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Using Landsat Satellite Imagery for Assessment and Monitoring of Long-term Forest Cover Changes in Dak Nong Province, Vietnam

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Abstract

Forests are essential in regulating climate and protecting land resources from natural disasters. In Vietnam's Dak Nong province, forest cover has changed significantly between 1989 and 2021. This study applies remote sensing and geographic information systems (GIS) approaches to detect negative changes in forest cover as well as other land cover types. The maximum likelihood classification tool was used to classify Landsat images for the years 1989, 2001, 2011, and 2021, with post-classification accuracy evaluated through kappa coefficient statistics. The potential to based classification on Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) to detect changes in forest cover compared with supervised classification was also evaluated. The land use and land cover change detection results show that the forest area decreased from 77.54% of the study area in 1989 to 33.97% in 2021, with a total forest loss of 2,953.48 km^2 and only 117.12 km^2 of newly planted forest during this period. Broadly, forest cover in the area has been severely reduced, often due to indiscriminate logging and expansion of agricultural land on the forest edge.

Keywords: Forest cover; Forest loss; Landsat; Vegetation Index; Remote sensing; Vietnam

Introduction

Studies of land use and land cover (LULC) change are essential to current strategies for monitoring environmental changes and managing natural resources (Kumari et al., 2014; Han et al., 2015; Meshesha et al., 2016). Performing LULC change detection represents an important tool to determine differences in the state of land cover over time. LULC changes are the conversion of different types of land use and are the result of complex interactions between people and the physical environment (Pielke et al., 2011). LULC changes, especially in developing countries (Hegazy & Kaloop, 2015; Larasati & Hariyanto, 2018), have resulted in decreases in important natural resources, including vegetation, soil, and water (Erb et al., 2018; Hyandye et al., 2018; Azimi Sardari et al., 2019). In addition, changes in LULC are closely related to the sustainable development of society and the economy. Rapidly increasing land use change trends can have significant impacts on local, regional, national, and worldwide environments (Meshesha et al., 2016; Olorunfemi et al., 2020). Therefore, assessing land use patterns and their variations at a regional level is important for resource-specific planning, management, and using resources effectively.

Globally, forest cover has undergone major and unprecedented changes in recent decades due to a range

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of human impacts, including accelerating urbanization, industrialization, agricultural expansion, logging, and mining (Atmiş et al., 2007; Agarwal et al., 2010; Hor et al., 2014; Ahammad et al., 2019; Caballero Espejo et al., 2018). In developing countries located in the tropics, logging activities have become the main cause of forest cover loss. Several drivers affect forest cover in such areas, including logging, unemployment, migration rates, population pressure, infrastructure development, and agriculture (Ranjan, 2019). In addition, the global population is increasing–in the revised 2019 World Population Prospects, the United Nations forecasts that the world population will increase from 7.7 billion in 2019 to 8.5 billion in 2030, 9.7 billion in 2050, and 10.9 billion people in 2100 (United Nations, 2019). In many areas of developing countries, rapid population growth often leads to LULC changes through deforestation and conversion to agricultural land to meet the growing needs of the population, and this transformation will continue in the future (Zeng et al., 2018; Pellikka et al., 2018).

Remote sensing technology and Geographic Information Systems (GIS) have been widely developed and applied globally to research, monitor, and track LULC changes. Remote sensing satellites are the most-used data source to detect, quantify, and map both current land use and LULC changes because of their ability to collect multitemporal spatial data in the form of precisely geolocated, high-resolution images to which a range of processing techniques can be applied (Lu et al., 2004; Yang et al., 2019; Thien et al., 2022a). Many change detection techniques have been developed and used to monitor changes in LULC from remotely sensed data, such as vegetation index differences, image disparity, post-classification comparison, and principal component analysis (Lu et al., 2004; Afify, 2011). The post-classification comparison method is considered to be the most accurate change detection technique, in which land cover changes are detected by comparing post-classification images from different dates (Singh, 1989; Long et al., 2014). In addition, vegetation index analysis has been widely used to increase accuracy when mapping forest cover through indices such as the Enhanced Vegetation Index, Normalized Difference Vegetation Index (NDVI), and Soil Adjusted Vegetation Index (SAVI) (Matsushita et al., 2007; Baloloy et al., 2020; Spadoni et al., 2020).

Vietnam is a country famous for its highly diverse tropical forest ecosystem. Since the 1990s, Vietnam's forests have undergone a transition from pure deforestation to pure reforestation (Meyfroidt & Lambin, 2008). However, in the early years of the 21st century, Vietnam was one of the leading countries in terms of tree cover loss (Hansen et al., 2013). Therefore, this study aims to constrain these changes by: (1) detecting forest land cover in a typical Vietnamese area of Dak Nong province from 1989 to 2021, (2) investigating detailed spatial and temporal variations in forest cover and other major cover types, and (3) linking vegetation indices with changes in forest cover.

