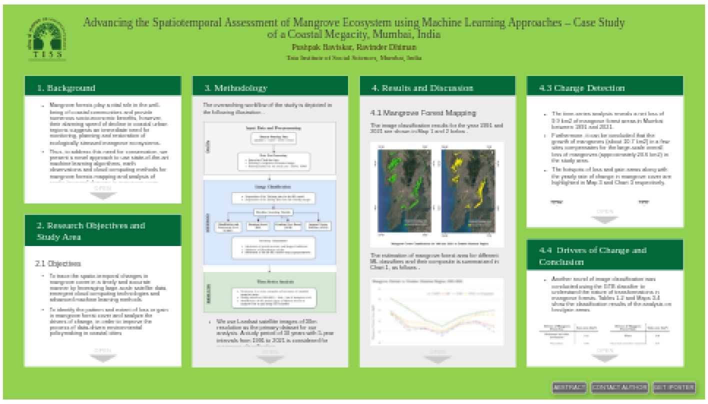
Advancing the Spatiotemporal Assessment of Mangrove Ecosystem using Machine Learning Approaches – Case Study of a Coastal Megacity, Mumbai, India



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PRESENTED AT:

1. BACKGROUND

- Mangrove forests play a vital role in the well-being of coastal communities and provide numerous socio-economic benefits. However, their alarming rate of decline in urban coastal regions points to an immediate need for monitoring, planning and restoration of the ecologically stressed mangrove ecosystems.

- Addressing this need for conservation this work presents a novel approach to use state-of-the-art machine learning algorithms, earth observations and cloud computing methods for mangrove forest mapping and analysis of spatio-temporal changes in mangrove cover.

- On the backdrop of the highly urbanizing and contested trajectory of coastal cities, the motivation of the study is to understand the distribution of mangroves, identify their rate and drivers of change, and advance the discussion on conservation policies and environmental planning of coastal cities.

2. RESEARCH OBJECTIVES AND STUDY AREA

2.1 Objectives

- To trace the spatio-temporal changes in mangrove cover in a timely and accurate manner by leveraging large-scale satellite data, emergent cloud computing technologies and advanced machine learning methods

- To identify the pattern and extent of loss or gain in mangrove forest cover and analyze the drivers of change, in order to improve the process of data-driven environmental policymaking and governance of mangroves in coastal cities

2.2 Study Area

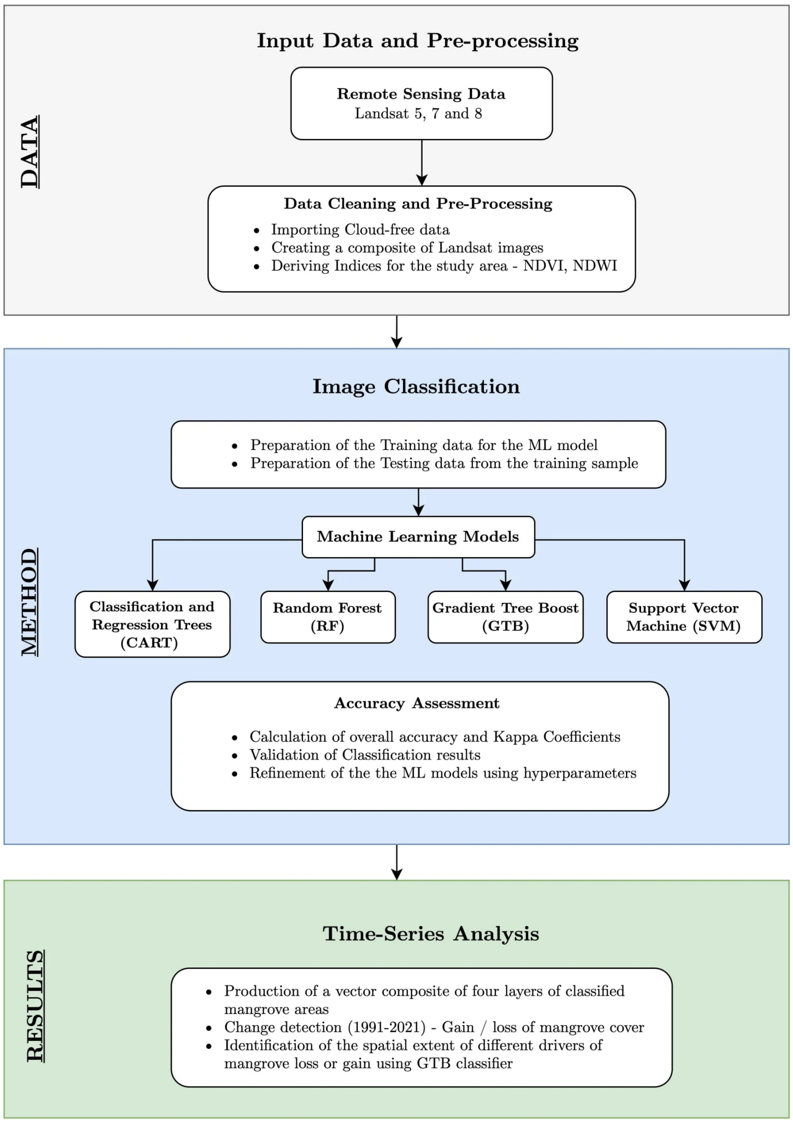
- Mumbai, a coastal megacity in India, is targeted for illustrating the machine learning based classification approach and studying the changes in mangrove cover.

