Enhancing coastal resilience through comprehensive Mangrove Management using Multi temporal satellite images and geospatial techniques

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Abstract

The world's most productive ecosystem, the mangrove forest, is a diverse collection of salt-tolerant plant communities in tropical and subtropical intertidal zones. They are found in tropical regions worldwide, with the Indo-Pacific area having the largest concentration. It ranges from 15 million hectares globally, with 123 nations and territories in tropical and subtropical regions, accounting for 1% of all tropical forests. Mangroves serve as a shoreline's natural barrier against ocean dynamics. However, due to human activities near the sea-sore area and other reasons, 35% of the world's mangrove forests were lost over the past two decades of the 20th century. Developers are increasingly targeting mangrove land due to urbanization. Consequently, mangrove afforestation and replanting have recently received much interest in lessening the effects of climate change. Conserving and restoring mangrove forests can lower the net CO^2, stabilize coastlines, and reduce erosion. Governments and non-governmental groups have set high standards to enhance the world's mangrove area by 20% by 2030. Remote sensing-based analysis is used for these studies because of the extensive area monitoring, repeated observations, information collection beyond human vision, cost-effective solution, and change detection accessibility. It can also significantly save expenses and time for processes and labour requirements, but these techniques are complex. Global acquisition of a multispectral satellite of Sentinel-2 with high temporal, spectral, and spatial resolution is possible, providing an opportunity to monitor mangroves more consistently and regularly and using this satellite imagery. The study aims to identify, monitor, and recommend suitable sites to plant new mangroves. In this study, 90.58 km² of mangrove areas were identified, of which approximately 31 km² were found to be in good health. Additionally, 48 km² of land was classified as suitable for new mangrove plantations. These findings support informed data-driven conservation strategies, future restoration, and afforestation efforts.

1. Introduction

The world's most productive ecosystem, mangrove forests, is a diverse collection of salt-tolerant plant communities in tropical and subtropical intertidal zones. (Thakur, Mondal, Ghosh, Das, & De, 2020). They are found in tropical regions worldwide, with the Indo-Pacific area having the largest concentration. (Xia, Qin, Li, Huang, & Su, 2014). It ranges from 15 million hectares globally, with 123 nations and territories in tropical and subtropical regions, accounting for 1% of all tropical forests. (BMC-India, 2015). There are many different types of species in mangroves that are identified worldwide. Mangroves serve as a shoreline's natural barrier against ocean dynamics. However, due to human activities near the sea-sore area and other reasons, 35% of the world's mangrove forests were lost over the past two decades of the 20th century. (Purwanto & Asriningrum, 2019)

Developers are starting to target mangrove land because of urbanization. They leave building debris close to the coast, which negatively impacts not just the water and mangroves but also the indigenous people's ability to exist, who thrive on the seashore. Because of this, mangrove afforestation and replanting have received much interest lately in lessening the effects of climate change. Conserving and restoring mangrove forests can lower the net CO^2, stabilize coastlines, and reduce erosion. Governments and non-governmental groups have set high standards to enhance the world's mangrove area by 20% by 2030. (Thakur, Mondal, Ghosh, Das, & De, 2020).

For this study, remote sensing datasets were used because of critical points like large-area coverage, frequent temporal data acquisition, cost-effectiveness, and the ability to access remote which can also be hazardous locations. Remote sensing-based analysis of mangroves is becoming popular due to its efficiency in monitoring changes over time, mapping inaccessible areas, and supporting data-driven conservation strategies. It can significantly save expenses and time for processes and labour requirements, but these techniques are complex. Global acquisition of a multispectral satellite of Sentinel-2 with high temporal, spectral, and spatial resolution is possible, providing an opportunity to monitor mangroves more consistently and regularly and using this satellite imagery. The objectives of the study, which are to identify, monitor, and provide suitable sites for planting new mangroves, were fulfilled by remote sensing. According to the ISFR 2018 report, most of the mangroves are in the southeast and southwest regions, with a total of 4,943 km^2, contributing 3% of the total South Asia region. This study aims to enhance coastal resilience in Mumbai through comprehensive mangrove management. The complex environmental restrictions and human activity near the coastal region restrict the natural development and spread of mangroves along the coastal area.

2. Literature Review

Coastline ecosystems such as mangroves provide a multitude of ecological and socioeconomic advantages. Sustainable Management is essential for mangroves to remain healthy and for the linked ecosystem functions. In mangrove management, numerous factors are considered for these different approaches and methods. Various studies used different remote sensing datasets like Landsat TM, WorldView-2, panchromatic, LiDAR, geo-referenced aerial photos, etc., while other studies were only based on field datasets. Some of the other studies are based on field surveys only. At the same time, few others are using Artificial Intelligence (AI)/ Machine Learning (ML) algorithms. Multi-scale object detection from a single satellite image or across many images from satellite data is made more accessible using a geographic object-based image analysis technique (GEOBIA) (Kamal, Phinn, & Johansen, 2015).

The first step in these mapping approaches was to create a conceptual hierarchical structure for mangrove objects using field data, local knowledge, and the analysis and literature on mangroves. Another study differentiates mangrove areas from other characteristics using object-based image analysis, predicated on segmentation, which divides the picture into pixel groups or meaningful, spectrally uniform, spatially continuous objects. To remove the difficulties in choosing suitable similarity metrics that distinguish items from one another. As a result, the satellite image's spectral profiles of distinguishable objects were examined. (Heenkenda, Joyce, Maier, & Bartolo, 2014). Some of the studies also consider high-tide and low-tide situations. A quantitative spectral index may be created to identify mangrove forests in tidal zones if two photos (high-tide and low-tide) of the region can be gathered and analyzed to compare the electromagnetic waves of the mangrove forests between the two tide levels. Relevant textural and geographic characteristics (such as homogeneity and contrast) that describe the geographical distribution of mangrove forests may also be incorporated into this framework to enhance the mapping findings further. Some researchers also used Classifiers based on pixels (reflectance properties and spectral signature).

