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Monitoring and Modeling of Spatio-Temporal Urban Expansion and Land Use/Land-Cover Change in Mountain Landscape: A Case Study of Dalat City, Vietnam

Cuong Huu Nguyen, Cuong Van Nguyen, and Tien My Ngoc Nguyen*

Faculty of Land Administration, Ho Chi Minh City University of Natural Resources and Environment, Ho Chi Minh City 72107, Vietnam

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*** Corresponding author:**
E-mail: tiennnm@hcmunre.edu.vn

ABSTRACT

The lack of ability to control human activities led to changes of land use/land cover (LULC) in Dalat City where rapid urbanization and the demand to expand agricultural land have resulted in dramatic forest reductions. This study assessed the rate and extent of LULC changes over the past 12 years and simulated future scenarios in Dalat City, Lam Dong Province, Vietnam by using an integrated model of Markov chain and logistics regression. Three land-use maps used to analyze land-use change were extracted from satellite images in 2010, 2016, and 2022 by classification approach. The outcome of this process indicates a significant increase in agricultural and built-up land of 48.22 km^2 and 9.36 km^2, respectively; a decrease in forest land of 55.61 km^2, and a minor change in water bodies and bare land in the 2010-2022 period. Prediction maps of land-use change in 2028 and 2034 are generated after the model is validated by comparing the actual map with the prediction map of LULC in 2022 using Kappa statistics. Transition of forest area to other land use types, especially land for expansion of built-up and agricultural land is the crucial trend of land-use change in the future according to the forecast model. Compared to 2022, forest area in 2034 will decrease by 60.65 km^2 while built-up and agricultural land will increase by 14.07 km^2 and 43.61 km^2, respectively. The research results provide valuable information as a foundation for land-use policy planning and local urban development to ensure sustainable development objectives.

1. INTRODUCTION

Urbanization has been taking place across many places throughout the world. Cities have expanded rapidly due to population growth and economic development (Xie et al., 2005; Al-Darwish et al., 2018). The urbanization ratio is an indicator of the development of a country, a region or locality (WB, 2011). The urbanization process of each country can occur fast or slowly depending on conditions and degrees of socioeconomic development.

Urbanization contributes to accelerating economic growth, shifting the economic-labor structure, and changing population distribution. Cities and towns create jobs and incomes for workers, consume a wide range of commodities, and employ a higher-skilled labor force together with modern infrastructure techniques (Fan et al., 2019). However, the urbanization process without scientific planning can cause challenges and risks for sustainable development. Rapid urbanization has socio-economic and environmental negative influences (Lambin et al., 2001), such as loss of agricultural land (Azadi et al., 2011; Mauro, 2020) and flooding (Huong and Pathirana, 2013).

Major cities in Vietnam such as Hanoi, Ho Chi Minh City, and Da Nang have been rapidly urbanizing for the past 10 years. In Vietnam, the urbanization rate increased from 19.6% in 629 cities in 2009 to 39.3% in 833 cities in 2020 (MC, 2022) and the proportion of urban population accounted for 35.0% of the total

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population. This rate is forecast to rise to 50.0% in 2030 and 64.8% in 2069 (GSO, 2020). On the one hand, this process brings positive effects on motivating urbanization rapidly across the country. The infrastructure of existing cities has been improved and refurbished, while a lot of new cities have been established. On the other hand, a large area of agricultural land and natural forest are converted to non-agricultural land due to urbanization process. Nearly all suburban farmers who lose their arable land are forced to change their careers. Vietnam has lost 73,000 hectares of annual arable land due to urbanization, affecting the livelihoods of 2.5 million farmers. Six percent of the rice production area decreased due to high-speed industrialization and urbanization (MF, 2009).

Urbanization is a growing challenge for city planners and policymakers who are continuously focusing on computer-based statistical models, and machine learning for a sustainable and livable city (Mustak et al., 2022). Some models of land use and urban expansion have been studied and used to allocate land-use changes explicitly on maps by using the prediction method over the past two decades. Their results are displayed as a land-use map which is a set of grid cells with each plot displaying the land use at a specific position (Verburg et al., 2002). Future urban growth scenario-analysis is crucial for planners to make effective decisions in spatial planning (Wang et al., 2021a). Therefore, developing efficient prediction models to anticipate future land-use changes and urban growth can better serve the work of planners (Ai et al., 2022; Sohl and Claggett, 2013).

A few researchers have used various theoretical and experimental modeling techniques, such as regression modeling, to model, simulate, and predict urban expansion, and land-use change (Alsharif and Pradhan, 2014; Nong and Du, 2011), CA (Cellular Automata) (Falah et al., 2020; Yeh et al., 2021), MC (Markov chain) (Arsanjani et al., 2011; Fathizad et al., 2015), CA-Markov intergrated models (Wang et al., 2021b; Ebrahimipour et al., 2016; Aburas et al., 2021), CA-logistic regression (Azizi et al., 2022; Wang et al., 2019), and machine learning algorithms (Tsagkis et al., 2023; Devendran and Gnanappazham, 2019). Each model has its limitations and has been discussed in many kinds of literature (Mas et al., 2014; Olmedo et al., 2015). The logistic regression analysis has been one of the most frequently utilized approaches for modeling land-use change over the past two decades. Logistics regression in urban expansion models helps to understand the urbanization process and provides an explicit picture of the weights of the independent variables and their related functions (Hu and Lo, 2007; Huang et al., 2009; Arsanjani et al., 2013).

In Vietnam, there haven't been many studies on land use change and urban development. Most research focuses on assessing land-use changes in the past by interpreting and analyzing remote-sensing images over time but not predicting land-use changes for the future. Urbanization studies have only concentrated on two large cities, Hanoi (Pham et al., 2015; Pham and Yamaguchi, 2011; Nguyen et al., 2019) and Ho Chi Minh City (Son et al., 2012).

Vietnam's terrain is very diversified, with hills and mountains occupying a quarter of the area (MARD, 2015). Dalat City, located in the Central Highlands, is one of Vietnam's most famous historical-tourist cities. The cool climate, gorgeous scenery, and historical architectures attract many tourists to this city. Over the past decade, this city has been rapidly developed but not strictly controlled. Urban expansion negatively affects natural resources such as forest land, agricultural land, and tourism landscapes. Dalat City is chosen to study future urban expansion in this research due to the importance of its historical, agricultural, and tourism environment. This research aims to analyze and anticipate urban expansion in Dalat City through land-use changes by interpreting remote-sensing images and applying the Markov chain-logistic regression integrated model. This model helps to better understand urban expansion, examine quantitatively the relationship between land-use change and driving factors, and predict various scenarios for Dalat City's future urban expansion.