- The physical and urban morphology of the study area as an island city contributes to a rich cluster of mangrove ecosystems in the concrete jungle of Mumbai.

- Furthermore, despite the existence of several environmental policies aimed at protecting wetlands, mangrove forests in Mumbai are succumbing to growing pressures of infrastructure development, overpopulation and pollution.

3. METHODOLOGY

The overarching workflow of the study is depicted in the following illustration –



- We use Landsat satellite images of 30m resolution as the primary dataset for our analysis. A study period of 30 years with 5-year intervals from 1991 to 2021 is considered for mangrove classification.

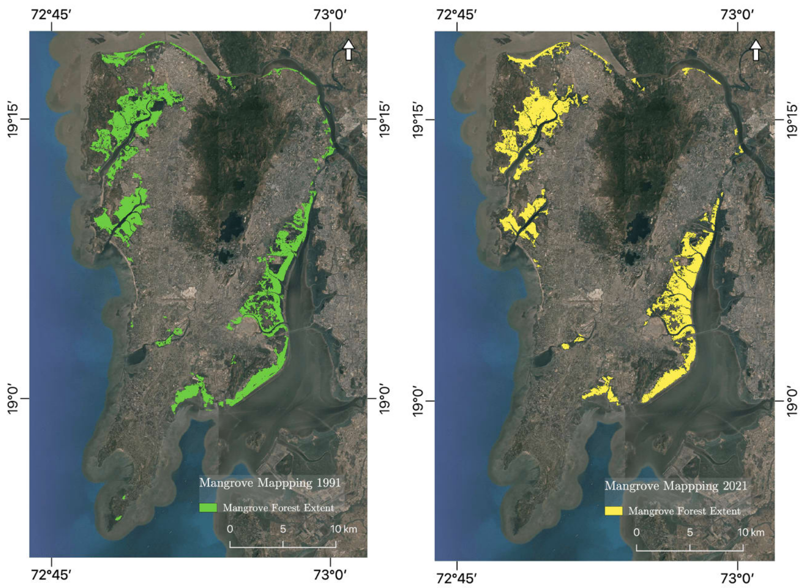
- Globally, recent studies have illustrated the feasibility and advantages of employing machine learning approaches on remote sensing data for the effective monitoring of mangrove cover (Toosi et al. (2019), Goldberg et al. (2020) and Liu et al. (2021)).

- Here, the Google Earth Engine (GEE) platform is utilized for end-to-end geospatial analysis, taking advantage of its integrated infrastructure, which includes JavaScript-based cloud computing, in-built machine learning algorithms, and easy accessibility to Landsat imagery (Barenblitt & Fatoyinbo, 2020; Bengtsson et al., 2021).

4. RESULTS AND DISCUSSION

4.1 Mangrove Forest Mapping

The image classification results for the year 1991 and 2021 are shown in Map 1 and 2 below–



Map 1-2 Mangrove cover extent in Mumbai for 1991 and 2021

The estimation of mangrove forest area for different ML classifiers and their composite is summarized in Figure 1. A steep decline in mangrove forest cover can be observed, followed by a period of increase in mangrove extent in the study area.