A pixel-based classification is a conventional method to examine each pixel's reflectance and spectral properties. Since the pixel is a fundamental unit of measurement for satellite photos, these techniques seek to explore the pixel values in an image to assign every image pixel to a class based on its spectral characteristics. (Maurya, Mahajan, & Chaube, 2021). Most of the study uses a criteria Decision Analysis (MCDA) approach using some of the parameters air temperature, tidal information, Normalised Differential Vegetation Index (NDVI), Digital Elevation Model (DEM), Normalised Differential Wet Vegetation Index (NDWVI), Modified Bare soil Index (MBI), and soil salinity by providing weightage for deriving. ((Muditha K. Heen Kenda, 2014).

3. Study Area

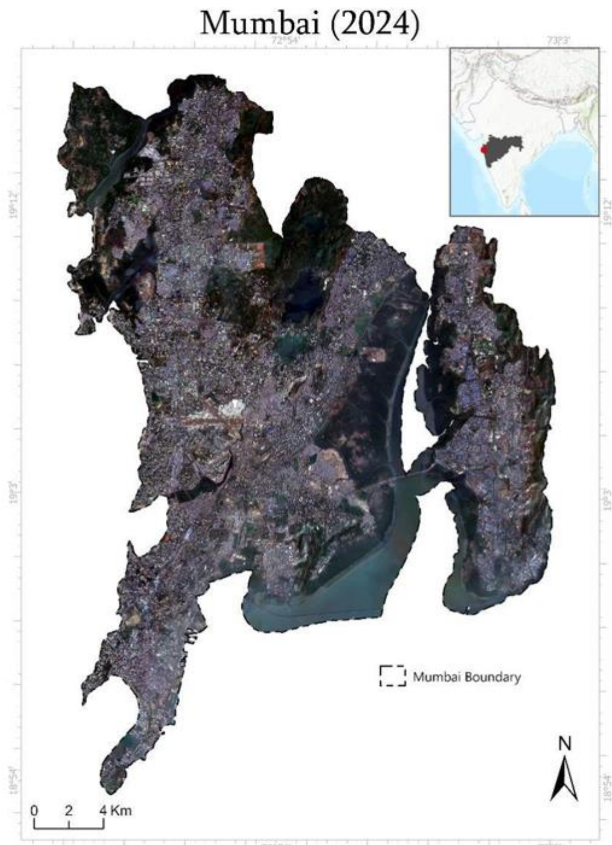

Figure 1. Mumbai (Suburban + new)

The study primarily emphasizes the metropolitan area of Mumbai, which has 12.5 million people. The town is bordered by mangroves on both banks by several rivers and creeks, with Thane Creek as the significant entry. In the southwest, this watercourse is connected to the Arabian Sea (Muditha K. Heenkenda, 2014). Some previous studies show that 13 types of mangroves are in the Mumbai region. There are 37 mangrove associates, and around 13 kinds of mangroves have been documented in Mumbai, as shown in Table 1. Avicennia marina var. acutissima, Avicennia marina var. acutissima forma pumila (forma nov.), Sonneratia apetala, Avicennia alba, Avicennia marina, and Brugueria cylindrica are the predominant species of mangroves. There are reports of Lumnitzera racemosa, an extremely uncommon mangrove in Mumbai, coming from Gorai and Charkop. (Dutta, 2021). However, this study does not focus on research types but only on the identification of mangroves in that study region.

Sr. No	Types of Mangrove Species	Chances of Presence in the Study Region	Locations
1	Avicennia marina	Common	All location.
2	Avicennia marina var. acutissima	Very Common	All location.
3	Avicennia marina var. acutissima forma	Very Common	All location.

4	Avicennia officinalis	Common everywhere present	All locations except Bandra, Lokhandwala, Charkop, Gorai, Vikhroli, and Nerul.
5	Diliavaria ilicifolia	Common everywhere present	All locations except Bandra and Lokhandwala.
6	Rhizophora mucronata	Rare	Bandra, Malad, Elephanta, Versova.
7	Rhizophora apiculata	Rare	Found only in cultivation.
8	Sonneratia apetala	Common everywhere present	All locations
9	Sonneratia alba	Common everywhere present	Elephanta Island, Manori, Bandra (only a few plants)
10	Ceriops tagel	Common everywhere present	All locations except Bandra
11	Bruguiera cylindrica	Common everywhere present	All locations except Bandra
12	Lumnitzera racemosa	Rare	Gorai, Charkop
13	Aegiceras corniculatum	Common everywhere present	All locations except Bandra

Table 1. Types of mangroves ((Dutta, 2021))

Due to rapid urbanization and high housing demand, developers are targeting mangrove land. They dump building waste close to the coast and river, which hurts mangroves, the sea, and the indigenous Koli people's way of life. Due to this, most of the water bodies in the Mumbai Metropolitan Region (MMRDA) are highly polluted and serve as drainage systems, according to the environmental status report of the MMRDA issued by The Energy and Resources Institute (TERI) in 2015.

4. Materials & Methodology

This study uses remote sensing datasets like Multispectral Images (MSI) and Digital Elevation Models (DEM) for comprehensive mangrove management.

4.1 Data Collection

No	Dataset	Source	Period	Spatial Resolution
1	Sentinel-2 MSI	Google Earth Engine (GEE)	Jan-24	10 m
2	ALOS PALSAR - DEM	Google Earth Engine (GEE)	Jan-24	12.5 m

Table 2. Details of the datasets.

