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Mapping Coastal Green Infrastructure by Integrating Remote Sensing and Machine Learning in Cuddalore, Southeast Coast of the Bay of Bengal

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Abstract

Mapping Coastal Green Infrastructure (CGI) and mangrove habitats along the Cuddalore coast in Southeast India, using advanced remote sensing technologies, analyzed changes in land use, land cover (LULC), and the distribution of Normalized Difference Vegetation Index (NDVI) through satellite imagery from Sentinel-2, the Multispectral Instrument (MSI), Landsat, the Thematic Mapper (TM), the Enhanced Thematic Mapper (ETM+), the Thermal Infrared Sensor (TIRS), and the Operational Land Imager (OLI) for the years 2000 to 2024. This investigation reveals the significant growth in plantation areas, mangrove swamps, and agricultural land, alongside an expansion of sand beaches and rivers. For mangroves, NDVI values are increased from 0.050 to 0.438, NDVI values shows good vegetation health, and a positive correlation between NDVI and temperature also highlights the rising temperatures in settlement areas. By using Google Earth Engine (GEE) with high-resolution Landsat and Sentinel data, CGI features were mapped with over 70% accuracy through a machine learning algorithm utilizing random forest techniques, with 30% validation from field surveys, particularly a random forest classifier. This study confirms the ongoing degradation of coastal vegetation and shoreline erosion, emphasizing the need for targeted conservation strategies and offering scalable methodologies for addressing similar issues in global coastal regions.

Keywords: Mangroves, Coastal Green Infrastructure, LULC, NDVI, GEE.

Introduction

Coastal green infrastructure (CGI) is used to describe natural and semi-natural systems like mangroves, salt marshes, dunes, and wetlands. These are ecosystem providers and natural buffers that function to protect the coast against coastal hazards. These ecosystems are very valuable for the mitigation of the effects of coastal erosion, storm surge, and sea level rise, thus improving the resilience of coastal communities. Mangrove forests are important coastal ecosystems that offer a variety of ecosystem services like carbon storage, protection against natural disasters, and assistance to coastal communities [1]. Mangroves are one of the most important ecosystems in the coastal wetland from the ecological viewpoint as well as the biodiversity viewpoint. This ecosystem is found primarily in the muddy substratum where the river and the ocean meet. Such types of ecosystems are primarily used in tropical and sub-tropical regions, and they are found on the side of the shore. These residues are typically burnt, which results in severe environmental health loss. Mangrove forests are extremely important for the balance of the marine ecosystem.

Mangrove forests can be monitored continuously and in a comprehensive manner utilizing remote sensing, which allows for monitoring of their health, identification of signs of degradation, and implementation of conservation activities [2]. Mangroves have a rich diversity of species, and by sequestering carbon, they help in the conservation of biodiversity and protection of endangered species [3]. Storage of carbon and the impact on climate change mitigation approaches is measured using remote sensing data. Mangroves are resilient because they are organic barriers to erosion, storm surges, and coastal floods [4]. Balance between conservation and development is enhanced through the utilization of accurate data on mangrove forests to inform sustainable land-use planning and development policies. Mangroves provide critical ecosystem services such as protection of coastal infrastructure, facilitation of tourism, and support for fisheries [5]. Environmentalists and policymakers need accurate and up-to-date information to make informed, sound decisions [6].

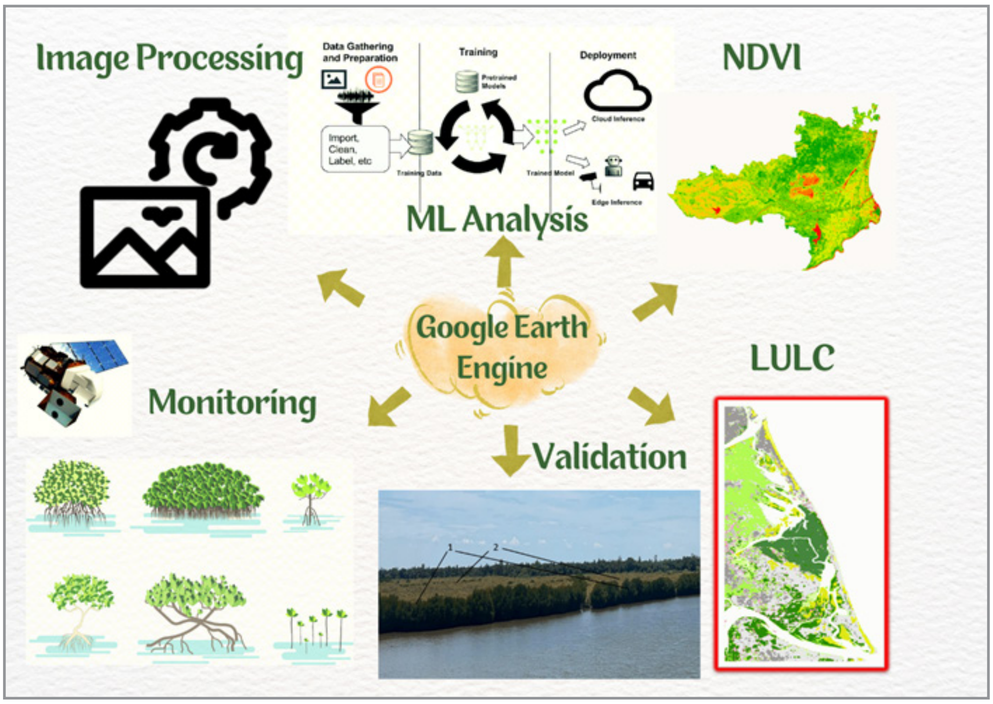
The geospatial data is more essential to study changes in Coastal Green Infrastructure (CGI) of mangrove forests due to various reasons. Observations need to be regularly carried out to ensure sustainability and viability in mangrove ecosystems, which contribute significantly to carbon sequestration, biodiversity conservation, and coastal protection [1]. Mangrove ecosystems serve as important sinks of carbon. Strategies for compensating the impacts of climate change must take into account variations in their distribution and their health status [1]. Healthy mangrove systems, as per, enhance the economy and livelihoods locally through the defense of coasts, support of tourism, and fisheries [7]. Dominant ecosystem services by mangrove forests are carbon sequestration, the stabilization of coasts, and the provision of refuge for marine fauna [8].

Human activities like pollution, coastal development, and deforestation, combined with the effects of climate change, are increasingly degrading these ecosystems [9]. Remote sensing technology can provide more benefits to the continuous monitoring and evaluation of mangrove forests, through tools like Google Earth Engine (GEE) [8]. Despite their essential importance, mangrove forests are facing a range of anthropogenic and natural threats. Conventional monitoring of these changes is often found to be time-consuming, expensive, and restricted by geographic extent [10]. There is a critical need for efficient and accurate tools based on state-of-the-art remote sensing technology to evaluate CGI health and cover in mangrove ecosystems [11].

Most existing mangrove forest studies are founded on sporadic, stand-alone field surveys, which fail to provide timely and comprehensive data. The consistent and large-scale exploitation of remote sensing data to monitor CGI changes is inadequate [12]. In addition, it is still challenging to combine remote sensing data with other socioeconomic data and ground observations [6]. The application of remote sensing for the monitoring of mangrove ecosystems has been established in different studies. For example, [8] applied satellite images to identify the global pattern of mangroves, hence the establishment of a baseline. Similarly, [13] pointed to the capacity of remote sensing for mangrove cover and health changes. Nonetheless, the use of extensive and long-term monitoring through the likes of GEE has yet to be fully maximized.

