

INTEGRATION OF GEOSPATIAL MODELS FOR OPTIMUM LAND USE ALLOCATION IN THREE DIFFERENT SCENARIOS

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Abstract

The study of land use and land cover simulation using the integration of geospatial models is very important in various aspects, especially sustainable use with minimum environmental impact. The main objectives of the study were: 1) to assess historical and recent LULC and its changes; 2) to simulate 3 different LULC scenarios using the CLUE-S model; 3) to assess soil erosion, water yield, and economic value and their changes; and 4) to allocate the optimum land use for 3 different scenarios. The 4 main components of the research methodology implemented here included: 1) data collection and preparation; 2) LULC simulation of 3 different scenarios; 3) soil erosion, water yield, and economic value assessment and their changes; and 4) the optimum land use allocation of 3 different scenarios. From the results of the LULC assessment between 2003 to 2013, urban and built-up land, cassava, sugarcane, water body, and miscellaneous land had increased while maize, perennial tree/orchard, and forest land had decreased. The most common important driving factor for location preference of the LULC types was population density. The simulation of 3 LULC scenarios in 2023 by the CLUE-S model revealed that urban and built-up land, cassava, sugarcane, water body and miscellaneous land would increase while maize, perennial tree/orchard, and forest land would decrease under Scenario I (Historical land use evolution). At the same time, the increase in cassava and sugarcane under Scenario II (Energy crop extension) came from maize, forest land, and miscellaneous land while most of the increasing forest land under Scenario III (Forest conservation and prevention) was converted from maize, sugarcane, and miscellaneous land. The optimum land use allocation of the 3 scenarios indicated that most of the agricultural land and forest land of Scenario I was allocated into the moderate and high suitability classes, respectively. In the meantime, most of the cassava and sugarcane as energy crops of Scenario II were located in the low and moderate suitability classes and moderate and high suitability classes, respectively, while the forest land with restriction rules was located in the high suitability class. Under Scenario III, the forest land was allocated in the moderate and high suitability classes and the agricultural land was distributed throughout all the suitability classes. On the basis of these results, it is suggested that the integration of the LULC change model (CLUE-S model), soil erosion model (USLE model), hydrologic model (SWAT model and SCS-CN method), and economic value measures (PV model) can be efficiently used as a tool for optimum land use allocation by considering LULC change and its impact from different scenarios.

Keywords: Geospatial model, optimum land use allocation, land use and land cover change, CLUE-S model, Upper Lam Pra Pleong watershed

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Introduction

The study of land use and land cover (LULC) and its change is very important with regard to a number of aspects. Helming *et al.* (2008) stated that land use implies human activities that exhibit a spatial dimension and change the biogeophysical conditions of the land and environment. From the spatial viewpoint, LULC is among those human activities which have the strongest impacts on the environment, e.g. soil degradation (Boardman and Poesen, 2006), desertification (Geist *et al.*, 2006), and water quality and biotic diversity (Poschlod *et al.*, 2005). Interrelation between LULC change and the ecosystem has been intensively studied (Metzger *et al.*, 2006). In recent years, there has been a focus on the role of LULC in accelerating/mitigating climate change processes (IPCC, 2001; Graveland *et al.*, 2002). Increasing understanding of the relationship between LULC changes and environmental impacts has been triggered by a series of studies related to the LULC change project of the International Geosphere-Biosphere Programme and International Human Dimension Programme on Global Environmental Change (Steffen *et al.*, 2005; Lambin *et al.*, 2006). In addition, prediction and simulation studies of LULC change have emerged by combining LULC change into the logical chain of driving forces and impacts, especially by use of the CLUE-S model. Many researchers have applied the CLUE-S model to simulate LULC scenarios and examined the changes (Verburg and Veldkamp, 2001; Verburg *et al.*, 2002; Verburg and Veldkamp, 2004; Verburg *et al.*, 2004; Overmars *et al.*, 2007; Verburg *et al.*, 2008; Zheng *et al.*, 2012) and the effects on sustainable management of natural resources (Castella *et al.*, 2007), environmental damage (Orekan, 2007), runoff (Githu *et al.*, 2009; Zhou *et al.*, 2013), biodiversity conservation (Trisurat *et al.*, 2010; Trisurat *et al.*, 2014), watershed management (El-Khoury *et al.*, 2014), and urban renewal areas (Zheng *et al.*, 2015).

In the case study of the Upper Lam Pra Pleong watershed, the growth of tourism has impacted agricultural and conservation areas and the misuse of suitable lands, deforestation, land degradation, and floods have caused several problems to the study site (Charupatt and

Mongkolsawat, 2003). So, a proper plan can give direction to protect the study site and reduce these problems. In addition, alternative goals and plans are also useful for limited soil and land resources management. Consequently, the establishment of multiple scenarios using simulation models will provide a good framework for the optimum land use allocation in the future. The specific objectives of the study were: 1) to assess the historical and recent LULC and the changes; 2) to simulate 3 different LULC scenarios using the CLUE-S model; 3) to assess soil erosion, water yield, and economic values and their changes; and 4) to allocate the optimum land use for the 3 different scenarios.

Materials and Methods

Study Area

The Upper Lam Phra Phloeng watershed, which is a sub-watershed of the Lam Phra Phloeng watershed of the Mun basin, is situated in the upper part of the basin and covers an area of about 77165 ha. The main river of the watershed is the Lam Phra Phloeng River which flows downstream to the Lam Phra Phloeng Dam. The topography is generally characterized by hilly, rolling terrain with undulating and flat areas. Its elevation varies from 260 m in the northeastern part to 1307 m in the southwestern part of the watershed (Figure 1). The study area covers Pak Chong and Wang Nam Khieo districts of Nakhon Ratchasima Province.

Research Methodology

The research methodology and its workflow consists of 4 components: (1) data collection and preparation, (2) LULC simulation of 3 different scenarios, (3) soil erosion, water yield, and economic value assessments and their changes, and (4) the optimum land use allocation of the 3 different scenarios (Figure 2).

Component 1: Data Collection and Preparation

The required input data included remote sensing and GIS data which were collected and prepared in advance (Table 1). Color orthoimages in 2003 from the Land Development Department

and Thaichote imagery in 2013 from the Geo-Informatics and Space Technology Development Agency were visually interpreted to determine the LULC types (urban and built-up land, paddy field, cassava, maize, sugarcane, perennial tree/orchard, forest land, water body, and miscellaneous land). The interpreted LULC in 2013 was also assessed for accuracy by field survey in 2014. The sample sizes were based on the binomial probability theory by Fitzpatrick-Lins (1981) and a stratified random sampling scheme was applied to allocate the sampling points. Meanwhile, the location preferences of the different LULC types in relation to the driving factors (physical and socio-economic conditions) were determined by a logistic regression model of the SPSS statistical software. The location preferences of the different LULC types based on the logistic regression model define the relationship between the occurrence of a particular LULC type and the physical and socio-economic conditions of a specific location (Verburg and Veldkamp, 2004) as:

$$\text{Log} \left(\frac{P_i}{1-P_i} \right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \dots + \beta_n X_{n,i} \quad (1)$$

where, P_i is the probability of a grid cell for the occurrence of the considered land use type on location i , and $X_{n,i}$ are the location factors as the explanatory factor (driving factor). The

coefficients β_i are estimated through the logistic regression model using the actual land use pattern as a dependent variable. In this study the physical factors to indicate the preference for a specific land use type were elevation, slope, aspect, distance from stream, annual rainfall, soil drainage, and land use capability of the watershed class. At the same time, the socio-economic factors influencing land use change were population density, distance from road, and income. In addition, the goodness-of-fit of a logistic regression model was evaluated here using the receiver operating characteristic (ROC). The ROC characteristic is a measure for the goodness of fit of a logistic regression model similar to the coefficient of determination (R^2) statistic in an ordinary least square regression (Pontius and Schneider, 2001). The value of the ROC ranges between 0.0 (completely unfit) and 1.0 (perfectly fit), where the area under curve 0.5 is completely random (Verburg *et al.*, 2005).