4.1.1 Multispectral Imagery Collection:
In multispectral imagery (MSI), only the Sentinel-2 satellite was used because of its high spatial resolution (10m) and temporal (10 days) resolution. The Satellite has a Sun-synchronous orbit with 13 multispectral bands, with four bands at 10-meter resolution (visible and near-infrared) and six bands at 20-meter resolution (red edge and shortwave infrared). Three bands at 60-meter resolution (atmospheric correction) with a Swath width of 290 km (180 mi). MSI datasets were collected from Google Earth Engine (GEE) for the Mumbai region, particularly in January 2024.

4.1.2 Digital Elevation Model (DEM) Collection:
In the Digital Elevation Model (DEM), ALOSOLSAR DEM, which is provided by Japan Aerospace Exploration Agency (JAXA), was used because of its high spatial resolution (12.5m) and accurate terrain height compared to other DEM. DEM datasets were also collected from Google Earth Engine (GEE) for the Mumbai region, particularly in January 2024.

4.2 Data processing

These datasets were further clipped in GEE using code. So, the author fully automates the dataset's acquisition process; the user needs to make a Region of Interest (ROI) or upload a shapefile (.shp) and change the date in GEE. Parameters for Study Using these two clipped datasets, different Indices were made that show or affect comprehensive mangrove management. A total of five indices and 1 DEM used as parameters for affecting mangrove management are listed below, and their detailed explanation is given in this article.

4.2.1 Normalized Difference Water Index (NDWI): For many years, satellite observation of water has extensively used the normalized difference vegetation index (NDWI). This index uses reflectance or radiances from two channels (B.C., 1996). NDWI effectively reduces and eliminates built-up land, vegetation, and soil noise while enhancing open water features. The area of the extracted water is exaggerated because the improved water information obtained from the NDWI is frequently combined with built-up land noise. These indices' values range from (-1) to (+1). That (-1) shows very few chances of water, which means some built-up or bare soil exists. Near 0 shows high vegetation. And (+1) indicates very high chances of waterbodies being present. (B.C., 1996)

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

The importance of NDWI for this study is in extracting the waterbodies. The mid values of this index, which are near 0, show vegetation that can be directly used in mangrove site suitability.

4.2.2 Normalized Difference Vegetation Index (NDVI): Currently, the most widely used index for vegetation evaluation, the Normalized Difference Vegetation Index (NDVI), was among the first remote sensing analytical solutions to reduce the intricacies of multi-spectral images. Previous Studies have shown that the NDVI is a valuable tool for distinguishing between the types of forests that are evergreen and seasonal, as well as for savannah, thick forest, non-forest, and agricultural lands. These index values range from (-1) to (+1). In that (-1) shows very little chance of vegetation, it means there is some built-up or bare soil. Near 0 shows water. And (+1) shows a very high chance of vegetation being present. (Huang, Tang, Hupy, & Shao, 2020)

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

The importance of NDVI for this study is to extract the Vegetation and its health. The high values of this index, which are near (+1), show vegetation that can be used directly in mangrove area identification and their health, as mangroves are also categorized as typical vegetation. The spectral range of this band indicates excellent health to terrible health as (-1) to (+1), respectively.

4.2.3 Normalized Difference Wetness Vegetation Index (NDWVI): It shows wet vegetation in the area. These indices are very useful in discriminating between typical vegetation in the urban area and vegetation near the seashore or rivers/lakes. These indices' values range from (-1) to (+1). (+1) shows very high wetness vegetation. And (-1) shows very high dry vegetation. (Sarkar, Gnanappazham, & Pandey, 2023)

$$NDWVI = \frac{(NIR - SWIR\ 2)}{(NIR + SWIR\ 2)}$$

Mangroves are in the wetland, which is near the shoreline. So (+1) values are directly used in identified mangroves, but (-1) values are not used for the mangrove area identification, as they are in dry vegetation.

4.2.4 Normalized Difference Moisture Index (NDMI): In remote sensing, the term "moisture index" refers to mathematical formulae that measure plants' water or soil's moisture content using the spectral response of distinct bands in the collected images. These indicators are especially helpful in determining vegetative stress, soil moisture content, and drought situations.

$$NDMI = \frac{(NIR\ 8A - SWIR)}{(NIR\ 8A + SWIR)}$$

As NDMI shows soil surface moisture, values range from (-1) to (+1). (+1) represents high surface moisture as mangroves are in a moisture area, and (-1) means a shallow moisture area. This index (+1) directly considered mangrove area identification and site suitability values. And (-1) is not required to be considered in further analysis for both.

4.2.5 Modified Bare-soil Index (MBI): In remote sensing, regions with low plant cover or patches of bare soil are identified using the Modified Bare Soil Index (MBI), a vegetation index. It is obtained from multispectral or hyperspectral photography and is especially helpful for monitoring soil conditions, determining planting sites, and evaluating soil erosion in agricultural applications.

$$NDMI = \frac{(SWIR\ 1 - SWIR\ 2 - NIR)}{(SWIR\ 1 - SWIR\ 2 - NIR)}$$

MBI is used to highlight bare soil in the area of interest. (AOI). The ranges of these indices are from (-1) to (+1). (-1) will indicate dense or green vegetation, and (+1) will indicate bare soil area. In this study, these indices highlight bare soil, which ranges near (+1) and is directly used in mangrove site suitability because, in that bare area, it is easier to intervene for any authority to convert it into mangrove areas. And (-1) indicated very dense vegetation used in mangrove area identification.

4.2.6 Digital Elevation Model (DEM): It is a digital representation of a terrain's topography. DEMs are widely used to depict and analyse the Earth's surface in remote sensing applications and Geographic Information Systems (GIS). In general, a DEM is made up of a grid or raster with elevation data contained in each cell or pixel. A digital elevation model's elevation data shows how high the landscape is above a reference datum, often the mean sea level. DEM can also be used as a primary parameter to discriminate vegetation in cities and near sea areas. Usually, sea-sore elevation is near 0. And the city area height can vary by location. So, elevation as a parameter study can remove vegetation in urban areas, which are situated in very high elevations compared to seashore vegetation. These parameters are directly used to determine the site's suitability for mangroves.

