

Article

Quantifying Mangrove Extent Using a Combination of Optical and Radar Images in a Wetland Complex, Western Region, Ghana

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Abstract: The classification of mangrove forests in tropical coastal zones, based only on passive remote sensing methods, is hampered by mangrove complexities, topographical considerations, and cloud cover effects, among others. This paper reports on a study that combines optical and radar data to address the challenges of distinguishing mangrove stands in cloud-prone regions. The Google Earth Engine geospatial processing platform was used to extract multiple scenes of Landsat surface reflectance Tier 1 and synthetic aperture radar (C-band and L-band). The images were enhanced by creating a feature that removes clouds from the optical data and using speckle filters to remove noise from the radar data. The random forest algorithm proved to be a robust and accurate machine learning approach for mangrove classification and assessment. Classification was evaluated using three scenarios: classification of optical data only, classification of radar data only, and combination of optical and radar data. Our results revealed that the scenario that combines optical and radar data performed better. Further analysis showed that about 16.9% and 21% of mangrove and other vegetation/wetland cover were lost between 2009 and 2019. Whereas water body and bare land/built-up areas increased by 7% and 45%, respectively. Accuracy was evaluated based on the three scenarios. The overall accuracy of the 2019 classification was 98.9% (kappa coefficient = 0.979), 84.6% (kappa coefficient = 0.718), and 99.1% (kappa coefficient = 0.984), for classification of optical data only, classification of radar data only, and combination of optical and radar data, respectively. This study has revealed the potential to map mangroves correctly, enabling on-site conservation practices in the climate change environment.

Keywords: algorithm; decision trees; cloud cover; NDVI; radar; tropical coastal zone



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1. Introduction

Mangroves grow and thrive in an environment that acts as a buffer zone for terrestrial and marine ecosystems. They are globally important ecosystems restricted to coastal areas where mean monthly air temperatures are above 20 °C and where there is, with rare exceptions, no ground ice formation [1,2]. These ecosystems are composed of trees and shrubs found in flat, sandy, or muddy areas adapted to estuarine or saline environments [2,3]. They are truly unique because they are the only trees that can tolerate large amounts of salt and water. This ability, as well as surviving in oxygen-poor soils, is a result of root adaptations. Mangrove forests occupy an insignificant fraction of land area (<1%) but are considered to be the most carbon-rich ecosystems in the tropics [2]. Mangrove ecosystems have recently been included in the IPCC climate protection strategy through a series of amendments to wetlands [4].

In Africa, mangrove forests occupy roughly 2,746,500 ha in 2010 [5] and support vulnerable coastal populations by providing important ecosystem services such as natural

marine protection, coastal erosion mitigation, water quality improvement, and alternative livelihoods [6–9]. Fatoyinbo and Simard [10] reported that mangroves cover about 7600 ha along the coast of Ghana and seven major mangrove species have been confirmed, including *Laguncularia racemosa* (white mangrove), *Avicennia germinans* (black mangrove), *Rhizophora harrisonii* (red mangrove), *Rhizophora racemosa* (red mangrove), *Rhizophora mangle* (red mangrove), *Acrostichum aureum* (golden leatherback), and *Cornocarpus erectus* (bottom mangrove) [11,12].

Although these ecosystems provide many valuable services, they have experienced significant degradation, are threatened, or lost [13,14]. The rate of loss over the past two decades has been estimated to be twice the rate of terrestrial rainforest loss over the same period [15]. It is also estimated that about two-thirds of mangrove forests have been lost in the past century, representing 1–8% mangrove loss per annum and at least 20–50% global land area decline (more than 3.6 million ha) in the last 4–5 decades [16–18]. The main cause of mangrove loss has been deforestation for land conversion, primarily for aquaculture, establishment of salt pans, and other agricultural intensification.

Quantification of changes for mangrove ecosystems is crucial for an improved understanding of many coastal and sea processes. Conventional mapping of mangrove forests involve huge capital for field work due to the difficulties associated with accessibility within the mangrove ecosystem [19]. Space-based technology, such as remote sensing, has a huge capacity to map and monitor changes in mangrove forests owing to the fact that data can be captured from a landscape which is otherwise difficult to access [20]. Several authors recommend the combination of synthetic aperture radar with optical satellite data for more accurate quantification of mangrove extent [21–23]. There are added advantages to utilizing the unique features of both optical and radar data to improve upon landcover classification. Using both datasets can provide more detailed characterization of landcover changes. This can be useful for agriculture, forest disturbances, and land degradation. Additionally, vegetation health indices such as NDVI can be used in conjunction with plant structure and volume data available from the radar.

The Google Earth Engine (GEE) provides a straightforward but robust mangrove assessment and monitoring framework with a high level of automation that can be easily implemented for frequent and accurate mapping at local, regional, or global scales [24,25]. GEE has a variety of ready-to-use non-parametric classifiers including but not limited to: classification and regression trees (CART), random forest (RF), naïve Bayes, and support vector machine (SVM) which are recommended for the classification of multi-source data in complex environments [2,21,26,27]. The random forest (RF) algorithm has the advantage of using a series of decision trees to select the best classification for all pixels within the imagery to reduce the risk of overfitting, training time, sensitivity to outliers in training data, and runs efficiently for a large dataset [2]. Accordingly, RF-supervised classification is reported to have the highest accuracy among the widely used machine learning algorithms [2,26,28].

There have been several studies on the mangrove extent across Africa [7,10,29–36], with most of them largely concentrating on few countries such as Gambia, Guinea-Bissau, Guinea, Mauritania, Mozambique, Madagascar, Nigeria, Senegal, Sierra Leone, South Africa, and Tanzania. However, a good number of the studies are global in nature but lack spatially explicit resolution suitable for locally tracking progress in the sustainable development goals (SDGs) adopted by the United Nations (2030 agenda) and the African Union (2063 agenda).

Mangroves support a number of SDGs, most notably Goal 6 (clean water and sanitation) and Goal 15 (life on land), as they serve as important indicators for monitoring progress at local, regional, and global levels. Specifically, indicator 6.6.1 (change in extent of water-related ecosystems over time) of Goal 6 aims to protect and restore water-related ecosystems such as mangroves. While indicator 15.1.1 of Goal 15 focuses on quantifying forest area as a proportion of total land area. Therefore, understanding mangrove ecosystems and mapping their extent both locally and globally is crucial to achieving these goals [37,38]. This can help coastal managers focus on conservation practices and reduce degradation

of water-related ecosystems by improving their knowledge of these ecosystems to drive conservation and restoration actions.

