MONITORING THE MANGROVES OF INDIAN SUNDARBANS USING GEOSPATIAL TECHNIQUES

T. Bhadra [1*], S. Banerjee [1], S. Ghosh[2], A. Saha [3], K. Mukherjee [1], R. Sardar[1], S. Roy[1], R. Das[1]

[1] Department of Geography, School of Basic and Applied Sciences, Adamas University, West Bengal, India
tuhin.bhadra@adamasuniversity.ac.in

[2] International Water Management Institute, Colombo, Sri Lanka

[3] Department of Biotechnology, School of Life Science and Biotechnology, Adamas University, West Bengal, India

KEYWORDS: AGB, ANN, biomass, carbon sequestration, EVI, Landsat 9, mangrove health, mangrove species classification, mangrove species diversity, machine learning, NDVI, OSAVI, Sundarbans, TDVI.

ABSTRACT:

The world's largest mangrove ecosystem Sundarbans lies in the southwestern part of the Ganges-Brahmaputra Delta. The health, function, and ecosystem services of the mangrove forest depend on the availability of freshwater flow within the deltaic system. The rivers, which used to feed the delta and nourish the mangrove ecosystem now stand disconnected from their upstream freshwater sources. The unavailability of freshwater restricts the growth of freshwater-loving mangroves and has the potential to affect the health of the existing mangroves limiting their ability to provide ecosystem services. Due to the high salinity, the natural reproduction of these valuable freshwater-loving floral species gradually got ceased. High salinity is considered a stress factor influencing the health, growth, productivity, and distribution of mangrove plants. In this circumstance, the main objective of the study is to monitor the spatiotemporal change of the mangrove ecosystem of Sundarbans in terms of species assemblage, floral diversity, biomass, canopy cover, forest health, etc. Remote sensing techniques and field measurements were used to perform an in-depth mangrove genus-level classification (Maximum Likelihood Classifier). To assess the plant species diversity, Shannon-Wiener Index was used in different plots of the Sundarbans to get an idea of the rich biodiversity of these coastal ecosystems. Different vegetation indices such as NDVI, OSAVI, SAVI, TDVI, etc. were estimated to assess the health of the mangrove forest. The biomass and carbon sequestration potential of the mangrove forest was assessed using field data and microwave remote sensing techniques. The result shows the declining trend of freshwater-loving mangroves from the central section of Sundarbans and an increasing trend of saline water-loving mangroves by replacing the others.

1. INTRODUCTION

Mangrove ecosystems are generally found in tropical and subtropical countries. They are mainly salt-tolerant species among which many of them prefer to grow in the high saline zone, and few of them grow in medium and low saline zones respectively. This ecosystem plays an important role in our environment by reducing storm surges, stabilizing coastlines while preventing soil erosion, providing ecosystem services, and is home to large numbers of flora and fauna. However, these barriers have been declining over time due to various kinds of factors like increasing salinity, tropical cyclones, waves, tides, etc. These extreme conditions have compelled the mangroves to develop necessary physiological and morphological adaptations (Spalding, 2010).

Remote Sensing serves as an effective tool in mapping this mangrove cover in terms of cost, time, and accuracy (Wang et al., 2004). Mangrove groups are mainly identified using their textural and structural analysis which are either pure or mixed assemblages (Ramsey Ill & Jensen, 1996). However, it is difficult to map individual trees if they are smaller than the resolution of the cell or if they are found in mixed communities (Maurya et al., 2021). Various techniques were applied in the past to map mangroves worldwide in forms of visual interpretation, vegetation-indexed images, unsupervised classification, and supervised classification techniques out of which only 12% included accuracy assessment in their analysis (Green et al., 2010). Object-based classification and image segmentation approaches were applied to map mangroves in the Mekong Delta of Vietnam using SPOT5 imagery (Vo et al., 2013). To map black mangroves on the Texas Gulf Coast supervised and unsupervised classification techniques were used on QuickBird satellite imagery (Everitt et al., 2008). Decision tree algorithms were incorporated to monitor mangrove forest changes using multi-temporal Landsat TM data (Liu et al., 2008). Several deep convolution neural network models were adapted for mangrove detection in the South Pacific Ocean and parts of Fiji using multispectral Worldview 2 and Sentinel 2 imagery (Corina et al., 2020). Mapping and monitoring of the Sundarbans mangrove forest has become an urgent need due to its enormous ecological and economic importance. In the Sundarbans, periodic forest inventories have taken place approximately every 15 to 20 years (Giri et al., 2007) which was last taken 30 years ago and a species level map was prepared for Bangladesh Sundarbans using aerial photos and ground survey. The spatial variation of these mangrove covers has been shown in a number of studies. Mangrove species-level classification for Indian Sundarbans was prepared by (Giri et al., 2014) with few species classes, and no distinction between mixed species was shown. Attempts were made by (Ghosh et al., 2016) to map long-term changes in mangrove species composition for the Sundarbans but a smaller number of mangrove species were shown. Detailed species-level analysis was done by (Mitra & Karmaker, 2010) using LISS-IV and Hyperion-1 data over Lothian Island and Saptamukhi Reserve Forest.

