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Using GIS Tools to Detect the Land Use/Land Cover Changes in Ha Nam province, Vietnam

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Abstract. Land is a crucial natural resource for any country. The study of land use and land cover (LULC) change has been instrumental in various areas such as natural resource management, monitoring, land planning, landslides, erosion, and addressing global change issues. In this study, geographic information systems (GIS) and remote sensing (RS) techniques were used to monitor LULC changes in Ha Nam province, Vietnam from 1992 to 2022. The supervised classification method in ArcGIS 10.8 software was applied to Landsat satellite data (Landsat 5-TM for 1992 and 2003, and Landsat 8-OLI/TIRS for 2022) to detect and classify five main LULC types: agricultural land, barren land, built-up, forest, and waterbodies. The classification accuracy was evaluated using kappa coefficients, which were 0.886, 0.905, and 0.933 for 1992, 2003, and 2022, respectively. During the period of 1992–2022, the agricultural land, forest, and waterbodies classes areas decreased by 102.85 km^2, 48.57 km^2, and 5.25 km^2, respectively. Meanwhile, the built-up and barren land classes areas increased by 150.08 km^2 and 6.59 km^2, respectively. Population growth, urbanization, urban planning policies, and the transition from an agricultural to an industrial economy have contributed to the expansion of built-up areas and the reduction of agricultural land, forests, and waterbodies in Ha Nam province. Moreover, we utilized the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI) to rapidly evaluate LULC changes, and we observed that their trends aligned with the results obtained from supervised classification. The environment faces substantial risks due to these LULC changes, and the outcomes of this study can provide valuable insights for upcoming land management and planning initiatives in the area.

Key words: Landsat, GIS, land use/land cover change, supervised classification, Ha Nam province

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Использование инструментов ГИС для обнаружения изменений в использовании и покрытии земли в провинции Ханам, Вьетнам

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Аннотация. Почва – это важный природный ресурс для любой страны. Изучение изменений в использовании и покрытии земли (LULC) играет важную роль в различных областях, таких как управление природными ресурсами, мониторинг, земельное планирование и решение проблем глобальных изменений. В этом исследовании использовались географические информационные системы (ГИС) и технологии дистанционного зондирования (ДЗ) для мониторинга изменений LULC в провинции Ханам, Вьетнам с 1992 по 2022 год. Метод классификации с обучением в программном обеспечении ArcGIS 10.8 применялся к данным спутника Landsat (Landsat 5-TM для 1992 и 2003 годов, и Landsat 8-OLI/TIRS для 2022 года) для выявления и классификации пяти основных типов LULC: сельскохозяйственные угодья, бесплодные угодья, застроенные территории, лес и водоемы. Точность классификации оценивалась с использованием коэффициентов каппа, которые составили 0,886, 0,905 и 0,933 для 1992, 2003 и 2022 годов, соответственно. За период с 1992 по 2022 годы площади классов сельскохозяйственных угодий, леса и водоемов уменьшились на 102,85 км^2, 48,57 км^2 и 5,25 км^2, соответственно. В то время как площади классов застроенных территорий и бесплодных угодий увеличились на 150,08 км^2 и 6,59 км^2, соответственно. Рост населения, урбанизация, политика городского планирования и переход от аграрной к индустриальной экономике способствовали расширению застроенных территорий и сокращению сельскохозяйственных земель, лесов и водоемов в провинции Ханам. Кроме того, мы использовали индекс нормализованной разницы вегетационного покрытия (NDVI) и индекс нормализованной разницы застроенных территорий (NDBI) для быстрой оценки изменений в LULC и обнаружили, что их тенденции соответствуют результатам, полученным с помощью надзорной классификации. Эти изменения в LULC представляют серьезные риски для окружающей среды, и результаты этого исследования могут предоставить ценные исследовательские данные для предстоящих инициатив по управлению и планированию земельных ресурсов в этом регионе.

Ключевые слова: Landsat, ГИС, изменение использования земли/покрытия земли, классификация с обучением, провинция Ханам

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Introduction

In recent years, studies on global environmental changes have increasingly focused on the issue of land use and land cover (LULC) changes [Msofe et al., 2019]. Researchers recognize LULC as primary factors that impact ecosystems and landscape values. As a result, LULC changes has gained significant attention in the global academic community [Tariq et al., 2022]. The research has primarily concentrated on comparing methodologies using GIS methods, fuzzy sets, and landscape metrics. Additionally, there has been an effort to develop a new approach that combines ecological, geographical, and social anthropological data in LULC changes studies [Vadrevu et al., 2019]. A study was presented by scientists, employing a high-resolution land use change model to downscale land use changes from macro-scale models to the landscape level [Aghsaei et al., 2020]. This approach aims to provide valuable insights for future land use change analysis. Understanding the relations and interactions between anthropogenic factors and the natural environment is crucial in comprehending LULC changes [Zadbagher et al., 2018; Thien et al., 2022]. Both these factors influence LULC changes to varying degrees. However, the current trends indicate a general degradation of the environment and significant fragmentation of the landscape. Numerous studies conducted globally highlight the rapid pace of LULC changes resulting from population growth, intensive land use, and the loss of natural areas [Thien, Phuong, 2023].

