Assessment of forest cover and forest loss using satellite images in Thua Thien Hue province, Vietnam

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ABSTRACT

Deforestation in the tropics continues inexorably with severe implications for biodiversity conservation, climate regulation and ecosystem services. This study investigated variation in forest cover in Thua Thien Hue province, Vietnam, using the Landsat Thematic Mapper and Operational Land Imager satellite images over the period 1989–2021. Imageries were classified using the maximum likelihood classification technique for the years 1989, 2006, and 2021 and were evaluated for accuracy using the kappa coefficient for each year. Furthermore, forest cover losses and gains were evaluated using the Normalized Difference Vegetation Index and Soil Adjusted Vegetation Index, which were compared with the output of the supervised classification. Results showed that the forest cover of Thua Thien Hue province has drastically declined over the years. The forest cover, which was estimated at 68.88% (3461.46 km^2) of the total land area in 1989, increased to 69.04% (3469.51 km^2) in 2006 and subsequently decreased to 57.55% (2891.81 km^2) in 2021. Severely reduced forest cover is often associated with the expansion of agriculture on the forest edge; other contributing factors include logging, illegal production land, and forest fires. Overall, our results show the necessity of forest management, rational land-use planning policy, and increased community awareness of conservation and sustainable development of forest resources in the study area in the future.

KEYWORDS

forest cover; vegetation index; remote sensing; GIS; Thua Thien Hue province

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1. Introduction

Particularly significant natural resources on the planet are forests. In order to effectively shield the riverbank and inland areas from natural disasters, it does create a sort of natural barrier (hurricanes, cyclones, and tsunamis) (Alongi 2008). It makes a substantial contribution to broad ecological protections such as soil preservation, improved biodiversity, and climate change mitigation. By providing supplies of medicine and materials for manufacturing and building, it effectively aids in the expansion of the wider national economy. The world's forest cover has seen substantial and unprecedented changes in recent decades as a result of a number of human factors, including increasing urbanisation, industrialization, agricultural expansion, logging, and mining (Atmiş et al. 2007; Agarwal et al. 2010; Hor et al. 2014; Ahammad et al. 2019). Logging operations, it was previously believed, had become the primary factor in the loss of forest cover in emerging countries with tropical climates. In these regions, logging, unemployment, migration rates, population pressure, infrastructure development, and agriculture are some of the main forces that alter forest cover (Ranjan 2019).

Vietnam, one of the nations with the almost largest sections of unquestionably main forests and annually changing plantations, is well known for its highly diverse and unique tropical forest ecology (Mermoz et al. 2021). Since 1990, Vietnam's forests have undergone the transition from net deforestation to reforestation (Meyfroidt and Lambin 2008). Although forest cover in Vietnam has increased, deforestation and forest degradation particularly continue (JICA, VNFOREST 2012). In an effort to prevent deforestation and forest degradation, Vietnam participates in the Reduction of Emissions from Deforestation and Forest Degradation (REDD+) (Pham et al. 2012). The total area of natural forests and planted forests with reserves in the entire Thua Thien Hue province is 2884.02 km^2, and the forest coverage rate is 57.38%, according to the results of the announcement of the forest status in Thua Thien Hue province in 2020 (People's Committee of Thua Thien Hue Province 2021). The management, preservation, prevention, and suppression of forest fires in Thua Thien Hue province are complicated by a sizable forest area that is dispersed throughout 9 districts and towns and stretches from the Truong Son mountain range to the East Sea. The complicated problem of illegal deforestation for agricultural land, timber, and other products, as well as the ongoing problem of forest fires brought on by the dry season's heat, the burning of votive paper, the burning of vegetation for ritual purposes, and other factors, have all contributed to the province's loss of forests.

The application of science and technology in detecting forest loss is essential to contribute to saving time and effort for the patrol and supervision of forest resources as well as improving the efficiency of management, conservation, forest protection, forest fire prevention and fighting. In Thua Thien Hue province, there is very little research related to the use of remote sensing and geographic information systems (GIS) to analyse the change in forest cover over the years (Dien 2004; Yen et al. 2005). However, these studies are conducted only in a small area and have not fully applied the vegetation index to analyse the change in forest cover more deeply.

Globally, there has been significant development in the use of remote sensing and GIS to track changes in forest areas and other types of land cover. Evidence is derived from remote sensor data using a variety of image analysis and change detection techniques (Lu et al. 2011; Chowdhury et al. 2020; Thien et al. 2022). Various sensors are available as a data source to study land use/land cover (LULC) variability. Among them, Landsat images provide an acceptable mean accuracy for analysis in the LULC study, which is generally accepted in the scientific community (Bakr et al. 2010). Therefore, remote sensing and GIS can help stakeholders identify the main areas where changes are occurring and obtain understanding of how various human behaviours and climate changes impact growth patterns. Consider your current actions and policies, foresee the future, and make the required preparations in light of the possibility that natural weather patterns and seasonal landscapes will trend through time (Mubako et al. 2018). Analysis of the Normalized Difference Vegetation Index (NDVI) and the Soil Adjusted Vegetation Index (SAVI) is used to map forest basically cover and for the most part is also useful for monitoring plant health (Huete 1988; Matsushita et al. 2007; Spadoni et al. 2020).

The study specifically focuses on Thua Thien Hue province in Vietnam. While there may have been previous studies on forest cover change at regional or national scales, this study narrows down the scope to a specific province (Jadin et al. 2013; Tran et al. 2022). By doing so, it provides detailed insights into the dynamics of forest cover change in this particular area, which may differ from broader-scale patterns observed in previous studies. In this study, our particularly goal was to generally integrate open-access remote sensing data and GIS to examine the spatial trends of forest and other land-cover changes in Thua Thien Hue province, Vietnam, over 32 years (1989–2021). By utilizing advanced remote sensing techniques, the study can provide new insights and potentially more accurate assessments of forest cover change in the study area. During the period from 1989 to 2021, many important changes in forest policy and management occurred in Vietnam and Thua Thien Hue province (Pham et al. 2021). In addition, this period has also witnessed significant environmental changes and human impacts on the forest cover in the study area. Factors such as agricultural expansion, urban development, logging, and climate change may have influenced the appearance of forest cover. Research during this period will help to better understand the forest management measures already in place, such as forest protection policies, sustainable forest development and land use planning. This study provides basic information to support land-use planning to basically avoid degradation and deforestation in the study area in a big way. The main objectives of this study mostly are defined as follows: (1) detecting forest cover in a typical Vietnamese area of Thua Thien Hue 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.

2. Materials and Methods

2.1 Study area

Thua Thien Hue province is located in the coastal strip of central Vietnam, geographical position of the study area lies in the coordinates of latitude 15°59′30″N–16°44′30″N and longitude 107°00′56″E–108°12′57″E, covering an area of 5025.30 km^2 (Fig. 1) (Thua Thien Hue General Statistical Office 2019). The study area is 675 km south of Hanoi capital, 94 km north of Da Nang city with the natural boundary of Bach Ma mountain range. The province of Thua Thien Hue features a variety of geography, including plains, mountains, hills, and coastal regions. One-fourth of the province's land area, or 250 to 1800 m, is made up of mountainous terrain, which is distributed in the west of the region. Half of the area is covered by hills with a height of 10 to 250 m. With a total size of around 1400 km^2, the plain was an abrasive, agglomerated, sandy, and lagoon plain (People's Committee of Thua Thien Hue Province 2005). The study area is located in tropical monsoon climate, so the weather occurs in a four-season cycle. The average temperature of the whole year is 25 °C, the number of sunny hours a year is 2000 hours. In terms of economic scale, the gross domestic product per person in 2018 was $1793. Agriculture, forestry, and fishery made up 11.60% of the economy, followed by the service sector at 31.20%, the service sector at 50.20%, and product taxes minus product subsidies at 7.00% (Thua Thien Hue General Statistical Office 2019).

