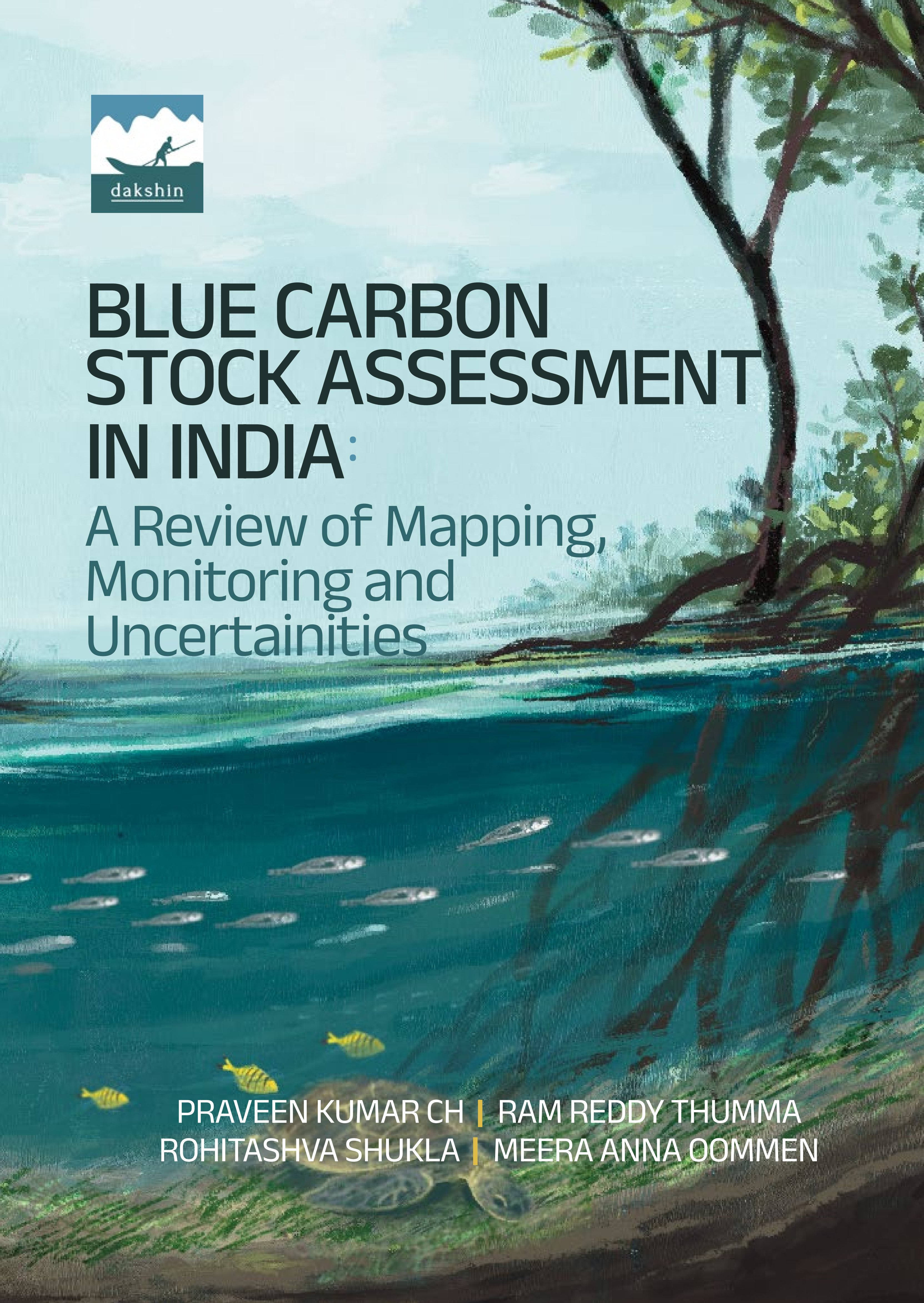

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BLUE CARBON STOCK ASSESSMENT IN INDIA:

A Review of Mapping, Monitoring and Uncertainities

PRAVEEN KUMAR CH | RAM REDDY THUMMA
ROHITASHVA SHUKLA | MEERA ANNA OOMMEN

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BLUE CARBON STOCK ASSESSMENT IN INDIA

A Review of Mapping, Monitoring and Uncertainities

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Contents

Executive Summary

Blue Carbon Ecosystems (BCEs), comprising mangroves, seagrasses, and salt marshes, serve as vital natural carbon sinks, capturing atmospheric carbon at rates far higher than most terrestrial systems. BCEs have carbon burial rates ranging from 138 to 226 g C m^{-2} per year, compared to just 4 to 5 g C m^{-2} per year in terrestrial forests. Carbon in these ecosystems is stored in both biomass and soils, with soil organic carbon (SOC) being the dominant pool, especially in seagrasses and mangroves. In the context of India's climate goals, particularly its commitment to achieving net-zero emissions by 2070, the assessment and conservation of BCEs have gained national significance. This report provides a comprehensive synthesis of current scientific knowledge and practices on mapping, monitoring, and estimating the carbon stocks of BCEs across India.

The first chapter of this report reviews methodologies for mapping, monitoring and accounting for blue carbon. To facilitate effective carbon accounting, the Intergovernmental Panel on Climate Change (IPCC) has developed a tiered framework, ranging from Tier-1 (simplified estimation using global emission factors) to Tier-3 (site-specific, high-resolution modelling and field validation). Although Tier-3 is more accurate, most Indian studies rely on Tier-1 due to financial and data constraints. In this context, remote sensing and GIS technologies have proven essential in scaling up BCE assessments. A wide array of satellite sensors, both active and passive, have been employed to map BCEs with varying degrees of accuracy. However, limited access to high-resolution commercial datasets forces most Indian assessments to rely on open-source imagery from platforms such as Landsat, Sentinel, and the Linear Imaging Self-Scanning (LISS) series from the Indian Space Research Organisation (ISRO). This chapter further examines various methodologies used in India for biomass estimation, including allometric equations specific to mangrove species. Conversion factors typically range from 0.45 to 0.5 for above-ground biomass (AGB) and around 0.39 for below-ground biomass (BGB) when converting biomass to carbon content. While these are effective, the absence of a standardised national conversion factor has led to considerable variation in carbon stock estimates. Such methodological inconsistencies become particularly significant when scaling up to national assessments.

The second chapter of this report explores the spatio-temporal dynamics of BCEs using datasets such as the India State of Forest Reports (ISFR), the National Wetland Inventory and Assessment (NWIA), and the Global Mangrove Watch (GMW). The ISFR indicates a net mangrove area gain of 530.68 km^2 between 2003 and 2023, while the GMW shows a net decline of 117.51 km^2 between 1996 and 2020. This stark contrast may be attributed to differences in methodology, classification thresholds, and data sources. States such as Gujarat and Maharashtra have recorded significant gains, possibly due to afforestation programs. In contrast, Tamil Nadu, Kerala, and West Bengal show substantial losses due to aquaculture expansion, urbanisation, and natural degradation. A further breakdown by canopy density reveals that moderate-density mangrove areas, especially in the Sundarbans, have declined, raising concerns about ecological degradation masked by area gains in national reports. A particularly concerning finding is the severe degradation of dense mangrove areas in the Andaman and Nicobar Islands, where 56% of mangrove forests have shown a reduction in canopy density over the last two decades. Although the overall area shows only a moderate decline, a closer analysis reveals a shift from very dense and moderately dense mangroves to more open and fragmented classes, underscoring the loss of ecological integrity and resilience in these critical ecosystems.

Salt marsh and seagrass ecosystems are less extensively studied, with the NWIA and limited published literature serving as primary data sources. Gujarat has shown a notable increase in mapped salt marsh areas, possibly due to improved classification methods, while Tamil Nadu and West Bengal report

declining extents. Seagrass data are fragmented, with significant variation across studies from Palk Bay, the Gulf of Mannar, and Lakshadweep. Overall, discrepancies in BCE mapping across different sources highlight the need for harmonised data protocols and long-term monitoring programs that integrate satellite data with ground validation.

The third chapter presents a meta-analysis of over 150 studies conducted between 1991 and 2024, providing a consolidated view of India's BCE carbon stock distribution. The vast majority of research has focused on mangroves, with comparatively limited attention to seagrasses and salt marshes. Sampling intensity varies widely by region. Eastern coastal states such as Odisha and West Bengal, along with the Andaman and Nicobar Islands, are relatively well studied, whereas key ecosystems in Andhra Pradesh, Goa, Karnataka, and Lakshadweep remain underrepresented. In several cases, the number of field plots is too limited to produce accurate spatial estimates, particularly in highly heterogeneous ecosystems like seagrass meadows and salt marshes. Using a compiled database of available mean carbon values, the report estimates carbon stocks for AGB, BGB, SOC, and litter pools, with an emphasis on ecosystem-specific variability.

Key findings indicate that India's mangroves store the majority of the national blue carbon, with the Sundarbans, Bhitarkanika, and the Andaman and Nicobar Islands identified as major carbon hotspots. SOC is the largest carbon pool, contributing over 60–70% of the total carbon in most mangrove areas. The estimated average carbon stock for mangroves is 89.48 t/ha, with national stock values ranging from 92.65 to 101.56 million tonnes depending on the spatial dataset used. Salt marshes and seagrasses, though less studied, are estimated to store 17.88 t/ha and 83.02 t/ha of carbon, respectively, with significant contributions from Gujarat and Tamil Nadu.

The final (fourth) chapter addresses key issues related to uncertainties associated with blue carbon measurement and monitoring in India, as well as the potential for integrating measurement with carbon financing and market mechanisms. With respect to measurement and monitoring, this study identifies several limitations, including spatial bias

Image Credits: Titus Immanuel

in sampling, inconsistent SOC depth reporting, variation in biomass to carbon conversion factors, and the absence of standardised national protocols. The study emphasises the need for harmonised methodologies, enhanced field validation, and the integration of high-resolution remote sensing (e.g., LISS-IV, NISAR) and artificial intelligence-based classification to improve BCE monitoring accuracy. Future research must address ecosystem-level data gaps, especially for seagrasses and salt marshes, and incorporate deep learning and spatial modelling frameworks. Policy implications include the need for formal integration of BCEs into national carbon accounting systems, inclusion in India's Nationally Determined Contributions (NDCs), and the establishment of centralised monitoring frameworks.

Beyond its scientific contributions, this report offers strategic value for advancing blue financing in India. By providing robust estimates of blue carbon stocks and identifying regional carbon hotspots, it establishes a foundation for developing carbon offset projects under voluntary and compliance markets. The integration of IPCC-compliant methodologies and geospatial datasets enables the creation of credible MRV (Measurement, Reporting, and Verification) systems, which are essential for accessing climate finance instruments such as blue bonds and nature-based solution funds. Furthermore, the identification of degraded but restorable BCE areas helps prioritise investment zones for ecosystem restoration tied to emission reduction goals. Importantly, the findings underscore the socio-ecological relevance of BCEs in supporting coastal livelihoods, food security, and resilience to natural disasters. By enabling ecosystem-based adaptation and community-led restoration initiatives, the report supports inclusive climate action and offers actionable insights for policy frameworks aimed at protecting biodiversity and improving the well-being of India's coastal populations.

List of Figures

List of Tables

List of Notations and Abbreviations

BCE	–	Blue Carbon Ecosystems
CMRI	–	Combined Mangrove Recognition Index
EVI	–	Enhanced Vegetation Index
EMVI	–	Enhanced Mangrove Vegetation Index
MFI	–	Mangrove Forest Index
MI	–	Mangrove Index
MRI	–	Mangrove Recognition Index
MMRI	–	Modular Mangrove Recognition Index
MNDWI	–	Modified Normalised Difference Water Index
MPVI	–	Mangrove Probability Vegetation Index
MVI	–	Mangrove Vegetation Index
NDMI	–	Normalised Difference Mangrove Index
NDVI	–	Normalised Difference Vegetation Index
NDWVI	–	Normalised Difference Wetland Vegetation Index
REMI	–	Red-Edge Mangrove Index
RVI	–	Ratio Vegetation Index
SOC	–	Soil Organic Carbon
SZDI	–	Sargassum and Zostera Distinguishing Index
ΔC_T	–	Total Carbon
ΔC_{AGB}	–	Carbon Stored as Above-Ground Biomass
ΔC_{BGB}	–	Carbon Stored as Below-Ground Biomass
ΔC_{DW}	–	Dead Wood Carbon
ΔC_L	–	Carbon in Litter

CHAPTER 1

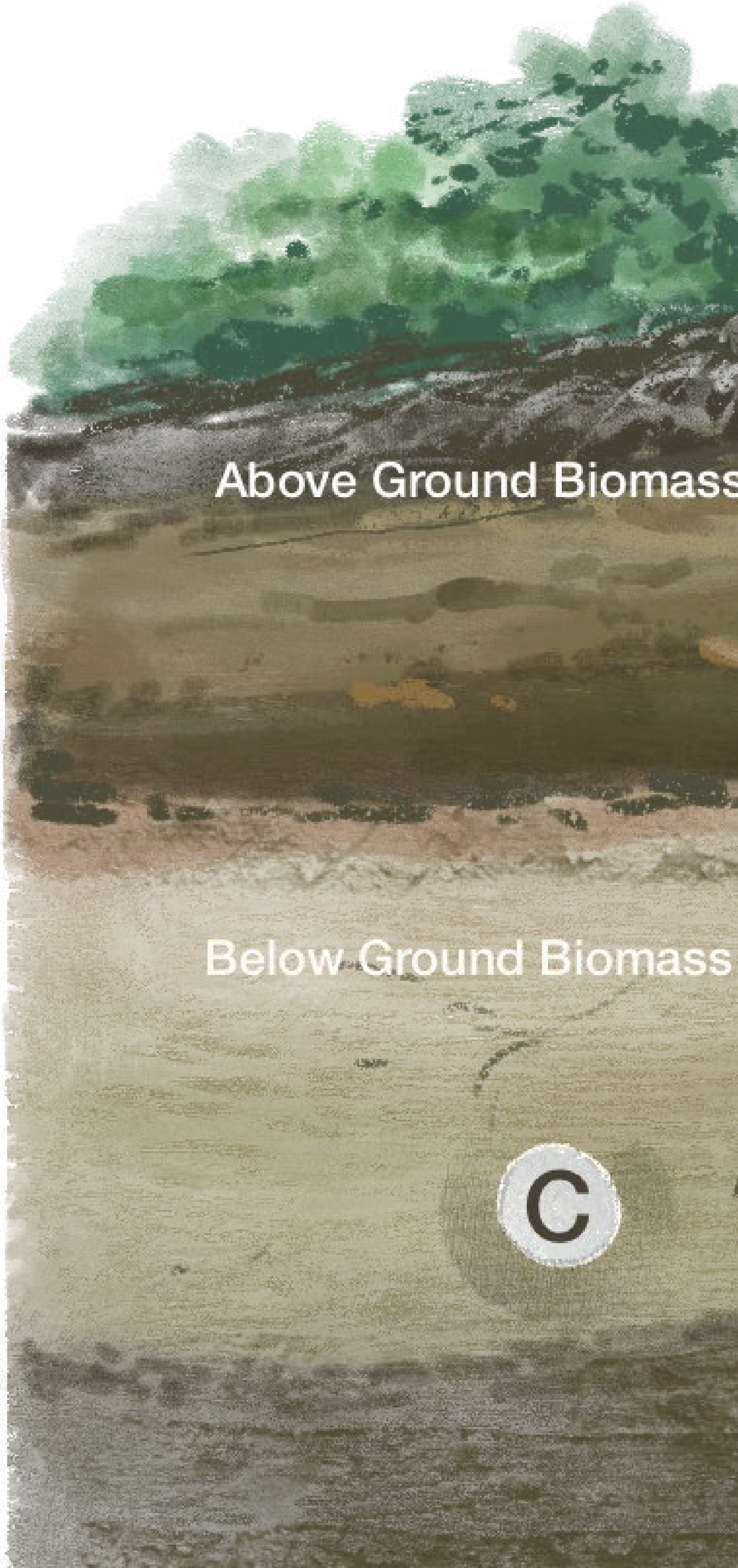
Approaches for Mapping, Monitoring and Accounting of Blue Carbon Ecosystems in India

1.1 Introduction

Blue carbon ecosystems (BCEs) refer to coastal and marine ecosystems that play a crucial role in capturing and storing large amounts of carbon from the atmosphere. Mangroves, seagrasses, and salt marshes, which have the potential to store carbon in coastal regions, are considered as BCE (Macreadie et al. 2019). The term ‘blue carbon’ emphasizes the significance of these coastal habitats in mitigating climate change by sequestering carbon in both above-ground biomass and in sediments below.

Mangroves, seagrasses, and salt marshes have the ability to capture and store carbon at rates much higher than many terrestrial ecosystems. Maurya et al. (2021a) reported that the average carbon burial rate of mangroves is 226 g C m^{-2} per year, and their rate of sequestration ranges from 20 to 949 g C m^{-2} per year, depending on age, density, and condition, among other factors. Similarly, they also reported that the average carbon burial rate of salt marshes is 218 g C m^{-2} per year, and their rate of sequestration ranges from 18 to 1713 g C m^{-2} per year owing to above mentioned factors. In the case of seagrasses, the average carbon burial rate is 138 g C m^{-2} per year, and their rate of sequestration ranges from 45 to 190 g C m^{-2} per year. Meanwhile, the average carbon burial rate of terrestrial ecosystems is significantly lower with key ecosystems such as temperate, tropical, and boreal forests sequestering only about 5.1, 4, and 4.6 g C m^{-2} per year, respectively (Maurya et al. 2021b). Therefore, from the carbon burial capacities listed above, it can be observed that BCEs are sequestering carbon from the atmosphere at a rate 30 to 45 times greater than terrestrial ecosystems. These figures underline the importance of BCEs in managing emissions along coastal areas.

The total carbon in BCE is mainly categorized into two types as the biomass pool and the soil organic carbon (SOC) pool. The carbon is primarily stored in the form of organic matter in the plants themselves and in the soils of coastal areas. When



these ecosystems are degraded or destroyed, the stored carbon is released back into the atmosphere, contributing to greenhouse gas emissions. Malerba et al. (2023) provided a governing relation to estimate the net change in the total carbon pool irrespective of any land use type, as shown in equation 1.

$$\Delta C_T = \Delta C_{AGB} + \Delta C_{BGB} + \Delta C_{DW} + \Delta C_L + \Delta C_{SOC} \quad (1)$$

Where, ΔC_T refers to the total carbon pool, ΔC_{AGB} is carbon stored as above ground biomass, ΔC_{BGB} is carbon stored as below ground biomass, ΔC_{DW} is dead wood carbon, ΔC_L accounts for carbon in litter, and ΔC_{SOC} is soil organic carbon

According to Malerba et al. (2023), the largest carbon store in BCE is soil organic carbon, which accounts for 68% in mangroves and 98% in seagrasses. They also mentioned that, unlike terrestrial soils which can store only organic carbon content, the soils present in BCE are capable of storing both inorganic and organic carbon. The ability of BCE soils to store both organic and inorganic carbon significantly enhances their carbon sequestration potential. While organic carbon accumulates in low-oxygen soils, inorganic carbon like calcium carbonate remains stable over time. This dual storage makes BCEs valuable for blue carbon finance, climate mitigation, and coastal resilience. BCE worldwide occupies around 49 million hectares, which is less than 5% of the world's land area (Maurya et al. 2021b). The global coverage of BCE was accounted for in the year 2019 by Maurya et al. (2021b), revealing that mangroves occupy around 1.4 lakh km², seagrasses spread across 3.2 lakh km², and salt marshes are observed in nearly 51,000 km². They also reported that the mangrove cover is potentially capable of storing carbon from 3100 to 4400 tons of CO_2 emissions per hectare. Since 1990, the world has lost around 20% of its mangrove cover, nearly 50% of its seagrasses, and about 25% of its salt marshes (Maurya et al. 2021b). The annual rate of loss at a global scale is in the range of 1 to 3% for mangroves, 1 to 2% for salt marshes, and around 0.9% in the case of seagrasses (Duarte et al. 2013).

Gupta et al. (2024) estimated the extent of mangroves and salt marshes in India for the year 2018-19. They reported that the mangrove area in India is 5139.7 km2, and the salt marsh area is 1497.7 km². Based on the above values, India contributes 3.7% of the global mangrove cover and 2.9% of the global salt marshes. Therefore, it underscores the necessity to map, monitor, and account for these rich resources within the country to meet India's net-zero emission targets. The importance of mapping and monitoring BCE in India is discussed in the following section.

1.2 BCEs Mapping, Monitoring and Accounting: A Necessity for India

According to the latest report on greenhouse gas (GHG) emissions from all countries worldwide by Crippa et al. (2023), India emitted 3.9 gigatons of CO_2 eq (7.3% of global emissions), making it the third-largest emitter after China and the United States (Figure 1.1). India announced its commitment to achieving net-zero emissions by 2070 during the 26th session of the Conference of the Parties (COP26) held in Glasgow, United Kingdom. India has also unveiled an action plan to reach this net-zero target by 2070. The key proposed measures include adopting sustainable methods in fisheries, marine research, and coastal tourism. Additionally, India aims to foster the blue economy to promote development in coastal regions in a sustainable and responsible manner, as reported by the Ministry of Science & Technology in its press release (Release ID: 1961797).

Akhand et al. (2023) quantified the total carbon stock at the ecosystem level for major mangrove forests in West Bengal, Odisha, Tamil Nadu, and Karnataka, covering an area of 2,417 km². They estimated India's total BCEs stock at 67.35 million tons by extrapolating the carbon stock values from these regions to the national mangrove cover of 4,991 km². According to Akhand et al. (2023), mangroves alone contribute approximately 67 million tons to the total carbon stock, with the remaining portion attributed to Indian seagrasses and salt marshes. Furthermore, they reported that India possesses a sequestration potential of 245.7 megatons of atmospheric carbon through its mangrove ecosystems. This suggests that India's BCE resources could sequester approximately 6.3% of the country's annual greenhouse gas (GHG) emissions.

The BCEs in India comprise a total of 46 species of mangroves, 16 species of seagrasses, and 15 species of saltmarshes (Akhand et al., 2023). These ecosystems act as nurseries, breeding grounds, shelters, and refuges for marine creatures, providing protection from heavy flows and severe tides. Duke and Larkum (2008) emphasized that sea turtles (e.g. green sea turtles Chelonia mydas) depend on seagrass beds for food during low tides and consume mangrove propagules during high tides. According to Duke and Larkum (2008), BCE ecosystems present at river estuaries and nearshore coastal areas

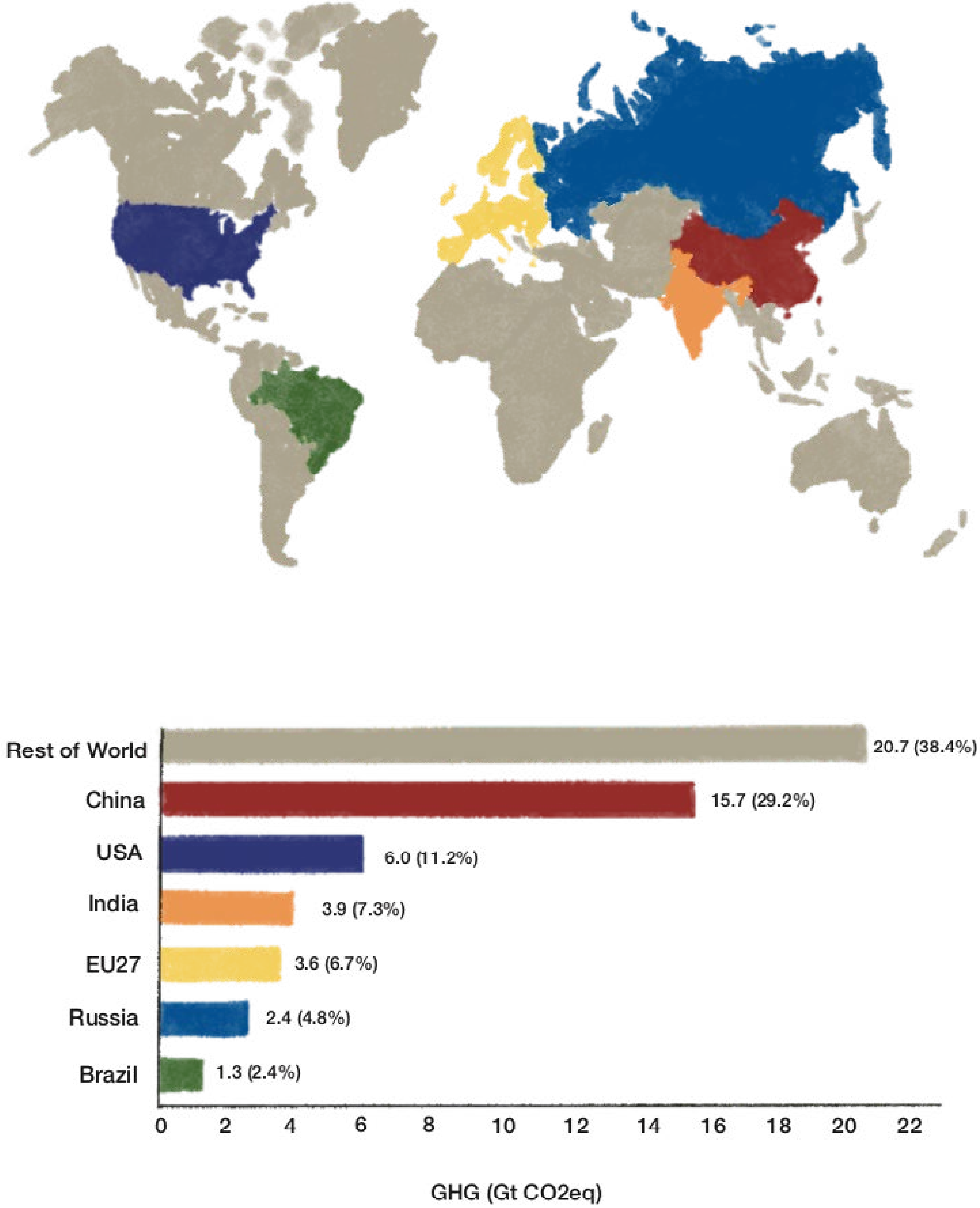


Figure 1.1: Regional Distribution of Global Greenhouse Gas Emissions (Gt CO_2eq)

are deeply interconnected and dependent. Thus, these ecosystems must be viewed as primary sources for marine life production; if one is affected, its impact is likely to propagate across complex trophic linkages. With India boasting one of the longest shorelines globally, nearly 11,099 km (Survey of India, 2025), the presence of BCE along the coast helps maintain coastal water quality, prevents coastal erosion from high tides, and provides livelihoods for coastal communities. Furthermore, India stands to benefit economically by leveraging BCE, for instance, by improving estuaries as parks to boost the country's coastal tourism targets. Although there are numerous benefits associated with BCE, these ecosystems are currently facing threats from various anthropogenic activities and natural calamities (Chanda and Akhand, 2023).

The impact of tropical cyclones on mangroves in the Sundarbans Forest over the last two decades has been studied by Chanda and Akhand (2023). They illustrated that although severe cyclones commonly cause significant destruction to BCEs in the Sundarbans, rapid regeneration of these ecosystems after cyclones have been observed in the past. However, recent observations suggest a substantial increase in global sea water temperature due to the effects of global warming and climate change, as reported by the IPCC in 2013 (Hiraishi et al., 2014). Additionally, Chanda and Akhand (2023) mentioned that anomalous increases in sea water temperature, observed at depths of up to 600m in the Bay of Bengal, have created favourable conditions for the occurrence of more cyclones in this region with heavier intensity in recent times. Given that India's coastline is predominantly along the Bay of Bengal, this poses a serious threat to BCE in this region from tropical cyclones.

Another significant threat to BCE in India is the increased salinity at river estuaries (Chanda and Akhand, 2023). The increased salinity in the soils beneath BCE is attributed to reduced freshwater flow, as most rivers in India have transitioned from perennial to intermittent (Jain et al., 2014). Although the National Green Tribunal (NGT) in India has directed all state governments to maintain a minimum of 15-20% of the average seasonal river discharge as environmental flow to address ecological imbalances in these estuaries (The Ministry of Environment, Forest and Climate Change, Govt. of India, Press Release ID: 1782294), many river ba-

sins are observed to be dry during the non-monsoon period, as streamflow in all river basins, which serves as a source of freshwater to BCE estuaries, is solely monsoon-driven. Consequently, due to the prolonged duration of non-monsoon periods (October to May in a water year[1]) in India, the soils beneath BCE lack freshwater resources from upstream, further intensifying the intrusion of seawater and accelerating soil salinity.

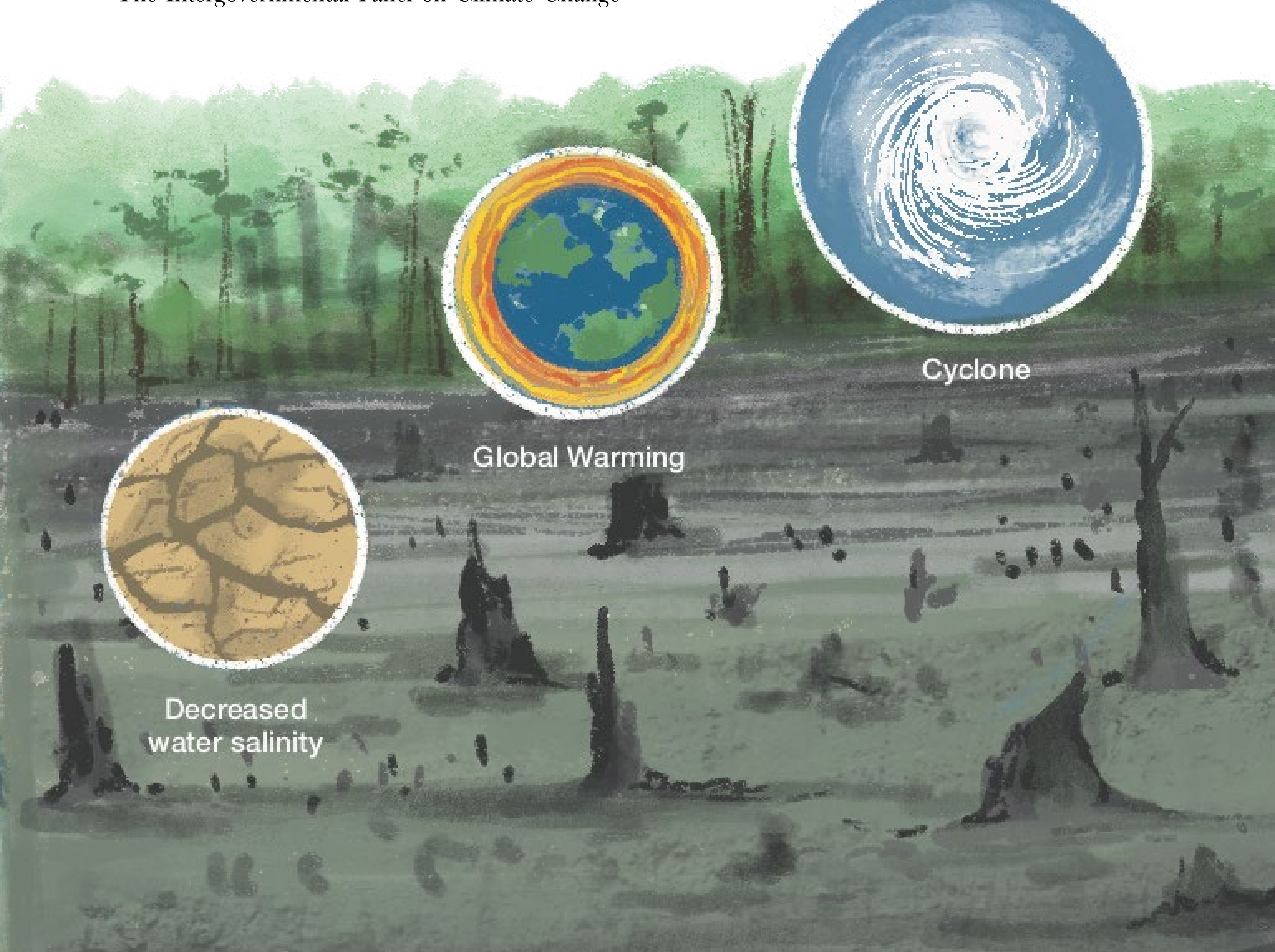
In addition to the natural threats discussed above, urbanization and population growth are also equally imposing various anthropogenic threats to BCEs in India. Consequently, the Intergovernmental Panel on Climate Change (IPCC) has formulated a set of guidelines to protect BCE and has also provided a framework for assessing carbon stocks from BCE. The IPCC framework and its carbon stock mechanism are discussed in the following section.

1.3 IPCC Framework for Assessing Carbon Stock in Coastal Environments

The Intergovernmental Panel on Climate Change (IPCC) was established in 1988 to support the United Nation Framework Convention on Climate Change (UNFCCC) by providing methodologies for quantifying national greenhouse gas inventories. Although the IPCC first issued guidelines for national greenhouse gas inventories in 2006, the complete framework for quantifying carbon stock in coastal wetlands was provided in its supplement report in 2013 (Hiraishi et al. 2014). According to the 2013 supplement to the 2006 IPCC guidelines, if the carbon stock assessment pertains to coastal areas, the relevant methodologies are defined in Chapter 4 of the IPCC wetlands supplement report by Hiraishi et al. 2014.

The IPCC classified assessment methodologies into three categories. The Tier-1 methodology represents the simplest approach with general relations and global standards for different emission factors, which eliminates the need for collecting scientific field data to estimate carbon stock values. However, as pointed

[1]A water year in India refers to the 12-month period from June 1st (typically considered the start of the southwest monsoon) to May 31st of the following year.



out by Hiraishi et al (2014), this methodology tends to accumulate errors at every stage of carbon stock estimation, from ecosystem mapping to total carbon stock assessment, and is therefore limited to large-scale applications (state or national level). The flow chart illustrating the appropriate Tier-1 methodology for estimating carbon stocks under various management practices along the coastal regions is shown in Figure 1.2 (Hiraishi et al. 2014). The Tier-2 methodology is similar to Tier-1 but considers field data to reflect site-specific conditions, thereby increasing assessment accuracy compared to Tier-1.

On the other hand, Tier-3 methodology involves spatially calibrated models with site-specific field data to quantify carbon stocks. Unlike Tier-1, which treats the total area as a homogeneous unit, Tier-3 represents the real conditions of the site at a local scale.

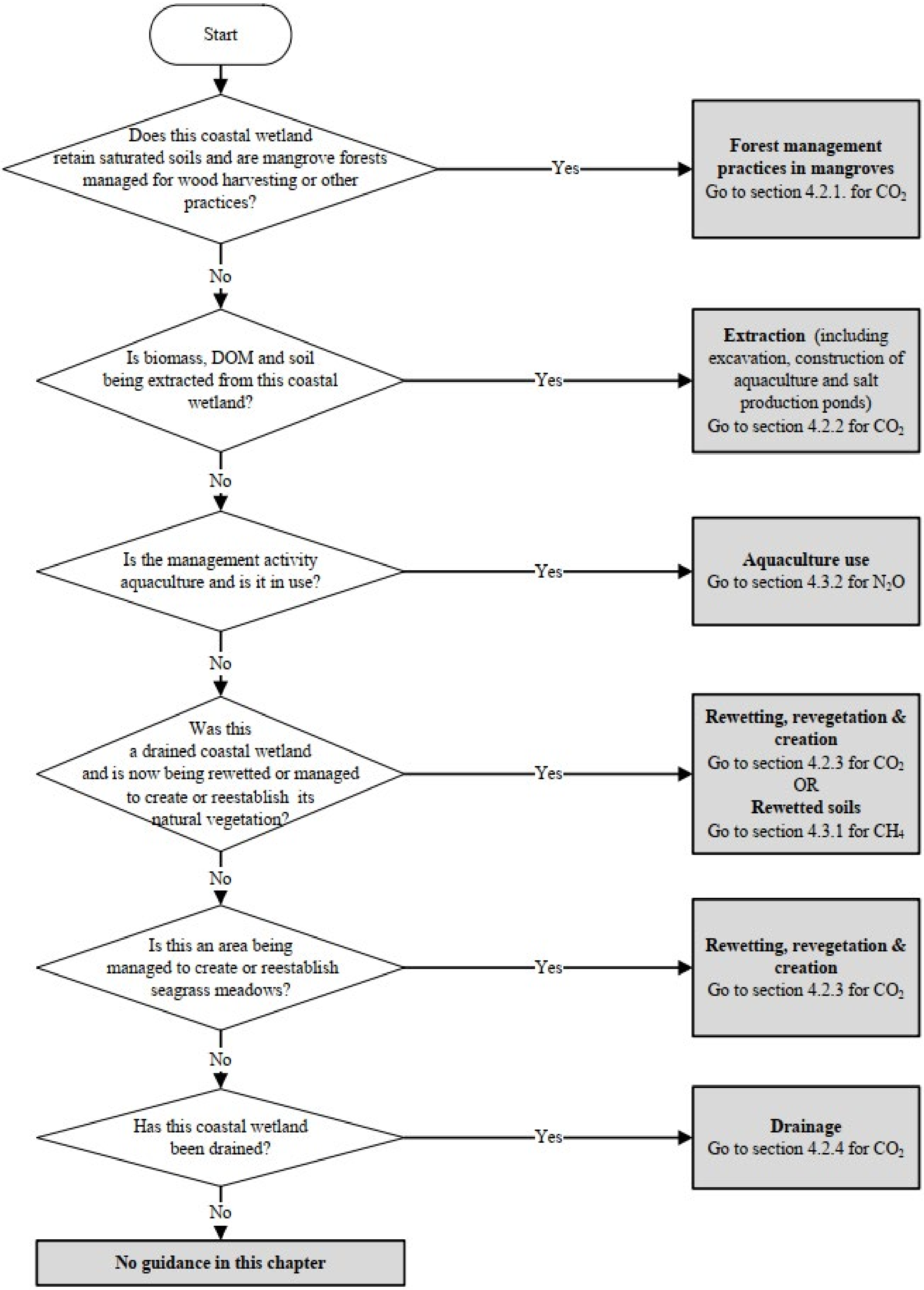


Figure 1.2: Flow chart to select the appropriate Tier-1 methodology for different management practices in coastal regions (Source: Hiraishi et al. 2014).

However, this approach to carbon assessment requires high-resolution datasets and complex field data collection, which may not be financially feasible for large-scale applications. Although the IPCC recommends the Tier-3 methodology for estimating carbon stocks, researchers who have estimated stock values at national and global scales have often relied on the Tier-1 approach due to data scarcity and limited financial resources (Hiraishi et al. 2014). In recent times, advancements in remote sensing technology have enabled the acquisition of large-scale land cover imageries with moderate to high spatial resolution, allowing for more accurate mapping of BCE with optimum resources. Given the significance of this new technology in mapping BCE, a detailed discussion is provided in the following section on various geospatial tools and techniques available for assessing BCE resources in India. Additionally, further discussion on the IPCC framework, including different categories of methodologies for assessing carbon stock values, is carried out in the later part of this report.

1.4 Remote Sensing and Geospatial Tools in BCEs Accounting: An In-depth Exploration

The process of acquiring scientific data to map BCE resources comprises two modes (Kerle et al., 2004). One involves collecting in-situ data using various field instruments and survey strategies, providing reliable information for accurate estimations. The other mode utilizes remote sensing techniques employing imagery acquired from sensors mounted on flying objects such as drones, aircraft, and satellites (Lillesand, 1990). As discussed in the previous section, large-scale resource mapping is not feasible with traditional in-situ data collection methods due to the requirement for more manpower, resources and time. However, advancements in remote sensing technology over the last three decades have made land data collection easier, overcoming these limitations. A list of remote sensing datasets available for mapping BCE resources in India is presented in Table 1.1.

