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USING LANDSAT SATELLITE IMAGES TO DETECT FOREST COVER CHANGES IN THE NORTHEAST REGION OF VIETNAM

Vu T. PHUONG[1,2] Bui B. THIEN[3,4]

Abstract: *Globally and in Vietnam, forests are crucial resources for economic activity and for the survival of flora and fauna. However, deforestation in tropical regions continues to have negative effects on ecosystem services, climate regulation, and biodiversity protection. This study used Landsat 5-TM and Landsat 9-OLI/TIRS satellite imagery to investigate the changes in forest cover in Tuyen Quang province, located in the Northeast region of Vietnam, from 1992 to 2022. The maximum likelihood algorithm was employed to classify the forests in 1992, 2010, and 2022, with classification accuracy evaluated using the kappa coefficient for each year (0.890, 0.897, and 0.937, respectively). Additionally, the Normalized Difference Vegetation Index (NDVI) and the Soil Adjusted Vegetation Index (SAVI) were used to assess forest cover losses and gains, and their outcomes were compared with the results of the supervised classification. The findings indicated a significant decline in forest cover in Tuyen Quang province over the years. In 1992, the forest cover was estimated at 89.63% (5,259.33 km*^{2}*) of the total land area, which decreased to 68.14% (3,998.61 km*^{2}*) in 2010, and subsequently increased to 75.14% (4,409.09 km*^{2}*) in 2022. The conversion of forested areas for agriculture often leads to a substantial reduction in forest coverage. Furthermore, logging and illegal land use conversion have significantly contributed to this problem. Although appropriate policies for forest management and conservation have been implemented in the research area from 2010 to 2022, a long-term plan is necessary to ensure sustainable land use and effective forest resource conservation and development in the future.*

Key words: *Deforestation; NDVI; remote sensing; GIS; Northeast Vietnam.*

[1] Faculty of Social Sciences, Hong Duc University, Thanh Hoa, Vietnam;
[2] Innovation Startup Support Center, Hong Duc University, Thanh Hoa, Vietnam;
[3] Southern Federal University, Rostov-on-Don, 344006, Russian Federation;
[4] Faculty of Social Sciences, National University of Laos, Vientiane, Laos;
Correspondence: Bui B. Thien; email: buibaothienha@gmail.com.

1. Introduction

The ecological and economic benefits of forests include the provision of clean air and water, the preservation of soil, the regulation of the climate, and the provision of timber, food, and shelter for animals. Forest cover changes are a dynamic and extensive process that is primarily driven by anthropogenic activities and natural events, which generate changes that have significant impacts on natural ecosystems [2], [5]. Rapid and extensive deforestation in recent decades has led to high interest in the sustainable management of forest resources on a global scale. To effectively manage forests and make better decisions, it is crucial to comprehend their patterns, changes, and interactions with human activity and natural phenomena [18], [20].

Research aimed at detecting changes in forest cover can now benefit greatly from satellite data. Accurate knowledge about forest ecosystem functions can be obtained by detecting forest conditions and monitoring changes in various structural and physiological factors [9], [12]. Earth observation satellite data and decision support tools such as Geographic Information Systems (GIS) can be used to address this issue due to the development of technology and almost limitless potential in various application domains. Among these, Landsat imagery is regarded highly by the scientific community and provides a suitable average accuracy for analyzing land use and land cover (LULC) in research studies [3], [31, 32], [35]. With the aid of remote sensing and GIS, maps of land cover for multiple years are needed to identify changes over time, and the analysis results help managers understand the changes that are occurring and gain deeper insights into how human behavior and climate change affect development patterns. Understanding natural climate trends and seasonal landscapes over time helps us evaluate current actions and policies, as well as predict and plan for appropriate changes in the future [23]. Analysis of the Normalized Difference Vegetation Index (NDVI) is performed by calculations based on the red and near-infrared spectral band of multispectral satellite images used to assess and monitor plant health [15], [27]. The Soil Adjusted Vegetation Index (SAVI) is used at the regional scale in semi-arid areas because it allows for the detection of changes in plant communities over many years [16], [19].

The Northeast region now has some of the largest forests in Vietnam. By 2020, the total forest area in the Northeast region of Vietnam was 39,492.49 km^2, with a coverage of 56.30% [12]. This study's primary goal was to employ remote sensing and GIS applications to assess the degree of changes in forest cover that happened in Tuyen Quang province, in Northeast Vietnam, over the last 30 years (1992-2022). However, the specific objectives included: (1) using satellite images to identify and create a model of LULC and forest cover change in Tuyen Quang province; (2) looking into the specific variation in forest cover and other major cover types through spatial and temporal analysis; and (3) connecting vegetation indices with changes in forest cover.

2. Materials and Methods
2.1. Study Area

Tuyen Quang is a mountainous province in the Northeast of Vietnam, about 165 km from the Hanoi capital (Figure 1). The province had a population of 801,668 in 2021, with a density of 137 people per km^2 over a total land area of 5,867.95 km^2 [34]. The study area has a wide variety of topography that covers deep valleys in high mountains; the dominant elevation of the province is in the range of 200 to 600 meters. Tuyen Quang's climate is divided into four distinct seasons: spring, summer, autumn, and winter, in which the winter is dry and cold and the summer is hot, humid, and rainy. The average annual rainfall is 1,650 mm; the average temperature is 23°C; and the average humidity is 85%. The province has a total forest area of approximately 4,486.80 km^2, which includes special-use forest land for protection and production. Over 4,224.00 km^2 of this area were covered by natural forests, while more than 1,407.00 km^2 of land was dedicated to forest plantations. With a forest cover rate of over 65%, Tuyen Quang is one of the provinces with the highest percentage of forest coverage in the country [13].