2. METHODOLOGY

Figure 1 depicts the process of predicting land-use change using remote sensing images and the Markov chain-logistic regression integrated model. The land-use prediction in 2022 is conducted after analyzing land-use change in the 2010-2016 period. The model accuracy is measured by comparing the prediction map of land-use and the actual map of land-use in 2022 based on the Kappa coefficient. Then, this model is used to forecast land-use change for future periods in 2028 and 2034 (6-year periods).

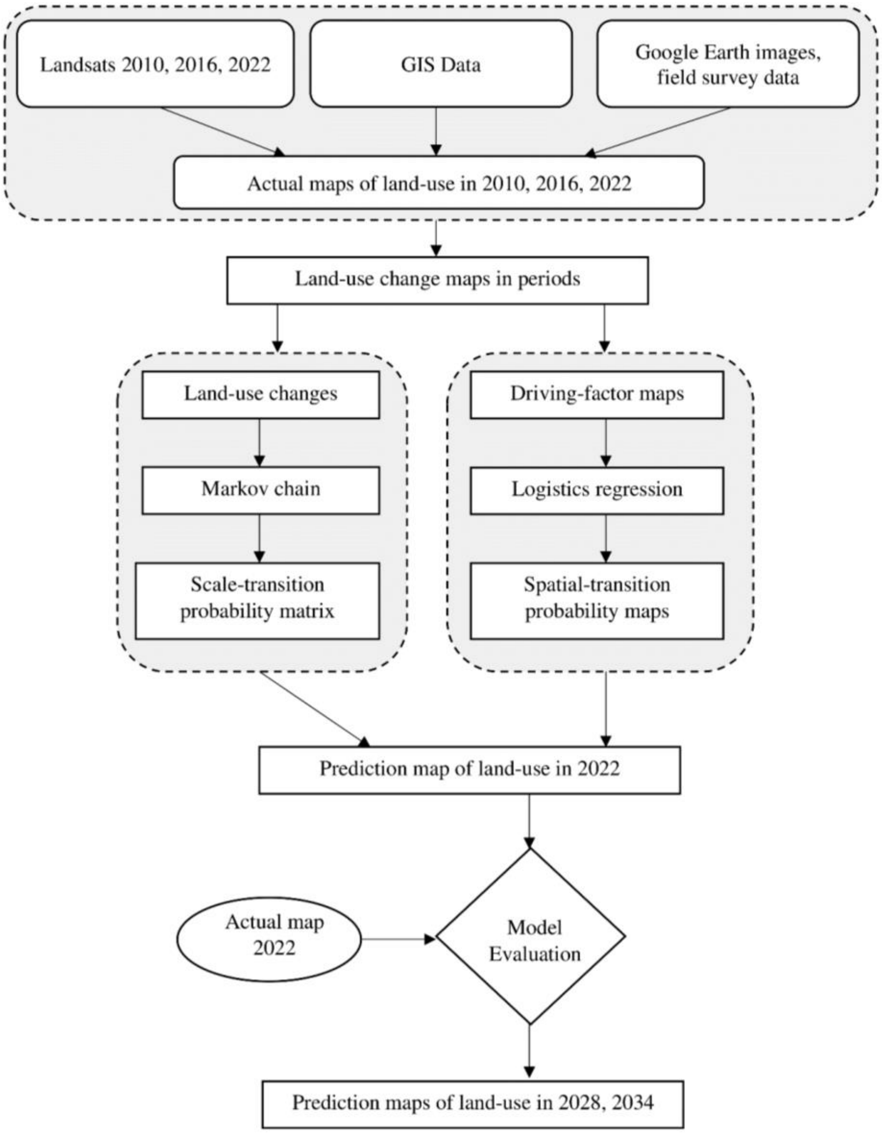

Figure 1. General methodology of the research

2.1 Study area

The research is conducted in Dalat, a city in the Central Highland, located on the Lam Vien Plateau, Lam Dong Province at an altitude of about 1,500 m (4,900 ft) above sea level (Latitude: 11°48′36″-12°01′07″ N; Longitude: 108°19′23″-108°36′27″ S) (Figure 2). With a population of 240,000 people, Dalat is the second most popular mountainous city in Vietnam (LDSO, 2023). It is a unique urban area in Vietnam which has been perfectly planned with famous constructions and exquisite villas from the very beginning. Therefore, it is considered as a museum of Western architecture in the early 20th century (Tranh, 2001).

The terrain of Dalat City is divided into two types: mountain and plain in mountain. It has a mild and cool mountainous climate all year round due to its elevation of 1,500 meters and surrounding mountain ranges and forest flora, particularly pine forests. This city has two distinct seasons: rainy and dry (Tro, 1993). It has favorable soil and climate conditions for the development of temperate plants. Its main arable land area has been allocated to vegetables. Tea and coffee plants are also crucial products in the city's processing industry.

2.2 Data acquisition and processing

The satellite images of Dalat City in three periods of 2010 (Landsat TM), 2016, and 2022 (Landsat OLI/TIR) shown in Table 1 were downloaded from https://earthexplorer.usgs.gov/. They were adjusted to the local coordinate system (VN-2000 with 6° projection zone, 48th zone in the Northern hemisphere, an axis meridian of 105° of East longtitude).

