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

Running head: Land Use and Land Cover Change 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 in the campus and its vicinity, various types of environmental impacts occur in the area. Main objectives are to quantify the characteristics of LULC change, to identify an optimum LULC change model for LULC prediction, and to examine LULC change on surface runoff at Mueang Maha Sarakham and Kantharawichai districts of Maha Sarakham province. Three main components of research methodology are LULC assessment by visual interpretation, an optimum predictive LULC change model identification, and impact of LULC changes on surface runoff.

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The study revealed that the dominate LULC type during 2001-2011 was agricultural land, while urban and built-up area had been continuously increased by conversion of agricultural and forest lands. The overall accuracy and Kappa hat coefficient for LULC data in 2011 was 98.03% and 95.85%. It was found that an optimum predictive LULC change model was CA-Markov model which provided higher accuracy than Land Change Modeler. Also, most of urban and built-up area sub-classes during 2001-2021 had continuously increased except dormitory while agricultural land except field crop had continuously decreased. This study also demonstrated that there is strongly related the change of urban area on surface runoff depth. Likewise, level of urbanization is strongly associated with mean surface runoff depth zonation. Evidence from the study suggests that LULC changes have an effect on surface runoff characteristic. In conclusion, it appears that geoinformatics technology and LULC change model can be used as tools for LULC change and environmental impact assessment.

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

Introduction

Understanding of land use and land cover (LULC) change, urbanization and urban growth are critical to city planners and resource managers in the rapidly changing environments because changes in LULC will cause changes in environmental conditions (Meyer and Turner, 1994; Eliasson, 2000; Pauleit *et al*., 2005; Seto and Fragkias, 2005; Chen. 2007; Deng *et al*., 2009; Seto and Shepherd, 2009; Yin *et al*., 2009). When LULC change occurs due to urbanization (the building up and paving over of undeveloped areas) and along a city boundary, it increases the size of the city as it grows (Fang *et al.*, 2005). Its process has a considerable environmental impact such as hydrological impact in terms of influencing the nature of runoff and other hydrological characteristics, stream flow response, delivering pollutants to rivers, and controlling rates of erosion. Surface runoff from storm events is part of the natural hydrologic process. It can arise from overland surface flow, flow within drainage pipes and sewers, or flow from the top, saturated layers of soil near the stream.

Due to the rapid growth of Mahasarakham University (MSU), LULC change takes place in the campus and its neighboring. As a result, the number of households in Mueang Maha Sarakham and Kantharawichai districts has continuously increased from 30,358 and 14,649 households, respectively, in 1995 to 46,332 and 22,678 households in 2010, respectively (Department of Provincial Administration, 2010). In addition, LULC assessment of Mueang Maha Sarakham and Kantharawichai districts was also showed that the explicit of urban area expanded from 53.91 sq.km in 2001 to 64.73 sq.km in 2011 (Pimjai and Ongsomwang, 2013).

In recent years, geoinformatics technology was popular to land use and urban planners and geographers as a geospatial simulation tool and LULC change modeling and prediction have been emphasized in the 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 *et al.* (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, (2011); Jjumba and Dragićević (2012); Arsanjani *et al*. (2013); Zhang *et al*. (2013).

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

Materials and Methods

Study Area

Mueang Maha Sarakham and Kantharawichai districts of Maha Sarakham province, where MSU is located, was selected as the study area (Figure 1). The study area, which covers area of 977 sq. km, is characterized by LULC change and urbanization.

Data and equipment

Remotely sensed and GIS datasets had been collected and prepared for this study while basic equipment such as hardware and software were employed to data collection and data analysis (Table 1).

Research methodology

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

(1) LULC assessment by visual interpretation

Three remotely sensed dataset included color orthophotos in 2001, SPOT imagery in 2006 and 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 mean of on-screen digitizing at the scale of 1:10,000. In this study LULC classification system was modified from 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, accuracy assessment for the interpreted LULC in 2011 was performed by field survey in 2011/2012 for overall accuracy and Kappa hat coefficient evaluation (Congalton and Green, 2008).

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

The interpreted LULC in 2001 and 2006 were used to predict LULC in 2011 by two LULC change model: CA-Markov and Land Change Modeler. After that the derived LULC data in 2011 were compared with the interpreted LULC in 2011 for an optimum predictive LULC change model identification based on overall accuracy and Kappa hat coefficient. An optimum LULC change model was further used for LULC in 2011 and 2016 prediction.

For CA-Markov model, two basic processes are required include Markov process and Cellular Automata (CA):

(i) Markov process. This process is considered in discrete time and characterized by variables that can be in one of N states from S = {S1, S2, …SN}. 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:

$$P = \left\| p_{ij} \right\| = \left\| \begin{matrix} p_{1,1} & p_{1,2} & \cdots & p_{1,N} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,N} \\ \cdots & \cdots & \cdots & \cdots \\ p_{N,1} & p_{N,2} & \cdots & p_{N,N} \end{matrix} \right\| \quad (1)$$

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:

$$\mathrm{Prob}(S_i \to S_j) = p_{ij} \quad (2)$$

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 one of the state” 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 of cellular automata *A* is defined by a lattice (*L*), a state space (*Q*), a neighborhood template (δ) and a local transition function (*f*):

$$A = (L, Q, \delta, f) \tag{3}$$

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, Land Change Modeler which applies three driving force for LULC change prediction under three modules: change analysis, transition potential, and change prediction (Eastman, 2007).

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

(ii) Transition potential module. Potential for transitional change between LULC types are firstly identified to generate variable transformation with specific transformation type (e.g. evidence likelihood). Then dominant driving forces are added to transition sub-model for MLP Neural Network operation to generate a potential transition map as from-to change detection.

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

(3) Impact of LULC changes on surface runoff

Under this component, the spatiotemporal surface runoff depth according to LULC change between 2001 and 2021 was firstly estimated using SCS-CN method (USDA, 1986) and impact of LULC change on surface runoff depth was then examined using spatial and simple linear regression analyses.