The remote sensing data acquisition sensors are classified into two types: active and passive (Figure 1.3). Passive sensors (e.g., QuickBird, IKONOS, SPOT, WorldView, GeoEye, KOMPSAT, Landsat, Sentinel-2, LISS, etc., as listed in Table 1.1) rely on light emitted from the sun and capture land imagery by detecting the reflected energy from earth's surface. On the other hand, active sensors (e.g., ALOS, RADARSAT, Sentinel-1, NISAR, etc., listed in Table 1.1) emit their own source of light onto the earth's surface to capture imagery. Thus, active remote sensing sensors have an advantage over passive sensors in providing data under any weather conditions. Furthermore, it is important to consider four types of data resolutions: spatial, spectral, temporal, and radiometric, when mapping the earth's features, as different objects exhibit various responses to the same incident light. Simpson et al. (2022) discussed the importance of

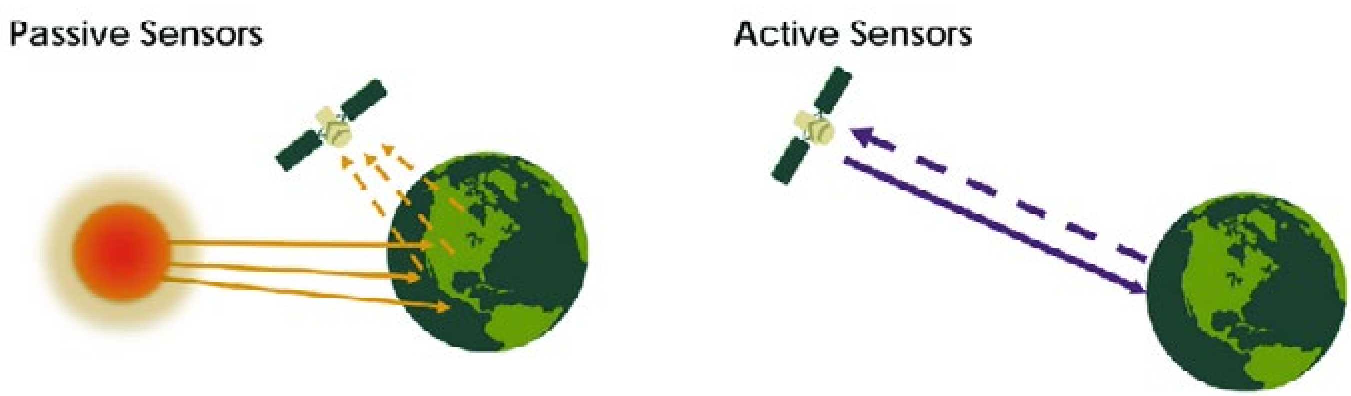


Figure 1.3: Active and Passive Remote Sensing process (Source: Bhooleshwari et al. 2024)

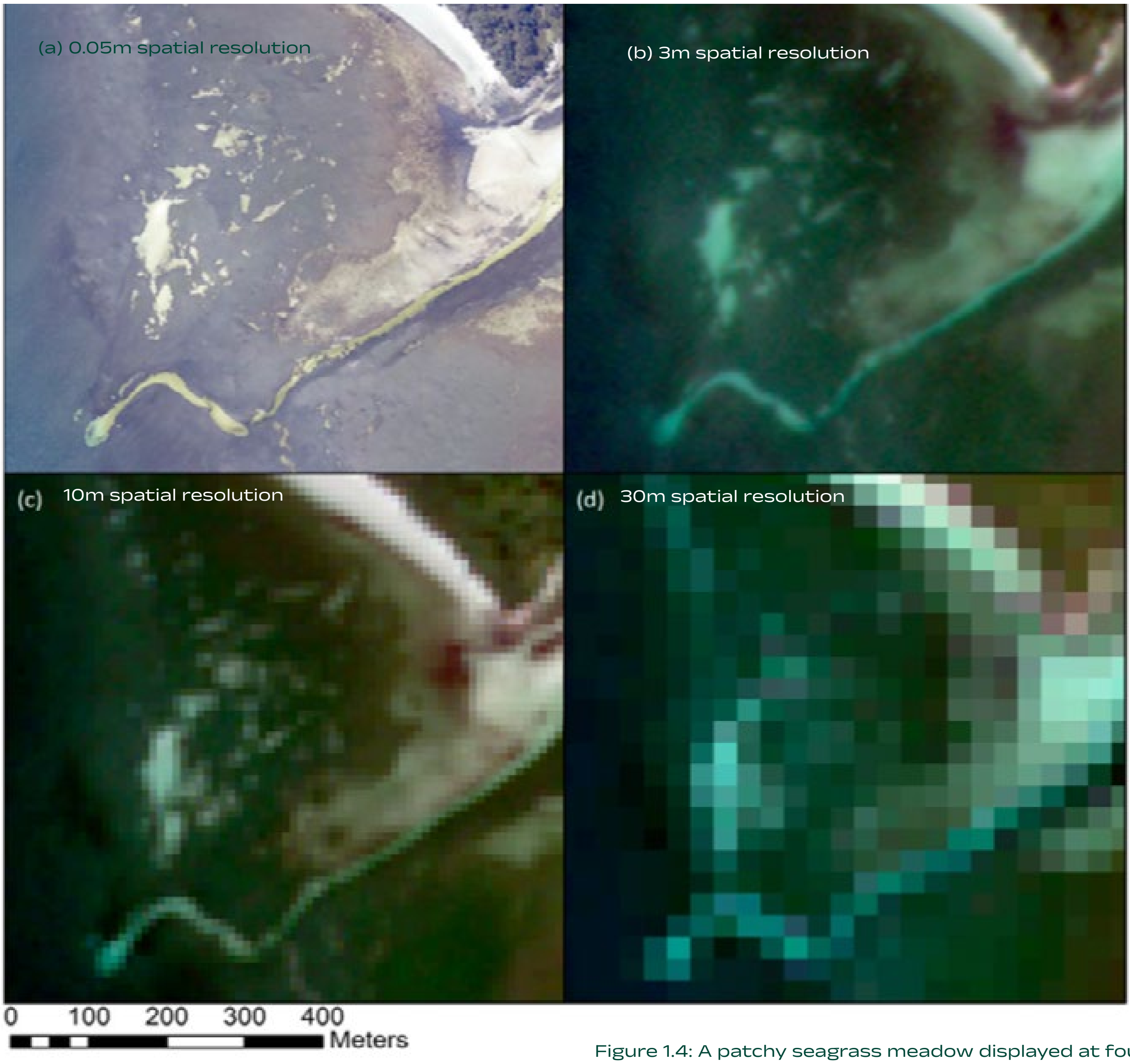


Figure 1.4: A patchy seagrass meadow displayed at four different spatial resolutions. (Source: Simpson et al. 2022)

spatial resolution (the ground area represented by a pixel in an image) in mapping seagrass meadows by comparing ArborCam aerial data (0.05m), PlanetScope aerial data (3m), Sentinel-2A (10m), and Landsat-8 data (30m) imagery (Figure 1.4). They illustrated the ease of mapping seagrass meadows using high spatial resolution data (pixel size < 1m) and also discussed the challenges associated while working with moderate/coarse spatial resolution data (pixel size > 10m).

More recently, Canty et al. (2025) demonstrated that pixel resolution strongly influences mangrove extent and carbon stock estimates. At the site level in Belize, mapped mangrove area decreased from 66.9 ha at 25 m resolution to 55.9 ha at 3 m resolution, resulting in a 19.7% reduction in overestimated carbon stocks. At the national scale, a shift from 25 m to 10 m resolution led to a 192.2 km^2 decrease in mangrove extent and a 9.82 million tonne (36.4%) reduction in carbon estimates. Globally, mangrove extent declined by approximately 2,200 km^2 (from 147,359 km^2 to 145,068 km^2), corresponding to a 120 million tonne (1.6%) decrease in carbon stock. These findings underscore the critical role of spatial resolution in ensuring accurate BCE mapping and carbon accounting.Spectral resolution refers to the number of bands or images captured by a sensor, which detects reflected light at different wavelengths from the same land region.

Table 1.1: List of remote sensing datasets available for mapping BCE resources in India.

Data availability mode	Type of acquisition	Type of sensor	Satellite Name	Spectral Bands and their wavelengths (λ)	Spatial Resolution (m)	Revisit period (days)	Starting year of data availability
Commercial data	Airborne	Optical high spatial resolution	Unmanned Aerial Vehicle (UAV)	Desired bands	0.1	Collection as per the requirement	2000
			HyMap	128 bands (440-2540 nm)	5		
			CASI	25 bands (350-2500 nm)	1		
	Space borne		QuickBird	Panchromatic (450 - 900 nm)	0.61	1.5 – 3	Oct 2001
				Blue (450 - 520 nm) Green (520 - 600 nm) Red (630 - 690 nm) NIR (760 - 900 nm)	2.4		
			IKONOS	Panchromatic (450 - 900 nm)	1	1.5 – 3	Sep 1999
				Blue (450 - 530 nm) Green (520 - 610 nm) Red (640 - 720 nm) NIR (760 - 860 nm)	4		
			SPOT-4	Panchromatic (610 - 680 nm)	10	2 – 3	Mar 1998
				Green (500 - 590 nm) Red (610 - 680 nm) NIR (790 - 890 nm) SWIR (1.58 – 1.75 µm)	20		
			SPOT-5	Panchromatic (480 - 710 nm)	5	2 – 3	May 2002
				Green (500 - 590 nm) Red (610 - 680 nm) NIR (780 - 890 nm)	10		
				SWIR (1.58 – 1.75 µm)	20		
			WorldView-2	Panchromatic (480 - 710 nm)	0.46	1.1	Oct 2009
				Coastal blue (400-450 nm) Blue (450-510 nm) Green (510-580 nm) Yellow (585-625 nm) Red (630-690 nm) Red Edge (705-745 nm) NIR1 (770-895 nm) NIR2 (860-1040 nm)	1.8		
			GeoEye-1	Panchromatic (450 - 900 nm)	0.41	2 – 3	Sep 2008
				Blue (450 - 510 nm) Green (520 - 580 nm) Red (655 - 690 nm) NIR (780 - 920 nm)	1.64		

Data availability mode	Type of acquisition	Type of sensor	Satellite Name	Spectral Bands and their wavelengths (λ)	Spatial Resolution (m)	Revisit period (days)	Starting year of data availability
Commercial data	Space borne	Optical high spatial resolution	KOMPSAT -2	Panchromatic (500 - 900 nm)	1	2 – 3	July 2007
				Blue (450 - 520 nm) Green (520 - 600 nm) Red (630 - 690 nm) NIR (760 - 900 nm)	4		
Open-source data or free			ALOS	PRISM- Panchromatic (500 - 900 nm)	4	2	Jan 2006
				AVNIR- Blue (420 - 500 nm) Green (520 - 600 nm) Red (610 - 690 nm) NIR (760 - 890 nm)	10		
		Optical multispectral	Landsat 5	Blue (0.45 - 0.52 μm) Green (0.52 - 0.60 μm) Red (0.63 - 0.69 μm) NIR (0.76 - 0.90 μm) SWIR (1.55 - 1.75 μm) MIR (2.08 - 2.35 μm) TIR (10.40 - 12.50 μm)	30	16	Apr 1984 – May 2013
			Landsat 7	Panchromatic (520 - 900 nm)	15	16	Apr 1999
				Blue (0.45 - 0.52 μm) Green (0.52 - 0.60 μm) Red (0.63 - 0.69 μm) NIR (0.77 - 0.90 μm) SWIR (1.55 - 1.75 μm) MIR (2.09 - 2.35 μm) TIR (10.40 - 12.50 μm)	30		
			Landsat 8&9	Panchromatic (520 - 680 nm)	15	16	Landsat-8 in Feb 2013, Landsat-9 in Sep 2021
				Coastal aerosol (0.43 - 0.45 μm) Blue (0.45 - 0.51 μm) Green (0.53 - 0.59 μm) Red (0.64 - 0.67 μm) NIR (0.85 - 0.88 μm) SWIR (1.57 - 1.65 μm) MIR (2.11 - 2.29 μm) Cirrus (1.36 – 1.38 μm) TIR1 (10.6 - 11.19 μm) TIR2 (11.5 - 12.51 μm)	30		
			Sentinel-2	Blue (490 nm) Green (560 nm) Red (665 nm) NIR (842 nm)	10	5 – 10	June 2015
Open-source data or free	Space borne	Optical multispectral	Sentinel-2	NIR1 (705 nm) NIR2 (740 nm) NIR3 (783 nm)	20		

Data availability mode	Type of acquisition	Type of sensor	Satellite Name	Spectral Bands and their wavelengths (λ)	Spatial Resolution (m)	Revisit period (days)	Starting year of data availability
				NIR4 (865 nm) MIR1 (1610 nm) MIR2 (2190 nm)			
				Coastal aerosol (443 nm) SWIR1 (940 nm) SWIR2 (1375 nm)	60		
			Indian Resource Sat (IRS)1D Linear Imaging Self Scanning (LISS-III)	Green (0.52 - 0.59 µm) Red (0.62 - 0.68 µm) NIR (0.77 - 0.86 µm) SWIR (1.55 - 1.70 µm)	23.5	24	Sep 1997
			Indian Resource Sat (IRS-2) Linear Imaging Self Scanning (LISS-IV)	Green (0.52 - 0.59 µm) Red (0.62 - 0.68 µm) NIR (0.77 - 0.86 µm)	5.8	5	Apr 2011
			Earth Observation (EO)-1	Hyperion- 220 bands (0.357 to 2.576 µm)	30	16	Nov 2000 to 2017
		Synthetic Aperture Radar (SAR)	ALOS	L-Band with multi-polarisation and multi-look (23cm)	10	46	Jan 2006
			ALOS-2	Spotlight (84 MHz) with single polarisation	1-3	14	May 2014
				Stripmap- Ultrafine (84 MHz) with single and dual polarisations	3		
				Stripmap- Highly sensitive (42 MHz) with full polarisations	6		
				Stripmap- Fine (28 MHz) with full polarisations	10		
				ScanSAR- Normal (14 & 28 MHz) with single and dual polarisations	100		
				ScanSAR- Wide (14 MHz)	60		
			RADARSAT-2	C-band (5.55 cm)	3	24	Dec 2007
Open-source data or free	Space borne	Synthetic Aperture Radar (SAR)	Sentinel-1	C-band (5.55 cm)	5	6	Apr 2014
			NASA-ISRO SAR (NISAR)	L-band (24 cm) S-band (10 cm)	7	12	June 2025

Data availability mode	Type of acquisition	Type of sensor	Satellite Name	Spectral Bands and their wavelengths (λ)	Spatial Resolution (m)	Revisit period (days)	Starting year of data availability
			BIOMASS	P-band (69 cm)	25	-	2024 (Planned)
			TanDEM	L-band (23.6 cm)	7	16	2028 (Planned)
Data collection from field surveys	Ground and Aerial	Light Detection and Ranging (LiDAR)	Aeroplane, UAV	Desired bands	0.1	Collection as per requirement	2000

Source: Pham et al. (2019) – Table updated with the present available information. NIR- Near infrared, SWIR- Shortwave infrared, MIR- Mid infrared, TIR- Thermal infrared.

This enables the classification of distinct land features, such as vegetation types, water bodies, soil, buildings, and roads, as objects reflect differently under varying wavelengths. Therefore, it is crucial to consider imagery acquired at appropriate wavelengths to map BCE resources effectively; for instance, vegetation often exhibits higher reflectance in the near-infrared (NIR) compared to green wavelengths.

As a result, researchers widely utilize multispectral sensors (with more than five bands, e.g., ALOS, Landsat, Sentinel, LISS, etc., as listed in Table-1.1) and hyperspectral sensors (with more than twenty bands, e.g., HyMap, CASI, EO-1, etc., as listed in Table-1.1) for mapping BCE resources worldwide (Geevarghese et al. 2018; Gupta et al. 2018; Jia et al. 2019; Pham et al. 2019; Ha et al. 2020; Zoffoli et al. 2020; Ha et al. 2021; Chen et al. 2023; Song et al. 2023; Suardana et al. 2023; Yang et al. 2023; Vasquez et al. 2024).

Further, temporal resolution refers to the time taken by a satellite or sensor to revisit the same location on the ground. The revisit time of a sensor is crucial for monitoring spatial changes and long-term decadal variations of BCE. The revisit periods of different satellites available for BCE mapping are shown in Table-1.1.

As can be inferred from Table-1.1, satellites with shorter revisit periods provide more images in a year, enabling users to choose higher-quality data, especially during the monsoon when clouds obstruct the visibility of land features in images. Additionally, satellites with high radiometric resolution (the sensor's ability to differentiate the energy reflected or emitted from land features at various levels) provide more variations in the image's digital number (DN) values for different features, making it possible to distinguish distinct objects within the image. With advancements in capturing technology, almost all sensors introduced after 2010 provide data with 16-bit resolution (e.g., Landsat-5 introduced in 1984 with 4-bit resolution, Landsat-7 introduced in 1999 with 8-bit resolution, and Landsat-8 introduced in 2013 with 16-bit resolution, as shown in Table-1.1).

Apart from the aforementioned data properties, it is worth mentioning that out of all the satellites reported in Table-1.1, a few sensors capture images with high spatial and spectral properties (HyMap, CASI, QuickBird, IKONOS, SPOT, WorldView, GeoEye, COMSAT, and LiDAR), but their data is not freely available to users, which requires additional financial assistance. This acts as a major barrier for research groups aiming to map and assess BCE carbon stock in India. Therefore, large-scale BCE carbon stock assessment studies around the world and in India are mostly carried out by utilizing open-source, moderate to coarse resolution datasets (ALOS, Landsat, Sentinel, LISS, EO, RADARSAT, and NISAR), as shown in Table 1.1 (Pham et al. 2019; Araya-Lopez et al. 2023).

In general, carbon stock assessment includes three stages: first, mapping the area of each ecosystem; next, estimating the total biomass at every site level; and lastly, computing the total carbon stock for every region using various conversion factors (IPCC 2013 guidelines, Hiraishi et al. 2014). The methodologies available for BCE carbon stock assessment at all three stages listed above are discussed in the following sections.

1.5 Diverse Approaches: Mapping Methodologies for BCEs Analysis

In blue carbon ecosystem (BCE) analysis, various methodologies (Figure 1.5) have been employed to map these crucial environments, yielding a range of accuracy metrics (see Table 1.2) including Overall Accuracy (OA) (the percentage of correct classifications) and Kappa (coefficient quantifying the agreement between predicted and actual results, accounting for chance agreement). Rouse et al. (1974) and Patil et al. (2015) examined mangroves in the USA and India, respectively, but did not provide accuracy data (see Table 1.2). Gupta et al. (2018) reported overall accuracies (OAs) of 0.56 to 0.867 for mangrove sites in India. Gupta et al. (2024) studied mangroves across Indian wetlands without specifying accuracy. Sun et al. (2023) achieved high accuracies for mangroves in Guangxi Province, China, with an OA > 0.89 and Kappa > 0.74. Dolbeth et al. (2023) found a FI Score of 0.89 for seagrass in the Minho River Estuary.

Suardana et al. (2023) reported an OA of 0.984 and Kappa of 0.961 for Benoa Bay, Indonesia. Lin et al. (2023) reported variable accuracies for Thailand's mangroves, with an OA of 0.762 and Kappa of 0.435, while Cambodia had lower values (OA = 0.543, Kappa = 0.139). Myanmar's mangroves had high accuracy (OA = 0.951, Kappa = 0.902), and India's mangroves showed an OA of 0.901 and Kappa of 0.795. Madagascar's mangroves had an OA of 0.914 and Kappa of 0.829. Liu et al. (2024) reported no data for Hangzhou Bay, China. Madagascar's mangroves had an OA of 0.914 and

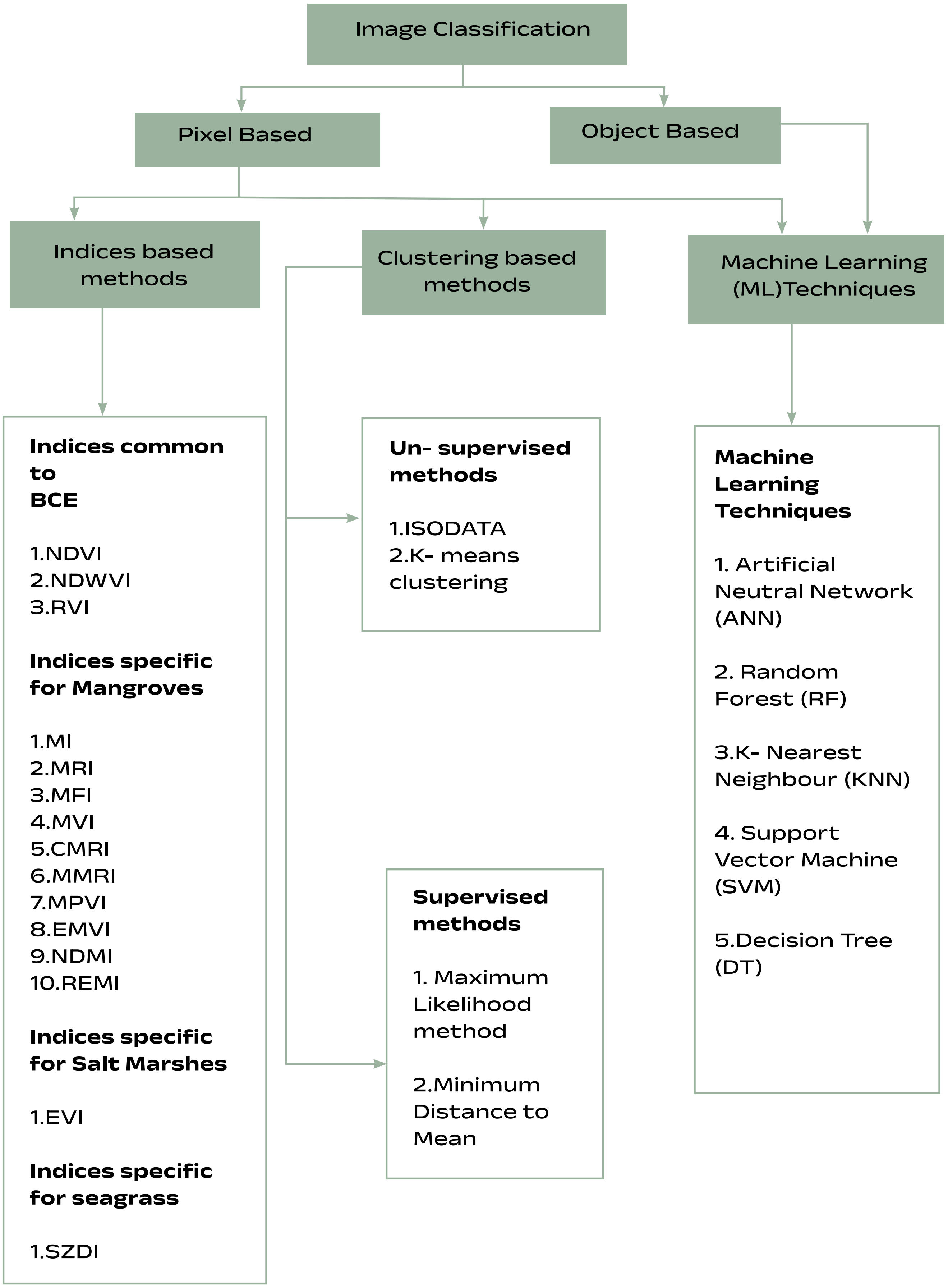


Figure 1.5: Flow chart illustrating methods available for mapping blue carbon ecosystems.

Table 1.2: List of indices available for mapping BCE

S.No.	Indices full name with equation	Location of study area	Reported mapping accuracy	Source
1.	$NDVI = \frac{NIR - Red}{NIR + Red}$	Great Plains mangrove corridor, USA.	No data.	*Rouse et al. (1974)
		Thane mangrove creek, Mumbai, India.	No data.	Patil et al. (2015)
		Mangrove forests of 3 sites in India. 1. Sundarbans, West Bengal. 2. Bhitarkanika, Odisha. 3. Andaman and Nicobar Islands.	Site1: OA = 0.56 Site2: OA = 0.597 Site3: OA = 0.531	Gupta et al. (2018)
		Mangroves in the entire wetlands of India	No data.	Gupta et al. (2021)
		Mangroves in Guangxi province, China.	OA > 0.89, Kappa > 0.74	Sun et al. (2023)
		Seagrass in the Minho River estuary, near Portugal and Spain border.	FI Score = 0.89	Dolbeth et al. (2023)
		Mangrove forest of Benoa Bay, Indonesia.	OA = 0.984, Kappa = 0.961	Suardana et al. (2023)
		Mangroves in Thailand	OA = 0.762, Kappa = 0.435	Lin et al. (2023)
		Mangroves in Cambodia	OA = 0.543, Kappa = 0.139	
		Mangroves in Myanmar	OA = 0.951, Kappa = 0.902	
		Mangroves in India	OA = 0.901, Kappa = 0.795	
		Mangroves in Honduras	OA = 0.68, Kappa = 0.418	
		Mangroves in Madagascar, Africa.	OA = 0.914, Kappa = 0.829	
		South coast of Hangzhou Bay, China.	No data.	Liu et al. (2024)

S.No.	Indices full name with equation	Location of study area	Reported mapping accuracy	Source
2.	$EVI = 2.5 * \left(\frac{NIR - Red}{NIR + 6Red - 7.5Blue + 1} \right)$	Salt marsh wetlands, Yangtze River estuary, China.	OA = 0.923, Kappa = 0.88	Yang et al. (2023)
3.	$RVI = \frac{NIR}{Red}$	Pa Khlok sub-district, Thailand.	OA = 0.923, Kappa = 0.77	Kongwongjan et al. (2012)
4.	$MI = \left(\frac{NIR - SWIR}{NIR * SWIR} \right) * 10000$	Mangroves in Hainan Island, China.	OA = 0.816, Kappa = 0.72	Chen et al. (2023)
5.	$NDMI = \frac{SWIR_2 - Green}{SWIR_2 + Green}$	Mangroves in Hainan Island, China.	OA = 0.85, Kappa = 0.75	Chen et al. (2023)
6.	$MRI = \lvert GVI_L - GVI_H \rvert * GVI_L * (WI_L + WI_H)$ Where, GVI = Green Vegetation Index $= -0.1603 * TM1 - 0.2819 * TM2 - 0.4939 * TM3$ $+0.794 * TM4 - 0.0002 * TM5 - 0.1446 * TM7$ WI = Wetness Index $= 0.0315 * TM1 + 0.2021 * TM2 + 0.3102 * TM3$ $+0.1594 * TM4 - 0.6806 * TM5 - 0.6109 * TM7$ In subscript, L = low tide level, H = high tide level Also, TM = Landsat Thematic Mapper bands 1 to 7	Mangrove forest in Beilunhekou National Nature Reserve Area, China.	PA=0.931, UA=0.980.	*Zhang and Tian (2013)
7.	$MMRI = \frac{\lvert MNDWI \rvert - \lvert NDVI \rvert}{\lvert MNDWI \rvert + \lvert NDVI \rvert}$ Where, $MNDWI = \frac{Green - SWIR1}{Green + SWIR1}$	Mangroves in Thailand	OA = 0.929, Kappa = 0.849	Lin et al. (2023)
		Mangroves in Cambodia	OA = 0.748, Kappa = 0.503	
		Mangroves in Myanmar	OA = 0.94, Kappa = 0.88	
		Mangroves in India	OA = 0.876, Kappa = 0.746	
		Mangroves in Honduras	OA = 0.832, Kappa = 0.626	
		Mangroves in Madagascar, Africa.	OA = 0.743, Kappa = 0.48	
8.	$CMRI = NDVI - NDWI$ (or) $CMRI = \left(\frac{NIR - Red}{NIR + Red} \right) - \left(\frac{Green - NIR}{Green + NIR} \right)$	Mangrove forests of 3 sites in India. 1. Sundarbans, West Bengal. 2. Bhitarkanika, Odisha. 3. Andaman and Nicobar Islands.	Site1: OA = 0.604 Site2: OA = 0.731 Site3: OA = 0.867	*Gupta et al. (2018)
		Mangroves in Hainan Island, China.	OA = 0.862, Kappa = 0.80	Chen et al. (2023)

S.No.	Indices full name with equation	Location of study area	Reported mapping accuracy	Source
9.	$MPVI = \dfrac{n\sum_{i=1}^{n} R_i r_i - \sum_{i=1}^{n} R_i \sum_{i=1}^{n} r_i}{\sqrt{n\sum_{i=1}^{n} R_i^2 - \left(\sum_{i=1}^{n} R_i\right)^2} * \sqrt{n\sum_{i=1}^{n} r_i^2 - \left(\sum_{i=1}^{n} r_i\right)^2}}$	Mangroves in Madagascar, Africa.	OA = 0.903, Kappa = 0.808	Lin et al. (2023)
10.	$NDWVI = \dfrac{R_{2203} - R_{559}}{R_{2203} + R_{559}}$	Mangroves in Madagascar, Africa.	OA = 0.866, Kappa = 0.734	Lin et al. (2023)
11.	$MFI = \left[\dfrac{(R_{\lambda 1} - R_{B\lambda 1}) + (R_{\lambda 2} - R_{B\lambda 2}) + (R_{\lambda 3} - R_{B\lambda 3}) + (R_{\lambda 4} - R_{B\lambda 4})}{4}\right]$ $where,\ R_{B\lambda i} = R_{2190} + \dfrac{(R_{665} - R_{2190}) * (2190 - \lambda i)}{(2190 - 665)}$ $\lambda 1, \lambda 2, \lambda 3, \lambda 4$ *are the center wavelengths – at* 705, 740, 783 *and* 865*nm respectively.*	Mangrove forests in 3 countries. 1. Zhenzhu Harbour, China. 2. Sundarbans, India. 3. Amazon Coast, Brazil.	Site1: OA = 0.97, Kappa = 0.94 Site2: OA = 0.96, Kappa = 0.93 Site3: OA = 0.92, Kappa = 0.83	*Jia et al. (2019)
12.	$MVI = \dfrac{NIR - Green}{SWIR1 - Green}$	Mangrove sites in the Philippines and Japan	OA = 0.92	*Baloloy et al. (2020)
		Mangroves in Hainan Island, China.	OA = 0.925, Kappa = 0.89	Chen et al. (2023)
		Mangroves in Thailand	OA = 0.936, Kappa = 0.865	Lin et al. (2023)
		Mangroves in Cambodia	OA = 0.731, Kappa = 0.464	
		Mangroves in Myanmar	OA = 0.965, Kappa = 0.93	
		Mangroves in India	OA = 0.892, Kappa = 0.78	
		Mangroves in Honduras	OA = 0.914, Kappa = 0.812	
		Mangroves in Madagascar, Africa.	OA = 0.717, Kappa = 0.421	
13.	$EMVI = \dfrac{Green - SWIR2}{SWIR1 - Green}$	Mangroves in Madagascar, Africa.	OA = 0.863, Kappa = 0.726	Lin et al. (2023)
14.	$REMI = \dfrac{Red\ edge - Red}{SWIR1 - Green}$	Mangroves in Hainan Island, China.	OA = 0.956, Kappa = 0.92	*Chen et al. (2023)
15.	$SZDI = R_{Green} - R_{Blue} - R^{\prime}_{Green}$ Also, $R^{\prime}_{Green} = \dfrac{\lambda_{Green} - \lambda_{Blue}}{\lambda_{Red} - \lambda_{Blue}}(R_{Red} - R_{Blue})$	Seagrass in Seto Inland Sea, Coastal Takehara City, Japan.	No data.	*Song and Sakuno (2023)

Note: * Indicates the authors responsible for developing the corresponding equations. R=Reflectance, λ=Wavelength, PA=Producer's accuracy, UA=User accuracy, OA=Overall accuracy (measure of total correct classification), Kappa=Kappa Coefficient (measure of accuracy adjusted for chance agreement), FI Score= F1 Score (measure of detailed class-wise performance).

Kappa of 0.829. Liu et al. (2024) reported no data for Hangzhou Bay, China.

Yang et al. (2023) found an OA of 0.923 and Kappa of 0.88 for salt marsh wetlands in China. Kongwongjan et al. (2012) achieved an OA of 0.923 and Kappa of 0.77 for Thailand. Chen et al. (2023) reported varying accuracies for Hainan Island, China, including an OA of 0.816 and Kappa of 0.72, and another OA of 0.85 and Kappa of 0.75 for different sites. Zhang and Tian (2013) found an OA of 0.931 for Beilunhekou Nature Reserve, China. Further, Lin et al. (2023) reported OAs of 0.929 to 0.936 for Thailand and Cambodia, with Kappas ranging from 0.464 to 0.865. Myanmar's mangroves had an OA of 0.965 and Kappa of 0.93, and India's had an OA of 0.892 and Kappa of 0.78. Honduras had an OA of 0.914 and Kappa of 0.812, while Madagascar showed varied results, with an OA of 0.717 and Kappa of 0.421.

Jia et al. (2019) assessed mangroves in China, India, and Brazil, reporting OAs of 0.97 to 0.917 and Kappas of 0.94 to 0.83. Baloloy et al. (2020) found an OA of 0.92 for the Philippines and Japan. Chen et al. (2023) also reported an OA of 0.925 and Kappa of 0.89 for Hainan Island, and Lin et al. (2023) found an OA of 0.936 and Kappa of 0.865 for Thailand. Further details for Madagascar included an OA of 0.717 to 0.956 and Kappa of 0.421 to 0.92. Song and Sakuno (2023) reported no data for seagrass in Japan.

Geevarghese et al. (2018) used Landsat-8 data from 2014 to map seagrass in India, employing the ISODATA clustering method. They identified a seagrass area of 516.59 km² with an overall accuracy of approximately 70%.

1.6 Biomass Assessment of BCEs: A Survey of Available Allometric Methods

Figure 1.6 illustrates the various components that contribute to the total carbon stock in Blue Carbon Ecosystems (BCEs), including Above-Ground Biomass (AGB), Below-Ground Biomass (BGB), and Soil Organic Carbon (SOC). Table 1.3 presents various allometric equations and study data available for estimating mangrove biomass, specifically AGB, BGB, and SOC. These allometric equations are essential for assessing the carbon storage and biomass of mangroves in different locations across Asia, primarily in India and surrounding countries. The studies listed provide detailed insights into the specific regions where the research was conducted, ranging from the Sundarbans in West Bengal, India, to the Thane mangrove creek in Mumbai, India. A diverse range of methods is employed across different studies to estimate mangrove biomass, using various parameters like tree diameter at breast height (DBH), height (H), and wood density (ρ). Some studies focused solely on Above Ground Biomass (AGB), while others measured Below Ground Biomass (BGB) or Soil Organic Carbon (SOC).

The studies by Chave et al. (2005), Komiyama et al. (2005), and Rani et al. (2023) focus on a global dataset covering sites in Asia, Oceania, and the Americas. This wide range of study areas allow for a more general application of allometric equations to various mangrove forests worldwide. The focus of studies such as those by Kathiresan et al. (2013) and Suresh et al. (2017) is on deriving the BGB from AGB measurements, where BGB is calculated as 0.26 times AGB.

These studies highlight the importance of understanding root biomass in evaluating total carbon storage in mangroves. Several studies, including those by Vinod et al. (2018, 2019) and Sigamani et al. (2023), provide insights into SOC estimation using a formula that involves bulk density, soil depth, and organic carbon percentage.

These parameters help in assessing the carbon sequestration potential of mangrove soils, which is a critical component in climate change mitigation efforts.

Overall, Table 1.3 provides a comprehensive overview of allometric methods and studies available for estimating mangrove biomass in different regions, emphasizing the variability in methods and geographic focus. The studies underscore the importance of location-specific equations and parameters to accurately assess biomass and carbon storage in mangrove ecosystems, crucial for conservation and climate change mitigation strategies.

1.7 Country-Specific Conversion Factors for BCE's Carbon Accounting

All vegetation types, including mangroves, salt marshes, and seagrass meadows, absorb carbon dioxide (CO_2) from the atmosphere through the photosynthesis process and store carbon in their biomass. Thus, carbon stock assessment of any

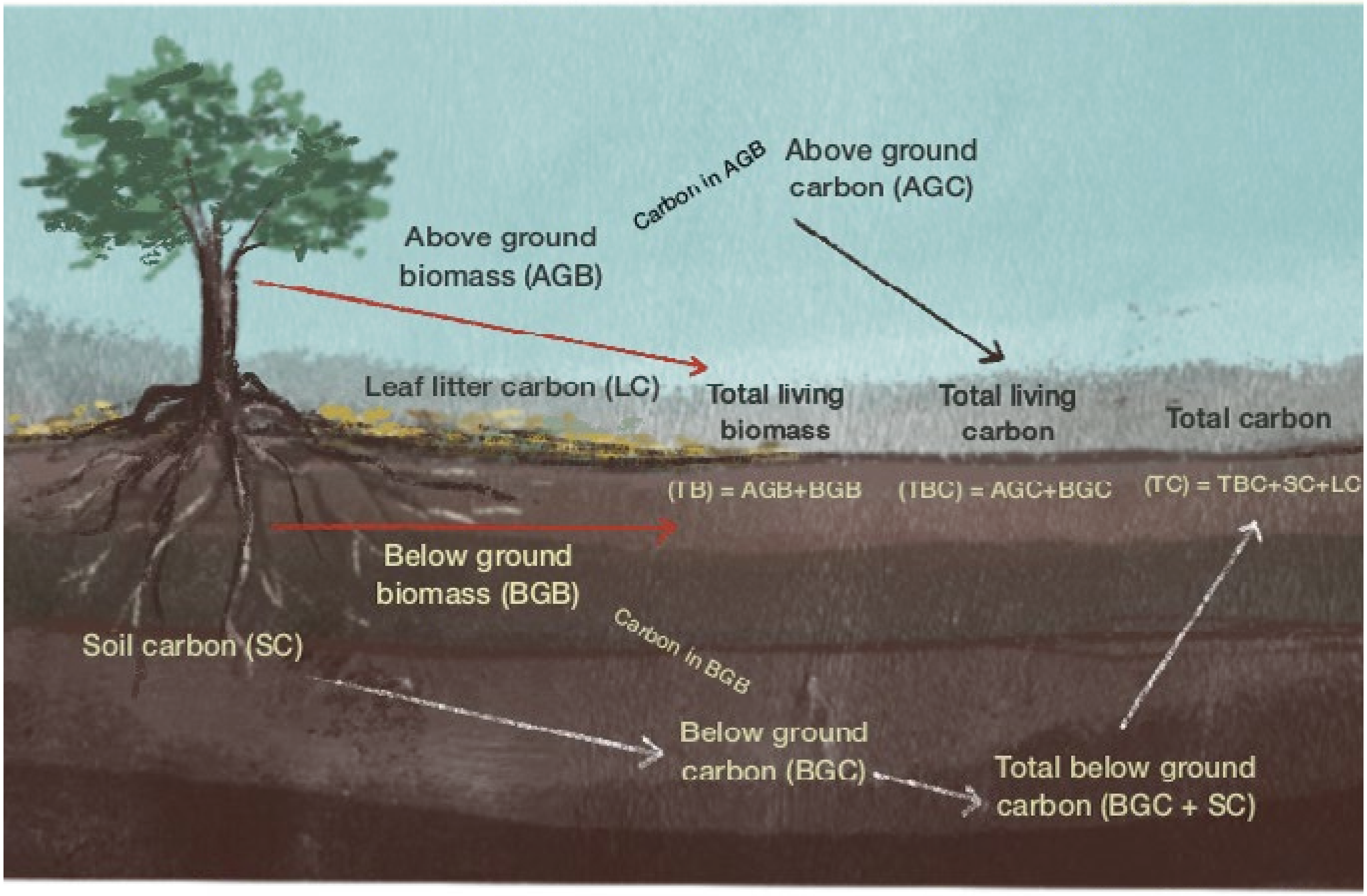


Figure 1.6: Components of total carbon stock in Blue Carbon Ecosystems (BCEs)

ecosystem is directly related to its biomass content. In general, wood samples collected from various branches of trees are analyzed using the CHN Elemental Analyzer instrument to estimate the carbon content present in them. Although the above process yields accurate estimates, researchers often rely on conversion factors to directly quantify the carbon stock from biomass, thereby streamlining the estimation process and minimizing the need for field data collection.

As discussed in the previous sections, carbon stock in BCE is present in different zones such as AGB, BGB, and SOC. Researchers in the past derived conversion factors for both AGB and BGB by analysing mangrove samples collected worldwide, as shown in Table 1.4.

Jaramillo et al. (2003) analysed samples of mangrove roots collected worldwide and reported that the carbon content of roots in tropical mangrove forests ranges from 36% to 42% of their biomass. Their study suggested a median of 39% for carbon content from BGB, thereby establishing a carbon conversion factor of 0.39. Similarly, Kauffman and Donato (2012) studied wood samples from mangrove trees collected worldwide and reported that the carbon content of mangrove AGB ranges from 46% to 50%. Unlike the AGB and BGB zones of BCE, there is no conversion factor available in the literature to estimate the carbon stock from the soils present below the BCE. This is because the carbon content in BCE soils varies at different depths (from the topsoil surface to 100 cm), and thus it can be measured only by testing field samples using the standard procedure described by Fourqurean et al. (2014).

