The Impacts of Land Use and Land Cover Change on Ecosystem Service Values at Lam Takhong Watershed, Thailand

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Abstract

Understanding the driving factors of land use and land cover (LULC) change, predicting LULC change, and assessing the effects of LULC change on future ecosystem service values are crucial for land managers and land use planners to mitigate their impacts. This research aims to identify driving factors on LULC change and apply them to predict LULC changes using the CLUE-S model for evaluating ecosystem service value and change in the Lam Takhong watershed. As a result, the most significant driving factors on LULC change were elevation, annual rainfall, and irrigation area. The predicted LULC data between 2024 and 2039 indicated an increase in urban and built-up areas, sugarcane, perennial trees and orchards, other agricultural areas, water bodies, and unused land. Conversely, there were decreases in paddy fields, corn, cassava, forest land, rangeland, and marsh and swamp. The total ecosystem service value is expected to decrease continuously between 2023 and 2039. By considering ecosystem service value by its function, gas regulation, climate regulation, soil formation, biodiversity protection, food production, and raw material functions are expected to decrease marginally from 2023 to 2039. Still, waste treatment, water supply, recreation and culture functions will be slightly increasing in the future. In conclusion, LULC change affects the value of ecosystem services in each category and function within the Lam Takhong watershed, particularly through the conversion of paddy fields and forest land into other LULC types in the future. Therefore, the Government should establish specific policies or interventions to prevent land use and land cover change in the Lam Takhong watershed.

Keywords: Binary logistic regression analysis, CLUE-S model, Ecosystem service value, Lam Takhong watershed, Simple benefit transfer method

Introduction

Land use and land cover (LULC) changes have been among the most critical observable changes around the World. They are increasingly becoming a global concern due to their impact on the local, regional and global environments (Veldkamp and Lambin, 2001; Tolessa et al., 2017; Karki et al., 2018). The LULC change reflects between human activities and the transformation of the Earth's surface. Especially, increasing anthropogenic activities, such as population growth, urbanization, and deforestation, are significant elements of environmental change (Meyer and Turner, 1996; Roy and Roy, 2010). Understanding historical, current and future LULC status and change information is critical for city planners, land managers, and resource managers in any rapidly changing environment (Munthali et al., 2020). Thus, the CLUS-S model, combined with a Markov Chain model, is selected in this study to predict LULC change. The CLUS-S model with the Markov Chain model has been applied in land use studies at national and international levels, such as Ongsomwang and Iamchuen, 2015; Ongsomwang and Boonchoo, 2016; Zhou et al., 2016; Zare et al., 2017; Liu et al., 2017; Srichaichana et al., 2019; Sun et al., 2019; Kulsoontornrat and Ongsomwang, 2021; Puangkaew and Ongsomwang, 2021; and Phinyoyang and Ongsomwang, 2021.

Meanwhile, the evaluation of ecosystem services in specific areas has been conducted at national and international levels after the global initiative in 1999 by the Millennium Ecosystem Assessment (MEA), such as Leh et al. (2013); Kindu et al., 2016; Mamat et al., 2018; Ongsomwang et al., 2019; Srichaichana et. al., 2019; Kulsoontornrat and Ongsomwang, 2021; Phinyoyang and Ongsomwang, 2021; Shuangao et al., 2021; Karki et al., 2022; and Mamat et al., 2024. Every ecosystem has a different capacity to provide ecosystem services, depending on its structure and condition (Nelson et al., 2009). The change in LULC would affect human well-being (Millennium Ecosystem Assessment, 2005).

The Lam Takhong watershed is a vital water resource for Nakhon Ratchasima Province and the Northeastern region of Thailand. Over the past few decades, rapid changes in land use and land cover, driven by human activities such as urban expansion, road construction, and deforestation, have significantly altered the landscape. These changes have impacted on the value of ecosystem services within the watershed.

Therefore, knowing the driving factors of LULC change and predicting LULC change in the future is very important. Moreover, the effects of LULC change on ecosystem service values are essential information for land managers and land use planners to mitigate such impacts. Research objectives are (1) to identify the driving factors of LULC change using binary logistic regression analysis, (2) to predict LULC changes from 2024 to 2039 using the CLUE-S model, and (3) to evaluate the ecosystem service value and changes.

Materials and Methods

Study area

The study area is the Lam Takhong watershed covering an area of approximately 3,353 sq. km (Figure 1). For topographic characteristics, the terrain of the study area can be divided into various zones based on its landform. In the northeast area, it is characterized by flat areas and gently undulating terrain; most land use types in this zone are paddy fields and field crops. While the eastern part of the study area is characterized by undulating and rolling terrain, this zone is mainly covered by field crops and forest land. At the same time, the hilly zone in the south and the mountainous areas in the southeast are covered by forest land. The main river in the Lamtakhong watershed is the Lamtakhong River, which measures approximately 220 km in length and flows from west to east within the watershed (Ruamkaew, 2011).

According to the 2023 land use data from the LDD, the main land use types in the watershed were as follows: agricultural land, approximately 54.83%; forest land, approximately 18.29%; urban and built-up area, approximately 17.89%; water body, approximately 2.35%; and miscellaneous land, approximately 5.67%.

Apan et al. (2000) mentioned that the Lam Takhong watershed was one of the sensitive areas affected by LULC change, improper land use practices, lack of appropriate land use planning and the measure for sustainable development adversely affects many natural processes that lead to terrestrial biodiversity change, habitat destruction, soil erosion, land degradation, and water pollution. It is identified as a significant case of environmental degradation.

Additionally, LULC in the Lam Takhong watershed has undergone rapid changes over the past two decades due to human activities such as building, road construction, deforestation, and numerous other anthropogenic activities. As a result, there has been an increased demand for land and modified in the status of LULC over time (Ruamkaew, 2011).

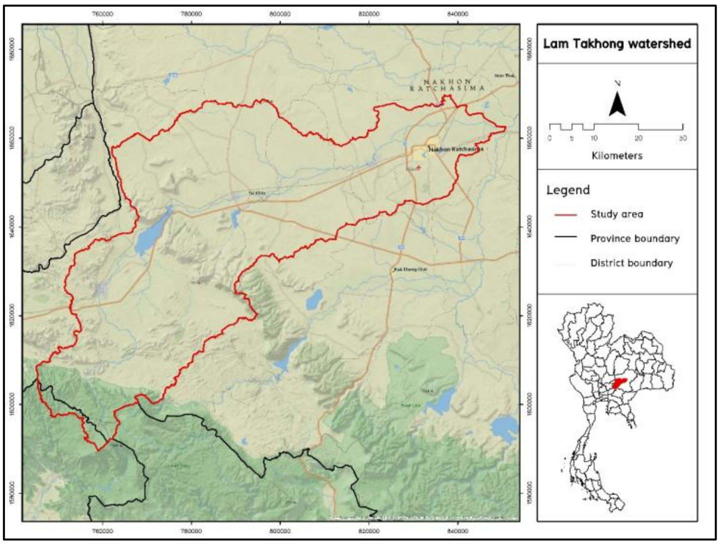


Figure 1 Study area: Lam Takhong watershed

Methods

The research methodology consists of four components, including (1) data collection and preparation, (2) Identification of driving factors on LULC change, (3) LULC prediction using the CLUE-S model and (4) evaluation of ecosystem service value and change. A brief description of each component is provided below.

1. Data collection and preparation

The relevant input data for the study were collected and prepared in advance, summarized in Table 1. Herein, land use datasets of LDD in 2015, 2019 and 2023 were reclassified into twelve LULC classes, including

(1) urban and built-up area, (2) paddy field, (3) corn, (4) sugarcane, (5) cassava, (6) perennial trees and orchards, (7) other agriculture, (8) forest land, (9) water body, (10) rangeland, (11) marsh and swamp, and (12) unused land for LULC prediction under the CLUE-S model by modification standard land use classification system of land Development Department (LDD). Later, the reclassified twelve LULC classes were reclassified into eight ecosystem service LULC types, including (1) urban and built-up area, (2) paddy field and (3) field crop, (4) forest land, (5) water body, (6) rangeland, (7) marsh and swamp, and (8) unused land according to a coefficient of ecosystem service value, as suggested by Mamat, Halik, and Rouzi (2018). See details of the reclassification criteria for LULC and ecosystem LULC type based on LDD's standard land use classification system in Table 2. To verify errors in the LULC data, the reclassified LULC types in 2023 were assessed for thematic accuracy using 757 stratified random points based on reference data from high-resolution Google Earth images.

Meanwhile, driving factors influencing LULC change, as reviewed by Phinyoyang (2021) and Allan et al. (2022), were collected and normalized to identify significant factors using binary logistic regression analysis in the next component.

