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Mangrove forest parameter estimation using synthetic aperture radar data

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ABSTRACT

One of the most productive ecosystems mangrove, is the largest carbon absorber. In order to safeguard, conserve, and plan for replanting these priceless natural resources, reliable thematic maps of mangrove ecosystems and models for mangrove above-ground biomass (AGB) assessment are essential. This research emphasizes the capacities of SAR images for mangrove characteristics mapping, and the model generated is verified using ground truth data collected from the field survey of 127 sample points. Mangrove vegetation is mapped using a pixel-based random forest (RF) classifier, with an average overall classification accuracy of 91% and RMSE of 0.506. For AGB model generation the machine learning techniques applied to the dataset are Extra Trees Regressor, XGB Regressor, Random Forest Regressor, Bagging Regressor, and Decision Tree Regressor. Comparatively, it is found that Extra Trees Regressor demonstrated a good validation accuracy of 66% with 0.10 RMSE. This work validates the applicability of Random Forest (RF) and Extra Trees Regressor algorithms for mapping and estimating AGB for a unique landlocked mangrove site of Guneri.

Keywords: AGB, SAR, remote sensing, machine learning, synthetic data, normalization.

INTRODUCTION

One of the most biodiverse habitats along tropical seacoasts and bays is mangrove forests, which are made up of salt-tolerant plants with aerial breathing roots that act as sediment traps and support a variety of marine creatures Mangrove serves as a barrier to stop hurricanes, tsunamis, and ocean waves from destroying the coastal area. Mangrove controls coastal flood and erosion and safeguards inland farms, ranches, and other settlements close to the coast from storms like cyclones and hurricanes. The mapping of the world's carbon stores is becoming increasingly accurate, and fluxes have accelerated significantly in recent years. However, these evaluations have mostly disregarded mangroves due to their modest area and difficult conditions (Le Toan *et al.* 2011). It has long been accepted that most of the regions with a diverse range of mangroves are either inaccessible or logistically challenging to do research in the field conditions and is time-consuming (Nandy *et al.* 2011). As dwarf mangroves' aboveground biomass (AGB) may be as little as 8 t/ha to as high as >500 t/ha in the Indo-Pacific region's riverine and fringe mangroves. One of the main markers of a forest's carbon content is its AGB, which is simple to measure in the field but necessitates the removal of trees; hence a different approach is needed (Molto *et al.* 2013). Radar sensors allegedly have the ability to identify the volumetric properties of dense foliage (Neumann *et al.* 2012). Due to polarization, sensitivity to moisture (dielectric constant), surface roughness, varying incident angles, and strong penetration capabilities, SAR has the potential to be used for forest investigations (Sinha *et al.* 2015). This study aimed to develop a robust model for distinguishing mangroves from non-mangroves and a model for mangrove above-ground biomass estimation using spectral signatures (produced by SAR remote sensing) and morphological characteristics of mangroves. This model's foundation is built on the mangrove vegetation, which was measured for height, width, latitude, and longitude. The model prepared here takes the sigma values generated by the SAR sensors and the ground truth values as input to distinguish mangroves and non-mangroves regions and then estimates the AGB for mangroves, with the help of machine learning algorithms and also validates allometric models for mangrove above-ground biomass estimation The research was conducted in the village of Guneri's mangrove forest.

MATERIALS AND METHODS

Study Area: The Kuchchh district in Gujarat is home to one of the most extensive mangrove forests in India. These mangroves are fast deteriorating earlier they used to be 30-35 hectares in size, but now they have reduced to just around 13 hectares. The hurricane of 1998

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devastated a large portion of the groves, and the wood borer bug decimated the rest. As a result, the Guneri mangrove is an important study site (Nesha *et al.* 2020). Avicennia Marina is the only species that dominates the site.

