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A multi-temporal Landsat data analysis for land-use/land-cover change in the Northwest mountains region of Vietnam using remote sensing techniques

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Abstract

Land-use change is one of the challenges that exacerbate environmental problems. Understanding the scope of land-use and land-cover change, past and present drivers and consequences is crucial for properly managing land resources. This study applies the supervised classification maximum likelihood algorithm in ArcGIS 10.8 software to detect changes in land use and cover in Hoa Binh city, Hoa Binh province, Vietnam using multimedia satellite data obtained from Landsat 7-ETM+, Landsat 5-TM and Landsat 8-OLI for the years 2000, 2010 and 2020 respectively. In addition, for each satellite scene we also applied spectral indices (NDVI-Normalized Differential Vegetation Index and NDWI-Normalized Differential Water Index) to classify and evaluate the change of LULC. The study area, located in the Northwest mountainous region of Vietnam, is classified into five land-use/cover classes: Agriculture, Forest, Water, Urban or built-up land and Bare soil or rock. The results reveal significant changes in the study area between 2000 and 2020. Accounting for the largest proportion of total area, the forest area has decreased from 243.20 km^2 in 2000 to 217.40 km^2 in 2020. Conversely, the urban/built-up land area has increased continuously for the last 20 years, from 9.31 km^2 in 2000 to 13.27 km^2 in 2010 and 51.80 km^2 in 2020. Changes in land use and cover have severe environmental impacts, such as climate change, loss of biodiversity, deterioration of water availability and quality, and reduced crop yields. Therefore, appropriate measures must be taken to limit drastic land-use changes and harmonize environmental conservation and human livelihoods.
Keywords: *Land use/cover change, Remote Sensing, GIS, Northwest Vietnam, Hoa Binh city*

Introduction

Land is an essential natural resource with numerous economic, social and ecological uses. A change in land use denotes the conversion of an area of land for a specified purpose and is caused by anthropogenic activities, while a change in land cover describes alterations in the characteristics of the land surface (Patel et al., 2019). Changes in land use/land cover (LULC) on the earth's surface are significant drivers of biodiversity loss and environmental problems worldwide (Homer et al., 2020; Field & Barros, 2014). LULC also impacts climate variability (Pielke Sr, 2005; Deng et al., 2013), land degradation (Meaza et al., 2016) and hydrology (Garg et al., 2019), affecting the capacity of ecosystem services (Arowolo et al., 2018; Rimal et al., 2019). Driven by changes in LULC, continuous environmental changes and their associated adverse impacts are becoming central issues globally (Li et al., 2020). Consequently, studying LULC dynamics is fundamental for the proper planning and use of natural resources as well as their management (Ahmad, 2012; Kotoky et al., 2012; Fonji & Taff, 2014; Rawat & Kumar, 2015; Belete et al., 2021; Thien et al., 2022a).

Remote Sensing (RS) and Geographic Information Systems (GIS) are effective tools to promote transboundary studies and explore transboundary data opportunities. Using overlays, they permit the detection and analysis of LULC variations over a given period to improve the selection of sites for agricultural, urban or industrial development (Selçuk et al., 2003; Dewan & Corner, 2013; Thien et al., 2022b). Remote sensor data allows for studying land cover changes in less time, with lower costs and higher accuracy (Kachhwala, 1985). Combined with GIS, RS provides a suitable platform for data analysis, updating and retrieval (Cihlar, 2000). Consequently, RS and GIS help stakeholders map where changes are occurring and gain insight into how development patterns are affected by human actions and climate change. Natural climates and seasonal landscapes can vary over time; hence, evaluating current actions and policies while anticipating and planning for appropriate changes in the future is critical (Mubako et al., 2018).

The study area is located in the Northwest mountainous region of North Vietnam, sharing the border with Laos and China. The terrain in this area is rugged, with numerous block-fault mountains and high mountain ranges running in the northwest-southeast direction. The highest peaks range from 2,800 to 3,000 m in altitude. The Northwest has a total area of 50,728 km^2, accounting for 15% of Vietnam's land area. However, the land area used for agricultural production is limited to around 7,000 km^2, about 13% of the region's total land area. The unused flat and forest production land area is approximately 6,000 km^2 or 12% of the total land area. Hence, there remains a significant potential for expansion of agricultural production in this region. However, agricultural production faces numerous challenges in the region. The productive land is scattered due to the strongly fragmented terrain, the rate of erosion in the area is increased, and the weather and climate are challenging, with prolonged droughts and unpredictable salt fog. While the irrigation system has been developed, the amount of water available for irrigation remains low. In the Northwest, the land, forest and water resources have a significant influence on land cover changes (Trincsi & Turner, 2014; Ngo et al., 2015; Phuong & Son, 2017; Son & Binh, 2020).

Therefore, our goal is to integrate open access RS data and GIS to examine the spatial trends of LULC change in the Northwest mountainous region (Hoa Binh city, Hoa Binh province, Vietnam) over a 20-year period (2000-2020). This study aims to provide basic information to support informed land use planning in the mountainous region of northwest Vietnam. Our specific objectives are as follows: (1) identify and delineate different types of LULC and patterns of land use change in the area of Hoa Binh city between 2000 and 2020, (2) determine the potential of integrating RS and GIS to study the spatial distribution of different LULC changes, and (3) identify shifts in LULC classes through the spatial comparison of maps.

Materials and methods

Study Area

The study was carried out in Hoa Binh city, Hoa Binh province, in the Northwest mountainous region of Vietnam. The geographical position of the study area lies in the coordinates of latitude 20°44'34.88"N–21°1'16.53"N and longitude 105°15'47.42"E–105°27'48.50"E (Fig. 1). Hoa Binh city has an average mountain topography with elevations ranging from 200 to 700 m, craggy, fragmented terrain, and steep slopes.