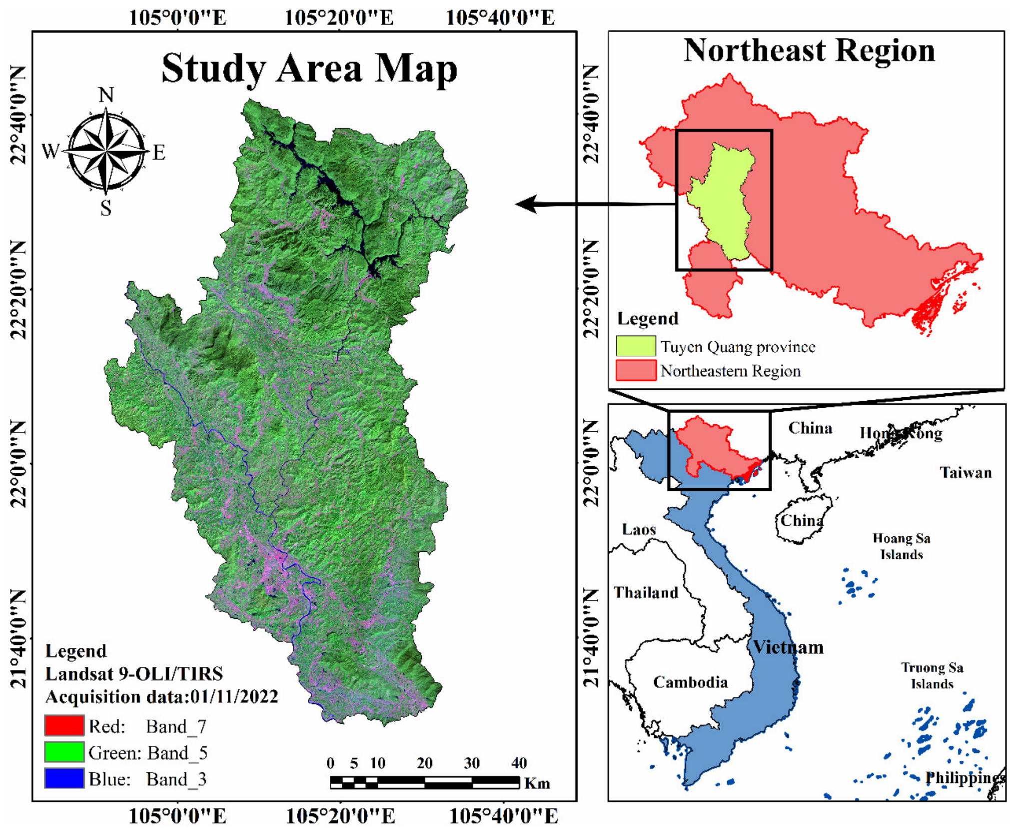

Fig. 1. *Map of the study area indicating Tuyen Quang province in Vietnam*

2.2. Data Used and Sources

Landsat satellite images in 1992, 2010, and 2022 were used to examine the dynamics of land cover and forest cover changes in Tuyen Quang province, Northeast region of Vietnam, in the last 30 years. These two periods correspond to changes related to policy changes, including land rights in Vietnam. We chose

1992 because the image is cloud-free and it marks the birth of a new forest law to replace the forest law in 1987. Subsequently, the Vietnamese government strengthened forest protection policies to ensure the sustainability of the country's valuable forest resources and began implementing reforestation and forest biodiversity conservation programs in 2010. By 2022, the Vietnamese government had implemented policy reforms related to forests, as well as programs to restore and protect forests. The availability of cloud-free images for the Tuyen Quang province was also considered. To cover the entire study area, six satellite images were acquired with a path/row of 127/44-45 for the selected years. The Landsat image dataset was downloaded from USGS Earth Explorer (https://earthexplorer.usgs.gov) and USGS Glovis (https://glovis.usgs.gov) (Table 1). The ground points of the Global Positioning System (GPS) with 300 points were collected in August 2022 to preserve the information regarding the land cover recorded during field surveys. To ensure precise classification and accuracy assessment, high-resolution real-time satellite data via Google Earth Pro and various composite combinations (false and true color) were utilized as the base map [19], [31].

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

Landsat Scene ID	Acquisition data	Satellite	Path/row	Resolution [m]	Source
LT51270441992295BJC02	21/10/1992	Landsat 5-TM	127/044	30	USGS Glovis
LT51270451992295BJC02		Landsat 5-TM	127/045	30	USGS Glovis
LT51270442010312BKT00	08/11/2010	Landsat 5-TM	127/044	30	USGS Glovis
LT51270452010312BKT00		Landsat 5-TM	127/045	30	USGS Glovis
LC91270442022305LGN00	01/11/2022	Landsat 9-OLI/TIRS	127/044	30	USGS EarthExplorer
LC91270452022305LGN00		Landsat 9-OLI/TIRS	127/045	30	USGS EarthExplorer

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 [1], 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 the Landsat satellite image classification, the five land-use classes identified in the study were Agriculture (land dedicated to cultivation of crops, mainly rice, maize, potatoes, and vegetables), Barren land (bare lands, rock-strewn, and other exposed soil surfaces that remain devoid of vegetation throughout the year), Forest (broadleaved, bamboo forest and mixed forest, either natural or planted are included in this class), Built-up areas (this class represents structures of all types including residential, commercial infrastructure, industrial zones, roads and other paved surfaces), and Waterbodies (this class is comprised of open water bodies such as lakes, rivers, ponds, streams). 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 [29].