Data Collection

The study site in the research is Guneri Mangroves of Kutch, which are different from coastal mangroves and are having tree-like structures instead of shrubs, hence they are a good carbon pool for AGB. The study area has an equal probability of being sampled and a total of 123 trees were randomly picked and measured for their height and DBH. DBH was calculated by measuring the circumference of the stem 4 and ½ feet above the ground. The circumference was calculated to |DBH| using equation 1:

$$DBH = circumference/\pi, \qquad where\ \pi = 3.14 \qquad (1)$$

This method can be used to construct allometric equations based on the measured data from the harvested trees, such as the diameter at breast height (DBH), tree height, and timber volume. In the current study to generate the ground truth AGB an existing allometric equation (Phillips *et al.* 2009) is used, as shown in equation 2; the choice of an allometric model is crucial and should be based on the study's goal and the dataset's characteristics. Allometric models should reflect the DBH range and ecology under investigation (Elmahdy *et al.* 2020).

$$AGB = 0.162 * H^{1.81} * DBH^{1.24} \qquad (2)$$

Where, H is height and DBH is breast height diameter.

Reference Samples

Accurate visual interpretation in this work required gathering reference data from high-resolution satellite images. To lessen the problem of mixed pixels by avoiding fragmented areas, homogeneous sites were taken into consideration for reference sample collecting. Three classes (mangrove, non-mangrove vegetation, and barren land) in total were created, each with sufficient reference samples and the right spatial distribution. The reference samples for the training and test were then arbitrarily split into two groups. Due to random splitting, the final classification scores exhibit little bias. SAR data extraction from ground truth data. In this study, ground truth data (height, width and DBH) were collected and tagged with a GPS location representing the coordinates (latitude and longitude), these collected coordinates were projected on a pre-processed-on Sentinel-1 SAR imagery, and VH VV backscatter coefficient values were extracted using QGIS 3.15 and a python script. The extracted VH and VV values were correlated with the actual biomass data which was calculated from the collected observations from the sites. Overall, 123 separate tree samples were collected and AGB was calculated from the study region for the purpose of estimating the biomass of the trees. In this study, generative adversarial networks were utilized to create artificial data (GAN). Ian Goodfellow (Elmahdy *et al.* 2020) introduced Generative Adversarial Networks (GANs) to address the adversarial challenge This part is divided into three subsections, each of which provides a detailed explanation of the AGB estimating model, classification methodology, and preparation of satellite data.

SAR Data Preprocessing

Each Sentinel-1 image underwent five pre-processing phases, including the following: orbit file correction, GRD border noise reduction, thermal noise removal, radiometric calibration, and terrain correction. Using the following equation, the digital numbers (DN) of SAR intensity data were transformed to Normalized Radar Cross section (NRCS or gamma-0) data (in dB):

$$y^{o}\,(dB) = 10 * log_{10}(DN)^{2} - CF \qquad (3)$$

CF is the calibration factor offered in the metadata file for each polarisation data point. The DN values of the SAR image were transformed into normalized backscatter values with the below coefficients (Manna *et al.* 2020):

$$y^{o}(dB) = 10 * log_{10}(DN)^{2} - 83 \qquad (4)$$

Here, 83 is the calibration factor for dual-polarized data.

Mangrove Classification

Machine learning algorithms must be used to accurately and affordably categorize and map mangrove forests, and these algorithms must be learned using training datasets that have greater spatial resolution and algorithm optimal parameterization. The RF technique has been used in the past to map and categorize mangroves using remote sensing data and can offer a greater grade of classification than linear classifiers. The system does well at mapping mangroves on a regional scale and at handling data that contains unclassified pixels. One of the most well-liked techniques for non-parametric ensemble machine learning and high-quality mangrove categorization and environmental modeling is the random forest algorithm. Regression and classification trees are combined in it (CART) (Mondal *et al.* 2019). Random forest (RF), a classifier, has consistently been shown to be a successful approach for mapping mangroves (Quang *et al.* 2020). For example, when researchers tested four regularly used non-parametric classifiers for mapping basis function kernels and regularised discriminant analysis. The tremendous potential of the RF classifier for mapping the mangrove environment led to the implementation of a pixel-based RF classifier within GEE for this project. The mangrove ecosystem, the RF classifier came out on top along with the support vector machine (SVM) with linear and outspread.