Studying urban dimensions, including LULC mapping, urban density, urban modeling, and the environmental effects of urban development over time intervals, can be effectively carried out using powerful tools such as the geographic information system (GIS) and remote sensing (RS) [Mehdi et al., 2016; Majeed et al., 2021]. RS data offers timely, reliable, and accurate information on degraded lands during specific time periods in a cost-effective manner. By utilizing GIS technology, spatial data can be managed and analyzed according to the requirements of the case study [Phuong, Thien, 2023b]. RS data proves valuable for conducting LULC inventory and mapping. Landsat sensors like Landsat-5 Thematic Mapper (TM), Landsat-7 Enhanced TM Plus (ETM+), and Landsat-8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) provide a range of satellite data that plays a crucial role in detecting changes in Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI) and LULC for LULC planners [Zheng et al., 2021; Florim et al., 2021; Dash et al., 2023]. Change detection involves quantitatively analyzing the previous effects of an occurrence using RS information, thereby assisting in identifying changes related to LULC properties with reference to various satellite datasets. Supervised classifications rely on prior knowledge of the scene regions, areas containing materials of interest, and training sites, which are stored and delineated for use in the supervised classification algorithm.

This study used GIS and RS technology to monitor LULC changes from 1992 to 2022 in Ha Nam province, Vietnam. The purpose of our research is (1) to identify and classify LULC types and to quantitatively analyze LULC changes from 1992 to 2022; (2) then conduct *NDVI* and *NDBI* change detection, mapping and analysis using satellite data; and (3) to evaluate the factors affecting the change of LULC in the study area in the period 1992-2022.

Materials and methods

Study area

Ha Nam province, located in the North of Vietnam, is situated at geographical coordinates with latitude 20°23'N – 20°52'N and longitude 105°49'E – 106°25'E, covering a total area of 861.92 km^2 (Fig. 1)[1]. The landscape of Ha Nam province is diverse, encompassing plains, hills, and river valleys. The majority of the province's land area consists of plains, while hilly terrain and rivers make up the remaining portions. The province experiences a humid subtropical climate, characterized by four distinct seasons: spring, summer, autumn, and winter. The average annual temperature ranges from 23 °C to 25 °C, with hot and humid summers and relatively cold winters. As of the latest available data, the population of Ha Nam province was approximately 878,306 people in 2022. The urban population accounts for around 45 % of the total population, residing in cities and towns, while the remaining 55 % represents the rural population. The province has been witnessing ongoing urbanization and economic development. Ha Nam province's economy is diverse, with agriculture, industry, and services being the main sectors. The province is known for its agricultural production, particularly in rice cultivation. Industrial activities are also prominent, with various industrial zones attracting investments and contributing to the economic growth of the province. Additionally, the services sector, including commerce, healthcare, and education, plays a vital role in the local economy.

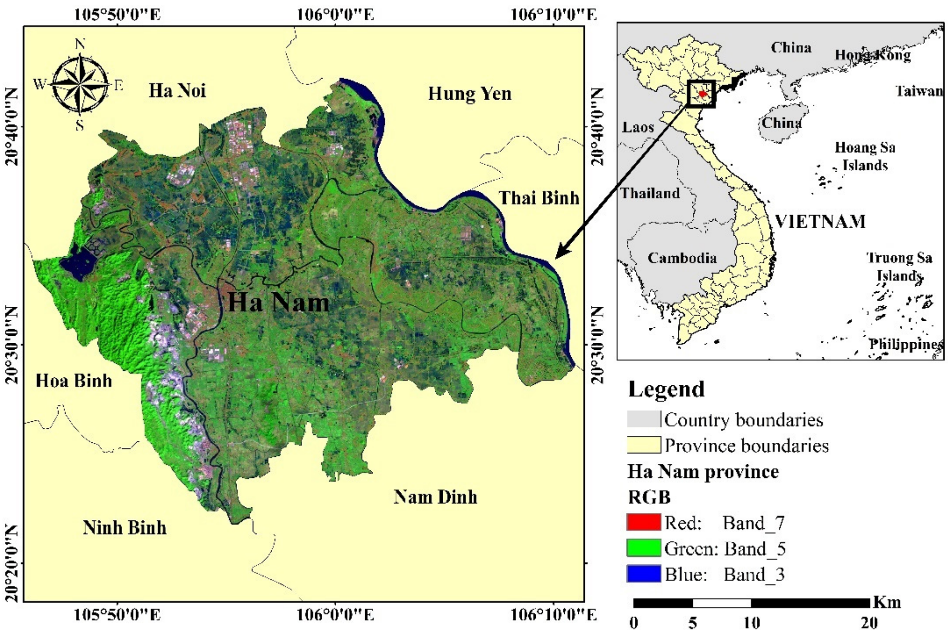

Fig. 1. Study area map of Ha Nam province
Рис. 1. Карта территории исследования провинции Ханам

[1] General Statistics Office. 2022. Statistical Yearbook of Viet Nam 2022. Statistical Publishing House. URL: https://www.gso.gov.vn/wp-content/uploads/2023/06/Sach-Nien-giam-TK-2022-update-21.7_file-nen-Water.pdf

Data collection

We used satellite images obtained from the USGS Glovis website (https://glovis.usgs.gov) to map LULC in Ha Nam province and assess LULC changes from 1992 to 2022. In this study, we employed *Landsat 5-TM* images for the years 1992 and 2003, while *Landsat 8-OLI/TIRS* images were utilized for 2022. To evaluate the accuracy of the LULC classification map, we collected point data, consisting of 300 points per year. For 1992 and 2003, *Google Earth Pro* software was employed to collect these points, while for 2022, we conducted field surveys and used GPS devices. Throughout the study, we utilized *ArcGIS 10.8* and *Microsoft Excel 2016* software. A comprehensive data summary can be found in Table 1.

