MANGROVE SPECIES MAPPING AND ABOVE-GROUND BIOMASS ESTIMATION IN SURINAME BASED ON FUSED SENTINEL-1 AND SENTINEL-2 IMAGERY AND NATIONAL FOREST INVENTORY DATA

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ABSTRACT

Obtaining state-of-the-art data on the Mangrove cover extent is important to monitor possible responses to environmental changes such as land use change and mangrove ecosystem degradation caused by climate change. In this study, we examined the possibility of species-specific mapping within the mangrove area in Suriname based on the fusion of Sentinel-1 and Sentinel-2 data using the Google Earth Engine platform and a Random Forest classifier. To do this, a 2-level classification scheme was developed. In the first level, the mangrove cover was discriminated from mangrove graveyards and other land cover classes (kappa index of 0.8). In the second level, the dominating mangrove species were successfully classified within the living mangrove cover (kappa index of 0.75). Secondly mangrove above-ground biomass (AGB) was estimated on a national scale, based on fused Sentinel-1 and Sentinel-2 data and national mangrove forest inventory data by using a Support Vector Regression (SVR) machine learning technique, resulting in a root mean square error (RMSE) of 32.181 $Mg.ha^{-1}$ and a R^2 of 0.542.

Index Terms— mangroves, species mapping, above-ground biomass, sentinel-1, sentinel-2, support vector regression

1. INTRODUCTION

Mangrove forests are proven to have a significant potential in the context of climate change mitigation [1]. Although coastal morphodynamics have not proven to result in net losses for the national mangrove forest cover of Suriname on a decadal scale [2], effects resulting from ongoing climate change have the potential to alter this balance, ultimately resulting in a decrease in the mangrove forest cover extent. Remote sensing offers the tools to efficient and accurate mapping of mangroves on large scales in a repetitive way, without the need for extensive field visits. This is especially crucial for Mangroves, where field visits are tough.

The overall goal of this study was to evaluate the potential of fused Sentinel-1 and Sentinel-2 data to assess the actual state of mangrove forests in Suriname. Two objectives are covered: (i) the development of classification method in order to map the distribution of (dominating) mangrove species and mangrove graveyard stands using Google Earth Engine[3], (ii) to evaluate the possibilities of regional mangrove above-ground biomass (AGB) mapping with the aforementioned remote sensing data based on national forest inventory data.

2. MATERIALS AND METHOD

2.1. Study area

The study area consists of the entire mangrove covered coastal area of Suriname. Mangroves are present at both the 350 km long coastline and upstream of ocean bound rivers [2]. Three mangrove species can be found frequently in the area: *Avicennia germinans* along the sea front, *Rhizophora mangle* inland along rivers under brackish conditions and *Languncularia racemosa*, a pioneer species present in small patches at the sea front and in estuarine stages.

2.2. Field survey

A field campaign was organised in 2018-2019 to collect mangrove forest inventory data as a part of the National Forest Inventory [2]. A total of 11 Sampling Units (SU) were established equally over the study area. Each SU consists out of 4 principal sampling plots (PSP) with a size of 20x100m, along a straight 700m transect. The PSP units were subdivided in 20 10x10m main assessment plots (MAP). Within the PSP's, all trees with a diameter at breast height (DBH) greater than 10cm were measured. In addition, trees with a DBH between 5-10 cm were measured in MAP 3, 4, 17 and 18 of every PSP. Other carbon pools, such as lying dead wood, soil and roots were also measured, but not further included in this study. Single tree AGB estimations were obtained by using allometric equations. A set of potential applicable equations were analysed by Wip [4], where the species-specific equations developed by Fromard *et al.* [5] and Smith & Whelan [6] were finally chosen. The used equation for each mangrove species is given in Table 1.

The forest inventory also included decay records of every standing tree, with levels ranging from 0.5 to 3 (Figure 1). For every level of decay the leave and branch loss was taken into account by an adjustment factor (Kauffman & Donato, [7]). In case of the level 3 decay trees, trunk specific equations where used as proposed by Fromard *et al.* [5].

Additional to the mangrove forest inventory, drone pictures were taken from the mangrove canopy, serving as reference material during the training sample collection for the image classification.

