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FOREST COVER DEPLETION AND LAND USE/LAND COVER CHANGE IN BAC KAN PROVINCE, VIETNAM

[1a]Bui B. Thien, [2b]Vu T. Phuong, [3c]Do T. V. Huong
[1] Southern Federal University. 105/42 Bolshaya Sadovaya Str., Rostov-on-Don, Russia
[2] Hong Duc University. 565 Quang Trung, Dong Ve Ward, Thanh Hoa, Vietnam
[3] University of Sciences, Hue University. 77 Nguyen Hue Str., Hue City, Vietnam
[a]buibaothienha@gmail.com, [b]vuthiphuong@hdu.edu.vn, [c]dtvhuong@hueuni.edu.vn

ABSTRACT

Deforestation is an important driver of climate change, both directly through the release of stored carbon and indirectly through its impact on ecosystems and weather patterns. This study investigated forest cover changes in Bac Kan province, Vietnam, using remote sensing (RS) and geographic information systems (GIS) techniques to monitor forest cover as well as land use and land cover types over the period 1992-2022. Landsat 5-TM and Landsat 9-OLI/TIRS images from 1992, 2010, and 2022 were classified using the maximum likelihood classification method, and the post-classification accuracy was assessed using kappa coefficient statistics. Additionally, to detect changes in forest cover, the Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) were utilized. The results show that the agricultural land area in 1992 was 70.97 km^2 (1.46 %), then increased in 2010 to 271.24 km^2 (5.58 %), and has continued to increase in 2022 to 575.24 km^2 (11.84 %). Meanwhile, the forest area has decreased from 4640.53 km^2 (95.50 %) in 1992 to 4438.95 km^2 (91.35 %) in 2010 and has continued to decrease to 4196.54 km^2 (86.36 %) in 2022, with a total forest loss area of 443.99 km^2 (9.14 %) in the period 1992-2022. The findings suggest that agriculture, settlements, and waterbodies have expanded while forest cover and bare soil/rock have declined. Overall, our findings underscore the importance of effective forest management strategies, sensible land-use policies, and heightened community engagement toward the preservation and sustainable utilization of forest resources within the examined region moving forward.

Keywords: forest cover; Landsat; vegetation index; Remote Sensing; Geographic Information Systems

DISMINUCIÓN DE LA COBERTURA FORESTAL Y CAMBIO DE USO/COBERTURA DEL SUELO EN LA PROVINCIA DE BAC KAN, VIETNAM

RESUMEN

La deforestación es un importante impulsor del cambio climático, tanto directamente a través de la liberación de carbono almacenado como indirectamente a través de su impacto en los

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ecosistemas y los patrones climáticos. Este estudio investigó los cambios en la cubierta forestal en la provincia de Bac Kan, Vietnam, utilizando técnicas de teledetección (RS) y sistemas de información geográfica (GIS) para monitorear la cubierta forestal, así como el uso y los tipos de cobertura del suelo durante el período 1992-2022. Las imágenes Landsat 5-TM y Landsat 9-OLI/TIRS de 1992, 2010 y 2022 fueron clasificadas utilizando el método de clasificación de máxima verosimilitud, y la precisión post-clasificación fue evaluada utilizando estadísticas de coeficiente kappa. Además, para detectar cambios en la cobertura forestal, se utilizaron el Índice de Vegetación de Diferencia Normalizada (NDVI) y el Índice de Vegetación Ajustado al Suelo (SAVI). Los resultados muestran que el área de tierras agrícolas en 1992 fue de 70.97 km^2 (1.46 %), luego aumentó en 2010 a 271.24 km^2 (5.58 %), y ha seguido aumentando en 2022 a 575.24 km^2 (11.84 %). Mientras tanto, el área forestal ha disminuido de 4640.53 km^2 (95.50 %) en 1992 a 4438.95 km^2 (91.35 %) en 2010 y ha continuado disminuyendo a 4196.54 km^2 (86.36 %) en 2022, con una pérdida total de área forestal de 443.99 km^2 (9.14 %) en el período 1992-2022. Los resultados sugieren que la superficie agrícola, el suelo urbano y las masas de agua han aumentado mientras que la cobertura forestal y el suelo/roca desnudo ha disminuido. De esta forma se subraya la importancia de implementar estrategias efectivas de manejo forestal, políticas de uso de la tierra sensatas y un mayor compromiso comunitario hacia la preservación y la utilización sostenible de los recursos forestales del área de estudio.

Palabras clave: cobertura forestal; Landsat; índice de vegetación; Teledetección; Sistemas de Información Geográfica

1. Introduction

Forest cover (FC) changes represent an ongoing and widespread process driven by both human activities and natural phenomena. These changes have far-reaching consequences, influencing natural ecosystems globally (Arowolo *et al.* 2018; Jiang *et al.* 2022). Forests are indispensable for minimizing the adverse impacts of climate change because they act as natural carbon sinks, regulate climate patterns, support biodiversity, and provide essential ecosystem services that benefit both humans and the environment (Clement & Amezaga 2009; Duguma *et al.* 2019; Thien *et al.* 2023b). Protecting and restoring forests is therefore critical in efforts to combat climate change and promote sustainable development.

In various regions, including Vietnam, about one-third of the population has experienced significant socioeconomic changes, impacting the local production system heavily reliant on forests and soil (Meyfroidt & Lambin 2008; Lattimore *et al.* 2009; Vu *et al.* 2014). The extent of Vietnam's FC may change dramatically due to land use, which can significantly affect forest characteristics.

Recognizing the importance of preserving forests for reducing greenhouse gas emissions and safeguarding environmental services like biodiversity and livelihoods, Vietnam has taken proactive steps (McElwee *et al.* 2016; Morita & Matsumoto 2018). Even before considering any REDD strategy, the country established laws aimed at improving carbon stocks and ensuring sustainable forest management within the REDD+ framework. Notably, during the 1990s, Vietnam underwent significant changes in forest policy, implementing programs like the 661 ("50,000 km^2 Reforestation Program") and the 327 ("Regreening the Barren Hills" Program) to increase FC from 28 % to the pre-decolonization level of 43 % (Jong *et al.* 2006; Clement & Amezaga 2009).