2.2 Data used and sources

Satellite images were used to map LULC in Thua Thien Hue province from 1989 to 2021 and assess changes in forest cover. Landsat 5 TM images were used for the years 1989 and 2006 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 Tab. 1.

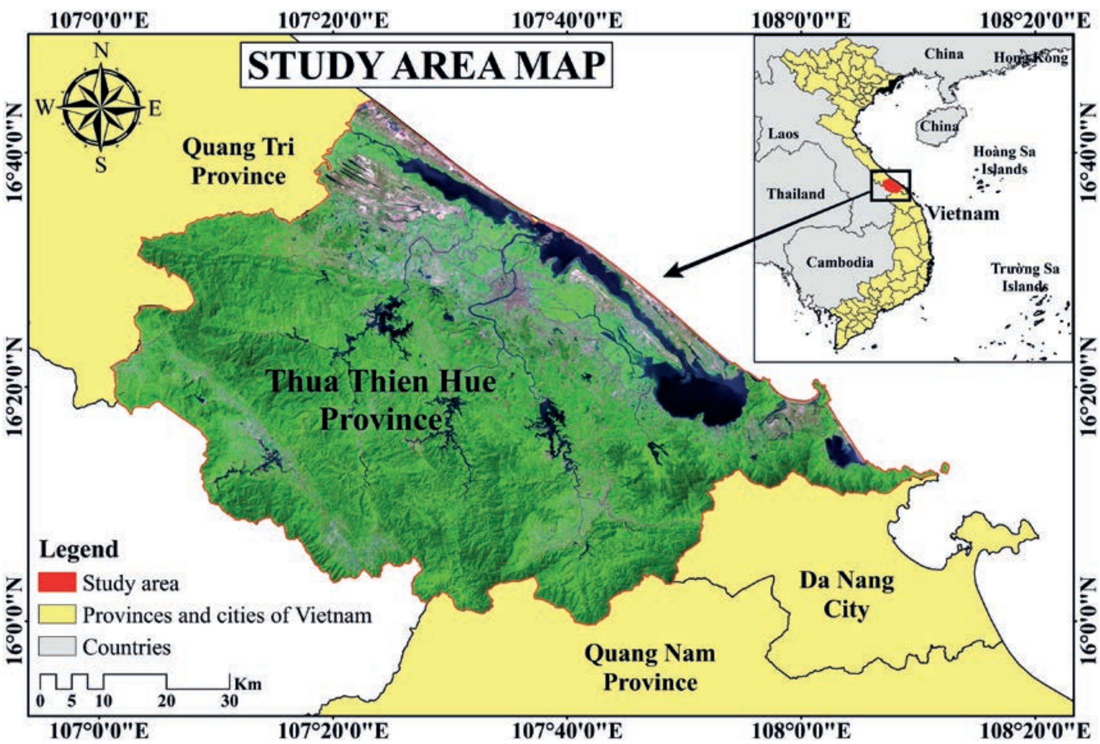

Fig. 1 Map showing the study area in Thua Thien Hue province.

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

Landsat Scene ID	Acquisition data	Satellite	Path/row	Resolution (m)	Source
LT51240491989009BKT00	09/01/1989	Landsat 5 TM	124/049	30	USGS Glovis
LT51250481989048BKT01	17/02/1989	Landsat 5 TM	125/048	30	USGS Glovis
LT51250491989048BKT01	17/02/1989	Landsat 5 TM	125/049	30	USGS Glovis
LT51250482006095BKT00	05/04/2006	Landsat 5 TM	125/048	30	USGS Glovis
LT51250492006095BKT00	05/04/2006	Landsat 5 TM	125/049	30	USGS Glovis
LC81250492021056LGN00	25/02/2021	Landsat 8 OLI	125/049	30	USGS EarthExplorer

2.3 Image pre-processing and classification

Based on Google Earth Pro satellite image data, modified Anderson LULC scheme level I (Anderson et al. 1976), Vietnam's regulation on LU, the existing condition of the study area, specific pixel values of different landscape elements and reference to related documents, five LULC classes were mapped using Landsat satellite image classification as agricultural land, barren land, forest, settlement, and water (Tab. 2).

In order to meet the main objective of this study which was to investigate the variation of the forest cover, detailed LULC classes of Thua Thien Hue province, Vietnam were considered from 1989 to 2021; this enabled comparison between the change in forest cover and other classes. Fig. 2 illustrates the primary steps taken during the LULC changes analysis and detection of forest cover change.

Image processing tasks were performed using ArcGIS 10.8 software. Atmospheric correction (dark-object subtraction (DOS) correction) was applied to remove the dust and haze effect from each image. The band set was defined (combination RGB colour (Red, Green, Blue) corresponds to bands 5, 4, 3 for Landsat 5 TM and bands 6, 5, 4 for Landsat 8 OLI), and the training input file was created. The choice of these specific bands for the RGB colour representation is based on their spectral characteristics and their ability to capture different aspects of the landscape, including vegetation health and density. The combination of these bands allows for visual interpretation and analysis of forest cover and forest loss within the study area (Dimyati et al. 2018; Osio et al. 2018). Training samples were selected for each predefined LULC class (Tab. 2) by delineating polygons around representative locations. We used the pixels enclosed by these polygons to generate the spectral signatures for the respective land coverings recorded by satellite images over time. We employed the spectral signature in the classification process using the maximum likelihood method when it was deemed to be satisfactory. To classify the research area's land cover and assess land use, supervised classification was used (Manandhar et al. 2009, Forget et al. 2018). This is a type of image classification approach that is mainly controlled by the analyst, who selects pixels that represent the desired classes (Butt et al. 2015; Shivakumar and Rajashekararadhya 2018). To improve classification accuracy and reduction of misclassifications, post-classification refinement was therefore used for simplicity and effectiveness of the method (Harris and Ventura 1995). The selected LULC categorization features unambiguous class borders based on changes in natural and anthropogenic elements within the examined area, consistency in the description of each category, and consistency across categories. This classification strategy is also scale-independent, making it practicable to use it at any level of spatial detail or size. The LULC differences between the categorised photos were found utilising a post-classification comparison method that used change detection comparison (pixel by pixel) to measure the change in forest cover.

Tab. 2 Identified classes by supervised classification.

