



West Africa Blue Mangrove Assessment Methodology

A Living Labs Report

June 2024



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List of Commonly Used Abbreviations

ALOS PALSAR: Advanced Land Observing Satellite Phased Array type L-band Synthetic Aperture Radar

CMRI: Combined Mangrove Recognition Index

ESA: European Space Agency

GEE: Google Earth Engine

GEEMMM: Google Earth Engine Mangrove Mapping Methodology

GMW: Global Mangrove Watch

HRP: Historical Reference Period

MMRI: Modular Mangrove Recognition Index

MNDWI: Modified Normalized Difference Water Index

NDMI: Normalized Difference Mangrove Index

NDVI: Normalized Difference Vegetation Index

QGIS: Quantum Geographic Information System

SAR: Synthetic Aperture Radar

SOPs: Standard Operating Procedures

SRE: Sherbro River Estuary



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Key Findings

- Mangroves act as significant carbon sinks, storing more carbon per unit area than any other ecosystem. The majority of this carbon is stored in the belowground soil, trapped by the root systems over decades (IUCN, 2017).
- Deforested mangrove areas experience loss of root structure, leading to soil erosion and carbon release. This erosion can cause significant shoreline degradation (Goldberg et al., 2020).
- The FAO (2023) reported a net loss of 284,000 hectares of global mangrove area but noted a decline in the rate of deforestation between 2000-2020.
- Accuracy of classified mangrove maps is validated using drone orthomosaics and a QGIS class assessment tool. Real class points generated from drone imagery are compared with classified mangrove points, ensuring high accuracy (100 points per class).
- Accessing remote mangrove forests is difficult due to their coastal nature and dense root networks. Collaboration with local communities aids in data collection.
- Differentiating similar land cover classes and stratifying short and tall mangroves are challenging due to spectral similarities. Height mapping and field data incorporation improve classification models.
- Decentralized degradation and hidden canopy gaps are difficult to detect via satellite imagery alone. Community-based monitoring and project-specific radar-biomass models are essential for early warning systems.
- Seasonal analysis is limited by cloud cover, and soil carbon data is lacking in West Africa, necessitating extensive field data collection.



Foreword

In the past three decades, West Africa has lost between 25% to 50% of its mangrove forests, according to USAID. Reaching as high as 60 meters tall, these are some of the largest mangroves left in the world. Illegal fishing practices and population pressures have strained these fragile ecosystems, as dwindling fish stocks force communities to turn to mangrove wood for income and sustenance. Rice cultivation, salt mining, and construction compound the issue. Alongside these challenges, coastal communities in Sierra Leone and Guinea face severe economic hardship, with many living on less than \$1.90 PP per day and ranking 166th and 157th, respectively, (out of 185) on the climate vulnerability index.

Nature plays a critical role in solving both local and global environmental crises. Today, the only way to sustainably finance the protection of ecosystems and biodiversity, take urgent action to combat climate change, and support economic development for coastal communities in West Africa is through carbon markets. This is the mission of West Africa Blue (“Blue”).

West Africa Blue is a community-centric developer of high integrity, large-scale, blue carbon projects in West Africa. Headquartered in Freetown, Sierra Leone, Blue partners with local communities and governments to develop and scale projects that mitigate climate change, protect biodiversity, and enhance community livelihoods, resilience, and adaptation.

The primary focus of this report is Blue’s comprehensive approach to mapping and analysing mangrove forests. Leveraging industry leading techniques, software and machine learning algorithms, Blue has developed a robust methodology to classify and monitor mangrove extents. This report sets forth the vital role of ground truthing and field data in validating remote sensing results. Despite advancements in satellite technology, accurately classifying mangrove forests still requires on-the-ground verification to address issues such as the misclassification of water bodies and the differentiation of tall and short mangroves.

In addition to mapping and classification, the report details Blue’s approach to mangrove carbon analysis. This includes stratifying mangrove layers into tall and short categories, collecting and modeling biomass and soil carbon data, applying allometric equations to estimate carbon stock and integrating drone imagery and radar data to enhance accuracy.

Ultimately, this report underscores the importance of integrating advanced technological tools and traditional field methods in the conservation of mangrove ecosystems. By sharing Blue’s methodologies and findings, alongside other learnings, models and tools in our ‘Living Labs’ offering, we aim to offer insights to support global efforts in preserving these critical habitats.



Elizabeth Littlefield
Senior Partner, West Africa Blue





1. Introduction

Blue carbon ecosystems, especially mangroves, provide critical services for the environment, biodiversity, and local communities. Mangroves support thriving fisheries, provide a protective barrier from coastal storms and are a carbon sink with more storage potential per unit area than any other ecosystem (Alongi, 2002). Unlike traditional forests, most of the carbon in mangrove ecosystems is stored not in woody biomass but in belowground soil (IUCN, 2017). Trapped and held in place by the mangroves' intricate root systems, these dense layers of soil organic carbon are formed over decades of deposition.

On the other hand, blue carbon ecosystems present a risk of significant carbon emissions when these long-term carbon stores are disturbed, thereby further contributing to global climate change. In the case of deforested mangrove areas, loss of root structure allows trapped soil (and carbon) to erode with the tide, resulting in shoreline erosion (Goldberg et al., 2020). In the heaviest impacted areas, shorelines can be seen breaking off in chunks like a cleaving iceberg. According to FAO, (2023), although mangrove deforestation rates decreased in the latter decade between 2000-2020, there was a net loss of 284,000 ha of global mangroves during this period.

