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Predicting Spatial Land Use and Land Cover Change Using an Integrated Mathematical Model in the Khlong Nam Lai Watershed, Kamphaeng Phet Province, Thailand

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Abstract

Assessment of land use and land cover (LULC) change in any region is one of the prominent features used in environmental resource management and its overall sustainable development. Tools to measure the past, present, and build a future scenario based on them are necessary for an effective evaluation of LULC changes. The changes in LULC are inevitable throughout the world, but especially in developing nations. Without the identification of acceptable methodologies and approaches, the future perdition will be less accurate since LULC is too complex and dynamic. The integrated Cellular Automata Markov Chain (CA-Markov) model is therefore regarded as a capable estimator. The Khlong Nam Lai Watershed (KNLW) LULC alterations were examined in this study using various images and data that were taken from satellite data in the years 2001 and 2021 to generate the LULC scenario in the year 2041. The model was validated using actual data and projected to the year 2021. The overall agreement on the two extracted maps was 97.23 % in the year 2001 and 96.41 % in the year 2021, respectively. According more detailed analysis of the validation of calibration based on the kappa index were showed the highest data reliability of 0.97 in 2001 and 0.96 in 2021, respectively. The LULC of KNLW in the year 2041 will undergo changes in the KNLW based on the past scenario (2001 to 2021). Concurrently, the forest, paddy field, para rubber, and other classes continue to decline, except cassava, sugarcane, urban, and orchard. The results obtained showed that the forest class had continued to reduce more than other classes. As a result, the research can aid in the prevention of LULC problems affecting life, ecology, and the environment, including developing the necessary planning guidelines for limited natural resources, such as planning for sustainable watershed management using systematic and sustainable concepts.

Keywords: Land Use and Land Cover Change; Integrated Mathematical Model; Watershed

1. Introduction

The land use and land cover (LULC) changes have raised concerns on a worldwide scale since they have an impact on the global system (Hailu *et al.,* 2020). Globally, variations in LULC are the key anthropogenic drivers of national resource change on all time-based and spatial scales (Naschen *et al.,* 2019). On a local and global scale, LULC changes have created unique concerns in natural resource management and sustainable development. Land use encompasses all forms of varying land usage for varying human demands. The most crucial criteria are making the best use of the land available, understanding land use patterns, and being aware of how each has changed through time. Human activity has had an impact on LULC resources on a local, regional, and global scales, such as rising land surface temperatures, rainfall distribution, ecosystem service disruption, and ecohydrological impacts (Gohin *et al.,* 2020; Bhattacharya *et al.,* 2020; Huang *et al.,* 2020; Banchongsak *et al.,* 2022). Therefore, the quality of the land cover is formed by complex interactions between ecological, physical, and hydrological characteristics in a particular area (Chemura *et al.,* 2020). Assessing the current spatial and temporal dynamics of LULC is vital to monitoring the trend of changes for better future assessment.

The spatial and temporal impacts of rapid land use change go beyond urban and rural boundaries (Kojuri *et al.,* 2020; Kamran *et al.,* 2020). The excessive use of LULC for different political and economic purposes can reduce the current and future capacities of the appropriate use of land. As a prime example, socioeconomic aspects of land use change in the agriculture sector have become a serious issue when the drought impacts have been followed by the expansion of roads and public transportation, which has made land abandonment in rural areas easier and faster to move. Consequently, productivity reduction, unsustainable agricultural development, and many other environmental and socioeconomic issues with strong spatial and temporal impacts appear. An effective current LULC assessment can help farmers save land in the future (Tang *et al.,* 2020). On the other hand, rapid urbanization can reduce rural resources by a wide range of environmental impacts (habitat quality, resource degradation, e.g.), as urban expansion and urban sprawl change arable lands to other urban land use and threaten natural resources.

The effects of LULC changes on ecological changes were commonly studied in a variety of fields using multi-temporal image methods. The studies revealed that human actions and natural resource disturbances are the fundamental drivers of LULC dynamics (Singh *et al.,* 2015; Basommi *et al.,* 2016; Singh *et al.,* 2018; Varga *et al.,* 2019; Banchongsak *et al.,* 2022). The effective evaluation for standardization and compatibility between data sets and the possibility of mapping maps depends on the appropriateness of present and future land use. In contrast to previous models, logistic regression models do describe the weights of the driving forces. The CA Markov is a mixed model that combines the ideas of the Markov Chain and Cellular Automata (CA), an open configuration that may be easily merged with knowledge-driven models (Modeling spatiotemporal dynamic high accuracy result). When, The Markov chain is made up of a set of probability values that show the probability of converting user interfaces over some time, depending on the amount of change in the past. It is theoretically possible for a certain region of the globe to go from one land use category to another at any moment. Matrix-based Markov Chain analysis is used to examine all changes in land use among all distinct groups that are accessible to represent land uses. In the past three decades, the Markov Chain model has become more widely used for a variety of LULC research due to its accuracy and dependability (Nadoushan et al., 2015). The transition probabilities of various land use interactions at various timeframes are evaluated using CA-Markov. These scale transitions allow for the spatial dominance of one or more land uses over other land uses. With this method, the matrix of the area changes shows how many pixels will shift from one land use class to another during specific periods. Coating classes have been employed as chain states in Markov Chain analysis.