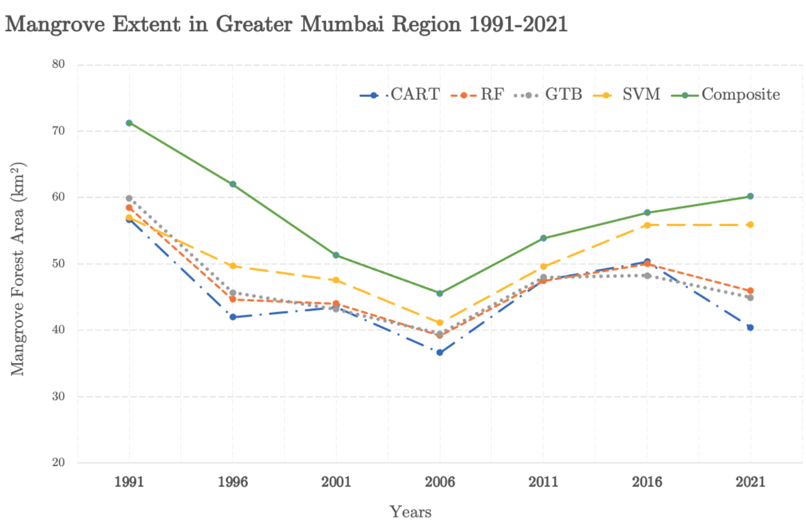


Figure 1 - Mangrove forest extent in the study area from 1991 and 2021

4.2 Accuracy Assessment

The supervised image classification obtained overall accuracy on the order of ~95% and Kappa coefficient values more than 0.80, highlighting the robustness of ML-based classification appraoches. The GTB classifier outperformed the other three classifier models for mangrove forests mapping in the study area.