This sobering reality has led to a surge of interest from scientists and conservationists with the joint aim of quantifying and addressing global mangrove deforestation. However, the same intricate structures of estuarine mangrove forests that provide habitat for fish, marine mammals, sea turtles, primates, and birds, also make them extremely difficult to reliably classify through remote analysis alone. While the use of proven terrestrial techniques has been tried, the result is often a large under-classification of the actual amounts of mangrove deforestation. In carbon projects, this risk of inaccuracies of deforestation rates translates into a loss of opportunity for indigenous peoples and local communities who may not have other means of receiving sustainable support for the conservation of their mangrove forests over the long-term. Thus, despite the growing emphasis on fully remote monitoring, reporting, and verification (MRV), ground-based verification and other advanced techniques are necessary to supplement satellite-based spatial analysis to ensure accuracy and reliability in classifying mangrove ecosystems.

2. Mangrove Extent and Deforestation Analysis

West Africa Blue's ("Blue") methodology for mapping mangroves is based on recent literature on best practice of mangrove mapping including: The Google Earth Engine Mangrove Mapping Methodology (GEEMMM) (Yancho et al., 2020) and cloud-computing and machine learning in support of country-level land cover and ecosystem extent mapping in Liberia and Gabon. (De Sousa et al., 2020). To date, Blue has primarily focused mapping efforts on the coastal region in Sierra Leone.

The remote analysis utilizes publicly available satellite imagery that can capture unique properties of mangrove blue carbon ecosystems and are often available within weeks of image capture.



Optical imagery enables the differentiation of vegetation, bare ground, and artificial surfaces while radar imagery enables the differentiation of vertical structures beneath the canopy (and through pervasive cloud cover). Using a combination of spectral bands from multiple satellites, Blue employs machine learning algorithms in the classification of land cover types. We are developing methods to enhance our capacity to understand long-term land cover changes over a large scale. We also make use of various available software for satellite image analysis such as the Google Earth Engine (GEE) platform (Gorelick et al., 2017), Google Earth Pro, QGIS (QGIS Development Team, 2024), and R (R Core Team, 2021; RStudio Team, 2020) to create shareable avenues to access this satellite imagery, generate new map layers, and improve land cover modelling on a broader scale. **Figure 1** is a visual representation of the process that Blue follows to conduct this analysis and the steps will be further explained in the following sections.

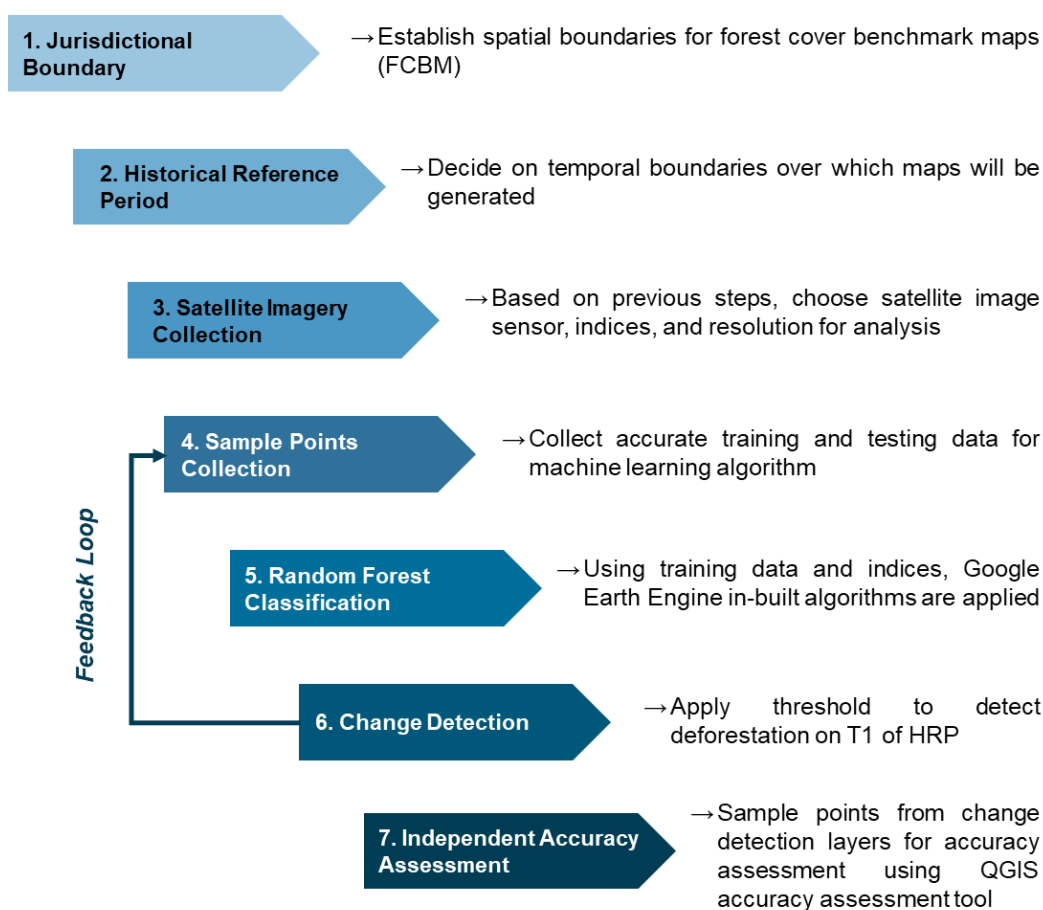


Figure 1: Step by Step process of generating jurisdictional mangrove extent and baseline deforestation over the historical reference period.