Applying Google Earth Engine remote sensing imagery to monitor the health and status of mangrove ecosystems. Next, identify and quantify temporal change within Coastal Green Infrastructure (CGI). To achieve an effective environmental assessment, integrate remote sensing imagery with ground survey. Examine mangrove climate change and anthropogenic drivers. Provide science-based recommendations for mangrove conservation and sustainable management. Mangroves are extremely important to enabling livelihood at the local level and coast defense, especially on the Parangipettai coast of Tamil Nadu, India. The urbanization, industrialization, and climate change pressures increasingly stress such important areas [14].

In application of the remote sensing data can evaluate the changes in the Coastal Green Infrastructure (CGI) has the potential to provide useful information for local conservation planning and policy-making. This article attempts to conduct an extensive assessment of changes in CGI within mangrove forest ecosystems by using the remote sensing features provided by Google Earth Engine. Fusing satellite-based information with empirical knowledge based on field measures, the study aims at enhanced understanding of drivers of change in mangrove ecosystems and providing actionable solutions for their conservation and sustainable management.



Materials and Methods

Study Area

The Cuddalore Coast is located on the southeast coast of the Bay of Bengal in India is located between latitudes 11°37' and 11°78' towards the north and longitudes 79°79' and 79°82' towards the east. The coast stretches from Nallavadu to Thirukazhipalai in Tamil Nadu, India, and is a significant ecological, economic, and cultural landscape. Around 57.5 kilometers of Cuddalore coast, it's home to a variety of ecosystems, such as sandy beaches, mangrove forests, and estuaries, it is an ecologically significant area [15]. Its flat terrain and tropical climates define it as a region that stretches along India's southeast coast. This Cuddalore coastal green infrastructure (CGI), covers India's second-largest mangrove forest Pichavaram, which is a significant ecological feature that plays a vital role in stabilizing the shoreline and carbon sequestration. Agriculture, aquaculture, and fishing are the main economic activities of the coastal communities for their livelihoods. However, this area is under pressure from industrialization, urbanization, and tourism, which are all difficult to manage CGI. Coastal ecosystems are threatened by industrial pollution, aquaculture-related deforestation, unplanned urban growth, and the effects of climate change. This study's findings are essential to safeguarding the ecological, economic, and social benefits provided by mangrove ecosystems. By providing critical data on the changes in CGI, it supports effective conservation, and sustainable development along the Cuddalore coast, as shown in Figure 1.

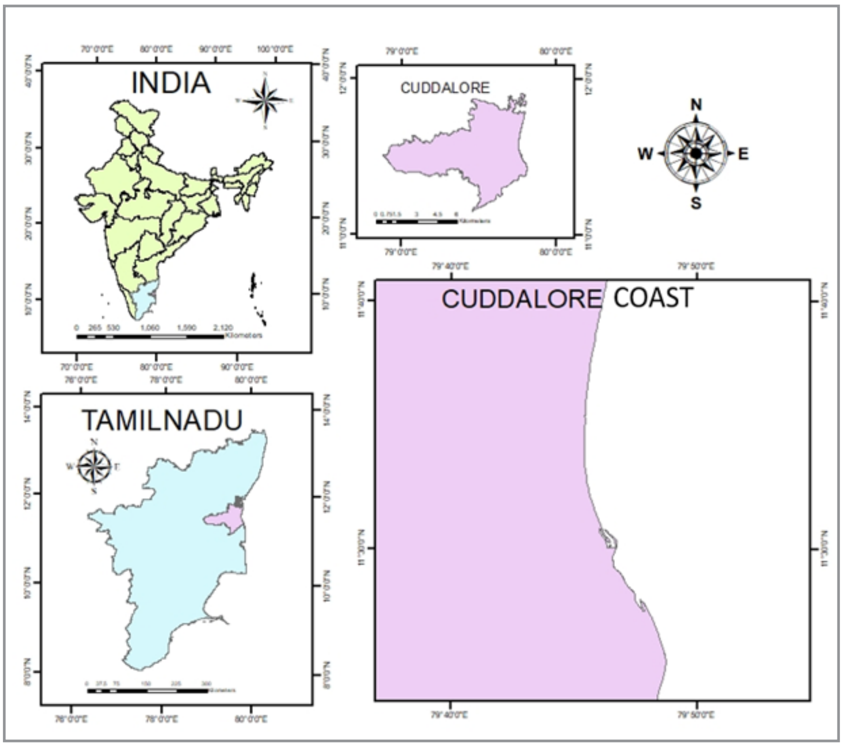


Figure 1: The Geographical Location of the Study Area

Remote Sensing and Geospatial Data

Sentinel-2 A&B (Active Mission)

The European Space Agency's (ESA) Copernicus Program launched the twin satellites Sentinel-2 A and B intending to provide high-resolution optical imagery for monitoring coastal waters and land. The Multispectral Instrument (MSI) on the satellites provides in-depth observations of the land and water surfaces by gathering data in 13 spectral bands detailed in Table 1. Their 290-kilometer swath width lets them cover a good bit of the surface of the Earth with every pass. Tracking dynamic environmental changes depends on a five-day revisit frequency at the equator, which Sentinel-2A and Sentinel-2B satellites together guarantee. The 12-bit radiometric resolution of the data improves the accuracy of reflectance value measurements. For varying user requirements, it offers various processed data levels, such as Level-1C data is radiometrically corrected imagery, while Level-2A data is atmospherically corrected surface reflectance. Sentinel-2 data helps with precision agriculture by detecting stress, estimating yields, and offering insights into crop health. Along with algal blooms and water quality, it allows us to track the forest cover, deforestation, and degradation. Sentinel-2 data made freely available by the Copernicus Open Access Hub allows everyone to use Earth observation technology for sustainable growth and conservation of the environment.

Table 1: Sentinel-2 A&B Spectral Resolution Bands

Band Number	Description	Sentinel-2A		Sentinel-2B		Spatial resolution (m)
		Central wavelength (nm)	Bandwidth (nm)	Central wavelength (nm)	Bandwidth (nm)	
B1	Coastal aerosol	442.7	442.7	442.7	442.7	60
B2	Blue	492.7	65	492.3	65	10

B3	Green	559.8	35	558.9	35	10
B4	Red	664.6	30	664.9	31	10
B5	Red edge 1	704.1	14	703.8	15	20
B6	Red edge 2	740.5	14	739.1	13	20
B7	Red edge 3	782.8	19	779.7	19	20
B8	Near-infrared (NIR)	832.8	105	832.9	104	10
B8a	Narrow NIR	864.7	21	864.0	21	20
B9	Water Vapor	945.1	19	943.2	9	60
B10	Shortwave infrared (SWIR) - Cirrus	1373.5	29	1376.9	6	60
B11	SWIR - 1	1613.7	90	1610.4	94	20
B12	SWIR - 2	2202.4	174	2185.7	184	20

Source: Copernicus Open Access Hub (European Space Agencies)

