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Estimating forest height and above-ground biomass in tropical forests using P-band TomoSAR and GEDI observations

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ABSTRACT

Knowledge about the vertical structure of forests, such as forest height, above-ground biomass (AGB), and the vertical biomass distribution is important for understanding carbon allocation, structural diversity, and succession and degradation dynamics in forest ecosystems. While the use of lidar (light detection and ranging) observations is well established to investigate the vertical structure of forests, the sensitivity of P-band synthetic aperture radar tomography (TomoSAR) observations to biomass and vertical forest structure is not yet well understood. Here we use lidar observations from NASA's Global Ecosystem Dynamics Investigation (GEDI) to analyse the sensitivity of airborne P-band SAR tomography backscatter to forest height and AGB at two tropical forests in Lopé and Mondah, Gabon, Africa. We use GEDI observations to parametrize an empirical model for estimating forest height and we use a random forest model for estimating AGB from TomoSAR profiles. The validation with Land, Vegetation, and Ice Sensor (LVIS) airborne lidar data shows moderate performance for estimating forest height (RMSE = 8.2 m in Lopé and 9.8 m in Mondah) and moderate to good performance for total AGB (RMSE = 115.3 Mg/ha in Lopé and 117.8 Mg/ha in Mondah). We also estimated the vertical distribution of AGB using the corrected TomoSAR backscatter and compared it with AGB profiles derived from field observations in Mondah, which indicates potential to use TomoSAR observations for estimating vertical AGB distribution over tropical forests. However, our results demonstrate the need for targeted field observations of vertical biomass profiles in order to make full use of P-band TomoSAR to map the vertical structure of tropical forests.

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1. Introduction

Forests are a critical storage of carbon in the global carbon cycle (Houghton, Hall, and Goetz 2009; E. T. A. Mitchard 2018). Forests store carbon in above- and below-ground

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biomass and as soil organic carbon. The above-ground biomass (AGB) is an essential climate variable in land ecosystem and is defined as the amount of dry mass stored above-ground per unit ground area (e.g. mega grams per hectare, Mg/ha). In addition to the total AGB, knowing biomass in different components of trees, such as crowns, stems and roots, is important for understanding various processes in forest ecosystems. The allocation of biomass regulates carbon use efficiency, autotrophic respiration, vegetation carbon turnover, or plant hydraulics (Manzoni et al. 2018; Thurner et al. 2019). The distribution of biomass in different components also influences the behaviour of forest fires, for example, if the availability of ladder fuels allows surface fires to propagate into tree crowns (Kramer et al. 2016; Leite et al. 2022). Remote sensing technology has been widely applied to estimate above-ground biomass (Avitabile et al. 2016; Baccini et al. 2012, 2017; Saatchi et al. 2011; Santoro et al. 2021). The estimation of AGB has a large uncertainty in tropical forests because of errors in wood density, tree height, allometric models, and spatial or temporal mismatch between remote sensing observations and field measurements (E. T. Mitchard et al. 2013; Réjou-Méchain et al. 2019). In comparison with the total above-ground biomass, biomass in different plant components is yet underexplored at large scales. Up to now, most knowledge about the AGB vertical distribution comes from a small amount of field measurements using harvesting (Falster et al. 2015; Kutchartt et al. 2021), modelling (Toraño Caicoya et al. 2016; Urban, Čermák, and Ceulemans 2015) or terrestrial laser scanning (Burt et al. 2021; Stovall, Anderson-Teixeira, and Shugart 2018).

Synthetic Aperture Radar (SAR) (Moreira et al. 2013) has been used to estimate biomass in branches and stems in boreal forests (Harrell et al. 1997; Kasischke, Christensen, and Bourgeau-Chavez 1995; Saatchi and Moghaddam 2000). Multi-wavelength or multi-polarization SAR data is usually required because the proposed methods assume SAR backscatter at single wavelength or single polarization is sensitive to specific biomass components (Santoro and Cartus 2018). SAR tomography (TomoSAR) (Reigber and Moreira 2000; Tebaldini and Rocca 2012) can retrieve the reflectivity profile of forests without using scattering models. TomoSAR-based forest height can be estimated through relating the backscatter peak with the highest location in TomoSAR profiles with an external forest height dataset (Tebaldini and Rocca 2012; Toraño Caicoya et al. 2015; Yang et al. 2020). Forest height can also be estimated using polarimetric interferometric SAR techniques based on a scattering model (Cloude and Papathanassiou 1998, 2003; Papathanassiou and Cloude 2001). For estimating TomoSAR-based AGB, several empirical methods were developed using TomoSAR metrics, for example, TomoSAR backscatter at certain height (Ho Tong Minh et al. 2014; Minh et al. 2016) or the cumulative backscatter between layers (Blomberg et al. 2021). These methods are based on pre-defined relationships, which may vary with forest height and forest structure. Non-parametric methods (Santoro and Cartus 2018) using TomoSAR backscatter from multiple height layers as predictors have not been developed yet.

