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Research Article

Land Use and Land Cover Simulation via Integrated Modelling with GIS Techniques for Sustainable Land Utilization Development in the Northeast Khong Subwatershed of Thailand

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Abstract

Land utilization is an important indicator of socioeconomic and environmental changes caused by both natural and man-made factors. Land use and land cover (LULC) simulation is a critical tool for monitoring and predicting LULC and is essential for sustainable development, land resource management and planning. The cellular automata (CA) Markov model is the basis for the current study's prediction of LULC changes in the Northeast Khong Sub Watershed (NKSW). Landsat data from 2013 to 2023 were used to investigate LULC classification and determine the spatiotemporal distributions of LULC. In addition, LULC data from 2013 and 2023 were used to generate simulations via the CA Markov model spanning eight decades (2033 to 2103) to determine how the LULC perspective has changed in the NKSW, which has undergone significant development over the years, including increases in population, settlements, the agriculture sector, and economic and social development. A population increase, according to the model, will cause rapid urbanization, rural expansion and a reduction in forest areas. In 2103, urban and built-up land is expected to account for 5.17% of the total land area, up from 4.12% in 2023. According to the CA Markov model results, the land use and settlement patterns changed significantly in the NKSW. This study urges environmentalists, planners, decision-makers, and those interested in studying LULC change to emphasize sustainable practices and make well-informed decisions for regional well-being. It is an essential tool for directing future planning efforts. Therefore, developing a future master plan for the watershed of Thailand, Lao People's Democratic Republic, and the world should be given top priority.

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Introduction

One essential source of productivity is the land, a location of livelihood, and a fundamental material necessary for human survival and development. The sustainable development goal of Thailand aims to provide better household facilities to all; we must strive harder to sustain planning and development in our immediate surroundings through scientific method-logies. Therefore, monitoring changes in land use and land cover (LULC) is essential for comprehending the dynamics of the Earth's landscape. The environment and climate are changing simultaneously with these rapid changes in the Earth's surface caused by human activity. It is crucial to keep an eye on all of these LULC changes to be aware of all of these changes and to make informed decisions that will benefit both nature and humanity. LULC changes can both hinder and benefit sustainable development, depending on several factors. For example, unexpected or unsustainable changes in land use, such as deforestation, urban development, economic development, or intensive agriculture, may hasten the degradation of land (Banchongsak et al., 2024; Swain et al., 2022a; b). These changes undermine an ecosystem's ability to deliver necessary services and could complicate long-term sustainability. Large-scale changes in land use can also isolate species populations, break up natural habitats, cause environmental changes, and interfere with ecological processes. Sustainable development is hampered by habitat fragmentation, which causes ecological imbalances and biodiversity loss.

In addition, natural resources, such as soil fertility, water, forests, and minerals, can be depleted by inappropriate land use strategies. Sustainability may be hampered by the overuse and improper management of these resources, which could compromise our capacity to satisfy demands in the present and the future. Additionally, LULC changes frequently exacerbate or lessen the consequences of natural hazards (Banchongsak et al., 2024; Guptha et al., 2021; 2022; Swain et al., 2022b). On the other hand, well-managed LULC alterations could benefit ecosystems, biodiversity, ecosystems, natural resources, the environment, watersheds, and mankind. Sustainable agricultural methods, such as agroforestry or organic farming, can support rural lives and contribute to sustainable food production by increasing biodiversity, conserving water resources, and improving soil fertility and ecological resource management (Swain et al., 2022a; Waiza et al., 2024). Furthermore, converting land for renewable energy initiatives might lessen reliance on fossil fuels, reduce energy consumption, and, as a result, serve as a useful climate change mitigation strategy. These adjustments support low-carbon economies, reduce the use of natural resources and the environment, and promote sustainable energy production.

Many studies have been conducted globally to track changes in LULC patterns. These studies have sufficiently motivated us to prepare for the protection of natural resources and the environment to ensure the long-term growth of ecosystems, biodiversity, the environment, and humanity (Mandal et al., 2019; Taloor et al., 2020). The utilization of remote sensing (RS) satellite data has increased the ability of geographic information systems (GISs) to swiftly assess all of these spatiotemporal changes, which are widely used globally to monitor various types of changes on the Earth's surface (Chowdhury et al., 2021; González-González et al., 2022; Kumar et al., 2021; Petron et al., 2022; Taloor et al., 2021). Changes in LULC are significant markers of environmental and socioeconomic shifts. Understanding the surface dynamics of Earth is crucial for managing the utilization of land for sustainable development and comprehending how humans interact with the natural environment. There is currently enough material regarding the specific uses of LULC classification for particular goals, including identifying forest cover, and LULC changes are monitored for an array of purposes via different types of satellite data (Agariga et al., 2021; Belayneh et al., 2020; Kamran et al., 2022). GIS combined with high-resolution satellite data has reportedly opened the door for sophisticated artificial intelligence, machine learning, and Google Earth engines to assess the planet's LULC dynamics. Numerous researchers in Thailand and overseas are effectively using these techniques to comprehend how the planet is changing (Banchongsak et al., 2024; Khan et al., 2022; Kumar et al., 2021; Taloor et al., 2020, Talukdar et al., 2020; Singh et al., 2021). LULC analysis increasingly uses machine learning approaches, such as random forests, support vector machines, and artificial neural networks. These algorithms can be trained via satellite images and other spatial data to classify various types of land cover and predict trends in LULC change.