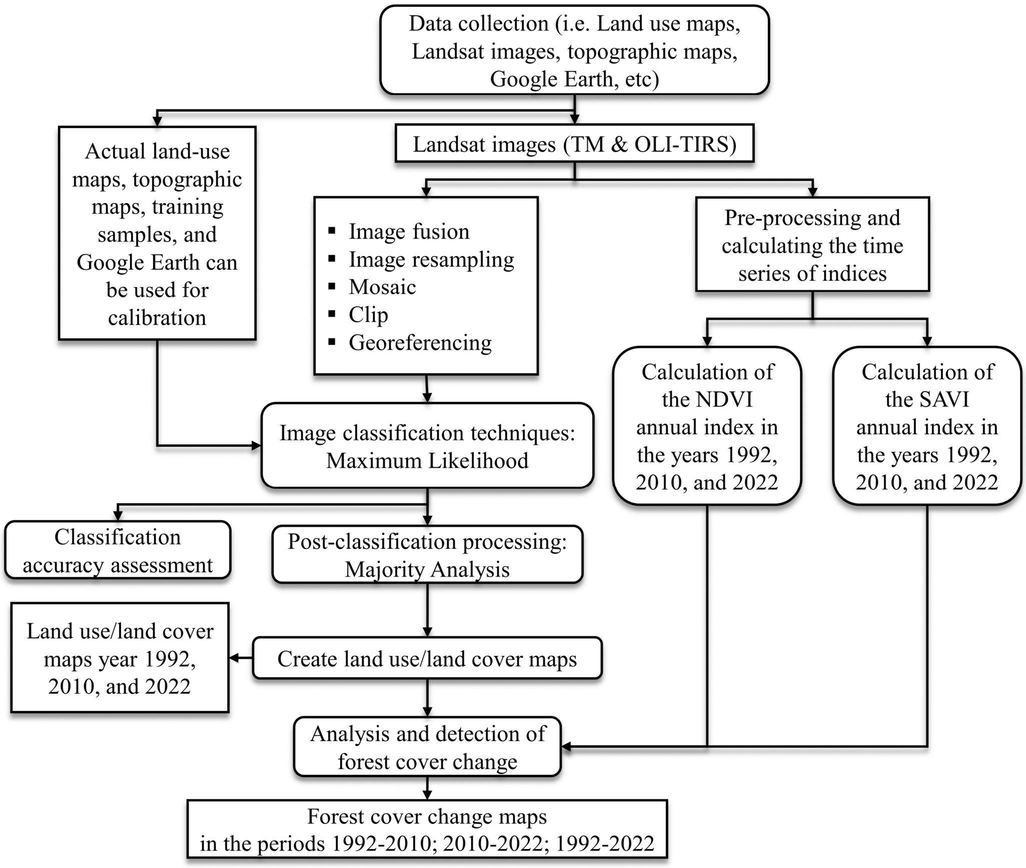

Fig. 2. *Overall process of forest cover change technique*

The preprocessing of the original satellite data involves a range of techniques, such as image enhancement, topographic corrections, noise removal, and geometric corrections [21]. 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 was utilized. To differentiate watersheds and assign signatures per pixel, all satellite data were analyzed. For each predefined LULC class (Table 2), 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 [29]. 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 [24, 31]. Post-classification refinement was applied to increase classification accuracy and reduce misclassifications [14]. The approved LULC categorization characteristics established class boundaries and consistent category definitions based on anthropogenic and natural factors changes within the study area. This categorization strategy is also size-independent, making it appropriate for use at any spatial scale or level of detail.

2.4. Analysis of Vegetation Indices to Detect Changes in Forest Cover

As part of the study and detection of forest cover, several vegetation indicators have been established to assess vegetation in forests [4, 15, 16, 17, 19, 27]. In this study, NDVI is frequently used to assess vegetation health and has been demonstrated to be a reliable indication of plant greenness. SAVI is frequently employed in dry and semi-arid locations to help mitigate the impact of soil reflectance. In this instance, we used the maximum and minimum NDVI and SAVI values to reclassify the classification table in order to map the forest land cover area for all other time periods. We did this by extracting the NDVI and SAVI values from every forest polygon that we had identified through the supervised classification of the Landsat 5-TM (1992 and 2010) and Landsat 9-OLI/TIRS (2022) images. NDVI and SAVI were calculated using equations (1) and (2), respectively, given below:

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

$$\mathrm{SAVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED} + \mathrm{L}} \cdot 1 + \mathrm{L} \tag{2}$$

where: *NIR* is the reflectance value of the near infrared band; *RED* is the reflectance of the red band, and *L* correction factor adjusts the original equation of *NDVI* to correct the soil brightness.

The appropriate L value varies based on the presence of vegetation, ranging from very high (L = 0) to no vegetation (L = 1), but in most cases, L = 0.5 is ideal as it minimizes soil brightness variations and eliminates the need for additional calibration for different soils [16]. We adopted L = 0.5 to generate our SAVI images used to edge detection and extract stats for detected circles.

2.5. Classification Accuracy Assessment

The classification accuracy of the Landsat 5-TM (1992 and 2010) and Landsat 9-OLI/TIRS (2022) images was evaluated using user accuracy, producer accuracy, overall accuracy, and kappa coefficient. With the support of the stratified random sampling technique, we selected 300 random points from each classified image of 1992, 2010, and 2022 and compared their digital values with the corresponding pixels of the original image in Google Earth Pro as reference data. These points, representing all LULC categories within the study area, were identified and placed on the Google Earth Pro maps using ground truth data and topographic maps. Creating an error matrix for each LULC map allowed us to assess overall accuracy [26]. The equations for user accuracy, producer accuracy, overall accuracy, and kappa coefficient, expressed in equations (3), (4), (5), and (6), respectively, are some of the best quantitative measures for satellite image classification [11, 25, 28].

$$\text{User Accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of reference pixels in each category (row total)}} \cdot 100 \quad (3)$$

$$\text{Producer Accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of reference pixels in each category (column total)}} \cdot 100 \quad (4)$$

$$\text{Overall Accuracy} = \frac{\text{Number of correct pixels}}{\text{Total number of pixels}} \cdot 100 \quad (5)$$

$$\text{Kappa coefficient (K)} = \frac{P_o - P_e}{1 - P_e} \quad (6)$$

where: *Po* is the proportion of pixels classified correctly, and *Pe* is the proportion of pixels classified correctly expected by chance.

3. Results and Discussion

3.1. Classification and Accuracy Assessment

The accuracy and validation of classification models are important prerequisites in studies of land cover and land use change for classification, detection, and prediction purposes. The high user and producer accuracies (mostly ranging from 80-100%) and the nearly perfect number of corrected pixels for land cover maps in all the years indicate the effectiveness and reliability of the land cover classification and resulting products [30]. The Kappa coefficients indicate the measure of agreement or accuracy between the reference data and the land use and land cover values classified in the image, and can range from +1 to −1 [11, 25]. Kappa values of <0 reflect no agreement, 0-0.2 as slight, 0.2-0.41 as fair, 0.41-0.60 as moderate, 0.60-0.80 as substantial and 0.81–1.0 as almost perfect agreement [11]. The overall Kappa coefficient values were 0.890, 0.897, and 0.937 for 1992, 2010, and 2022, respectively (Table 2). Furthermore, the overall classification accuracy values for this study for 1992, 2010, and 2022 were 93.51%, 92.67%, and 95.67%, respectively (Table 2). The overall accuracy results indicate that the percentage of accuracy in all the years is much higher than 90%, representing an excellent agreement for LULC classification [6, 8].

The LULC classification maps were estimated from Landsat satellite images using the Maximum Likelihood algorithm for the years 1992 (Figure 3a), 2010 (Figure 3b), and 2022 (Figure 3c), as shown in Figure 3. The distribution of LULC classes by category from 1992 to

2022 is shown in Table 3 to help comprehend the amount of LULC changes. The findings demonstrate that the coverage of the agriculture and forest areas underwent considerable changes. The agriculture coverage was 421.49 km^2 (7.18%) in 1992, which was increased significantly by 1,129.14 km^2 (19.24%) in 2022, with 12.06%. Meanwhile, in 1992 forest coverage was 5259.33 km^2 (89.63%), which decreased to 4,409.09 km^2 (75.14%) in 2022, resulting in a decrease of 14.49% (Table 3). From 1992 to 2022, there were noticeable changes in the area coverage of barren land, built-up areas, and waterbodies. Barren land coverage, which was 149.98 km^2 (2.56%) in 1992, was reduced to 2.65 km^2 (0.05%) in 2022, resulting in a change of 2.51%. In 1992, the built-up areas class covered 5.92 km^2 (0.10%) of area and was increased by 227.39 km^2 (3.88%) in 2022, leading to a 3.77% positive change. Waterbodies coverage was 31.23 km^2 (0.53%) in 1992 and increased to 99.68 km^2 (1.70%) in 2022, a net increase of 1.17% (Table 3).