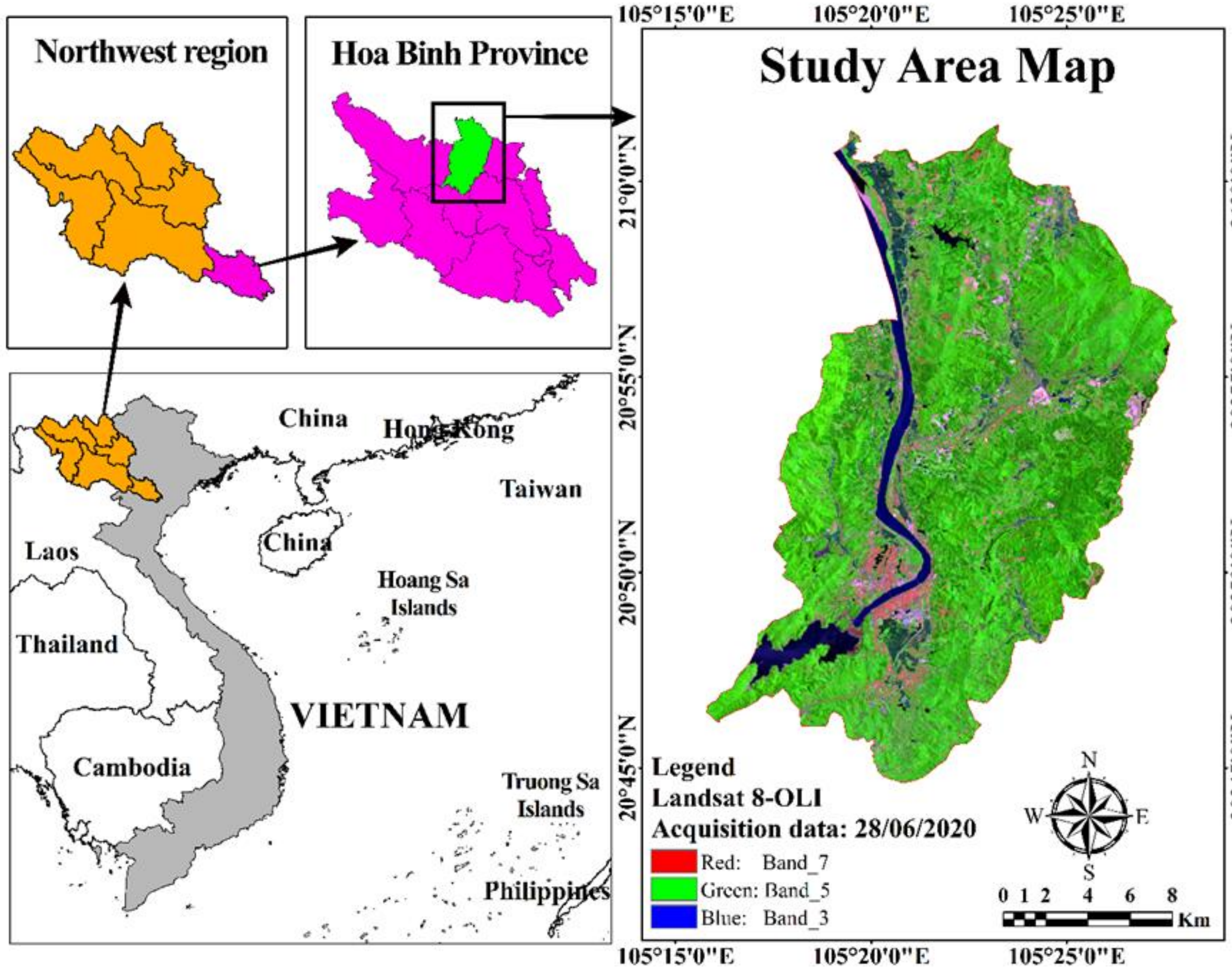

Figure 1. Map of the study site in Hoa Binh city, Hoa Binh province, Viet Nam

The study area has a humid subtropical climate: cold, dry, non-tropical winters with little rain and hot, rainy summers, with average rainfall from 1,400 mm to 2,800 mm per year. The average annual temperature is above 24 °C. June has the highest temperature of the year, averaging 30–32 °C, whereas January has the lowest temperature, averaging 17.4–19.5 °C (HoaBinh Statistics Office, 2021) (Fig. 2).

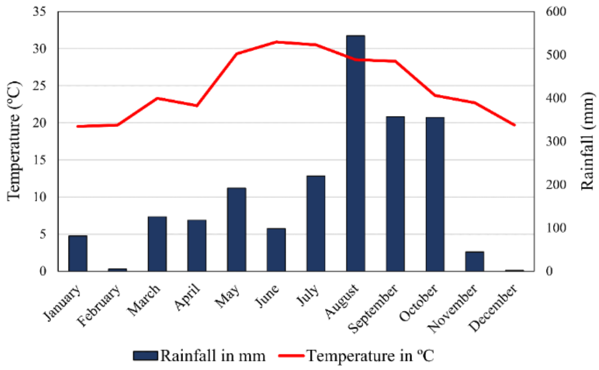

Figure 2. Mean monthly rainfall and temperature values of the study area

The Da River is the largest confluence of the Red River flowing through the study area. The river has a large volume of water and is considered a critical resource for the Vietnamese electricity industry. The Hoa Binh Dam, constructed between November 6, 1979 and December 20, 1994, was the largest hydroelectric plant in Vietnam and Southeast Asia from 1994 to 2012. The Hoa Binh hydroelectric plant is the main power supply for the entire Vietnamese electricity system. It is also the primary flood protection facility of the northern delta, facilitating transport in the downstream river and providing irrigation water.

Data Collection

The data used in this study were divided into satellite data and ancillary data. Ancillary data include accurate ground-truth data, aerial images of the study area and its vicinity, and topographic maps. The ground-truth data were collected using a Global Positioning System (GPS) from May to December 2020. An image from 2020 was used for image classification and assessment of the overall accuracy of the classification results. Landsat satellite data for three years, including multispectral data, were obtained free of charge from USGS EarthExplorer (http://earthexplorer.usgs.gov/) and USGS GloVis (http://glovis.usgs.gov/). The ArcGIS 10.8 software was used for image classification and zoning of the study area. The acquisition dates, sensors, path/row resolutions and image sources used in this study have been summarized in Table 1.