Research on the effects of land use and climate change on land use patterns, the prediction of the effects of urbanization on ecosystem services, natural resources, watershed systems, and policy guidance are only a few of the many uses for LULC modelling (Banchongsak et al., 2022; Sang et al. 2021). Some of the limitations and challenges associated with this type of research include the requirement for high-quality input data, the challenge of modelling the complex interplay between biophysical and socioeconomic elements, and the uncertainty associated with estimating future land use patterns. Over time, there have been recent developments in prospective models for LULC scenarios, and many models have been used to determine the spatiotemporal changes in LULC. More complicated models that may be used to examine the behavior of complex model systems and account for a wide range of external elements have been developed as a result of this field (Sohl et al., 2016). Numerous model types, including agent-based models, econometric models, and cellular automata (CA) models, are used in LULC simulation research (Banchongsak et al., 2022; Rosa et al., 2014). These external factors can be taken into consideration by the CA model, which can then be utilized to forecast how the system would behave in scenarios. These models could help in the creation of new technologies and solutions as well as offer new perspectives on how complex systems behave to plan land management and development better (Baqa et al., 2021; Banchongsak 2023; Chachondhia et al., 2021; Daba and You, 2022; Khaldi et al., 2022; Sintayehu et al., 2025; Zheng et al., 2021). For forecasting changes in LULC, the Markov model has become increasingly popular over time. However, predicting the spatial layout of land use changes is challenging when the Markov model alone is used.

Modelling the spatiotemporal variation over a specified time period, the CA model provides a solution when integrated with authoritative spatial computing. The analysis of CA via the Markov model has focused on several important topic areas. The development of increasingly complex techniques that use the Markov model to model the behavior of CA has been a topic of research. In addition, the scientific community has created methods for employing the Markov model to simulate the behavior of multidimensional CA and for adding stochastic components to models to consider system uncertainty, which leads to further improvements in model accuracy (Wang et al., 2022).

In recent years, the scenarios of LULC classification investigations have been substantially changed by the CA and Markov models. The integration of these models within a GIS framework provides a robust approach to simulate and predict LULC dynamics over space and time. RS data further increase the accuracy of model predictions (Al-Hameedi et al., 2022; Getachew et al., 2021; Liang et al., 2021; Mathewos et al., 2022; Sintayehu et al., 2025). This study focuses on the Northeast Khong Sub Watershed (NKSW), employing Landsat 7 (2013) and Landsat 8 (2023) imagery to analyse historical LULC changes and predict future patterns up to 2103. The main objectives of this study are to (1) analyse spatiotemporal patterns and transitions of LULC in the NKSW using multi-temporal satellite data; (2) apply the integrated CA Markov and GIS framework to simulate and predict future LULC dynamics; (3) evaluate the environmental implications of projected LULC changes; and (4) provide scientific evidence to support sustainable watershed management and land use planning in alignment with the United Nations Sustainable Development Goals (SDGs).

The NKSW was chosen as the study area because of its transboundary characteristics between Thailand and Lao People's Democratic Republic (Lao PDR), where rapid agricultural expansion, urbanization, and socio-economic development have led to diverse land use practices. Understanding LULC dynamics in this region is crucial for assessing environmental impacts, guiding sustainable land use decisions, and contributing to SDGs, including SDG 13 (climate action) and SDG 15 (life on land).

Methods

1) Overview of the study area

The NKSW area is in northeast Thailand, between latitudes 17°32′43.54″E and 18°16′26.11″E, and longitudes 102°44′47.79″N and 104°32′37.67″N, covering an area of 2,384.16 km2. It covers areas of Nong Khai and Nakhon Phanom Provinces. The NKSW is the most important part of the Northeast Khong watershed (Figure 1(A)). The NKSW has diverse topography, ranging from lowland floodplains along the Mekong River to gently undulating hills and scattered highlands. The elevation varies from approximately 150 m in the river valleys to over 400 m in the upland areas. This variation in topography strongly influences hydrological processes, soil erosion susceptibility, and land use patterns. The region experiences a tropical climate with a pronounced wet season, which interacts with the terrain to shape runoff, sediment transport, and agricultural productivity.

The LULC types of the NKSW were classified into 13 classes: cassava, eucalyptus, field crop, forestland, marsh and swamp, miscellaneous, orchard, paddy field, para rubber, rangeland, reservoir, urban and built-up land, and water bodies. The classification was conducted on the basis of high-resolution satellite imagery and followed the Land Development Department of Thailand (LDD) guidelines. Paddy fields make up almost all of the NKSW, which covers 870.16 km². or 36.05% of the total watershed area. This is followed by para rubber, forestland, and water bodies, covering areas of 467.48, 319.55, and 142.61 km^2, or 19.61, 13.40, and 5.98% of the total watershed area, respectively (Table 1). The NKSW has a digital elevation model (DEM) that ranges from 127 to 535 mean sea level (MSL), and it is surrounded by mountains of medium elevation. (Figure 1(B)).

2) Methods and approaches

The results were obtained via Arc GIS software onscreen digitization to delineate the LULC and primary maps from 2013 and 2023 of the study area via Landsat 7 and Landsat 8 data (30 m resolution) downloaded from the USGS Explorer (https://earthexplorer.usgs.gov/). Specifically, Landsat 7 and Landsat 8 imagery were utilized because of their long-term data continuity and moderate spatial resolution, which are suitable for LULC change detection. For Landsat 7, the visible (Bands 1-3), near infrared (Band 4), and shortwave infrared (Bands 5 and 7) bands were used, whereas for Landsat 8, the corresponding spectral bands (Bands 2-7) were applied to ensure consistency in spectral characteristics. The classification was conducted via a supervised classification approach with the maximum likelihood algorithm, which has been widely adopted for its statistical robustness and high accuracy in multi-spectral classification. An accuracy assessment was performed via confusion matrix analysis, with the overall accuracy and kappa coefficient calculated to evaluate the reliability of the classification results. The overall accuracies for all classified years exceeded the generally accepted threshold of 85%, with kappa coefficients above 0.80, indicating strong agreement between the classified and reference data. Furthermore, these LULC data from 2013 and 2023 were used as inputs to determine the CA Markov model-based future simulation from 2033 to 2103 by using the transition area and transition probability matrix in the CA Markov model to derive the LULC simulation for sustainability management planning.