(Ricklefs & Latham, 1993) conducted a comprehensive study on global patterns of diversity in mangrove floras. They examined the historical and geographical perspectives of mangrove ecosystems, highlighting the diverse species composition across different regions. (Ellison et al., 1999) investigated the origins of mangrove ecosystems and the peculiar biodiversity patterns observed in mangrove habitats. (Mulya et al., 2021) conducted a study comparing four species diversity indices in mangrove communities to determine the most suitable index for measuring mangrove diversity. The study examined the Simpson (1-D), Shannon, Menhinick, and Margalef indices, which are commonly used in ecological research. (Sreelekshmi et al., 2020) conducted a case study in the Sundarbans delta on the east coast of India to investigate mangrove species diversity, stand structure, and zonation patterns in relation to environmental factors. (Joshi & Ghose, 2014) focused on the community structure, species diversity, and aboveground biomass of the Sundarbans mangrove swamps. The study assessed the composition and structure of mangrove communities, emphasizing the importance of understanding their ecological characteristics and biomass accumulation. (Ardiansyah & Safe'i, 2021) conducted an analysis of changes in the health of coastal mangrove forests on the East Coast of Lampung. The study utilized remote sensing data to assess the health status of the mangrove ecosystems. (Chellamani et al., 2014) conducted a study to assess the health status of Indian mangrove ecosystems using multi-temporal remote sensing data. The study aimed to understand the spatial and temporal variations in mangrove health indicators.

Globally, there have been concerted endeavors to accurately measure above-ground carbon in the form of biomass within mangrove forests. (Baccini et al., 2017; Baret, 2015; Hutchison et al., 2014; Sanderman et al., 2019). Allometric models tailored for a particular mangrove species within specific geomorphological conditions prove inadequate in predicting the Above-Ground Biomass (AGB) of the same species in distinct geomorphological settings. Additionally, these models tend to generate errors when applied to species without employing destructive sampling methods.(Mahmood et al., 2019; Mitchard et al., 2013; Ngomanda et al., 2014). Estimation discrepancies ranged from +18% to -14% when comparing biome-specific models to species-specific models in Brazilian mangrove forests. (Pereira et al., 2018). Global models are frequently demonstrated to provide more accurate estimations of above-ground biomass compared to models tailored to specific local conditions. (Rutishauser et al., 2013), and incorporating tree height and wood density into the analysis allows for a comprehensive understanding of geographical conditions and factors influencing mangrove health, such as salinity. (Mahmood et al., 2019; Virgulino et al., 2020).

The study by (Asgarian & Soffianian, 2023) was focused on the past and potential future distribution of white mangroves in an arid estuarine environment. The researchers employed a combination of Maxent and CA-Markov models to analyze the distribution patterns of white mangroves. By integrating these models, they aimed to understand how environmental factors influenced the presence and expansion of white mangroves in the specific estuarine environment. Mafi-Gholami et al., 2020 examined the spatially explicit predictions of changes in the extent of mangroves in Iran by the end of the 21st century. The researchers employed modeling techniques to project the potential future distribution of mangroves in Iran based on different climate change scenarios. The study by Chanda et al., 2016 focused on the blue carbon stock of the Bangladesh Sundarban mangroves and explored the potential scenario of its future state over the century. Collectively, these studies contribute to our understanding of mangrove ecosystems in different geographical contexts. They provide valuable insights into the past distribution, potential future scenarios, and ecological functions of mangroves in estuarine environments.

2. STUDY AREA

The Indian Sundarbans is situated between 21° 30′ - 22° 15′N latitude and 88° 10′ - 89° 10′ E longitude in the lower delta plain of West Bengal covering an area of about 2400 km^2 (Figure 1). The mangrove ecosystem of Sundarbans plays an important role in reducing storm surges, acts as a carbon sink, protects the coastal population, and supports the livelihood of people by providing various types of ecosystem services. The Sundarbans mangrove vegetation consists of a group of plants of special adaptation that thrive in a wide gradient of salinity. About 100 species of mangrove plants representing 34 families and 57 genera are present in Indian Sundarbans (Gopal and Chauhan, 2006) out of which 25 are true mangrove species, 30 are mangrove associates and 37 are black mangroves. The Indian Sundarban is dominated by the Rhizophoraceae and Avicenniaceae whereas the Bangladesh Sundarbans is dominated by the Heritiera and Excoecaria (Gopal and Chauhan, 2006). The Heritiera (Sundari) is considered an endangered species in Indian Sundarbans as it is rapidly disappearing due to less freshwater inflow from upstream and high salinity conditions (Gopal and Chauhan, 2006; Barik and Chowdhury, 2014). The Nypa fruticans, Phoenix paludosa, Xylocarpus mekongensis are the other rare and endangered flora in the Indian Sundarbans.

3. METHODOLOGY

3.1 Genus-level mangrove classification and diversity calculations

Sentinel 2A data were downloaded from the Copernicus Open Access Hub portal having less than 5% cloud cover on 15th December 2022. The atmospheric correction of these datasets was performed using the Sen2cor processor in the Sentinel Application Platform (SNAP) Toolbox. Sen2cor executes several processes including cloud detection, scene classification, removal of water vapour and aerosol effects, and finally 'bottom of atmosphere conversion'. Spectral bands of Blue (Band 2), Green (Band 3), Red (Band 4), and NIR (Band 8) each having a spatial resolution of 10m were composed and mosaicked together which was further used for classification. Field visits to the Indian Sundarbans including all the wildlife sanctuaries, reserved forests, and national parks in the east, west, and central zone were planned accordingly with the revisit time of the Sentinel-2A satellite over the Sundarbans. The ground reference points were collected using Garmin eTrex 32x Handheld GPS from the maximum possible parts of the study area to make the training dataset as strong as possible (Figure 1). Pure homogenous species patches distributed evenly over an area of more or less than 100 square meters were considered primarily for ground reference points. Dominant mixed patches that are distributed widely were also considered. The survey was done for a period of two weeks covering 18 forest camps and 19 forest blocks, traversing the maximum possible locations by water route and working in the open forest accompanied by the forest guards provided by

