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Research article

Modeling land-use changes using logistic regression in Western Highlands of Vietnam: A case study of Lam Dong province

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Abstract

Importance of the work: Land-use changes substantially affect global environmental changes, namely greenhouse gases emissions, loss of biodiversity and soil resources.
Objectives: To model land use changes in Lam Dong province, Vietnam using the logistic regression approach with a geographic information system (GIS).
Materials & Methods: Remote sensing images were used to develop land use maps to analyze the trends in land use type changes in 2010, 2015 and 2020. A GIS was used to conduct spatial analysis of land use. Logistic regression was used to generate a probability surface of land-use changes based on the land use map and six driving factor maps (distance to primary roads, distance to secondary roads, distance to water source, distance to residential area, elevation and slope). The model was verified and validated by comparing the simulation and actual maps in 2020 based on Kappa index statistics. Then, land use prediction maps in 2025 and 2030 were generated using the MOLUSCE and QGIS software packages.
Results: Six land-use types were retrieved for analysis of spatial and temporal variation of land use: arable land, permanent cropland, forest, built-up land, water bodies and bare land. The results of the remote sensing image classification based on the supervised classification method had an overall accuracy from 90% to over 96% and a Kappa coefficient from 0.87 to 0.95. The results of the forecast model were evaluated by comparing the current status map and the simulation map in 2020, with the overall accuracy being 83.76% and the Kappa coefficient at 0.74 being considered as good.
Main finding: The investigation indicated an expected rapid change in land use/land cover (LULC) for the near future. The forecast results showed that the forest area in Lam Dong province will be substantially decreased due to transition trends from forest land to agricultural production land and residential land.

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Introduction

Land use changes caused by human activities, such as the expansion of agricultural production, industry and urban areas, have many negative impacts on natural resources, such as biodiversity, ecosystems, land and water (Lambin et al., 2001). With rapid population growth, sustainable land use management becomes increasingly important to human life and these issues of sustainable land use management have led to the development of models for describing and explaining the process of land-use changes, predicting future scenarios and measuring the impact of land use activities (Verburg et al., 2006). Changes can be simulated based on the relationship between land use and driving factors in the context of competitive dynamics for adapting to different land uses. Therefore, the model is a key tool used to explore future land-use changes (Verburg et al., 2006).

Over the past two decades, various land use models have been studied and used to explicitly allocate land use changes on maps using a simulation approach. The results are presented in the form of land use maps, namely a set of grid cells with each plot showing the land use at a specific site (Verburg et al., 2002). The forecast results of the land use change model may be used as the foundation to support managers in the decision-making processes associated with land use planning.

Several statistical and geospatial modeling techniques have been developed and carried out in many kinds of studies to predict land use changes at different scales, such as regression analysis (Verburg et al., 2002; Li et al., 2020), cellular automata (CA; Al-Darwish et al., 2018; Feng and Qi, 2018), Markov chain (Kumar et al., 2014; Zhang et al., 2011), CA-Markov integration modeling (Darmawan et al., 2020; Wang et al., 2012) and machine learning algorithms (Gibson et al., 2018; Simwanda et al., 2021). All these models have specific limitations and these have been discussed in the literature (Jean-Francois et al., 2014; Maria et al., 2015). From these reviews, the Markov series model is the most common approach used to simulate land-use dynamics based on a transition matrix by analyzing two land use maps at different times. However, the Markov series can only be used for area-scale modeling. Therefore, it is often integrated with another spatial analysis model, for example, the CA-Markov integration model. Nevertheless, the disadvantage of CA is that it does not take into account the factors that directly drive land-use change.

Logistic regression analysis has been one of the most popular approaches for modeling land use forecasts for the past two decades. Empirical estimation models use statistical techniques to model the relationships between land use changes and driving factors based on historical data. Therefore, the advantage of the logistic regression model to identify the relationships between land-use change and causal factors quantitatively as natural and socio-economic factors allows us to analyze the dynamics of change. As an empirical estimation method, logistic regression has been used in the analysis of deforestation (Miriam and Taylor, 2010; Pir, 2015), agriculture (Meiyappan et al., 2014) and urban development (Tayyebi et al., 2010; Jamal et al., 2013). Statistical approaches can readily measure the effects of the independent variables and provide the reliability of variables in the models. These models are commonly consistent with the spatial processes and the results of land use changes.

The Western Highlands, also known as Tay Nguyen, is a region with highland topography in central Vietnam. Depending on geographical position, the region stretching from north to south includes Kon Tum, Gia Lai, Dak Lak, Dak Nong, and Lam Dong provinces. The total area of the Western Highlands is about 54,700 km^2, or nearly 6.5% of Vietnam's total land area. With the feature of red basalt soil at elevations of 500–600 m above sea level, the Western Highlands are suitable for industrial crops, such as coffee, cocoa and pepper (Ministry of Agriculture and Rural Development of Vietnam, 2016). However, deforestation, destruction of natural resources and illegal logging can accelerate the risks of forest degradation and ecological and environmental changes. Consequently, land use in the Western Highlands has changed substantially in recent decades. The present forest area in the Western Highlands is about 2.6 million ha, accounting for 17.5% of the total national forest area (Ministry of Agriculture and Rural Development of Vietnam, 2021). Over the past decade, the estimated average loss of natural forest in the Western Highlands has been 46,267 ha/yr.

