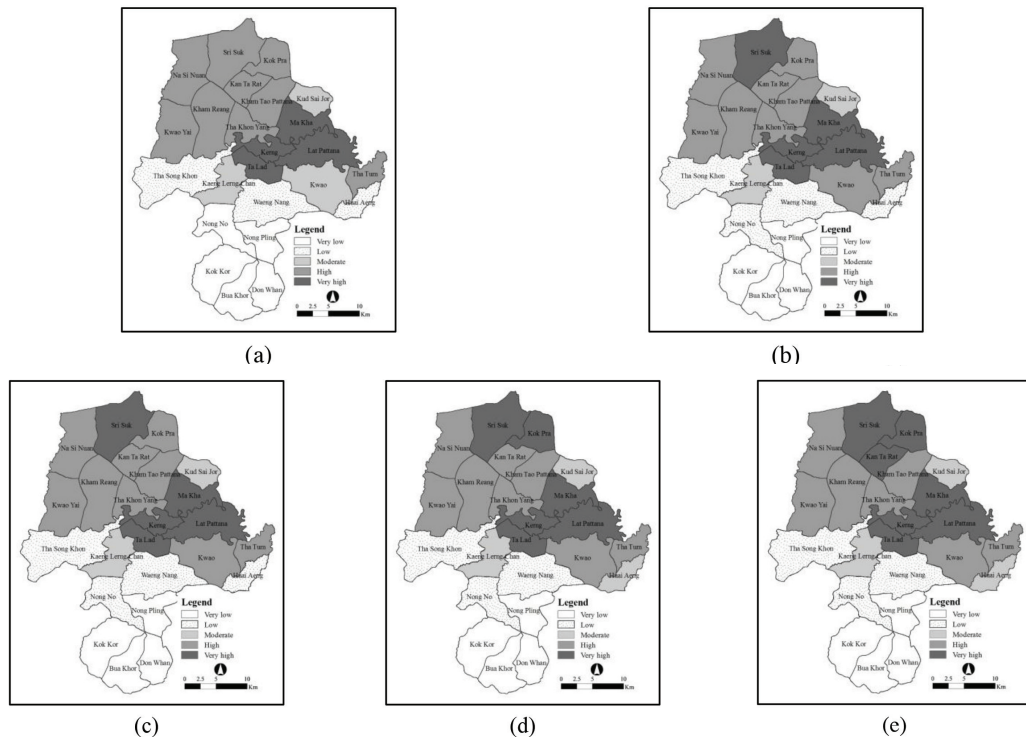
Figure 10. Distribution of urban land percentage (PU) as urbanization: (a) in 2001, (b) in 2006, (c) in 2011, (d) in 2016, and (e) in 2021

predictive LULC change model was the CA-Markov model which provided an overall accuracy and K hat coefficient (96.84% and 93.27%, respectively) higher than the Land Change Modeler (96.04% and 91.60%, respectively). Herewith Therefore, the CA-Markov was chosen to predict the LULC data in 2016 and 2021.

For the LULC development in the past and future, most of the urban and built-up area sub-classes continuously increased during 2001 to 2021, except the dormitory. In contrast, most of the agricultural land, except the field crop, continuously decreased. These results indicate that the urban area has will continuously

increase in the study area in the near future.

Furthermore, the results of the spatiotemporal surface runoff depth estimation during 2001 to 2021 by the SCS-CN method showed that the mean and total surface runoff depth had continuously increased. Similarly, the urban area continues to increase in these periods. This study also demonstrated that there is a strongly relationship in the change of urban area on the surface runoff depth with R^2 at 98.30%. Likewise, the level of urbanization is strongly associated with the mean surface runoff depth zonation. Evidence from this study suggests that LULC changes, especially urban expansion and urbanization, have an effect on



Classification of mean surface runoff depth at sub-district level

Very low	=	81 mm > Mean < 91 mm
Low	=	91 mm ≤ Mean < 111 mm
Moderate	=	111 mm ≤ Mean < 136 mm
High	=	136 mm ≤ Mean < 151 mm
Very high	=	151 mm ≤ Mean

Figure 11. Surface runoff depth zonation based on its mean value in each sub-district: (a) in 2001, (b) in 2006, (c) in 2011, (d) in 2016, and (e) in 2021

the surface runoff depth characteristics. Hence, an optimal land use policy and urban planning are urgently required to be implemented in the study area for urban flood mitigation and prevention caused by the rapid LULC change. The existing comprehensive city plans for the Tha Khon Yang-Kham Reang community and the Mueang Maha Sarakham Public Works and Town & Country Planning should be revised by considering the effect of urban expansion.

In conclusion, it appears that the remote sensing, GIS, and LULC change model can be used as efficient tools and information providers for LULC change and an impact assessment for scientists, researchers, land use planners, and policy and decision makers.

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