2.1. Satellite Imagery Collections – Steps 1-3

Following Steps 1-3 in **Figure 1**, we establish both temporal and spatial boundaries of the analysis. This includes establishing jurisdictional boundaries, the historical reference period (HRP) and available datasets that will be used in the analysis.

Jurisdictional Boundary – Step 1: Initially, all of the coastal prefectures of the target country were used. While this enabled a defined administrative boundary for comparison, due to the size of the files, this created memory issues during the analysis. In response, a 10km buffer around the 1996 mangrove layer from the Global Mangrove Watch (GMW) of the target country was used instead. The advantage of this is add a further accuracy in the identification of mangroves in the country.

Historical reference period (HRP) – Step 2: A challenge in mangrove assessment often is selecting the date range for satellite imagery collection for an analysis for a target year. This is usually a calendar year (01/01/XXXX – 12/31/XXXX) year XXXX. However, when there is significant cloud cover as was found in Cameroon, the satellite imagery collection was extended for 6-12months on either side of the date range. This usually ends up spanning 3 years with the middle as the target year. For example, 2013 analysis year spanning 01/01/2012 – 12/31/2014. According to the [Request for Proposal document](#) for Data Service providers for Jurisdictional Activity Data and Forest-Cover Benchmark Maps, the current HRP for Sierra Leone is Jan 1, 2014 – Dec 31, 2023. However, the document states that the dates are provisional with minor changes and allows for +/- one year of the HRP to allow for imagery availability.

Available dataset – Step 3: Datasets available for analysis usually depend on the target years of analysis. As of 2023, the HRP of most countries in West Africa spans 2013/2014 – 2022/2023 based on Verra's requests for proposed analyses from DSPs. While Landsat imagery covers this HRP, Sentinel data only starts from 2014/5 and as such is limited in covering the HRPs. As a result, the earliest HRP that will comfortably use exclusively only Sentinel imagery is 2016-2025. As of March 2024, we currently use an HRP of 2013-2023.

Satellite Image Collection: Image Resolution – Step 3: According to Verra methodology (as exemplified in VM0048), a resolution of 10m or finer must be used for analysis for 2015 onwards and a minimum of 30m pre-2015. This means Landsat must be used for the first analysis year of the HRP (2013) and Sentinel for the remaining two (2018, 2023). As a result of Landsat imagery only having a 30m resolution in the first HRP, there is always a challenge of overestimation of mangrove cover and misclassification of water as mangrove (the width of some waterways is less than 30m wide with overhanging canopy). To match Sentinel 10m resolution, Landsat imagery is resampled to 10m resolution.

2.2. Sample Points Collection: Vegetative Indices – Step 4

Research into detecting mangrove ecosystems using satellite imagery has progressed over the years. Common indices used in differentiating mangrove and non-mangrove classes include (Figure 2):

- Modified Normalized Difference Water Index (MNDWI):** This is an enhanced version of the Normalized Difference Water Index (NDWI) that improves detection of open water. It is beneficial in mangrove mapping because of the flooded nature of this ecosystem. (Xu, 2006)
- Modular Mangrove Recognition Index (MMRI):** The MMRI was designed to better discriminate mangroves from other surrounding vegetation. (Diniz *et al.*, 2019)
- Normalized Difference Vegetation Index (NDVI):** NDVI is an index that is used to identify vegetation from non-vegetation. It can also be used to assess vegetation health and density.
- Normalized Difference Mangrove Index (NDMI):** NDMI, like MMRI improves differentiation of mangrove from surrounding vegetation types (Shi *et al.*, 2016).
- Combined Mangrove Recognition Index (CMRI):** The CMRI is an index generated from using NDVI and NDWI representing the greenness and water content of mangrove forests (Gupta *et al.*, 2018).