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

2.4 Analysis of vegetation indices to detect changes in forest cover

Several vegetation indices have been developed to assess forest vegetation and are used in forest cover detection and analysis (Huete 1988; Matsushita et al. 2007; Huete 2012; Liang et al. 2018; Spadoni et al. 2020; Pesaresi et al. 2020). In this study, the Normalized Difference Vegetation Index (NDVI) and the Soil Adjusted Vegetation Index (SAVI) were used to detect forest cover in Thua Thien Hue province. NDVI is widely used to analyse vegetation health and has been shown to be a relevant indicator of plant greenness. SAVI is often used in arid and semi-arid regions to help reduce the influence of soil reflectance. In this case, we extracted the NDVI and SAVI values from

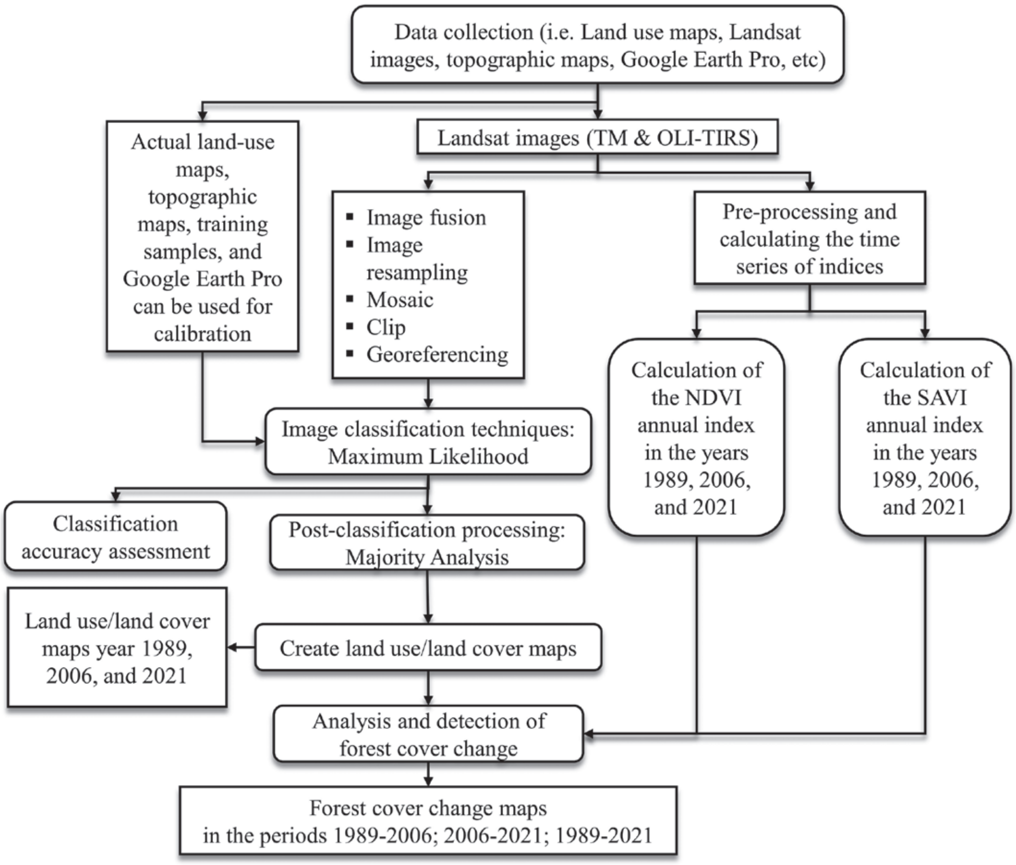

Fig. 2 Overall process of land use/land cover change technique.

all the forest polygons that we detected through the supervised classification of the Landsat 8 OLI images, then used the maximum and minimum values of NDVI and SAVI to reclassify the classification table to map the area of forest land cover for all other periods. NDVI and SAVI were calculated using equations (1) and (2), respectively, given below:

$$\text{NDVI} = \frac{NIR - RED}{NIR + RED} \tag{1}$$

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.

$$\text{SAVI} = \left(\frac{NIR - RED}{NIR + RED + 1}\right) \times (1 + \text{L}) \tag{2}$$

where L is 0.5, the default value.

2.5 Classification accuracy assessment

We assessed the accuracy of the thematic maps produced to determine the quality of the information derived from the data and to reflect the actual discrepancy between our classification and the map or reference data (Owojori et al. 2005, March; Disperati et al. 2015; Tsutsumida et al. 2015). The accuracy of the classified images for the years 1989, 2006, and 2021 was assessed using error matrices, overall accuracy, producer accuracy, user accuracy, and kappa coefficients. With the help of a stratified random technique, we chose 150 random points from each image that was classed, and we digitally compared them with the corresponding pixels of the original images in Google Earth Pro as reference data. These spots, which represent all of the LULC categories in the research area, were found and located using Google Earth Pro maps, ground truth information, and topographic maps. By creating an error categorization matrix for each LULC map, the overall accuracy was evaluated. The equations for the kappa coefficient, overall accuracy, user accuracy, and producer accuracy shown in equations (3), (4), (5), and (6), respectively are among the best quantitative measurements for classifying satellite images (Chowdhury et al. 2020; Hasan et al. 2020; Thakur et al. 2021):

$$\text{Kappa} = \frac{\Sigma_{i=1}^{k} n_{ii} - \Sigma_{i=1}^{k} n_{ii}\,(G_i C_i)}{\text{n}^2 - \Sigma_{i=1}^{k} n_{ii}\,(G_i C_i)} \tag{3}$$

where, i is the class number, n is the total number of classified pixels that are being compared to actual data, n_{ii} is the number of pixels belonging to the actual data class i, that were classified with a 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. Number of correctly classified pixels in each category / Total number of reference pixels in each category (row total)

$$\text{Overall Accuracy} = \frac{\text{Number of correctly classified pixels (diagonal)}}{\text{Total number of reference pixels}} \times 100 \quad (4)$$

$$\text{User's Accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of reference pixels in each category (row total)}} \times 100 \quad (5)$$

$$\text{Producer's Accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of reference pixels in each category (column total)}} \times 100 \quad (6)$$

3. Results

3.1 Land use/land cover classification and accuracy

The LULC classification map of Thua Thien Hue province for the years 1989, 2006, and 2021 are presented in Fig. 3. In 1989, the majority of the study area was covered by forest, accounting for over 68% of the total area. Forest covered an area of 3461.46 km^2, followed by agriculture at 14.34% (720.75 km^2), barren land at 11.17% (561.22 km^2), water at 5.03% (252.77 km^2), and finally, settlement occupying only 0.58% (29.10 km^2) of the total study area (Tab. 3). By 2006, the forest area decreased to 3469.51 km^2, representing 69.04% of the total study area, and further declined to 2891.81 km^2 (57.55%) by 2021. The agricultural class increased to 980.33 km^2 (19.51%) in 2006 and continued to expand to 1296.62 km^2 (25.80%) in 2021 (Tab. 3). The area occupied by settlement and water also steadily increased to 182.46 km^2 (3.63%) and 260.09 km^2 (5.18%), respectively, in 2006. By 2021, these two classes had further expanded to 465.15 km^2 (9.26%) and 295.74 km^2 (5.89%), respectively. However, the barren land class continuously decreased to 132.91 km^2 (2.64%) in 2006 and 75.98 km^2 (1.51%) in 2021 (Tab. 3).