The results of several studies on land use changes in the Western Highlands in Vietnam (Müller and Zeller, 2002; Castella and Verburg, 2007; Stephen, 2009) have shown that the most obvious impact is the decline in forest land area since 2000. However, the trend of changing land use has brought many benefits, such as improving infrastructure, increasing income and creating more jobs in local industrial plants and service production companies. Nonetheless a major limitation of these studies has been their failure to forecast likely changes.

The objectives of the current study were: 1) to assess land use changes based on analysis of remote sensing images from 2010 to 2020; and 2) to predict future land use changes using a logistic model in Lam Dong province in 2025 and 2030. This analytical research should help in effectively applying sustainable development and regional management.

Materials and Methods

Study area

Lam Dong province, located in the Southwestern Highlands (11˚12'–12˚15'N; 107˚15'–108˚45'E), has a natural area of 9,782 km^2. Most of this region is mountainous with plateaus and an average elevation of 800–1,000 m above sea level, with the remaining areas in small, flat valleys. A distinctive characteristic of Lam Dong province is the tiered topography from north to south. The Yang Bong mountain range in the north has a peak of 1,749 m above sea level. The southern mountain ranges consist of the Dan Sena peak at 1,950 m above sea level, Lang Biang peak at 2,163 m above sea level and Hon Giao peak at 1,948 m above sea level. In addition, the Lang Biang plateau in the south of this province, which includes Da Lat city, is located at an altitude of 1,475 m above sea level. The Di Linh plateau in the east and south of the province has an altitude of 1,010 m above sea level and its terrain is rather flat and so it is densely populated. The headwaters of the La Nga River start from here.

Lam Dong province has fertile and high-quality soil. The basaltic soil concentrated in Bao Loc city and Di Linh district provides suitable conditions for planting long-term industrial crops, such as coffee, tea and mulberry that have high economic value. Although other types of agricultural production cover a large area, they are situated far from residential areas and have low-capacity exploitation because of flood or drought, thin layers of soil with exposed rocks or clumped soil, low fertility and low-capacity utilization rates (Ministry of Agriculture and Rural Development of Vietnam, 2017).

Lam Dong province is in the upstream area of a large river system that has high hydroelectric potential with 73 reservoirs and 92 dams. The population of Lam Dong province is about 1.4 million people, and the population density is 125 people/km^2 (General Statistics Office of Vietnam, 2021).

Data acquisition and processing

The study utilized satellite images with a spatial resolution of 30 m based on Landsat Thematic Mapper (TM) images in 2010 and Landsat Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) images in 2015 and 2020 (downloaded from https://earthexplorer.usgs.gov/) to develop the land use maps. These images had been captured in July and August to get the best quality. In addition, the study used other data from maps of Lam Dong province that were provided by the Department of Natural Resources and Environment of Lam Dong province (topographic map at scale 1:50000 and the current land use map in 2010 at a scale of 1:100,000).

The study applied the supervised classification method (Richards, 2013) and the Envi software (RSI, 2001). The collected satellite images were true color composites of bands 3-2-1 for the TM images (Fig. 2A) and of bands 4-3-2 for the OLI/TIRS images (Fig. 2B, 2C; Inzana et al., 2003). The process of decoding satellite images involved the following steps: 1) image geometric corrections, involving registrations according to the VN2000 coordinate system with a projection zone of 6° and an axis meridian of 1050 E, zone 48; 2) image quality enhancements; 3) cropping the image to the boundary of the study area of Lam Dong province; 4) setting up the image interpretation keys; 5) classifying the remote sensing images based on the maximum likelihood algorithm; and 6) evaluating the image classification results.

