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MONITORING LAND USE/LAND COVER CHANGE USING REMOTE SENSING AND GIS TECHNIQUES IN PHU QUOC ISLAND, KIEN GIANG PROVINCE, VIETNAM

SEGUIMIENTO DE LOS CAMBIOS EN EL USO DEL SUELO Y LA COBERTURA DEL SUELO UTILIZANDO TECNICAS DE TELEDETECCION Y SIG EN LA ISLA DE PHU QUOC, PROVINCIA DE KIEN GIANG, VIETNAM

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ABSTRACT

The changes in land use and land cover (LULC) are among the primary drivers of global environmental changes in many developing countries. In this study, LULC changes were assessed on Phu Quoc Island, located in Kien Giang province, Vietnam, from 2001 to 2022. The study utilized remote sensing and Geographic Information System (GIS) technology using Landsat images for the years 2001, 2009, and 2022. Image classification for each year was conducted through supervised classification using a maximum likelihood classifier, with the main LULC classes being forests, bare land, agricultural areas, water bodies, and built-up areas. The accuracy of the classification was evaluated using the kappa coefficient, achieving values consistently above 0.8 for all three images. Over the 20-year period (2001-2022), the area of forest, agriculture, and water bodies decreased by 14.90 km^2, 30.96 km^2, and 0.64 km^2, respectively. Meanwhile, the areas of bare land and built-up areas increased by 22.22 km^2 and 24.28 km^2, respectively. Additionally, this study employed the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI) to quickly assess LULC changes, obtaining results consistent with the supervised classification. The findings underscore the importance of closely monitoring LULC changes to facilitate effective natural resource management and maintain a sustainable environment.

Keywords: Remote Sensing; Geographic Information System; Land Use/Land Cover Change; Supervised Classification; Phu Quoc Island.

RESUMEN

Los cambios en el uso y cobertura del suelo (LULC) se encuentran entre los principales impulsores de los cambios ambientales globales en muchos países en desarrollo. En este estudio, se evaluaron los cambios en el LULC en la Isla de Phu Quoc, ubicada en la provincia de Kien Giang, Vietnam, desde 2001 hasta 2022.

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El estudio utilizó tecnología de teledetección y Sistema de Información Geográfica (SIG) mediante imágenes Landsat para los años 2001, 2009 y 2022. La clasificación de imágenes para cada año se llevó a cabo mediante clasificación supervisada utilizando un clasificador de máxima verosimilitud, con las principales clases de LULC siendo bosques, terrenos baldíos, áreas agrícolas, cuerpos de agua y áreas urbanizadas. La precisión de la clasificación se evaluó utilizando el coeficiente kappa, logrando valores consistentemente por encima de 0.8 para las tres imágenes. En el periodo de 20 años (2001-2022), la superficie de bosques, agricultura y cuerpos de agua disminuyó en 14.90 km^2, 30.96 km^2 y 0.64 km^2, respectivamente. Mientras tanto, las áreas de terrenos baldíos y áreas urbanizadas aumentaron en 22.22 km^2 y 24.28 km^2, respectivamente. Además, este estudio empleó el Índice de Vegetación de Diferencia Normalizada (NDVI) y el Índice de Construcción de Diferencia Normalizada (NDBI) para evaluar rápidamente los cambios en el LULC, obteniendo resultados consistentes con la clasificación supervisada. Los hallazgos subrayan la importancia de monitorear de cerca los cambios en el LULC para facilitar la gestión efectiva de los recursos naturales y mantener un medio ambiente sostenible.

Palabras clave: Sensores Remotos; Sistema de Información Geográfica; Cambio en el Uso/Cobertura del Suelo; Clasificación Supervisada; Isla Phu Quoc.

1. INTRODUCTION

Land use and land cover (LULC) changes refers to the alteration of the Earth's surface due to human activities or natural processes that affect the distribution and arrangement of different land cover types (Tadese *et al*., 2020). Land use involves various ways in which land is utilized by human societies, including residential, industrial, agricultural, and recreational purposes (MohanRajan *et al*., 2020). On the other hand, land cover represents the physical attributes of the land surface, encompassing vegetation, water bodies, urban areas, and bare soil (Moniruzzaman *et al*., 2020). In recent years, the world has witnessed significant and rapid changes in LULC patterns, driven primarily by population growth, urbanization, industrialization, and agricultural expansion (Patel *et al*., 2019). These transformations have profound implications for ecosystems, biodiversity, and the overall health of the planet. Urban sprawl, deforestation, and the conversion of natural habitats for agricultural purposes contribute to the loss of biodiversity and the degradation of ecosystems (Thien *et al*., 2023a). The intensification of agriculture, along with the expansion of infrastructure, further amplifies the impact on the environment (Tilahun *et al*., 2022).

In the realm of contemporary Earth observation and spatial analysis, the integration of remote sensing and Geographic Information System (GIS) assumes paramount significance (Tadese *et al*., 2020; Thien and Phuong, 2023). Remote sensing, the acquisition of Earth's surface information from a distance, is primarily facilitated through satellite or airborne sensors. Conversely, GIS stands as a potent tool for the management, analysis, and visualization of spatial data. Their synergy yields profound insights into diverse facets of our environment, particularly the dynamics of LULC (MohanRajan *et al*., 2020). This convergence has sparked a paradigm shift in the exploration of LULC alterations, with vigilance and comprehension of LULC dynamics holding paramount significance for sustainable land administration, urban planning, and ecological preservation. Remote sensing technologies bestow the capability to capture extensive spatial data, facilitating the identification and delineation of distinct land cover types and their temporal transformations (Anwar *et al*., 2022). The assessment of LULC dynamics commonly employs widely recognized metrics such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI) (Thien and Phuong, 2023; Keerthi Naidu and Chundeli, 2023). NDVI, derived from satellite imagery, quantifies the presence and vitality of vegetation by measuring the variance between near-infrared and red light reflectance. Conversely, NDBI emphasizes built-up regions by calculating the disparity between near-infrared and shortwave infrared reflectance (Keerthi Naidu and Chundeli, 2023). These indices provide invaluable data for scrutinizing alterations in vegetation cover, urban sprawl, and land metamorphosis. NDVI proves particularly advantageous for evaluating vegetation health and variations, while NDBI aids in pinpointing built-up areas and the expansion of urban territories (Singh *et al*., 2023).

Previous studies on Phu Quoc Island in Kien Giang province, Vietnam, have primarily focused on aspects such as tourism, economics, environmental pollution, various flora and fauna species, and energy resources (Tran and Chen, 2016; Phong and Tien, 2021; Quyet *et al*., 2022; Kerber and Kramm, 2022). However, there is a notable gap in understanding the fundamental factors influencing LULC changes. This study addresses this gap by providing a comprehensive analysis of LULC changes from 2001 to 2022 using advanced remote sensing and GIS techniques. Unlike prior studies, our research employs a multi-temporal approach to assess both the spatial and temporal dynamics of LULC, offering new insights into the drivers of these changes and their implications for sustainable land management and environmental conservation. This study's unique contribution lies in its detailed quantification of LULC changes and its integration of spectral indices (NDVI and NDBI) for enhanced accuracy and understanding of land transformation processes. In the ambit of this research, our principal objective is to employ a fusion of remote sensing and GIS to scrutinize spatial trends and changes in LULC from 2001 to 2022 on Phu Quoc Island in the Kien Giang province, Vietnam. The specific aims encompass (i) identification and classification of diverse LULC types, coupled with a quantitative analysis of LULC variations spanning from 2001 to 2022; (ii) subsequent detection, mapping, and analysis of alterations in the NDVI and NDBI through satellite data; and (iii) assessment of the factors influencing LULC transformations in the study area throughout the 2001-2022 timeframe.