Landsat-7 (Completed mission)

The Landsat programme, which NASA and the U.S. Geological Survey (USGS) oversee together, Landsat-7 is launched on April 15, 1999, Landsat-7 has the Enhanced Thematic Mapper Plus (ETM+) instrument, which provides high-resolution multispectral imagery to monitoring the environment and their studies. The Landsat-7 satellite has a 183-kilometer swath width and records data in 9 spectral bands were detailed in Table. 2. For routine monitoring of changes to the Earth's surface, it features a 16-day repeat cycle. By improving reflectance measurements, the 8-bit radiometric resolution makes it possible to analyze environmental conditions and land cover in detail. It offers various processed levels of data, including Level-1 (geometrically corrected) and Level-2 (atmospherically corrected) products. These applications include monitoring vegetation, water quality, algal bloom, land cover, climate research, hurricanes, wildfires, and disaster management. The data is publicly available on the USGS Earth Explorer and GloVis (Global Visualisation Viewer) platforms, allowing users worldwide to use it for environmental research, planning, and conservation. The Landsat-7 collection helps scientists better understand how the Earth's ecology is evolving and develop sustainable management and conservation strategies.

Table 2: Landsat-7 Spectral Resolution Bands

Band Number	Description	Wavelength (µm)	Spatial resolution (m)
B1	Blue	0.45 - 0.52	30
B2	Green	0.52 - 0.60	30
B3	Red	0.63 - 0.69	30
B4	Near-infrared	0.77 - 0.90	30
B5	Shortwave infrared 1	1.55 - 1.75	30
B6_VCID_1	Low-gain Thermal Infrared	10.40 - 12.50	60
B6_VCID_2	High-gain Thermal Infrared	10.40 - 12.50	60
B7	Shortwave infrared 2	2.08 - 2.35	30
B8	Panchromatic	0.52 - 0.90	15

Source: U.S. Geological Survey (USGS) (National Aeronautics and Space Administration)

Landsat-8 (Active Mission)

In 2013, the USGS and NASA launched the Landsat-8 satellite, which offers high-resolution optical imagery for monitoring land and coastal waters. It collects data in 11 spectral bands detailed in Table 3. Thermal Infrared Sensor (TIRS) and Operational Land Imager (OLI), cover a sizable area of the Earth's surface with each pass. For monitoring environmental changes, the satellite's 16-day revisit frequency is essential. Landsat-8 offers improved radiometric resolution and additional spectral bands and provides more accurate and detailed observations for various applications when compared to Landsat-7. This makes it a valuable tool for monitoring environmental changes and supporting sustainable development efforts globally. The ability of Landsat-8 data to detect stress, calculate yields, and provide crop health information is useful for precision agriculture. It also helps monitor water quality, algal blooms, forest cover, degradation, and deforestation. The USGS Earth Explorer and GloVis (Global Visualisation Viewer) platforms make Landsat-8 data publicly available, enabling users worldwide to use Earth observation technology for environmental preservation and sustainable development. Table 3 lists the satellite's main features, which include its 12-bit radiometric resolution, 16-day revisit frequency, and 185-kilometer swath width.

Table 3: Landsat-8 Spectral Resolution Bands

Band Number	Description	Spatial resolution (m)	Wavelength (µm)
B1	Coastal aerosol	30	0.43 - 0.45
B2	Blue	30	0.45 - 0.51
B3	Green	30	0.53 - 0.59
B4	Red	30	0.64 - 0.67
B5	Near infrared	30	0.85 - 0.88
B6	Shortwave infrared 1	30	1.57 - 1.65
B7	Shortwave infrared 2	30	2.11 - 2.29
B8	Band 8 Panchromatic	15	0.52 - 0.90
B9	Cirrus	30	1.36 - 1.38
B10	Thermal infrared 1	30	10.60 - 11.19
B11	Thermal infrared 2	30	11.50 - 12.51

Source: U.S. Geological Survey (USGS) (National Aeronautics and Space Administration)

HLS (Active Mission)

In order to build a continually updated dataset that includes data from Sentinel-2 and the Landsat 7 & 8 satellites, NASA and the European Space Agency (ESA) teamed together to get the Harmonized Landsat Sentinel-2 (HLS) project. For a range of uses, especially land cover mapping, which includes environmental research, agriculture, and forest monitoring the dataset strives to deliver continuous, high-quality, and temporally rich surface reflectance products. such datasets are continuously delivering, high-quality, and temporally rich surface reflectance of satellite products. Sentinel-2A and 2B data, together with Landsat 8 and 9, are used in the program to provide consistent worldwide coverage with a revisit duration of two to three days at mid-latitudes. They were standardized to ensure consistent surface reflectance outputs by accounting for variations in spectral calibration, spatial resolution, and radiometric observations. The data comprises atmospherically corrected surface reflectance, visible, near-infrared, and shortwave infrared bands, as well as a spatial resolution of 30 meters, detailed in Table 4. HLS data supports a wide range of applications, including urban development, climate science, agriculture, and environmental monitoring. Its public accessibility makes it easily accessible to users worldwide. The HLS process takes into account the differences in spectral and radiometric calibration between Landsat and Sentinel-2 sensors, cloud masking and atmospheric correction, and spatial resolution and viewing geometries.

Table 4: Harmonized Landsat Sentinel-2 (HLS) Satellite Spectral Resolution Bands

Sentinel-2 A & B				Landsat-8 & 9				Harmonized Landsat Sentinel-2 (HLS)			
Band Number	Description	Wavelength (nm)	Spatial resolution (m)	Band Number	Description	Wavelength (µm)	Spatial resolution (m)	Band Number	Description	Wavelength (µm)	Spatial resolution (m)
B1	Coastal aerosol	443.9 - 442.3	60	B1	Coastal aerosol	0.43 - 0.45	30	B1	Coastal aerosol	0.43 - 0.45	30
B2	Blue	496.6 - 492.1	10	B2	Blue	0.45 - 0.51	30	B2	Blue	0.45 - 0.51	30
B3	Green	560 - 559	10	B3	Green	0.53 - 0.59	30	B3	Green	0.53 - 0.59	30
B4	Red	664.5 - 665	10	B4	Red	0.64 - 0.67	30	B4	Red	0.64 - 0.67	30
B5	Red edge 1	703.9 - 703.8	20	B5	Near-infrared	0.85 - 0.88	30	B5	Near-infrared	0.85 - 0.88	30
B6	Red edge 2	740.2 - 739.1	20	B6	Shortwave infrared 1	1.57 - 1.65	30	B6	Shortwave infrared 1	1.57 - 1.65	30
B7	Red edge 3	782.5 - 779.7	20	B7	Shortwave infrared 2	2.11 - 2.29	30	B7	Shortwave infrared 2	2.11 - 2.29	30
B8	Near-infrared	835.1 - 833	10	B8	Band 8 Panchromatic	0.52 - 0.90	15	B9	Cirrus	1.36 - 1.38	30
B8a	Narrow NIR	864.8 – 864	20	B9	Cirrus	1.36 - 1.38	30	B10	Thermal infrared 1	10.60 - 11.19	30
B9	Water Vapor	945 - 943.2	60	B10	Thermal infrared 1	10.60 - 11.19	30	B11	Thermal infrared 2	11.50 - 12.51	30
B10	Cirrus	1613.7 - 1610.4	60	B11	Thermal infrared 2	11.50 - 12.51	30	-	-	-	-
B11	SWIR - 1	2202.4 - 2185.7	20	-	-	-	-	-	-	-	-
B12	SWIR - 2	443.9 - 442.3	20	-	-	-	-	-	-	-	-

Source: National Aeronautics and Space Administration (LP DAAC) and Google Earth Engine (GEE)

Remote Sensing and Geospatial Analysis

Land Use Land Cover (LULC)

The concepts of land use and land cover (LULC) play a vital role in knowing how lands are used and the types of components in the Earth's surface. Understanding LULC is essential for environmental monitoring, conservation efforts, urban planning, agricultural management, and climate change research. Common formulas include NDVI, Accuracy Assessment, Change Detection, and Land Cover Classification. These analyses are essential for sustainable land management, urban planning, and environmental preservation.