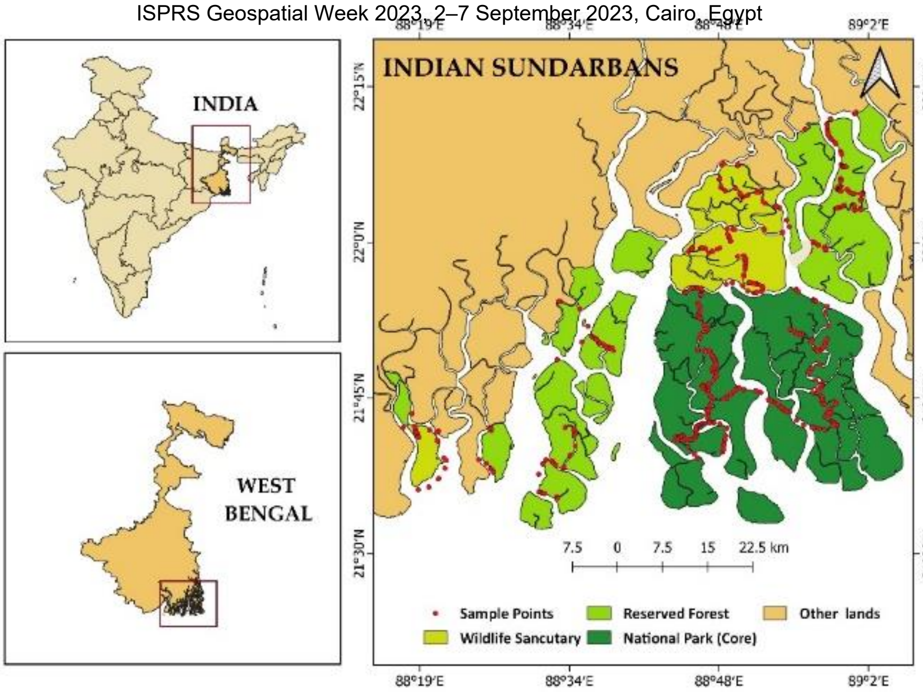

Figure 1: Location of the Study Area

the Directorate of Forest, Government of West Bengal. Pure patches of mangroves were considered while creating the training samples to make the classification as accurate as possible. From a total of 462 sample points collected, 324 sample points (70%) were used to classify the image, and 138 sample points (30%) were used to validate it. The final composite image was classified using the machine learning algorithms such as Maximum Likelihood Classifier (MLC). Maximum Likelihood Classification is a supervised classification method that is based on the Bayes theorem. This genus-level map was used for calculating Shannon Diversity Index using the Lekos Pulgin of QGIS.

3.2 Above-Ground Biomass and Carbon Stock estimation

Acquiring Landsat 9 imagery with minimal cloud cover, below 5%, was conducted through the USGS Earth Explorer portal on December 12, 2022. The satellite's multispectral sensors offer a spatial resolution of 30 meters, while the panchromatic sensors provide a finer resolution of 15 meters. Employing selected bands from the imagery, various vegetation indices were computed. These indices are valuable indicators, offering insights into biomass estimation by capturing the spectral responses of the vegetation cover.(Manna et al., 2014). In our investigation, we harnessed four key vegetation indices—Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Optimized Soil Adjusted Vegetation Index (OSAVI), and Transformed Difference Vegetation Index (TDVI). Notably, NDVI, widely employed in biomass studies. (Roy & Ravan, 1996; Santin-Janin et al., 2009), particularly suits regions with lower biomass content like the Indian Sundarbans and is very much suitable for areas having low biomass content like the Indian Sundarbans. OSAVI, adept at mitigating soil interference, proved valuable in our study area characterized by saline banks and prevalent dry soil exposure. TDVI, chosen for its non-saturation at higher biomass values, addressed limitations seen in NDVI, SAVI, and OSAVI. (Manna et al., 2014). Field data, encompassing parameters like diameter at breast height (DBH) and canopy height (H), were incorporated into pan-tropical mangrove species allometric equations. (Chave et al., 2005, 2014). These equations, derived from established studies, utilized wood density data from species databases. The resultant allometric equations were employed to predict above-ground biomass (AGB) and carbon stock across the entire study area, providing a comprehensive understanding of the mangrove ecosystem's ecological dynamics. The allometric equations are as follows.

$$AGB = 0.0673\ (\rho \times DBH^2 \times H)^{0.976} \quad \text{(Chave et al., 2014)} \quad (1)$$

$$AGB = 0.0776\ (\rho \times DBH^2 \times H)^{0.940} \text{(Chave et al., 2005)} \quad (2)$$

$$AGB = 0.0509\ (\rho \times DBH^{2} \times H) \quad \text{(Chave et al., 2005)} \quad (3)$$

here, AGB = Above Ground Biomass in tonnes ρ = Wood density in gcm^3, DBH = Diameter at breast height in cm, and H = Tree height in m

$$C = AGB \times CF \text{ (Chave et al., 2014)} \quad (4)$$

here, C = Carbon Stock in tonnes, AGB = Above Ground Biomass in tonnes, CF = Carbon Fraction (0.5).

3.3 Change Detection and prediction using CA Markov Model

Change detection analysis and prediction were performed in Idrisi Terrset Software by incorporating the CA Markov Model. The layers were taken from the prepared genus level classification map and estimated above-ground biomass map from the year 1992 and prediction was made till the year 2050 by training using Artificial Neural Network (ANN) and validating using the present year.