Table 1: Satellite data specifications of the study area

Satellite image	Sensor	Path/row	Resolution (m)	Acquisition data	Source
Landsat 7	ETM+	127/46	30*30	17/09/2000	USGS GloVis
Landsat 5	TM	127/46	30*30	17/06/2010	USGS GloVis
Landsat 8	OLI	127/46	30*30	28/06/2020	USGS EarthExplorer

Image pre-processing and classification

Image pre-processing was performed to extract meaningful information from satellite data so that they may become easier to interpret (Thien & Phuong, 2023). This process is used for the initial processing of the raw data and typically involves procedures like geometric corrections, image enhancement, noise removal, and topographic corrections (Jianya et al., 2008). All satellite images were geometrically corrected to the Universal Transfer Mercator (UTM) coordinate system and georeferenced to the data for the study area selected by the World Geodetic System (WGS) zone 48N. Data were processed in ArcGIS 10.8 to stitch and crop images based on existing study area boundaries. Satellite data were processed by assigning signatures per pixel and categorizing watersheds into five classes depending on the specific numerical values of various landscape elements: Agriculture, Forest, Water, Urban or built-up land and Bare soil or rock (Table 2).

Table 2: Classes delineated on the basis of supervised classification

No.	Class name	Description
1	Agriculture	Cultivated outfields, homestead garden fields and small scattered plots of grazing lands
2	Forest	Land covered with natural and plantation forests
3	Water	River, open water, lakes, ponds and reservoirs
4	Urban/built-up land	Residential, commercial, industrial, transportation, roads, mixed urban
5	Bare soil/rock	Land areas of exposed soil and barren area influenced by human influence

For each predefined LULC class, training samples were selected by delineating polygons around representative locations. Spectral signatures for the respective types of land cover obtained from satellite images were recorded using the pixels within these polygons. A satisfactory spectral signature ensures "minimum confusion" among the land cover types (Gao & Liu, 2010).

The study has used the rule-based supervised classification - maximum likelihood classifier (MLC) algorithm for LULC classification for acquired images of 1992, 2010, and 2022 (Rawat & Kumar, 2015; Thien et al., 2022b). The analyst controls this picture classification method by choosing the appropriate classes of pixels. Therefore, due to its simplicity and efficacy, post-classification refinement was employed to enhance classification accuracy and decrease misclassifications (Harris & Ventura, 1995). The approved LULC categorization characteristics defined class boundaries and consistent category definitions based on anthropogenic and natural factors changes within the study area. Additionally, as a size-independent, this categorization strategy can be successfully used at any spatial scale or level of detail. The LULC differences between the categorized photos were found utilizing a post-classification comparison method that used change detection comparison (pixel by pixel) to measure the change in LULC (Thien et al., 2022b). The methodology for classification is shown in Fig. 3.

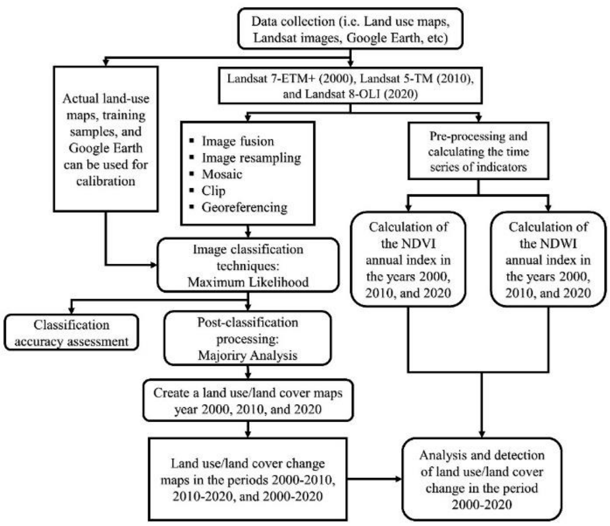

Figure 3. Overall process of land use/land cover change technique

Accuracy Assessment

The classification accuracy of 2000, 2010 and 2020 images were evaluated to determine the quality of the information obtained from the data. We sampled the reference points using a stratified random sampling approach, a probabilistic sampling method applied to assess the precision of each class (Olofsson et al., 2014; Thien & Phuong, 2023) that allows the selection of a relative number of points proportional to the size of each type of land cover. This ensures that each land cover is accurately represented by reference points to reduce bias in accuracy estimates. The accuracy assessment was conducted using 700 validation points on Google Earth Pro satellite images for the years 2000, 2010 and 2020. A comparison of reference data and classification results was performed to generate an error matrix. In addition, the accuracy of the classifier was measured using a nonparametric kappa test that considers not only the diagonal elements but also all elements in the error matrix (Rosenfield & Fitzpatrick-Lin, 1986; Ariti et al., 2015). The kappa coefficient is a measure of agreement between a predefined manufacturer rating and a user specified rating (Viera & Garrett, 2005). According to (Cohen, 1960), the kappa coefficient is calculated using the formula (Equation (1)):

$$Kappa\ coefficient\ (K) = \frac{Po-Pe}{1-Pe} \quad (1)$$

where *Po* is the number of times the k raters agree, and *Pe* is the number of times the k raters are expected to agree only by chance.

NDVI and NDWI analysis

The Normalized Difference Vegetation Index (NDVI) is suitable to detect vegetation cover of the study area (Gao, 1996; Cao et al., 2014). NDVI is a satellite-based index to quantify vegetation greenness and to understand plant density and health. The NDVI of an area can be obtained from a range of numerical values from -1 to 1, depending on the response of photosynthetic activity carried out by green vegetation. High values of NDVI represent high vegetation density, and negative values indicate water. The more active the NDVI, the greener the vegetation within a pixel and the NDVI index calculated using equation (2) given below:

$$NDVI = \frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED}} \quad (2)$$

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.

Similarly, the Normalized Disparity Water Index (NDWI) is an index developed to analyze the features of open water and the water content of vegetation (Huete, 2012). The NDWI is a valuable indicator for monitoring drought, water stress and land degradation. NDWI has no dimensions and its value ranges from -1 to +1. High values of NDWI represent water content in vegetation and high open water features, and low values indicate lower water content, and the NDWI index is calculated using equation (3) given below:

$$NDWI = \frac{\mathrm{GREEN-NIR}}{\mathrm{GREEN+NIR}} \quad (3)$$

where NIR is the reflection in the near-infrared spectrum, GREEN is the reflection in the green range spectrum.

Land use/land cover Change Detection

The post-classification change detection technique was applied using the ArcGIS 10.8 software. Information that changes on a pixel-by-pixel basis was generated using a pixel-based comparison. Therefore, the changes were interpreted more efficiently by taking advantage of "from-to" information. Pairs of categorical images of two different data were compared using cross-tabulation to identify qualitative and quantitative aspects of changes between 2000 and 2020. This procedure generated a two-way cross-matrix that was used to characterize the main patterns of change in the study area.