2. MATERIALS AND METHODS

2.1. Overview of the study area

Phu Quoc Island, situated in Kien Giang province, Vietnam, stands as a radiant jewel nestled in the Gulf of Thailand at the coordinates with latitude 10°02'N - 10°27'N and longitude 103°49'E - 104°04'E (Figure 1). Spanning approximately 560.84 km^2, this island not only beckons as a captivating tourist haven but also entices those with a penchant for culture and nature (Phong and Tien, 2021). The population of Phu Quoc is on a steady ascent, particularly as the island transforms into a burgeoning tourist hotspot. Blessed with a tropical climate, Phu Quoc basks in year-round sunlight, fostering ideal conditions for the flourishing of tourism and outdoor pursuits (Quyet *et al*., 2022). Phu Quoc Island's climate is characterized by two distinct seasons: the dry season and the rainy season. The dry season typically spans from November to April, bringing warm air and abundant sunshine to the island, with temperatures generally ranging from 25 to 32 ºC. In contrast, the rainy season extends from May to October, accompanied by heavy rainfall that contributes to the lush greenery of the island's landscape. During this period, temperatures typically hover between 24 and 30 ºC. The island's economy is undergoing robust growth, diversifying from the service industry and seafood processing to encompass tourism and agriculture. However, the changing landscape due to development projects and urban planning presents a significant challenge, exerting considerable impacts on the island's pristine scenery and natural milieu. In the face of these challenges, the island is evolving into a destination not merely for tourists but also as a symbol of immense economic development potential. This transformation unfolds against the backdrop of pressing issues related to environmental conservation and prudent land use management.

2.2. Data set

We used satellite images obtained from the United States Geological Survey (USGS) Glovis website (https://glovis.usgs.gov) to map LULC in Phu Quoc Island and assess LULC changes from 2001 to 2022. In this study, we employed Landsat 5-TM images for the years 2001 and 2009, and Landsat 8-OLI/TIRS images were utilized for 2022 (Table 1). The Landsat satellite images cover the research area for selected years during the dry season to mitigate the impact of weather factors on LULC classification and spectral index calculations. To classify and evaluate the accuracy of the LULC classification map, we collected point data, consisting of 100 points per year. For 2001 and 2009, 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.

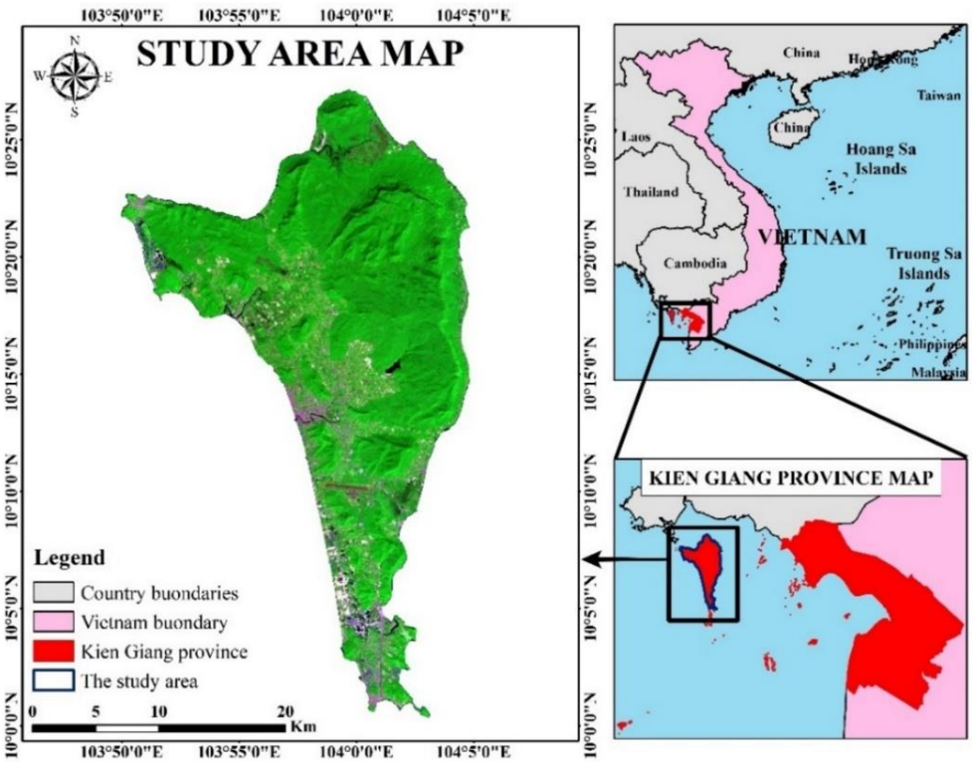

Figure 1. Location of the study area.

Table 1. Specification of Landsat satellite images.

Years	**Satellite**	**Sensor**	**Path/Row**	**Resolution (m)**	**Acquisition date**
2001	Landsat 5	TM	124/051	30	09/02/2001
2009	Landsat 5	TM	124/051	30	14/01/2009
2022	Landsat 8	OLI/TIRS	124/051	30	20/12/2022

2.3. Image pre-processing and classification

To create a usable image from Landsat data, layer stacking was used to combine 7 bands (bands 1-7 for the Landsat-5 images and bands 2-7, 10 for the Landsat-8 image) into a single composite image. The relevant portion of the image for the study area was selected through the extract by mask feature within ArcGIS 10.8 software (Thien *et al*., 2023b). Multi-band and multi-temporal raster images were then subject to image interpretation and classification algorithms to detect LULC changes (Tadese *et al*., 2020). Supervised classification image, which automatically sorts pixels into specific LULC classes, was utilized in this study (Thien and Phuong, 2023). The maximum likelihood classifier (MLC) was chosen for its efficient computational speed and the underlying principle that each pixel was assigned to its corresponding class, although many other supervised classification methods have also been extensively utilized (MohanRajan *et al*., 2020). The Landsat multi-band data (2001, 2009, and 2022) were processed using MLC in ArcGIS 10.8 software after geo-referencing, pre-processing, mosaicking, and subsetting to the area of interest (AoI) (Thien *et al*., 2023b). LULC classifications were extracted from each Landsat image and saved as distinct signature files before being applied to several groups of images processed by supervised MLC (Keerthi Naidu and Chundeli, 2023). Figure 2 illustrates the classification approach.