Normalized Differential Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a remote sensing index used to evaluate vegetative health, cover, and density. Examining how vegetation absorbs and reflects various light wavelengths, aids in the monitoring of plant growth and health. In contrast to unhealthy or sparse vegetation, which reflects more visible light and less near-infrared light, healthy vegetation absorbs most visible light for photosynthesis and reflects a significant amount of near-infrared light.

NDVI is calculated using the following formula

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

Where:

- NIR = Reflectance in the near-infrared band
- Red = Reflectance in the red band

The red and near-infrared bands' reflectance values are derived from satellite images. The difference between the amount of visible red light and near-infrared light reflected by vegetation is highlighted by calculating the difference between the red reflectance and the NIR reflectance where shown. NDVI has applications in agriculture, forestry, and environmental monitoring providing valuable insights to understanding Earth's vegetation dynamics.

Google Earth Engine (GEE)

Google Earth Engine (GEE) is used to analyze large-scale free-accessible datasets from the Earth Observatory. It offers a free available dataset, of satellite photography, topographical data, historical data, and climate data. They process and analyze vast volumes of datasets using Google's cloud storage, which provides quick analysis through parallel processing. Figure 2 describes how users can create custom scripts for data processing, analysis, and visualisation using its programming interface, which includes Python and JavaScript APIs. Through GEE some of the environmental monitoring applications like deforestation, water resource assessments, climate change research, crop health monitoring, disaster management, urban planning, and infrastructure monitoring.

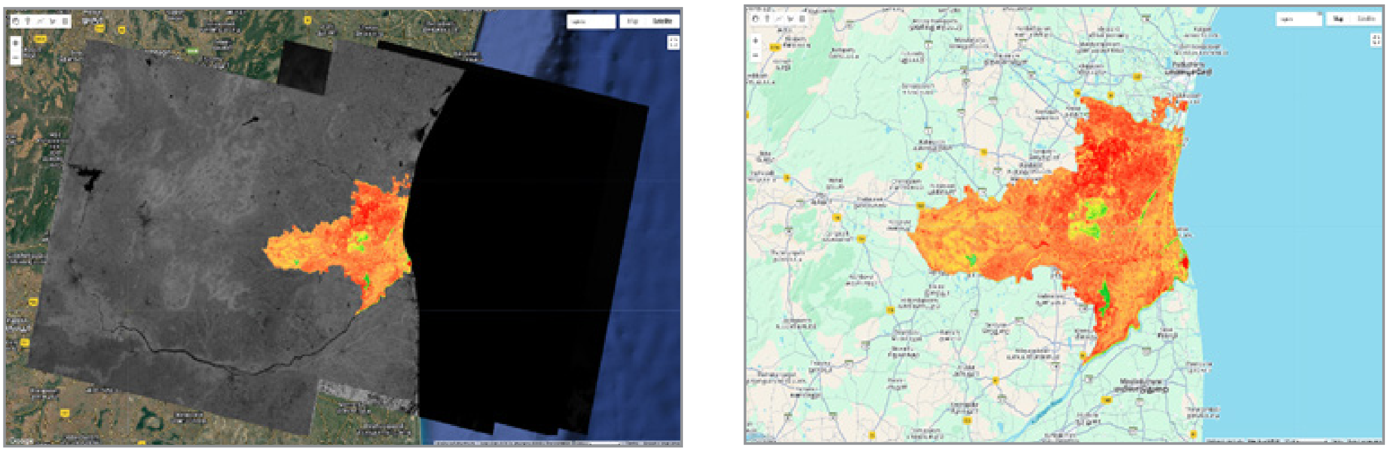


Figure 2: Google Earth Engine Platform to Run Machine Learning for CGI Mapping.

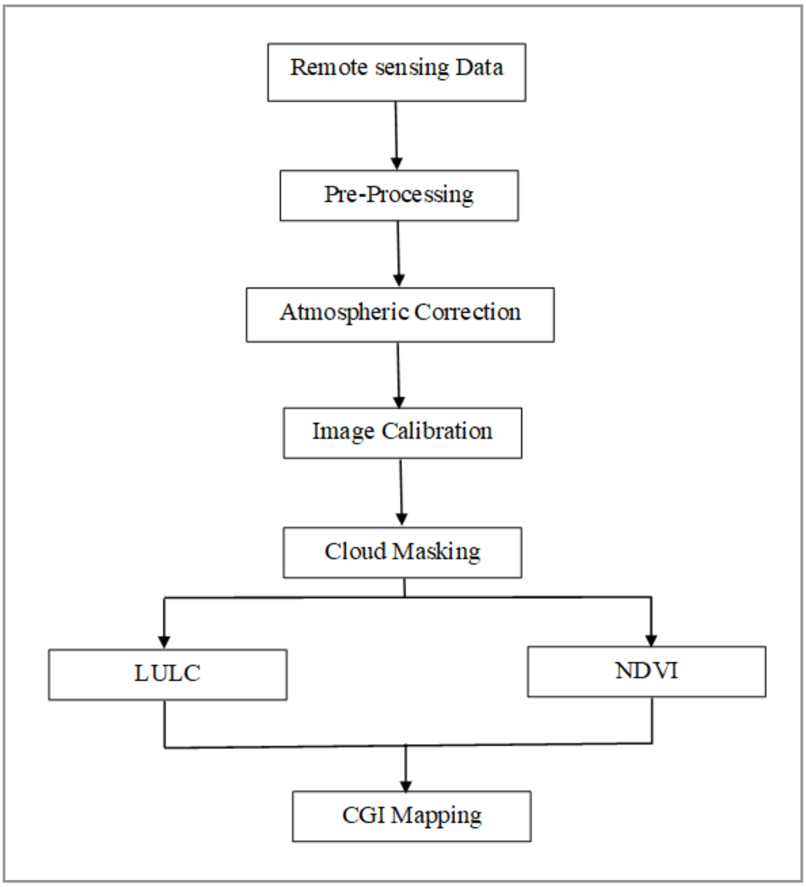


Figure 3: Flow Chart of Methodology

Machine Learning Algorithm

Google Earth Engine is a geospatial analysis tool that uses machine learning algorithms and satellite imagery to monitor the Earth's surface at various spatial and temporal resolutions. This tool uses a large collection of satellite imagery from sources like Sentinel-2, Landsat, and MODIS, which undergoes pre-processing procedures to ensure clear observations. Spectral bands, vegetation indices, textural features, and temporal features are extracted from satellite data for the machine-learning models. GEE supports various machine-learning algorithms for classification, regression, and clustering problems. Unsupervised classification accepts spectral similarity without labeled data, while supervised classification accepts labeled training data to categorize images into predetermined categories. Linear regression models predict continuous variables using linear regression models. After being trained, the machine learning model can be used to categorize the forecast features such as vegetation health, environmental monitoring, and land cover classification using satellite images. We can able to generate the temporal analysis, that displays results, and perform geospatial analysis using GEE's interactive map viewer with visualization tools.