2.3. Sentinel-1/2 data preprocessing in Google Earth Engine

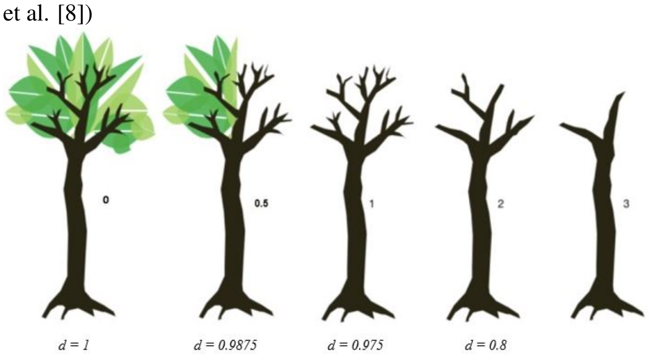
Both the Sentinel-1 SAR and Sentinel-2 MS data were accessed and preprocessed through the Google Earth Engine platform [3].

A 10m cloud-free Sentinel-2 composite was created for the entire coastal zone of Suriname within the period of August-November 2019, covering the dry season. The Sentinel-2 surface reflectance collection was filtered to a maximum of 30% cloud probability and

Table 1. Overview of the selected biomass equations. B= biomass (kg), D_{bh}= diameter at breast height, d= an adjustment factor for tree decay.[4] ([a]used for trees with $D_{bh} > 10$ cm)

Species group	Equation	Source
Allometric relations for tree decay levels 0, 1 & 2		
Avicennia germinans	$B = d * 0.14 * {D_{bh}}^{2.4}$	[5]
Rhizophora mangle	$B = d * 0.128 * {D_{bh}}^{2.6}$	[5]
Laguncularia racemosa	$B = d * 0.1023 * {D_{bh}}^{2.5}$	[5]
Laguncularia racemosa[a]	$B = d * 0.362 * {D_{bh}}^{1.93}$	[6]
Allometric relations for tree decay level 3		
Avicennia germinans	$B = 0.070 * {D_{bh}}^{2.59}$	[7]
Rhizophora mangle	$B = 0.05875 * {D_{bh}}^{2.62}$	[7]
Laguncularia racemosa	$B = 0.203 * {D_{bh}}^{2.09}$	[7]

Fig. 1. Mangrove tree decay levels, with corresponding adjustment factor d for the levels 0 - 2, as used in Table 1 (adapted from Howard et al. [8])



clouds were masked based on the *'Sen2Cloudless'* cloud masking algorithm [9]. Sentinel-2 derived vegetation indices (NDVI, MNDWI, NDWI, IRECI) were added to the image stack, together with a Mangrove specific Vegetation Index (MVI) developed by [10]. Finally, a median reducer was applied on the remaining image collection.
The Sentinel-1 Ground Range Detection (GRD) collection in Google Earth Engine is already preprocessed to a calibrated, ortho-corrected product with the aid of the Sentinel-1 toolbox [11]. The S1-collection was further filtered to retain only images in Interferometric Wide (IW) mode, both VV and VH-polarizations and to the same area and period as the Sentinel-2 composite. A speckle filter was applied to reduce the pepper-salt effect. To retrieve a final image for both the VV and VH polarisation, a mean reducer was applied.
Ultimately the Sentinel-2 composite, the vegetation indices and the Sentinel-1 VV,VH backscatter images were merged into one final image.

2.4. Mangrove cover and species mapping

A two-level classification approach was chosen in order to distinguish the mangrove cover and mangrove graveyard stands from other land use classes in a first level and to enable a species-specific classification within the mangrove cover in the second level (Table 2). *Languncularia racemosa* was not included in the species classification, because it grows only in small patches in the *Rhizopora* belts [2]. Training and validation samples were collected based on: 1) The forest inventory campaign, with GPS data collection, 2) visual interpretation of the UAV imagery, 3) visual interpretation of the Sentinel-2 data, 4) overflights by plane and 5) historical data on the mangrove ecosystem.

Table 2. The two-leveled classification scheme

Mangrove Cover Map (Level 1)	**Mangrove Species Map (Level 2)**
1. Mangrove (living)	1a. *Rhizopora spp.*
	1b. *Avicennia germinans*
2. Mangrove 'graveyards'	
3. Other Forest	
4. Grass/shrub vegetation	
5. Water	
6. Urban area	

For the mangrove cover classification, a Random Forest (RF) classifier was chosen for the image classification due to its combination of robustness, good performances in similar studies on mangroves [12]. It also is computationally light and simple to set-up and automate [13]. The RF classifier was initialized in GEE with a maximum number of trees (ntree) of 60, based on parameter testing.
After classification, a Mode filter was applied to the classification result, in order to remove isolated pixels and noise.