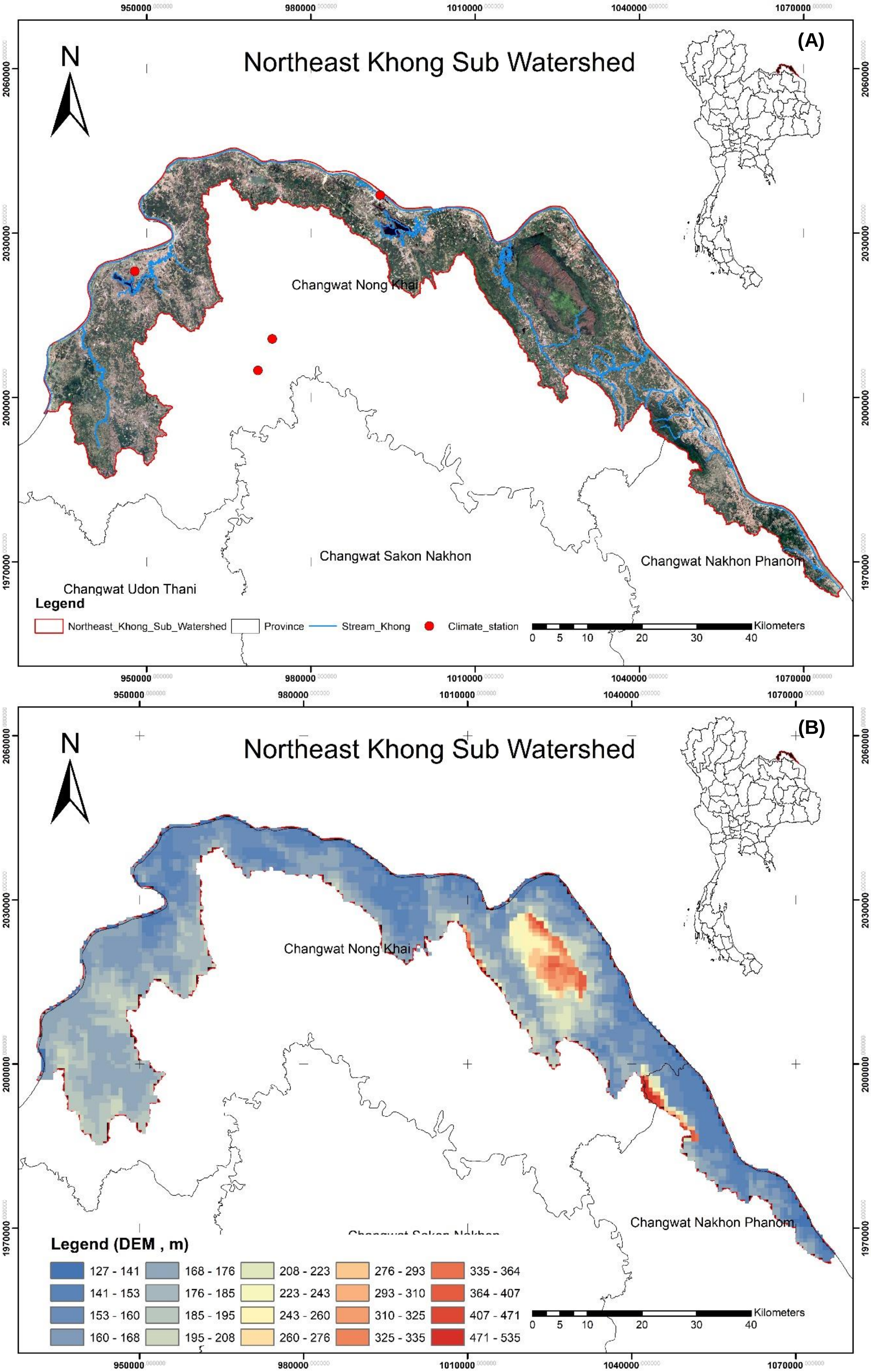

Figure 1 Maps of (A) the location of the NKSW and (B) digital elevation model of the NKSW.

Table 1 Harmonization codes are shown as symmetry codes for the 2013 LULC classes

Order	Name of LULC classes	Symmetry codes
1	Rangeland	1
2	Paddy field	2
3	Field crop	3
4	Orchard	4
5	Miscellaneous	5
6	Urban and built-up land	6
7	Water bodies	7
8	Forestland	8
9	Marsh and swamp	9
10	Cassava	10
11	Para rubber	11
12	Eucalyptus	12
13	Reservoir	13

3) Cellular automata (CA) Markov model

Complex systems of various types have been studied via the CA Markov model. A preset set of rules is used in CA to update the situation of every lattice cell, which depends on the situation of the neighboring cells. The CA is frequently employed to replicate a variety of natural and artificial systems, including biological, social, and physical systems (Abijith and Saravanan, 2021; Jafarpour et al., 2024; Yutong et al., 2024; Zhou et al., 2020). It can be applied to predict the future behavior of LULC types over time. In addition, it enables us to identify patterns and trends in system activity and forecast long-term LULC behavior (Guha et al., 2018; Hirpa et al., 2023; Kamran et al., 2022; Tariq et al., 2020). The model depends on how the grid size, transition rules, cellular space, and cell neighbourhood interact.