Table 1 Lists data collection and preparation for data analysis in the study

Data Collection	Data Preparation	Source
	Basic data	
Land use in 2015, 2019, and 2023	Reclassify using the Reclassify function of ESRI ArcGIS	LDD
Sub-district boundary	-	LDD
Watershed boundary	-	ONWR
	Driving factor on LULC change	
Elevation	Extract from SRTM DEM	USGS
Slope	Extract from SRTM DEM using the Slope function of ESRI ArcGIS	USGS
Average annual rainfall	Interpolate average annual rainfall data (1975-2019) and 1975-2023) using the IDW function of ESRI ArcGIS.	TMD
Population density	Population density at sub-district level in 2019 and 2023	DOPA
Income per capita	Income per capita at sub-district level in 2019 and 2023	CDD
Irrigation area	Reclassify using the Reclassify function of ESRI ArcGIS	RID
Road network	Calculate distance to the road network in 2019 and 2023 using Euclidean Distance function of ESRI ArcGIS	NOSTRA
Railway	Calculate the distance to the railway using Euclidean Distance function of ESRI ArcGIS	NOSTRA
Urban area	Calculate distance to existing urban areas in 2019 and 2023 using Euclidean Distance function of ESRI ArcGIS	LDD
Steam and Waterbody	Calculate the distance to stream and waterbody in 2019 and 2023 using the Euclidean Distance function of ESRI ArcGIS.	LDD & NOSTRA

Note: LDD: Land Development Department; ONWR: Office of the National Water Resources; USGS: US Geological Surveys; TMD: Thai Meteorological Department; DOPA: Department of Provincial Administration; CDD: Community Development Department; RID: Royal Irrigation Department.

Table 2 Reclassification criteria for LULC and ES LULC type based on LDD's standard land use classification system

LULC type	Remark #1: LDD Land use level and code	ESV LULC type	Remark #2: Reclassified LULC type
1. Urban and built-up areas	Level 1: U	1. Urban and built-up areas (UB)	Urban and built-up area
2. Paddy field	Level 2: A1	2. Paddy field (PD)	Paddy field
3. Corn	Level 3: A202	3. Field crop (FC)	Corn, sugarcane, cassava, and other agriculture
4. Sugarcane	Level 3: A203	4. Forest land (FL)	Forest land, perennial trees and orchards
5. Cassava	Level 3: A204	5. Water body (WB)	Water body
6. Perennial trees and orchards	Level 2: A3 and A4	6. Rangeland (RL)	Rangeland
7. Other agriculture	Level 1: A, excluding A1, A202, A203, A204, A3 and A4	7. Marsh and swamp (MS)	Marsh and swamp
8. Forest land	Level 1: F	8. Unused land (UN)	Unused land
9. Water body	Level 1: W		
10. Rangeland	Level 2: M1		
11. Marsh and swamp	Level 2: M2		
12. Unused land	Level 1: M, excluding M1 and M2		

2. Identification of driving factors on LULC change

Since the measured units of driving factors are different, the selected driving factors on LULC change were first normalized using the benefit criterion (Malczewski, 1999) as:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

After that, the normalized driving factors of LULC change are used to examine multicollinearity using tolerance (TOL) or variance inflation factor (VIF) values to prevent correlation among the driving factors. The general rule of thumb is that the TOL values should be more than 0.10, or the VIF values should not exceed 10. The TOL and VIF value is calculated (Rogerson, 2006; O'brien, 2007) as:

$$TOL = 1 - r^2 \quad (2)$$

$$VIF = \frac{1}{1 - r^2} \quad (3)$$

Where, r^2 is associated with the regression of the independent variable on all other independent variables.

Finally, driving factors without multicollinearity problems were applied to identify significant driving factors on LULC change by binary logistics regression analysis. In this study, multiple linear regression of binary logistic regression analysis was conducted with Python programming. The significant identified driving factors were further applied for LULC prediction with the local parameters under the CLUE-S model.

3. LULC prediction using the CLUE-S model

Two significant steps under this component were undertaken for LULC prediction using the CLUE-S model: (1) validation of the CLUE-S model parameter for LULC prediction and (2) LULC prediction from 2024 to 2039 (Figure 2).

Validation of the CLUE-S model parameter for LULC prediction

The basic parameters of the CLUE-S model, which include (1) identified driving factors for LULC allocation, (2) elasticity value, (3) LULC conversion matrix, and (4) land requirement of each LULC type in 2023, which were extracted using the Markov Chain model, are applied to predict LULC in 2023 using the CLUE-S model (Verburg, 2010). After that, the predicted LULC in 2023 was compared with the reclassified LULC data in 2023 of LDD using wall-to-wall thematic accuracy assessment, with overall accuracy and Kappa hat coefficient values. The thresholding values of overall accuracy and Kappa hat coefficient values for validation CLUE-S model parameter for LULC prediction are equal to or more than 80%. The identified significant driving factors, elasticity value, and LULC conversion matrix, which are defined as local parameters for LULC prediction under the CLUE-S model, will be updated to predict LULC data between 2024 and 2039 under the CLUE-S model in the next step.

LULC prediction between 2024 and 2039

The updated driving factors, elasticity values, LULC conversion matrix, and new land requirements of each LULC type between 2024 and 2039, which were extracted using the Markov Chain model based on LULC data from 2015 and 2023, were applied to predict LULC data from 2024 to 2039 under the CLUE-S model. In this study, long-term time series of predicted LULC data are selected to identify the trends in ecosystem service values and changes in the watershed resulting from LULC changes.

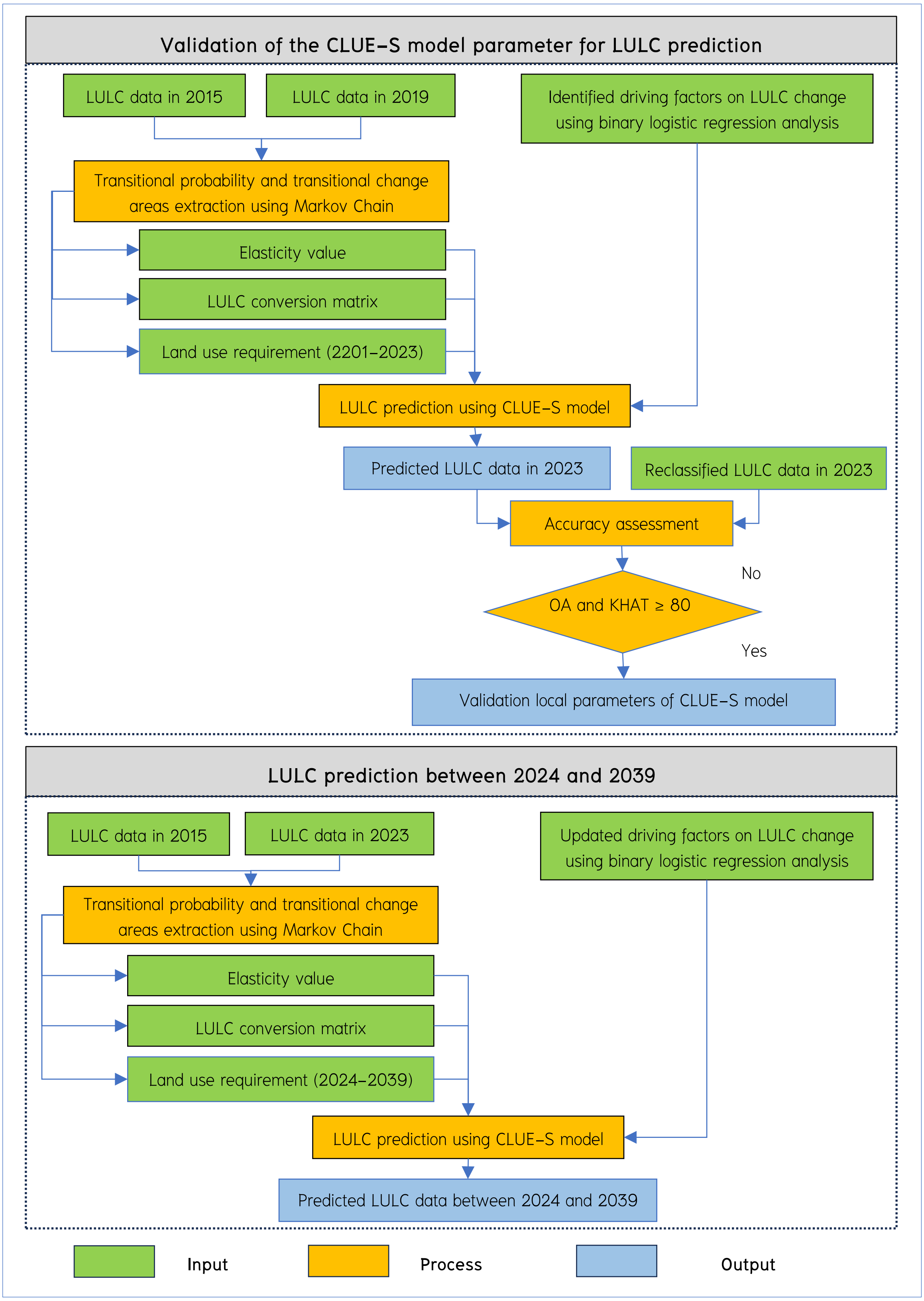


Figure 2 Schematic workflow of optimum local parameter for LULC prediction and LULC prediction of two periods using the CLUE-S model

4. Evaluation of ecosystem service value and change

The reclassified LULC in 2023 and predicted LULC data between 2024 and 2039 were first applied to evaluate ecosystem service values (ESV) using a simple benefit transfer method (Costanza et al., 1997) according to the coefficient value for different LULC types (Table 3) as:

$$ESV = \sum(A_k \times VC_k) \quad (4)$$

Where ESV is estimated ecosystem service value; A_k is an area of land use category k; VC_k is the value coefficient for land use category k (Su et al., 2012).