Random Forest

Using satellite imagery and machine learning algorithms such as Random Forest, land cover, vegetation health, and other environmental parameters were analyzed. Step-by-step procedures are followed for data acquisition, preprocessing, feature extraction, training data collection, and Random Forest model training. Sentinel-2, Landsat, and MODIS are the sources of satellite imagery, that provide detailed information about the Earth's surface. Preprocessing includes cloud masking, atmospheric correction, geometric correction, and feature extraction. Obtaining training data involves sampling using field surveys, pre-existing maps, or high-resolution photographs, as well as collecting ground truth data that represent different land cover types or classes, as shown in the methodology flow chart in Figure 3. The Random Forest algorithm consists of a collection of decision trees that are trained using a random subset of features and data. The output from each tree is added up to determine the final classification. The model is used for image classification, mapping prediction, and visualizing classified maps and indices.

Ground Truth Data Acquisition

The Ground truth data is essential for the present study. Because the field surveys ensure the accuracy of the study. The Cuddalore coast cover from Nallavadu, Reddichavadi, Subauppalavadi, Tiruchchepuram, Parangipettai, Pichavaram, Kodiyampalayam, and Thirukazhipalai were carried out between January and October 2024 in order to gather the data. In order to ensure that remote sensing observations are all in actual conditions, this data is used as a benchmark for validation and calibration through field surveys, utilizing pre-existing data, and community involvement for the validation. Classifying land cover requires confirming that maps produced by remote sensing accurately depict the various elements of coastal vegetation. Vegetation health monitoring compares field measurements with NDVI, LULC (Land Use/Land Cover), and other vegetation indices to assess plant health and growth. 70% of the data was used for training, and 30% was used for validation. Disaster management uses ground truth data to validate coastal hazard information, enabling accurate planning for response and recovery.

Results and Discussion

LULC

The study area is the Indian part of the Cuddalore delta, which includes blocks from the state of India (Fig. 1). This research investigates the land use and land cover changes along the Cuddalore Coast in Southeast India over 24 years (2000-2024). These findings prove what are all the patterns involved in mangrove dynamics, coastal erosion, and human-induced changes using geospatial analysis and remote sensing data through this study. The results are intended to guide conservation and sustainable coastal management plans. With a network of tidal rivers, estuaries, and inlets that are crisscrossed by rugged, thunderous channels, the area is made up of flat islands with dense forests, lagoons, sand dunes, and salt marshes. It is near estuaries and the Bay of Bengal and experiences a monsoon climate with high humidity levels of 80 to 90%. It is located between latitudes 11°37' and 11°78' towards the north and longitudes 79°79' and 79°82'. The coast receives a lot of rainfall during the monsoon season, from June to September.

This region has previously seen cyclones that have caused fatalities and property damage due to its high vulnerability to cyclonic activity. The forest has a high level of biodiversity, except mangrove forests, which are the predominant flora. The Cuddalore Delta is made up of the saltwater swamp and the majority of the coastal mangrove forest. The westernmost side is more affected by human activities, even though the majority of the Coastal Green Infrastructure (CGI) is on the eastern side. LULC changes have become normalised due to the high volume of tourism in the coastal area of the reserve. The changes in the period of 2000 – 2024, land use, and land cover (LULC) along the Cuddalore District coast were described in Figure 4.

