CS6611 – CREATIVE AND INNOVATIVE PROJECT

SECOND REVIEW – TEAM NO. 37

ANALYSIS OF THE SPATIOTEMPORAL FLUCTUATIONS IN MANGROVES USING MACHINE LEARNING FOR HEALTH ASSESSMENT

TEAM MEMBERS
MADHUMITHA P S (2021503520)
ACHYUT PRASAD D C (2021503002)
SANDHIYA S (2021503552)

SUPERVISOR
DR. R. KATHIROLI
ASSISTANT PROFESSOR

PROBLEM STATEMENT:

Mangrove forests are important for the ecosystem; however, they are at risk from various factors like rising water levels and changing weather. We should understand how these significant forests are evolving and how healthy they are throughout time to protect them. Large areas like Pichavaram are hard to monitor because traditional methods for analyzing these changes are inconsistent and slow. Through the analysis of satellite pictures, we will apply machine learning techniques to map locations within Pichavaram, monitor changes in the total mangrove area over a specified timeframe, and even estimate the density of the mangroves.

OBJECTIVE:

- To utilize satellite imageries from different sources and assess mangrove ecosystems' temporal dynamics and health.
- To develop a robust model utilizing machine learning algorithms to accurately differentiate and map mangroves, non-mangroves, and water bodies within satellite imagery and quantify the temporal changes in mangrove extent from 1990 to 2024 spanning over 35 years.
- To estimate mangrove density within the study area and investigate the relationships between NDVI values and established density classes (Open Canopy/ Sparse, Moderate, Closed Canopy/ Dense) for each year in the specified timeframe.

LITERATURE SURVEY:

In [1], a novel method for mangrove identification, REMI (Remote sensing for Mangrove Identification), has been introduced. This approach leverages specific satellite bands to effectively capture distinctive mangrove characteristics. REMI index is prone to misclassifying non-mangrove trees and exhibiting instability in non-vegetation areas hindering the accuracy and applicability.

In [2], this approach involves integrating GF-2, GF-3, and UAV-LiDAR data for comprehensive geospatial analysis and applying random forest regression to retrieve height information. However, limitations include constraints faced by RF and SVM studies due to data availability challenges and geographic specificity.

In [3], this paper evaluates the Random Forest's efficiency in mangrove mapping using Sentinel-1, and Sentinel-2 (with red-edge bands) data by comparing three scenarios: sentinel 1 only, sentinel 2 only, and the combined data. However, a limitation observed in related works tends to the ineffectiveness of Landsat images with 30m resolution in identifying and monitoring isolated mangrove forest patches smaller than 1 ha.

In [4], this paper introduces the Generalized Composite Mangrove Index (GCMI) and the utilization of Sentinel-2 time series data to improve the separability between mangroves and other land covers. It achieves this by compositing vegetation and water indices and using similarity trend distance measures to determine the optimal indices. Despite these advancements, limitations persist in the phenological information in the time series data.

In [5] this involves using sentinel 1 and sentinel 2 for glacier mapping. By leveraging sentinel 1 structural information and sentinel 2 spectral data, the method aims to achieve more accurate delineation of glaciers including debris-covered areas, and differentiate between snow and ice. However, a significant limitation surfaces with persistent cloud cover affecting the reconstruction of minimum snow cover, particularly when relying on optical data such as Sentinel-2.

In [6], the study aims to map mangrove ecosystems by using Sentinel-1 and Sentinel-2 data. The integration of the Random Forest algorithm in Google Earth Engine ensures both precision and computational efficiency, promising advancements in ecosystem mapping. However, it recognizes a limitation in the moderate accuracy observed for the aerial roots class.

In [7], this introduces the integration of Object-Based Image Analysis (OBIA) and Random Forest (RF) for accurate mangrove mapping, utilizing GF-2 and Sentinel-2 (S2) data. A key objective is to compare dataset efficiency and accuracy and limitations are acknowledged, encompassing restricted scalability, difficulties in discerning small mangrove fragments (MFs), and challenges specific to the detection within certain datasets

In [8], the novel GEEMMM method is proposed for global mangrove mapping, incorporating cloud computing and tidal calibration to enhance precision. However, GEEMMM encounters hurdles when mapping larger areas, influencing its reliability.

In [9], the paper elevates the analysis of Random Forest (RF) and Support Vector Machine (SVM), aiming for improved accuracy through the incorporation of temporal trends.

In [10], this paper aims to assess the dynamic changes within mangrove ecosystems. This involves a comprehensive analysis of satellite imagery to understand the evolving landscape. Despite its potential, a limitation surfaces due to the inherent constraints in satellite image precision, placing restrictions on the overall accuracy of the assessment.