After that, the time-series ecosystem service value changes due to LULC change were assessed using the ecological service change index (ESCI) (Mansoor et al., 2013) as:

$$ESCI_x = \left[\frac{ES_{FutureX_i} - ES_{BaseyearX_j}}{ES_{BaseyearX_j}}\right] \quad (5)$$

Where, $ESCI_x$ is the ecosystem services change index of service X, $ES_{FutureX_i}$ and $ES_{BaseyearX_j}$ are the current and predicted ecosystem service state values of service X at times j and i, respectively.

Table 3 Coefficient value of different LULC types for ESV evaluation

		Coefficient value for different ES LULC types (million Baht/sq km/year)								
Ecosystem services category	Ecosystem services function	Urban and built-up area (UB)	Paddy field (PD)	Field crop (FC)	Forest land (FL)	Water body (WB)	Rangeland (RL)	Marsh and swamp (MS)	Unused land (UL)	Total
1. Regulating services	1.1 Gas regulation	0.00	0.26	0.26	1.03	0.00	0.36	0.92	0.01	**2.83**
	1.2 Climate regulation	0.00	0.46	0.46	0.97	0.24	0.37	8.75	0.03	**11.27**
	1.3 Waste treatment	0.00	0.84	0.84	0.41	9.32	0.31	9.31	0.06	**21.08**
2. Supporting services	2.1 Soil formation	0.00	0.75	0.75	0.95	0.01	0.53	0.88	0.04	**3.90**
	2.2 Biodiversity protection	0.00	0.36	0.36	1.07	1.27	0.45	1.28	0.09	**4.89**
3. Provisioning services	3.1 Water supply	0.00	0.31	0.31	0.97	10.44	0.36	7.93	0.02	**20.34**
	3.2 Food production	0.00	0.51	0.51	0.08	0.05	0.10	0.15	0.00	**1.41**
	3.3 Raw materials	0.00	0.05	0.05	0.71	0.01	0.09	0.04	0.01	**0.95**
4. Cultural services	4.1 Recreation and culture	0.04	0.01	0.01	0.49	2.22	0.21	2.84	0.06	**5.87**
	Total	**0.04**	**3.54**	**3.54**	**6.68**	**23.55**	**2.77**	**32.10**	**0.33**	**72.54**

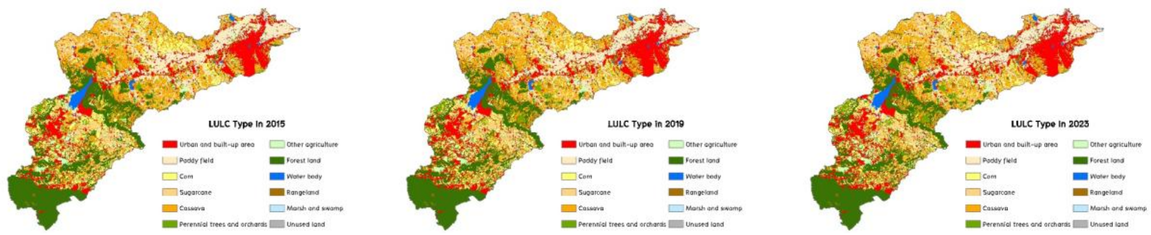
Source: Modified from Mamat et al., 2018.

Results

1. LULC data in 2015, 2019 and 2023

The results of the reclassified LULC in 2015, 2019, and 2023, based on the land use data from LDD, are presented in Figure 3 and Table 4. As a result, urban and built-up areas, sugarcane, perennial trees and orchards, water bodies, and unused land tend to increase in the future. In contrast, paddy fields, cassava, forest land, and rangeland tend to decrease in the future. Meanwhile, corn, other agriculture, and marsh and swamps are fluctuating.

According to the thematic accuracy assessment of the reclassified LULC data in 2023, the overall accuracy and Kappa hat coefficient values were 89.04% and 87.56%, respectively. As a result, the reclassified LULC map from 2023, with twelve classes, can be accepted as suggested by Anderson et al. (1976). A Kappa hat coefficient value of over 80% represents strong accuracy between the reclassified and reference data (Fitzpatrick-Lins, 1981; Rosenfield and Fitzpatrick-Lins, 1986).



(a) (b) (c)

Figure 3 Spatial distribution of LULC data in: (a) 2015, (b) 2019 and (c) 2023

Table 4 Area and percentages of LULC data in 2015, 2019 and 2023

LULC type	2015		2019		2023	
	Sq. km	Percentage	Sq. km	Percentage	Sq. km	Percentage
Urban and built-up area	505.15	15.07	571.75	17.05	599.64	17.89
Paddy field	477.81	14.25	399.65	11.92	388.42	11.59
Corn	267.56	7.98	295.23	8.81	267.11	7.97
Sugarcane	217.03	6.47	276.47	8.25	281.82	8.41
Cassava	649.37	19.37	590.88	17.62	574.98	17.15
Perennial trees and orchards	162.58	4.85	184.51	5.50	190.18	5.67
Other agriculture	133.20	3.97	117.76	3.51	135.31	4.04
Forest land	646.86	19.29	614.48	18.33	613.12	18.29
Water body	67.66	2.02	72.78	2.17	78.62	2.35
Rangeland	199.51	5.95	198.63	5.92	191.05	5.70
Marsh and swamp	14.32	0.43	11.08	0.33	12.71	0.38
Unused land	11.60	0.35	19.42	0.58	19.69	0.59
Total	**3,352.64**	**100**	**3,352.64**	**100**	**3,352.64**	**100**

2. Driving factors on LULC change

The spatial driving factors on LULC change after normalization are displayed in Figure 4. These factors are selectively used to validate the CLUE-S model parameter for LULC prediction and LULC prediction between 2024 and 2039.

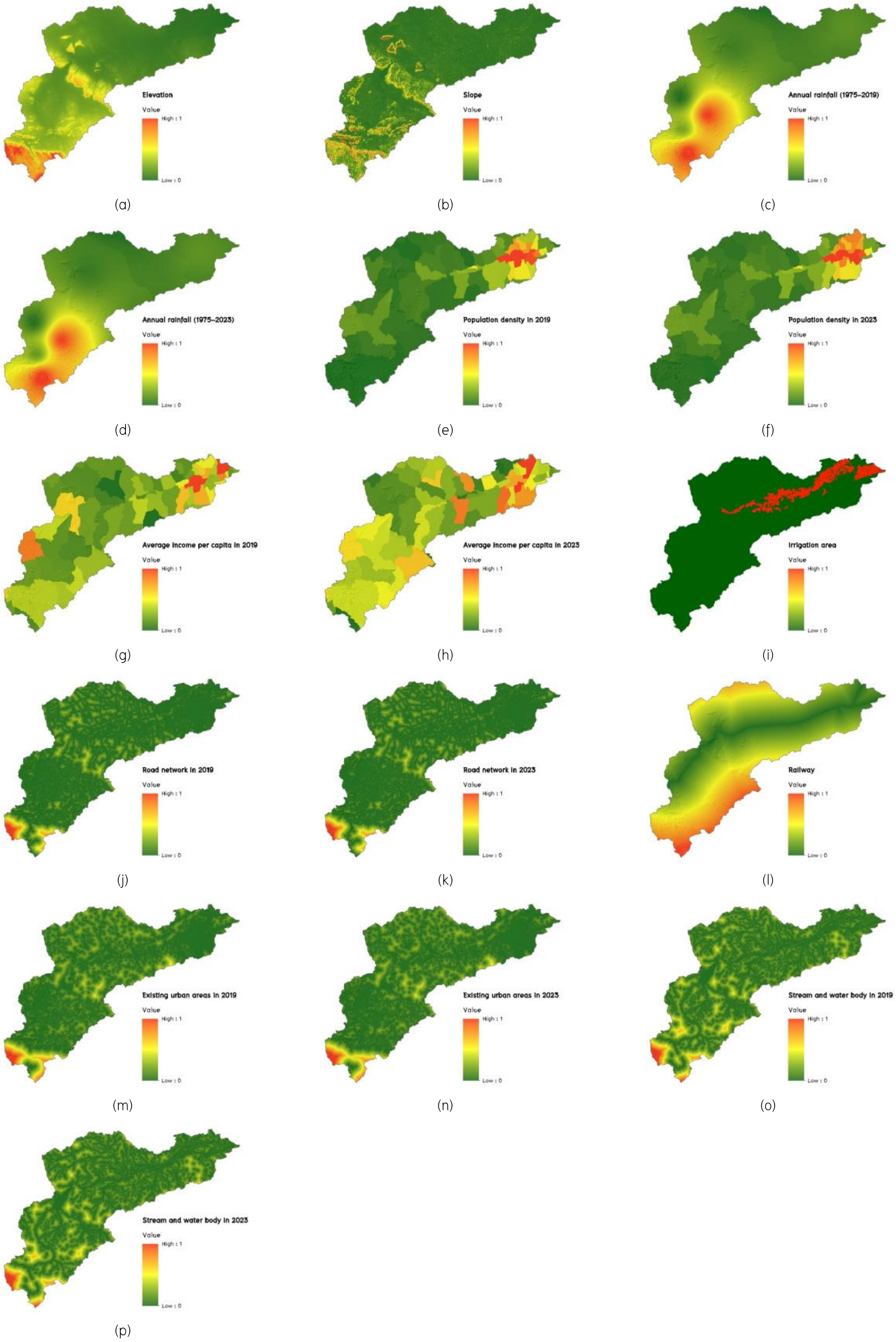


Figure 4 Driving factors on LULC change: (a) elevation, (b) slope, (c) annual rainfall between 1975-2019, (d) annual rainfall between 1975-2023, (e) population density at the sub-district level in 2019, (f) population density at the sub-district level in 2023, (g) average income per capita at the sub-district level in 2019, (h) average income

per capita at the sub-district level in 2023, (i) irrigation area, (j) distance to the road network in 2019, (k) distance to the road network in 2023, (l) distance to the railway, (m) distance to the existing urban areas in 2019, (n) distance to the existing urban areas in 2023, (o) distance to stream and water body in 2019, and (p) distance to stream and water body in 2023

3. Multicollinearity test

The results of the multicollinearity test among independent variables, using VIF and TOL, are summarized in Table 5. The results demonstrated that all TOL values of the driving factors were greater than 0.10, and all VIF values of the driving factors were less than 10. These values indicate that the driving factors are not correlated, making them suitable for binary logistic regression analysis for specific LULC type allocation (Rogerson, 2006; O'brien, 2007; Shrestha and Shrestha, 2017; Liang et al., 2020).