Given the importance of preserving and improving forests in Vietnam, it is crucial to objectively map and track changes in FC. However, conducting field studies to monitor FC is impractical and prohibitively expensive. Remote sensing (RS) and geographic information systems (GIS) continue to be crucial tools for measuring and monitoring Earth's surface processes (Lu *et al.*, 2004; Yang *et al.* 2019; Thien *et al.* 2023c). RS is the most practical method for mapping land use and land cover (LULC) change as it is scalable, repeatable, and cost-effective. Landsat sensors have been optimized and successfully deployed for LULC mapping in agriculture, non-forest, and forest areas (Bakr *et al.* 2010; Yang *et al.* 2019; Thien *et al.* 2023b). Landsat data is readily available for LULC mapping due to the US Geological Survey's Landsat program, which has been in operation since 1972, and the free distribution of Landsat was a fact in 2008. A range of methods for detecting change and analyzing images are employed to obtain information from remotely sensed data. In contrast, GIS combines data from RS to offer a holistic approach to modeling LULC.

Furthermore, the most efficient and dependable approach to supervise LULC and alterations in FC is the merged application of satellite RS and GIS. The progress in RS and GIS techniques has facilitated the mapping of LULC, which is a comprehensive and practical method for enhancing the selection of land for diverse purposes such as urban planning, agricultural development, environmental conservation, and resource management (Mubako *et al.* 2018). Multiple vegetation indices are available to identify and analyze vegetation and FC occurrences. In semi-arid areas, the Soil Adjusted Vegetation Index (SAVI) is utilized on a regional scale, as it enables the identification of changes in plant communities over several years (Huete, 1988; Rhyma *et al.* 2020). The monitoring of vegetation health can also be accomplished through the utilization of multispectral satellite imagery's red and near-infrared band combinations, which facilitates the calculation of the Normalized Difference Vegetation Index (NDVI) (Matsushita *et al.* 2007, Spadoni *et al.* 2020, Huang *et al.* 2021).

In this study, our goal was to integrate open access RS data and GIS to examine the spatial trends of forest and other changes in land cover in Bac Kan province, Vietnam, over a 30-year period (1992–2022). This study provides basic information to support land-use planning to avoid degradation and deforestation in the study area. The specific objectives of this study are determined as follows: (1) identifying and delineating different types of LULC and patterns of change in land use in Bac Kan province; (2) investigating the detailed variation in FC and other major types of cover through spatial and temporal analysis; and (3) linking vegetation indices with changes in FC.

2. Materials and methods

2.1. Study area

Bac Kan province is located in the northeast of Vietnam, most of the area is covered with forests, including special-use, protection, and production forests, which account for 95 % of the province (Figure 1). The economy of Bac Kan has not been developed much, mainly due to its rugged mountainous landscapes, though lowland valleys are suitable for rice cultivation. Agriculture serves as the primary source of income for households, with rice (paddy) production being the mainstay. Some farmers sell their produce in local markets. Bac Kan has enormous potential for tourism development, given its mountainous terrain rich in natural resources such as minerals and forests. As of 2021, the population of Bac Kan was 323,700, with a population density of 67 persons per km^2 over a land area of 4859.40 km^2 (General Statistics Office, 2023).

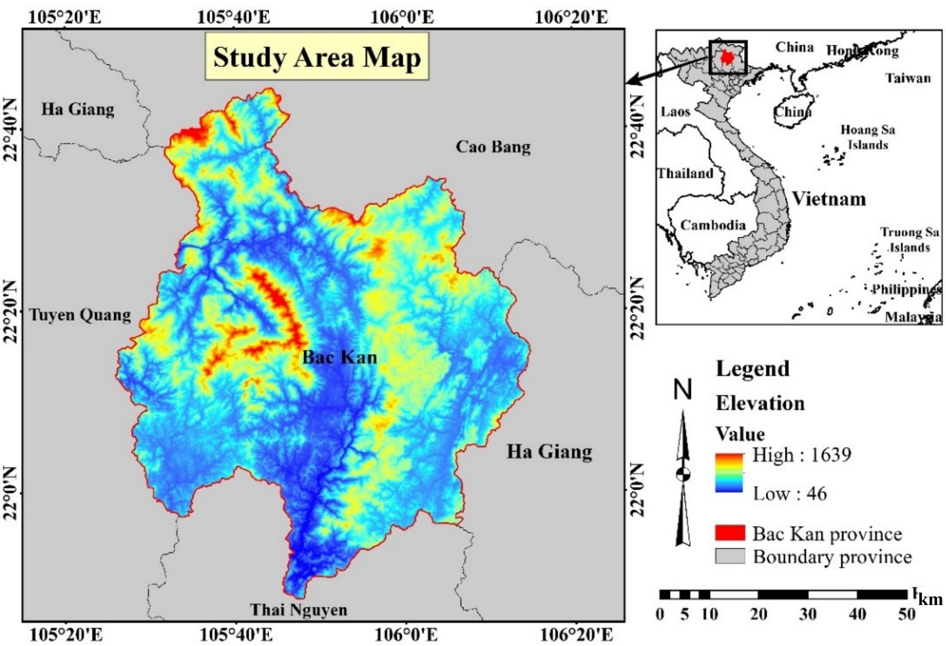

Figure 1. Map showing the study area in Bac Kan province, Vietnam.
Source: The authors, 2023.