The Markov chain component estimates the probability of land use transition from one category to another between two time periods via a transition probability matrix (P), expressed as follows in Eq.1.

$$\mathbf{S}(\mathbf{t}+\mathbf{1}) = \mathbf{P} * \mathbf{S}(\mathbf{t}) \qquad \text{(Eq.1)}$$

where S(t) and S(t+1) represent the state of land use at times t and t + 1, respectively, and P is an n × n matrix of transition probabilities among n land use categories. Each element P_{ij} denotes the probability of transition from class i to class j within a given time interval.

The CA component incorporates spatial contiguity and neighborhood effects to generate realistic spatial patterns of land use change. The CA rule can be expressed as follows in Eq.2.

$$\mathbf{S}_{\mathbf{i,j}}^{\mathbf{t+1}} = \int\left(\mathbf{S}_{\mathbf{i,j}}^{\mathbf{t+1}}, \mathbf{N}_{\mathbf{i,j}}^{\mathbf{t}}, \mathbf{P}\right) \qquad \text{(Eq.2)}$$

where $S_{i,j}^{t+1}$ represents the land use state of cell (i, j) at time t, $N_{i,j}^{t}$ denotes the neighborhood configuration influencing that cell, and $\int$ is the transition function based on the Markov transition probability and spatial filter.

The integration of CA and Markov allows the model to account for both the temporal probability of land use transition and the spatial dependency among neighboring cells, producing more realistic and spatially coherent LULC predictions. The possibility of transitioning from a particular current state to a particular future state is represented by each entry or value in the matrix (Li, et al., 2016; Sejati et al., 2019). The methodological framework used in this study is shown in Figure 2.

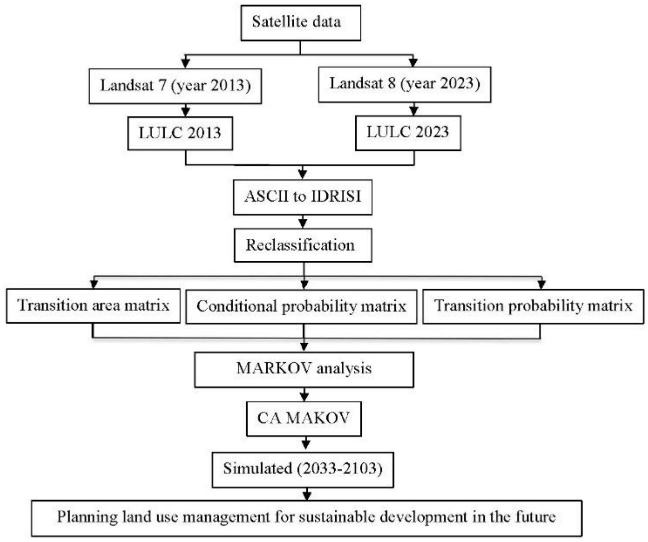

Figure 2 Methodological framework for the CA Markov model.

On the basis of the IDRISI program, several rounds utilizing 5×5 kernels as contiguity filters are required to forecast changes in LULC (Khwarahm et al., 2021; Tobore et al., 2024). The GIS environment was generated to construct the LULC for 2013 and 2023, and Google Earth engines were used to validate it among the different classes in Table 1. Furthermore, as shown in Table 2, the classes were harmonized by providing the LULC class symmetry codes. The symmetry field code found (Table 2) was used to convert the LULC 2013 and 2023 vector files into raster format, which was then transformed into ASCII format. This conversion used a cell size with a resolution of 30 m. In addition, the LULC raster needs to be snapped to one another and resampled to eliminate ambiguity.

The ASCII data were processed further via the IDRISI. The LULC classes for 2013 and 2023 were once more reclassified via the IDRISI format (Table 3). The Markov model was used to create transition area files and transition probability matrix files for the years 2013 to 2023. The easily comprehensible initials of the years used for prediction, such as 203 for 2033 and 204 for 2043, can be used as the image prefix. The background cell of 0.0 was chosen because it was thought that the LULC simulations would be suitable for maintaining a proportional error of 0.15%. The results from the Markov model are implemented in the integrated CA Markov model to provide improved simulations of land utilization. The CA Markov model was extended with the LULC 2023, and future predictions can be obtained via transition area files and a transition probability matrix. For a better understanding of the model-based output, 50 CA iterations were used to calculate the CA Markov-based decadal simulated LULC from 2033 to 2103 (Table 4).

An accuracy assessment was rigorously performed to evaluate the reliability of the LULC classification results. The assessment employed a stratified random sampling design to ensure representative sampling across all LULC classes. A total of 500 validation points were generated for each classified year (2013 and 2023), which were proportionally distributed according to class area.

Reference data were derived from high-resolution Google Earth imagery and field survey records collected within the same temporal window as the corresponding Landsat imagery (±1 year). For each LULC class, the producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA), and the kappa coefficient with 95% confidence intervals were calculated via the confusion matrix approach.

The results demonstrated high classification reliability, with OA values exceeding 85% and kappa coefficients above 0.80 for both years. These values indicate a strong level of agreement between the classified and reference datasets, aligning with widely accepted accuracy standards for RS-based LULC mapping (Congalton et al., 2019). This robust accuracy assessment confirms that the classified LULC maps provide a reliable foundation for subsequent CA Markov modelling and long-term scenario simulation.

Table 2 The IDRISI program follows the format of reclassification tables.