Table 5 Multicollinearity diagnostic test of driving factors on LULC change

Driving factor	Unstandardized Coefficients		Standardized Coefficient	t-test	Sig.	TOL	VIF
	Beta	Std. error					
Elevation (X_1)	6.496	0.061	0.300	106.985	0.000	0.231	4.326
Slope (X_2)	11.427	0.097	0.195	117.596	0.000	0.659	1.518
Annual rainfall (X_3)	0.221	0.025	0.018	8.867	0.000	0.430	2.323
Average income per capita at the sub-district level (X_4)	0.000	0.000	-0.001	-0.460	0.645	1.000	1.000
Population density at the sub-district level (X_5)	0.000	0.000	0.000	0.057	0.955	1.000	1.000
Irrigation area (X_6)	-1.334	0.016	-0.123	-85.862	0.000	0.883	1.132
Distance to the road network (X_7)	-0.681	0.095	-0.021	-7.200	0.000	0.218	4.590
Distance to the railway (X_8)	-0.470	0.026	-0.036	-18.338	0.000	0.475	2.106
Distance to the existing urban areas (X_9)	5.952	0.079	0.210	75.089	0.000	0.231	4.329
Distance to stream and water body (X_{10})	-4.773	0.061	-0.163	-77.892	0.000	0.414	2.414

4. Significant driving factors on LULC change

The results of significant driving factors on LULC change, as determined by binary logistic regression analysis, are reported in Table 6. This analysis comprises multiple linear regression equations for each LULC type allocation under the CLUE-S model, along with their area under the curve (AUC) values. As a result, the most significant driving factors for LULC allocation are elevation, annual rainfall, and irrigation area. Meanwhile, the common driving factors influencing the LULC allocation of economic crops (paddy fields, corn, sugarcane, and cassava) include elevation, slope, annual rainfall, and irrigation area. These findings indicate the influence of driving factors on LULC allocation under the CLUE-S model. Regarding common driving factors for economic crops (paddy fields, corn, sugarcane, and cassava), the results suggest that areas of economic crops are more prevalent in irrigated and rain-fed areas. The elevation and slope play a role related to crop type, i.e., paddy fields are frequently situated in floodplains with lower elevations.

Additionally, the common driving factors for crops in this study are similar with the previous works of Pinyoyang (2021), who applied CLUE-S model to predict LULC at the Second Part of Lam Nam Chi watershed, Chaiyaphum, He found that the most important driving force for field crops (sugarcane, cassava, and other field crops) are elevation, slope, and annual rainfall.

Moreover, the AUC values for allocating 12 LULC types range from 0.65 to 0.98, indicating a poor to excellent fit between the predicted and actual LULC transitions (Pontius and Schneider, 2001; Hosmer et al., 2013; Liang et al., 2020). As a result, the allocation of corn, perennial trees and orchards, and rangeland was a poor fit in accordance with their applied significant driving factors. The primary cause of this phenomenon may be the randomly fragmented areas of these LULC types, as previously mentioned by Srichaichana et al. (2019).

Table 6 Identified the driving factors for each LULC type allocation in equation form with AUC using binary logistic regression analysis

LULC type	Driving factors											AUC
	Constant	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	
Urban and built-up areas (UB)	1.865	–1.737	n. s.	n. s.	n. s.	1.441	–2.029	–11.043	–0.891	–245.424	2.211	0.98
Paddy field (PD)	–0.185	–14.685	–41.237	–3.517	n. s.	n. s.	3.051	8.409	2.497	n. s.	–13.091	0.92
Corn (CO)	–2.046	0.841	–13.105	0.619	n. s.	n. s.	–2.750	–9.618	n. s.	3.188	–0.684	0.69
Sugarcane (SU)	–2.755	–5.722	–33.576	0.993	n. s.	n. s.	–0.750	n. s.	4.723	1.933	–2.293	0.80
Cassava (CA)	–0.860	–0.709	–14.748	–3.675	n. s.	n. s.	–2.390	–0.960	1.977	3.054	n. s.	0.80
Perennial trees and orchards (PO)	–3.048	4.926	–12.026	–0.300	0.324	n. s.	–0.440	–4.785	n. s.	n. s.	–1.097	0.65
Other agriculture (OA)	–3.146	n. s.	–18.131	2.221	n. s.	n. s.	0.648	–16.770	–0.958	3.038	0.926	0.73
Forest land (FO)	–5.323	7.105	34.689	1.480	n. s.	n. s.	n. s.	8.735	–1.115	4.498	n. s.	0.97
Water body (WB)	0.164	–5.716	–19.122	1.105	n. s.	n. s.	–3.797	14.025	–3.290	n. s.	–191.884	0.98
Rangeland (RL)	–2.535	3.620	–5.299	0.934	n. s.	n. s.	–1.776	n. s.	–1.501	–3.642	–3.132	0.68
Marsh and swamp (MS)	–2.192	–46.695	n. s.	6.288	n. s.	n. s.	–2.471	9.782	–2.761	n. s.	–15.009	0.91
Unused land (UN)	–4.083	–6.230	n. s.	1.926	n. s.	n. s.	–0.265	–10.708	–2.038	n. s.	n. s.	0.89

Note 1: X1 is elevation, X2 is slope, X3 is annual rainfall (1975–2019), X4 is average income per capita at the sub-district level in 2019, X5 is population density at the sub-district level in 2019, X6 is irrigation area, X7 is distance to the road network in 2019, X8 is distance to the railway, X9 is distance to the existing urban areas in 2019, and X10 is distance to stream and water body in 2019.

Note 2: All explanatory variables are significant at $p < 0.05$ error level; n. s. is insignificant at the 0.05 level; AUC is the area under the curve.

5. Validation of CLUE-S model parameters for LULC prediction

The local parameters for predicting LULC in 2023, including elasticity value, LULC conversion matrix, and land requirement in 2023, which were extracted based on LULC in 2015 and 2019 with the Markov chain model, are summarized in Tables A1 to A3 in the Appendix. The spatial distribution of the reclassified LULC data in 2023, derived from LDD data, and the predicted LULC data in 2023, generated by the CLUE-S model, are displayed in Figure 5. The result of the accuracy assessment for local parameters of the CLUE-S model validation is reported in Table A4 in the Appendix.

As a result in Table A4, the overall accuracy and Kappa hat coefficient values of the predicted LULC in 2023, when compared with the reclassified LULC in 2023 of LDD, were 89.86% and 88.35%, respectively. Both values are higher than the thresholding value, with equal to or more than 80%. Therefore, the predefined local parameters of the CLUE-S model can be accepted for LULC prediction between 2024 and 2039.

Additionally, the overall accuracy value of more than 85% of the predicted LULC map can provide an acceptable result (Anderson et al., 1976). Additionally, a Kappa hat coefficient value of more than 80% indicates strong agreement or accuracy between the predicted map and the reference map (Fitzpatrick-Lins, 1981; Rosenfield and Fitzpatrick-Lins, 1986).

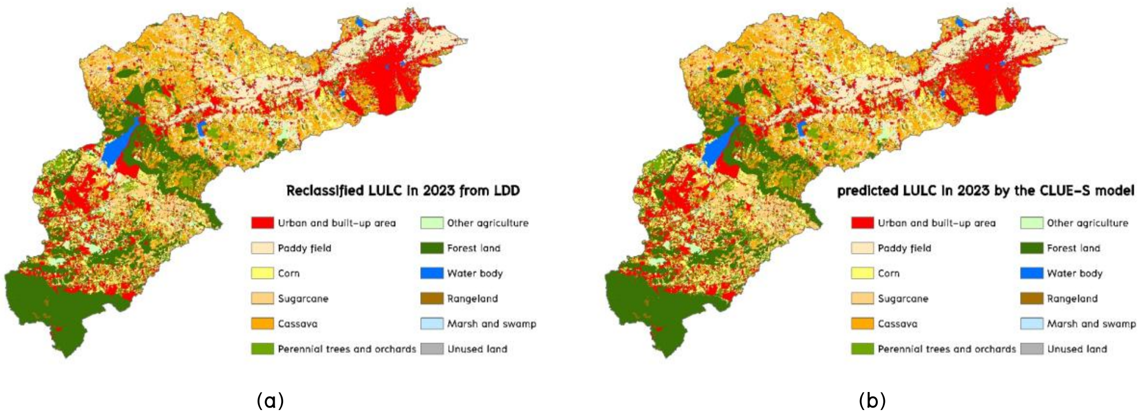


Figure 5 Comparison of spatial LULC distribution in 2023:
(a) classified LULC from LDD and (b) predicted LULC by the CLUE-S model.