Bac Kan province is entirely situated within the tropical monsoon belt of Southeast Asia. Due to the province's location between two bow-shaped systems of mountains in the Northeast, Bac Kan experiences an Asian continental climate with cold weather during the winter and limited influence of storms during the summer. With the tropical monsoon regime, the region experiences two distinct seasons throughout the year. The hot and humid rainy season, which accounts for 70 – 80 % of the annual rainfall, falls between May and October. In the dry season, which lasts from November to April, rain accounts for only about 20 – 25 % of the total rainfall in the year. December is the least rainy month of the year (Provincial People's Committee of Bac Kan, 2020).

2.2. Data used and sources

Landsat satellite images with a resolution of 30 meters were used to map LULC in Bac Kan province for 3 years (1992, 2010, and 2022) and evaluate changes in FC. These time points were selected to coincide with significant policy shifts, particularly regarding land rights, in Vietnam. The year 1992 was chosen due to the absence of cloud cover and the enactment of new forest legislation, succeeding the forest law of 1987. Subsequent to this, the Vietnamese government bolstered its forest protection policies to safeguard the nation's valuable forest resources, initiating reforestation and biodiversity conservation programs in 2010. By 2022, the government had enacted further policy reforms concerning forests, alongside initiatives for their protection and restoration.

The availability of cloud-free imagery for Bac Kan province was also taken into account. 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. RS images collected at the end of the rainy season (October) and the beginning of the dry season of Bac Kan province (November) are less affected by clouds and have good quality so they were used for analysis in this study. Landsat 5 TM images were used for the years 1992 and 2010 and Landsat 9 OLI/TIRS images were used for 2022 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 in March 2022 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.

Table 1. Satellite data set for image interpretation.

Landsat Scene ID	Acquisition data	Cloud cover (%)	Satellite	Path/row
LT51270441992295BJC02	21/10/1992	0.00	Landsat 5-TM	127/044
LT51270451992295BJC02		0.00	Landsat 5-TM	127/045
LT51270442010312BKT00	08/11/2010	1.00	Landsat 5-TM	127/044
LT51270452010312BKT00		1.00	Landsat 5-TM	127/045
LC91270442022305LGN00	01/11/2022	0.74	Landsat 9-OLI/TIRS	127/044
LC91270452022305LGN00		1.69	Landsat 9-OLI/TIRS	127/045

Source: United States Geological Survey, 2022.

2.3. Classification of images and change detection

The LULC classification system employed for this study utilized satellite images from Google Earth Pro, as well as the Anderson LULC classification scheme modified at the level I (Anderson *et al.* 1976), the regulations on land use in Vietnam, the prevailing conditions in the study area, specific pixel values for different landscape features, and relevant literature sources. Based on Landsat satellite image classification, five LULC categories were identified and mapped, including agriculture, bare soil/rock, forest, settlement, and waterbodies (Table 2).

Table 2. Description of different land use/land cover categories.

Class	Description
Agriculture land	Cultivated fields, homestead garden fields, industrial crop land, and agriculture bare
Bare soil/rock	Fallow land, sands, earth dumps, bare hills
Forest	Forestry, forest reserve, natural forests, individual trees
Settlement	Residential, communicating roads, playgrounds
Waterbodies	Rivers, lakes, artificial ponds

Source: The authors, 2023.

Figure 2 illustrates the methodological framework utilized in this research. Satellite data were pre-processed to extract meaningful information, making them more accessible for interpretation (Coppin *et al.*, 2004). The preprocessing of the original satellite data involves a range of techniques, such as image enhancement, topographic corrections, noise removal, and geometric corrections (Jianya *et al.* 2008).

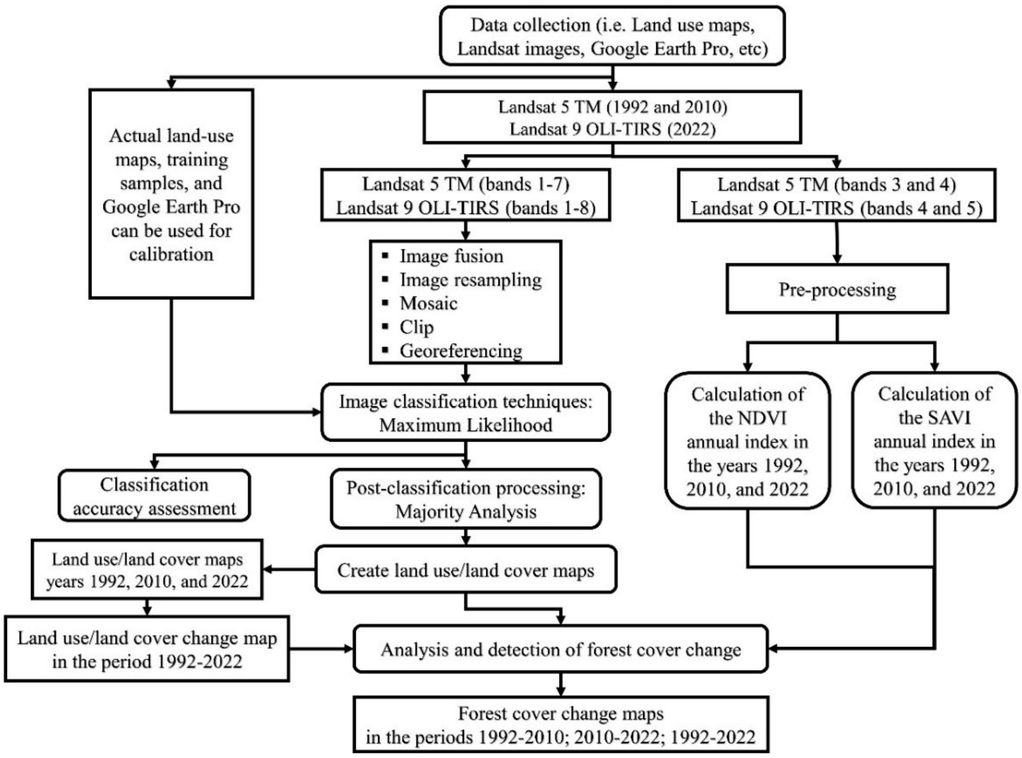

Figure 2. The overall process of forest cover change technique.
Source: The authors, 2023.