4.3 Spatial analysis for weightages

Spatial analysis using weighted overlay techniques allows for the integration of multiple thematic parameters based on their relative importance. Each layer is assigned a weight reflecting its influence on the outcome, enabling a comprehensive suitability assessment. This method is particularly effective for environmental planning, such as identifying optimal sites for mangrove restoration. It supports data-driven decision-making by quantifying spatial relationships among key factors.

No.	Parameter Name	Weightage (%)
1	Normalized Difference Vegetation Index (NDVI)	29%
2	Normalized Difference Wetness Vegetation Index (NDWVI)	21%
3	Modified Bare Soil Index (MBI)	24%
4	Digital Elevation Model (DEM)	26%

Table 3. AHP Table for Mangrove Area Identification

Consolidate ratio (C.R.) = 0.09 < 0.1. Acceptable.

No.	Parameter Name	Weightage (%)
1	Normalized Difference Vegetation Index (NDVI)	27%
2	Normalized Difference Moisture Index (NDMI)	23%
3	Modified Bare Soil Index (MBI)	27%
4	Digital Elevation Model (DEM)	25%

Table 4. AHP Table for Mangroves site suitability

Consolidate ratio (C.R.) = 0.086 < 0.1. Acceptable.

5. Results & Discussion

This study generated all the indices, and by using those indices study generates 3 outputs:

- ✓ Mangrove Area Identification,
- ✓ Mangrove Health, and
- ✓ Site Suitability for planting New Mangrove.

5.1 Vegetation and other indices

5.1.1 Normalized Difference Water Index (NDWI): Figure 2 shows NDWI values in the study region and categorizes them into three classes: most suitable, less suitable, and not suitable. Higher values of NDWI are shown in red, and lower values are shown in green. And that red color is not suitable, & Green represents the most appropriate new site suitability for mangroves.

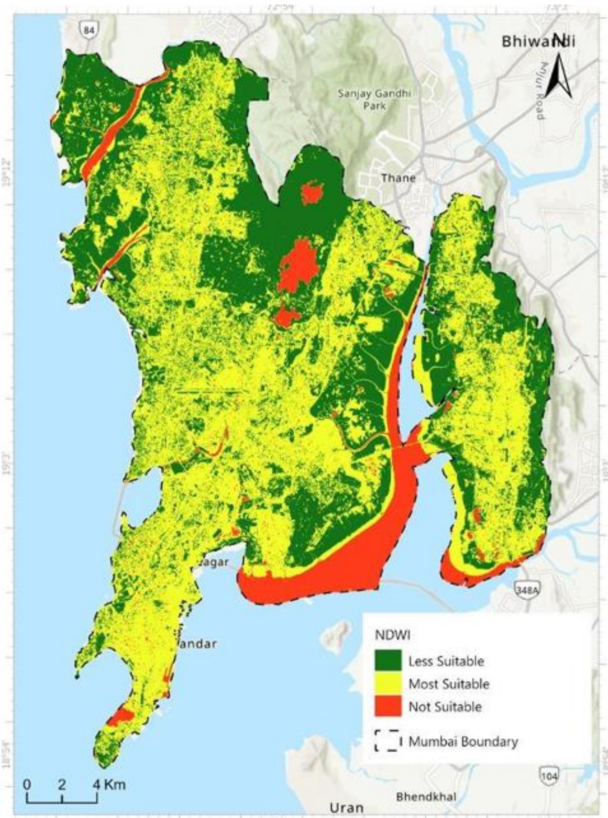

Figure 2. NDWI.

5.1.2 Normalized Difference Vegetation Index (NDVI): Figure 3 shows NDVI values in the study region and categorizes them into five classes: Very High Suitable, High Suitable, Suitable, Less Suitable, and Very Less Suitable. Higher values of NDVI are shown on the green side, and lower values are displayed on the red side. The red color is unsuitable because it consists of waterbodies, & Green represents the most suitable for mangrove area identification because it consists of dense vegetation, mangroves, forests, etc. Also, these NDVI values are used for mangrove health in the identified areas.

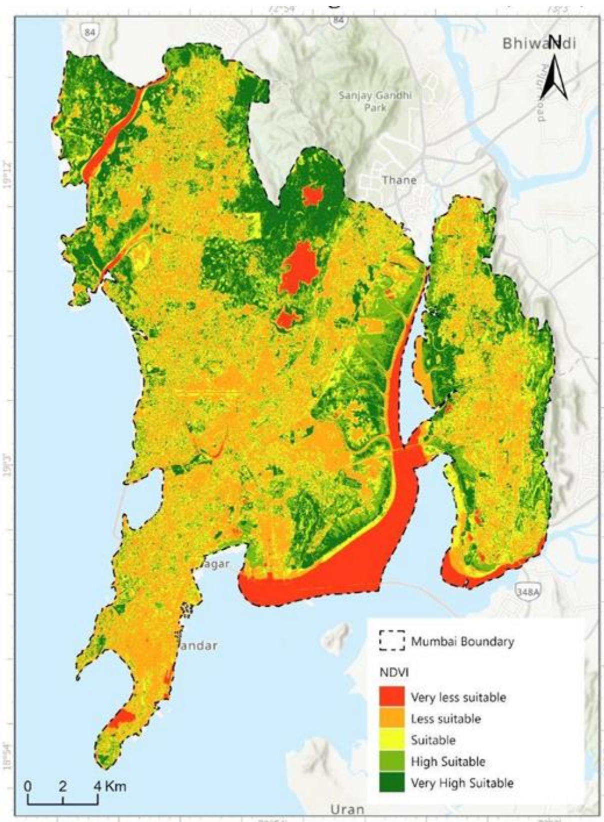

Figure 3. NDVI.