From Table 1.4, it can be observed that researchers in the past have adopted diverse conversion factor values while estimating carbon content, even from the same site locations. For instance, Ajanta Dey (2015) adopted 0.47, which differs from 0.5, as adopted by Mizanur Rahman et al. (2015) and

Table 1.3: Various allometric equations available for estimating mangrove biomass.

S. No	Above Ground Biomass (AGB)	Below Ground Biomass (BGB)	Soil Organic Carbon (SOC)	Location of study area	Source
1.	$AGB_{with\ \rho\ factor} = 1.0471 D^{0.864} H^{0.635} \rho^{-1.37}$ $AGB_{without\ \rho\ factor} = 1.3799 D^{0.955} H^{0.687}$ $If\ tree\ height(H)\ is\ 4-10.55m.$ $AGB = 0.162 D^{1.24} H^{1.81}$ $If\ tree\ height(H)\ is\ 0.5-4m.$	$LBGB = AGB^{1.63} * 0.033$	-	100 samples in the Sundarbans, West Bengal, India.	*Ray et al. (2011)
			-	Sundarbans, West Bengal, India.	Barik et al. (2021)
		-	-	Sundarbans, West Bengal, India.	Ajanta Dey (2015)
		-	-	Bhitarkanika Wildlife Sanctuary, Odisha, India.	Ghosh et al. (2021)
2.	$AGB = 0.251 \rho D^{2.46}$	$BGB = 0.199 \rho^{0.899} D^{2.22}$	-	104 samples from five study sites in Thailand and Indonesia	*Komiyama et al. (2005)
				Pichavaram and Vellar in Tamil Nadu, India.	Kathiresan et al. (2013)
				Mahanadi mangrove wetland, Odisha, India.	Sahu et al. (2016)
				Kala Oya estuary, Sri Lanka.	Perera et al. (2017)
			SOC (t/ha) = Bulk density (g/cm3) * Soil depth (cm) * Organic carbon (%)	Kadalundi mangrove wetland, Kerala, India.	Vinod et al. (2018)
				Thalassery mangrove estuary, Kerala, India.	Vinod et al. (2019)
				Kerala state, India.	Sreelekshmi et al. (2022)
			-	Bhitarkanika Wildlife Sanctuary, Odisha, India.	Bal and Banerjee (2019)
				Kerala state, India.	Harishma et al. (2020)
				379 sites around the globe.	Song et al. (2023)
				Vypin Island, Kerala, India.	ShyleshChandran et al. (2020)
				43 samples covering the	Ragavan et al. (2021)

S. No	Above Ground Biomass (AGB)	Below Ground Biomass (BGB)	Soil Organic Carbon (SOC)	Location of study area	Source
				entire Andaman and Nicobar Islands, India.	
				Bhitarkanika Wildlife Sanctuary, Odisha, India.	Ghosh et al. (2021)
				Kochi, Kerala, India.	Rani et al. (2023)
				Gulf of Kutch, Gujarat, India	Sigamani et al. (2023)
3.	$AGB = 0.168\rho D^{2.47}$		-	388 samples along the Kochi coast in Kerala, India	Rani et al. (2023)
		-	-	84 samples around the world	*Chave et al. (2005)
4.	$AGB = \rho \times \exp(-1.349 + 1.98\ln(D) + 0.207(\ln(D))^2 - 0.0281(\ln(D))^3)$	-	-	Study sites from three continents: America, Asia, and Oceania (2410 trees).	*Chave et al. (2005)
		-	-	Kochi, Kerala, India.	Rani et al. (2023)
		$BGB = 0.26 * AGB$	-	An area of 0.1 ha of each mangrove forest is sampled in the entire India.	Suresh et al. (2017)
		$BGB = 0.199\rho^{0.899}D^{2.22}$	-	Sundarbans, Bangladesh.	Mizanur Rahman et al. (2015)
			-	Sundarbans Reserve Forest, Bangladesh.	Kamruzzaman et al. (2018)
			-	Bhitarkanika Wildlife Sanctuary, Odisha, India.	Ghosh et al. (2021)
5.	$AGB = 0.308D^{2.11}$	$BGB = 1.28D^{1.17}$	-	Thane mangrove creek, Mumbai, India.	Pachpande and Pejaver (2015)
6.	$AGB = 0.3404D^{2.0273}$	$BGB = 0.3335D^{1.7294}$	-	Thane mangrove creek, Mumbai, India.	*Patil et al. (2014)

Note: * Indicates the authors responsible for developing the corresponding equations. LBGB = Live below-ground biomass, D = Mangrove tree diameter at breast height, H = Mangrove tree height and ρ = Mangrove wood density.

Kamruzzaman et al. (2018) in their study to estimate the carbon content from AGB in mangroves located at Sundarbans Forest (Table 1.4). Similarly, Rani et al. (2023) used conversion factors of 0.45 and 0.39 for obtaining carbon content from AGB and BGB respectively at mangrove sites located near Kochi in Kerala state, India (Table 1.4). In contrast, other studies considered a different conversion factor of 0.5 to derive carbon content from both AGB and BGB of mangroves located near the islands of Kerala state in India (Vinod et al. 2018; Vinod et al. 2019; Harishma et al. 2020; Shylesh Chandran et al. 2020). This difference arises due to the fact that mangroves within the same region may have different species and may present with different field conditions. Thus, researchers have wisely selected the conversion factors from the ranges proposed above.

To estimate the carbon content from mangrove biomass located at Thane Creek near Mumbai in India, Patil et al. (2014) and Pachpande and Pejaver (2015) considered a conversion factor of 0.5. Similarly, Sahu et al. (2016) adopted the same value to estimate the carbon content from the Mahanadi Mangrove Wetland in Odisha, India. Furthermore, Suresh et al. (2017) used 0.5 in their study while assessing the carbon stocks from mangrove biomass across India. In contrast to Indonesia, where there is a defined national-level conversion factor (0.47 for AGB) for carbon estimates, no such standardized value exists in India. Consequently, researchers in India are utilizing diverse values from the available range.

1.8 Challenges in Scaling BCE Monitoring to National Levels

Scaling blue carbon ecosystem (BCE) conservation and monitoring to the national level presents significant scientific, logistical, and governance-related challenges. BCEs are dynamic environments influenced by tidal variations, seasonal changes, and anthropogenic activities, making consistent monitoring complex. While remote sensing provides scalable solutions, limitations such as cloud cover, spatial resolution constraints, and the need for field validation hinder comprehensive assessments. The absence of standardised protocols for BCE mapping, biomass estimation, and carbon stock accounting leads to inconsistencies in national-level studies. Financial and resource constraints further limit the collection and analysis of BCE samples to determine site-specific carbon mean values. Additionally, rapid coastal development, aquaculture expansion, and industrialization contribute to habitat loss, posing a major governance challenge. Furthermore, climate change intensifies the vulnerability of BCEs through rising sea levels, increased cyclone intensity, and altered sedimentation patterns. Addressing these challenges requires a holistic approach integrating technological advancements, financial investments, policy interventions, and community-driven conservation strategies to effectively scale BCE conservation at the national level.

1.9 Summary

Blue carbon ecosystems (BCEs), including mangroves, seagrasses, and salt marshes, play a crucial role in carbon sequestration, far surpassing the sequestration rates of terrestrial ecosystems. Given India's commitment to achieving net-zero emissions by 2070, the conservation and monitoring of BCEs have become a national priority. However, large-scale implementation faces multiple challenges,

Table 1.4: Available country-specific conversion factors for carbon stock estimation from biomass.

S.No.	Above Ground Biomass (AGB)	Below Ground Biomass (BGB)	Soil Organic Carbon (SOC)	Location of study area	Source
1.	-	0.36 – 0.42 (0.39 median)	-	samples around the world.	*Jaramillo et al. (2003)
2.	0.46 – 0.5 (0.48 median)	-	-	samples around the world.	*Kauffman and Donato (2012)
3.	0.42	-	-	Pichavaram and Vellar in Tamil Nadu, India.	Kathiresan et al. (2013)
4.	0.5	0.5	-	Thane mangrove creek, Mumbai, India.	Patil et al. (2014)
5.	0.47	-	-	Sundarbans, West Bengal, India.	Ajanta Dey (2015)
6.	0.5	0.5	-	Sundarbans, Bangladesh.	Mizanur Rahman et al. (2015)
7.	0.5	0.5	-	Thane mangrove creek, Mumbai, India.	Pachpande and Pejaver (2015)
8.	0.5	0.5	-	Mahanadi Mangrove Wetland, Odisha, India.	Sahu et al. (2016)
9.	0.5	0.5	-	An area of 0.1 ha of each mangrove forest is sampled in the entire India.	Suresh et al. (2017)
10.	0.5	0.5	-	Kadalundi mangrove wetland, Kerala, India.	Vinod et al. (2018)
11.	0.5	0.5	-	Sundarbans Reserve Forest, Bangladesh.	Kamruzzaman et al. (2018)
12.	0.5	0.5	-	Thalassery mangrove estuary, Kerala, India.	Vinod et al. (2019)
13.	0.5	0.5	-	Kerala state, India.	Harishma et al. (2020)
14.	0.46	-	-	Vypin Island, Kerala, India.	ShyleshChandran et al. (2020)
15.	0.48	0.39	-	43 samples covering the entire Andaman and Nicobar Islands, India.	Ragavan et al. (2021)
16.	0.45	0.39	-	Kochi coast in Kerala, India.	Rani et al. (2023)
17.	0.45	0.39	-	Kochi, Kerala, India.	Rani et al. (2023)
18.	0.48	0.39	-	Gulf of Kutch, Gujarat, India.	Sigamani et al. (2023)
19.	0.47	-	-	Mangrove forest of Benoa Bay, Indonesia	Suardana et al. (2023)

Note: * Indicates the authors responsible for proposing the conversion factor to account for carbon stock.

including data limitations, financial constraints, policy integration issues, and land-use conflicts.

Remote sensing and geospatial tools have significantly improved BCE mapping and monitoring, but issues such as cloud cover, data resolution, and the need for field validation remain obstacles. Standardized methodologies for biomass estimation and carbon stock accounting are lacking, resulting in inconsistencies across different studies. Financial constraints further limit the deployment of high-resolution imagery and advanced field surveys.

In addition to technological and financial barriers, anthropogenic activities such as urbanization, industrial expansion, and unregulated coastal development threaten BCEs. Policy and regulatory challenges persist, with limited integration of BCEs into national carbon accounting frameworks. Furthermore, community participation remains crucial, but awareness and engagement levels vary across different regions. Climate change poses another challenge, affecting BCE stability and necessitating adaptive conservation strategies. To scale BCE conservation at the national level, a holistic approach which comprises of adopting advancements in technologies, regulatory support, financial investments, and community-driven conservation initiatives is required.

CHAPTER 2

Spatio-Temporal Dynamics of India's Blue Carbon Ecosystems

2.1 Introduction

India, with its vast shoreline spanning approximately 11,099 km from the east coast to the west coast as well as its oceanic island systems, has blue carbon ecosystems (BCEs) such as mangroves, seagrasses, and salt marshes that play a crucial role in maintaining ecological balance and providing various ecosystem services. As climate change intensifies threats to BCEs in this region, the increasing severity of natural disasters, particularly tropical cyclones, further impacts these ecosystems, which are already under pressure from various anthropogenic activities. This chapter aims to analyse the current extent of these ecosystems as well as the extent of degradation that has occurred over the last two and half decades using data from open-source geospatial platforms and various published sources. The spatial and temporal dynamics of mangroves, seagrasses, and salt marshes are discussed in the following sections.

2.2 Overview of Existing BCEs Datasets and their Limitations

The availability of BCE geospatial datasets largely depends on global mapping programs such as the Global Mangrove Watch (GMW), the World Atlas of Mangroves (WAM), and the Global Distribution of Seagrass and Saltmarshes (GDS), developed by the World Conservation Monitoring Centre (WCMC) under the United Nations Environment Program (UNEP). The geospatial datasets available for studying changes in Indian BCEs are listed in Table 2.1. While mangrove forests have the most extensive temporal coverage, with datasets spanning from 1996 to 2020, data availability for seagrass meadows (2003) and salt marshes (2006) remains highly limited (Table 2.1).

In addition to the open-source geospatial datasets listed in Table 2.1, various national organizations in India also map these ecosystems at different temporal scales and provide state-level estimates in their reports. The Indian Space Research Organisation (ISRO) has been mapping both mangroves and salt marshes as part of its National Wetland Inventory and Assessment Atlas (NWIA) program. The fifth edition of the NWIA report by Gupta et al., released in 2024, provides state-level estimates of mangrove and salt marsh extents for the assessment year 2018–2019.

Similarly, the Forest Survey of India has been mapping mangroves as part of the India State of Forest Report (ISFR) program, which was initiated in 1993 to publish biennial reports. While state-level mangrove estimates from ISFR have been available since 1993, an additional classification of mangroves into dense (>70% canopy density), moderately dense (40–70% canopy density), and open (<40% canopy density) was introduced only in 2003. Consequently, this study considers state-level mangrove area estimates from ISFR starting in 2003 and analyses them to assess degradation over the last two decades (2003–2023) (Forest Survey of India, 2023).

Data for seagrass meadows are highly limited, with available information primarily published by individual researchers. Nobi et al. (2012) conducted the first study in India on seagrasses and reported 3.6 km^2 of seagrass area in selected lagoons of the Lakshadweep Islands. Geevarghese et al. (2018) and Seal et al. (2023), mapped seagrass extent across India and along the Tamil Nadu coast, respectively. Seal et al. (2023) mapped 5.42 km^2 seagrass area along the Tamil Nadu coast using remote sensing techniques. Consequently, D'Souza et al. (2015) reported 44 seagrass meadows in the Andaman and Nicobar Islands (ANI) with a combined area of 0.712 km^2, dominated by Halophila and Halodule species, and demonstrated the influence of dugong grazing on meadow persistence. Long-term monitoring in the Lakshadweep Islands revealed historically extensive lagoon meadows, including Agatti (16.8 km^2), Bangaram (15.2 km^2), Kavaratti (6.2 km^2), Kalpeni (26.0 km^2), and Kadmat (20.9 km^2), which experienced progressive declines between 2005 and 2020 due to sequential overgrazing by green

Table 2.1: Open-source geospatial data sources for Blue Carbon Ecosystems (BCEs) in India

S. No.	Blue Carbon Ecosystem	Data Availability (Years)	Data Source/Program
1.	Mangrove Forest	1996, 2007, 2008–2010 (3 years), 2015–2020 (6 years)	Global Mangrove Watch (GMW) by WCMC-UNEP
		2010	World Atlas of Mangroves (WAM)
2.	Seagrass Meadow	2003	Global Distribution of Seagrass (GDS) by WCMC-UNEP
3.	Salt marshes/Tidal marshes	2006	Global Distribution of Saltmarshes (GDS) by WCMC-UNEP

turtles (Gangal et al., 2021). More recently, Gole et al. (2023) conducted extensive surveys across the ANI, documenting 66 meadows, including 32 newly recorded, and identified depth-restricted and species-specific habitat patterns. Collectively, these studies highlight that seagrass extent in India spans from less than 1 km² in some localized surveys to tens of km² in lagoon systems. But national-scale estimates remain uncertain due to uneven geographic coverage, methodological differences, and the lack of systematic, countrywide mapping. Thus, variations in seagrass coverage in this study are assessed based solely on these sources. Similarly, Viswanathan et al. (2020) is the only available source for comparing state-level salt marsh estimates with NWIA data.

The major limitations of the datasets discussed above include gaps in temporal continuity, inconsistent spatial resolutions, and reliance on different methodologies across datasets, making direct comparisons challenging. Additionally, all of these datasets are derived from remote sensing, which may introduce classification errors due to cloud cover, mixed pixels, and sensor limitations. The lack of high-resolution, regularly updated national-scale datasets restricts the accuracy of long-term BCE monitoring, impacting conservation planning and policy decisions.

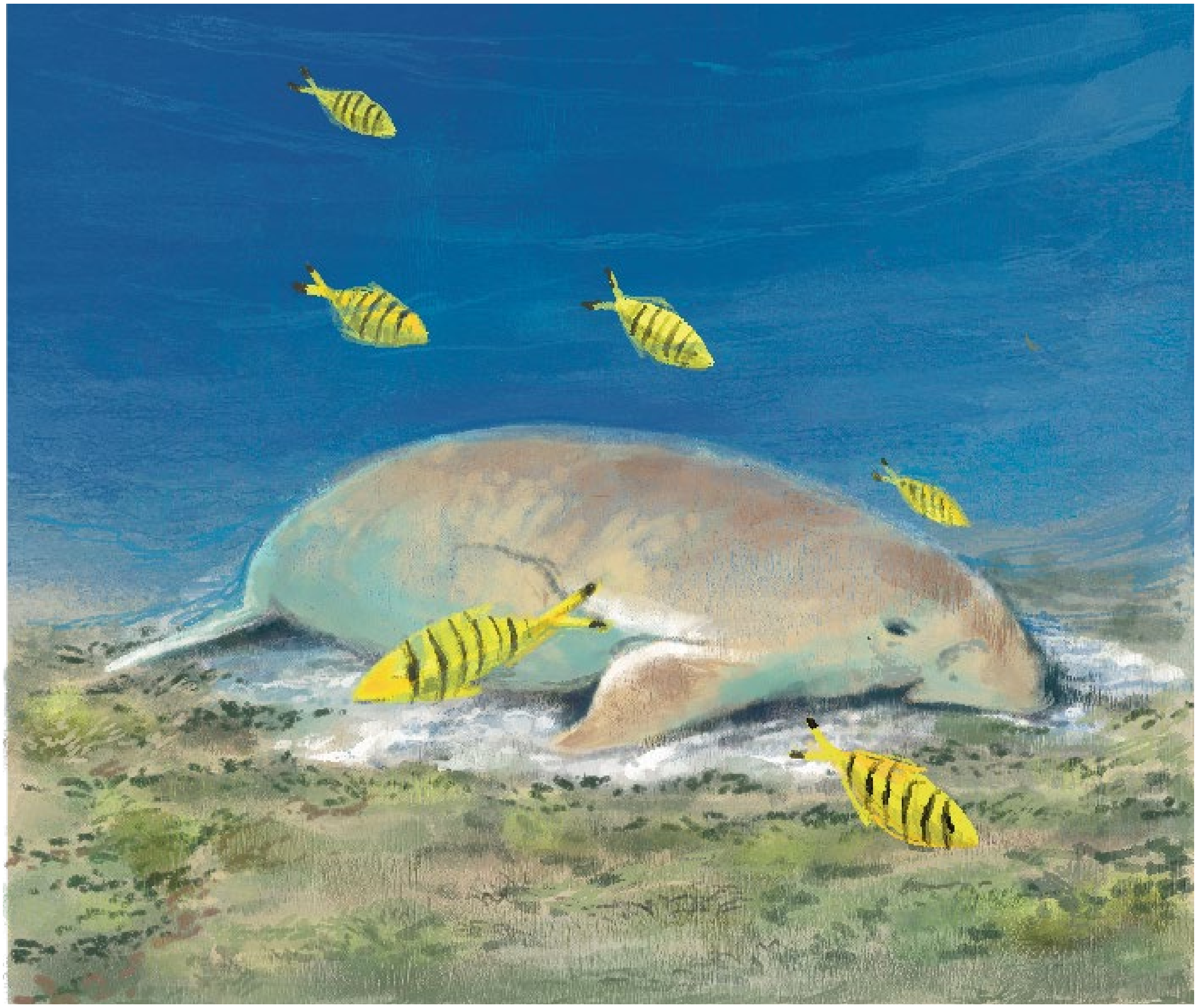
Although data scarcity poses a challenge for studying BCEs, particularly in India, this study analyses the spatial and temporal variations in mangroves, seagrasses, and saltmarshes using the aforementioned sources. The details of the long-term variations are provided in the following sections.

2.3 Temporal Trends in BCE Distribution across India

The long-term trends in BCEs such as mangroves, saltmarshes, and seagrasses are presented in the following sections. Temporal variations in mangroves are analysed using long-term area estimates available from two data sources, namely Global Mangrove Watch (GMW) (1996–2020) and India State of Forest Report (ISFR) (2003–2023), as discussed above. Unlike GMW geospatial data, which maps only the presence of mangroves at different time scales, ISFR provides mangrove area estimates classified into dense, moderately dense, and open categories. This classification enables a more detailed assessment of mangrove degradation across coastal states in India over the last two decades.

As previously mentioned, long-term datasets for studying temporal variations in salt marshes and seagrasses in India are unavailable. Therefore, their temporal changes are analysed using the limited observations reported in the published literature. A detailed discussion on the distribution of mangroves in India over the past two decades is presented in the following section.

2.3.1 Patterns in Mangrove



Distribution and Decline

Figure 2.1 presents the comparison of mangrove area estimates in India obtained from two different sources: the India State of Forest Report (ISFR) and the Global Mangrove Watch (GMW). The ISFR dataset provides estimates from 1993 to 2023, while GMW data covers the period from 1996 to 2020. A critical comparison of these datasets reveals significant differences in trends and absolute areas, indicating variations in methodology and classification criteria.

The ISFR data shows a consistent increase in mangrove area over time, with fluctuations in certain periods. In 1993, the reported mangrove area was 4,256 km², which increased steadily to 4,871 km² in 1999 (Figure 2.1). However, there was a decline to 4,482 km² in 2001, followed by fluctuations until 2005. After 2005, ISFR estimates resumed an upward trend, reaching 4,740 km² in 2015 and then sharply increasing to 4,921 km² in 2017. The growth continued, with the latest estimate in 2023 reaching 4,991.68 km². This upward trend, especially after 2015, suggests that ISFR data may reflect afforestation efforts, conservation initiatives, or methodological changes that incorporate a more expansive classification of mangroves. However, at this stage, it is difficult to determine the primary driver of the observed increase in area.

On the other hand, it is observed from Figure 2.1 that the GMW dataset starts with a significantly higher estimate of 4,760.23 km² in 1996. Unlike ISFR, GMW data shows a general declining trend until 2010, when the area was estimated at 4,632.29 km². After 2010, GMW data indicates a slow but steady recovery, peaking at 4,695.99 km² in 2018 before experiencing minor fluctuations (Figure 2.1). By 2020, the reported area was 4,642.72 km², which remains lower than the 1996 estimate, suggesting long-term mangrove loss according to this dataset.

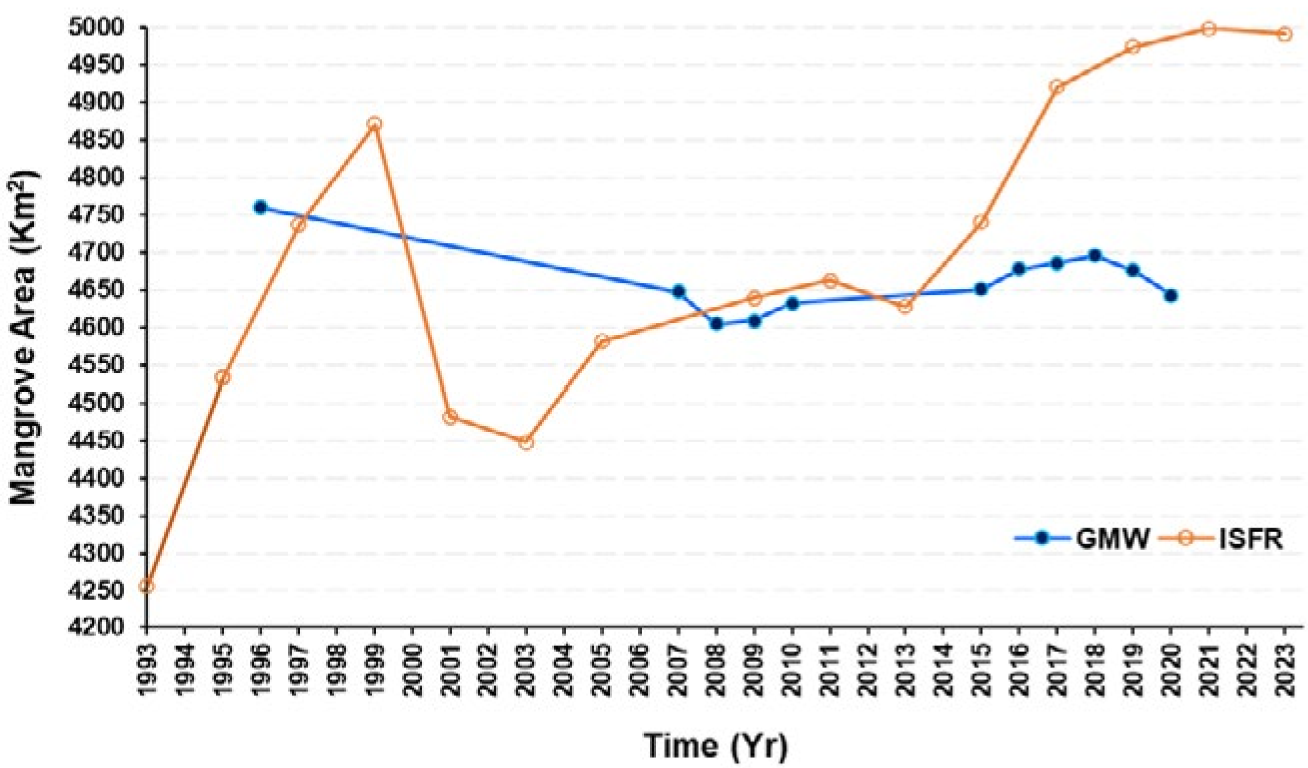
A key observation from Figure 2.1 is the discrepancy between the two datasets in both absolute values and trends. The ISFR dataset shows an increase of approximately 735 km² from 1993 to 2023, while GMW data indicates a net decline from 1996 to 2020. The ISFR data consistently reports lower initial estimates but a sharper increase over time, whereas GMW showed a more stable trend with slight declines and recoveries. The divergence becomes more apparent after 2015, where ISFR records a steep rise, while GMW shows a more modest recovery.

This discrepancy of about 350 km² may arise from differences in methodologies. The significant difference in mangrove area estimates for Gujarat between the ISFR and GMW datasets can be attributed to the above national-level discrepancy. ISFR data is influenced by national forest assessments, policy-driven reclassification, and afforestation projects, potentially leading to an optimistic estimate. In contrast, GMW relies on a globally standardized remote sensing approach that may be less affected by policy considerations but could underestimate certain mangrove regrowth areas.

Overall, the comparative analysis of ISFR and GMW data highlights the complexity of mangrove monitoring in India. While ISFR suggests a strong recovery and expansion, GMW data presents a more cautious assessment, indicating a potential long-term decline. This underscores the need for multi-source validation and harmonization to improve accuracy in mangrove conservation assessments. To gain a deeper understanding of the trends and decline patterns in India's mangroves, mangrove estimates are compared at the state level, and the results from the last two decades are discussed below.

The long-term trends in mangrove cover across Indian states and Union Territories (UTs) from 1996 to 2020 were analysed using geospatial data obtained from GMW, and the results are presented in Table 2.2. The GMW data reveal significant spatial and temporal variations, with notable declines in several regions. A comparative analysis of mangrove loss over the years provides important insights into patterns of degradation, resilience, and

Figure 2.1: Comparison of mangrove area estimates in India from GMW and ISFR data (1993–2023)



potential causes behind the observed trends.

According to Table 2.2, GMW mangrove estimates indicate that between 1996 and 2020, India experienced a net mangrove loss of 117.51 km², accounting for approximately 2.47% of the total mangrove area recorded in 1996. The decline was particularly significant in Tamil Nadu, which saw a reduction of 45.9 km² (44.5%), the highest percentage of mangrove loss among all states. This sharp decline is likely due to land conversion for agriculture and salt pans, combined with coastal erosion and reduced sediment deposition, which are clearly observed in the two prominent mangrove areas of Pichavaram and Muthupet, as shown in Figure 2.2. The Muthupet mangrove forest lost more than 50% of its area between 1996 to 2020 (Figure 2.2).

Kerala witnessed a loss of approximately 5 km² (25.1%) from 1996 to 2020, making it one of the states with the highest percentage declines. Figure 2.3 shows that this steep reduction occurred due to major destruction observed in the Kochi mangroves. The conversion of mangrove areas into aquaculture is identified as the primary cause of this reduction. Similarly, other small mangrove patches also experienced area loss, indicating significant anthropogenic pressures on the already limited mangrove habitat.

West Bengal lost 27.72 km² of mangrove area between 1996 and 2020 (Table 2.2). Given that the Sundarbans is one of the most extensive mangrove ecosystems globally, this reduction raises serious concerns about the long-term stability of this critical habitat. Figure 2.4 illustrates both newly gained and lost mangrove areas in the Sundarbans of West Bengal from 1996 to 2020. It is evident from Figure 2.4 that mangroves in the Sundarbans are primarily affected by natural calamities and other factors such as sea-level rise, increasing salinity, water temperature fluctuations, tidal height variations, and coastal erosion, all of which are intensified by climate change.

Gujarat followed a trend similar to that of West Bengal, with an overall loss of 28.01 km². The decline in Gujarat's mangroves, primarily located in the Rann of Kutch and Gulf of Kutch, is alarming and likely attributed to coastal industrialization and altered hydrological regimes (Figure 2.5).

On the east coast, unlike other coastal states that exhibited a declining trend, Odisha recorded a gain in mangrove area, increasing from 186.94 km² in 1996 to 215.65 km² in 2020 with an increase of nearly 10%. Although some areas along the Odisha coast experienced mangrove loss, the two prominent mangrove forests, Bhitarkanika and Mahanadi, witnessed substantial new growth as shown in Figure 2.6. This made Odisha the state with the highest mangrove area gain from 1996 to 2020, as per GMW data (Figure 2.6).

Andhra Pradesh, which shares similar characteristics with Odisha in having major mangrove areas along large riverine estuaries, lost 13.89 km² between 1996 and 2020 (Table 2.2). Figure 2.7 indicates that despite experiencing localized gains, certain areas in Andhra Pradesh saw mangrove decline due to erosion, aquaculture expansion, and infrastructure development over time.

On the west coast, Maharashtra recorded a loss of nearly 10 km², while Goa experienced a reduction of 2.85 km² from 1996 to 2020 (Table 2.2). Figure 2.8 shows that the Mandovi Estuary and Kundaim mangrove forests experienced severe mangrove loss in Goa. Meanwhile, parts of the mangroves in Thane Creek and the majority of the Vaitarna Estuary mangroves have been destroyed due to conversion for aquaculture (Figure 2.9).

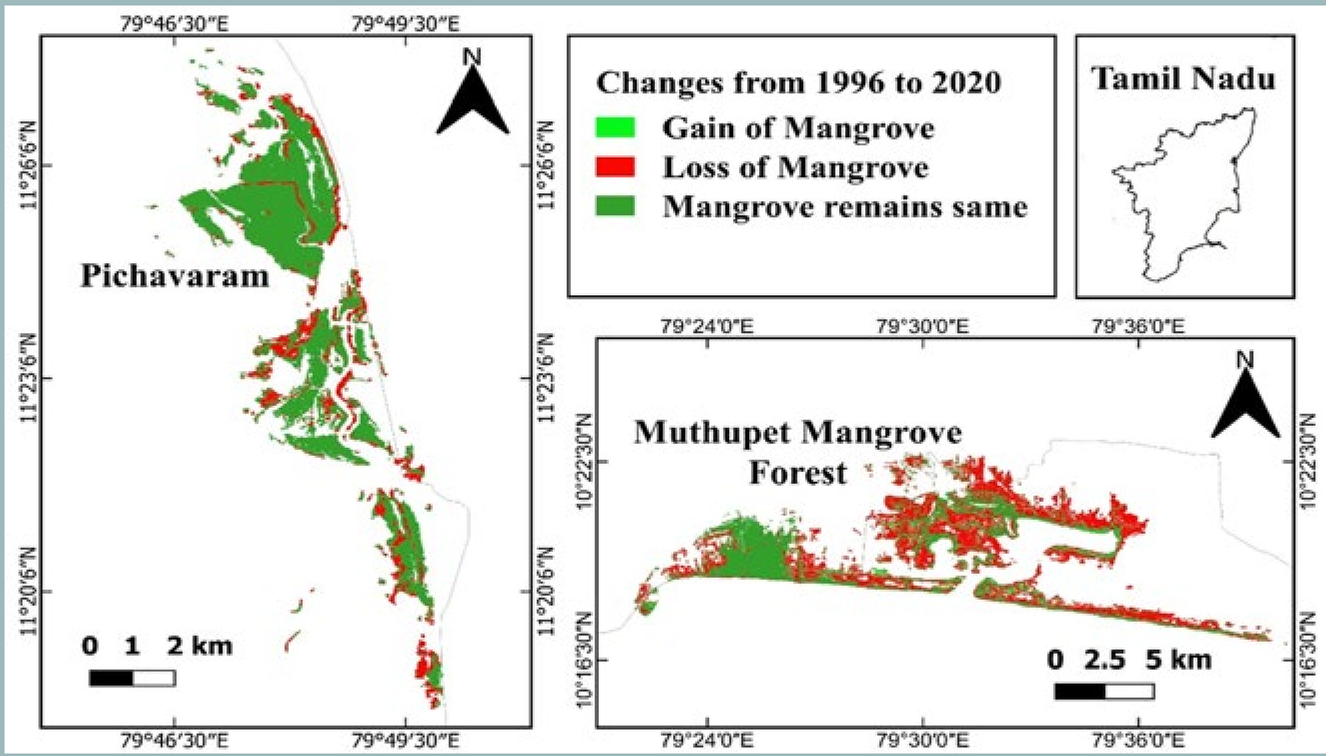


Figure 2.2: Changes in mangrove cover observed along the Tamil Nadu coast (1996–2020): Stable, Newly gained, and Lost areas.

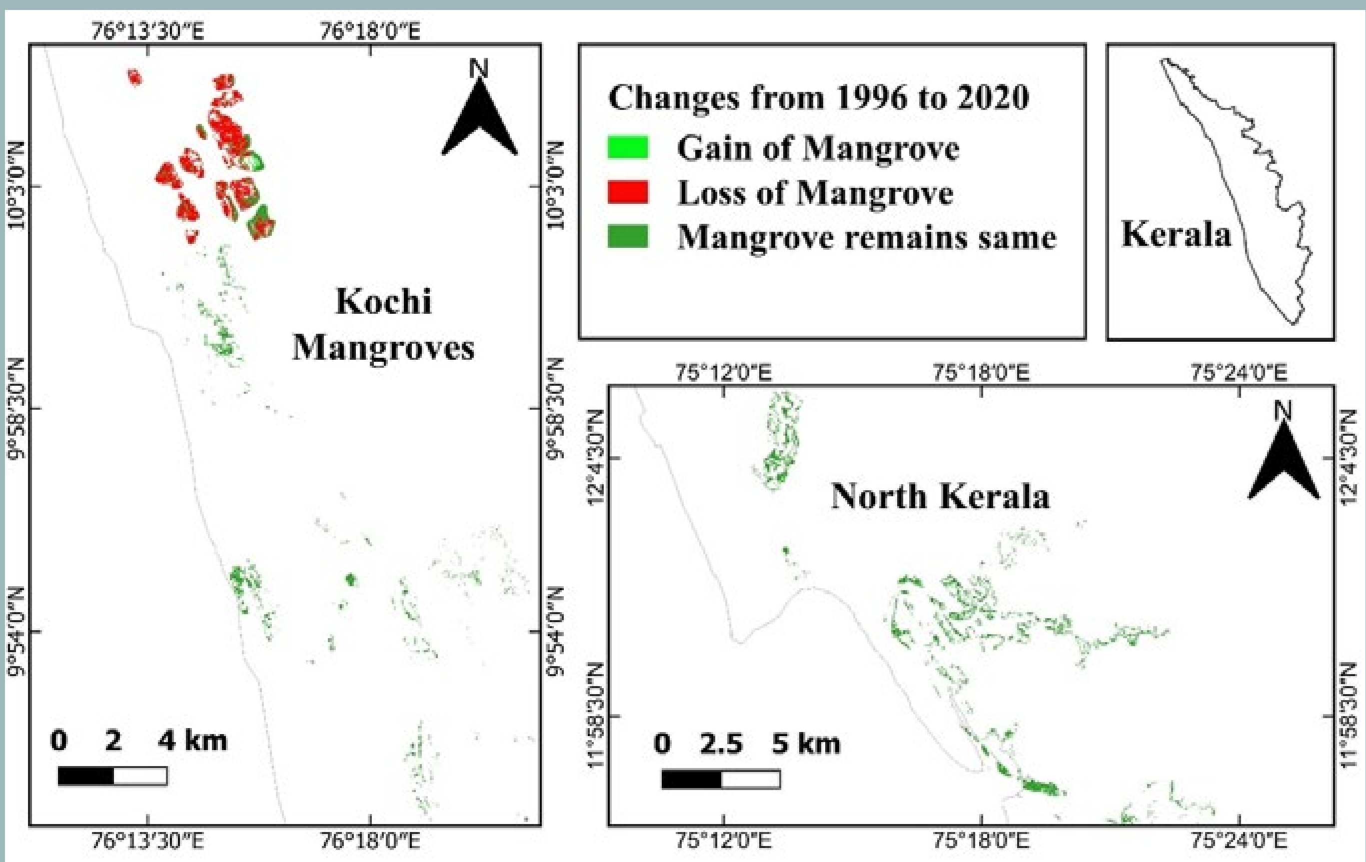
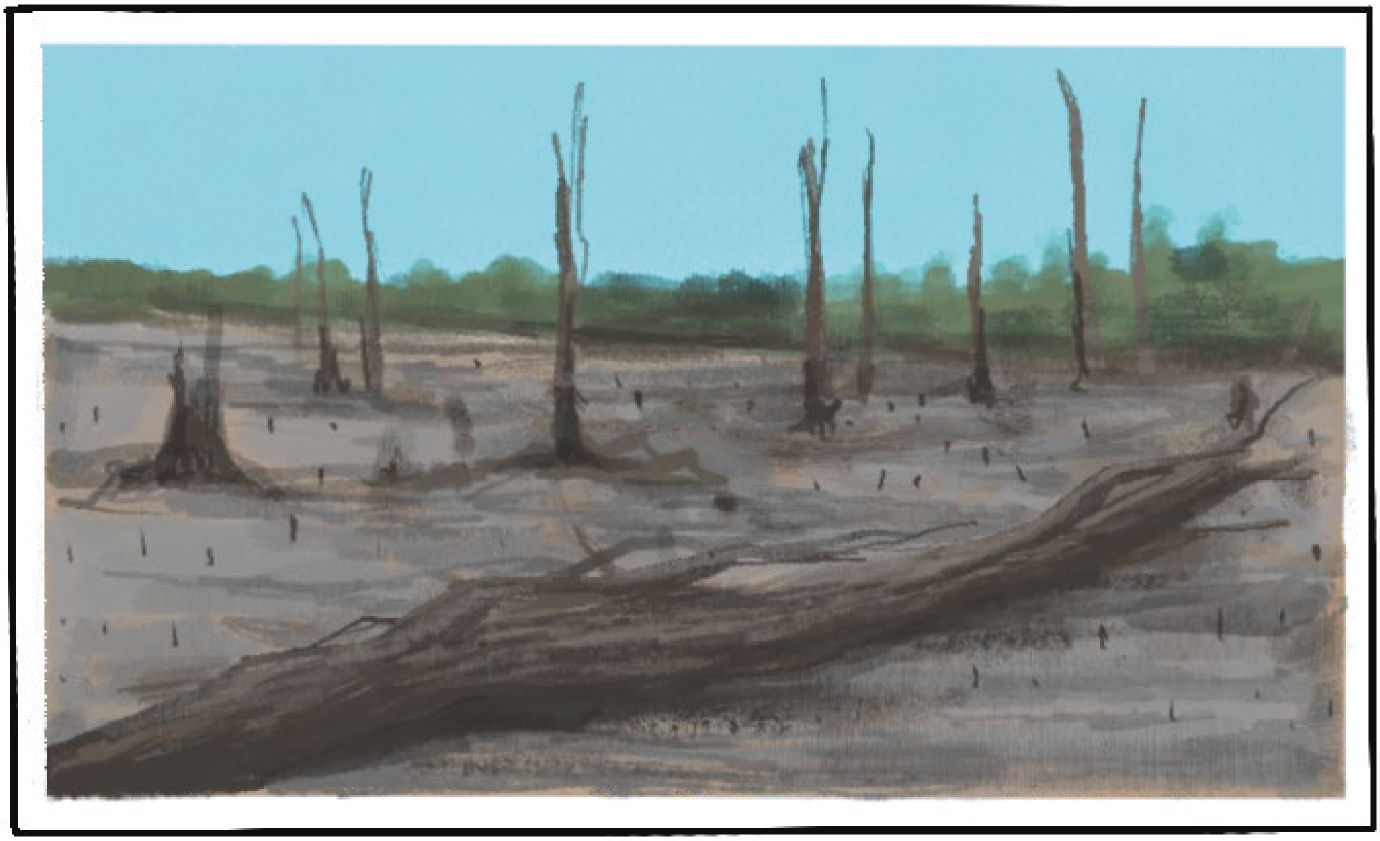


Figure 2.3: Changes in mangrove cover observed along the Kerala coast (1996–2020).