The accuracy rating reflects the actual difference between our classifier and the reference data. The overall accuracy scores for the three years 1989, 2006, and 2021 were 92.00%, 91.33%, and 92.72%, respectively, with kappa coefficients of 0.888, 0.885, and 0.903 (Tab. 4). Kappa values greater than 0.8

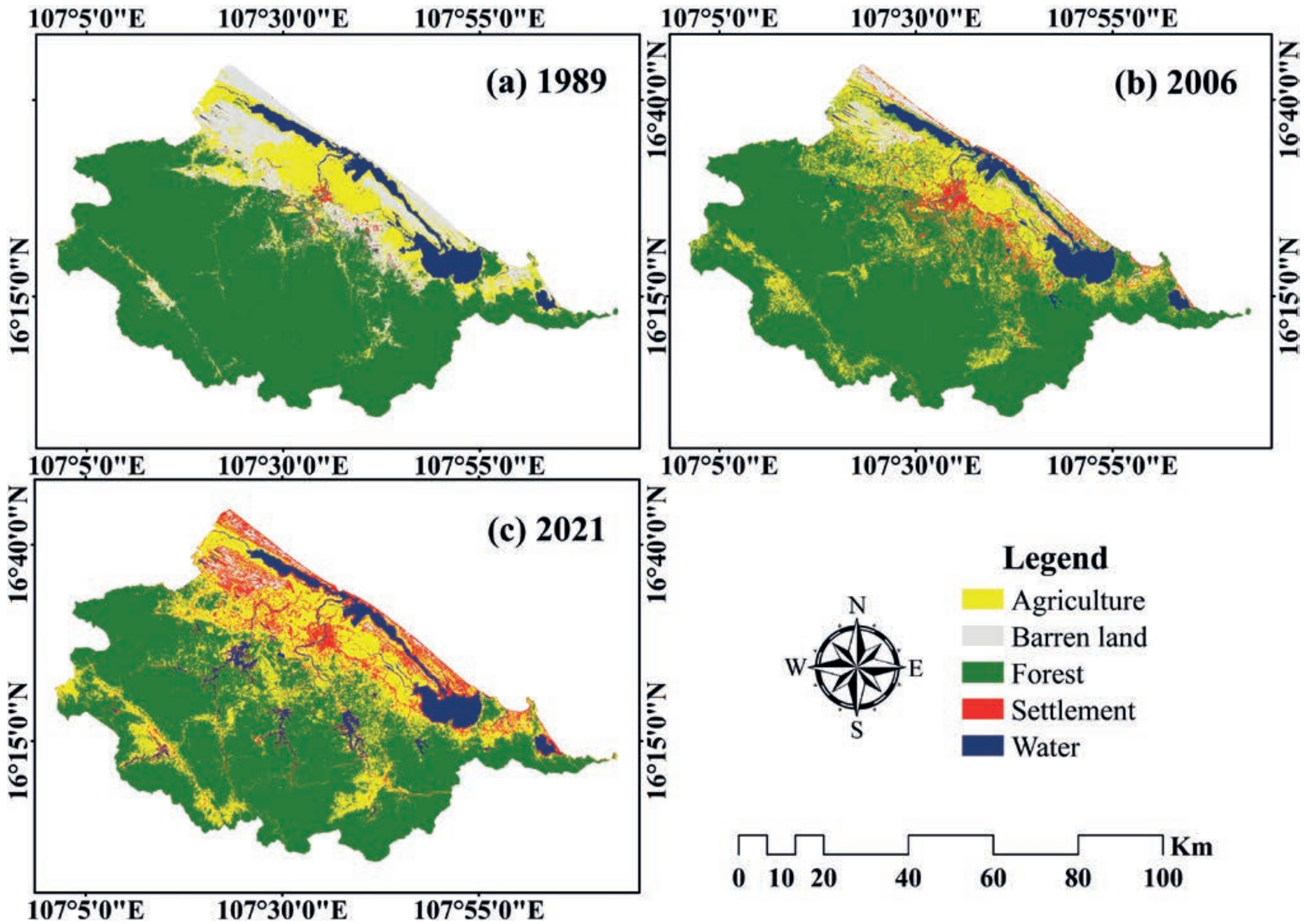

Fig. 3 Land use/land cover of Thua Thien Hue province in (a) 1989, (b) 2006, and (c) 2021.

Tab. 3 Results of land use/land cover classification in Thua Thien Hue province from 1989 to 2021.

Class	Land cover in 1989		Land cover in 2006		Land cover in 2021	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Agriculture	720.75	14.34	980.33	19.51	1296.62	25.80
Barren land	561.22	11.17	132.91	2.64	75.98	1.51
Forest	3461.46	68.88	3469.51	69.04	2891.81	57.55
Settlement	29.10	0.58	182.46	3.63	465.15	9.26
Water	252.77	5.03	260.09	5.18	295.74	5.89
Total	**5025.30**	**100.00**	**5025.30**	**100.00**	**5025.30**	**100.00**

Tab. 4 Accuracy assessments for 1989, 2006 and 2021.

Land cover class	1989		2006		2021	
	Producers accuracy (%)	Users accuracy (%)	Producers accuracy (%)	Users accuracy (%)	Producers accuracy (%)	Users accuracy (%)
Agriculture	85.71	90.91	87.50	90.32	88.37	92.68
Barren land	88.24	88.24	82.61	90.48	87.50	87.50
Forest	96.97	95.52	94.83	94.83	94.23	96.08
Settlement	88.89	80.00	94.44	89.47	100.00	90.32
Water	91.30	91.30	94.74	85.71	90.00	90.00
Overall accuracy	92.00		91.33		92.72	
Kappa coefficient	0.888		0.885		0.903	

indicate strong agreement between our classification and the reference data (Lea et al. 2010). The user accuracy results show that, for the year 1989, the maximum accuracy was achieved for the forest class (95.52%) and the minimum for the settlement class (80.00%). For 2006, user accuracy ranged from a minimum of 85.71% (water class) to a relatively precise classification of 94.83% (forest class). For 2021, user accuracy was 96.08% for the forest classes and was lowest for the barren land class (87.50%). The results of the producer accuracy assessment show that classification was relatively accurate for the forest class in 1989 and 2006 (96.97% and 94.83%, respectively) (Tab. 4). In 2021, classes achieved 100% accuracy (settlement land class). The lowest accuracy ratings in 1989, 2006, and 2021 were for agriculture land class (85.71%), barren land class (82.61%), and barren land class (87.50%), respectively (Tab. 4).

3.2 Land use/land cover change from 1989 to 2021

The area statistics and model on land-cover changes in Thua Thien Hue province in each period (1989–2006, 2006–2021, and 1989–2021) are shown in Tab. 5 and Fig. 4. During the period 1989–2006, the area of barren land decreased the most with 8.52% (428.31 km^2), while agricultural land increased the most with 5.17% (259.58 km^2). In addition, the forest, settlement and water classes also increased by 0.16% (8.05 km^2), 3.05% (153.36 km^2) and 0.15% (7.32 km^2). By the period 2006–2021, the area of agricultural land and settlement classes has increased continuously by 6.29% (316.29 km^2) and 5.63% (282.69 km^2), respectively. The water class area during this period also increased by 0.71% (35.65 km^2). As for the area of barren land class has continued to decrease by 1.13% (56.93 km^2). The area of forest

Tab. 5 Change statistics of land use/land cover in Thua Thien Hue province from 1989 to 2021.