4. RESULT AND DISCUSSION

4.1 Genus Level Classification

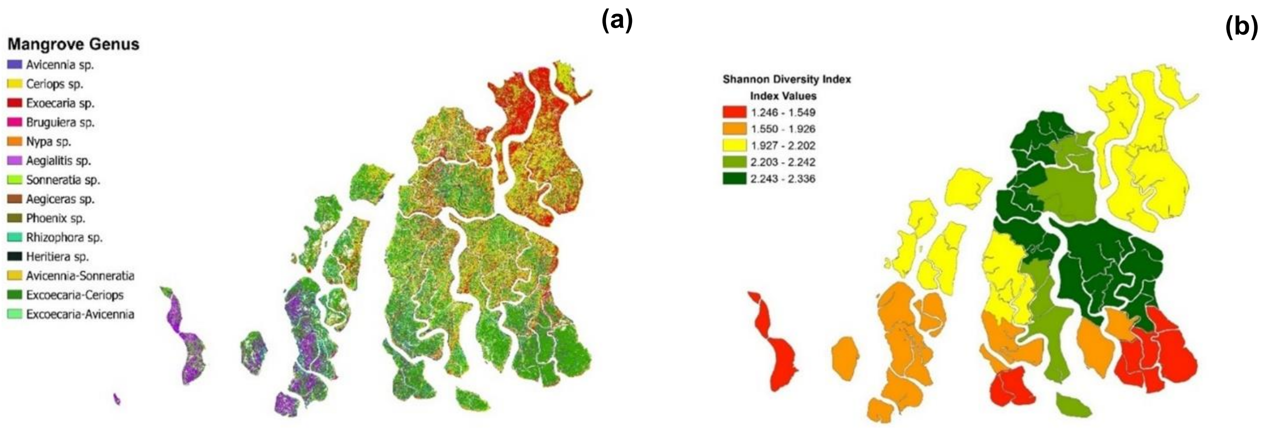

Figure 2: (a) Genus Level Classification of the Mangroves (b) Species Diversity of the Mangroves

As multispectral sensors could not adequately differentiate between two species of the same genus (although they could distinguish between *Avicennia sp.* and *Excoecaria sp.*, they could not distinguish between *Avicennia marina* and *Avicennia alba*) (Prakash Hati et al., 2021), the Sentinel Image is used to prepare genus level map of the mangroves in the Indian Sundarbans. Using Sentinel 2A data, 16 different classes could be distinguished including 11 pure mangrove classes, 3 mixed mangrove classes, and geomorphological features like saline banks, rivers, etc. (Figure 2(a)). The pure mangrove classes include – *Avicennia sp., Ceriops sp., Exoecaria sp., Bruguiera sp., Rhizophora sp., Aegialitis sp., Aegiceras sp., Nypa sp., Phoenix sp., Sonneratia sp., Heritiera sp.*, whereas the dominant mixed mangrove classes include *Exoecaria-Ceriops, Exoecaria-Avicennia,* and *Avicennia-Sonneratia*. Based on the classification, it is observed that the dominant species class observed to be the *Exoecaria – Ceriops* mixed forest, occupying about 334.25 km^2 area approximately. The lowest species distribution is observed in the case of *Heritiera sp.* which occupies a total 2.90 km^2 area approximately. The western side of the forest tends to be dominated by *Avicennia* governed by Saptamukhi and Thakuran River while the eastern side of the forest tends to be hemmed with *Exoecaria-Ceriops* mainly governed by Matla, Gosaba, Raimangal and Harinbhanga River.

4.2 Species Diversity

The analysis of plant species diversity in different beats of the Indian Sundarbans using the Shannon Diversity index revealed interesting patterns. The highest Shannon Diversity Index value was observed in the Chandkhali Beat (2.299), indicating a greater variety of plant species present in this area. Conversely, the lowest Shannon Diversity Index value was recorded in Lothian Island (1.246), suggesting lower species