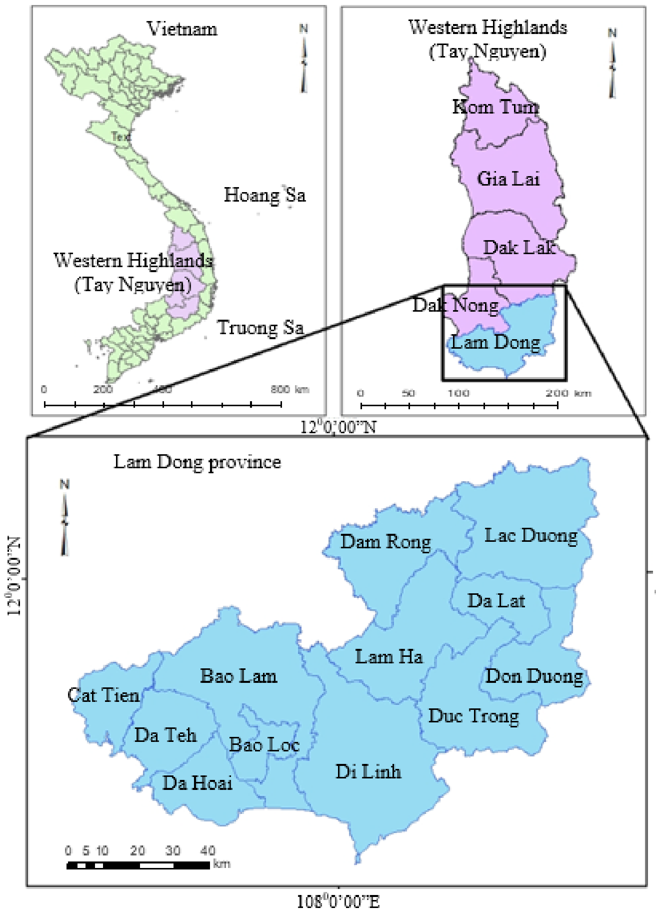

Fig. 1 Geographical location and map of Lam Dong province and its districts

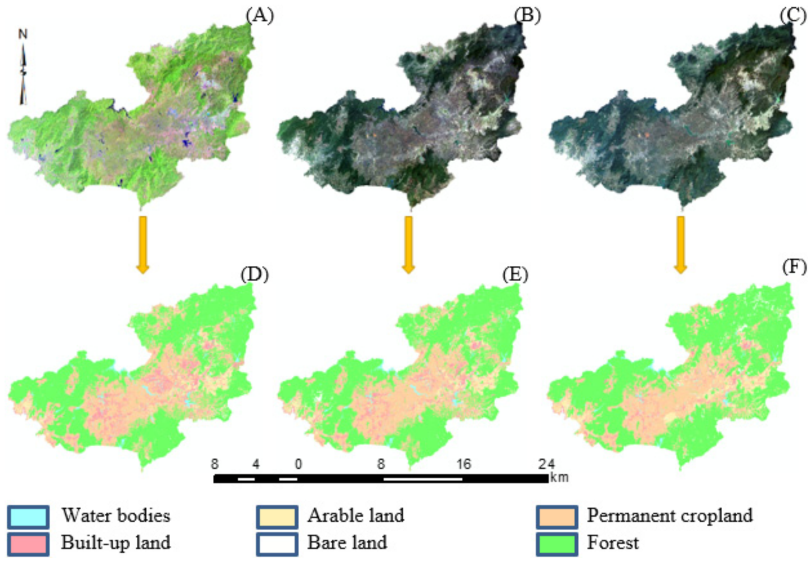

Fig. 2 Extracted land use maps of Lam Dong province for 2010, 2015 and 2020: (A) Landsat Thematic Mapper 2010; (B) Landsat Operational Land Imager/Thermal Infrared Sensor (OLI/TIR) 2015; (C) Landsat OLI/TIR 2020; (D) actual land use (LU) 2010; (E) actual LU 2015; (F) actual LU 2020

The study classified and interpreted six land types consisting of water bodies, built-up land, arable land, permanent cropland, forest and bare land. The satellite images after classification were evaluated based on the Kappa index; the overall accuracy was from 90% to over 96% and the Kappa coefficient was in the range 0.87–0.95 (Table 1). The final mapping results were current land use maps in 2010, 2015 and 2020 (Figs. 2D, 2E, 2F, respectively).

In addition, a dataset of factors affecting land changes was created in the form of Euclidean distance maps measuring distances to primary roads, distances to secondary roads, distances to water sources, distances to residential areas, elevation and slope. All these maps were created using ArcGIS (Law and Collins, 2018) as a raster with a 90 m grid cell size that was considered appropriate for this study. The driving factor maps are shown in Fig. 3.

Table 1 Accuracy of remote sensing image interpretation

Year	Overall accuracy (%)	Kappa coefficient
2010	92.97	0.88
2015	96.39	0.95
2020	90.36	0.87

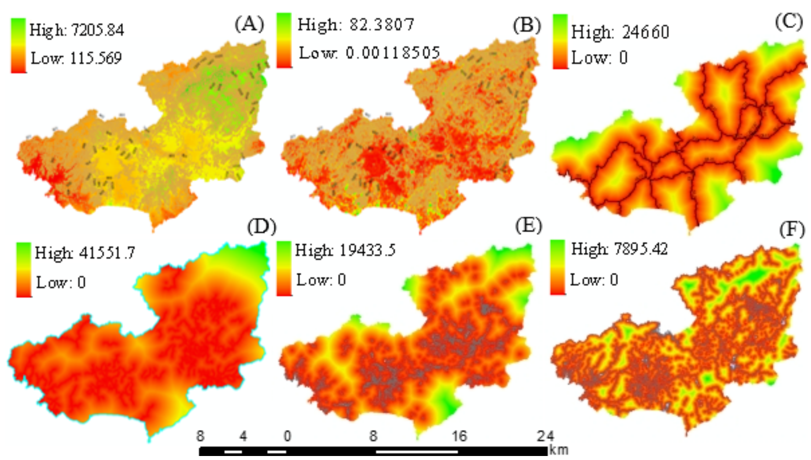

Fig. 3 Maps of driving factors in Lam Dong province: (A) elevation. (B) slope; (C) Euclidean distance (ED) primary roads; (D) ED secondary roads; (E) ED residential areas; (F) ED water sources

Logistic regression

This study used a logistic regression model to link land use changes with driving factors. In raster GIS modeling, data layers are joined to form a grid of cells. The pattern of a plot's land use changes is binary, where a value of 1 represents the presence of land use changes, while a value of 0 represents the absence of land use changes (Verburg et al., 2004). The dependent variable of the logistic regression model is a probability function of one of the land use types. The model was stated as Equation 1:

$$P(y = 1 \| X_1, X_2, ..., X_n) = exp(\Sigma_{i=1}^{n} B_i X_i) / (1 + exp(\Sigma_{i=1}^{n} B_i X_i)) \quad (1)$$

where P is the probability of each pixel for the occurrence of land use types and X = (x_1, x_2, x_3, …, x_n) are independent variables corresponding to the driving factors and the coefficients B = (b_0, b_1, b_2, b_3, …, b_n) are estimated based on logistic regression using the samples of the current land use layers.