Component 2: LULC Simulation of 3 Different Scenarios

The CLUE-S model was developed to simulate land use change (the scenario) using empirically quantified relationships between land use and its driving factors in combination with dynamic modeling of competition between land use types (Veldkamp and Fresco, 1996;

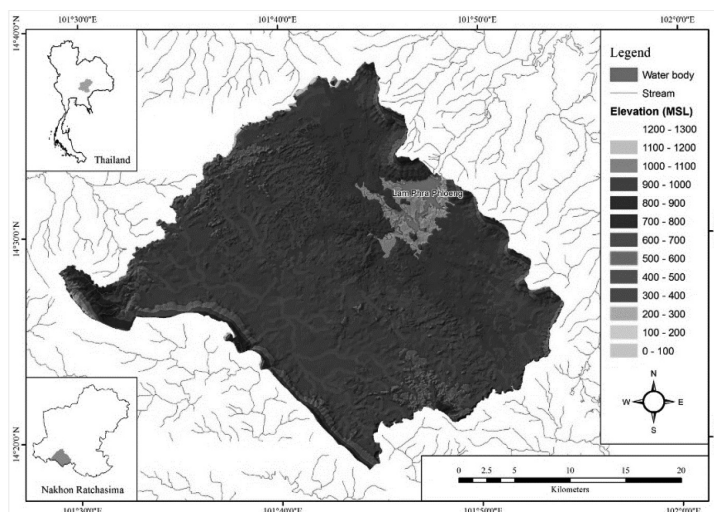


Figure 1. Location and topography of the study area

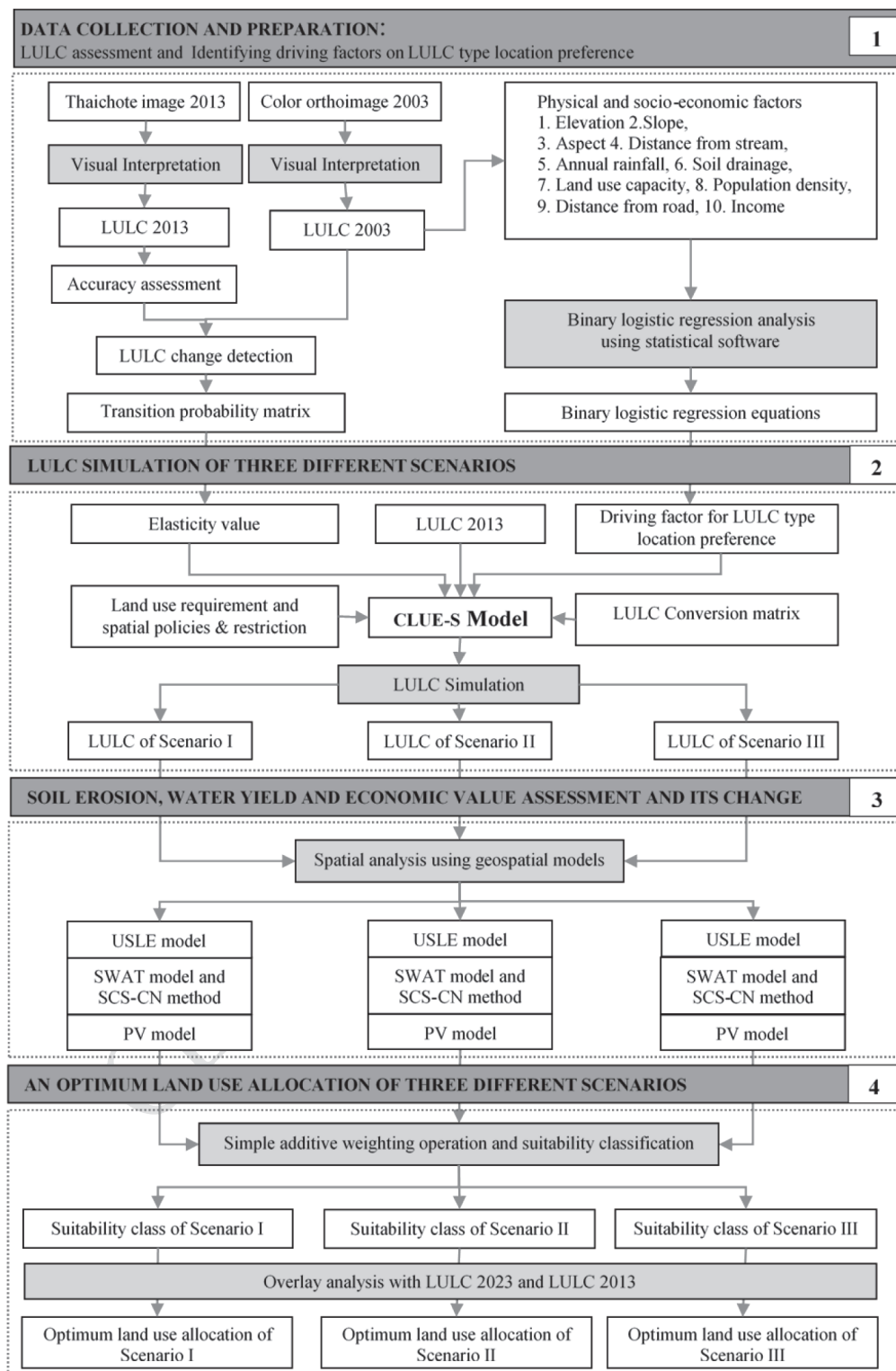


Figure 2. Research methodology component and its workflow

Verburg *et al.*, 1999). It requires 4 input data to allocate a set of conditions and possibilities of LULC patterns which include (1) land use requirements, (2) location characteristics, (3) spatial policies and restrictions, and (4) land use type specific conversion settings (Verburg, 2010).

In this study, 3 different scenarios of LULC change in 2023 including Scenario I (Historical land use evolution), Scenario II (Energy crop extension), and Scenario III (Forest conservation and prevention) were simulated in accordance with their land use requirements and spatial policies and restrictions (Table 2). The derived physical and socio-economic factors by the logistic regression model to indicate the preference for a specific type of land use were set up to the model. In addition, the LULC conversion matrix, which shows the possibility for LULC change among LULC types, was also set up (Table 3). Meanwhile the elasticity value, which represents the cost for change among LULC types ranging

from 0 (easy conversion) to 1 (irreversible change), was obtained from the transition probability matrix of the LULC change between 2003 and 2013. In this study the elasticity values of the urban and built-up land, paddy field, cassava, maize, sugarcane, perennial tree/orchard, forest land, water body, and miscellaneous land were set up as 1.0, 1.0, 0.8, 0.8, 0.9, 0.7, 1.0, 1.0, and 0.9, respectively.

Component 3: Soil Erosion, Water Yield, and Economic Value Assessment and Their Changes

The actual LULC data in 2013 and the 3 simulated scenarios from the LULC data in 2023 were firstly used as the main input data to assess soil erosion, water yield, and economic value by the USLE model, SWAT model and CSC-CN method, and PV model, respectively. The derived data were then used to compare their changes by overlay analysis and to analyze the effects of LULC change on soil loss, water yield, and economic

Table 1. Data collection and preparation and its source

Data collection	Data preparation	Source	Year
Color orthoimage	LULC data interpretation	Land Development Department (LDD)	2003
Thaichote image	LULC data interpretation	Geo-Informatics and Space Technology Development Agency (GISTDA)	2013
Contour line and spot height	DEM generation with IDW	Royal Thai Survey Department (RTSD)	1992
Digital elevation model (DEM)	Slope extraction from DEM	RTSD	1992
DEM	Aspect extraction from DEM	RTSD	1992
Stream network	Buffering by distance	RTSD	1992
Rainfall data	Rainfall interpolation	Thai Meteorological Department (TMD)	2003-2012
Soil data	Drainage capacity extraction	LDD	1991
Watershed classification	Land use capability extraction	Office of Natural Resources and Environmental Policy and Planning (ONEP)	1988
Demography data	Population density at sub-district level	National Statistical Office (NSO)	2012
Road network	Buffering by distance	RTSD	1992
Income	Income at sub-district level	NSO	2003

value by simple linear regression analysis. A basic concept of each model and its application was separately summarized, as below:

(1) USLE model. The universal soil loss equation (USLE) developed by Wischmeier and Smith (1978) was used to estimate annual soil erosion based on 5 factors as:

$$A = R \times K \times LS \times C \times P \quad (2)$$

where A is the annual soil loss (t/ha/yr), R is the rainfall-runoff erosivity factor (MJ mm/ha/h per year), K is the soil erodibility factor (t h/MJ mm), LS is the slope length and steepness factor, C is the vegetation cover factor, and P is

Table 2. Land use requirement of each LULC type by each scenario

LULC type	Land use requirement (in ha)		
	Scenario I ^a	Scenario II ^b	Scenario III ^c
Urban and built-up land (UR)	3130	2465	2465
Paddy field (PA)	237	237	237
Cassava (CA)	4661	30354	3688
Maize (MA)	17514	-	15433
Sugarcane (SU)	12496	30354	8948
Perennial tree/orchard (PE)	4882	-	5116
Forestland (FO)	25417	12,590	34035
Water body (WA)	1222	1165	1165
Miscellaneous land (MI)	7606	-	6078

Note a: Land use requirement was calculated based on annual change rate of LULC between 2003 and 2013.

b: Maize, perennial tree/orchards, and miscellaneous land were devoted for cassava and sugarcane expansion in 2023 at the ratio of 50 and 50 (Bank of Thailand, 2012), forest land in a national park and watershed class I was preserved as restriction areas, and urban and built-up land, paddy field, and water body were fixed as LULC data in 2013.

c. Forest land was assigned according to areas of watershed classes I and II, a national park's boundary, and existing forest in 2013 according to the 11th National Economic and Social Development Plan (2012-2016) of the National Economic and Social Development Board (2011). Meanwhile, urban and built-up land, paddy field, and water body were fixed as LULC data in 2013 and other LULC types were modified based on the annual change rate of LULC between 2003 and 2013.