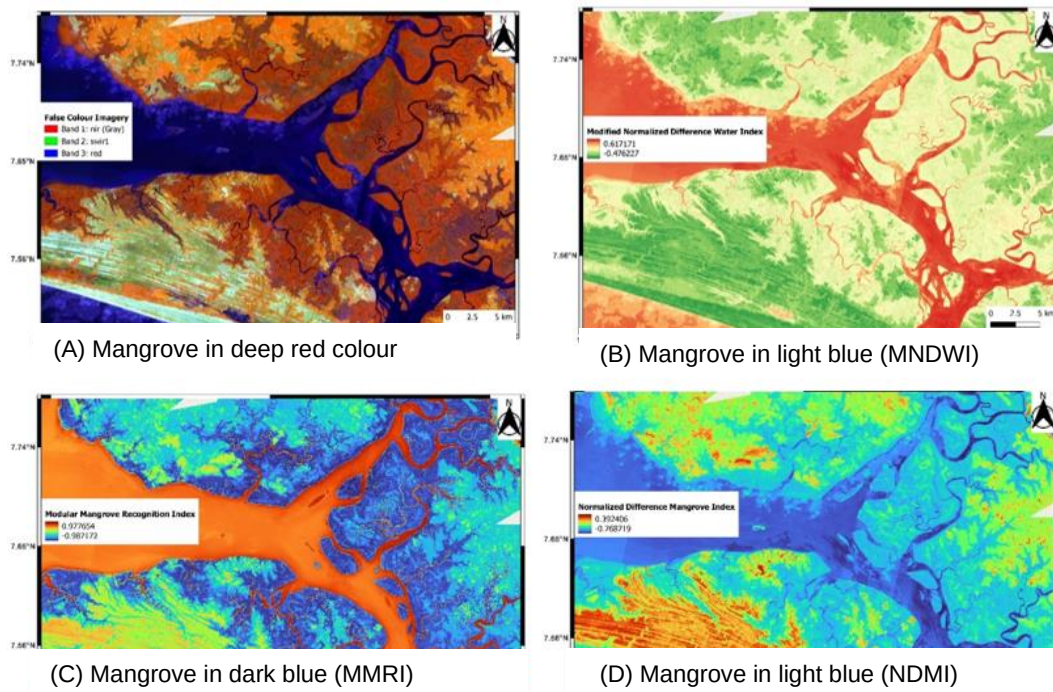


Figure 2: Figure of SRE region showing distinctive spectral signature of mangrove in false colour imagery (A), MNDWI (B), MMRI (C) and NDMI (D).

Land cover specific indices enable the binary classification of various land cover classes including water and bare ground. By including these indices, we were able to create a more accurate classification of mangroves. As well, we magnified the mangrove signal by combining relevant mangrove specific indices (**Figure 3**).

- Sum of mangrove Indices (MMRI, NDMI)
- Sum of mangrove and water indices (MMRI, NDMI, MNDWI)

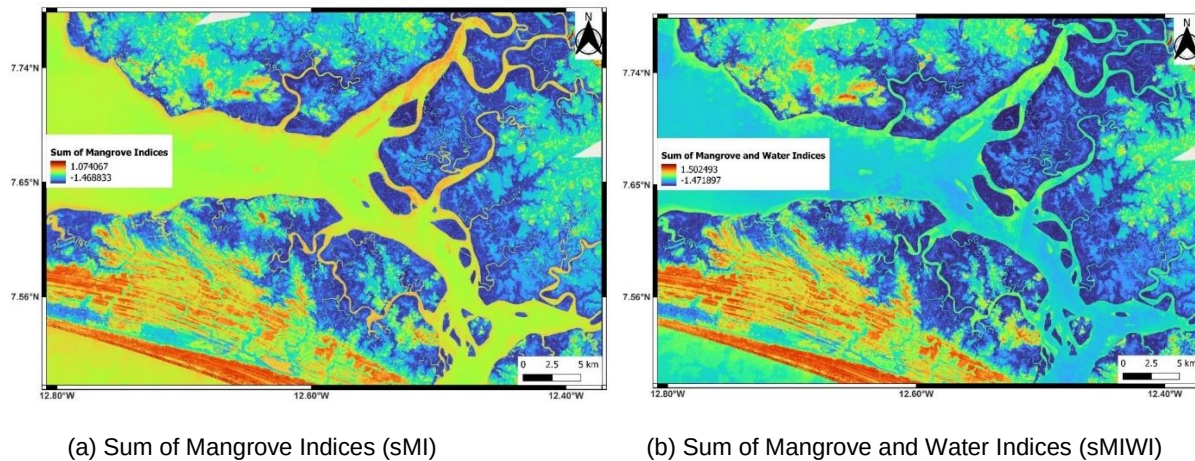


Figure 3: Figure of SRE region showing distinctive spectral signature of mangrove in modified indices: (a) Sum of Mangrove Indices (sMI) and (b) Sum of Mangrove and Water Indices (sMIWI).

These indices are used as input for the classification algorithms and a threshold is applied to mask the satellite imagery, leaving enough range for non-mangrove data to be differentiated as well (De Sousa et al., 2020).

2.3. Sample Points Collection: Training Data Collection – Step 4

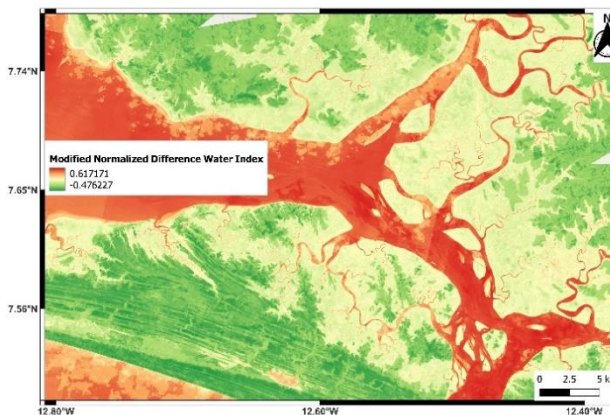
Training data collection: We used a threshold based on research by De Sousa et al., (2020) for pre-classifying by masking land cover classes. These thresholds are applied to the mangrove indices from the previous section, increasing the accuracy of differentiating mangrove and non-mangrove classes. However, during the collection of class and non-class training points, care is taken to generate equal number of points for accuracy analysis.

Google Earth Pro: Additional training data is collected after a first run of analysis based on stable mangrove during the HRP. The collection of these stable mangrove points will reduce the inaccuracies encountered using different satellite imagery and temporal variation. This is used for a second-tier mangrove classification.