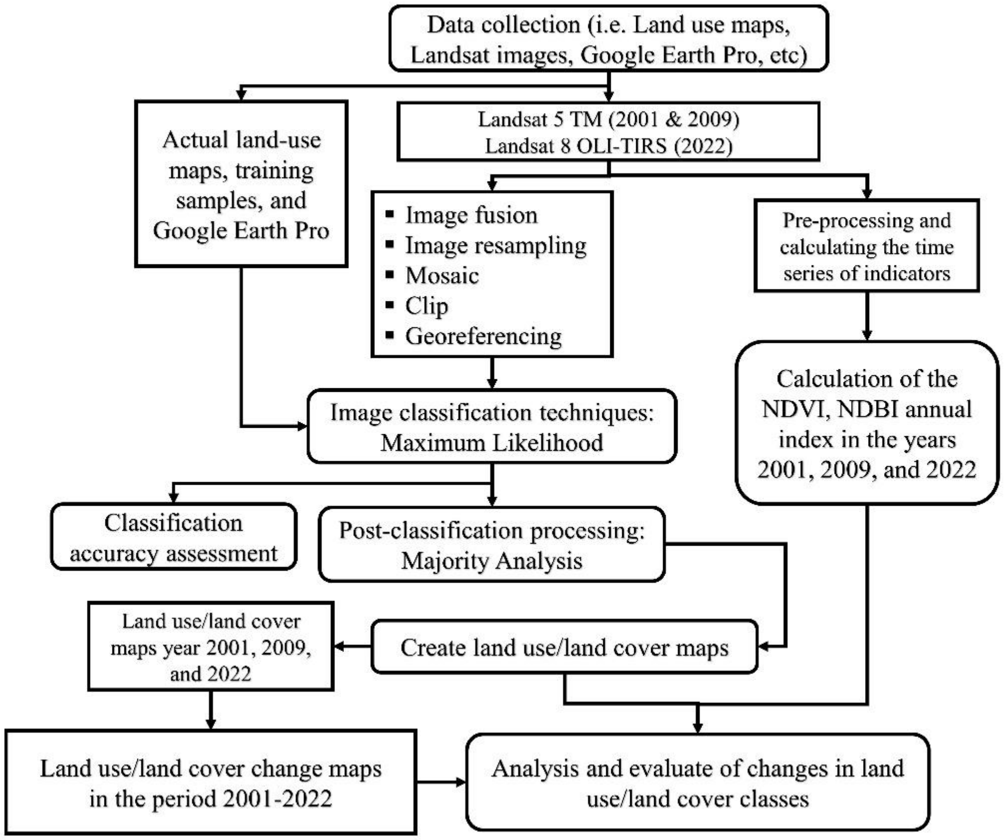

Figure 2. Methodology of the study in work flowchart.

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: forest, bare land, agricultural areas, water bodies, and built-up areas (Table 2).

Table 2. Classes delineated from field survey.

Class	Description
Forest	Natural forest, plantations and mixed forest lands
Bare land	Fallow land, sands and earth dumps
Agricultural areas	Cultivated land, crop fields, vegetable fields
Water bodies	Ponds, lakes, and ocean surfaces
Built-up areas	Residential, industrial, roads and other manmade structures

2.4. Accuracy assessment

The accuracy assessment is crucial for measuring the difference between our classification and the reference map or dataset (MohanRajan *et al*., 2020; Tadese *et al*., 2020). This involves comparing the classification with ground-truth evidence to validate a classified image. To assess the accuracy of the classification results, we utilized an error matrix and compared the classification results with 50 reference data points collected for each year (Thien and Phuong, 2023). We conducted an error matrix test to calculate the user's accuracy

(UA) and producer's accuracy (PA) percentages. Subsequently, we calculated the overall accuracy (OA) and kappa coefficient using formulas (1) and (2).

$$\text{OA} = \left(\frac{1}{N}\right)\sum_{i=1}^{r} x_{ii} \quad (1)$$

$$\text{Kappa coefficient} = \frac{N\sum_{\mathrm{i=1}}^{\mathrm{r}} \mathrm{x_{ii}} - \sum_{\mathrm{i=1}}^{\mathrm{r}}(x_{\mathrm{i+}})(x_{\mathrm{i+}})}{\mathrm{N}^2 - \sum_{\mathrm{i=1}}^{\mathrm{r}}(x_{\mathrm{i+}})(x_{\mathrm{i+}})} \quad (2)$$

where r is the number of rows in the matrix, x_{i+} and x_{ii} are the marginal totals of row r and column i, respectively, and N is the total number of observations.

2.5. Spectral indices

By estimating the NDVI and NDBI through the analysis of satellite imagery, we gain valuable insights into the health of vegetation and the progression of urbanization (Guha *et al*., 2018; Singh *et al*., 2023). The NDVI functions as a vegetation index, distinguishing vegetation by utilizing the near-infrared (NIR) and red (RED) bands of satellite images. As vegetation cover increases, the NDVI value rises, and conversely, it decreases with a decrease in vegetation cover (Keerthi Naidu and Chundeli, 2023). On the flip side, the NDBI operates as an urban index, detecting built-up areas by employing the shortwave infrared (SWIR) and near-infrared (NIR) bands of satellite images. The NDBI value increases as built-up areas expand and decreases with a reduction in built-up areas (Singh *et al*., 2023). Formulas (3) and (4) are applied to calculate the NDVI and NDBI indices, respectively.

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \quad (3)$$

$$\text{NDBI} = \frac{\text{SWIR} - \text{NIR}}{\text{SWIR} + \text{NIR}} \quad (4)$$

The study employed regression analysis to quantify the correlation between NDVI and NDBI in Phu Quoc Island for the years 2001, 2009, and 2022. The correlation coefficients resulting from the regression analysis were confined to the -1 to +1 range (Degerli and Çetin, 2022). The methodology involved the use of the random point generator feature in ArcGIS 10.8 software, generating 50 random points within the specified study area boundaries. Subsequently, the extract multi values to points tool was employed to extract values for each point from the NDVI and NDBI pixels (Shahfahad *et al*., 2020). The obtained values were exported to Microsoft Excel 2016 software (Microsoft, USA) to formulate the regression equation that elucidates the relationship between NDVI and NDBI. This process ensures a systematic and rigorous approach to assess the correlation dynamics over the specified years in Phu Quoc Island.

3. RESULTS AND DISCUSSION

3.1. Land use/land cover classification and accuracy assessment

The supervised classification analysis conducted between 2001 and 2022 revealed that the study region was characterized by diverse land features, including forest, bare land, agriculture, waterbodies, and built-up. To classify LULC, a classification scheme was applied that integrated field survey information with high-resolution maps from Google Earth Pro for Phu Quoc Island. Figure 3 shows space-time LULC models for the study area from 2001 to 2022, and Table 3 shows data on the area and proportion for each land use category as determined by the classification outcomes.

Based on the results of the LULC classification in Table 3, the forest class occupied the largest area in all three years, with respective total areas of 394.12 km^2 (70.27%) in 2001, 397.99 km^2 (70.96%) in 2009, and

379.22 km^2 (67.62%) in 2022 (Table 3). Following this is the area of agriculture class, which in 2001 was 111.56 km^2 (19.89%), in 2009 was 81.06 km^2 (14.45%), and in 2022 was 80.60 km^2 (14.37%) (Table 3). The bare land class secured the third position in terms of land cover types for all three years, with respective areas of 47.95 km^2 (8.55%) in 2001, 63.14 km^2 (11.26%) in 2009, and 70.17 km^2 (12.51%) in 2022 (Table 3). The built-up class area ranked fourth, with respective areas of 4.83 km^2 (0.86%) in 2001, 16.35 km^2 (2.92%) in 2009, and 29.11 km^2 (5.19%) in 2022 (Table 3). Lastly, the waterbodies class occupied the smallest area in the study area, comprising 2.38 km^2 (0.42%) in 2001, 2.30 km^2 (0.41%) in 2009, and 1.74 km^2 (0.31%) in 2022 (Table 3).

