# Assessing Mangrove Ecosystem Health and Identifying Optimal Planting Regions Using Remote Sensing and GIS in the UAE

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**Abstract**

Mangrove forests play a critical role in carbon sequestration, biodiversity preservation, and coastal resilience, making their conservation and restoration essential in climate change mitigation. This study uses traditional field evaluations and remote sensing and geoinformatics (GIS) methods to examine how mangrove ecosystems in the United Arab Emirates (UAE) have changed over time and space. We used Landsat satellite data from 2001 to 2024 and a set of vegetation indices, including SMRI, NDVI, GNDVI, EVI, and NDCI, to examine spatial patterns in biomass distribution, vegetation density, and overall ecosystem health. $CO_2$ sequestration is a bit more climate-impact resilient. Even though the findings from the spatial images indicate a slight decline in healthy mangrove coverage alongside increased shrub growth, primarily driven by climate change impacts. So, spatially identified areas were considered vegetative plantations to be recovered and grown, with potential biomass, to avoid future $CO_2$ impacts. Some coastal zones still show lower vegetation density and limited carbon uptake potential. Future efforts should prioritize replanting and rehabilitation in these sparse or degraded areas, particularly in the southern and inland tidal zones where vegetation loss was detected. These results highlight the need for targeted conservation strategies to counter the degradation of mangrove ecosystems.
In addition to evaluating ecosystem health, this study employs computational GIS techniques to identify optimal locations for mangrove restoration. By leveraging spatial modelling, we pinpoint potential vegetative planting sites that maximize carbon sequestration stability, enhance biodiversity, and improve coastal protection in the UAE region. This data-driven approach ensures the effectiveness of reforestation initiatives, addressing gaps in mangrove coverage while contributing to the UAE's net-zero carbon emissions target by 2050. The research provides policymakers and environmental managers with a robust decision-making framework. It also shows how important GIS-based methods are for planning and managing ecosystems sustainably. Moreover, the methodology can be replicated and adapted across other regions, offering a time- and cost-efficient solution for large-scale ecosystem restoration and climate action.

## 1. Introduction

The world today is going through a crisis: climate change. Anthropogenic $CO_2$ emissions and sequestration have increased relentlessly over the past century despite international efforts to mitigate the problem (Dowell et al., 2017). While engineered solutions such as carbon capture technologies exist, mangrove forests naturally sequester carbon and thus represent an essential ecological ally in addressing climate change. Globally, mangroves are declining at an alarming rate, although they play a vital role as coastal wetlands that stabilize shorelines, support biodiversity, and regulate nutrient cycles (Vaghela et al., 2018; Gnanappazham et al., 2021).

In response to escalating climate challenges, the UAE has aligned with global climate agreements, including the Vienna Convention, the Montreal Protocol, and the UNFCCC (Clarke et al., 2022). Its Energy Policy 2050 aims to produce 50% of the nation's electricity from renewable sources whilst reducing carbon emissions by 70%. As part of this strategy, mangroves, considered a national treasure, are central to conservation and restoration programs. They are especially important because the UAE has promised to plant 100 million mangroves by 2030 to sustenance its broader goal of net-zero carbon emissions by 2050 (Alsumaiti et al., 2015; Mizen et al., 2024).

Mangroves are salt-tolerant halophytes that thrive in intertidal, marshy environments. Though they occupy only 1.9% of tropical and subtropical coastlines, they account for nearly 30% of global carbon burial in these regions (Ellison, 2015). They exhibit unique ecological traits of both terrestrial and marine ecosystems, which explain their high productivity and carbon storage efficiency (Alongi & Mukhopadhyay, 2015). Yet they remain vulnerable to climate change impacts, such as sea-level rise, salinity shifts, and catastrophic natural events, alongside human-induced pressures, such as urbanization and pollution (Ellison, 2015; Godoy & De Lacerda, 2015).

In the UAE, mangroves are dominated by Avicennia marina, the gray mangrove, which tolerates high salinities and temperatures. Approximately 70% of the country's mangroves are found in Abu Dhabi, covering about 110 km², providing habitats for fish, birds, and other wildlife (Alsumaiti & Shahid, 2019). Restoration projects have planted hundreds of thousands of new mangroves, but monitoring their health and distribution remains essential.