Mangrove AGB Estimation

Hypothetically, stand density, DBH, and species all have a direct impact on forest AGB. An important topic is how to utilize multisource remote sensing datasets to their maximum potential. We have the biomass and associated imagery data over a set of sites inside a research region following the field campaign, remote sensing data acquisition, and processing. Assume, B ij = 1,2, 3,..., N is the biomass, and X is assumed to be the data vector. The AGB estimation is to discover the prediction model P:

$$\hat{B} = P(X) \qquad (5)$$

The purpose of developing this model to minimize the error of estimation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{B}_i - B_i)}{N}} \qquad (6)$$

Machine learning techniques such as neural networks, K nearest neighbor, regression trees (RT) like Extra Tree Regressor, XGB Regressor, AdaBoost Regressor, Random Forest, and MaxEnt are some linear and nonlinear regression machine learning methods that can be used as the prediction model. When creating prediction models using a parametric method like regression analysis, factors such as the spectral responses at optical data, backscattering, and attributes obtained from PolSAR and PolInSAR data, various indices from lidar data, and picture textures can be employed directly. However, the precise selection of the training dataset accounts for a portion of the output error in a single RT. Random Forests are made to generate precise forecasts without over-fitting the data. Random forests refer to the process of building multiple trees using a randomized subset of variables using bootstrap samples. Non-parametric methods utilizing a variety of ML algorithms have shown to be more successful than parametric techniques using linear models for mapping and predicting forest AGBs. A lot of research is done in the field of mangrove AGB mapping using non-parametric regression methods such as artificial neural network (ANN), random forest regression (RFR), and support vector regression (SVM), and some recent studies have experimented with gradient boosting decision trees (GBDT) and extra gradient boost regression (XGBR) techniques.

RESULTS AND DISCUSSION

The generated data were then tested using several regression methods such as Extra Trees Regressor, XGB Regressor, Random Forest Regressor, Bagging Regressor, and Decision Tree Regressor. Table 1 displays the performances of the models on different SAR band combinations. The mean cross-validation score of 0.37 was high on the VH band when the extra tree model was used, whereas the score was only 0.35 for the same VH band when the XGB regressor was used. From this, we can conclude that VH band contributes more in estimating above-ground biomass. After taking the VH band into consideration, we used an extra tree regressor to make a prediction about the AGB of the entire Guneri area. The heat map shown in Figure 1 was generated from the predicted AGB by using the VH SAR band. The area with an AGB ranging from 171-193 kg/m2 had the highest biomass, followed by the area with an AGB ranging from 128-171 kg/m2. Land that has a biomass of anywhere between 0 and 107 kg/m2 can be referred to as barren land.

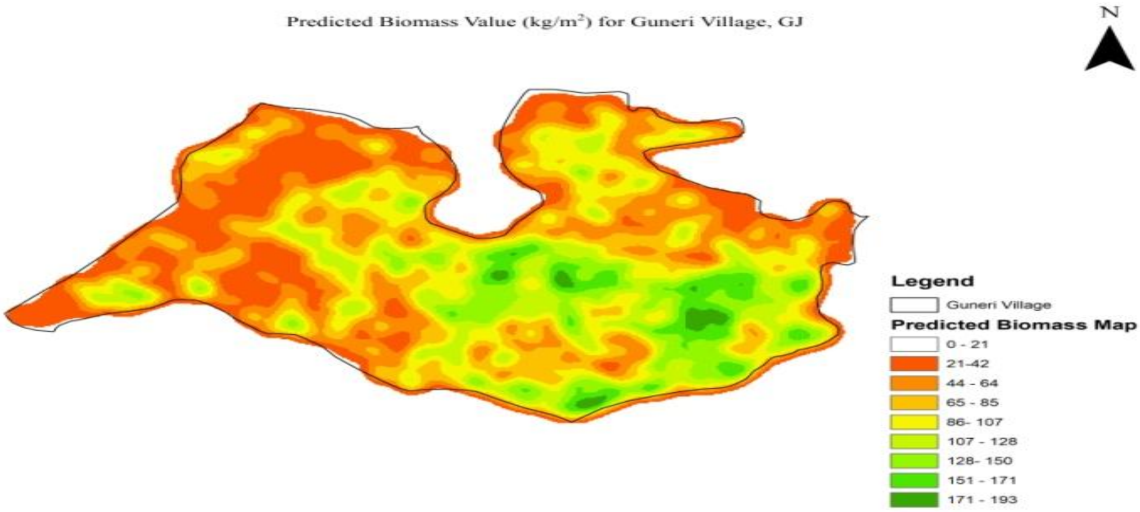

Fig. 1: Heat map generated from predicted AGB using VH band

Table 1: Mangrove discrimination from other vegetation using Sentinel imaging and machine learning