Table 1
Таблица 1

Detailed data summary of satellite imagery used in the study
Подробные данные спутниковых снимков, использованных в исследовании

Satellite image	Sensor	Acquisition data	Path/row	Landsat scene ID
Landsat 5	TM	01/12/1992	126/046	LT51260461992336BJC00
		21/10/1992	127/046	LT51270461992295BJC02
Landsat 5	TM	16/12/2003	126/046	LT51260462003350BJC00
		23/12/2003	127/046	LT51270462003357BKT01
Landsat 8	OLI/TIRS	17/10/2022	126/046	LC81260462022290LGN00
		16/10/2022	127/046	LC81270462022289LGN01

Image pre-processing and supervised classification

We combined distinct bands from *Landsat 5-TM* and *Landsat 8-OLI/TIRS* through layer stacking to create a comprehensive image of the study area. During the subset setup process, we delineated the desired study area using extract by mask tools within *ArcGIS 10.8* [Kumari et al., 2019; Phuong, Thien, 2023a]. Referring to the scheme proposed by Anderson et al. [1976] and verifying it through field surveys, we identified five primary LULC categories in the study area: agricultural land, barren land, built-up areas, forest, and waterbodies (Table 2). Using *ArcGIS 10.8* software, we drew polygons around pixels with similar reflectance values for each category, forming training samples [Verma et al., 2020]. Pixels enclosed by these polygons in each *Landsat* image were marked to extract spectral signatures for different LULC classes [Thien et al., 2023]. Next, we applied a maximum likelihood classification algorithm to classify LULC based on these spectral signatures [Verma et al., 2020; Isma'il et al., 2023]. Fig. 2 provides a detailed illustration of the methodology employed in this research.

Table 2
Таблица 2

Classes delineated from field survey
Классы, выделенные на основе полевых исследований

Class	Description
Agricultural land	Cropland and paddy field
Barren land	Fallow land, sands and earth dumps
Built-up	Residential, industrial, roads and other manmade structures
Forest	Natural forest, plantations and mixed forest lands
Waterbodies	Reservoirs, rivers and lakes

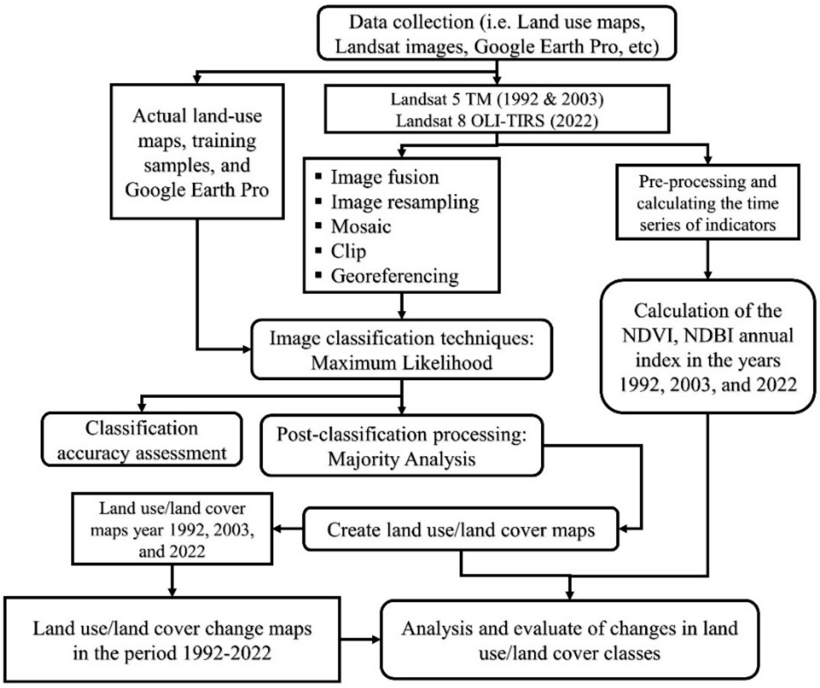

Fig. 2. Flow chart for methodology
Рис. 2. Блок-схема методологии

Classification accuracy assessment

During the LULC classification process, it is important to evaluate the accuracy to account for potential misclassifications between pixels [Zadbagher et al., 2018; Thien, Phuong, 2023a]. To assess the accuracy of the classification results, we utilized an error matrix and compared the results with 150 reference data points collected for each year. We calculated various metrics based on the error matrix for each respective year, including user's accuracy, producer's accuracy, overall accuracy, and kappa coefficient [Vadrevu et al., 2019; Phuong, Thien, 2023a]. These metrics provide valuable insights into the reliability of the classification results by measuring the agreement between the predicted and actual classifications. Formulas (1), (2), (3), and (4) were employed to calculate the user's accuracy, producer's accuracy, overall accuracy, and kappa coefficient, respectively.

$$\text{User's accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of reference pixels in each category (row total)}} \times 100 \quad (1)$$

$$\text{Producer's accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of reference pixels in each category (column total)}} \times 100 \quad (2)$$

$$\text{Overall accuracy} = \frac{\text{Number of sampling classes classified correctly}}{\text{Number of reference sampling classes}} \times 100 \quad (3)$$

$$\text{Kappa} = \frac{\text{Po} - \text{Pe}}{1 - \text{Pe}} \quad (4)$$

where P_o is the agreement ratio between the predicted classification results and the actual classification results. P_e is the random agreement ratio between the predicted classification results and the actual classification results.

