CS6611 – CREATIVE AND INNOVATIVE PROJECT

FIRST REVIEW – TEAM NO. 37

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

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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 the temporal dynamics and health of mangrove ecosystems.
- 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 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, 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 indices and water indices and using a similarity trend distance measures to determine the optimal indices. Despite these advancements, limitations persist in the phenological information it contains within 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.

CONTRIBUTIONS:

- Composite images are created by combining multiple satellite images to produce a single, more comprehensive image. This process can enhance the quality and depth of the imagery used for analysis, allowing for better interpretation, and understanding of the mangrove ecosystems.

- Hybrid unsupervised and supervised learning: Combine unsupervised and supervised learning approaches to leverage the strengths of both techniques. Unsupervised techniques can help identify initial clusters, which can then be refined and labeled for supervised classification, potentially improving accuracy and efficiency.

LIST OF MODULES:

1. Data Collection Module
2. Data Preprocessing Module
3. Mangrove Dynamics Module
4. Mangrove Health Module

DETAILED ALGORITHM FOR HEALTH ANALYSIS:

(Mangrove Health Module)

Step 1: Calculate the Normalized Difference Vegetation Index (NDVI) pixel values from the preprocessed satellite imagery.

Step 2: Label the NDVI images with specific mangrove health categories (e.g., sparse, moderate, dense) and split the labeled NDVI images into training and validation datasets.

Step 3: Train the CNN model using the training dataset and validate it using the validation dataset.

Step 4: Use the trained CNN model to classify NDVI images into mangrove health categories (e.g., sparse, moderate, dense) and generate predictions for the entire dataset.

NDVI range vs Classes:

RANGE	CLASSES
<= 0	Water
<= 0.1	Shallow Region
<= 0.3	Open Canopy (Sparse)
<= 0.5	Moderate
> 0.5 to 1	Closed Canopy (Dense)

EVALUATION METRICS:

F1-Score:

F1-Score balances precision (correctly identified mangroves) and recall (identified all actual mangroves) and provides a single score summarizing model performance, making comparison between different models easier. This helps choose the most effective model for mangrove health assessment.

Cohen's Kappa Coefficient:

This metric measures the agreement between predicted and observed classifications, providing insights into the reliability of the model's assessments of mangrove health dynamics.

Intersection over Union (IoU):

It measures the overlap between the model's predicted mangrove extent and the ground truth.

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