The Landsat RS image data collected were first rectified using the Universal Transverse Mercator (UTM) zone 48N projection on the WGS84 datum. Then, composite bands were utilized to produce an image with a combination of bands. To extract the data from the study area, the ArcGIS 10.8 software's extract by mask tools were utilized (Thien *et al.* 2023a). To differentiate watersheds and assign signatures per pixel, all satellite data were analyzed. For each predefined LULC class (Table 2), 300 training samples were selected by defining area of interest (AOI) polygons around representative regions, and the satellite images' spectral signatures for each LULC classes were then acquired based on these polygons to minimize confusion between the mapped LULC classes (Gao & Liu 2010). The study employed the rule-based supervised classification-maximum likelihood classifier (MLC) algorithm for the LULC classification of the acquired images from 1992, 2010, and 2022 (Rawat & Kumar 2015, Shivakumar & Rajashekararadhya 2018, Thien *et al.* 2023c). Post-classification refinement was applied to increase the classification accuracy and reduce the misclassifications (Harris & Ventura, 1995). We applied a 4×4 majority filter to the classified soils to minimize salt-chili interference. The adopted LULC classification includes consistency in the definition of each category and a clear distinction in class boundaries based on variations in natural and anthropogenic features within the studied area. This classification approach is also scale-independent and can thus feasibly be applied at any spatial scale or level of detail (Santos & Simionatto 2023).

2.4. Analysis of vegetation indices to detect changes in forest cover

NDVI and SAVI are two of the most commonly used indices for studying FC changes (Huete 1988, Huete 2012, Huang *et al.* 2021, Islam *et al.* 2021, Thien & Phuong 2024). These indicators are measurements of the reflection of the soil and vegetation surface. To assess the extent of FC and the degree of greenness in the ecosystem and its surrounding region, this study examined the suitability of these two commonly used vegetation indices. To map the forest LULC area for all time periods, the classification raster was reclassified using the NDVI and SAVI values maximum and minimum values. The NDVI and SAVI values were calculated for all forest polygons detected through supervised classification of Landsat 5-TM and Landsat 9-OLI/TIRS images. NDVI and SAVI were calculated using equations (1) and (2) respectively.

$$NDVI = \frac{NIR-RED}{NIR+RED} \qquad (1)$$

$$SAVI = \frac{NIR-RED}{NIR+RED+L} \times 1 + L \quad (2)$$

where NIR is the reflectance radiated in the near-infrared wave band, RED is the reflectance radiated in the visible red wave band of the satellite radiometer, and L is 0.5, the default value.

2.5. Classification accuracy assessment

The mechanism for determining accuracy is a crucial component of the classification process. It serves to identify factual errors in the classification and offers a way to express precision (Owojori & Xie 2005). To evaluate the accuracy of the FC thematic maps and to reflect the actual differences between the classification and the reference data, various measures were used (Owojori & Xie 2005, Chowdhury *et al.* 2020, Thien & Phuong 2023). The classification accuracy of the resulting images for the years 1992, 2010, and 2022 was assessed using error matrices and quantitative measurements such as overall accuracy (OA), user accuracy (UA), producer accuracy (PA), and kappa coefficients. The kappa coefficient is a crucial measure in assessing the accuracy of LULC classification. It indicates the consistency and precision of the classification between the reference data and the classified LULC classes, with a range of values from -1.00 to +1.00 (Lea & Curtis 2010). A stratified random technique was employed to select 300 random points from each classified image, which were then compared digitally to the corresponding pixels on Google Earth Pro maps as reference data. These points represented all the LULC categories within the study area as found on the ground truth data and topographic maps. The OA was determined by constructing an error categorization matrix for each LULC map. The kappa coefficient, OA, UA, and PA equations (3), (4), (5), and (6), respectively, were used as the best quantitative measurements for satellite image classification (Chowdhury *et al.* 2020, Hasan *et al.* 2020, Thakur *et al.* 2021, Thien & Phuong 2024).

$$Kappa\ coefficient\ = \frac{\sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k} n_{ii}\,(G_i C_i)}{n^2 - \sum_{i=1}^{k} n_{ii}\,(G_i C_i)} \quad (3)$$

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.

$$OA = \frac{Total\ number\ of\ corrected\ classified\ pixels\ (diagonal)}{Total\ number\ of\ reference\ pixels} \times 100\ (4)$$

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

$$PA = \frac{Number\ of\ correctly\ classified\ pixels\ in\ each\ category}{Total\ number\ of\ reference\ pixels\ in\ each\ category\ (column\ total)} \times 100\ (6)$$

3. Results and discussion

3.1. Land use/land cover classification

The outcomes of image classification for these three years using the maximum likelihood algorithm can be seen in Figure 3. Based on the data presented in Table 3, it can be inferred that forest is the dominant LULC type in the study area across the three focal years. Based on the classification results in 1992, the majority of the research area was covered by forest, accounting for 95.50 % (4640.53 km^2) of the total area. This was followed by bare soil/rock area, accounting for 2.94 % (142.81 km^2), and agriculture area, accounting for 1.46 % (70.97 km^2). Waterbodies and settlement areas accounted for at least 0.06 % (3.02 km^2) and 0.04 % (2.07 km^2), respectively (Table 3). In 2010, the forest and bare soil/rock areas decreased by 91.35 % (4438.95 km^2) and 2.83 % (137.76 km^2), respectively. In contrast, the agriculture, settlement, and waterbodies areas increased by 5.58 % (271.24 km^2), 0.16 % (7.66 km^2), and 0.08 % (3.79 km^2), respectively (Table 3). By 2022, the forest and bare soil/rock areas decreased by 44.85 % (740.49 km^2) and 3.06 % (50.49 km^2), respectively. The area of agriculture, settlement, and waterbodies class increased by 11.84 % (575.24 km^2), 1.68 % (81.57 km^2), and 0.11 % (5.33 km^2), respectively (Table 3).