The coast of Ghana, as other coastal zones, faces the threat of flooding, erosion, and saltwater intrusion with rising sea levels. Mangroves in this area may be threatened by a rise in sea levels. There is a need to understand where mangroves are currently found and how they have changed over time, by constantly monitoring and modeling their vulnerability to climate change or land use change. Therefore, the main objective of this case study is to map and quantify the changes in the mangrove ecosystem over time to show how mangrove mapping can help coastal managers to focus on conservation practices.

2. Materials and Methods

2.1. Study Location

This study was conducted at the Anlo Beach Wetland complex which is situated along the coastal belt in the Shama District, Western Region of Ghana as shown in Figure 1. The area covers about 50.42 km², lying approximately within latitudes 5°1'30" N and 5°3'5" N, and longitudes 1°34'30" W and 1°37'30" W, and it is covered by mangroves which have been comparatively disturbed [39]. Hydrologically, the area lies within the plains of the Pra River, which opens directly into the ocean.

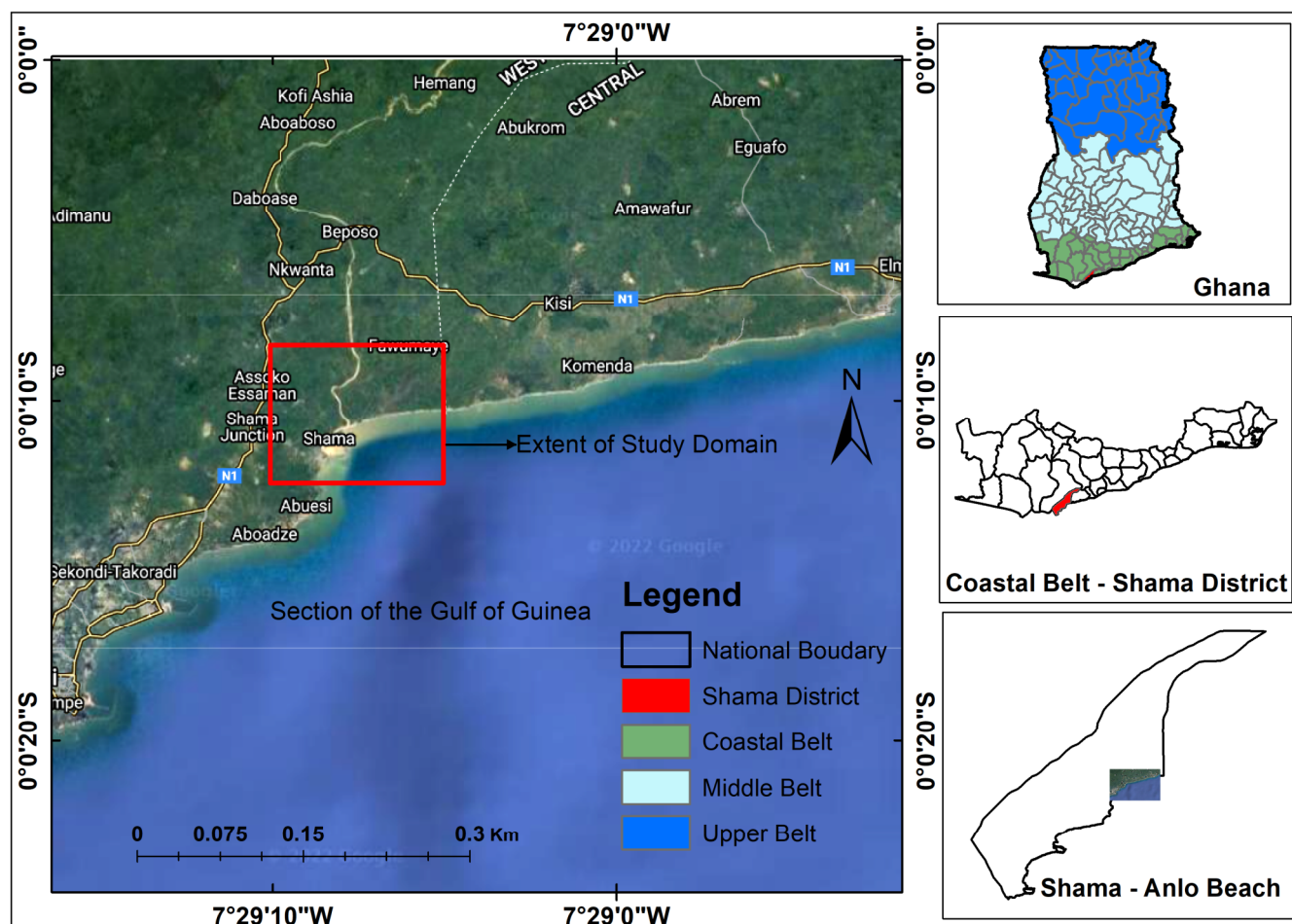


Figure 1. Map of Study Location.

Anlo Beach is located at the lower part of the Pra River Basin which is characterized by a high surface temperature of about 21.74 °C to 31.6 °C, for minimum and maximum, respectively [40]. The climate of this area is classified as tropical monsoon (Am) [41], with a mean monthly relative humidity greater than 70%, all year round [42]. The mean annual value of rainfall from 1981–2010 was 1446 mm [43] and the upper part of the basin is

characterized by soil with moderately high runoff potential [44], making the low areas of the basin vulnerable to water disasters during extreme rainfall events [45].

According to a study conducted in the location by Friends of the Nation [39], the topography is largely flat, the shoreline has an irregular sandy beach, and the ocean areas are generally open and characterized by pounding surf with medium to high energy. The coastline has eroded by an average of 100 m in the last 50 years [46]. The wetland is largely shallow (0.25–1.5 m) with fluctuating hydrology and chemical parameters. The dominant mangrove species include: *Avicennia*, *Rhizophora*, and *Laguncularia* genera, and the adjoining marshland has saltwater grass *Paspalum vaginatum* (Poaceae) as the main vegetation [47].

The inhabitants of the Anlo Beach community are predominantly fishermen with an estimated population of about 2231, consisting of 1028 males and 1203 females [46]. This population also relies on the mangrove ecosystem for various activities thereby, creating some intense land use change dynamics.