(3.1) Surface runoff estimation by SCS-CN method. Major steps of surface runoff estimation, which was processed in raster format with cell size of 30 m under Model Builder of ERSI ArcGIS, are as followings.

(i) Analysis of hydrologic soil group–land cover complex. Soil and LULC data are used to create the hydrologic soil group–land cover complex for runoff curve number (*CN*) extraction using the standard SCS-CN table.

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

$$S = 25.4 \times \frac{1000}{CN} - 10 \qquad (4)$$

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

(iii) Surface rainfall interpolation. Maximum rainfall data from 30 years climatological data of Thailand (1981-2010) from Kosum Pisai meteorological station and 8 neighboring stations are used to interpolate surface rainfall event using kriging method.

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

$$Q = \frac{(P - 0.2S)^2}{(P + 0.8S)} \qquad (5)$$

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 LULC change on surface runoff depth

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

(ii) Impact of urbanization on surface runoff depth. Spatial relationship between urbanization, which measure as urban land percentage (PU), and mean surface runoff depth in each district was here examined by spatial simple linear regression analysis of IDRISI software for describing its impact on surface runoff depth. The derived correlation coefficient (R) and coefficient of determination (R^2) values of regression analysis were also used to explain the spatiotemporal relationship between urbanization and surface runoff depth. Herein, urban land percentage (PU) that describes the percentage of urban areas of the total areas (Tian *et al.*, 2005) was calculated as:

$$PU = \frac{UL}{UT} \times 100 \quad (6)$$

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

Results and Discussion

Visual interpretation and LULC assessment during 2001-2011

LULC assessment in 2001, 2006 and 2011 were extracted from visual interpretation of remotely sensed data under GIS environment. The distribution of

LULC pattern was presented in Figure 3 while area and percentage of LULC types and theirs change was reported in Table 2.

As results, the dominate LULC type in 2001, 2006 and 2011 were agricultural land included paddy field, field crops, perennial trees and orchards. Meanwhile, urban and built-up area including commercial, city and village, institution, dormitory and real estate had been continuously increased in these periods. Herewith percent 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 4a). These phenomena correspond to the increasing of the registered students at MSU. In fact, number of MSU students was increased from 12,658 in 2001 to 46,273 in 2011 (Mahasarakham University, 2011).

In addition, most of urban and built-up areas in 2006 and 2011 were converted from agricultural and forest lands. Annual increasing rate of commercial, city and village, institution, dormitory and real estate during 2001-2006 was about 0.16, 0.16, 0.10, 0.14 and 0.05 sq. km, respectively and was 0.20, 0.90, 0.06, 0.22, and 0.16 sq. km, respectively during 2006-2011. It reveals that most of urban and built-up area sub-classes had continuously increased except institution area (Figure 4b).

Accuracy assessment for visual interpretation of LULC in 2011

In the study, 862 randomly stratified sampling points based on the multinomial distribution theory with desired level of confidence at 85% and a precision at 5% were used for accuracy assessment. The overall accuracy and

Kappa hat coefficient for the visually interpreted LULC in 2011 was 98.03% and 95.85%, respectively. According to Landis and Koch (1977) Kappa 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: CA-Markov model and Land Change Modeler were here examined for an optimum predictive LULC change model identification under IDRISI software. For CA-Markov model, the interpreted LULC data in 2001 and 2006 were used to generate a transition probability matrix with a transition area matrix and it then applied to predict LULC in 2011 with Cellular Automata model. Similarly, Land Change Modeler also used both LULC data for LULC in 2011 prediction but it required more three dominant driving forces for LULC change prediction. In this study the most dominate factors for urban and built-up area expansion were per capita income, population density, and slope according to coefficient values from spatial multiple linear regression analysis of the relevant data in 2011 as:

$$UNU2011 = 0.367 + 3.0930*INCOME + 0.7897*MSU + 0.6045*DISTU + 0.4746*ROAD + 1.6858*SLOPE - 1.6877*POP$$

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

It was found that CA-Markov model provided an overall accuracy and Kappa hat coefficient with values of 96.84% and 93.27% higher than Land Change Modeler with values of 96.04% and 91.60%, respectively. Therefore, 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 CA-Markov model as an optimum predictive model for future urban growth prediction. Furthermore, the derived Kappa hat coefficient of CA-Markov model which was higher than 80% is acceptable and suitable for LULC change prediction according to suggestion of Subedi *et al.* (2013).

LULC development in the past and future

According to 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 urban and built-up area sub-classes had continuously increased during 2001-2021 except dormitory. In contrary, most of sub-classes of agricultural land except field crop and secondary forest had continuously decreased in these periods. Meanwhile, marsh land had trended to decrease but development land had trended to increase in the future. At the same times, water body was unpredictable. Area of LULC change in term of gain (+) and loss (-) for each LULC type in 4 different periods was summarized in Table 3.

Furthermore, future trend of sub-classes of urban and built-up area were examined using various regression types including exponential, linear, logarithmic, polynomial, power, and moving average types under Trend Analysis of MS-Excel as summary in Table 4 and Figure 6. As results, it was found that the best fit for commercial, city and village, institution and real estate areas was linear regression type while the best fit for dormitory was logarithmic regression type. The R^2 of the regression analysis varies between 90.51-98.70%. These show a nearly perfect explanation of time to area of urban and built-up area sub-classes. The predictive area of urban and built-up area sub-classes until 2046 with 5 year interval was also reported in Table 5. It was found that the highest percentage of change of urban and built-up area sub-class between 2011 (at the present) and 2046 (in the future) was real estate (240.52%) while the lowest percentage of change was institution (19.01%). These results indicate that urban expansion has continuously increased in the study area in the near future.