6. LULC prediction between 2024 and 2039

The local parameters of the CLUE-S model, including elasticity value, LULC conversion matrix, and land requirement, were updated with new input data (LULC in 2015 and 2023) using a Markov Chain model, as reported in Tables 7, 8, and 9, respectively. Meanwhile, the results of the updated significant driving factors on LULC change, as determined by binary logistic regression analysis, are reported in Table 10.

The spatial distribution of the predicted LULC data for the period from 2024 to 2039, using the CLUE-S model with updated parameters and driving factors, is presented in Figure 6. Meanwhile, the area of predictive LULC types between 2024 and 2039 is summarized in Table 11.

Table 7 Elasticity of LULC change for LULC prediction between 2024 and 2039

LULC type	Resistance value
Urban and built-up area (UB)	0.986
Paddy field (PD)	0.7791
Corn (CO)	0.4946
Sugarcane (SU)	0.6059
Cassava (CA)	0.6352
Perennial trees and orchards (PO)	0.661
Other agriculture (OA)	0.5893
Forest land (FO)	0.9401
Water body (WB)	0.9658
Rangeland (RL)	0.6978
Marsh and swamp (MS)	0.5935
Unused land (UN)	0.5604

Table 8 Conversion matrix of possible LULC change for LULC prediction between 2024 and 2039

LULC type in 2023	Possible change in 2039											
	UB	PD	CO	SU	CA	PO	OA	FO	WB	RL	MS	UN
Urban and built-up area (UB)	1	0	0	0	0	0	0	0	0	0	0	0
Paddy field (PD)	1	1	1	1	1	1	1	0	1	0	1	1
Corn (CO)	1	0	1	1	1	1	1	0	1	0	0	1
Sugarcane (SU)	1	0	1	1	1	1	1	0	1	0	0	1
Cassava (CA)	1	0	1	1	1	1	1	0	1	0	0	1
Perennial trees and orchards (PO)	1	0	1	1	1	1	1	0	1	0	0	1
Other agriculture (OA)	1	1	1	1	1	1	1	0	1	0	0	1
Forest land (FO)	1	0	1	1	1	1	1	1	1	1	0	1
Water body (WB)	0	0	0	0	0	0	0	0	1	0	1	1
Rangeland (RL)	1	0	1	1	1	1	1	0	1	1	0	1
Marsh and swamp (MS)	0	0	0	0	0	0	1	0	1	0	1	1
Unused land (UN)	1	1	1	1	1	1	1	1	1	0	0	1

Note: 0 is not allowed to change, 1 is allowed to change.

Table 9 Annual land requirement of each LULC type for LULC prediction between 2024 and 2039

Year	LULC type (sq km)												
	UB	PD	CO	SU	CA	PO	OA	FO	WB	RL	MS	UN	Total
2023	599.64	388.42	267.11	281.82	574.98	190.18	135.31	613.12	78.62	191.05	12.71	19.69	3,352.64
2024	611.10	379.73	266.53	284.89	570.66	192.22	135.45	609.17	79.85	190.32	12.55	20.16	3,352.64
2025	622.56	371.04	265.96	287.97	566.35	194.27	135.60	605.21	81.08	189.60	12.39	20.62	3,352.64
2026	634.01	362.35	265.39	291.04	562.04	196.31	135.75	601.26	82.30	188.87	12.22	21.09	3,352.64
2027	645.47	353.65	264.82	294.11	557.72	198.36	135.89	597.31	83.53	188.15	12.06	21.55	3,352.64
2028	656.93	344.96	264.25	297.18	553.41	200.40	136.04	593.36	84.76	187.42	11.90	22.02	3,352.64
2029	668.39	336.27	263.68	300.26	549.10	202.45	136.18	589.41	85.99	186.70	11.74	22.49	3,352.64
2030	679.84	327.58	263.11	303.33	544.79	204.49	136.33	585.45	87.21	185.97	11.58	22.95	3,352.64
2031	691.30	318.88	262.54	306.40	540.47	206.54	136.48	581.50	88.44	185.25	11.42	23.42	3,352.64
2032	702.76	310.19	261.97	309.48	536.16	208.58	136.62	577.55	89.67	184.52	11.25	23.88	3,352.64
2033	714.22	301.50	261.40	312.55	531.85	210.63	136.77	573.60	90.90	183.80	11.09	24.35	3,352.64
2034	725.67	292.81	260.83	315.62	527.53	212.67	136.91	569.65	92.12	183.07	10.93	24.82	3,352.64
2035	737.13	284.11	260.26	318.69	523.22	214.72	137.06	565.70	93.35	182.35	10.77	25.28	3,352.64
2036	748.59	275.42	259.69	321.77	518.91	216.76	137.20	561.74	94.58	181.62	10.61	25.75	3,352.64
2037	760.05	266.73	259.12	324.84	514.60	218.81	137.35	557.79	95.81	180.90	10.44	26.21	3,352.64
2038	771.50	258.04	258.55	327.91	510.28	220.85	137.50	553.84	97.03	180.17	10.28	26.68	3,352.64
2039	782.96	249.34	257.98	330.99	505.97	222.90	137.64	549.89	98.26	179.45	10.12	27.15	3,352.64
Annual rate	11.46	−8.69	−0.57	3.07	−4.31	2.04	0.15	−3.95	1.23	−0.73	−0.16	0.47	

Table 10 Updated driving factors for each LULC type allocation for LULC prediction between 2024 and 2039

LULC type	Driving factors											AUC
	Constant	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	
Urban and built-up areas (UB)	1.865	−1.737	n.s	n.s	n.s	1.441	−2.029	−11.043	−0.891	−245.424	2.211	0.979
Paddy field (PD)	−0.185	−14.685	−41.237	−3.517	n.s	n.s	3.051	8.409	2.497	n.s	−13.091	0.923
Corn (CO)	−2.046	0.841	−13.105	0.619	n.s	n.s	−2.750	−9.618	n.s	3.188	−0.684	0.683
Sugarcane (SU)	−2.755	−5.722	−33.576	0.993	n.s	n.s	−0.750	n.s	4.723	1.933	−2.293	0.796
Cassava (CA)	−0.860	−0.709	−14.748	−3.675	n.s	n.s	−2.390	−0.960	1.977	3.054	n.s	0.797
Perennial trees and orchards (PO)	−3.048	4.926	−12.026	−0.300	0.324	n.s	−0.440	−4.785	n.s	n.s	−1.097	0.666
Other agriculture (OA)	−3.146	n.s	−18.131	2.221	n.s	n.s	0.648	−16.770	−0.958	3.038	0.926	0.724
Forest land (FO)	−5.323	7.105	34.689	1.480	n.s	n.s	n.s	8.735	−1.115	4.498	n.s	0.968
Water body (WB)	0.164	−5.716	−19.122	1.105	n.s	n.s	−3.797	14.025	−3.290	n.s	−191.884	0.975
Rangeland (RL)	−2.535	3.620	−5.299	0.934	n.s	n.s	−1.776	n.s	−1.501	−3.642	−3.132	0.670
Marsh and swamp (MS)	−2.192	−46.695	n.s	6.288	n.s	n.s	−2.471	9.782	−2.761	n.s	−15.009	0.903
Unused land (UN)	−4.083	−6.230	n.s	1.926	n.s	n.s	−0.265	−10.708	−2.038	n.s	n.s	0.715

Note 1: X1 is elevation, X2 is slope, X3 is annual rainfall (1975–2023), X4 is average income per capita at the sub-district level in 2023, X5 is population density at the sub-district level in 2023, X6 is irrigation area, X7 is distance to the road network in 2023, X8 is distance to the railway, X9 is distance to the existing urban areas in 2023, and X10 is distance to stream and water body in 2023.

Note 2: All explanatory variables are significant at $p < 0.05$ error level; n. s. is insignificant at the 0.05 level; AUC is the area under the curve.