The Markov Chain model produces a possible change matrix and an output picture from a possible change matrix for the last year after it has analyzed images of land use zoning. The likelihood that each class of land use classification will switch to different land use in the future is displayed in a probable change matrix. One of the best bottom-up approaches for simulating land use change is the Markov Chain and cellular automata model. As a user-friendly model for predicting the future spatial model and LULC through the identification of complex system dynamics. Furthermore, it is acknowledged as an effective two-dimensional technique for illustrating both the spatial and temporal dynamics of place and space dynamics. In tropical and subtropical regions, the Markov model's efficacy has been demonstrated on various scales and with excellent accuracy (Gidey *et al.,* 2017). Recent developments in

Geographic Information Systems (GIS) and Remote Sensing (RS) increase the precision of computation and modeling. Several studies indicate that the CA–Markov model when combined with RS and GIS creates a suitable method for studying the dynamics of LULC changes (Riccioli *et al.,* 2013; Roose and Hietal, 2018; Banchongsak *et al.,* 2022). In this study, the quantification of the transition probabilities of various land cover categories from discrete time steps is frequently done using a Markov Chain model. Then, a Cellular Automata (CA) model is applied to these probabilities to forecast spatially explicit changes over a predetermined period. An initial distribution and a transition matrix serve as the foundation of a CA-Markov model, which assumes that the factors responsible for the observable patterns of land cover categories will continue to operate as they have in the past. Because we are interested in extrapolating the pre-intervention landscape into the future while assuming no change in the type of intervention, this very assumption makes a CA-Markov model acceptable for a counterfactual approach.

The current LULC of the Khlong Nam Lai Watershed (KNLW) issue is likely to worsen and intensify, due to the high concentration of agricultural activities. The natural resources become a serious issue for the KNLW, affecting the quality of life for people and other creatures living along in the surrounding areas. This study uses historical and contemporary analyses to predict future LULC changes in the KNLW. The objective of this study to simulate each LULC using CA and Markov Chain in the KNLW and prepares data for the LULC map from the years 2001 to 2021, forecasts using the Markov model to improve simulation accuracy in the 2041 analyzes of KNLW. The result of this study will contribute to the existing or assist in building a new scientific knowledge base on the spatial-temporal change of LULC and link to the natural resource protection of KNLW. This will benefit all stakeholders, including natural resource professionals, policymakers, and researchers, as well as the community regarding sustainable management and monitoring of LULC and the ecosystem.

2. Materials and Methods

2.1 Study site

The Khlong Nam Lai Watershed (KNLW) area is in Northern Thailand, between latitudes 99°10′57.14′′E and 99°20′49.63′′E, and longitudes 16°18′52.41′′N and 16°09′29.54′′N. The KNLW, with a 193.27 Km2 area, is the most important part of the Ping Watershed. The land use was classified into 9 classes: paddy field, water body, sugarcane, cassava, para rubber, forest, orchard, urban, and other. The land east of the KNLW area is predominantly agricultural, filled with cassava and paddy field. To the west are the foothills, mostly covered with forests and mountains, with elevations rising to 1,100 meters above mean sea level in Figure 1 (A). The KNLW experiences bimodal conditions in which the wet and dry seasons are distinguished. The wet season normally occurs between May to October and the dry season between November to April. The climate of the KNLW area in terms of annual rainfall observed from the years 2020 to 2021 was 1,304.60 mm and the highest rainfall from May to October was between 159.4 - 268.8 mm, which covers about 88.23 % of the annual rainfall, and only 11.77 % of the rainfall from November to April was 2.3 - 52.80 mm in Figure 1 (B). The average humidity and temperature were 75.80 %, and 28.16°C, respectively in Figure 1 (C and D). According to the Thai classification system, there are 2 soil groups.

2.2 Cellular Automata (CA)

The CA model demonstrates the nearest neighbor effect and how many elements alter substantially over time mathematically. In actuality, CA frequently creates homogeneous states and self-similar patterns. In general, it is used to investigate chaos and self-organization in dynamic systems more thoroughly (Wolfram, 1983). Additionally, CA demonstrates how cells interact; it displays the quantity and geographic variation of each value in several cells (Arsanjani *et al.,* 2011). Due to the complexity and dynamic nature of LULC, CA is a dynamic model that may be mixed with other models and is discrete in time, place,