Estimation and correlation between NDVI and NDBI

By utilizing satellite imagery, we can estimate the *NDVI* and *NDBI*, which provide valuable information for monitoring vegetation health and urbanization processes [Florim et al., 2021]. The *NDVI* serves as a vegetation index, utilizing the near-infrared (NIR) and red (RED) bands of satellite images to distinguish vegetation [Florim et al., 2021]. As vegetation cover expands, the *NDVI* value increases, while it decreases with diminishing vegetation cover. On the other hand, the *NDBI* serves as an urban index, utilizing the shortwave infrared (SWIR) and near-infrared (NIR) bands of satellite images to detect built-up areas [Zheng et al., 2021]. The *NDBI* value increases as built-up areas expand and decreases with a reduction in built-up areas. We calculate the *NDVI* and *NDBI* indices using formulas (5) and (6), respectively.

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \quad (5)$$

$$\mathrm{NDBI} = \frac{\mathrm{SWIR} - \mathrm{NIR}}{\mathrm{SWIR} + \mathrm{NIR}} \quad (6)$$

We utilized regression analysis to quantify the correlation between *NDVI* and *NDBI* in Ha Nam province for the years 1992, 2003, and 2022. The regression analysis yielded correlation coefficient values within the range of –1 to +1 [Pal, Ziaul, 2017]. To conduct the regression analysis, we employed the random point generator feature within *ArcGIS 10.8* software to generate 200 random point data within the study area boundaries. The extract multi values to points tool facilitated the extraction of a value for each point data from the *NDVI* and *NDBI* pixels. Subsequently, we exported these values to *Microsoft Excel 2016* software (Microsoft, USA) to estimate the regression equation between *NDVI* and *NDBI*.

Results and discussion

Land use/land cover classification

The map of LULC status in Ha Nam province in the three years 1992, 2003 and 2022 is shown in Fig. 3. Table 3 shows the area and proportions of each LULC type respectively. From Fig. 3 and the data in Table 3, it can be seen that significant changes have occurred in agricultural land and built-up classes over the 30 years in the study area.

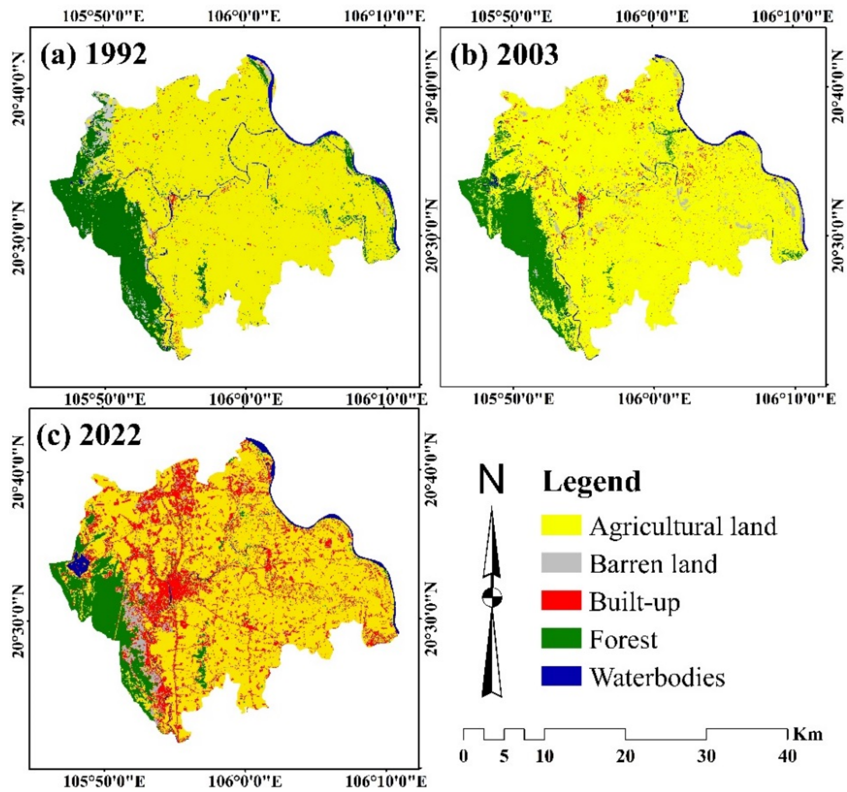

Fig. 3. Land use/land cover maps for Ha Nam province in 1992 (a), 2003 (b), and 2022 (c)
Рис. 3. Карты землепользования/земельного покрова провинции Ханам
в 1992 г. (a), 2003 г. (b) и 2022 г. (c)

Based on the LULC classification results in Table 3, in the year 1992, agricultural land class accounted for the largest area in Ha Nam province, accounted for 78.17 % (673.75 km^2) of the total area. Forest class area accounted for 15.88 % (136.85 km^2), waterbodies class area accounted for 2.80 % (24.16 km^2), barren land class area accounted for 2.05 % (17.71 km^2), and built-up class area had the smallest coverage at only 1.10 % (9.45 km^2) (Table 3). By 2003, the areas of forest and waterbodies classes had decreased to 11.47 % (98.85 km^2), and 2.03 % (17.53 km^2), respectively (Table 3). In contrast, the areas of agricultural land, barren land, and built-up classes had increased to 81.12 % (699.21 km^2), 3.15 % (27.12 km^2), and 2.23 % (19.21 km^2), respectively (Table 3). By 2022, the area of built-up class had further increased and accounted for 18.51 % (159.53 km^2). Additionally, the area of waterbodies class had continued to increase and accounted for 2.19 % (18.91 km^2) in 2022. Meanwhile, the areas of agricultural land, barren land, and forest classes had decreased to 66.24 % (570.90 km^2), 2.82 % (24.30 km^2), and 10.24 % (88.28 km^2), respectively (Table 3).