Table 3. Conversion matrix of possible change among LULC types between 2013 and 2023

LULC in 2013	LULC Types	Possible LULC change in 2023								
		UR	PA	CA	MA	SU	PE	FO	WA	MI
	Urban and built-up land (UR)	1	0	0	0	0	0	0	0	0
	Paddy field (PA)	1	1	1	1	1	1	1	1	1
	Cassava (CA)	1	0	1	1	1	1	1	1	1
	Maize (MA)	1	0	1	1	1	1	1	1	1
	Sugarcane (SU)	1	0	1	1	1	1	1	1	1
	Perennial tree/orchard (PE)	1	0	1	1	1	1	1	1	1
	Forest land (FO)	1	0	1	1	1	1	1	1	1
	Water body (WA)	1	0	0	0	0	0	0	1	0
Miscellaneous land (MI)	1	0	1	1	1	1	1	1	1	

Note: 0 is not allowed and 1 is allowed

the conservation support practice.

(2) SWAT model with SCS-CN method.

The soil and water assessment tool (SWAT), which is a spatially distributed hydrological model developed by the United States Department of Agriculture–Agricultural Research Service (Neitsch *et al.*, 2011), was firstly used to generate the curve number (CN) value in each hydrologic response unit (HRU) for the actual and simulated LULC. Then, the SCS-CN method developed by the USDA Natural Resources Conservation Service (1972) was used to calculate the potential maximum storage (S) in each HRU as:

$$S = 25.4 \times \frac{1000}{CN} - 10 \quad (3)$$

where S is the potential maximum storage in mm, and CN is the runoff curve number of the hydrologic soil group–land cover complex in the HRU. After that, water yield as the runoff depth was estimated based on the average monthly rainfall from 2002-2011 as:

$$Q = \frac{(P-0.2S)^2}{P+0.8S} \quad (4)$$

where Q is the runoff depth in mm, and P is the rainfall (mm).

(3) PV model. The future values of the agricultural and forest land in the LULC data in 2013 and 2023 were calculated from their

present values using the Present Value (PV) model as suggested by Rossiter (1995) as:

$$PV = FV \cdot \left[\frac{100}{100+IR} \right]^Y \quad (5)$$

where PV is the present value, FV is the future value, IR is the interest rate in percent, and Y is the number of years from present, counting from zero. Table 4 shows the present value and future value of the agricultural and forest land for estimating the economic values of the LULC types, except the urban and built-up land, water body, and miscellaneous land.

Component 4: An Optimum Land use Allocation of 3 Different Scenarios

The derived soil loss, water yield, and economic values of each scenario in 2023 were separately normalized according to their characteristics as below:

Soil loss data, which represents a negative effect of LULC change on the land, was normalized based on the score range procedure for cost criteria (Young *et al.*, 2010) as:

$$\hat{x}_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \quad (6)$$

Meanwhile, water yield, which is assigned as the availability of water for certain areas (pixels), indicates a positive effect on the land. The water

Table 4. Present value and future value of LULC types

LULC type	Price (Thai baht/ kg.)	Yield (kg/ hectare)	Present value (Thai baht/ hectare)	Discount Rate 4 in %	Period from Present (year)	Future value (Thai baht/ hectare)
Paddy field ¹	14.62	2530	36996.70	7	10	72778
Cassava ¹	2.02	20835	42114.48	7	10	82846
Maize ¹	7.84	4093	32098.16	7	10	63142
Sugarcane ¹	1.00	73238	72973.85	7	10	143551
Perennial tree/orchard ²	13.33	6846	91232.14	7	10	179467
Forest land ³			250000.00	7	10	491788

Source 1 OAE, 2011, 2012 and 2013.

2 Marketing Organization for Farmers, 2014.

3 Wittawatutikul and Jirasuktaveekul, 2005.

4 Discount rate was based on that of the Bank for Agriculture and Agricultural Cooperatives, 2014.

yield is normalized based on the score range procedure for benefit criteria (Young *et al.*, 2010) as:

$$\hat{x}_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad (7)$$

At the same time, economic value is normalized based on the maximum score procedure for benefit criteria (Young *et al.*, 2010) as:

$$x'_{ij} = x_{ij} / x_j^{\max} \quad (8)$$

where x_{ij} is the standardized score for the i^{th} object and the j^{th} attribute, x_{ij} is the raw score, $x_j^{\max}$ is the maximum score for the j^{th} attribute, $x_j^{\min}$ is minimum score for the j^{th} attribute, and $x_j^{\max} - x_j^{\min}$ is the range of a given criterion.

Then the standardized scores for each criterion were combined using the simple additive weighting (SAW) method (Malczewski, 1999) with the specific weight as:

$$A_i = \sum_j w_j x_{ij}, \quad (9)$$

where A_i is the total score which is obtained by multiplying the score and weight, w_j is the normalized weight, x_{ij} is the score of the i^{th} alternative with respect to the j^{th} attribute, and $\sum w_j = 1$. In this study, the weights for soil loss, water yield, and economic value by scenario were here assigned as 1, 1, and 1 for Scenario I,

respectively; 1, 2, and 3 for Scenario II, respectively; and 3, 2, and 1 for Scenario III, respectively.

The derived total score of each scenario was further reclassified into 3 suitability classes (low, moderate, and high) for the optimum land use allocation. Herein, the equal interval method was applied for Scenario I because it has no relative importance among the 3 factors. On the contrary, the natural break method, which appropriates for the skewed distribution data, was applied for Scenarios II and III which have relative importance among the 3 factors. After that, the derived suitability data of each scenario were combined with the LULC data in 2023 by overlay analysis for the optimum land use allocation and the results were further superimposed with the actual LULC assessment in 2013 for implementation in a short period (1-3 years), medium period (4-7 years), and long period (8-10 years) of time.

Results and Discussion

Historical and Recent LULC Assessments and Their Changes

According to the historical and recent LULC data in 2003 and 2013, the major increased LULC types were sugarcane and urban and built-up land with annual change rates of 171 and 66.5 ha, respectively. In contrast, the major

Table 5. LULC change between 2003 and 2013 as a transition area matrix

LULC types	LULC 2013 (ha)									Total
	UR	PA	CA	MA	SU	PE	FO	WA	MI	
Urban and built-up land (UR)	1800	-	-	-	-	-	-	-	-	1800
Paddy field (PA)	-	237	-	-	-	-	-	-	-	237
Cassava (CA)	18	-	3316	454	168	133	-	-	143	4231
Maize (MA)	313	-	661	16141	1383	551	-	8	637	19693
Sugarcane (SU)	21	-	-	287	8448	293	-	-	25	9074
Perennial tree/orchard (PE)	163	-	340	1,165	659	5014	-	2	109	7452
Forestland (FO)	17	-	28	174	34	42	25970	10	247	26523
Water body (WA)	-	-	-	-	-	-	-	1108	-	1108
Miscellaneous land (MI)	133	-	101	382	94	134	-	37	6,165	7046
Total	2465	237	4446	18603	10786	6167	25970	1165	7326	77165

decreased LULC types were perennial tree/orchard and maize with annual change rates of 128.5 and 108.9 ha, respectively. The overall accuracy of the LULC data in 2013 using 203 stratified random sampling points was 90.1% and the Kappa hat coefficient was 87.21%. According to Fitzpatrick-Lins (1981), a Kappa hat coefficient of more than 80% represents a strong accuracy between the interpretation map and the ground reference information. In addition, a transitional change matrix of LULC between 2003 and 2013, which provides from-to change class information, is summarized in Table 5. It revealed that the changed areas among the field crops existed. For example, areas of cassava in 2003 had changed to become maize and sugarcane areas in 2013 with about 454 and 168 ha, respectively, while maize in 2003 had been converted to become cassava and sugarcane in 2013 with about 661 and 1383 ha, respectively. These changeable areas of LULC types may be related to price, landform, labor, and availability of water.