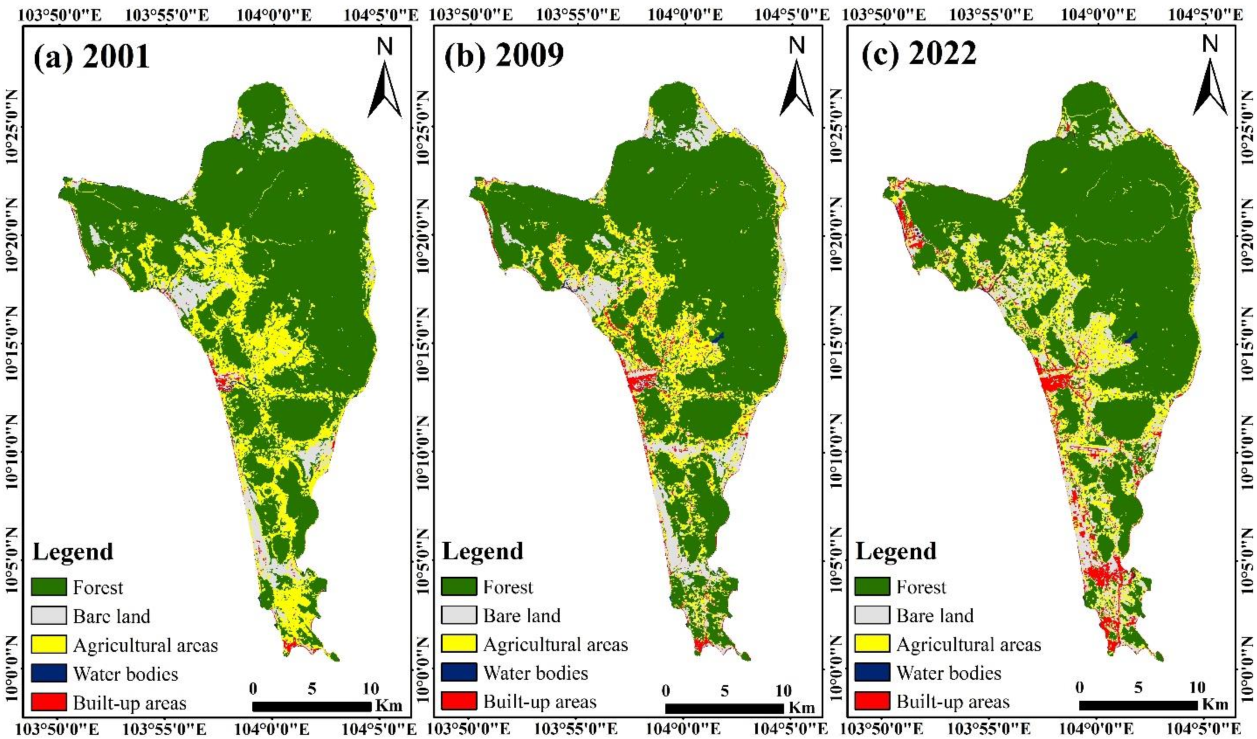

Figure 3. Land use/land cover maps for Phu Quoc Island in (a) 2001, (b) 2009, and (c) 2022.

Table 3. The land use/land cover area distribution from 2001 to 2022 in Phu Quoc Island.

Class	**2001**		**2009**		**2022**	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Forest	394.12	70.27	397.99	70.96	379.22	67.62
Bare land	47.95	8.55	63.14	11.26	70.17	12.51
Agricultural areas	111.56	19.89	81.06	14.45	80.60	14.37
Water bodies	2.38	0.42	2.30	0.41	1.74	0.31
Built-up areas	4.83	0.86	16.35	2.92	29.11	5.19
Total	560.84	100.00	560.84	100.00	560.84	100.00

The assessment of the post-classification accuracy in this study was performed by comparing the classified LULC classes with the reference data (Balha *et al*., 2021). The results of the classification evaluation showed that the OA of the years 2001, 2009, and 2022 was 88.00%, 89.80%, and 92.00%, respectively (Table 4). Overall, the PA and UA for each LULC class in all 3 years were above 80% (Table 4). The kappa coefficient values in 2001, 2009, and 2022 in the study area were recorded as 0.845, 0.867, and 0.894, respectively

(Table 4). Kappa coefficients ranging from 0.81 to 1.00 are considered almost perfect in LULC classification (Foody, 2020; Verma *et al*., 2020). These results show reliable land cover classification and good consistency between referenced and classified maps.

Table 4. Accuracy assessments for classified maps.

LULC classes	**2001**		**2009**		**2022**	
	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)
Forest	86.67	92.86	93.33	87.50	94.12	100.00
Bare land	90.00	90.00	88.89	100.00	88.89	88.89
Agricultural areas	83.33	83.33	81.82	81.82	100.00	83.33
Water bodies	100.00	100.00	100.00	100.00	100.00	100.00
Built-up areas	88.89	80.00	90.91	90.91	83.33	90.91
Overall accuracy (%)	88.00		89.80		92.00	
Kappa Coefficient	0.845		0.867		0.894	

3.2. Land use/land cover change

The identification of LULC changes based on remote sensing imagery has found extensive applications in LULC research, environmental monitoring, and protection, as well as natural resource management (Hashim *et al*., 2020). Utilizing ArcGIS 10.8 software, we employed supervised classification to derive the area and percentage of each land cover layer from classified images for each respective year (Seyam *et al*., 2023). Analyzing the LULC maps of Phu Quoc Island through spatial analysis reveals notable transformations spanning the last two decades, from 2001 to 2022. These alterations, influenced by both natural forces and human activities, can yield both positive and negative repercussions. The changes in LULC on Phu Quoc Island are presented in Table 5 for the periods 2001-2009, 2009-2022, and 2001-2022 and in Figure 4 for the whole period of study. During the period 2001-2009, the area of forest, bare land, and built-up classes increased, while the areas of agricultural land and waterbodies decreased. The bare land class exhibited the highest positive shift, expanding by 15.19 km^2 (2.71%), and the agricultural land class experienced the highest negative shift, contracting by 30.50 km^2 (5.44%) (Table 5). Additionally, the waterbodies class decreased by 0.08 km^2 (0.01%). Meanwhile, the areas of forest and built-up increased by 3.87 km^2 (0.69%) and 11.52 km^2 (2.05%), respectively (Table 5). Moving to the period 2009-2022, the trend in forest area reversed, decreasing by 18.77 km^2 (3.35%). Furthermore, the areas of agricultural land and waterbodies continued to decline by 0.46 km^2 (0.08%) and 0.56 km^2 (0.10%), respectively. Conversely, the areas of bare land and built-up continued to increase during this period, with the total area increasing by 7.03 km^2 (1.25%) and 12.76 km^2 (2.28%), respectively (Table 5).

Table 5. The land use/land cover change analysis from 2001 to 2022 in Phu Quoc Island.