2.2. Datasets and Sources

For this study, the Google Earth Engine (GEE) cloud-based platform and random forest classification algorithm were used. Mangrove extent maps were generated by classifying both optical and radar images separately and in combination. The maps were created for two time periods, namely 2009 and 2019, to examine changes in mangrove extent and other LULC over time. The Google Earth Engine database was filtered for Sentinel-1 imagery that is in wide swath (IW) interferometric mode, descending pass, 25 m resolution, VH and VV polarization, and falls within the region of interest. The Sentinel-1 dataset was filtered by date to retrieve images from 2019. The 2009 ALOS PALSAR-2 image was acquired from the JAXA website (Table 1). The corresponding Landsat 8 and Landsat 7 images were also extracted from the Google Earth Engine database. The images: Landsat 8 surface reflection Tier 1, Landsat 7 surface reflection Tier 1, Sentinel-1 image (COPERNICUS), ALOS PALSAR-2 image, and global mangrove distribution vector file were loaded into the Google Earth Engine code editor. Then, the images were added to the layer bar for visualization. A speckle filter was applied to the synthetic aperture radar (SAR) images to minimize speckle noise (Ayman et al., 2017) and the speckle-filtered images were also added to the layer bar (Figure 2).

Table 1. Description of Datasets used for Mangrove Extent Mapping and Quantification.

S/N	Data Type & Date	Description	Source
1	Sentinel-1 (2019)	A synthetic aperture radar (C-Band) with interferometric wide swath mode (IW), having a descending pass, a resolution of 25 m, dual polarization of VV and VH. Image Collection ID: ee.ImageCollection("COPERNICUS/S1_GRD"), more details can be found at https://developers.google.com/earth-engine/guides/sentinel1 (accessed on 30 November 2020)	Google Earth Engine platform database
2	ALOS PALSAR-2 (2009)	A synthetic aperture radar at L-Band, having a $10^0 \times 10^0$ in longitude and latitude, a resolution of 25 m, dual polarization of HH and HV. Image Collection ID: N06W002_09_sl_HH, N06W002_09_sl_HV available at https://www.eorc.jaxa.jp/ALOS-2/en/about/palsar2.htm (accessed on 30 November 2020)	Japan Aerospace Exploration Agency (JAXA) EORC

Table 1. Cont.

S/N	Data Type & Date	Description	Source
3	Landsat 8 Surface Reflectance Tier 1 (2019)	Has been atmospherically corrected and contains five visible and near-infrared bands, two short wave infrared bands, and two thermal infrared bands. Image Collection ID: ee.ImageCollection('LANDSAT/LC08/C01/T1_SR'). More details at https://www.usgs.gov/landsat-missions/landsat-surface-reflectance (accessed on 30 November 2020)	Google Earth Engine platform database
4	Landsat 7 Surface Reflectance Tier 1 (2009)	Has been atmospherically corrected and contains four visible and near-infrared bands, two short wave infrared bands, and one thermal infrared band. Image Collection ID: ee.ImageCollection('LANDSAT/LE07/C01/T1_SR'). More details at https://www.usgs.gov/landsat-missions/landsat-surface-reflectance (accessed on 30 November 2020)	Google Earth Engine platform database
5	Global mangrove distribution vector (GMW) (2010)	A baseline global distribution map of mangroves for year 2010. GMW was produced by Aberystwyth University in collaboration with solo earth observation (soloEO). It provides geospatial information about mangrove extent and changes.	https://data.unep-wcmc.org/datasets/45 (accessed on 30 November 2020)

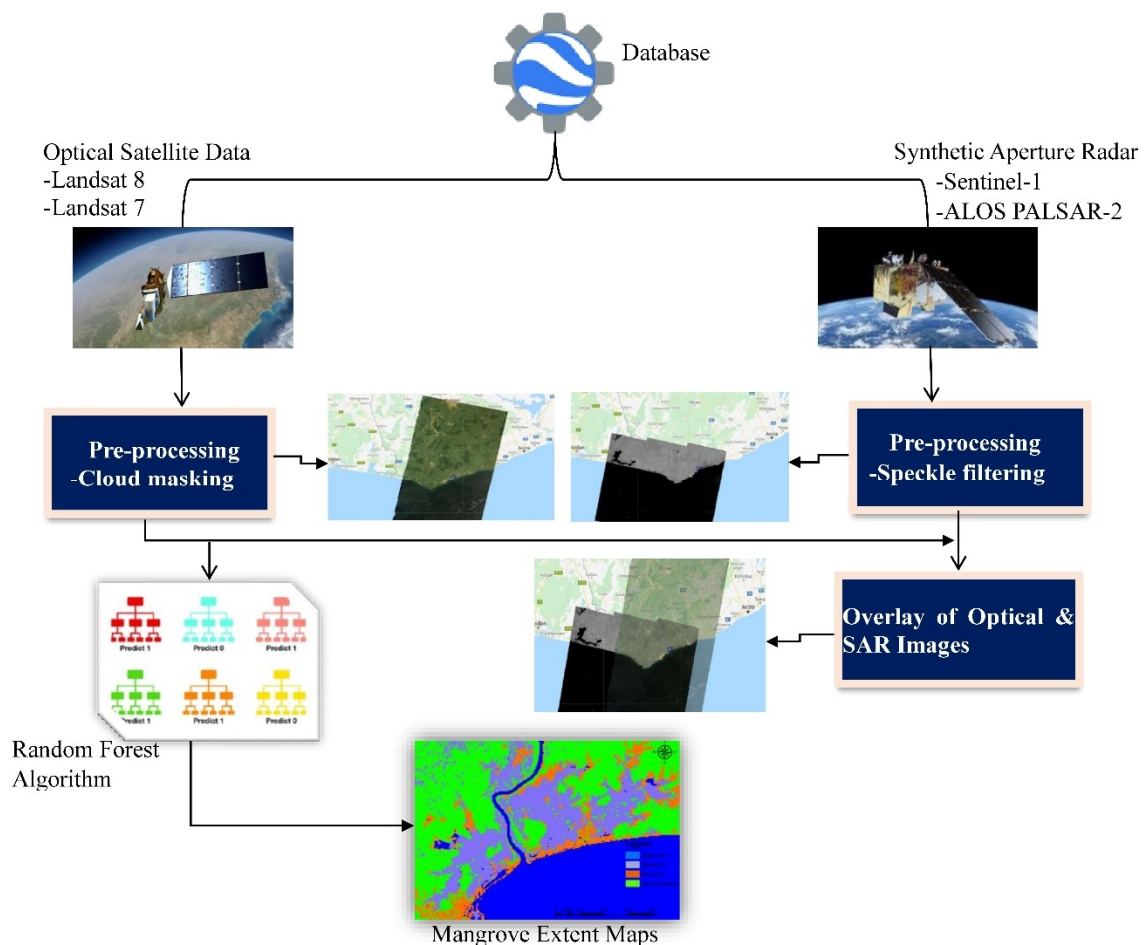


Figure 2. Flowchart of Data Extraction and Iteration Process for Random Forest Model.