LULC Changes Maps Given Below

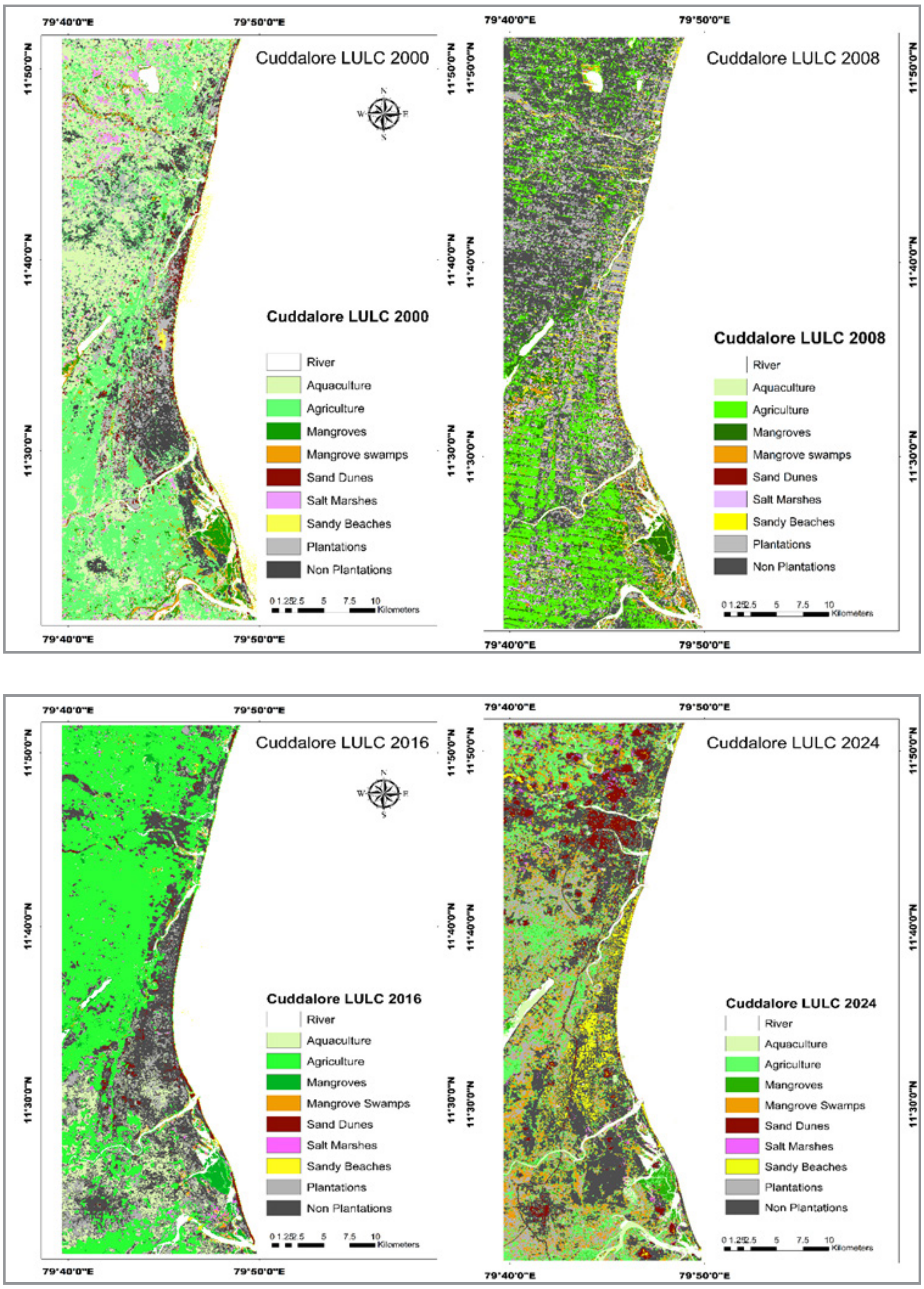


Figure 4: LULC Changes Maps From 2000, 2008, 2016 and 2024

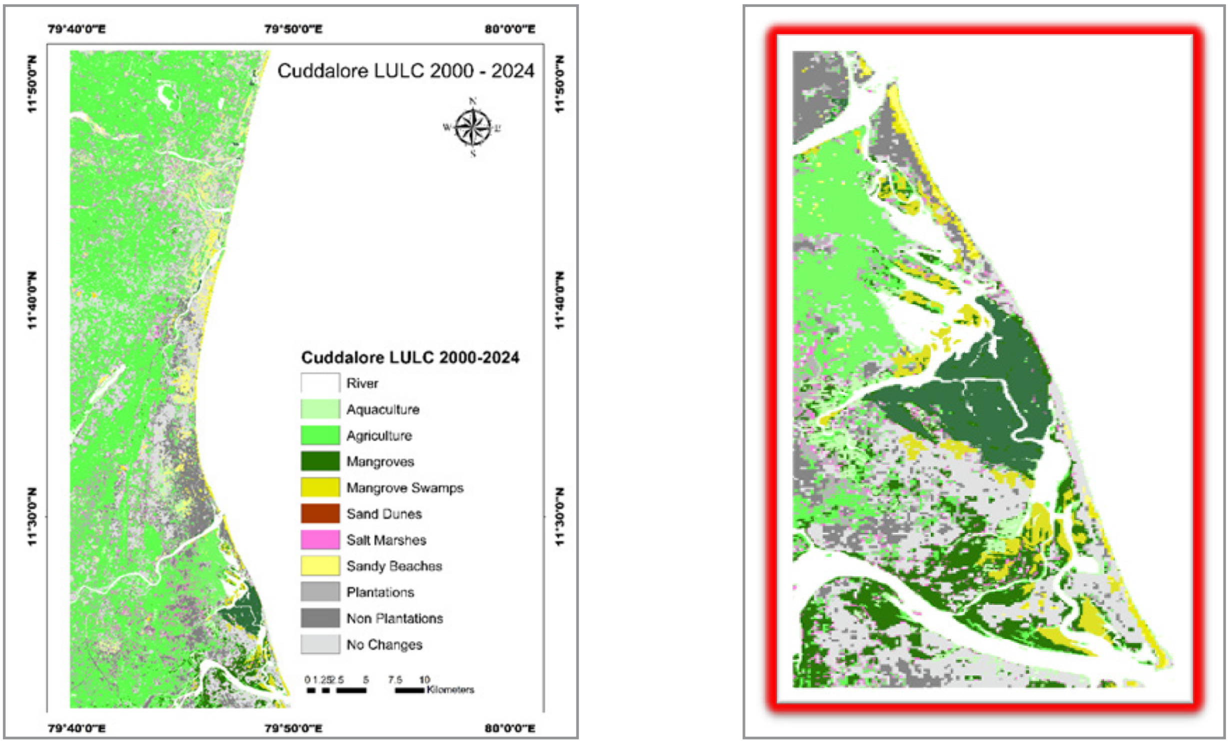


Figure 5: LULC changes in the Pichavaram Mangroves in Tamil Nadu, Southeast India

This helps to preserve the diverse ecosystems and rich vegetation along the Pichavaram mangrove forest shown in Figure 5. These changes were primarily driven by waterlogging, which occurs when excessive water in the soil hinders plant growth. This issue was mainly caused by cyclonic events and storm surges that increased water levels in the area. Approximately, plantation growth decreased agricultural land, 325655.07 hectares, with a reduction due to saltwater intrusion. This forced farmers to relocate in search of better land. Changes in land cover also included a decline in mangrove forests, which decreased from 23.4% to 18.42% of the study area. The study found that sediment deposition is the reason for the low deposition index in the northern and southern sections of the Vellar River. On the other hand, some regions are highly vulnerable due to alluvium deposition and their gently sloping shelf. In the south, there is a lot of deposition towards Cuddalore Old Town and the Raasapettai region due to groynes and the construction of hard structures. The northern part has low and moderate deposition due to the higher topographic elevation along the Gaddilam River. There is less deposition in Reddiyarpetai to Tiruchchepuram, and more land was created naturally. Forest destruction driven due to industrialization and urbanization was caused by improper planning.

The growing population exerted pressure on natural resources, leads a reduction in mangroves by 19.3%, an increase in planting areas by 58.2%, and open scrubs by 22.5%. Beach areas grow by 61.6%, river areas by 28.3%, and aquaculture areas by 10.1%. Significant changes in land use and cover along the Cuddalore coast in 2024 are highlighted through this study, finds the population growth and natural disasters. Planning for the future and managing the environment depends on an understanding of these changes.

Normalized Difference Vegetation Index NDVI

The study area is located on the Coromandel Coast and it was the second largest coast in India and also covers the southeast coast of the Bay of Bengal. This study investigated the condition of the vegetation along the Cuddalore coast to see how it has changed over time. To get a better understanding of the vegetative condition, the Normalised Difference Vegetation Index (NDVI) values were categorized in Table 5. The NDVI values range from -1 to +1, with higher values indicating good and denser vegetation in coastal regions. This analysis of NDVI values provided information about the general condition of the vegetation in specific locations.

Table 5: Here's a Quick Breakdown of NDVI Values and their Implications,

Color	Names	Land Types	Indications
	Red	Water Bodies & Urban landscapes	Non-vegetated areas
	Orange	Rocks and Sandy Areas	Barren areas
	Cornsilk	Shrubs & Grasslands	Sparse vegetation like
	Yellow	Dry season Agricultures	Moderate vegetation
	Light Green	Rainy season Agricultures	Dense vegetation
	Dark Green	Mangroves & CGI	Very dense and healthy vegetation

Such analysis reveals the variations in NDVI values throughout the CGI of the Cuddalore coast, the NDVI values from 0.050 in 2000 to 0.438 in 2024, indicating a dense and healthy NDVI value; it increased from 0.023 in 2000 to 0.281 in 2024 for some agricultural areas, most likely as a result of changes in land use that decreased natural water coverages shown in Figure 6.