Class	**2001-2009**		**2009-2022**		**2001-2022**	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Forest	3.87	0.69	-18.77	-3.35	-14.90	-2.66
Bare land	15.19	2.71	7.03	1.25	22.22	3.96
Agricultural areas	-30.50	-5.44	-0.46	-0.08	-30.96	-5.52
Water bodies	-0.08	-0.01	-0.56	-0.10	-0.64	-0.11
Built-up areas	11.52	2.05	12.76	2.28	24.28	4.33

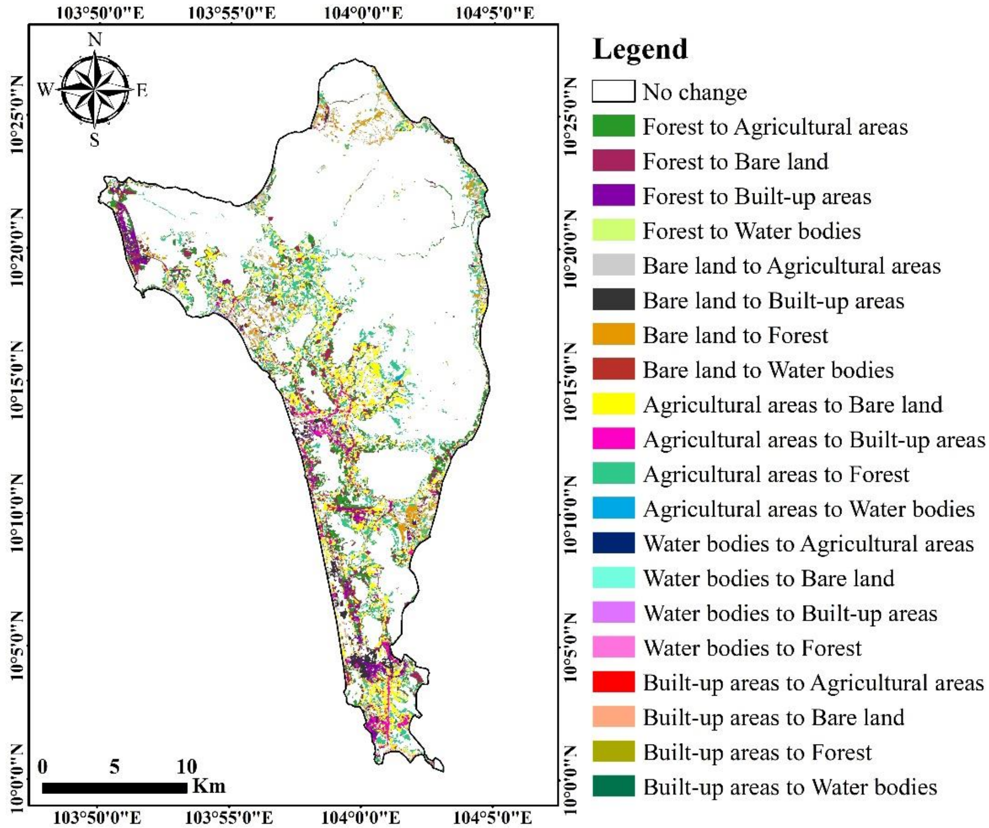

Figure 4. Land use/land cover change map of Phu Quoc Island from 2001 to 2022.

Over the past two decades (2001-2022), Phu Quoc Island has undergone significant transformations in land use across various categories. Changes in land use are characterized by pronounced shifts in different types of land, revealing a dynamic landscape shaping by various factors. The area of forest cover has notably decreased by 14.90 km^2 (2.66%) in the last 20 years. This reduction is attributed to a combination of factors such as deforestation for agricultural purposes and urbanization, contributing to the gradual decline in natural forest coverage (Tilahun *et al*., 2022; Kovyazin *et al*., 2023). Additionally, natural climate conditions like storms and strong winds have also impacted the loss of natural forest areas (Hall *et al*., 2020). In contrast, the area of vacant land has increased notably, with a total increase of 22.22 km^2 (3.96%). The expansion of bare land may be related to urban development, infrastructure projects, or changes in land management policies leading to the conversion of existing land into open spaces (Koroso *et al*., 2020). On the other hand, agricultural land has decreased significantly by 30.96 km^2 (5.52%). This decline is attributed to the conversion of agricultural land for purposes such as urbanization or changes in economic activities, reducing the demand for agricultural production in the region (Prabhakar, 2021). Currently, Phu Quoc Island primarily focuses on developing its tourism economy, leveraging the natural beauty of the area. As a result, the local population has gradually shifted towards tourism-related businesses as an alternative to the previously dominant agricultural sector (Surya Suamba *et al*., 2022). Furthermore, the shortage of fresh water for agricultural production is considered a significant contributing factor to the current decrease in agricultural land (Schneider and Asch, 2020). The area of waterbodies has modestly decreased by 0.64 km^2 (0.11%). Factors contributing to this reduction may include environmental changes, human activities impacting water ecosystems, or alterations in hydrological patterns (Chen *et al*., 2020). Simultaneously, the built-up area has expanded by an additional 24.28 km^2 (4.33%). This increase emphasizes the ongoing urbanization and infrastructure development occurring on Phu Quoc Island, leading to the conversion of land for residential, commercial, or industrial purposes (Thien *et al*., 2022). The growth of the tourism industry has necessitated accommodation for visitors to Phu Quoc, resulting in the strong development of resort areas and service districts, driving the continuous increase in built-up areas (Ngo *et al*., 2021). The changes in land use on Phu Quoc Island over the past two decades stem from the complex interaction of various factors, including deforestation, urbanization, agricultural conversion, environmental dynamics, and infrastructure development. These changes have led to alterations in the allocation of land across different types, reflecting the evolving socioeconomic and environmental context of the island.

GIS analysis was used for post-classification comparison of the detected changes, with change map generated for the period 2001-2022 to understand the spatial patterns of change (Figure 4). The classified maps were overlayed to create a LULC change map; a cross-tabulation matrix was also generated for the period 2001-2022 (Table 6) to show the nature of changes in different land cover classes. In the total area of 394.12 km^2 of forest in the year 2001, 343.95 km^2 still remained as forest in 2022. However, 43.65 km^2 had been converted into agricultural land and bare land, while the remaining 6.52 km^2 had been transformed into built-up areas and water bodies (Table 6). The bare land type retained an area of 20.79 km^2 out of the initial 47.95 km^2 in 2001, with the majority being evenly distributed among forest, agricultural land, and built-up areas. Only 0.20 km^2 had been converted into water bodies (Table 6). Most of the total agricultural land area of 111.56 km^2 in 2001 has been converted into forest (25.86 km^2) and bare land (30.82 km^2), with 44.99 km^2 retained as agricultural land in 2022 (Table 6). Over the same period, the water body area witnessed a decrease, with 0.80 km^2 of the initial 2.38 km^2 in 2001 remaining unchanged and 1.58 km^2 converting into other land cover types by 2022 (Table 6). During the 2001-2022 period, the built-up area increased rapidly due to the conversion of other land cover classes. Additionally, out of the total built-up area in 2001, 1.27 km^2 had been converted into bare land, and 0.63 km^2 had been converted into other land cover classes (Table 6).

Table 6. Cross-tabulation of land cover classes between 2001 and 2022 (area in km^2).