LIST OF MODULES:

1) Data Collection
2) Data Preprocessing
3) Object-based Image Analysis
4) Time Series Analysis

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MODULE 1 – DATA COLLECTION:

Optical satellite imagery refers to images of the Earth's surface captured by satellites using visible and near-infrared light. Optical satellites capture images by detecting different parts of the electromagnetic spectrum, with some capabilities on either side of the visible spectrum. Data was collected in multiple spectral bands with a Pixel resolution of 10-30 meters.

Satellites Utilized: Landsat and Sentinel

TIME PERIOD	SATELLITE IMAGE USED
1990 – 1999	Landsat 5 TM (Thematic Mapper)
2000 - 2012	Landsat 7 ETM+ (Enhanced Thematic Mapper)
2013 – 2016	Landsat 8 OLI (Operational Land Imager)
2017 - 2024	Sentinel – 2 MSI (Multispectral Instrument) Level 2A

Table 1: Time Periods and Associated Satellite Imagery used

MODULE 2 – DATA PROCESSING:

2.1 Cloud Masking: Cloud masking is a technique that identifies and removes clouds from satellite images to create a cloud-free image.

2.2 Composite Satellite Image:

- The process of combining multiple satellite images captured over a period of time to create a single, more complete image.
- By identifying and removing clouds from individual images, composite image creation can produce a clearer and more representative image of the land below.

Optical satellite imagery, like those captured by Landsat and Sentinel-2, introduces inconsistencies due to cloud factors. To overcome this we need to do cloud masking and composite images. Each satellite has specific bands called QA bands contain information specifically about the quality of data in the corresponding spectral bands.

Satellite	QA Band
Landsat 5, 7	Surface Reflectance Cloud Quality Assessment Band (SR_Cloud_QA)
Landsat 8	Pixel Quality Assessment Band (QA_PIXEL)
Sentinel 2	QA60

Table 2: Satellites and their corresponding quality bands

This QA bands stores the information as Bitwise Flags.

- Bitmask for (SR_Cloud_QA):
  - Bit 1 for Cloud
  - Bit 2forCloud Shadow
- Bitmask for QA_PIXEL:
  - Bit 3 for Cloud
  - Bit 4 for Cloud Shadow
- Bitmask for QA60:
  - Bit 10 for Opaque Clouds
  - Bit 11 for Cirrus Clouds

2.3 Implementation Steps for Cloud masking and creating a composite satellite image:

Step 1: Access the image's cloud-quality band.

Step 2: Use bitwise AND operations on specific bits to identify cloudy pixels based on the sensor's masking scheme.

Step 3: Create and update the image mask to exclude cloudy pixels.

Step 4: Apply the cloud masking function to each image in the collection.

Step 5: Reduce the image collection using the median to create the composite image.

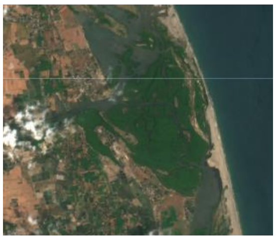
INPUT	OUTPUT
Original Image (Before removing clouds)	**Composite Image (After removing clouds)**
	

Table 3: Results obtained from preprocessing – Cloud Masking and Composite Image Creation

MODULE 3 – OBJECT-BASED IMAGE ANALYSIS

- OBIA, or Object-Based Image Analysis, transcends the limitations of traditional pixel-based analysis in remote sensing.
- It leverages the spatial and spectral characteristics of pixels to segment satellite imagery into meaningful objects, akin to grouping pixels into thematic classes that represent real-world features such as forests, urban areas, or water bodies.
- This facilitates a more nuanced interpretation of the imagery compared to per-pixel analysis, analogous to the improved understanding gained by sorting a mixed assemblage of objects by their spectral and spatial attributes.
- By enabling the analysis of image objects, OBIA fosters the generation of more accurate land cover maps and facilitates the identification of subtle changes in land use patterns.
- It serves as a critical tool for researchers and land management professionals seeking to unlock the wealth of information embedded within satellite imagery.

3.1 Detailed Algorithm for Object-based Image Analysis Module:

Step 1: Employ segmentation algorithms like DeepLabV3+ for accurate partitioning of satellite imagery.

Step 2: Utilize Random Forest for accurate object classification.

Step 3: Categorize mangrove areas by canopy density into open/sparse canopy, moderate, and dense/closed canopy.

Step 4: Assess accuracy using evaluation metrics like Cohen's Kappa coefficient, IoU, and F1 score.

MODULE 4 – TIME SERIES ANALYSIS

- The process of analyzing changes in mangrove cover over a period of time using satellite imagery.
- Analyzes data points collected at regular intervals to understand how land coverage changes over time.
- Explores data across different periods to reveal trends and recurring patterns in the data.
- Examines past changes to predict potential future behavior of the data.

4.1 Detailed Design for Time Series Analysis:

- Quantify the extent of each density class for all the years in the specified timeframe.
- By analyzing the extent of each class across the years, identify the trend of each class as increasing, decreasing, and stable.
- Calculate the net change in extent for each density class between the first and last year of the time series.

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