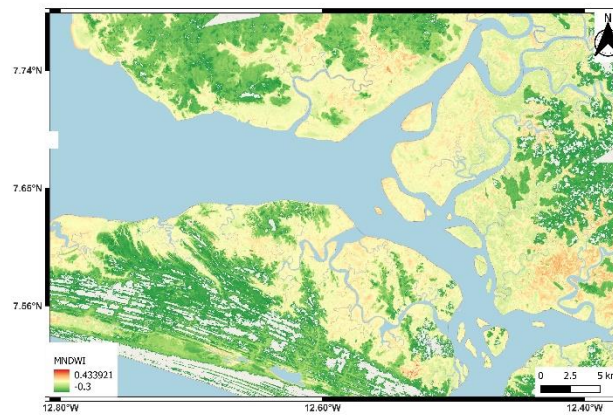
2.4. Random Forest Classification: Classification Algorithm – Step 5

The Classification Algorithm methodology has been successfully applied in Liberia and Gabon (de Sousa et al., 2020), and involves a two-step process: first, thresholds for various vegetative indices (normalised ratios of satellite imagery bands) characteristic of mangrove ecosystems are applied and validated (**Figure 4**). Second, a supervised random forest classification, which considers unique satellite data properties for the land cover in focus, divides the pixels into Class/Non-class categories based on the similarities of these select properties with those from the provided training points. We employ a random forest classification algorithm in Google Earth Engine using 80% of sample points for training the algorithm and 20% to test for accuracy. Using the training points, we run the model with 500 trees and 5 randomly selected predictors per split (dependent on number of bands/ indices used in the model). The testing points are used to check the accuracy of the model and a confusion matrix, a ratio of how many of the testing points have been categorized correctly by the model, is then generated to display the results of the accuracy assessment. We also use a combination of optical (Landsat/ Sentinel 2), radar (ALOS PALSAR/ Sentinel 1) and spectral indices as training data for classification. A binary classification with 0 (non-class) and 1 (class) is then run.

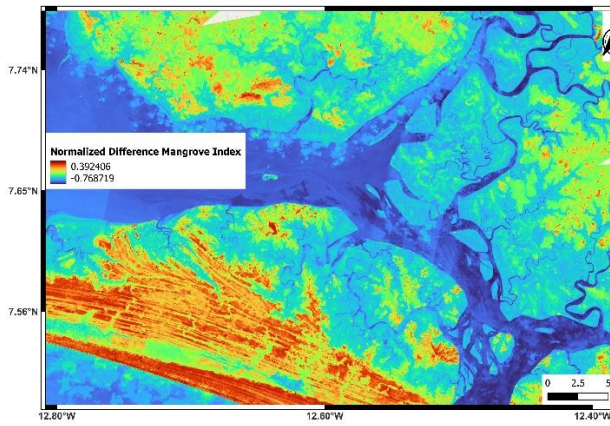
(a)



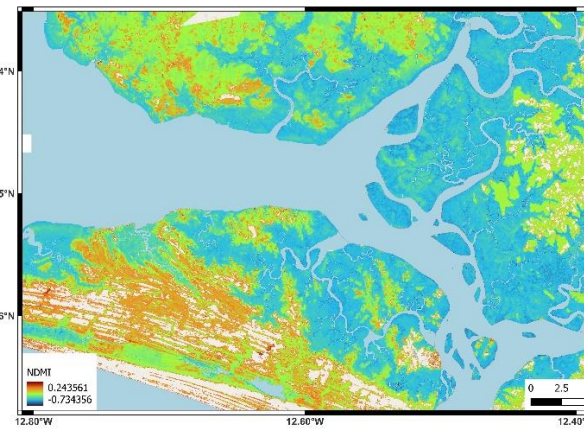
(a)



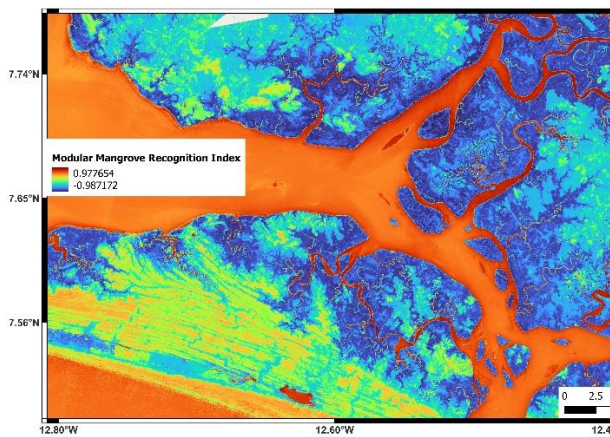
(b)



(b)



(c)



(c)

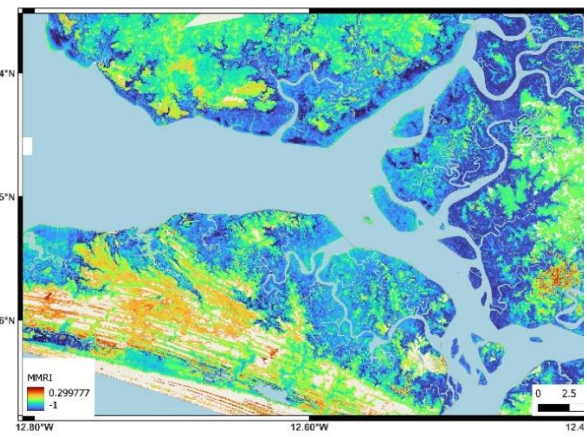


Figure 4: Imagery showing application of threshold to classifying mangrove using MNDWI- Mangrove in light green (a), NDMI- Mangrove in light blue (b), and MMRI- Mangrove in blue (c). The first image of each pair has no mask. The second image in each pair has a threshold water masked and thresholds on NDMI (<0.3), MMRI (<0.3), MNDWI (<-0.3) and NDVI (>0.1).