Class	Period					
	1989–2006		2006–2021		1989–2021	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Agriculture	259.58	5.17	316.29	6.29	575.87	11.46
Barren land	−428.31	8.52	−56.93	1.13	−485.24	9.66
Forest	8.05	0.16	−577.70	11.50	−569.65	11.34
Settlement	153.36	3.05	282.69	5.63	436.05	8.68
Water	7.32	0.15	35.65	0.71	42.97	0.86

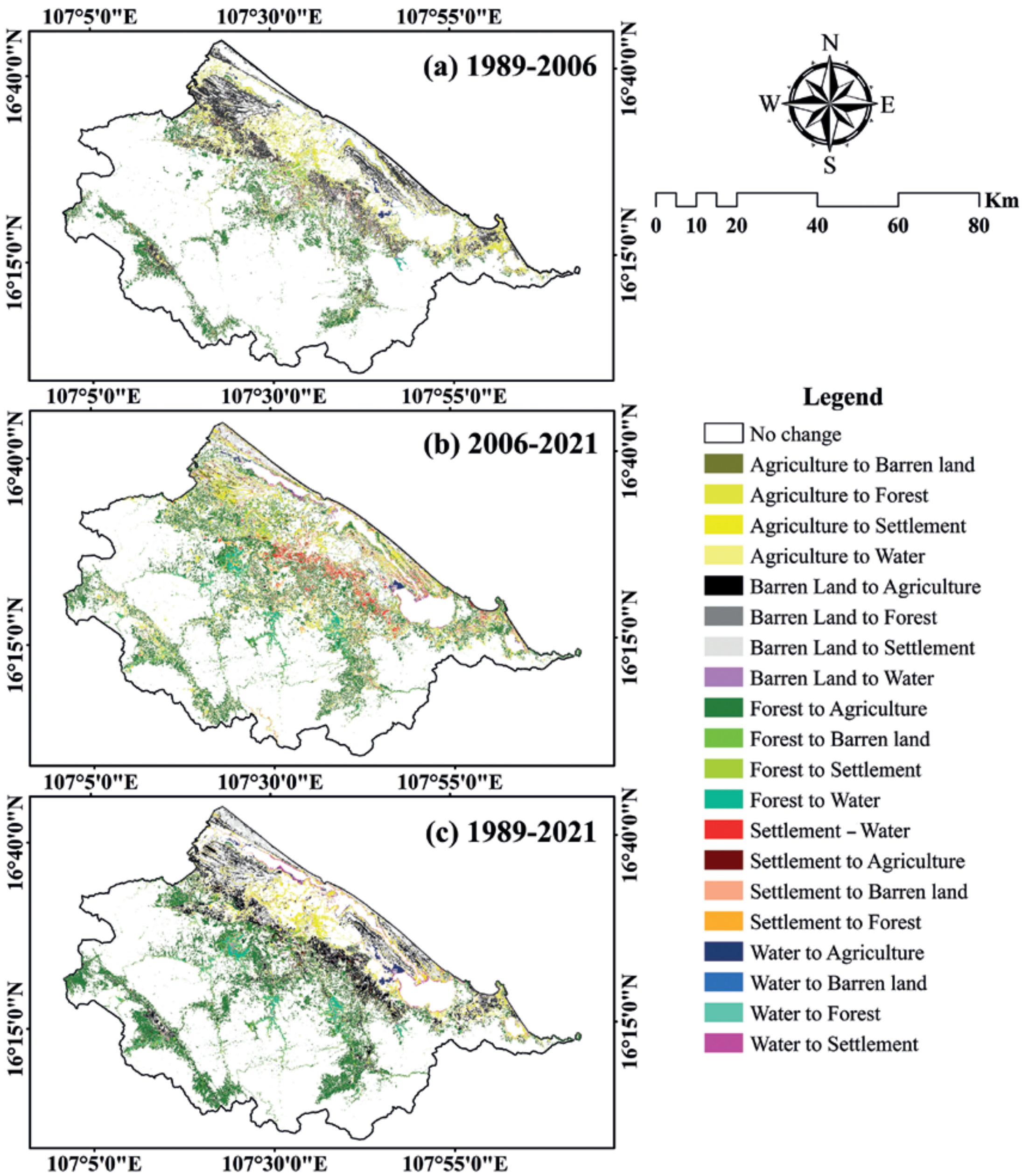

Fig. 4 Land use/land cover changes maps in Thua Thien Hue province (a) 1989–2006, (b) 2006–2021, and (c) 1989–2021.

class in the period 2006–2021 has tended to decrease sharply compared to the period 1989–2006, with the area reduced by 11.50% (577.70 km^2). Overall, over the past 32 years, agricultural land, settlement and water classes have increased continuously by 11.46% (575.87 km^2), 8.68% (436.05 km^2) and 0.86% (42.97 km^2), respectively. For the barren land class in this period (1989–2021) has decreased continuously by 9.66% (485.24 km^2). Particularly for the forest class, in the first period (1989–2006) there was increased but still very low compared to the area lost in the second period (2006–2021), so in general, the forest area in over 32 years has decreased by 11.34% (569.65 km^2).

3.3 Relationship between vegetation indices and decadal forest cover changes

Maps showing the NDVI and SAVI in Thua Thien Hue province from 1989 to 2021 are shown in Fig. 5 and Fig. 6, respectively. During this process, we looked at all NDVI and SAVI pixel values from our graded image in 2021 and observed that NDVI values greater than 0.26 and SAVI values greater than 0.41 all belong to the forest polygons. Considering these NDVI and SAVI values, we reclassified all other classified images for 1989, and 2006 as forest and non-forest. The area covered by forest from 1989 to 2021 according to the vegetation indices is presented in Tab. 6.