Table 3
Таблица 3

The land use/land cover area distribution from 1992 to 2022 in Ha Nam province
Распределение землепользования/земельного покрова с 1992 по 2022 год в провинции Ханам

Class	1992		2003		2022	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Agricultural land	673.75	78.17	699.21	81.12	570.90	66.24
Barren land	17.71	2.05	27.12	3.15	24.30	2.82
Built-up	9.45	1.10	19.21	2.23	159.53	18.51
Forest	136.85	15.88	98.85	11.47	88.28	10.24
Waterbodies	24.16	2.80	17.53	2.03	18.91	2.19
Total	861.92	100.00	861.92	100.00	861.92	100.00

The assessment of the post-classification accuracy in this study was performed by comparing the classified LULC classes with the reference data [Islami et al., 2022; Thien, Phuong, 2023a]. The results of the classification evaluation showed that the overall accuracy of the years 1992, 2003, and 2022 was 91.58 %, 93.00 %, and 95.00 %, respectively (Table 4). Overall, the producer's accuracy and the user's accuracy for each soil layer in all 3 years were above 80 % (Table 4). The kappa coefficient values in 1992, 2003 and 2022 in the study area were recorded as 0.886, 0.905, and 0.933, respectively (Table 4). Kappa coefficients ranging from 0.81 to 1.00 are considered almost perfect in LULC classification [Regasa et al., 2021; Wahla et al., 2023]. These results show reliable land cover classification and good consistency between referenced and classified maps.

Table 4
Таблица 4

Accuracy assessments for classified maps
Оценка точности классифицированных карт

LULC classes	1992		2003		2022	
	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)
Agricultural land	94.87	91.36	94.87	90.24	95.83	95.83
Barren land	90.91	83.33	91.67	84.62	93.33	82.35
Built-up	83.33	88.24	88.89	92.31	96.61	98.28
Forest	90.57	96.00	93.75	97.83	93.33	96.55
Waterbodies	90.32	93.33	91.43	96.97	91.67	91.67
Overall accuracy (%)	91.58		93.00		95.00	
Kappa Coefficient	0.886		0.905		0.933	

Land use/land cover change

Fig. 4 illustrates the specific changes in each LULC class during the period of 1992–2022 in Ha Nam province. The analysis of area changes for each LULC class in different periods (1992–2003, 2003–2022, and 1992–2022) is also presented in Table 5. During the period of 1992–2003, the forest area experienced the highest decrease by 4.41 % (38.00 km^2) compared to the initial area. The decrease in forest area could be attributed to illegal logging, conversion of forests to agricultural or built-up land, and urban expansion. The waterbodies also decreased by 0.77 % (6.63 km^2). The reduction in waterbodies could be due to drought, water mismanagement, and climate change. The decrease in waterbodies may impact water availability for domestic use and agricultural irrigation. In contrast, the agricultural land, barren land, and built-up areas increased by 2.95 % (25.46 km^2), 1.09 % (9.41 km^2), and 1.13 % (9.76 km^2), respectively. The increase in agricultural land could be a result of agricultural expansion to meet the growing demands for food production and population growth. Meanwhile, the built-up area has increased possibly due to urban development, infrastructure construction and other construction projects to accommodate population and economic growth. Examining the LULC change model during the period of 2003–2022, a significant decrease of 14.89 % (128.31 km^2) was observed in agricultural land. The decrease in agricultural land could be due to the conversion of agricultural land to built-up or other land types, shifting economic structure with increased industrial and service activities. Additionally, the barren land and forest areas decreased by 0.33 % (2.82 km^2) and 1.23 % (10.57 km^2) respectively. The reasons for the decrease in barren land might include climate change, unsustainable resource exploitation, and the expansion of other activities on barren land. Meanwhile, the built-up area continued to increase during the 2003–2022 period, reaching 16.28 % (140.32 km^2) (Table 5). The increase in built-up areas could be a result of urban development, expansion of industrial zones, and other construction projects. Furthermore, in the period of 2003–2022, the waterbodies experienced a slight increase, with a total increase of 0.16 % (1.38 km^2) (Table 5). The slight increase in waterbodies could be attributed to improved water resource management, environmental restoration efforts, and conservation measures.