5.1.3 Normalized Difference Vegetation Wetness Index (NDWVI): Figure 4 shows NDWVI values in the study region and categorizes them into High Suitable, Not Suitable, and Restricted areas. Higher values of NDWVI are shown on the green side, and lower values are displayed on the red side. The red color represents a restricted area because it consists mainly of built-up areas, & Green represents the most suitable for mangrove area identification because it shows wet vegetation in the study region, as mangroves are found primarily in wet areas only.

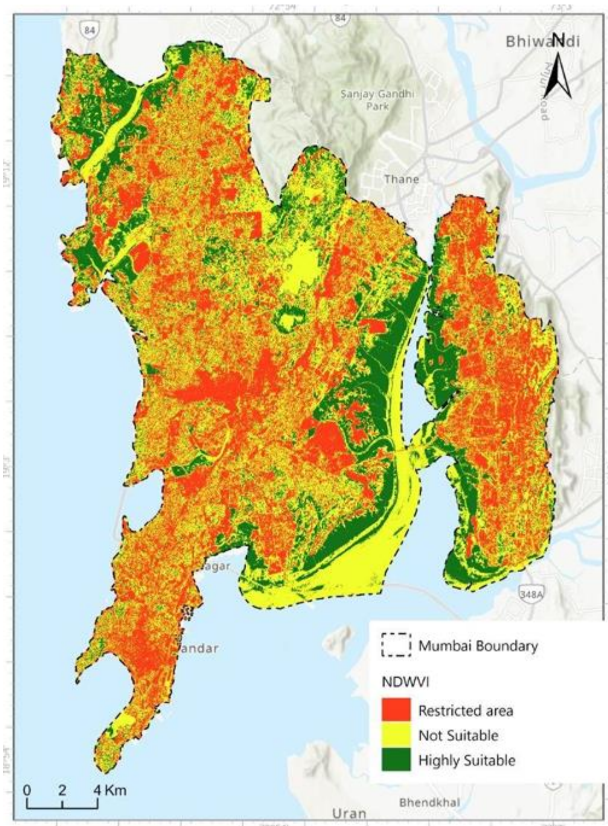

Figure 4. NDWVI

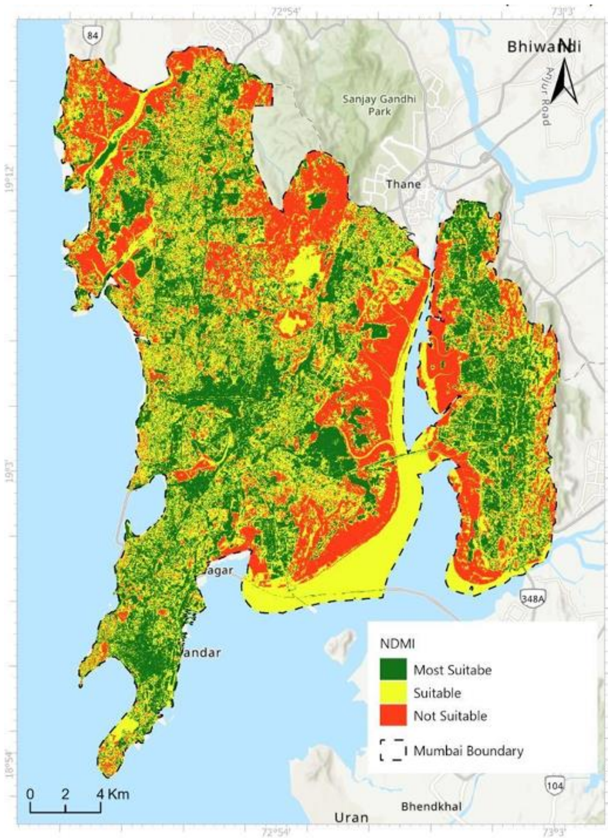

Figure 5. NDMI

5.1.4 Normalized Difference Moisture Index (NDMI): Figure 5 shows NDMI values in the study region and categorizes them into three classes: Most suitable, Suitable, and Not suitable. Higher values of NDMI are shown in red, intermediate values are displayed in green, and lower values are shown in yellow. The red color is unsuitable because it consists of vegetation and a high moisture area, & Green represents the most suitable site for new mangroves because it consists of bare soil. Also, these NDMI values are used for mangrove health in the identified areas.

5.1.5 Modified Bare Soil Index (MBI): Figure 6 shows MBI values in the study region and categorizes them into the highly suitable, not suitable, and Restricted areas. Higher values of MBI are shown in red, lower values are shown in green, and intermediate values are represented in yellow. The red color consists of bare soil and a buildup area unsuitable for mangrove area identification, & Green represents the most suitable because it consists of dense vegetation and mangroves, which are ideal for mangrove identification. The exact reverse thing is used for mangrove site suitability. Bare soil was most appropriate, and dense vegetation was restricted for new sites for mangrove plantations.

