Aboveground Biomass Assessment Using GEDI Data across Diverse Forest Ecosystems in India

I. Indirabai[1], R. Mukhopadhyay[1], L. I. Duncanson[2], J. D. Armston[2], M. Ekström[1,3], T. Gobakken[4], E. Næsset[4] and S. Saarela[4]

[1]Department of Forest Resource Management, Swedish University of Agricultural Sciences, Umeå, Sweden
Email: {indu.indirabai; ritwika.mukhopadhyay; magnus.ekstrom}@slu.se
[2]Department of Geographical Sciences, University of Maryland, College Park, MD, USA
Email: {lduncans; armston}@umd.edu
[3]Department of Statistics, USBE, Umeå University, Sweden
Email: magnus.ekstrom@umu.se
[4]Faculty of Environmental Sciences and Natural Resource Management, Norwegian University of Life Sciences, Ås, Norway
Email: {terje.gobakken; erik.naesset; svetlana.saarela}@nmbu.no

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1. Introduction

Aboveground biomass (AGB) and its quantification play an important role in understanding the global carbon cycle as well as carbon budget at the regional and national levels (Houghton et al., 2009; Narine et al., 2019; Quegan et al., 2019). The Kyoto Protocol is an international agreement linked to United Nations Framework Convention on Climate Change (UNFCCC). It promotes sustainable forest management and measures, enables the mitigation of climate change by conservation and enhancement of forests as sinks and reservoirs of greenhouse gases, and recognises the significance of forests in carbon sequestration (Kuh et al., 2018). Intergovernmental Panel on Climate Change (IPCC), - the international body to regular assessments of the scientific basis of climate change, its impacts, future risks and mitigation, - demands the member countries to generate national-level estimates of carbon stocks and exchanges (IPCC, 2007; IPCC, 2018). Indian forests can significantly contribute to climate change mitigation by carbon sequestration. Forest Survey of India (FSI) is an organisation under the Ministry of Environments and Forests, Government of India. It conducts surveys of forest resources, including national forest inventory (NFI), in the country and it has been regularly estimating growing stocks in Indian forests. The primary objective of NFI is to assess growing stock of trees, number of trees, bamboo, soil carbon, invasive species and other parameters depicting forest health and growth using a grid-based sampling. FSI estimates carbon stock in different pools at the national and state level using the NFI data following the methodology of Good Practices Guidance (GPG) developed by IPCC (FSI, 2019). Over 57% of the total forest cover constitute mainly very dense and moderately dense forests (FSI, 2019). There is a need for regional assessment of forest biomass and carbon stocks, due to the diverse forest ecosystems along with highly variable climatic and geographic features. (Salunkhe et al., 2018).

NASA's Global Ecosystem Dynamics Investigation (GEDI) launched on December 5, 2018, is the first spaceborne LiDAR designed for producing high resolution laser ranging observations of 3D structure for Earth's tropical and temperate forests. Quantifying the effects of vegetation disturbance and recovery on carbon storage, distribution of AGB, the potential of forests to sequester carbon and quantifying the spatio-temporal distribution of canopy structure and its influence on habitat and biodiversity are the main scientific objectives of GEDI (Dubayah et al., 2020). GEDI data products include footprint and gridded data, which are publicly available with lower-level products (L1 and L2) from NASA's Land Product Distributed Active Archive Centre (LPDAAC) and higher-level products (L3 and L4) from Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC). The L4A products are footprint-level predictions of aboveground biomass density (AGBD) obtained by parametric models that describe the relationship between L2A relative height metrics with field plot estimates of AGBD. Model calibration using simulated GEDI waveforms and a cross validation framework is developed to ensure geographic transferability (Hancock et al., 2019; Dubayah et al., 2020; Duncanson et al., in review).