Spatiotemporal surface runoff depth estimation using SCS-CN method

Spatiotemporal surface runoff depth estimation by SCS-CN method was implemented based on the LULC change during 2001-2021 with a presumable permanent soil texture and the interpolated maximum rainfall during 1981-2010 under Model Builder of ArcGIS software (Figure 7). Distribution of the spatiotemporal surface runoff depth estimation in the study period was displayed in Figure 8 while the minimum, mean, maximum, and total values of surface runoff depth was presented in Table 6.

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

Impact of urban expansion on total surface runoff depth

The result of urban area and total surface runoff depth changes in the study period was presented in Table 7. It was found that both changes had continuously increased. Meanwhile, the relationship between urban area and total surface runoff depth during 2001 to 2021 was linear regressed by Trend Analysis of MS-Excel as presented in Figure 9. The simple linear equation between urban area and total surface runoff depth showed positive relationship with R^2 at 98.30% as:

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

Where y is total surface runoff depth in mm and x is urban area in sq. m in the study period. This equation implies that when urban area increases then total surface runoff depth increase. Meanwhile, the derived R^2, which is the percentage of the response variable variation that is explained by a linear model, indicated that expansion of urban area regulates the total surface runoff depth in the study area. Herewith, it should be here noted that total surface runoff depth basically derives from all various LULC type based on variation of runoff curve number of hydrologic soil group–land cover complex (*CN*). However, *CN* values of urban and built-up area are relative higher than others LULC types except 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.

Impact of urbanization on surface runoff depth

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

It was found that urbanization level strongly correlated with mean surface runoff depth zonation by sub-district. Because the spatial pattern between urbanization level, which describes the percentage of urban areas in sub-district, and mean surface runoff depth zonation, which creates by mean surface runoff depth value in each sub-district, are similar. Herewith, the highest value of R and R^2 was 87.80% and 77.09% in year 2016 while the lowest value of R and R^2 was 84.98% and 72.21% in year 2001 (Table 8). This result implies that when urbanization is taken place in each sub-district, then the surface runoff depth increase 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 dataset for variety applications and modellings. This study applied geoinformatics technology (remote sensing and GIS) and LULC change model as a basic tools to assess LULC and its impact on surface runoff. The study demonstrate that the dominate LULC type in 2001, 2006 and 2011, which were visually interpreted from remotely sensed data, was agricultural land. At the same time urban and built-up area had been continuously increased by conversion of agricultural and forest lands. In addition, accuracy assessment of the interpreted LULC data in 2011 as a baseline data for an optimum LULC change model identification shown that overall accuracy and Kappa hat coefficient was 98.03% and 95.85%, respectively.

This study has revealed that an optimum predictive LULC change model was CA-Markov model which provided overall accuracy and Kappa hat coefficient (96.84% and 93.27%) higher than Land Change Modeler (96.04% and 91.60%). Herewith, CA-Markov was chosen to predict LULC data in 2016 and 2021.

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

Furthermore, results of spatiotemporal surface runoff depth estimation during 2001 to 2021 by SCS-CN method showed that the mean and total surface runoff depth had continuously increased. Similarly, urban area had continued to increase in these periods. This study also demonstrated that there is strongly related the change of urban area on surface runoff depth with R^2 at 98.30%. Likewise, level of urbanization is strongly associated with mean surface runoff depth zonation. Evidence from this study suggests that LULC changes, especially urban expansion and urbanization have an effect on surface runoff depth characteristic. Hence, an optimal land use policy and urban planning are urgently required to implement in the study area for urban flood mitigation and prevention due to a rapid LULC change.

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

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Table 1 Dataset and equipment

Dataset and equipment	Date	Resolution/Scale	Source
1. Remote sensing datasets			
1.1 Digital color orthophoto data	2001	1:4,000	LDD
1.2 SPOT data	2006	10x10	GISTDA
1.3 THEOS pansharpened data	2011	2x2 m.	GISTDA
2. GIS datasets and documents data			
2.1 Soils series data	2002	1:100,000	LDD
2.2 Digital Elevation Model (DEM) data	2009	30x30	NASA
2.3 Administrative boundary data	2000	1: 50,000	DOPA
2.3 Rainfall data	1981-2010	NA	TMD
2.4 Per capita income	2011	NA	CDD
2.5 Number of population	2011	NA	DOPA
3. Equipment			
3.1 Software			
3.1.1 ERDAS Imagine Version 8.7			Remote sensing
3.1.2 ESRI ArcGIS Version 9.3			Lab, SUT
3.1.3 IDRISI Taiga			
3.2 Hardware			
3.2.1 GPS			Remote sensing
3.2.2 Computer and Notebook			Lab, SUT and
			Personal

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.

Table 2 Area and percent of LULC types in 2001, 2006 and 2011 and theirs change.

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 3 Development of LULC area during 2001 to 2021.

LULC types	Change in term 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 Village	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

Table 4 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 = 1.3744ln(x) + 0.088	90.51
Real estate	Linear regression	y = 0.425x - 0.303	92.60

Note: y is dependent variable which represents area of urban and built-up area sub-class in sq.km

x is independent variable which represents as 5 year interval such as 1 for year 2001, 2 for year 2006, 3 for year 2011, and so on.

Table 5 Predictive area of sub-classes of urban and built-up areas in 2046.

	Area in sq. km in Year				
LULC Types	**2026**	**2031**	**2036**	**2041**	**2046**
Commercial	5.41	6.16	6.92	7.67	8.43
City and Village	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

Table 6 Summary of the minimum, mean and maximum values of surface runoff depth estimation during 2001 to 2021.

Year	Surface runoff depth in mm.			
	Minimum value	**Maximum value**	**Mean value**	**Total value**
2001	10.312	204.035	127.721	138,670,420
2006	10.312	204.035	128.073	139,052,900
2011	10.319	203.707	128.645	139,674,640
2016	10.319	205.527	129.252	140,334,100
2021	10.319	205.527	129.481	140,581,730

Table 7 Surface runoff depth and urban area during 2001-2021.