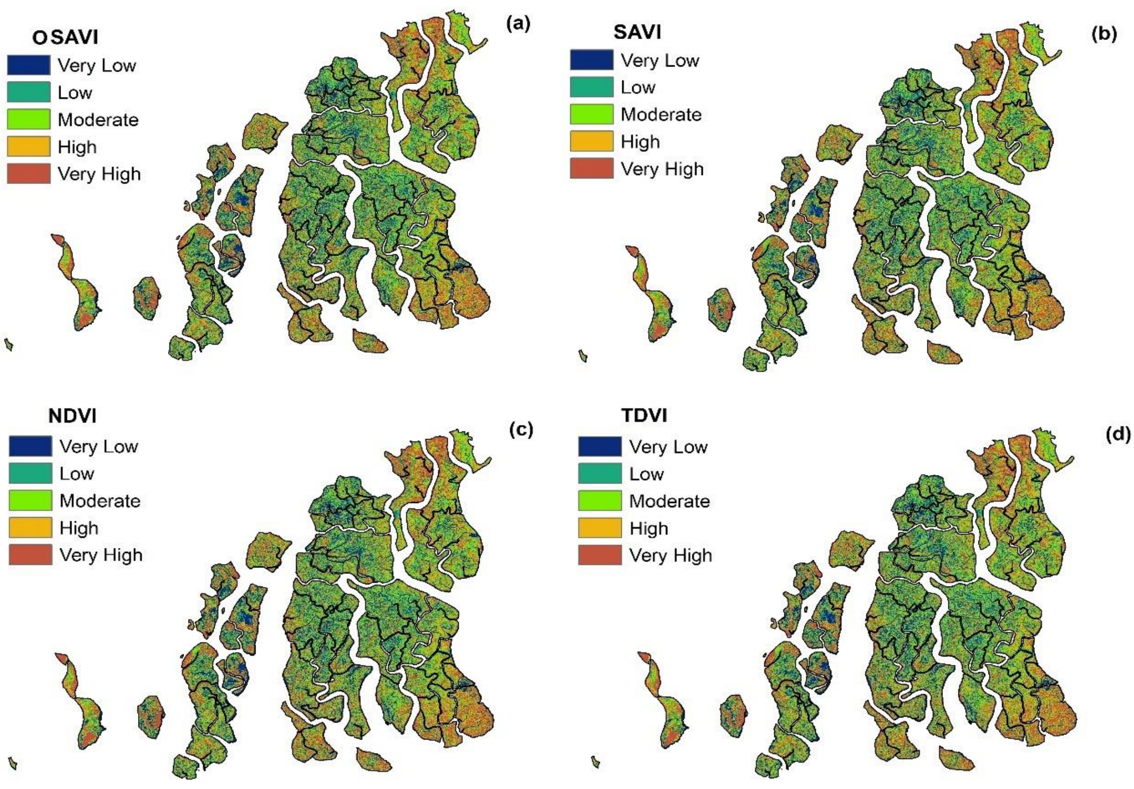

Figure 3: Mangrove Health Indices using (a) OSAVI (b) SAVI (c) NDVI (d) TDVI

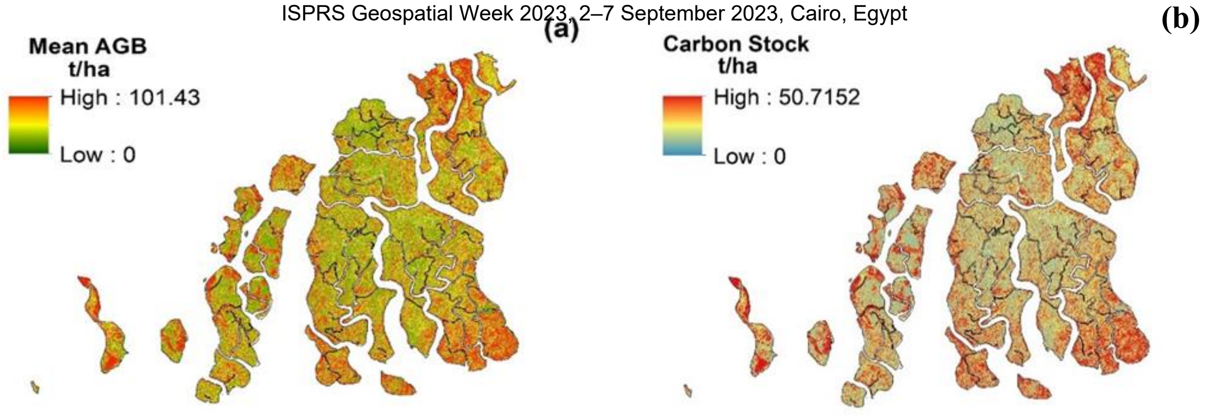

Figure 4: OSAVI based (a) Mean AGB of the Indian Sundarbans (b) Carbon Stock of the Indian Sundarbans

richness in this particular beat (Figure 2 (b)). These findings suggest that the southern section of the Indian Sundarbans, which is closer to the ocean, experiences increased salinity levels, leading to a decline in plant species diversity. The presence of higher salinity in this region restricts the growth and survival of various plant species. In contrast, the northern section of the Indian Sundarbans benefits from a comparatively higher freshwater flow, which supports a greater variety of plant species and contributes to higher biodiversity.

4.3 Mangrove Health Assessment, Above Ground Biomass (AGB) and Carbon Stock Estimation

Utilizing simple linear regression models, we established empirical connections between field-measured Above-Ground Biomass (AGB) and key vegetation indices—NDVI, SAVI, OSAVI, and TDVI, as depicted in Figure 3. Notably, robust correlations were observed, with OSAVI exhibiting the highest r2 value of 0.95 ($p < 0.01$), followed closely by SAVI (r2 = 0.95, $p < 0.01$), NDVI (r2 = 0.93, $p < 0.01$), and TDVI (r2 = 0.84, $p < 0.01$). The predictive capacity of OSAVI, SAVI, and NDVI reached maximum AGB values of 101.43 t ha-1, 93.05 t ha-1, and 72.61 t ha-1, respectively. Conversely, TDVI underestimated the maximum AGB range, projecting it to 43.45 t ha-1. Carbon conversion, derived by multiplying field AGB estimates with a carbon fraction of 0.5, allowed us to estimate overall carbon stock. OSAVI outperformed other indices in predicting carbon stock, ranging from 0 to 50.71 t ha-1, followed by SAVI and NDVI with ranges of 0 to 46.52 t ha-1 and 0 to 36.30 t ha-1, respectively. TDVI, however, displayed a narrower range of 0 to 21.72 t ha-1. The findings underscore OSAVI as the most reliable indicator for accurately predicting carbon stock in the area, with SAVI and NDVI closely trailing. In contrast, TDVI consistently underestimated mean carbon stock compared to the surveyed plots. The OSAVI based prediction of AGB and Carbon Stock in shown in Figure 4.

The intricate geography of the Indian Sundarbans isn't conducive to the growth of low and moderately salt-tolerant species. Surging salinity levels, driven by sea-level rise, altered freshwater flow, and human activities, have severely hampered the growth of various species. This impact is particularly harsh on those reliant on freshwater, resulting in reduced biomass and compromised carbon sequestration. The adverse effects on mangroves and other plants have led to diminished biomass and a weakened ability to sequester carbon, posing significant challenges to these ecosystems' ecological balance. The predicted maximum AGB is 101.43 t ha-1, notably lower than the Bangladesh Sundarbans. (Mahmood et al., 2019). The overall canopy structure exhibits moderate density with occasional gaps, exposing the ground surface. This condition favors the use of indices like OSAVI, which mitigates soil background interference. NDVI, widely employed in studies involving dense canopies, is less effective in estimating AGB in the Indian Sundarbans context. While TDVI has demonstrated efficacy in denser canopies, it tends to underestimate AGB in the Sundarbans.

4.4 Change Detection and Prediction

Change Detection and Prediction Analysis (1990 – 2050) is prepared using CA Markov Model. The result shows the declining trend of freshwater-loving mangroves like *Bruguiera sp.* and *Xylocarpus sp.* from the central section of the map and an increasing trend of saline water-loving mangroves such as Ceriops and Avicennia by replacing the others. *Exoecaria sp.* remains more or less in the same location. *Exoecaria sp.* and *Ceriops sp.* started to dominate Lothian Island from the year 1998 till the present. By the time 2050, most of freshwater species will be declined and one can only find high salt-tolerant species existing in the Indian Sundarbans (Figure 5).