European Space Agency's Sentinel-2 launched on June 23, 2015, is a wide-swath, high resolution, multispectral imaging mission (Drusch et al., 2012). Sentinel-2 data with high revisit frequency and systematic coverage have been tested to have potential applications in estimating forest biophysical

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variables including tree cover (e.g., Godinho et al., 2017), AGB (e.g., Majasalmi and Rautiainen,2016; Pandit et al., 2018; Puliti et al., 2019), growing stock volume (e.g., Chrysafis et al., 2017; Mura et al., 2018), and classifying highly diverse forest species in challenging mountainous environments (e.g., Grabska et al., 2019) and in riparian vegetation at regional scales (Daryaei et al., 2020). Mensah et al., (2020) studied the potential use of Sentinel-2 imagery in modelling tree growth and forest canopy dynamics by using heterogeneity indices.

Hierarchical model-based (HMB) inference is a novel inferential mode for environmental surveys using a combination of several sources of remotely sensed (RS) data including wall-to-wall multispectral optical data (e.g., Landsat, Sentinel) and LiDAR (e.g., airborne, spaceborne) data sets and field data. Typically, in HMB inference, the first source of information is RS data available wall-to-wall across the study region. The intermediate information source is sampled RS data, assumed to be more strongly correlated with the target variable than the wall-to-wall RS data. The third source of information is field data. Since two types of RS data are involved in the prediction of the target variable, two modelling steps are involved, one linking the target variable with sampled RS data and the other linking the expectation of the target variable with RS data available wall-to-wall. The method provides a theoretical approach for uncertainty assessment accounting for uncertainties due to the two modelling steps. The concept was first introduced by Saarela et al. (2016) for ordinary least squares (OLS) regression models, then it was elaborated for generalized least squares (GLS) regression models (Saarela et al., 2018) and nonlinear GLS (Saarela et al., 2020). In Saarela et al. (in review), the advantages and disadvantages, as well as under what conditions the novel inferential framework can outperform other estimation methods were outlined and discussed. The HMB inference can accommodate both the estimation of the target population parameters such as population mean or total and corresponding uncertainties over large areas, and the mapping of the variable of interest complementing with a map of uncertainties (e.g., Saarela et al. 2020).

The main objective of this study is to estimate the AGB and corresponding uncertainty and produce AGB maps over three large areas in India: Mudumalai (90 km^2), Betul (50 km^2)and Araku (120 km^2), using a combination of sampled GEDI data and wall-to-wall Sentinel-2 data within the HMB inferential framework. The study explores the possibility to identify whether GEDI data can be used alone or in a combination with Sentinel-2 data, for the accurate AGB estimation in Indian forests.

2. Material and Method

The selected study area consists of the three protected forest ecosystems: Mudumalai forest in the which is a part of Western Ghats, Betul forest in the central part of India, and Araku forest, a part of Eastern Ghats (Figure 1). The Western Ghats includes a diversity of ecosystems ranging from tropical wet evergreen forests to montane grasslands containing numerous medicinal plants with unique shola ecosystem with evergreen forest patches. The Eastern Ghats geologically older than the Western Ghats supports a diverse array of tropical forests and has great conservation significance. The Eastern Ghats has tropical wet evergreen, semi evergreen, moist deciduous, dry deciduous, dry evergreen and thorn forests (Reddy et al., 2008; Reddy et al., 2014). Field data were collected by the sampling procedure from FSI and AGB were estimated using the volume and specific density of tree species present in each sampling plot (FSI, 1996).

Sentinel-2 data of December 2019 are used in the study. Using SNAP tools, Sentinel-2 imagery were subsetted for the corresponding study areas based on the bounding coordinates. Resampling and cloud masking were done as part of the preprocessing of Sentinel-2 imagery using the SNAP software (ESA, 2021; Zuhlke et al., 2015; Nuthammachot et al., 2018). Spectral bands Short Wave Infrared SWIR-1 (B11), Near Infrared (B8) and Blue (B2) of the imagery required for the study are selected, extracted and are resampled to 30m spatial resolution corresponding to the size of the sampling plot. The band combinations B11, B8 and B2 are suitable to monitor and highlight dense vegetation (Wang et al., 2019; Huete et al., 2002; Pandit et al., 2020). The variables in the L4A footprint data files are the AGDB prediction, associated uncertainty metrics, quality flags identifying the most useful L2 data for biomass predictions and simplifying the predictions selection, and the scaled and transformed GEDI L2A relative height metrics. The data are available to download from ORNL DAAC.

