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Land cover object change monitoring and environmental suitability confirmation in Cat Ba Biosphere Reserve of Vietnam

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ABSTRACT

The study examined the core, buffer, and transition zones within the Cat Ba Biosphere Reserve in Vietnam to assess changes in five land cover categories (water surface, cropland, vacant land, residential land, and forestland) between 2018 and 2022. Additionally, we aimed to evaluate water quality using three indicators (normalized difference turbidity index, normalized difference chlorophyll index, total suspended solids) and air quality using four indicators (nitrogen dioxide, sulfur dioxide, carbon monoxide, ozone) for the 2022 data. Land cover change analysis and monitoring of water and air quality indicators were conducted using the Google Earth Engine platform, employing Sentinel-2 imagery for land cover and water quality assessment and Sentinel-5P images for air quality assessment. The findings revealed correlations between changes in land cover and water and air quality indicators within the Cat Ba Biosphere Reserve. While occasional instances of values surpassing permissible limits were noted, the average values over the 12-month period in 2022 indicated that water and air quality indicators remained within acceptable thresholds. These results suggest effective preservation efforts in the Cat Ba Biosphere Reserve, indicating no significant signs of degradation.

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Introduction

The International Network of Biosphere Reserves has been established under United Nations Educational Scientific and Cultural Organization (UNESCO) Man and the Biosphere Programme to conserve biodiversity and promote its sustainable use. Biosphere reserves are internationally recognized landscapes that are set aside to protect various ecological characteristics. Ensuring the management and protection of biosphere reserves is a collective responsibility that encompasses society at large, with particular emphasis placed on leveraging new technologies for the effective monitoring of these reserves. There are 738 biosphere reserves in 134 countries, including 22 transboundary sites, forming the World Network of Biosphere Reserves (UNESCO 2023). According to the UNESCO Man and the Biosphere Programme, UNESCO introduced related notions and concepts as early as the 1970s and 1980s. These ideas align with current thinking on integrated conservation and development models, the conservation and sustainable use of biodiversity, and broader discussions on sustainable development. Biosphere reserves can serve as platforms for policies and practices that promote the conservation and sustainable use of biodiversity, foster

the economic growth of local communities, and contribute to the emergence of knowledge-based management arrangements at regional, provincial, and national levels (Nam, Bosch, and Maani 2009). However, despite this development, the Cat Ba Biosphere Reserve is experiencing significant tourism and revenue growth. Simultaneously, environmental degradation persists, and high levels of poverty remain in several of the communes in the area (Bosch, Maani, and Smith 2007).

Monitoring of ecological change within such reserves is a central component of biosphere reserve management, and traditional methods have proven difficult and costly. The management and protection of biosphere reserves represent cooperative social responsibilities. The utilization of cutting-edge technology, such as satellite imagery, is particularly crucial in fulfilling this duty (Machlis and Wright 1984). Currently, remote sensing data are harnessed from various satellite sources and find widespread applications across multiple industries and fields (Hung, Asaeda, and Thao 2021; Hung, Giang, and Quang 2016; Volke and Abarca-Del-Rio 2020; Thao, Giang, and Anh 2024). Satellite imagery can provide comprehensive spatiotemporal characterizations of ecosystem functions at local to global scales (Cazorla et al. 2023).

Specifically, Sentinel-2 imagery has a positive impact on land use and land cover (LULC) monitoring, particularly in the monitoring of crops, forests, residential land areas, and water resources (Phiri et al. 2020). Notably, the Sentinel-2 mission is designed to support land monitoring services, encompassing changes in LULC for environmental assessment, crop monitoring for food safety, detailed analyses of vegetation and forests, and the measurement of vegetation indices (chlorophyll concentration, carbon mass estimation, leaf area, leaf water content). Additionally, it is employed in observing coastal areas for marine environment monitoring, and for monitoring of inland waters (Iurist (Dumitraşcu), Stătescu, and Lateş 2016).

Water quality indicators were analysed by assessing water samples collected during field measurements. However, field studies are often expensive, time-consuming, and labour-intensive. In some cases, logistical constraints may prevent the execution of field surveys. Therefore, the most viable alternative for obtaining water quality measurements is through remote sensing satellite data, which can capture spatial and temporal changes in water turbidity and other assessment criteria (Soriano-González et al. 2019).

Moreover, scientific investigations related to atmospheric compounds, such as nitrogen dioxide (NO₂), sulfur dioxide (SO₂), carbon monoxide (CO), ozone (O₃), and aerosols (ultra-fine particles), have been conducted utilizing Sentinel-5P imagery (Bodah et al. 2022; Kang et al. 2021; Prunet et al. 2020; Saw et al. 2021). The Sentinel-5P mission plays a crucial role in collecting valuable data for assessing global air quality, enabling analyses on climate, air quality, and surface ozone/ultra-violet ray (UV). Key data products such as nitrogen dioxide (NO₂), sulfur dioxide (SO₂), carbon monoxide (CO), and ozone (O₃) provide quality parameters for the troposphere (Frost, Kopacz, and Kondragunta 2020; Vries et al. 2016). Recently, Sentinel-5P TROPOMI satellite image data have been stored and shared using cloud computing technology, enabling effective and rapid monitoring and assessment of air pollution levels in large areas. This approach is characterized by its speed, accuracy, and high spatial and multi-temporal resolution (Chinh, Hang, and Quynh 2023). The Sentinel-5P satellite is equipped with the TROPospheric Monitoring Instrument (TROPOMI), designed to measure trace gases and aerosols in the troposphere, impacting air quality and climate. This instrument enables the monitoring of various pollutants, including CO, NO₂, O₃, SO₂, and formaldehyde (CH₂O/H₂CO), as well as applications related to climate and ozone/surface UV (Frost, Kopacz, and Kondragunta 2020; Vries et al. 2016).