Table 5
Таблица 5

The land use/land cover change analysis from 1992 to 2022 in Ha Nam province
Анализ землепользования/изменения земельного покрова с 1992 по 2022 год в провинции Ханам

Class	1992–2003		2003–2022		1992–2022	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Agricultural land	25.46	2.95	–128.31	–14.89	–102.85	–11.93
Barren land	9.41	1.09	–2.82	–0.33	6.59	0.76
Built-up	9.76	1.13	140.32	16.28	150.08	17.41
Forest	–38.00	–4.41	–10.57	–1.23	–48.57	–5.64
Waterbodies	–6.63	–0.77	1.38	0.16	–5.25	–0.61

In general, over the past 30 years (1992-2022) in the study area, there have been significant changes in LULC. Fig. 4 and Table 5 show that the built-up area has continuously increased, with a total increase of 17.41 % (150.08 km^2), and the highest increase occurred during the period of 2003-2022. There are several factors contributing to the expansion of built-up areas, with the main factors being population growth, urbanization, and urban planning policies [Waiyasusri, 2021; Singh et al., 2022]. The population growth during this period has led to an increasing demand for housing, driving the expansion and development of urban areas and residential areas in Ha Nam province [Niu et al., 2022].

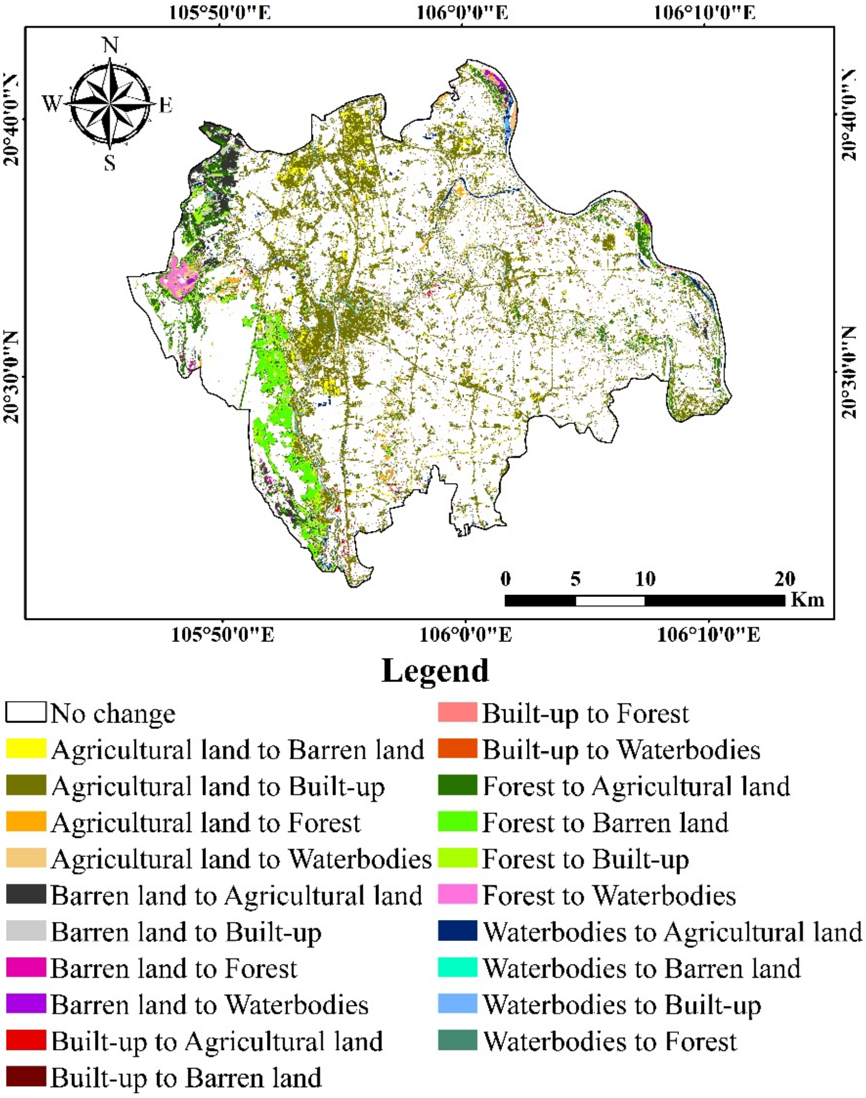

Fig. 4. Land use/land cover changes map for Ha Nam province from 1992 to 2022
Рис. 4. Карта изменений землепользования/земного покрова провинции Ханам с 1992 по 2022 год

Additionally, the process of urbanization and the expansion of urban areas have resulted in the development of new urban areas, the renovation and expansion of urban infrastructure, and the construction of urban areas outside existing urban centers [Wang et al., 2021]. During the period of 1992–2022, due to rapid urbanization, a significant portion of agricultural land, forests, and water bodies had to be converted for construction purposes [Getu Engida et al., 2021; Herrera Arango et al., 2022]. The total area of agricultural land, forest, and waterbodies decreased by 11.93 % (102.85 km^2), 5.64 % (48.57 km^2), and 0.61 % (5.25 km^2), respectively (Table 5). Furthermore, previously, the main economic activity in the study area was rice cultivation, but water shortages for irrigation due to drought conditions led the local authorities to gradually shift towards an industrial economy. Meanwhile, the area of barren land increased by 0.76 % (6.59 km^2) during the period of 1992–2022, mainly resulting from housing and industrial construction projects. Overall, the increase in built-up areas in Ha Nam province from 1992 to the present can be attributed to population growth, urbanization, and urban planning policies. The conversion of agricultural land, forests, and waterbodies for construction purposes was driven by the rapid urbanization process. Additionally, the shift from an agricultural to an industrial economy and the presence of abandoned land from housing and industrial projects also contributed to the expansion of built-up areas [Thekkeyil et al., 2023; Thien et al., 2023].