Materials and methods

Study area

This study focuses on Dak Nong province, located in the southwest of the Central Highlands of Vietnam between 11°45' to 12°50' N and 107°13' to 108°10' E (Figure 1). Dak Nong covers an area of 6,509.27 km², with a population of 625,822 according to statistics in 2019 (Dak Nong Statistics Office, 2020). The study area shares 130 km of its border with Cambodia's Mondulkiri province. Dak Nong province lies entirely on the M'Nong plateau, with an average altitude of 600 m to 700 m above sea level; its highest altitude of 1,982 m occurs in Ta Dung. In general, the terrain of Dak Nong decreases in elevation from east to west. The terrain is diverse, rich, and strongly dissected, alternating between high mountains, with large plateaus and gently sloping, wavy, fairly flat, low-lying plains.

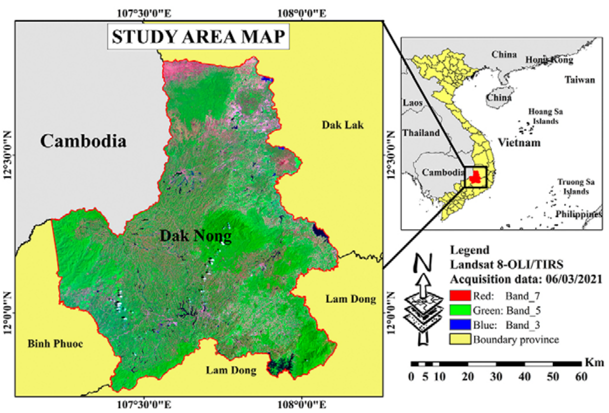

Figure 1. Map showing the study area in Dak Nong province, Vietnam

Dak Nong is a transitional area between the two climatic sub-regions of the Central Highlands and the Southeast. The climate regime has the common characteristics of the sub-equatorial monsoon tropical climate, however, given the elevation of its topography, it has unique characteristics. It is characterized by a humid tropical highland climate and is influenced by the hot and dry southwest monsoon. The climate is divided into two distinct seasons: a rainy season from April to the end of November, during which over 90% of the annual rainfall of 2,513 mm occurs, and a dry season from December to the end of the following March. The average annual temperature is 22 to 23 °C.

Satellite image data acquisition

Satellite images were used to map LULC in Dak Nong province from 1989 to 2021 and assess changes in forest cover. Images without unwanted shade and cloud were set as criteria in the image selection process because their presence can significantly reduce the accuracy of the classification and assessment of vegetation based on vegetation indicators. Remote sensing images acquired during Dak Nong province's dry season (December to March next year) are less affected by clouds and have good quality, thus they were used for the analysis in this work. Landsat 5 TM images were used for the years 1989, 2001, and 2011 and Landsat 8 OLI/TIRS images were used for 2021 in this study. The Landsat image dataset was downloaded from the USGS EarthExplorer (https://earthexplorer.usgs.gov) and USGS GloVis websites (https://glovis.usgs.gov). A detailed data summary is given in Table 1. The ground truth data was collected from January to February 2021 using Global Positioning System (GPS) and used to classify satellite images and accuracy assess post-classification in combination with the historical view of Google Earth images.

Image pre-processing and classification

Image pre-processing was performed to extract meaningful information from satellite data so that they may become easier to interpret (Jensen, 1996). Landsat satellite images were processed, classified and analysed using ArcGIS 10.8. The satellite images listed in Table 1 were geometrically corrected to the Universal Transverse Mercator (UTM) coordinate system 48N on the WGS84 datum. The data were then composited and cropped based on the predefined boundaries of the study area. Although the primary objective of this study was to investigate forest cover changes, we also investigated other major LULC classes in the area to identify detailed variations in forest cover compared to other classes. Based on the field visit to the study area, the modified Anderson LULC scheme level I (Anderson et al., 1976), Vietnam's regulation on LU, the existing condition of the study area and reference to relevant literature, five LULC classes were identified: forest, agriculture, settlements, water, and barren land (Table 2).

For each image classification, a minimum of 300 training samples were selected by drawing polygons around representative classes. The training samples represented the five land-use classes and the number of training samples varied for different classes based on variabilities and ease of identification of each land-use class. Moreover, through false color composites of the satellite images enhances the visualization of the various features when classifying. The pixels enclosed by these polygons were used to record the spectral signatures for the respective classes of the satellite imagery. A satisfactory spectral signature was used to ensure minimum error among the land-uses to be mapped (Gao & Liu, 2010). The study has used the rule-based supervised classification - maximum likelihood classifier (MLC) algorithm for LULC classification for acquired images of 1989, 2001, 2011, and 2021 (Rawat & Kumar,

Table 1. Detailed data summary of satellite imagery used in the study

Year of acquisition	Satellite	Sensor	Path/row	Resolution (m)	Source
10/02/1989	Landsat 5	TM	124/051	30	USGS GloVis
	Landsat 5	TM	124/052	30	USGS GloVis
10/01/2001	Landsat 5	TM	124/051	30	USGS GloVis
	Landsat 5	TM	124/052	30	USGS GloVis
07/02/2011	Landsat 5	TM	124/051	30	USGS GloVis
	Landsat 5	TM	124/052	30	USGS GloVis
06/03/2021	Landsat 8	OLI/TIRS	124/051	30	USGS EarthExplorer
	Landsat 8	OLI/TIRS	124/052	30	USGS EarthExplorer

Table 2. Identified classes by supervised classification

Class	Description
Forest	Forestry, natural forests, individual trees, mangroves
Agriculture	Cultivated outfields, homestead garden fields, aquaculture, salt field and small scattered plots of grazing lands
Settlements	Residential buildings, industrial use, roads, villages, other impervious surfaces
Water	Rivers, canals, lakes, artificial ponds
Barren land	Fallow land, sands, earth dumps

2015; Shivakumar & Rajashekararadhya, 2018; Nguyen et al., 2020a; Thien et al., 2022a). The post-classification refinement was used for the simplicity and effectiveness of the method to improve classification accuracy and reduce misclassifications (Harris & Ventura, 1995).