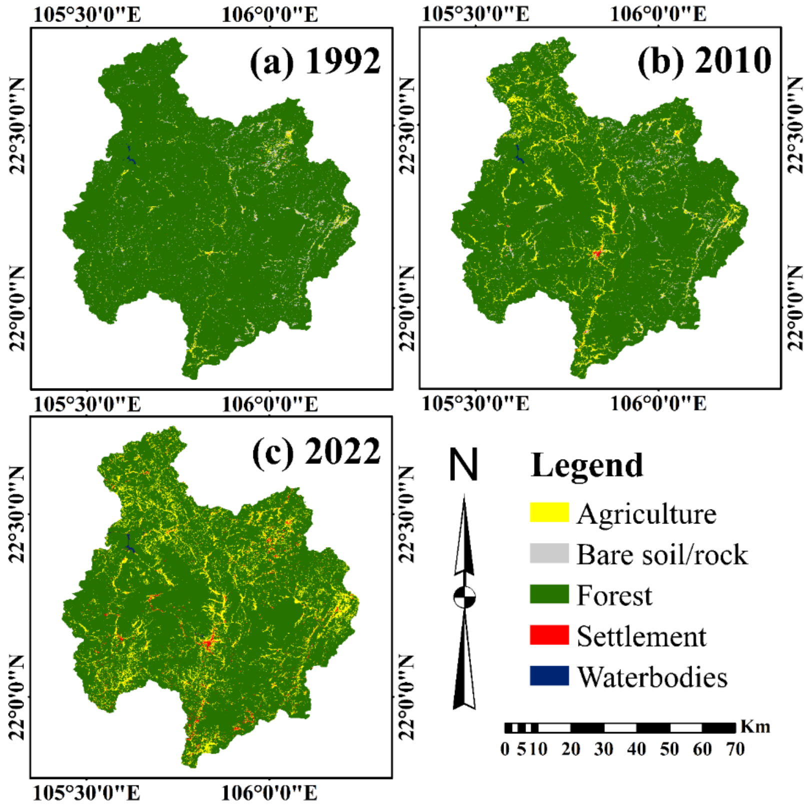

Figure 3. Land use/land cover of Bac Kan province in (a) 1992, (b) 2010, and (c) 2022.
Source: The authors, 2023.

Table 3. Land use/land cover classification results in Bac Kan province from 1992 to 2022.

Class	LULC in 1992		LULC in 2010		LULC in 2022	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Agriculture	70.97	1.46	271.24	5.58	575.24	11.84
Bare soil/rock	142.81	2.94	137.76	2.83	0.72	0.01
Forest	4640.53	95.50	4438.95	91.35	4196.54	86.36
Settlement	2.07	0.04	7.66	0.16	81.57	1.68
Waterbodies	3.02	0.06	3.79	0.08	5.33	0.11
Total	4859.40	100.00	4859.40	100.00	4859.40	100.00

Source: The authors, 2023.

3.2. Accuracy assessment

The results of the classification evaluation showed that the OA of the years 1992, 2010, and 2022 was 92.00 %, 91.33 %, and 92.72 %, respectively (Table 4). The UA results show that, for the year 1992, the maximum accuracy was achieved for the forest class (95.52 %) and the minimum for the settlement class (80.00 %). For 2010, UA ranged from a minimum of 85.71 % (water class) to a relatively precise classification of 94.83 % (forest class). For 2022, UA was 96.08 % for the forest classes and was lowest for the bare soil/rock class (87.50 %). The results of the PA assessment show that classification was relatively accurate for the forest class in 1992 and 2010 (96.97 % and 94.83 %, respectively) (Table 4). In 2022, classes achieved 100 % accuracy (settlement class). The lowest accuracy ratings in 1992, 2010, and 2022 were for agriculture land class (85.71 %), bare soil/rock class (82.61 %), and bare soil/rock class (87.50 %), respectively (Table 4). The fact that both PA and UA for all classes in all three years surpassed the 80 % threshold indicates a consistent and accurate representation of various land cover types (Thien & Phuong, 2024). The kappa coefficient values in 1992, 2010, and 2022 in the study area were recorded as 0.888, 0.885, and 0.903, respectively (Table 4). Kappa coefficients between 0.60 and 0.80 indicate high consistency in classification, while values of 0.80 - 1.00 indicate a nearly perfect agreement (Congalton & Green 2019; Thien *et al.* 2023c). The kappa coefficient values obtained in this study exceed 0.80 (Table 4), indicating excellent agreement between the classified results and reference data (Lea & Curtis 2010; Manonmani & Suganya 2010).

Table 4. Accuracy assessments for 1992, 2010 and 2022.

Land cover class	**1992**		**2010**		**2022**	
	Producers accuracy (%)	Users accuracy (%)	Producers accuracy (%)	Users accuracy (%)	Producers accuracy (%)	Users accuracy (%)
Agriculture land	85.71	90.91	87.50	90.32	88.37	92.68
Bare soil/rock	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
Waterbodies	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	

Source: The authors, 2023.