Table 2

Accuracy assessments for 1992, 2010 and 2022

Land cover class	1992		2010		2022	
	Producer accuracy [%]	User accuracy [%]	Producer accuracy [%]	User accuracy [%]	Producer accuracy [%]	User accuracy [%]
Agricultural	90.77	89.39	90.63	89.23	90.28	95.59
Barren land	83.33	88.24	79.17	82.61	87.50	87.50
Forest	95.65	97.24	94.93	97.04	97.89	97.20
Built-up areas	95.00	90.48	94.12	91.43	100.00	91.89
Waterbodies	90.48	82.61	95.00	90.48	95.45	95.45
Overall accuracy	93.51		92.67		95.67	
Kappa Coefficient	0.890		0.897		0.937	

Table 3

Land use/land cover classification and change results from 1992 to 2022

Class	1992		2010		2022		Area change 1992-2022	
	Area [km^2]	%	Area [km^2]	%	Area [km^2]	%	Area [km^2]	%
Agricultural	421.49	7.18	1622.82	27.66	1129.14	19.24	707.65	12.06
Barren land	149.98	2.56	149.17	2.54	2.65	0.05	-147.33	-2.51
Forest	5,259.33	89.63	3,998.61	68.14	4,409.09	75.14	-850.24	-14.49
Built-up areas	5.92	0.10	28.75	0.49	227.39	3.88	221.47	3.77
Waterbodies	31.23	0.53	68.60	1.17	99.68	1.70	68.45	1.17
Total	5,867.95	100.00	5,867.95	100.00	5,867.95	100.00		

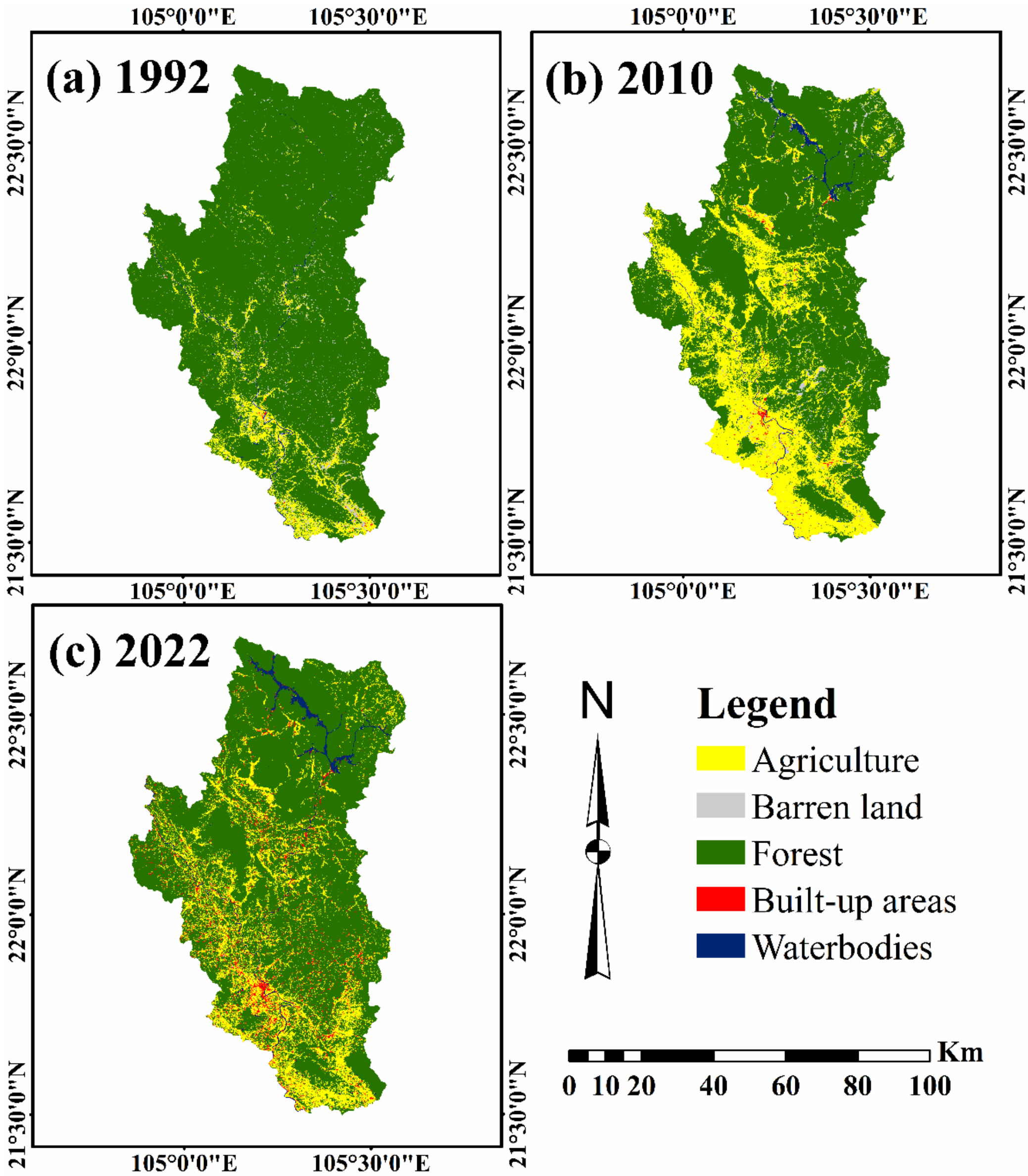

Fig. 3. *Land use/land cover of Tuyen Quang province in: a. 1992; b. 2010; c. 2022*

The classification results presented in Table 3 indicate an unprecedented increase in agricultural land cover, while forest cover in Tuyen Quang province has significantly decreased by 850.24 km^2 and 14.49% from 1992 to 2022. The reduction in forest cover is a concerning issue as it not only affects the environment and biodiversity but also has negative impacts on local communities and the economy. Forest land conversion for agricultural use has resulted in a depletion of forest resources, causing ecosystem degradation and reducing forest resilience to climate challenges. Legal and illegal logging also contributes to forest loss, destroying forests and hindering their ability to recover [7, 10]. Additionally, forest land conversion for development projects such as infrastructure and hydropower plants has resulted in the loss of valuable forest land. In the period from 2010 to 2022, forest cover increased due to effective law enforcement and forest management in the region. However, the increase in forest cover during this period is still small compared to the forest loss that occurred from 1992 to 2010. To address this issue, there is a need for close collaboration among government agencies, as well as raising community awareness of the importance of forest protection and development [7, 19].

