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Article

Assessment of mangrove cover and biomass with remote sensing technologies to conserve Gulf of Khambhat, Gujarat, India

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Abstract: Natural resource conservation is vital for maintaining ecosystems that support biodiversity, regulate climate, and provide essential resources for human well-being. As ecosystems face growing pressures from deforestation, pollution, and climate change, remote sensing has become a key tool for monitoring and protecting these environments. Through satellite imagery, LiDAR, and aerial photography, remote sensing offers detailed insights into land cover changes, habitat degradation, and forest health, enabling data-driven conservation strategies. Mangroves play a crucial role in natural resource conservation by protecting coastlines from erosion, reducing the impacts of storms, and providing habitat for diverse marine species. They also act as significant carbon sinks, helping to mitigate climate change while supporting fisheries and local livelihoods. Specifically, for mangroves, remote sensing plays a critical role in assessing ecosystem health, species composition, and disturbances like illegal logging and coastal erosion, supporting effective conservation and restoration efforts to ensure their sustainability. The study of mangroves in the Gulf of Khambhat, Gujarat, emphasizes the critical role of mangrove ecosystems in biodiversity conservation, coastal protection. Leveraging remote sensing techniques such as microwave (ALOS PALSAR-2-L band with 25 m resolution) and optical (multi-spectral) (Sentinel-2 MSI with 10m resolution), the research integrates the mangrove and non-mangrove delineation, change detection to offer insights into natural resource conservation of mangroves and Above Ground Biomass (AGB) estimation. In this study the area of mangroves obtained is 94.94 km^2 from L-band SAR data (25 m resolution and 2020), 98.55 km^2 from Optical data (10m resolution and 2020) while the Forest Survey of India Report (2021) illustrate 101.53 km^2 mangrove area at Gulf of Khambhat, India. The accuracy of the area of mangroves obtained from remote sensing is 93.50 % from L-band SAR) and 97.06 % from Optical data (Sentinel-2 MSI) with respect to area reported in Forest Survey of India Report (2021). These results are crucial for loss and recovery monitoring of mangrove forest, to enable targeted conservation efforts. This study offers a comprehensive approach to conserving natural resources by enhancing the accuracy of biomass mapping and ecosystem monitoring, ensuring effective conservation strategies for the biodiversity-rich mangrove regions of the Gulf of Khambhat.

Keywords: mangroves; remote sensing; Above Ground Biomass (AGB); Support Vector Machine (SVM) classification

1. Introduction

Natural resource conservation is an essential priority due to growing anthropogenic pressures on ecosystems. Healthy ecosystems are critical for supporting biodiversity, regulating the Earth's climate, and providing essential resources for human well-being, such as clean air, water, and fertile soil. The ecosystems also play a central role in sustaining livelihoods, especially in regions dependent on agriculture, forestry, and fishing. However, accelerated deforestation, industrial pollution, urbanization etc. are impacting the climate and leading to degraded ecosystems worldwide [1]. As these pressures intensify, innovative methods for monitoring, protecting, and managing natural resources are urgently required. Remote sensing technologies have emerged as powerful tools for environmental monitoring and conservation, offering scalable, cost-effective way for understanding ecosystems [2]. By leveraging satellite imagery, LiDAR (Light Detection and Ranging), Synthetic Aperture Radar (SAR), and aerial photography, remote sensing enables researchers to track land cover changes, identify habitat degradation, and assess forest health [3]. With the capability to provide spatially continuous data over large and often inaccessible areas, remote sensing supports the development of data-driven conservation strategies that are critical for long-term ecosystem management of ecosystems, from forests and wetlands to coastal mangrove habitats.

Mangrove ecosystems are among the most critical coastal habitats, offering a unique combination of ecological, economic, and protective functions. These intertidal forests serve as biodiversity hotspots, providing habitat and breeding grounds for diverse marine and terrestrial species. In addition, mangroves play a vital role in stabilizing coastlines, reducing erosion, and mitigating the impact of natural disasters such as tsunamis and cyclones [4]. They are also important carbon sinks, storing large amounts of carbon in their biomass and sediments, thereby contributing to climate change mitigation. Globally, mangrove forests cover over 146,500 km^2 of shoreline, making them a key focus of coastal conservation [5]. In India, mangroves account for 4992 km^2 of forest cover, which is approximately 0.15% of the country’s total land area, with significant concentrations in the Sundarbans, Gujarat, and Andaman and Nicobar Islands [6].

Advances in Synthetic Aperture Radar (SAR) remote sensing, have revolutionized the estimation of Above Ground Biomass (AGB) for mangrove forests, due to its ability to capture structural and volumetric properties of vegetation, even in cloudy or challenging weather conditions [7]. Longer wavelength SAR signals, such as L-band and P-band, are particularly suited for tropical regions with high biomass concentrations, as they can penetrate deep into the vegetation canopy, overcoming the saturation limitations of shorter wavelengths SAR and optical data. Remote sensing-based biomass assessment relies on correlation of field-measured biomass data with satellite imagery to develop predictive models for biomass estimation. This approach is widely used in mangrove mapping and has proven to be both cost-effective and scalable. The ‘Combined Mangrove Recognition Index (CMRI)’ uses outputs from the NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index) indices to analyze mangrove vegetation using information such as greenness and water content [8]. The Mangrove Vegetation Index (MVI) is a new simplified mangrove index that uses Sentinel-2’s NIR, SWIR1, and green bands for speedy and accurate mapping of mangroves without the need for sophisticated categorization algorithms [5].

The present study focuses on the mangrove ecosystems of the Gulf of Khambhat (GOK), Gujarat, an area that underscores the ecological and protective value of mangroves. This region has witnessed significant environmental changes due to natural processes and human activities, making it a vital site for research and conservation efforts. The study integrates remote sensing datasets from Sentinel-2 MSI optical image and ALOS PALSAR-2 L-band SAR data with 10 and 25-meter resolution respectively. The combination of optical and microwave datasets enables the delineation of mangrove and non-mangrove areas, change detection more effectively. The first objective of the study is to delineate mangrove from other land features using Sentinel-2 MSI data and the second objective of the study is the estimation of Above Ground Biomass (AGB) using ALOS PALSAR-2-L band data with field measurements in the study area. Results of both the objectives are used to estimate area of mangroves in GOK.

2. Materials and methods

2.1. Study area

The study area is located in Gujarat State on India's west coast. The Gulf of Khambhat, also known as the Gulf of Cambay, is a bay on the Arabian Sea coast of India. The Gulf of Khambhat is about 200 km (120 mi) long, about 20 km (12 mi) wide in the north and up to 70 km (43 mi) wide in the south. Ghogha (21°40′ N, 72°17′ E), Dahej (21°71° N, 72°52° E), and Kantiyajal (21°30′ N, 72°39′ E) are chosen based on the abundance of mangroves for the field measurements in the Gulf of Khambhat's intertidal region for this research work.