2.3. Comparison of Mangrove Extents

2.3.1. Mangrove Extent Mapping

It is important to note that the Sentinel-1 dataset is ready for image analysis in Google Earth Engine as it has already been processed by implementing formal denoising, radiometric, terrain correction, and the backscatter coefficient is in decibels (dB). The ALOS PALSAR-2 data was converted from log10 to decibels (dB) [48,49] using the formula below.

$$\gamma_0 = 10 \log_{10} \langle DN^2 \rangle + CF \quad (1)$$

where γ_0 = Sigma naught (dB), DN = pixel value (digital number), CF (calibration factor) = -83.0 for the PALSAR images.

The optical images were improved by creating a function that masks cloud shadows and clouds [50,51]. The normalized difference vegetation index (NDVI) was calculated from the optical image to obtain a composite image, which was used as an information layer to inform the classifier [52,53]. This procedure was performed for Landsat 8 (2019) imagery and Landsat 7 (2009) imagery.

2.3.2. Construction of Random Forest Model

Supervised classification (random forest classification) involves creating training samples (Figure 2) to 'train' the classifier [54,55]. The approach used in the current study follows the method described by Erika et al. [3]; Barenblitt and Fatoyinbo, [56], which involves collecting representative samples of backscatter values for each landcover class of interest. The random forest algorithm (RF) was run using a hundred trees and five randomly selected predictors per split [24]. Training and validation data for this work is based on field campaigns conducted between December 2020 and April 2021. The global mangrove distribution vector (Table 1) was also needed as a reference data to guide the creation of training samples.

2.3.3. Synthetic Aperture Radar (SAR) Classification

The speckle-filtered Sentinel-1 (VH) image was displayed in the map section of GEE and a polygon symbol was selected from the geometry imports box next to the geometry drawing tool to add training data. Each new layer created, for example 'open water' represents one class within the training data, and it was saved as FeatureCollection called landcover. Training samples were selected for four different land cover classes: open water, mangroves, bare land/built-up, and other vegetation/wetlands. The defined classes were then merged into a single collection called 'new FeatureCollection'.

The 'new FeatureCollection' created was used to extract backscatter values for each landcover identified for the Sentinel-1 image. The Sentinel-1 (SAR) image was defined with the code in bracket (`var final = ee.Image.cat(SARVV_filtered, SARVH_filtered)`) and the training data was created by overlaying the training points (new FeatureCollection) on the image. This created a 'training point' statistics based on the classes (new FeatureCollection) and was used to 'train' the random forest classifier. The classification was 'run' and results were displayed on the 'layers' bar.

2.3.4. Landsat Image Classification

Again, the 'new FeatureCollection' created was used to extract reflectance values for each landcover class from the Landsat 8 image which was also defined (`var trainingl8 = composite.select(bandsl8).sampleRegions()`). The 'training' data was created by overlaying the training points (new FeatureCollection) on the image and used 'B1', 'B2', 'B3', 'B4', 'B5', 'B6', 'B7', 'NDVI' to generate the statistics. This was used to 'train' the random forest classifier. The classification was 'run' and results were displayed on the 'layers' bar.

2.3.5. Both Landsat and SAR Classification

Now, the 'new FeatureCollection' created was used to extract reflectance and backscatter values for each landcover class from the Landsat 8 and Sentinel-1 images to be used in the classification. Both the Landsat 8 and Sentinel-1 images were defined (`var opt_sar = ee.Image.cat(composite, SARVV_filtered, SARVH_filtered)`) and the 'training' data was created by overlaying the 'training' points on the defined image (Figure 2). This was used to 'train' the random forest classifier. The classification was 'run' and the results were displayed on the 'layers' bar.

2.3.6. Time Series Comparison

The above process was repeated using the ALOS PALSAR-2 image (2009 SAR image) and Landsat 7 image (2009 optical satellite image). Mangrove extent and other LULC for the two different time periods were calculated for each scenario using a 'reduce region' function in the GEE code editor and the values were converted to hectares [56].

2.3.7. Independent Accuracy Assessment

A total of 2131 training sample points were created. The sample points were randomly split for 'training' and validation: 80% (1705 points) of the sampling points were used to 'train' the model while 20% (426 points) were used for validation.

This was done to remove any systematic error as a result of using the same pixels to train and validate classifiers [53,57]. The accuracy of the classification in GEE was assessed using confusion matrix based on the classifier. The overall accuracy and the kappa coefficient were calculated using the following formula:

$$\text{Overall Accuracy} = \frac{\text{Number of correctly classified pixels (sum of diagonal)}}{\text{Number of total sampled pixels}} * 100 \quad (2)$$

$$\text{Kappa} = \frac{P_0 - P_C}{1 - P_C} \quad (3)$$

where, P_0 = observed accuracy and P_C = chance agreement.

For independent accuracy assessment, stratified random samples were created using 20% of the training sample, comprising of at least 100 points per class with a 15 m radius buffer around each point. The output of the stratified random sampling points was exported to Google Drive and used to perform independent accuracy assessment following the method described by Barenblitt and Fatoyinbo [56]. This method involves the use of high-resolution satellite imagery available in QGIS to validate each point (Figures 3 and 4).