Remote sensing (RS) and geographic information systems (GIS) are indispensable. Through electromagnetic radiation, RS acquires data without physical contact (Gupta, 2017; Roy et al., 2017). Combined with GIS, it allows large-scale, spatiotemporal analysis of land cover and vegetation trends. These technologies overcome the limitations of fieldwork in coastal areas, enabling the mapping of mangrove dynamics, ecosystem health, and potential restoration sites (Rondon et al., 2023; Gnanappazham et al., 2021).

This project focuses on assessing the health of mangrove ecosystems in the UAE and identifying optimal planting regions using RS and GIS. By integrating satellite data, field validation, and spatiotemporal analysis, the study aims to evaluate mangrove distribution and growth between 2001 and 2024, examine the effects of $CO_2$ and climatic stressors on mangrove health, and support national restoration strategies that contribute to net-zero emissions and the SDGs (Wardlow & Egbert, 2010; Abu Dhabi Blue Carbon Report (AGEDI), 2014; Elmahdy & Ali, 2022; Salem IB, 2025).

Building on this context, the study aims to track the development of mangrove forests in the UAE between 2001 and 2024 by analysing remotely sensed datasets. It will map mangrove dispersion, growth trends, and the activities influencing these ecosystems, while also evaluating the effects of $CO_2$ concentrations and climatic conditions on mangrove health. Field-based research will complement this work by classifying mangrove types and documenting local climate conditions. A further objective is to identify the causes of delays in mangrove development, thereby offering insights into the ecological challenges of these ecosystems.

The research results will contribute to establishing a rehabilitation strategy aligned with the UAE's goal of planting 100 million mangroves by 2030 and achieving zero $CO_2$ emissions by 2050. In particular, the study will:

- Analyse remote sensing data to determine the factors affecting mangrove development and the potential for expanding vegetative cover in Abu Dhabi.
- Map mangrove ecosystems' dynamics, growth, and distribution between 2001 and 2024.
- Assess how $CO_2$ concentrations and climatic stressors influence mangrove health, supported by field-based validation.

**Study Design**

In the present study, we selected six regions as addresses for mangrove sites with vegetation (Table 1). We have selected the regions to disclose mangrove changes and growth. The study's chosen areas are shown in Figure 1.


Figure 1. Location map of the study area

Ground truth data connects the remotely sensed imagery to actual features and materials on the ground. This enables scientists to understand what the pixels in an image truly represent. Ground truth data plays a vital role in evaluating the accuracy of classification maps generated from remote sensing data. Comparisons between the two Landsat images were used to assess mangrove health and the potential for new mangrove ecosystems. The field observations ground truth for the current investigation is displayed in Figure 2.

| S.No | Area Name | Location (Decimal - Longitude and Latitude) |
|---|---|---|
| 1. | Jubail Mangrove Park | 24.5452, 54.4854 |
| 2. | Saadiyat Mangrove Park | 24.5303, 54.4452 |
| 3. | Mangrove Marine National Park | 24.4567, 54.4251 |
| 4. | Bul Sayayeef Marine Protected Reserve | 24.2580, 54.3616 |
| 5. | Ras Ghanadah | 24.7118, 54.6506 |
| 6. | Ras Al Ghurab | 24.6086, 54.5031 |

Table 1. Selected Mangrove Study Sites and Their Geographic Coordinates in the UAE


Figure 2. The Field Photographs (Ground Truth) of Selected Locations

## 2. Materials and Methodology

### 2.1 Materials

This study aimed to assess the condition of Abu Dhabi's mangrove ecosystems. The QGIS and ArcMap 10.4 (ArcGIS) geographic information systems were used in this study. These programs display, modify, and analyse datasets in the study area. The results for the SMRI, NDVI, GNDVI, EVI, NDCI, and vegetation biomass index from Landsat imagery were obtained using the raster calculator in ArcGIS 10.4 and QGIS.

Using USGS Earth Engine, the Landsat 5 (2001) and 8 (2013, 2024) images were downloaded (Table 2 summarizes the spectral, spatial, and wavelength specifications for the Landsat 5 and Landsat 8 sensors used in this study). The raster calculator results were then obtained using QGIS and ArcGIS 10.4. The two Landsat pictures compared the potential land for future mangrove ecosystems and the existing mangrove condition.