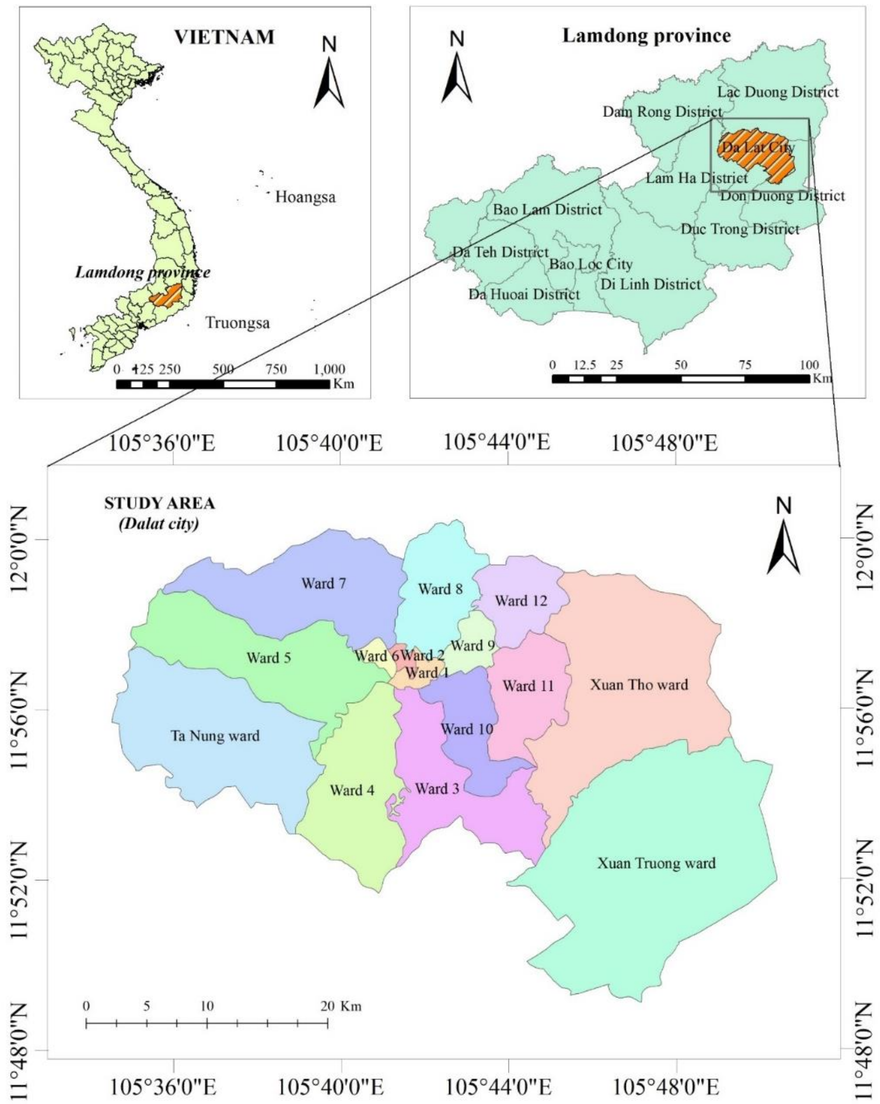

Figure 2. Map of the study area (Dalat City)

Table 1. Characteristics of collected data

Sensor	Month/day/year	Resolution	Path/row
Landsat TM 2010	04/02/2010	30 m × 30 m	124/052
Landsat OLI/TIR 2016	08/03/2016	30 m × 30 m	124/052
Landsat OLI/TIR 2022	20/01/2022	30 m × 30 m	124/052

Furthermore, this study uses GIS data gathered from the People's Committee of Dalat and the Department of Natural Resources and Environment of Lam Dong Province as a reference to support in image interpretation and the generation of driving factor maps. These materials include: (1) a land-use actual map of 2010, 2015, and 2020 at a scale of 1:10000 to assist with image interpretation and mapping of impact factors; (2) a topographic map of Lam Dong Province at a scale of 1:50000 to build slope maps and elevation maps; (3) a high-resolution satellite image data from google earth to assist in satellite image; and (4) the administrative boundary map of Dalat City to determine the study area for the landsat image.

The study used the method of supervised image classification with the Maximum likelihood classifier (Perumal and Bhaskaran, 2010; Richards, 2022). This method works on the principle of using sample data to determine the probability distribution density function, which defines land use types to be classified for each pixel. Then, each land use type is determined according to the LULC having the prior probability.

This interpretation result is evaluated by the Kappa statistical index and the overall accuracy. The

Kappa coefficient is a measure of overall agreement of a matrix (Richards, 2022) with formula (1). The evaluation results show that the accuracy of image interpretation through the Kappa index is very good (Richards, 2022) from 0.9457 to 0.9876. In addition, the overall accuracy of the interpretation results ranges from 95.94% to 99.08% (Table 2).

$$K = \frac{P_0 - P_e}{1 - P_e} \quad (1)$$

The accuracy of observed agreement (P_0) is determined according to the following formula:

$$P_0 = \frac{\sum X_{ii}}{N} \quad (2)$$

The estimate of chance agreement (P_e) is determined according to the following formula:

$$P_e = \frac{\sum X_{i+} X_{+i}}{N^2} \quad (3)$$

Where; N: total number of observations; X_{ii}: observation in row i and column i; Xi+: marginal total of row i; X+i: marginal total of column i.

Table 2. Accuracy of remote-sensing image interpretation

Years	Overall accuracy (%)	Kappa coefficient
2010	98.23	0.9765
2016	99.08	0.9876
2022	95.94	0.9457

The LULC map of land-use in three periods was successfully interpreted (Figure 3). The interpretation of LULC types on the actual map of land use consists of built-up land (residential area, industrial zones, and traffic infrastructure), water bodies (rivers, streams, ponds, and lakes), agricultural land (crops, industrial plants, fruit trees, etc.), and bare land. The manipulated process of image interpretation included the six following steps on Envi 5.3 software (RSI, 2001): (1) geometric correction of satellite images matching to the VN-2000 coordinate system; (2) enhance image quality; (3) crop the image according to the boundary of the study area; (4) set up the image decoding key; (5) classification of remote sensing images; (6) evaluation of classification results (Table 2).