3.2. Relationship between Vegetation Indices and Decadal Forest Cover Changes

In order to detect and map vegetation, the two most extensively used vegetation indices are NDVI and SAVI [22, 27, 30, 33]. Figures 4 and 5, respectively display maps of the NDVI and SAVI values in Tuyen Quang province from 1992 to 2022. Throughout this procedure, we examined all of the NDVI and SAVI pixel values from our graded image from 2022 and discovered that the NDVI values larger than 0.32 and the SAVI values greater than 0.48 are all associated with the forest polygons. All other classified pictures for 1992 and 2010 were reclassified as forest and non-forest based on these NDVI and SAVI values. The area covered by forest from 1992 to 2022 according to the vegetation indices is presented in Table 4.

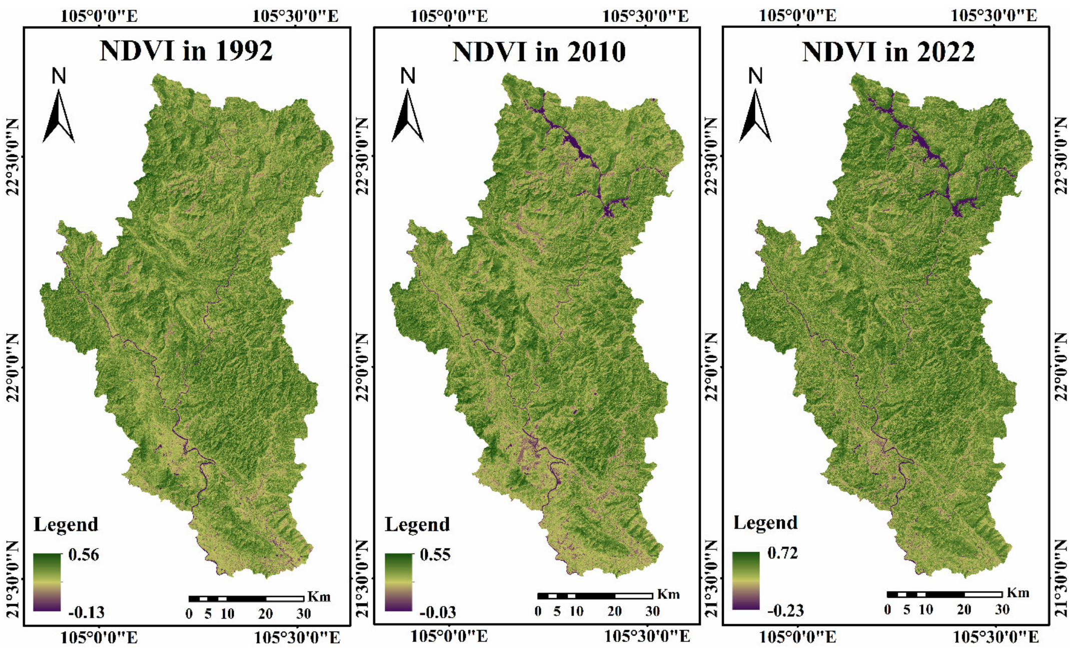

Fig. 4. *Spatial distribution of NDVI for 1992, 2010 and 2022*

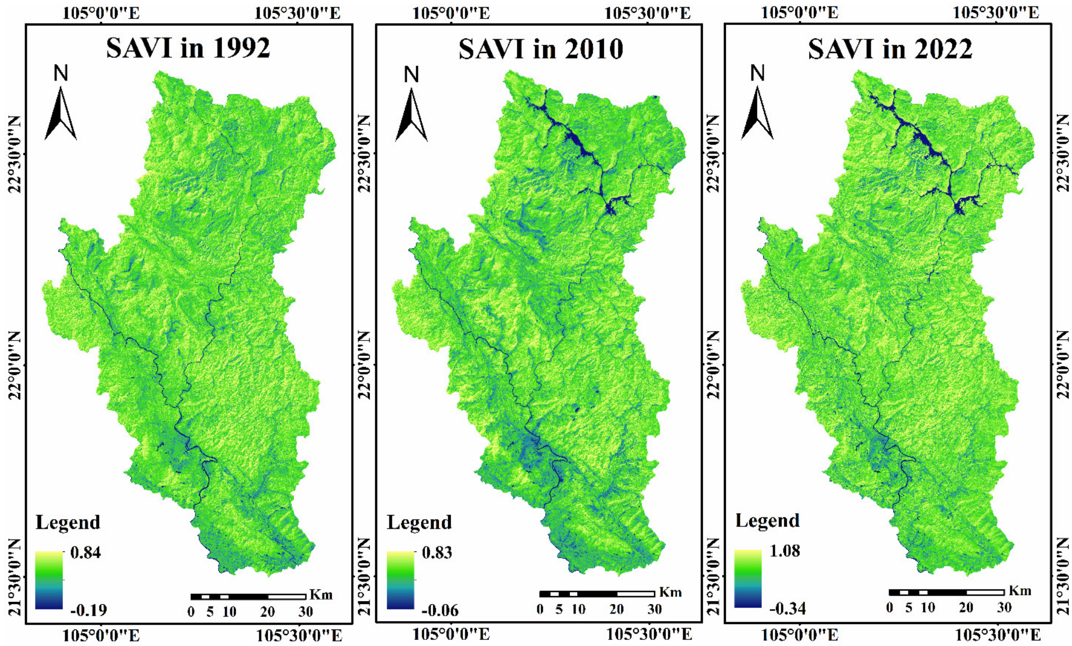

Fig. 5. *Spatial distribution of SAVI for 1992, 2010 and 2022*

The forest area estimated using NDVI shows a negative trend in the first period (1992–2010) and a positive trend in the later period (2010–2022), an estimate that is similar to, but slightly higher in 1992 and 2022, and slightly lower in 2010 than the estimates obtained using supervised classification. While SAVI provides similar estimates for 2010 and 2022, it yields much lower estimates for 1992 (Table 4). Given that SAVI disregards soil reflectance, this may be due to the scanty vegetation of 1992 rather than the lush forest of 1992. These results suggest that NDVI is an effective indicator to identify and track the presence of forest cover in Tuyen Quang province, particularly in the context of rapid forest cover assessments [10, 15, 30].