Year	Urban area in sq. m	Total Surface runoff depth in mm
2001	53,910,000	138,670,420
2006	56,980,000	139,052,900
2011	64,730,000	139,674,640
2016	68,320,000	140,334,100
2021	70,820,000	140,581,730

Table 8 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

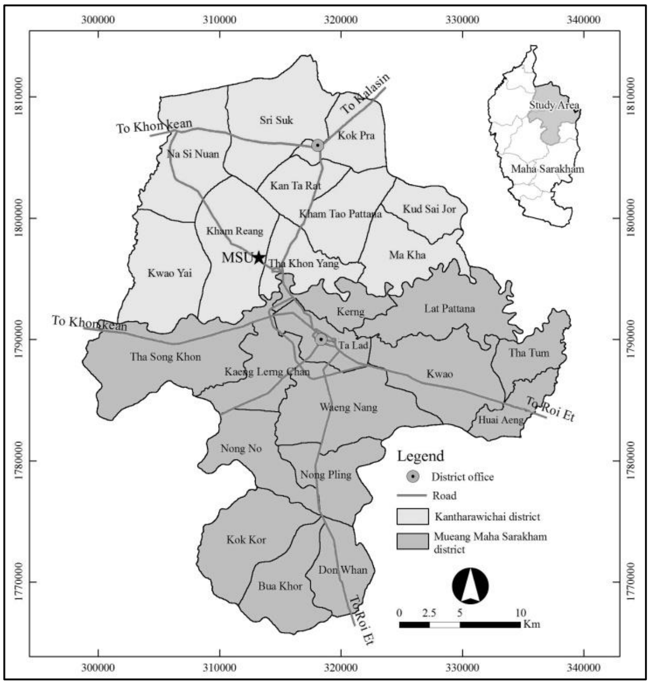


Figure 1 The study area.

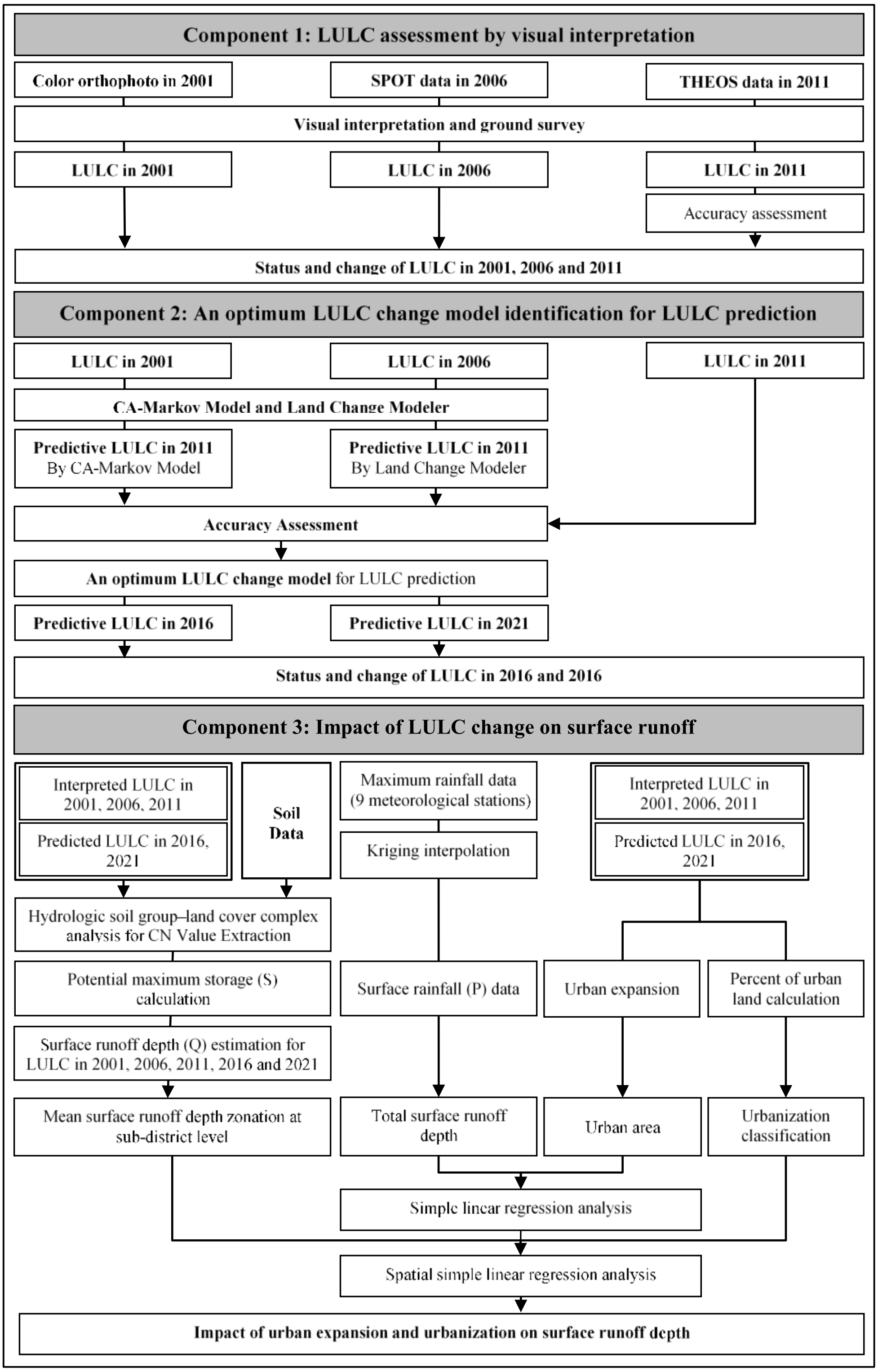


Figure 2 Work flow of research methodology.