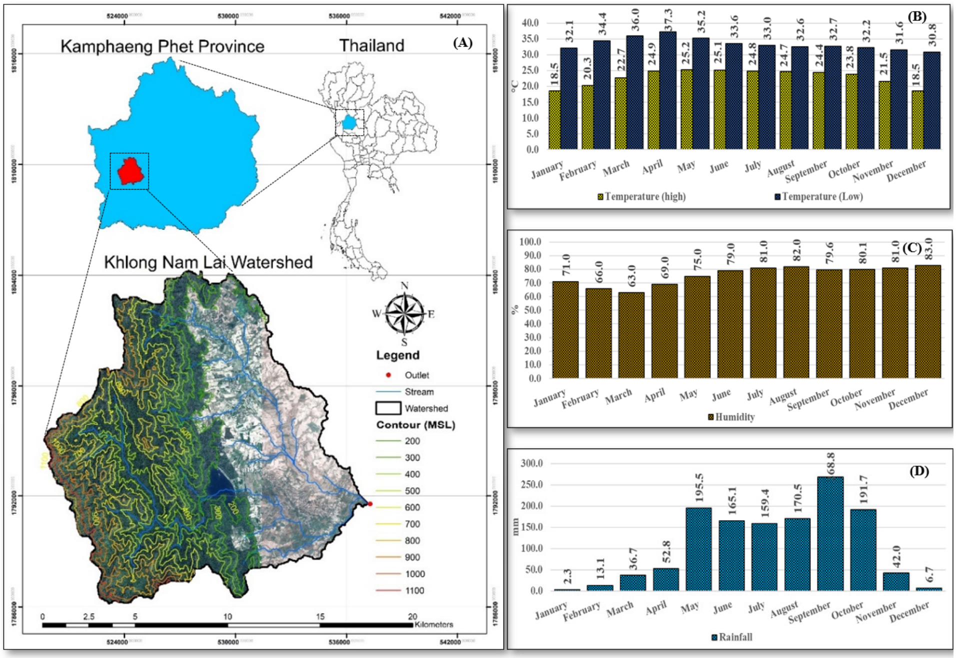

Figure 1. Geographical location of KNLW area; (A), Annual temperature; (B), Annual humidity; (C), and Annual rainfall; (D)

and state. Cells can alter their state in time and space using geometrical relationships and spatial order. These modifications could be taking place at the edge or in the middle of a cluster of cells. In general, and geographically, borders move very frequently, but when they begin at the heart of a clump of cells, the effects on the future will be profound (hydrologic changes, e.g.). The negative and positive dimensions of the quality of change are clarified by the computation of all these nonlinear dynamical transitions from one value of a cell to another value.

With the combination of the spatial and temporal aspects of the dynamic method, the CA model reliability makes it a popular and successful technique to address LULC alterations (Zhou *et al.,* 2020). By combining conditional and statistical principles, this model can be modified to predict the transition of each land use classes on a calibrated geographical and temporal scale. The modeler can apply the knowledge of important elements influencing past LULC changes practically. How sensitive the model was to calibration, classification, parameter value, chosen time, and the CA model must address space. Additionally, how well did the model simulate LULC changes, presence, and location (Jabbarian Amiri *et al.,* 2017).

2.3 Markov Chain model

A Markov Chain is a random process in which a single limiting condition moves from point i to point j in a system with a transition probability of pij. These transitions between the many components of this system vary; some of them change while others stay the same in terms of time. Each class that is identified in land use research may persist for a long period, and some individuals may switch to different classes. Accordingly, using historical data for each class, a matrix of actual transition probabilities can be utilized to forecast future land use change. The model of self-working cells has found widespread use in anticipating land use change due to its dynamic nature and unique properties in simulating the natural and physical elements of the earth's surface (Alimohammadi *et al.,* 2008).

The Markov Chain is a collection of random processes where each process' current outcome solely depends on the outcome of the process immediately to its left or right. However, Markov Chain random variables might have multiple probability distributions, and each one only depends on the variable that came before it (Behbahani and Heidarizadi, 2019). The following is a list of random variables in Equation 1.

$$X^{(0)}, X^{(1)}, X^{(2)}, \ldots \quad (1)$$

In Equation (1), *X* is the state of the system at a time. The Markov Chain sample space for random variables might be continuous or discrete, small or large. Any random variable can be represented by its probability distribution under the assumption that the sample space has a finite number of discrete states. With the use of a vector that contains the probabilities for each value in the sample space, we can visualize this distribution in Equation 2.

$$P_0, P_1, P_2, \ldots P_i = [P(X^i = X1), \ldots, P(X^i = \bar{X}_n)] \quad (2)$$

In Equation (2), *P* is the probability of making a transition from the state. According to the Markov chain definition, knowing the first - (i) of the component (1 – i) of the chain component and the interface that my component produces is enough to make the chain. The conversion of probability vector components by this function is obtained according to Equation 3.

$$P\,(X^{i+1} = X) = \sum P\,(X^i = \tilde{X})\,T_i\,(\tilde{X}, \bar{X}) \quad (3)$$

In Equation (3), *T* is the t-step transition probability given by the matrix. If in the Markov chain, the relationship between successive random variables does not depend on their position in the chain. The relationship homogeneous chains in Equation 4.

$$T_i\,(\tilde{X}, \bar{X}) = T_j\,(\tilde{X}, \bar{X}) = T\,(\tilde{X}, \bar{X}) \quad (4)$$

These relationships can be summarized in Equation 5.

$$T_{nn} = \begin{pmatrix} T(X_1, X_1) & \ldots & T(X_1, X_n) \\ \ldots & \ldots & \ldots \\ T(X_n, X_1) & \ldots & T(X_n, X_n) \end{pmatrix} \quad (5)$$

Two raster maps are always used in this analysis as the model inputs. Additionally, the two generated maps, the gap in time between the two photos, and the prediction are all taken into account in this model. The model's output also contains the potential for changing the status, a matrix of the converted areas for each rank, and, after the images, conditional probabilities for the conversion of various uses. A Markov Chain analysis is a method of calculating the transition probability matrix for a future evaluation based on a first-time assessment (past and present) (Asadzadeh *et al.,* 2018).