Order	Provide new value	To every values from	To slightly less than
1	0	-9999	0
2	1	1	1
3	2	2	2
4	3	3	3
5	4	4	4
6	5	5	5
7	6	6	6
8	7	7	7
9	8	8	8
10	9	9	9
11	10	10	10
12	11	11	11
13	12	12	12
14	13	13	13
15	0	14	9999

Table 3 The inputs and outputs from the Markov and CA model iterations are assigned for different years

Order	LULC	Prefix for transition	Iteration	Names of output	Error proportionality
1	2013	-	-	2013	-
2	2023	-	-	2023	-
3	2033	203	50	2033	0.15
4	2043	204	50	2043	0.15
5	2053	205	50	2053	0.15
6	2063	206	50	2063	0.15
7	2073	207	50	2073	0.15
8	2083	208	50	2083	0.15
9	2093	209	50	2093	0.15
10	2103	210	50	2103	0.15

Table 4 LULC classification based on Landsat data (Landsat 7, 8) for 2013 and 2023

Order	LULC classes	Year 2013		Year 2023	
		km^2	%	km^2	%
1	Rangeland	105.21	4.41	104.00	4.36
2	Paddy field	869.29	36.46	870.16	36.50
3	Field crop	107.73	4.52	111.99	4.70
4	Orchard	42.77	1.79	43.62	1.83
5	Miscellaneous	5.33	0.22	5.27	0.22
6	Urban and built-up land	95.29	4.00	98.15	4.12
7	Water bodies	142.75	5.99	142.61	5.98
8	Forestland	329.14	13.81	319.55	13.40
9	Marsh and swamp	67.33	2.82	65.31	2.74
10	Cassava	44.17	1.85	43.55	1.83
11	Para rubber	462.85	19.41	467.48	19.61
12	Eucalyptus	85.70	3.59	85.87	3.60
13	Reservoir	26.61	1.12	26.61	1.12
	Total	2,384.16	100.00	2,384.16	100.00

Results

1) Probabilities of transition and classification for LULC

The correctness and reliability of the CA Markov model depend on the quality and availability of the data used to calculate the probability matrix and transition probabilities. Therefore, it is critical to choose and handle the data carefully to guarantee that they are accurate and representative of the study area. Using onscreen digitization, two different LULC thematic maps for 2013 and 2023 (from Landsat 7, 8) were created to assess the degree and possible changes (in percentages) in land use. It provides a detailed overview of the LULC changes that took place between 2013 and 2023 (Table 4). This highlights significant shifts in paddy fields, para rubber, and forestland. Over a decade, paddy fields, rubber, field crops, urban and built-up land, eucalyptus, and orchard areas have increased, whereas forestland, rangeland, marsh and swamp, cassava, and miscellaneous areas have decreased (Figure 3).

2) LULC prediction via the integrated model

The CA Markov model considers the geographical and temporal features of LULC changes, which can help decision-makers or management planners create effective land management plans for sustainable development. To simulate LULC changes over time, the concepts of the CA and Markov models are combined in the integrated CA Markov model. The geographical distribution of LULC and its variations are simulated via the CA model, whereas the temporal changes in LULC are simulated via the Markov model via the transition probability matrix, conditional probability matrix and transition area matrix. The integrated CA Markov model may predict future changes in LULC based on historical data. The model can simulate the future location and magnitude of LULC changes by accounting for both the spatial and temporal characteristics of LULC changes. The model can also be used to evaluate the different land management scenarios that affect changes in land use and clearance. By modelling different scenarios, the model can assist decision-makers, conservationists, environmentalists, and management planners as well as those interested in studying LULC changes to minimize negative effects and maximize favourable effects. Model-based prediction highlights the environment's changes and potential repercussions by highlighting significant changes in LULC and land management planning over the specified periods (Figure 4).

The trends observed indicate a significant decline in the area covered by forestland, rangeland, marsh and swamp, together with an increase in paddy fields, para rubber, and field crops. Additionally, the percentages of marshes and swamps decreased from 2.82% in 2013 to 2.50% in 2053 and then to 2.15% in 2103. Furthermore, both urban and built-up land are expanding. Forestland decreased from 13.81% in 2013 to 9.15% in 2103. Underscore the challenges caused by factors such as changing weather conditions, urbanization, changes in the monsoon period, and socioeconomic changes.

Rangeland areas show a similar decreasing trend, emphasizing the need for conservation efforts to mitigate the loss of biodiversity. Deforestation, dry environments, inappropriate land use, agricultural practices in highlands lack proper management, erosion of the soil surface, variable summer monsoon rain patterns, demand for residential land use, population growth, and economic expansion, all of which are the main causes of land use change, as indicated by a bar diagram (Figure 5).