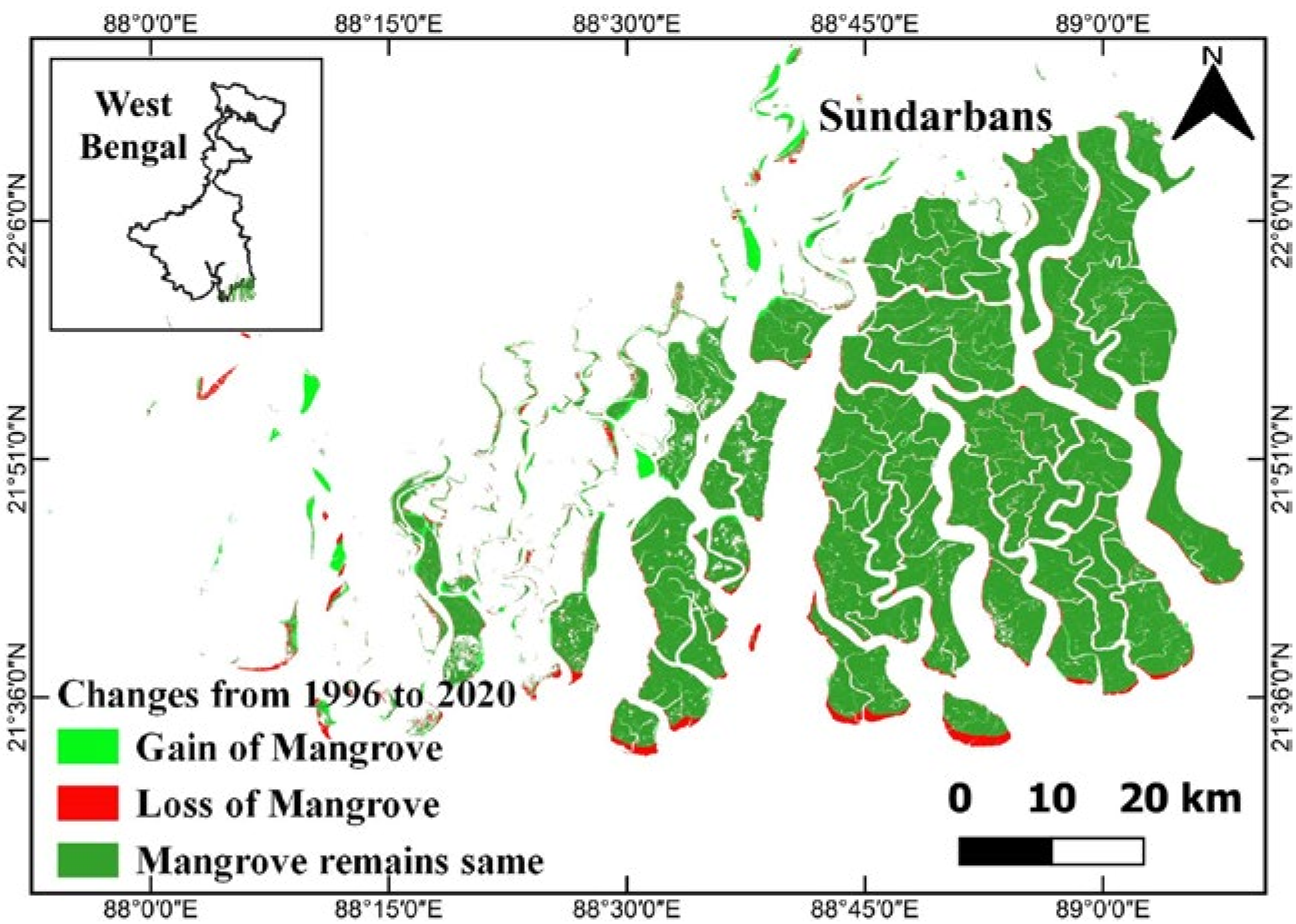


Figure 2.4: Mangrove cover trends in Sundarbans, West Bengal (1996–2020): Stable, Newly gained, and Lost areas.

Gujarat followed a trend similar to that of West Bengal, with an overall loss of 28.01 km^2. The decline in Gujarat's mangroves, primarily located in the Rann of Kutch and Gulf of Kutch, is alarming and likely attributed to coastal industrialization and altered hydrological regimes (Figure 2.5).

On the east coast, unlike other coastal states that exhibited a declining trend, Odisha recorded a gain in mangrove area, increasing from 186.94 km^2 in 1996 to 215.65 km^2 in 2020 with an increase of nearly 10%. Although some areas along the Odisha coast experienced mangrove loss, the two prominent mangrove forests, Bhitarkanika and Mahanadi, witnessed substantial new growth as shown in Figure 2.6. This made Odisha the state with the highest mangrove area gain from 1996 to 2020, as per GMW data (Figure 2.6).

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Both Maharashtra and Goa states are characterized by smaller, fragmented mangrove patches, often impacted by rapid urbanization and tourism-related activities. In contrast, Karnataka's mangrove cover remained nearly stable between 1996 and 2020 with a negligible loss of 0.34 km^2 (Table 2.2). Above mentioned mangrove area reduction is observed in the Aghnashini estuary and Kali estuary (Figure 2.10).

Among the Union Territories, the Andaman & Nicobar Islands, which host extensive mangrove forests, recorded a total loss of 11.06 km^2 (Table 2.2). Though not as drastic as some mainland states in terms of overall mangrove area reduction, this loss in a biodiversity-rich region is concerning, given the role of mangroves in coastal protection and ecosystem stability. Figure 2.11 illustrates the changes in the mangroves of Andaman from 1996 to 2020. It is evident from Figure 2.11 that mangrove in North Andaman experienced new growth along the west coast, while some areas along the east coast partially vanished. In South Andaman, concentrated mangrove loss occurred near the Bombooflat region due to urban expansion and agricultural conversion (Figure 2.11).

Daman & Diu and Dadra & Nagar Haveli recorded a loss of 0.13 km^2, a substantial reduction considering their already minimal mangrove coverage. Puducherry exhibited a decline of 0.32 km^2 (10.74%), highlighting its vulnerability to coastal modifications.

Comparing the east and west coasts, mangrove degradation is more evident in Tamil Nadu and Kerala, with 44.5% and 25.1% area loss, respectively. While most west coast states, except Kerala (i.e., Goa, Gujarat, Karnataka, and Maharashtra), recorded relatively lower reductions, the losses were more significant along the east coast, particularly in Tamil Nadu and West Bengal, which had larger initial mangrove extents. Kerala lost over 25.1% of its mangrove cover, while Gujarat also experienced significant degradation. In contrast, states such as Andhra Pradesh and the Andaman & Nicobar Islands showed smaller percentage declines, though the absolute loss remained substantial.

The temporal trend indicates that the most intense degradation occurred between 1996 and 2010, during which India lost 127.94 km^2 of mangroves. However, between 2010 and 2020, the country witnessed a partial recovery of approximately 10 km^2. The slightly lower area gain in the latter decade suggests a slowing decline, potentially due to conservation efforts and afforestation initiatives. However, despite localized gains, the overall trend remains negative in most coastal states, emphasizing the urgent need for stricter conservation policies, sustainable coastal management, and restoration programs.

In summary, according to GMW area estimates, while some regions have managed to stabilize or regain mangrove areas, the overall pattern is one of decline, with Kerala, Tamil Nadu, Gujarat, and West Bengal experiencing the most significant losses. Given the critical role of mangroves in coastal resilience, biodiversity conservation, and carbon sequestration, immediate and effective intervention is essential to curb further degradation and restore lost habitats.

Table 2.2: Long-term changes in mangrove cover across coastal states of India (1996–2020) (Source: Global Mangrove Watch by UNEP)

State/UT Name	Mangrove area (km²)											
	Area (1996)	Area (2010)	Area (2020)	Changes from 1996 to 2010			Changes from 2010 to 2020			Changes from 1996 to 2020		
				Area remains the same	Area gained	Area lost	Area remains the same	Area gained	Area lost	Area remains the same	Area gained	Area lost
Andhra Pradesh	382.76	358.34	368.87	345.65	12.69	37.11	336.67	32.2	21.67	354.94	13.93	27.82
Goa	49.93	45.19	47.08	42.64	2.55	7.29	42.54	4.54	2.65	44.68	2.4	5.25
Gujarat	544.69	537.76	516.68	456.7	81.06	87.99	442.62	74.06	95.14	422.7	93.98	121.99
Karnataka	29.2	26.21	28.86	24.91	1.3	4.29	25.42	3.44	0.79	26.76	2.1	2.44
Kerala	20.72	15.5	15.71	15.31	0.19	5.41	14.65	1.06	0.85	15.52	0.19	5.2
Maharashtra	310.05	295.94	299.06	286.18	9.76	23.87	282.2	16.86	13.74	284.78	14.28	25.27
Odisha	186.94	187.9	215.65	157.08	30.82	29.86	179.24	36.41	8.66	164.38	51.27	22.56
Tamil Nadu	103.13	55.5	57.23	54.06	1.44	49.07	43.73	13.5	11.77	55.57	1.66	47.56
West Bengal	2524.81	2522.2	2497.09	2405.01	117.19	119.8	2426.27	70.82	95.93	2349.18	147.91	175.63
A&N Islands	603.24	583.44	592.18	572.89	10.55	30.35	569.86	22.32	13.58	573.47	18.71	29.77
Daman & Diu and Dadra & Nagar Haveli	1.78	1.66	1.65	1.41	0.25	0.37	1.22	0.43	0.44	1.31	0.34	0.47
Puducherry	2.98	2.65	2.66	2.51	0.14	0.47	2.37	0.29	0.28	2.62	0.04	0.36
Total	4760.23	4632.29	4642.72	4364.35	267.94	395.88	4366.79	275.93	265.5	4295.91	346.81	464.32

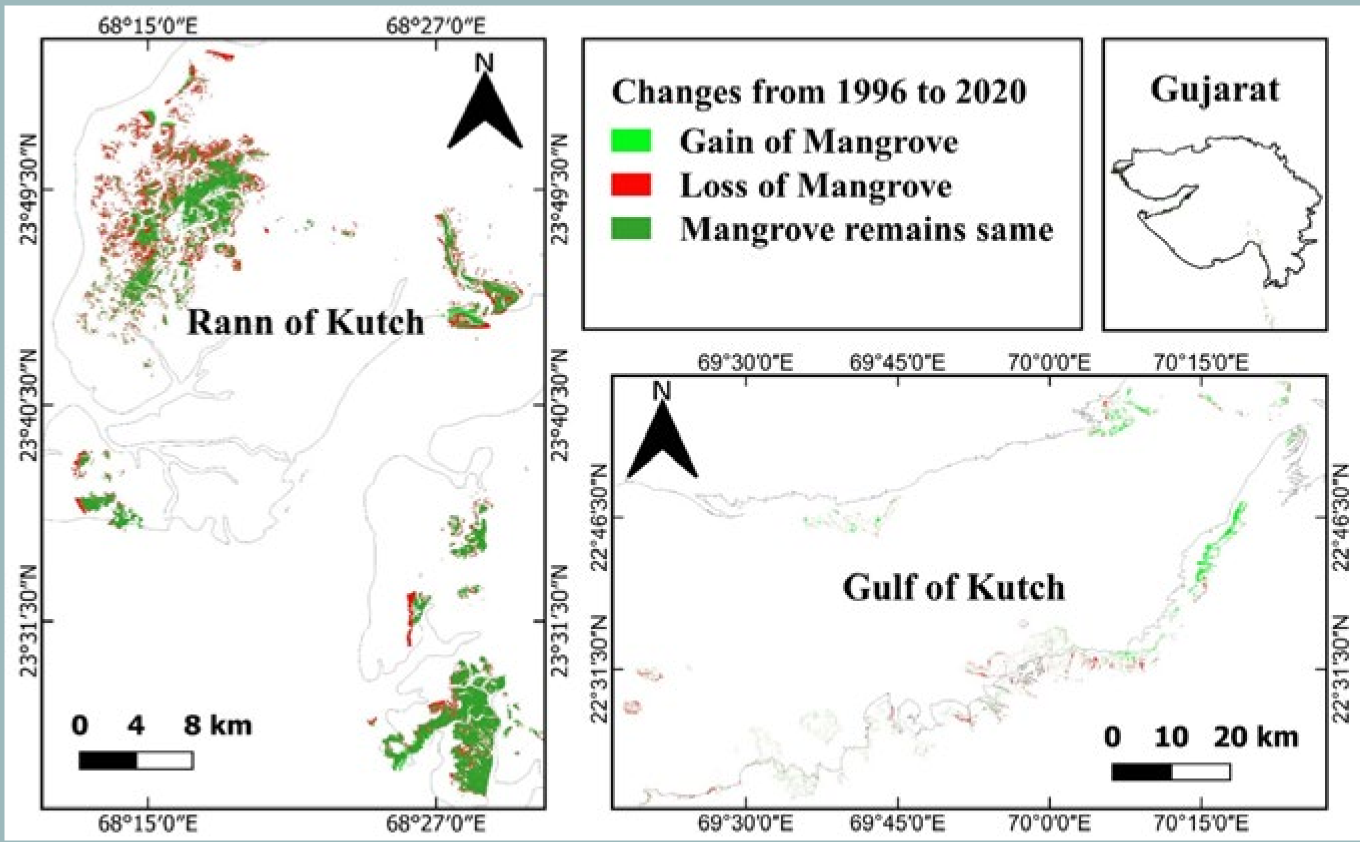
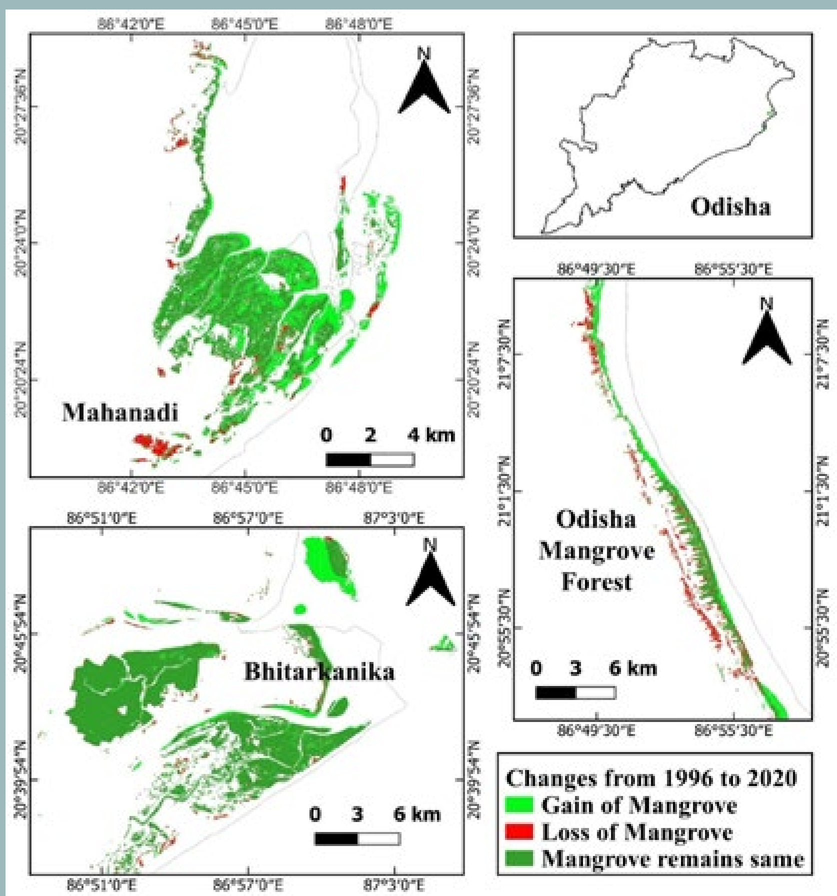


Figure 2.5: Changes in mangrove cover observed in the Kutch region of Gujarat state (1996–2020)

Figure 2.6: Changes in mangrove cover observed along the Odisha coast (1996–2020): Stable, Newly gained, and Lost areas.



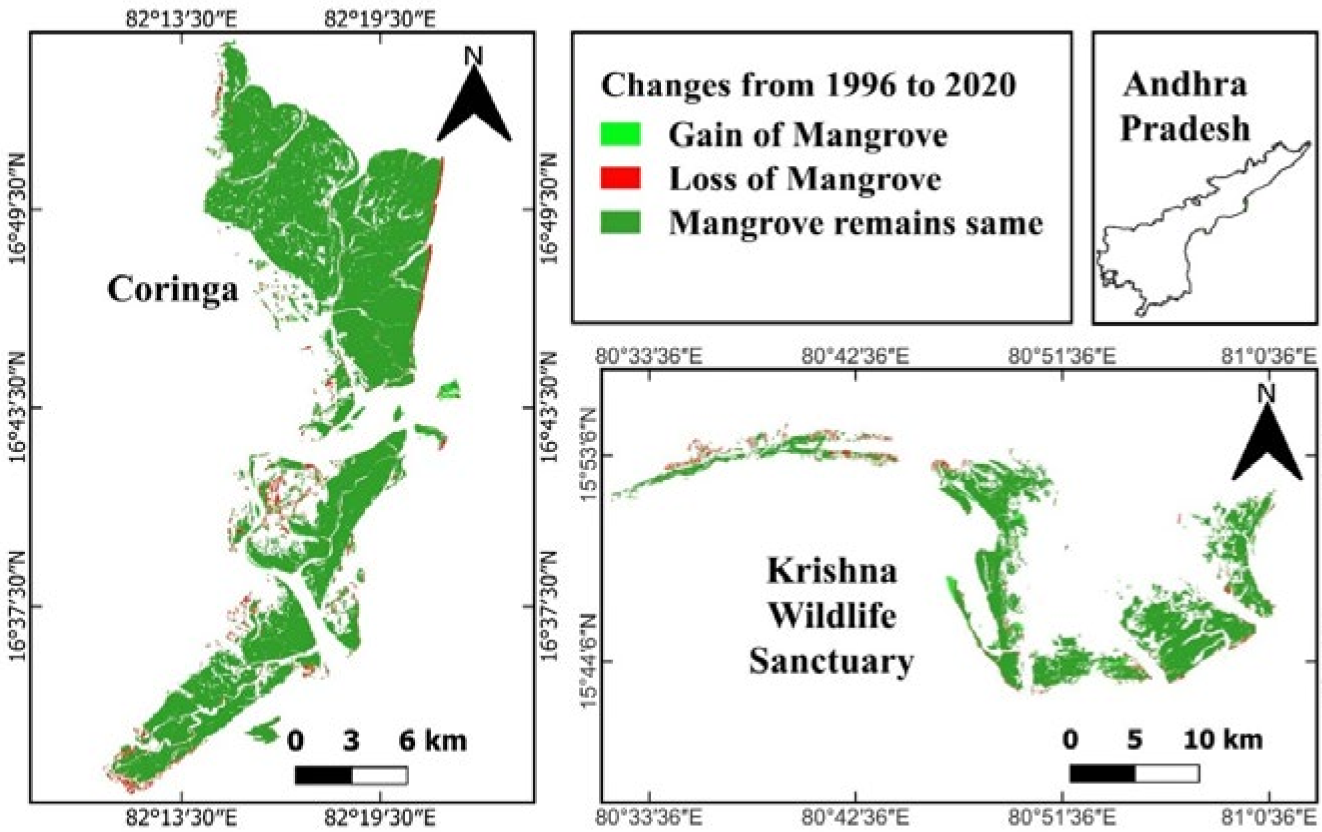


Figure 2.7: Changes in mangrove cover observed along the Andhra Pradesh coast (1996–2020).

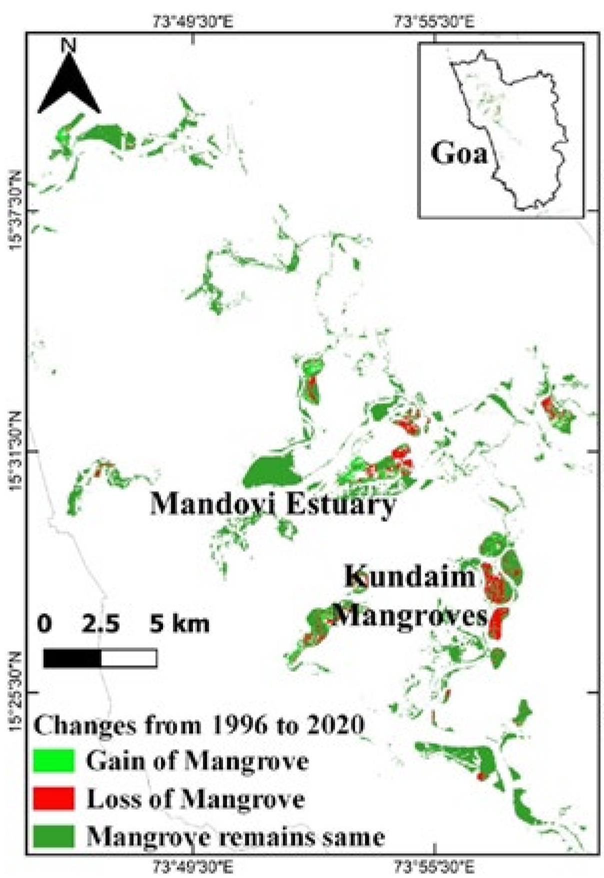


Figure 2.8: Changes in mangrove cover observed along the Goa coast (1996–2020).

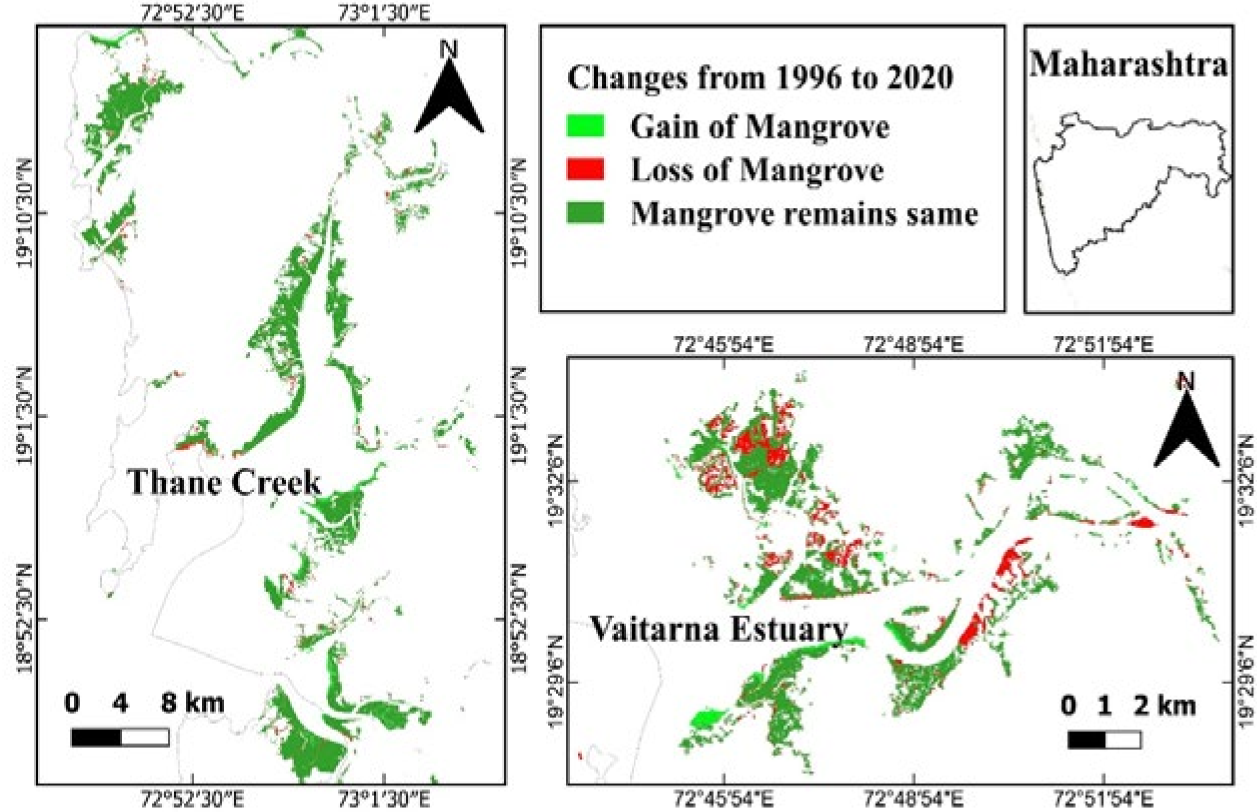
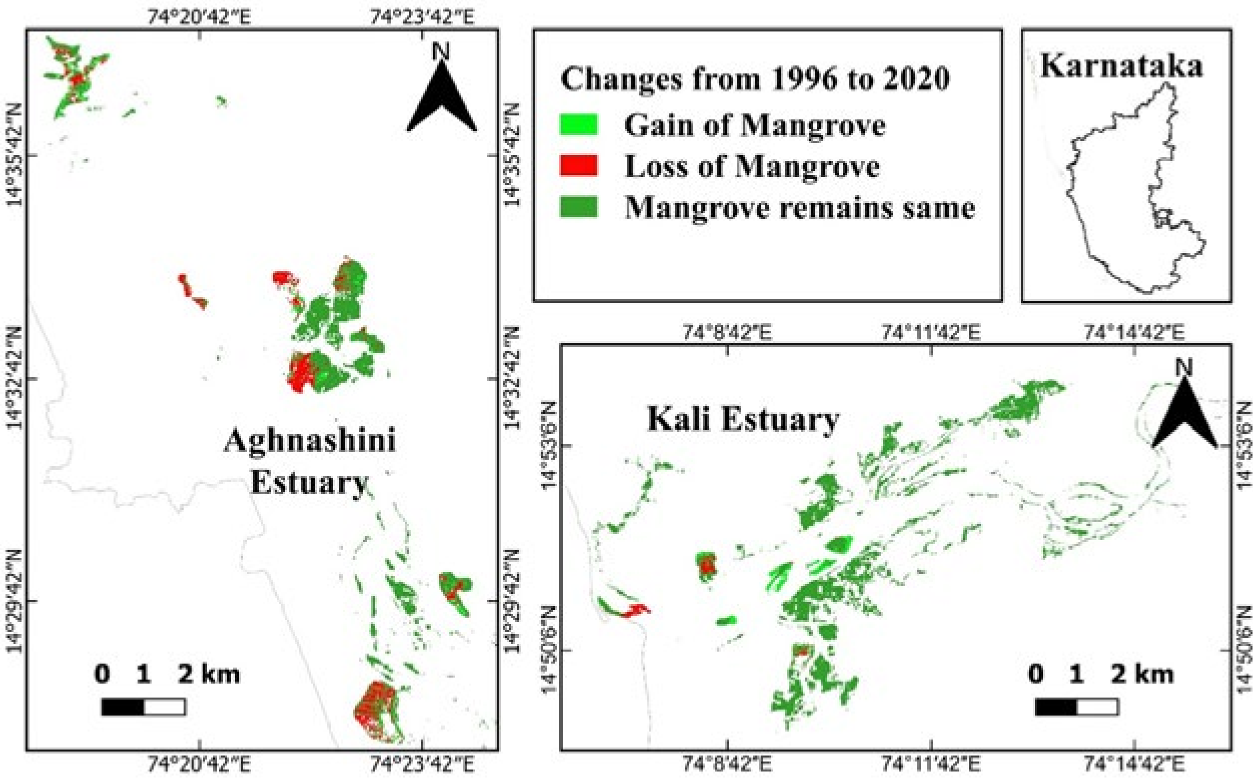


Figure 2.9: Changes in mangrove cover observed in the Thane Creek region and Vaitarna estuary of Maharashtra state (1996–2020)

Figure 2.10: Changes in mangrove cover observed in the Aghnashini and Kali estuary of Karnataka state (1996–2020)



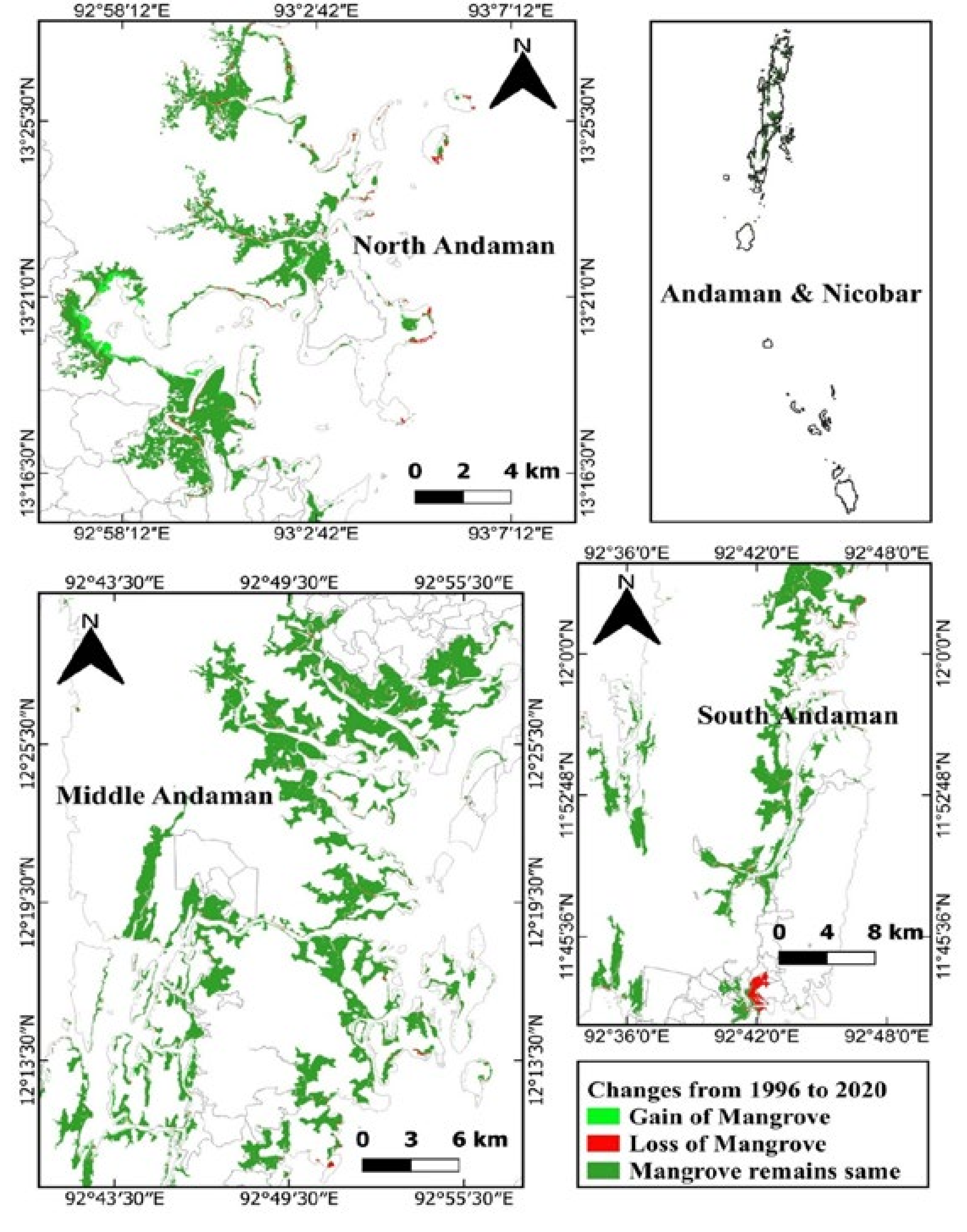


Figure 2.11: Changes in mangrove cover observed from 1996 to 2020 in Andaman & Nicobar Islands.

The long-term trends in mangrove cover across coastal states of India from 2003 to 2023 were analysed using data from ISFR biennial reports, and the results are presented in Table 2.3. As discussed earlier, unlike GMW data, which provides only the total area, ISFR data categorizes mangrove cover into three classes: dense, moderately dense, and open. This classification offers additional insights into mangrove degradation beyond overall area loss.

By distinguishing between these categories, the ISFR data allows for the assessment of degradation due to the transition of mangrove areas from dense to moderately dense and from moderately dense to open over time. According to Table 2.3, India's total mangrove cover increased from 4,461 km² to 4,991.68 km², reflecting a net gain of 530.68 km² (an 11.89% increase) between 2003 and 2023. This growth is primarily observed in the Very Dense and Open mangrove categories, which expanded by 25.98% and 23.44%, respectively. However, the moderately dense category declined by 9.42%, suggesting possible degradation or conversion to either denser or more fragmented mangrove stands.

At the state level, Maharashtra experienced the highest relative increase in mangrove cover, growing by 171.63%, from 116 km² in 2003 to 315.09 km² in 2023 (Table 2.3). Although the state recorded the highest increase in open mangrove areas since 2003, concerns remain, as all of its very dense mangrove areas (8 km² in 2003) have completely disappeared. Similarly, Gujarat saw the highest absolute gain, adding 204.06 km², likely due to conservation efforts and afforestation programs. However, it also witnessed mangrove degradation of 18.91 km², resulting from the conversion of moderately dense mangroves to open mangroves over the past two decades (Table 2.3).

Andhra Pradesh and Odisha also showed significant growth, increasing by 28.09% and 25.15%, respectively. In contrast, West Bengal, which holds the largest mangrove cover, remained largely stable, with only a marginal decline of 0.04%, indicating minimal changes in total extent. However, a closer examination of different canopy density classes reveals a significant reduction of 190.21 km² in moderately dense mangroves, from 894 km² in 2003 to 703.79 km² in 2023. Meanwhile, very dense mangroves in the region expanded by 89.63 km². Assuming that some of the moderately dense mangroves transitioned to very dense mangroves over time, there is still an estimated net reduction of approximately 100 km² in moderately dense mangroves. This reduction correlates with an observed gain in open mangroves (Table 2.3).

Therefore, it is evident that nearly 100 km² (11.18% of the moderately dense category) of mangrove area in the Sundarbans has degraded due to its conversion into open mangroves. This is a serious concern, as the Sundarbans is one of the world's most prominent mangrove ecosystems and supports a rich diversity of flora and fauna in India.

In states with historically low mangrove coverage, considerable percentage growth has been observed. Karnataka exhibited a 373.33% increase, although from a small baseline of 3 km² in 2003 to 14.2 km² in 2023. Goa's mangrove cover expanded by 213.4%, from 10 km² to 31.34 km², reflecting successful restoration efforts. Tamil Nadu and Kerala experienced moderate growth of 19.74% and 18.13%, respectively, indicating incremental progress in conservation (Indian Forest Report, 2024).

A comparison between the West Coast (Gujarat, Maharashtra, Goa, Karnataka, and Kerala) and the East Coast (West Bengal, Odisha, Andhra Pradesh, Tamil Nadu, and Puducherry) reveals contrasting trends. The West Coast exhibited a significantly higher percentage increase of 39.84%, driven primarily by Gujarat and Maharashtra. In contrast, the East Coast, while still holding the majority of India's mangroves, recorded a much slower growth rate of 5.56%, with most of the increase concentrated in Andhra Pradesh and Odisha. The decline in moderately dense mangroves on the East Coast raises concerns regarding degradation, particularly in West Bengal, which remains India's largest mangrove-holding state.

The Andaman and Nicobar Islands (A&N), home to the second-largest mangrove cover in India, showed a relatively stable trend over the two decades. However, the total mangrove area declined from 671 km² in 2003 to 608.29 km² in 2023, reflecting a 9.36% reduction. A closer examination of canopy density changes reveals that 97 km² of open mangroves has been reduced to just 46.28 km², marking a 52% loss in this category. Additionally, approximately 12 km² of moderately dense mangroves transitioned into open mangroves, accounting for 3.84% loss in this category. Overall, the category-wise assessment highlights that nearly 56% of mangroves in A&N have undergone degradation between 2003 and

2023, according to the latest Indian Forest Report (2024). This decline is likely attributed to coastal erosion, rising sea levels, and human disturbances. Given the ecological significance of A&N's mangroves in supporting marine biodiversity, urgent conservation measures are necessary to address this ongoing degradation.

Among the Union Territories, Puducherry, Daman & Diu and Dadra & Nagar Haveli have historically had minimal mangrove cover. Puducherry's mangrove area increased from 1 km^2 in 2003 to 3.83 km^2 in 2023, reflecting a 283% increase due to restoration efforts. Similarly, Daman & Diu and Dadra & Nagar Haveli recorded an increase from 1 km^2 to 3.86 km^2, indicating successful afforestation initiatives. While these increases are encouraging, the overall extent remains too small to significantly impact national mangrove coverage.

These findings underscore the success of mangrove afforestation and conservation programs, particularly in Gujarat and Maharashtra, where large-scale restoration projects have significantly expanded coverage. However, the decline in moderately dense mangroves suggests that while total area is increasing, structural integrity and canopy density are being affected. The 56% degradation of mangroves in A&N is especially concerning, as these ecosystems play a critical role in coastal protection, carbon sequestration, and biodiversity conservation. Conservation efforts should prioritize the protection and restoration of degraded mangrove areas, particularly in states and Union Territories experiencing mangrove fragmentation and degradation.

While the overall increase in mangrove cover is a positive development, several challenges persist. The loss of moderately dense mangroves, the slower growth on the East Coast, and the significant degradation in the A&N Islands highlight areas requiring urgent intervention. Moving forward, strengthening policy frameworks, promoting community-led restoration programs, and leveraging advanced remote sensing technologies will be crucial for long-term mangrove conservation in India.

A comparative analysis of mangrove cover trends in India, based on Global Mangrove Watch (GMW) and India State of Forest Report (ISFR)

Table 2.3: State-wise mangrove area distribution in India (2003–2023) (Source: India State of Forest Report)

State/UT Name	Mangrove Area in 2003				Mangrove Area in 2013				Mangrove Area in 2023			
	Very Dense (km^2)	Moderately Dense (km^2)	Open (km^2)	Total (km^2)	Very Dense (km^2)	Moderately Dense (km^2)	Open (km^2)	Total (km^2)	Very Dense (km^2)	Moderately Dense (km^2)	Open (km^2)	Total (km^2)
Andhra Pradesh	0	15	314	329	0	126	226	352	0	213.9	207.53	421.43
Goa	0	10	0	10	0	20	2	22	0	23.75	7.59	31.34
Gujarat	0	198	762	960	0	175	928	1103	0	179.09	984.97	1164.06
Karnataka	0	3	0	3	0	3	0	3	0	3.15	10.94	14.2
Kerala	0	3	5	8	0	3	3	6	0	4.73	4.72	9.45
Maharashtra	0	44	64	116	0	69	117	186	0	89.82	225.27	315.09
Odisha	0	160	47	207	82	88	43	213	81.67	94.61	82.78	259.06
Tamil Nadu	0	18	17	35	0	16	23	39	1.19	25.07	15.65	41.91
West Bengal	892	894	334	2120	993	699	405	2097	981.63	703.79	433.74	2119.16
A&N Islands	262	312	97	671	276	258	70	604	399.37	162.64	46.28	608.29
Daman & Diu and Dadra & Nagar Haveli	0	0	1	1	0	0	1	1	0	0.21	3.65	3.86
Puducherry	0	0	1	1	0	0.14	1.49	1.63	0	0.08	3.75	3.83
Total	1162	1657	1642	4461	1351	1457	1819	4628	1463.97	1500.84	2026.87	4991.68

data, reveals notable contrasts in decline and gain patterns across key states. GMW data indicates an overall net mangrove loss of 117.51 km² between 1996 and 2020, with Tamil Nadu experiencing the steepest decline (44.5%), followed by Gujarat (28.01 km²), West Bengal (27.72 km²), and Kerala (25.1%). Tamil Nadu's losses, particularly in Pichavaram and Muthupet, were primarily attributed to land conversion, coastal erosion, and sediment loss, while Kerala's decline was driven by aquaculture expansion, especially in Kochi.

