Quantification of Mangrove Extent using a Combination of Optical and Radar Images in Google Earth Engine Platform: The case of Anlo Beach Wetland Complex, Shama District, Western Region, Ghana

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Abstract

Mangrove Forest classification in tropical coastal zones based on only passive remote sensing methods is hampered by Mangrove complexities, topographic considerations and cloud cover effects among other things. This paper reports on a novel approach that combines Optical Satellite images and Synthetic Aperture Radar alongside their derived parameters to overcome the challenges of distinguishing Mangrove stand in cloud prone regions. Google Earth Engine (GEE) cloud-based geospatial processing platform was used to extract several scenes of Landsat Surface Reflectance Tier1 and synthetic aperture radar (C-band and L-band). The imageries were enhanced by creating a function that masks out clouds from the optical satellite image and by using speckle filter 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. Our result show that about 16% of the mangrove extent was lost in the last decade. The accuracy was assessed based on three classification scenarios: classification of optical data only, classification of SAR data only, and combination of both optical and SAR data. The overall accuracies were 99.1% (Kappa Coefficient = 0.797), 84.6% (Kappa Coefficient = 0.687) and 98.9% (Kappa Coefficient = 0.828) respectively. This case study demonstrates how mangrove mapping can help focus conservation practices locally in climate change setting, coupled with sea level rise and related threats to coastal ecosystems.

1. Background

Mangrove grows and flourishes in an environment that acts as a buffer zone for terrestrial and marine ecosystems. They are globally important ecosystem that are restricted to coastal areas where mean monthly air temperatures are higher than 20°C and where there is no ice formation on the ground with rare exceptions (Blasco et al., 2019). These ecosystems are made up of trees and shrubs that are found in shallow sandy or muddy areas that are adapted to estuarine or saline environment (Erika et al., 2020). They are truly unique because they are the only trees capable of tolerating large amount of salt and water. This capability as well as surviving in low oxygen soil is a result of the root adaptations. Mangrove forests occupy an insignificant proportion of land area (< 1%) but they are considered as the most carbon abundant ecosystems within the tropics. Mangrove ecosystems have recently been included in the IPCC climate mitigation strategy through a number of wetland supplements (Lucas et al., 2014).

In Africa, mangrove forests occupy roughly 2,746,500ha in 2010 (Bunting et al., 2018) and support vulnerable coastal population by providing important ecosystem services such as natural sea defense, mitigation of coastal erosion, water quality improvement as well as providing alternative livelihood (Gedan et al., 2011; Kuenzer and Tuan, 2013; Lee et al., 2014; Mondal et al., 2018). Fatoyinbo and Simard (2013) reported that mangrove cover about 7600ha along the coast of Ghana and seven major mangrove varieties have been confirmed including *Laguncularia racemose* (white mangrove), *Avicennia germinans* (black mangrove), *Rhizophora harrisonii* (Red mangrove), *Rhizophora racemose* (Red mangrove), *Rhizophora mangle* (Red mangrove), *Acrostichum aureum* (golden leather fern) and *Cornocarpus erectus* (botton mangrove) (Ellison et al., 2015; Nortey et al., 2016).

Despite providing many valuable services, these ecosystems have experienced significant degradation and they are being threatened or lost (Alongi, 2012; Breithaupt et al., 2012). The rate of loss in the last two decades have been estimated to double terrestrial rainforest loss over the same period (Mayaux, et al., 2005). It is also estimated that about 2/3 of mangrove forest 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 (FAO, 2007; Miththapala, 2008; World Mangrove Network, 2012). The primary cause of mangrove loss has been deforestation for land conversion, primarily for Aquaculture, Saltpans establishment and other Agricultural intensification.

Quantification of changes both in space and time for mangrove ecosystem is crucial for an improved understanding of many coastal and sea processes. Conventional mapping of mangrove forest involves huge capital for field work due to the difficulties associated with accessibility within the mangroves ecosystem (Zhang et al., 2014). 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 (Son et al., 2015). Several authors recommend the combination of Synthetic Aperture Radar with Optical satellite data for more accurate quantification of mangrove extent (Attarchi and Gloaguen, (2014); Ayman et al., 2017; Hu et al., 2020)

There have been several studies on mangrove extent across Africa (Kovacs et al., 2010; Salami et al., 2010; Omo-Irabor et al., 2011; De Santiago et al., 2013; Fatoyinbo and Simard, 2013; Kuenzer et al., 2014; Hoppe-Speer et al., 2015; Brown et al., 2016; Lagomasino et al., 2019), 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 African Union (2063 agenda).