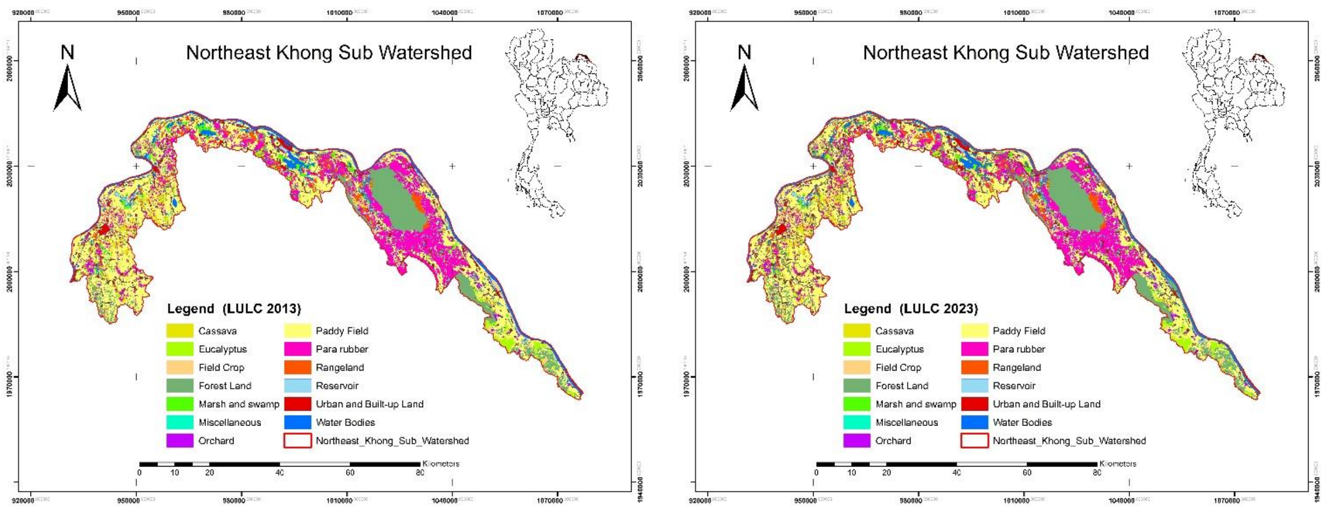

Figure 3 (A) LULC 2013 and (B) LULC 2023 of the NKSW.

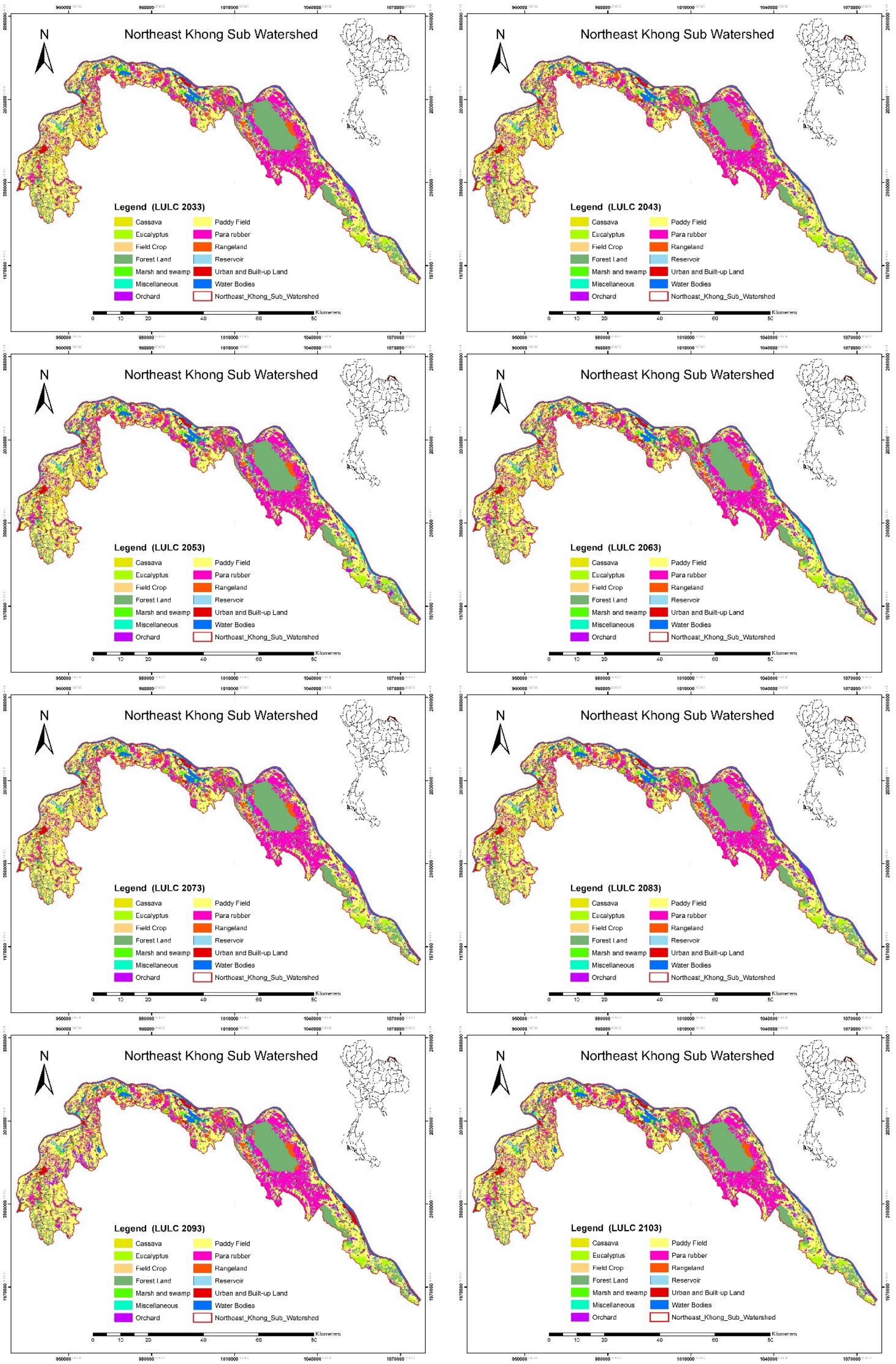

Figure 4 LULC simulation map of the NKSW from 2033 to 2103.