Nasiri et al. (2022) leveraged the Google Earth Engine (GEE) cloud computing platform to generate a cloud-free Sentinel-2 time series covering the Tehran Province in Iran for the year 2020. Two composition methods, namely seasonal composites and percentile metrics, were employed to create four datasets, integrating satellite time series, vegetation indices, and topographic layers. The random forest (RF) classifier played a key role in LULC classification and the identification of crucial variables. The study concluded that this methodology, utilizing cloud computing on GEE, can rapidly and accurately produce LULC maps, making it applicable for large-scale mapping (Anh et al. 2023; Thao and Sengchanh 2022).

Currently, various methods are employed to enhance the accuracy of remote sensing image classification and LULC mapping (Lu and Weng 2007). In addition to conventional techniques such as controlled classification and object-oriented classification, recent approaches like decision tree methods, artificial neural networks, support vector machines (SVMs), and k-nearest neighbours widely adopted in research on object classification from remote sensing images (Apte and Patravali 2015; Mora et al. 2017). These methods fall under the umbrella of machine learning models. Among these methods, RF has emerged as a promising approach for classifying remote sensing images with high accuracy (Anh et al. 2021; Hien et al. 2022; Noi and Kappas 2017; Thao and Sengchanh 2022).

The assessment of water quality using satellite remote sensing, specifically Sentinel-2, focusses on optically active constituents (Khan et al. 2021; Sherjah et al. 2023). These approaches involve utilizing simple water quality indices based on these parameters for classifying the quality of a water body (Kwong et al. 2022; Tyagi et al. 2013). To manage the computational load associated with processing a large number of satellite imageries, the cloud computing capabilities of GEE are employed. Sherjah et al. (2023) demonstrate the effectiveness of GEE as a rapid water quality monitoring tool by showcasing temporal and spatial variations in water quality.

Note that the accuracy of results in LULC monitoring, especially in tracking changes within objects in biosphere reserves using Sentinel-2 images, is contingent upon the precision of the classification. The outcome of classifying objects in remote sensing images is influenced by various factors, including sensor types, data used for classification and testing, the number of classes, and, notably, the methods and algorithms employed in image processing and classification (Tung et al. 2021; Tuan et al. 2022).

This article focusses on several key issues: (1) tracking changes in five LULC objects using a built-in

machine learning model, (2) determining three water quality indicators, and (3) assessing four air quality indicators, all carried out in the GEE environment using Sentinel-2 images from 2018 to 2022 across four zones in the Cat Ba Biosphere Reserve area.

Methodology

Study area

On 29 October 2004, UNESCO officially designated the Cat Ba archipelago as a World Biosphere Reserve, acknowledging its exceptional ecological and biological significance. Figure 1 is shown the Cat Ba Archipelago which located at coordinates 20°42' to 20°54'N, 106°52' to 107°07' E, covering an area of about 300 km² with a population of 45,000 people (2019). Comprising 367 islands, Cat Ba is situated to the south of Ha Long Bay in Vietnam.

Cat Ba Island stands as a testament to the evolution of marine and island ecosystems, showcasing a rich diversity of animal and plant communities both on land and

underwater. The Cat Ba Archipelago encompasses seven distinct tropical ecosystems, with limestone mountain forests being the dominant type, covering approximately 9800 ha. This ecosystem features tropical evergreen vegetation and includes various forest types, including lowland, steep limestone, high peak, and inland flooded forests. Additionally, the island hosts invaluable mangrove forests, situated in the northwest, representing the largest natural mangrove expanse in Hai Phong.

In the Cat Ba Biosphere Reserve, thousands of species find sanctuary, many of which are under threat of extinction. As of 2017, the reserve and its vicinity boasted 4637 terrestrial, freshwater, mangrove, and marine species. Remarkably, this diverse roster includes 83 endemics, 114 species on the International Union for Conservation of Nature (IUCN) Red List, and 14 species in Vietnam's own Red Book. A notable resident is the white-headed langur (*Trachypitecus poliocephalus*), one of Vietnam's five primates and among the world's top 25 most endangered species, exclusively inhabiting this island (LAP 2023).