The NDVI and NDBI

The high *NDVI* index values indicate denser and healthier vegetation, while lower values correspond to sparse or no vegetation [Florim et al., 2021]. In 1992, the *NDVI* value ranged from –0.51 to +0.65 (Fig. 5a); in 2003, *NDVI* values ranged from –0.99 to +0.97 (Fig. 5b); and in 2022, *NDVI* values ranged from –0.17 to +0.55 (Fig. 5c). Significant spatial changes in vegetation cover and green area were observed between the lowest and highest *NDVI* values recorded in 2003, along with improved agricultural productivity in areas such as forests and vegetation cover (Figs. 5 a, b, c). The *NDBI* index is used to assess the level of urban development in the study area, the *NDBI* values increase as the built-up area increases and decreases when the built-up area decreases [Degerli, Çetin, 2022]. In 1992, the *NDBI* value ranged from –0.96 to +0.78 (Fig. 5d); in 2003, *NDBI* values ranged from –0.97 to +0.98 (Fig. 5e); and in 2022, the *NDBI* values ranged from –0.41 to +0.31 (Fig. 5f) The red areas in Figs. 5d, 5e, and 5f show minimal vegetation cover, such as built-up and barren land.

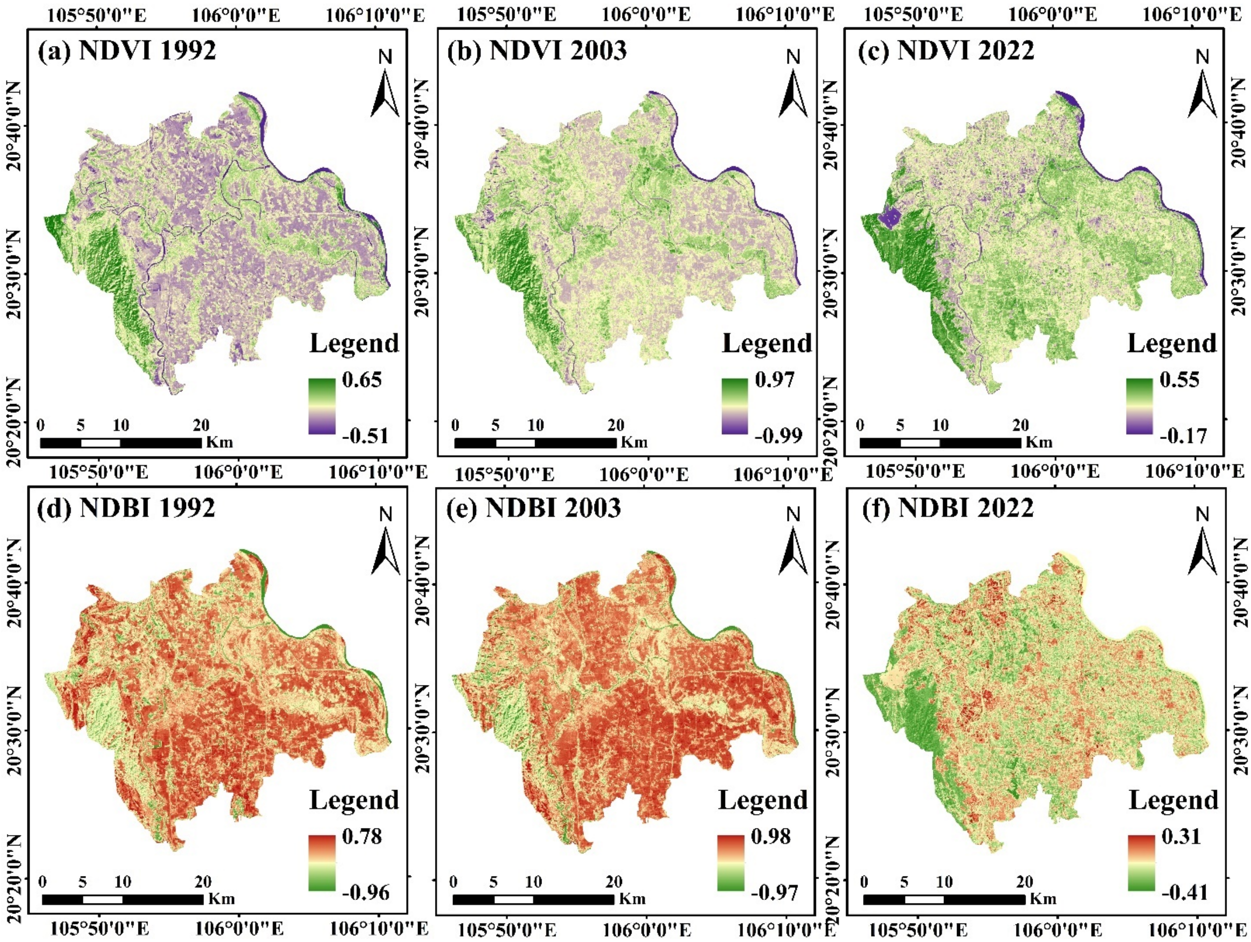

Fig. 5. NDVI and NDBI maps for Ha Nam province in 1992, 2003, and 2022
Рис. 5. Карты NDVI и NDBI провинции Ханам в 1992, 2003 и 2022 годах