Table 5 Areal distributions of the LULC simulations based on the CA Markov model

LULC classes	2013		2023		2033		2043		2053		2063		2073		2083		2093		2103	
	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%
Rangeland	105.21	4.41	104.00	4.36	101.18	4.24	97.77	4.10	93.92	3.94	90.07	3.78	86.23	3.62	81.63	3.42	78.03	3.27	74.51	3.13
Paddy field	869.29	36.46	870.16	36.50	876.25	36.75	882.39	37.01	888.56	37.27	894.78	37.53	901.05	37.79	907.35	38.06	913.70	38.32	920.10	38.59
Field crop	107.73	4.52	111.99	4.70	115.35	4.84	118.81	4.98	122.37	5.13	126.04	5.29	129.83	5.45	133.72	5.61	137.73	5.78	140.86	5.91
Orchard	42.77	1.79	43.62	1.83	44.49	1.87	45.38	1.90	46.29	1.94	47.22	1.98	48.16	2.02	49.12	2.06	50.11	2.10	51.11	2.14
Miscellaneous	5.33	0.22	5.27	0.22	5.22	0.22	5.17	0.22	5.12	0.21	5.06	0.21	5.01	0.21	4.96	0.21	4.91	0.21	4.87	0.20
Urban and built-up land	95.29	4.00	98.15	4.12	101.09	4.24	104.13	4.37	107.25	4.50	110.47	4.63	113.78	4.77	117.20	4.92	120.71	5.06	123.33	5.17
Water Bodies	142.75	5.99	142.61	5.98	142.47	5.98	142.33	5.97	142.18	5.96	142.04	5.96	141.90	5.95	141.76	5.95	141.62	5.94	141.47	5.93
Forest Land	329.14	13.81	319.55	13.40	307.02	12.88	294.74	12.36	282.55	11.85	269.97	11.32	257.02	10.78	245.44	10.29	232.57	9.75	218.22	9.15
Marsh and swamp	67.33	2.82	65.31	2.74	63.35	2.66	61.45	2.58	59.60	2.50	57.82	2.42	56.08	2.35	53.40	2.24	50.77	2.13	51.18	2.15
Cassava	44.17	1.85	43.55	1.83	42.94	1.80	42.34	1.78	41.74	1.75	41.16	1.73	40.58	1.70	40.02	1.68	39.46	1.65	38.90	1.63
Para rubber	462.85	19.41	467.48	19.61	472.16	19.80	476.88	20.00	481.65	20.20	486.46	20.40	491.33	20.61	496.24	20.81	501.20	21.02	506.21	21.23
Eucalyptus	85.70	3.59	85.87	3.60	86.04	3.61	86.21	3.62	86.38	3.62	86.56	3.63	86.73	3.64	86.90	3.65	87.08	3.65	87.25	3.66
Reservoir	26.61	1.12	26.61	1.12	26.61	1.12	26.57	1.11	26.54	1.11	26.50	1.11	26.47	1.11	26.40	1.11	26.28	1.10	26.13	1.10
Total	2,384.16	100.00	2,384.16	100.00	2,384.16	100.00	2,384.16	100.00	2,384.16	100.00	2,384.16	100.00	2,384.16	100.00	2,384.16	100.00	2,384.16	100.00	2,384.16	100.00

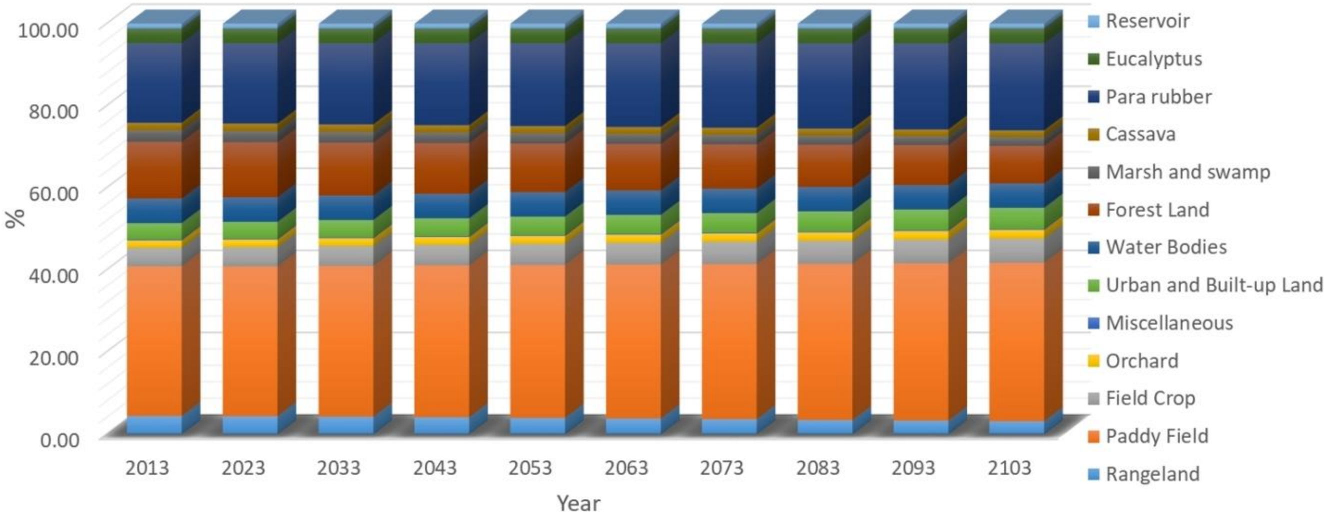

Figure 5 LULC classifications from 2013 and 2023 based on Landsat data and simulated LULC classifications from 2033 to 2103 based on CA Markov are displayed in a bar diagram.

According to the CA Markov model, there will be a steady trend in land use, which is mostly made up of reservoirs and water bodies suitable for agriculture and pasture. Among all LULC classes, this settlement is one of the most developed in terms of urban and built-up land. It has grown steadily, from 4.00% in the year 2013 to 4.12% in the year 2023 and then to 4.50% of the entire study area in the year 2053, which then increased to 5.17% of the whole area in the year 2103. The water yield (quantity, quality and timing of water), environmental system, and ecosystem dynamics may all suffer as a result of this increase. An increase in aridity, which is linked to deforestation, soil degradation, altered rainfall patterns, and arid conditions, indicates the environmental stresses that impact land production as well as the life of living things.