The **Figure 1** illustrates the True color Google image of Gulf of Khambhat taken from Google image. The image provides the information about the study area in the white colored rectangular. The three ground truth locations Ghogha (Bhavnagar), Dahej (Bharuch) and Kantiyajal (Bharuch), are highlighted in yellow square dots in **Figure 1**.

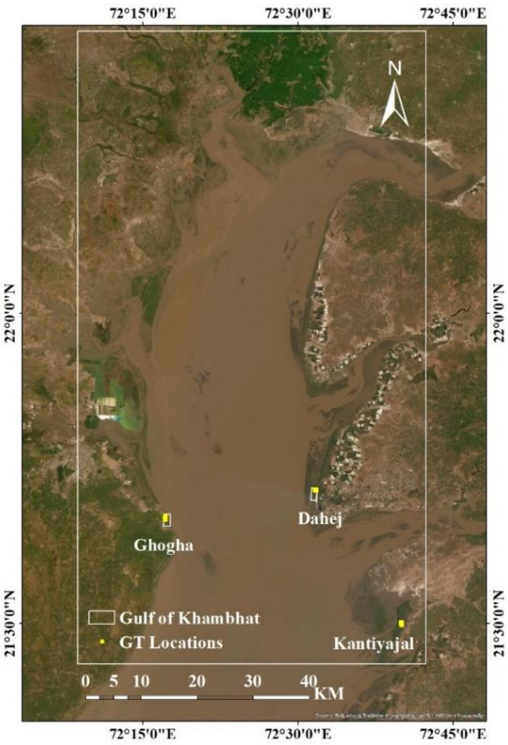


Figure 1. Study area with GT locations in GOK.

2.2. Datasets used

The L-band ALOS PALSAR-2 provides the yearly mosaic backscatter in 25m resolution, with polarizations HH and HV. NASA ORNL DAAC has released the Global AGB in 2020 [7] which is processed with Annual (Jan-Dec 2010) data harmonization, % tree cover and land use land cover at 300m resolution. Year 2020 mosaicked backscatter and NASA Global AGB are used in this study for AGB estimation along with GT.

The optical data from Sentinel-2 Multi-Spectral Instrument (MSI) with a resampled spatial resolution of 10m is used in this study for mangrove delineation. The 13 band data is acquired for different resolutions, 4 bands at 10m, 6 bands at 20m and 3 bands at 60m in Visible, Near Infra-Red (NIR) and Short Wave Infra-Red (SWIR) spectrum.

The **Table 1** depicts the details with sensor frequency, incident angle, date of data acquisition and resolution.

Table 1. Data products with sensors used, its parameters and date of acquisition.

S. No.	Data Products	Sensor/ Frequency Band	Date of Acquisition	Incidence Angle	Resolution (m)
1	25m global mosaic product-HH+HV (Fine Beam Dual-pol)	ALOSPALSAR-2/L-band	2020 Yearly mosaic	38.382 (near range) & 42.561 (far range)	25
2	NASA-Global-AGB https://doi.org/10.3334/ORNLDAAC/1763		2010-01-01 to 2010-12-31		300
3	Multispectral Sentinel-2-MSI-13 bands	Visible, NIR & SWIR	2020-05-07	Zenith angle: 2.559° to 3.30° Azimuth angle: 152.89° to 159.11°	10
4	Field Data with No. of GT points = 30		2024-02-11 to 2024-02-14		10m × 10m grid
5	India State of Forest Report		2021		

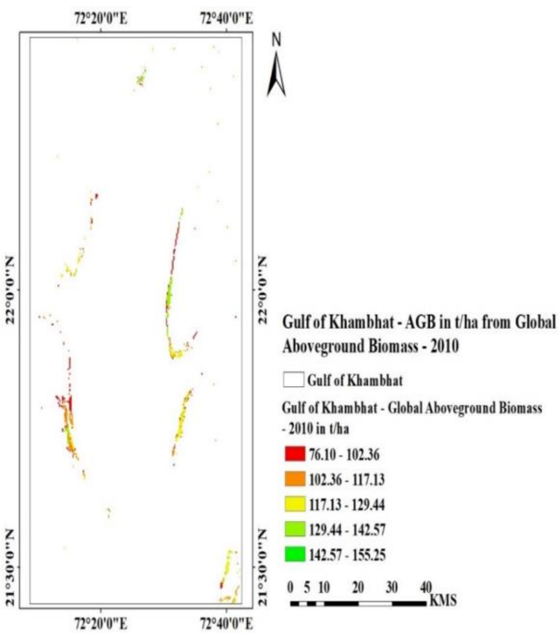
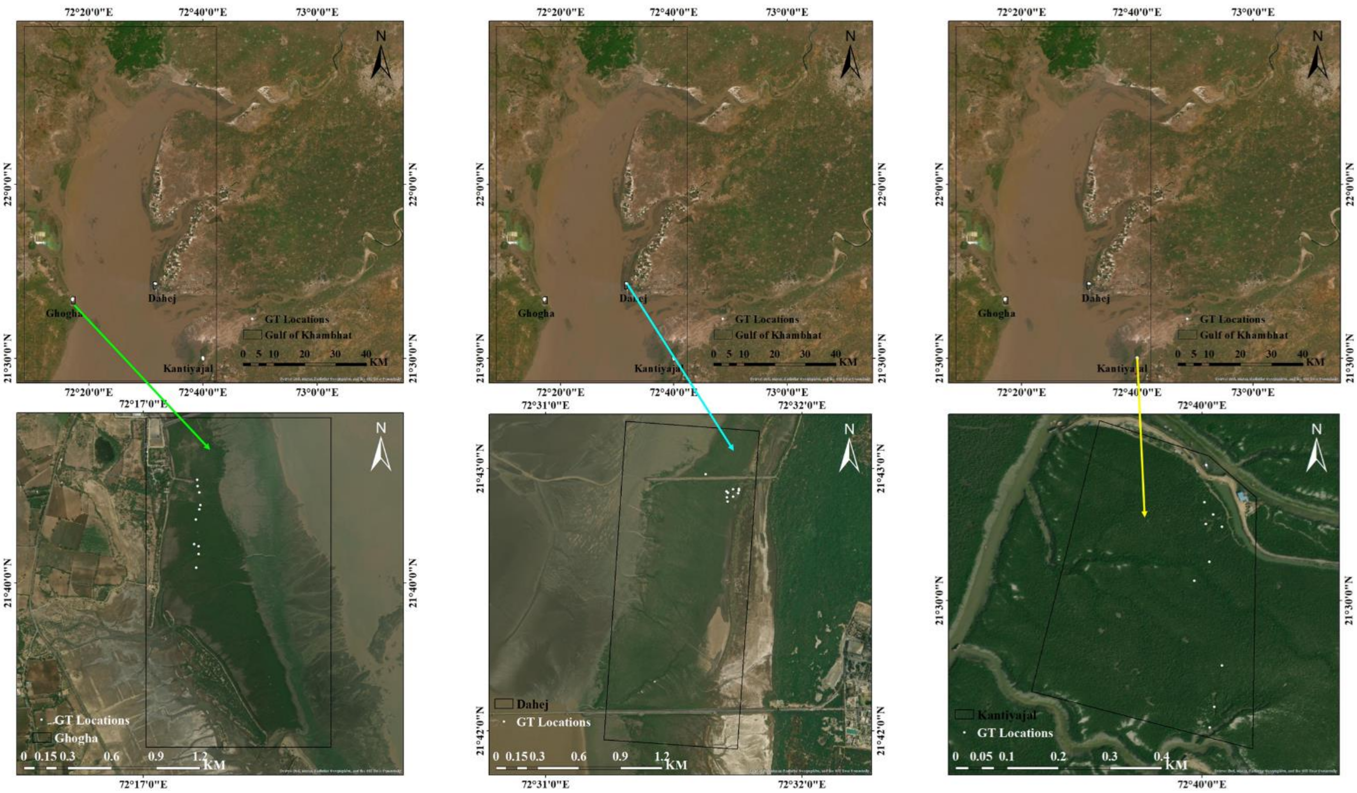