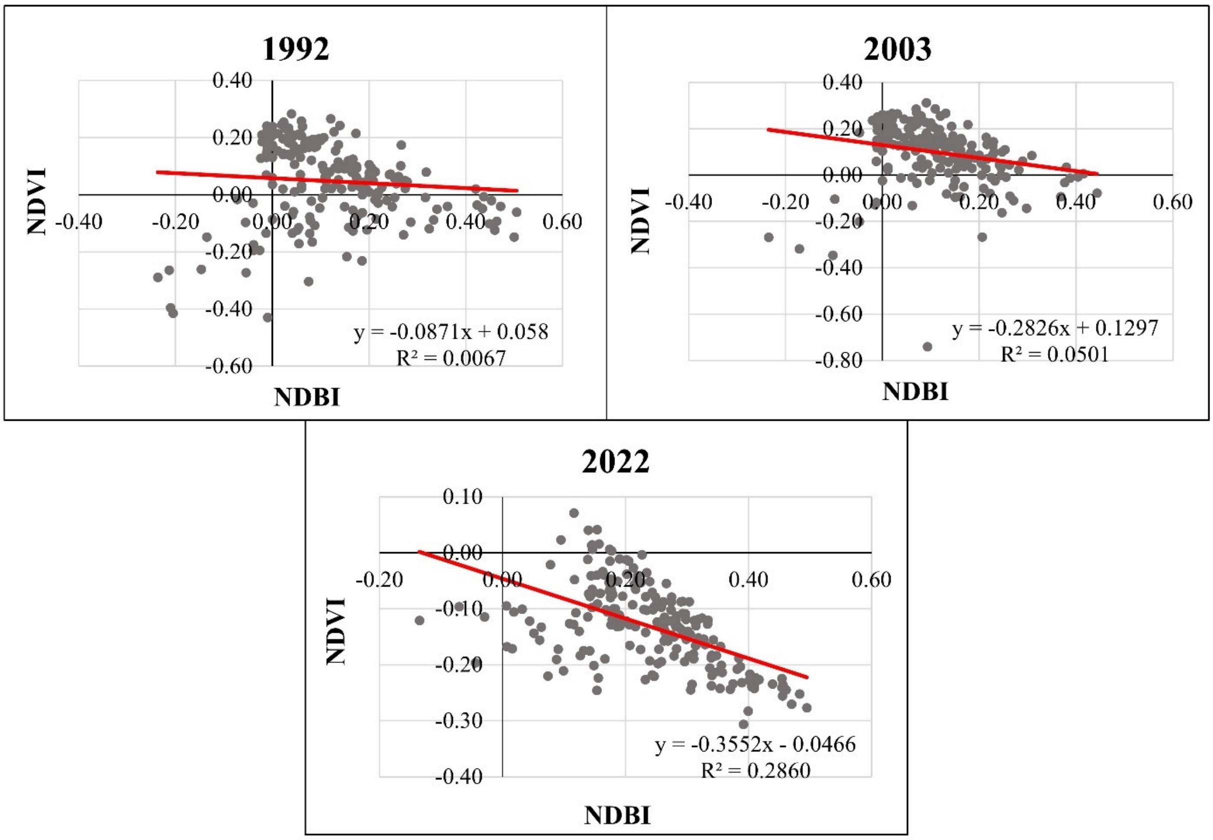

Fig. 6. Regression analyses between NDVI and NDBI in Ha Nam province
Рис. 6. Регрессионный анализ между NDVI и NDBI в провинции Ханам

A linear regression analysis was conducted to demonstrate the relationship between two indices (*NDVI* and *NDBI*) [Florim et al., 2021]. The changes in *NDBI* values related to land use were assessed by evaluating the variations in land use intensity within the LULC units through regression analysis (R^2) [Majeed et al., 2021]. Furthermore, a negative correlation between *NDVI* and *NDBI* was identified. Specifically, correlation coefficients of R^2 = 0.0067 for 1992, R^2 = 0.0501 for 2003, and R^2 = 0.2860 for 2022 were depicted in Fig. 6. As observed in Fig. 6, this illustrates the relationship between the vegetation index (*NDVI*) and the integrated component derived from *NDBI*. In addition, linear regression analysis shows that R^2 values have gradually increased, which indicates that urbanization has negatively affected vegetation covers. The regression analysis also revealed that the highest *NDBI* values corresponded to areas with the lowest *NDVI* values, and vice versa. This clearly indicates that the increase in built-up areas and barren land leads to a decrease in vegetation coverage.

Conclusion

The study highlights that the combined use of GIS and RS techniques provides valuable insights into LULC changes. Ha Nam province has undergone significant LULC changes from 1992 to 2022, the study area has experienced a decline in agricultural land, forest, and waterbodies classes, with area decreases of 11.93 %, 5.64 %, and 0.61 %, respectively. In addition, there has been a significant increase in the areas of built-up and barren land classes from 1992 to 2022, with a total increase of 17.41 % and 0.76 % respectively. These changes are primarily driven by rapid urbanization, leading to deforestation, and conversion of agricultural land. In general, the effects of urbanization, population growth, and climate change create negative trends in land use, which causes a number of medical, economic, and environmental problems for research area. The *NDVI* and *NDBI* indices were also employed to evaluate changes in land cover characteristics, revealing a strong correlation between impervious surfaces and vegetation cover. The data also indicated that there are limited natural resources and significant environmental areas that authorities could designate as hotspots for conservation or mitigation. The study emphasizes the importance of understanding these changes for effective conservation and mitigation efforts, utilizing spatial-temporal analysis enabled by GIS and RS technologies. The findings have implications for future policies promoting sustainable land use practices in Ha Nam province.

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