In contrast, ISFR data suggests an overall increase of 530.68 km² between 2003 and 2023, with Gujarat recording the highest absolute gain (204.06 km²) and Maharashtra showing the largest relative increase (171.63%). However, despite the net increase in mangrove area, ISFR data also highlights significant degradation within canopy density classes, particularly in West Bengal, where 190.21 km² of moderately dense mangroves declined, despite an increase in very dense cover. This raises concerns about structural degradation masked by afforestation gains. Similarly, the Andaman & Nicobar Islands show conflicting trends, with ISFR reporting a 9.36% loss, primarily due to a 56% degradation of open mangroves, while GMW data indicates a moderate decline (11.06 km²). These differences underscore the importance of integrating multiple data sources to capture both quantitative and qualitative changes in mangrove ecosystems, ensuring conservation efforts address not only area expansion but also structural and ecological integrity

Meanwhile, the discrepancies between ISFR and GMW could be attributed to differences in classification systems. ISFR's classification into dense, moderate, and open categories may overestimate gains by including sparsely vegetated areas, while GMW's remote sensing approach might detect loss more effectively but could underestimate regrowth. Both datasets highlight the urgent need for standardized mangrove monitoring, integrating satellite-based assessments with field surveys.

Therefore, the latest state-wise mangrove area estimates in India, available from three different sources namely NWIA, ISFR, and GMW, are considered in accounting for the national-level total carbon stock in this study. Figure 2.12 presents the most recent mangrove areas across all coastal states in India.

From Figure 2.12, a comparison of mangrove area estimates from NWIA, ISFR, and GMW highlights significant discrepancies, underscoring methodological and classification differences across these datasets. Gujarat exhibits the notable variation, with NWIA and ISFR reporting 1081.8 km² and 1164.1 km² respectively, both more than double the mangrove extent estimated by GMW (518.3 km²). This difference suggests potential underestimation in global datasets or the impact of afforestation initiatives captured in recent national assessments.

Similar trends are observed in Andhra Pradesh, Maharashtra, and Odisha, where NWIA consistently records higher mangrove extents than ISFR and GMW, possibly reflecting differences in classification thresholds or temporal updates. In contrast, Tamil Nadu presents a striking anomaly, with ISFR estimating only 41.9 km² compared to 118.3 km² in NWIA and 57.2 km² in GMW, indicating potential degradation overlooked by national datasets or inconsistencies in mangrove mapping. West Bengal, India's largest mangrove-holding state, also demonstrates notable variation, with GMW estimating the highest cover (2497.1 km²) compared to ISFR (2119.2 km²) and NWIA (2134.1 km²), suggesting possible overestimation in the global dataset. The Andaman & Nicobar Islands exhibit relative consistency across all sources, reinforcing their stable mangrove extent. However, discrepancies in smaller states such as Goa and Kerala, where GMW reports higher cover than ISFR, likely arise from differences in the classification of open and fragmented mangrove patches.

Overall, due to the variations in mangrove area estimates across states from the three different sources, this study separately estimated the national-level mangrove carbon stock based on areas reported by each dataset. The state level variations in saltmarshes are discussed in the following section.

2.3.2 Temporal Dynamics in the Extent of Salt Marshes

As discussed in the above sections, the data available for studying the spatial and temporal variations in salt marsh area in India is very limited. Viswanathan et al. (2020) was the first study to map state-wise salt marshes in India for the assessment year 2010–2011 using Linear Imaging and Self Scanning Mission-4 (LISS-IV) sensor data with a spatial resolution of 5.4 m. Recently, Gupta et al. (2024) also mapped state-level salt marshes in India (NWIA-2024) using the same sensor data for the assessment year 2018–2019. Thus, a comparison of salt marsh extent in India from these two datasets was conducted, revealing substantial temporal and spatial variations. The total recorded salt marsh area increased significantly from 290.49 km² (Viswanathan et al., 2020) to 1497.71 km² (Gupta et al., 2024), suggesting improved mapping methodologies, dataset updates, or actual expansion.

As shown in Figure 2.13, Gujarat exhibits the most dramatic increase, from 157.94 km² in the 2010–2011 dataset to 1368.77 km² in NWIA-2024, now accounting for approximately 91.4% of India's total salt marshes. This surge may reflect improved classification methodologies, afforestation initiatives, or natural accretion processes. Similarly, Maharashtra, the Andaman & Nicobar Islands, and Andhra Pradesh show moderate increases in salt marsh extent. However, several states, including Tamil Nadu, Odisha, Goa, and West Bengal, exhibit substantial declines, with Tamil Nadu's salt marsh cover shrinking from 57 km² to 14.98 km² and West Bengal's disappearing entirely in the NWIA-2024 dataset. These declines could indicate degradation, land-use changes, or inconsistencies in classification approaches between the two assessments. The absence of salt marshes in West Bengal, despite prior records, raises concerns regarding habitat loss due to coastal development and erosion.

Overall, while the NWIA-2024 dataset reports a major expansion in total saltmarsh area, particularly in Gujarat, the decline in certain coastal states underscores the need for further investigation into habitat dynamics and conservation efforts. Therefore, due to the significant differences in salt marsh area estimates from the two datasets, particularly in Gujarat, both values are considered in this study to estimate the total carbon stocks for salt marshes in India.

2.3.3 Seagrass Variability over Time

The assessment of seagrass extent in India varies significantly across different studies, reflecting differences in mapping methodologies, sensor capabilities, and temporal changes. As shown in Figure 2.14, Geevarghese et al. (2018) estimated the total seagrass area in India as 516.59 km² across key coastal and island ecosystems, while more recent estimates by Seal et al. (2023) indicate substantial expansions in Palk Bay (566 km²) and the Gulf of Mannar (307 km²). The increase in these regions suggests either an improvement in mapping techniques, actual seagrass growth, or both. However, the comparison also highlights potential declines in certain areas. For instance, Lakshadweep recorded a seagrass extent of 25.9 km² in Nobi et al. (2012), but Geevarghese et al. (2018) reported only

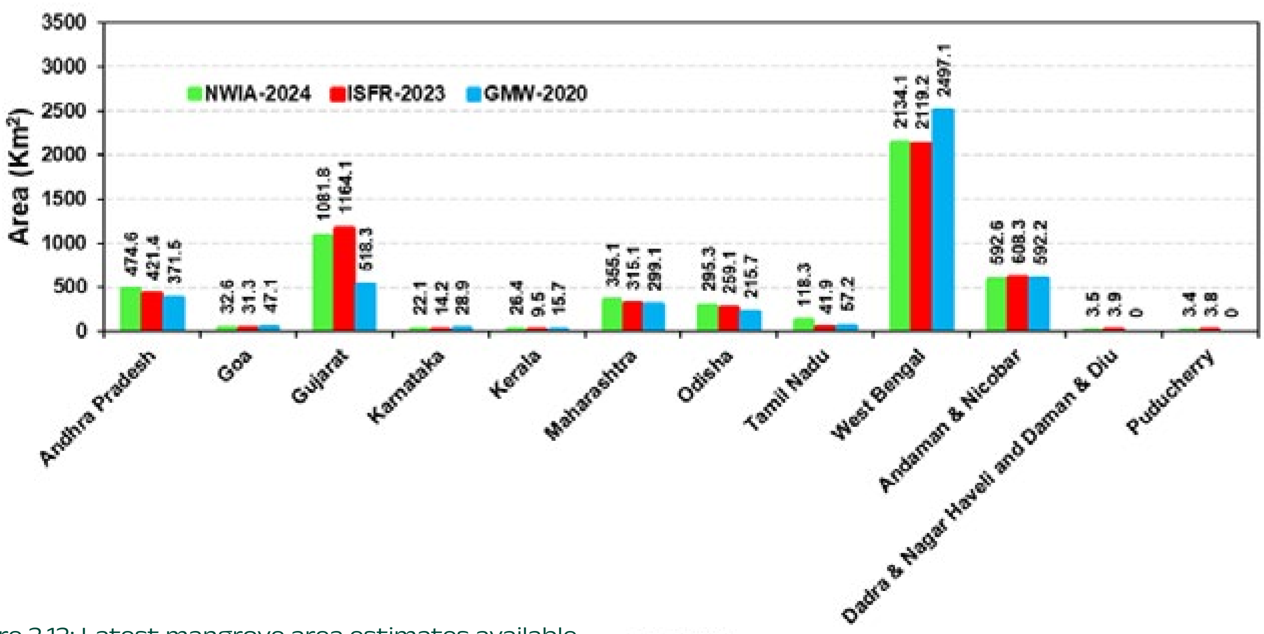


Figure 2.12: Latest mangrove area estimates available from various sources for all coastal states of India

0.72 km², indicating a significant loss, potentially due to sequential overgrazing by green turtles (Gangal et al. 2021). Other regions, such as the Gulf of Kutch, Chilka Lake, and Andaman & Nicobar, were not assessed in the Seal et al. (2023) dataset, leaving uncertainties regarding their current status. The discrepancies between datasets emphasize the need for standardized long-term monitoring to accurately assess seagrass dynamics and inform conservation strategies.

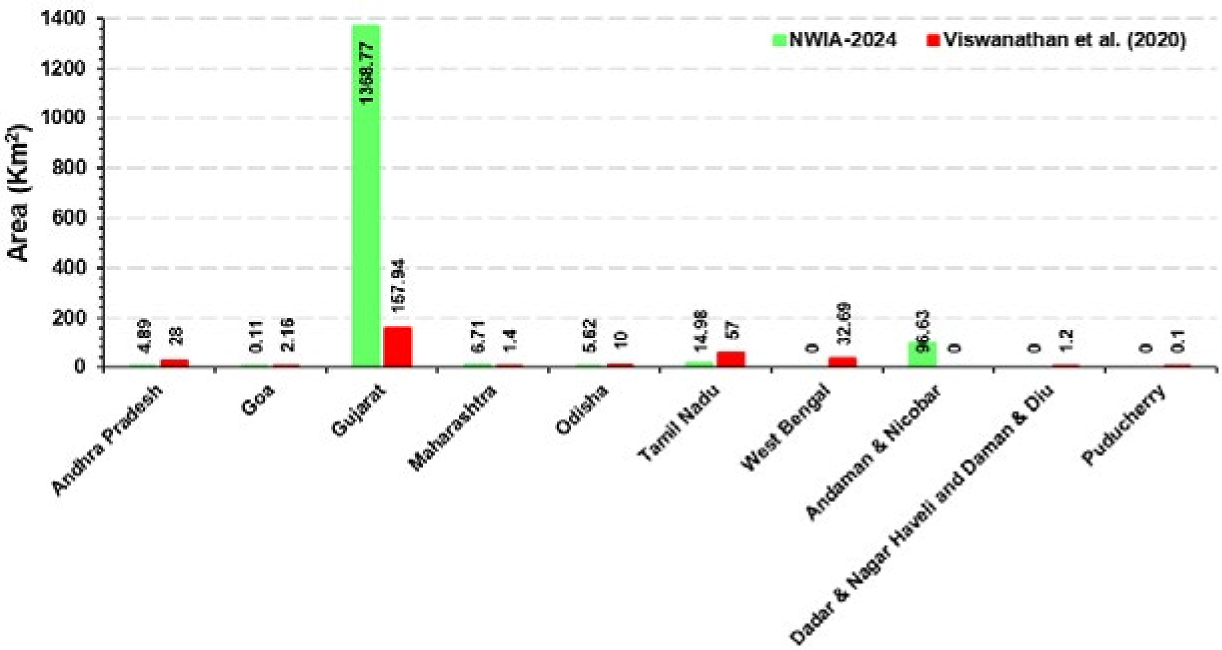


Figure 2.13: Variations in saltmarshes area estimates across coastal states of India.

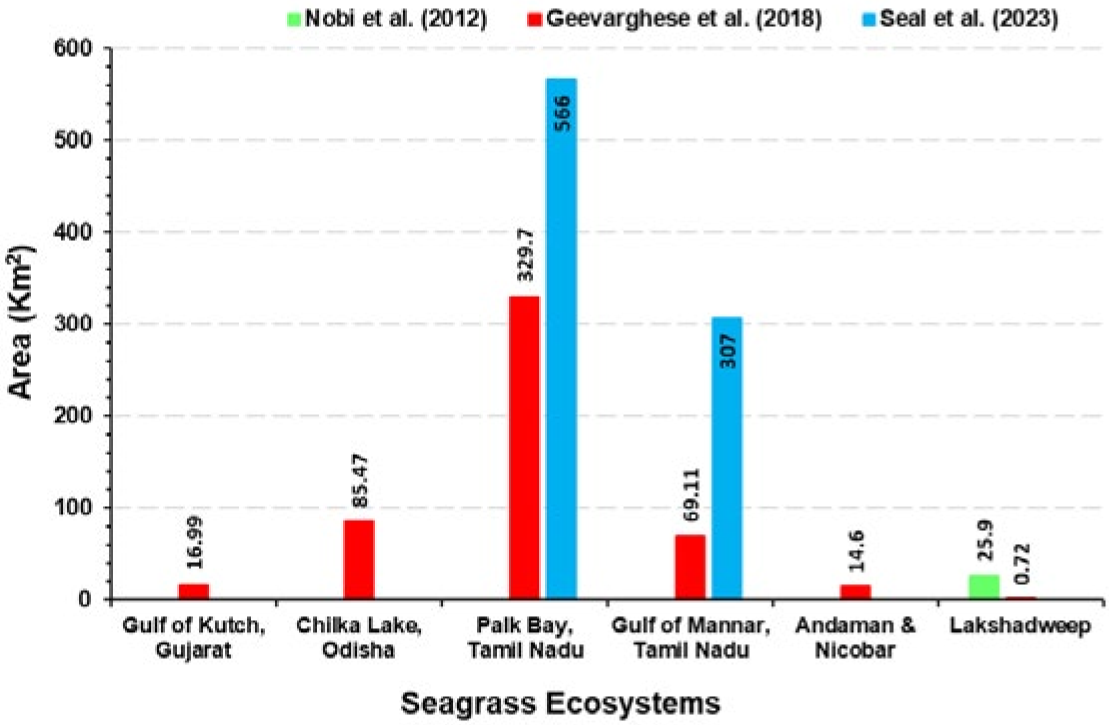


Figure 2.14: Variations in area estimates of Seagrass ecosystems in India.

2.4 Summary

This chapter presents a comprehensive assessment of mangrove ecosystems, focusing on their spatial distribution, ecological functions, and observed trends in coverage across different regions. Utilizing multiple datasets, including NWIA, ISFR and GMW, the analysis reveals significant variations in mangrove extent, underscoring methodological differences in remote sensing approaches. Gujarat exhibits the notable discrepancy in mangrove area, with national datasets (NWIA and ISFR) reporting over double the extent compared to GMW, suggesting potential underestimation in global assessments. Andhra Pradesh, Maharashtra, and Odisha follow similar trends, with national datasets indicating higher mangrove cover than GMW, likely due to differences in classification thresholds or recent afforestation initiatives. Further, Tamil Nadu shows substantial variation, with ISFR reporting significantly lower mangrove area than NWIA and GMW, raising concerns about degradation or mapping inconsistencies.

West Bengal, the state with the largest mangrove coverage, exhibits notable differences, with GMW estimating a higher extent than both national sources, hinting at possible overestimation in global datasets. The Andaman & Nicobar Islands show relative consistency across sources, suggesting stability in mangrove cover. Further, saltmarsh and seagrass datasets highlight significant spatiotemporal changes, with Gujarat alone accounting for 91.4% of India's saltmarshes in NWIA data, while several states show declining trends. Seagrass assessments across sources also reveal major discrepancies, with substantial reductions observed in Lakshadweep and variations in Tamil Nadu's Palk Bay and Gulf of Mannar. These findings emphasize the critical need for harmonized methodologies in mapping coastal blue carbon ecosystems and call for targeted conservation strategies to address regional declines.

CHAPTER 3

Blue Carbon Stocks of India: Database Synthesis and Meta-Analysis

3.1 Introduction

India, being the fifth-largest economy in the world ($4.27 trillion), is projected to surpass Japan ($4.39 trillion) to become the fourth-largest economy by the end of 2025, and further expected to overtake Germany ($4.92 trillion) by the end of 2027 (International Monetary Fund, 2025). At the same time, India is striving to align its major growth sectors with sustainable development pathways to meet its emission reduction targets.

Despite continuous efforts over recent decades, India remains the third-largest CO_2 emitting country, with 2,955 million tonnes (Mt) of emissions in 2023, following the USA (4,682 Mt) and China (13,260 Mt) (CO_2 Emissions by Country, 2025). In response, researchers around the world are focusing on developing new technologies to reduce carbon emissions. One such emerging technology is Carbon Capture, Utilization, and Storage (CCUS), which involves trapping atmospheric CO_2 and injecting it at high pressure into deep saline aquifers for long-term storage (Hanson et al., 2024). This stored carbon can also be utilized in the production of biofuels.

Although CCUS appears to be a promising technology and is currently under trial in several countries including the USA, European Union member states, China, and Norway, recent cost analyses indicate that the implementation of such projects is unlikely to be economically viable due to high operational costs and the limited efficiency of existing capture methods (both pre-combustion and post-combustion systems) (Hanson et al., 2024).

Moreover, several environmental concerns have emerged, such as potential geological instability caused by high-pressure CO_2 injection, the risk of groundwater contamination from carbon seepage, and the leakage of stored CO_2 through inadequately sealed wells. These risks are particularly problematic in developing countries like India and further hinder the large-scale adoption of CCUS (Hanson et al., 2024).

Given these limitations, environmental scientists are increasingly advocating for natural carbon sequestration through both inland and marine ecosystems as a viable strategy for emission reduction. As discussed in the previous chapters, marine ecosystems, particularly blue carbon ecosystems (BCEs) such as mangroves, salt marshes, and seagrasses play a more active role than inland ecosystems due to their higher carbon sequestration rates.

Therefore, quantifying total blue carbon stocks at the national level and integrating them into carbon mitigation strategies and policy development is crucial for achieving sustainability goals. In India, mangroves along the coastline contribute more significantly to total carbon stocks compared to the other two BCEs. Notably, mangroves store a larger portion of their carbon in sediment rather than in aboveground biomass.

Accordingly, this study provides a comprehensive review of BCE-related research in India, followed by a meta-analysis to estimate the country's total BCE carbon stock. The methodology for compiling the literature database on BCEs in India is presented in the following section.

3.2 Literature Compilation Methodology: Building a Robust Database

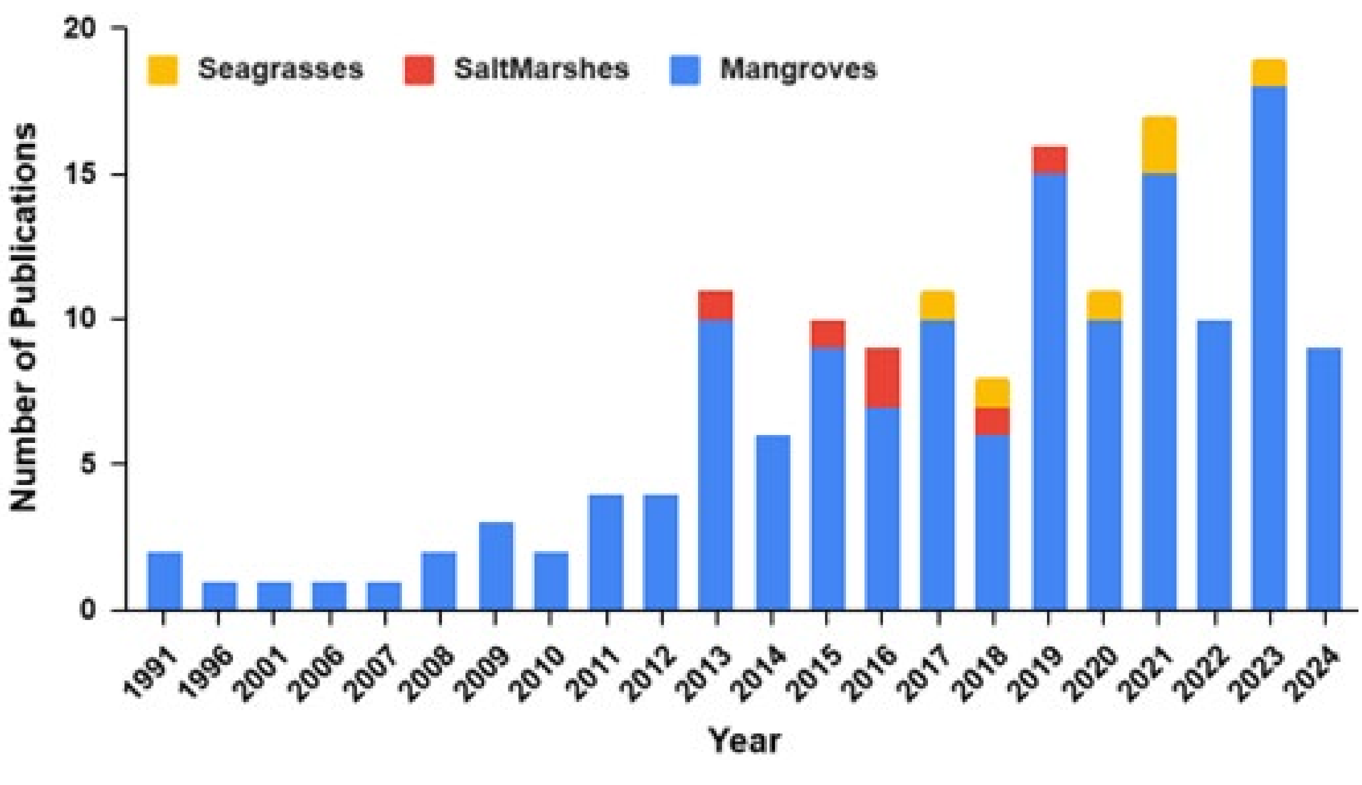
To understand India's blue carbon storage potential which includes mangroves, salt marshes, and seagrasses, an extensive literature survey was conducted, resulting in the compilation of two key datasets: first, the area covered by these blue carbon habitats; and second, the total carbon content as well as various associated components stored within these ecosystems. The primary search platforms used for identifying relevant literature included Scopus, ScienceDirect, Web of Science, ResearchGate, Google Scholar, and PubMed.

A variety of keyword combinations were used, such as "India," "Blue Carbon," "Mangrove," "Salt Marsh," "Tidal Marsh," "Sediment/Soil Carbon," and "Blue Economy," among others. The literature search was further expanded using backreferencing, by reviewing the reference lists of initially identified relevant publications. Through this review process, over 200 publications were collected, of which approximately 158 were found to be directly relevant to the scope of this study. Additionally, literature from governmental and non-governmental sources, including technical reports, review documents, and relevant websites, was also examined to gather supplementary information on India's blue carbon ecosystems.

The year-wise count of peer-reviewed publications on blue carbon research in India from 1991 to 2024 is shown in Figure 3.1. A distinct variation in research attention across different ecosystem types is evident from Figure 3.1. Mangrove ecosystems have received the most consistent and substantial research focus, with a total of 146 publications over the 34-year period. Carbon accounting research on mangroves began as early as 1991 and has shown a steady increase over time, with notable peaks in 2013, 2019, 2021, and a maximum in 2023 with 18 publications (Figure 3.1). This trend likely reflects a growing recognition of the carbon sequestration potential of mangroves, policy relevance, and the relative availability of ecological data. In contrast, salt marsh ecosystems in India have been significantly understudied, with only six publications appearing between 2013 and 2019 and no further research reported in subsequent years (Figure 3.1). Similarly, seagrass ecosystems in India also received limited attention, with six publications published only after 2017, suggesting that this area of research remains in its early stages of development (Figure 3.1). The highest number of publications on seagrass is observed in 2021, with just two studies.

The overwhelming focus on mangroves, comprising more than 90% of the total publications indicates a skewed research landscape. This imbalance may be attributed to factors such as greater accessibility of mangrove ecosystems, better funding opportunities, and stronger alignment with national conservation priorities. It needs to be noted that both seagrass as well as saltmarsh ecosystems have limited distribution compared to mangroves. At the same time, the absence of concurrent or integrated research efforts spanning all three ecosystem types in any given year further suggests that blue carbon research in India remains largely ecosystem-specific rather than holistic. Following a detailed review of the available literature, the reported values for area extent and carbon stock values were extracted

Figure 3.1: Annual publication count on Blue Carbon Ecosystems (BCEs) research in India (1991–2024).



and compiled across multiple carbon pools, including above-ground biomass, below-ground biomass, sediments, and litterfall/deadwood. A detailed discussion of the study areas reported in the literature, including spatial extent and carbon stock values for various blue carbon ecosystems, is presented in the following section.

3.3 Study Area Characterization and Spatial Data Integration

Figure 3.2 maps the spatial distribution of study sites where carbon stock assessments for mangroves, salt marshes, and seagrasses have been conducted in India, including mainland and island territories, based on published literature from 1991 to 2024. Notably, mangrove carbon stock studies have been reported across all coastal states and union territories except Andhra Pradesh (AP), despite the presence of the ecologically significant Coringa mangrove forest located in the Godavari River Estuary. The absence of comprehensive carbon stock assessments in this region is concerning, given that Coringa represents one of the largest and most productive mangrove ecosystems on the east coast. The only relevant published information is by Bouillon et al. (2003), who reported a wide range of organic carbon content (0.6% to 8.5%) in the top 5 cm of sediment, indicating substantial spatial variability that warrants further investigation.

In contrast, assessments of seagrass carbon stocks have been largely restricted to two regions: Tamil Nadu (TN), which harbours over 80% of India's seagrass meadows, and the Chilika Lagoon in Odisha. Similarly, salt marsh carbon stock studies are sparsely distributed and have been documented only in the Sundarbans (West Bengal), the Gulf of Mannar (TN), the Mandovi River Estuary (Goa), and Coastal Gujarat.

Figure 3.3 presents the number of sampling plots employed in carbon stock assessments across various regions along the east coast, highlighting notable disparities in sampling intensity. In the A&N Islands, mangrove carbon stock studies have involved between 2 and 13 plots per site (Figure 3.3a), suggesting a moderate level of spatial representation. In the Sundarbans, sampling effort varies from 1 to 19 plots depending on location (Figure 3.3b), while in Odisha, particularly in the Bhitarkanika mangrove forest, studies have sampled up to 25 plots at a single site (Figure 3.3c), which is the highest among all east coast regions. This relatively intensive sampling in Odisha reflects a more detailed and potentially robust estimation of carbon stocks.

In Tamil Nadu, however, sampling efforts have been more limited. Although the state hosts several mangrove patches, research has predominantly focused on the Pichavaram mangroves, with a maximum of six plots reported in the literature (Figure 3.3e). This limited sampling contrasts sharply with Odisha's more extensive approach and may hinder accurate carbon stock estimations in TN's diverse mangrove systems.

Seagrass ecosystems in Tamil Nadu have been comparatively better covered in terms of geographic extent, but still exhibit limited plot-level resolution. Along the Palk Bay coast, sample plots per site range from 1 to 6 (Figure 3.3f), while in the Gulf of Mannar, most studies have been based on a single plot per site (Figure 3.3g). Although this sampling provides initial insights, it may be insufficient to capture the spatial heterogeneity of carbon stocks in these dynamic and patchy ecosystems.

Taken together, these observations underscore significant regional imbalances in sampling effort and spatial coverage. While areas like Bhitarkanika and the Sundarbans have benefited from relatively intensive and spatially distributed studies, ecologically critical regions such as Coringa in AP and the broader seagrass meadows in the Gulf of Mannar remain underexplored. This uneven distribution of research effort limits our ability to develop a comprehensive and accurate national inventory of blue carbon stocks.

Figure 3.4 illustrates the spatial distribution and sampling intensity of BCE studies conducted along the west coast of India. Among all west coast states, Kerala demonstrates the most comprehensive sampling coverage for mangroves, with studies encompassing four major regions: South Kerala, Kochi, Kadalundi, and North Kerala (Figures 3.4h–k). The number of sampled plots varies significantly across these regions.

In South Kerala and Kochi, sampling intensity ranges from 7 to 25 plots per site, indicating relatively robust coverage. In the Kadalundi mangroves, the number of sampled plots ranges from 1 to 6, while North Kerala shows a broader range, with 1 to 19 plots recorded at different locations (Figure 3.4k).

Outside Kerala, however, mangrove carbon stock studies are notably sparse along the west coast. No published assessments have been reported

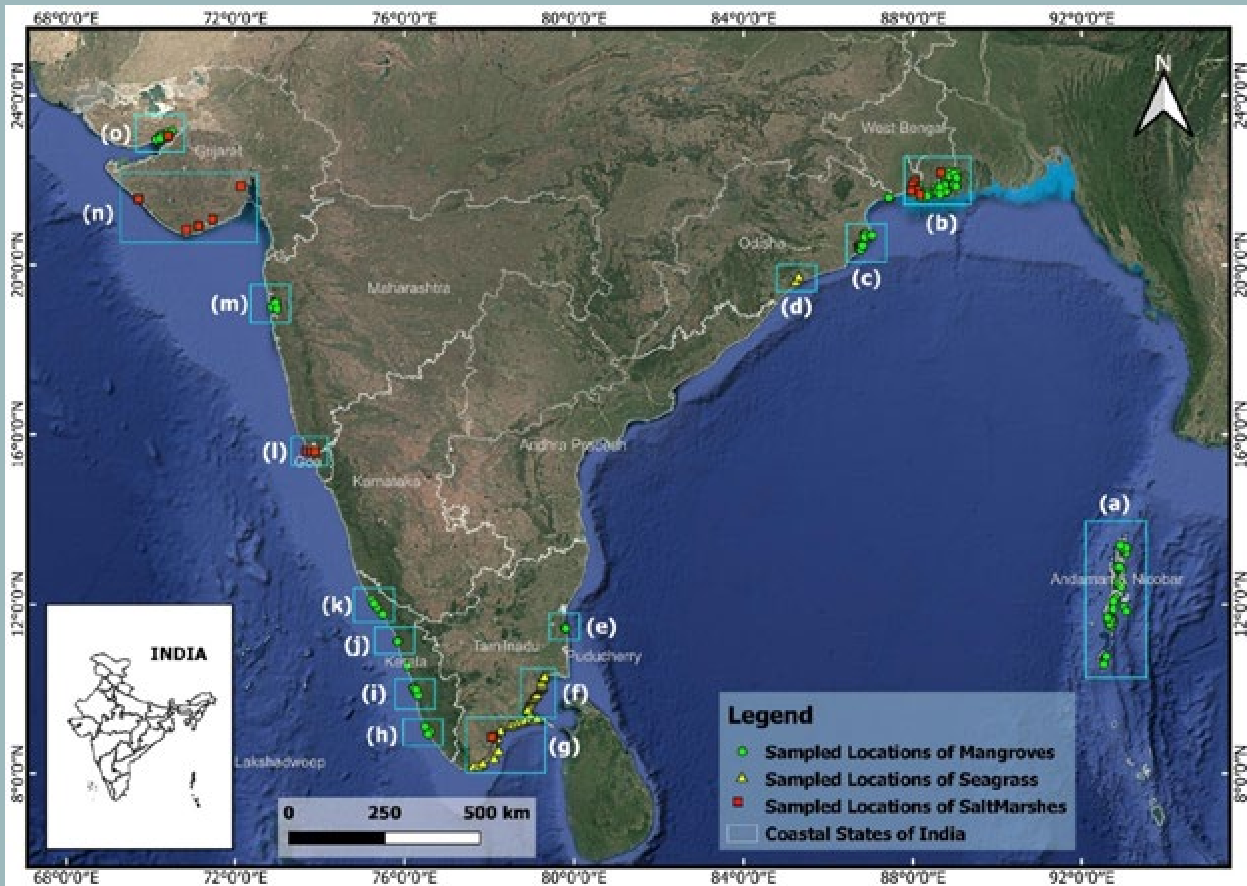


Figure 3.2: Map showing the sampled study locations from published research articles on BCEs along the Indian coast and its islands (1991–2024).

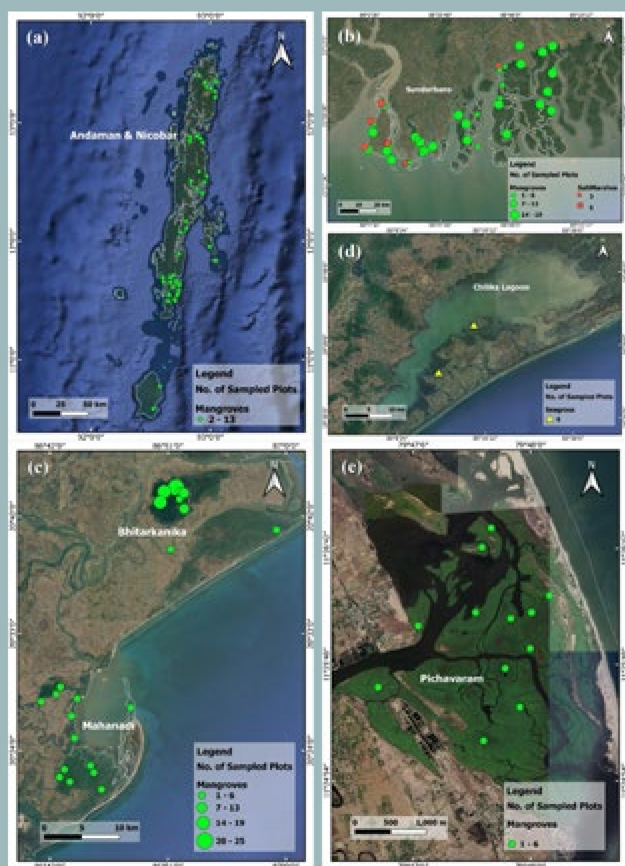
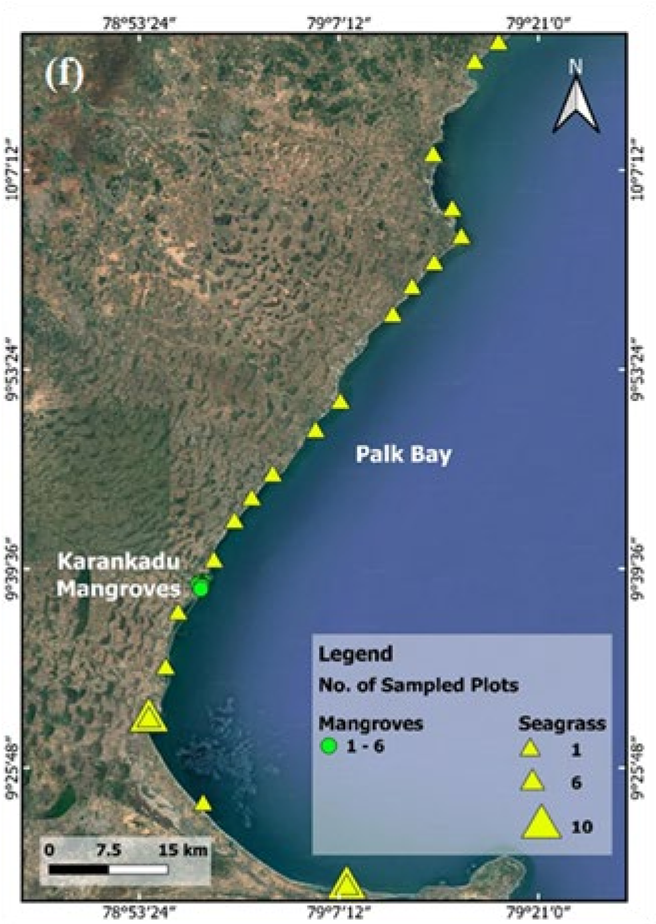
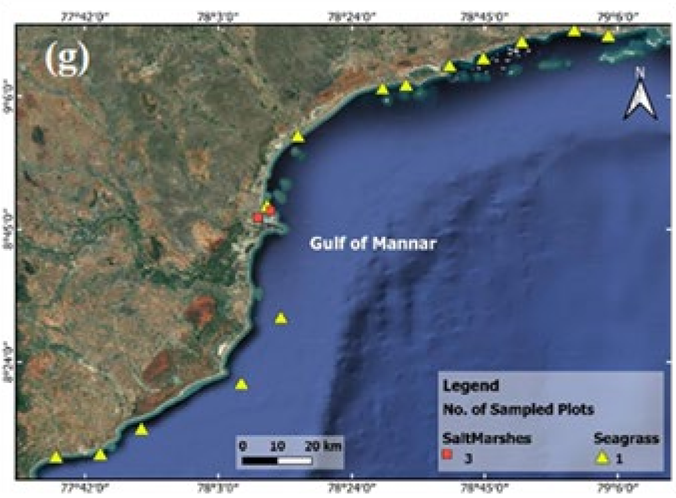


Figure 3.3: Map showing the number of sampled plots at reported study sites for BCEs along the east coast of India, including Andaman & Nicobar Islands (1991–2024). Study sites include: (a) A&N Islands, (b) Sundarbans, (c) Bhitarkanika and Mahanadi, (d) Chilika Lagoon, (e) Pichavaram, (f) Palk Bay and (g) Gulf of Mannar.



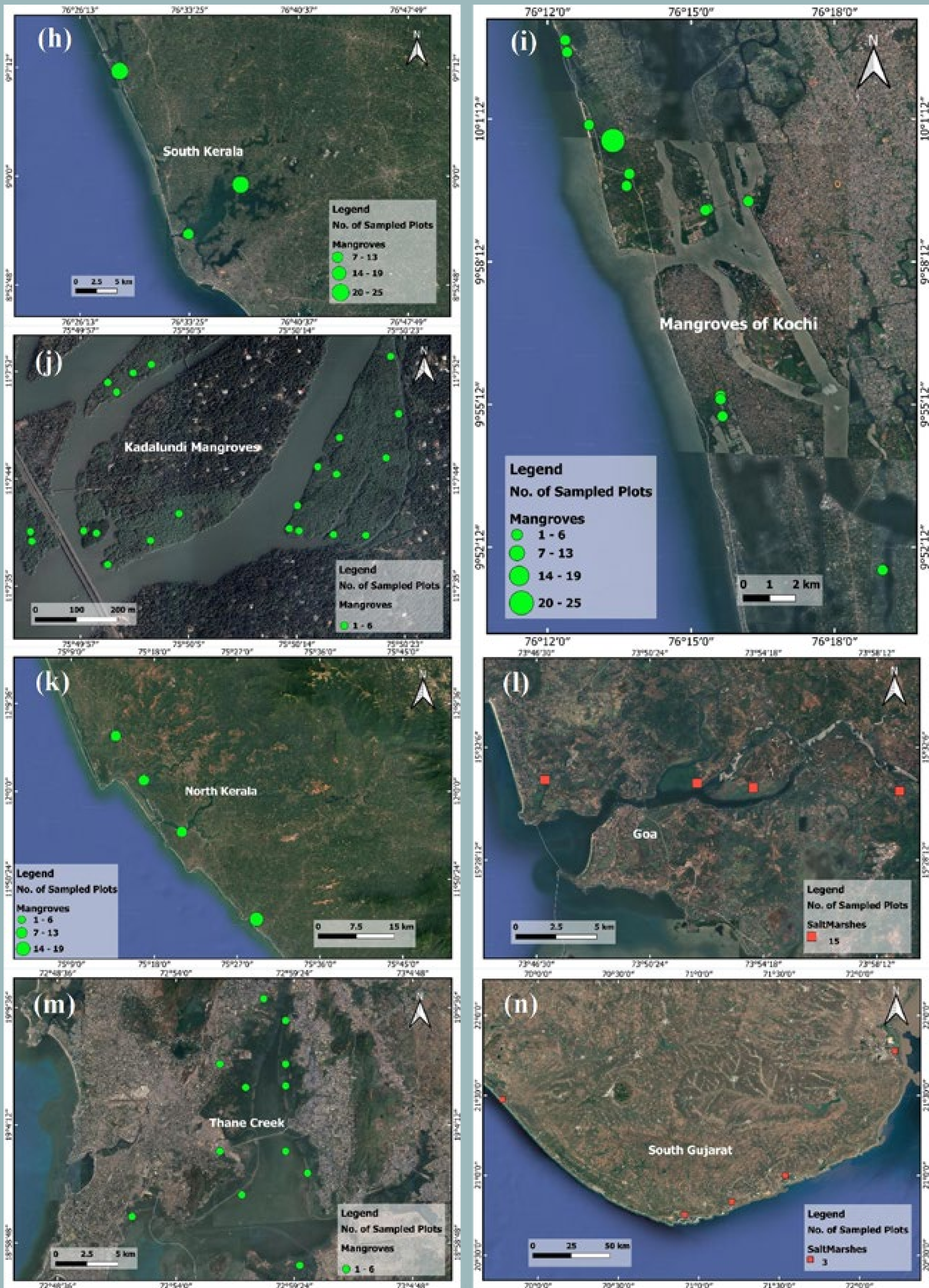


from Karnataka and Goa, despite the presence of small, fragmented mangrove patches along their coastlines. In Maharashtra, studies have been limited to the mangroves of Thane Creek, with a sampling intensity ranging from 1 to 6 plots (Figure 3.4m). Similarly, in Gujarat, sampling efforts have focused on mangroves in the Gulf of Kutch region, again with only 1 to 6 plots per site (Figure 3.4o). These limited datasets suggest that the mangrove carbon stocks in most west coast states remain poorly characterised, potentially leading to underrepresentation in national-level carbon inventories.