Classification accuracy assessment

An evaluation of the accuracy of the thematic maps was produced to determine the quality of the information obtained from the data (Owojori & Xie, 2005; Thien et al., 2022b). The error matrix, overall accuracy, producer accuracy, user accuracy, and kappa coefficient metrics were used to evaluate the accuracy of the classified images for the years 1989, 2001, 2011, and 2021. The accuracy validation was performed against 300 random points that were identified and located using stratified randomization in ArcGIS 10.8 software to represent the area's different LULC classes. The comparison of point data and classification results was performed using an error matrix. The equations for kappa coefficient, overall accuracy, user accuracy, and producer accuracy are among the best quantitative measurements for classifying satellite images and are shown in equations (1), (2), (3), and (4) respectively (Chowdhury et al., 2020; Hasan et al., 2020; Thakur et al., 2021):

$$\text{Kappa coefficient} = \frac{\sum_{i=1}^{k} n_{ii} - \sum_{i-1}^{k} n_{ii}(G_i C_i)}{n^2 - \sum_{i=1}^{k} n_{ii}(G_i C_i)} \qquad (1)$$

where i is the class number, n is the total number of classified pixels that are being compared to the actual data, nii is the number of pixels belonging to actual data class i that were classified as class i, C_i is the total number of classified pixels belonging to class i, and G_i is the total number of actual data pixels belonging to class i.

Overall accuracy = Total number of corrected classified pixels (diagonal) / Total number of reference pixels · 100 (2)

User accuracy = Number of corectly classified pixels in each category / Total number of reference pixel in each category (row total) · 100 (3)

Producer accuracy = Number of corectly classified pixels in each category / Total number of reference pixel in each category (column total) · 100 (4)

Analysis of vegetation indices to detect forest cover changes

Several vegetation indices can be employed to detect and analyze the existence and extent of vegetation and forest cover. Among the commonest ones are NDVI and SAVI (Huete, 1988; Huete, 2012; Islam et al., 2021). These indices are measures of vegetation and soil surface reflectance. In this research, the viability of these two widely used vegetation indices was therefore investigated to further determine the extent of forest cover and greenness in the ecosystem and its adjourning impact area. In this case, we extracted NDVI and SAVI values from all the forest polygons we detected through supervised classification of Landsat 8 OLI/TIRS imageries, and then we used the maximum and minimum values of NDVI and SAVI to reclassify the classification raster for mapping the area of forest land cover for all other periods. To do so, the NDVI and SAVI values used the raster calculator tool in ArcGIS 10.8 based on the formulas below (Eqs. 5 and 6):

$$\text{NDVI} = \frac{\text{NIR - RED}}{\text{NIR + RED}} \qquad (5)$$

where NIR is the reflectance radiated in the near-infrared wave band, and RED is the reflectance radiated in the visible red wave band of the satellite radiometer.

$$SAVI = \frac{\text{NIR - RED}}{\text{NIR + RED + L}} \cdot 1 + \text{L} \qquad (6)$$

where L is 0.5, the default value.

Results

Accuracy of classified images

The results of image accuracy assessment after classification for the four studied years are summarized in Table 3. The overall accuracy values for 1989, 2001, 2011, and 2021 are 86.71%, 87.33%, 89.00%, and 92.67%, respectively, with kappa coefficient statistics of 0.82, 0.83, 0.86, and 0.90, respectively. The user accuracy results show that in 1989, the maximum accuracy was for the forest class (93.52%) and the minimum for the barren land class (78.69%). In 2001, the user accuracy ranged from the lowest accuracy of 80.43% (barren land class) to a maximum of 91.43% (water class), while in 2011 it ranged from 82.50% for the barren land class to 95.12% for the water class (Table 3). A high user accuracy was achieved for 2021, with values of at least 90.63% (barren land class). The

Table 3. Land use/land cover classification and accuracy assessment analysis

Year	Producer Accuracy (%)					User Accuracy (%)					Overall Accuracy (%)	Kappa Coefficient
	Forest	Agriculture	Settlements	Water	Barren land	Forest	Agriculture	Settlements	Water	Barren land		
1989	90.99	86.57	77.78	86.84	82.76	93.52	84.06	80.77	89.19	78.69	86.71	0.82
2001	91.09	86.08	86.84	86.49	82.22	89.32	87.18	86.84	91.43	80.43	87.33	0.83
2011	90.53	88.89	90.00	88.64	84.62	92.47	83.12	91.84	95.12	82.50	89.00	0.86
2021	95.52	95.10	91.07	92.50	82.86	94.12	92.38	92.73	92.50	90.63	92.67	0.90

manufacturer's accuracy results show that the forest class was classified relatively accurately year by year at 90.99%, 91.09%, 90.53%, and 95.52% in 1989, 2001, 2011, and 2021, respectively. The corresponding lowest percentages were settlements (77.78%) in 1989 and barren land in 2001, 2011, and 2021, with values of 82.22%, 84.62%, and 82.86%, respectively (Table 3).