2.5. Above-ground biomass modeling

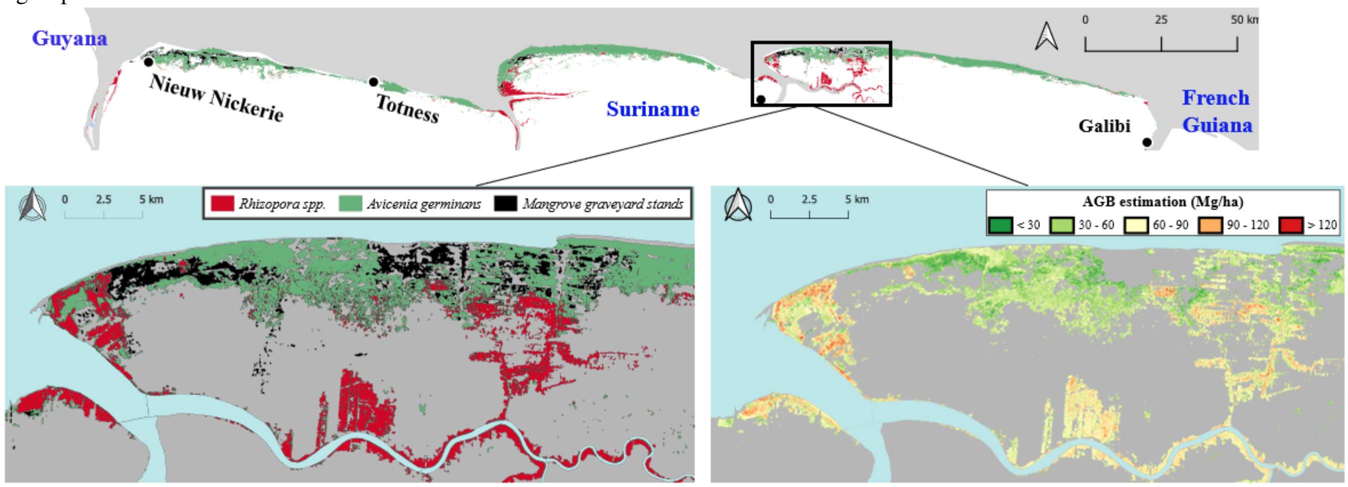
The Sentinel-1 and Sentinel-2 image stack was masked in GEE with the classified area of the living Mangrove and downloaded for further use in python. The AGB-values (in kg) on tree level derived from the mangrove forest inventory data was used. Every PSP was divided into areas of 20x20m, further called a Biomass Assessment Plot (BAP). Only trees with a $D_bh > 10$ cm were considered for analysis. The AGB values per tree where summed for every BAP and divided by the BAP area. Finally, the AGB-values were recalculated to Mg.ha^{-1}.
Within every BAP, the mean pixel values for the Sentinel-1 and Sentinel-2 derived features were calculated. Also, the dominating tree species derived from the species map was added as an additional feature. The features were then scaled by removing the mean and scaling to unit variance. The data was then randomly splitted into train- and test-data, with a portion of 25% as test data.
A Support Vector Regression (SVR) model available within the scikit-learn package in Python was chosen to predict the region mangrove AGB-values [14]. Multiple studies have already shown that using a machine learning approach such as SVR can succesfully estimate Mangrove AGB with fused multispectral and SAR data. [15]. A grid search optimization with a 10-fold cross validation on the traindata was used in order to find the optimal parameters for the SVR model. Different kernels ('rbf', 'linear', 'sigmoïd'), regularisation parameters 'C' (0.1, 1, 10, 100, 1000), kernel coefficients 'gamma' (1, 0.1, 0.01, 0.001, 0.0001) and epsilon values (0, 0.1, 0.2, ..., 1) were included during the grid search. The resulting performance parameters root mean square error($RMSE$) an the coefficient of determination (R^2) are used to calculated the performance of the final model based on the testdataset.

3. EXPERIMENTAL RESULTS AND DISCUSSION

3.1. Mangrove species map

The used Random Forest classifier used in Google Earth engine was successful for both the Level-1 and Level-2 mangrove cover maps.