5. CONCLUSION

The observed decline in freshwater-loving mangrove species and the dominance of salt-tolerant species indicate the ongoing transformation of the Indian Sundarbans. It is crucial to develop and implement effective conservation and management strategies to safeguard the biodiversity and ecological integrity of this unique ecosystem. These strategies should focus on maintaining freshwater flow, reducing salinity levels, and preserving critical habitats for endangered species. The influence of salinity on species diversity in the Indian Sundarbans highlights the need to address the sources of increased salinity, such as sea-level rise, freshwater diversion, and human activities. Integrated coastal zone management approaches should be adopted to balance human development and conservation goals, ensuring the sustainability of the mangrove ecosystem. Long-term monitoring programs should be established to regularly assess changes in mangrove composition, distribution, and biodiversity. Remote sensing techniques, combined with field surveys, can be employed to detect and monitor changes over time. This will facilitate the identification of critical areas that require immediate conservation measures and help predict future trends in mangrove dynamics.

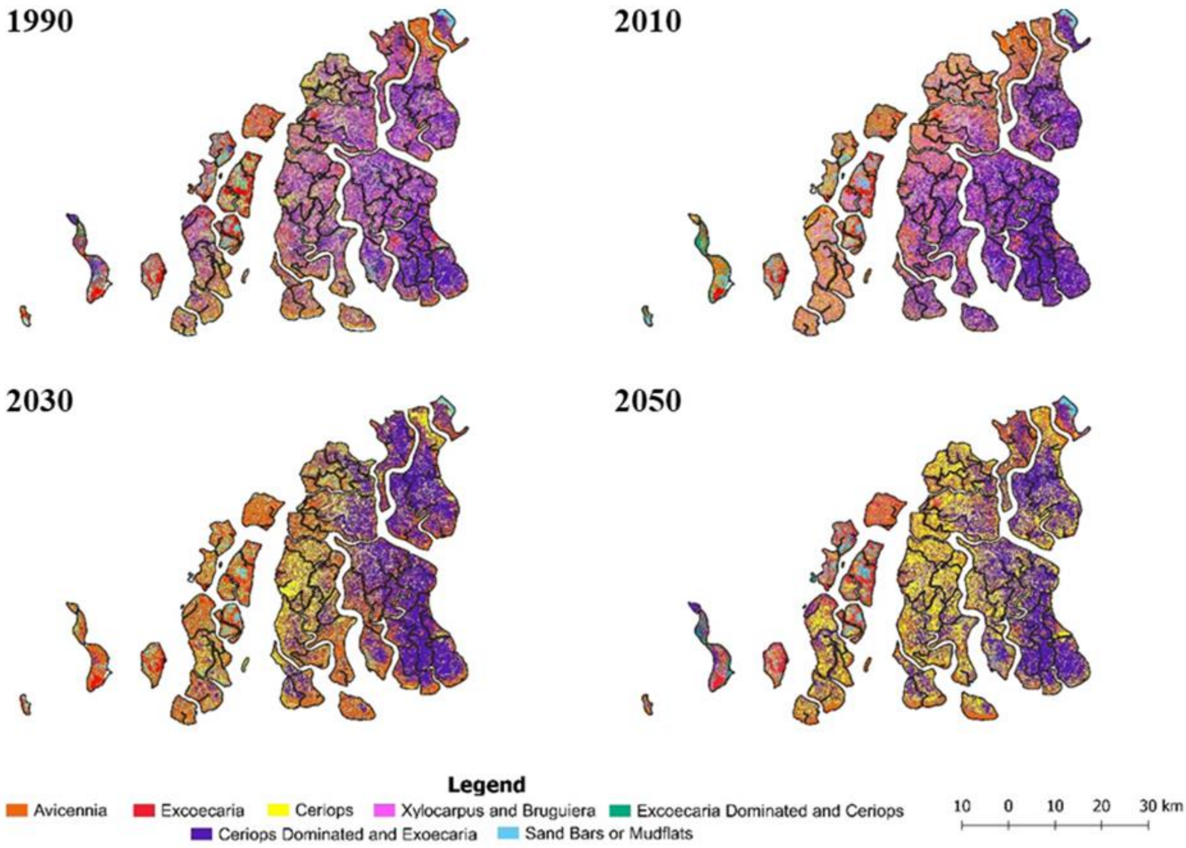

Figure 5: Temporal Change of the Mangrove Distribution in the Indian Sundarbans

ACKNOWLEDGEMENTS

The study was conducted under the Core Research Grant project (CRG/2021/008376) funded by the Science and Engineering Research Board (SERB), Department of Science and Technology, Government of India. The authors would like to express their heartfelt gratitude to the SERB for providing the fund support to conduct the study.

REFERENCES

Ardiansyah, F., & Safe'i, R., 2021. Analysis of Changes in Health of Coastal Mangrove Forest on the East Coast of Lampung. IOP Conference Series: Earth and Environmental Science, 755(1), 012028. https://doi.org/10.1088/1755-1315/755/1/012028

Asgarian, A., & Soffianian, A., 2023. Past and potential future distribution of white mangroves in an arid estuarine environment: Integration of Maxent and CA-Markov models. Marine Policy, 147, 105345. https://doi.org/10.1016/J.MARPOL.2022.105345

Baccini, A., Walker, W., Carvalho, L., Farina, M., Sulla-Menashe, D., & Houghton, R. A., 2017. Tropical forests are a net carbon source based on aboveground measurements of gain and loss. Science, 358(6360), 230–234. https://doi.org/10.1126/SCIENCE.AAM5962/SUPPL_FILE/AAM5962_BACCINI_SM.PDF

Baret, F., 2015. Aboveground Terrestrial Biomass and Carbon Stock Estimations from Multisensor Remote Sensing. Land Resources Monitoring, Modeling, and Mapping with Remote Sensing, 47–68. https://doi.org/10.1201/B19322-4