2022 / **2001**	Forest	Bare land	Agricultural areas	Water bodies	Built-up areas	**Total**
Forest	**343.95**	17.22	26.43	0.36	6.16	**394.12**
Bare land	9.08	**20.79**	8.81	0.20	9.07	**47.95**
Agricultural areas	25.86	30.82	**44.99**	0.20	9.69	**111.56**
Water bodies	0.23	0.07	0.02	**0.80**	1.26	**2.38**
Built-up areas	0.10	1.27	0.35	0.18	**2.93**	**4.83**
Total	**379.22**	**70.17**	**80.60**	**1.74**	**29.11**	**560.84**

3.3. Spectral indices

High NDVI index values indicate denser and healthier vegetation, while lower values correspond to sparse or no vegetation (Guha *et al*., 2018; Keerthi Naidu and Chundeli, 2023). In 2001, the NDVI value ranged from -0.73 to +0.75 (Figure 5a); in 2009, NDVI values ranged from -0.47 to +0.70 (Figure 5b); and in 2022, NDVI values ranged from -0.23 to +0.59 (Figure 5c). Significant spatial changes in vegetation cover and green area were observed between the lowest and highest NDVI values recorded in 2001, along with improved agricultural productivity in areas such as forests and vegetation cover (Figure 5). 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 decrease when the built-up area decreases (Singh *et al*., 2023). In 2001, the NDBI value ranged from -0.83 to +0.52 (Figure 6a); in 2009, NDBI values ranged from -0.63 to +0.50 (Figure 6b); and in 2022, the NDBI values ranged from -0.42 to +0.38 (Figure 6c) The red areas in Figure 6 show minimal vegetation cover, such as built-up and barren land.

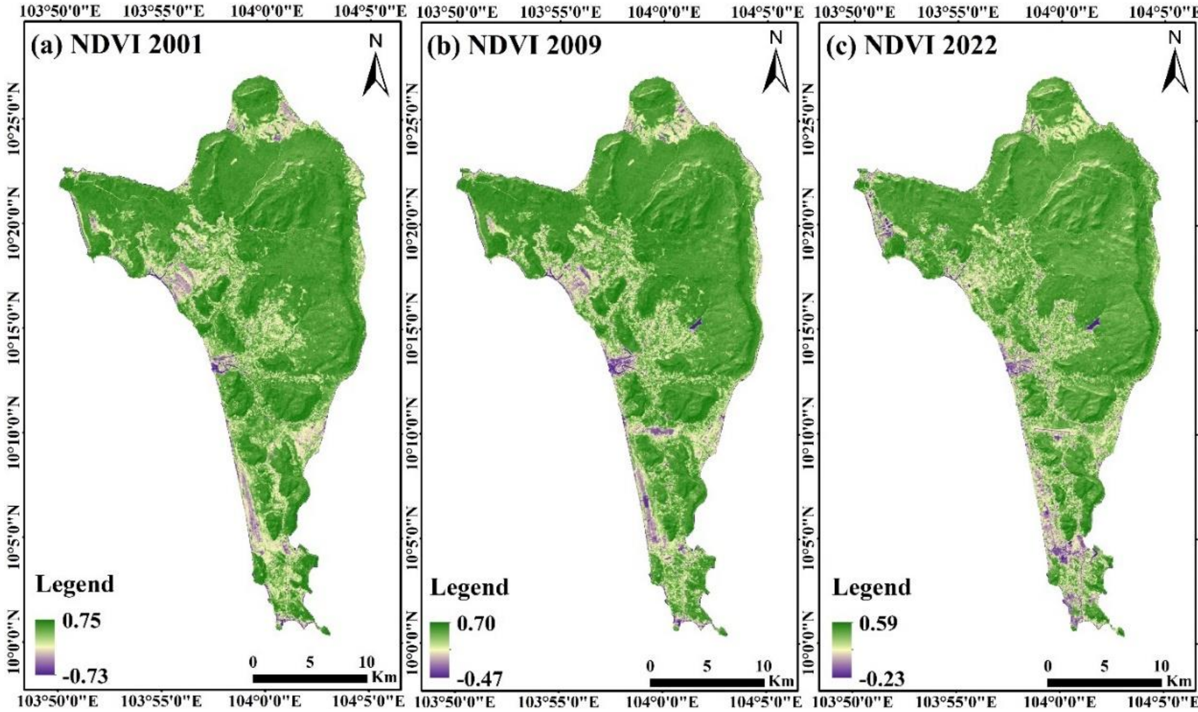

Figure 5. NDVI maps for Phu Quoc Island in (a) 2001, (b) 2009, and (c) 2022.

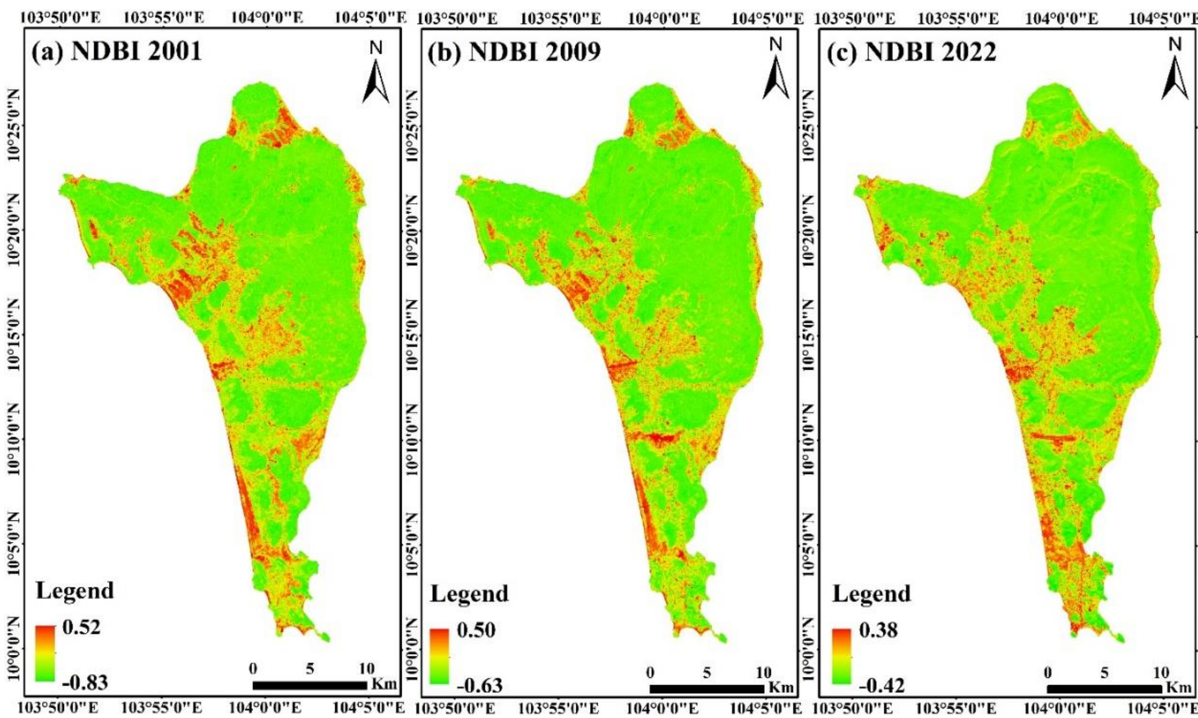

Figure 6. NDBI maps for Phu Quoc Island in (a) 2001, (b) 2009, and (c) 2022.