| **Spectral** | **Wavelength** (Microns) | **Resolution** | **Landsat 5** | **Landsat 8** |
|---|---|---|---|---|
| Coastal/aerosol | 0.43-0.45 | 30m | - | Band 1 |
| Band 2-Blue | 0.45-0.52 | 30m | Band 1 | Band 2 |
| Band 3-Green | 0.53-0.59 | 30m | Band 2 | Band 3 |
| Band 4-Red | 0.64-0.67 | 30m | Band 3 | Band 4 |
| Band 5-NIR | 0.85-0.88 | 30m | Band 4 | Band 5 |
| Band 6-Shortwave IR (1) | 1.57-1.65 | 30m | Band 5 | Band 6 |
| Band 7-Shortwave IR (2 | 2.11-2.29 | 30m | Band 7 | Band 7 |
| Band 8-Panchromatic | 0.5-0.68 | 15m | - | Band 8 |
| Band 9-Cirrus | 1.36-1.38 | 30m | - | Band 9 |
| Band 10-Thermal wave IR (1) | 10.6-11.19 | 100m | - | Band 10 |
| Band 11-Thermal wave IR (2) | 11.5-12.51 | 100m | Band 6 (60m) | Band 11 |

Table 2. Datasets and their specifications.

### 2.2 Methods

In this study, we have adopted the following techniques: Green Normalized Difference Vegetation Index (GNDVI), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Difference Chlorophyll Index (NDCI), Submerged Mangrove Recognition Index (SMRI), and Biomass Index.

#### 2.2.1 Normalized Difference Vegetation Index (NDVI)

It assesses and tracks plants' growth, density, and health. It is calculated by subtracting the reflectance of red (visible) light from that of near-infrared (NIR) light, as measured by satellite or remote sensors (Borgogno-Mondino et al., 2016).

$$NDVI = (NIR - R) / (NIR + R) \quad (1)$$

Near-infrared (NIR) and R are the red bands. In Landsat 5, the NIR is band number 4, and the R is band number 3. However, for the Landsat 8 images, the NIR is band 5, and the R is band 4.

#### 2.2.2 Green Normalized Difference Vegetation Index (GNDVI)

It is comparable to the NDVI; however, it analyzes the green spectrum between 0.54 and 0.57 microns rather than the red spectrum. When evaluating moisture content and nitrogen concentration in plant leaves using multispectral data lacking an extreme red channel, this indicator of vegetation photosynthetic activity is most commonly used. It is more sensitive to chlorophyll content than the NDVI measure. It is used to evaluate old and depressed vegetation (Chen et al., 2019).

$$GNDVI = (NIR-GREEN/NIR+GREEN) \quad (2)$$

#### 2.2.3 Enhanced Vegetation Index (EVI)

It is used to assess vegetation condition and density with greater sensitivity in densely vegetated areas. It adjusts for extraneous signals from the soil and atmospheric conditions. The Enhanced Vegetation Index (EVI) is a satellite-derived measurement of vegetation greenness and biomass. It monitors vegetation, assesses exposure to green space, and evaluates changes across large areas. Using red, blue, and near-infrared (NIR) bands, EVI is calculated. It corrects for atmospheric conditions and canopy background noise using blue light. EVI is particularly sensitive to thick vegetation (Wardlow & Egbert, 2010).

$$EVI = G^* ((NIR - R) / (NIR + C1^*R - C2^* B + L)) \quad (3)$$

#### 2.2.4 Submerged Mangrove Recognition Index (SMRI)

A "Submerged Mangrove Recognition Index (SMRI)" is a specific calculation used in remote sensing to identify and map mangrove forests that are submerged underwater during high tide, by analyzing the difference in their spectral signatures between high and low tide imagery, essentially allowing researchers to distinguish mangrove areas even when partially submerged; it typically utilizes a combination of near-infrared (NIR) and visible bands from satellite imagery to achieve this differentiation (Xia et al., 2020). It is a measurement based on remote sensing technologies used to locate and examine mangrove regions that are occasionally or permanently submerged. The primary objective of this measure is to differentiate the submerged mangroves from the non-submerged mangroves. An SMRI for mangrove forest classification was tested. SMRI was compared with existing vegetation indices and higher- and moderate-resolution RS imagery. SMRI distinguishes submerged mangrove habitats with greater precision. SMRI compares NDVI (or other vegetation indices) values from high-tide satellite imagery with those from low-tide imagery, highlighting areas where the vegetation signature changes significantly between the two conditions, indicating submerged mangroves (Xia et al., 2020).

$$SMRI = (NDVI_l – NDVI_h)\ NIR_l−NIR_h / NIR_h \tag{4}$$

Where l is the low tide, and h is the high tide.