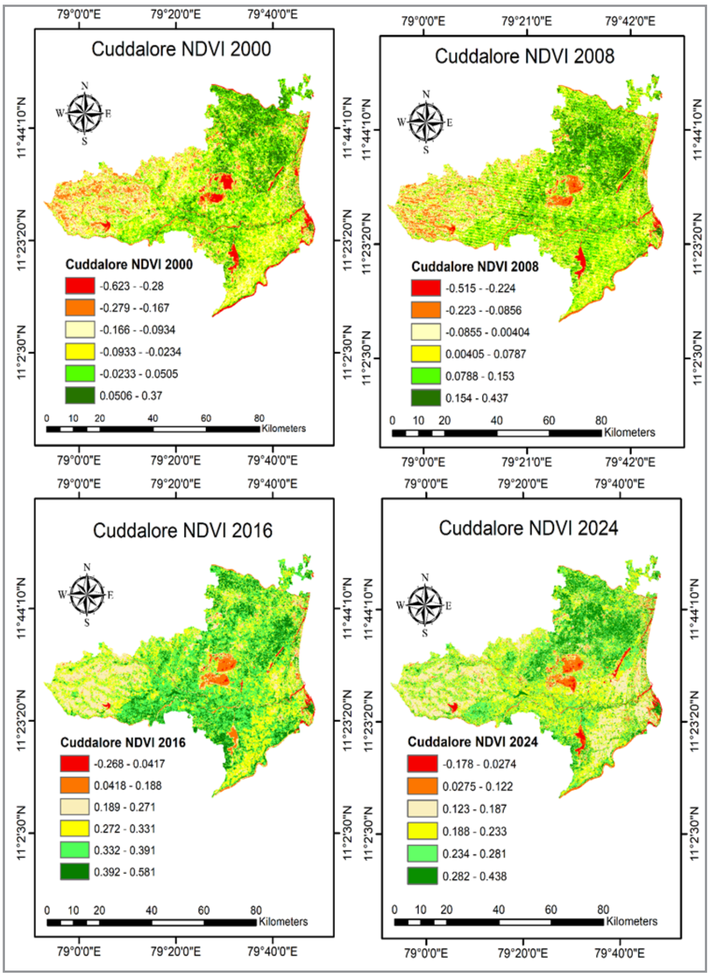


Figure 6: NDVI changes Maps from 2000, 2008, 2016 & 2024

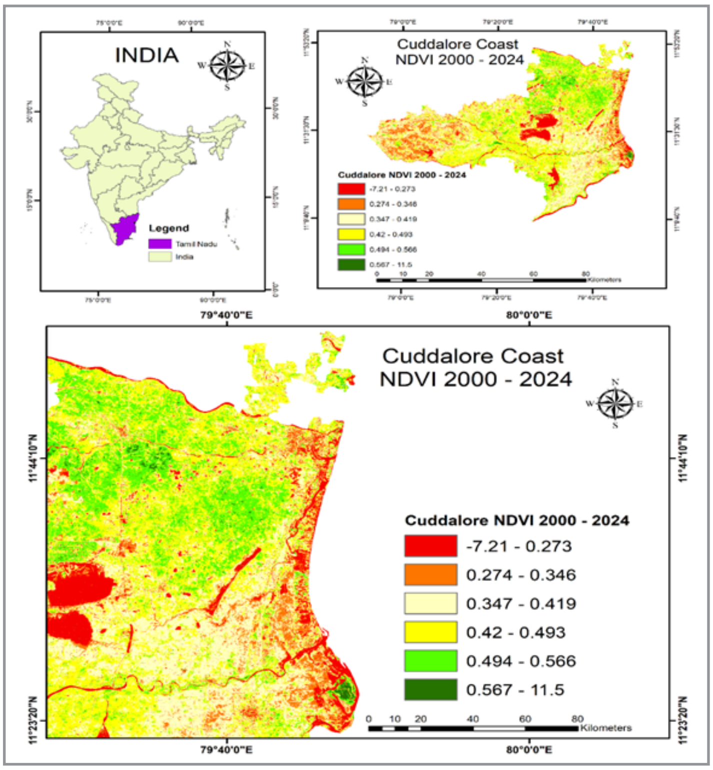


Figure 7: LULC changes for 2000 – 2024

These findings show the important ecological consequences throughout the Cuddalore coastline. Then the decreasing NDVI values suggest that these important ecosystems are becoming less healthy due to the growing stress on dense CGI. It highlights how it's important to monitor NDVI values to figure out how changing land use affects these coastal ecosystems; it shows the conservation strategies of CGI depicted in Figure 7. High NDVI values from the agricultural and CGI regions signify more vegetation and enhance natural ecosystems.

CGI Mapping

The Coastal Green Infrastructure (CGI) mapping evaluates and enhances Cuddalore coast's ecological resources through Google Earth Engine and machine learning approaches. Through CGI mapping for local project development, it identifies several coastal vegetation types and tree species (mangroves, sand dunes, salt marshes, mesquite tree (Prosopis glandulosa), teak tree (Tectona grandis), she-oak tree (Casuarina eucalyptus), neem (Azadirachta indica), pongamia tree (Millettia pinnata), etc.). CGI mapping is a useful tool with satellite imagery that studies can now use to locate and map these ecological resources that support local economic development and environmental sustainability. It is vital to maintain a diverse ecological system along the Cuddalore coast. Larger species along with smaller trees and shrubs provide productive habitats for local wildlife. The potential habitat of diesel/gasoline powered vehicles indicates what is likely already left of wildlife habitat likely exists on the vegetation growth along the Cuddalore coast. CGI mapping also identifies urban growth areas with high concentrations of nearby urban vegetation identified as 'neem' and 'pongamia' which are important items to have when we consider environmental shading for improved air quality and shading local areas with new populations. This is illustrated in Figure 8.

a) Millettia Pinnata **b) Casuarina Eucalyptus** **c) Prosopis Glandulosa** **d) Tectona Grandis**

Figure 8: a,b,c & d are the Other Tree Species of Coastal Vegetation

This study identifies coastal sites of essential protective vegetation to prevent soil erosion above the beach and allow for waves or swells to dissipate. Mangroves, in this case are important not only to long-term ecological integrity and benefit, but also for long-term abiotic amenity for all. The Rhizophora mucronata and Avicennia marina species discussed earlier as Figures 9 and 10 indicate are important to providing stabilization of the shoreline. This study has applied the numerous sandy beaches for recreational endeavours while potentially moderating the density of coastal vegetation to prevent being over-spaced.

Figure 9: 1) Rhizophora Sp. and 2) Avicennia Sp.

Due to their ability to support aquatic life and provide important habitats for marine organisms, mangroves are an essential component of Cuddalore's coastal ecosystem. Plants such as Ipomoea pes-caprae, Spinifex littoreus dominate sand dunes along the coast, as sand dunes can be recognized by their unique flora adapted to extreme conditions. Salt marshes are also an important ecosystem located along Cuddalore's coast. They have a dominance of salt marsh plants and provide highly valuable habitat to migratory birds and other wildlife. They also provide important habitat for other kinds of animals, such as: animals red-listed by IUCN (e.g. olive ridley turtle); bird species such as black-headed ibis and spot-billed pelican. Their biological importance relative to these habitats can be improved by increasing community involvement in conservation efforts that foster an understanding of the significance of coastal plants along with their contributions to ecological balance.