Light detection and ranging (lidar) can provide forest structure profiles (Drake et al. 2002), but it mostly records the crown structure information since lidar mainly works in infrared band and with nadir geometry. NASA's Global Ecosystem Dynamics Investigation (GEDI) (R. Dubayah et al. 2020) can be an alternative for providing the training data at global level for estimating TomoSAR-based forest height and AGB. GEDI is a spaceborne lidar system for measuring forest structure and has three main products: forest height (R. Dubayah et al. 2021), forest structure (R. Dubayah et al. 2021) and AGB (Duncanson et al. 2022). Because of the relatively high

accuracy of GEDI products but sparse sampling, GEDI has been integrated with other optical and SAR observations for mapping forest height (Choi et al. 2023; Lang et al. 2023; Potapov et al. 2021) and AGB (Liang et al. 2023; Qi et al. 2019; Silva et al. 2021) at large scale. Lidar and TomoSAR are complementary since they are sensitive to different vegetation elements (Ngo et al. 2022). ESA's upcoming P-band SAR satellite BIOMASS (Quegan et al. 2019) will provide a first TomoSAR dataset for multiple continents. Hence, there is potential to jointly exploit the information from GEDI and from TomoSAR measurements to estimate forest height and AGB.

As an alternative to estimate biomass in different plant components, biomass within certain aboveground height intervals (i.e. the vertical distribution of AGB) could indirectly represent biomass in different components, which results from the allocation of assimilated carbon. The vertical distribution of vegetation elements and their dielectric properties (i.e. their water content) effects the magnitude of TomoSAR backscatter profiles (Pardini et al. 2019). However, it is unclear yet whether there is a relationship between TomoSAR backscatter profiles and AGB profiles. Comparisons of L-band TomoSAR profiles and biomass profiles from field measurements at temperate forests in Traunstein, Germany, represent similar changes along height (Papathanassiou et al. 2021). Cazcarra-Bes et al. (2017) used an exponential relationship to model L-band TomoSAR backscatter from simulated biomass profiles. Thereby, a constant extinction factor was applied to all profiles to describe the attenuation of the microwaves along the vertical gradient. A similar approach was used by Toraño Caicoya et al. (2015) with L-band TomoSAR profiles in the Traunstein site, whereby the extinction factor was adaptive to each TomoSAR profile. These empirical methods to relate TomoSAR profiles with vertical AGB distribution are based on a very limited number of parameters and none of them has been validated due to the lack of theoretical foundation.

The aim of this study is to assess the sensitivity of P-band TomoSAR backscatter to forest height, AGB and the vertical distribution of biomass by making use of airborne TomoSAR backscatter observations and spaceborne lidar observations from GEDI. In addition, we use airborne lidar observations to validate our results because airborne lidar can accurately measure the forest structure with large spatial coverage. We use observations from two study sites located in Lopé and Mondah, Gabon, Africa. Our objectives are firstly to estimate forest height from TomoSAR profiles by using the height from GEDI where 100% energy is received relative to the ground (i.e. RH100); secondly to estimate total AGB from multiple TomoSAR height layers by using the GEDI AGB product as reference in a random forest regression model; and thirdly to estimate the vertical distribution of AGB from TomoSAR profiles at field plots in Mondah. However, for the latter we have to point out that a direct validation of the vertical distribution of AGB is not possible because appropriate reference data is not existing. Hence as an alternative, we use the available field measurements of tree height, tree diameter and total AGB to estimate the vertical distribution with an allometric model and by using a pantropical tree biomass database.