Driving Factors on Location Preference of LULC Types

The significant driving factors and coefficients of the logistic regression model on LULC type location preference with the ROC is summarized in Table 6. The most important driving factor for all LULC types was population density while the common driving factor for field crops (cassava, maize, and sugarcane) included slope, annual rainfall, soil drainage, land use capability of watershed class, population density, and distance from road. Each driving factor plays an important role for land use allocation in each scenario. According to Pontius and Schneider (2001), the ROC values of the logistic regression model which varied between 0.651 and 0.929 can be accepted here.

LULC Simulation of 3 Different Scenarios and the Changes

The 3 different scenarios of LULC in 2023 are comparatively summarized in Table 7 and spatially displayed along with the LULC in

Table 6. Significant location factor of each LULC type and its coefficient

Driving forces	UR	PA	CA	MA	SU	PE	FO	WA	MI
Constant	-8.329	-60.9	2.225	15.047	-52.655	-16.829	5.456	-0.949	10.338
Elevation (X_1)	-	-	0.001	-0.003	-	0.008	-0.005	-0.031	-
Slope (X_2)	0.023	-0.48	-0.029	-0.01	-0.04	-0.018	0.049	-0.033	0.004
Aspect (X_3)	-0.001	0.007	-	-	0.001	-	0.001	-	-0.001
Distance from stream (X_4)	-	-	0.001	-0.001	-	-0.0002	-0.001	-0.004	-0.001
Annual rainfall (X_5)	-	0.049	-0.002	-0.01	0.054	0.009	-0.007	-	0.001
Soil drainage (X_6)	0.195	0.956	0.036	-0.108	0.14	-	-0.085	-0.933	-
Land use capacity (X_7)	-	2.864	0.337	-0.304	0.253	0.113	-0.575	0.94	-
Population density (X_8)	0.813	-4.88	0.297	-1.393	-2.178	-0.56	1.211	-2.31	-1.593
Distance from road (X_9)	-0.005	-	-0.001	-0.0004	-0.001	-0.001	0.002	0.001	-0.0004
Income (X_{10})	0.002	-0.01	-0.001	-	-0.008	-	0.002	0.005	0.001
ROC	0.82	0.929	0.681	0.627	0.808	0.703	0.894	0.893	0.651

2013 in Figure 3. From the results, the areas of each simulated LULC type in 2023 reflect the characteristics of each scenario. Under Scenario I, the increased LULC types were urban and built-up land, cassava, sugarcane, water body, and miscellaneous land while the decreased LULC types were maize, perennial tree/orchard, and forest land. The LULC change between 2013 and

2023 increased and decreased according to the annual change rate of the LULC type between 2003 and 2013. Conversely, the areas of the simulated LULC in 2023 in Scenarios II and III increased and decreased according to the policies' settings for each scenario. In the case of Scenario II, the areas of cassava and sugarcane as energy crops increased by about 26252 and 19613 ha,

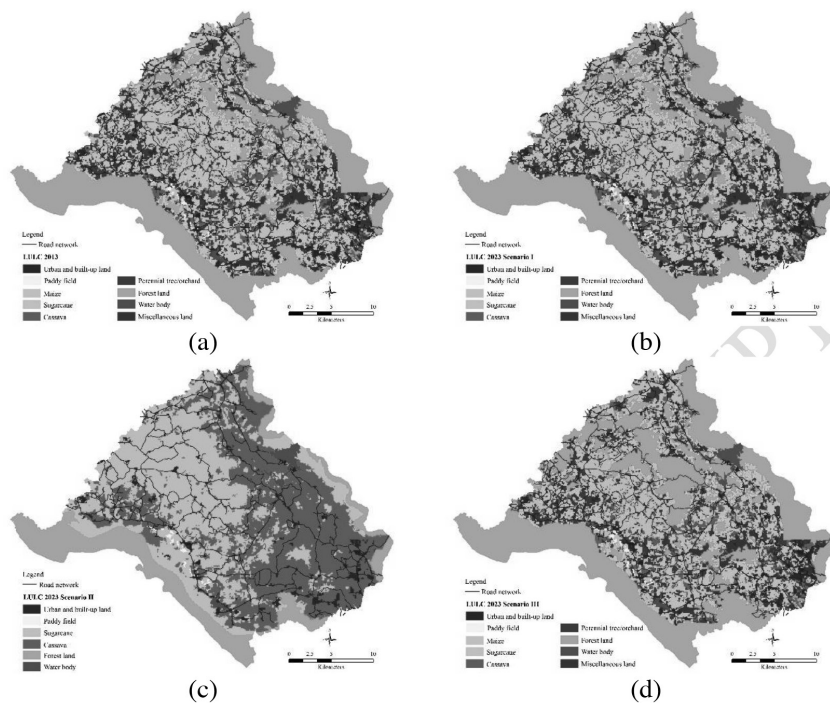


Figure 3. LULC distribution: (a) in 2013, (b) Scenario I, (c) Scenario II, and (d) Scenario III

Table 7. Comparison of LULC areas and the changes between 2013 and 2023

LULC data Year	LULC Types (in ha)								
	UR	PA	CA	MA	SU	PE	FO	WA	MI
LULC in 2013 by visual interpretation	2465	237	4446	18603	10786	6167	25970	1165	7326
LULC in 2023 of Scenario I	3136	237	4633	17593	12478	4843	25428	1213	7604
LULC in 2023 of Scenario II	2465	237	30698	-	30399	-	12199	1167	-
LULC in 2023 of Scenario III	2515	237	3815	15991	9225	5347	32601	1155	6279
Change by Scenario I	671	-	187	-1010	1692	-1324	-542	48	278
Change by Scenario II	-	-	26252	-18603	19613	-6167	-13771	2	-7326
Change by Scenario III	50	-	-631	-2612	-1561	-820	6631	-10	-1047

respectively, while the forest land decreased by 13771 ha. Likewise, in the case of Scenario III, the forest land increased from 25970 ha in 2013 to 32601 ha in 2023.

Soil Erosion Assessment and Its Impact due to LULC Change

Soil loss and its severity from the actual LULC in 2013 and the simulated LULC scenarios in 2023 is compared in Table 8 and displayed in

Figure 4. The most and least dominant soil loss severity classes were very low and very severe, respectively. Meanwhile, the moderate severity class from Scenario II was higher than the others and covered an area of 24.05%. The total soil loss of the actual LULC and the scenarios were 40,213,210, 40,856,714, 87,959,870, and 28,779,226 ton/ha/year, respectively. It can be observed that the total soil loss of Scenario II was higher than that of Scenarios I and III by

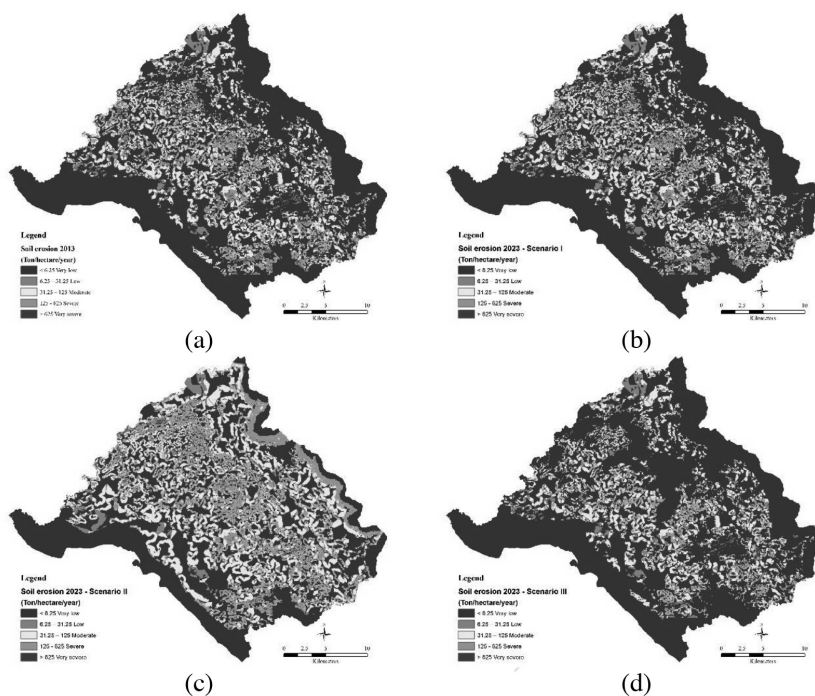


Figure 4. Distribution of soil loss and its severity from LULC: (a) in 2013, (b) in 2023 of Scenario I, (c) in 2023 of Scenario II, and (d) in 2023 of Scenario III