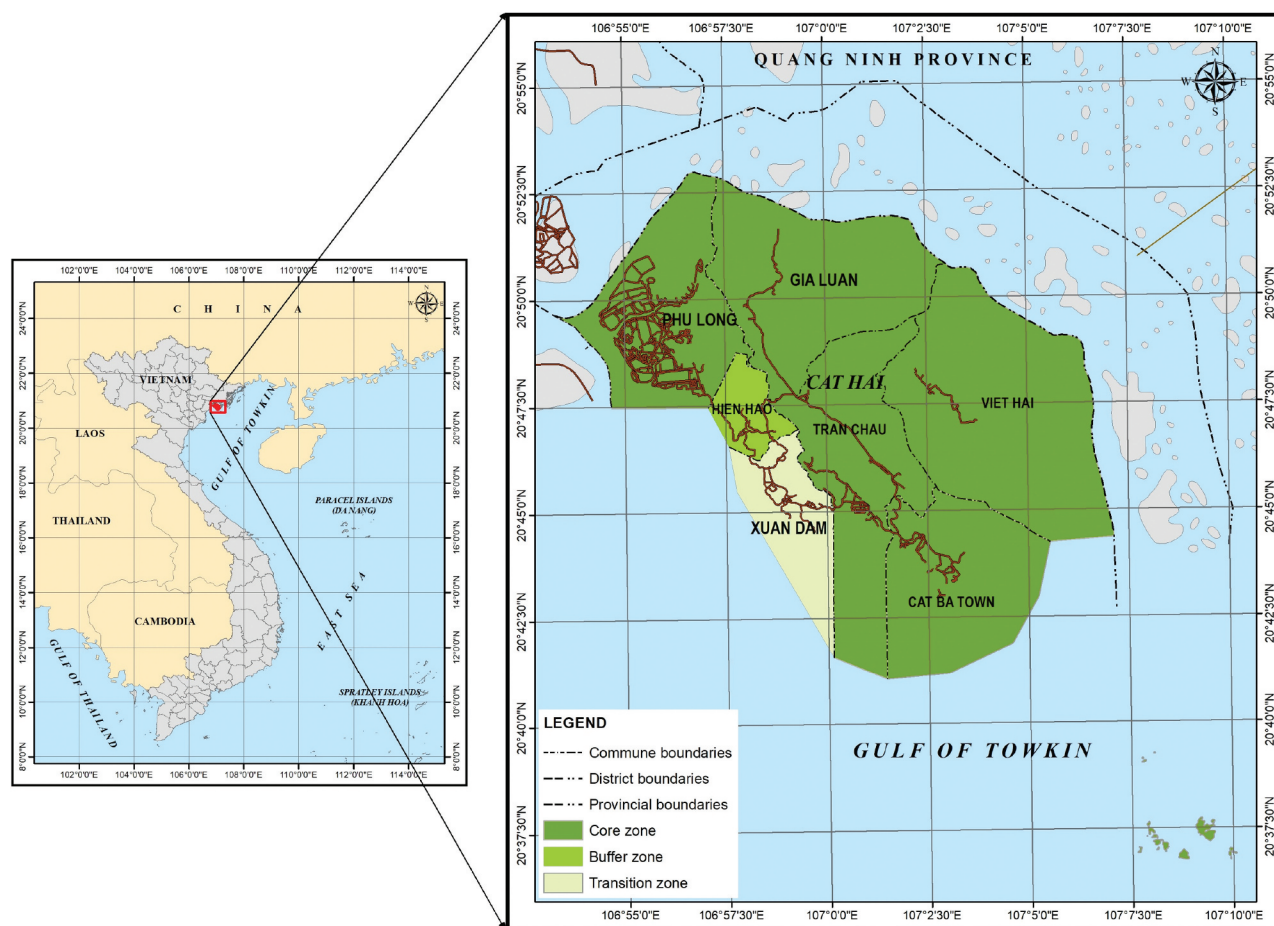


Figure 1. Illustration of the study area. Source: Center for Environmental Resources and Climate Change Monitoring, Vietnam National Remote Sensing Department.

Data collection

Sentinel-2 remote sensing data in Single Look Complex (SLC) format at level 1 were utilized for three time points to monitor LULC in the years 2018, 2020, and 2022 as well as water quality indicators in the year 2022. Sentinel-2 images used in this study were downloaded from the Earth Explorer data portal of U.S. Geological Survey at the website of <https://earthexplorer.usgs.gov> of the total 13 channels of Sentinel-2 images collected, 10 image bands (band 2, 3, 4, 5, 6, 7, 8, 8A, 11, and 12) were selected for inclusion in the classification; bands 1, 9 and 10 were used for atmospheric correction (Tuan et al. 2022). We also used the average value from analysing field samples during the 12 months of the year 2022 as a correlation to calculate the total suspended solids (TSS) content in water.

Sentinel-5P TROPOMI radar remote sensing image data was collected continuously for 12 months in the year 2022 from the Copernicus Data Space Ecosystem at <https://dataspace.copernicuseu> (Wessel, Brandmeier, and Tiede 2018) to use in the determination of four air quality indicators in the study area. Sentinel-5P TROPOMI radar satellite image data have been processed at the L3 level using the `harconvert-bin_spatial` tool on the GEE platform to remove pixels with Quality Assurance (QA) values less than 80% for Aerosol AER_AI, 75% tropospheric density of NO₂ and 50% for all other data except O₃ and SO₂.

LULC monitoring

LULC classification was automated on the GEE platform using a machine learning model for spatial data analysis and parameter computation from Sentinel-2 imagery (Anh et al. 2021, 2023; Hien et al. 2022; Iurist (Dumitraşcu), Stătescu, and Lateş 2016; Mora et al. 2017; Noi and Kappas 2017; Pirotti et al. 2016; Volke and Abarca-Del-Rio 2020; Thao and Sengchanh 2022). The RF algorithm, a machine learning technique, was applied to all pixels in the Sentinel-2 imagery for the classification process. In the Cat Ba Biosphere Reserve, LULC was divided into five main categories – water surface, cropland, vacant land, residential land, and forestland – during three different time points (2018, 2020, 2022). This classification process was executed within the boundaries marked on the 1:100,000 scale map. The fundamental steps for LULC classification using GEE included the collection of the study area data, imagery filtering, training data (sampling), merging training points, creating a training dataset based on sampling areas, imagery classification, displaying the classification result, constructing a confusion matrix to

evaluate classification accuracy and reliability, and computing the area for each object. The classification results for the three different time points were integrated, overlaid, and calculated for the five objects using ArcGIS software, enabling the observation of LULC changes in two distinct periods.

Evaluating accuracy is a pivotal element of any classification process, involving the comparison of classified imagery with another data source deemed ‘accurate’ or ‘ground-truthed’. The primary method for assessing the accuracy of a classification process typically involves generating a set of random points from the fundamental ground truth data and juxtaposing them against the classified data within an error matrix (Ma and Redmond 1995).