The conducted linear regression analysis has provided valuable insights into the relationship between two key indices, NDVI and NDBI (Shahfahad *et al*., 2020; Degerli and Çetin, 2022). The focus of the analysis was on assessing changes in NDBI values with respect to land use, gauged by variations in land use intensity within the LULC units through regression analysis (R^2) (Das and Angadi, 2020). The negative correlation identified between NDVI and NDBI is a noteworthy finding. The correlation coefficients of $R^2 = 0.8703$ for 2001, $R^2 = 0.8596$ for 2009, and $R^2 = 0.7202$ for 2022, as illustrated in Figure 7, emphasize the strength and consistency of this negative relationship over time. Figure 7 further elucidates the connection between the vegetation index (NDVI) and the integrated component derived from NDBI. The regression analysis not only confirms the negative correlation but also sheds light on the spatial distribution of NDBI values. Specifically, the highest NDBI values were found to correspond to areas with the lowest NDVI values, and conversely, areas with the lowest NDBI values exhibited the highest NDVI values. This spatial relationship emphasizes that regions characterized by increased built-up areas and barren land experience a reduction in vegetation coverage. This analytical approach enhances our understanding of the intricate dynamics between land use changes and vegetation health, providing valuable insights for sustainable land management and environmental conservation efforts.

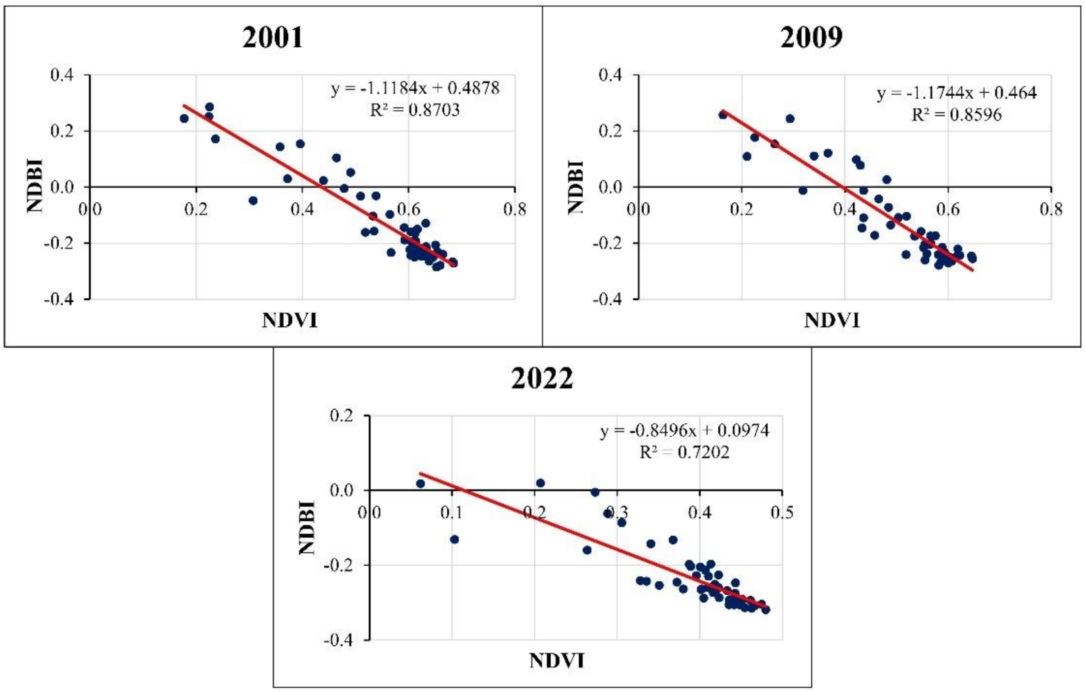

Figure 7. Regression analyses between NDVI and NDBI in Phu Quoc Island.

The supervised classification analysis conducted between 2001 and 2022 revealed significant and varied changes in land features. Compared to previous studies, our analysis provides a more detailed and accurate quantification of these changes. For instance, while earlier research primarily focused on tourism and economic impacts, our study highlights substantial environmental transformations, such as a 14.90 km^2 decrease in forest area and a 24.28 km^2 increase in built-up areas. This detailed classification offers a clearer understanding of the implications for local biodiversity and ecosystem health. Additionally, by employing NDVI and NDBI indices, our study presents a more nuanced assessment of vegetation health and urban expansion, which were not addressed in prior research on Phu Quoc Island. These findings underscore the necessity for proactive land use planning and sustainable development strategies to mitigate adverse environmental impacts.

4. CONCLUSION

The study underscores the pivotal role of integrating remote sensing and GIS techniques, emphasizing their capacity to yield valuable insights into LULC changes. Over the period from 2001 to 2022, Phu Quoc Island has experienced noteworthy alterations in LULC, witnessing a decline in forest, agriculture, and waterbodies by 2.66%, 5.52%, and 0.11%, respectively. In contrast, built-up and bare land areas have exhibited substantial growth rates of 3.96% and 4.33% during the same timeframe. These changes are predominantly attributed to human-induced factors, particularly the rapid urbanization shaping the landscape features associated with forest and agricultural land classes. The primary driving force behind these shifts is the current tourism-driven economic development, which exerts significant pressure to fulfill accommodation requirements for the increasing influx of tourists resorting to Phu Quoc Island. This surge has manifested in heightened urbanization to address the demand for housing, hotels, and tourist infrastructure. In the assessment of land cover characteristics, the study employs NDVI and NDBI indices, revealing a robust correlation between impervious surfaces and vegetation cover. Furthermore, the data highlights that limited natural resources and crucial environmental areas subject to authoritative designations emerge as hotspots for conservation or mitigation efforts. The study underscores the necessity of comprehending these changes, advocating for conservation endeavors and the mitigation of adverse environmental impacts. The approach involves employing spatiotemporal analysis supported by remote sensing and GIS technology. These findings carry substantial implications for the formulation of future policies aimed at promoting sustainable land use practices on Phu Quoc Island.

AUTHOR CONTRIBUTION CReDiT

BBT conceived the study, handled formal analysis, interpreted the results, wrote the first draft as well as edited the manuscript. VTP handled the review of literature and data collection. ANK handled the review of literature, interpreted the results, and wrote the first draft. All authors read and approved the final draft of the manuscript.

DECLARATION OF COMPETING INTERESTS

The authors declare no competing interests.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

Anderson J.R., Hardy E.E., Roach J.T., & Witmer R.E. (1976). A land use and land cover classification system for use with remote sensor data. *Geological survey professional paper, U.S. government printing office. Washington DC*, 964, 1-28.

Anwar, Z., Alam, A., Elahi, N., & Shah, I. (2022). Assessing the trends and drivers of land use land cover change in district Abbottabad lower Himalayan Region Pakistan. *Geocarto International*, 37 (25), 10855-10870.

Balha, A., Mallick, J., Pandey, S., Gupta, S., & Singh, C.K. (2021). A comparative analysis of different pixel and object-based classification algorithms using multi-source high spatial resolution satellite data for LULC mapping. *Earth Science Informatics*, 14, 2231-2247.

Chen, H., Liu, H., Chen, X., & Qiao, Y. (2020). Analysis on impacts of hydro-climatic changes and human activities on available water changes in Central Asia. *Science of the Total Environment*, 737, 139779.

Das, S., & Angadi, D.P. (2020). Land use-land cover (LULC) transformation and its relation with land surface temperature changes: A case study of Barrackpore Subdivision, West Bengal, India. *Remote Sensing Applications: Society and Environment*, 19, 100322.