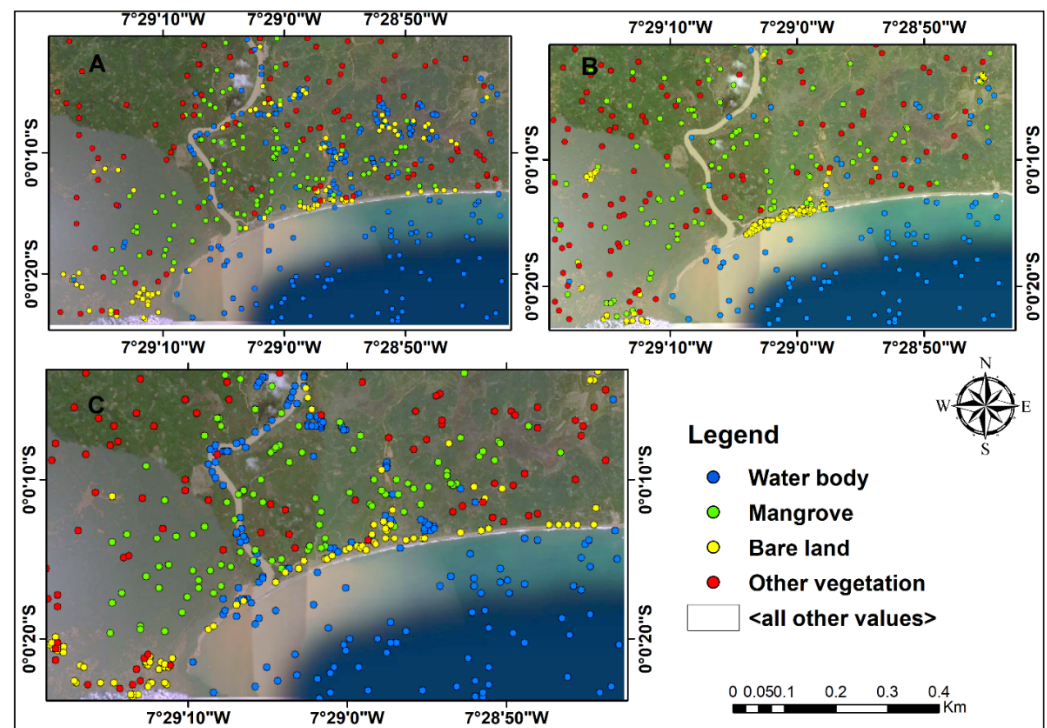


Figure 3. Independent Accuracy Assessment for the year 2009, (A) Independent Accuracy Assessment for Landsat 7 Image, (B) Independent Accuracy Assessment for ALOS PALSAR-2 Image, (C) Independent Accuracy Assessment for both ALOS PALSAR-2 and Landsat 7.

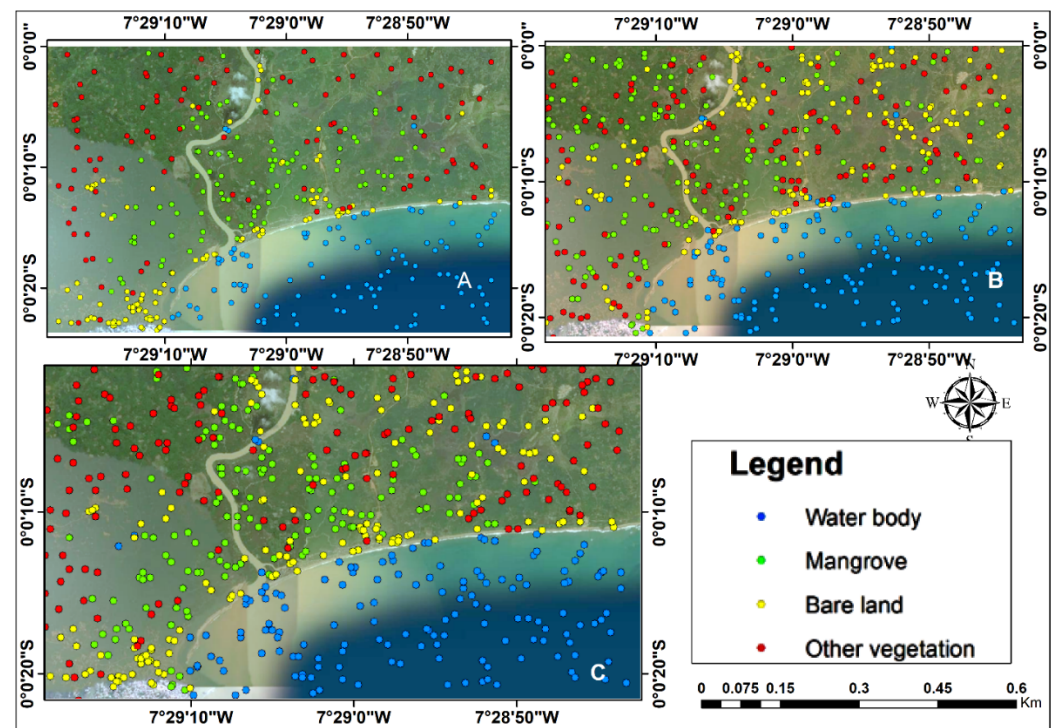


Figure 4. Independent Accuracy Assessment for the year 2019, (A) Independent Accuracy Assessment for Landsat 8 Image, (B) Independent Accuracy Assessment for Sentinel-1 Image, (C) Independent Accuracy Assessment for both Sentinel-1 and Landsat 8.

3. Results

Several iterations were run using different datasets of Sentinel-1, Landsat 8 separately, and a combination of both (i.e., Sentinel-1 + Landsat 8) which represents the three scenarios for 2019. This process was repeated using ALOS PALSAR-2 and Landsat 7 to obtain the corresponding scenarios for 2009. The results of mangrove extent and other land cover changes for the two time periods are presented in Figure 5.