Salt marsh studies along the west coast are equally limited. As shown in Figures 3.4l and 20n, researchers have reported only two key locations: the Mandovi estuary in Goa, where 15 plots were sampled, and the southern Gujarat coastline, where a maximum of 3 plots per site were used to estimate carbon stocks. Although the sampling near Mandovi suggests a moderate level of detail, the low sampling density in Gujarat underscores the need for more extensive surveys to capture the spatial heterogeneity of these ecosystems.

In comparison to the East Coast, which features relatively well-distributed studies in certain states (e.g., Odisha, West Bengal), the West Coast exhibits a pronounced spatial bias, with intensive sampling confined mainly to Kerala. The lack of studies in ecologically important but under-sampled regions, such as the mangroves of Karnataka, Goa, and parts of Gujarat, highlights significant knowledge gaps. Furthermore, the overall low sampling intensity in several regions may compromise the accuracy of carbon stock estimates and the ability to detect spatial patterns or ecosystem-level differences.

To enhance the scientific robustness of blue carbon accounting in India, future research should aim to address these spatial imbalances by expanding both geographic coverage and plot-level sampling density.



(h)
South Kerala
Legend
No. of Sampled Plots
Mangroves
7 - 13
14 - 19
20 - 25
0 2.5 5 km
76°26'13" 76°33'25" 76°40'37" 76°47'49"
(i)
Mangroves of Kochi
Legend
No. of Sampled Plots
Mangroves
1 - 6
7 - 13
14 - 19
20 - 25
0 1 2 km
76°12'0" 76°15'0" 76°18'0"
10°1'12" 9°58'12" 9°55'12" 9°52'12"
(j)
Kadalundi Mangroves
Legend
No. of Sampled Plots
Mangroves
1 - 6
0 100 200 m
75°49'57" 75°50'5" 75°50'14" 75°50'23"
(k)
North Kerala
Legend
No. of Sampled Plots
Mangroves
1 - 6
7 - 13
14 - 19
0 7.5 15 km
75°9'0" 75°18'0" 75°27'0" 75°36'0" 75°45'0"
(l)
Goa
Legend
No. of Sampled Plots
SaltMarshes
15
0 2.5 5 km
73°46'30" 73°50'24" 73°54'18" 73°58'12"
(m)
Thane Creek
Legend
No. of Sampled Plots
Mangroves
1 - 6
0 2.5 5 km
72°48'36" 72°54'0" 72°59'24" 73°4'48"
(n)
South Gujarat
Legend
No. of Sampled Plots
SaltMarshes
3
0 25 50 km
70°0'0" 70°30'0" 71°0'0" 71°30'0" 72°0'0"

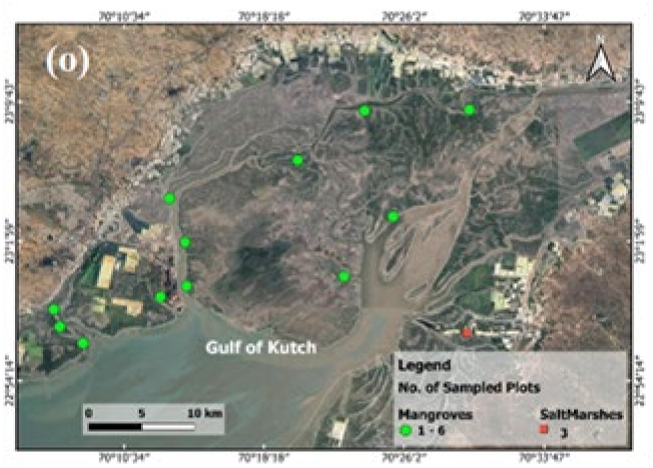


Figure 3.4: Map showing the number of sampled plots at reported study sites for BCEs along the west coast of India (1991–2024). Study sites include: (h) South Kerala, (i) Mangroves of Kochi, (j) Kadalundi Mangroves, (k) North Kerala, (l) Goa, (m) Thane Creek, (n) South Gujarat, and (o) Gulf of Kutch.

3.4 Methodological Frameworkfor Blue Carbon Stock Quantification

The methodology that we adopted to estimate the national-level Blue Carbon Ecosystem (BCE) stock in India is as follows:

- The total national blue carbon stock is estimated by aggregating the carbon stocks from the three major blue carbon ecosystems in India: mangroves, saltmarshes, and seagrasses.
- Carbon pools for mangroves, saltmarshes, and seagrasses are estimated separately across the entire country, including the islands. The national-level stock is obtained by summing these ecosystem-specific carbon stocks.
- For each ecosystem, national-level carbon stock values are derived by first estimating carbon pools at the state level and then aggregating these values across all coastal states and union territories.
- The state-level carbon pools for each ecosystem are estimated under different components: above-ground carbon (AGC), below-ground carbon (BGC), soil organic carbon (SOC), and total leaf litter/dead wood carbon. For each component, the mean carbon value is multiplied by the area of the respective ecosystem within the state to estimate the state-level stock.
- A database was created comprising reported carbon mean values for various sites in India, based on studies conducted by individual researchers between 1991 and 2024. This database serves as the primary data source for deriving state-level carbon mean values.
- The database includes components such as above-ground biomass (AGB), below-ground biomass (BGB), total biomass (TB), AGC, BGC, total biomass carbon (TBC), SOC, total leaf litter/dead wood carbon, and overall carbon (OC). Studies that reported estimated values along with their standard deviations for any of these components were included.
- In cases where only biomass values were reported (without corresponding carbon values), a carbon conversion factor of 0.5 was used to estimate carbon content. This factor, commonly used in Indian BCE studies (as referenced in Table 1.4) and applied to fill in missing carbon values by converting biomass to carbon.
- For SOC, it was observed that many studies reported values for various soil depths. Although IPCC guidelines recommend estimating soil carbon for a depth of 1 meter, due to variability and limitations in the available data, extrapolation to 1 meter was attempted by analysing SOC distribution across depth profiles. However, due to the challenges outlined in later sections, state-level SOC mean values were ultimately derived only from the actual reported values, regardless of depth.
- Once the database was complete with carbon mean values for all components, a statistical analysis was conducted to compute state-

level mean carbon values. These were then multiplied by ecosystem area estimates (sourced from various references listed in Chapter 2) to calculate the carbon stock for each state. Finally, the national-level blue carbon stock was obtained by aggregating all state-level values.

3.5 National Estimates of BCE Carbon Stocks

As outlined in the above methodology section, national-level estimates of carbon stocks in BCEs including mangroves, saltmarshes, and seagrasses were obtained by aggregating ecosystem-specific carbon stock values across all states and union territories. These national estimates were derived from the sum of carbon pools quantified at the state level for each BCE type. The following sections provide a detailed account of the state-wise carbon stock estimations that underpin the national-level synthesis.

3.5.1 Mangroves: Carbon Pools and State-wide Contributions

Mangrove carbon pools were quantified at the state level across four key components: above-ground carbon (AGC), below-ground carbon (BGC), soil organic carbon (SOC), and carbon stored in leaf litter and dead wood. To derive representative state-level estimates, mean carbon values for each component were synthesized using statistical analyses of site-level data reported in the literature from various coastal regions across India. The following sections present a detailed breakdown of these component-wise carbon estimates across individual coastal states.

The mangrove ecosystems along the east coast of India represent a wide biogeographic and ecological spectrum, which is reflected in their variable carbon stock estimates across different states and study sites. The values reported in Table 3.1 provide insights into both above-ground and below-ground biomass carbon, SOC, and other associated pools such as leaf litter and deadwood carbon. Collectively, these data highlight the significant role east coast mangroves play in carbon sequestration, while also underscoring the influence of local conditions, methodological differences, and sampling depths on reported values.

In Andhra Pradesh, Manhas et al. (2006) reported a notably high total biomass carbon value of 628.94 t/ha and a corresponding carbon stock of 284.21 t/ha. Although detailed component-wise breakdowns are lacking, this highlights the relatively high biomass density in this region's mangroves. From Figure 3.5, Odisha presents a far more variable picture, with carbon estimates from several distinct mangrove systems, particularly Bichitrapur, Bhitarkanika, and Mahanadi. In Bichitrapur, Dey et al. (2024) reported highly variable AGB and BGB values (164.36 ± 151.3 t/ha and 72.32 ± 80.06 t/ha, respectively), leading to an overall carbon stock of 306.8 ± 106.5 t/ha from a 100 cm soil sample depth (Table 3.1). This heterogeneity is further emphasized in the SOC value of 248.92 t/ha from Datta et al. (2022), which was derived from the same region. Bhitarkanika, one of India's most prominent mangrove systems, shows a wide range of biomass and SOC values across studies. Rasquinha and Mishra (2021) estimated AGC and BGC values of 179.72 ± 66.98 t/ha and 68.34 ± 17.12 t/ha, respectively, based on a relatively shallow 10 cm soil sampling depth that yielded an SOC value of 16.49 ± 6.59 t/ha. Anand et al. (2020) and Banerjee et al. (2020) reported additional data on AGB but lacked comprehensive carbon pool estimates.

A particularly high estimate was made by Bal and Banerjee (2019), who reported total biomass carbon of 866.67 ± 166.1 t/ha, a remarkably high value indicative of either exceptional site conditions or the presence of dense, mature mangrove trees in this region. This was accompanied by a SOC value of 3.73 ± 2.1 t/ha (from 10 cm depth) and a deadwood carbon component of 0.59 ± 0.2 t/ha, leading to a total carbon stock estimate of 444.68 t/ha. In contrast, older studies like Manhas et al. (2006) and Suresh et al. (2017) reported relatively lower values in Odisha, reflecting possible temporal changes, differing methodologies, or regional discrepancies.

In Tamil Nadu, Kandasamy et al. (2021) documented carbon values for the Vellar–Coleroon mangroves, including total biomass carbon of 36.75 ± 3.3 t/ha and a substantial SOC component of 23.52 ± 2.2 t/ha from a 100 cm depth, culminating in a total carbon stock of 60.27 ± 5.8 t/ha (Table 3.1). The Pichavaram mangroves shown in Figure 3.6, long recognized for their ecological importance, were reported to have an SOC stock of 96.06 t/ha from a 90 cm soil sample depth (Gnanamoorthy et al., 2019), underscoring the significance of soil carbon in this region. Prasanna et al. (2017) and Kathiresan et al. (2013) further contributed biomass estimates, with the latter providing one of the more comprehensive assessments combining Vellar Estuary and Pichavaram, reporting AGB and BGB

Table 3.1: Carbon mean values reported in the literature for the mangroves located along the east coast regions in India

S. No.	Study area	AGB (t/ha)	BGB (t/ha)	Total biomass (t/ha)	AGC (t/ha)	BGC (t/ha)	Total biomass carbon (t/ha)	SOC (t/ha)	Depth of soil sample (cm)	Total leaflitter/ deadwood carbon (t/ha)	Overall carbon stock (t/ha)	Reference
Andhra Pradesh												
1.				628.94			284.21					Manhas et al. (2006)
Odisha												
1.	Bichitrapur	164.36±151.3	72.32±80.06					306.8±106.5	100			Dey et al. (2024)
2.	Bichitrapur							248.92	100			Datta et al. (2022)
3.	Bhitarkanika				179.72±66.98	68.34±17.12	248.06±84.1	16.49±6.59	10			Rasquinha and Mishra (2021)
4.	Bhitarkanika	278.86±23.57			131.06±11.08							Anand et al. (2020)
5.	Bhitarkanika				143.61±38.04			5.46±1.68				Banerjee et al. (2020)
6.	Mahanadi				93.22±21.56			5.92±1.54				Banerjee et al. (2020)
7.	Bhitarkanika			866.67±166.1			433.33	3.73±2.1	10	0.59±0.2	444.68	Bal and Banerjee (2019)
8.	Bhitarkanika							57.6±3.2	30			Pattnayak et al. (2019)
9.	Orissa	70.27	18.19	88.46	35.13	9.09	44.14					Suresh et al. (2017)
10.	Bhitarkanika						100±11	102.5±12.3	100	3.5±0.6		Bhomia et al. (2016)
11.	Odisha			400			180.95					Manhas et al. (2006)
12.	Mahanadi	125±10.9	53.8±4.5	178.8±15.3	62.61±8.85	26.9±2.2	89.4±7.6	57.6±11.1	30	147±8.1		Sahu et al. (2016)
Tamil Nadu												
1.	Vellar- Coleroon				21.96±2.1	13.79±1.2	36.75±3.3	23.52±2.2	100		60.27±5.8	Kandasamy et al. (2021)
2.	Pichavaram							96.06	90			Gnanamoorthy et al. (2019)

S. No.	Study area	AGB (t/ha)	BGB (t/ha)	Total biomass (t/ha)	AGC (t/ha)	BGC (t/ha)	Total biomass carbon (t/ha)	SOC (t/ha)	Depth of soil sample (cm)	Total leaflitter/ deadwood carbon (t/ha)	Overall carbon stock (t/ha)	Reference
3.	Karankadu Mangroves	10.71±3.69			5.37±1.78							Prasanna et al. (2017)
4.	Vellar Estuary and Pichavaram	177.6±55.75	73.65±16.4	251.25±70.5			105.52±29.62					Kathiresan et al. (2013)
West Bengal												
1.	Lothian Island, Sundarbans	20.23										Hati et al. (2024)
2.	Sundarbans	40.36	19.57					140.8	90			Barik et al. (2021)
3.	Indian Sundarbans	73.68										Saha et al. (2019)
4.	Sundarbans	61.61±29.7	16.01±7.7									Suresh et al. (2017)
5.	Sagar Island, Sundarbans							14.15	20			Bhunia et al. (2016)
6.	Indian Sundarbans, Sagar Island	123.13			53.4							Bhattacharyya et al. (2015)
7.	Sundarbans Biosphere Reserve	29.9										Joshi and Ghose (2014)
8.	Indian Sundarbans	184.51			84.63							Raha et al. (2013)
9.	Indian Sundarbans						53.2±2.87	18.52±2.77	30			Ray et al. (2013)
10.	Western Indian Sundarbans							46.63	40			Mitra et al. (2012)
11.	Eastern Indian Sundarbans							28.82	40			Mitra et al. (2012)
12.	Indian Sundarbans (Central region)	76.02±3.59			33.66±4.15							Mitra et al. (2011)
13.	Indian Sundarbans (Western region)	250.49±3.6			112.74±3.98							Mitra et al. (2011)
14.	Indian Sundarbans	93.74±32.98	21.69±7.61		39.93±14.05	9.61±3.37	49.54±17.42	25.98	30			Ray et al. (2011)
15.	West Bengal			907.07			408					Manhas et al. (2006)

values of 177.6 ± 55.75 t/ha and 73.65 ± 16.4 t/ha, respectively, resulting in a total biomass of 251.25 ± 70.5 t/ha and an SOC value of 105.52 ± 29.62 t/ha.

West Bengal, dominated by the Sundarbans delta, presents a vast array of carbon data as shown in Figure 3.7. Hati et al. (2024), Barik et al. (2021), and others have documented a wide range of values for different regions within the Sundarbans, reflecting the complexity of this deltaic ecosystem. Barik et al. reported a SOC value of 140.8 t/ha from a 90 cm sample in the Sundarbans, while Bhunia et al. (2016) recorded a lower value of 14.15 t/ha from 20 cm depth in Sagar Island (Table 3.1). Bhattacharyya et al. (2015) and Raha et al. (2013) presented estimates of AGB and AGC across Indian Sundarbans, with AGB reaching as high as 184.51 t/ha in some cases. Mitra et al. (2011, 2012) contributed extensively to understanding regional differences, noting that the western Indian Sundarbans had higher SOC stocks (46.63 t/ha) compared to the eastern part (28.82 t/ha), with both datasets derived from 40 cm depth samples. From Table 3.1, it is also observed that Ray et al. (2011, 2013) offered more recent and comprehensive estimates, with their 2011 study showing total biomass carbon of 49.54 ± 17.42 t/ha and SOC of 25.98 t/ha (30 cm depth) in the central Sundarbans.

Overall, the data illustrate those mangroves along India's east coast store substantial amounts of carbon, with significant regional variability. These variations are shaped by geomorphology, hydrology, forest structure, and sampling approaches. The consistent inclusion of SOC data, especially from depths up to 100 cm, in recent studies reflects an increasing recognition of the importance of soil carbon in mangrove ecosystems. Such data are essential for accurate carbon accounting.

The west coast of India, though less extensive in mangrove cover compared to the east coast, showcases a diverse range of carbon stock values across different ecological zones and administrative states. The reported studies on above-ground biomass (AGB), below-ground biomass (BGB), total biomass carbon (TBC), soil organic carbon (SOC), and associated carbon pools such as deadwood and litter carbon reflect both the ecological variability and methodological diversity prevalent in the region's carbon assessments as observed from the mean carbon values reported in Table 3.2.

In Goa state in India, Suresh et al. (2017) documented mean AGB and BGB values of 117.69 ± 40.8 t/ha and 30.59 ± 10.6 t/ha, respectively, totalling a biomass of 148.28 ± 51.4 t/ha (Table 3.2). However, further carbon pool details for this region remain unexplored in this study. Moving northward to Gujarat, significant variability in mean carbon values is observed as shown in Figure 3.8. Sigamani et al. (2023) provided a relatively detailed account for the Gulf of Kutch, with AGB of 96.9 t/ha and BGB of 19.6 t/ha, resulting in a TBC of 54.1 t/ha (Table 3.2). They also reported the SOC value in this region as 25.87 t/ha based on a 100 cm sampling depth. Other studies from this region, such as Thivakaran et al. (2020) and Pandey and Pandey (2013), offer SOC values of 72.33 t/ha and 88.95 t/ha, respectively, while Manhas et al. (2006) reported a TBC of 154.4 t/ha, suggesting the possibility of high spatial heterogeneity or differences in forest structure and age.

Karnataka's mangroves, represented by sites like Mangalore and Uttara Kannada, show moderate biomass levels. Suresh et al. (2017) reported AGB values of 90.31 ± 59.1 t/ha and 65.27 ± 40.2 t/ha, respectively, with corresponding BGB values, leading to total biomass figures around 113.76 ± 74.4 t/ha and 82.24 ± 50.6 t/ha (Table 3.2). These are indicative of patchy mangrove stands often constrained by narrow estuarine configurations.

Kerala, however, offers the most comprehensive and diverse carbon data among the west coast states. The mangroves in the Kochi region stand out with high carbon estimates as shown in Figure 3.9. Rani et al. (2023) reported multiple datasets, with AGB values ranging from 353.99 ± 175.8 t/ha to 484.18 ± 241.0 t/ha, and BGB values from 199.74 ± 89.32 t/ha to 213.9 ± 108.2 t/ha (Table 3.2). The total biomass carbon in these sites ranged from 237.19 ± 113.8 t/ha to as high as 295.78 ± 143.1 t/ha. One study also reported a substantial SOC value of 73.22 ± 39.4 t/ha and litter/deadwood carbon of 7.12 ± 2.8 t/ha, culminating in an overall carbon stock of 335.32 ± 184.4 t/ha. Sreelekshmi et al. (2022) added to this with carbon stock values across Kerala's mangroves, reporting exceptionally high BGB of 423.55 ± 496.9 t/ha and SOC of 22.52 ± 13.7 t/ha from 100 cm depth (Table 3.2), reflecting considerable variance likely due to species composition and site-specific conditions.

Other regions in Kerala, such as Valapattanam, Edat, Thalassery, Kadalundi, and Vypin, also show appreciable carbon values. Vinod et al. (2019, 2018)

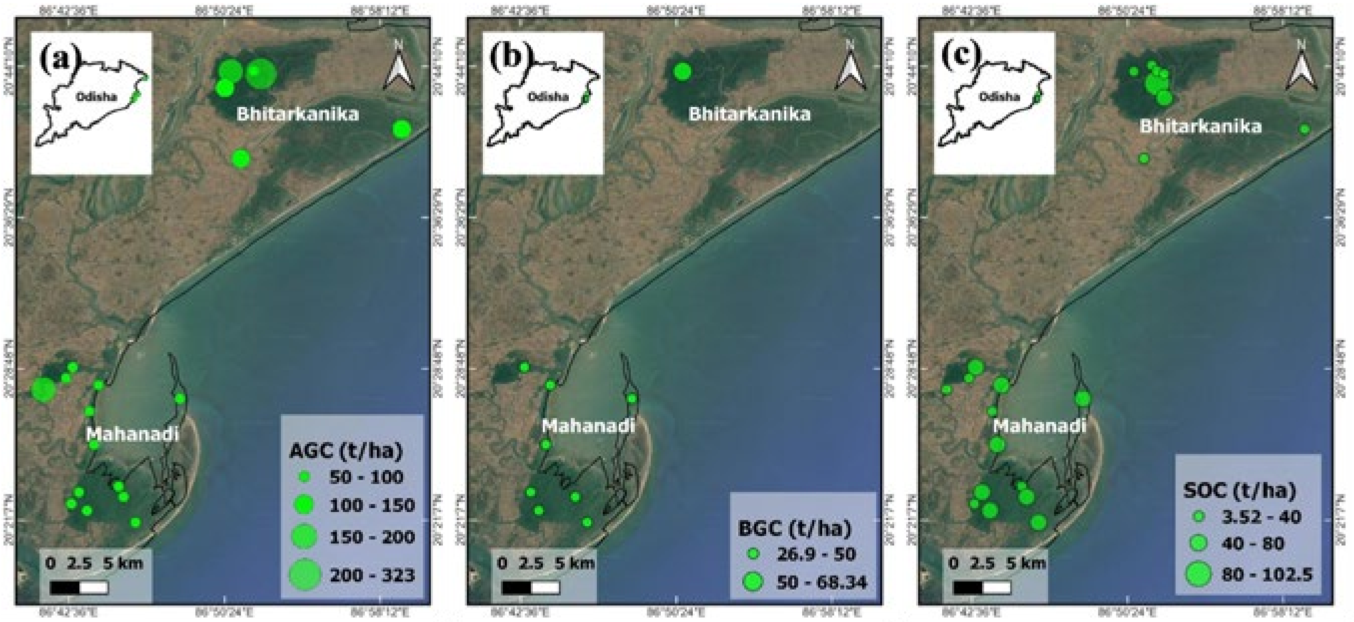


Figure 3.5: Map showing the mean carbon values reported at study sites for mangroves in Odisha state: (a) AGC, (b) BGC, and (c) SOC.

reported moderate to high total biomass carbon (e.g., 136.16 ± 69.1 t/ha at Thalassery and 118.28 ± 15.26 t/ha at Kadalundi), combined with SOC ranging from 17.48 ± 7.3 to 63.87 ± 8.67 t/ha from 30 cm soil depths. Harishma et al. (2020) presented a slightly more modest profile with a total carbon stock of 139.82 ± 10.67 t/ha. The site-specific variations are indicative of localized geomorphic conditions, salinity gradients, and anthropogenic pressures affecting carbon stocks.

In Maharashtra, particularly in Thane Creek, Singh et al. (2023) presented a thorough account with AGB and BGB of 84.83 t/ha and 32.25 t/ha, respectively, and a TBC of 52.79 ± 23.38 t/ha as shown in Figure 3.10. The SOC contribution of 63.79 t/ha from a 40 cm soil profile, coupled with litter/deadwood carbon of 116.58 t/ha, resulted in a robust total carbon stock (Table 3.2). Other studies such as Patil et al. (2015) and Pachpande and Pejaver (2015) provided additional insights into biomass carbon with more limited data. AGB values as low as 4.85 t/ha in Mumbai (Suresh et al., 2017) suggest heavily degraded or fragmented mangrove patches. From Table 3.2, Manhas et al. (2006) again reported a high total biomass carbon of 200 t/ha for Maharashtra, pointing to possible older or more intact mangrove systems in parts of the state.

In conclusion, the mangroves along India's west coast, while generally occupying narrower belts compared to the east, still contribute significantly to coastal carbon storage. Sites in Kerala and parts of Maharashtra, particularly Kochi and Thane Creek, exhibit notably high carbon stocks, influenced by high biomass densities and rich soil carbon reservoirs. The broad range in carbon values across studies and locations highlights the ecological diversity of India's west coast mangroves and reinforces the need for site-specific monitoring and carbon accounting, particularly in the context of climate change mitigation and blue carbon policy

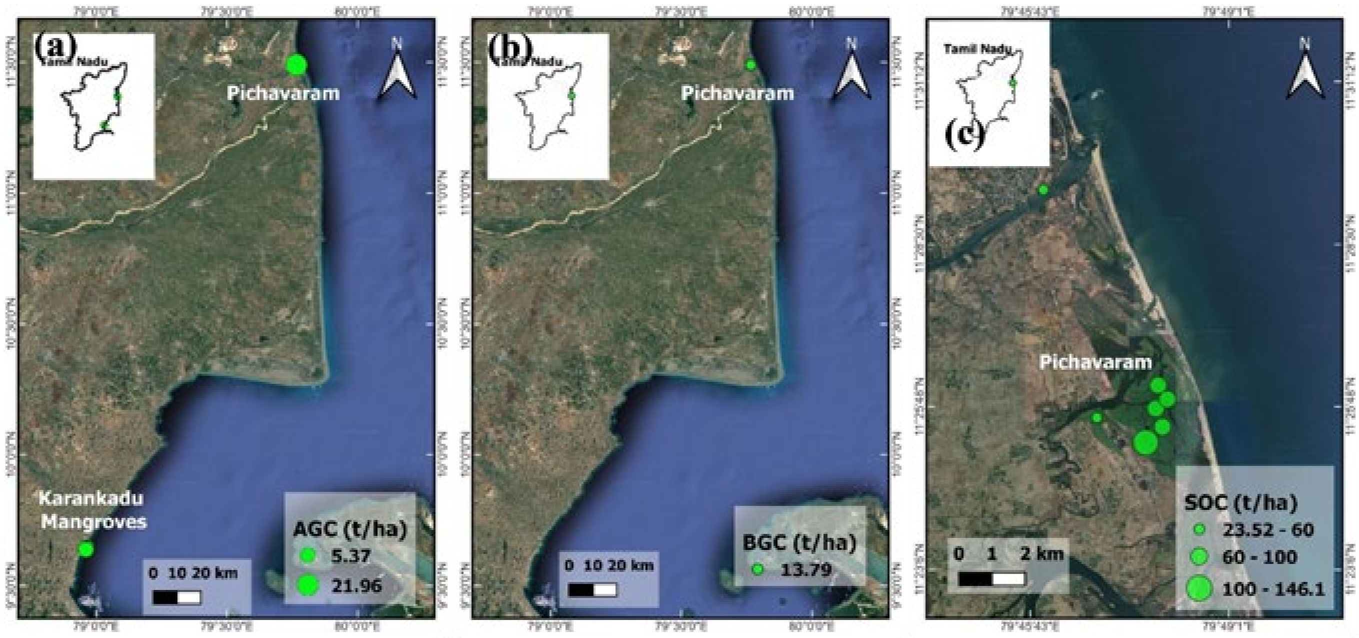


Figure 3.6: Map showing the mean carbon values reported at study sites for mangroves in TN state: (a) AGC, (b) BGC, and (c) SOC.

frameworks. The mangroves of the A&N Islands, located in the Bay of Bengal, due to their unique geomorphological and climatic conditions, host a range of mangrove species with varying biomass and carbon storage capacities. The studies synthesized in Table 3.3 provide a comprehensive overview of the mean carbon values across different mangrove settings within the Andaman Islands, highlighting the spatial and methodological heterogeneity in carbon assessments.

From Figure 3.11, the recent assessments by Ragavan et al. (2023) provide SOC data for two dominant mangrove types in Andaman: estuarine and marine. The estuarine mangroves report a notably high SOC stock of 345.31 ± 97.22 t/ha, while marine mangroves follow closely with 307.02 ± 103.93 t/ha. These values were derived from samples taken at a standard soil depth of 100 cm, aligning with IPCC guidelines for national greenhouse gas inventories. The high SOC values underscore the importance of these sediment-rich environments in long-term carbon sequestration, even in the absence of detailed biomass component data.

In a more comprehensive analysis, Ragavan et al. (2021) quantified all major biomass pools in the Andaman mangroves, reporting an AGB of 469.2 ± 41.25 t/ha and a BGB of 166.78 ± 12.79 t/ha, amounting to a total biomass of 635.98 ± 12.79 t/ha (Table 3.3). Correspondingly, the above-ground carbon (AGC) and below-ground carbon (BGC) were estimated at 225.22 ± 19.8 t/ha and 65.04 ± 4.99 t/ha, respectively, resulting in a total biomass carbon stock of 290.26 ± 24.75 t/ha. This study represents one of the most detailed carbon assessments in the region and demonstrates the significant carbon storage capacity of these forests.

Earlier studies, such as those by Komiyama et al. (2008) and Manhas et al. (2006), reported lower biomass and carbon stock values. Komiyama et al. (2008) documented a total biomass of 212.94 t/ha, with corresponding carbon stocks of 84.5 t/ha (AGC) and 21.97 t/ha (BGC) (Table 3.3). These differences may stem from variations in sampling methodology, spatial coverage, species composition, and biomass estimation models. For instance, the Komiyama et al. study used allometric models developed for Southeast Asian mangroves, which may not fully capture the structural characteristics of Andaman mangroves. Manhas et al. (2006) reported only the total biomass carbon stock (122.68 t/ha) and above-ground carbon (55.67 t/

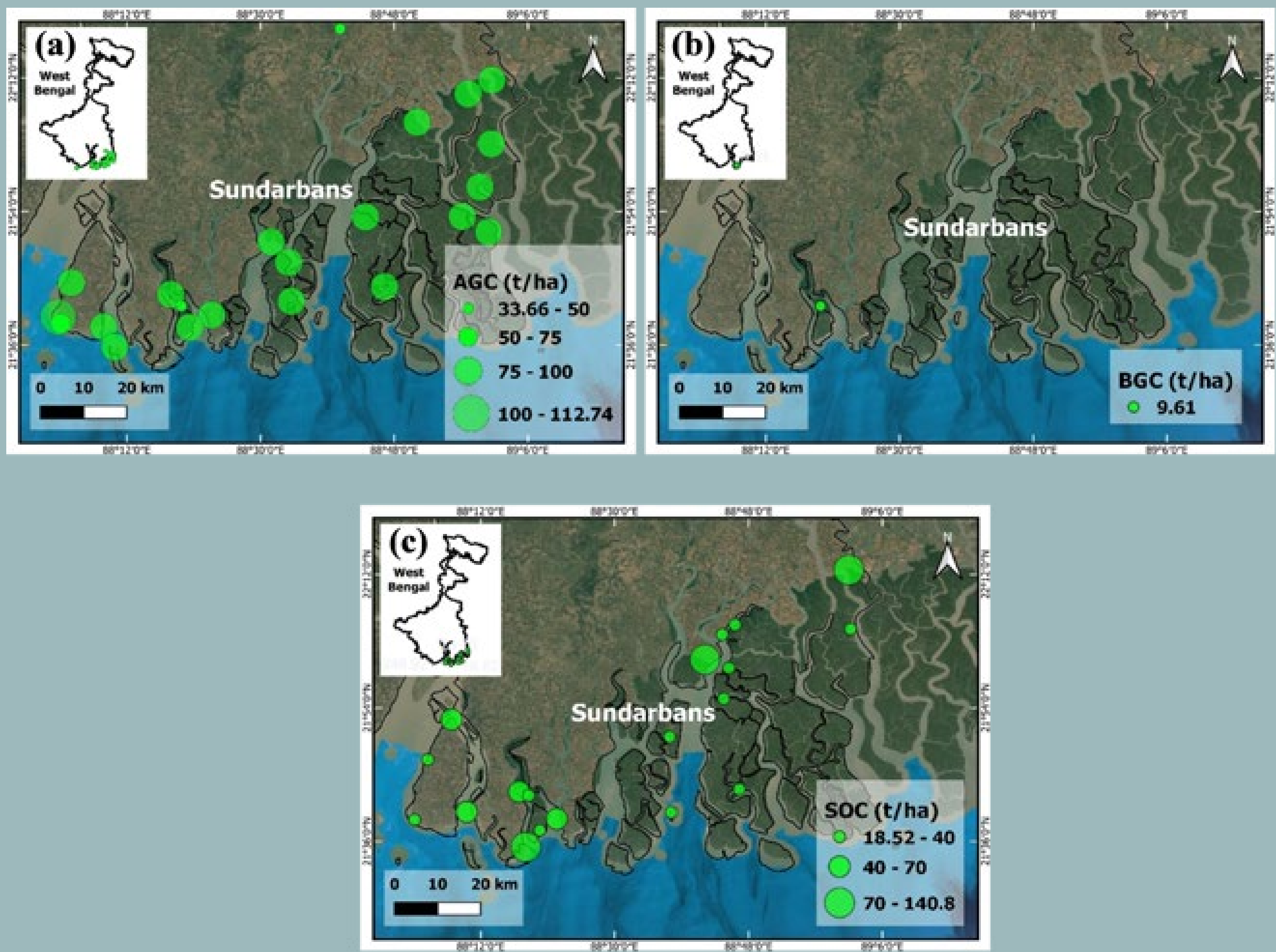


Figure 3.7: Map showing the mean carbon values reported at study sites for mangroves in West Bengal state: (a) AGC, (b) BGC, and (c) SOC.

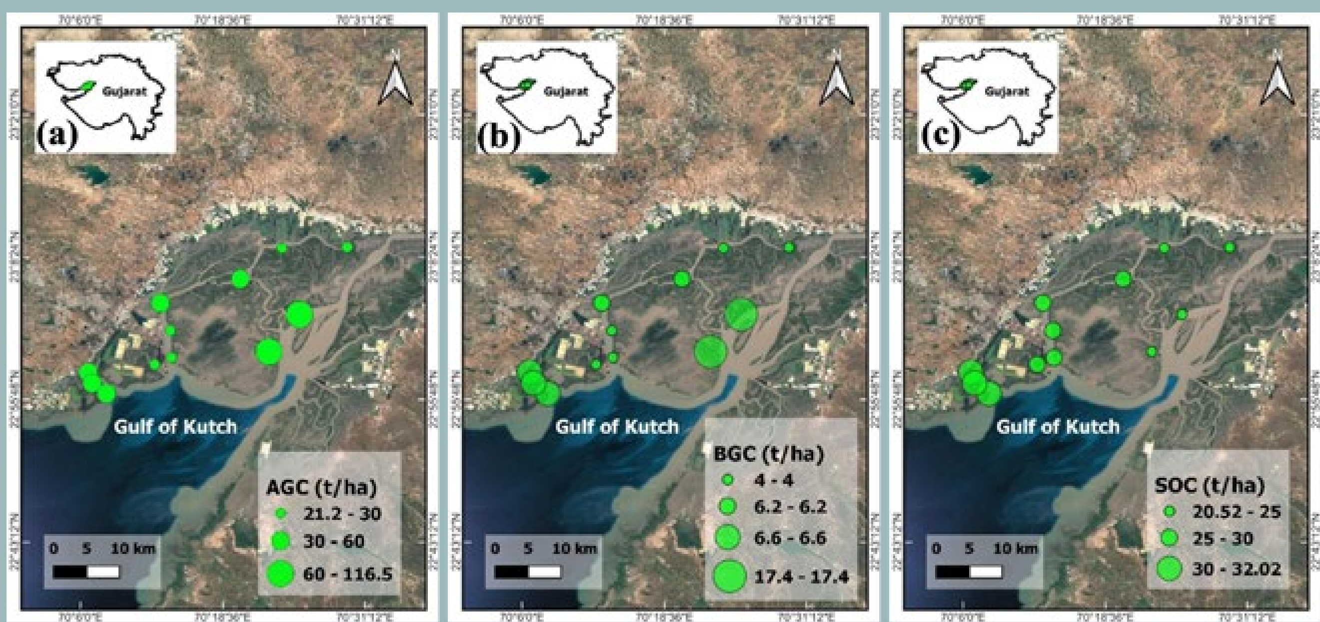


Figure 3.8: Map showing the mean carbon values reported at study sites for mangroves in Gujarat state: (a) AGC, (b) BGC, and (c) SOC.

Table 3.2: Carbon mean values reported in the literature for the mangroves located along the west coast regions in India

S. No.	Study area	AGB (t/ha)	BGB (t/ha)	Total biomass (t/ha)	AGC (t/ha)	BGC (t/ha)	Total biomass carbon (t/ha)	SOC (t/ha)	Depth of soil sample (cm)	Total leaflitter/ deadwood carbon (t/ha)	Overall carbon stock (t/ha)	Reference
Goa												
1.	South Goa	117.69±40.8	30.59±10.6	148.28±51.4								Suresh et al. (2017)
Gujarat												
1.	Gulf of Kutch	96.9	19.6	116.5	46.5	7.6	54.1	25.87	100			Sigamani et al. (2023)
2.	Gulf of Kutch	72.33										Thivakaran et al. (2020)
3.	Mangroves of Gujarat										88.95	Pandey and Pandey (2013)
4.	Mangroves of Gujarat			343.17			154.4					Manhas et al. (2006)
Karnataka												
1.	Mangalore	90.31±59.1	23.45±15.3	113.76±74.4								Suresh et al. (2017)
2.	Uttara Kannada	65.27±40.2	16.97±10.4	82.24±50.6								Suresh et al. (2017)
Kerala												
1.	Edat Mangroves						25.98	52.18	60		78.17	Manoj et al. (2024)
2.	Valapattanam Mangroves						19.23	38.59	60		57.56	Manoj et al. (2024)
3.	Kochi Mangroves	381.2±231.6	213.9±108.2	595.1±339.8	171.68±104.4	83.3±41.98	254.98±146.3	73.22±39.4	30	7.12±2.8	335.32±184.4	Rani et al. (2023)
4.	Kochi Mangroves	353.99±175.8		553.73±264.8	159.29±79.11		237.19±113.8					Rani et al. (2023)
5.	Kochi Mangroves	484.18±241.0	199.74±89.32	683.92±329.9	217.88±108.4	77.9±34.83	295.78±143.1					Rani et al. (2023)

S. No.	Study area	AGB (t/ha)	BGB (t/ha)	Total biomass (t/ha)	AGC (t/ha)	BGC (t/ha)	Total biomass carbon (t/ha)	SOC (t/ha)	Depth of soil sample (cm)	Total leaflitter/ deadwood carbon (t/ha)	Overall carbon stock (t/ha)	Reference
6.	Kochi Mangroves	432.27±218.3		632.01±306.9	194.52±98.25		272.42±132.7					Rani et al. (2023)
7.	Mangroves of Kerala	130.43±163.8	423.55±496.9	553.98±660.7	51.42±49.87	142.61±127.6	194.03±177.5	22.52±13.7	100	3.03±3.26	218.98±169.8	Sreelekshmi et al. (2022)
8.	Mangroves of Kerala	80.22±15.95	36.89±6.23	117.11±1.02			58.56±0.51	81.26±10.16	60		139.82±10.67	Harishma et al. (2020)
9.	Vypin-Cochin Region	69.55±80.38			30.57		35.69	18.26±3.29	30	0.35	54.3±36	shyleshChandran et al. (2020)
10.	Thalassery Mangroves	189.26±97.8	83.06±40.48	272.32±138.2	94.63±48.9	41.53±20.24	136.16±69.1	17.48±7.3	30		153.64	Vinod et al. (2019)
11.	Kadalundi Mangroves	166.63±22.1	69.92±8.61	236.56±30.5	83.32±11.06	34.96±4.3	118.28±15.26	63.87±8.67	30		182.15	Vinod et al. (2018)
12.	Central Kerala	50.66±32.6	13.17±8.4	63.83±41								Suresh et al. (2017)
13.	North Kerala	105.38±77.4	27.45±20.1	132.83±97.5								Suresh et al. (2017)
Maharashtra												
1.	Thane Creek	84.83	32.25	117.08	40.38	12.41	52.79±23.38	63.79	40	116.58		Singh et al. (2023)
2.	Mumbai	4.85	1.26	6.11								Suresh et al. (2017)
3.	Thane Creek	54.9	19.7	74.6			37.6					Pachpande and Pejaver (2015)
4.	Thane Creek				21.65	18.05	39.71					Patil et al. (2015)
5.	Maharashtra			425			200					Manhas et al. (2006)

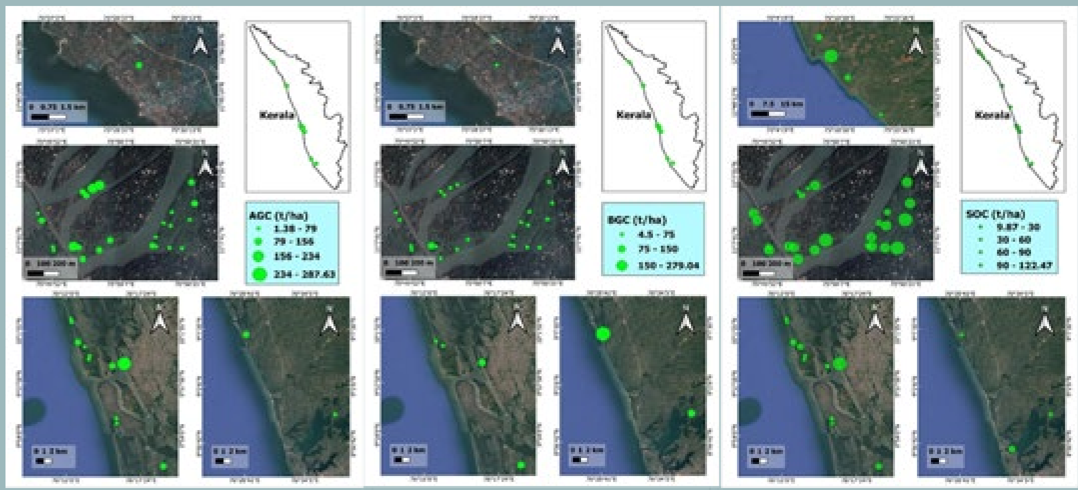


Figure 3.9: Map showing the mean carbon values reported at study sites for mangroves in Kerala state: (a) AGC, (b) BGC, and (c) SOC.