2.5. Change Detection – Step 6

We use two methods for assessing change in mangrove extent over the HRP. First, we use the first year in the HRP as our baseline year and track deforestation based on change in vegetative indices signals. We test for these signals by extracting descriptive statistics of deforested, stable and shrub mangrove layers. These statistics give us a threshold of these layers over time. We then apply these thresholds over the later analysis years, T2 and T3, to determine baseline deforestation. This creates a more accurate deforestation rate based on the loss of greenness of mangrove cover over time (**Figure 5**). The three mangrove cover benchmark maps during the HRP are also used to run a change detection, enabling us to detect mangrove gain in addition to loss. We also check for accuracy of mangrove deforestation detected and generate more training data for classification.

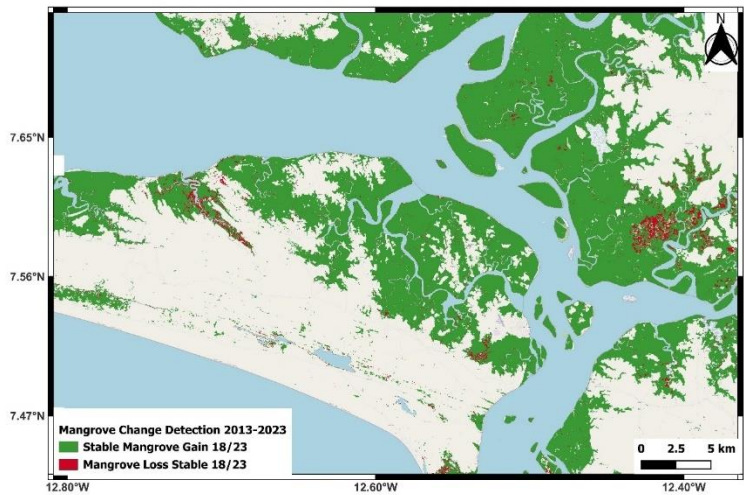


Figure 5: Mangrove forests and deforestation during HRP 2013-2023.

2.6. Independent Accuracy Assessment – Step 7

A QGIS class assessment tool- Class Accuracy is used to generate accuracy of the classified mangrove map. Drone orthomosaics of various blocks of the coastline are used to generate real class points that are compared with classified mangrove points. At least 100 points are generated for each class for accuracy.

While there are global datasets of mangrove cover such as the Global Mangrove Watch and land cover maps such as the European Space Agency (ESA) WorldCover 2021, some of these global datasets lack regional validation, which reduces accuracy in classifying mangrove ecosystems and the land cover they transition to when they are lost.



Figure 6: A comparison of Delkin, a community on Sherbro Island, Sierra Leone, as seen by Planet satellite imagery (top) and drone orthomosaics (bottom) in March 2023. The most recent Google Earth imagery of this location is from 2018.

To overcome this, Blue generates project-specific map layers using a combination of geo-tagged photos and high-resolution (<5cm/pixel) orthomosaics from drone-based photogrammetry to capture the exact locations of various land cover types and monitor transitions in real time. These field data are critical for validating and training our remote sensing models, allowing accuracy that would be unattainable through satellite analysis alone.

These high-resolution maps are not only useful for Blue's team to select training and validation points for our classification models, but can also be easily shared with technical partners, policymakers, and other stakeholders to understand the present situation more clearly on the ground. For example, **Figure 6** shows a comparison of Delkin, a community on Sherbro Island, Sierra Leone, as seen by Planet satellite imagery (top) and drone orthomosaics (bottom) in March 2023. The most recent Google Earth imagery of this location is from 2018. This example clearly highlights the need for high-resolution maps in order to create the most accurate understanding of the present-day situation.