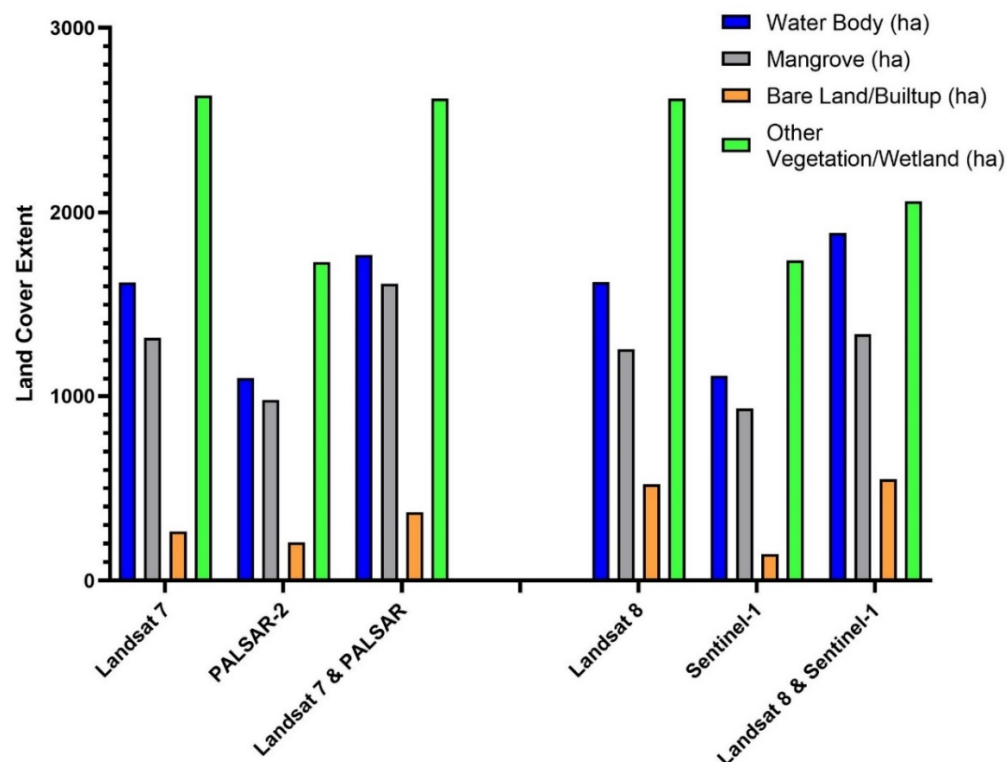


Figure 5. LULC Change Detection for the Time Period using Different Classification Scenarios.

Three main classification scenarios were established to quantify the extent of mangroves and other land cover classes for two time periods: classification of optical data only, classification of SAR data only, and the third scenario combined both optical and SAR data (Figures 6 and 7). The result of Landsat 8 data only (2019) showed a mangrove extent of 1259 ha, water body extent of '1622 ha', bare land extent of 524 ha, and other vegetation extent of 2617 ha, while the Landsat 7 (2009) data showed a mangrove extent of 1321 ha, water body extent of '1620 ha', bare land extent of 266 ha, and other vegetation extent of 2634 ha (Figure 5). The overall classification accuracy for Landsat 8 was 98.9% with a kappa coefficient of 0.979, while the overall accuracy for Landsat 7 was 96.8% with a kappa coefficient of 0.94. The second classification scenario showed a mangrove extent of 933 ha, water body extent of '1115 ha', bare land extent of 144 ha, and other vegetation extent of 1741 ha for Sentinel-1 (2019), while ALOS PALSAR-2 (2009) data showed a mangrove extent of 979 ha, water body extent of '1104 ha', bare land extent of 208 ha, and other vegetation extent of 1731 ha (Figure 5). The overall classification accuracy for Sentinel-1 classification was 84.6% with a kappa coefficient of 0.718, while the overall accuracy for ALOS PALSAR-2 was 96.6% with a kappa coefficient of 0.938. The third classification scenario showed a mangrove extent of 1340 ha, water body extent of '1891 ha', bare land extent of 549 ha, and other vegetation extent of 2062 ha for Sentinel-1 and Landsat 8 combined (2019), while the ALOS PALSAR-2 and Landsat 7 (2009) combination showed a mangrove extent of 1613 ha, water body extent of '1770 ha', bare land extent of 370 ha, and other vegetation extent of 2617 ha. The overall classification accuracy for both Sentinel-1 and Landsat 8 when combined together was 99.1% with a kappa coefficient of 0.984, while the overall

accuracy for both ALOS PALSAR-2 and Landsat 7 was 99.6% with a kappa coefficient of 0.992 (Tables 2–7).

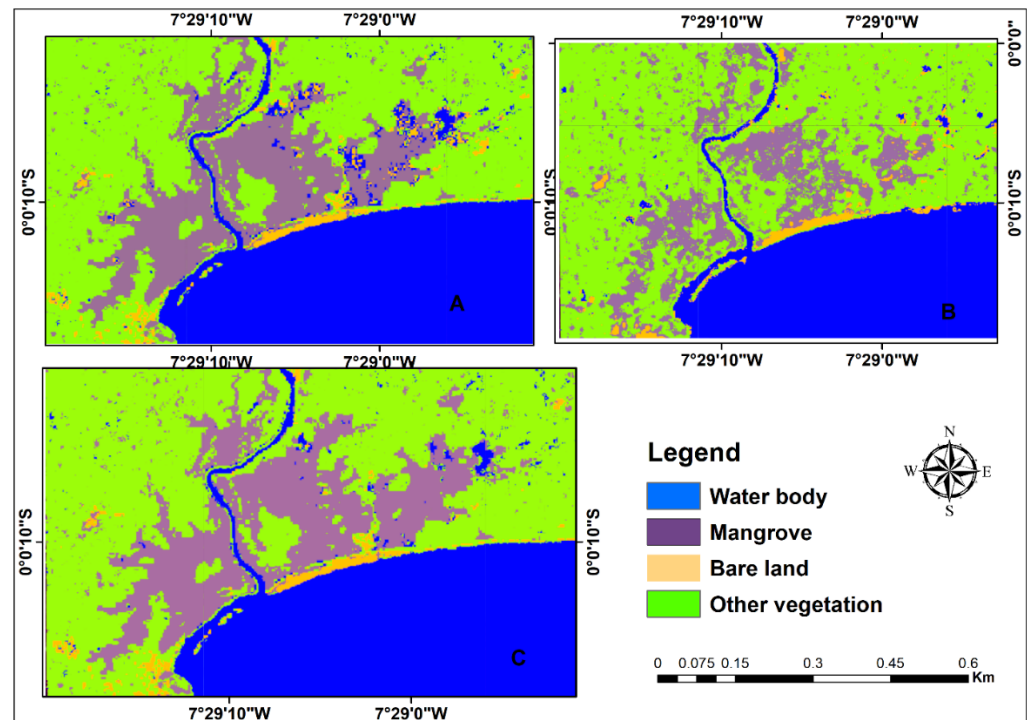


Figure 6. Different Scenarios of Mangrove Extent Maps for the year 2009. (A) Classification Scenario using Optical Image only (Landsat 7); (B) Classification Scenario using PALSAR Image; (C) Classification Scenario using both Optical (Landsat 7) and PALSAR Data.