3.3. Land use/land cover change from 1992 to 2022

The examination of multiple LULC maps of Bac Kan Province through spatial analysis reveals significant changes that have occurred over a 30-year period, from 1992 to 2022. These changes, attributed to natural factors such as droughts, storms, floods, and the consequences of climate change, along with human-induced activities, can yield both positive and negative impacts, constituting an ongoing process. In developing countries, LULC changes have been linked to the depletion of critical natural resources such as vegetation, soil, and water (dos Santos *et al.* 2023). Therefore, a comprehensive understanding and monitoring of all factors contributing to LULC change is essential (Santos & Simionatto 2023). Comparing forest class groups in Tables 5 and 6 with LULC class distribution in Figure 4 allows for a comprehensive analysis. Between 1992 and 2010, there was a substantial reduction in forest and bare soil/rock, while agriculture, settlement, and waterbodies increased. Agriculture land has the highest positive displacement (more than 200 km^2), while forest has the highest negative removal (nearly 202 km^2). The forest area decreased dramatically (4.15 %), from 4640.53 km^2 in 1992 to 4438.95 km^2 in 2010 (Table 5). Also, from 1992-2010, the bare soil/rock class decreased slightly by 0.10 % from 142.81 km^2 in 1992 to 137.76 km^2 in 2010 (Table 5). Meanwhile, the agriculture, settlement, and waterbodies classes all increased by 200.27 km^2 (4.12 %), 5.59 km^2 (0.12 %), and 0.77 km^2 (0.02 %), respectively. By 2010-2022, the volatility of the classes remained the same as in the early period (1992-2010). The area of the forest and bare soil/rock classes has continued to decrease with 242.41 km^2 (4.99 %) and 137.04 km^2 (2.82 %), respectively (Table 5).

The remaining classes still retain positive displacements, such as agriculture, settlement, and waterbodies classes, with 304.00 km^2 (6.26 %), 73.91 km^2 (1.52 %), and 1.54 km^2 (0.03 %), respectively (Table 5).

Table 5. Change statistics of land use/land cover in Bac Kan province from 1992 to 2022.

Class	Period					
	1992-2010		2010-2022		1992-2022	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Agriculture	200.27	4.12	304.00	6.26	504.27	10.38
Bare soil/rock	-5.05	-0.10	-137.04	-2.82	-142.09	-2.92
Forest	-201.58	-4.15	-242.41	-4.99	-443.99	-9.14
Settlement	5.59	0.12	73.91	1.52	79.50	1.64
Waterbodies	0.77	0.02	1.54	0.03	2.31	0.05

Source: The authors, 2023.

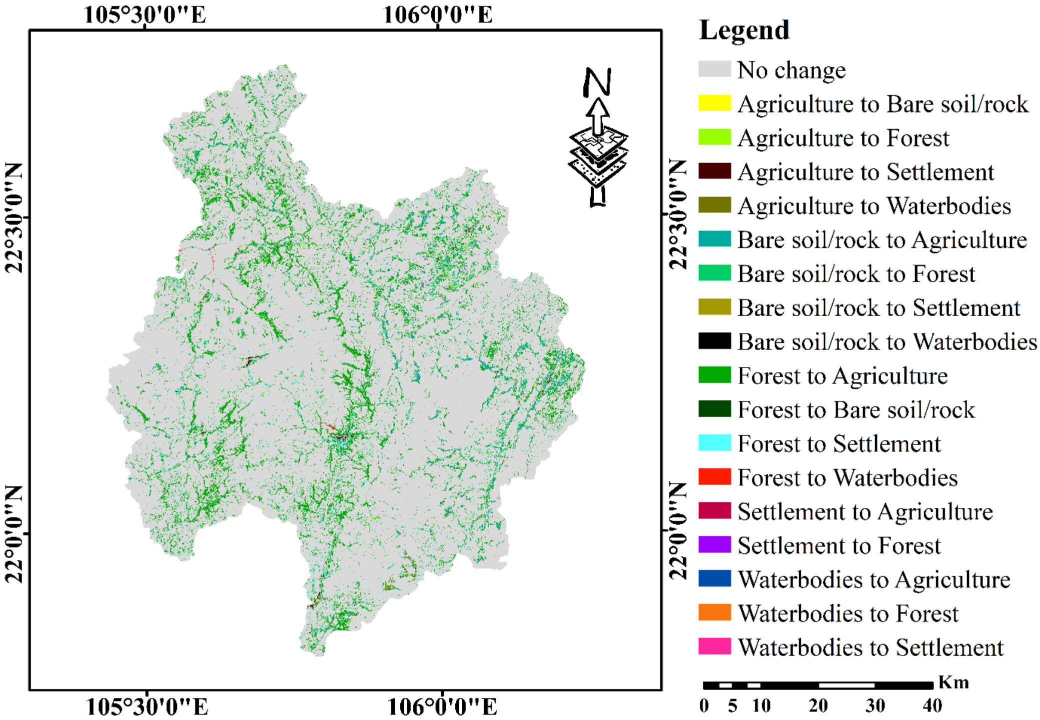

Figure 4. Land use/land cover changes map in Bac Kan province in the period 1992-2022.
Source: The authors, 2023.

Forests play a critical role in human society and the environment, serving as a source of resources such as timber and fuel, and playing a vital role in climate regulation and natural disaster mitigation (Watson *et al.* 2018, Thien *et al.* 2023b). While deforestation may provide short-term economic benefits, such as timber and land for agriculture or development, the long-term costs can be significant. Loss of ecosystem services, such as clean water and climate regulation, can have economic repercussions for communities and countries (Santos & Simionatto 2023). Over the 30-year study period (1992-2022), the area covered by forest and bare soil/rock classes has consistently decreased, while the size of the agriculture, settlement, and waterbodies classes has increased. The findings reveal numerous drivers of FC decline in Bac Kan province, with many associated with human activities, such as uncontrolled logging, deforestation, forest fires, conversion of forest land for infrastructure development purposes, and planting trees with high economic value (Santos de Lima *et al.* 2018, Duguma *et al.* 2019). The expansion of agricultural land has resulted in a substantial decline in the province's natural forest area, as natural forests are cleared for agricultural purposes. Planting industrial trees, as previously mentioned, is one of the most significant drivers of deforestation (Rambo *et al.* 1995, Nguyen *et al.* 2020).

The utilization of forest resources for various purposes such as construction, energy, livestock grazing, and household furniture has led to a decline in FC. Furthermore, the demand for forest resources, particularly firewood and charcoal, within and beyond the study area, combined with inadequate local management practices, has indirectly contributed to forest degradation in Bac Kan province. Indirect drivers of deforestation and forest degradation, including high agricultural prices and ineffective forest management techniques, also exist in the region (Thien *et al.* 2023a).