Degerli, B., & Çetin, M. (2022). Evaluation from rural to urban scale for the effect of NDVI-NDBI indices on land surface temperature, in Samsun, Türkiye. *Turkish Journal of Agriculture-Food Science and Technology*, 10 (12), 2446-2452.

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. *Remote Sensing of Environment*, 239, 111630.

Guha, S., Govil, H., Dey, A., & Gill, N. (2018). Analytical study of land surface temperature with NDVI and NDBI using Landsat 8 OLI and TIRS data in Florence and Naples city, Italy. *European Journal of Remote Sensing*, 51 (1), 667-678.

Hall, J., Muscarella, R., Quebbeman, A., Arellano, G., Thompson, J., Zimmerman, J.K., & Uriarte, M. (2020). Hurricane-induced rainfall is a stronger predictor of tropical forest damage in Puerto Rico than maximum wind speeds. *Scientific Reports*, 10 (1), 4318

Hashim, A.M., Elkelish, A., Alhaithloul, H.A., El-Hadidy, S.M., & Farouk, H. (2020). Environmental monitoring and prediction of land use and land cover spatio-temporal changes: a case study from El-Omayed Biosphere Reserve, Egypt. *Environmental Science and Pollution Research*, 27, 42881-42897.

Keerthi Naidu, B.N., & Chundeli, F.A. (2023). Assessing LULC changes and LST through NDVI and NDBI spatial indicators: a case of Bengaluru, India. *GeoJournal*, 88, 4335-4350.

Kerber, H., & Kramm, J. (2022). From laissez-faire to action? Exploring perceptions of plastic pollution and impetus for action. Insights from Phu Quoc Island. *Marine Policy*, 137, 104924.

Kovyazin, V.F., Lepikhina, O.Y., Demidova, P.M., Kolesnik, O.A., Shobairi, S.O.R., & Nguyen, A.T. (2023). Problems of Forest Resource Management in the Arctic Zone of the Russian Federation. Russian Forestry Journal, (3), 185-194.

Koroso, N.H., Zevenbergen, J.A., & Lengoiboni, M. (2020). Urban land use efficiency in Ethiopia: An assessment of urban land use sustainability in Addis Ababa. *Land Use Policy*, 99, 105081.

MohanRajan, S.N., Loganathan, A., & Manoharan, P. (2020). Survey on Land Use/Land Cover (LU/LC) change analysis in remote sensing and GIS environment: Techniques and Challenges. *Environmental Science and Pollution Research*, 27, 29900-29926.

Moniruzzaman, M., Thakur, P.K., Kumar, P., Ashraful Alam, M., Garg, V., Rousta, I., & Olafsson, H. (2020). Decadal urban land use/land cover changes and its impact on surface runoff potential for the Dhaka City and surroundings using remote sensing. *Remote Sensing*, 13 (1), 83.

Ngo, K.D., Nghiem, S.V., Lechner, A.M., & Vu, T.T. (2021). Building Structure Mapping on Level Terrains and Sea Surfaces in Vietnam. *Remote Sensing*, 13 (13), 2439.

Patel, S.K., Verma, P., & Shankar Singh, G. (2019). Agricultural growth and land use land cover change in peri-urban India. *Environmental Monitoring and Assessment*, 191, 600.

Phong, N.T., & Tien, H.V. (2021). Water resource management and island tourism development: insights from Phu Quoc, Kien Giang, Vietnam. *Environment, Development and Sustainability*, 23 (12), 17835-17856.

Prabhakar, S.V.R.K. (2021). A succinct review and analysis of drivers and impacts of agricultural land transformations in Asia. *Land Use Policy*, 102, 105238.

Quyet, L.V., Duy, P.T., & Toan, V.P. (2022). Sustainable development of tourism economy in Phu Quoc Island, Kien Giang province, Vietnam: current situation and prospects. *In IOP Conference Series: Earth and Environmental Science, IOP Publishing*, 1028 (1), 012005.

Schneider, P., & Asch, F. (2020). Rice production and food security in Asian Mega deltas—A review on characteristics, vulnerabilities and agricultural adaptation options to cope with climate change. *Journal of Agronomy and Crop Science*, 206 (4), 491-503.

Seyam, M.M.H., Haque, M.R., & Rahman, M.M. (2023). Identifying the land use land cover (LULC) changes using remote sensing and GIS approach: A case study at Bhaluka in Mymensingh, Bangladesh. *Case Studies in Chemical and Environmental Engineering*, 7, 100293.

Shahfahad, Kumari, B., Tayyab, M., Ahmed, I.A., Baig, M.R.I., Khan, M.F., & Rahman, A. (2020). Longitudinal study of land surface temperature (LST) using mono-and split-window algorithms and its relationship with NDVI and NDBI over selected metro cities of India. *Arabian Journal of Geosciences*, 13, 1040.

Singh, P., Verma, P., Chaudhuri, A.S., Singh, V.K., & Rai, P.K. (2023). Evaluating the relationship between Urban Heat Island and temporal change in land use, NDVI and NDBI: a case study of Bhopal city, India. *International Journal of Environmental Science and Technology*, 1-12.

Surya Suamba, I.B., Anom Wiryasa, N.M., Acwin Dwijendra, N.K., & Diasana Putra, I. (2022). Characteristics and deviation patterns of agricultural land use in tourism area of Canggu, Bali, Indonesia. *Caspian Journal of Environmental Sciences*, 20 (2), 423-430.

Tadese, M., Kumar, L., Koech, R., & Kogo, B.K. (2020). Mapping of land-use/land-cover changes and its dynamics in Awash River Basin using remote sensing and GIS. *Remote Sensing Applications: Society and Environment*, 19, 100352.

Thien, B.B., & Phuong, V.T. (2023). Detection of Land Use and Land Cover Change Using Remote Sensing and GIS in Ba Ria-Vung Tau Province, Vietnam. *Geography and Natural Resources*, 44 (4), 383-393.
Thien, B.B., Phuong, V.T., & Komolafe, A.A. (2023a). Assessment of forest cover and forest loss using satellite images in Thua Thien Hue province, Vietnam. *AUC Geographica*, 58 (2), 172-186.

Thien, B.B., Sosamphanh, B., Yachongtou, B., & Phuong, V.T. (2022). Land use/land cover changes in the period of 2015–2020 in AngYai Village, Sikhottabong District, Vientiane Capital, Lao PDR. *Geology, Geophysics and Environment*, 48 (3), 279-286.

Thien, B.B., Yachongtou, B., & Phuong, V.T. (2023b). Long-term monitoring of forest cover change resulting in forest loss in the capital of Luang Prabang province, Lao PDR. *Environmental Monitoring and Assessment*, 195 (8), 947.

Tilahun, D., Gashu, K., & Shiferaw, G.T. (2022). Effects of Agricultural Land and Urban Expansion on Peri-Urban Forest Degradation and Implications on Sustainable Environmental Management in Southern Ethiopia. *Sustainability*, 14 (24), 16527.

Tran, V.T., & Chen, T.H. (2016). Wind energy resources on Phuquoc island, Vietnam. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 38 (11), 1612-1619.

Verma, P., Raghubanshi, A., Srivastava, P.K., & Raghubanshi, A.S. (2020). Appraisal of kappa-based metrics and disagreement indices of accuracy assessment for parametric and nonparametric techniques used in LULC classification and change detection. *Modeling Earth Systems and Environment*, 6, 1045-1059.