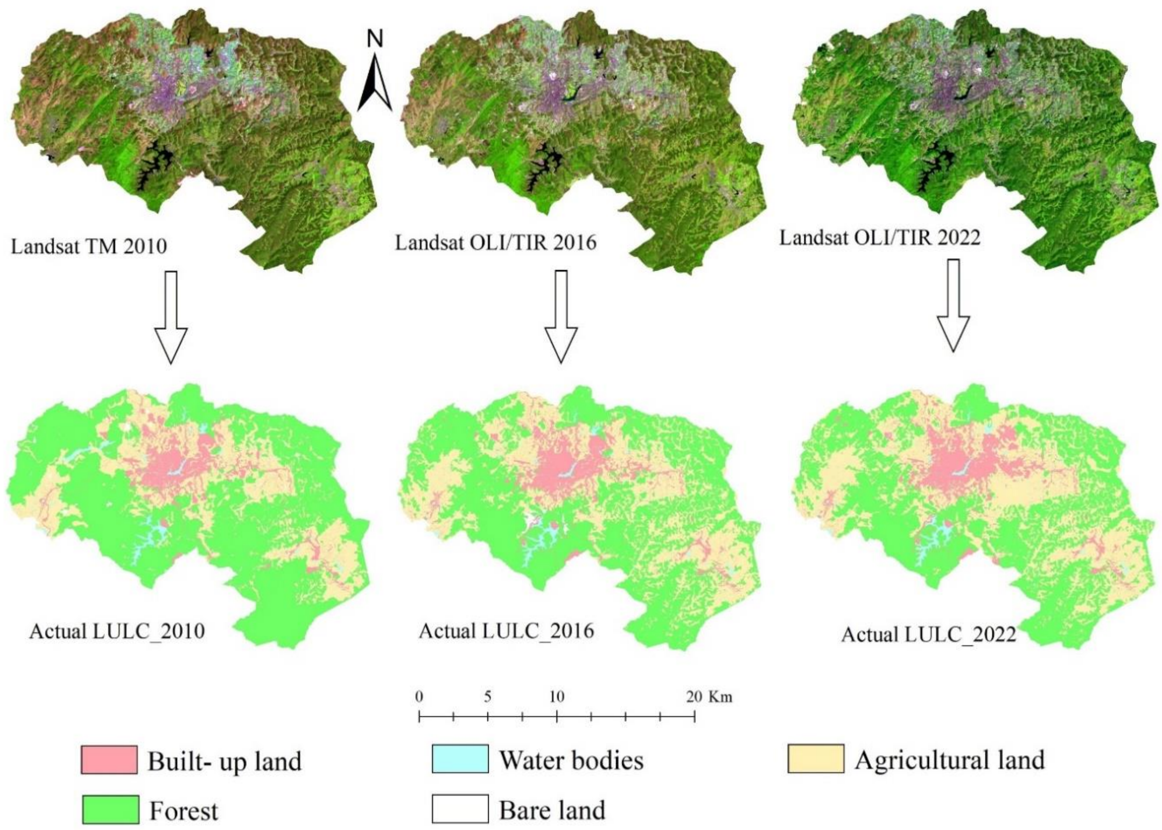

Figure 3. Extracted land use maps of Dalat City in 2010, 2016, and 2022

As an empirical estimation model, logistics regression is a data-driven rather than knowledge-based approach to the choice of predictor variables (Hu and Lo, 2007). Previous studies identified the significant factors that determine the potential for urban expansion and land-use changes (Park et al., 2011; Arsanjani et al., 2013; Musa et al., 2017; Aburas et al., 2017; Shafizadeh-Moghadam et al., 2017; Hassan and Elhassan, 2020; Cheng et al., 2022). This study used 12 factors driving the land-use change process and the data generated as Euclidean Distance maps in the ArcGIS environment (Figure 4).

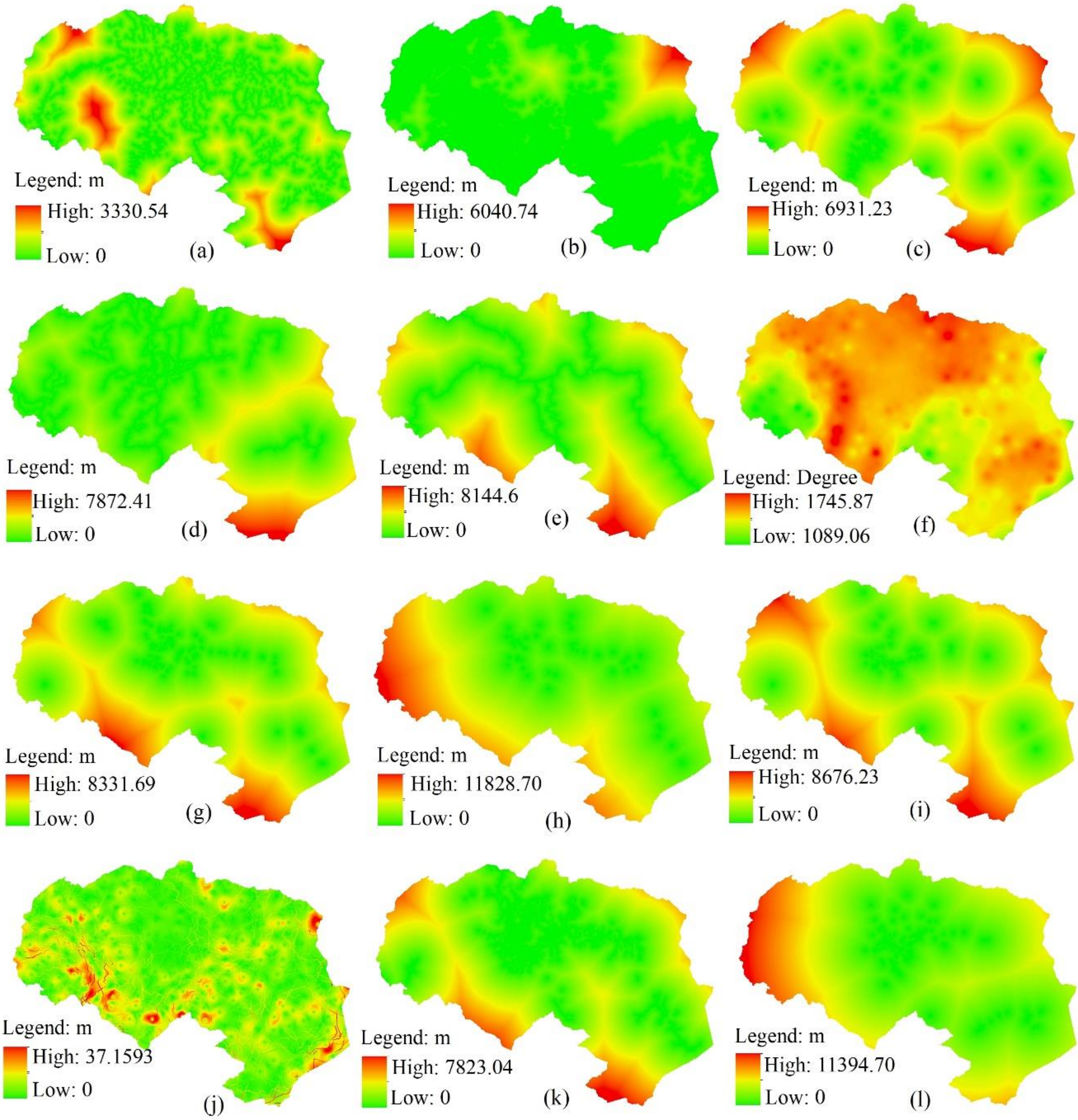

Figure 4. Driving variables associated with the simulation of land use and land cover in Dalat City: (a) distance to water source, (b) distance to nature reserve, (c) distance to tourist area, (d) distance to secondary traffic, (e) distance to main roads, (f) altitude/elevation, (g) distance to educational institutions, (h) distance to religious places, (i) distance to administrative office, (j) slope, (k) distance to residential area, (l) distance to commercial area

2.3 Intergrated model of Markov chain and logistic regression for the future LULC change prediction

The combination of Markov chain and logistics regression has been the most popular integrated model used for modeling spatio-temporal changes. Markov chain analysis, which is a stochastic modeling, has been widely used for land cover variation modeling (Fathizad et al., 2015). It is assumed that the probability of a system at an initial time and condition can be determined if the change rate observed during the calibration interval (t_1 to t_2) remains the same over the simulation period (t_2 to t_3). Markov chain analysis determines how much land-cover change will occur at a specific time in the future through land cover cross-tabulation (Kamusoko et al., 2009). The Markov chain is applied to determine the future land-use demand for each type of land use according to the following formula (Sang et al., 2011):

$$S_{(t+1)} = P_{ij} \times S_{(t)} \quad (4)$$

Where; $S_{(t)}$ and $S_{(t+1)}$ are the states of the system at an initial time t and t + 1. P_{ij} is the matrix of the transition probability in a specific state and is calculated as follows:

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \quad (5)$$

Where; $0 \le P_{ij} \le 1$ and $\sum_{j=1}^{n} P_{ij} = 1$.