2. Material and method

2.1. Study sites

Our research areas are located in Mondah and Lopé, Gabon, Africa (Figure 1). According to the ESA WorldCover 10 m 2020 product (Zanaga et al. 2021), the Mondah site is covered by 76% trees and the Lopé site is covered by 79% trees. Only tree-covered areas were included in this

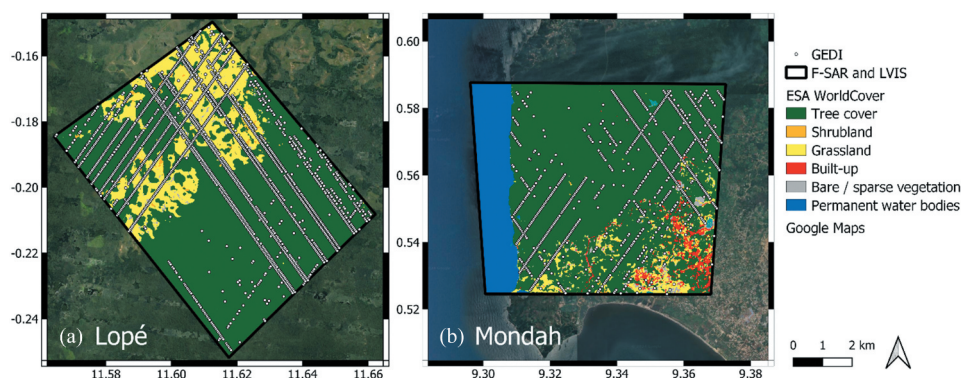


Figure 1. Land cover and data coverage in the two study sites (a) Lopé and (b) Mondah.

analysis. Due to the human disturbance, Mondah forest area has the highest deforestation rate in Gabon (Hansen et al. 2013) and around half of this area is secondary forest (Walters et al. 2016). The mean tree species richness in Mondah and Lopé is around 35 species per hectare in both areas. The maximum terrain slope in Lopé reaches 22° while the slope in Mondah is no more than 12° .

2.2. Data

Properties of the used remote sensing datasets are listed in Table 1.

2.2.1. F-SAR tomographic synthetic aperture radar

The P-band TomoSAR data were collected by DLR's (German Aerospace Center) F-SAR system (Horn, Nottensteiner, and Scheiber 2008) in the AfriSAR 2016 campaign (European Space Agency 2017). Images were acquired along 11 flight tracks on 4 February 2016 in Mondah and along 10 flight tracks on 10 February 2016 in Lopé. The P-band sensor in F-SAR system works at 435 MHz. The platform flies at $\sim 6,096$ m above ground at reference track, with off-nadir angles between 25° and 55° , having an approximate $5 \text{ km} \times 8 \text{ km}$ (range-azimuth) coverage. For the TomoSAR dataset, the vertical distances between each acquisition with respect to reference acquisition are -80 m , -60 m , -40 m , -20 m , 0 m , 10 m , 20 m , 40 m , 60 m and 80 m (one more track with -30 m vertical distance in Mondah). The vertical Rayleigh resolution of TomoSAR profiles is determined by the longest baseline and incidence angle, which is about 15 m at near range and decreases to 25 m at far range. Phase calibration has been implemented for compensating the residual baseline errors (European Space Agency 2017). Full polarization data was collected along each track.

2.2.2. Global Ecosystem Dynamics Investigation spaceborne lidar

Global Ecosystem Dynamics Investigation (GEDI) is a spaceborne full-waveform lidar installed on the International Space Station (R. Dubayah et al. 2020). GEDI is specifically designed to estimate the vegetation structure and above-ground biomass between 51.6° N and 51.6° S . It started collecting science data in 2019 with an expected 2 years' lifetime for the primary mission. GEDI consists of 3 lasers, 4 beams and 8 ground tracks (4 full power tracks and 4

Table 1. Properties of the used remote sensing data.

Sensor	Platform	Wavelength	Acquisition time	Spatial resolution	Reference ellipsoid	Geolocation accuracy	Vertical resolution	Along-track separation	Link
F-SAR	Airborne	69 cm	2016	2 × 3.84 m (Azimuth × slant range)	WGS-84	0.15 m	<15 m (near range)	–	https://earth.esa.int/eogateway/campaigns/afrisar-2016
GEDI ¹	Spaceborne	1064 nm	2019, 2020	25 m ²	WGS-84	10 m	1 m	60 m	https://gedi.umd.edu/
LVIS	Airborne	1064 nm	2016	22 m	WGS-84	1 m	10 cm	9 m	https://lvis.gsfc.nasa.gov/Data/Maps/Gabon2016Map.html

¹ The GEDI L2A version 2 (R. Dubayah et al. 2021) and L4A version 2 (R. Dubayah et al. 2022) products.