Mangrove Mapping

The study aims to employ advanced remote sensing techniques to identify and map mangrove forests on the Cuddalore coast. By using Google Earth Engine along with machine learning, researchers will be able to analyze aerial or satellite images to delineate water, land, or vegetation, as well as assessing plant health and type in the site with the use of vegetation indices, through mathematical calculations [(Donato et al., 2011)]. The research conducted by [(Balasaraswathi and Srinivasalu, 2016)] indicates that to distinguish and map the different types of mangrove trees present along the coast, including the red mangrove, Rhizophora mucronata, and grey mangrove, Avicennia marina, located in Cuddalore coast, as shown in Figure 10. The researchers will be identifying land cover classes on the site to record vegetation, built-up area, and water [2]. Several mangrove species will be recorded, to name a few, which include: Bruguiera gymnorhiza (Black Mangrove), Rhizophora mucronata (Red Mangrove), and Avicennia marina (Grey Mangrove). These mangrove species have complex root systems and saline-adaptive mechanisms [(Sunkur et al., 2024)].

a) Rhizophora mucronata **b) Avicennia marina** **c) Bruguiera gymnorhiza**

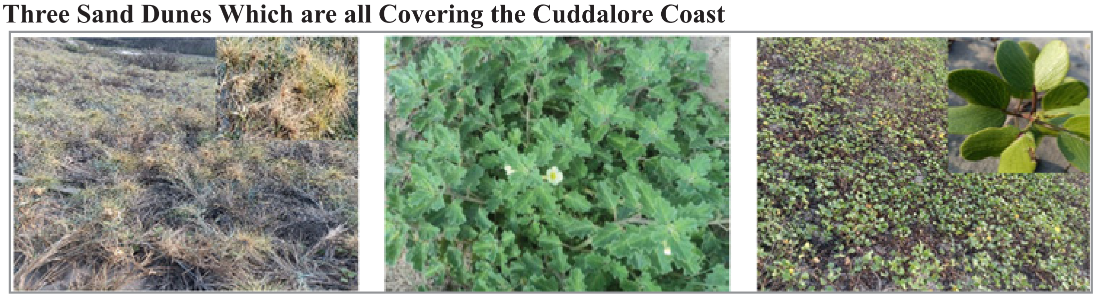
Figure 10: a,b, & c are the Dominant Mangrove Tree Species

The results can be applied to monitoring and managing other coastal ecosystems in a similar way. The ecological knowledge combined with the latest remote sensing technologies can provide a more informed set of decisions regarding conservation opportunities in Cuddalore's richly endowed coastal ecosystem. The study reinforces the importance of mapping and monitoring mangrove forests for ecological sustainability and adaptive management decisions which support resilience, and adaptive management to climate change issues.

Salt Marsh and Sand Dune Mapping

Sand dunes and coastal salt marshes are vital and natural barriers that protect the Cuddalore coast from problems associated with flooding and ocean storms. Beyond those important ways to protect land from natural hazards, both elements absorb wave energy, thereby providing a more resilient and adaptable coastal ecosystem. Using high resolution data from Landsat imagery - Land Use Land Cover (LULC) and Normalized Difference Vegetation Index (NDVI), scientists prepare detailed management maps of Cuddalore's sand dunes, which can enable much better management and monitoring [(Sugumaran and Avudainayagam, 2017)]. When examining how role sand dunes protect coasts, scientific literature indicates that for dunes or sand dunes to work effectively the mean height to at least one meter-which will help protect land further back from the shoreline. As dunes become taller, they provide a greater resilience toward the coupled combination of storm surge and erosion (Arulmoorthy and Srinivasan, 2017).

i) Significant Three Sand Dunes Which are all Covering the Cuddalore Coast



a) Spinifex littoreus **b) Pedalium murex** **c) Ipomoea pes-caprae**

ii) Significant three Salt Marshes which are all covering the Cuddalore coast

a) Sesuvium portulacastrum **b) Suaeda maritima** **c) Suaeda monoica**

Coastal vegetation techniques create and promote shoreline sand dunes, which trap sand for dune development. Dunes should be over (at least 1.5 meters) for optimal protection. Sand dune vegetation and salt marshes like those in Cuddalore protect shorelines, assist healthy coastal ecosystems. The important sand dune species such as Suaeda monoica, Suaeda maritima, and Sesuvium portulacastrum filter pollutants and provide wildlife habitat services. Coastal dune species such as Spinifex littoreus, Pedalium murex, and Ipomoea pes-caprae, etc. [(Arulmoorthy and Srinivasan, 2017)] are all creeping plants that stabilize sand dunes and dunes with roots as they bind soil and help prevent wind erosion. Knowing the height of coastal sand dunes and salt marshes, when they grow and seasonal changes, and the maintenance practices are critical information for effective coastal management. If we can combine ecological knowledge and new mapping practices, we can also increase the resilience of natural barriers against climate change.

Accuracy Assessment

In the assessment of land use and land cover (LULC) and the Normalized Difference Vegetation Index (NDVI) using Google Earth Engine and machine learning, accuracy is considered to be a critical component of mapping coastal infrastructure. For the Cuddalore district to make well-informed decisions about conservation and coastal management plans, high accuracy is considered necessary. When a classification model identifies various land cover types with 70% accuracy and 30% validation, for example, it means that 70% of the classified pixels correspond to the actual land cover as confirmed by ground truth data. The precise discrepancy between the actual observations is classifying the data as denoted by the absolute value.

In several ways, the quality control investigation ensured accuracy through the validation, standardization, and calibration protocols. The calibration protocols used standardization of the data-collection and data-processing protocols, classifications of data to known land cover classes, and calibrations of the machine learning models developed. Each calibration protocols used validation of our classifications using high-resolution imagery of the study areas and in-field validation surveys. The statistical accuracy measures relevant to the study included error analysis, uncertainty quantification, and error propagation. Error analysis is to look at the source of errors that may influence the classifications and which errors relate to the total accuracy of mapping errors. Uncertainty quantification measures what we mapped uncertainty, while error propagation measures what the input measurement errors are, and how those influence the classification results.

This study estimates the total accuracy for each land cover class using observations from field investigations. By comparing the classified data and real observations from coast of Cuddalore, we then assess the representation of actual conditions in our models. In conclusion, precision is an important aspect of mapping coastal infrastructure based on LULC and NDVI assessments, and ensures that the results could be trusted and informed coastal management decisions. Improvements in the accuracy of results can be made by using the right methods and techniques, which will result in better conservation plans and better outcomes for Cuddalore's coastal ecosystems.

Conclusion

This research demonstrates the importance of accurate mapping to make informed decision on conservation and coastal management strategies. The successful integration of a variety of high resolution data sources, particularly the Normalized Difference Vegetation Index (NDVI) and land use and land cover (LULC) in the Cuddalore district. The use of Google Earth Engine (GEE) and machine learning (ML) learning has enhanced our understanding of coastal features such as salt marshes, sand dunes, and mangrove forests, through the holistic approach to monitoring changes along the coastline in real-time, providing the opportunity to adapt management strategies to ongoing changes in the physical environment. This study also highlights the significance of conserving high-value ecosystems such as mangroves, which provide a variety of ecosystem services including coastal protection and habitat for marine life. The findings encourage community participation in conservation initiatives, national approaches to restoration and reinforces the importance of local stewardship and awareness of the value of coastal ecosystems.

This study not only has implications for the Cuddalore district but can be replicated in other coastal regions and support global initiatives monitoring and conserving fragile ecosystems. This study proposes to contribute to sustainability practices aimed at improving the livelihoods of local communities, benefits to ecosystems and enhancing resilience to climate change impacts leveraging technological multiplicity and community engagement.

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