An evaluation was previously conducted to determine the reliability of the object classification process. The method used for this assessment is the Kappa Khat error matrix method, as described by Bishop et al. in 1975 and Congalton in 1991. This method involved comparing the classification results against known reference data to quantify the agreement or disagreement between the classified objects and the actual ground truth. The first step in the accreditation process was to identify high-resolution image areas on Google Earth for the years 2018, 2020, and 2022. Checkpoints were randomly generated in the ArcGIS software and then loaded into buffering areas with a size of 2 ha. These areas were converted into the KML file format and loaded into Google Earth. Through visual image analysis, the land cover properties were assigned to random checkpoints. The number of these checkpoints was then verified, and they were attributed to topographic mapping data simultaneously. The checking process was conducted using the number of sampling points for each year.

Calculation of water and air quality indicators

In this study, multispectral data from Sentinel-2 were utilized to evaluate the water quality in specific zones, influencing the habitat of various species, especially cropland and forest. The analysis was conducted using the GEE platform and a machine learning model (Hasan, Al-Hameedawi, and Ismael 2021; Kwong et al. 2022; Sherjah et al. 2020).

Water quality indicators in the Cat Ba Biosphere Reserve were classified into three main categories: normalized difference turbidity index (NDTI), normalized difference chlorophyll index (NDCI), and total suspended solids (TSS), together representing the total suspended solid content in water. This classification was performed in the year 2022. In the process, Level-1C Sentinel-2 data containing

spectral values representing top-of-atmosphere (TOA) reflectance were used. Atmospheric correction was crucial to obtain water-leaving reflectance by eliminating atmospheric interference from the total signal received by the satellite sensor (Soriano-González et al. 2019). Out of the 13 spectral bands acquired by Sentinel-2, bands 9 (water vapour) and 10 (cirrus) were eliminated as they do not contain water surface information. Additionally, Band 8 Near Infrared Band (NIR) was removed since its wavelength overlaps with Band 8A, and the latter provides a more precise spectral measurement. The difference in spatial resolutions among spectral bands was not a concern in GEE, as it uses a scale specified by the output to determine the appropriate level of input image pyramids. It is important to note that various algorithms have been proposed for retrieving water quality parameters from remote sensing reflectance (Flores-Anderson et al. 2020; Ritchie, Zimba, and Everitt 2003; Tian et al. 2014; Wang and Yang 2019; Yoon et al. 2019). To establish a suitable model, band ratios and arithmetic variables were computed as input predictors, developed concerning the bio-optical properties of water (Matthews 2011). Two-band ratios were employed, as they theoretically reduce the effects of seasonal variations and maximize sensitivity to water quality parameters against other constituents (Gons 1999). The basic steps for exacting water indicators using GEE are: the collection of data for the study area, importing images, rectifying and filtering images, training data (sampling), merging training points, creating a training dataset based on sampling areas, extracting information on NDTI, NDCI, TSS, and mapping for each water indicator.

The Sentinel-5P mission enables analyses of air quality indicators such as CO, NO₂, O₃, and SO₂ (Chinh, Hang, and Quynh 2023; Danilo et al. 2023; Frost, Kopacz, and Kondragunta 2020; Savenets 2021; Voors et al. 2017; Vries et al. 2016). Also, Veeffkind et al. (2012) confirmed that Sentinel-5P TROPOMI data can be used to determine the total content in the vertical column of the troposphere of various chemicals, including CO, NO₂, O₃, and SO₂. In this study, the process of processing Sentinel-5P remote sensing image data involved the following steps: importing images, rectifying images (calibrating to the VN2000 flat coordinate system, 6° zone, with a 105° axial meridian, and converting formats for ease in subsequent calculations), and extracting information on CO, NO₂, O₃, SO₂ concentrations in the year 2022 across the entire area research area. These analytical operations are conducted using the GEE platform, which organizes TROPOMI data into thematic sets corresponding to individual chemical compounds, as detailed in the GEE datasets catalogue (Gorelick et al. 2017; Okoduwa and Amaechi, 2020; <https://developers.google.com/earth-engine/datasets/catalog/sentinel-5P>). The Level 2 (L2) data is divided into

a regular grid for each orbit, without aggregation by component. Quality thresholds applied in the resulting datasets are 80% for the aerosol index, 75% for NO₂, and 50% for all other substances. This set-up provides extensive possibilities for statistical and spatial analysis for each pixel in the data cube, eliminating the need for additional source data preparation (Morozova et al. 2022).

The water quality assessment results derived from Sentinel-2 remote sensing data in this study were compared and verified against the specified water parameter limits outlined in the QCVN 08:2023/BTNMT (in which, QCVN means Vietnam standards means, and BTNMT means Ministry of Natural Resources and Environment of Vietnam) regulations, of the National Technical Regulation on Surface Water Quality (MONRE 2023b).

The air quality assessment results obtained from Sentinel-5P TROPOMI remote sensing data in the study were compared and verified against the prescribed air parameter values detailed in the QCVN 05:2023/BTNMT regulations, corresponding to the National Technical Regulations on Ambient Air Quality (MONRE 2023a). To compare with the threshold of air indicators prescribed according to standard 05:2023/BTNMT (in units of mol/m²), it is necessary to convert to µg/m³ using the following formula (Chinh, Hang, and Quynh 2023):

$$C = \frac{C_{\text{column}}}{H} MA$$

in which C is the air parameter concentration, converted to µg/m³; C_{column} is the emission concentration calculated from Sentinel-5P TROPOMI remote sensing data, in mol/m²; H is the height of the atmosphere, in metres (H = 10,000 m); M is the mass of gas molecules, calculated in units of g/mol (M_{NO₂} = 46.0055 g/mol; M_{SO₂} = 64.0648 g/mol; M_{CO} = 44.0098 g/mol; M_{O₃} = 47.998 g/mol); and A is the conversion constant from g/m³ to µg/m³ (A = 1,000,000).