#### 2.2.5 Normalized Difference Chlorophyll Index (NDCI)

The Normalized Difference Chlorophyll Index (NDCI) has been used for assessments of interior freshwater lakes since it was first introduced for using satellite remote sensing data in estuaries and coastal turbid productive waters to forecast chlorophyll a concentration. (Mishra & Mishra, 2012).

$$NDCI= (Red\ Edge\ 1- Red)/ (Edge\ 1+Red) \tag{5}$$

Where, RedEdge1 = Red/NIR.

#### 2.2.6 Biomass Index and $CO_2$ Equivalent Estimation

The Biomass Index estimates the total amount of living material, including vegetation, in a given location. A carbon dioxide equivalent ($CO_2e$ or $CO_2$-eq) is a standardized unit used to measure the impact of various greenhouse gases on global warming, expressed in terms of the amount of carbon dioxide that would cause the same amount of warming over a specific period.

The following parameters were adopted to measure total biomass, carbon biomass, and $CO_2$ equivalent.

- $A_{mod}$ = area of moderate (NDVI 0.10-0.35)

$$A_{mod}\ (ha) = (\text{total vegetation pixels - total healthy vegetation pixels}) \times 0.09 \tag{6}$$

- $A_{healthy}$ = area of healthy (NDVI ≥ 0.35)

$$A_{healthy}\ (ha)=\text{total healthy vegetation pixels} \times 0.09 \tag{7}$$

(Note that 0.09 ha was calculated from the Landsat resolution.)

- $N_{mod}$, $N_{healthy}$= mean NDVI in each class (8)

- Above Ground Biomass density (Mg/ha):

$$AGB_{dens\_mod}= a^* N_{mod} + b \tag{9}$$

$$AGB_{dens\_healthy} = a^* N_{healthy} + b \tag{10}$$

(a = open canopy vegetation and b = closed canopy vegetation)

- Total AGB (t):

$$AGB_{total} = A_{mod}\cdot AGB_{dens,\ mod} + A_{healthy}\cdot AGB_{dens,\ healthy} \tag{11}$$

- Total BGB (t):

$$BGB_{total}= RSR\times AGB_{total} \tag{12}$$

(such as RSR = Root to Shoot Ratio = 0.42)

- Total Biomass (t):

$$Total\_Biomass = AGB_{total} + BGB_{total} \tag{13}$$

(Where BGB is the belowground biomass, AGB is the aboveground biomass.)

- Carbon Biomass (tC):

$$Carbon = \text{Average carbon content} \times \text{Total Biomass} \tag{14}$$

(Such as the average carbon content = 0.47)

- CO2 equivalent (tCO2):

$$CO_2e = 3.6 \times Carbon \tag{15}$$

(3.6 represents the carbon biomass factor)

Field and aerial-based mangrove counts were conducted to map $CO_2$ associated with the field inventory data. Fieldwork has been conducted to count mangroves and verify the ground truth of the selected regions. After collecting the mangrove count at 20 m x 20 m intervals, the average has been calculated. Followed by Carbon dioxide ($CO_2$), which is measured using an averaging calculation. Furthermore, the carbon analysis indexes have shown gradual variations across years, such as 2010, 2015, 2020, and 2024 (Aerial-based observations and Field inventory data).

## 3. Results and Discussion

The results of this study provide valuable information for mapping and monitoring mangroves within and outside the United Arab Emirates (UAE). The discussion covers key topics, including traditional field research data and remote sensing and geoinformatics (GIS). After thoroughly reviewing the strengths and shortcomings of the aforementioned models, our goal in this study was to develop an algorithm that outperforms current models. Two of the most important criteria for a successful spectral algorithm development include (1) application to satellite data, and (2) transferability to extensively variable geographic regions without creating significant uncertainties. Additionally, the identification parameters include the Submerged Mangrove Recognition Index (SMRI), Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Enhanced Vegetation Index (EVI), Normalized Difference Chlorophyll Index (NDCI), and Biomass Index.

The results of this study offer valuable information for mapping and monitoring mangroves within and outside the UAE. The field research assessments are combined with remote sensing and GIS. The NDVI for the Landsat 8 (2024) image was much lower than for the Landsat 5 image, indicating much less vegetation than in 2001. The NDVI range results differ greatly because the images were taken 24 years apart (2001-2024). The NDVI ranges were categorized into low vegetation (Dark green), mangroves (Light green), shallow water bodies (Light blue), land (Orange), deep water (Dark blue), and barren land (Red), which are shown in Figure 3.