Table 4

Based 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	5,318.32	90.63	3,721.54	63.42	4,489.92	76.52
	Other	549.63	9.37	2,146.41	36.58	1,378.03	23.48
	Total	5,867.95	100.00	5,867.95	100.00	5,867.95	100.00
SAVI	Forest	4,523.28	77.08	3,798.71	64.74	4,245.23	72.35
	Other	1,344.67	22.92	2,069.24	35.26	1,622.72	27.65
	Total	5,867.95	100.00	5,867.95	100.00	5,867.95	100.00

3.3. Forest Cover Changes from 1992 to 2022

With a particular emphasis on persistence and swaps, forest cover patterns can be summarized in terms of net change, gross gains, and losses (Table 5). A survey of forest-cover changes showed that, from a total of 5,259.33 km^2 of forest cover in 1989, 75.06% existed until the end of the period 1992–2010. In the next period (2010–2022), from the total of 3,998.61 km^2 of forest that existed in 2010, 92.70% existed in 2022 (Table 5). The remaining forest was converted to non-forest use.

The model showing the gain, loss, and persistence of forest cover in the study area in each period is shown in Figure 6. The first period observed an increase in total forest area of only 44.82 km^2, while the second period saw a more significant increase of 696.12 km^2. The total gross gain in the forest class comes with the total loss of the other layers; thus, the total gross gain is equivalent to the total loss in the landscape. In our study, most of the forest cover was lost to the remaining LULC, mainly the agricultural land class. The conversion of forest land to high-quality agricultural land is an indication that the community in this area depends on agriculture as its main livelihood. In contrast, gross gains came mostly from barren and agricultural land in both periods, with the most in the second period. More forests were lost during the period 1992–2010 than during the period 2010–2022, which saw the least deforestation (Table 5). Forest cover decreased by 1,260.60 km^2 in the first period and increased in the second period by 410.41 km^2. In terms of annual variation, the annual change in forest cover in the first period was 79.43 km^2 and in the second period, it decreased to 65.46 km^2 (Table 5).

Table 5

Summary of forest cover change in Tuyen Quang province between 1992 and 2022

Forest Cover	Period					
	1992-2010		2010-2022		1992-2022	
	Area [km^2]	[%]	Area [km^2]	[%]	Area [km^2]	[%]
Initial Year	5,259.33		3,998.61		5,259.33	
Final Year	3,998.61		4,409.09		4,409.09	
Persistence	3,947.88	75.06	3,706.90	92.70	4,295.50	81.67
Loss	1,305.42	24.82	285.71	7.15	957.76	18.21
Gain	44.82	0.85	696.12	17.41	107.58	2.05
Annual Loss	76.79		19.05		29.93	
Annual Gain	2.64		46.41		3.36	
Annual Change	79.43		65.46		33.29	
Swap	2,610.84	49.64	571.42	14.29	1,915.52	36.42
Net Change	-1,260.60	-23.97	410.41	10.26	-850.18	-16.17

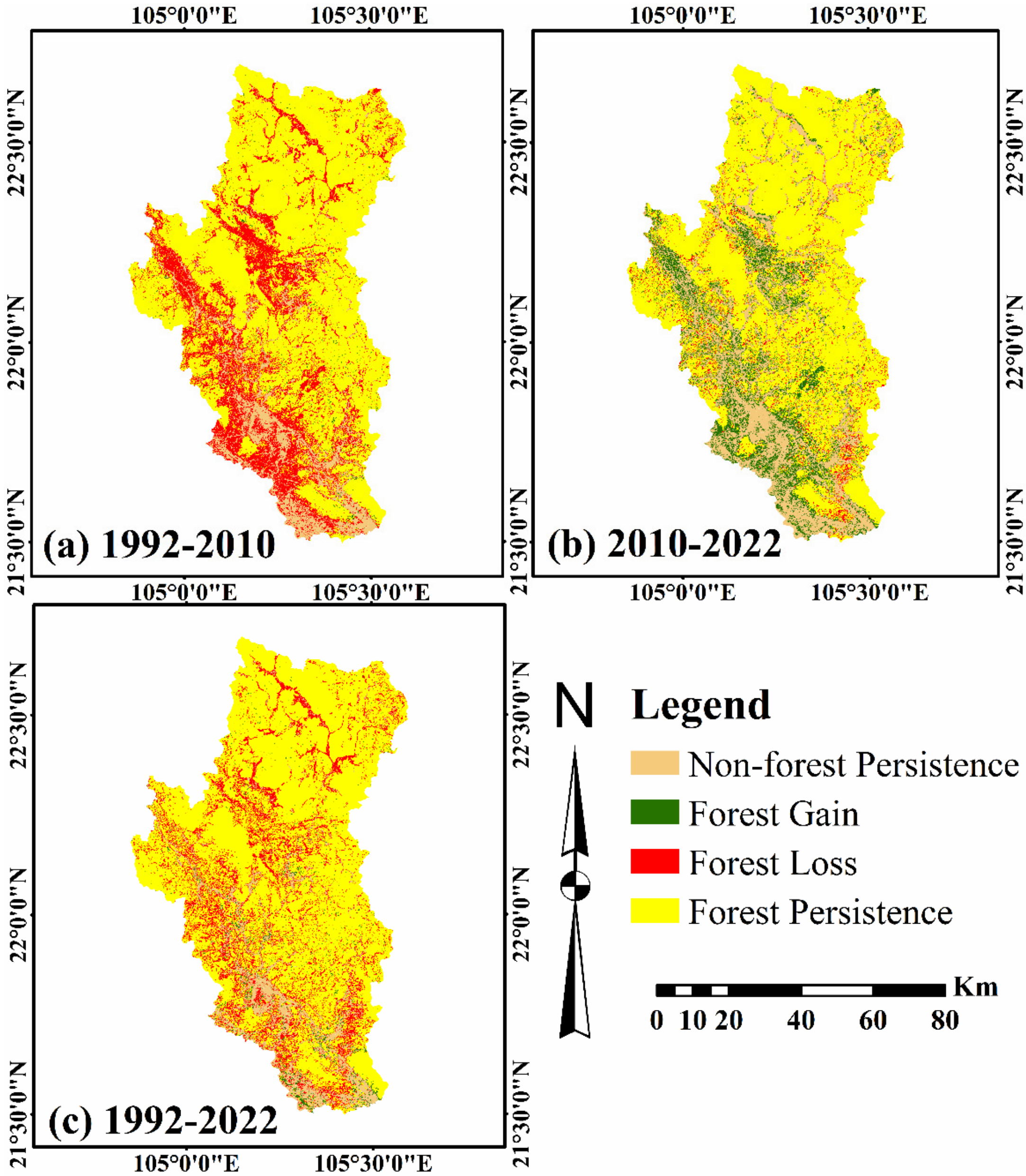

Fig. 6. *Forest cover changes in Tuyen Quang province during: a. 1992-2010; b. 2010-2022; c.1992-2022*