Chanda, A., Mukhopadhyay, A., Ghosh, T., Akhand, A., Mondal, P., Ghosh, S., Mukherjee, S., Wolf, J., Lázár, A. N., Rahman, M. M., Salehin, M., Chowdhury, S. M., & Hazra, S., 2016. Blue Carbon Stock of the Bangladesh Sundarban Mangroves: What could Be the Scenario after a Century? Wetlands, 36(6), 1033–1045. https://doi.org/10.1007/S13157-016-0819-7/FIGURES/8

Chave, J., Andalo, C., Brown, S., Cairns, M. A., Chambers, J. Q., Eamus, D., Fölster, H., Fromard, F., Higuchi, N., Kira, T., Lescure, J. P., Nelson, B. W., Ogawa, H., Puig, H., Riéra, B., & Yamakura, T., 2005. Tree allometry and improved estimation of carbon stocks and balance in tropical forests. Oecologia, 145(1), 87–99. https://doi.org/10.1007/S00442-005-0100-X/METRICS

Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M. S., Delitti, W. B. C., Duque, A., Eid, T., Fearnside, P. M., Goodman, R. C., Henry, M., Martínez-Yrízar, A., Mugasha, W. A., Muller-Landau, H. C., Mencuccini, M., Nelson, B. W., Ngomanda, A., Nogueira, E. M., Ortiz-Malavassi, E., … Vieilledent, G., 2014. Improved allometric models to estimate the aboveground biomass of tropical trees. Global Change Biology, 20(10), 3177–3190. https://doi.org/10.1111/GCB.12629

Chellamani, P., Prakash Singh, C., & Panigrahy, S., 2014. Assessment of the health status of Indian mangrove ecosystems using multi temporal remote sensing data. Tropical Ecology, 55(2), 245–253. www.tropecol.com

Corina, I., Michel, K., Eric, M., Iovan, C., Kulbicki, M., & Mermet, E., 2020. Deep Convolutional Neural Network for Mangrove Mapping. https://doi.org/10.1109/IGARSS39084.2020.9323802

Debashis, M., & Karmaker, S., 2010. Mangrove Classification in Sundarban using High Resolution Multi-Spectral Remote Sensing Data and GIS. Asian Journal of Environment and Disaster Management (AJEDM) - Focusing on Pro-Active Risk Reduction in Asia, 02(02), 197. https://doi.org/10.3850/S179392402010000268

Ellison, A. M., Farnsworth, E. J., & Merkt, R. E., 1999. Origins of mangrove ecosystems and the mangrove biodiversity anomaly. Global Ecology and Biogeography, 8(2), 95–115. https://doi.org/10.1046/J.1466-822X.1999.00126.X

Everitt, J. H., Yang, C., Sriharan, S., & Judd, F. W., 2008. Using high resolution satellite imagery to map black mangrove on the Texas Gulf Coast. Journal of Coastal Research, 24(6), 1582–1586. https://doi.org/10.2112/07-0987.1

Ghosh, M. K., Kumar, L., & Roy, C., 2016. Mapping Long-Term Changes in Mangrove Species Composition and Distribution in the Sundarbans. Forests 2016, Vol. 7, Page 305, 7(12), 305. https://doi.org/10.3390/F7120305

Giri, C., Pengra, B., Zhu, Z., Singh, A., & Tieszen, L. L., 2007. Monitoring mangrove forest dynamics of the Sundarbans in Bangladesh and India using multi-temporal satellite data from 1973 to 2000. Estuarine, Coastal and Shelf Science, 73(1–2), 91–100. https://doi.org/10.1016/J.ECSS.2006.12.019

Giri, S., Mukhopadhyay, A., Hazra, S., Mukherjee, S., Roy, D., Ghosh, S., Ghosh, T., & Mitra, D., 2014. A study on abundance and distribution of mangrove species in Indian Sundarban using remote sensing technique. Journal of Coastal Conservation, 18(4), 359–367. https://doi.org/10.1007/S11852-014-0322-3

Green, E. P., Clark, C. D., Mumby, P. J., Edwards, A. J., & Ellis, A. C., 2010. Remote sensing techniques for mangrove mapping. Https://Doi.Org/10.1080/014311698215801, 19(5), 935–956. https://doi.org/10.1080/014311698215801

Hutchison, J., Manica, A., Swetnam, R., Balmford, A., & Spalding, M., 2014. Predicting Global Patterns in Mangrove Forest Biomass. Conservation Letters, 7(3), 233–240. https://doi.org/10.1111/CONL.12060

Joshi, H. G., & Ghose, M., 2014. Community structure, species diversity, and aboveground biomass of the Sundarbans mangrove swamps. Tropical Ecology, 55(3), 283–303.

Liu, K., Li, X., Shi, X., & Wang, S., 2008. Monitoring mangrove forest changes using remote sensing and GIS data With decision-tree learning. Wetlands, 28(2), 336–346. https://doi.org/10.1672/06-91.1/METRICS

Mafi-Gholami, D., Zenner, E. K., Jaafari, A., & Bui, D. T., 2020. Spatially explicit predictions of changes in the extent of mangroves of Iran at the end of the 21st century. Estuarine, Coastal and Shelf Science, 237, 106644. https://doi.org/10.1016/J.ECSS.2020.106644

Mahmood, H., Siddique, M. R. H., Rubaiot Abdullah, S. M., Costello, L., Matieu, H., Iqbal, M. Z., & Akhter, M., 2019. Which option best estimates the above-ground biomass of mangroves of Bangladesh: pantropical or site- and species-specific models? Wetlands Ecology and Management, 27(4), 553–569. https://doi.org/10.1007/S11273-019-09677-0/METRICS