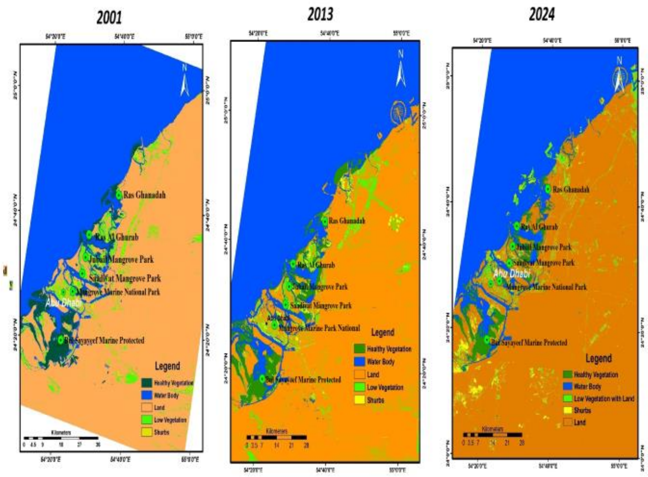


Figure 3. Normalized Difference Vegetation Index (NDVI) map of the study area for 2001, 2013, and 2024.

The differences in NDVI results across the overall ranges of both Landsat images were closer to -1 with Landsat 5 images (close to 1) than with Landsat 8 images (much less than 1). These results show that the variance in Landsat 5 NDVI is higher. The NDVI values range from -1.0 to 1.0. Negative NDVI values indicate clouds and water; soil is indicated by positive values closer to zero; and dense vegetation (>0.6) is indicated by higher positive NDVI values (Borgogno-Mondino et al., 2016). Moreover, the Landsat 8 data from 2024 shows a large area of land that could be a potential site for planting more mangrove forests, such as on Saadiyat Island. Also, negative to low values indicate water, bare soil, sand, or built-up areas. Deep spatial analysis shows that healthy vegetation is reduced year by year, whereas low vegetation and shrubs are increasing, especially in southern and coastal regions (also in central regions). The northern coastal regions are also affected by mangrove growth.

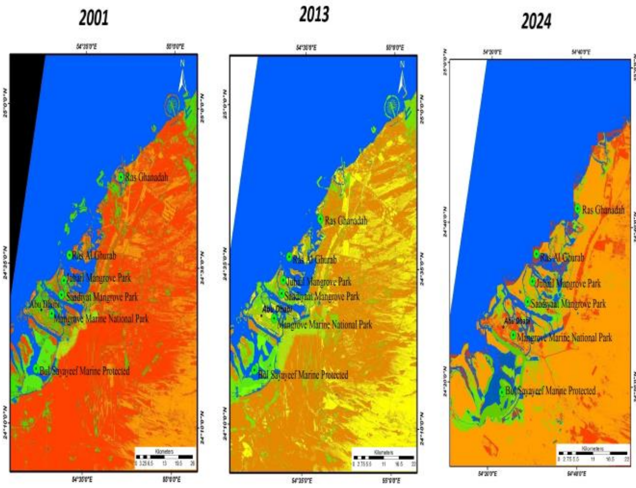


Figure 4. Green Normalized Difference Vegetation Index (GNDVI) map of the study area for 2001, 2013, and 2024.

The Landsat GNDVI imagery from 2001, 2013, and 2024 (which fully reveals greenery, as shown in Figure 4) highlights a common vegetation pattern; however, the 2013 and 2024 imagery showed drastic changes in mangroves and vegetation. The values for 2001 and 2013, more or less as shown, were low vegetation (-0.987µm - -0.250µm), land (-0.250µm - -0.025µm), mangroves (-0.025µm - 0.138µm), shallow water body (0.138µm - 0.410µm), deep water (0.410µm - 0.728µm), and barren land (0.728µm - 0.992µm). On the contrary, the values for Landsat 8, as shown in Figure 5, were low vegetation (-0.459µm - -0.067µm), land (-0.067µm - -0.036µm), mangroves (-0.036µm - 0.011µm), shallow water body (0.011µm - 0.050µm), deep water (0.050µm - 0.073µm), and barren land (0.073µm - 0.539µm). GNDVI indicates that 2001 was less vegetated, and the northern parts of the mangroves were richer in the southern coastal areas.