Land use/land cover classification of Dak Nong province from 1989 to 2021

The land cover classification images of Dak Nong province for the years 1989, 2001, 2011, and 2021 are shown in Figure 2. We observe that in 1989, most of the study area was covered with forest, accounting for around 77% of the total area. Forests covered 5,047.51 km², followed by barren land covering 1,244.54 km² (around 19%), agricultural land covering 182.74 km² (nearly 3%), settlements with a total area of 22.26 km² (0.34%), and, finally, water, which covered only 12.22 km² (0.19% of the study area) (Table 4). In 2001, the forested area was 4,417.58 km², accounting for 67.87% of the study area; this value decreased sharply to 2,456.62 km² (37.74%) in 2011 and 2,211.15 km² (33.97%) in 2021. The settlement land class in 1989 covered 22.26 km², accounting for 0.34% of the study area. This value increased significantly to 192.88 km², accounting for 2.96% in 2021 (Table 4). This increase in settlements also corresponds to a dramatic increase in agricultural land cover from only 182.74 km² (2.81%) in 1989 to 3,861.68 km² (59.33%) in 2021, at which time it represented the LULC class with the total land area proportion in the region. In addition,

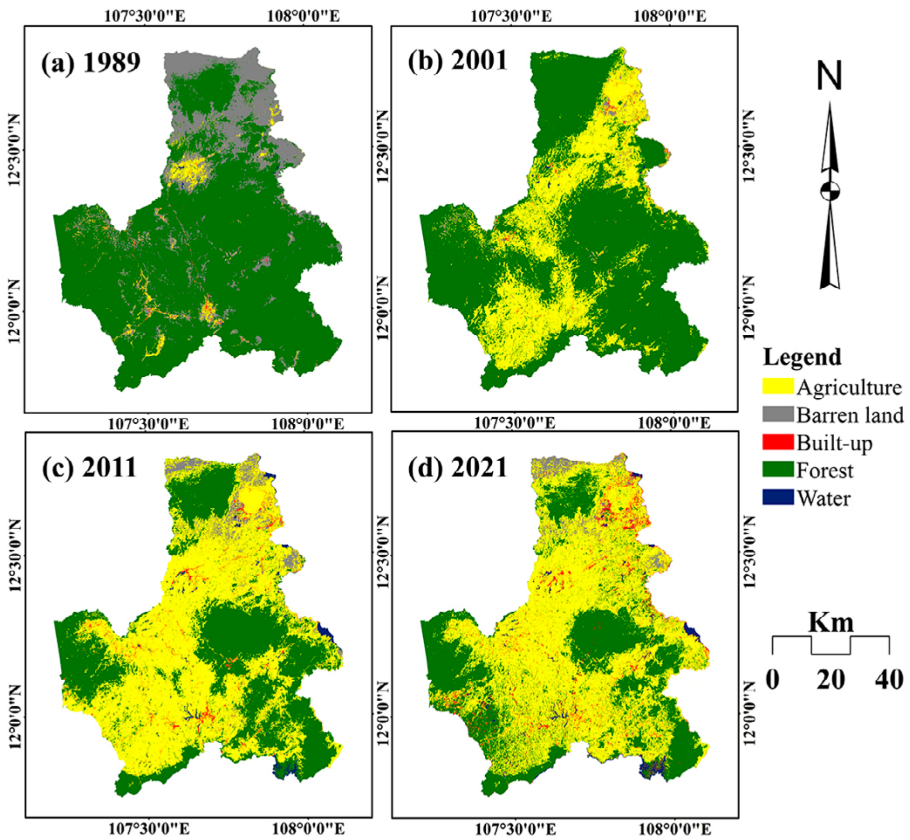

Figure 2. Land use/land cover of Dak Nong province in (a) 1989, (b) 2001, (c) 2011, and (d) 2021

Table 4. Results of land use/land cover classification in Dak Nong province from 1989 to 2021

Class	Land cover in 1989		Land cover in 2001		Land cover in 2011		Land cover in 2021	
	Area (km²)	%	Area (km²)	%	Area (km²)	%	Area (km²)	%
Forest	5047.51	77.54	4417.58	67.87	2456.62	37.74	2211.15	33.97
Agriculture	182.74	2.81	1964.60	30.18	3631.12	55.78	3861.68	59.33
Settlements	22.26	0.34	32.47	0.50	87.20	1.34	192.88	2.96
Water	12.22	0.19	13.72	0.21	89.19	1.37	89.85	1.38
Barren land	1244.54	19.12	80.90	1.24	245.14	3.77	153.71	2.36
Total	6509.27	100.00	6509.27	100.00	6509.27	100.00	6509.27	100.00

the water land class area also increased significantly from 12.22 km² (0.19%) in 1989 to 89.85 km² (1.38%) in 2021. In contrast, the barren land area of 1,244.54 km² (19.12%) in 1989 decreased sharply to 153.71 km² (2.36%) in 2021 (Table 4).