The Markov chain model is not able to allocate the estimated amount of change and must be integrated with other geospatial models (Arsanjani et al., 2013). Therefore, the Markov chain model integrates with logistics regression spatially to solve this problem.

Logistics regression is used to model and explain the relationship of several independent variables (X) with a binary dependent variable (Y), representing the occurrence or non-occurrence of an event. Logistics regression is applied to determine the probability of the existence or non-existence of each land-use type at all locations and quantify the interaction between different land-use types and transition driving factors (Lin et al., 2011). Spatial land-use change is the dependent variable represented in a raster-binary map. A value of 1 on the generated probability map indicates the presence of a change, and a value of 0 indicates no change. The change probability for each pixel in the raster map is generated based on the following logistic regression equation:

$$P(Y = 1|X_1, X_2, \ldots, X_k) = 1/(1 + e^{-(\alpha + \sum \beta_i X_i)}) \quad (6)$$

Where: X_i, which is the independent variable representing driving factors of the land-use change process, can be a continuous or categorical variable; α is the coefficient of the model formula; $P(Y=1|X_1, X_2, ..., X_k)$ is the probability of the dependent variable Y, means that the probability of a pixel changed in land use; and β_i is the coefficient of the variable X_i. The regression coefficient (β_i) reflects the function of the independent explanatory variables. Logistics regression creates the land transition probability map through the regression analysis of driving factors. The land-use prediction map is generated by allocating the number of pixels in the order of spatial transition probability defined by the Markov chain.

3. RESULTS AND DISCUSSION

3.1 Description of land-use change in 2010-2022 period

The land-use change from 2010 to 2022 was determined to quantify the extent and location of the changes. Table 3 and Figure 5 illustrated the changes. The analysis of LULC change was carried out by using land cover data over a 12-year period (2010-2022), with two 6-year sub-periods: 2010-2016 and 2016-2022.

Table 3. Statistical distribution of LULCs from 2010 to 2022

LULC types	2010		2016		2022		2010-2016	2016-2022	2010-2022
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Δ (km^2)	Δ(km^2)	Δ (km^2)
Built-up	33.79	8.57	38.59	9.78	43.15	10.94	4.80	4.56	9.36
Water bodies	8.32	2.11	7.79	1.98	7.78	1.97	-0.53	-0.01	-0.54
Agriculture	104.61	26.52	136.41	34.59	152.83	38.75	31.80	16.42	48.22
Forest	245.39	62.22	209.89	53.22	189.78	48.12	-35.50	-20.11	-55.61
Bare land	2.29	0.58	1.72	0.44	0.86	0.22	-0.57	-0.86	-1.43