The forest area in Tuyen Quang province experienced a sharp decline between 1992 and 2010 due to various reasons. One of the main reasons was the conversion of forest land to agricultural land for crop production to meet the demands of agricultural production in the region. Legal and illegal logging also contributed to the reduction of forest area, leading to the destruction of forested areas that are difficult to restore [7]. The conversion of forest land for infrastructure development and hydropower plants also resulted in the loss of valuable forest areas [31]. Additionally, during this period, forest management policies and solutions were not implemented effectively. The monitoring and control of logging activities were inadequate, resulting in widespread illegal logging. Policies to support forest protection and sustainable agricultural development were also ineffective, leading to a lack of consistency and suitability with the realities of the region [19], [30].

However, between 2010 and 2022, the forest area in Tuyen Quang province increased due to the effective implementation of law enforcement and forest management in the region. The Vietnamese government implemented a range of policies and solutions for forest protection during this period, including strengthening the monitoring and control of logging activities, focusing on sustainable agricultural development and forest protection, as well as promoting forest restoration projects. These policies helped to increase the forest area during this period [2], [20]. Furthermore, during this period, the community increased their awareness of forest and environmental protection, and actively participated in forest protection activities. Many social organizations and local communities participated in forest protection activities and supported households indeveloping sustainable agriculture and changing their way of life to minimize their impact on the environment [5]. These efforts contributed significantly to the increase in forest area in Tuyen Quang province during this period.

4. Conclusion

The spatiotemporal changes of forest cover in Tuyen Quang province, Northeast region of Vietnam, were explored from 1992 to 2022 using remote sensing data and GIS. The Landsat images were processed and classified based on the maximum likelihood algorithm that creates an overall accuracy of over 90%, which is suitable for monitoring forest cover. Furthermore, the Vegetation Index (NDVI and SAVI) was used in the study to aid in the rapid assessment of the condition of the forest cover. Overall, between 1992 and 2022, agricultural land, built-up areas, and waterbodies increased, while forest cover and barren land decreased. The results show that the forest cover changed drastically in the study region between 1992 and 2022, with the total forest area reduced to 850.24 km^2, corresponding to 14.49%, especially in the period 1992–2010, during which 1,260.60 km^2 of forest was cleared. Although forest cover increased to 410.41 km^2 from 2010 to 2022, the increased area is too small compared with the lost forest area; thus, the forest cover over this 30-year period has overall been reduced.

The following recommendations are based on our study: (1) Policy makers and decision makers should review legal and illegal logging, as well as national development projects such as the construction of infrastructure and hydroelectric power plants, because forest areas have decreased significantly over the years as a result of the conversion of forest land to agricultural land; (2) Relevant agencies require more staff to monitor and protect forests from illegal logging. The conservation of forest areas in the study region also necessitates the strict enforcement of rules and regulations.

The results of this study will be helpful to future researchers and conservationists in continuing their work, as well as to decision makers in taking into account the tendencies of this severe forest loss when formulating future policies to conserve forest cover in this study area.

References

1. Anderson, J.R., Hardy, E.E., Roach, J.T. et al., 1976. A land use and land cover classification system for use with remote sensor data. In: Geological Survey Professional Paper, U.S. government printing office. Washington DC, vol. 964, pp. 1-28.
2. Atmiş, E., Özden, S., Lise, W., 2007. Urbanization pressures on the natural forests in Turkey: An overview. In: Urban Forestry and Urban Greening, vol. 6(2), pp. 83-92. DOI: 10.1016/j.ufug.2007.01.002.
3. Bakr, N., Weindorf, D.C., Bahnassy, M.H. et al., 2010. Monitoring land cover changes in a newly reclaimed area of Egypt using multi-temporal Landsat data. In: Applied Geography, vol. 30(4), pp. 592-605. DOI: 10.1016/j.apgeog.2009.10.008.
4. Baloloy, A.B., Blanco, A.C., Ana, R.R.C.S. et al., 2020. Development and application of a new mangrove vegetation index (MVI) for rapid and accurate mangrove mapping. In: ISPRS Journal of Photogrammetry and Remote Sensing, vol. 166, pp. 95-117. DOI: 10.1016/j.isprsjprs.2020.06.001.
5. Biswas, P.K., 2003. Forest, people and livelihoods: The need for participatory management. In: In Quebec City, Canada: XII World Forestry Congress, ID article 0586-C1.
6. Congalton, R.G., Green, K., 2019. Assessing the accuracy of remotely sensed data: principles and practices. In: CRC Press, Taylor and Francis Group. DOI: 10.1201/9780429052729.
7. Dan, K.O., David, P.K., Pierre, N.L.J. et al., 2018. Analysis of the Causes of Deforestation and Degradation of the Forest of Katako Village. In: Elixir Environment and Forestry, vol. 123, pp. 51945-51948.
8. Disperati, L., Virdis, S.G.P., 2015. Assessment of land-use and land-cover changes from 1965 to 2014 in Tam Giang-Cau Hai Lagoon, central Vietnam. In: Applied Geography, vol. 58, pp. 48-64. DOI: 10.1016/j.apgeog.2014.12.012.
9. El Jazouli, A., Barakat, A., Khellouk, R. et al., 2019. Remote sensing and GIS techniques for prediction of land use land cover change effects on soil erosion in the high basin of the Oum Er Rbia River (Morocco). In: Remote Sensing Applications: Society and Environment, vol. 13, pp. 361-374. DOI: 10.1016/j.rsase.2018.12.004.
10. Faruque, M.J., Vekerdy, Z., Hasan, M.Y. et al., 2022. Monitoring of land use and land cover changes by using remote sensing and GIS techniques at human-induced mangrove forests areas in Bangladesh. In: Remote Sensing Applications: Society and Environment, vol. 25, ID article 100699. DOI: 10.1016/ j.rsase. 2022.100699.
11. Foody, G.M., 2020. Explaining the unsuitability of the kappa coefficient in the assessment and comparison of