The probability value of the continuous land use types from 0 to 1 was converted to a linear regression using Equation 2:

$$ln(p/(1 - p)) = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + ... + b_nx_n + \varepsilon \quad (2)$$

Thus, the probability of the occurrence of the land use types could be determined at each pixel using the GIS with logistic regression analysis. The GIS facilitated the analysis and extraction of data for the regression analysis.

Data simulation

The integrated model from the GIS and logistic regression was used to analyze land use changes in the 2010–2020 period. The MOLUSCE (Modules for Land Use Change Evaluation) software, a tool based on QGIS (NEXTGIS, 2017) was applied to simulate land use changes for the periods. The simulation of land use changes involved the following basic steps: 1) using the GIS to provide the statistics and build a matrix of changes between land use types based on the change in values of pixels based on overlaying the past land use maps; 2) establishing a transition potential map among land use types based on logistic regression model analysis; and 3) simulation of the land use change map by the allocation process, starting from the probability value of the grid cells from high to low.

Then, land use changes were analyzed for the 2010–2015 period and land use was simulated for 2020. The model's accuracy was evaluated by comparing the land use simulation map to the current land use map for 2020 based on Kappa index statistics (Wang et al., 2012). Finally, the model was used to forecast land use change for 2025 and 2030.

Results and Discussion

Dynamics of land use changes between 2010 and 2020

Because the study area was mountainous, forest area accounted for a large proportion of the total area. The results extracted from the land use map in 2020 estimated the forest area as 5,384.6 km^2, accounting for 55.1% of the total natural area, followed by agricultural land (including arable land and permanent cropland) with 3,267.2 km^2, accounting for 33.4% of the natural area. The areas of built-up land, water bodies and bare land accounted for 7.8%, 2.8% and 0.9%, respectively (Table 2).

Table 2 Proportion and changes in land use types from 2010 to 2020

Land use type	2010		2015		2020		2010–2015	2015–2020	2010–2020
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Δ (km^2)	Δ (km^2)	Δ (km^2)
Water bodies	189.2	1.9	246.7	2.5	277.5	2.8	57.5	30.8	88.3
Built-up land	357.6	3.7	569.7	5.8	760.9	7.8	212.1	191.2	403.3
Arable land	732.8	7.5	608.3	6.2	581.1	5.9	-124.5	-27.2	-151.7
Permanent cropland	2,403.1	24.5	2,817.0	28.8	2,686.1	27.5	413.9	-130.9	283.0
Forest	5,933.8	60.7	5,404.2	55.3	5,384.6	55.1	-529.6	-19.6	-549.2
Bare land	165.3	1.7	135.9	1.4	91.6	0.9	-29.4	-44.3	-73.7
Total	9,781.8	100.0	9,781.8	100.0	9,781.8	100.0	-	-	-

In recent years, Lam Dong province has experienced substantial land use changes in forest land, agricultural land and built-up land. Figs. 4 and 5 show land use changes for the 2010–2015 period, the 2015–2020 period and the entire period from 2010 to 2020 in the form of graphs and maps. During the study period from 2010 to 2020, forest decreased by 549.2 km^2 representing the greatest land use change. The direct causes of deforestation and forest degradation in the area were: 1) unsustainable logging (both legal and illegal); 2) transition of forest to agricultural land (high-value permanent cropland and other croplands); 3) transition of forest to infrastructure and built-up land, especially the construction of hydroelectric power plants; and 4) population growth, mainly due to free migration (Pham et al., 2019).

The transition from forest to agricultural land, including high-value permanent cropland, was one of the foremost causes of deforestation of both natural and planted forests in Vietnam. Vietnam's economy heavily relies on agricultural products and the export of natural resources; as one of the world's largest countries exporting coffee, rubber and pepper, Vietnam has become the second-largest coffee-producing country in the world, so coffee is one of the primary exported agricultural commodities (Ministry of Agriculture and Rural Development of Vietnam, 2015). The Western Highlands has more than 450,000 ha of coffee plantations, accounting for nearly 90% of Vietnam's coffee-growing area. In addition, the Western Highlands accounted for 26% of the national rubber production in 2015, while the natural forests as well as other short-rotation trees in the Western Highlands have been exploited and converted to high commercial value crops, such as pepper and cashew (Ministry of Natural Resources and Environment of Vietnam, 2021). For these reasons, permanent cropland in Lam Dong province sharply increased by 283.0 km^2 while the arable land area decreased by 151.7 km^2 in the 2010–2020 period. Agricultural production expansion has a major impact on soil erosion, loss of biodiversity, the carbon cycle and the livelihoods of local people (Pham et al., 2019).

Over the past few decades, the construction of roads and hydropower plants has led to major reductions in the forest area in the Western Highlands. Hydropower plays a critical part in electricity generation in Vietnam; therefore, to meet the rapidly growing demand, the hydropower industry has increased dam areas, leading to large-scale deforestation. The impact of dam construction on deforestation is not limited to the hydropower plant but also has indirect effects on forest area reduction from land acquisition, migration and resettlement. Currently, Lam Dong province has 33 hydropower projects in operation and hydropower development has increased the area of water bodies by 88.3 km^2 during the study period (Ministry of Industry and Trade of Vietnam, 2020).