3.4. Relationship between vegetation indices and decadal forest cover changes

Vegetation indices obtained through RS techniques are a straightforward and efficient means of quantifying and evaluating plant coverage, vitality, and growth patterns (Pesaresi *et al.* 2020, Pasternak & Pawluszek-Filipiak 2022, dos Santos *et al.* 2023, Thien & Phuong 2023). To delineate forest areas, we analyzed all NDVI and SAVI pixel values from our classified image in 2022 and identified NDVI values greater than 0.26 and SAVI values greater than 0.48 as dark green, which represent forest polygons. Based on these thresholds, we conducted image classification for the years 1992 and 2010 into forest and non-forest regions. The NDVI and SAVI values in Bac Kan province ranged from -0.14 to 0.64 (Figure 5) and -0.20 to 0.96 (Figure 6), respectively, throughout the assessment period, with higher values indicating forest, low positive values indicating sparse vegetation, and negative values representing water (Huete 2012, Islam *et al.* 2021; Pasternak & Pawluszek-Filipiak 2022).

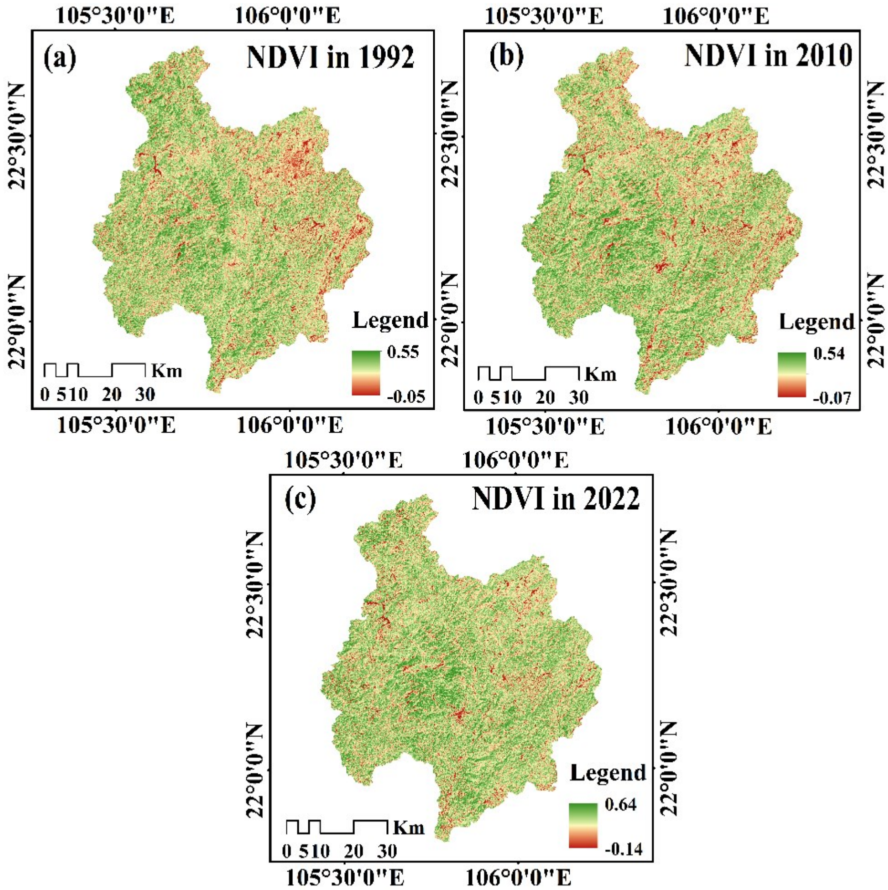

Figure 5. Spatial distribution of NDVI for 1992 (a), 2010 (b), and 2022 (c).
Source: The authors, 2023.

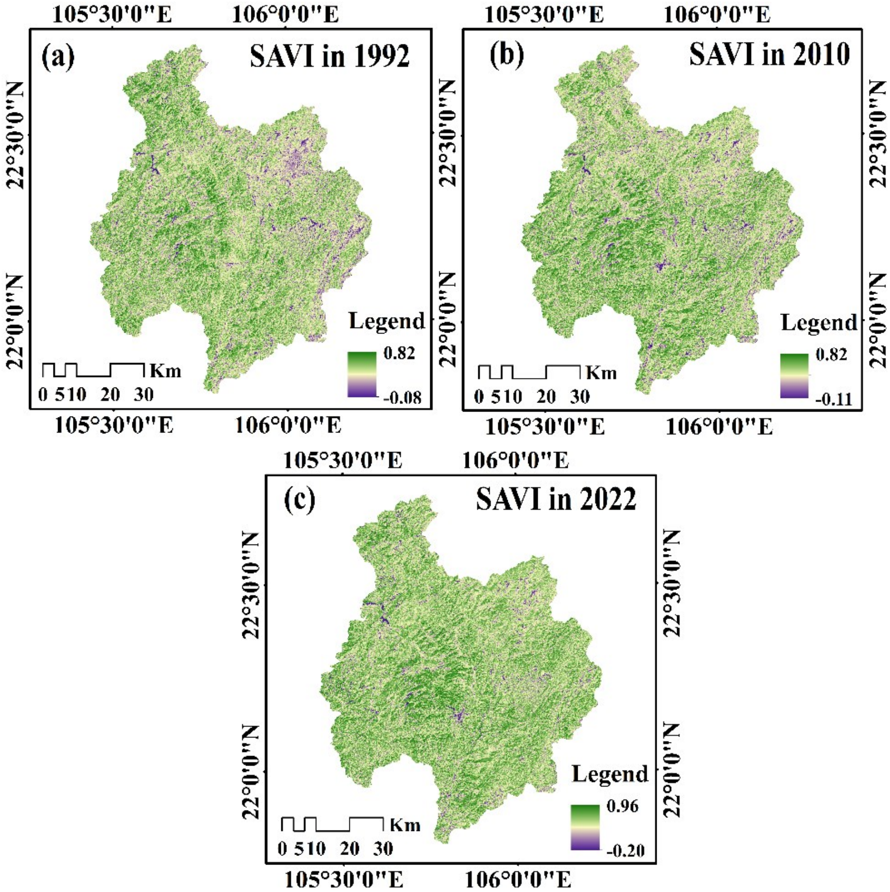

Figure 6. Spatial distribution of SAVI for 1992 (a), 2010 (b), and 2022 (c).