The results of water and air quality indicators in the Cat Ba Biosphere Reserve were used to confirm appropriate plant growth as indicated by the results from the LULC monitoring process.

Results

LULC monitoring

Within the study area, we compiled classes to delineate five distinct categories of land cover: water surface, cropland, vacant land, residential land, and forestland (Figure 2). The latter category, forestland, includes various forest types such as evergreen broad-leaved forests, deciduous forests, planted forests, and other forest

types; cropland includes annual cropland, perennial cropland, wet rice, and mangroves.

In the GEE platform, the RF algorithm was used to classify land cover objects. Imagery bands of the study area and training area data (training data) are imported through the 'raster' package. The package allows the extraction of pixel values in the training regions for each band image and stores them in a database. We used the RF algorithm in the package with bands of satellite images with parameters by 500 decision trees in the years of 2018, 2020, and 2022. It was necessary to find the most suitable number of decision trees and error variations of the five classification surface objects in this study. In addition, the number of variables used to divide at each node in decision trees is four variables during the classification process. At the same time, based on the reliability assessment method, it was necessary to identify

high-resolution image areas on Google Earth three times. Testing was conducted for the entire study area with a total of 236 sampling points for 2018, 234 sampling points for 2020, and 261 sampling points for 2022. The classification results achieved high overall accuracy and a high kappa coefficient (Table 1). A land cover status map was developed to show the five indicators based on the Sentinel-2 image classification results (Figure 2).

Land use and land cover (LULC) category changes are highlighted in Table 2 for the Cat Ba Biosphere Reserve. In general, there are evident land-use changes in the core zone and transition zones from 2018 to 2020 and 2022, while the buffer zone and economic development zone show little to no change over that time. The coefficient of variation was used to look at the relative degree of change over time. The coefficient of variation represents the relative

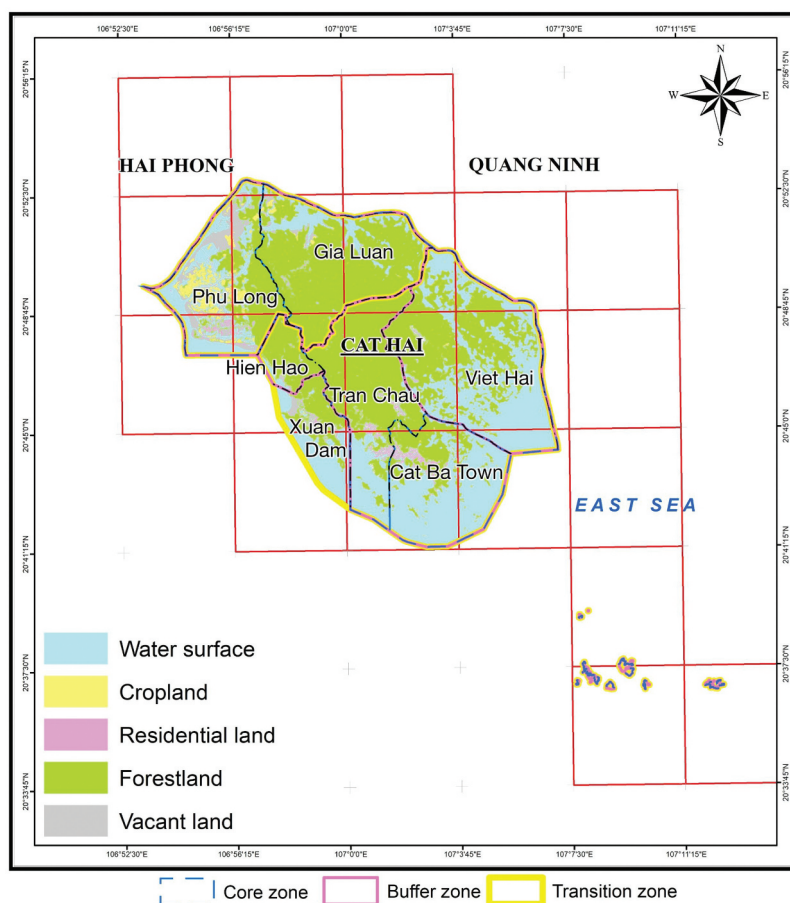


Figure 2. Illustration of the land cover status map for Cat Ba Biosphere Reserve, from a Sentinel-2 image (2022).

Table 1. Results of accuracy and reliability assessment for Sentinel-2 image classification.

N ^o	Content	2018	2020	2022
1	Training overall accuracy	98.82%	95.52%	95.08%
2	Validation kappa	88.51	84.20	83.72

Table 2. Calculated results for land use and land cover (LULC) status and changes for Cat Ba Biosphere Reserve.