Land use/land cover changes of Dak Nong province from 1989 to 2021

Figure 3 shows the changes in land cover classes during the period 1989–2021. The corresponding area statistics on land cover change in the Dak Nong province are shown in Table 5. During the studied period, agricultural land showed the largest increase (1,781.86 km²), while barren land exhibited the greatest decrease (1,163.64 km²). The forest land class also showed a similar negative trend, with a 9.68% decrease from 5,047.51 km² in 1989 to 4,417.58 km² in 2001. Over the subsequent two decades, the area covered by forest continued to decrease. The largest decrease in forest area of 1,960.96 km² (30.13%) occurred during the period 2001–2011; in the period 2011–2021, this class further decreased but only by 245.47 km² (3.77%). Thus, in the two decades from 2001 to 2021, the agricultural area increased by 1,897.08 km² (29.14%). The residential area class expanded by 170.62 km² (2.62%) in the period 1989–2021, from 22.26 km² (0.34%) in 1989 to

Table 5. Land use/land cover changes assessment of Dak Nong province

Class	Change from 1989 to 2001		Change from 2001 to 2011		Change from 2011 to 2021		Change from 1989 to 2021	
	Area (km²)	%	Area (km²)	%	Area (km²)	%	Area (km²)	%
Forest	-629.93	-9.68	-1960.96	-30.13	-245.47	-3.77	-2836.36	-43.57
Agriculture	1781.86	27.37	1666.52	25.60	230.56	3.54	3678.94	56.52
Settlements	10.21	0.16	54.73	0.84	105.68	1.62	170.62	2.62
Water	1.50	0.02	75.47	1.16	0.66	0.01	77.63	1.19
Barren land	-1163.64	-17.88	164.24	2.52	-91.43	-1.40	-1090.83	-16.76

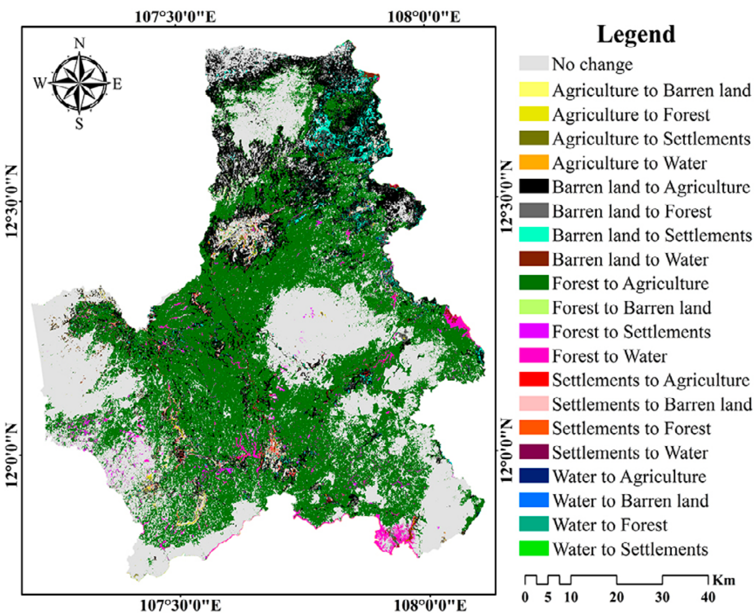

Figure 3. Land use/land cover change map of Dak Nong province from 1989 to 2021

192.88 km² (2.96%) in 2021. The area of barren land increased in the period from 2001 to 2011 by a total of 164.24 km² (2.52%). However, in the following decade (2011–2021), many of these barren land areas were covered by other classes, and the barren land area decreased to 91.43 km² (1.40%). Figures 3 and 4 and Table 5 also highlight that the water area has increased continuously over the past 30 years. However, in the two periods 1989–2001 and 2011–2021, the water class showed the smallest increases of any class, with values of only 1.50 km² (0.02%) and 0.66 km² (0.01%), respectively. From 2001 to 2011, the water class underwent its largest increase in area during the studied period, growing by 75.47 km² (1.16%) (Table 5).

Table 6. Cross-tabulation of land cover classes between 1989 and 2021 (area in km²)

1989 \ 2021	Forest	Agriculture	Settlements	Water	Barren land	Total
Forest	2094.03	2804.50	86.62	55.09	7.27	5047.51
Agriculture	20.51	137.22	18.23	6.10	0.68	182.74
Settlements	1.78	17.26	2.94	0.24	0.04	22.26
Water	1.05	1.26	2.77	7.13	0.01	12.22
Barren land	93.78	901.44	82.32	21.29	145.71	1244.54
Total	2211.15	3861.68	192.88	89.85	153.71	

To perform a detailed assessment of LULC changes, two classified maps were superimposed to create a LULC volatility map for the period 1989–2021 (Figure 3); in addition, a diagonal matrix was also created to illustrate the conversion of LULC classes (Table 6). Of the 5,047.51 km² of forest cover in 1989, a total of 2,094.03 km² was still forested in 2021, however, 2,804.50 km² had been converted to agricultural land and the remainder to settlements, barren land, and water. During this period, the areas of forest class gain from 1989 to 2021 were mainly from the barren land class (93.78 km²). Of the total area of 1,244.54 km² of barren land in 1989, in addition to the losses to the forest class mentioned above, most of the area has been lost to the agricultural land class (901.44 km²), with a total of 145.71 km² retained in 2021. The settlement land class area increased from 22.26 km² in 1989 to 192.88 km² in 2021. This class has retained only 2.94 km² of its original area and has mainly been replaced by agriculture. The main classes replacing settlement areas in 2021 were the forest class (86.62 km²) and the barren land class (82.32 km²) (Table 6). The agricultural class area retained 137.22 km² of its total 182.74 km² from 1989 and had mainly been replaced by forest and settlements by 2021. The water area also increased from 12.22 km² (1989) to 89.85 km² (2021), with 7.13 km² of its original area from 1989 retained (Table 6).