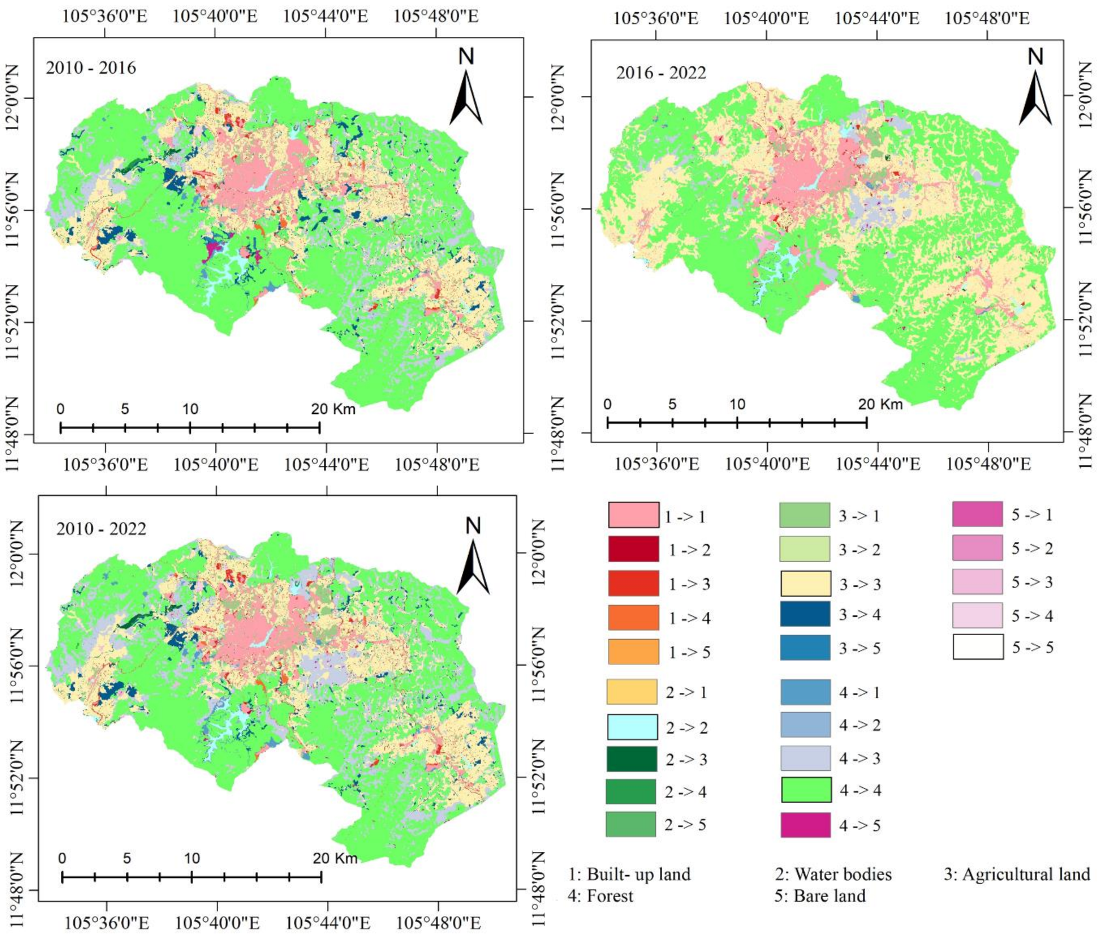

Figure 5. Maps of land use changes in Dalat City

From 2010 to 2022, the land-use types in Dalat City changed dramatically. Specifically, agricultural and built-up land expanded rapidly, while forest land sharply declined. In 2010, forest land covered the most land area, followed by agricultural land, built-up land, water bodies, and bare land. The majority of built-up land was in the city center, with the remainder in the Southeast and West along main roads. Agricultural land was located near residential areas while the forest was in remote areas with complex topography. Over a 12-year period, agriculture land area increased from 104.61 km^2 (26.52% of total land area) to 152.83 km^2 (38.75% of total land area), especially in 2010-2016; the built-up land area expanded steadily in 2010-2022 from 33.79 km^2 (8.57% of total land area) to 43.15 km^2 (10.94% of total land area). However, the forest land area sharply diminished by 55.61 km^2 (from 62.22% to 48.12%). Water bodies and bare land area decreased by 0.54 km^2 and 1.43 km^2, respectively. Built-up land was likely to spread northward from existing residential areas in the central area. Furthermore, a portion of built-up land could be seen expanding along the main road. In addition to expanding from existing areas, agricultural land was also found in forested areas. To better understand the transitions among land use types for the 2010-2022 period, a transition matrix table was created by analyzing in the ArcGIS environment (Table 4). The table data demonstrates the forest area decreased as a result of agricultural growth and built-up land expansion. During the research period, 67.68 km^2 of forest land was lost due to changing to 4.38 km^2 of built-up land and 61.93 km^2 of agricultural land. In addition, 21.39 km^2 of agricultural land decreased due to the transition of 10.78 km^2 to built-up land and 9.14 km^2 to forest land. Currently, the greenhouse area in Dalat City accounts for approximately 57% of the total greenhouse area in Lam Dong Province. (Lam Dong online, 2023). Greenhouses built without planning have disrupted the landscape and urban aesthetic, increased local greenhouse effect and limited biodiversity. Therefore, to reduce greenhouse area during this period, the local goverment made efforts to demolish many greenhouses built for agricultural production, which resulted in a noticeable transition from built-up land to agricultural and forest land.

Table 4. Transition area matrix of land-use types from 2010 to 2022

	LULC types	2022 (km^2)					
		Built-up	Water bodies	Agriculture	Forest	Bare land	Total
2010 (km^2)	Built-up	27.49	0.25	4.34	1.69	0.02	33.79
	Water bodies	0.36	5.43	2.18	0.33	0.02	8.32
	Agriculture	10.78	1.19	83.22	9.15	0.27	104.61
	Forest	4.38	0.87	61.93	177.71	0.50	245.39
	Bare land	0.14	0.04	1.16	0.90	0.05	2.29
	Total	43.15	7.78	152.83	189.78	0.86	

The reduction of forest area and its causes are typical characteristics of localities in the Central Highlands of Vietnam. Due to the suitability of the local soil and climate, vegetable-producing activities thrive. Population increase is also a major source of forest loss in the region, since it leads to the expansion of urban centers, residential areas, industrial production regions, and infrastructure (Müller and Zeller, 2002; Pham et al., 2019). The reduction of forests and vegetation leads to severe degradation of ecosystems, loss of biodiversity, reduction of water holding capacity leading to depletion of water resources, and extreme events such as landslides and erosion (Lambin et al., 2001). The analysis results of land use change from 2010 to 2022 build the foundation for future forecasts.

3.2 Prediction results

3.2.1 Quantification of land change and transition probability maps

In this study, the 2010 LULC map of Dalat City is the first image (t_1), the 2016 LULC map is the second image (t_2), and the 2022 LULC map is the reference image to compare to evaluate the model. The Markov sequence analysis built into the module of TerrSet software to generate a transition probability matrix representing the total area is varied from one LULC layer to another in a given time unit. The Markov series assumed that the policies and development conditions in future scenarios would be the same as in the past. Table 5 show the prediction probability matrix for transition among land types from 2022 to 2034. Figure 6 illustrates the transition probability maps in 2028 and 2034. Forest land with the probability of not changing will be 79.06%, with the remainder continuing to decrease, namely, converting 18.84% to agricultural land, and 1.43% to built-up land. Meanwhile, built-up land is forecast to expand, in addition to converting from forest land to agricultural land at the rate of 6.59%.

An input of logistics regression is driving factor maps combining 2010 and 2016 LULC maps to generate a spatial transition probability map, showing the probability that each pixel changes to another layer or remains constant. Visually, it is possible to see the pixels distributed in the vicinity of existing residential areas and along the roads with the highest transition probability. These results are the basis for forming prediction maps and forecasting future land use changes.

Table 5. Transition probability matrix for 2022-2028 and 2028-2034 periods

	LULC types	Built-up	Water bodies	Agriculture	Forest	Bare land
Probability value 2028	Built-up	0.9025	0.0037	0.0621	0.0314	0.0002
	Water bodies	0.0159	0.8107	0.1208	0.0508	0.0018
	Agriculture	0.0386	0.0074	0.8802	0.0669	0.0069
	Forest	0.0043	0.0008	0.1134	0.8778	0.0037
	Bare land	0.0412	0.0168	0.4531	0.4777	0.0111
Probability value 2034	Built-up	0.8219	0.0066	0.1109	0.0598	0.0007
	Water bodies	0.0327	0.6756	0.1971	0.0922	0.0024
	Agriculture	0.0659	0.0119	0.8006	0.1152	0.0065
	Forest	0.0143	0.0027	0.1884	0.7906	0.0040
	Bare land	0.0570	0.0177	0.4595	0.4575	0.0083

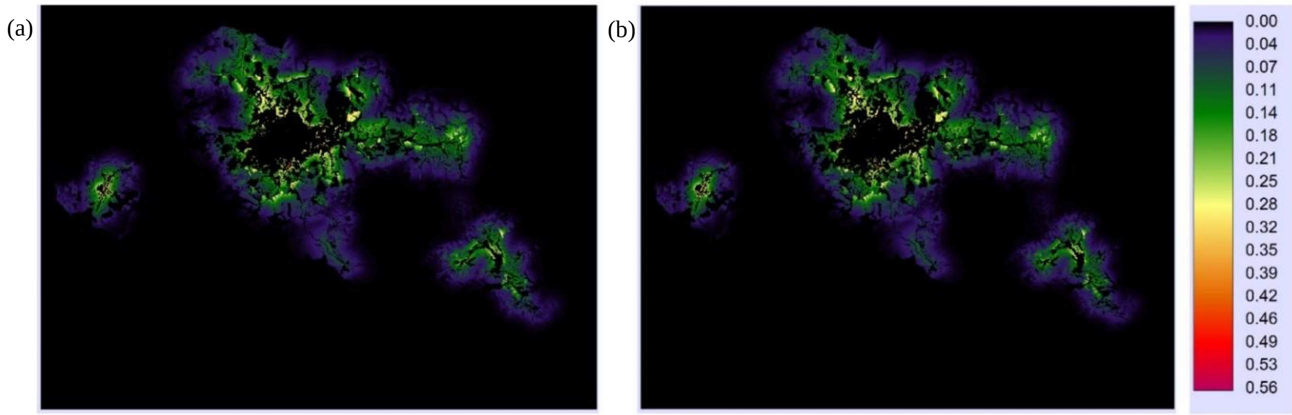

Figure 6. Spatial-transition probability maps in 2028 (a) and 2034 (b)