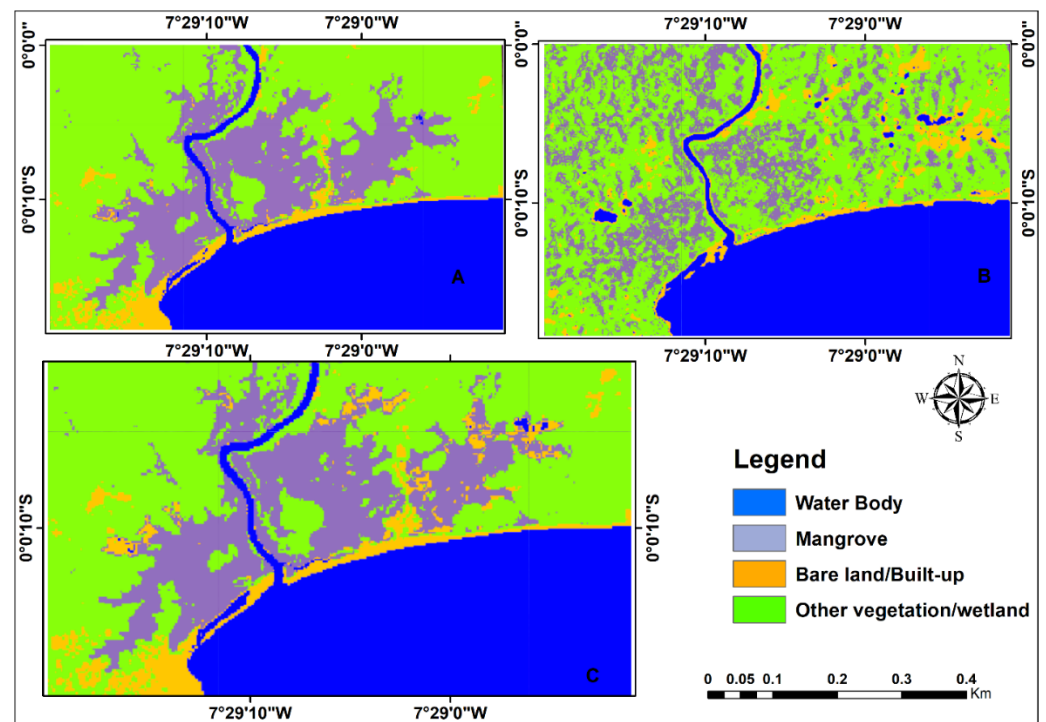


Figure 7. Different Scenarios of Mangrove Extent Maps for the year 2019. (A) Classification Scenario using Optical Image only (Landsat 8); (B) Classification Scenario using Sentinel-1 Image only; (C) Classification Scenario using both Optical (Landsat 8) and Sentinel-1.

Table 2. Confusion/Error Matrix of Land Cover Classification using Landsat 7 Image.

Classes	Open Water	Mangroves	Bare Land	Vegetation/ Wetland	Row Total	User's Accuracy (%)
Open Water	76	0	2	3	81	93.8
Mangroves	4	615	1	27	647	95.1
Bare Land	1	4	26	1	32	81.3
Vegetation/Wetland	0	12	0	933	945	98.7
Column Total	81	631	29	964	1705	
Producer's Accuracy (%)	93.8	97.5	89.7	96.8		

Overall accuracy = 96.8%; kappa coefficient = 0.936.

Table 3. Confusion/Error Matrix of Land Cover Classification using ALOS PALSAR-2 Image.

Classes	Open Water	Mangroves	Bare Land	Vegetation/ Wetland	Row Total	User's Accuracy (%)
Open Water	76	0	0	5	81	93.8
Mangroves	0	615	0	32	647	95.1
Bare Land	1	4	23	4	32	71.9
Vegetation/Wetland	0	12	0	933	945	98.7
Column Total	77	631	23	974	1705	
Producer's Accuracy (%)	98.7	97.5	100	95.8		

Overall Accuracy = 96.6%; Kappa Coefficient = 0.938.

Table 4. Confusion/Error Matrix of Land Cover Classification using a combination of Landsat 7 Image and ALOS PALSAR-2.

Classes	Open Water	Mangroves	Bare Land	Vegetation/ Wetland	Row Total	User's Accuracy (%)
Open Water	81	0	0	0	81	93.8
Mangroves	0	647	0	0	647	95.1
Bare Land	0	1	26	5	32	81.3
Vegetation/Wetland	0	1	0	944	945	98.7
Column Total	81	649	26	964	1705	
Producer's Accuracy (%)	93.8	97.5	96.9	99.5		

Overall accuracy = 99.6%; kappa coefficient = 0.992.

Table 5. Confusion/Error Matrix of Land Cover Classification using Landsat 8 Image.

Classes	Open Water	Mangroves	Bare Land	Vegetation/ Wetland	Row Total	User's Accuracy (%)
Open Water	81	0	0	0	81	100
Mangroves	0	635	0	12	647	98.1
Bare Land	4	0	28	0	32	87.5
Vegetation/Wetland	0	3	0	942	945	99.7
Column Total	85	638	28	954	1705	
Producer's Accuracy (%)	95.3	99.5	100	98.7		

Overall accuracy = 98.9%; kappa coefficient = 0.979.

Table 6. Confusion/Error Matrix of Land Cover Classification using Sentinel-1 Data.

Classes	Open Water	Mangroves	Bare Land	Vegetation/ Wetland	Row Total	User's Accuracy (%)
Open Water	79	0	2	0	81	97.5
Mangroves	0	521	0	126	647	80.5
Bare Land	2	0	23	7	32	71.9
Vegetation/Wetland	0	119	6	820	945	86.8
Column Total	81	640	31	953	1705	
Producer's Accuracy (%)	97.5	81.4	74.2	86		

Overall accuracy = 84.6%; kappa coefficient = 0.718.

Table 7. Confusion/Error Matrix of Land Cover Classification using a combination of Landsat 8 and Sentinel-1 Images.

Classes	Open Water	Mangroves	Bare Land	Vegetation/ Wetland	Row Total	User's Accuracy (%)
Open Water	81	0	0	0	81	100
Mangroves	0	642	1	4	647	99.2
Bare Land	0	0	32	0	32	100
Vegetation/Wetland	0	9	0	936	945	99
Column Total	85	651	33	940	1705	
Producer's Accuracy (%)	100	98.6	96.9	99.6		

Overall accuracy = 99.1%; kappa coefficient = 0.984.

4. Discussion

Mwita et al. [58] and Wijedasa et al. [59] highlighted several limitations of using only optical satellite images for long-term mapping and monitoring of coastal ecosystems. In recent years, advances in machine learning classifiers and a proliferation of high-performance cloud computing platforms such as Google Earth Engine (GEE) offer the possibility to combine optical and radar imagery for efficient land-use and land-cover mapping [3,60,61].