Results and discussion

Results of Classification and Analysis

The classification results of the pre-processed images for the years 2000, 2010 and 2020 are presented in Fig. 4.

The three-year statistics of the land-use classes and their corresponding importance rates are shown in Table 3. The classification results shown in 2000, most of the study area was covered by forest, accounting for 69.75% (243.20 km^2), followed by agriculture area with 22.78% (79.41 km^2), water area with 4.61% (16.09 km^2), and urban/built-up land and bare soil/rock area with at least 2.67% (9.31 km^2) and 0.18% (0.64 km^2), respectively (Table 3). In 2010, the size of the forest and water class all decreased by 64.22% (223.90 km^2) and 4.12% (14.35 km^2), respectively (Table 3). On the other hand, in terms of agriculture, urban/built-up land, and bare soil/rock, the class increased by 27.29% (95.13 km^2), 3.81% (13.27 km^2), and 0.57% (2.00 km^2), respectively (Table 3). In 2020, the forest, agriculture, water and bare soil/rock classes area decreased by 62.36% (217.40 km^2), 18.34% (63.95 km^2), 4.04% (14.09 km^2) and 0.40% (1.41 km^2), respectively. Meanwhile, the area of the urban/built-up land class increased sharply by 14.86% (51.80 km^2) (Table 3).

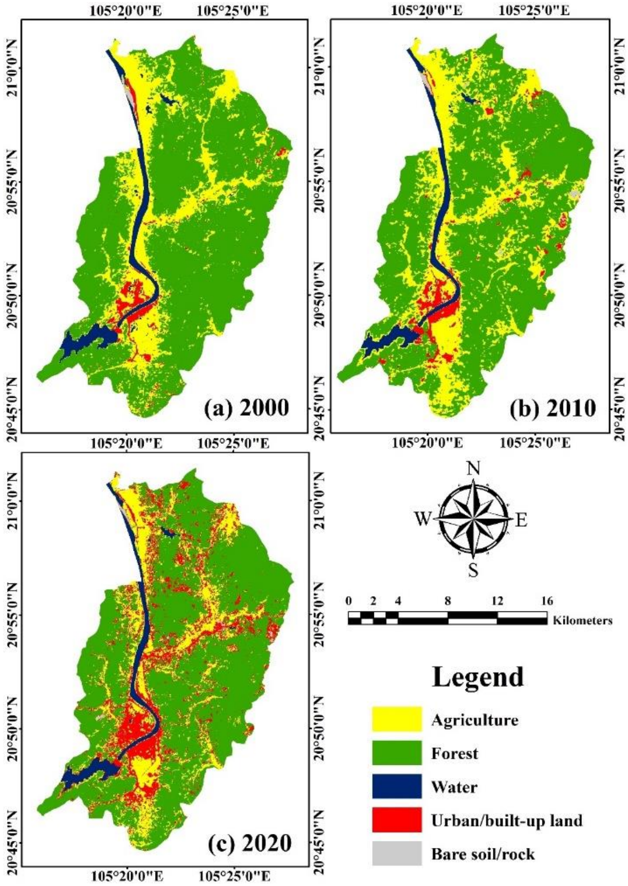

Figure 4. Maps of classified land use/land cover in Hoa Binh city (a) in 2000, (b) in 2010 and (c) in 2020

A total of 700 points were randomly selected to assess the accuracy of three land-use status maps in 2000, 2010, and 2020. The confirmation data were manually and randomly selected using Google Earth Pro. The overall classification accuracy was 95.56%, 95.09% and 94.07% and the overall kappa coefficients were 0.944, 0.938 and 0.926 for 2000, 2010 and 2020, respectively. The study requirements were met, as evidenced by the overall classification accuracy of more than 90% and kappa coefficients over 0.9 (Lea & Curtis, 2010).

Table 3: Area statistics land use/land cover in Hoa Binh city for 2000, 2010 and 2020

LULC classes	2000		2010		2020	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Agriculture	79.41	22.78	95.13	27.29	63.95	18.34
Forest	243.20	69.75	223.90	64.22	217.40	62.36
Water	16.09	4.61	14.35	4.12	14.09	4.04
Urban/built-up land	9.31	2.67	13.27	3.81	51.80	14.86
Bare soil/rock	0.64	0.18	2.00	0.57	1.41	0.40
Total	**348.65**	**100.00**	**348.65**	**100.00**	**348.65**	**100.00**

Analysis of land-use/land cover changes

Table 4 presents statistics on LULC in Hoa Binh city in the periods 2000-2010, 2010-2020, and 2000-2020. The results in Table 4 and Fig. 5a show that between 2000 and 2010, the forest area exhibited the most significant change, losing 19.30 km^2 or 5.54% of its area. During this period, the agricultural land area increased the most, with the total area of 15.72 km^2, showing an increase of 4.51% increase in 2000 as compared to 2010. The water area decreased by 1.74 km^2 or 0.50%. In addition, urban/built-up land and bare soil/rock areas showed a slight increase of 3.96 km^2 and 1.36 km^2, respectively, equivalent to 1.14% and 0.39%.

The results presented in Table 4 and Fig. 5b give an overview of the change in land cover from 2010 to 2020. During this period, the urban/built-up land area displayed the largest increase, with its total area increasing by 11.05% or 38.53 km^2. Agricultural land decreased the most, with a loss of 31.18 km^2 or 8.94% as compared to the previous period. Land areas covered by forest, water and bare soil/rock were reduced by 6.50 km^2 (1.86%), 0.26 km^2 (0.07%) and 0.59 km^2 (0.17%), respectively in the period 2010-2020 mentioned above (Table 4).