Area	Category	2018 (ha)	2020 (ha)	2022 (ha)	Coefficient of variation
Core zone	Water surface	10,575.19	10,987.02	10,325.69	3%
	Cropland	1773.73	1929.44	1763.23	5%
	Vacant land	2557.91	3012.02	3021.92	9%
	Resident area	1888.31	1869.89	1891.39	1%
	Forestland	13,983.25	12,980.02	13,776.17	4%
	Total	30,778.39	30,778.39	30,778.39	
Buffer zone	Water surface	17,857.25	17,505.44	17,147.11	2%
	Cropland	3377.82	3373.13	3368.44	0%
	Vacant land	5180.16	5260.83	5626.56	4%
	Resident area	3277.04	3149.66	3215.27	2%
	Forestland	20,260.31	20,663.51	20,595.20	1%
	Total	49,952.57	49,952.57	49,952.57	
Transition zone	Water surface	15,106.64	14,770.56	14,292.60	3%
	Cropland	3457.11	3695.79	3988.74	7%
	Vacant land	4913.44	4979.11	5506.87	6%
	Resident area	3549.88	3615.71	3384.86	3%
	Forestland	17,591.37	17,557.27	17,445.37	0%
	Total	44,618.43	44,618.43	44,618.43	
Economic development zone	Water surface	414,485.513	414,643.34	413,040.36	0%
	Cropland	146,263.417	145,313.61	145,248.87	0%
	Vacant land	152,419.572	153,861.18	154,771.27	1%
	Resident area	149,823.682	149,797.47	149,862.68	0%
	Forestland	179,506.711	178,883.31	179,575.71	0%
	Total	1,042,498.90	1,042,498.90	1,042,498.90	

variability of the datasets. It is used to compare the variability of the datasets and provide a standardized measure of dispersion relative to the mean. A lower coefficient of variation indicates a more consistent set of values relative to their mean, while a higher coefficient of variation suggests greater variability relative to the mean.

Statistical analysis (Table 1) indicated that the results achieved a reliability of 98.51% for the year 2018, 94.20% for the year 2020, and 93.72% for the year 2022, which shows that this method obtained a high accuracy in the LULC classification. The result of evaluating the classification accuracy shows errors in the classification process that were distributed over most layers. However, the largest error percentages were for the forest and cropland. The cause of this confusion comes from the fact that these two objects have large spectral homogeneity for their subcategories, which created two of these categories. The vacant class was also easily confused with the residential class during classification. The classification process indicated that the grassland was easily confused with forestland due to its great spectral homogeneity, whereas the residential land and vacant land belonged to other land types (Yifan et al. 2018). The changes in the five land cover objects in each zone were consistent with the classification results in the study by Hung, Asaeda, and Thao (2021). Therefore, these changes in the five land cover objects in the Cat Ba Biosphere Reserve area should continue to be monitored to adjust the suitability for each sub-zone.

All zones are crucial areas that directly impact the biodiversity and habitat of the biosphere reserve. The

LULC objects in the Cat Ba Biosphere Reserve, such as cropland and forest, have shown stable development with no significant changes over the three years from 2018 to 2022.

Calculations of water and air quality indicators

In the Cat Ba Biosphere Reserve area, Sentinel-2 remote sensing data in SLC format at Level 1 was utilized for 12 months in the year 2022 for monitoring the three water quality indicators (Table 3).

The average water quality indicator values for 2022 in the Cat Ba Biosphere Reserve area did not fluctuate significantly and were within the allowable limits according to QCVN 05:2023/BTNMT (Table 3). The average NDTI

Table 3. Values of the three water quality indicators in Cat Ba Biosphere Reserve over 12 months (in 2022).

Month	NDTI	NDCI	TSS (mg/L)
January	−0.023	0.614	46.366
February	−0.010	0.080	43.903
March	−0.009	0.665	84.188
April	−0.002	0.546	74.241
May	0.013	0.386	38.393
June	0.002	−0.264	67.293
July	0.013	0.793	82.457
August	−0.026	0.372	51.083
September	0.002	−0.264	67.293
October	−0.017	0.353	46.724
November	−0.025	0.548	36.546
December	−0.011	0.204	33.028
Limit threshold for water quality indicators by QCVN 08:2023/BTNMT (MONRE 2023b)			
	−1 to +1	−1 to +1	≤ 100

for the 12 months of 2022 ranged from -0.026 to 0.013 . The average NDCI for the 12 months of 2022 ranged from 0.264 to 0.793 . The average TSS value for the 12 months of 2022 fluctuated around 33.028 to 84.138 (mg/L). The red areas on the water maps (Figure 3) show that some indicators exceed the threshold. Although there were instances where water and air quality indicators exceeded permissible limits, the average values for each month confirmed that indices such as NDTI, NDCI, and TSS in the study area were within the prescribed thresholds. Similarly, the four air quality indicators CO, NO₂, O₃, and SO₂ in the study area (Figure 4) were within the prescribed thresholds. Therefore, after a comparison of water quality indicators with QCVN 08:2023/BTNMT and air quality indicators for QCVN 05:2023/BTNMT (Tables 3 and 4), we concluded that the four air quality indicators were consistent with the conservation progress of biosphere reserves in Vietnam in general, corresponding to the results of Chinh, Hang, and Quynh (2023). It can be suggested that the Cat Ba Biosphere Reserve is being effectively preserved, showing no signs of significant degradation.

Overall, the Cat Ba Biosphere Reserve experiences seasonal variations in CO and SO₂, with higher levels in the colder months; this is likely due to increased heating and combustion activities happening in areas outside the reserve. O₃ levels were slightly higher in the warmer months, likely due to photochemical reactions facilitated by sunlight. O₃ levels were the most stable among the four pollutants, with only slight variations across different months. NO₂ levels fluctuated throughout the year without a clear seasonal pattern, suggesting variable sources and atmospheric conditions affecting its concentration.

These trends can help in understanding the seasonal behaviour of air pollutants and in developing strategies for air quality management (Table 4).

Interestingly, we found that the CO levels showed a decreasing trend from January to August, reaching their lowest point in July ($125.743 \mu\text{g}/\text{m}^3$) (Table 4). After July, the levels rose again, peaking in March ($218.982 \mu\text{g}/\text{m}^3$) and October ($201.245 \mu\text{g}/\text{m}^3$). This suggests that the highest CO levels occurred in the colder months (January, February, and March), while the lowest levels were in the summer months (June, July, August).