Table 8. Area of soil loss and its severity of actual LULC in 2013 and simulated LULC in 2023

Severity Class	Soil loss rate (t/ha/y)	LULC in 2013		LULC of Scenario I		LULC of Scenario II		LULC of Scenario III	
		ha	%	ha	%	ha	%	ha	%
Very low	≤ 6.25	52241	67.70	52391	67.89	38452	49.82	56838	73.66
Low	6.25 – 31.25	6380	8.27	6039	7.83	5364	6.95	5,311	6.88
Moderate	31.25 – 125	12018	15.57	12074	15.65	18556	24.05	10456	13.55
Severe	125 - 625	6402	8.30	6532	8.46	14248	18.46	4535	5.88
Very severe	> 625	124	0.16	129	0.17	545	0.71	25	0.03
Minimum value by cell (t/ha/y)			0		0		0		0
Maximum value by cell (t/ha/y)			1165.9		1165.9		1256.3		984.0
Mean value by cell (t/ha/y)			32.6		33.1		71.2		23.3
Total soil loss (t/ha/y)			40213210		40856,714		87959,870		28779226

about twofold and threefold, respectively, due to the decrease of forest land.

From the results, Scenario I creates soil loss due to LULC change by the increase of cassava and sugarcane and the decrease of perennial tree/orchard and forest land. Conversely, Scenario II generates more soil loss because areas of perennial tree/orchard, forest land, and miscellaneous land in 2013 were converted to become cassava and sugarcane in 2023. In the opposite direction, Scenario III creates less soil loss because areas of maize, sugarcane, and miscellaneous land were converted to become forest land with a total of about 6,631 ha between 2013 and 2023. In addition, the C and P factors, which are dynamic and relate to the LULC type, dictate the amount of soil erosion here because other factors, including the R, K, L and S factors, are applied as static factors. This finding can lead to the conclusion that LULC change among the scenarios creates both positive and negative effects on soil erosion. These characteristics agreed with the previous work of Ongsomwang and Thinley (2009) which assessed soil erosion between 2000 and 2008 and its change in the Upper Lam Phra Phloeng watershed. They stated that the higher erosion rate had increased by usage of land for agricultural purposes.

For the impact of LULC change on soil loss, the results of the linear regression analysis showed a positive relationship between the percentage of agricultural land in the watershed area (x) and the total soil loss in million ton/ha/year (y) with R^2 at 99.93% as:

$$y = 1.7113x - 48.114 \quad (10)$$

In contrast, the simple linear equation between the percentage of forest land in the watershed area (x) and the total soil loss in million ton/ha/year (y) showed a negative relationship with R^2 at 96.84% as:

$$y = -2.3335x + 122.18 \quad (11)$$

Water Yield Assessment and Its Impact due to LULC Change

The results of the water yield estimation of the actual LULC in 2013 and the simulated LULC scenarios in 2023 are comparatively summarized in Table 9. The minimum and maximum values of water yield by pixel were equal because the derived water yield (runoff depth) by pixel was directly related with the CN value, which is associated with the LULC and soil types' data and is commonly found in 2013 and 2023. However, the mean and total water yield values were different from each other. These results show the influence of LULC changes on water yield because soil types and rainfall values were here applied as static factors. Therefore, the total water yield (runoff depth) reflects the characteristics of the LULC types and their changes. Here, Scenario III provided the lowest water yield for surface runoff while Scenario II provided the highest water yield for surface runoff.

For the impact of LULC change on water yield, the result of linear regression analysis showed a positive relationship between the percentage of agricultural land in the watershed area (x) and the total water yield in million cu. m (y) with R^2 at 99.72% as:

Table 9. Basic statistic of water yield value by pixel of actual LULC in 2013 and simulated LULC in 2023

Water yield data	LULC in 2013	LULC in 2023		
		Scenario I	Scenario II	Scenario III
Minimum value by cell (mm)	0.16	0.16	0.16	0.16
Maximum value by cell (mm)	106.32	106.32	106.32	106.32
Mean value by cell (mm)	48.97	49.30	59.79	46.93
Total water yield (mm)	60460484.79	60856521.32	73813681.57	57945451.26
Total water yield (million cu. m)	37.79	38.04	46.13	36.22

$$y = 0.2905x + 22.983 \quad (12)$$

Conversely, the relationship between the percentage of forest land in the watershed area (x) and the total water yield in million cu. m (y) showed a negative relationship with R^2 at 95.63% as:

$$y = -0.3941x + 51.826 \quad (13)$$

These results imply that LULC change has an impact on total water yield for surface runoff. This finding agreed with the study of Ongsomwang and Koonto (2013) about the impact of land use change on runoff in which they stated that the most important factors on runoff quantity were land use types and land use changes.

Economic Value Assessment and Its Change due to LULC Change

The basic statistical data of economic value by pixel for the actual LULC data in 2013 and the 3 scenarios of LULC data in 2023 are summarized in Table 10. From the results, the minimum and maximum economic values by pixel from the actual LULC in 2013 and the simulated LULC in 2023 of the 3 scenarios were 0 Baht and 30737 Baht, respectively. These results were generated because the derived economic value was directly related to the future value of the LULC types. The forest land provided an economic value higher than the agricultural land. However, the mean and total economic values from LULC in 2013 and LULC in 2023 of the 3 scenarios were different from each other. The future highest economic value occurred in Scenario III while the future lowest

economic value occurred in Scenario II. These results show the influence of LULC changes on economic return.

For the effect of LULC change on the economic value, the result of the simple linear regression analysis showed a negative relationship between the percentage of agricultural land in the watershed area (x) and the total economic value in billion Thai baht (y) with R^2 at 91.69% as:

$$y = -0.1729x + 26.421 \quad (14)$$

In contrast, the simple linear regression between the percentage of forest land in the watershed area (x) and the total economic value in billion Thai baht (y) showed a positive relationship with R^2 at 98.72% as:

$$y = 0.2485x + 8.816 \quad (15)$$

From the results, it can be concluded that when the percentage of agricultural land increases, the total future value decreases. In the opposite direction, when the percentage of forest land increases, the total future value increases. This finding implies that LULC change has an effect on the economic value. However, it is necessary to consider the cost and benefit in practice, i.e. field crops require a short period of time (1-2 years) while forestry products need a long period of time (30-60 years).

Suitability Classification for Land use Allocation of Scenarios I, II, and III

The distribution of suitability classes (low, moderate, and high) for land use allocation of the 3 different scenarios is spatially displayed in Figure 5. Meanwhile, the area of the optimum

Table 10. Basic statistics of economic value by pixel of actual LULC in 2013 and simulated LULC in 2023

Economic value	LULC in 2013	LULC in 2023 (in ha)		
		Scenario I	Scenario II	Scenario III
Minimum (Thai baht)	3946	3946	4549	3946
Maximum (Thai baht)	30737	30737	30737	30737
Mean (Thai baht)	13759	13508	10468	15924
Total in Thai baht	16987053440	16677332110	12923638890	19660126530
Total in million Thai baht	16987.05	16677.33	12923.64	19660.13

allocated land use type with suitability classes of Scenarios I, II, and III is summarized in Table 11. Details of the optimum land use allocation for the 3 scenarios with suitability classes and the implementation time were separately described, as follows.