2.4 CA-Markov model

CA-Markov is used for time and purposes. We lack knowledge or our understanding is constrained by physical and temporal constraints in the future. The CA-Markov Chain model is frequently used to display the transitional probabilities of various LULC across various time intervals. The CA model employs these probabilities to demonstrate significant geographic shifts in LULC. Additionally, given the significant influence of the drivers who have established this pattern, these changes may persist in the future. This is highly helpful in predicting the dominance of LULC in the future and understanding how it will affect the environment, natural resources, and the creation of the landscape (Firozjaei *et al.,* 2018). Different environmental dimensions cannot be incorporated into the simulation using the CA model alone. For modelers like Markov Chain, CA's ability to combine with other models makes it particularly intriguing. An efficient mixed model for simulating future LULC modifications and natural complexity is the CA-Markov Chain model (Moein *et al.,* 2018; Mirzaeizadeh *et al.,* 2015). The CA-Markov model takes time into account when displaying trends and the factors that will lead to transitions that will manifest in the future. The CA-Markov cells change systemically by influencing adjacent neighborhoods, producing the spatial formation for each class. This is how the cells' value changes produce a new spatial pattern for the area, and these changes are associated with a cohesive transition in entire cells over and done with time and space. Additionally, if the center of a certain set of cells has less effect, the other classes will have greater influence, and changes will occur much more quickly. The importance of these classes in the overall system can demonstrate where and how positive and negative make the transitions when a collection of cells occasionally shifts between a few different classes throughout time. Significantly, because of consistent transition rules, nearby cell's values change, making them more like themselves and affecting the entire system.

2.5 Data preparation for LULC changes analysis

To explain LULC changes in the context of this study, Google Earth Engine employed satellite data search images. Landsat images, including those taken from the real two satellite observations in 2001 and 2021, were used because of their spectral and geographic resolution, capacity to modify the topography and availability. Since the satellite data for the KNLW (2001 and 2021) was produced by various Landsat data collections via various routes, This satellite offers precise maps with high resolution that have both been preprocessed (atmospherically and geometrically). This study used the supervised classification of the Support Vector Machine (SVM) for the pre-identification of the precisely targeted classification once the photos were transferred using the ENVI program. The images were categorized using supervised classification using maximum likelihood estimation, which produced a pixel-by-pixel land use map of the KNLW. Finally, Terrasat software processed CA-Markov for LULC prediction in KNLW for 20 years in the future. 9 classifications were therefore identified as the main LULC (forest, urban, sugarcane, cassava, orchard, paddy field, para rubber, water body, and others). The correctness of the data was validated by calibration based on the Kappa coefficients to model future LULC changes, and the overall agreement on the two extracted maps was 97.23 in the year 2001 (from Landsat 5) and 96.41 in the year 2021 (from Landsat 8) in Table 1, respectively.

3. Results and Discussion

3.1 Transition probabilities and matrix for LULC in 2021

The combination of the two images, which were extracted from two distinct Landsat images collected in 2001 and 2021, was used to estimate the potential magnitude and percentage of LULC. The significant LULC variations in KNLW after about 20 years of the study indicated that the areas of land under different LULC types and percentage rate of changes are given in Table 2 and Figure 2. According to the statistics gathered, the forest was the biggest LULC in the KNLW with 62.10 %, 60.17 %, and 58.24 % or around 120.02 km^2, 116.29 km^2, and 112.56 km^2 in the years 2001, 2021, and 2041, respectively. Following the significant LULC changes in the KNLW depicted, there were an increase in cassava, sugarcane, and urban areas of 2.206 %, 0.273 %, and 0.197 %, or around 4.263 km^2, 0.528 km^2, and 0.380 km^2 from the year 2001 to 2021, and 2.244 %, 0.286 %, and 0.119 %, or around 4.337 km^2, 0.552 km^2, and 0.230 km^2 from the year 2021 to 2041, respectively. In the same way, orchards increased slowly but steadily between the years 2001 and 2021 by 0.060 % or around 0.115 km^2, and 0.182 % or around 0.352 km^2 in year 2021 to 2041. In contrast, the paddy field shrank considerably during 2001 to 2021 by about 0.674 %, which is equal to 1.302 km^2, and 1.503 km^2 in year 2021 to 2041, as well as para rubber and other area during 2001 to 2021 decreased by 0.062 % and 0.064 %, which was about 0.120 km^2 and 0.123 km^2, and 0.061 % and 0.061 % or around 0.118 km^2 and 0.118 km^2 in year 2021 to 2041, respectively. There is a slower decrease in the water body by less than 0.005 % and 0.002 %, which is roughly about 0.009 km^2 and 0.004 km^2 from 2001 to 2041.