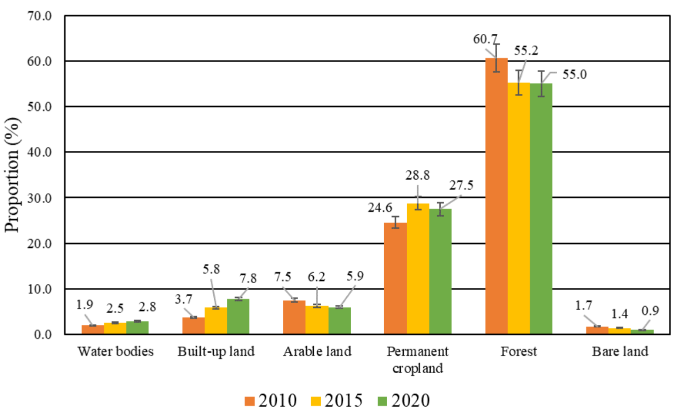

Fig. 4 Proportion of land use types of the study area, where error bars indicate ± SD

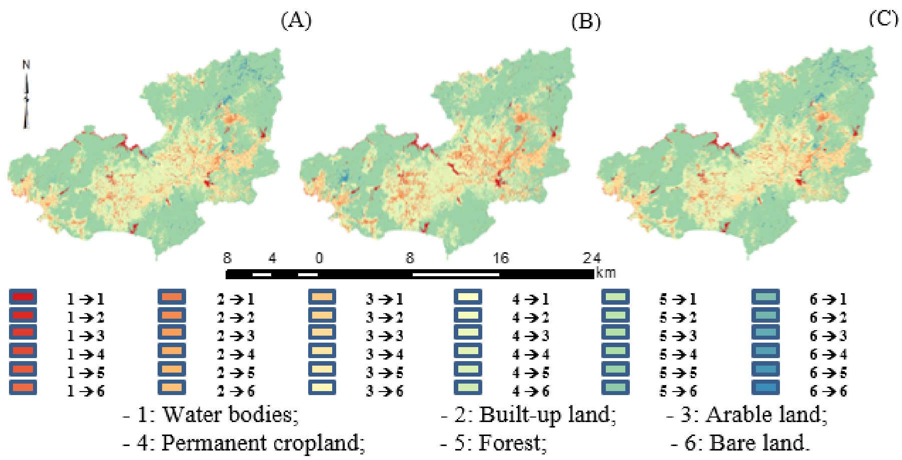

Fig. 5 Maps of land use changes in Lam Dong province: (A) 2010–2015; (B) 2015–2020; (C) 2010–2020

Population growth has led to the expansion of urban areas, residential areas, industrial production areas and infrastructure, further impacting the decrease in forested area in Lam Dong province. In the 2010–2020 period, the built-up land area increased by 403.3 km^2. However, as urban development can adversely affect natural habitats and biodiversity, during this period, the local government had many projects to plant bare land to recover lost forest area, so that bare land only decreased by 73.7 km^2.

Model validation

Land use purpose change is a complicated process influenced by natural, economic and social factors. Therefore, each simulation produced a certain result, with the model results never capable of accurately reflecting the real situation based on the experimental data. Model accuracy is often assessed based on pixel-by-pixel comparisons between the land use simulation map and the actual land use map. Using Kappa index statistics is one of the most common methods (van Vliet et al., 2011). The Kappa index statistic lies within the range from -1 to +1, with the value 0 representing predictive ability equivalent to a random model, whereas a value closer to +1 indicates higher accuracy.

To validate the land use change model, the land use simulation map in 2020 was compared with the actual current land use map in 2020 (Fig. 6) using the Kappa index statistics. The land use simulation map in 2020 was generated based on the land use maps for 2010 and 2015. The overall level of correctness was 83.76% for the evaluation mapping and the Kappa coefficient of 0.74 was consider good (Landis and Koch, 1977); thus, the model was acceptable for forecasting for future periods.

The model for forecasting land use changes for future periods of 5 yr (in 2025 and 2030) was based on the current land use base maps in 2010 and 2015 (Fig. 7). The land use

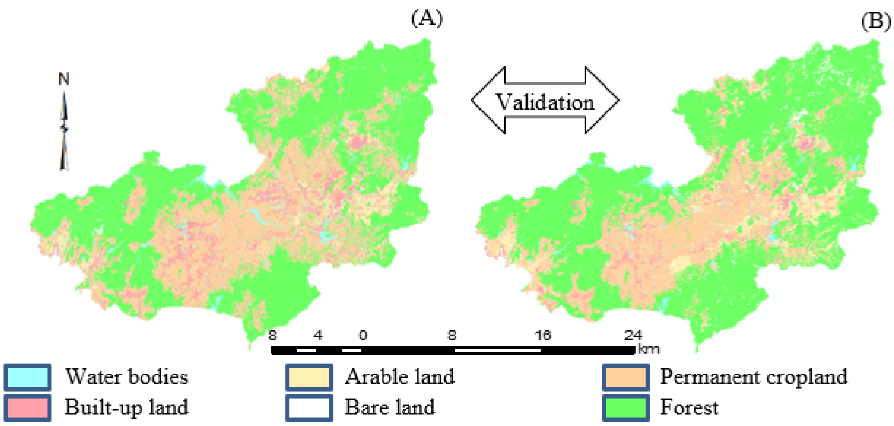

Fig. 6 Land use maps in Lam Dong province for 2020: (A) actual land use; (B) simulated land use