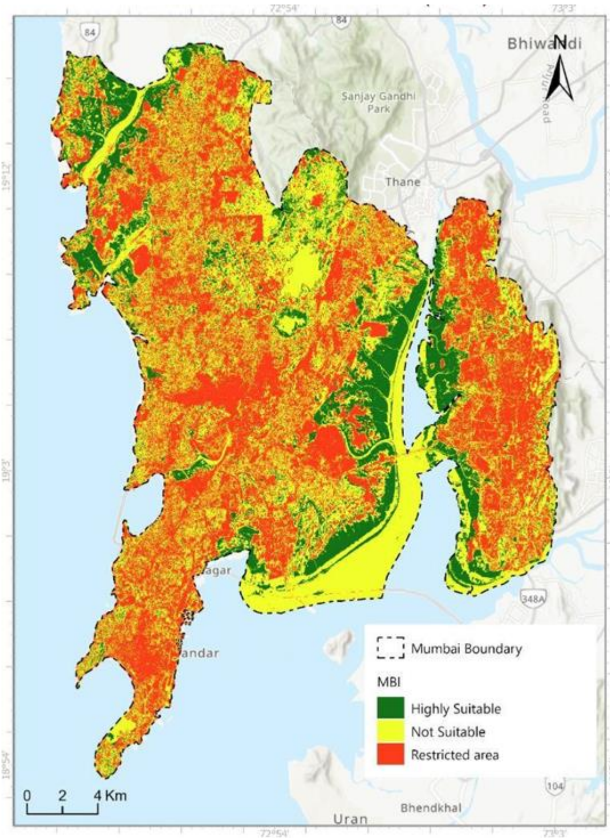

Figure 6. MBI

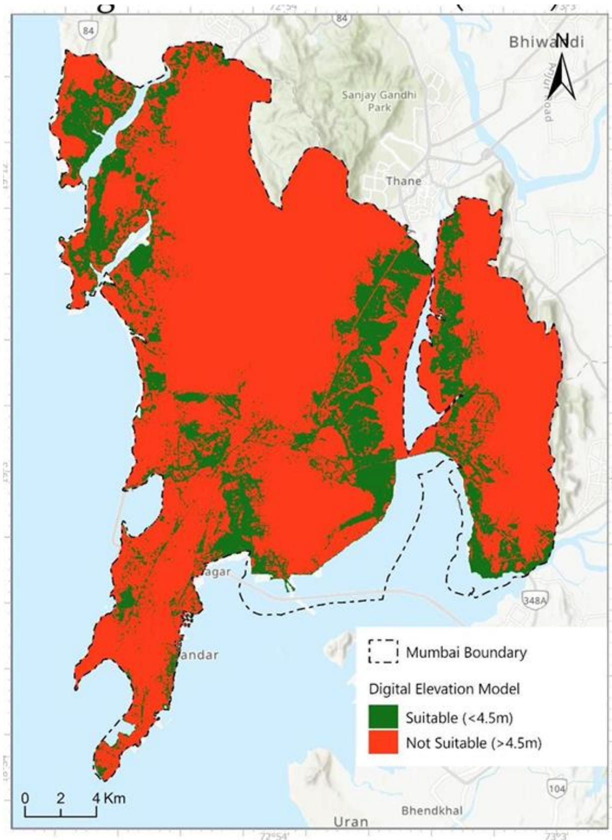

Figure 7. DEM

5.1.6 Digital Elevation Model (DEM): Figure 7 shows DEM values in the study region and categorizes them into two classes. The height above 4.5m is red, whereas less below 4.5m is green. The red color is unsuitable because it shows the core city area, and Green is the most suitable because a height of less than 4.5m could be achieved only in the sea area. This type of condition is used for mangrove area identification and new site suitability.

After all this, all parameters were used for observed mangrove, health, and site suitability. The results of that are shown in the next chapter of this report.

5.2 Spatial analysis

5.2.1 Observed mangrove regions: The Observed mangrove regions are shown in Figure 8 was generated by giving the weightage from Table 1 using NDVI, NDWVI, MBI, and DEM, and verified with base imagery, area comparison, and spectral reflectance. Almost 65% of the area is marked as restricted or unsuitable because of built-up regions and bare soil areas. Nearly 17% of the area was marked as a mangrove-identified area after being verified with base imagery. The results of satellite-based verification are shown below.

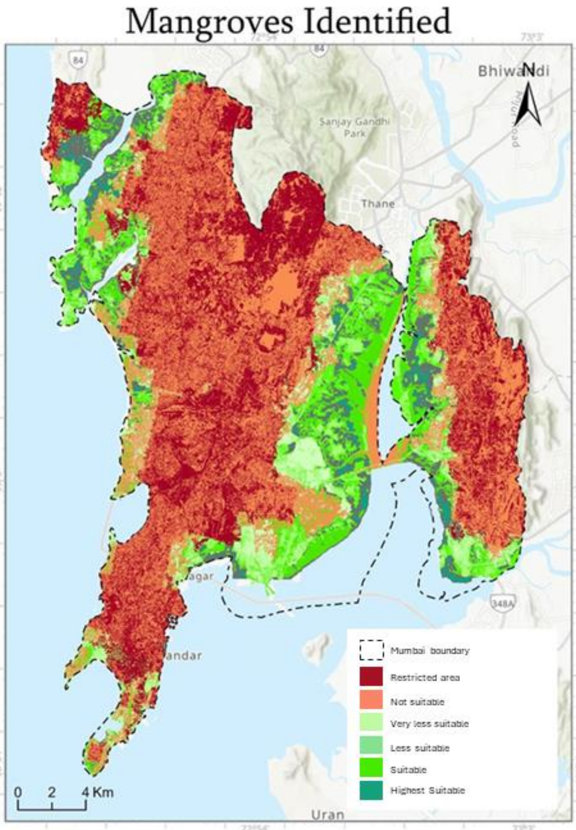

Figure 8. Observed mangrove region.

5.2.1.1 Satellite-based verification for Observed mangroves results: It was done in 2 stages. The first one was a visual comparison with base imagery, and the second one was a spectral signature comparison with (Sarkar, Gnanappazham, & Pandey, 2023) Study within the identified region. In these, they have mentioned the spectral signature graph of mangroves.