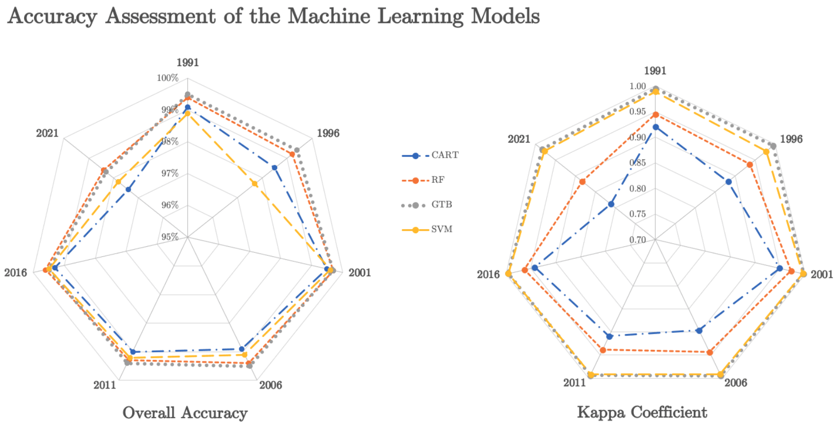


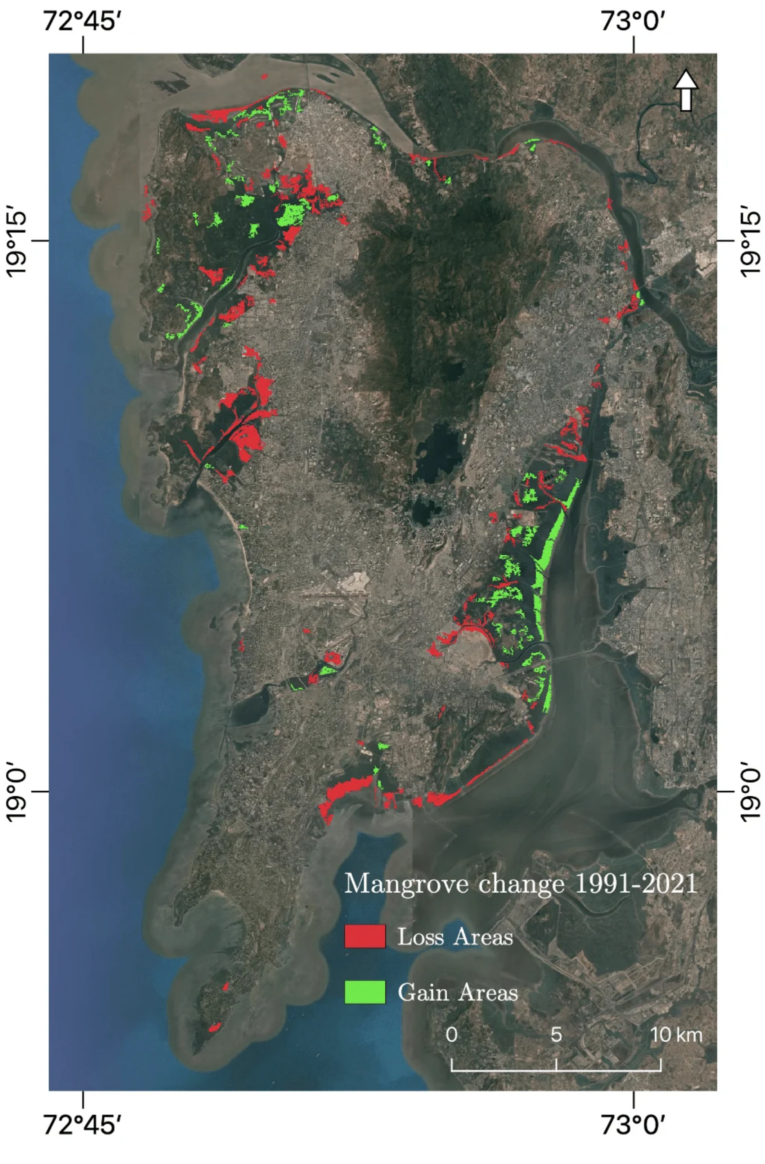
Figure 2 - Overall accuracy and Kappa Coefficient of mangrove classfication

4.3 CHANGE DETECTION

- The time-series analysis reveals a net loss of 9.9 km^2 of mangrove forest areas in Mumbai between 1991 and 2021.

- Furthermore, it can be concluded that the growth of mangroves (about 10.7 km^2) in a few sites compensates for the large-scale overall loss of mangroves (approximately 20.6 km^2) in the study area.

- The hotspots of loss and gain areas along with the yearly rate of change in mangrove cover are highlighted in Map 3 and Figure 3 respectively.



Map 3 - Mangrove Loss and Gain areas

- The increase in mangroves since 2006 might be a consequence of local mobilization and landmark court orders that substantially augmented the protection of mangroves in the study area.