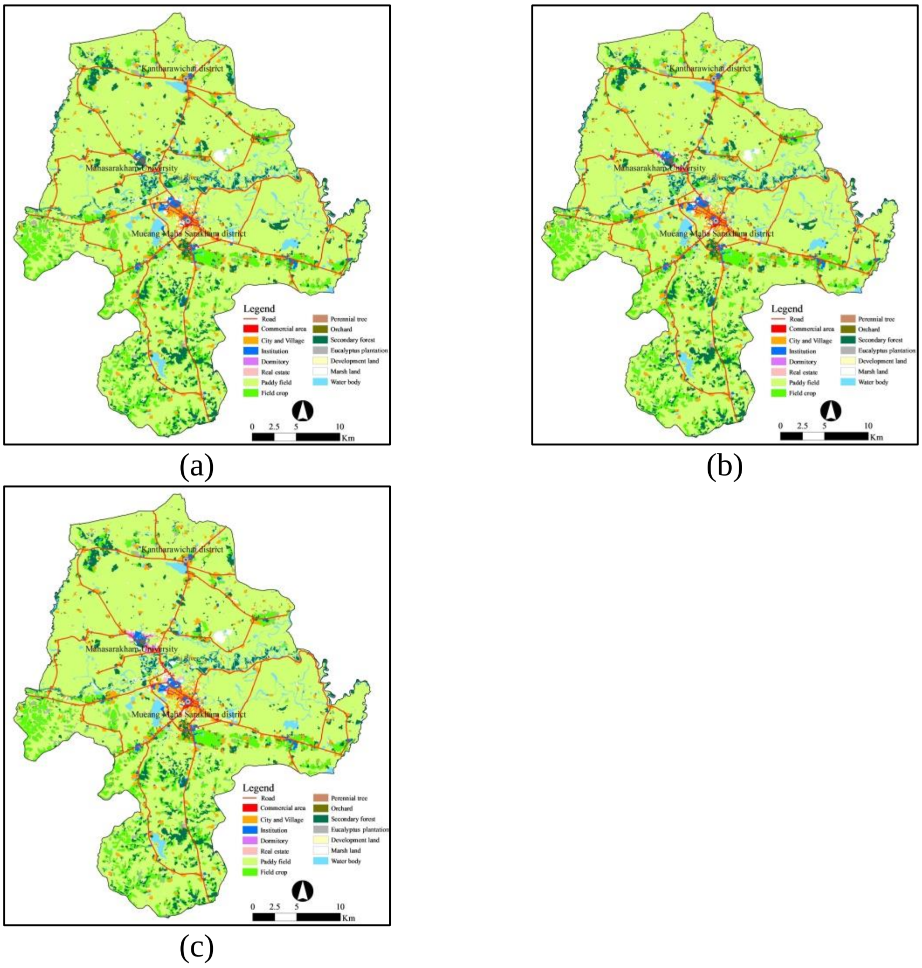
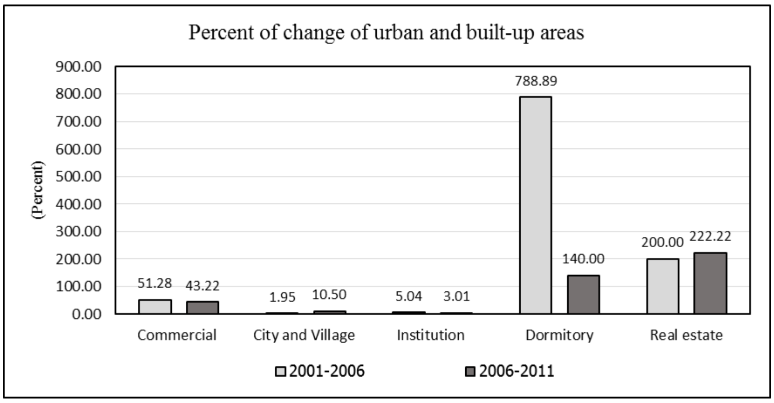
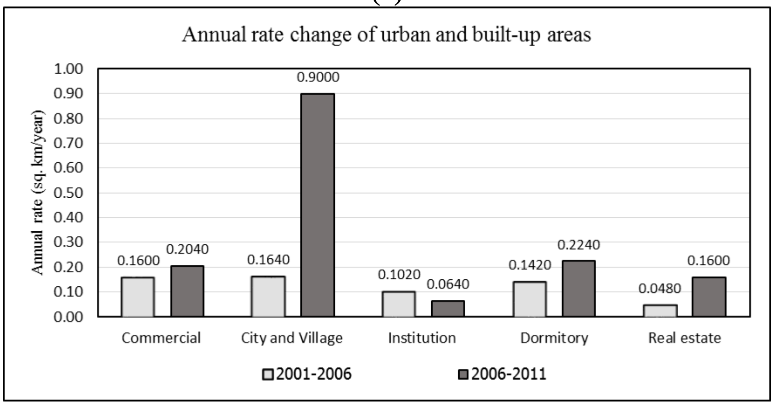


Figure 3 Distribution of the interpreted LULC pattern: (a) in 2001, (b) in 2006, and (c) in 2011.

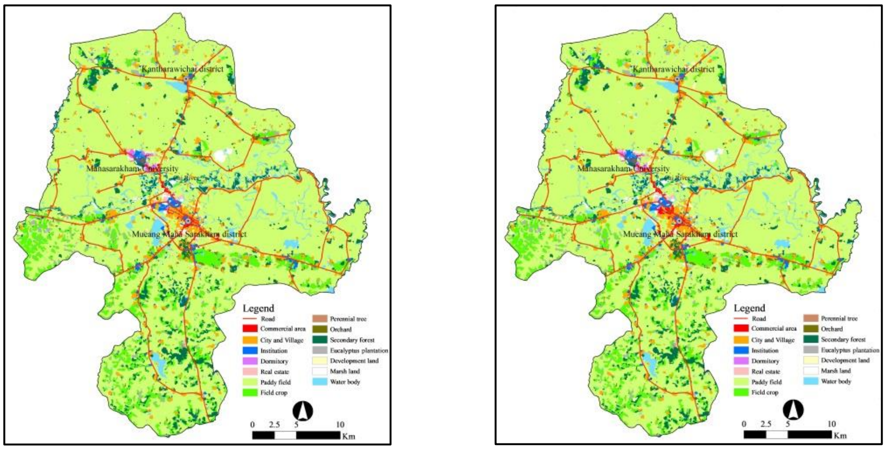


(a)



(b)

Figure 4 Comparison of urban and built-up area sub-classes between 2001-2006 and 2006-20111: (a) percent of change and (b) annual increasing rate.