the accuracy of thematic maps obtained by image classification. In: Remote Sensing of Environment, vol. 239, ID article 111630. DOI: 10.1016/j.rse.2019.111630.
12. Fortin, J.A., Cardille, J.A., Perez, E., 2020. Multi-sensor detection of forest-cover change across 45 years in Mato Grosso, Brazil. In: Remote Sensing of Environment, vol. 238, ID article 111266. DOI: 10.1016/j.rse.2019.111266.
13. General Statistics Office. 2020. Statistical Yearbook of Viet Nam 2020. In: Statistical Publishing House. Available at: https://www.gso.gov.vn/wp-content/uploads/2021/07/Sach-NGTK-2020Ban-quyen.pdf. Accessed on: November 2022.
14. Harris, P.M., Ventura, S.J., 1995. The integration of geographic data with remotely sensed imagery to improve classification in an urban area. In: Photogrammetric Engineering and Remote Sensing, vol. 61(8), pp. 993-998.
15. Huang, S., Tang, L., Hupy, J.P. et al., 2021. A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. In: Journal of Forestry Research, vol. 32(1), pp. 1-6. DOI: 10.1007/s11676-020-01155-1.
16. Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI). In: Remote Sensing of Environment, vol. 25(3), pp. 295-309. DOI: 10.1016/0034-4257(88)90106-X.
17. Huete, A.R., 2012. Vegetation indices, remote sensing and forest monitoring. In: Geography Compass, vol. 6(9), pp. 513-532. DOI: 10.1111/j.1749-8198.2012.00507.x.
18. Hunter, Jr. M.L., 1990. Wildlife, forests, and forestry. Principles of managing forests for biological diversity. 2nd Edition. In: Prentice Hall, 288 p.
19. Islam, M.R., Khan, M.N.I., Khan, M.Z. et al., 2021. A three decade assessment of forest cover changes in Nijhum dwip national park using remote sensing and GIS. In: Environmental Challenges, vol. 4, ID article 100162. DOI: 10.1016/j.envc.2021.100162.
20. Jandl, R., Spathelf, P., Bolte, A. et al., 2019. Forest adaptation to climate change - is non-management an option? In: Annals of Forest Science, vol. 76(2), pp. 1-13. DOI: 10.1007/s13595-019-0827-x.
21. Jiang, H., Xu, X., Zhang, T. et al., 2022. The relative roles of climate variation and human activities in vegetation dynamics in coastal China from 2000 to 2019. In: Remote Sensing, vol. 14(10), ID article 2485. DOI: 10.3390/rs14102485
22. Liang, L., Chen, F., Shi, L. et al., 2018. NDVI-derived forest area change and its driving factors in China. In: PloS One, vol. 13(10), ID article e0205885. DOI: 10.1371/journal.pone.0205885.
23. Mubako, S., Belhaj, O., Heyman, J., et al., 2018. Monitoring of land use/land-cover changes in the arid transboundary middle Rio grande basin using remote sensing. In: Remote Sensing, vol. 10(12), ID article 2005. DOI: 10.3390/rs10122005.
24. Rawart, J.S., Kumar, M., 2015. Monitoring land use/cover change

using remote sensing and GIS techniques: A case of Hawallbagh block, district Almora, Utterkland, India. In: The Egyptian Journal of Remote Sensing and Space Science, vol. 18(1), pp. 77-84. DOI: 10.1016/j.ejrs.2015.02.002.

25. Rwanga, S.S., Ndambuki, J.M., 2017. Accuracy assessment of land use/land cover classification using remote sensing and GIS. In: International Journal of Geosciences, vol. 8(4), ID article 611. DOI: 10.4236/ijg.2017.84033.
26. Salem, M., Tsurusaki, N., Divigalpitiya, P., 2020. Remote sensing-based detection of agricultural land losses around Greater Cairo since the Egyptian revolution of 2011. In: Land Use Policy, vol. 97, ID article 104744. DOI: 10.1016/j.landusepol.2020.104744.
27. Spadoni, G.L., Cavalli, A., Congedo, L. et al., 2020. Analysis of Normalized Difference Vegetation Index (NDVI) multi-temporal series for the production of forest cartography. In: Remote Sensing Applications: Society and Environment, vol. 20, ID article 100419. DOI: 10.1016/ j.rsase.2020.100419.
28. Subedi, P.B., Mahara, S., Paudel, S. et al., 2022. Agroforestry potential of Kanchanpur District, Nepal using remote sensing and Geographic Information System. In: Asian Journal of Forestry, vol. 6(2), pp. 64-73. DOI: 10.13057/asianjfor/r060202.
29. Tadese, M., Kumar, L., Koech, R., et al., 2020. Mapping of land-use/land-cover changes and its dynamics in Awash River Basin using remote sensing and GIS. In: Remote Sensing Applications: Society and Environment, vol. 19, ID article 100352. DOI: 10.1016/j.rsase.2020.100352.
30. Thien, B.B., Phuong, V.T., 2023. Using Landsat satellite imagery for assessment and monitoring of long-term forest cover changes in Dak Nong province, Vietnam. In: Geographica Pannonica, vol. 27(1), pp. 69-82. DOI: 10.5937/gp27-41813.
31. Thien, B.B., Phuong, V.T., Huong, D.T., 2023. Detection and assessment of the spatio-temporal land use/cover change in the Thai Binh province of Vietnam's Red River delta using remote sensing and GIS. In: Modeling Earth Systems and Environment, vol. 9(2), pp. 2711-2722. DOI: 10.1007/s40808-022-01636-8.
32. Thien, B.B., Sosamphanh, B., Yachongtou, B. et al., 2022. Land use/land cover changes in the period of 2015–2020 in AngYai Village, Sikhottabong District, Vientiane Capital, Lao PDR. In: Geology, Geophysics and Environment, vol. 48(3), pp. 279-286. DOI: 10.7494/geol.2022.48.3.279.
33. Truong, N.C.Q., Nguyen, H.Q., Kondoh, A., 2018. Land use and land cover changes and their effect on the flow regime in the upstream Dong Nai River Basin, Vietnam. In: Water, vol. 10(9), ID article 1206. DOI: 10.3390/w10091206.
34. Tuyen Quang Statistics Office. 2022. Tuyen Quang statistical yearbook 2021 (552 pages). In: Statistics Publishing House. Available at: https://thongketuyenquang.gso.gov.v

n/Upload/DieutraTK/24.Sach%20NGTK%20tuyen%20Quang%202021%20(1).pdf. Accessed on: November 2022.

35. Yang, Q., Zhang, H., Peng, W. et al., 2019. Assessing climate impact on forest cover in areas undergoing substantial land cover change using Landsat imagery. In: Science of the Total Environment, vol. 659, pp. 732-745. DOI: 10.1016/j.scitotenv.2018.12.290.