3.2.2 Validation

Before creating the LULC forecast maps in 2028 and 2034, it is necessary to validate the model output. The validation is performed by matching the LULC actual map with the LULC prediction map in 2022 (Figure 7) using the VALIDATE module in IDRISI software. The accuracy of prediction results is evaluated based on comparing each pair of pixels, expressed by the Kappa statistical index system, including Kappa for locationStrata ($K_{locationStrata}$), location ($K_{location}$), no information (K_{no}), and Kappa standard ($K_{standard}$) (Pontius, 2002; Pontius, 2000). The Kappa values for these variants range from 0 to 1 (0% and 100%); The closer to 100% the value reaches, the higher the agreement accuracy (Christensen and Arsanjani, 2020). Overall, there was a significant level of agreement between the prediction and actual LULC maps (Table 6). The overall Kappa statistical variations of K_{no}=0.8987, $K_{location}$=0.9112, $K_{locationStrata}$=0.9112, $K_{standard}$=0.8743 were achieved. These values are accepted when they are related to the reliability of the model validation for further use (Pontius and Millones, 2011).

Table 6. Land-use prediction map Kappa coefficient in 2022

Kappa coefficient	Value
K_{no}	0.8987
$K_{location}$	0.9112
$K_{locationStrata}$	0.9112
$K_{standard}$	0.8743

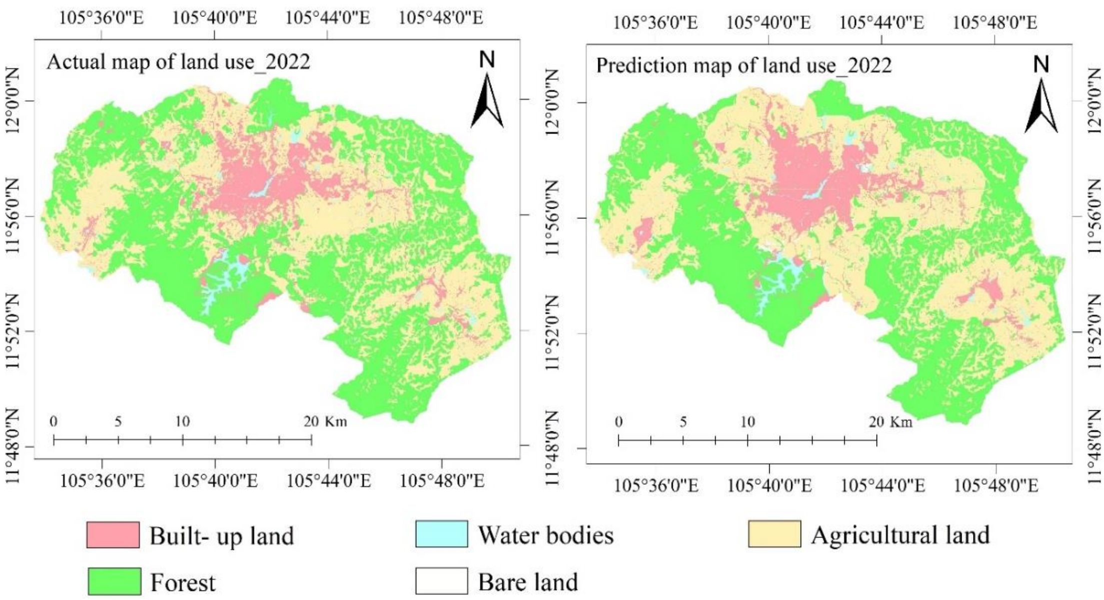

Figure 7. Land use maps in Lam Dong Province in 2022

3.2.3 Land use change prediction results

The results of the LULC forecast for 2028 and 2034 using the integrated model of Markov chain-logistic regression are illustrated in Table 7 and Figure 8. Compared to 2022, the forecast data for 2034 shows that forest land use continues to decrease from 48.12% to 32.74% (from 189.78 km^2 to 129.13 km^2). The agricultural and built-up land areas are forecast to increase by 43.61 km^2 and 14.07 km^2, respectively, accounting for 49.81% and 14.51% of the natural area by 2034.

Figure 8 shows that the spatial destruction of forest area in LULCs is predicted for 2034. Forest cover is fragmented into small and narrow patches by agricultural areas, especially in the Western part of the city. A vast degradation of forest areas can have a negative influence on the local ecological environment.

Table 7. Area statistics of land-use prediction in 2028 and 2034

LULC types	Simulated area (in km^2)		Change detection (in km^2)	
	2028	2034	2028-2022	2034-2022
Built-up	53.30	57.22	10.15	14.07
Water bodies	9.12	9.88	1.34	2.10
Agriculture	185.84	196.44	33.01	43.61
Forest	144.46	129.13	-45.32	-60.65
Bare land	1.68	1.73	0.82	0.87