The NO₂ levels fluctuated throughout the year without a clear trend (Table 4). The lowest value was in October ($0.257 \mu\text{g}/\text{m}^3$), and the highest value was in December ($0.687 \mu\text{g}/\text{m}^3$). The tropospheric ozone levels were relatively stable throughout the year, with slight increases observed in the warmer months, but this should not have a significant impact on vegetation. There is a slight increase in O₃ levels during the summer months (May to August), which is consistent with increased sunlight and higher temperatures promoting ozone formation.

SO₂ levels showed considerable variation throughout the year, with the highest levels in January ($2.204 \mu\text{g}/\text{m}^3$) and November ($1.230 \mu\text{g}/\text{m}^3$) and the lowest in August ($0.062 \mu\text{g}/\text{m}^3$) and July ($0.100 \mu\text{g}/\text{m}^3$) (Table 4).

Discussion

Water surface, cropland, vacant land, residential land, and forestland have different spectral characteristics in

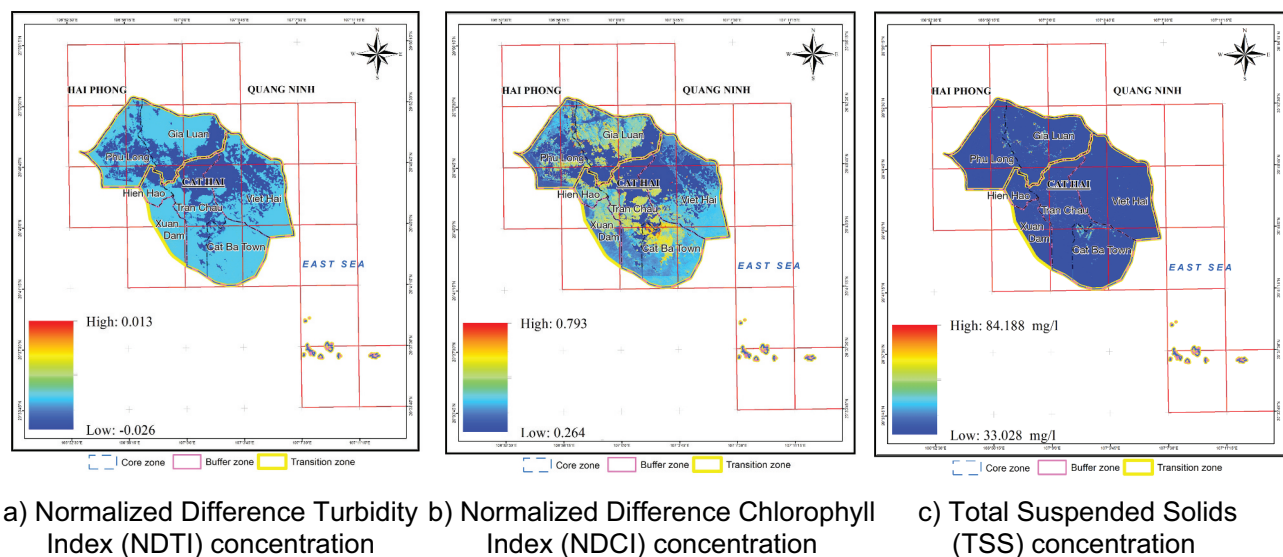


Figure 3. Illustration of values for the three water quality indicators in Cat Ba Biosphere Reserve in August 2022.