An Optimum Land use Allocation for Scenario I (Historical land use Evolution)

The spatial LULC change between the actual LULC in 2013 and the optimum land use allocation in 2023 of Scenario I with its suitability classes is summarized in Table 12

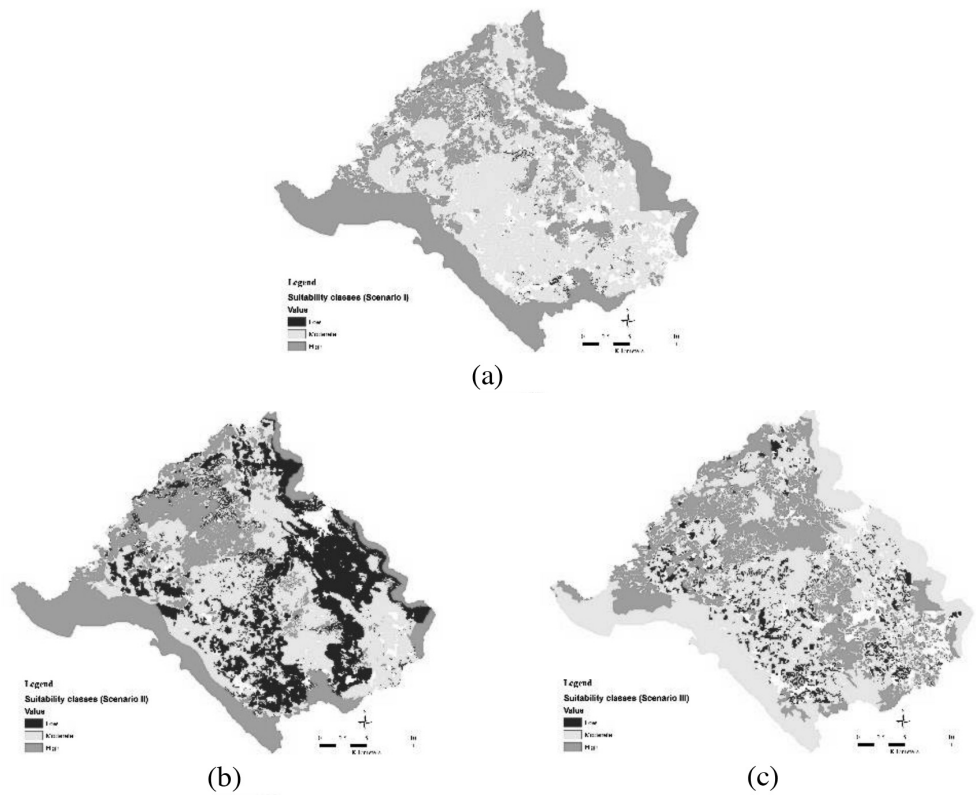


Figure 5. Suitability class for land use allocation: (a) Scenario I, (b) Scenario II, and (c) Scenario III

Table 11. Area of optimum land use type within the suitability classes in each scenario

Land use class	Scenario I			Scenario II			Scenario III		
	Area of suitability class (ha)			Area of suitability class (ha)			Area of suitability class (ha)		
	Low	Moderate	High	Low	Moderate	High	Low	Moderate	High
Paddy field	0	205	32	205	32	0	0	205	32
Cassava	18	3678	937	15921	14777	0	228	2195	1392
Maize	475	16297	821	0	0	0	1710	8971	5309
Sugarcane	24	7805	4649	3539	15808	11052	385	5785	3055
Perennial tree/orchard	3	3808	1033	0	0	12199	2852	1141	1354
Forest land	0	0	25428				0	22682	9920
Total	520	31793	32900	19665	30617	23251	5175	40979	21062
Percent	0.80	48.75	50.45	26.74	41.64	31.62	7.70	60.97	31.33

and displayed in Figure 6. Most of the optimum allocated agriculture land in 2023 situated in the moderate and high suitability classes came from the actual LULC in 2013 and covered areas of 31794 and 7472 ha, respectively, or about 98.69% of the total agriculture area. Meanwhile, the optimum allocated forest land covered an area of 25428 ha located in the high suitability

class. The changed allocated land use types between 2013 and 2023, which covered an area of 1880 ha or 2.88% of the total area with multiple suitability classes, play an important role in terms of environmental impact. They should be implemented in short, medium, and long periods of time according to their suitability classes to minimize the environmental impact.

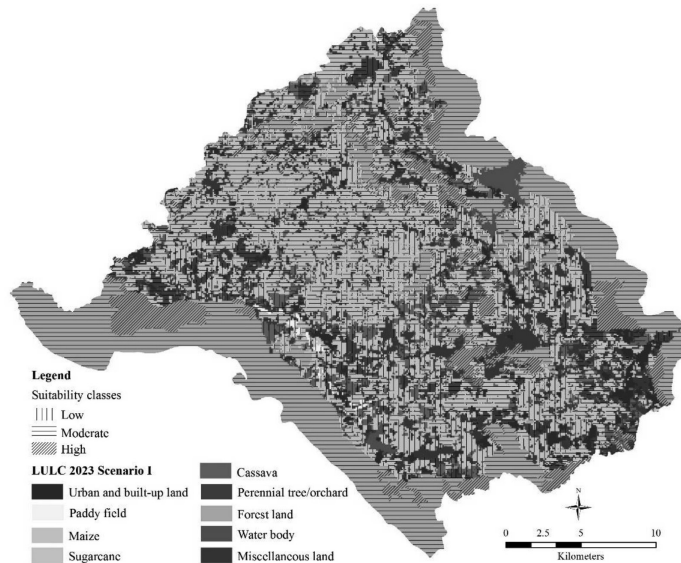


Figure 6. Optimum land use allocation distribution with suitability classes of Scenario I

Table 12. Spatial LULC change between actual LULC in 2013 and the optimum allocated land use in 2023 of Scenario I by overlay analysis

Actual LULC in 2013	Allocated Land use in 2023	Suitability class (in ha)				Spatial LULC change
		Low	Moderate	High	Total	
Paddy field	Paddy field	0	205	32	237	Non-change
Cassava	Cassava	18	3511	917	4446	Non-change
Maize	Cassava	0	55	3	58	Change
Forest	Cassava	0	34	7	41	Change
Miscellaneous land	Cassava	0	79	10	89	Change
Maize	Maize	475	16297	821	17593	Non-change
Sugarcane	Sugarcane	14	7046	3726	10786	Non-change
Maize	Sugarcane	4	422	498	924	Change
Forest land	Sugarcane	4	46	95	145	Change
Miscellaneous land	Sugarcane	2	291	330	623	Change
Perennial tree/orchard	Perennial tree/orchard	3	3808	1033	4844	Non-change
	Total of agricultural land	520	31794	7472	39786	
Forest land	Forest land	0	0	25428	25428	Non-change

An Optimum Land use Allocation for Scenario II (Energy Crop Extension)

The spatial LULC change between the actual LULC in 2013 and the optimum land use allocation in 2023 of Scenario II with its suitability classes is summarized in Table 13

and displayed in Figure 7. It revealed that the optimum allocated cassava areas in 2023 were situated in the low and moderate suitability classes and covered an area of 15922 and 14778 ha, respectively, while the optimum allocated sugarcane areas were located in the low,

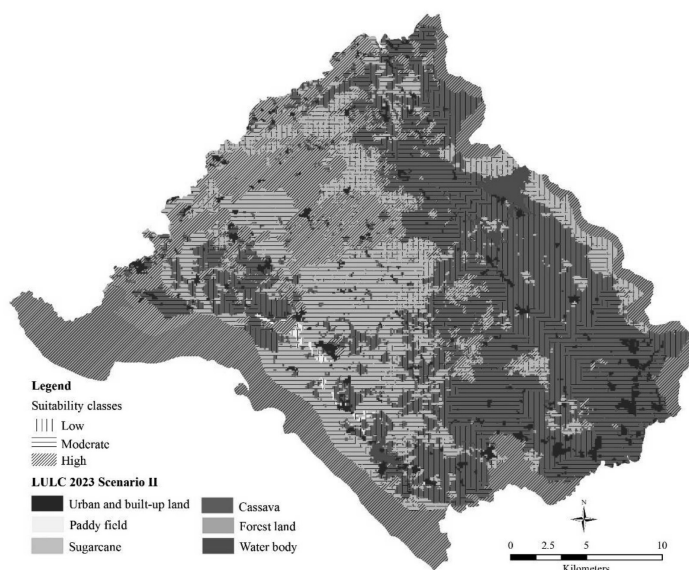


Figure 7. Optimum land use allocation distribution with suitability classes of Scenario II

Table 13. Spatial LULC change between actual LULC in 2013 and the optimum allocated land use in 2023 of Scenario II by overlay analysis

Actual LULC in 2013	Allocated land use in 2023	Suitability class (ha)				Remark
		Low	Moderate	High	Total	
Paddy field	Paddy field	205	32	0	237	Non-change
Cassava	Cassava	2265	2181	0	4446	Non-change
Maize	Cassava	5957	5561	0	11518	Change
Perennial tree	Cassava	1876	1937	0	3813	Change
Forest	Cassava	3782	2594	0	6376	Change
Miscellaneous land	Cassava	2042	2505	0	4547	Change
	Total area of cassava	15922	14778	0	30700	
Sugarcane	Sugarcane	363	6686	3737	10786	Non-change
Maize	Sugarcane	610	3147	3329	7086	Change
Perennial tree	Sugarcane	83	1242	1029	2354	Change
Forest land	Sugarcane	2178	3402	1814	7394	Change
Miscellaneous land	Sugarcane	306	1331	1143	2780	Change
	Total area of sugarcane	3540	15808	11052	30400	
Forest land	Forest land	0	0	12199	12199	Non-change

moderate, and high suitability classes and covered areas of 3539, 15808, and 11052 ha, respectively. At the same time, the forest land with restriction rules was allocated in the high suitability class and covered an area of 12199 ha.