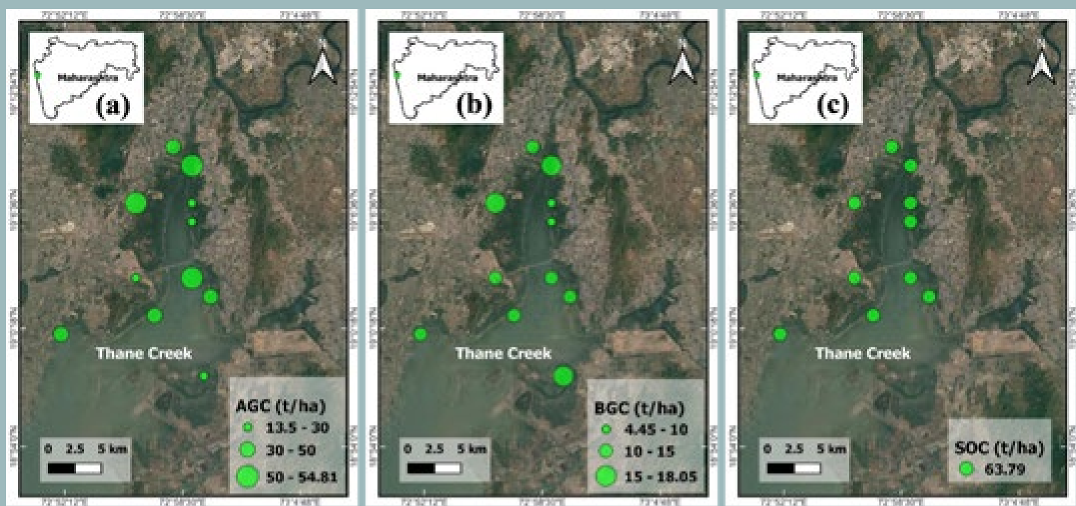


Figure 3.10: Map showing the mean carbon values reported at study sites for mangroves in Maharashtra state: (a) AGC, (b) BGC, and (c) SOC.

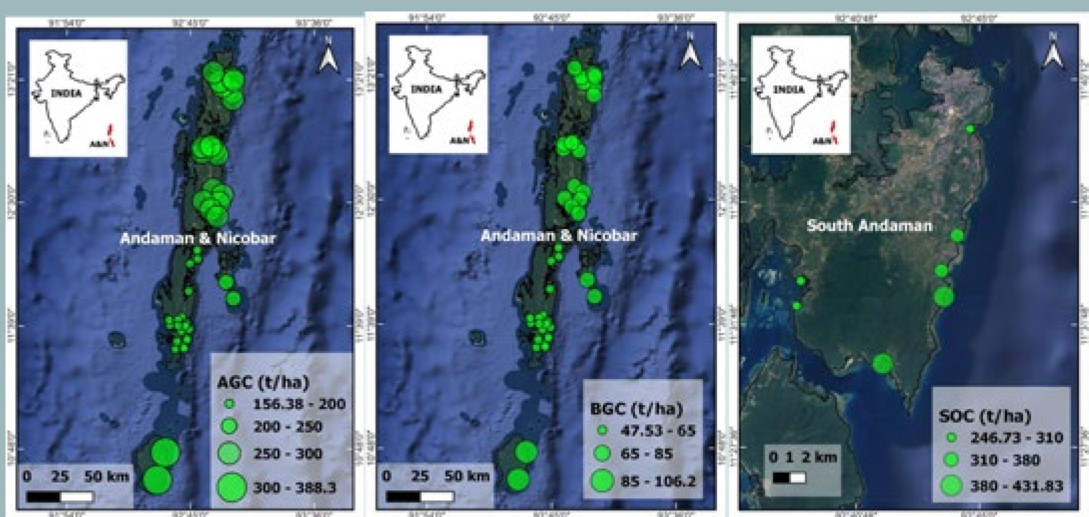


Figure 3.11: Map showing the mean carbon values reported at study sites for mangroves in A&N Islands: (a) AGC, (b) BGC, and (c) SOC.

ha), without detailing component pools or sampling depths. These earlier datasets, while limited in scope, are valuable for temporal comparisons and highlight the need for standardized protocols in blue carbon assessments.

To derive state-level estimates of total biomass carbon, statistical analyses were conducted on site-specific mean carbon values reported across various coastal regions. These analyses enabled the aggregation of mean values for above-ground and below-ground biomass components across all coastal states. However, soil organic carbon (SOC) values reported in the literature often correspond to varying depth intervals, presenting a challenge for standardization. To address this, we employed an extrapolation approach to estimate SOC to a uniform reference depth of one meter, based on the observed vertical distribution patterns of organic carbon across depth profiles. The methodological challenges and assumptions associated with this extrapolation are discussed in the following section.

3.5.1.1 Challenges in extrapolation of SOC values

This section outlines the methodology used to extrapolate SOC values reported in the literature across various sampling depths to a standardized one-meter soil depth. Prior to extrapolation, all available SOC values from the literature were plotted against their corresponding sampling depths to assess variability across different sites and to evaluate depth-dependent SOC distribution. As illustrated in Figure 3.12, SOC values reported from studies across India demonstrate substantial heterogeneity, with sampling depths ranging from 10 cm to 100 cm.

At shallower depths (e.g., 10 cm), SOC values were relatively low, ranging from 4.28 to 16.49 t/ha, with a mean value of approximately 9.88 t/ha. This limited carbon stock in surface layers likely reflects minimal organic matter accumulation, influenced by dynamic environmental factors such as tidal flushing and bioturbation. In contrast, samples collected at intermediate depths (15–30 cm) exhibited a significant increase in SOC, ranging from 9.87 to 122.47 t/ha. Notably, the 30 cm depth category was the most frequently reported in the literature, with values spanning a wide range and a mean of approximately 58.4 t/ha. This variability may be attributed to differences in mangrove species composition, geomorphological settings, organic matter inputs, and methodological inconsistencies across studies.

Deeper samples within the 40–60 cm range continued to show increasing SOC values, ranging from 23.76 to 124.99 t/ha, consistent with the hypothesis that deeper soil horizons in undisturbed systems accumulate more refractory organic matter. At the 0-100 cm soil depth, SOC stocks were among the highest observed, with a maximum value of 500.9 t/ha and numerous measurements exceeding 300 t/ha. These elevated values suggest the presence of long-term carbon sinks in mature mangrove stands with minimal anthropogenic disturbance and favourable hydrological conditions for organic matter preservation.

Figure 3.12: Distribution of mean soil organic carbon values across different depth profiles.

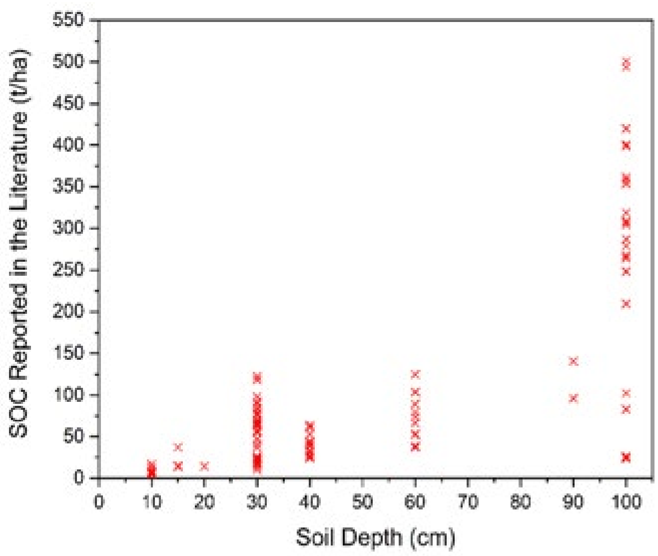
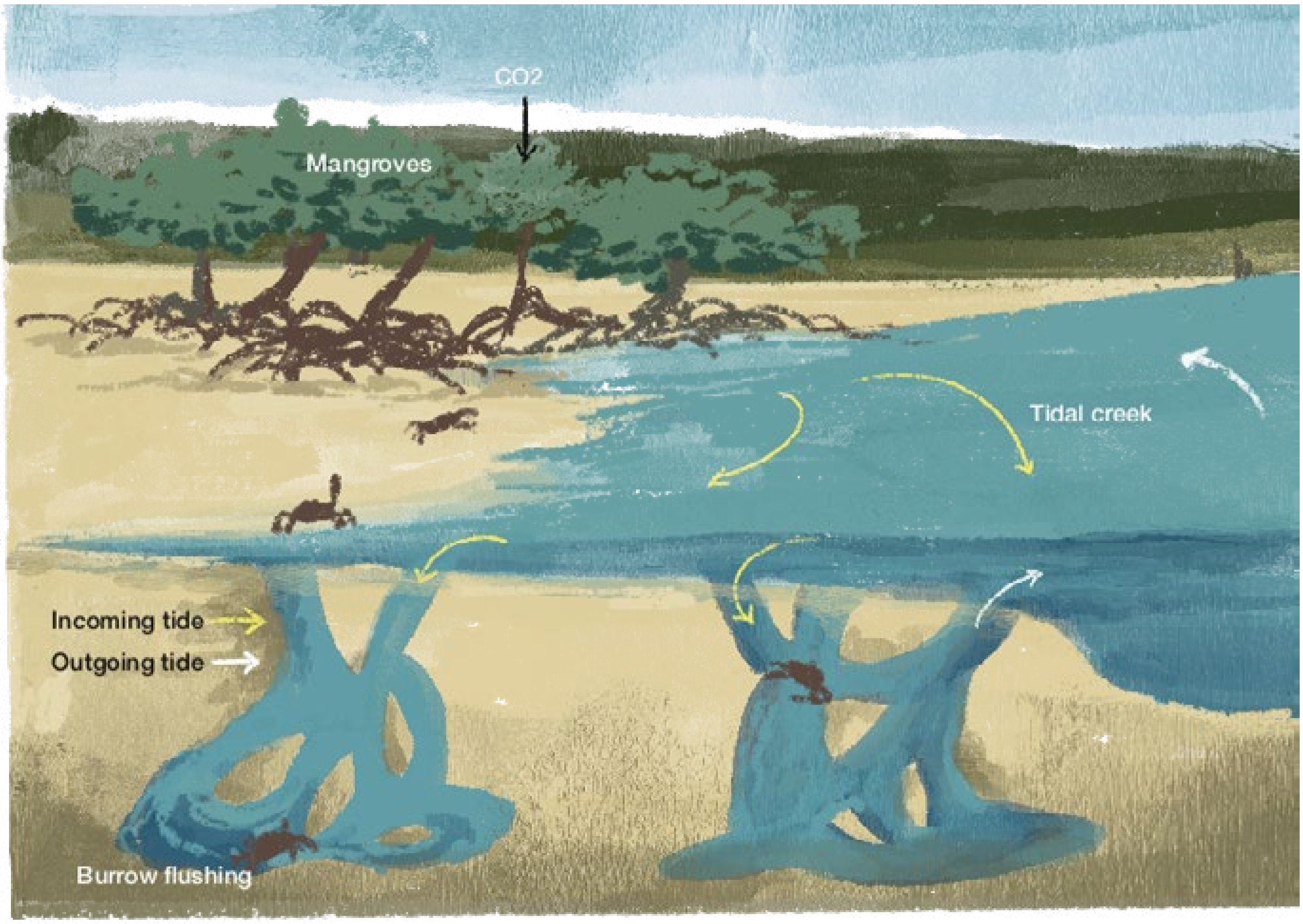


Table 3.3: Carbon mean values reported in the literature for the mangroves located in the islands of India

S. No.	Study area	AGB (t/ha)	BGB (t/ha)	Total biomass (t/ha)	AGC (t/ha)	BGC (t/ha)	Total biomass carbon (t/ha)	SOC (t/ha)	Depth of soil sample (cm)	Total leaflitter/ deadwood carbon (t/ha)	Overall carbon stock (t/ha)	Reference
Andaman and Nicobar												
1.	Andaman (Estuarine)							345.31±97.22	100			Ragavan et al. (2023)
2.	Andaman (Marine)							307.02±103.93	100			Ragavan et al. (2023)
3.	Andaman	469.2±41.25	166.78±12.79	635.98±12.79	225.22±19.8	65.04±4.99	290.26±24.75					Ragavan et al. (2021)
4.	Andaman	169	43.94	212.94	84.5	21.97	106.47					Komiyama et al. (2008)
5.	Andaman			122.68			55.67					Manhas et al. (2006)



The observed depth-dependent variation in SOC highlights the necessity of standardized depth intervals for national and regional carbon accounting. It also emphasizes the importance of deep-soil sampling to capture the full extent of carbon storage in blue carbon ecosystems. Extrapolating total SOC from shallow depths alone could significantly underestimate carbon stocks, particularly in mature or undisturbed systems. To explore this issue further, we attempted to extrapolate literature-reported sub-meter SOC values to a uniform one-meter depth.

SOC stock was estimated using the standard equation involving three components: soil organic carbon content (%OC), bulk density (g/cm^3), and soil depth (cm). Although both %OC and bulk density vary with soil depth, previous studies have attempted to model the typical vertical distribution of %OC in the Sundarbans region. For instance, Mitra et al. (2012) analysed %OC variation across eastern and western Sundarbans and across different seasons (pre-monsoon, monsoon, and post-monsoon). According to their results, %OC in the top 10 cm of soil averaged 0.75, decreasing to 0.73 between 10–20 cm, 0.70 between 20–30 cm, and 0.66 between 30–40 cm. Barik et al. (2021) similarly reported %OC values as follows: 1.99 (0–15 cm), 1.82 (15–30 cm), 1.60 (30–45 cm), 1.42 (45–60 cm), 1.16 (60–75 cm), and 0.95 (75–90 cm).

Using these reported %OC values and maintaining the same bulk densities and soil depths as in the original literature, SOC values were re-estimated using both models. The estimated values were then compared to the originally reported SOC values through scatterplot analysis (Figure 3.13).

SOC estimates derived using the %OC values from Mitra et al. (2012) revealed a very weak correlation with literature-reported SOC, with an R^2 value of just 0.05, suggesting that only 5% of the observed variation in reported SOC could be explained by the model. This points to systematic underestimation. For example, a reported SOC of 118.45 t/ha was estimated as only 17.14 t/ha. Similarly, moderate SOC values like 54.83 t/ha and 65.25 t/ha were underestimated as 8.03 t/ha and 16.28 t/ha, respectively.

In contrast, estimates based on Barik et al. (2021) showed moderately better alignment with the reported values, with an R^2 value of 0.34. Although still insufficient for predictive purposes, this result indicates that 34% of the observed SOC variation could be explained using Barik's %OC profile.

However, the estimates still displayed notable inconsistencies across the SOC range, including both overestimations and underestimations. For instance, a reported SOC of 17.7 t/ha was overestimated as 33.72 t/ha, and 20.35 t/ha as 68.01 t/ha, which is more than triple the actual value. Conversely, at higher SOC levels, estimates based on Barik et al. (2021) study often underestimated values; for example, a reported SOC of 248.23 t/ha was estimated at only 131.42 t/ha, and 398.56 t/ha as merely 128.74 t/ha. These results suggest that the %OC values proposed by Barik et al. (2021) may not be generalizable beyond the Sundarbans region, particularly for carbon-rich mangrove soils in other parts of India.

Overall, this analysis demonstrates that applying generalized %OC values from either Mitra et al. (2012) or Barik et al. (2021) for extrapolating SOC across India introduces significant error. Mitra's model consistently underestimates SOC, potentially leading to substantial undervaluation of blue carbon resources. While Barik's model offers relatively better predictive capability, it still suffers from inconsistent accuracy, especially for high-carbon sites. Given these limitations, we relied on the original reported SOC values at various depths for subsequent state-level SOC assessments. As such, the final SOC stock estimates presented in this study may reflect near-actual or slightly underestimated values, but not overestimations. This conservative approach ensures robustness in national-level carbon accounting without inflating the ecosystem service value of India's blue carbon habitats.

3.5.1.2 Estimates of State-Wide Biomass and Soil Organic Carbon Stocks in Mangrove Ecosystems

Based on the detailed discussions presented in the previous sections, which explore the variation in mean carbon values for both biomass and soils in mangrove ecosystems across India, state-wise mean carbon values were derived using statistical analysis of an extensive database compiled from the published literature. As discussed in Chapter 2, mangrove area estimates in India are available from three key sources: the National Wetland Inventory and Assessment (NWIA, 2024), the India State of Forest Report (ISFR, 2023), and the Global Mangrove Watch (GMW, 2020). Using these datasets, state-wise mangrove carbon stocks were estimated for three components: above-ground carbon (AGC), below-ground carbon (BGC), and soil organic carbon (SOC). Total biomass carbon was calculated as the sum of AGC and BGC, while SOC was assessed independently. These values were obtained by multiplying the respective state-wise mean carbon values with mangrove area extents from each of the three datasets.

The estimates of total biomass carbon stocks for

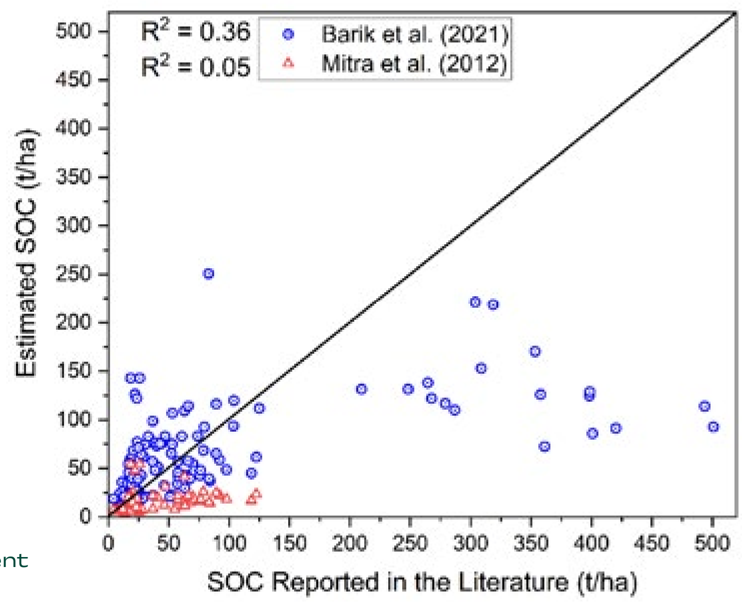


Figure 3.13: Correlation between mean soil organic carbon values estimated using %OC data from different depths in the studies by Barik et al. (2021) and Mitra et al. (2012) versus reported soil organic carbon values from the literature.

mangroves across India's coastal states and union territories are presented in Figure 3.14. Likewise, Figure 3.15 depicts state-wise SOC stock estimates for mangrove ecosystems.

To derive robust and comparative estimates of biomass carbon stocks, state-level mean biomass carbon values were applied to mangrove area extents from the three aforementioned sources. These datasets vary in terms of their spatial resolution, temporal coverage, and mapping methodologies, which result in differing estimates of mangrove extent and, consequently, of associated carbon stocks. As shown in Figure 3.14, West Bengal consistently emerged as the state with the highest biomass carbon stocks, with values of 18.60 Mt C (NWIA), 18.47 Mt C (ISFR), and 21.76 Mt C (GMW), owing to its expansive Sundarbans mangrove forests.

Andhra Pradesh followed with estimates ranging from 10.56 Mt C (GMW) to 13.49 Mt C (NWIA), while other significant contributors included Gujarat (4.53 to 10.18 Mt C) and the Andaman & Nicobar Islands (8.93 to 9.17 Mt C), highlighting the importance of both mainland and island mangroves as blue carbon reservoirs. In contrast, Karnataka, Kerala, Goa, and Tamil Nadu recorded lower carbon stocks, primarily due to their smaller mangrove extents. Notably, NWIA-based estimates were generally the highest among the three datasets, likely reflecting its recent high-resolution mapping and wetland-specific classification protocols. These results underscore the importance of harmonized, accurate spatial inventories for national-level carbon accounting and emphasize the role of reliable geospatial data in shaping blue carbon policy and ecosystem management strategies.

Similarly, SOC stocks were estimated by multiplying state-specific mean SOC values with mangrove area extents derived from NWIA, ISFR, and GMW. This comparative approach highlights how spatial discrepancies in mangrove mapping influence SOC stock estimations. As illustrated in Figure 3.15, the Andaman & Nicobar Islands emerged as the most significant SOC reservoir, with values ranging from 19.31 Mt C (GMW) to 19.84 Mt C (ISFR), reaffirming the crucial role of island mangroves in long-term carbon sequestration. West Bengal followed with values between 9.71 Mt C (ISFR) and 11.44 Mt C (GMW), attributable to its extensive, organic-rich soils in the Sundarbans. Moderate SOC stocks were recorded in Andhra Pradesh, Gujarat, Maharashtra, and Odisha (ranging from 1.34 to 4.25 Mt C), corresponding to their broader mangrove coverage and deltaic soil conditions. States with limited mangrove presence such as Karnataka, Kerala, Goa, and Tamil Nadu showed lower SOC values, likely due to both smaller extents and the presence of less organic-rich substrates. As with biomass estimates, NWIA-based SOC stocks were generally higher than those from ISFR and GMW, likely due to NWIA's detailed spatial resolution and recent data acquisition. These findings collectively emphasize the significance of integrating high-quality spatial datasets with regionally calibrated carbon metrics for accurate blue carbon assessments and informed ecosystem-based management.

3.5.2 Salt Marsh Carbon Stocks: Estimation and Variability

Salt marsh ecosystems, although less extensively studied than mangroves and seagrasses, play a critical role in coastal blue carbon sequestration. Existing literature from various coastal regions in

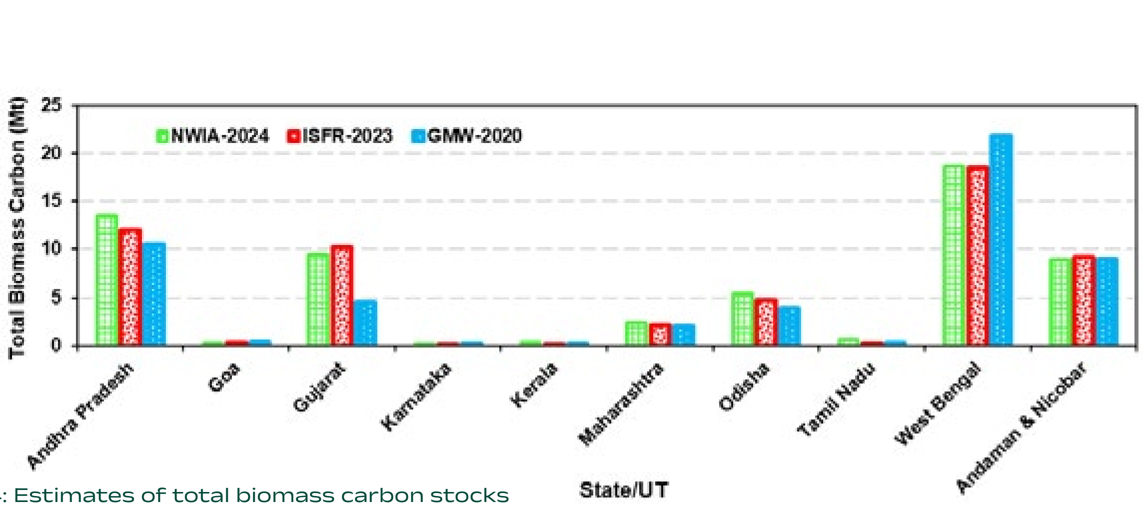


Figure 3.14: Estimates of total biomass carbon stocks for mangroves across the coastal states of India

India has provided localized estimates of above-ground biomass (AGB), below-ground biomass (BGB), soil organic carbon (SOC), and carbon stored in deadwood and leaf litter (Table 3.4). These studies highlight the spatial heterogeneity in saltmarsh productivity and carbon storage potential across different ecological zones. While salt marshes occur in fragmented patches across most Indian coastal states, scientific assessments have been limited to a few locations in four states: Goa, Gujarat, West Bengal, and Tamil Nadu. From the limited data available, a national mean carbon value was derived by combining the average values of total biomass carbon and soil organic carbon, providing a comprehensive estimate of the carbon sequestration potential of salt marshes in India. The variability in reported carbon metrics is discussed below.

In Goa, Jana et al. (2013) reported modest biomass values from the Mandovi Estuary, with AGB and BGB of 1.28 t/ha and 1.78 t/ha, respectively (Table 3.4), corresponding to an AGC of 0.44 t/ha and BGC of 0.36 t/ha (Figure 3.16). These relatively low values reflect the herbaceous and patchy structure of saltmarsh vegetation in the region.

In Gujarat, Chaudhary et al. (2018) recorded AGB and BGB of 1.24 t/ha and 0.12 t/ha, respectively, translating to AGC and BGC values of 0.33 t/ha and 0.22 t/ha (Figure 3.17). In contrast, Rathore et al. (2016) reported a higher AGB value of 4.29 t/ha from the same region, although they did not provide BGB or carbon conversion values. Such discrepancies may be attributed to site-specific differences in vegetation density, seasonal variability, or methodological variations.

In the Sundarbans region of West Bengal, salt marsh sediments were found to be particularly rich in organic carbon. Bhunia et al. (2016) reported a high SOC value of 5.65 t/ha at Sagar Island (20 cm soil depth). Das et al. (2015) reported AGC and BGC values of 0.71 t/ha and 0.03 t/ha from Frazergaunge and 0.64 t/ha and 0.024 t/ha from Bali Island, respectively (Figure 3.18). Additionally, Jana et al. (2013) observed relatively high biomass values in the Hooghly Estuary, including BGB of 2.65 t/ha, AGC of 0.74 t/ha, and BGC of 0.55 t/ha, indicating robust below-ground biomass in the region (Table 3.4).

In Tamil Nadu, Kaviarasan et al. (2019) reported a wide range of SOC values from the salt marshes along the Tuticorin coast in the Gulf of Mannar, ranging from 8.42 ± 0.64 to 54.46 ± 1.46 t/ha (Figure 3.19). The corresponding AGC and BGC values ranged between 0.06–0.15 t/ha and 0.02–0.04 t/ha, respectively (Table 3.4). These high SOC values likely result from sediment trapping and low decomposition rates in the semi-arid intertidal zones.

Although carbon stored in deadwood and leaf litter is less frequently reported, it forms an important but underrepresented component of the total salt marsh carbon stock. Most Indian studies lack sufficient data on this component, highlighting the need for expanded research

In summary, salt marsh ecosystems across India exhibit considerable variability in biomass and soil carbon stocks, but collectively function as valuable blue carbon sinks. Regions such as the Sundarbans and Gulf of Mannar, with their dense biomass and organic-rich soils, show particular promise. This variability underscores the importance of region-specific assessments and the adoption of standardized methodologies for carbon accounting in salt marsh ecosystems.

A statistical analysis of the reported site-level carbon values across Indian salt marshes was conducted to derive a nationally representative mean. This analysis yielded a mean total biomass carbon value of 0.834 t/ha and a mean SOC value of 17.048 t/ha, resulting in a combined average carbon stock of 17.883 t/ha for Indian saltmarshes. These values were subsequently applied to state-wise salt marsh area estimates from two sources: the National Wetland Inventory and Assessment (NWIA, 2024) and Viswanathan et al. (2020) to estimate state-level carbon stocks. The results are illustrated in Figure 3.20.

To ensure consistency and national comparability, a standardized methodology was employed whereby the derived national mean carbon value was multiplied with state-wise salt marsh areas from both datasets. As detailed in Chapter 2, these two data sources differ in terms of mapping methodologies, spatial resolution, and classification systems, leading to significant variation in the resulting carbon stock estimates.

According to NWIA, Gujarat is the dominant contributor to India's salt marsh carbon stocks, with an estimated 2.45 Mt C, reflecting the extensive tidal flats and saline wetlands of the Gulf of Khambhat and Kutch. However, Viswanathan et al. (2020) report a substantially lower stock of 0.28 Mt C for

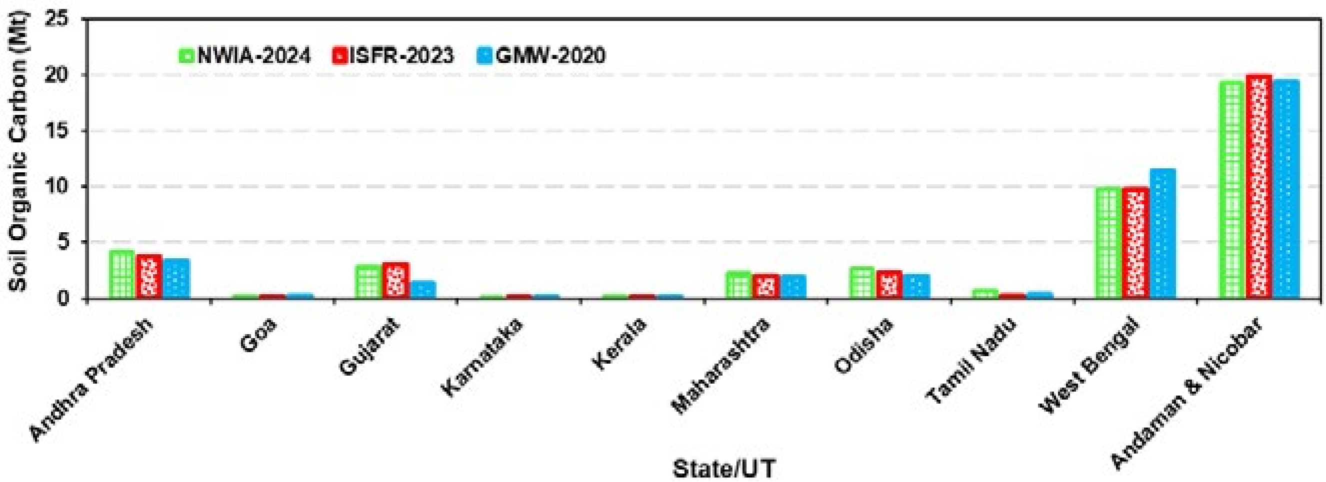


Figure 3.15: Estimates of soil organic carbon stocks for mangroves across the coastal states of India

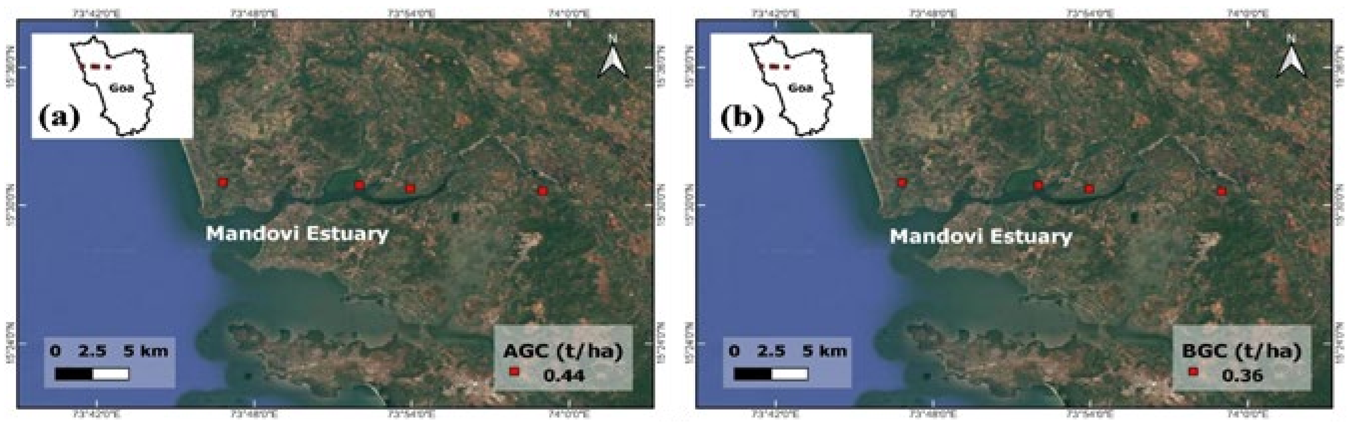


Figure 3.16: Map showing the mean carbon values reported at study sites for salt marshes in Goa state: (a) AGC, and (b) BGC.

Table 3.4: Carbon mean values reported in the literature for the salt marshes located in India

S. No.	Study area	AGB (t/ha)	BGB (t/ha)	Total biomass (t/ha)	AGC (t/ha)	BGC (t/ha)	Total biomass carbon (t/ha)	SOC (t/ha)	Depth of soil sample (cm)	Total leaflitter/ deadwood carbon (t/ha)	Overall carbon stock (t/ha)	Reference
Goa												
1.	Mandovi Estuary	1.28	1.78		0.44	0.36						Jana et al. (2013)
Gujarat												
1.	South Gujarat	1.24	0.12		0.33	0.22						Chaudhary et al. (2018)
2.	South Gujarat	4.29			1.35							Rathore et al. (2016)
West Bengal												
1.	Sagar Island, Sundarbans							5.65	20			Bhunia et al. (2016)
2.	Frazergaunge, Sundarbans	1.53	0.07		0.71	0.03						Das et al. (2015)
3.	Bali Island, Sundarbans	1.37	0.06		0.64	0.024						Das et al. (2015)
4.	Hooghly Estuary	2.15	2.65		0.74	0.55						Jana et al. (2013)
Tamil Nadu												
1.	Tuticorin, Gulf of Mannar				0.06 – 0.15	0.02 – 0.04		8.42±0.64 – 54.46±1.46	30			Kaviarasan et al. (2019)

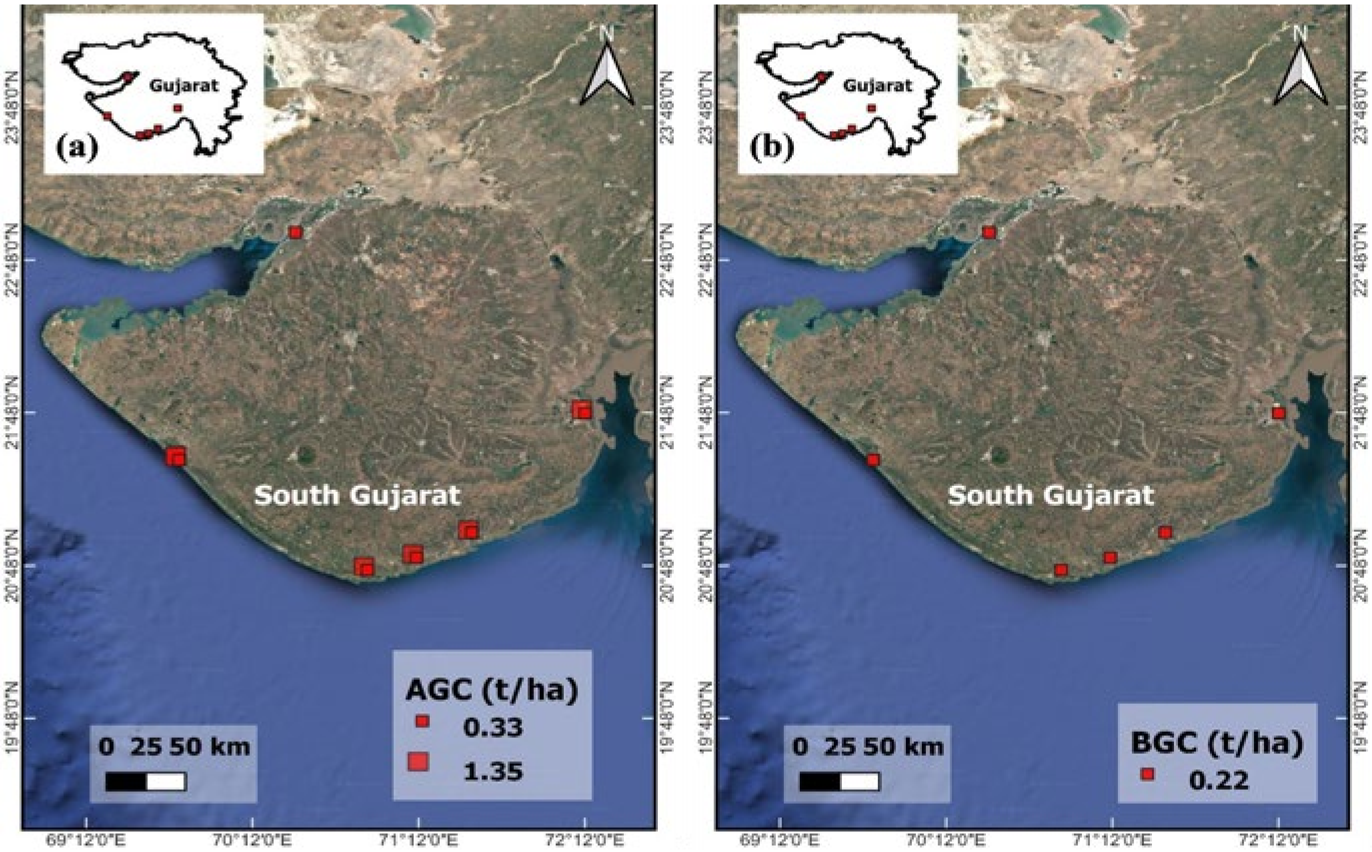


Figure 3.17: Map showing the mean carbon values reported at study sites for salt marshes in Gujarat state: (a) AGC, and (b) BGC.

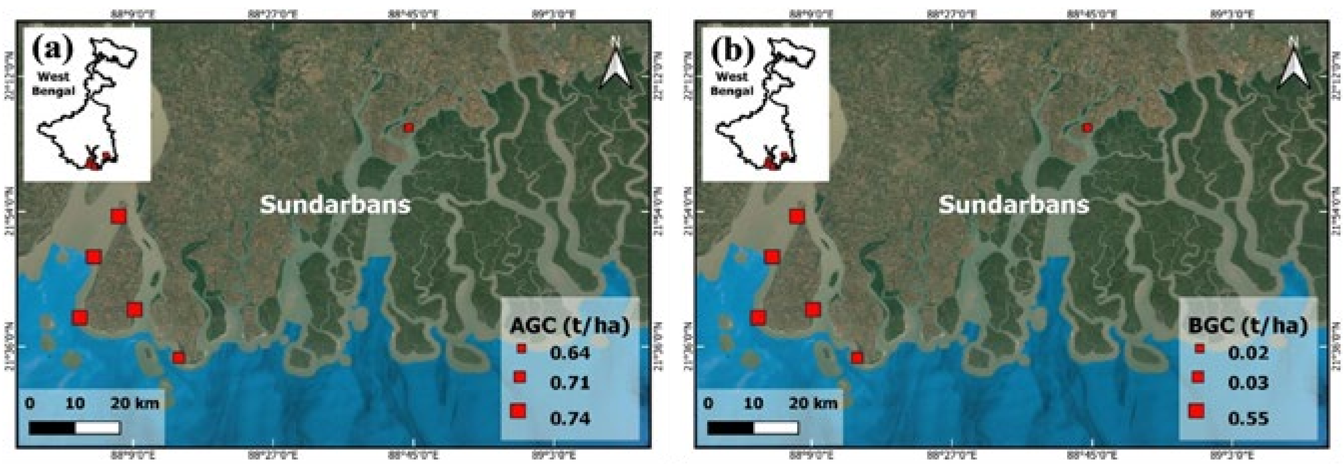


Figure 3.18: Map showing the mean carbon values reported at study sites for salt marshes in Sundarbans, WB state: (a) AGC, and (b) BGC.