Mangroves support a range of SDGs, especially Goal 6 (Clean water and sanitation) and Goal 15 ('Life on Land') (Fig. 2), as they serve as important indicators for monitoring progress locally, regionally and globally. Specifically, indicator 6.6.1 (Change in extent of water-related ecosystems over time) of Goal 6 aims at protecting and restoring 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 locally as well as globally is critical in meeting these goals (Barenblitt and Fatoyinbo, 2020a). This can help coastal managers to focus conservation practices and reduce the degradation of water-related ecosystems by improving our knowledge of these ecosystems to drive action towards protection and recovery.

The coastline of Ghana, just like other coastal zones, faces imminent flooding, erosion and saltwater intrusion as sea level rises. Mangroves in this area may be threatened by sea level rise. There is the need to understand where mangroves are currently found and how they have changed over time by steady monitoring and modelling of their vulnerability to either climate change or land use change. Therefore, the

main objective of this case study is to map the temporal changes of Coastal-Wetland surface characteristics and to show how mangrove mapping can help coastal managers to focus conservation practices.

2. Materials And Methods

2.1 Study Location

This study was conducted at the Anlo Beach Wetland complex which is situated in the Shama District, Western Region of Ghana as shown in Figure (1). The area covers about 50.42km², 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 (Friends of the Nation. 2014). Hydrologically, the area lies within the plains of Pra River, which opens directly into the ocean.

According to a study conducted in the location by Friends of the Nation (2014), the topography is largely flat and 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 100m in the last 50 years (Coastal Resources Center / Friends of the Nation, 2010). The wetland is largely shallow (0.25–1.5 m) with fluctuating hydrology and chemical parameters.

The inhabitants of Anlo Beach community are predominantly fishermen with an estimated population of about 2,231 consisting of 1,028 males and 1,203 females (Coastal Resources Center / Friends of the Nation, 2010).

Figure 1: Map of Study Location

Figure 2: Key concepts related to sustainable development and links to the most relevant sustainable development goals, targets, indicators and series

2.2 Datasets and Sources

Table 1
Description of Datasets and their Sources

S/N	Data Type	Description	Source
1	Sentinel-1	C-band Synthetic Aperture Radar with Interferometric Wide Swath Mode (IW), Descending Pass, 25-meter resolution, VV and VH polarization	Google Earth Engine Platform Database
2	ALOS PALSAR-2	L-band Synthetic Aperture Radar (SAR), 10x10 degrees in latitude and longitude, ortho-rectified, slope corrected with pixel size approximately 25m by 25m. HH and HV polarization	Japan Aerospace Exploration Agency (JAXA) EORC
3	Landsat 8 Surface Reflectance Tier 1	Atmospherically corrected surface reflectance from the Landsat 8 OLI/TIRS sensors, contain 5 visible and near-infrared (VNIR) bands, 2 short-wave infrared (SWIR) bands and 2 thermal infrared (TIR) bands	Google Earth Engine platform database
4	Landsat 7 Surface Reflectance Tier 1	Atmospherically corrected surface reflectance from the Landsat 7 ETM+ sensor containing 4 visible and near-infrared (VNIR) bands, 2 short-wave infrared (SWIR) bands and one thermal infrared (TIR) band processed to ortho-rectified surface reflectance and brightness temperature.	Google Earth Engine platform database
5	SRTM DEM	Shuttle Radar Topography Mission which has undergone a void-filling process using the following open-source data: ASTER GDEM2, GMTED2010, and NED.	Google Earth Engine platform database
6	Global Mangrove distribution vector	Global baseline map of mangroves distribution for 2010	https://data.unep-wcmc.org/datasets/45