Manna, S., Nandy, S., Chanda, A., Akhand, A., Hazra, S., & Dadhwal, V. K., 2014. Estimating aboveground biomass in Avicennia marina plantation in Indian Sundarbans using high-resolution satellite data. Https://Doi.Org/10.1117/1.JRS.8.083638, 8(1), 083638. https://doi.org/10.1117/1.JRS.8.083638

Maurya, K., Mahajan, S., & Chaube, N., 2021. Remote sensing techniques: mapping and monitoring of mangrove ecosystem—a review. Complex and Intelligent Systems, 7(6), 2797–2818. https://doi.org/10.1007/S40747-021-00457-Z/TABLES/8

Mitchard, E. T. A., Saatchi, S. S., Baccini, A., Asner, G. P., Goetz, S. J., Harris, N. L., & Brown, S., 2013. Uncertainty in the spatial distribution of tropical forest biomass: A comparison of pan-tropical maps. Carbon Balance and Management, 8(1), 1–13. https://doi.org/10.1186/1750-0680-8-10/FIGURES/6

Mulya, H., Santosa, Y., & Hilwan, I., 2021. Comparison of four species diversity indices in mangrove community. Biodiversitas Journal of Biological Diversity, 22(9), 3648–3655. https://doi.org/10.13057/BIODIV/D220906

Ngomanda, A., Engone Obiang, N. L., Lebamba, J., Moundounga Mavouroulou, Q., Gomat, H., Mankou, G. S., Loumeto, J., Midoko Iponga, D., Kossi Ditsouga, F., Zinga Koumba, R., Botsika Bobé, K. H., Mikala Okouyi, C., Nyangadouma, R., Lépengué, N., Mbatchi, B., & Picard, N., 2014. Site-specific versus pantropical allometric equations: Which option to estimate the biomass of a moist central African forest? Forest Ecology and Management, 312, 1–9. https://doi.org/10.1016/J.FORECO.2013.10.029

Pereira, F. R. de S., Kampel, M., Soares, M. L. G., Estrada, G. C. D., Bentz, C., & Vincent, G., 2018. Reducing Uncertainty in Mapping of Mangrove Aboveground Biomass Using Airborne Discrete Return Lidar Data. Remote Sensing 2018, Vol. 10, Page 637, 10(4), 637. https://doi.org/10.3390/RS10040637

Prakash Hati, J., Samanta, S., Rani Chaube, N., Misra, A., Giri, S., Pramanick, N., Gupta, K., Datta Majumdar, S., Chanda, A., Mukhopadhyay, A., & Hazra, S., 2021. Mangrove classification using airborne hyperspectral AVIRIS-NG and comparing with other spaceborne hyperspectral and multispectral data. Egyptian Journal of Remote Sensing and Space Science, 24(2), 273–281. https://doi.org/10.1016/J.EJRS.2020.10.002

Ramsey Ill, E. W., & Jensen, J. R., 1996. Remote Sensing of Mangrove Wetlands: Relating Canopy Spectra to Site-Specific Data.

Ricklefs, R. E., & Latham, R. E., 1993. Global Patterns of Diversity in Mangrove Floras.

Roy, P. S., & Ravan, S. A., 1996. Biomass estimation using satellite remote sensing data - An investigation on possible approaches for natural forest. Journal of Biosciences, 21(4), 535–561. https://doi.org/10.1007/BF02703218/METRICS

Research Letters, 14(2), 025002. https://doi.org/10.1088/1748-9326/AAF0DE

Santin-Janin, H., Garel, M., Chapuis, J. L., & Pontier, D., 2009. Assessing the performance of NDVI as a proxy for plant biomass using non-linear models: A case study on the kerguelen archipelago. Polar Biology, 32(6), 861–871. https://doi.org/10.1007/S00300-009-0586-5/METRICS

Spalding, M., 2010. World Atlas of Mangroves. World Atlas of Mangroves. https://doi.org/10.4324/9781849776608/WORLD-ATLAS-MANGROVES-MARK-SPALDING

Sreelekshmi, S., Nandan, S. B., Kaimal, S. V., Radhakrishnan, C. K., & Suresh, V. R., 2020. Mangrove species diversity, stand structure and zonation pattern in relation to environmental factors — A case study at Sundarban delta, east

Rutishauser, E., Noor'an, F., Laumonier, Y., Halperin, J., Rufi'ie, Hergoualch, K., & Verchot, L., 2013. Generic allometric models including height best estimate forest biomass and carbon stocks in Indonesia. Forest Ecology and Management, 307, 219–225. https://doi.org/10.1016/J.FORECO.2013.07.013

Sanderman, J., Hengl, T., Fiske, G., -, al, Chen, G., Chen, B., Yu, D., Lagomasino, D., Fatoyinbo, T., Lee, S., Feliciano, E., Trettin, C., Shapiro, A., & Mangora, M. M., 2019. Measuring mangrove carbon loss and gain in deltas. Environmental

coast of India. Regional Studies in Marine Science, 35, 101111. https://doi.org/10.1016/J.RSMA.2020.101111

Virgulino, P. C. C., Carneiro, D. N., Nascimento, W. R., Cougo, M. F., & Fernandes, M. E. B., 2020. Biomass and carbon estimation for scrub mangrove forests and examination of their allometric associated uncertainties. PLOS ONE, 15(3), e0230008. https://doi.org/10.1371/JOURNAL.PONE.0230008

Vo, Q. T., Oppelt, N., Leinenkugel, P., & Kuenzer, C., 2013. Remote Sensing in Mapping Mangrove Ecosystems — An Object-Based Approach. Remote Sensing 2013, Vol. 5, Pages 183-201, 5(1), 183–201. https://doi.org/10.3390/RS5010183

Wang, L., Sousa, W. P., Gong, P., & Biging, G. S., 2004. Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of Panama. https://doi.org/10.1016/j.rse.2004.04.005