Table 1. SVM classification accuracy for LULC

Images	SVM classification images	
	Overall accuracy	Kappa index
2001 (Landsat 5)	97.23	0.97
2021 (Landsat 8)	96.41	0.96

Table 2. The trend of LULC perdition between 2001 and 2021, as well as 2041

Order	LULC Type	2001		2021		LULC Change		2041		LULC Change	
		Km²	%	Km²	%	Km²	%	Km²	%	Km²	%
1	Forest	120.02	62.10	116.29	60.17	- 3.732	- 1.931	112.56	58.24	- 3.728	- 1.929
2	Urban	7.41	3.83	7.79	4.03	0.380	0.197	8.02	4.15	0.230	0.119
3	Sugarcane	2.68	1.39	3.21	1.66	0.528	0.273	3.76	1.95	0.552	0.286
4	Cassava	30.57	15.82	34.83	18.02	4.263	2.206	39.17	20.27	4.337	2.244
5	Orchard	2.27	1.18	2.39	1.24	0.115	0.060	2.74	1.42	0.352	0.182
6	Paddy field	19.95	10.32	18.65	9.65	- 1.302	- 0.674	17.15	8.87	- 1.503	- 0.778
7	Para rubber	2.57	1.33	2.45	1.27	- 0.120	- 0.062	2.33	1.21	- 0.118	- 0.061
8	Water body	4.05	2.09	4.04	2.09	- 0.009	0.005	4.03	2.09	- 0.004	0.002
9	Other	3.75	1.94	3.63	1.88	- 0.123	- 0.064	3.51	1.82	- 0.118	- 0.061
	Total	193.27	100.00	193.27	100.00	-	-	193.27	100.00	-	-

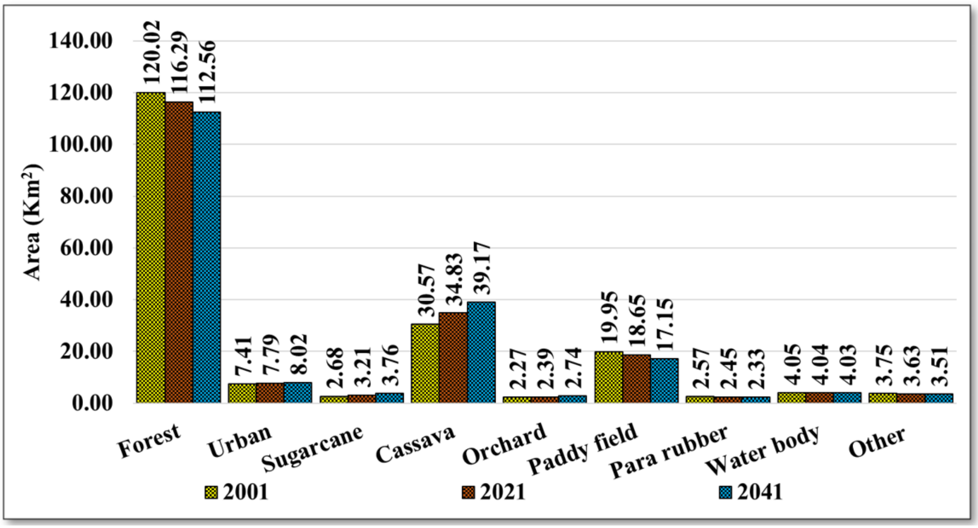

Figure 2. LULC change graph between 2001 and 2021, as well as 2041

The changes in LULC for the study period (2001 to 2041) are in Figure 3. The results reveal that the highest net gain showed an increase of cassava by 4.45 %, followed by sugarcane (0.56 %), urban (0.32 %), and orchard (0.24 %), while net loss was in a forest (3.86 %), followed by paddy field (1.45 %), para rubber and other (0.12 %), and water body (0.01 %), respectively.

3.2 Validation of the model

Verification of models by calculating the information needed to match the created thematic map with the actual map of the area is frequently essential to assess image correctness. The thematic map created by the classification of satellite images should be contrasted with the two-subject map of terrestrial reality. It is not possible to demonstrate the reliability of the image by measuring merely two points in one or two classes. Although the LULC class changes in a certain area may not have altered, the LULC geographical distribution in the area has changed dramatically. As a result, their location should be taken into account in addition to the class location. The number of map readings and matching maps can be expressed in a variety of ways, and these methods are based on the many functions that have been made available to accomplish. The percentage of map cells with equal values is shown by the general accuracy criterion (depending on their location). This criterion is not satisfied by cells that do not match. It refers to the proper classification, which may be followed by a random agreement between the two images, about the observed accuracy of the error in the expected error matrix (Moein *et al.,* 2018). Comparing maps based on chosen classes from 2001 and 2021 reveals that they are trustworthy. The reliability of the findings demonstrates the veracity of each classes declining and growing spatiotemporal rates. As a result, the CA-Markov model can be trusted to forecast future LULC. Because CA-Markov is a forecasting model built on historical data collection, it examines the relationship between past trends and then offers potential future outcomes. CA-Markov, on the other hand, excludes the environment and socioeconomic factors.