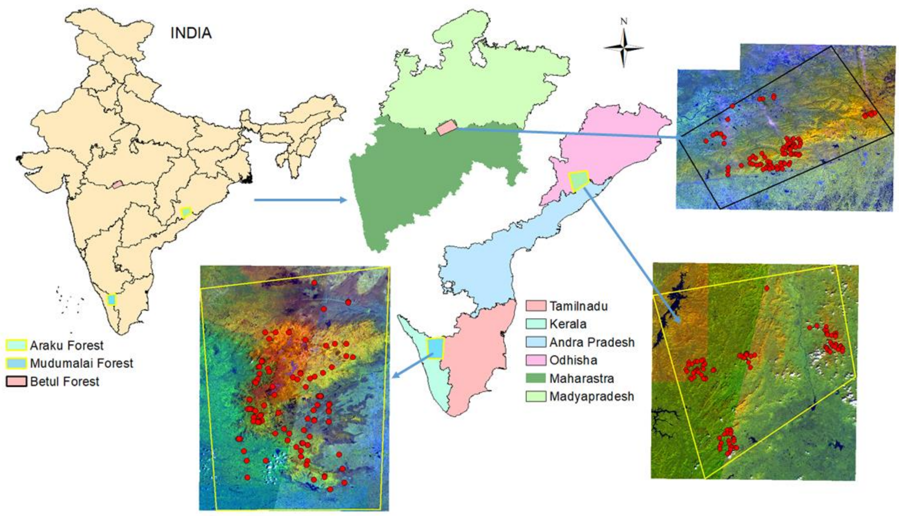

Figure 1: Study areas' locations (color composite of Bands B11, B8 and B2 of Sentinel-2 images were used for study area representation).

The estimation of the target population mean follows the HMB inference. We define two superpopulation models, the first model describes a relationship between AGB and GEDI data. The model information, such as estimated model coefficients and their estimated variance-covariance matrices, estimated R-squared and RMSE, are provided with the GEDI L4A product (Duncanson et al., in review). Then, we train a second model, linking L4A AGB with Sentinel-2 variables. The latter model is then used to predict AGB over our study areas using Sentinel-2 wall-to-wall data. It contains elements of uncertainty from each of two modelling steps, thus the variance-covariance matrix of estimated model parameters in the model is decomposed in two parts: one due to the conditional uncertainty related to the Sentinel-2 model fitting, and the second part is a propagated uncertainty due the GEDI L4A model fit.

For the mapping of AGB across our study areas, the Sentinel-based prediction model is applied at the Sentinel-2 pixel-level, and a complementary map of uncertainties is produced following the HMB theory (Saarela et al., 2020). The results will be compared with estimates obtained from a survey using a combination of field data and Sentinel-2 data within the model-based inferential framework (e.g., McRoberts, 2010).

3. Expected Results and Discussion

The methodology proposed in the study for the AGB estimation and the uncertainty measurements of AGB by utilizing GEDI L4A and Sentinel-2 can significantly contribute to quantifying the amount of carbon stored in the Indian forests thereby can help to calculate the carbon sequestration potential of forests under future climate and land-use scenarios. The resultant AGB uncertainty measurements and the AGB maps from the study can support intergovernmental policy initiatives such as REDD, UNFCCC and Kyoto Protocol in which India is involved in Clean Development mechanism (CDM) by giving information for climate adaptation and mitigation, sustainable land use and conservation of biodiversity. The combination of GEDI data with wall-to-wall Sentinel-2 data within the HMB inferential framework can predict the future response of forest carbon to climate change and land management decisions which is of high societal relevance and potential to simplify the reporting to IPCC. GEDI can reduce the uncertainty in the measurements of carbon loss and carbon gain by measuring the current biomass of forests globally thereby giving the net impact of forest disturbance and subsequent regrowth. Thus, information on the missing sink of carbon and carbon balance can be obtained which is the potential data needed for IPCC which can be used for the alternative conservation and development strategies.

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