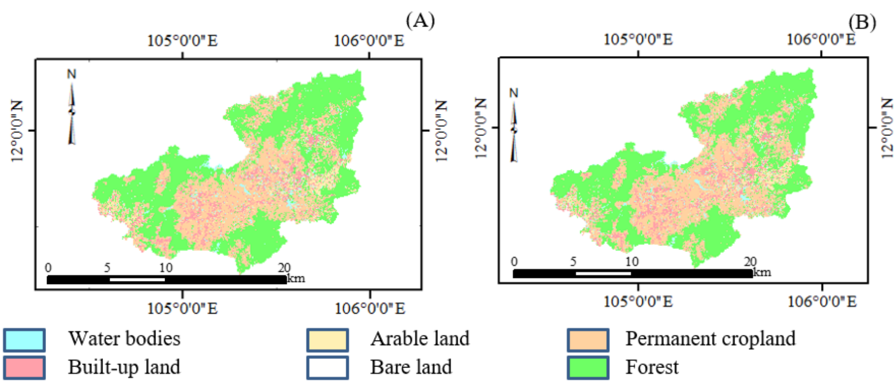

Fig. 7 Predicted land use maps in Lam Dong province: (A) 2025; (B) 2030

change prediction maps were generated by a combination of the transition probabilities matrices between land use types (Table 3) and the transition potential map generated based on logistic regression analysis. The model predicted that there would be a reduction of 340.6 km^2 in the forest area in the 2020–2025 period, so the remaining forest area would be 5,044.0 km^2 in 2025. In addition, the areas of arable land and bare land would decrease by 111.7 km^2 and 55.1 km^2, respectively. In contrast, permanent cropland, built-up land and water bodies would continue to increase (249.0 km^2, 218.3 km^2 and 40.1 km^2, respectively). A similar trend was predicted after 2025, with the forecast of the forest area in 2030 decreasing by 129.5 km^2 and arable land and bare land decreasing by 19.5 km^2 and 9.5 km^2, respectively. However, built-up land and water bodies were predicted to increase by 191.6 km^2 and 28.4 km^2 in 2030, respectively, and permanent cropland in this period would decrease by 61.5 km^2 (Table 4).

The forecast results showed that there will be major changes in future land use in Lam Dong province, specifically a sharp decrease in forest area due to human activities to promote agricultural production and to expand urban and residential areas and infrastructure. This study finding was in agreement with the results from other studies that confirmed the major drivers of LULC change (Castella and Verburg, 2007; Müller and Zeller, 2002; Stephen, 2009). The forecast results suggest a concerning major degradation in the area of natural vegetation.

The advantage of the logistic regression model used in the current study was that it could quantitatively identify the relationships between land-use change and driving factors from natural, economic and societal viewpoints. However, the model also has its limitations in predicting land use changes because the spatial transformation probabilities generated by the logistic model depended on the quantity and completeness of the driving factors. Difficulties in collecting data and integrating factors, such as demographics and development policy, could reduce the accuracy of the model. Furthermore, determining the probability of quantitative transitions between future land use types based on the recent history of land use changes is appropriate only when conditions affecting land use changes in the past and the future are identical. In the 2010–2015 period, the area of water bodies sharply increased due to the construction of hydroelectric power plants, leading to the model predicting that in the next period the area of water bodies will continue to increase. However, recognizing the negative

Table 3 Transition probabilities matrices for periods 2020–2025 and 2025–2030

LU type		Water bodies	Built-up land	Arable land	Permanent cropland	Forest	Bare land
Probability value 2025	Water bodies	0.9812	0.0073	0.0055	0.0030	0.0024	0.0006
	Built-up land	0.0040	0.9576	0.0011	0.0291	0.0077	0.0005
	Arable land	0.0093	0.0808	0.7515	0.1571	0.0002	0.0011
	Permanent cropland	0.0065	0.0601	0.0284	0.8552	0.0498	0.0000
	Forest	0.0012	0.0019	0.0000	0.0627	0.9318	0.0024
	Bare land	0.0773	0.0647	0.0115	0.1387	0.3234	0.3844
Probability value 2030	Water bodies	0.9848	0.0075	0.0049	0.0017	0.0008	0.0003
	Built-up land	0.0034	0.9619	0.0013	0.0273	0.0055	0.0006
	Arable land	0.0067	0.0780	0.7660	0.1481	0.0002	0.0010
	Permanent cropland	0.0066	0.0611	0.0296	0.8531	0.0496	0.0000
	Forest	0.0011	0.0017	0.0000	0.0532	0.9427	0.0013
	Bare land	0.0541	0.0655	0.0166	0.1256	0.2152	0.5230

Table 4 Area statistics for predicted land use in 2025 and 2030

LU type	2025		2030		2020–2025	2020–2030
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Change (km^2)	Change (km^2)
Water bodies	317.6	3.2	346.0	3.5	40.1	68.5
Built-up land	979.2	10.0	1,170.8	12.0	218.3	409.9
Arable land	469.4	4.8	449.9	4.6	-111.7	-131.2
Permanent cropland	2,935.1	30.0	2,873.6	29.4	249.0	187.5
Forest	5,044.0	51.6	4,914.5	50.2	-340.6	-470.1
Bare land	36.5	0.4	27.0	0.3	-55.1	-64.6
Total	9,781.8	100.0	9,781.8	100.0	-	-

effects of hydropower construction on natural resources, the Vietnamese government has withdrawn more than 470 small hydropower projects from future land use planning, including in Lam Dong province. Therefore, the projected forecast of continuing increase in the area of water bodies may not be realistic. Therefore, to increase the accuracy of the forecast, the MOLUSCE model needs to be refined to better build future land use scenarios decided by humans.