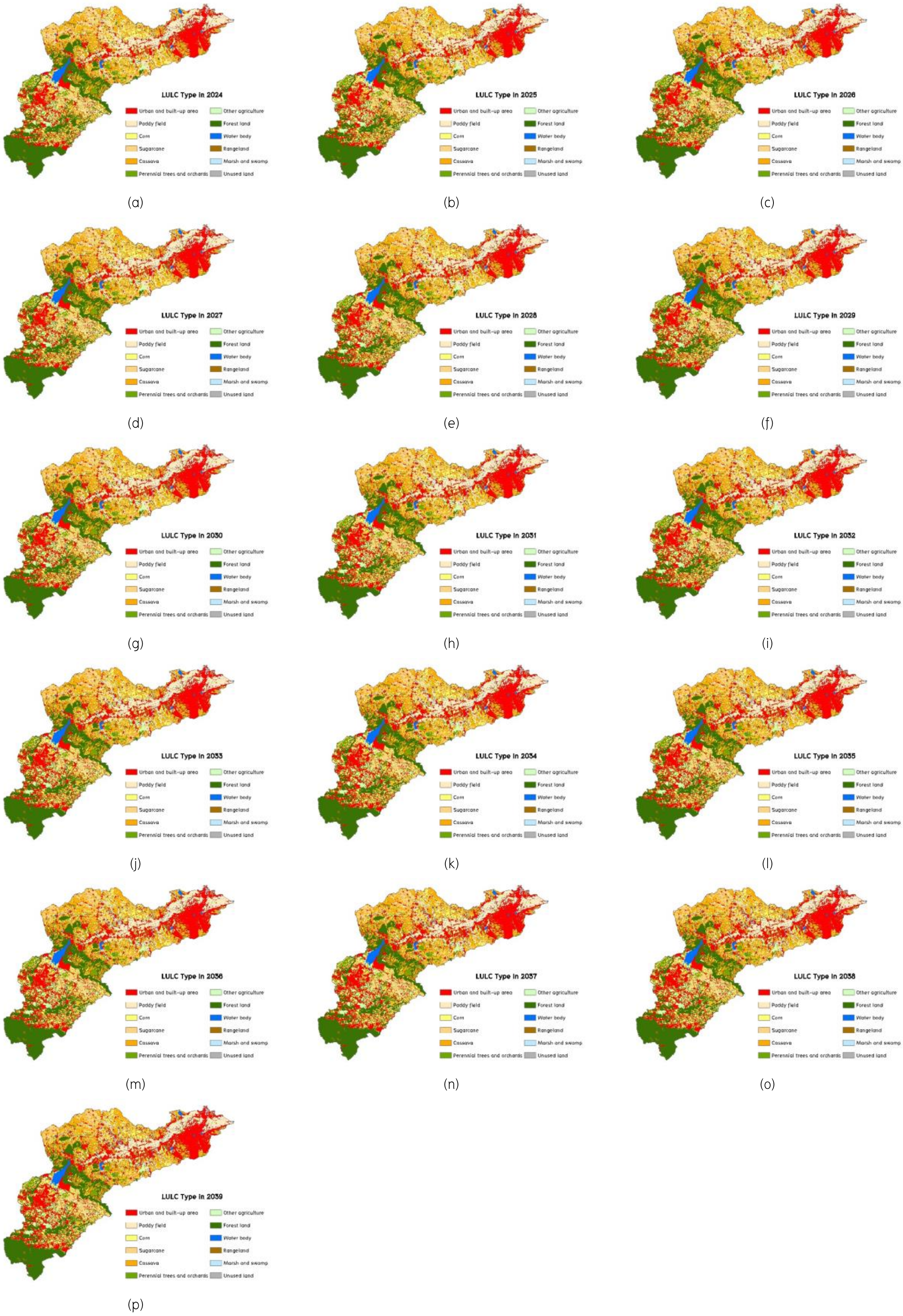


Figure 6 Spatial distribution of predicted LULC data: (a) 2024, (b) 2025, (c) 2026, (d) 2027, (e) 2028, (f) 2029, (g) 2030, (h) 2031, (i) 2032, (j) 2033, (k) 2034, (l) 2035, (m) 2036, (n) 2037, (o) 2038, and (p) 2039

Table 11 Predicted LULC type areas between 2024 and 2039

LULC types	Area of predicted LULC type in sq km.															
	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039
Urban and built-up area (UB)	611.20	622.51	633.97	645.47	656.88	668.42	679.82	691.31	702.73	714.17	725.63	737.08	748.57	760.03	771.47	782.96
Paddy field (PD)	379.51	370.88	362.33	353.53	344.92	336.27	327.54	318.84	310.17	301.47	292.77	284.09	275.38	266.70	258.00	249.31
Corn (CO)	266.66	265.82	265.37	264.80	264.19	263.44	263.02	262.56	261.94	261.37	260.79	260.22	259.65	259.09	258.51	257.94
Sugarcane (SU)	285.16	288.14	291.01	294.10	297.16	300.27	303.31	306.40	309.43	312.51	315.59	318.66	321.73	324.81	327.89	330.95
Cassava (CA)	570.77	566.37	561.99	557.77	553.38	549.14	544.75	540.48	536.12	531.81	527.50	523.19	518.85	514.56	510.25	505.93
Perennial trees and orchards (PO)	191.84	194.11	196.28	198.32	200.36	202.46	204.47	206.52	208.56	210.60	212.65	214.67	216.72	218.78	220.82	222.86
Other agriculture (OA)	135.30	135.47	135.73	135.92	136.02	136.24	136.30	136.49	136.62	136.80	136.93	137.13	137.29	137.32	137.46	137.59
Forest land (FO)	609.67	605.80	601.21	597.31	593.35	589.44	585.43	581.50	577.52	573.57	569.62	565.67	561.72	557.76	553.80	549.84
Water body (WB)	79.75	81.06	82.30	83.59	84.75	86.06	87.21	88.46	89.65	90.86	92.09	93.31	94.54	95.80	97.04	98.24
Rangeland (RL)	190.44	189.49	188.81	188.19	187.39	186.75	185.95	185.25	184.48	183.76	183.03	182.30	181.58	180.85	180.14	179.41
Marsh and swamp (MS)	12.67	12.67	12.59	12.38	12.26	12.02	11.92	11.73	11.59	11.42	11.26	11.09	10.92	10.76	10.59	10.39
Unused land (UN)	19.67	20.33	21.06	21.28	21.98	22.14	22.92	23.10	23.84	24.32	24.78	25.23	25.71	26.20	26.68	27.22
Total	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64

LULC change detection between 2023 and 2039, as determined by a post-comparison detection algorithm, which provides from-to-change information (Jensen, 2015), is reported in Table 12. As a result, urban and built-up areas, as well as water bodies, in 2023 did not change into any LULC type in 2039. In contrast, paddy fields, corn, sugarcane, cassava, perennial trees and orchards, other agriculture, forest land, rangeland, marsh and swamp and unused land in 2023 are changed into other LULC types in 2039. This result indicates the persistence of LULC change by each LULC type (Takada et al., 2010. The extracted LULC change patterns between 2023 and 2039 play a crucial role in evaluating the value of ecosystem services and changes in the watershed.

Table 12 Change detection matrix of LULC change between 2023 and 2039

		LULC type in 2039 (sq km)												
	LULC change 2023-2039	**UB**	**PD**	**CO**	**SU**	**CA**	**PO**	**OA**	**FO**	**WB**	**RL**	**MS**	**UN**	**Total**
LULC type in 2023 (sq. km)	Urban and built-up areas (UB)	599.64	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	599.64
	Paddy field (PD)	54.13	249.31	4.84	33.50	1.19	24.03	1.58	0.00	11.74	0.00	0.00	8.12	388.42
	Corn (CO)	14.90	0.00	250.69	0.24	0.00	0.00	0.00	0.00	1.28	0.00	0.00	0.00	267.11
	Sugarcane (SU)	4.28	0.00	0.00	277.33	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.00	281.82
	Cassava (CA)	57.05	0.00	0.00	5.36	504.55	0.69	3.95	0.00	3.38	0.00	0.00	0.00	574.98
	Perennial trees and orchards (PO)	7.37	0.00	0.00	0.00	0.00	182.80	0.00	0.00	0.02	0.00	0.00	0.00	190.18
	Other agriculture (OA)	6.03	0.00	0.00	0.00	0.00	0.00	129.27	0.00	0.01	0.00	0.00	0.00	135.31
	Forest land (FO)	25.40	0.00	2.41	14.53	0.19	15.35	2.13	549.84	1.00	1.65	0.00	0.62	613.12
	Water body (WB)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	78.62	0.00	0.00	0.00	78.62
	Rangeland (RL)	12.69	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	177.76	0.00	0.00	191.05
	Marsh and swamp (MS)	0.03	0.00	0.00	0.00	0.00	0.00	0.67	0.00	1.38	0.00	10.39	0.24	12.71
	Unused land (UN)	1.45	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	18.24	19.69
	Total	**782.96**	**249.31**	**257.94**	**330.95**	**505.93**	**222.86**	**137.59**	**549.84**	**98.24**	**179.41**	**10.39**	**27.22**	**3,352.64**

Moreover, the changes in ES LULC type (decrease or increase) between 2023 and 2039 are reported in Table 13. As a result, it can be observed that top three increasing areas of ES LULC type are urban and built-up areas (UB), water body (WB) and Unused land (UN) while top three decreasing areas of ES LULC type are paddy field (PD), forest land (FL) and field crop (FC).