Figure 2. NASA Global AGB for Gulf of Khambhat.

The **Figure 2** illustrates the spatial distribution of NASA Global AGB across the mangrove ecosystems in the study area, with a color-coded scheme for AGB values, measured in tons per hectare (t/ha). Red areas (76.10–102.36 t/ha) indicate regions with the lowest AGB, potentially signifying sparse or degraded mangrove patches. While, dark green areas (142.57–155.25 t/ha) represent regions with the highest biomass, highlighting dense and well-preserved mangrove stands. Intermediate colours orange, yellow, and light green denote varying levels of AGB, reflecting differences in vegetation structure, health and coverage within GOK. This map serves as an invaluable resource for understanding the ecological characteristics of the Gulf of Khambhat's mangroves, which are critical for coastal protection, carbon sequestration, and biodiversity conservation. The scale and resolution of the map allow researchers and policymakers to identify high-biomass areas that serve as significant carbon sinks, as well as low-biomass regions that may require restoration efforts. The data also highlights the spatial variability in mangrove health and density, providing insights into natural and anthropogenic factors influencing these ecosystems. The Ground Truth (GT) data collected at three primary locations—Ghogha in Bhavnagar and Dahej and Kantiyajal in Bharuch for the rich mangrove presence and logistical feasibility to approach. GT was collected for four days, from 11th February to 14th February 2020.



(a) Ghogha, Bhavnagar **(b)** Dahej, Bharuch **(c)** Kantiyajal, Bharuch

Figure 3. Gulf of Khambhat GT Locations: **(a)** Ghogha, Bhavnagar; **(b)** Dahej, Bharuch; **(c)** Kantiyajal, Bharuch.

The fieldwork was meticulously planned to ensure comprehensive spatial and ecological representation of the region and was carried out from selected sampling sites during low tide. Line Transect Plot Method and Sample Plot is used for measurements of mangrove vegetation condition. Following steps were followed for data sampling with Line Transect Plot:

- In each observation zone line transects were put from the coastal waters toward the land which are rectangular to the coastal line along the mangrove forest zonation in the intertidal.
- In each mangrove zone along the transect line, the rectangular sample plots were randomly placed.
- A 10 × 10 m transect was used to count the number of trees having a diameter greater than 10 cm.
- Mangrove species are determined, the total number of individuals is counted by species, tree height and stem circle are measured using Diameter at Breast Height (DBH) method for each sample plot.

Figure 3 provides a visual depiction of the chosen sampling sites. The dominant vegetation in this mangrove-dense region is Avicennia marina, known for its ecological significance and adaptability to saline environments. Another species, Rhizophora Mucronata, was also identified, although it was in lesser abundant compared to the dominant species. Field measurements focused on key structural attributes such as tree height (h) and diameter at breast height (dbh), which are critical for assessing mangrove health and biomass.

2.3. Methodology

The methodology employed in this study integrates field measurements, microwave SAR and multi-band optical satellite data preprocessing and Support Vector Machine (SVM) classification technique to estimate the mangrove area and Above Ground Biomass (AGB) in the Gulf of Khambhat as illustrated in the flow diagram in **Figure 4**.

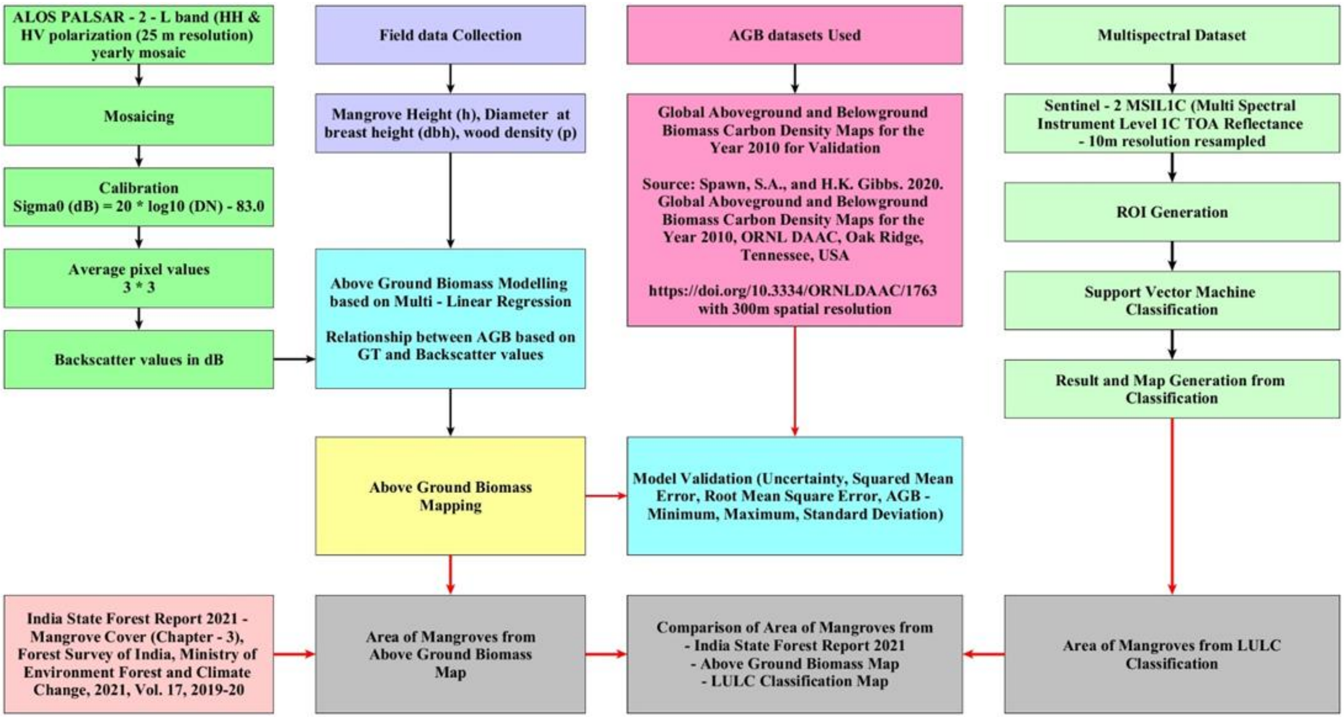


Figure 4. Methodology flow chart.