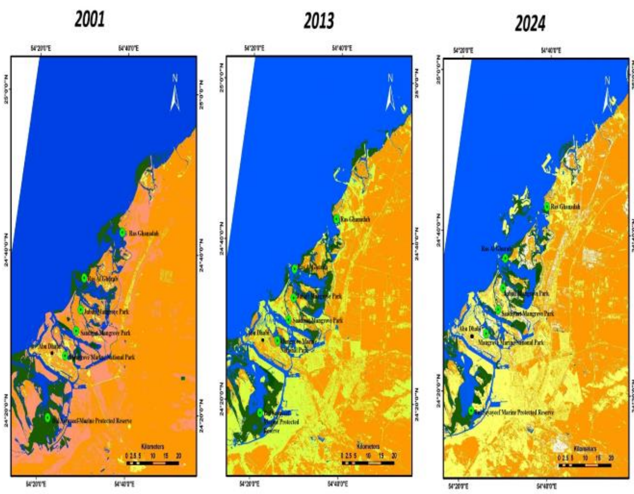


Figure 5. The Submerged Mangrove Recognition Index (SMRI) map of the study area for 2001, 2013, and 2024.

SMRI produced images showing anthropogenic activities that also disturbed healthy vegetation, as reflected in the 2013 and 2024 images. The SMRI of the

Landsat 5 image, as shown in Figure 5, had a maximum value of 1.975977 and a minimum value of -1.974601. The Landsat 5 image results showed a much larger difference between the maximum and minimum values. On the contrary, the SMRI of the Landsat 8 image had a maximum value of 0.300439 and a minimum value of -1.605316. The Landsat 8 image results had a much lower maximum value than the Landsat 5 image. This indicates much less vegetation than in the Landsat 5 image.

Furthermore, non-mangrove regions, including open water, bare soil, sand, or built-up areas, are indicated by negative to low values (-1 - 0.2) (Xia et al., 2020). These values occur in areas with little moisture retention and minimal vegetation. Transition zones or deteriorated mangroves are represented by moderate numbers (0.2 - 0.5), including areas in rehabilitative zones at the initial phase of mangrove development or with patchy mangrove cover (Xia et al., 2020). Healthy mangrove forests are characterized by high positive values (0.5-1), indicating living mangrove ecosystems with high vegetation density and moisture levels (Xia et al., 2020). So that 2001 has moderate mangrove depth but less in the northern parts, and is rich in mangroves southwestern region. The 2013 and 2024 show that the southern and western parts dominate vegetated areas, including mangrove, but with less mangrove density loss, so those areas need careful consideration.

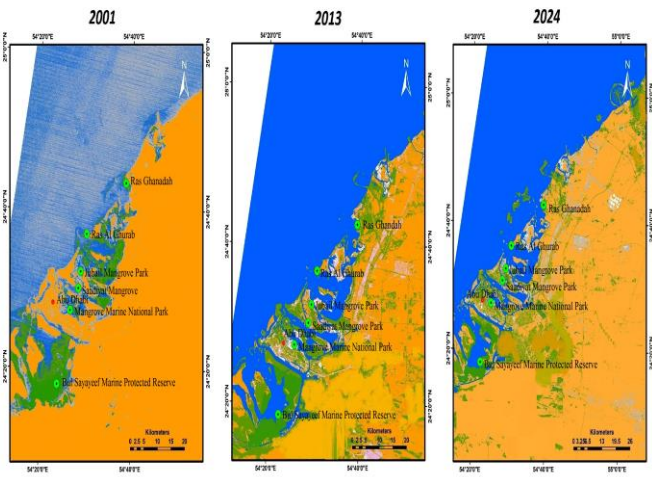


Figure 6. Enhanced Vegetation Index (EVI) map of the study area for 2001, 2013, and 2024.

When the entire green space area is zero, the EVI is expected to be 0.24. This is comparable to the average EVI of 0.28. EVI indicates that 2001 has fewer mangroves but is rich in mangroves in the southern regions, whereas vegetative cover is lower in quantity. 2013 and 2024 show that the southern parts are dominant in vegetation, radiating north-north-eastward in Figure 6. In future studies, EVI will be used to indicate biomass, as places with more biomass are associated with greater biodiversity. This may be especially important in providing evidence to assist health policy, as research suggests that biodiversity may promote pathways associated with favourable health outcomes. EVI ratings do not always reflect greater or lesser access or different forms of publicly accessible green space, nor do they capture green space patterns in three dimensions.