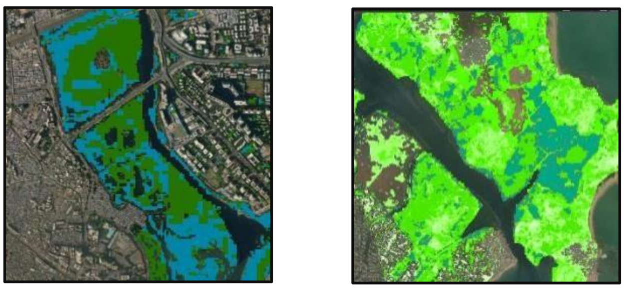

Figure 9. Observed Mangroves (Part - I)

Figure 10. Actual satellite image (Part - I)

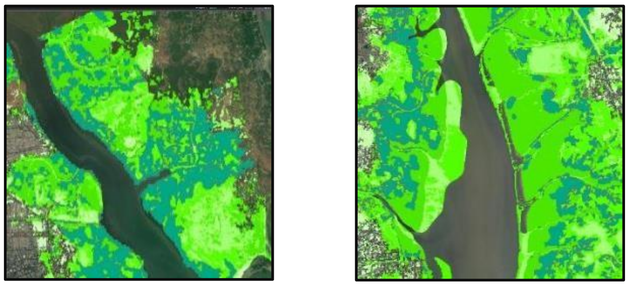

Figure 11. Observed Mangroves (Part - II)

Figure 12. Actual satellite image (Part - II)

Mangroves in the study region are accurately observed after excluding all bare soil, built-up, and urban vegetation. There were more ground-truthing comparisons, some of which are mentioned above in Figure 9 (Identified mangroves) and Figure 10 (Base imagery). The result was confirmed visually and then further verified with the spectral signature.

To compare the spectral signature of the identified region with the reference signature, which was mentioned in (Sarkar, Gnanappazham, & Pandey, 2023), Study: All the bands were stacked and made into one TIFF image. After that, the SNAP tool was used to make a comparison.

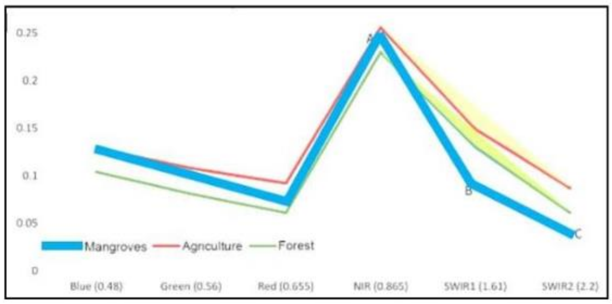

Figure 13. Mangrove spectral signature (Sarkar, Gnanappazham, & Pandey, 2023).

The spectral signature of the identified region matches with the (Sarkar, Gnanappazham, & Pandey, 2023) Study. This shows that the results were obtained. This correspondence indicates that the results obtained in the present analysis are consistent with their observations, thereby validating the accuracy and reliability of the current classification or detection approach.

5.2.2 Mangrove Health: This output was generated from NDVI and categorized into three classes: good, bad, and balanced health. Bad health was directly input as a parameter in site suitability because it shows mangroves have terrible health, so intervening in that area is easier and faster. The health of mangroves within the identified mangrove region is shown in Figure 14. As we can see, only 34% of the area is in excellent health near the sea. After that, 28% and 38% of the area had balanced and very bad health, respectively, which was very close to urban areas/built-up areas. The main factors behind this bad health near built-up areas may be urban development, human activities, and cutting mangroves, which can degrade the health of mangroves. The same situation is also mentioned in the (Purwanto & Asriningrum, 2019) Study.

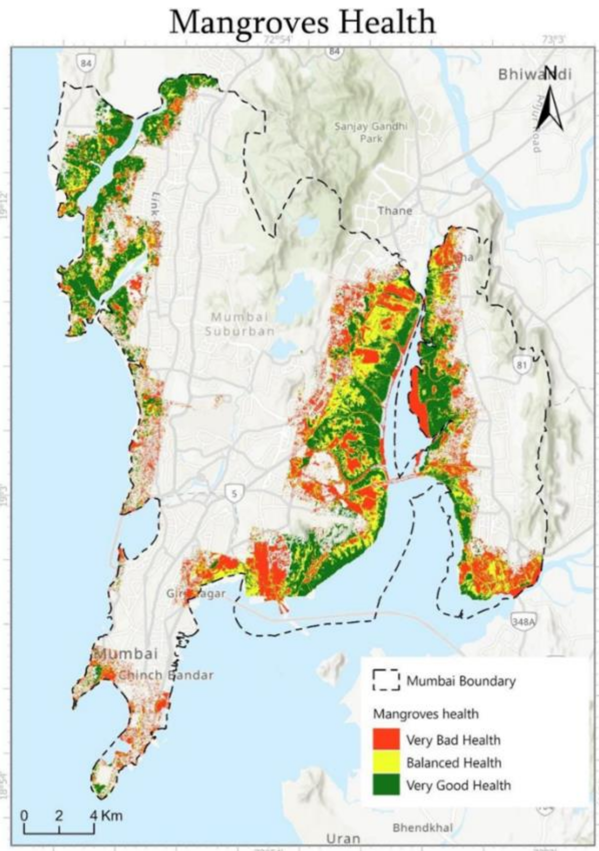

Figure 14. Mangrove Health

5.2.3 Site suitability for planting new mangrove: As we can see from Figure 15 was generated by giving the weightage from Table 2 using NDVI, NDMI, MBI, and DEM, and verified with base imagery. Satellite-based verification for identified mangroves and site suitability was done using visual comparison with base imagery, and for identified mangroves, one additional verification was done using a spectral signature; the new mangrove site is suitable for the study region. 73% of the total land was marked as a restricted area consisting of a built-up area, an airport, existing vegetation, and existing vegetation. In the study region, 9% of the land can be used for new mangrove site suitability as it is near the sea and existing mangrove areas. And it is easy to intervene in that area. And approx. 19% of the total land was marked as unsuitable or significantly less suitable, as it consists of existing mangrove areas.