Table 13 Changed areas (decrease or increase) of ES LULC type between 2023 and 2039

Year	Area of actual and predicted ES LULC types in sq km.								
	UB	PD	FC	FL	WB	RL	MS	UN	Total
2023	599.64	388.42	1259.21	803.3	78.62	191.05	12.71	19.69	3352.64
2024	611.2	379.51	1257.89	801.51	79.75	190.44	12.67	19.67	3352.64
2025	622.51	370.88	1255.8	799.91	81.06	189.49	12.67	20.33	3352.64
2026	633.97	362.33	1254.1	797.49	82.3	188.81	12.59	21.06	3352.64
2027	645.47	353.53	1252.59	795.63	83.59	188.19	12.38	21.28	3352.64
2028	656.88	344.92	1250.75	793.71	84.75	187.39	12.26	21.98	3352.64
2029	668.42	336.27	1249.09	791.9	86.06	186.75	12.02	22.14	3352.64
2030	679.82	327.54	1247.38	789.9	87.21	185.95	11.92	22.92	3352.64
2031	691.31	318.84	1245.93	788.02	88.46	185.25	11.73	23.1	3352.64
2032	702.73	310.17	1244.11	786.08	89.65	184.48	11.59	23.84	3352.64
2033	714.17	301.47	1242.49	784.17	90.86	183.76	11.42	24.32	3352.64
2034	725.63	292.77	1240.81	782.27	92.09	183.03	11.26	24.78	3352.64
2035	737.08	284.09	1239.2	780.34	93.31	182.3	11.09	25.23	3352.64
2036	748.57	275.38	1237.52	778.44	94.54	181.58	10.92	25.71	3352.64
2037	760.03	266.7	1235.78	776.54	95.8	180.85	10.76	26.2	3352.64
2038	771.47	258	1234.11	774.62	97.04	180.14	10.59	26.68	3352.64
2039	782.96	249.31	1232.41	772.7	98.24	179.41	10.39	27.22	3352.64
Changes area (2023–2039)	**183.32**	–139.1	–26.8	–30.6	**19.62**	–11.64	–2.32	**7.53**	0

7. Evaluation of ecosystem service value between 2023 and 2039

The ecosystem service values between 2023 and 2039 are reported in Table 14. As a result, the ESV for the Lam Takhong watershed has been continuously decreasing from 2023 to 2039. In addition, considering ecosystem service value by category, the regulating, supporting, and provisioning services are continuously decreasing between 2023 and 2039. However, cultural service is continuously increasing in the same period. The increase in cultural services is attributed to the growth of urban and built-up areas, water bodies, and unused land during this period. See also Table 13. The most important ecosystem service category in the watershed is the regulating service, including gas regulation, climate regulation, and waste treatment functions. This category contributes approximately 41% of the total ecosystem service value.

In the meantime, by considering ecosystem service value based on its function (gas regulation, climate regulation, waste treatment, soil formation, biodiversity protection, water supply, food production, raw materials, recreation, and culture), as shown in Table 15. As a result, gas regulation, climate regulation, soil formation, biodiversity protection, food production, and raw material functions decreased marginally from 2023 to 2039, but waste treatment, water supply, and recreation and culture functions increased slightly during the same period. The most important ecosystem service function in the watershed is waste treatment, since it contributes about 20–21% of the total ecosystem service value.

These findings indicate the impact of LULC change on ecosystem service value in each category and function in the watershed. For example, the areas of the water body, which play an important role with a high coefficient value in waste treatment, water supply, and recreation and cultural functions, will increase from 78.62 sq. km in 2023 to 98.24 sq. km in 2039. The increase in water bodies between 2023 and 2039 results in an increase in ecosystem service value for waste treatment, water supply, and recreation and cultural functions during the same period.

On the contrary, the areas of forest land that serve an important role in ecosystem services, with high coefficient values in gas regulation, climate regulation, soil formation, biodiversity protection, and raw material production, are expected to decrease from 613.12 sq. km in 2023 to 549.84 sq. km in 2039. Thus, the decrease in forest land between 2023 and 2039 results in a decrease in ecosystem service values for gas regulation, climate regulation, soil formation, biodiversity protection, and raw material functions during the same period.

Table 14 Ecosystem service value by its category and total between 2023 and 2039

Year	Ecosystem service value by category (million Baht)				Total
	Regulating services	Supporting services	Provisioning services	Cultural services	
2023	5,515.08	3,600.33	3,709.78	589.78	13,414.96
2024	5,502.88	3,584.57	3,707.46	590.80	13,385.71
2025	5,492.08	3,568.18	3,706.57	592.09	13,358.91
2026	5,478.22	3,550.76	3,703.48	592.71	13,325.18
2027	5,463.75	3,534.30	3,700.95	593.39	13,292.38
2028	5,449.24	3,517.48	3,697.45	594.00	13,258.17
2029	5,434.43	3,501.00	3,694.90	594.63	13,224.96
2030	5,420.06	3,484.10	3,691.37	595.25	13,190.78
2031	5,405.70	3,467.67	3,688.62	595.87	13,157.85
2032	5,391.02	3,450.79	3,685.22	596.49	13,123.52
2033	5,376.32	3,434.14	3,682.03	597.08	13,089.57
2034	5,361.93	3,417.46	3,679.06	597.73	13,056.19
2035	5,347.34	3,400.82	3,675.97	598.34	13,022.46
2036	5,332.74	3,384.12	3,672.93	598.97	12,988.76
2037	5,318.56	3,367.43	3,670.24	599.70	12,955.93
2038	5,304.06	3,350.76	3,667.30	600.35	12,922.46
2039	5,288.56	3,333.93	3,663.67	600.82	12,886.98

Table 15 Ecosystem service value by its function and its total between 2023 and 2039

Year	Ecosystem service function values between 2023 and 2039 (million Baht)									
	Gas regulation	Climate regulation	Waste treatment	Soil formation	Biodiversity protection	Water supply	Food production	Raw materials	Recreation and culture	Total
2023	1,179.31	1,631.03	2,704.74	2,072.23	1,528.10	2,150.45	1,014.34	544.99	589.78	**13,414.96**
2024	1,173.32	1,623.47	2,706.09	2,062.17	1,522.40	2,155.72	1,009.67	542.07	590.80	**13,385.71**
2025	1,166.86	1,615.86	2,709.36	2,051.69	1,516.49	2,162.72	1,005.02	538.83	592.09	**13,358.91**
2026	1,159.78	1,607.10	2,711.34	2,040.88	1,509.88	2,167.86	1,000.50	535.12	592.71	**13,325.18**
2027	1,153.25	1,597.81	2,712.69	2,030.48	1,503.82	2,173.12	995.94	531.89	593.39	**13,292.38**
2028	1,146.65	1,589.10	2,713.49	2,019.92	1,497.56	2,177.57	991.28	528.60	594.00	**13,258.17**
2029	1,140.09	1,579.55	2,714.79	2,009.52	1,491.48	2,182.80	986.74	525.36	594.63	**13,224.96**
2030	1,133.45	1,570.96	2,715.65	1,998.92	1,485.18	2,187.26	982.08	522.03	595.25	**13,190.78**
2031	1,126.93	1,561.85	2,716.92	1,988.59	1,479.08	2,192.25	977.59	518.78	595.87	**13,157.85**
2032	1,120.29	1,552.95	2,717.78	1,977.98	1,472.81	2,196.84	972.91	515.47	596.49	**13,123.52**
2033	1,113.71	1,543.90	2,718.71	1,967.52	1,466.62	2,201.50	968.33	512.20	597.08	**13,089.57**
2034	1,107.13	1,534.92	2,719.88	1,957.02	1,460.44	2,206.42	963.72	508.92	597.73	**13,056.19**
2035	1,100.55	1,525.88	2,720.91	1,946.56	1,454.26	2,211.18	959.14	505.65	598.34	**13,022.46**
2036	1,093.96	1,516.81	2,721.97	1,936.05	1,448.07	2,216.03	954.53	502.37	598.97	**12,988.76**
2037	1,087.36	1,507.81	2,723.39	1,925.52	1,441.91	2,221.25	949.91	499.08	599.70	**12,955.93**
2038	1,080.76	1,498.75	2,724.55	1,915.02	1,435.74	2,226.20	945.30	495.80	600.35	**12,922.46**
2039	1,074.12	1,489.39	2,725.05	1,904.47	1,429.46	2,230.48	940.67	492.52	600.82	**12,886.98**

Furthermore, the impact of ES LULC changes on ecosystem service value in each category and function, according to the changes in area size of each ES LULC type between 2023 and 2039, as reported in Table 13, and their corresponding coefficient values, as reported in Table 3, are presented in Table 16 and Figure 7.