Multispectral Sentinel-2 MSI Level 1C Top-of-Atmosphere Reflectance data, is used for land-use/land-cover (LULC) classification [9]. Regions of Interest (ROI) are generated for various land-use classes to guide the SVM process. The SVM is a robust supervised machine learning algorithm that excels in handling complex and noisy datasets. SVM is based on statistical learning theory and is particularly effective in delineating classes with clear boundaries by constructing a decision surface, or hyperplane, that maximizes the separation between data classes. The support vectors, which are the data points nearest to the hyperplane, play a critical role in defining this boundary and are key elements of the training dataset. These vectors ensure that the classification process is resilient, accurate and capable of generalizing well across the entire dataset.

The classification of multi-spectral image was carried out across six distinct land-cover categories: built-up areas, mudflats, ocean, vegetation (other than mangroves), mangroves, and unclassified regions. The multispectral data, with high spatial detail, enabled precise differentiation of mangroves from other vegetation and land-cover types. Regions of Interest (ROIs) were carefully selected for each category to train the SVM model effectively. The algorithm then classified each pixel into the most probable category based on spectral signatures and spatial characteristics. Mangroves were accurately delineated as a separate class, benefiting from the distinctive spectral reflectance properties of mangrove vegetation.

ALOS PALSAR-2/L-band SAR yearly mosaic data with HH and HV polarizations, is Radiometric calibrated by converting the DN (digital number) values to backscatter values (σ°) in decibels (dB), using the equation-1 and 3×3 averaging to reduce noise [10].

$$\sigma^{\circ}(\mathrm{dB}) = 20 \times \log_{10}(\mathrm{DN}) - 83.0 \tag{1}$$

Field-based observations of essential parameters (h, dbh and *p*) for mangrove biomass modeling are used for development of allometry. This data forms the basis for establishing the relationship between GT biomass and SAR backscatter values. A multi-linear regression model is developed to estimate AGB based on the relationship between SAR backscatter values (HH and HV polarizations) and field-measured biomass data. The regression model utilizes mangrove height, dbh, and wood density as input parameters. The developed AGB model is validated against the Global AGB-2010 [11]. AGB Model is validated with Global AGB-2010 and its accuracy is assessed using statistical metrics, including:

- Uncertainty: To measure the variability in predictions [4].
- Root Mean Squared Error (RMSE): To assess the accuracy of the AGB model [4].
- Statistical Measures of AGB: Minimum, maximum, and standard deviation of estimated biomass values.
- These metrics provide a quantitative assessment of the model's reliability and highlight areas for improvement.

The Mangrove Area is estimated using AGB Map (derived from the AGB modeling process using SAR data) and LULC Classification Map (generated from the SVM classification of optical data). The estimated Mangrove area from the AGB map and LULC classification map is compared with area reported in the India State Forest

Report 2021 (Forest Survey of India) [6]. This comparison ensures cross—validation of results and identifies potential discrepancies between methodologies.

Thus, integrated methodology approach combines SAR and optical data, field measurements, and advanced classification methods to provide a comprehensive analysis of mangrove ecosystems in the Gulf of Khambhat, facilitating informed conservation and management decisions.

3. Results and discussion

The outcome of the integrated methodology is discussed in this section. The spatial distribution of mangroves and AGB estimation are given in details with accuracy and sensitivity analysis of developed AGB models.

3.1. Spatial distribution of mangrove in the gulf of Khambhat

The LULC Classes identified from the SVM classification are Mangroves, Barren Land, Vegetation, Seawater, Built-up, and Unclassified are shown in **Figure 5**. The classification successfully distinguished mangroves from other land-cover types, leveraging the spectral resolution of Sentinel-2 data and the robustness of the SVM model. The mangrove area identified through this classification was 98.55 km^2, which aligns closely with the mangrove area reported in the India State of Forest Report (ISFR) 2021, which is 101.53 km^2. This indicates a high accuracy of 97.06% for mangrove area estimation using Sentinel-2 MSI data, demonstrating the reliability of optical remote sensing for such analyses.

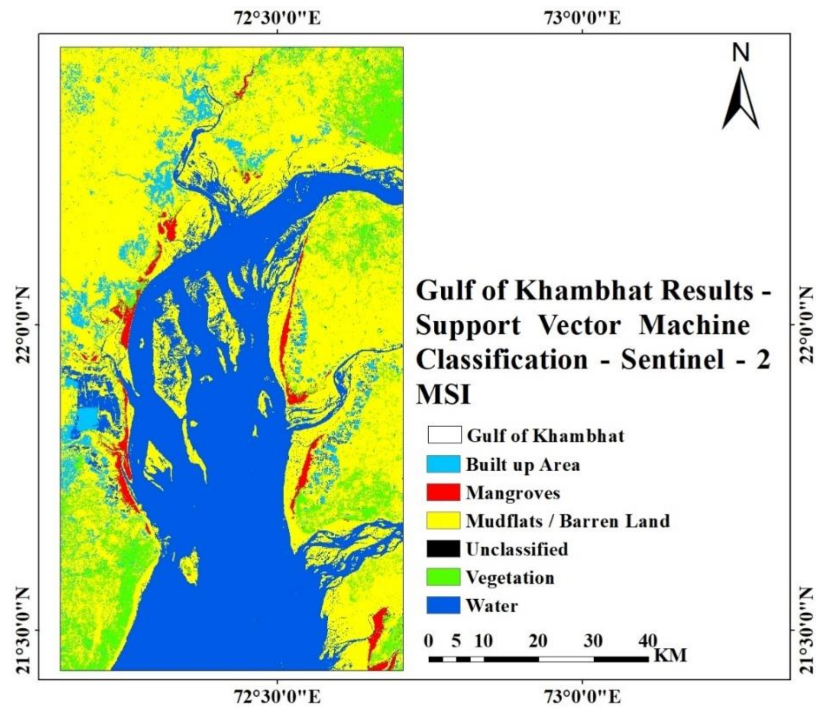


Figure 5. SVM Classification map from Sentinel-2 MSI.