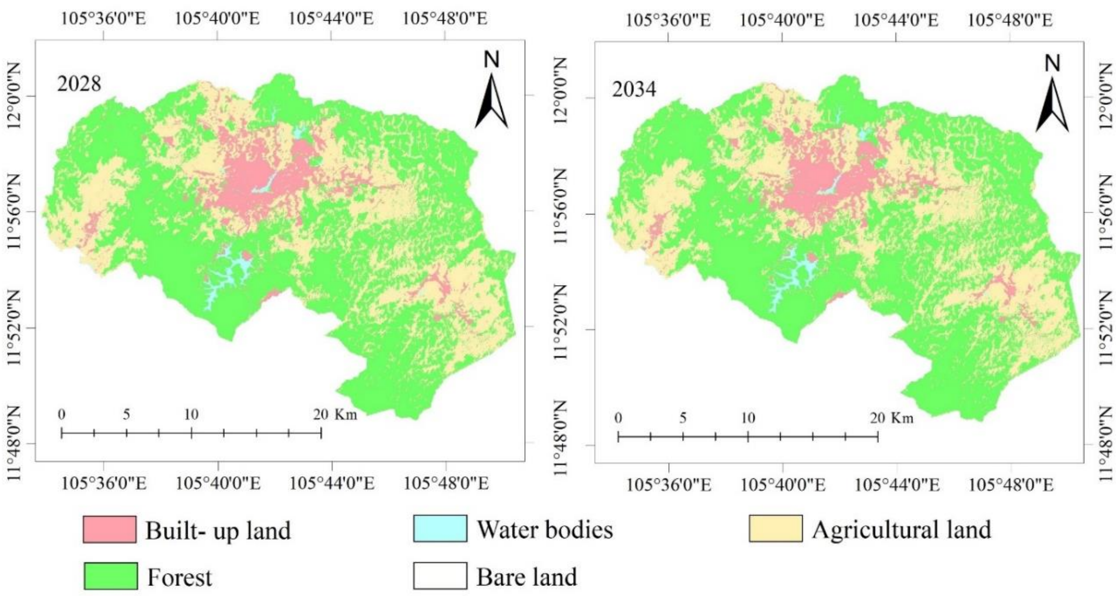

Figure 8. Prediction maps of land-use in Dalat City

Figure 9 shows the development forecast of built-up land area over time and space. According to the simulated output of the Markov chain model, the built-up land area will increase by 53.30 km^2 in 2028 and 57.22 km^2 in 2034. The prediction maps and transition matrix show that agricultural and forest land are converted into built-up land in the study area. Built-up land is forecast to expand in the central urban area, existing residential areas, and across roads. Small and narrow arable land areas are scattered throughout the city. The study results on urban expansion trends occupying other important land types such as forest and agricultural land are similar to other research in developing countries (Ntakirutimana and Vansarochana, 2021; Wang et al., 2021b). The results of the study reinforce the results of previous studies on land use change in mountainous areas. The Central Highlands of Vietnam have experienced a decline in forest land, particularly from 2000 to the present (Müller and Zeller, 2002; Castella and Verburg, 2007; Stephen, 2009). The following factors are the direct causes of deforestation and forest degradation in the area: (i) unsustainable logging, both legal and illegal; (ii) transition of forest land to agricultural land, including high-value perennial crops and other crops; (iii) transition of forest land to infrastructure construction, particularly hydroelectric power plants; and (iv) population growth, primarily due to free migration (Pham et al., 2019).

Logistics regression used in the study has the advantage of quantitatively determining the relationships between land use change and driving factors such as natural, economic, and social factors. However, the model that incorporates Markov chain - logistic regression also has drawbacks. The spatial-transition probability map generated by the logistic model depends on the quantity and accuracy of the driving factors. Difficulties in data collection and the integration of multiple factors, including demographics and development policy, can reduce the model's accuracy. The Markov chain forecasts future land-use changes based on an analysis of historical land-use changes, assuming the same factors affecting land use over time.

The Markov chain illustrates that changes between land-use types in the future will take place over and over based on historical principles. However, it is a fact that a few phenomena and principles that happened in the past are unlikely to happen again.

However, no specific research method can fully explain all of the processes affecting land use. Hence, to obtain a more comprehensive view, a synthesis of results from various methods is required.

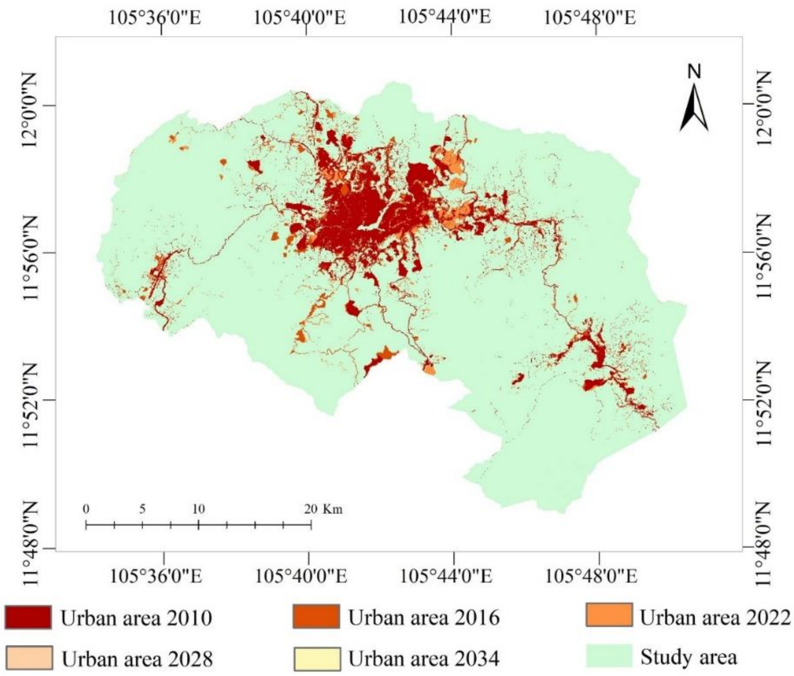

Figure 9. Change in built-up land from 2010 to 2034

4. CONCLUSION

Understanding changes in the spatial pattern of land cover and the urban growth dynamics of any area over time is critical for effective land management and sustainable urban planning. This study used the integrated model of the Markov chain-logistic regression to simulate and forecast land-use changes and urban expansion in Dalat City, especially, applying GIS to create the spatial analysis of land-use changes, building a scale-transition probability matrix among land-use types by the Markov chain, and creating a probability surface of land-use change by logistic regression. This integrated model provides an understanding of the quantity and location of spatial transition probabilities. Twelve driving-factor maps are established from GIS data, and five land-use types are extracted from remote sensing images in 2010, 2016, and 2022 by using supervised classification for analysis.

In the 2010-2022 period, there has been a dramatic shifting trend of LULC categories from agricultural and built-up land to forest land, but water bodies and bare land changed insignificantly. The total area of urban areas was 33.79 km^2 in 2010, increasing by 38.59 km^2 in 2016, and 43.15 km^2 in 2022 at a fairly even rate. A higher rate of urbanization has mainly occurred on formerly agricultural land near existing urban areas, road networks, and easily accessible zones. The high-speed expansion of agricultural and built-up land converted from forest land can have serious ecological consequences. Therefore, the priority is that policies to boost agricultural production and urban development are obligated to be built in a balanced way to ensure sustainable development for the locality with two objectives: (1) economic development and (2) environmental protection. Through the research results, the integrated model of Markov chain-logistic regression is proposed as an effective tool for further research on the complicated characteristics of urban areas and LULCs.

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