In conclusion, this study analyzed the land use changes in the past and used them to forecast land use changes in the future in Lam Dong province, in the Western Highlands of Vietnam, using an integrated approach combining remote sensing images, GIS and logistic regression modeling. An advantage of logistic regression models is that they can quantitatively explore the relationships between land use transition and driving factors. The results of land use change analysis in the 2010–2020 period showed that the loss in forest area was 5.6% (549.2 km^2) due to the transition from forest to agricultural production and the expansion of urban and residential areas and infrastructure. The generated land use change prediction maps in 2025 and 2030 predicted the scale and location of the changes, the suggested there will be major changes in future land use in Lam Dong province. While the forest area was predicted to sharply decrease by 4.8% (470.1 km^2), the construction area will increase by 4.2% (409.9 km^2). Therefore, if future conditions remain unchanged, future land use changes will cause serious environmental and biodiversity consequences. Agriculture and the exploitation of natural resources are the major sectors in the region; however, they could be affected by unsustainable development. The main driving factor of economic growth is the agricultural sector, especially the production of coffee, rubber and pepper, which are readily susceptible to climate change. To ensure sustainable development for local people, policies to promote the development of agricultural production should require a balance between the objectives of economic development and environmental protection.

Conflict of Interest

The authors declare that there are no conflicts of interest.

Acknowledgements

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References

Al-Darwish, Y., Ayad, H., Taha, D., Saadallah, D. 2018. Predicting the future urban growth and it's impacts on the surrounding environment using urban simulation models: Case study of Ibb city – Yemen. Alex. Eng. J. 57: 2887–2895. doi.org/10.1016/j.aej.2017.10.009

Castella, J.C., Verburg, P.H. 2007. Combination of process-oriented and pattern-oriented models of land-use change in a mountain area of Vietnam. Ecol. Model. 202: 410–420. doi.org/10.1016/j.ecolmodel.2006.11.011

Darmawan, S., Sari, D.K., Wikantika, K., Tridawati, A., Hernawati, R., Sedu, M.K. 2020. Identification before-after forest fire and prediction of mangrove forest based on Markov-cellular automata in part of Sembilang National Park, Banyuasin, South Sumatra, Indonesia. Remote Sens. 12: 3700. doi.org/10.3390/rs12223700

Feng, Y., Qi, Y. 2018. Modeling patterns of land use in Chinese cities using an integrated cellular automata model. ISPRS Int. J. Geo-Inf. 7: 403. doi.org/10.3390/ijgi7100403

General Statistics Office of Vietnam. 2021. Results of the 2020 Population and Housing Census. Statistical Publishing House. Ha Noi, Vietnam. [in Vietnamese]

Gibson, L., Munch, Z., Palmer, A., Mantel, S. 2018. Future land cover change scenarios in South African grasslands - implications of altered biophysical drivers on land management. Heliyon 4: e00693. doi.org/10.1016/j.heliyon.2018.e00693

Inzana, J., Kusky, T., Higgs, G., Tucker, R. 2003. Supervised classifications of Landsat TM band ratio images and Landsat TM band ratio image with radar for geological interpretations of central Madagascar. J. African Earth Sci. 37: 59–72. doi.org/10.1016/S0899-5362(03)00071-X

Jamal, J.A., Marco, H., Wolfgang, K., Ali, D.B. 2013. Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. Int. J. Appl. Earth Obs. Geoinf. 21: 265–275. doi.org/10.1016/j.jag.2011.12.014

Jean-Francois, M., Melanie, K., Martin, P., Maria, C.O., Thomas, H. 2014. Modelling land use/cover changes: A comparison of conceptual approaches and softwares. Environ. Model. Softw. 51: 94–111. doi.org/10.1016/j.envsoft.2013.09.010

Kumar, S., Radhakrishnan, N., Mathew, S. 2014. Land use change modelling using a Markov model and remote sensing. Geomatics, Nat. Hazards Risk. 5: 145–156. doi.org/10.1080/19475705.2013.795502

Lambin, E.F., Turner, B.L., Geist, H.J., et al. 2001. The causes of land-use and land-cover change: Moving beyond the myths. Glob. Environ. Change. 11: 261–269. doi.org/10.1016/S0959-3780(01)00007-3

Landis, J.R., Koch, G.G. 1977. The measurement of observer agreement for categorical data. Biometrics. 33: 159–174. doi.org/10.2307/2529310

Law, M., Collins, A. 2018. Getting to Know ArcGIS Desktop, 5th ed. Esri Press. California, CA, USA.

Li, K., Feng, M., Biswas, A., Su, H., Niu, Y., Cao, J. 2020. Driving factors and future prediction of land use and cover change based on satellite remote sensing data by the LCM model: A case study from Gansu province, China. Sensors 20: 2757. doi.org/10.3390/s20102757

Maria, T.C.O., Robert, G.P., Martin, P., Jean-François, M. 2015. Comparison of simulation models in terms of quantity and allocation of land change. Environ. Model. Softw. 69: 214–221. doi.org/10.1016/j.envsoft.2015.03.003

Meiyappan, P., Dalton, M., O'Neill, B., Atul, K.J. 2014. Spatial modeling of agricultural land use change at global scale. Ecol. Modell. 291: 152–174. doi.org/10.1016/j.ecolmodel.2014.07.027

Ministry of Agriculture and Rural Development of Vietnam. 2015. Agricultural Land-use Manual, Vol. 3. Land Resources in Vietnam: Land-use Current Status and Potential. Scientific and Technical Publishing. Ha Noi, Vietnam. [in Vietnamese]