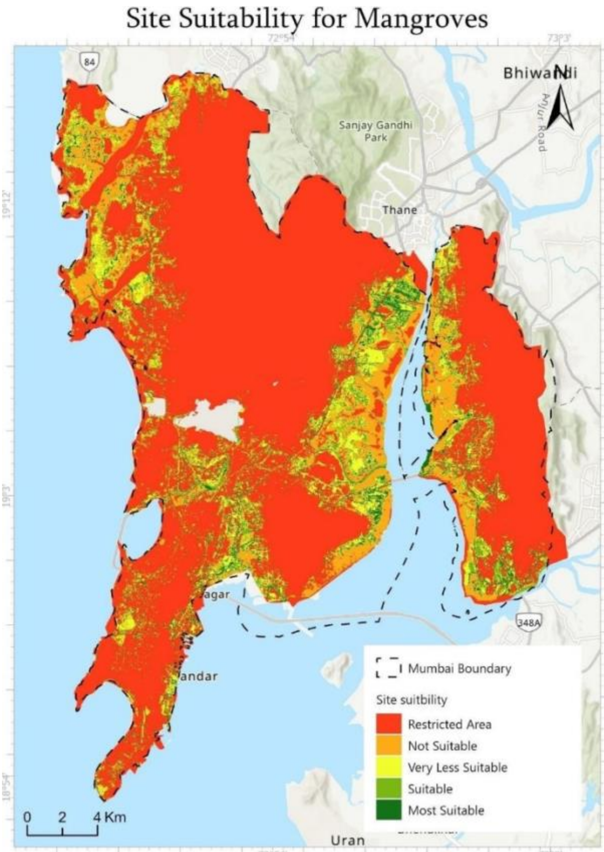

Figure 15. Site suitability for planting a new mangrove

5.2.3.1 Satellite-based verification for planting new mangrove results: After the result was achieved, Satellite-based verification was done visually based on base imagery.

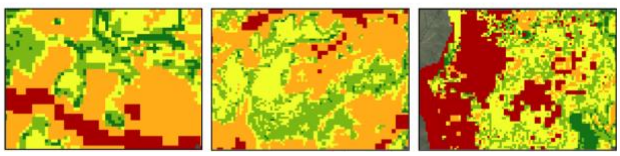

Figure 16. Site suitability results.

Figure 17. Actual satellite image

Satellite-based verification images clearly show that results obtained from parameters distinguish between existing mangrove areas and bare soil areas. Much Satellite-based verification was done; some are in Figures 15 (Site suitability result) and 16 (Ground Condition).

5.3 Accuracy Assessment

5.3.1 Accuracy Verification:

The accuracy is established through multiple, mutually reinforcing checks rather than a single point estimate.

First, the mapped mangrove extent (90.58 km²; ~13% of the study area) aligns with independent prior assessments for the region, indicating consistency at the order-of-magnitude/areal level.

Second, the final mangrove mask was verified against high-resolution base imagery of observed Mangrove locations as mentioned in Section 5.2 Spectral Analysis, showing close spatial correspondence between classified mangrove patches and visually identifiable mangrove stands.
Third, the spectral reflectance of our mapped mangrove pixels matches a published (Sarkar, Gnanappazham, & Pandey, 2023) mangrove spectral signature when bands are stacked and compared in SNAP, which supports class-level correctness of the target class and reduces the risk of systematic confusion with look-alike vegetation.

5.3.2 Modes of verification: We have considered 3 modes of verification.

Visual Verification: Refer second point as mentioned in Section 5.3.1.
Spatial Verification: Refer third point as mentioned in Section 5.3.1
Kappa Coefficient: The classification yielded a Cohen's Kappa coefficient of 0.80, indicating strong agreement beyond chance.

6. Conclusion

The conclusion of this study is divided into three zones, which are shown below.

6.1 Observed Mangrove Region

A total of 90.58 km^2 areas were identified as mangrove regions. Which is nearly. 13% of the total area. This area approximately matches the (IISS, 2018) Annual Report. It was noticed that the total area is increasing compared to research of Vijay et al., 2005.

6.2 Mangrove Health

Approx. 28.17 km^2 & 23 km^2 areas having very bad health and balanced health, respectively, and nearly 31 km^2 area having good health within the mangrove identified area.

6.3 Site Suitability for Planting a New Mangrove

48 km^2 of areas were suggested for new mangrove sites, which is approximately. 6.9% of the total area. Planting and managing these mangroves in the region serve as a natural barrier against tsunamis, storm surges, and coastal erosion. (Heenkenda, Joyce, Maier, & Bartolo, 2014). Their deep roots stabilize the ground, lessening the force of waves and safeguarding coastal areas. Also, it helps numerous marine and terrestrial species, which can find homes and nidification sites in the very biodiverse ecosystems known as mangroves. They provide food for a variety of fish, crabs, birds, and animals.

7. Future Work

7.1 Habitat Modelling

Integrate species-specific ecological requirements (example salinity tolerance, inundation frequency, sediment type) into the site suitability analysis to predict optimal zones for different mangrove species.
Couple habitat models with projected sea-level rise and climate change scenarios to forecast shifts in mangrove distribution and identify potential migration corridors.

7.2 Mangrove Continuous Monitoring

Establish an automated, cloud-based monitoring pipeline using multi-temporal Sentinel-1 and Sentinel-2 data to detect seasonal variations, degradation hotspots, and recovery trends.
Develop an interactive dashboard for stakeholders to visualise mangrove health trends, area changes, and risk alerts at multiple spatial and temporal scales.

7.3 Ground Truth for Future Refinement

To use UAV imagery and in-situ measurements to validate satellite-derived indicators and refine classification thresholds.
Build a spatially and temporally rich ground-truth database that supports model calibration, enhances classification accuracy, and enables robust cross-regional comparisons.

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