The conversion of LULC types in 2013 to be cassava and sugarcane in 2023 were situated in multiple suitability classes and covered an area of 45868 ha or 75.07% of the total area of cassava and sugarcane (61100 ha). Herein,

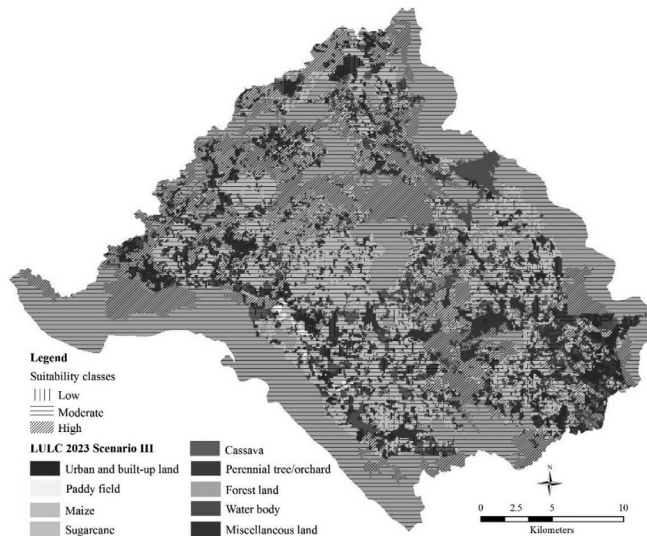


Figure 8. Optimum land use allocation distribution with suitability classes of Scenario III

Table 14. Spatial LULC change between actual LULC in 2013 and the optimum allocated land use in 2023 of Scenario III by overlay analysis

Actual LULC in 2013	Allocated Land use in 2023	Suitability class (in ha)				Remark
		Low	Moderate	High	Total	
Paddy field	Paddy field	0	205	32	237	Non-change
Cassava	Cassava	228	2195	1392	3815	Non-change
Maize	Maize	1525	8457	5160	15143	Non-change
Sugarcane	Maize	113	244	50	407	Change
Cassava	Maize	54	209	94	357	Change
Perennial tree/Orchard	Maize	17	61	6	84	Change
Sugarcane	Sugarcane	385	5785	3055	9225	Non-change
Perennial tree/Orchard	Perennial tree/Orchard	2852	1141	1354	5347	Non-change
Forest land	Forest land	0	19540	6429	25969	Non-change
Urban and built-up land	Forest land	0	179	137	316	Change
Maize	Forest land	0	1558	1902	3460	Change
Sugarcane	Forest land	0	525	507	1032	Change
Cassava	Forest land	0	82	182	264	Change
Perennial tree/Orchard	Forest land	0	224	356	580	Change
Miscellaneous land	Forest land	0	570	400	970	Change
Water body	Forest land	0	4	6	10	Change
	Total area of forest land	0	22682	9919	32601	

the optimum allocated cassava areas in 2023 with the low and moderate suitability classes which were converted from other LULC types in 2013 and covered areas of 13657 and 12597 ha, respectively, should be implemented in long and medium periods of time, respectively. Likewise, the optimum allocated sugarcane areas in 2023 with the low and moderate suitability classes, which were converted from other LULC types in 2013 and covered an area of 3177 and 9122 ha, respectively, should be implemented in the long and medium periods of time, respectively. In contrast, the optimum allocated sugarcane areas with the high suitability class, which were converted from other LULC types in 2013 and covered 7315 ha, can be implemented in a short period of time due to the minimal environmental impact.

An Optimum Land use Allocation for Scenario III (Forest Conservation and Prevention)

The spatial LULC change between the actual LULC in 2013 and the optimum land use allocation in 2023 of Scenario III with its suitability classes is summarized in Table 14 and displayed in Figure 8. It was found that the optimum allocated forest land in 2023 was situated in the moderate and high suitability classes and covered an area of 22682 and 9919 ha, respectively. Most of the optimum allocated forest land in 2023 in both suitability classes came from the existing forest land in 2013 and covered an area of 25970 ha or 79.66% of the total area of forest land in 2023. The rest of the optimum allocated forest land which covered an area of 6632 ha or 20.34% was converted from other LULC types in 2013. In this regard, the optimum allocated forest land with the moderate suitability class, which was converted from other land use types in 2013 and covered an area of 3,142 ha, should be carefully implemented in a medium period of time to minimize the environmental impact. Conversely, the optimum allocated forest lands with the high suitability class, which were converted from other land use types in 2013 and covered an area of 3490 ha, can be implemented in a short period of time.

Conclusions

The optimum land use allocation of 3 different scenarios in 2023 is here successfully implemented by integration of the CLUE-S model, USLE model, SWAT model with the SCS-CN method, and PV model. The spatial distribution of the allocated land use types with the suitability classes and the implementation time is displayed and quantified for each scenario. These findings can be used as a guideline for land use planners, developers, and decision makers for identifying the optimum land use allocation in the future.

In conclusion, it has been found that the integration of the LULC change model (CLUE-S model), hydrologic model (SWAT model and SCS-CN method), soil erosion model (USLE model), and economic value measures (PV model) can be efficiently used as a tool for optimum land use allocation by considering LULC changes and their impact on different scenarios.

References

- Bank for Agriculture and Agricultural Cooperatives. (2014). Personal Loan Rate. Available from: http://www.baac.or.th/content-rate.php?content_group_sub=2.
- Bank of Thailand. (2012). Ethanol Annual Report in 2012. Klangnanavittaya Press, Khon Kaen, Thailand, 122p.
- Boardman, J. and Poesen, J. (2006). Soil Erosion in Europe. John Wiley & Sons, Chichester, UK, 855p.
- Charupatt, T. and Mongkolsawat, C. (2003). Land evaluation for economic crops of Lam Phra Phloeng Watershed in Thailand using GIS modeling. *Asian J. Geo.*, 3(3):89-98.
- Castella, J.C., Kamb, S.P., Quangc, D.D., Verburg, P.H., and Hoanh, C.T. (2007). Combining top-down and bottom-up modeling approaches of land use/cover change to support public policies: Application to sustainable management of natural resources in northern Vietnam. *Land Use Policy*, 24(3): 531-545.
- El-Khoury, A., Seidou, O., Lapen, D.R., Sunohara, M., Zhenyang, Q., Mohammadian, M., and Daneshfar, B. (2014). Prediction of land-use conversions for use in watershed scale hydrological modeling: a Canadian case study. *Can. Geogr.*, 58(4):1-18.
- Fitzpatrick-Lins, K. (1981). Comparison of sampling procedures and data analysis for a land-use and land-cover map. *Photogramm. Eng. Rem. S.*, 47(3): 343-351.