The overall accuracy of the SVM classification is 83.285%, which reflects the classifier's ability to classify six distinct land-cover categories, including built-up areas, mudflats, ocean, other vegetation, mangroves, and unidentified regions.

Additionally, the Kappa Coefficient, a statistical measure of classification consistency, is 0.7891, indicates substantial agreement between the classified map and the reference data. These results highlight the robustness of the SVM classifier in handling multi-class classification tasks in a complex coastal environment. The **Figure 6** illustrates the Training Samples taken for carrying out the SVM Classification in study area.

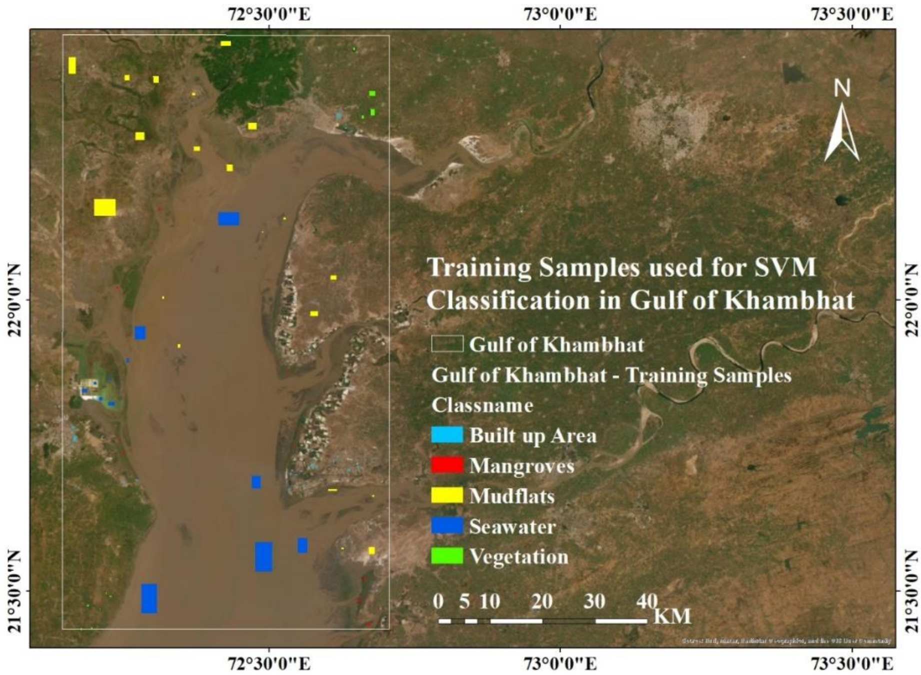


Figure 6. Training samples in GOK for SVM classification.

When comparing mangrove area estimates, the SVM-derived results showed a slight underestimation of 2.93 km^2 compared to the ISFR 2021 report [6]. However, this small difference underscores the accuracy of the classification process, as optical data inherently captures fine spatial details. The close agreement between the SVM classification and ISFR values reaffirms the methodology's credibility. The overall classification accuracy and Kappa Coefficient further validate the model's effectiveness in distinguishing mangroves from other land-cover types, contributing significantly to resource mapping and ecosystem monitoring efforts in the GOK.

The SVM kernel parameters are listed in **Table 2**, directly influence the SVM's ability to delineate complex ecosystems by balancing the trade-offs between classification accuracy and computational efficiency. The Confusion Matrix for the results obtained from the SVM Classification for the GOK is given in **Table 3**.

Table 2. Parameters used for SVM classification for Gulf of Khambhat.

S. No.	Parameters	Values
1	Kernel Type	Radial Basis Function
2	Gamma in Kernel Function	0.333
3	Penalty Parameter	100.000
4	Pyramid Levels	0
5	Classification Probability Threshold	0.00

Table 3. Confusion matrix for SVM classification for Gulf of Khambhat.

Ground Truth (Pixels)							
Class	Unclassified	Mangroves	Barren Land/Mudflats	Vegetation	Sea Water	Built-up	Total
Unclassified	0	0	0	0	0	0	0
Mangroves	0	14,216	0	703	2	0	14,921
Barren Land /Mudflats	0	1	18,416	2772	915	4770	26,874
Vegetation	0	936	56	15,277	28	284	16,581
Sea Water	0	0	436	627	15,922	160	17,145
Built-up	0	0	3036	36	0	9727	12,799
Total	0	15,153	21,944	19,415	16,867	14,941	88,320

The results for mangrove classification are particularly encouraging for GOK. The overall accuracy of 83.29% and Kappa coefficient of 0.7891 for GOK indicate that 83.29% of the classified pixels matched the ROIs, highlighting the robustness of the classification model.

The producers' accuracy for mangroves is obtained as 93.82%, indicates that nearly all actual mangrove pixels were correctly classified by the model. Similarly, the users' accuracy for mangroves is 95.28%, suggests that the majority of pixels classified as mangroves in the SVM output were indeed mangroves on the ground. These high accuracy values for mangroves underscore the effectiveness of the SVM classification in accurately identifying and delineating mangrove ecosystems within the study area. However, there is room for improvement in reducing misclassification errors, which would further enhance the model's reliability for mangrove mapping.

The high overall accuracy and significant agreement (Kappa coefficient) affirm the effectiveness of the integrated methodology, SVM classification of Sentinel-2 MSI data, for land-use and land - cover mapping in the Gulf of Khambhat. The exceptional performance for mangrove classification, as demonstrated by the producers' and users' accuracy, highlights the potential of this approach for supporting mangrove conservation and management efforts. The accurate delineation of mangrove areas contributes to reliable AGB estimation and aids in evaluating mangrove ecosystem services, critical for coastal protection and biodiversity conservation.

3.2. Mangrove biomass estimation in the Gulf of Khambhat

Multi-linear regressions are used to estimate the mangrove forest AGB using backscatter data from ALOS PALSAR-2-L band (HH and HV polarization) and GT allometry for the Gulf of Khambhat. The results obtained from Backscatter based datasets for GOK is depicted in the **Table 4**.

Table 4. Statistical analysis of AGB model for Gulf of Khambhat.