Source: The authors, 2023.

Table 6 shows the forest-covered areas between 1992 and 2022, as determined by these vegetation indices. The year-on-year changes during the study period are illustrated in Figure 7. The reclassification analysis of the NDVI index for each year, namely 1992, 2010, and 2022, yielded forest class areas of 4589.28 km^2, 4454.91 km^2, and 4136.85 km^2, respectively, which correspond to 94.44 %, 91.68 %, and 85.13 % (Table 6). Furthermore, the SAVI index-based forest classification results were comparable to those of the NDVI index, with 4513.98 km^2 (92.89 %) in 1992, 4272.56 km^2 (87.92 %) in 2010, and 3991.62 km^2 (82.14 %) in 2022 (Table 6).

Table 6. Forest cover area analyzed by vegetation indices (NDVI and SAVI) from 1992 to 2022.

Category		Distribution in 1992		Distribution in 2010		Distribution in 2022	
		Area (km^2)	(%)	Area (km^2)	(%)	Area (km^2)	(%)
NDVI	Forest	4589.28	94.44	4454.91	91.68	4136.85	85.13
	Other	270.12	5.56	404.49	8.32	722.55	14.87
	Total	4859.40	100.00	4859.40	100.00	4859.40	100.00
SAVI	Forest	4513.98	92.89	4272.56	87.92	3991.62	82.14
	Other	345.42	7.11	586.84	12.08	867.78	17.86
	Total	4859.40	100.00	4859.40	100.00	4859.40	100.00

Source: The authors, 2023.

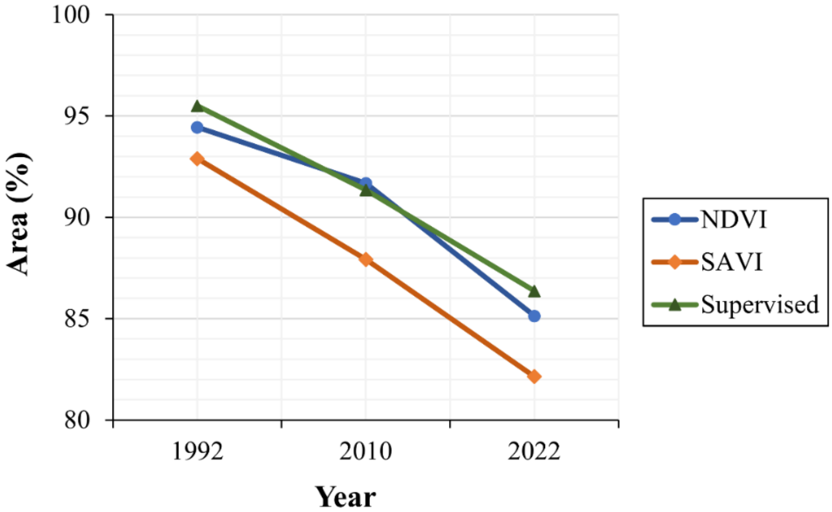

Figure 7. Comparison of forest cover from 1992 to 2022 through NDVI, SAVI, and supervised classification.

Source: The authors, 2023.

These findings demonstrate that NDVI and SAVI are effective indicators for detecting and monitoring FC in Bac Kan province, particularly for a rapid evaluation of FC. The increase in NDVI (0.64 > 0.54) and SAVI (0.96 > 0.82) from 2010 to 2022 indicates a significant improvement in forest quality in the study area. However, it is necessary to conduct additional validation of these indicators to determine the accuracy of their FC assessments, as shown in Figure 7 and Table 6. A comparative assessment of forest area estimates from both indices with the results of the supervised classification revealed similar trends, but the SAVI estimate was relatively lower than that of the monitored classification in all three years (1992, 2010, and 2022). These estimated discrepancies may be attributed to the sensitivity of vegetation indices to soil reflections, soil surface, atmosphere, and cloud shadows, which require calibration of RS techniques (Huete 1988, Pasternak & Pawluszek-Filipiak 2022; Thien & Phuong 2023).

4. Conclusion

This research utilized geospatial techniques to examine spatial and temporal alterations in FC in Bac Kan province, using Landsat 5-TM and Landsat 9-OLI/TIRS images. Our investigation indicated a significant decline in FC, amounting to 443.99 km^2 (9.14 %) over the 30-year period of study. In contrast, agricultural land area increased from 70.97 km^2 (1.46 %) in 1992 to 271.24 km^2 (5.58 %) and 575.24 km^2 (11.84 %) in 2010 and 2022, respectively. Our findings suggest that agricultural growth and timber, charcoal, and fuelwood production are the primary drivers of FC loss in Bac Kan province. Based on our analysis using the NDVI and SAVI indices, we have identified significant changes in the FC characteristics of Bac Kan province from 1992 to 2022.

These findings suggest the need for policymakers and decision-makers to take more proactive measures to protect and promote sustainable development of the province's forests. Specifically, we urge the forest department to hire more personnel to enhance forest monitoring and protection against unauthorized logging to avoid further forest depletion. Moreover, the results of our study offer significant contributions to future research endeavors focused on examining LULC changes in the region. Additionally, these findings could be useful for policymakers and decision-makers as they work to address the pressing issue of deforestation and develop effective strategies to safeguard and foster the sustainable development of forests.

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