3.3 LULC transition probabilities and transition matrix for the year 2041

Natural resources are a significant problem in KNLW because of the high concentration of agricultural activities in this area. Natural forest with high environmental values was found to be continuously declining under the current land management trend, causing the loss of the KNLW ecological values. The current and simulated LULC dynamics of the KNLW indicate that the cassava, sugarcane, and urban land LULC classes are very likely to continue to supplant other LULC classes. Due to the extensive use of water and soil resources for agricultural purposes, humans have a considerable negative impact on the KNLW region. It seems any reduction and increases in each LULC class in this region is highly related to the quality of one of them both. However, the east appears to offer a better environment for the extension of agricultural fields in addition to changing forest areas. According to the results, forest area will continue to decrease gradually over time. For example, it will decrease by 60.17 % in 2021 and 58.24 % in 2041. Significantly, the increase in urban land not only continues throughout the entire period but also is the primary factor behind the declines in other classes, starting with 4.03 % in 2021 and continuing with 4.15 % in 2041. On the other hand, the decline in other classes will continue with a slower rhythm of reduction in comparison to previous times. Paddy fields fell from 9.65 % in 2021 to 8.87% in 2041, while para rubber fell from 1.27 % in 2021 to 1.21 % in 2041 in Figure 4 and Figure 5. Accurate measurement of change in different LULC classes, on the other hand, can be made possible by incorporating the effects of other variables such as market influence, population growth, and technological advancement. Typically, decision-makers and planners for sustainable land resources might benefit from understanding the primary factors in the area.

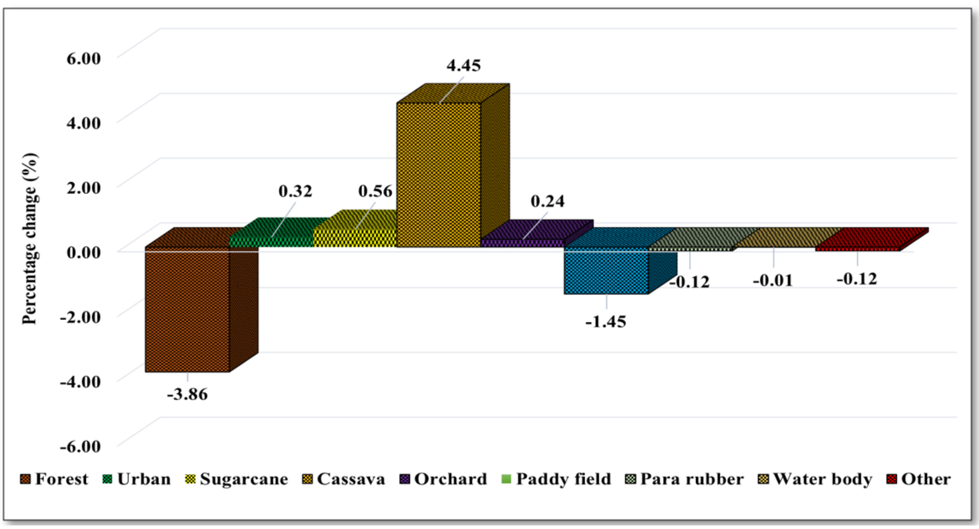

Figure 3. Net LULC changed from 2001 to 2041

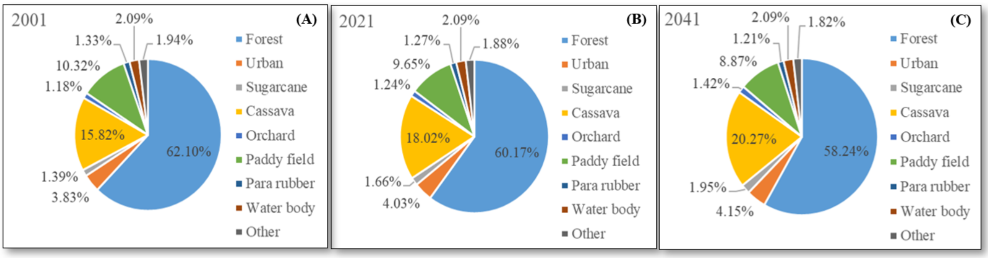

Figure 4. The trend of LULC changes perdition between 2001; (A), 2021; (B), and 2041;(C)

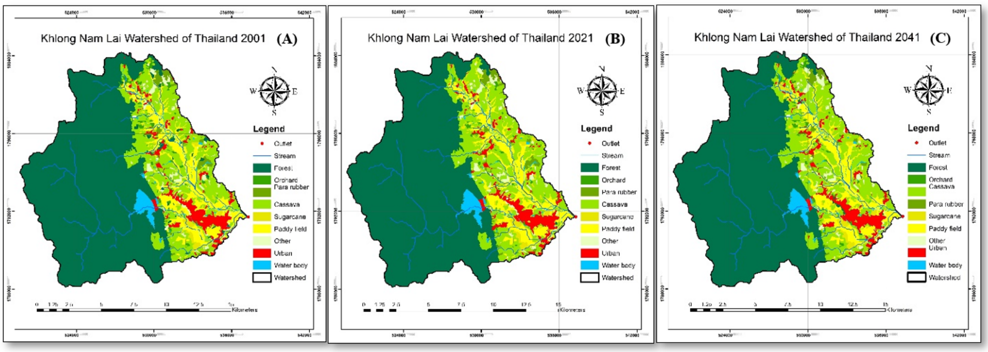

Figure 5. LULC map of 2001; (A), Extracted LULC map of 2021; (B), The Simulated LULC 2041 through the calibrated CA-Markov model of the 2001 to 2021 period; (C)

Comparing results under past, present, and future scenarios demonstrates that agricultural activities are significant in LULC in the future. Importantly, the KNLW eastern regions, where agricultural activities are particularly concentrated, have seen the greatest changes in the LULC classes. As changes in the number of cells indicate, the west part of the KNLW does not appear to have seen any substantial alterations, in contrast to the east part of the region. The overuse of land and water resources in the north of the KNLW is primarily due to the expansion of community areas. Agricultural activities related to water are the most significant factor in the LULC transition from one class to another. However, the body of water itself does not appear to be very big in comparison to the other classes, but it is extremely important in every class.