Gulf of Khambhat AGB model Results	**NASA Global AGB data—Spawn SA [11]**	**Developed AGB Model from GT Parameters**	**Developed AGB Model—Backscatter & GT allometry**
	Global AGB-2010 (t/ha)	**AGB (t/ha) = −150.6922 + 5.5782 * h + 1862.6525 * dbh**	**AGB (t/ha) = 180.99 + 6.28 * HH − 0.79 * HV**
Minimum	51.00	35.50	76.10
Maximum	214.00	193.00	155.25
Difference = Max−Min	163.00	157.50	79.15
Standard Deviation	33.94	31.11	14.21
Squared Mean Error	6.09	5.58	5.45
RMSE	87.90	13.33	29.86
Uncertainty (u)	6.20	5.68	2.59
R^2	1.00	0.728	0.42

The R^2 value of the developed AGB model is low as limited ground truthing was carried out during the COVID-19 pandemic. The more Ground Truth measurements will lead to further improvement in the developed model. The Global AGB 2010 has not used sufficient GT points over India and global AGB model inaccuracy is also affecting the accuracy of developed AGB model. In future, with the launch of Biomass mission more accurate AGB will be available. The **Figure 7** presents a comparison of Above-Ground Biomass (AGB) values across 30 Ground Truth (GT) locations, expressed in tons per hectare (t/ha). It shows the estimated AGB from GT allometry and the estimated AGB from SAR backscatter along with NASA Global AGB.

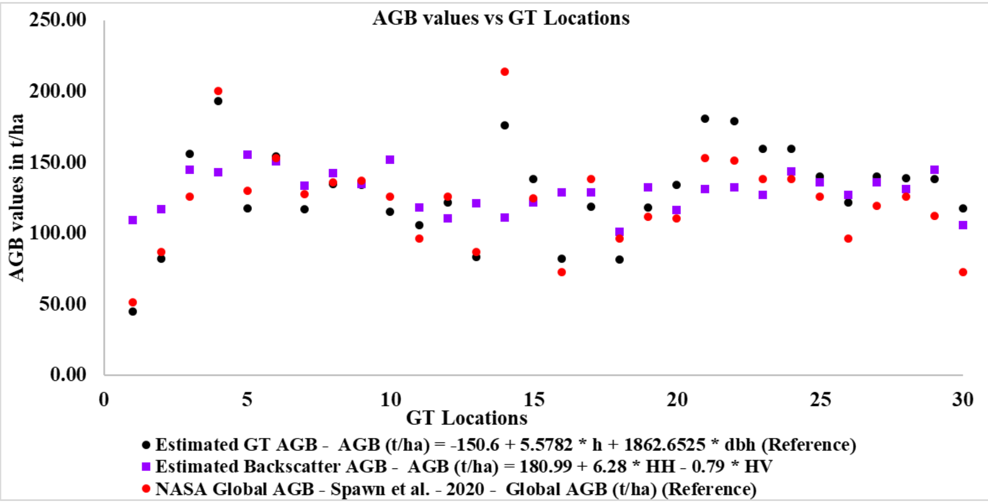


Figure 7. Comparison of AGB from developed model and global AGB data.

The **Figure 8** illustrates the estimated Above ground biomass (AGB) map of mangroves in the GOK. The sparse mangroves are represented in the red color with AGB values ranging from 76.10 t/ha to 102.36 t/ha. The dense mangroves are represented in the green color with AGB values varying between 142.57 t/ha to 155.25 t/ha. **Figure 8** has more variability as compared to **Figure 2** as NASA Global AGB is not considered adequate GT points over India. The area of the mangroves obtained from the AGB map is 94.94 km^2. The area of Mangroves found from the India State

Forest of Forest Report, 2021 is 101.53 km^2. The accuracy of the area of mangroves obtained from microwave remote sensing (L-band SAR) is 93.50 %.

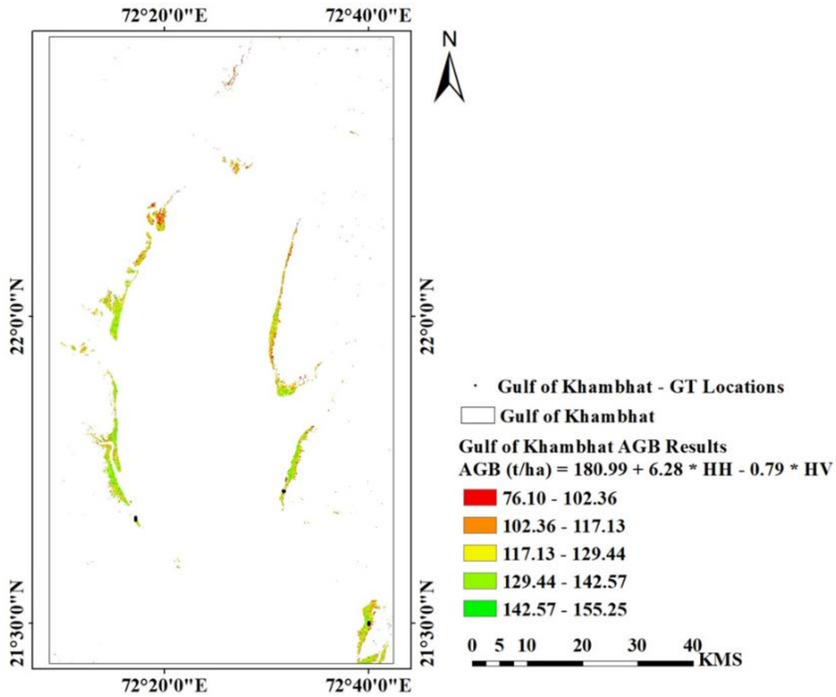


Figure 8. AGB map of Gulf of Khambhat using from developed backscatter AGB model.

Sensitivity analysis of the developed model equation

The georeferenced site allows for contextual understanding of the analysis and validation of the model against real-world conditions. The ground truth carried out for this site, forming the basis for the analysis. Sensitivity analysis is a quantitative technique used to understand how variations in input parameters of a model affect its output. It evaluates the robustness of a model by identifying the degree of influence that each input variable or parameter has on the results. In the context of remote sensing models, sensitivity analysis can highlight the importance of different physical or empirical parameters (e.g., radar backscatter coefficients or calibration constants) in estimating key environmental metrics, such as Above Ground Biomass (AGB). By systematically varying parameters and observing changes in outputs, it is possible to identify the most critical variables to optimize the model for specific conditions. The location of mangrove area on Google Earth is taken for the sensitivity analysis is shown in **Figure 9** as red color triangle. The HH and HV values are extracted from the ALOS PALSAR-2 (L band) images. The **Figure 9** illustrates the Sensitivity Analysis of the Developed model to examines AGB variations with the radar polarizations and constant parameters around the georeferenced point location.