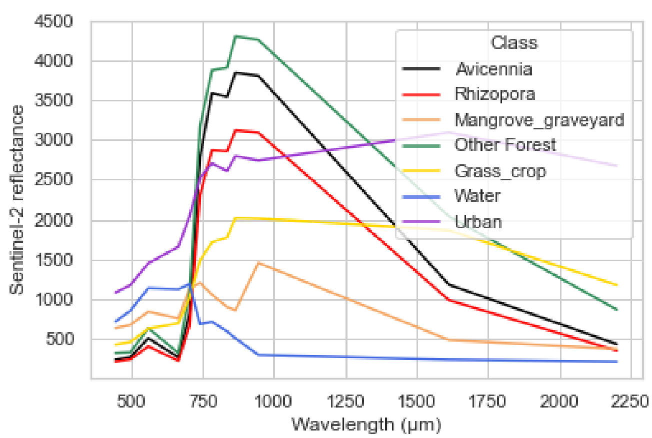
Fig. 2. Top: the coastal zone of Suriname with the classified mangrove map. Bottom left: subset of the final mangrove species map. Bottom right: predicted AGB values for the subset.



The results are evaluated by calculating an error matrix and deriving accuracy metrics, as overall accuracy (OA) and kappa index of agreement (KIA). For the Level 1 map, an OA of 84,81% and a KIA of 0.80 was reached. The Level 2 map reached an OA of 91.57% and a KIA of 0.76. After classification, the mangrove species map was merged with the mangrove graveyard cover, resulting in one general mangrove map, as shown in Figure 2.

The spectral separability was analyzed by plotting a spectral response curve for each of the land cover classes, shown in Figure 3, indicating sufficient spectral separability between the (mangrove) cover classes.

Fig. 3. Spectral profiles of the land cover classes extracted from the Sentinel-2 image.

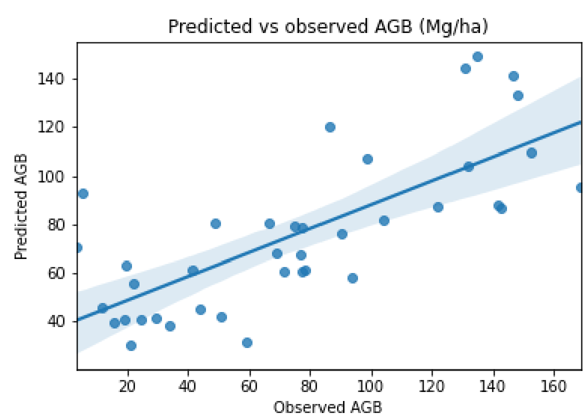


3.2. Mangove AGB in relation to Sentinel-1 and Sentinel-2 data

A grid search algorithm was performed in order to find the optimal parameters for a Support Vector Regression (SVR) model. The grid search was fitted on AGB estimates derived from the mangrove forest inventory data and the optimal parameters were evaluated by a 10-fold cross validation strategy. The resulting optimized SVR-model reached a root mean square error (RMSE) of 32.195 Mg/ha and a R^2 of 0.475, based on the test dataset (Figure 4).

The final map was visualized with the aid of QGIS. The field observations support this map, confirming that the riverine mangroves (dominated by *Rhizopora* spp.) have the largest carbon storing potential per surface area and area with mangrove decay, has a lower AGB value.

Fig. 4. Scatter plot of the observed vs predicted mangrove aboveground biomass, resulting from the final SVR model.



4. CONCLUSIONS AND PROSPECTS

In this research the current state of the mangrove forest in Suriname was succesfully determined, based on Sentinel-1 and Sentinel-2 fused data in GEE. The classification approach yielded good results, for both the mapping of the living mangrove cover and mangrove graveyard stands (kappa of 0.80). Within the living mangrove cover, a species-specific classification was performed to gain insight in the distribution of the two dominating mangrove species: *Avicen-*

nia germinans and *Rhizopora* spp. (kappa of 0.75).

Preliminary results indicated also that AGB estimations based national forest inventory data and the sentinel-1/2 fused data is promising. By taking spatial characteristics of the area into account, national estimations of mangrove carbon stock - classically only based on field inventory data - could be improved. Addition of other above-ground carbon pools, such as trees with $D_{bh} < 10$cm, could further improve the estimations.

Recent and future sensors could also improve the estimates. Space light detection and ranging (LiDAR) samples taken by the Global Ecosystem Dynamics Investigation (GEDI) for example have the ability to measure biomass relevant variables as forest canopy height and canopy vertical structure. We want to investigate how GEDI-derived features could further improve the AGB model.

Suriname is relatively species-poor. For further studies, the method that has been applied in this research will also be evaluated in Bangka Island, Indonesia with a higher richness of mangrove tree species.

5. ACKNOWLEDGEMENT

This study was conducted under the ”Setting up a Biodiversity Monitoring System” project, a subproject within the Suriname Global Climate Change Alliance (GCCA+) project, funded by the European Union and the UNDP. The project was coördinated by the Foundation for Forest Management and Production Control of Suriname (SBB).

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