- Geist, H., McConnell, W., Lambin, E.W., Moran, M., Alves, D., and Rudel, T. (2006). Causes and trajectories of land-use/cover change. In: *Land-Use and Land-Cover Change: Local Processes and Global Impacts*. Lambin, E.F. and Geist, H., (eds). Stürtz AG, Würzburg, Germany, p. 1-8.
- Githu, F., Mutua, F., and Bauwens, W. (2009). Estimating the impacts of land-cover change on runoff using the soil and water assessment tool (SWAT): Case study of Nzoia catchment, Kenya. *Hydrolog. Sci. J.*, 54(5):899-908.
- Graveland, C., Bouwman, A.F., de Vries, B., Eickhout, V., and Strengers, B.J. (2002). Projections of multi-gas emissions and carbon sinks, and marginal abatement cost functions modeling for land use related sources. RIVM report 461502026. Rijksinstituut voor Volksgezondheid en Milieu RIVM, Bilthoven, Netherlands, 92p.
- Helming, K., Tscherning, K., König, B., Sieber, S., Wiggering, H., Kuhlman, T., Wascher, D., Pérez-Soba, M., Smeets, P., Tabbush, P., Dilly, O., Hüttl, R., and Bach, H. (2008). Sustainability impact assessment of land use changes in European regions—the SENSOR approach. In: *Sustainability Impact Assessment of Land Use Changes*. Helming, K., Pérez-Soba, M., and Tabbush, P., (eds). Springer Publishing, NY, USA, p. 77-105.
- IPCC. (2001). *Climate Change 2001: the Scientific Basis. Contributions of Working Group 1 to the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC)*. Cambridge University Press, Cambridge, UK, 83p.
- Lambin, E. F., Geist, H., and Rindfuss, R.R. (2006). Introduction: local processes with global impacts. In: *Land-Use and Land-Cover Change: Local Processes and Global Impacts*. Lambin, E.F. and Geist, H., (eds). Stürtz AG, Würzburg, Germany, p. 1-8.
- Malczewski, J. (1999). *GIS and Multi-criteria Decision Analysis*. John Wiley & Sons, New York, NY, USA, 392p.
- Marketing Organization for Farmers. (2014). *Agriculture data: Mango*. Available from: <http://www.mof.or.th/web/agriculture.php?id=58&cat=25>.
- Metzger, M.J., Rounsevell, M.D.A., Acosta-Michlik, L., Leemans, R., and Schroter, D. (2006). The vulnerability of ecosystem services to land use change. *Agr. Ecosyst. Environ.*, 114(1):69-85.
- National Economic and Social Development Board. (2011). *The 11th National Economic and Social Development Plan (2012-2016)*. Office of the Prime Minister, Bangkok, Thailand.
- Neitsch, S.L., Arnold, J.G., Kiniry, J.R., and Williams, J.R. (2011). *Soil and Water Assessment Tool. Theoretical Documentation. Version 2009*. Texas Water Resources Institute, Texas A&M University, College Station, TX, USA, 618p.
- OAE. (2011). *Annual Report and Trend in Agricultural Production in 2011*. Office of Agricultural Economics, Bangkok, Thailand, 164p.
- OAE. (2012). *Annual Report and Trend in Agricultural Production in 2012*. Office of Agricultural Economics, Bangkok, Thailand, 164p.
- OAE. (2013). *Annual Report and Trend in Agricultural Production in 2013*. Office of Agricultural Economics, Bangkok, Thailand, 162p.
- Ongsomwang, S. and Koonto, S. (2013). Estimating water runoff from CA-Markov predicting land use using SWAT model: Case study of Huay Tunglung watershed in the Mun Basin. *J. Remote Sensing GIS Assoc. Thailand*, 14(1):1-7.
- Ongsomwang, S. and Thinley, U. (2009). Spatial modeling for soil erosion assessment in Upper Lam Phra Phloeng Watershed, Nakhon Ratchasima, Thailand. *Suranaree J. Sci. Technol.*, 16(3): 253-262.
- Orekan, V.O.A. (2007). Implementation of the local land-use and land-cover change model CLUE-S for Central Benin by using socio-economic and remote sensing data, [Ph.D. thesis]. Universität Bonn, Bonn, Germany, 204p.
- Overmars, K.P., Verburg, P.H., and Veldkamp, T. (2007). Comparison of a deductive and an inductive approach to specify land suitability in a spatially explicit land use model. *Land Use Policy*, 24(3):584-599.
- Pontius, R. G. and Schneider, L. C. (2001). Land-use change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA. *Agr. Ecosyst. Environ.*, 85:239-248.
- Poschlod, P., Bakker, J.P., and Kahmen, S. (2005). Changing land use and its impact on biodiversity. *Basic Appl. Ecol.*, 6(2):93-98.
- Rossiter, D.G. (1995). Economic land evaluation: why and how. *Soil Use Manage.*, 11:132-140.
- Steffen, W., Sanderson, A., Tyson, P., Jäger, J., Matson, P., Moore III, B., Oldfield, F., Richardson, K., Schellnhuber, J.H., Turner II, B.L., and Wasson, R. (2005). *Global Change and the Earth System: a Planet Under Pressure*. Springer, Berlin, Germany, 336p.
- Trisurat, Y., Alkemade, R., and Verburg, P. (2010). Projecting land use change and its consequences for biodiversity in Northern Thailand. *Environ. Manage.*, 45:626-639.
- Trisurat, Y., Bhumpakphan, N., Kalyawongsa, S., Boonsermsuk, S., Wisupakan, K., and Dechyosdee, U. (2014). Predicting land-use and land-cover patterns driven by different scenarios in the Emerald Triangle Protected Forests Complex. *Thai J. Forestry*, 33(3):56-74.
- USDA Natural Resources Conservation Service. (1972). *National Engineering Handbook, Section 4: Hydrology*. US Department of Agriculture, Washington, DC, USA.
- Veldkamp, A. and Fresco, L.O. (1996). CLUE: A

- conceptual model to study the conversion of land use and its effects. *Ecol. Model.*, 85(2-3): 253-270.
- Verburg, P.H. (2010). The CLUE model Hands-on exercises. Institute for Environmental Studies, Vrije Universiteit Amsterdam, Amsterdam, Netherlands, 53p.
- Verburg, P.H. and Veldkamp, A. (2001). The role of spatially explicit models in land-use change research: a case study for cropping patterns in China. *Agr. Ecosyst. Environ.*, 85(1-3):177-190.
- Verburg, P.H. and Veldkamp, A. (2004). Projecting land use transitions at forest fringes in the Philippines at two spatial scales. *Landscape Ecol.*, 19(1):77-98.
- Verburg, P.H., Van de Steeg, J., and Schulp, N. (2005). Manual for the CLUE-Kenya application. Department of Environmental Sciences, Wageningen University, Wageningen, Netherlands, 54p.
- Verburg, P.H., Eickhout, B., and Meijl, H.V. (2008). A multi-scale, multi-model approach for analyzing the future dynamics of European land use. *Ann. Regional Sci.*, 42(1):57-77.
- Verburg, P.H., De Koning, G.H.J., Kok, K., Veldkamp, A., and Bouma, J. (1999). A spatial explicit allocation procedure for modeling the pattern of land use change based upon actual land use. *Ecol. Model.*, 116(1):45-61.
- Verburg, P.H., Schot, P.P., Dijst, M.J., and Veldkamp, A. (2004). Land use change modeling: current practice and research priorities. *Geo J.*, 61(4): 309-324.
- Verburg, P.H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., and Mastura, S.S. (2002). Modeling the spatial dynamics of regional land use: the CLUE-S model. *Environ. Manage.*, 30(3):391-405.
- Wischmeier, W.H. and Smith, D.D. (1978). Predicting Rainfall Erosion Losses - A Guide to Conservation Planning. Agriculture Handbook Number 537. Agricultural Research Service, USDA, Washington, DC, USA, 69p.
- Wittawatutikul, P. and Jirasuktaveekul, W. (2005). The technique for court witness: In case of compensation from deforestation. Technical Report 9/2548. Department of National Parks, Wildlife and Plant Conservation, Bangkok, Thailand.
- Young, J., Rinner, C., and Patychuk, D. (2010). The effect of standardization in multi-criteria decision analysis on health policy outcomes. In: *Advances in Intelligent Decision Technologies*. Phillips-Wren, G., Jain, L.C., Nakamatsu, K., and Howlett, R.J., (eds). Springer-Verlag, Berlin, Germany, p. 299-307.
- Zheng, H.W., Shen, G.Q., Wang, H., and Hong, J. (2015). Simulating land use change in urban renewal areas: A case study in Hong Kong. *Habitat Int.*, 46:23-34.
- Zheng, X.O., Zhao, L., Xiang, W.N., Li, N., Lv, L.N., and Yang, X. (2012). A coupled model for simulating spatio-temporal dynamics of land-use change: A case study in Changqing, Jinan, China. *Landscape Urban Plan.*, 106(1):51-61.
- Zhou, F., Xu, Y., Chen, Y., Xu, C.-Y., Gao, Y., and Du, Y. (2013). Hydrological response to urbanization at different spatio-temporal scales simulated by coupling of CLUE-S and the SWAT model in the Yangtze River Delta region. *J. Hydrol.*, 485:113-125.