Relationship between vegetation indices and decadal forest cover changes

Maps showing the NDVI and SAVI values in Dak Nong province from 1989 to 2021 are shown in Figures 4 and 5. In this process, we evaluated all NDVI and SAVI pixel values from our graded image in 2021 and classified NDVI values greater than 0.35 and SAVI values greater than 0.58 in a dark green color, which corresponds to the forest polygon areas. Considering these NDVI and SAVI thresholds, we reclassified the classified images for 1989, 2001, and 2011 into forest and non-forest areas.

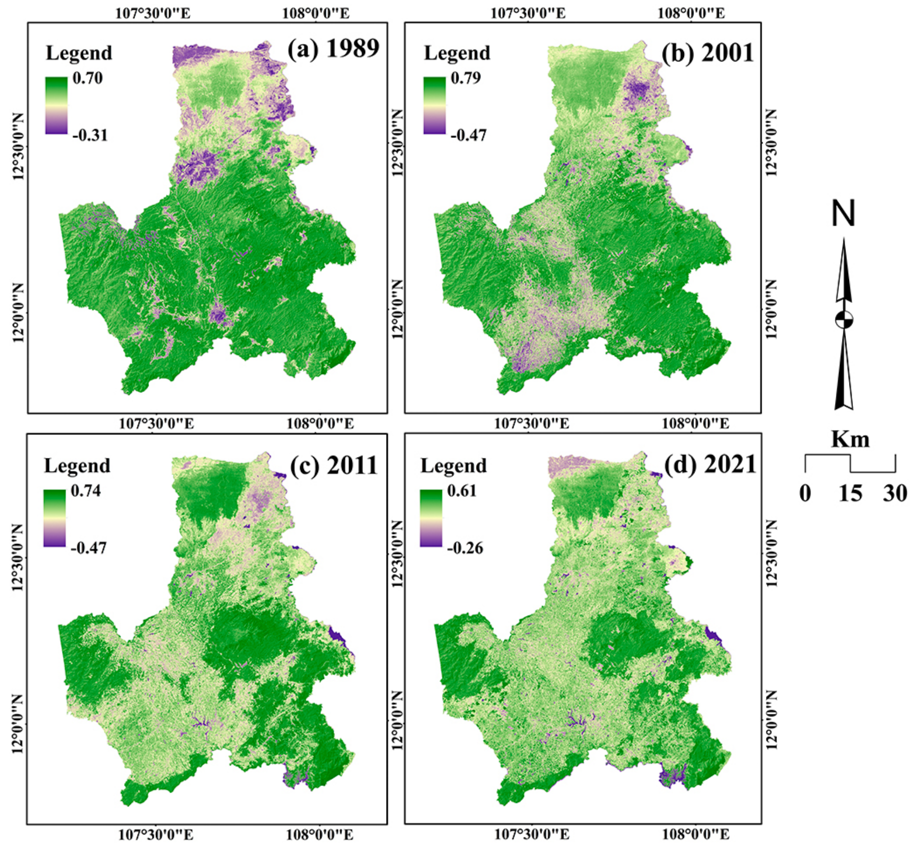

Figure 4. Spatial distribution of NDVI for 1989, 2001, 2011, and 2021

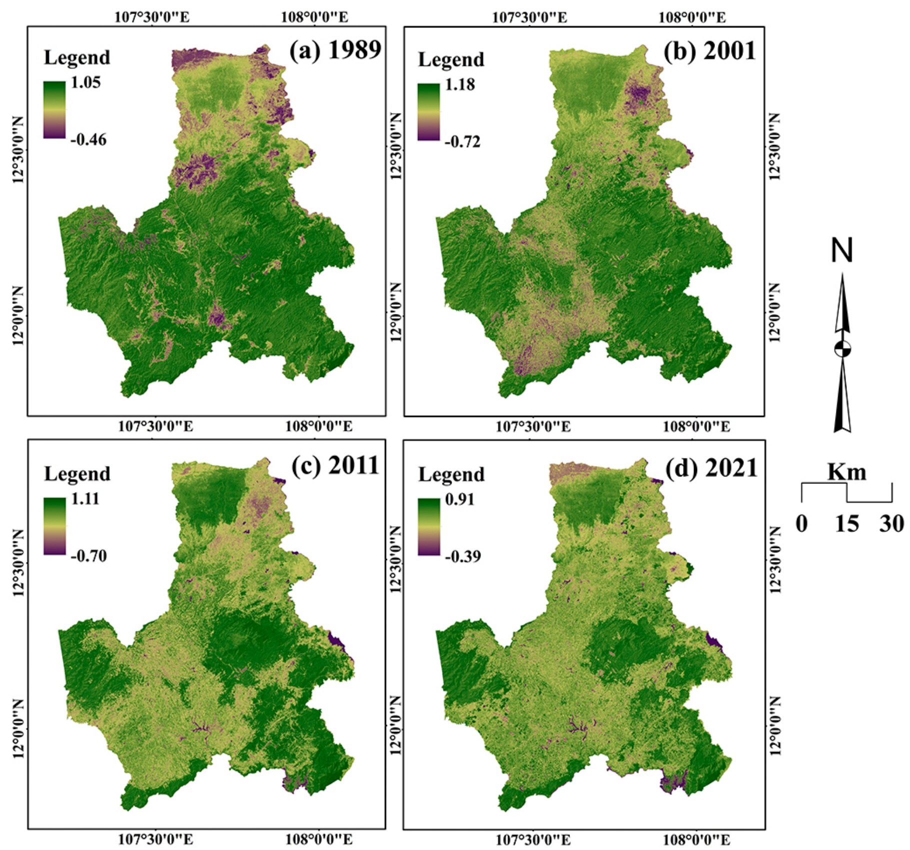

Figure 5. Spatial distribution of SAVI for 1989, 2001, 2011, and 2021

The areas covered by forests from 1989 to 2021 based on these vegetation indices are presented in Table 7. The trend of year-over-year change in the study period was also shown in Figure 6. Analysis results reclassification of forest class based on NDVI index through each year 1989, 2001, 2011 and 2021 are 5452.61 km², 4936.29 km², 3843.98 km² and 2724.91 km² respectively, equivalent to 83.77%, 75.83%, 59.05% and 41.86% (Table 7). In addition, based on the SAVI index the forest class classification results are quite similar to the NDVI index with 5340.68 km² (82.05%) in 1989, 4935.01 km² (75.82%) in 2001, 3540.91 km² (54.40%) in 2011 and 2657.19 km² (40.82%) in 2021 (Table 7).

Table 7. Based forest cover area analyzed by vegetation indices (NDVI and SAVI) from 1989 to 2021

Category		Distribution in 1989		Distribution in 2001		Distribution in 2011		Distribution in 2021	
		Area (km²)	(%)	Area (km²)	(%)	Area (km²)	(%)	Area (km²)	(%)
NDVI	Forest	5452.61	83.77	4936.29	75.83	3843.98	59.05	2724.91	41.86
	Other	1056.66	16.23	1572.98	24.17	2665.29	40.95	3784.36	58.14
	Total	6509.27	100.00	6509.27	100.00	6509.27	100.00	6509.27	100.00