Table 4: Table of area land use/land cover changes in Hoa Binh city from 2000 to 2010, 2010 to 2020, 2000 to 2020

LULC classes	2000-2010		2010-2020		2000-2020	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Agriculture	15.72	4.51	-31.18	-8.94	-15.46	-4.43
Forest	-19.30	-5.54	-6.50	-1.86	-25.80	-7.40
Water	-1.74	-0.50	-0.26	-0.07	-2.00	-0.57
Urban/built-up land	3.96	1.14	38.53	11.05	42.49	12.19
Bare soil/rock	1.36	0.39	-0.59	-0.17	0.77	0.22

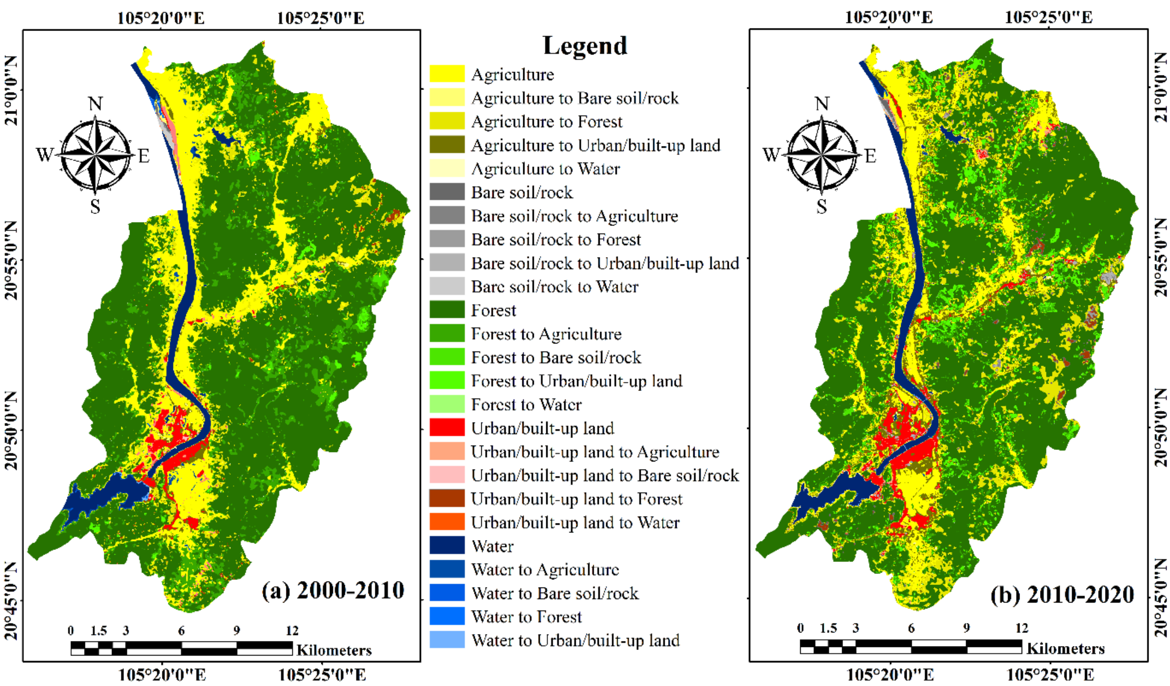

Figure 5. Land use/land cover changes maps in Hoa Binh city from (a) 2000 to 2010, (b) 2010 to 2020

Based on Table 3 and Table 4, the results for the period 2000-2020 show a considerable decline in the land cover area for the Forest, Agriculture and Water classes while the area of the Urban/built-up and Bare soil/rock classes increased. Forest land decreased from 69.75% to 62.36% of the total area and agricultural land decreased from 22.78% to 18.34%. Although the water surface area was relatively small in 2000, it was further reduced from 4.61% to 4.04%. The proportion of urban/built-up land was 2.67% of the total area in 2000, substantially increasing to 14.86% in 2020. The bare soil/rock area has also increased from 0.18% to 0.40% (Table 3).

The comparison of each class showed a marked change in LULC over the 20-year study period (Fig. 6). Between 2000 and 2020, the percentage of the area belonging to the Urban/built-up class in the study area increased by 12.19% (Table 4), an increase attributable to residential, farm and recreational projects that have been flourishing in the city center and surrounding areas. In addition, the dynamism of residential areas is closely related to urban population growth, specifically an increase in population size due to natural increase and higher fertility as well as migration from rural areas out into the city. According to the Department of Statistics of Hoa Binh province, the study area reached 92,754 people in 2014, and by 2020 the population has increased to 137,091, with an increase of nearly 7,400 people/year. Hoa Binh city is the political, administrative, economic, cultural and social center of Hoa Binh province, so the city attracts the most investment in the province with 203 projects, mainly in the public sector industry, infrastructure and cities. Along with these developments, infrastructure to access the area, such as new sidewalks, highways and roads, has been constructed (Zhang et al., 2018). The Bare soil/rock class exhibited a total increase of 0.22% during the study period (Table 4). This increase in the Bare soil area is associated with the loss of agricultural land, with previously cultivated land becoming barren open space, as farmers abandoned unproductive land due to economic inefficiencies. In addition, several construction site planning projects, where the land has been cleared but is left unconstructed, contribute to this increase in vacant land. The area covered by the Forest class decreased by 7.40% from 2000 to 2020 (Table 4). The main drivers of forest depletion in this typical study area are human activities such as illegal logging of high-value forest wood (Malhi et al., 2008). In addition, the lack of effective and strict forest fire management played an important role in forest decline. The area of Agricultural land decreased by 4.43% from 2000 to 2020 (Table 4), primarily due to challenges in land cultivation. In addition, rapid urbanization caused a large area of Agricultural land to be converted to Urban/built-up land, further contributing to the decline in the agricultural land area (Peerzado et al., 2019; Youssef et al., 2020). Therefore, the increase in the settlement land can be termed a positive increase, whereas the decrease in the agricultural land can be called a negative change. In addition, plowing, improper farming practices, and overgrazing are the leading causes of anthropogenic soil erosion, which drives decreases in agricultural land area. The area covered by water has decreased by 0.57% between 2000 and 2020 (Table 4). Water depletion, drought or little precipitation and intense evaporation in downstream river basins were factors in this decrease, as were the impacts of global climate change, the El Niño phenomenon and human activities (Haddeland et al., 2014; Gosling & Arnell, 2016). Moreover, the Hoa Binh hydroelectric power plant and irrigation efforts caused a considerable change in the water regime, water quality and aquatic systems in both upstream and downstream rivers (Young et al., 2011).