2.3 Time Series of Mangrove Extent (Comparison of Mangrove Extents)

2.3.1 Google Earth Engine

Data analyses for this study were performed using Google Earth Engine (GEE) cloud-based platform. Google earth engine is a free open source cloud-based geospatial processing platform which comprises of a catalogue of publicly available datasets e.g. Landsat imageries, Google computation power, an application programming interface (API) as well as a code editor. GEE provides access to a variety of satellite imageries from a number of NASA and ESA satellites including Landsat and Sentinel images. It operates on a client versus server function where users can manipulate 'proxy' objects through the server to send instruction to Google for processing and the results sent back to web browser for display. GEE defaults to WGS84 projections with access to data at planetary scale.

2.3.2 Random Forest Classification

Random Forest Classification algorithm was applied in this study for mapping of mangrove extents. The random forest classification is a type of machine learning that uses statistics to identify patterns in large data sets. It is a type of artificial intelligence that learns from data and allows the user to process large quantities of data to answer a particular research question. This is an ensemble tree based learning algorithm that creates trees that are looking at a single pixel of a data with each tree looking at different variables such as NDVI or different bands of Landsat images that help us to identify mangroves and each tree is using that information to cast a vote. This decision trees select the best option based on how many trees vote in one direction. It is a type of supervised machine learning classification.

2.3.3 Mangrove Extent Mapping

The images for the analysis were loaded into the Google Earth Engine code editor including Landsat8 surface reflectance tier1, Landsat7 surface reflectance tier1, SAR image (COPERNICUS), ALOS PALSAR image, SRTM digital elevation and global mangrove distribution vector file. Note that the SRTM elevation is from the shuttle radar topographic mission and it provides elevation and slope to narrow down the study area to areas where mangroves are more likely to be found. The global mangrove distribution vector was required to identify areas where Mangroves exist.

2.3.3.1 Optical Images (Landsat 7 & 8)

The map was setup by centering it to the area of interest, which in this case is the Anlo beach wetland complex and its environs, using a geometry drawn over the area of interest. Then, the Landsat composites were filtered to a cloud free mosaic (Fig. 3) by using a function that masks out clouds (Giri et al., 2011; Hansen et al., 2013). Seven spectral indices: Normalized difference vegetation index (NDVI), Normalized difference mangrove index (NDMI), Modified normalized difference water index (NDWI), Simple ratio (SR), Ratio54, Ratio35, and Green chlorophyll vegetation index (GCVI) were added to the Landsat imageries to provide information on not only vegetation in the pixels but also water content because mangroves are found close to water (Shi et al., 2016; Nathan et al., 2018).

Figure 3: Cloud Free Landsat 8 Imagery

The Landsat data were filtered by date and region. This was done by setting up a temporal parameter by creating a variable called 'year' and then indicating the required year. The mask function and the various spectral indices were applied to the final image which has been narrowed down to the study area using median reducer. Then the SRTM data was clipped to the study area (Landsat data) to further narrow down to elevations less than 45m as mangroves occur mostly in low elevations. The NDVI and NDWI masks were created by selecting the bands of interest (NDVI bands) to mask areas greater than 0.25, all the indices range from - 1 to 1, areas that are greater than 0.25 are assigned to highly vegetative areas and for NDWI, areas that are greater than - 0.5 were assigned.

Figure 4: False Color Composite of Landsat Image Clipped to Study Area

The visualization parameters were set and a false color composite (Fig. 4) was generated using B5, B6 and B4 combination. Then, the composite was added to the layer bar for visualization. This process was performed for Landsat 8 (2019) imagery and Landsat 7 (2009) imagery.

2.3.3.2 Synthetic Aperture Radar (C-band & L-band)

Then, the Sentinel-1 database was loaded and filtered for images that are in interferometric wide swath mode (IW), descending pass, 25m resolution and VV polarization. The code queries the Sentinel-1 database (COPERNICUS) and filter according to instrument mode and polarization. It is important to note that the Sentinel-1 data set in Google earth engine is image analysis ready as it has been processed already by implementing formal noise removal, radiometric and terrain correction. The values of PALSAR data set are still in Log10 which must be converted to decibel (db) (Lavalle & Wright, 2009) using the formula below.