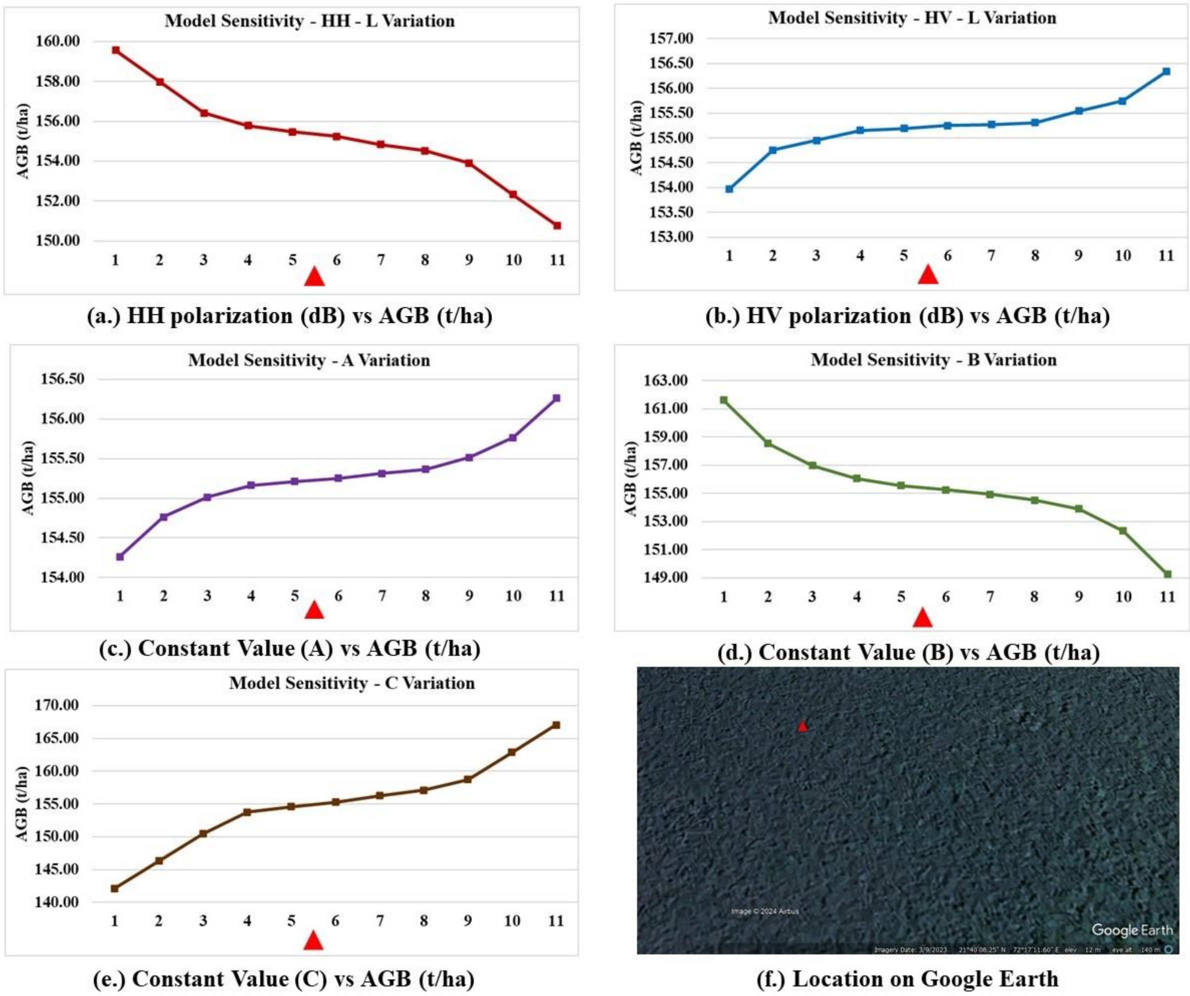


Figure 9. Sensitivity analysis of the developed backscatter AGB model. **(a)** AGB variation with change in HH; **(b)** AGB variation with change in HV; **(c)** AGB variation with change in A; **(d)** AGB variation with change in B; **(e)** AGB variation with change in C; **(f)** Location at which sensitivity analysis is carried out is shown in red color;

(a) HH Polarization (dB) vs. AGB (t/ha)

The HH polarization represents the radar backscatter for horizontally transmitted and received signals, which is strongly influenced by surface structure and vegetation canopy properties. The graph shows that AGB decreases steadily as HH polarization increases. This behaviour is somewhat counterintuitive given the positive coefficient (+6.28) for HH in the model equation, which suggests that higher HH values should increase AGB.

This discrepancy indicates that while HH contributes positively to biomass estimation, there is a saturation point where the relationship diminishes, particularly in dense vegetation where backscatter is less sensitive to biomass variation. This highlights the model’s dependency on HH polarization and its limitations under specific conditions, such as dense forests where structural scattering dominates.

(b) HV Polarization (dB) vs. AGB (t/ha)

HV polarization captures radar backscatter for horizontally transmitted and vertically received signals. It is sensitive to vegetation volume scattering and is an important indicator of biomass. The graph reveals that AGB increases with rising HV values, which seems to contrast the negative coefficient (–0.79) for HV in the equation.

This trend may occur due to interactions between HH and HV polarizations in the modelled environment, particularly where vegetation properties or environmental factors influence both scattering types. The model shows relatively weak sensitivity to HV, as the overall change in AGB across the HV range is smaller compared to HH.

(c) Constant Value (*A*) vs. AGB (t/ha)

The constant "*A*" in the model represents an offset or calibration term. The graph shows that AGB increases linearly with increasing values of *A*, but the slope of the increase is relatively small. This suggests that the impact of *A* is incremental and serves primarily to adjust the baseline AGB estimates.

The linearity of this relationship indicates that constant *A* does not introduce significant variability or nonlinear effects into the model. Instead, it acts as a straightforward tuning parameter to align the model with observed data. Its limited sensitivity highlights that the model relies more heavily on HH and HV polarizations for predictive accuracy.

(d) Constant Value (*B*) vs. AGB (t/ha)

The constant "*B*" shows a negative linear relationship with AGB. As *B* increases, AGB decreases steadily, with a relatively larger sensitivity compared to constant *A*. This suggests that *B* plays a more significant role in counteracting overestimation or correcting the model for specific environmental conditions.

The strong negative sensitivity to *B* highlights its importance in balancing the contributions of HH and HV polarizations. In practical terms, constant B could reflect an environmental adjustment factor, such as soil moisture or vegetation density, that reduces the overall AGB estimate in the presence of certain conditions.

(e) Constant Value (*C*) vs. AGB (t/ha)

The constant "*C*" exhibits a positive linear relationship with AGB, with a relatively steep slope compared to *A*. As *C* increases, AGB rises steadily, indicating a stronger influence on biomass estimation. This highlights that constant *C* is a significant positive contributor to the model, potentially serving as a scaling factor for calibrating the overall biomass estimates. The linearity and magnitude of the relationship suggest that *C* could represent an environmental or structural parameter that enhances AGB predictions under specific scenarios, such as regions with high vegetation density or specific canopy characteristics.