We compared a satellite-derived environmental exposure metric (EVI) with two vector-based access measures for public and private green space. Our findings revealed that satellite-derived measures, such as EVI, provided an objective and uniform way to assess greenness across populations at wide spatial and temporal scales. EVI quantifies vegetation greenness and serves as a biomass indicator. To evaluate incremental variations in EVI (e.g., 0.1 or the interquartile range) within a 300 m buffer zone, it's important to keep in mind that these changes may not always reflect changes in overall greenness.

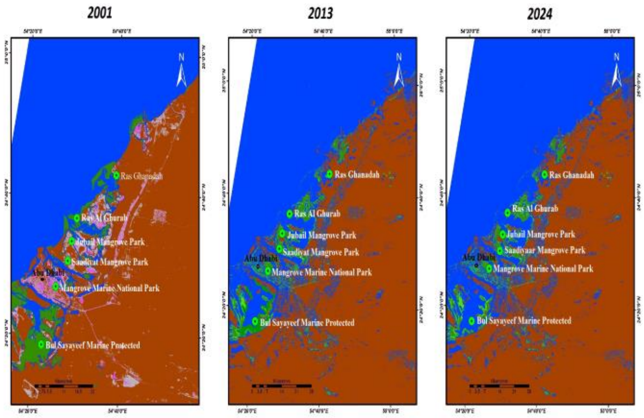


Figure 7. Normalized Difference Chlorophyll Index (NDCI) map of the study area for 2001, 2013, and 2024.

Figure 7 shows that 2001 had fewer mangroves in the northern coastal regions, whereas it was rich in mangroves in the southwestern coastal regions. We propose a novel, Normalized Difference Chlorophyll Index (NDCI), and demonstrate its sensitivity to regional waters. We validated and verified with NDCI by investigating three datasets that represent distinct performance and sensitivity to a wide range of water optical properties. The calibration and validation results from Landsat datasets demonstrate their potential use for a wide range of water types and geographical areas. In this work, we evaluated both criteria during model validation. In addition, ground truths via field observations are silently matched with remote sensing observations.

To calculate the $CO_2$ equivalent for both Landsat 5 and Landsat 8 data, the Overall NDVI pixels (vegetation) obtained through the moderate vegetative pixels (threshold) (0.010-0.35) and healthy vegetative pixels (0.35-0.55) were obtained using equations of 6,7,8. Further, AGB and BGB were measured (eq.9, 10, 11,12,13,14) using existing canopy values from previous studies as references, as well as the Moderate and vegetative area-based threshold values observed from the NDVI (Elmahdy & Ali, 2022; Abu Dhabi Blue Carbon Demonstration Report (AGEDI), 2014).

Mangrove biomass increased from 29.7 t/ha (2001) to 32.7 t/ha (2024), reflecting improved vegetation density and productivity. Healthy vegetation cover rose from 23.8% to 27.7%, indicating successful restoration and stronger ecosystem health.

Carbon storage capacity grew from 13.9 tC/ha to 15.4 tC/ha, enhancing the mangroves' role as natural carbon sinks. $CO_2$ sequestration potential increased from 51 $tCO_2$/ha to 56 $tCO_2$/ha, demonstrating greater climate-mitigation impact. Overall, the NDVI-based biomass index confirms that Abu Dhabi's mangroves are recovering, resilient, and vital for blue-carbon initiatives.

Results indicate that in 2001 (Landsat5), the proportion of healthy mangrove vegetation was higher than in 2024 (Landsat8); this may explain why the vegetative cover was more dominated by mangrove shrubs or less vegetation, rather than healthy vegetation (including mangroves) (Figure 2). Although $CO_2$-equivalent values in the datasets show only slight variation, they have increased gradually over the 24-year interval. So overall, the mangroves are showing better vegetation health and a higher capacity to store carbon, confirming their important role in supporting the UAE's blue-carbon and climate goals. Table 3 shows the Total Biomass, Healthy Vegetation, Carbon Biomass, and $CO_2$ Equivalent from Landsat images by using GIS techniques.

| **Years** | **NDVI total vegetation** | **Area of total vegetation (ha)** | **NDVI (Healthy Vegetation)** | **Area of Healthy (ha)** |
|---|---|---|---|---|
| **2001** | 988797 | 88991.73 | 235359 | 21182.3 |
| **2013** | 10628502 | 956565.18 | 264448 | 23800.32 |
| **2024** | 841925 | 75773.35 | 232129 | 20891.61 |
| | | | | |
| | **Healthy Vegetation (%)** | **Total Biomass (t/ha)** | **Carbon Biomass (tC/ha)** | **$CO_2$ Equivalent ($tCO_2$/ha)** |
| **2001** | 23.80% | 29.66 | 13.94 | 51.15 |
| **2013** | 24.88% | 30.54 | 14.35 | 52.66 |
| **2024** | 27.68% | 32.74 | 15.38 | 56.44 |

Table 3. Total Biomass, Healthy Vegetation (ha), Carbon Biomass, and $CO_2$ Equivalent from Landsat Analysis.