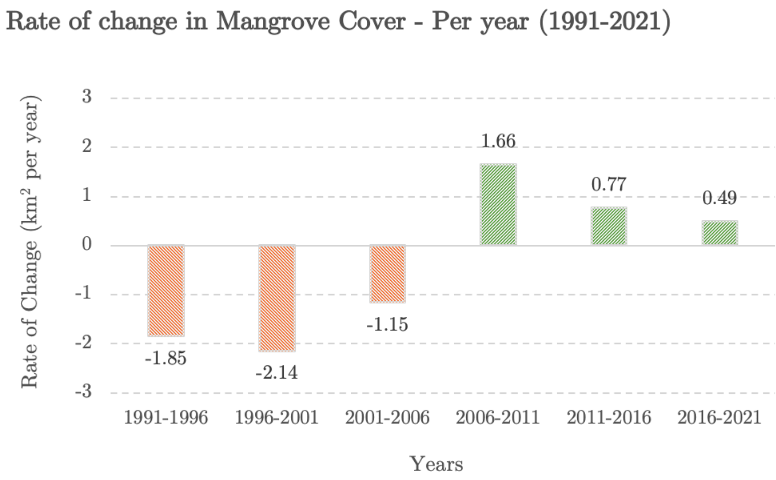


Figure 3 - Rate of yearly change in mangrove cover

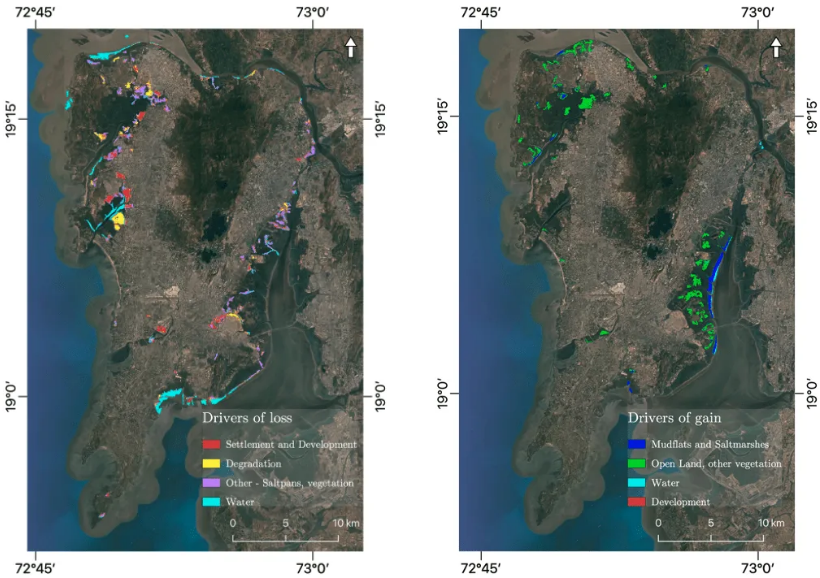
4.4 DRIVERS OF CHANGE AND CONCLUSION

- A second stage of image classification was conducted using the GTB classifier to understand the nature of transformations in mangrove forests. Tables 1-2 and Maps 4-5 show the classification results of the analysis on loss/gain areas.

Drivers of Mangrove Forest loss	Loss area (km^2)
Settlements and other development	5.11
Degradation	3.58
Other land uses - salt pans and other vegetation	5.99
Water and Mudflats	5.88
Total mangrove area lost	20.56

Drivers of Mangrove Forest Gain	Gain area (km^2)
Water	0.39
Open land and other vegetation	6.87
Salt Marshes and Mudflats	3.3
Developed land	0.1
Total mangrove area gained	10.66

Table 1-2 - Analysis of loss or gain in mangrove forest cover in Mumbai 1991-2021



Maps 4-5 - Spatial extent of drivers for loss and gain in mangrove areas

- It can be inferred that the conversion of mangrove forests for urban land uses such as housing, infrastructure development, salt pans, open land, etc., represent the dominant drivers of mangrove loss in the study area.

- Additionally, the growth of mangroves on open lands, mudflats, other vegetation, etc., reflects the areas where the increase in mangrove areas is primarily observed.

5. Conclusion

- The methodology and outcomes of the study can be utilized to monitor mangrove cover in a periodic, accurate, and cost-effective manner which can assist stakeholders in the governance, conservation and restoration of mangrove ecosystems.

- The machine learning-based mangrove assessment approach can also be used to create an integrated framework for sustainable coastal planning and environmental policymaking in coastal cities.

ABSTRACT

Mangrove ecosystems are an essential component of tropical and subtropical urban coastal regions where they provide critical ecosystem services and ensures climate mitigation while playing a pivotal role in the livelihoods of coastal communities. However, growing anthropogenic pressures from rampant urbanization and infrastructural demands are leading to an unparalleled loss and degradation of mangrove cover especially in coastal cities of the global south. Addressing the immediate need for monitoring, protection and restoration of the ecologically stressed mangroves, this study uses earth observations, machine learning and cloud computing methods for advancing timely and accurate spatiotemporal mangrove mapping and change detection. Image classification through four different models i.e. Classification and Regression Trees (CART), Random Forest (RF), Gradient Tree Boost (GTB) and Support Vector Machine (SVM) was performed using Google Earth Engine to classify mangrove extent along the coastal regions of Mumbai, India. Spatially explicit temporal trend in mangrove extent was studied and used to estimate the rate of change of mangrove extent over a period of 30 years. Accuracy assessment was conducted to validate the robustness of trained classifier models alongside their comparative performance. Classification accuracies on the order of 95% were achieved through the machine learning-based classifier models in distinguishing mangrove areas from other land cover types. The time-series analysis combined with image classification reveals the pattern and causes of spatiotemporal changes in mangrove cover and highlights the hotspots of mangrove loss and gain. This approach can aid stakeholders in the management and restoration of mangrove ecosystems through periodic and cost-effective monitoring of mangrove cover particularly in data deficient coastal cities. The outcomes of the study will contribute towards efficient decision-making in achieving the localization of Sustainable Development Goals 6 and 11 of the United Nations.

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