Table 16 Change of ecosystem service value by category and function of ES LULC type

Ecosystem service category	Ecosystem service function	Ecosystem service value of ES LULC type (Million Baht)							
		UB	PD	FC	FO	WB	RL	MS	UN
1. Regulating service	1.1 Gas regulation	0.00	-36.17	-6.97	-31.52	0.00	-4.19	-2.13	0.08
	1.2 Climate regulation	0.00	-63.99	-12.33	-29.68	4.71	-4.31	-20.30	0.23
	1.3 Waste treatment	0.00	-116.85	-22.51	-12.55	182.86	-3.61	-21.60	0.45
	Sub-total	0.00	-217.01	-41.81	-73.75	187.57	-12.11	-44.03	0.75
2. Supporting service	2.1 Soil formation	0.00	-104.33	-20.10	-29.07	0.20	-6.17	-2.04	0.30
	2.2 Biodiversity protection	0.00	-50.08	-9.65	-32.74	24.92	-5.24	-2.97	0.68
	Sub-total	0.00	-154.41	-29.75	-61.81	25.11	-11.41	-5.01	0.98
2. Provisioning service	3.1 Water supply	0.00	-43.12	-8.31	-29.68	204.83	-4.19	-18.40	0.15
	3.2 Food production	0.00	-70.95	-13.67	-2.45	0.98	-1.16	-0.35	0.00
	3.3 Raw materials	0.00	-6.96	-1.34	-21.73	0.20	-1.05	-0.09	0.08
	Sub-total	0.00	-121.03	-23.32	-53.86	206.01	-6.40	-18.84	0.23
4. Cultural service	4.1 Recreation and culture	7.33	-1.39	-0.27	-14.99	43.56	-2.44	-6.59	0.45
	Sub-total	7.33	-1.39	-0.27	-14.99	43.56	-2.44	-6.59	0.45
Total		7.33	-493.84	-95.14	-204.41	462.25	-32.36	-74.47	2.41

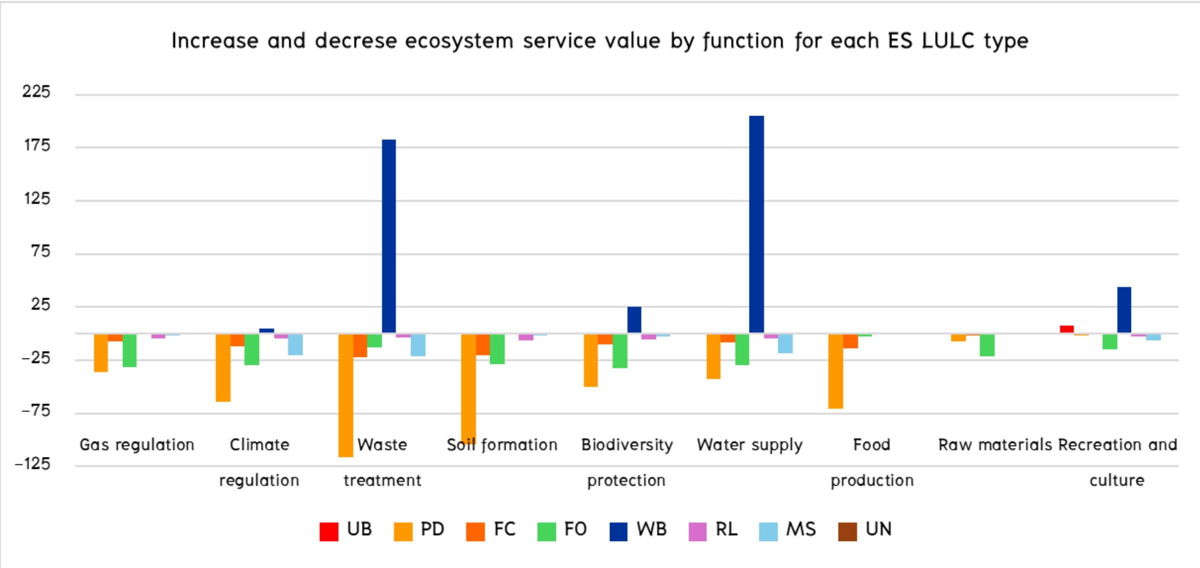


Figure 7 Change of ecosystem service value by each function of ES LULC type.

As a result, the decrease in paddy fields (PD) due to conversion to other ES LULC types between 2023 and 2039, approximately 139 sq. km, reduces ecosystem values for the regulation, supporting, provisioning, and cultural service categories by about 271, 154, 121, and 1 million Baht, respectively. In the meantime, the decrease in paddy fields (PD) during the same period reduces ecosystem values for all ecosystem service functions. See details in Table 16 and Figure 7.

Similar to paddy fields, the decrease in forest land (FL) due to conversion to other ES LULC types between 2023 and 2039, approximately 31 sq. km, reduces ecosystem values for the regulation, supporting, provisioning, and cultural service categories by about 74, 62, 54, and 15 million Baht, respectively. Meanwhile, the decrease in forest land (FL) during the same period reduces ecosystem values for all ecosystem service functions. See details in Table 16 and Figure 7.

In contrast, the increase in water bodies (WB) by conversion from other ES LULC types between 2023 and 2039, approximately 20 sq. km, enhances ecosystem values for the regulation, supporting, provisioning, and cultural service categories, at approximately 188, 25, 206, and 44 million Baht, respectively. In the meantime, the increasing water body (WB) in the same period increases ecosystem values for all ecosystem service functions. See details in Table 16 and Figure 7. Meanwhile, the increasing urban and built-up area (UB) by conversion from other ES LULC types between 2023 and 2039, approximately 183 sq. km, increases ecosystem values for the cultural service category and its function by about 7 million Baht. See details in Table 16 and Figure 7.

These findings confirm the impact of LULC change on ecosystem services in each category and function in the Lam Takhong watershed, especially the conversion of paddy fields and forest land into other LULC types in the future. The results suggest that implementing a proper land use plan and measures to prevent illegal forest encroachment for urban construction is necessary to minimize the decline of ecosystem services in the watershed.

8. Change of ecosystem service value between 2023 and 2039

The results of the change in ecosystem service value between 2023 (base year) and 2039, as calculated using ESCI, are reported in Table 17. As a result, the total ecosystem service value in the watershed is expected to decrease continuously from 2023 to 2039. In addition, the change in total ESV based on ESCI over 16 periods is slightly decreasing, with a marginally different value between consecutive periods.

The primary causes of declining ecosystem value are the loss of paddy fields (PD) and forest land (FL) in the watershed. The loss of paddy fields and forest land has a high impact on regulating, supporting, and provisioning services, amounting to 681.86 million Baht.

Table 17 Ecosystem services values change between 2023 and 2039.

Year	Total ESV (million Baht)	Ecosystem services values change		
		Year of change	By index	By percentages
2023	13,414.96	Y2023		
2024	13,385.71	Y2023-Y2024	-0.00218	-0.22
2025	13,358.91	Y2023-Y2025	-0.00418	-0.42
2026	13,325.18	Y2023-Y2026	-0.00669	-0.67
2027	13,292.38	Y2023-Y2027	-0.00914	-0.91
2028	13,258.17	Y2023-Y2028	-0.01169	-1.17
2029	13,224.96	Y2023-Y2029	-0.01416	-1.42
2030	13,190.78	Y2023-Y2030	-0.01671	-1.67
2031	13,157.85	Y2023-Y2031	-0.01917	-1.92
2032	13,123.52	Y2023-Y2032	-0.02172	-2.17
2033	13,089.57	Y2023-Y2033	-0.02426	-2.43
2034	13,056.19	Y2023-Y2034	-0.02674	-2.67
2035	13,022.46	Y2023-Y2035	-0.02926	-2.93
2036	12,988.76	Y2023-Y2036	-0.03177	-3.18
2037	12,955.93	Y2023-Y2037	-0.03422	-3.42
2038	12,922.46	Y2023-Y2038	-0.03671	-3.67
2039	12,886.98	Y2023-Y2039	-0.03936	-3.94

Conclusion and Discussion

The study on the impacts of land use and land cover change on ecosystem service values in the Lam Takhong Watershed, Thailand, was successfully conducted through the integration of geospatial models and methods. Based on binary logistics regression analysis, the most significant driving factors on land use and land cover change were elevation, annual rainfall, and irrigation area. Meanwhile, the significant driving factors on rice, corn, sugarcane, and cassava were elevation, slope, annual rainfall, and irrigation. The validation of the local parameters for land use and land cover prediction using the CLUE-S model yielded an acceptable outcome, as the accuracy of the predicted land use and land cover in 2023 exceeded the threshold value, with overall accuracy and Kappa coefficient values of more than 80%. The predicted land use and land cover data between 2024 and 2039 indicated an increase in urban and built-up areas, sugarcane, perennial trees and orchards, other agricultural areas, water bodies, and unused land. Conversely, there were decreases in paddy fields, corn, cassava, forest land, rangeland, and marsh and swamp. The land use and land cover prediction results obtained from the CLUE-S model were strongly aligned (i.e., either a decrease or an increase) with the annual rate of land requirement projections derived from the Markov chain model.

For the evaluation of ecosystem service value, the total ecosystem service value continuously decreased between 2023 and 2039. By considering ecosystem services by category, the regulating, supporting, and provisioning services are expected to decrease continuously between 2023 and 2039. However, cultural services are expected to continue increasing during the same period. The most important ecosystem service category in the watershed is the regulating service, which plays a crucial role in ecosystem function through gas regulation, climate regulation, and waste treatment. Meanwhile, considering ecosystem service by function, gas regulation, climate regulation, soil formation, biodiversity protection, food production, and raw material functions are expected to decrease marginally from 2023 to 2039. However, waste treatment, water supply, and recreation and culture functions are expected to increase slightly in the future. The most crucial ecosystem service function in the watershed is waste treatment.

In conclusion, land use and land cover changes impact ecosystem service value in each category and function in the Lam Takhong watershed, especially the conversion of paddy fields and forest land into other LULC types in the future. We recommend that the Government establish specific policies or interventions to prevent land use and land cover change in the Lam Takhong watershed. The Land Development Department should implement land-use planning to ensure proper land utilization and management. Meanwhile, the Royal Forest Department and the Department of National Parks, Wildlife and Plant Conservation should be preventing illegal forest encroachment in the watershed. Additionally, the disturbed national reserve forest areas should be reforested to increase forest land by the Royal Forest Department.

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