SAVI	Forest	5340.68	82.05	4935.01	75.82	3540.91	54.40	2657.19	40.82
	Other	1168.59	17.95	1574.26	24.18	2968.36	45.60	3852.08	59.18
	Total	6509.27	100.00	6509.27	100.00	6509.27	100.00	6509.27	100.00

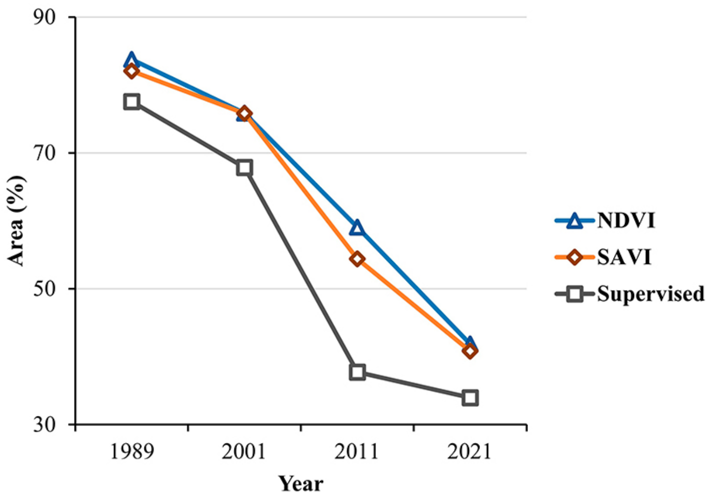

Figure 6. Comparison of forest cover from 1989 to 2021 through NDVI, SAVI, and supervised classification

Discussion

The study adopted contemporary, time and cost-efficient methods to investigate the dynamics to the LULC and forest cover change during the research period from 1989 to 2021 in Dak Nong province, Vietnam. The use of MLC to categorize the Landsat images (TM and OLI/TIRS) has produced maps showing the distribution of the five prevalent LULC classes in the study area for the years 1989, 2001, 2011, and 2021 (Figure 2) and the results of each classes area were also shown in Table 4. Classification results show that in 1989 and 2001 the forest class accounted for the largest area of coverage, but by 2011 and 2021 the forest class area was reduced, instead the area of agricultural land increased to become the cover with the highest area. In addition, evaluating the accuracy and determining the plausibility of the resulting map is an important step after the classification of the soil cover by evaluating the error for each class and in general for the whole classified image. The kappa coefficient values represent a measure of the consistency or precision between the reference data and the classified LULC classes and can take values from -1.00 to +1.00. Kappa coefficients between 0.60 and 0.80 indicate high simulation consistency, while values of 0.80-1.00 indicate near-perfect character (Congalton & Green, 2019, Thien et al., 2022a). In this study, the kappa coefficient values all exceed 0.80 (Table 3), indicating excellent agreement between the classified results and reference data (Manonmani & Suganya, 2010; Lea & Curtis, 2010).