According to Field and aerial imagery analysis, the northern and western regions of Mangrove Marine Park, Jubail Island, Saadiyat Mangrove Park, and Ras Al Ghurab have been chosen to count and study because we observed that those are priority areas for targeted mangrove and vegetative planting to reduce atmospheric $CO_2$ (Figure 8) from remote sensing observation. Therefore, the study also shows a similar drastic increase in $CO_2$ year by year, along with a slight decrease in vegetation, including mangroves. Those are the impacted areas that need vegetation rejuvenation to avoid $CO_2$ impacts.

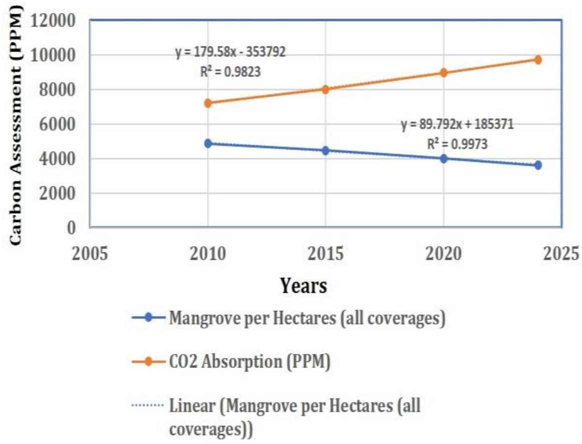


Figure 8. The Graphical plot of the Mangrove field inventory observation based on the CO2 estimation

Our findings also confirm that ecological health and entire greenspace are not linearly associated, and both should be recognized as distinct exposures to identify the most promising locations for adopting plantation (vegetative) measures to reduce carbon. As highlighted by Friend et al. (2014), it is difficult to develop effective policies for complex environmental and public health issues when definitions of exposure to greenness and access to green space vary. (Figures 2, 7, 8, and Table 3).

## 4. Conclusion and Recommendations

This study provides significant data on mangrove mapping and monitoring in the United Arab Emirates using geoinformatics, remote sensing, and conventional field assessments. The findings show significant changes in land use, vegetation health, and mangrove coverage over 24 years. There were more shrubs and fewer healthy mangroves, which were probably due to rising atmospheric $CO_2$ levels and related climate effects. Compared to 2024, data from 2001 showed greater regions of healthy mangroves, with a decrease in healthy vegetation and an increase in shrubs. These shifts point to possible environmental factors that may have altered growth patterns and ecosystem health, such as rising atmospheric carbon dioxide levels and climate change. These results were further supported by the SMRI and NDVI investigations, which revealed lower vegetation and density in 2024 than in 2001.

The NDVI and field analyses reveal that Abu Dhabi's mangroves have shown steady improvement in biomass, vegetation health, and $CO_2$ sequestration from 2001 to 2024. However, some coastal zones still show lower vegetation density and limited carbon uptake potential. Future efforts should prioritize replanting and rehabilitation in these sparse or degraded areas, particularly in the southern and inland tidal zones where vegetation loss was detected. Expanding mangrove plantations using native species, improving water circulation, and applying continuous satellite-based monitoring will further enhance carbon storage and ecosystem resilience, supporting the UAE's Net Zero 2050 goal.

Also, we are concerned and would like to suggest areas that should be given much consideration in vegetative planning to reduce $CO_2$. The study further demonstrated the significance of contemporary remote sensing capabilities for precise monitoring, finding that Landsat 8 (2013 and 2024) provided more accurate and trustworthy data than Landsat 5 imagery. Also, we suggest that a highly spatially and spectrally available remotely sensed dataset would be better for future calculations, and that these calculations should be detailed, including spatially accurate multispectral and hyperspectral data. These findings highlight the critical need for focused conservation and restoration initiatives to lessen these effects, as they show a two-decade trend in mangrove health decline. Additional training and practice are needed to perform this study more accurately, which may help acquire more data.

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