(a) (b)

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

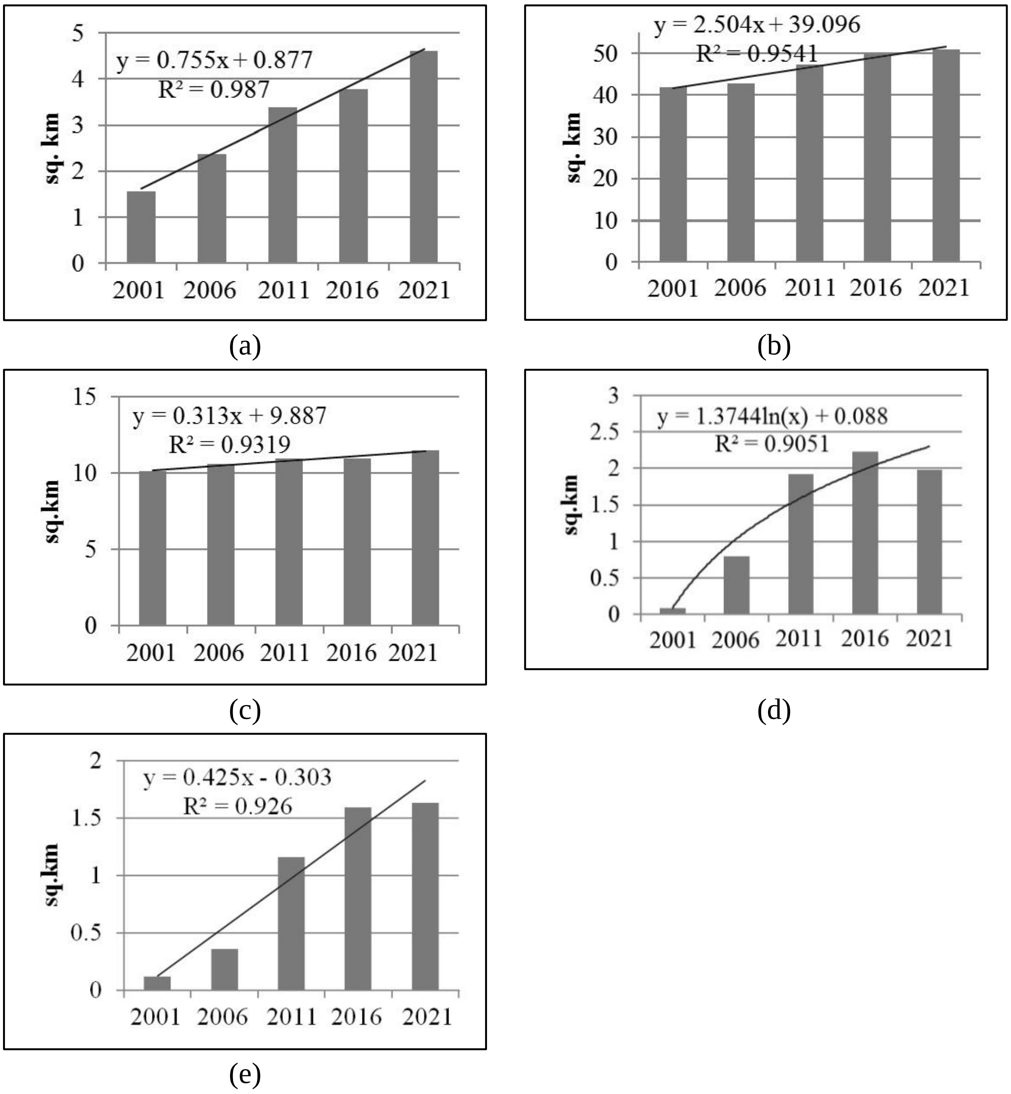


Figure 6 Trend analysis of urban and built-up areas sub-class: (a) commercial, (b) city and village, (c) institution, (d) dormitory, and (e) real estate.

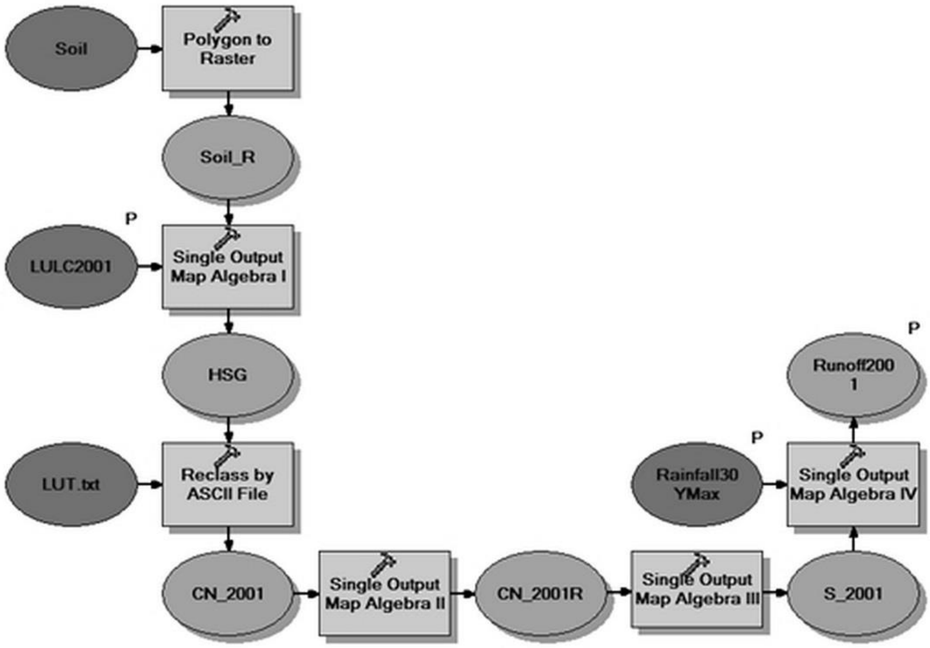


Figure 7 Schematic diagram of Model Builder of ESRI ArcGIS for spatiotemporal surface runoff depth estimation.