Ministry of Agriculture and Rural Development of Vietnam. 2016. Agricultural Land-use Manual, Vol. 4. Regional Land Resources: Land-use Current Status and Potential. Scientific and Technical Publishing. Ha Noi, Vietnam. [in Vietnamese]

Ministry of Agriculture and Rural Development of Vietnam. 2017. Agricultural Land-use Manual, Vol. 5. Provincial Land-use Management. Scientific and Technical Publishing. Ha Noi, Vietnam. [in Vietnamese]

Ministry of Agriculture and Rural Development of Vietnam. 2021. Announcement of National Forest Status in 2020. Ministry of Agriculture and Rural Development of Vietnam, Ha Noi, Vietnam. [in Vietnamese]

Ministry of Industry and Trade of Vietnam. 2020. Planning of Hydropower System in the Central Highlands. Ministry of Industry and Trade of Vietnam, Ha Noi, Vietnam. [in Vietnamese]

Ministry of Natural Resources and Environment of Vietnam. 2021. Results of Land Inventory in the 2011–2020 Period. Ministry of Natural Resources and Environment of Vietnam, Ha Noi, Vietnam. [in Vietnamese]

Miriam, S.W., Taylor, V.S. 2010. Modeling social and land-use/land-cover change data to assess drivers of smallholder deforestation in Belize. Appl. Geogr. 30: 329–342. doi.org/10.1016/j.apgeog.2009.10.001

Müller, D., Zeller, M. 2002. Land use dynamics in the central highlands of Vietnam: A spatial model combining village survey data with satellite imagery interpretation. Agric. Econ. 27: 333–354. doi.org/10.1016/S0169-5150(02)00073-7

NEXTGIS. 2017. MOLUSCE–quick and convenient analysis of land cover changes. Harjumaa, Estonia. https://nextgis.com/, 10 June 2021.

Pham, T.T., Hoang, T.L., Nguyen, D.T., Dao, T.L.C., Ngo, H.C., Pham, V.H. 2019. The Context of REDD+ in Vietnam: Drivers, Agents and Institutions, 2nd ed. Center for International Forestry Research. Bogor, Indonesia. doi.org/10.17528/cifor/007402

Pir, B.M. 2015. Deforestation modelling using logistic regression and GIS. J. For. Sci. 61: 193–199. doi.org/10.17221/78/2014-JFS

Richards, J.A. 2013. Clustering and unsupervised classification. In: Remote Sensing Digital Image Analysis. Springer, Berlin, Germany, pp. 319–341. https://doi.org/10.1007/978-3-642-30062-2_9

RSI. 2001. ENVI Tutorials. StoneTablet. Portland, PO, USA.

Simwanda, M., Murayama, Y., Phiri, D., Nyirenda, V.R., Ranagalage, M. 2021. Simulating scenarios of future intra-urban land-use expansion based on the Neural Network–Markov model: A case study of Lusaka, Zambia. Remote Sens. 13: 942. doi.org/10.3390/rs13050942

Stephen, J.L. 2009. Dynamics of land cover and land use changes in the upper Ca river basin of Nghe An, Vietnam. Southeast Asian Stud. 47: 287–308. doi.org/10.20495/tak.47.3_287

Tayyebi, A., Delavar, M.R., Yazdanpanah, M.J., Pijanowski, B.C., Saeedi, S., Tayyebi, A.H. 2010. A spatial logistic regression model for simulating land use patterns: A case study of the Shiraz metropolitan area of Iran. In: Chuvieco, E., Li, J., Yang, X. (Eds.). Advances in Earth Observation of Global Change. Springer. Dordrecht, the Netherlands, pp. 27–42. doi.org/10.1007/978-90-481-9085-0_3

van Vliet, J., Bregt, A.K., Hagen-Zanker, A. 2011. Revisiting Kappa to account for change in the accuracy assessment of land-use change models. Ecol. Modell. 222: 1367–1375. doi.org/10.1016/j.ecolmodel.2011.01.017

Verburg, P.H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., Mastura, S.S.A. 2002. Modeling the spatial dynamics of regional land use: The CLUE-S model. Environ. Manage. 30: 391–405. doi.org/10.1007/s00267-002-2630-x

Verburg, P., Nijs, T., Eck, J.V., Visser, H., Jong, K.D. 2004. A method to analyse neighbourhood characteristics of land use patterns. Comput. Environ. Urban Syst. 28: 667–690. doi.org/10.1016/j.compenvurbsys.2003.07.001

Verburg, P.H., Kok, K., Pontius, R.G., Veldkamp, A. 2006. Modeling land-use and land-cover change. In: Lambin, E.F., Geist, H. (Eds.). Land-Use and Land-Cover Change. Global Change - The IGBP Series. Springer. Heidelberg, Germany, pp. 117–135. doi.org/10.1007/3-540-32202-7_5

Wang, S.Q., Zheng, X.Q., Zang, X.B. 2012. Accuracy assessments of land use change simulation based on Markov-cellular automata model. Procedia Environ. Sci. 13: 1238–1245. doi.org/10.1016/j.proenv.2012.01.117

Zhang, R., Tang, C., Ma, S., Yuan, H., Gao, L., Fan, W. 2011. Using Markov chains to analyze changes in wetland trends in arid Yinchuan Plain, China. Math. Comput. Model. 54: 924–930. doi.org/10.1016/j.mcm.2010.11.017