² GEDI footprint size.

coverage tracks). GEDI Level 2A product (L2A) contains the ground elevation, canopy top height and relative height metrics derived from geolocated waveforms (Hofton et al. 2020). GEDI level 4A product (L4A) contains AGB density and AGB uncertainty (Duncanson et al. 2022; Kellner, Armston, and Duncanson 2021). GEDI L4A algorithm is based on the field measurements and simulated GEDI waveforms from 21 countries and various plant functional types. Both GEDI L2A and L4A products are at footprint-level. GEDI L2A product processed using algorithm a5 was used here since a5-based RH100 matches better with RH100 from airborne lidar in dense forests (Liu, Neigh, and Forkel 2021). The GEDI L2A and L4A products were linked via the shot number of each laser shot (Hofton et al. 2020; Kellner, Armston, and Duncanson 2021) and filtered using criteria listed in Table S1 in the supplementary material. GEDI products were rasterized to 25 m spatial resolution using the geocube package (Snow et al. 2023) and resampled to 50 m spatial resolution using bilinear resampling.

2.2.3. *Land, vegetation, and ice sensor airborne lidar*

Airborne lidar can acquire robust and accurate forest structure information with large coverage (Fatoyinbo et al. 2021). Therefore, forest height and AGB products from NASA's airborne Land, Vegetation, and Ice Sensor (LVIS) waveform laser altimeter system were used to validate TomoSAR-derived tree height and AGB. As a part of the AfriSAR 2016 campaign, LVIS acquired the full-waveform lidar data on 25 February 2016 and 3 March 2016 (Mondah) and 3 February 2016 (Lopé) (Blair and Hofton 2018; Fatoyinbo et al. 2021). The gridded relative height metrics (25 m resolution) were derived by aggregating all shots located within individual grids (Armston et al. 2020). LVIS RH metrics were resampled to the 50 m spatial resolution using bilinear resampling. The 50 m (0.25 ha) resolution gridded AGB was estimated using a generalized linear model trained with relative heights and cover metrics against gridded field AGB. The 50 m pixel-level LVIS AGB ranges between 2 Mg/ha and 746 Mg/ha in Lopé, and between 1 Mg/ha and 845 Mg/ha in Mondah. The 50 m pixel-level standard deviation of LVIS AGB ranges between 1 Mg/ha and 493 Mg/ha in Lopé, and between 1 Mg/ha and 577 Mg/ha in Mondah (Armston et al. 2020). Mondah has more forest with height below 30 m and AGB below 400 Mg/ha than Lopé (Figure 2).

3. Methods

3.1. *Estimating TomoSAR backscatter*

Cross-polarization contains less ground scattering than co-polarization (Freeman and Durden 1998; Papathanassiou et al. 2021). Therefore, in this study, HH polarization was used to detect ground while HV polarization was used to characterize forest structure. The Capon spectral estimator (Lombardini and Reigber 2003) was applied for detecting ground at HH polarization and TomoSAR profiles at HV polarization were calculated with beamforming (Gini, Lombardini, and Montanari 2002). Details of Capon and beamforming can be found in the supplementary material (SI 1). The TomoSAR methods were selected based on: (1) the ground scattering is more distinguishable in Capon-derived profiles, and (2) beamforming has better radiometric accuracy than Capon. The location of the lowest peak in each HH TomoSAR profiles was extracted as the topography and the topography phase was removed from HV TomoSAR profile. Both HH and HV TomoSAR backscatter are at 50 m spatial resolution. Topographical effect in TomoSAR backscatter was compensated using local incidence angle (Ho Tong Minh