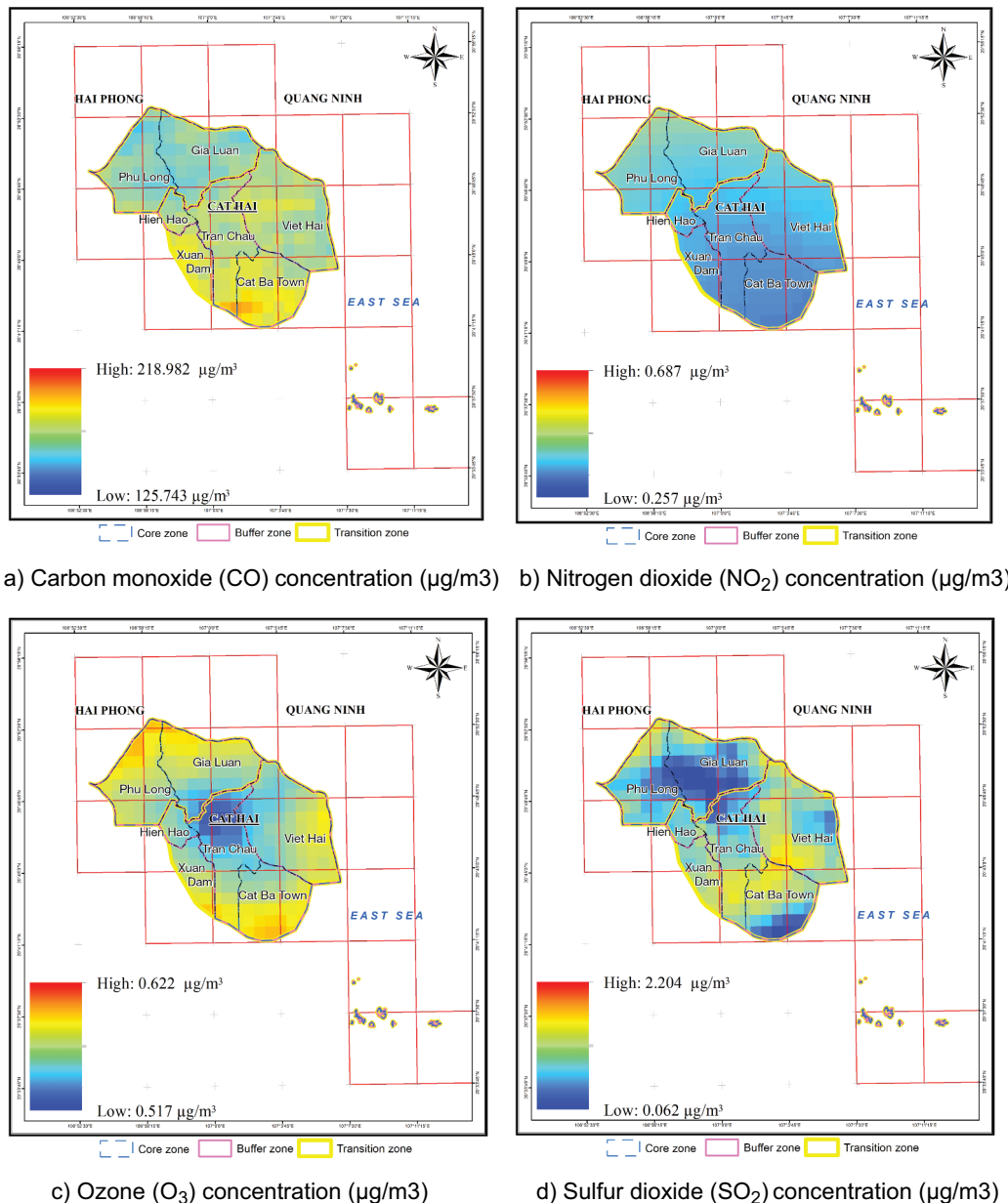


Figure 4. Illustration of values for the four air quality indicators in Cat Ba Biosphere Reserve in August 2022.

the remote sensing images (Yu et al. 2017). In this study, we focussed on these basic land cover categories and illustrated the status of and changes to land cover in the Cat Ba Biosphere Reserve.

In the Cat Ba Biosphere Reserve, comprehensive monitoring of LULC was conducted using Sentinel-2 imagery and the RF algorithm. The study categorized five primary land cover types: water surface, cropland, vacant land, residential land, and forestland. The RF classification method proved robust, achieving high overall accuracy and high kappa coefficients across the years 2018, 2020, and 2022. This methodology provided

detailed insights into LULC changes within different zones of the biosphere reserve, highlighting significant transformations in the core and transition zones compared to stable conditions in the buffer and economic development zones.

Despite challenges such as spectral homogeneity within forest and cropland categories, the study demonstrated the consistent monitoring capabilities necessary for adaptive management and conservation planning. The results show the importance of ongoing monitoring to refine sub-zoning suitability and maintain ecological integrity within the reserve. In previous studies, similar

Table 4. Monthly average values of four air quality indicators in Cat Ba Biosphere Reserve for 2022.

Date	CO ($\mu\text{g}/\text{m}^3$)	NO ₂ ($\mu\text{g}/\text{m}^3$)	O ₃ ($\mu\text{g}/\text{m}^3$)	SO ₂ ($\mu\text{g}/\text{m}^3$)
January	215.039	0.286	0.558	2.204
February	204.197	0.499	0.553	0.640
March	218.982	0.344	0.559	1.214
April	195.656	0.487	0.576	0.237
May	181.969	0.396	0.612	0.996
June	146.126	0.294	0.622	1.136
July	125.743	0.504	0.620	0.100
August	126.671	0.330	0.621	0.062
September	177.589	0.579	0.602	0.464
October	201.245	0.257	0.587	0.290
November	161.618	0.387	0.543	1.230
December	185.174	0.687	0.517	0.396
Limit threshold for air quality indicators by QCVN 05:2023/BTNMT (MONRE 2023a)				
	10,000	200	200	350

parameters were measured (Superczynski and Christopher 2011), and in some cases a significant negative correlation between land cover objects and water quality deterioration were observed (Ogbozige and Alfa 2019). Others have also shown that there is a significant link between LULC and air quality (Superczynski and Christopher 2011). We did not observe the same trends in our study. In the Cat Ba Biosphere Reserve we did see fluctuations from year to year in land cover, but over time the only significant changes were an increase in vacant land within the core zone and transition zone.

Water quality indicators in the Cat Ba Biosphere Reserve were assessed using Sentinel-2 remote sensing data, focussing on NDTI, NDCI, and TSS concentrations throughout 2022. Results showed that these indicators generally remained within permissible limits according to QCVN 08:2023/BTNMT standards, albeit with occasional exceedances in isolated instances. This suggests effective preservation efforts but highlights the need for continued monitoring to mitigate potential environmental stressors.

Air quality within the biosphere reserve was monitored using Sentinel-5P data, focussing on CO, NO₂, O₃, and SO₂ concentrations across 2022. Seasonal variations were observed, with CO and SO₂ levels peaking in colder months, likely influenced by external combustion activities. O₃ levels showed slight increases during warmer months, indicative of photochemical reactions. Overall, air quality indicators consistently met QCVN 05:2023/BTNMT thresholds, affirming effective conservation practices within the reserve.

Conclusion

The integrated approach to LULC and environmental monitoring in the Cat Ba Biosphere Reserve provides valuable insights into ecosystem health and conservation efficacy. Despite observed fluctuations and occasional

exceedances in environmental indicators, overall trends indicate stable conditions suitable for biodiversity conservation. Future efforts should focus on refining monitoring strategies, particularly in areas prone to LULC changes and environmental stressors, to sustain the ecological balance and resilience of the biosphere reserve.

This study contributes to the broader understanding of environmental monitoring practices and underscores the importance of data-driven conservation management in safeguarding biosphere reserves against anthropogenic pressures and climate variability.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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