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

Where γ_0 = Sigma naught (dB), DN = pixel value (digital number), CF (Calibration Factor) = -83.0 for the PALSAR images.

The same process is repeated for VH polarization. The entire data set was filtered to get the desired date (2019).

Figure 5: Filtered Synthetic Aperture Radar Image

The filtered images (Fig. 5) were added to the layer bar in order to display them for visualization. The same procedure was followed to load ALOS PALSAR 2009 image which corresponds to the Landsat 7 image date. Now that both the SAR and Landsat imageries have been identified, the next thing was to apply speckle filter to the SAR data to reduce noise.

2.3.4 Construction of Random Forest Model

Training samples were selected for four different land cover classes (Open water, Mangrove, Bare land and other vegetation/Wetland) in order to perform a supervised classification using random forest algorithm. The training samples were then merged into a single collection called FeatureCollection to create a new variable called 'classes'. The various bands and spectral indices to be included in the model were defined. This involves a number of iteration processes as shown in Fig. 6 below.

Figure 6: Iteration Process for Random Forest Model

The SAR and Optical imageries were then classified separately first and later a classification was run on both of them together. To classify the SAR data, the FeatureCollection was used to extract the backscatter values for each land cover class, the random forest classifier was implemented and the result displayed on the layer bar with the colors which were assigned to each of the classes. This was done based on the

backscatter characteristics of SAR imagery making sure that the selected samples are also within the Landsat imagery since it will also be used to train the Optical classifier.

In order to run the classifier on the satellite image, the first thing was to pick the training polygons created earlier and overlay them on the Landsat image. This was done by using the FeatureCollection to extract reflectance value for each land cover class. Now, the random forest classifier was 'run' on both the Optical and SAR data (Fig. 7) by overlaying the training samples on both the Optical and SAR data. The classifier was 'trained' and 'run'.

Figure 7: Overlay of Optical and SAR Data

2.3.5 Time Series Comparison

The above process was repeated using ALOS PALSAR 2009 and Landsat 7 image of 2009. However, a different function to add spectral indices was created because Landsat 7 has different band numbers from Landsat 8 which also collects images in wider swath. Mangrove area/extent for the two different time period was calculated using a 'reduce region' function in the GEE code editor to calculate the sum of pixels within the study area that are Mangroves and then convert it to hectares.

2.3.6 Independent Accuracy Assessment

A total of 1553 points were created using the stratified random sampling method (Fig. 8) for the study site. The accuracy of the classification was assessed using confusion matrix based on the classifier. The sample points were randomly split for 'training' and validation; 80% (1232 points) of the sampling points were used to 'train' the model while 20% (321 points) was used for validation. This was done to remove any systematic error as a result of using the same pixels to train and validate classifiers (Shi et al., 2016; Pimple et al., 2018). An independent accuracy assessment was performed in QGIS using the class accuracy plugin.

Figure 8: Training and Validation Points for the study area

To do this, a variable for the stratified random sample was created by taking the final classification and using '.stratifiedsample' to create a number of random samples (Barenblitt and Fatoyinbo, 2020b). A buffer was added to the points so that points with 30m diameter can be visualized and to also reflect the scale of the imageries. Then, the layers of interest were exported to Google drive for further processing.

3. Results

Image classification was carried out using Random Forest algorithm which is an ensemble tree based learning algorithm. It creates decision trees that use the pixel values of a data as well as different variables such as NDVI or different bands of Landsat images to identify different spatial classes by casting a vote. Several iterations were run using different datasets of SAR, PALSAR, Landsat 7, Landsat 8 as well as a combination of both SAR or PALSAR and optical data with adjustment of different classification parameters.

Table 2
Mangrove Extent for the Time Period using Different
Classification Scenario

Classification Scenarios	Mangrove Extent	
	2009 (ha)	2019 (ha)
Optical data	1067.38	1636.81
SAR data	1566.1	1492.2
Optical & SAR	1792.1	1488.53

Three main classification scenarios were established to quantify the extent of mangroves for two-time period; classification of optical data only, classification of SAR data only, and the third scenario combined both optical and SAR data (Figs. 9 and 10). The first classification scenario using optical data (Landsat 7 and Landsat 8 showed high performance in terms of the vegetation but fail to pick-up certain features correctly. The Landsat 8 data performed better than the Landsat 7 data with Mangrove extent of 1067.38ha (Landsat 7) and 1636.81ha (Landsat 8) for 2009 and 2019 respectively (Table 2).