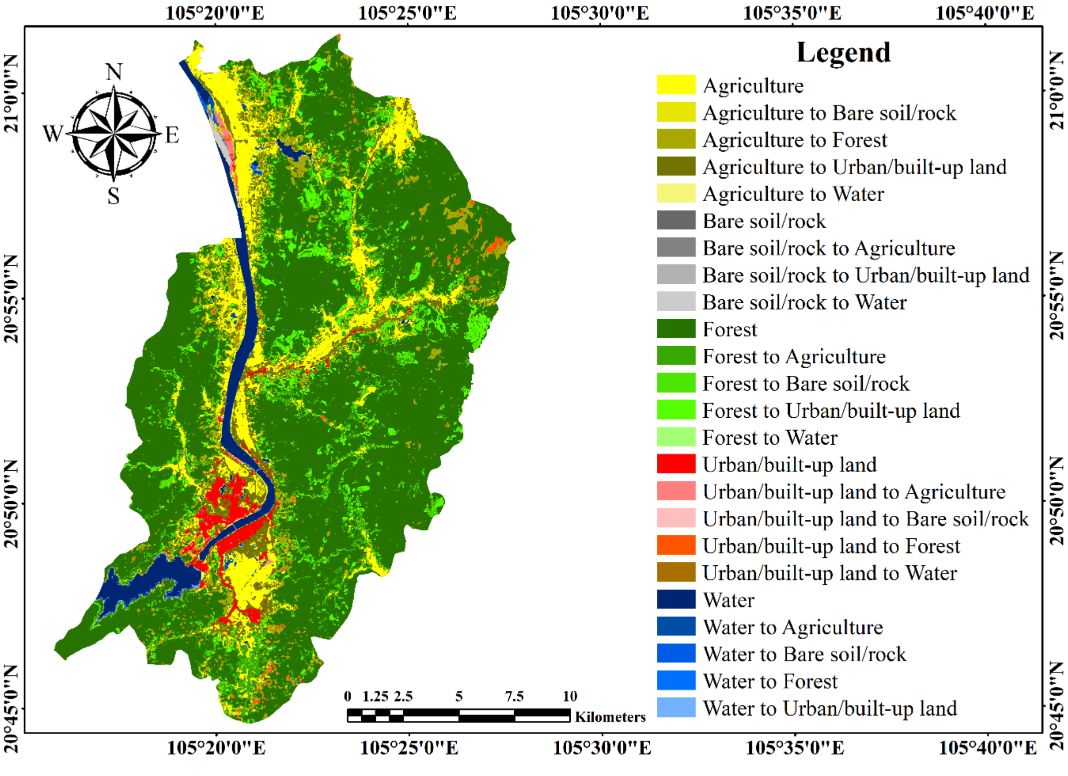

Figure 6. Land use/land cover changes map in Hoa Binh city from 2000 to 2020

Post-classification comparison of the detected change was conducted using GIS by mapping change to understand its spatial pattern (Fig. 5, Fig. 6). The 2000, 2010 and 2020 classified maps were overlaid in stages to create a map of LULC changes. The cross-tabulation matrix was also generated to assess the “from-to” transition between land covers.

The cross-tabulation matrices (Table 5) show the shift in the land cover classes. Out of the 243.79 km^2 that was Forest area in 2000, 199.38 km^2 was still Forest area in 2020 but 43.58 km^2 was converted to Agriculture and Urban/built-up, and rest to Water and Bare soil/rock. At the same time the increase of Forest, from 2000 to 2020, was mainly from Agriculture (16.53 km^2). Agriculture out of 78.81 km^2 in 2000 lost area mainly to Forest as mentioned before, Bare soil/rocks, a small part to Urban/built-up and Water, and retained 38.56 km^2 of total in 2020. Urban/built-up increased from 9.32 km^2 in 2000 to 51.80 km^2 in 2020. It retained 6.46 km^2 of it and was mainly replaced by Agriculture and Forest. The class which Urban/built-up mainly replaced in 2020 was Agriculture (23.09 km^2) (Table 5). Water class retained 13.18 km^2 of the total 16.09 km^2 in 2000. It was reduced to 14.09 km^2 and mainly replaced by Agriculture and Urban/built-up. The area of other land cover classes replaced by Water was small. Bare soil/rock area increased from 0.64 km^2 in 2000 to 1.41 km^2 in 2020. Bare land/rock only retained 0.05 km^2 of the total area in 2000 and was mainly replaced by Water (Table 5).

Table 5: Crosstabulation of the change in land cover between 2000 and 2020 (area in km²)

2020 \ 2000	Agriculture	Forest	Water	Urban/built-up land	Bare soil/rock	**Total**
Agriculture	**38.56**	22.14	1.86	1.33	0.06	63.95
Forest	16.53	**199.38**	0.09	1.40	0.00	217.40
Water	0.31	0.04	**13.18**	0.06	0.50	14.09
Urban/built-up land	23.09	21.44	0.78	**6.46**	0.03	51.80
Bare soil/rock	0.32	0.79	0.18	0.07	**0.05**	1.41
Total	78.81	243.79	16.09	9.32	0.64	

This study emphasizes the importance of incorporating RS and GIS for LULC change detection. This method offers crucial information about the spatial distribution as well as the nature of changes in land cover. The 90% overall accuracy of LULC maps indicates that integrating supervised classification of satellite imagery with visual interpretation is an effective method for characterizing and analyzing LULC change in an area such as the Northwest mountainous region of Vietnam.

Spatial distribution of NDVI and NDWI over 2000 to 2020

The study area was also analyzed with two widely used NDVI and NDWI indices. Both indices produce similar types of results. The selected five land cover features are distinguishable by both indices. The values of NDVI show the amount of chlorophyll content present in vegetation, where the greater NDVI value shows healthy and dense vegetation, but a lower NDVI value shows sparse vegetation. Fig. 7 represents the spatial distribution of NDVI values for three specified years (2000, 2010 and 2020) and values range between −0.53 to 0.66. The NDVI values in 2000 ranged from −0.53 to 0.45; in 2010, the NDVI value indicated the minimum value that is −0.20 and maximum 0.62; while in 2020, the NDVI value indicated the minimum value that is −0.19 and maximum 0.66. The highest values of NDVI were found in 2020, while the lowest were in 2000. Higher values showed the most productive areas like forest and crops. Similarly, lower values showed fewer and least productive areas like built-up area, water and bare soil. The NDVI analysis also revealed that urban/built-up land areas have risen dramatically while forest areas have significantly been reduced over time period.

The study area was also investigated with the NDWI, and the results are quite similar to the NDVI results. Fig. 8 represents the spatial distribution of NDWI values of three specified years. The NDWI values range between −0.58 and 0.56 in the specified period. The NDWI values in 2000 ranged from −0.33 to 0.56. In 2010, the NDWI value indicated a minimum of −0.58 and a maximum of 0.18. In 2020, it slightly increased from −0.58 to 0.29. The spatial variation of the NDWI values is evident across different years. The NDWI analysis also shows that the forest area shown in red has shrunk significantly between 2000 and 2020, and the urban/built-up land area shown in green has expanded centrally and along the length of the foot of the mountain over time, as can be seen in Figure 8. From these results, we can conclude that both NDVI and NDWI are good indicators that can effectively support the classification and spatial mapping of LULC layers in Hoa Binh city, especially to quickly assess the fluctuation of LULC layers.