3. Mangrove Carbon Analysis

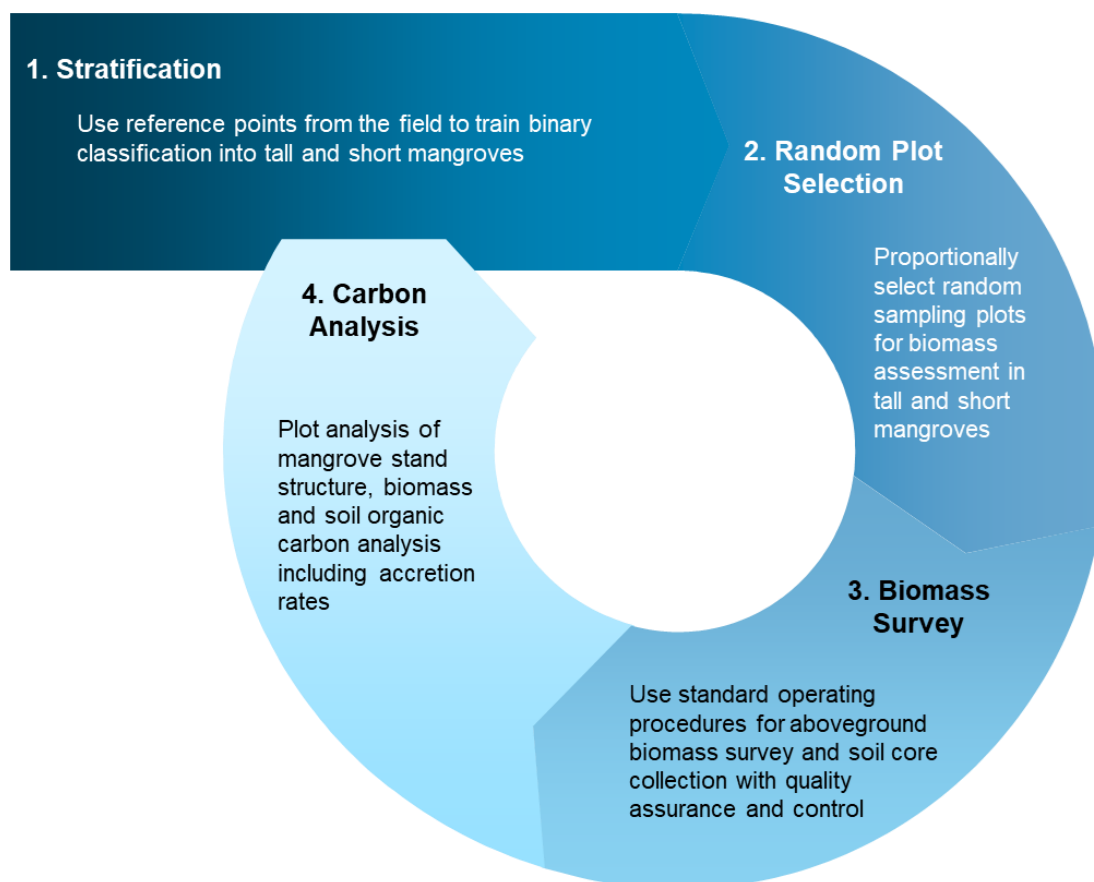


Figure 7: Mangrove carbon analysis process

As with Figure 1, **Figure 7** showcases the mangrove carbon analysis process that is implemented by Blue, with the steps explained in further detail in the following sections. This analysis first requires the stratification of mangrove layers into tall and short mangroves. We based our stratification on the height of mangrove stands. Tall mangroves were defined as having a height above 5m and short mangroves 5m or less. Based on this stratification, we conducted a preliminary field survey to collect in-situ training data for a binary classification of mangrove at the end of the HRP. We then used a machine learning algorithm and radar back scatter from Sentinel 1 and ALOS PALSAR to train the sample data. After stratification, random sampling plots are generated based on the proportion of tall and short mangroves. Biomass carbon is estimated using standard procedures.



Figure 8: *Sediment cores showing measurement of depth*

Aboveground biomass is determined through allometric equations that use measurable characteristics, such as trunk diameter and tree height, to estimate tree volume and biomass carbon. Allometric equations are specific to the species and region in which they were developed, hence biomass estimation is dependent on using the proper allometric equations. However, the generation of new species or regional equations requires the removal of a significant number of live trees. For this reason, Blue uses existing equations that are species-specific to the project regions. Soil carbon storage is assessed using 1 meter soil cores collected and split into sections representing periods of soil deposition over time. The total carbon content in these soil sections is estimated using a Carbon-Nitrogen analyser. Tree-level biomass and soil carbon is then aggregated over a plot area, which can be extrapolated over a project region to give an estimate of total ecosystem carbon stock.

3.1. Stratification and Random Plot Selection – Steps 1-2

Initial field data on mangrove heights is collected using a rangefinder. These are then divided into tall mangroves ($>5\text{m}$ height) and short, or 'shrub', mangroves ($\leq 5\text{m}$ height). The division of these sample points are used for a binary classification of tall and short mangrove of the last HRP analysis year (2022/ 2023). We use radar data for the classification of mangrove into tall and short layers, namely ALOS PALSAR 25m and Sentinel 1 10m, which are freely available on GEE. Using a combination of both data sets further improves the accuracy of stratifying the mangrove layer. This stratified mangrove layer is then used as input to generate plot locations for aboveground analysis (**Figure 9**).

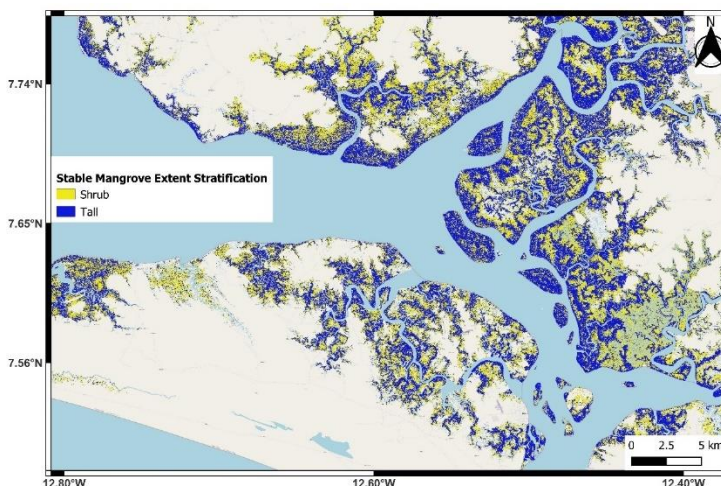


Figure 9: *Mangrove stratification into tall and short mangroves*



The stratified mangrove extent is randomly sampled to select plot locations for aboveground biomass and soil core analysis. The number of plots selected for the field study is determined using a biomass plot selection tool.

3.2. Biomass Survey and Carbon Analysis – Steps 3-4

At Blue, we use a standard operating procedures (SOPs) manual in the collection of aboveground biomass data based on best practices (Howard et al., 2014; Kauffman & Donato, 2012), including training and quality control. These SOPs describe the steps to collect mangrove biometric data that will be used to estimate with an accuracy above 90% the carbon stock contained in the biomass of tall and short mangrove forests.

Once a sufficient sample of region-specific field data has been collected through soil coring and biomass surveying, these data may finally be applied to remote sensing products. At Blue, we are developing a region-specific radar-biomass model comparing radar properties from satellite with plot specific biomass data collected during field surveys. This allows us to generate a radar (backscatter) to biomass equation (with an error estimate), from which mangrove biomass densities can be remotely extrapolated across large regions of mangrove ecosystems.