Models	Band Used	R2	RMSE	MSE	Mean CV Scores
Extra Trees Regressor	Sigma0 VH db	0.65	0.12	0.01	0.37
Extra Trees Regressor	Sigma0 VV db	0.65	0.11	0.01	0.29
Extra Trees Regressor	Sigma0 VH db & Sigma0 VV db	0.65	0.11	0.01	0.34
XGB Regressor	Sigma0 VH db	0.65	0.12	0.01	0.35
XGB Regressor	Sigma0 VV db	0.65	0.12	0.01	0.27
XGB Regressor	Sigma0 VH db & Sigma0 VV db	0.65	0.11	0.01	0.31

LULC mapping of the study area

If broadly categorized the land cover features present in the study area, then it contains only three types of features namely barren land, mangrove forest, and grass/non-mangrove. We will be using supervised classification techniques to classify the study area into three mentioned categories. Random Forest machine learning algorithm was used for LULC classification.

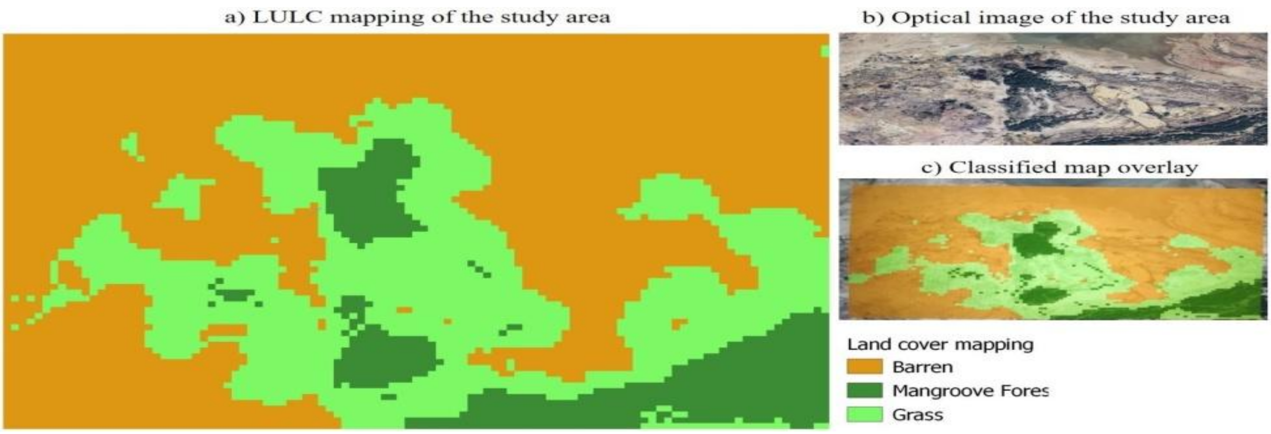

Fig. 2 Classified LULC map using random forest ML techniques

Figure 2 (a) shows the classified map generated using RF, (b) an optical image of the study area, and (c) a geo-referenced classification map overlay on a google earth image. The achieved accuracy with K fold RF classification is 91%, the RMSE is 0.526, the contribution of the VH spectrum is 0.506, and the contribution of the VV spectrum is 0.339. According to the classified map, the overall land distribution of the study area is as follows: 28% barren land, 18% mangroves, and 54% grass/non-mangrove.

CONCLUSION

In this study, a workflow is proposed to produce a mangrove ecosystem map and mangrove AGB estimation resulting in respectable accuracy. For mangrove and non-mangrove classification, a simple but robust Random Forest classifier is used, which produces an average accuracy of 91% and RMSE of 0.506. For AGB model generation machine learning techniques are applied to the datasets. The generated data were then tested using several regression methods such as Extra Trees Regressor, XGB Regressor, Random Forest Regressor, Bagging Regressor, and Decision Tree Regressor. The comparative study of the selected models is shown in Table 1, and Extra Trees Regressor demonstrated a good validation accuracy of 66% with 0.10 RMSE, followed by XGB Regressor (65%), and Random Forest Regressor (65%). This work validates the applicability of Random Forest (RF) and Extra Trees Regressor algorithms for mapping and estimating AGB for a unique landlocked mangrove site of Guneri, and it is observed that the results and robustness of the model are highly affected by the usage of a larger dataset and the geographical parameters of the study site.

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