Gujarat, potentially due to narrower classification criteria or underrepresentation of salt marsh extent.

The Andaman & Nicobar Islands also show substantial carbon stock estimates (0.17 Mt C) under NWIA, though they are not represented in the Viswanathan et al. dataset, highlighting the need to better incorporate island ecosystems in national assessments.

In Tamil Nadu, the estimated carbon stock ranges from 0.027 Mt C (NWIA) to 0.10 Mt C (Viswanathan et al., 2020), consistent with the expansive salt marshes in the Gulf of Mannar and Palk Bay. West Bengal, although showing no salt marsh area under NWIA, registers 0.06 Mt C according to Viswanathan et al., likely capturing the fringe salt marshes of the Sundarbans delta.

Other states such as Andhra Pradesh, Odisha, Maharashtra, and Goa exhibit modest carbon stocks (ranging from <0.001 to 0.05 Mt C), with generally higher values observed in the Viswanathan et al.

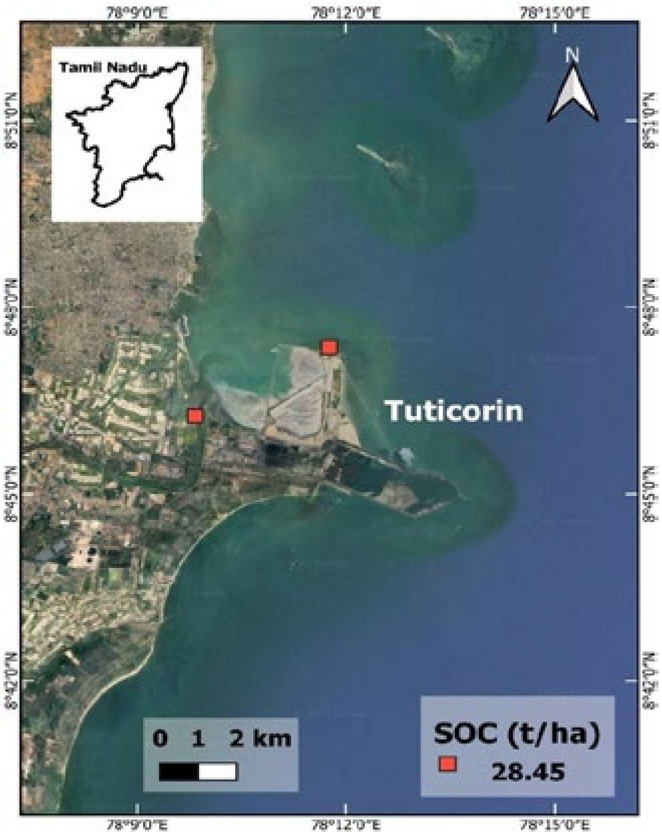


Figure 3.19: Map showing the mean soil organic carbon values reported at study sites for salt marshes in TN state.

dataset. Coastal union territories like Daman & Diu and Puducherry report minimal but non-negligible stocks, underscoring the importance of including microhabitats in national blue carbon inventories.

Overall, the discrepancies between datasets emphasize the significant influence of spatial data quality on carbon stock estimation. This highlights the urgent need for harmonized, high-resolution salt marsh mapping to support accurate blue carbon accounting. Integrating these estimates into national climate mitigation strategies is essential for acknowledging the ecological and carbon storage value of these underrepresented coastal ecosystems.

3.53 Seagrass Carbon Contributions in Indian Coastal Zones

Seagrass meadows are increasingly recognized as vital coastal ecosystems with substantial blue carbon sequestration potential, largely due to their capacity for below-ground carbon storage and the accumulation of sedimentary organic matter. In India, however, research on seagrass carbon stocks remains limited and spatially scattered, with studies conducted at selected sites across the Andaman & Nicobar Islands, Odisha, and Tamil Nadu, as summarized in Table 3.5. The reported carbon stock values exhibit wide variability, reflecting differences in habitat types, seagrass species composition, environmental conditions, and methodological approaches. Across the literature, seagrass carbon assessments typically include above-ground biomass (AGB), below-ground biomass (BGB), their respective carbon equivalents (AGC and BGC), soil organic carbon (SOC), and, in a few cases, contributions from deadwood and leaf litter.

In the Andaman & Nicobar Islands, seagrass meadows are located in some of the least disturbed marine habitats in India. Mishra et al. (2023) reported modest biomass carbon values from Neil, and Havelock islands, and Burmanallah on South Andaman Island, with AGC and BGC recorded at 0.5 t/ha and 0.7 t/ha, respectively. Additionally, a SOC value of 13.17 t/ha was recorded from a 10 cm soil core (Table 3.5), yielding a total carbon stock of 14.37 t/ha. This emphasizes the significance of sedimentary carbon even at shallow depths. In contrast, Stankovic et al. (2021) reported an exceptionally high SOC value of 184.24 ± 23.84 t/ha from the same region, although the sampling depth was not specified. This stark contrast highlights how differences in sampling protocols and local ecological conditions can greatly influence carbon stock estimates. The high SOC value reported by Stankovic et al. may be attributable to prolonged sediment accumulation, low anthropogenic interference, and favourable conditions for organic matter preservation.

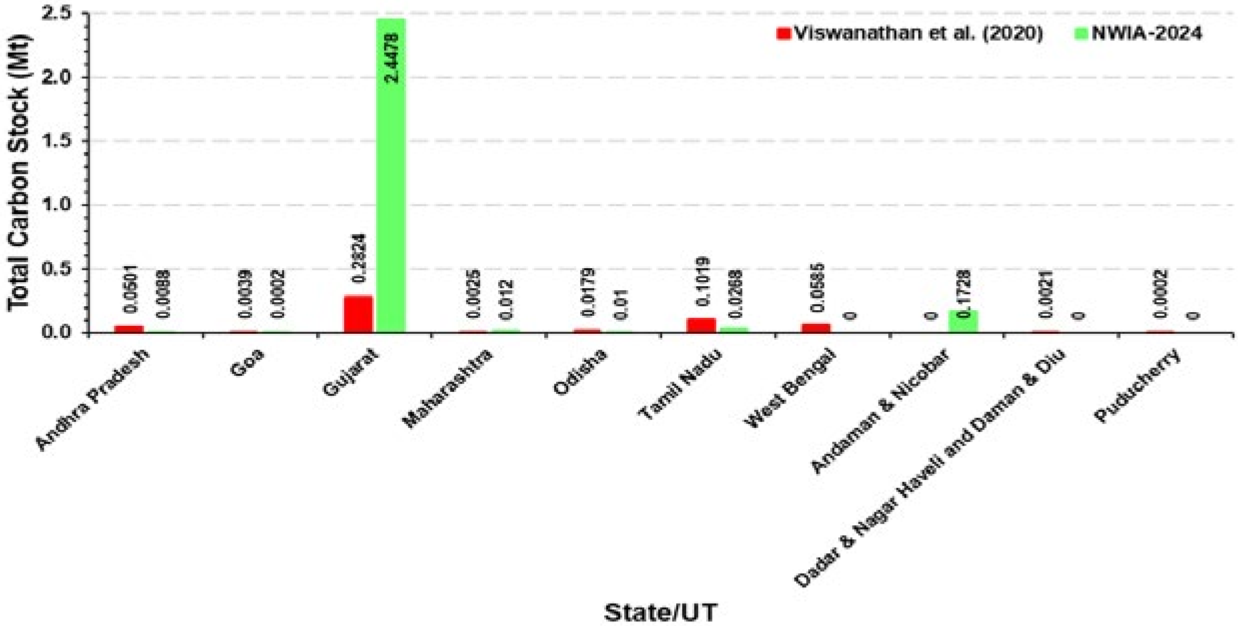


Figure 3.20: Estimates of total carbon stocks for salt marshes across the coastal states of India

In eastern India, the Chilika Lagoon in Odisha is one of the country's largest brackish water bodies which supports substantial seagrass cover. Kaladharan et al. (2021) recorded a SOC value of 2.02 ± 0.67 t/ha (Table 3.5), suggesting limited carbon accumulation in this highly dynamic and flushed system. However, Ganguly et al. (2018) reported considerably higher values from the same region, including a total biomass carbon stock of 6.2 t/ha and a SOC of 120.98 t/ha from a 100 cm deep soil core (Figure 3.22b). These divergent estimates underscore the influence of sampling depth and spatial heterogeneity within the lagoon, shaped by variations in hydrology, sediment characteristics, and species composition.

Along the Tamil Nadu coast, seagrass meadows in Pulicat Lake, Palk Bay, and the Gulf of Mannar display notable species richness and habitat extent. Kaladharan et al. (2021) measured a low SOC value of 0.998 ± 0.418 t/ha from Pulicat Lake. In earlier studies, Kaladharan et al. (2020) reported biomass carbon values of 3.9 t/ha in Palk Bay and 0.35 t/ha in the Gulf of Mannar (Figure 3.22), based on samples taken from a 20 cm depth. These modest values may reflect the high-energy coastal dynamics in the region, where sediment resuspension and organic matter decomposition limit long-term carbon burial. Conversely, Ganguly et al. (2018) found significantly higher carbon stocks in Palk Bay, with a total biomass carbon of 24.11 t/ha and a SOC of 135.42 t/ha from a 100 cm depth.

An earlier study by Ganguly et al. (2017) also reported high AGC and BGC values of 2.685 t/ha and 7.735 t/ha, respectively, along with a SOC of 82.416 t/ha from a 60 cm profile. These findings suggest that the relatively protected and sediment-rich environment of Palk Bay favours high biomass productivity and substantial sub-surface organic carbon storage.

A comparative synthesis of the compiled data reveals that soil organic carbon overwhelmingly dominates the total carbon stock in Indian seagrass ecosystems, often contributing more than 80% of the total. The highest SOC value of 184.24 t/ha and one of the highest biomass carbon estimates (24.11 t/ha) originate from relatively undisturbed and productive sites in the Andaman & Nicobar Islands and Palk Bay, respectively. The observed increase in SOC with depth from 13.17 t/ha at 10cm to over 130 t/ha at 100cm emphasizes the importance of standardized sampling protocols for meaningful cross-site comparisons. Notably, across all reported studies, carbon contributions from leaf litter and deadwood are largely undocumented, representing a critical gap in comprehensive ecosystem carbon assessments.

Overall, the available evidence indicates that

Indian seagrass meadows despite being under-studied and under-mapped, play a significant role in coastal carbon sequestration. The below-ground and sedimentary carbon pools vastly exceed above-ground biomass in magnitude, consistent with global observations. However, the marked variability in carbon stock estimates driven by ecological, methodological, and spatial differences underscores the urgent need for a standardized, national-scale monitoring framework.

Building on these site-specific estimates, a national mean carbon value of 83.02 t/ha for Indian seagrasses was derived through statistical analysis of the compiled literature dataset. This mean value was then used to estimate total seagrass carbon stocks by multiplying it with seagrass area estimates from two independent spatial datasets: Geevarghese et al. (2018) and Seal et al. (2023).

Seagrass carbon stock estimations across coastal India were thus standardized using the national mean carbon value, applied to spatially explicit seagrass extent data from the two aforementioned studies. This approach enables robust and scalable assessments of India's seagrass carbon sequestration potential, particularly in the absence of uniform field-based data across regions. Estimates derived from Geevarghese et al. (2018) indicate that the Andaman & Nicobar Islands host the highest carbon stock at 2.737 million tonnes (Mt C), as shown in Figure 3.23. This aligns with earlier findings that highlight the region's extensive and relatively pristine seagrass meadows. Lakshadweep also demonstrates significant carbon storage potential with an estimated 0.574 Mt C, attributed to its widespread lagoonal seagrass habitats. On mainland India, the Gulf of Mannar (0.710 Mt C), Chilka Lake (0.141 Mt C), and the Gulf of Kutch (0.121 Mt C) report moderate carbon stocks, likely shaped by dynamic coastal processes and relatively smaller seagrass extents.

Seal et al. (2023), offering a more recent and potentially improved spatial dataset, provide estimates for select regions. According to their analysis, Tamil Nadu emerges as a major seagrass carbon hotspot, with Palk Bay and the Gulf of Mannar accounting for 4.699 Mt C and 2.549 Mt C, respectively (Figure 3.23). These values substantially exceed earlier estimates, potentially reflecting improved mapping accuracy, methodological advancements, or broader spatial coverage. The particularly high stock reported for Palk Bay underscores its ecological importance, characterized by dense seagrass cover and substantial below-ground carbon storage.

Disparities between the two datasets highlight how differences in mapping resolution and classification criteria affect total carbon stock estimates. While Geevarghese et al. (2018) relied on earlier

Figure 3.21: Map showing the mean carbon values reported at study sites for Seagrasses in Palk Bay, TN state: (a) AGC, and (b) BGC.

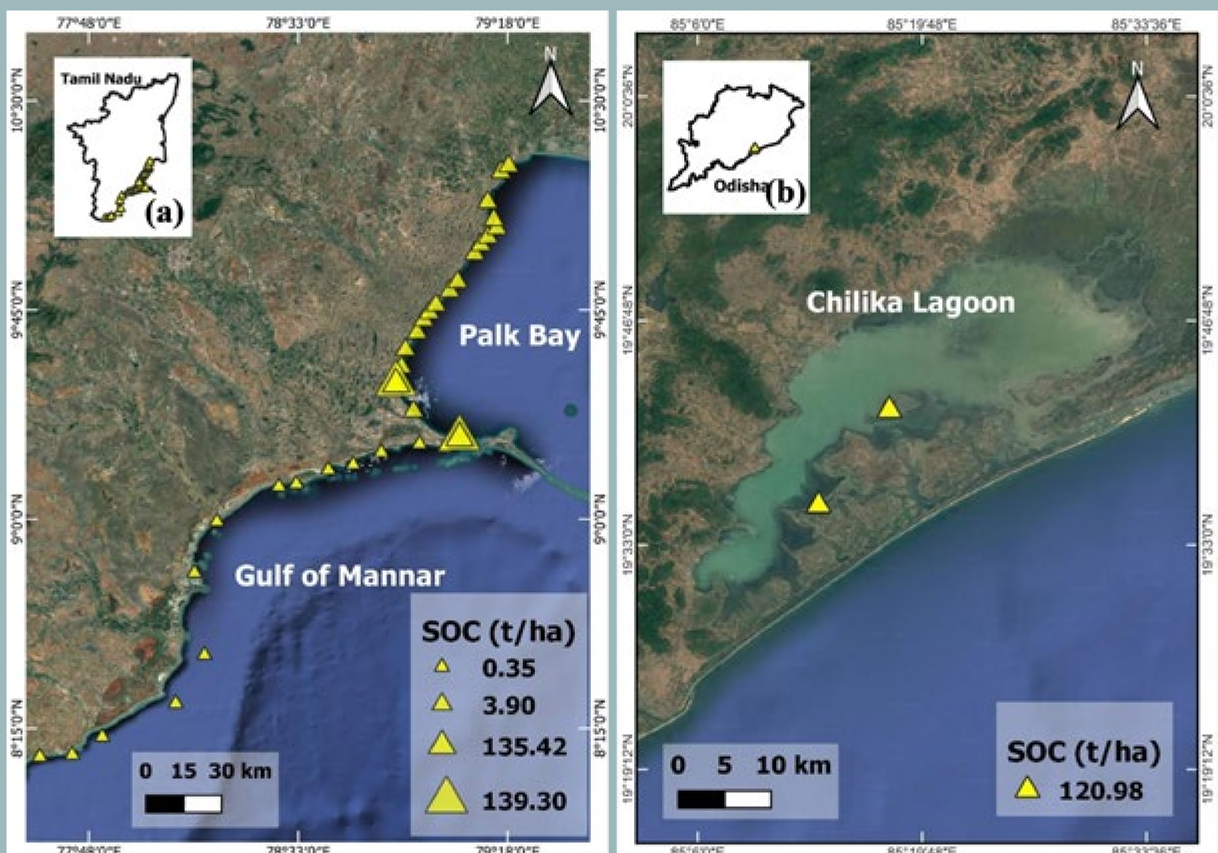


Figure 3.22: Map showing the soil organic carbon values reported at study sites for Seagrasses: (a) Palk Bay in TN state, and (b) Chilika Lagoon in Odisha state.

Table 3.5: Carbon mean values reported in the literature for the seagrasses located in India

S. No.	Study area	AGB (t/ha)	BGB (t/ha)	Total biomass (t/ha)	AGC (t/ha)	BGC (t/ha)	Total biomass carbon (t/ha)	SOC (t/ha)	Depth of soil sample (cm)	Total leaflitter/ deadwood carbon (t/ha)	Overall carbon stock (t/ha)	Reference
Andaman and Nicobar												
1.	Neil, Havelock and Burmanallah Islands				0.5	0.7		13.17	10			Mishra et al. (2023)
2.	Andaman and Nicobar										184.24±23.84	Stankovic et al. (2021)
Odisha												
1.	Chilika Lake										2.018±0.673	Kaladharan et al. (2021)
2.	Chilika Lagoon						6.2	120.98	100			Ganguly et al. (2018)
Tamil Nadu												
1.	Pulicat Lake										0.998±0.418	Kaladharan et al. (2021)
2.	Palk Bay							3.9	20			Kaladharan et al. (2020)
3.	Gulf of Mannar							0.35	20			Kaladharan et al. (2020)
4.	Palk Bay						24.11	135.42	100			Ganguly et al. (2018)
5.	Palk Bay				2.685	7.735		82.416	60			Ganguly et al. (2017)

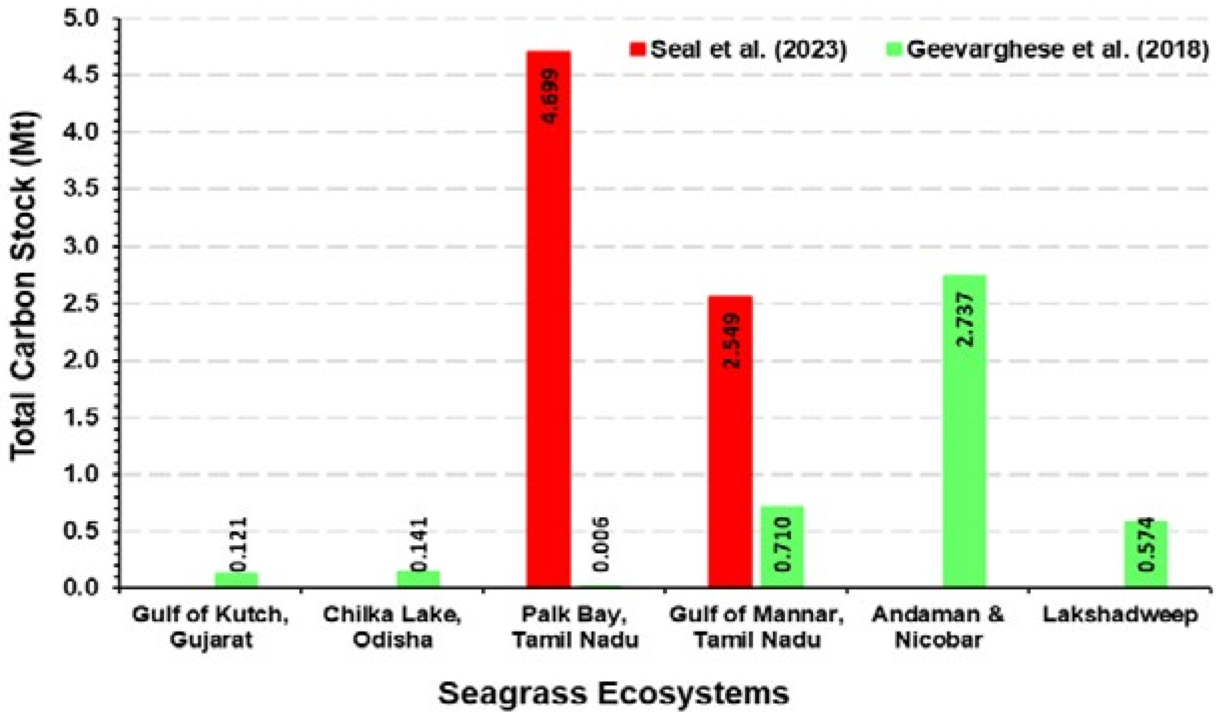


Figure 3.23: Total carbon stock estimated from prominent seagrass ecosystems located in India

remote sensing methods and conservative area delineation, Seal et al. (2023) likely employed more advanced technologies capable of capturing finer-scale spatial variability. These discrepancies have important implications for national carbon accounting, conservation prioritization, and policy development within India's blue carbon strategy.

In summary, this analysis underscores the ecological significance and spatial heterogeneity of seagrass carbon stocks in India. The integration of high-resolution habitat maps with a standardized national carbon mean offers a pragmatic and scientifically sound approach to improve blue carbon inventories.

3.6 Critical Analysis of Results: Key Insights and Regional Trends

The national-level blue carbon stock in India has been estimated by aggregating carbon stock data across three key coastal ecosystems: mangroves, saltmarshes, and seagrasses using various spatial datasets and literature sources. The results, shown in Figure 3.24, highlight notable variability in estimated carbon stocks depending on the source and method of area estimation. For mangroves, estimates range from 92.65 million tonnes of carbon (Mt C), based on the Global Mangrove Watch (GMW-2020) dataset, to 98.36 Mt C and 101.56 Mt C, as reported in the India State of Forest Report (ISFR-2023) and the National Wetland Inventory and Assessment (NWIA-2024), respectively (Figure 3.24). These differences reflect underlying variation in spatial extent, classification criteria, and remote sensing techniques employed by each dataset. Salt marsh carbon stocks have been derived from recent literature, with Viswanathan et al. (2020) estimating a total of 2.68 Mt C based on field data and spatial mapping, while Geevarghese et al. (2018) report a significantly lower value of 0.52 Mt C. Such discrepancies are likely driven by differing assumptions related to carbon density, sampling depth, and spatial coverage. For seagrasses, a national estimate of 4.29 Mt C is provided exclusively by Geevarghese et al. (2018), derived using area data in conjunction with a national mean carbon value. The combined insights from these datasets emphasize the critical role of improved ecosystem mapping and harmonized carbon accounting methodologies in producing accurate and policy-relevant blue carbon inventories for India.

Based on the highest available estimates for each ecosystem type, the total blue carbon ecosystem (BCE) stock potential of India is estimated at approximately 108.53 million tonnes of carbon, while the lowest estimate is 97.46 million tonnes. In contrast, Akhand et al. (2023) reported a lower estimate of 67.35 million tonnes, derived by extrapolating mangrove carbon stocks from selected regions to the national scale and supplementing them with seagrass and saltmarsh contributions. The higher range reported in this study likely reflects the incorporation of broader datasets and methodological differences in extrapolation. Similarly, Canty et al. (2025) reported in their supplementary data that India's mangrove carbon stock alone is 202.6 million tonnes when mapped using 10 m pixel resolution data. When mangrove area was estimated using 25 m resolution imagery, the carbon stock increased slightly to 206.33 million tonnes. Canty et al. (2025) used IPCC (2014) recommended global mean mangrove carbon values of 511 t/ha to estimate total carbon stocks. Their relatively high estimate is likely due to the application of the global mean value, which exceeds values reported in site-specific studies of mangroves in India. These consolidated values underscore the substantial role that India's coastal and marine ecosystems play in national climate mitigation strategies, while also highlighting the urgent need for integrated monitoring, protection, and restoration efforts across these vital habitats.

3.7 Summary

The detailed assessment of blue carbon ecosystems (BCEs) in India namely mangroves, salt marshes, and seagrasses is carried out. Against the backdrop of India being the third-largest CO_2 emitter globally, discussed the limitations of technological solutions like Carbon Capture, Utilization, and Storage (CCUS), citing high operational costs and environmental risks such as groundwater contamination and geological instability. In contrast, natural carbon sinks, especially marine ecosystems, offer a more sustainable and cost-effective alternative for carbon mitigation. Mangroves, in particular, are highlighted due to their high sedimentary carbon storage and widespread presence along India's tropical coastline.

To evaluate the national blue carbon potential, the study compiled data from over 200 sources and 158 of which were directly relevant which were sourced from published journals and scientific reports. These sources were used to quantify the area and carbon content of BCEs, forming the basis of a meta-analysis. The review reveals that mangroves dominate BCE research in India, accounting for more than 90% of publications, while salt marshes and seagrasses remain significantly understudied. Spatial analysis showed uneven research distribution, with the east coast (notably Odisha and West Bengal) being better studied than the west coast, where states like Andhra Pradesh and regions like the Gulf of Mannar lack adequate carbon stock assessments.

The methodology section details the estimation of carbon stocks across various components such as above-ground carbon (AGC), below-ground carbon (BGC), soil organic carbon (SOC), and carbon in litter and deadwood using reported mean values multiplied by ecosystem area. Biomass was converted to carbon using a standard factor of 0.5. While the IPCC recommends assessing SOC to a depth of 1 meter, the study used actual reported values due to variability in soil depth data. This conservative approach ensures realistic, if slightly underestimated, national estimates.

In the case of mangroves, the study found significant carbon storage, especially in the Sundarbans (West Bengal), Bhitarkanika (Odisha), and Andaman & Nicobar Islands. These areas showed high biomass and sediment carbon values, though substantial regional variability exists due to local ecological conditions and differing methodologies. On the west coast, Kerala emerged as a key carbon sink, though other states like Goa and Maharashtra remain underrepresented. Salt marsh data, derived from limited studies in Gujarat, Goa, Tamil Nadu, and West Bengal, yielded an average carbon stock of 17.88 t/ha. Gujarat stood out as the major contributor, especially under NWIA mapping. Similarly, the study on seagrasses, mainly from the Andaman & Nicobar Islands, Odisha's Chilika Lake, and Tamil Nadu's coastal waters showed highly variable carbon stocks. SOC dominated total seagrass carbon storage, with values ranging from a few tonnes to over 180 t/ha depending on site conditions and sampling methods. Overall, based on the highest available estimates for each ecosystem type, the total blue carbon ecosystem (BCE) stock potential of India is estimated at approximately 108.53 million tonnes of carbon.

This chapter concludes by highlighting the methodological and spatial challenges in estimating

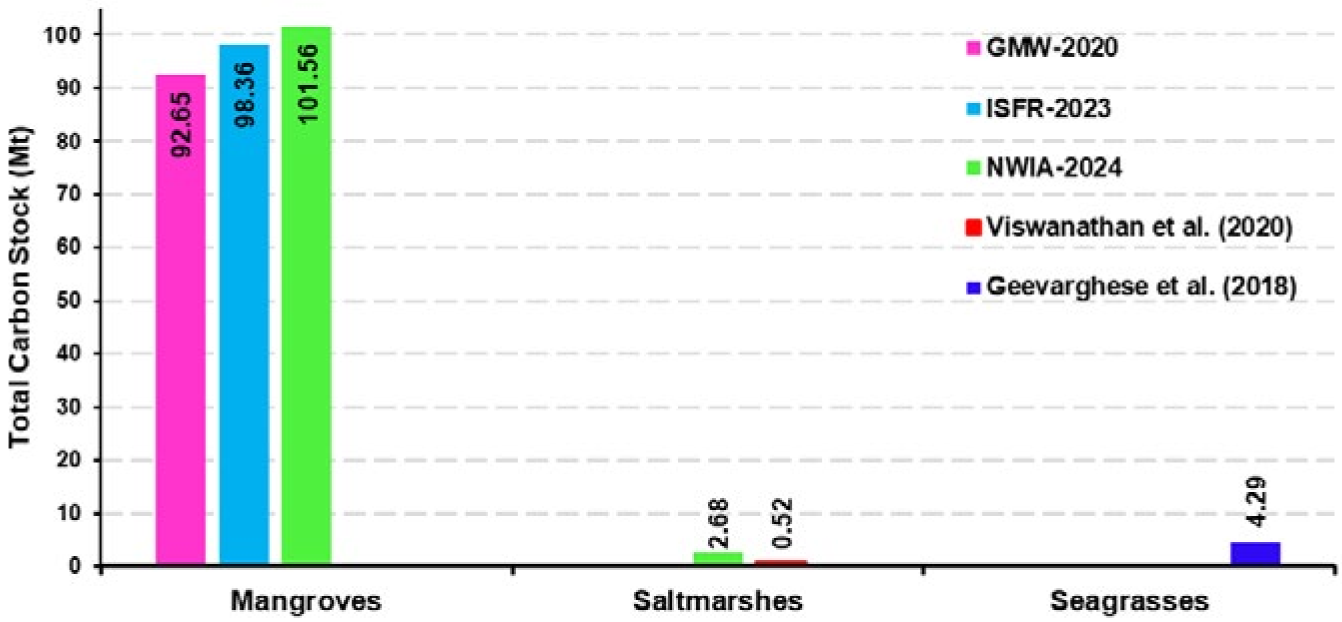


Figure 3.24: National wide estimates of total carbon stocks for BCE in India

blue carbon stocks. It stresses the need for standardized data collection protocols, especially for SOC, and more comprehensive mapping across all BCE types and regions. Ultimately, integrating these findings into national climate policy is essential for leveraging the ecological and climate mitigation benefits of India's blue carbon ecosystems.

CHAPTER 4

Addressing Uncertainties and advancing BCE monitoring in India

4.1 Sources of Uncertainties in BCE Stock Estimations

The estimation of blue carbon ecosystem (BCE) stocks in India is subject to multiple sources of scientific uncertainty that hinder the accuracy and consistency of national-level assessments. A primary source of uncertainty arises from the widespread reliance on Tier-1 methodologies as prescribed by the IPCC, which utilise global/national default carbon factors and assume ecological homogeneity across sites. This approach lacks site-specific calibration and is unsuitable for India's diverse coastal landscapes. Another significant uncertainty stems from the variability in remote sensing datasets, particularly differences in spatial, spectral, and temporal resolutions, which lead to inconsistencies in mapping accuracy. Cloud cover, mixed pixels, and sensor limitations further exacerbate classification errors in remote sensing-based BCE mapping. Field data inconsistencies also contribute to uncertainty, as biomass and soil carbon sampling are often unevenly distributed across regions, with key ecosystems on the west coast and island territories underrepresented.

Furthermore, the absence of standardised carbon conversion factors introduces methodological variation; different studies employ values ranging from 0.45 to 0.50 for above-ground biomass and 0.36 to 0.50 for below-ground biomass, depending on wood density, species, and site conditions. Soil Organic Carbon (SOC) estimation is particularly problematic due to inconsistent reporting of soil depth. While the IPCC recommends a standard depth of 1 meter, many studies report values for shallower or unspecified depths, complicating data normalisation and leading to potential over- or under-estimation of carbon stocks. The intrinsic ecological variability of BCEs, driven by tidal regimes, salinity gradients, sedimentation, and vegetation heterogeneity, further challenges the generalisation of site-specific findings to regional scales.

Temporal mismatches between ground-based measurements and satellite observations introduce additional biases, particularly in ecosystems that undergo rapid changes due to disturbances such as cyclones, sea-level rise, or land-use conversion. These episodic and anthropogenic events can cause abrupt alterations in carbon pools, which are not adequately captured in periodic monitoring. The absence of unified national protocols for ecosystem classification, biomass estimation, and SOC sampling compounds these issues, resulting in fragmented and non-comparable datasets. Lastly, limited access to high-resolution commercial satellite imagery due to financial constraints forces researchers to rely on moderate-resolution open-source data, thereby limiting the spatial precision of carbon stock estimates.

4.2 Challenges in Nationwide BCE Accounting

Estimating national-level Blue Carbon Ecosystem (BCE) stocks in India involves a complex interplay of scientific, technical, and institutional challenges. One of the foremost challenges is the significant spatial heterogeneity in ecosystem distribution and data availability. While certain regions like the east coast of India (e.g., West Bengal and Odisha) are relatively well-studied, vast areas along the west coast and island territories such as Karnataka, Goa, and parts of the Andaman and Nicobar Islands remain underrepresented or entirely unsampled. This uneven geographic coverage introduces substantial bias and limits the representativeness of national estimates. Another issue is the disparity in sampling intensity across sites, with some locations having just one to six sampling plots, which compromises statistical robustness and spatial extrapolation. A further major challenge is the methodological inconsistency in carbon estimation techniques across studies. There is a lack of standardised national protocols for biomass measurement, soil carbon sampling, and carbon pool classification. Studies frequently use varied biomass to carbon conversion factors, ranging from 0.45 to 0.5, depending on species-specific wood density or researcher preference, resulting in non-comparable datasets. For Soil Organic Carbon (SOC), a key carbon pool in BCEs, the IPCC recommends assessments to a depth of one meter; however, many Indian studies report SOC at varying depths or do not specify depth at all, necessitating conservative approaches that likely underestimate national stocks.

The scaling up of BCE assessments also faces limitations in remote sensing and spatial data infrastructure. Although open-source satellite datasets like Sentinel-2 and Landsat have improved spatial monitoring, they suffer from limitations such as cloud cover, low spatial resolution, and inconsistencies in classification accuracy. Additionally, the absence of consistent ecosystem classification schemes and temporal mismatches between field data and satellite imagery introduce further errors in area estimation. The availability of high-resolution commercial datasets remains restricted due to financial constraints, particularly for large-scale applications. Another key challenge is the lack of harmonised carbon accounting frameworks at the national level. While multiple datasets (e.g., Global Mangrove Watch, India State of Forest Report, NWIA) provide mangrove extent estimates, the spatial resolution, classification criteria, and base years differ, leading to wide variability in derived carbon stock values. For instance, mangrove carbon stock estimates range from 92.65 to 101.56 million tonnes depending on the dataset used.

Governance and institutional limitations also play a critical role in impeding the nationwide scaling of BCE assessments. The absence of a centralised monitoring authority, limited inter-agency coordination, and insufficient funding restrict the implementation of field validation surveys and long-term ecological monitoring. Furthermore, anthropogenic pressures such as urbanisation, aquaculture expansion, and coastal industrialisation lead to habitat fragmentation and degradation, directly impacting carbon stock stability. These challenges are exacerbated by the effects of climate change, including rising sea levels, altered salinity gradients, and increased cyclone frequency, all of which contribute to rapid ecosystem transformation that current monitoring systems are ill-equipped to track. Therefore, achieving accurate and policy-relevant national-level BCE carbon estimates in India necessitates a concerted effort to address these scientific, technological, financial, and governance-related barriers through a holistic, integrated, and standardised monitoring and reporting framework.

4.3 Integrating Remote Sensing, Field Surveys, and Machine Learning for Improved Accuracy

The integration of high-resolution satellite data, such as LISS-IV, advanced radar imaging from NISAR, field-based ecological surveys, and Machine Learning (ML) or Deep Learning (DL) algorithms, represents a transformative approach to enhancing the accuracy of Blue Carbon Ecosystem (BCE) mapping and carbon stock estimation at the national level. This synergy addresses the key challenges currently limiting BCE assessments, particularly spatial resolution, classification accuracy, and carbon pool quantification.

LISS-IV (Linear Imaging Self-Scanning Sensor-4) provides high spatial resolution imagery (5.8 m) across green, red, and near-infrared (NIR) bands, making it well-suited for distinguishing fine-scale vegetation features such as mangrove patches, salt marshes, and seagrass beds. Its greater spatial detail allows for more precise delineation of BCE boundaries, especially in heterogeneous and fragmented coastal landscapes where moderate-resolution sensors like Sentinel-2 or Landsat often misclassify or overlook small and narrow features. In parallel, the NASA-ISRO Synthetic Aperture Radar (NISAR) mission, with its dual L-band and S-band radar systems, provides all-weather, day-and-night imaging capabilities. NISAR is particularly advantageous for monitoring BCEs in cloud-prone coastal zones and during monsoon seasons, overcoming the optical limitations of passive sensors. Furthermore, radar backscatter is sensitive to vegetation structure, biomass, and moisture content, enabling the derivation of biophysical parameters that are directly linked to above-ground and below-ground biomass estimation.

Field surveys serve as a critical component of this integration, providing ground-truth data required for algorithm calibration, model validation, and biomass-to-carbon conversions. Parameters such as species composition, canopy height, tree diameter at breast height (DBH), soil organic carbon (SOC), and bulk density can be collected across representative sites and linked to spectral or radar-derived indices. These field measurements serve as training and testing datasets for supervised ML or

DL classification models, thereby improving model accuracy and generalisability. When integrated into the processing chain, machine learning algorithms such as Random Forest, Support Vector Machines, and Gradient Boosted Trees have demonstrated strong performance in classifying complex land cover types. Meanwhile, deep learning architectures, especially Convolutional Neural Networks (CNNs), are particularly effective in handling high-dimensional imagery and extracting spatial-contextual patterns, which are crucial for BCE classification across varied coastal terrains.

The fusion of LISS-IV's optical resolution, NISAR's structural sensitivity, field-based ecological measurements, and AI-based classification models enables a multi-dimensional analysis pipeline. This facilitates the generation of high-accuracy BCE distribution maps and biomass estimates at a national scale. Moreover, this integrated approach can support temporal change detection, disturbance monitoring, and ecosystem recovery assessments, thereby allowing dynamic tracking of carbon stock variations. When implemented within the IPCC's Tier-2 or Tier-3 frameworks, this methodology significantly reduces uncertainty and enhances confidence in national-level greenhouse gas inventories associated with coastal ecosystems. Consequently, it supports India's commitments under climate agreements such as the Paris Accord and contributes to the operationalisation of natural climate solutions through evidence-based policy and management interventions.

4.4 Limitations of Current Methodologies and Suggestions for Improvement

The following are the limitations of the current study.

- West coast regions such as Karnataka, Goa, and Maharashtra had minimal or no sampling plots for BCE carbon estimation.
- Sampling intensity was very low in several areas, with only 1–6 plots reported at certain study sites.
- Soil Organic Carbon (SOC) values were reported for inconsistent depth intervals, and many studies did not specify soil depth, preventing standardisation to the IPCC-recommended 1-meter depth.
- SOC stock estimates were not extrapolated to 1 meter due to a lack of uniform depth reporting, resulting in conservative values.
- Different studies used varying carbon conversion factors (e.g., 0.45, 0.47, 0.50) for above-ground and below-ground biomass, causing inconsistencies in carbon stock calculations.
- Mangrove extent estimates varied significantly between datasets such as NWIA, ISFR, and GMW, affecting derived carbon stocks.
- The study relied exclusively on secondary data and literature values; no new field sampling was conducted for validation.
- Salt marsh and seagrass carbon stock data were sparse and limited to only a few coastal states, resulting in incomplete ecosystem coverage.
- Field data and remote sensing images used in different studies were not temporally synchronised.

4.5 Opportunities for Future Research and Policy Implications

To advance national-level blue carbon accounting in India, future research must address key knowledge gaps and methodological limitations identified in the current assessment. A primary research priority is expanding geographic coverage and plot-level sampling intensity, particularly in underrepresented regions such as the west coast (e.g., Karnataka, Goa, and Gujarat) and islands like Lakshadweep. The inclusion of these regions will improve the representativeness of national carbon estimates and allow for more robust spatial analyses. Furthermore, the development and adoption of standardised protocols for field measurements, carbon pool classification, and carbon conversion factors are essential for ensuring consistency across studies and enabling data harmonisation at the national scale.

Technological advancements should also be leveraged to enhance blue carbon ecosystem (BCE) mapping and monitoring. The integration of high-resolution optical data (e.g., LISS-IV), synthetic aperture radar (e.g., NISAR), and machine learning algorithms can significantly improve the detection, classification, and quantification of BCEs. Deep learning models, when trained with field-validated datasets, offer the potential for automated, accurate, and scalable ecosystem classification. These tools can address the limitations of traditional remote sensing techniques, such as cloud interference and spectral confusion in complex coastal environments.

On the policy front, the inclusion of blue carbon ecosystems in India's national carbon accounting and reporting mechanisms remains a critical gap. While mangroves have received policy recognition, salt marshes and seagrasses are still largely excluded from conservation frameworks and carbon offset strategies. Future policies should adopt an ecosystem-based management approach that encompasses all three BCE types and promotes their integration into climate mitigation instruments such as Nationally Determined Contributions (NDCs), carbon markets, and the REDD+ mechanism. Establishing a centralised institutional framework to coordinate BCE monitoring, data sharing, and policy implementation will further strengthen governance and accountability.

In addition, future research should explore the socio-economic co-benefits of BCE conservation, including fisheries enhancement, coastal protection, and livelihood support, to justify policy investments and foster inclusive, community-driven conservation models. Collectively, these future directions will enable the development of a scientifically rigorous, spatially comprehensive, and policy-relevant blue carbon strategy for India, contributing meaningfully to its net-zero targets and broader climate resilience goals.

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