Figure 9: (A) Classification Scenario using Optical data only (Landsat 7); (B) Classification Scenario using PALSAR data; (C) Classification Scenario using both Optical and PALSAR data

The overall classification accuracy for this scenario is 99.1% and the Kappa Coefficient is 0.797.

Table 3
Confusion/Error Matrix of Land Cover Classification using Optical Satellite Image

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	81	651	33	940	1705	
Producer's Accuracy (%)	100	98.6	96.9	99.5		
Overall Accuracy = 99.18%; Kappa Coefficient = 0.797						

Table 4
Confusion/Error Matrix of Land Cover Classification using Synthetic Aperture Radar 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 = 0.687						

Figure 10: (A) Classification Scenario using Optical data only (Landsat 8); (B) Classification Scenario using SAR data only; (C) Classification Scenario using both Optical and SAR data.

The second classification scenario using SAR data (C-band) did not classify the vegetation units into much detail despite using the same training samples. However, the PALSAR (L-band) data performed better than the SAR (C-band) data. The second classification scenario showed Mangrove extent of 1566.1ha (PALSAR L-band) and 1492.2ha (SAR C-band) for 2009 and 2019 respectively.

Table 5

Confusion/Error Matrix of Land Cover Classification using a combination of Optical Satellite Image and SAR

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	99.2
Bare Land	4	0	28	0	32	100
Vegetation/Wetland	0	3	0	942	945	99
Column Total	85	638	28	954	1705	
Producer's Accuracy (%)	95.3	99.5	100	98.7		
Overall Accuracy = 98.9%; Kappa Coefficient = 0.828						

The overall classification accuracy for this scenario is 84.6% and the Kappa Coefficient is 0.687. The third classification scenario using a combination of both optical and SAR data achieved the best classification results as the classes were relatively well distributed with mangroves clustered together close to the water body. The third classification scenario showed Mangrove extent of 1792.1ha and 1488.53ha for 2009 and 2019 respectively. The overall classification accuracy for this scenario is 98.9% with Kappa Coefficient of 0.828.

4. Discussion

This study confirms that the combination of Synthetic Aperture Radar data with optical satellite data is the way forward in mangrove assessment and mapping as recommended by several authors (Attarchi and Gloaguen, (2014); Ayman et al., 2017; Hu et al., 2020). The Random forest algorithm performed well to clearly classify the different land cover classes within the area under investigation. The resulting classification is in agreement with other studies that used random forest for land cover classification (Ming et al., 2016; Thanh et al., 2020). The outputs of the random forest classification were compared by overlaying them to visualize some of the differences. The results show that there are differences in all the three classifications for each time period (2009–2019). For example, the classification using Synthetic Aperture Radar data indicates that most of the structural aspects of the vegetation were picked up as compared to when Optical satellite data was used which agrees with the observations in other studies (Carreiras et al., 2013; Lucas et al., 2014; Nathan et al., 2018). In contrast, Optical satellite image classification tend to more accurately represent the forest canopy and was able to distinguish between water bodies from areas of very low vegetation.

The ALOS PALSAR L-Band data was more effective than the Sentinel 1 C-Band SAR data in the characterization of mangroves probably because of the high penetration capabilities of L-band into forests canopy. The confusion matrix for SAR image classification alone showed that out of 81 pixels which were identified as water body, 72 pixels were correctly classified while the confusion matrix for Optical image alone showed that out of 81 pixels which were identified as water body, all were correctly classified (Table 3–5). The overall classification accuracy for SAR image alone showed 84% while the overall accuracy for Optical image alone showed 99.1% and the overall accuracy when both images were used showed 98.9%. However, the Kappa coefficient value (0.828) shows that the classification using both Optical and Radar data has better agreement in the observations. The maps produced are suitable to inform coastal management in the area and the methodology can be reproduced for the entire coastal zone of Ghana.