The expansion of the LULC area indicates an increase in changes in land use patterns that are conducive to agriculture, which could be caused by alterations in land use or the consequences of climate change and natural resource and environmental changes. The continuous expansion of urban and built-up land is the most noticeable trend. The significant increase in urbanization from 4.00% in the year 2013 to 5.17% in the year 2103 is indicative of this phenomenon. The development of infrastructure, resource management, agricultural land development, and the overall socioeconomic environment are all impacted by this expansion.

The trends found in this investigation, which were generated by the CA Markov model, are helpful tools for future planning and decision-making. Environmentalists, urban planners, and policymakers or anyone interested can learn from data about the challenges associated with change. It is critical to contemplate tactics related to conservation, land use planning, watershed management, and sustainable development to address this concern and ensure an integrated approach to environmental preservation and development for humanity and all living things.

Discussion

Numerous studies have analysed LULC trends in various regions via advanced modelling techniques. Using RS and GIS methodologies, Shukla et al. (2018) examined how land use has changed in the Ganga watershed, emphasizing the effects of agriculture and urbanization on land cover. Sintayehu et al. (2025) examined the trends and frequencies of LULC changes in the Upper Blue Nile Basin's Guder watershed from 1985 and 2021, with forecasts for 2039 and 2057. Banchongsak et al. (2022; 2024) and Banchongsak (2023) examined model responses of land use and land cover dynamics to groundwater, surface runoff, hydrological processes, and various land use activities, with the results indicating that all are statistically significantly interrelated. Additionally, Nimish et al. (2018) examined the effects of urban sprawl caused by migration, population growth, and changes in land use. The dynamics of land surface temperature (LST) were also examined in this study, and the mean LST increased noticeably throughout the investigation. LULC changes must integrate ecological, socioeconomic, and environmental considerations to promote sustainable development. However, rapid transformations in recent decades have posed substantial challenges to this goal. The CA Markov model has proven to be a reliable tool for analysing and predicting LULC dynamics, providing essential support for land management, resource allocation, and long-term sustainability assessment.

In the NKSW, projected LULC changes are driven primarily by resource exploitation, urban expansion, and agricultural intensification. These trends highlight the urgent need for strategic land management, effective urban monitoring, and conservation-oriented policies to maintain ecosystem integrity and watershed resilience.

Consistent with other studies in Thailand, the findings reaffirm the usefulness of CA Markov- and GIS-based frameworks in sustainable land use planning and integrated watershed management. For example, studies in Koh Chang (Waiyasusri and Chotpantarat, 2022) and the Prachinburi-Sakaeo basin (Waiyasusri et al., 2024) demonstrated that urban expansion significantly altered land use and hydrological functions, underscoring the importance of integrated planning to balance development and resource conservation. Overall, this research contributes to understanding LULC dynamics in rapidly developing regions and emphasizes the necessity of sustainable land management for long-term ecological and socioeconomic stability.

Conclusions

Research on LULC dynamic simulations is highly important, as it provides valuable implications for environmental sustainability and land management policy decisions. Urban and built-up land expansion will likely occur at the expense of rangeland, whereas forest conversion for agricultural use is expected to continue due to inadequate land management practices. Although the Markov model has proven to be an effective tool for simulating and forecasting LULC transitions, further research and model refinement are needed to improve precision and reliability. RS and GIS technologies are indispensable for spatial and temporal LULC analysis, providing critical insights from local to regional scales.

The integrated CA Markov model applied in this study effectively simulated the spatial and temporal dynamics of LULC in the NKSW, Thailand. Landsat data for 2013 and 2023 were analysed to construct LULC maps, and future projections from 2033 to 2103 were generated to understand potential land use transitions. The model predicted substantial increases in settlement and built-up areas, increasing from 4.10% in 2023 to 5.20% in 2103, accompanied by the expansion of paddy fields. In contrast, forestland, rangeland, marsh and swamp, cassava, and miscellaneous categories are expected to decline, indicating ongoing land degradation processes. These findings emphasize the need for integrated watershed planning and policy interventions to ensure sustainable land utilization across Thailand, the Lao PDR, other Mekong subregions, and the world.

However, this study also has certain limitations. The accuracy of LULC classification relies heavily on the spatial resolution and quality of Landsat imagery, which may not fully capture fine-scale land transformations. Moreover, the absence of explicit socioeconomic, policy, and climate drivers in the modelling framework introduces uncertainty into long-term projections. Future research should incorporate higher-resolution satellite datasets (e.g., Sentinel or PlanetScope), socioeconomic parameters, and projected climate scenarios to enhance model robustness and predictive capability.

Future studies are encouraged to integrate the CA Markov approach with process-based or agent-based models to capture human decision-making and environmental feedback mechanisms more realistically. Additionally, transboundary comparative studies within the Mekong region should be conducted to examine cross-border LULC dynamics and assess policy implycations for regional sustainability.

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Data availability statement

Information and data used in the study will be disclosed upon request.

Author contributions

Banchongsak Faksomboon: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – Original draft, Writing – Review & editing, Visualization, Supervision, Project administration, Funding acquisition

Thipphaphone Keoviyavong: Validation, Data curation, Supervision, Project administration, Funding acquisition

Conflicts of interest

The authors declare that there are no conflicts of interest in competing financial or personal relationships that could have appeared to influence the work reported in this work.

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