The results obtained from the CA-Markov model appear to be logically plausible for the future. To develop a future scenario, only one model that successfully passes validation and calibration should be used. Therefore, based on validation and calibration of historical data, which, as was previously indicated, has been the longest period for calibration. Additionally, because LULC is too dynamic and complicated, it is impossible to calibrate and validate all changes in both space and time using CA-Markov strength alone.

4. Conclusion

In this study, the comparing extracted LULC map from 2001 to 2041, show that cassava and sugarcane area expansion in the east part of the KNLW. As a result, the forest area of about 3.89 % reduced from 120.02 Km² in 2001 to 112.56 km² in 2041. However, the simulated scenario for 2041 shows that the urban and orchard area will have a gradual increase and significant growth from 7.41 and 2.27 Km² in 2001 to 7.79 and 2.39 Km² in 2021 in the east and southern part of the KNLW and it will continue to 2041. On the other hand, paddy field, para rubber, and other area will reduce due to the expansion of agricultural activities and development. For the sustainable use of natural resources, it is crucial to understand the trends and directions of LULC in a given area. Rapid LULC changes are the main cause of many problems, including water yield, erosion, flood, and drought. It is very useful to understand the most important current causes and assess the future impact of LULC changes for sustainable use of land resources. Water resources and the amount of precipitation in the past and future are important to the spatial and temporal expansion of LULC classes. Furthermore, the socioeconomic and human dimensions of LULC changes, such as GDP, population, and the level of technology used to collect or utilize natural resources, are not taken into consideration by CA-Markov. Each LULC's spatial expansion can be evaluated in calibrated time. These changes in the area are crucial to understanding how detrimental human activities have been, in particular LULC classes in the same region. As a result, the CA-Markov model appears to be a very useful one for other locations with comparable circumstances because it can account for both time and space, like the KNLW. The wise use of natural resources can lessen future harm and destruction by comparing results based on various scenarios and approaches. Additionally, the study period (2001-2021-2041) was chosen based on the significant socioeconomic choices that affected the environment in Thailand. The findings of the simulations reveal that the trend of LULC has an impact on natural resources and the environment. The need for water may continue to rise in the future. This affects people living in Pong Nam Ron, Khlong Nam Lai, and Sakngam sub-district as well as surrounding areas and all living things. A rational land use plan must be made to control the increase of cultivated land and urban area counting a rational land use plan, ecosystem, and environmental protection guidelines. Decision makers should involve stakeholders to support improved LULC management for balanced and sustainable natural resources

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References

Alimohammadi A, Shamsoddini A, Zeaiean P. Comparison of Spectral and Spatial Performance of Image Fusion Methods in Several Difference Resolutions of Multi-Spectral and Pan Images: Tehran. Journal of Spatial Planning 2008; (12): 119–137.

Arsanjani JJ, Kainz W, Mousivand AJ. Tracking dynamic land-use change using spatially explicit Markov Chain based on cellular automata: the case of Tehran. International Journal of Image and Data Fusion 2011; (2): 329–345.

Asadzadeh F, Khosravi AK, Parviz L, Ramazanpour H, Mahabadi NY. Prediction of the land use change using markov chain and cellular automata (case study: roze Chay basin, Uremia). Journal of Water and Soil Resources Conservation 2018; (8): 105–116.

Banchongsak F, Wilailak S, Nopparat C, Pimprapai K, Nares K, Siraprapa M, Saksri S, Bunchongsri P. Application of Mathematical Model with Geoinformatics System for Prediction of Land use change in Pong Nam Ron Sub-Watershed Khlong Lan District, Kamphaengphet Province. Journal of Science and Technology 2022; 15(27): 119-130.

Basommi LP, Qing-feng G, Dan-dan C, Singh S.K. Dynamics of land use change in a mining area: a case study of Nadowli District, Ghana. Journal of Mountain Science 2016; 13(4): 633–642.

Behbahani AM, Heidarizadi Z. Monitoring and predicting the trend of sand zone changes using the CA-Markov model (case study: Abu Ghovair Plain, Dehloran, Ilam Province). Journal of Environmental Sciences 2019; (16): 153–166.

Bhattacharya RK, Chatterjee ND, Das K. An integrated GIS approach to analyze the impact of land use change and land cover alteration on groundwater potential level: A study in Kangsabati Basin, India. Journal of Groundwater for Sustainable Development 2020; (11): 100399.