5. Conclusion

The destruction of the world's tropical and sub-tropical mangrove forests is one of the most pressing environmental disasters of our time. The world may not reach the sustainable development goals without addressing deforestation and increasing restoration of mangroves as well as other forests. This paper elaborated on a novel approach to synthesize the relevant database in a spatial framework using Google Earth Engine platform and random forest algorithm to produce mangrove extent maps. Cloud computing techniques and machine learning algorithm such as Google Earth Engine as used in this study has shown the potential for accurate quantification of Mangrove stand as well as various other land uses particularly for cloud prone areas. This could allow for more accurate estimation of mangrove changes locally, regionally or globally 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 mapping changes in mangrove ecosystems and their surroundings to fill knowledge gaps essential for Mangrove management and conservation. Overall, there is a significant (16%) decadal decrease of mangrove extent in the study location which presents the need for conservation and proper monitoring and management. This would require a deliberate management plan encompassing current and alternative livelihood strategies, sustainable resource management schemes and sustained sensitization of the people about mangrove services and their value under climate change, beyond providing the immediate needs of the community. There should be continuous re-planting of Mangrove propagules in areas where there has been degradation.

Although our model estimates mangrove extent fairly well, the main limitation to this study is the lack of up to date data e.g. 2020 data as at the time of this analyses.

Abbreviations

ALOS – Advanced Land Observation Satellite

ASTER – Advanced Space-borne Thermal Emission and Reflection Radiometer

DEM – Digital Elevation Model

ESA - European Space Agency

ETM+ - Enhanced Thematic Mapper

GCVI - Green chlorophyll vegetation index

GDEM – Global Digital Elevation Model

GEE – Google Earth Engine

GMTED – Global Multi-resolution Terrain Elevation Data

HH - single co-polarization, horizontal transmit/horizontal receive

NASA - National Aeronautics and Space Administration

NDMI - Normalized difference moisture index

NDVI - Normalized difference vegetation index

NDWI - Modified normalized difference water index

NED – National Elevation Data (US Geological Survey)

OLI/TIRS - Operational Land Imager/Thermal Infrared Sensor

PALSAR – Phase Array L-band Synthetic Aperture Radar

SAR – Synthetic Aperture Radar

SDGs – Sustainable Development Goals

SR - Simple ratio

SRTM – Shuttle Radar Topographic Mission

VV- single co-polarization, vertical transmit/vertical receive

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The datasets generated and/or analyzed during the current study are available in Google Earth Engine database. The Java codes used for this study can be found at <https://code.earthengine.google.com/a2400e2ce048914ccf1b16aba2702951>

Competing interests

The authors declare no competing interests

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Authors' contributions

Conceptualization, D.A., M.M and D.B.A.; methodology, D.A., M.M and D.B.A.; software, D.A.; validation, D.A.; writing—original draft preparation, D.A.; writing—review and editing, D.A., M.M and D.B.A. All authors have read and agreed to the published this manuscript.

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Figures

Figure 1

Map of Study Location. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

Key concepts related to sustainable development and links to the most relevant sustainable development goals, targets, indicators and series. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

OPTICAL SATELLITE IMAGE

Figure 3

Cloud Free Landsat 8 Imagery. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 4

False Color Composite of Landsat Image Clipped to Study Area. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

FILTERED SYNTHETIC APERTURE RADAR IMAGE

Figure 5

Filtered Synthetic Aperture Radar Image. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 6

Iteration Process for Random Forest Model

Overlay of Optical and SAR Images

Figure 7

Overlay of Optical and SAR Data. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 8

Training and Validation Points for the study area. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Optical and Radar Image Classification for 2009

Figure 9

(A) Classification Scenario using Optical data only (Landsat 7); (B) Classification Scenario using PALSAR data; (C) Classification Scenario using both Optical and PALSAR data. The overall classification accuracy for this scenario is 99.1% and the Kappa Coefficient is 0.797. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Mangrove Extent 2019

Figure 10

(A) Classification Scenario using Optical data only (Landsat 8); (B) Classification Scenario using SAR data only; (C) Classification Scenario using both Optical and SAR data. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.