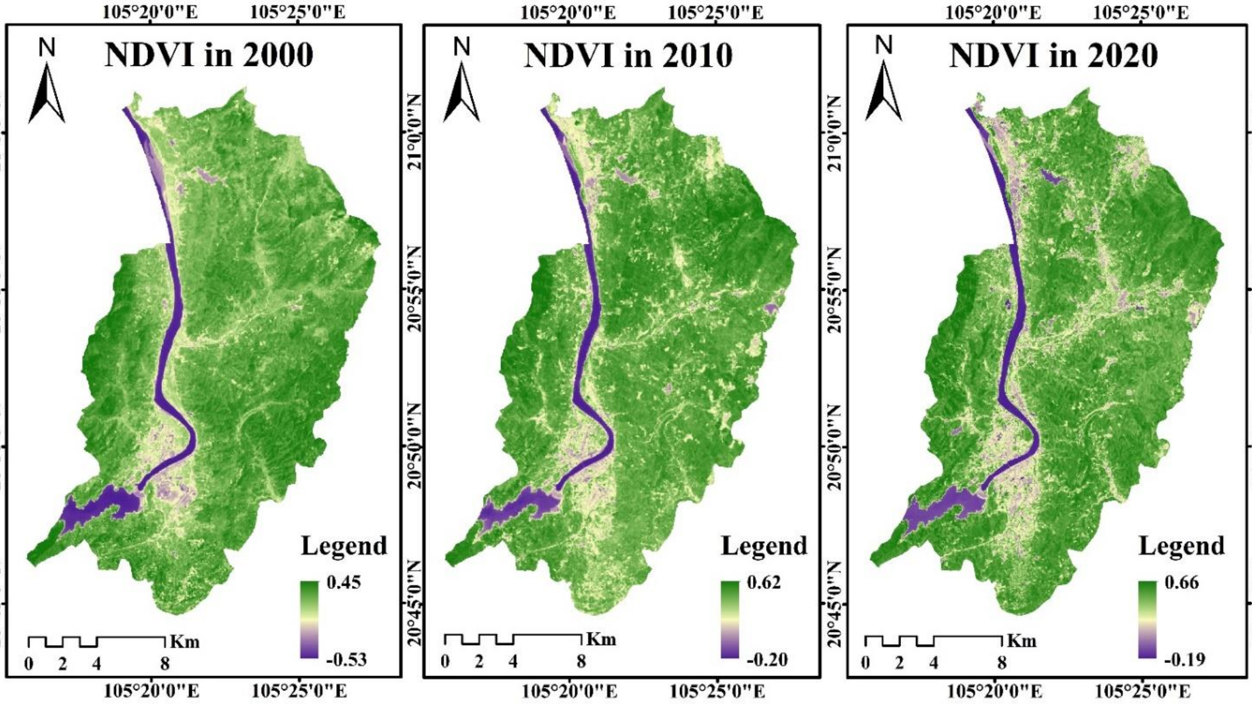

Figure 7. Spatial distribution of NDVI for 2000, 2010 and 2020

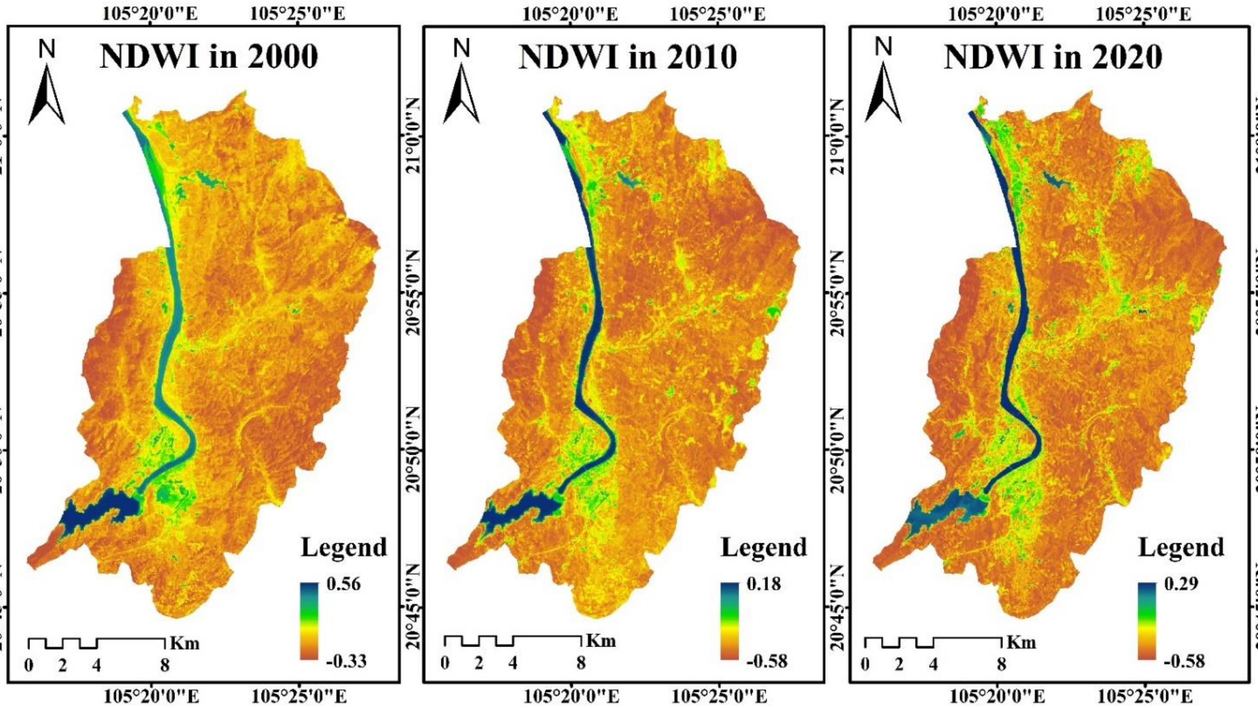

Figure 8: Spatial distribution of NDWI for 2000, 2010 and 2020

Relationships between NDVI and NDWI were created using linear regression analysis. In Hoa Binh city, the consequences of urban expansion were visible in both the calculated NDVI and NDWI. To determine how variations in LU intensity inside LULC units vary across space and lead to intra-LU fluctuation of NDWI, regression analysis (R^2) is conducted. However, NDVI and NDWI had a negative connection, as shown in Fig. 9, between the vegetation index (NDVI) and NDWI-derived built-up fractions, with correlation coefficients of R^2 = 0.9737 for 2000, 0.9656 for 2010, and 0.9639 for 2020 displayed in all images. Regression analysis reveals that NDWI values were lowest in the area with the highest NDVI values.