The sensitivity analysis of the developed model equation reveals distinct roles and impacts of the input parameters. The radar polarizations (HH and HV) exhibit non-linear sensitivity to AGB, with HH showing a stronger overall influence but diminishing returns at higher values. HV's sensitivity, though weaker, reflects the influence of volume scattering in vegetation canopies. The constants *A*, *B*, and *C* provide important calibration functions, with B exerting a negative influence and *C* contributing positively. This analysis emphasizes the importance of understanding parameter interactions and environmental conditions in refining biomass estimation models.

The graph in **Figure 10** compares Global AGB, Developed Ground Truth (GT) AGB, and Developed Backscatter AGB Model predictions. This analysis evaluates how closely the estimated AGB values and allometry align with the reference Global AGB. The degree of correlation between Global AGB and Developed GT AGB is 0.728, indicating a strong positive relationship. The black dots in the graph show that the GT AGB estimates align closely with Global AGB values for a wide range of biomass (approximately 80–160 t/ha). However, deviations are noticeable at both lower (< 80 t/ha) and higher (> 160 t/ha) biomass levels.

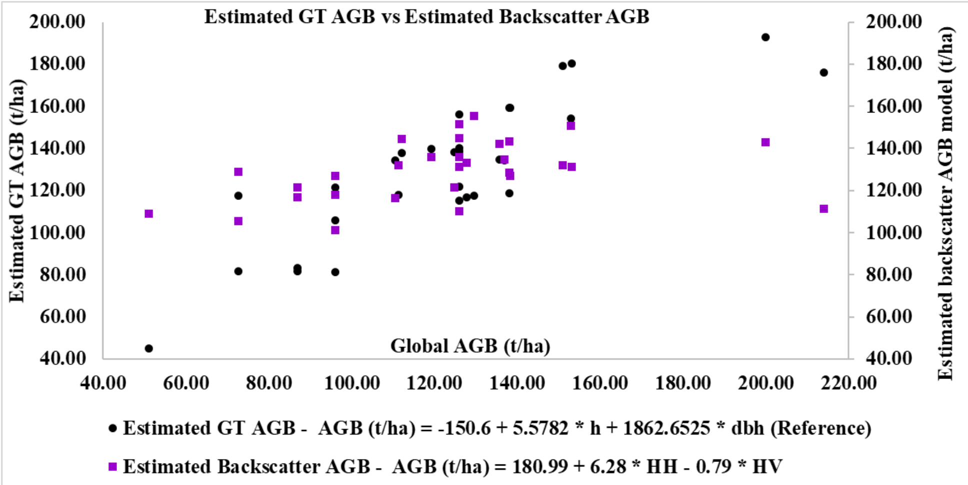


Figure 10. Comparison of global AGB with developed GT AGB and backscatter AGB.

The degree of correlation between the Developed GT AGB and the Developed Backscatter AGB Model is 0.42, suggesting a moderate relationship. Backscatter AGB aligns relatively well with GT AGB values, indicating that the backscatter model performs reliably within 80–140 t/ha range. The Backscatter AGB model is underestimating biomass above 140 t/ha. This is likely due to saturation effects in L-band SAR signals, where the backscatter response becomes less sensitive to increases in biomass density.

GT AGB Model shows lower uncertainty in the mid-range biomass levels, making it a robust reference for validating remote sensing models. However, uncertainty increases at the extremes of biomass, reflecting challenges in field data collection and extrapolation. It higher confidence in mid-range biomass predictions, making it a suitable validation dataset.

Backscatter AGB Model demonstrates consistent performance for low to medium biomass levels but exhibits higher uncertainty at high biomass densities due to saturation effects and structural complexity in mangrove forests. The backscatter model, while consistent in low-to-mid biomass ranges, requires improvements, such as integrating multi-frequency SAR data (e.g., P-band) or advanced calibration techniques, to reduce uncertainty in high biomass regions.

4. Conclusion

The estimation of mangrove area in the Gulf of Khambhat using satellite remote sensing data revealed insightful findings. Based on the Above Ground Biomass (AGB) map generated from ALOS PALSAR-2 L-band SAR data, the mangrove area was estimated to be 94.94 km^2. This estimation is validated against the official mangrove area reported in the India State of Forest Report (ISFR) 2021 [6], which recorded the mangrove extent as 101.53 km^2. The AGB map's accuracy is 93.50% also determined using ground truth. It demonstrates the reliability of the microwave (SAR) data for mangrove delineation. Additionally, the Support Vector Machine (SVM) classification of Sentinel-2 MSI optical data provided a mangrove area estimate of 98.55 km^2, with an impressive accuracy of 97.06%, highlights the precision of optical remote sensing in distinguishing mangroves from other land-cover types.

GT AGB Model shows lower uncertainty in the mid-range biomass levels, making it a robust reference for validating remote sensing models. However, uncertainty increases at the extremes of biomass, reflecting challenges in field data collection and extrapolation. It higher confidence in mid-range biomass predictions, making it a suitable validation dataset. Backscatter AGB Model demonstrates consistent performance for low to medium biomass levels but exhibits higher uncertainty at high biomass densities due to saturation effects and structural complexity in mangrove forests. It requires improvements to reduce underestimation for dense vegetation areas. The backscatter model, while consistent in low-to-mid biomass ranges, requires improvements, such as integrating multi-frequency SAR data (e.g., P-band) or advanced calibration techniques, to reduce uncertainty in high biomass regions.

The integration of optical and microwave remote sensing technologies, coupled with ground-truth data, underscores the significance of using complementary datasets for mangrove mapping. The study not only demonstrates the potential of microwave SAR data for biomass mapping but also showcases the utility of multispectral optical data for enhancing classification accuracy. These results are pivotal for monitoring both mangrove loss due to anthropogenic activities or natural disturbances and their recovery over time. By providing accurate and spatially detailed data on mangrove distribution and biomass, this research offers valuable insights into natural resource conservation. The findings emphasize the importance of mangroves as biodiversity hotspots and carbon sinks, and the methodologies presented enable targeted conservation strategies, ensuring the long-term sustainability of these vital ecosystems. This comprehensive approach sets a benchmark for ecosystem monitoring and resource management in coastal regions.

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Data availability: The open-source datasets from the Sentinel-2 MSI sensor of the European Space Agency (ESA) are used in this study for doing the Classification Studies in the project area. Similarly, for the Above ground Biomass Studies the SAR datasets are taken from the "Global PALSAR-2/PALSAR/JERS-1 Mosaic and

Forest/Non-Forest Map” provided by the Earth Observation Research Center, ALOS-Gr, Japan Aerospace Exploration Agency (JAXA).

Conflict of interest: The authors declare that they have no conflict of interest.

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