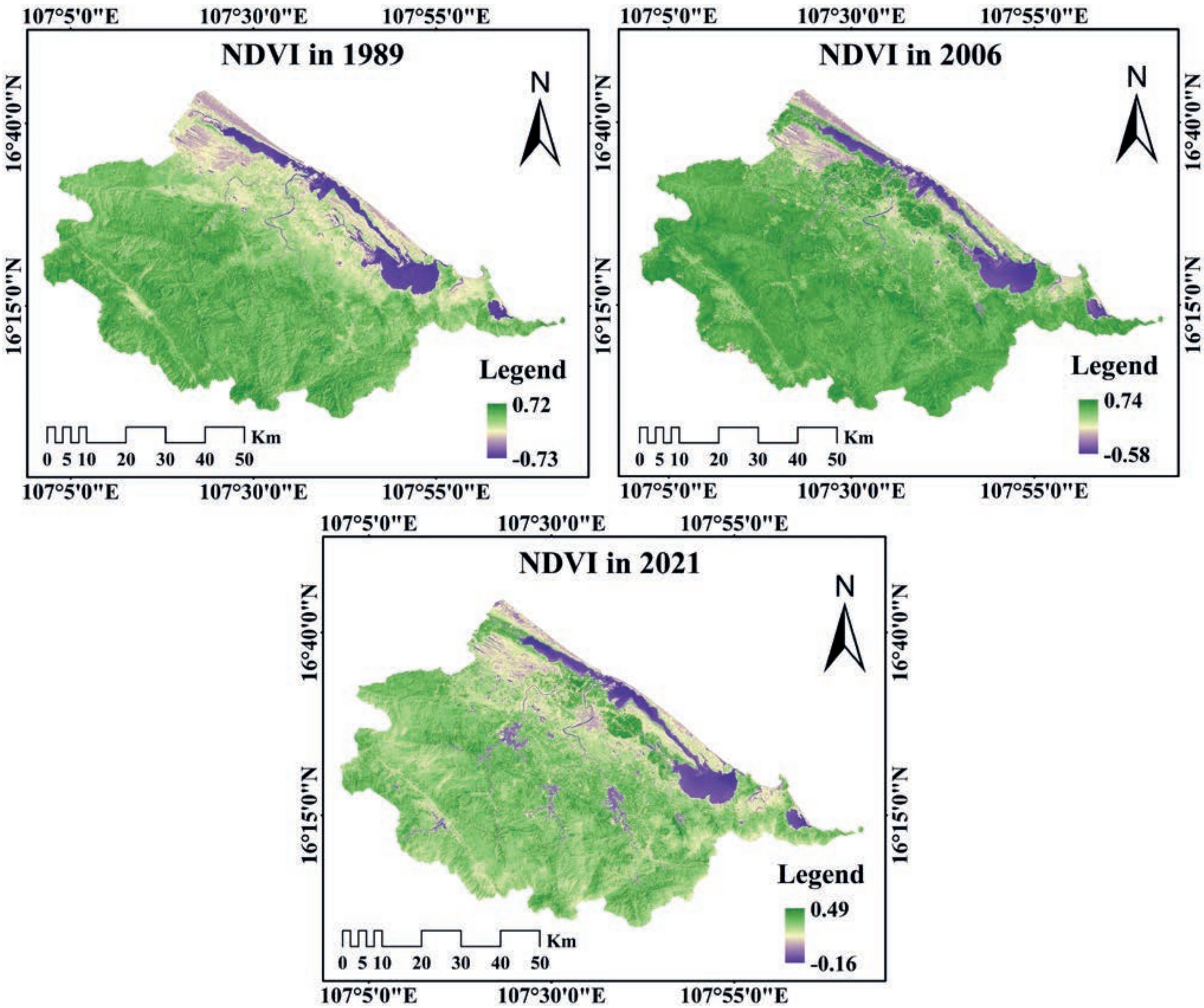

Fig. 5 Spatial distribution of NDVI for 1989, 2006 and 2021.

Forest cover from 1989 to 2021 based on these vegetation indices is presented in Tab. 6. The trend of year-over-year changes during the study period is also shown in Fig. 7. The results of the analysis of forest class reclassification based on the NDVI index through each of the years 1989, 2006 and 2021 are 3527.49 km^2, 3580.58 km^2 and 2905.27 km^2 respectively, corresponding to 70.19%, 71.25% and 57.81% (Tab. 6). In addition, based on the SAVI index, the forest classification results are quite similar to the NDVI index with 3501.11 km^2 (69.67%) in 1989, 3295.26 km^2 (65.57%) in 2006 and 2619.65 km^2 (52.13%) in 2021 (Tab. 6).

3.4 Forest cover changes from 1989 to 2021

Forest cover patterns can be summarized in terms of net change and gross gains and losses, with a

Tab. 6 Based forest cover area analyzed by vegetation indices (NDVI and SAVI) from 1989 to 2021.

Category		Distribution in 1989		Distribution in 2006		Distribution in 2021	
		Area (km^2)	(%)	Area (km^2)	(%)	Area (km^2)	(%)
NDVI	Forest	3527.49	70.19	3580.58	71.25	2905.27	57.81
	Other	1497.81	29.81	1444.72	28.75	2120.03	42.19
	Total	5025.30	100.00	5025.30	100.00	5025.30	100.00
SAVI	Forest	3501.11	69.67	3295.26	65.57	2619.65	52.13
	Other	1524.19	30.33	1730.04	34.43	2405.65	47.87
	Total	5025.30	100.00	5025.30	100.00	5025.30	100.00

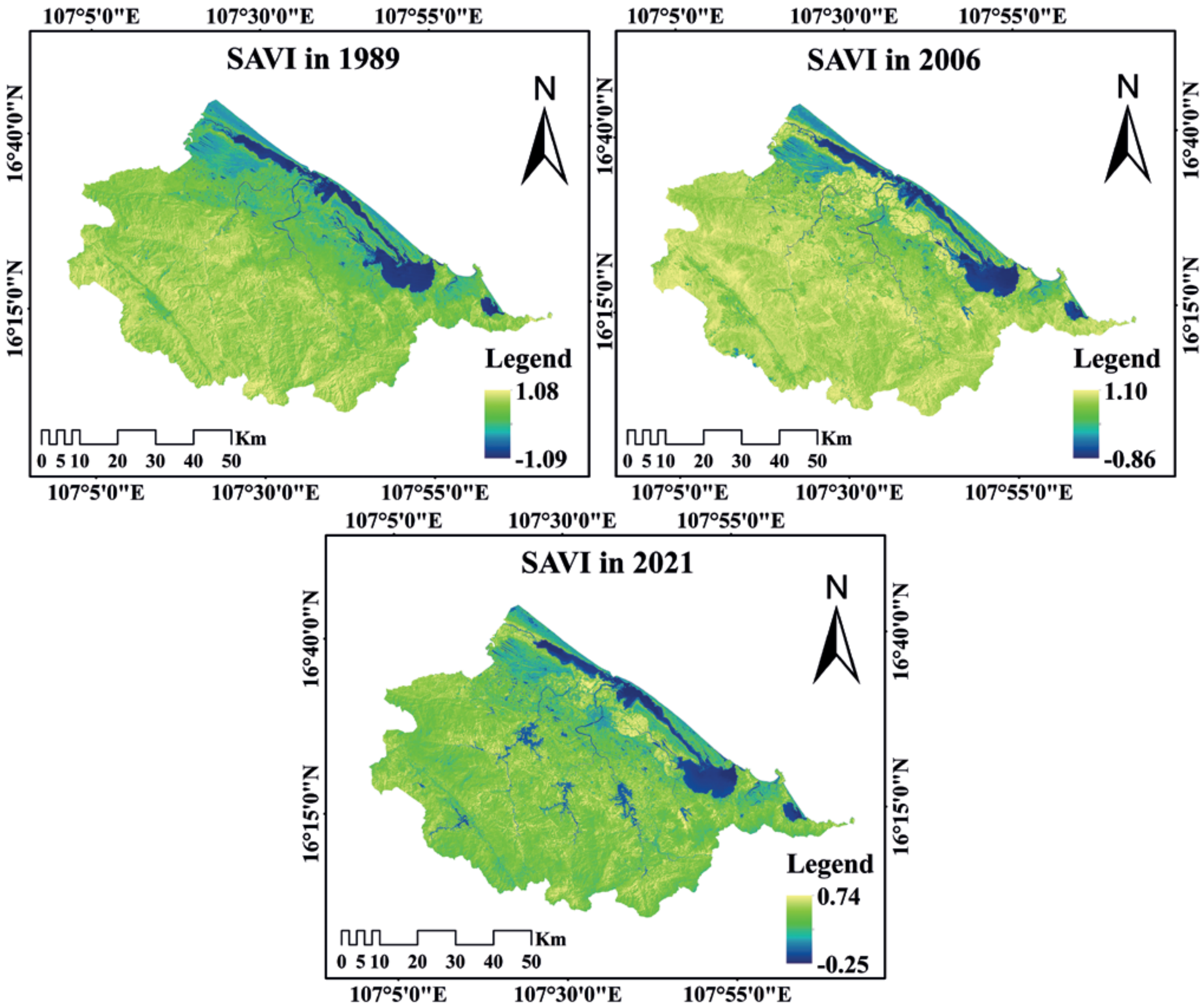

Fig. 6 Spatial distribution of SAVI for 1989, 2006 and 2021.