The results show that there are differences in all three classification scenarios for each period (2009–2019). For example, classification using synthetic aperture radar data showed that most structural aspects were captured but it underestimated the vegetation cover and this is consistent with observations in other studies [4,52,62]. In contrast, optical satellite image classification captured the tree canopy more [3] but seemed to overestimate [38] the extent. The ALOS PALSAR-2 data was more effective in characterizing mangroves than the Sentinel-1 data, likely due to the high penetrability of the L-band into the mangrove tree canopy as compared to the C-band.

The LULC changes for the study area between 2009 and 2019 are as presented in Figure 5. The results of the scenario that combined both optical and radar images showed that there have been changes in the various LULC (water body, mangrove, bare lands/built-up, and other vegetation/wetland) over the two time periods. In 2009, mangroves covered 1613 ha, bare land/built-up areas accounted for 370 ha, other vegetation/wetland accounted for 2617 ha, while water body covered about '1770 ha' equivalent. In 2019, mangroves decreased to 1340 ha, bare lands/built-up increased to 549 ha, other vegetation/wetland decreased to 2062 ha, while water body increased to 1891 ha. There was observed a significant change in mangrove cover (16.9% loss), bare land/built-up areas (45% gain), other vegetation/wetland (21% loss), and water body (7% gain). This indicates that mangroves and other vegetation have been converted to either bare land (which could be agricultural land) or built-up areas. Water body has also taken up part of the areas which were previously covered by either mangroves or other vegetation.

We used confusion matrices and an independent accuracy assessment to provide detailed statistical information for each classification scenario. The confusion matrix for

Sentinel-1 image classification alone showed that out of 647 pixels which were identified as mangrove, 521 pixels were correctly classified, while the confusion matrix for the corresponding optical image alone showed that out of 647 pixels which were identified as mangroves, 635 pixels were correctly classified (Tables 2–7). However, relatively high confusion was found between mangrove and other vegetation for Sentinel-1 and ALOS PALSAR-2 classification as revealed by the independent accuracy assessment (Figures 3 and 4). It was also revealed that the Sentinel-1 and ALOS PALSAR-2 images alone tended to underestimate the mangrove vegetation canopy; however, ALOS PALSAR-2 performed better than Sentinel-1 (Figures 6 and 7). On the other hand, Landsat 7 and Landsat 8 alone tended to overestimate the vegetation cover. The overall classification accuracy for the Sentinel-1 image was 84.6%, while the overall accuracy for the Landsat 8 alone was 98.9%. The overall accuracy when both images were combined was 99.1% with a kappa coefficient of 0.984, showing that the classification using a combination of optical and radar data has a better agreement in the observations (Tables 2–7). It was observed that the combination of Landsat 7 and ALOS PALSAR-2 produced better accuracy indicating that L-band performs better than C-band (Tables 4 and 7).

The third classification scenario that combines optical and radar data yielded the best classification results for 2009 and 2019 as the classes were relatively well distributed, capturing both clustered mangroves and mangrove patches near the water body (Figures 6 and 7). The visual interpretation showed that the third classification scenario achieved a better result, indicating the high potential of this mangrove assessment and monitoring method, as well as agreeing with the findings of Attarchi and Gloaguen, [21] and Ghorbanian et al. [24]. The independent accuracy assessment underscores the robustness of this approach, as shown in Figures 3 and 4. Despite the fact that the same ‘training sample’ was used to train the classifier, the accuracies differ depending on the scenario. The scenario combining both optical and radar data showed better agreement and less confusion compared to when either optical or radar data was used.

This study confirms that combining synthetic aperture radar data with optical satellite data is the way forward in mangrove assessment and mapping, as recommended by several authors [21–24,26]. The random forest algorithm performed well to clearly classify the different land cover classes within the study area. The resulting classification is consistent with other studies that used random forest algorithms for land cover classification [24,26,63,64].

5. Conclusions

The destruction of tropical and subtropical mangrove forests worldwide is one of the most urgent environmental catastrophes of our time. The world may not achieve the sustainable development goals without addressing deforestation and increasing restoration of mangroves and other forests. In this paper, we elaborated an approach to synthesizing the relevant database in a spatial framework using the Google Earth Engine platform and a random forest algorithm to generate more accurate mangrove extent maps. Cloud computing techniques and machine learning algorithms, such as Google Earth Engine as used in this study, have demonstrated the potential for accurate quantification of mangrove stands as well as various other land uses, particularly in cloud-prone areas. This could allow for a more accurate estimation of mangrove changes at local, regional, or global scales and to track progress in the sustainable development goals (SDGs).

The combination of optical satellite data alongside synthetic aperture radar and random forest algorithm could be valuable for quantifying changes in mangrove ecosystems and their surroundings to fill knowledge gaps essential for mangrove management and conservation. Overall, there is a significant (16.9%) decadal decline in mangrove extent at the study site which could be attributed to land conversion, reflecting the need for conservation, appropriate monitoring, and management. This would require a conscious management plan that includes current and alternative livelihood strategies, sustainable resource management systems, and a sustained awareness of people about mangrove services and their value under climate change, beyond providing for the immediate needs

of the community. Continuous replanting of mangrove propagules is encouraged in areas where degradation has occurred.

This type of study can help coastal managers to understand where mangroves are currently found and how they have changed over time. The maps produced in this study are suitable to inform coastal management in the region and the methodology can be reproduced for the entire coastal zone of Ghana and beyond. Although our model estimates mangrove extent fairly well, the main limitation to this study is the lack of up-to-date data for the study area, e.g., 2020 data and high-resolution images (e.g., 10 m) as at the time of these analyses. While the results for the combined application of optical and radar data for mangrove classification are promising for this case study, further research and testing is needed, particularly for larger areas of interest (e.g., the entire coastal zone of West Africa) to fill a critical gap in the accuracy of mangrove mapping and natural capital accounting.

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Abbreviations

ALOS	Advanced land observation satellite
ETM+	Enhanced thematic mapper
GEE	Google Earth Engine
HH	Single co-polarization, horizontal transmit/horizontal receive
NDVI	Normalized difference vegetation index
PALSAR	Phase array L-band synthetic aperture radar
SAR	Synthetic aperture radar
SDGs	Sustainable development goals
VV	Single co-polarization, vertical transmit/vertical receive

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