At the end of the biomass field campaign, improvements are made on the stratification analysis by feeding back data from the field into the division of tall and short mangroves.

4. Challenges

West Africa Blue continually aims to improve the accuracy of detecting mangrove ecosystems and deforestation using a combination of satellite imagery and field data. While satellite data and processing abilities have increased over the last decade, there are still several challenges when working in mangrove ecosystems. Mangrove specific indices have improved our ability to differentiate mangrove ecosystem from other land covers. However, the differentiation of degradation and deforestation remains an issue.

- i. **Difficulty in reaching remote mangrove forests:** The coastal nature of mangrove ecosystems, and the sometimes-impenetrable network of roots created by mangroves, makes access difficult for field surveys, especially if they involve heavy equipment. Blue's approach to collecting these vital field data has always been to collaborate closely with local communities through our teams of community coordinators and local staff to benefit from local knowledge and community-based monitoring.
- ii. **Similarity of land cover classes:** Some land cover classes can be very difficult to distinguish from one another (for example intermittently cleared agricultural land and open ground; natural forests and plantations), making land cover classification difficult. To address this, we iteratively dial in on a variety of satellite indices that are unique to each land cover until



reaching a threshold at which a minute difference among two similar land covers can be detected.

- iii. **Mangrove stratification:** One of the requirements in mangrove methodologies is the division of the forest class, which applies to mangroves when both short and tall mangrove classes are present. This stratification is difficult through remote analysis since short and tall mangroves can be of the same species and thus exhibit the same spectral signature. To better distinguish these classes, height mapping exercises have been conducted to collect canopy height data across large areas. These field data are being incorporated into our classification models to improve the accuracy of defining short and tall mangroves within the project areas.
- iv. **Decentralized degradation:** Traditional satellite models are most adept at capturing deforestation occurring along a frontier, or within predictable limits of roads and villages. With mangroves, access by boat along rivers and narrow channels allows degradation to occur even in remote and uninhabited areas. Smaller creeks and streams are typically completely covered by the mangrove canopy and not visible via satellite until they are degraded to the point that the canopy opens above them.
- v. **Hidden degradation:** Decentralized cutting and thinning typical of subsistence-based harvesting leads to the emergence of canopy gaps randomly distributed throughout the mangroves, creating a 'Swiss cheese effect' visible in satellite imagery. Before canopy gaps become visible via satellite, however, degradation may still be taking place beneath the canopy. This makes it impossible to identify truly pristine mangroves via satellite analysis alone, as areas may appear pristine until ground truthing reveals cutting of the understory. In addition to community-based monitoring to detect these areas, Blue is developing project-specific radar - biomass models to help serve as an early warning system that degradation is taking place beneath the canopy.
- vi. **Capturing seasonality within time periods:** Optical data has the advantage of long term and global coverage but is limited by high cloud cover typical of tropical mangrove areas. This results in some monthly data missing to perform seasonal analysis, which can be useful in differentiating some land cover classes. Seasonal flooding, tide patterns, and long-term oceanic events such as ENSO must also be considered in mangrove analysis.
- vii. **Soil carbon data availability:** Unlike carbon stocks in terrestrial forests, most of the carbon in mangrove ecosystems is stored below ground. Mangrove soil carbon data is currently lacking in West Africa, so soil sampling must be completed as a precursor to project development. Blue aims to address these challenges by conducting rigorous field data collection and soil carbon analyses throughout the region and comparing multiple methodologies to save costs and increase efficiency.



- viii. **Extrapolated biomass data:** The use of region and plot-specific biomass data to extrapolate total carbon stock in biomass is currently the best approach available but is still an estimation. Full quantification of aboveground biomass in a mangrove ecosystem requires drone-based Lidar assessment, which is prohibitively expensive for most projects. Blue is testing several unique methodologies to improve the accuracy of current biomass models and looks forward to the availability of satellite-based P-band (the first capable of fully seeing through dense canopies) expected from the ESA Biomass Mission (expected launch in 2024).

Lessons Learned

One of the major discoveries in developing Blue's methodology is the critical need for data from the field combined with remote sensing analysis to maximize accuracy, as the spatial analysis alone does not provide an accurate view of degradation and deforestation below the canopy. The dense structure of mangrove forests makes it impossible for traditional remote sensing to detect degradation from cutting and thinning beneath the canopy, which can lead to degraded areas appearing pristine in classification models. This necessitates the use of frequent ground truthing and the development of new techniques in biomass modelling to accurately assess degradation. Communities living around blue carbon environments can also provide information on historical changes to these ecosystems that can sometimes be undetectable from remote sensing imagery.

Carbon models developed to quantify deforestation emissions in the terrestrial landscape are similarly not suitable for mangrove blue carbon projects. Blue is working with industry-leading scientists to further our level of research and understanding in the fate of carbon after mangrove loss through erosion, oxidation, and remineralization.

5. Conclusion

Satellite imagery alone is inadequate to generate a complete and accurate understanding of mangrove deforestation and degradation. As well, currently available land cover classification models are insufficient for analysing mangrove ecosystems in West Africa due to a lack of regional validation. The unique challenges of these coastal environments including seasonal flooding, hydrological shifting, and frequent cloud cover require unique modelling solutions, which creates an opportunity for West Africa Blue to experiment, improve and deliver high accuracy mangrove models that can be shared and utilized by other projects within the region.

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