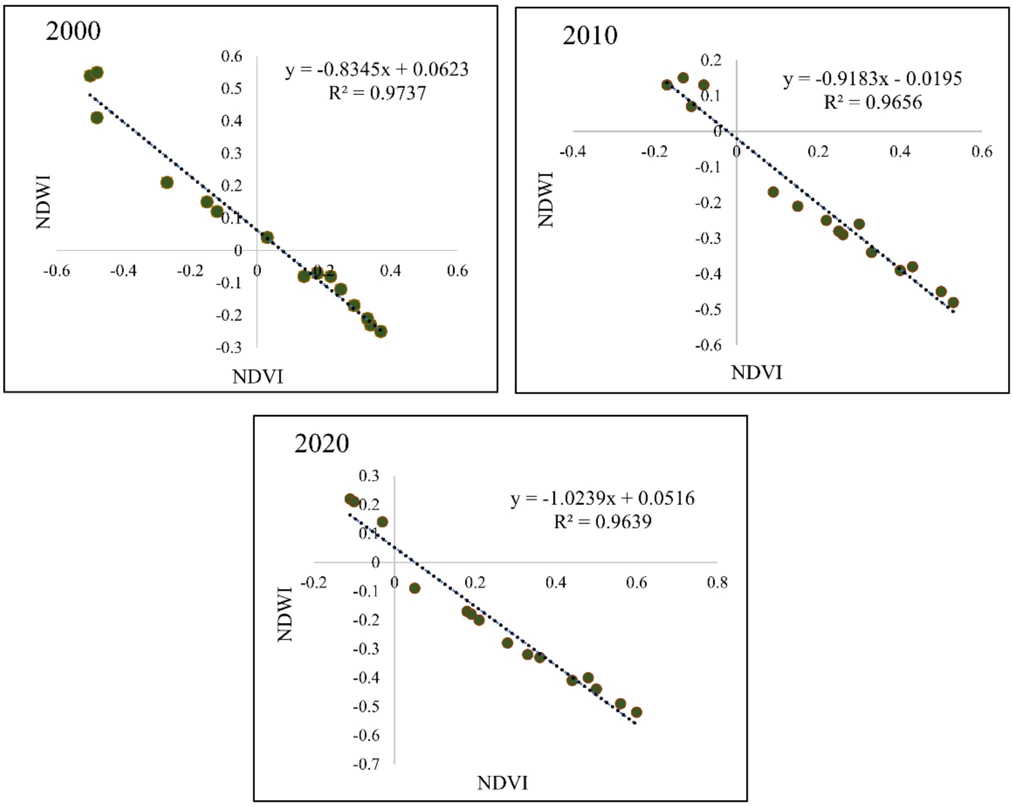

Figure 9: Regression analyses between NDVI and NDWI in the study area

Limitation of the study

This study faced some limiting factors that need to be highlighted. Firstly, the satellite data used in this investigation has a resolution of 30 m. Although it might work for small-scale studies, it isn't the best option for in-depth research. The investigation had to be done with free, average-quality Landsat pictures because the current study couldn't access high-resolution images. Since small-scale green spaces cannot be seen due to the 30 m pixel size, many rooftop gardens or plants growing along roadways may have gone unnoticed throughout the investigation, leading to errors. Second, the land cover map was produced using maximum likelihood classification algorithms, but due to Vietnam's diverse and complex land use pattern, the Landsat pictures may have been misclassified or significantly incorrectly classified. We used the post-classification feature in the ArcGIS 10.8 program to get the most out of this restriction. To address the aforementioned issues and employ a different and multi-model approach for further elucidation, more study is required.

Conclusion

Since the 2000s, the land use of Hoa Binh city, located in the Northwest mountainous region of Vietnam, has substantially changed due to economic development and the impact of human activities. In this study, Landsat 7-ETM+, Landsat 5-TM and Landsat 8-OLI image data were used to obtain LULC maps for 2000, 2010 and 2020. The results obtained by integrating RS and GIS analysis demonstrate that LULC has changed significantly in Hoa Binh city between 2000 and 2020. According to the classification results, the land cover class with the largest area was forest, with 234.20 km^2 in 2000, 223.90 km^2 in 2010 and 217.40 km^2 in 2020. The area of urban/built-up land increased steadily from 2000 to 2020, while changes in the Water, Agriculture, and Bare soil/rock classes were closely related to human activities. The NDVI and NDWI indices have also contributed to clarifying notable changes in land cover characteristics between 2000 and 2020.

Persistence of this trend of LULC change will result in severe environmental and economic consequences, impacting the livelihood of the local people. The outcome of the study shows that the policy maker and stakeholder of this region need to be conscious about the rapid development and changes in the land use pattern in Hoa Binh city. Implementing appropriate measures to ensure the sustainable use of natural resources and the efficient use of land is, therefore, critical. Moreover, this study offers evidence that integrating open-access RS and GIS constitutes a valuable approach for providing baseline spatial information. Therefore, it is suggested that RS and GIS techniques be used to detect the change in LULC in other parts of Vietnam as well as the world. Such spatial information is vital to informed land use and sustainable regional development worldwide. In addition, the complementary future studies may integrate quantitative and qualitative methods to understand and discuss the reasons for these quantitative descriptive results.

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Authors contributions

Conceptualization, B.B.T. and V.T.P.; methodology, B.B.T. and V.T.P.; software, B.B.T.; validation, V.T.P.; formal analysis, B.B.T.; writing—original draft preparation, B.B.T. and V.T.P.; writing—review and editing, B.B.T. All authors have read and agreed to the published version of the manuscript.

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Declaration of interests

The authors declare no conflict of interest.

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