Spatial analysis of the multi-time LULC maps of Dak Nong province shows significant changes in the 32 years from 1989 to 2021. LULC changes have both positive and negative effects and are a continuous process caused by many natural and human factors. Changes in LULC, especially in developing countries, have led to reductions in other important natural resources, including vegetation, soil and water. Therefore, the study of LULC alteration requires a comprehensive understanding and monitoring of all the factors that cause it. In this study, to get an overview of changes in forest class and identify the causes of their change during the 32 years of the study (1989-2021), we compared the forest class group based on the statistics in Tables 5 and 6 and the spatial change in the distribution of the LULC class as in Figure 3.

Forests play an essential role in human life and the environment, providing not only resources such as wood and firewood but also an important part in regulating the climate and protecting the land from natural disasters (Fedler, 2018; Watson et al., 2018). According to the results shown in Table 5, the forest layer area during the study period from 1989 to 2021 has been seriously reduced, while the area of agricultural layers and settlements has continuously increased. Additionally, Figure 3 and Table 6 clearly show that the lost forest area has been largely converted into agricultural land and settlements. This shows that there are many reasons for forest cover degradation in Dak Nong province but most of them are related to human activities such as indiscriminate logging, deforestation, forest fires and conversion to agricultural land (Santos de Lima et al., 2018; Duguma et al., 2019). The population has increased rapidly both naturally and through spontaneous immigration since the reforms took effect in 1990. From 1999 to 2009, Dak Nong province had the highest population growth rate in the country because it has a sub-tropical monsoon climate, so the landscape is highly diverse, with favorable conditions for growing crops such as coffee, pepper, cocoa and strawberries (Central Population and Housing Census Steering Committee, 2010). The expansion of agricultural area has caused the province's natural forest area to decrease sharply, they have destroyed natural forests for agriculture, of which the largest cause of deforestation is to plant industrial trees as mentioned above (Rambo et al., 1995; Nguyen et al., 2020b). Most of the farmland has been converted into farmland and settlements are increasingly causing damage to the natural forests of immigrants. In addition, prioritizing socio-economic development also greatly affects the loss of natural forest area. A large part of the natural forest area of Dak Nong province has been cut down to build hydropower, transport and switch to rubber plantations (MARD, 2019). In addition, there are indirect causes of deforestation and forest degradation such as high agricultural prices and inefficient forest management methods (Dan et al., 2018).

Remotely sensed vegetation indices are a simple and effective method for quantifying and assessing plant cover, vigour, and growth dynamics (Pesaresi et al., 2020; Pasternak & Pawluszek-Filipiak, 2022). The NDVI and SAVI values of the area ranged from -0.47 to 0.79 (Figure 4) and -0.72 to 1.18 (Figure 5) across the years of evaluation, with the higher values indicating forest, low positive values characterizing sparse vegetation and negative values representing water (Huete, 2012; Islam et al., 2021; Pasternak & Pawluszek-Filipiak, 2022). The increased values of the NDVI (0.79 > 0.70) and SAVI (1.18 > 1.05) in 2001 compared to 1989 have partly confirmed earlier evidence of reduced deforestation and increased forest conversion at the end of that period (Table 5). However, further comparative validation of reports of this indicator is necessary to determine deviations in their forest cover assessment, as provided in Figure 6 and Table 7. A comparative review of forest area estimates from both indicators versus supervised classification results showed relatively similar trends but with a relative overestimate in 2011 for both NDVI and SAVI. These estimated deviations may be due to the sensitivity of plant indicators to the effects of soil reflections, soil surface, atmosphere, and cloud shadows, which require calibration of remote sensing (Huete, 1988; Pasternak & Pawluszek-Filipiak, 2022). From these results, we can conclude that NDVI and SAVI are both good indicators that can effectively detect and monitor forest cover in Dak Nong province, especially for quick assessments of forest cover.

Conclusion

In this study, geospatial techniques were used to analyze spatial and temporal forest cover changes in Dak Nong province using Landsat 5 and 8 remote sensing images. The results of this work indicate a significant decrease in forest cover over the studied 32 years. In 1989, forest cover was 77.54%; this value decreased to 67.87% in 2001 and further decreased to 37.74% in 2011, with a final value of only 33.97% in 2021. In contrast, the agricultural land area percentage increased rapidly from 2.81% in 1989 to 30.18%, 55.78%, and 59.33% in the years 2001, 2011, and 2021. This study also illustrates that the NDVI and SAVI indices show notable changes in the characteristics of forest cover from 1989 to 2021. Based on our research results, we encourage policymakers and decision-makers to take more effective measures for conservation and sustainable development in Dak Nong province. In particular, we recommend that the forestry agency needs additional staff to better monitor and protect forests from illegal logging and prevent future forest loss. In addition, the results of this study provide a useful reference for future researchers investigating LULC changes in this area and those examining severe deforestation in future policymaking to ensure forest protection and development.

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Conflict of interest

The authors declare no conflict of interest.

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