Chemura A, Rwasoka D, Mutanga O, Dube T, Mushore T. The impact of land use/ land cover changes on water balance of the heterogeneous Buzi sub-catchment, Zimbabwe. Journal of Remote Sensing Applications: Society and Environment 2020; (18): 100292.

Firozjaei MK, Kiavarz M, Alavipanah SK, Lakes T, Qureshi S. Monitoring and forecasting heat island intensity through multi-temporal image analysis and cellular automata-Markov chain modelling: A case of Babol city, Iran. Journal of Ecological Indicators 2018; (91): 155–170.

Gidey E, Dikinya O, Sebego R, Segosebe E, Zenebe A. Cellular automata and Markov Chain (CA_Markov) model-based predictions of future land use and land cover scenarios (2015–2033) in Raya, northern Ethiopia. Journal of Modeling Earth Systems and Environment 2017; (3): 1245–1262.

Gohin F, Bryère P, Lefebvre A, Sauriau P.G, Savoye N, Vantrepotte V, Bozec Y, Cariou T, Conan P, Coudray S, Courtay G. Satellite and in situ monitoring of Chl-a, Turbidity, and Total Suspended Matter in coastal waters: experience of the year 2017 along the French Coasts. Journal of Marine Science and Engineering 2020; (8): 665.

Hailu A, Mammo S, Kidane M. Dynamics of land use, land cover change trend and its drivers in Jimma Geneti District, Western Ethiopia. Journal of Land Use Policy 2020; (99): 105011.

Huang F, Ochoa CG, Chen X, Cheng Q, Zhang D. An entropy-based investigation into the impact of ecological water diversion on land cover complexity of restored oasis in arid inland river basins. Journal of Ecological Engineering 2020; (151): 105865.

Jabbarian AB, Asgarian A, Sakieh Y. Introducing landscape accuracy metric for spatial performance evaluation of land use/land cover change models. Journal of Geocarto International 2017; (32): 1171–1187.

Kamran JG, Musa KK, Sadegh GF. An Investigation Into Urban Development Patterns With Sprawl and Other Corresponding Changes: A Case Study of Babol City. Journal of Urban Culture Research 2020; (20): 26–43.

Kojuri MK, Ghalehteimouri KJ, Janbazi A, Azizpour F. Urban sprawl functional structural changes in neighborhood settlements: case of study Shiraz. Indonesian Journal of Geography 2020; (52): 260–268.

Mirzaeizadeh V, Mahdavi A, Karmshahi A, Jaefarzadeh A.A. Application of an Integrated CA-Markov Model in Simulating Spatiotemporal Changes in Forest Cover: a Case Study of Malekshahi County Forests, Ilam Province. Journal of Ecology of Iranian Forest 2015; (5): 42–52.

Moein M, Asgarian A, Sakieh Y, Soffianian, A. Scenario-based analysis of land-use competition in central Iran: finding the trade-off between urban growth patterns and agricultural productivity. Journal of Sustainable Cities and Society 2018; (39): 557–567.

Nadoushan M.A, Soffianian A, Alebrahim A. Modeling land use/cover changes by the combination of markov chain and cellular automata Markov (CA-Markov) models. Journal of Earth, Environment and Health Sciences 2015; (1): 16–21.

Naschen K, Diekkrüger B, Evers M, Hollermann B, Steinbach S, Thonfeld F. The Impact of Land Use/Land Cover Change (LULCC) on Water Resources in a Tropical Catchment in Tanzania under Different Climate Change Scenarios. Journal of Sustainability 2019; (24): 7083.

Riccioli F, El Asmar T, El Asmar JP, Fratini R. Use of cellular automata in the study of variables involved in land use changes: An application in the wine production sector. Journal of Environmental Monitoring and Assessment 2013; (185): 5361–5374.

Roose M, Hietal R. A methodological Markov-CA projection of the greening agricultural landscape—a case study from 2005 to 2017 in southwestern Finland. Journal of Environmental Monitoring and Assessment 2018; 190 (7): 411.

Singh SK, Mustak S, Srivastava PK, Szab´o S, Islam T. Predicting Spatial and Decadal LULC Changes Through Cellular Automata Markov Chain Models Using Earth Observation Datasets and Geo-information. Journal of Environmental Processes 2015; (2): 61–78.

Singh SK, Basommi BP, Mustak SK, Srivastava P.K, Szabo S. Modelling of Land Use Land Cover Change using Earth Observation Datasets of Tons River Basin, Madhya Pradesh, India. Journal of Geocarto International 2018; 33 (11): 1-34

Tang D, Liu H, Song E, Chang S. Urban expansion simulation from the perspective of land acquisition-based on bargaining model and ant colony optimization. Journal of Environment and Urbanization 2020; (82): 101504.

Varga OG, Pontious Jr RG, Singh SK, Szabo S. Intensity Analysis and the Figure of Merit's components for assessment of a Cellular Automata – Markov simulation model. Journal of Ecological Indicators 2019; (101): 933–942.

Wolfram, S. Statistical mechanics of cellular automata. Journal of Reviews of Modern Physics 1983; 55: 601.

Zhou L, Dang X, Sun Q, Wang S. Multi-scenario simulation of urban land change in Shanghai by random forest and CA-Markov model. Sustain. Journal of Sustainable Cities and Society 2020; (55): 102045.