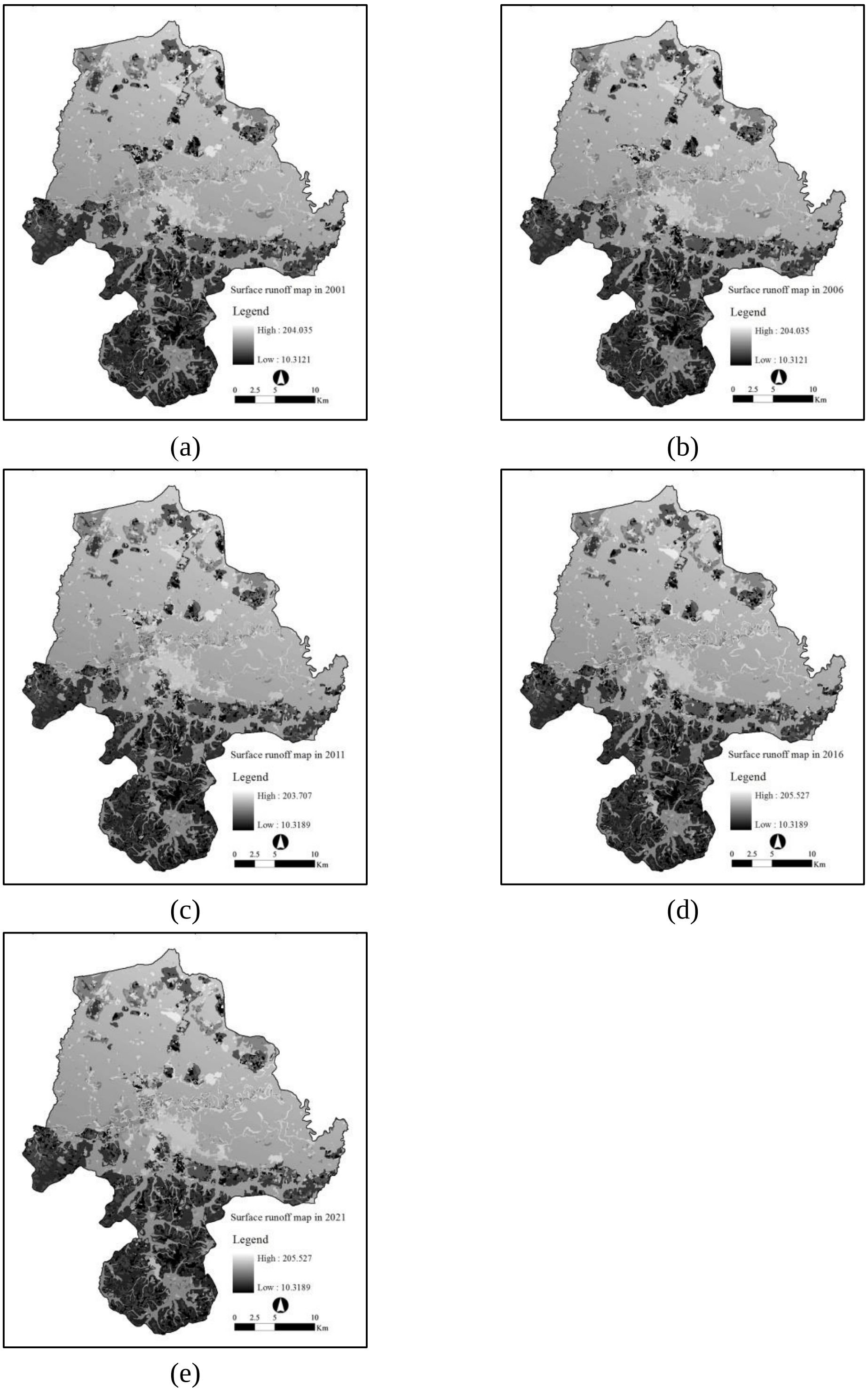


Figure 8 Distribution of the spatiotemporal surface runoff depth estimation: (a) in 2001, (b) in 2006, (c) in 2011, (d) in 2016, and (e) in 2021.