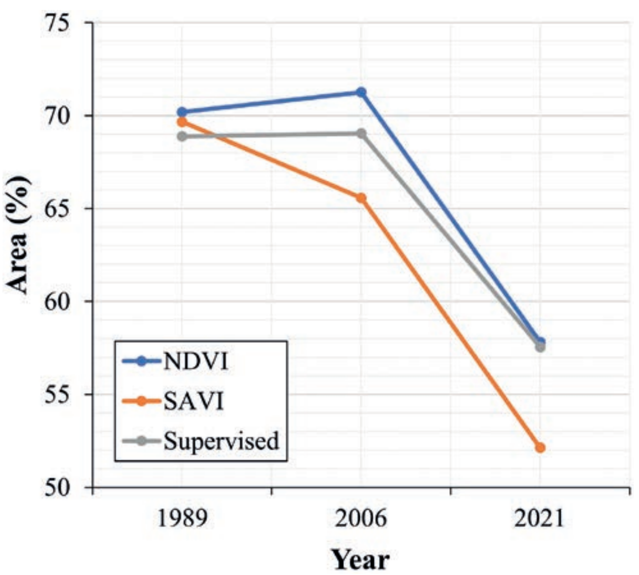

Fig. 7 Comparison of forest cover from 1989 to 2021 through NDVI, SAVI and supervised classification.

special focus on persistence and swaps (Tab. 7). A survey of forest-cover changes showed that, of a total 3461.46 km^2 of forest cover in 1989, 91.66% existed until the end of the period 1989–2006. In the next period (2006–2021), of the total 3469.51 km^2 of forest that existed in 2006, 80.03% existed in 2021 (Tab. 7). The remaining forest was converted to non-forest use.

The model showing the gain, losses, and persistence of forest cover in the study area in each period is shown in Fig. 8. The first period (1989–2006) observed a more significant increase in total forest area by 301.91 km^2, while the second period (2006–2021) saw an increase of only 120.63 km^2. The area of forest loss in the first phase was 293.86 km^2, which was lower than the increase in forest area, while in the second phase, the area of forest loss was greatly increased compared to the increased forest area of 698.33 km^2. More forest was lost during the period 1989–2006 than during the period 2006–2021 saw the least deforestation (Tab. 7). That results in the annual loss and gain in each

Tab. 7 Summary of forest cover change in Thua Thien Hue province between 1989 and 2021.

Forest Cover	Period					
	1989–2006		2006–2021		1989–2021	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Initial Year	3461.46		3469.51		3461.46	
Final Year	3469.51		2891.81		2891.81	
Persistence	3172.76	91.66	2776.70	80.03	2824.61	81.60
Loss	293.86	8.49	698.33	20.13	642.00	18.55
Gain	301.91	8.72	120.63	3.48	72.35	2.09
Annual Loss	17.29		46.56		20.06	
Annual Gain	17.75		8.04		2.26	
Annual Change	35.04		54.60		22.32	
Swap	587.72	16.98	1396.66	40.26	1284.00	37.09
Net Change	8.05	0.23	−577.70	16.65	−569.65	16.46

period also changing. During the period 1989–2006, the annual loss and gain were roughly equivalent at 17.29 km^2 and 17.75 km^2, respectively. From 2006 to 2021, the annual loss and gain area had a clear difference of 46.56 km^2 and 8.04 km^2, respectively. Forest cover increased by 8.04 km^2 in the first period and decreased in the second period by 577.70 km^2. In terms of annual variation, the annual change in forest cover in the first period was 35.04 km^2; and in the second period, it increased to 54.60 km^2 (Tab. 7).

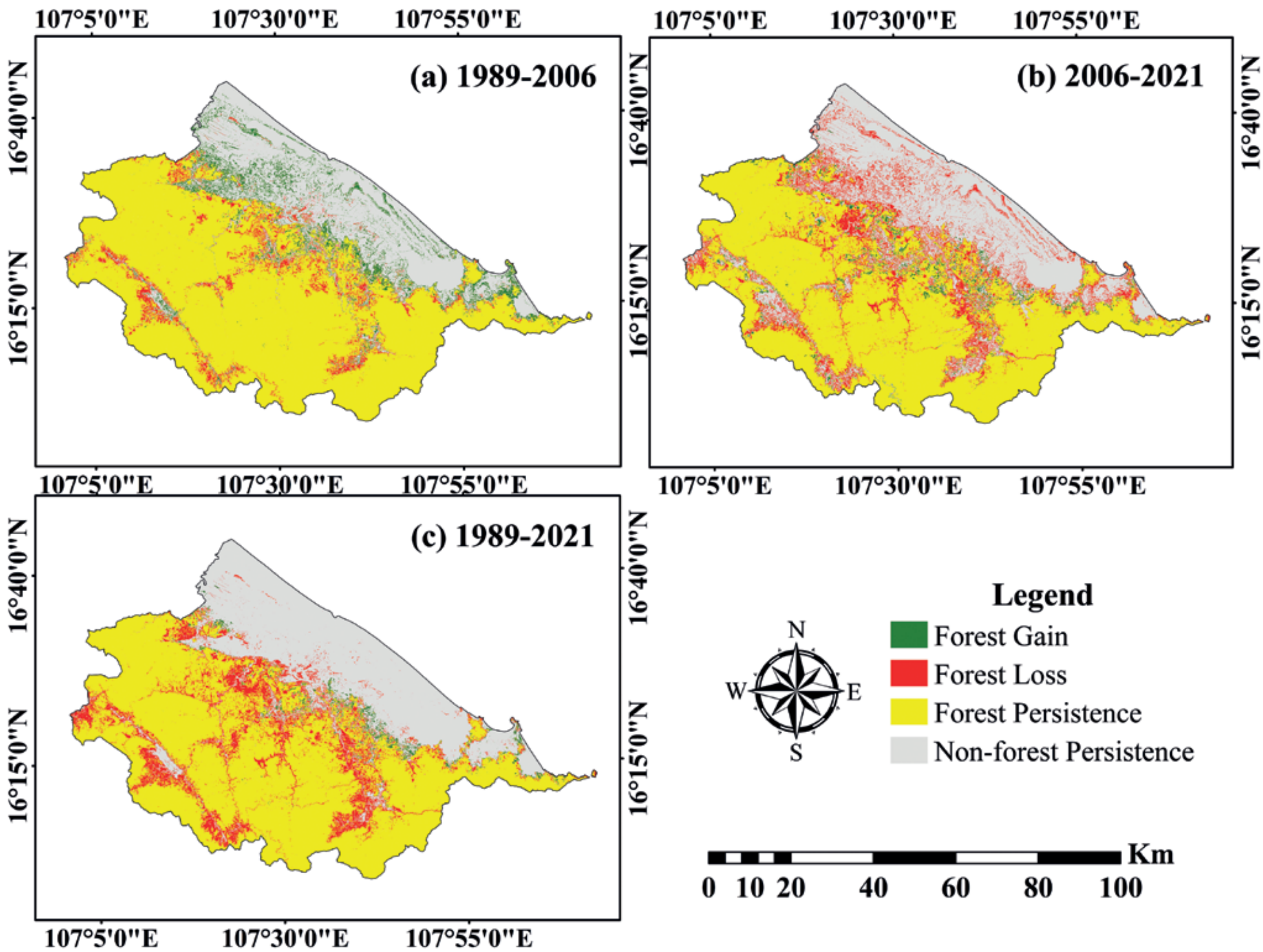

Fig. 8 Forest cover changes in Thua Thien Hue province during: (a) 1989–2006; (b) 2006–2021; and (c) 1989–2021