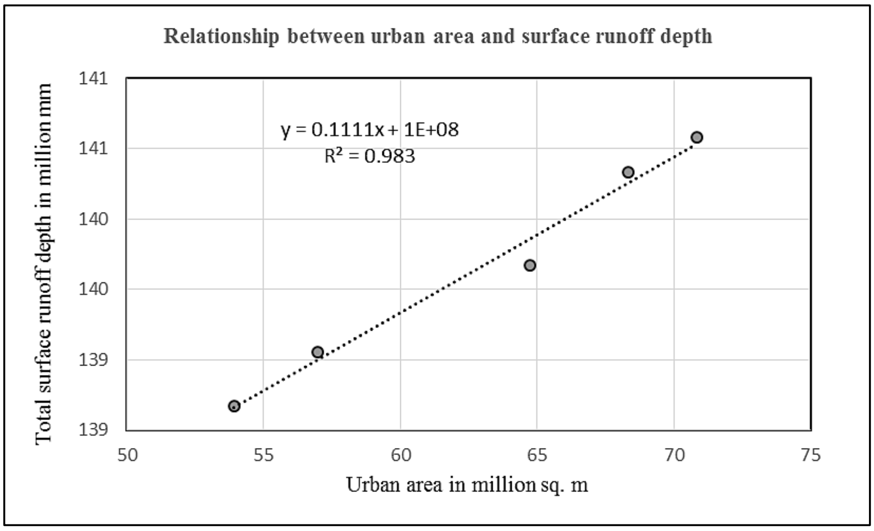
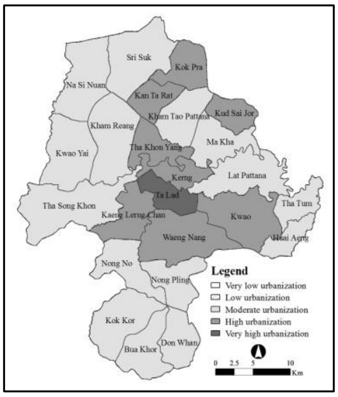
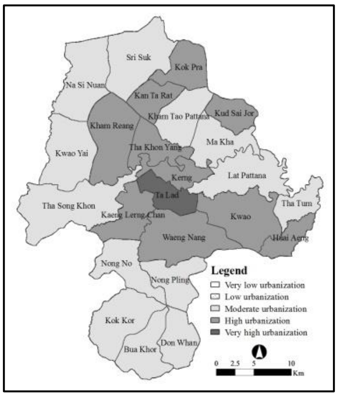


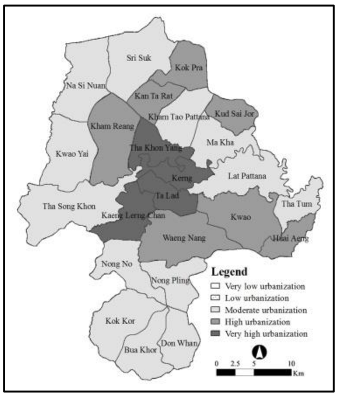
Figure 9 Simple linear regression analysis between urban area and surface runoff depth.



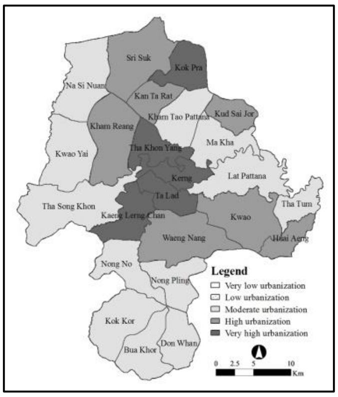
(a)



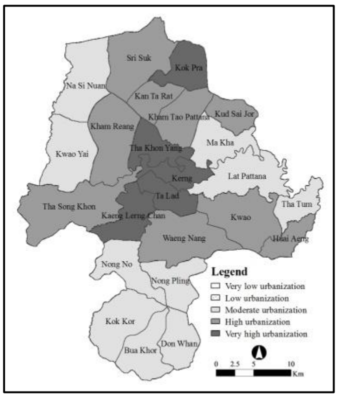
(b)



(c)



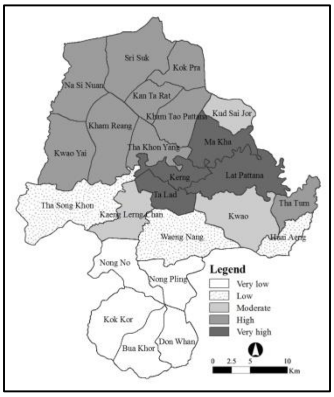
(d)



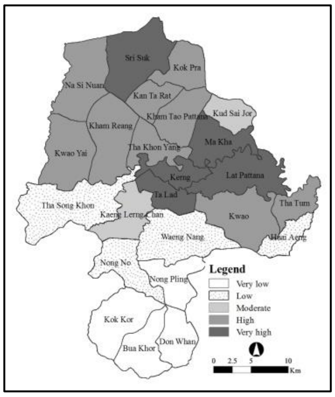
(e)

Classification of urbanization Based on urban land percentage (PU)
Very low urbanization = PU < 0.001% Low urbanization = 0.001% ≤ PU < 1% Moderate urbanization = 1% ≤ PU < 5% High urbanization = 5% ≤ PU < 10% Very high urbanization = 10% ≤ PU

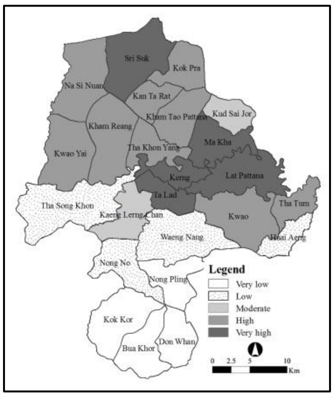
Figure 10 Distribution of urban land percentage (PU) as urbanization: (a) in 2001, (b) in 2006, (c) in 2011, (d) in 2016 and (e) in 2021.



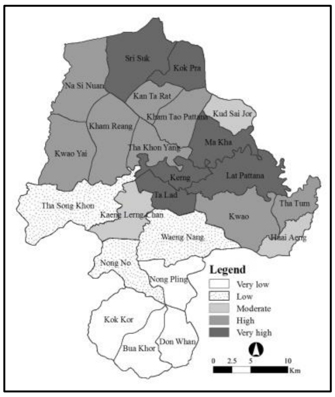
(a)



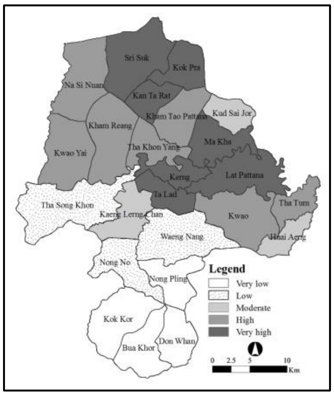
(b)



(c)



(d)



(e)

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.