4. Discussion

Multi-spectral satellite images (Landsat TM and OLI) for the years 1989, 2006, and 2021 were used to classify LULC and evaluate changes in forest cover in Thua Thien Hue. These images were divided into five LULC classes: agricultural land, barren land, forest, settlement, and water (Tab. 2). The classification of these images was used the maximum likelihood algorithm for the three years is shown in Fig. 3 (Faruque et al. 2022; Thien and Phuong 2023). The results of the LULC distribution over the three focal years indicate that forests are the predominant class in the study area (Tab. 3). Forests are more common in the southwest region, while agricultural land and settlements are located near freshwater lakes, coastal areas, and plains. Generally, over the past 32 years, the forest cover has decreased, while the areas of other LULC classes have increased. Furthermore, it is crucial to assess the accuracy and validate the reliability of the resulting land cover map after classifying the LULC (Hasan et al. 2020; Thakur et al. 2021; Thien et al. 2023). This involves evaluating the errors associated with each land cover category and the overall accuracy of the classified image. The kappa coefficient values serve as a metric for measuring the consistency or precision between the reference data and the classified LULC classes. These coefficients range from −1.00 to +1.00, where values between 0.80 and 1.00 indicate a high level of agreement between the classification results and the actual data, approaching near-perfect consistency (Thakur et al. 2021). In this study, the kappa coefficient values for all land cover exceed 0.80 (Tab. 4), indicating an excellent agreement between the classified results and the reference data. This suggests that the classification process has provided highly accurate and reliable land cover information, increasing confidence in the obtained results.

The analysis of Thua Thien Hue province's multi-year LULC maps reveals significant changes that have occurred over a span of 32 years, from 1989 to 2021. These changes in LULC have both positive and negative impacts and are influenced by various natural and human factors (Phuong and Thien 2023). In particular, developing countries have experienced LULC changes that have resulted in the depletion of important natural resources such as vegetation, land, and water. Therefore, studying LULC alterations requires a comprehensive understanding and continuous monitoring of all contributing factors. In this study, our objective was to understand the changes in the forest class and identify the factors driving these changes over the 32 year period (1989–2021). We achieved this by comparing the statistical data of the forest class group in Tab. 3 and Tab. 5 and analyzing the spatial changes in the distribution of the LULC classes, as shown in Fig. 4. Through this examination, we aimed to provide a comprehensive overview of the changes in the forest class and their underlying causes during the study period.

Forests play a vital role in human life and the environment, providing not only valuable resources like timber and firewood but also playing a significant role in climate regulation and natural disaster protection (Thien and Phuong 2023). However, the findings presented in Tab. 5 indicate a severe decline in forest area during the study period from 1989 to 2021, while agricultural land and settlements have continuously expanded. Fig. 4 visually illustrates that a significant portion of the lost forest area has been converted into agricultural land and settlements, with a smaller portion transformed into water bodies. This suggests that multiple factors contribute to the decrease in forest cover in the study area, largely driven by human activities such as unsustainable logging practices, deforestation, wildfires, and land use conversion. The conversion of forest land into highly productive agricultural areas highlights the local community's dependence on agriculture as their primary livelihood (Muhati et al. 2018; Pendrill et al. 2022). Furthermore, over the past 32 years, the study area has experienced population growth, resulting in urbanization and the development of new residential areas accompanied by the necessary public infrastructure. This has led to an increased demand for food and subsequently expanded agricultural land. Water bodies have emerged in areas previously covered by forests in 1989 and 2006, serving the irrigation needs of farmers in agricultural areas. Unsustainable logging practices, forest fires for land clearance, and a lack of awareness among the local population regarding forest conservation have contributed to the significant decline in forest area. Additionally, indirect factors such as high agricultural commodity prices and ineffective forest management practices have also contributed to deforestation and forest degradation (Dan et al. 2018; Islam 2021).

The NDVI and SAVI are widely used vegetation indices for vegetation detection and mapping (Liang et al. 2018; Truong et al. 2018; Spadoni et al. 2020). In the study area, the NDVI values ranged from −0.73 to 0.74 (Fig. 5), and the SAVI values ranged from −1.09 to 1.10 (Fig. 6) across the assessment years. Higher values indicate forested areas, lower positive values represent sparse or no vegetation cover, and negative values indicate water. The increasing values of NDVI ($0.74 > 0.72$) and SAVI ($1.10 > 1.08$) in 2006 compared to 1989 indicate an increased in forest cover. However, the values of these two indices have decreased a lot in 2021 compared to 2006 with NDVI ($0.49 < 0.74$) and SAVI ($0.74 < 1.10$) which partly confirms the previous evidence about the deforestation and forest conversion resulted in a reduced forest area (Tab. 5). The estimation of forest area using the NDVI showed a positive trend in the first period (1989–2006) and a negative trend in the later period (2006–2021), similar to but slightly higher than the estimates obtained using the supervised classifier. On the other hand, the

SAVI provided similar estimates for 1989 but yielded much lower estimates for 2006 and 2021 (Fig. 7). This discrepancy may be due to sparse vegetation in 2006 and 2021, rather than dense forest, as the SAVI does not account for soil reflectivity. Based on these findings, the NDVI is a reliable indicator for detecting and monitoring forest cover in Thua Thien Hue province, especially in the context of rapid forest cover assessment (Chakraborty et al. 2018; Pesaresi et al. 2020; Huang et al. 2021; Faruque et al. 2022). In addition, Tab. 7 and Fig. 8 provide more detailed information on forest area loss and gain from 1989 to 2021. The total gross gain in the forest class is accompanied by a total loss in the other land use, particularly in the agricultural land class. Conversely, gross gains primarily came from barren and agricultural land in both periods, with the highest gains observed in the first period.

5. Conclusion

This study examines changes in forest cover and other LULC classes in Thua Thien Hue province, Vietnam, over a period of 32 years (1989–2021). By combining multi-temporal remote sensing data and GIS techniques, we quantified and analyzed the spatial and temporal patterns of LULC changes, with a particular focus on forest cover. The LULC classification results achieved an overall accuracy of over 90% during the research phase. The findings reveal significant changes in LULC classes over the study period. Forest cover and barren land decreased by 11.34% (569.65 km^2) and 9.66% (485.24 km^2) respectively, while agricultural land, settlements, and water areas increased by 11.46% (575.87 km^2), 8.68% (436.05 km^2), and 0.86% (42.97 km^2), respectively. These results indicate a strong correlation between the increase and decrease in these LULC classes. Notably, the study area experienced substantial deforestation, with 577.70 km^2 of forest being lost, particularly between 2006 and 2021. Although there was a small increase in forest cover from 1989 to 2006 (8.05 km^2), it was outweighed by the overall loss of forest cover during the 32 year period. The main drivers of changes in forest cover are agricultural expansion, urbanization and logging for housing and firewood. The study highlights the suitability of using the NDVI for mapping forest cover during rapid monitoring.

Based on these findings, we propose several recommendations to enhance forest protection and management. Firstly, policymakers should reconsider the conversion of forest land into agricultural areas, which has significantly contributed to the reduction in forest cover over the decades. Additionally, strong laws and regulations should be implemented to address both legal and illegal logging activities. Secondly, the relevant agencies should increase their personnel to effectively monitor and protect forest cover from illegal logging. By implementing these recommendations, we can better preserve the forest areas in the study region. Ultimately, we hope that this study can provide valuable insights to forest managers and agencies, assisting them in creating informative and educational materials, formulating policies, and making informed decisions regarding the conservation and monitoring of forest ecosystems. These efforts are crucial for preventing forest loss and degradation, particularly in relation to illegal logging activities.

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