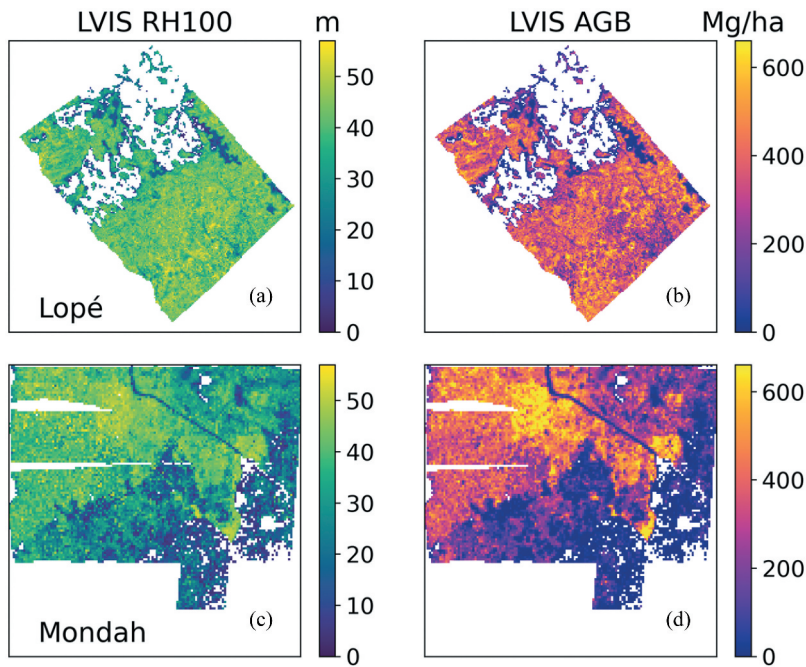


Figure 2. LVIS RH100 and AGB at 50 m spatial resolution in Lopé (a–b) and Mondah (c–d).

et al. 2014). Tomograms were transformed from radar geometry to Universal Transverse Mercator coordinate using the look up tables and TanDEM-X digital elevation models. Here, we use $P(h)$ to represent the beamforming-derived TomoSAR backscatter at HV polarization at a certain height h .

3.2. Estimating forest height from TomoSAR profiles

We define the volume peak as the backscatter peak with the highest location in TomoSAR profile. The volume peak is usually lower than tree height due to the penetration of microwave signal (Pardini et al. 2018; Tebaldini and Rocca 2012). An approach proposed in Toraño Caicoya et al. (2015) and Yang et al. (2020) was used to estimate TomoSAR RH100 by minimizing the RMSE between GEDI RH100 and a reference location in TomoSAR profile, as shown in Figure 3. This reference location is determined as a threshold of the backscatter at volume peak. The optimal threshold for estimating RH100 is 45% in Lopé and 40% in Mondah. RH0 was assumed as zero. TomoSAR RH metrics between RH0 and RH100 were estimated from TomoSAR backscatter profiles.

3.3. Estimating AGB from TomoSAR profiles with Random Forest

Random Forest (RF) regression (Breiman 2001) was applied to estimate TomoSAR AGB against GEDI AGB at 50 m spatial resolution. The RF regression uses the average of responses from multiple decision trees to make the final prediction. This method can effectively mitigate overfitting. Before developing the RF-AGB model, TomoSAR data were filtered using the

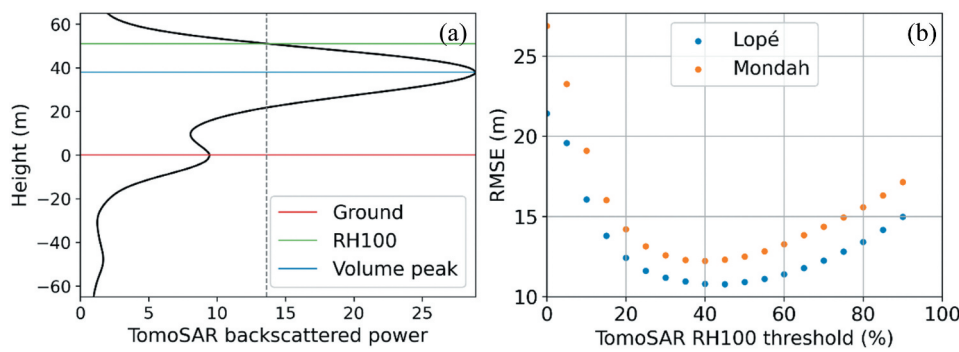


Figure 3. Illustration of estimating TomoSAR RH100. (a) Estimating RH100 from HV TomoSAR profiles. The grey solid line corresponds to the threshold for TomoSAR RH100. (b) Determining the optimal threshold by minimising the RMSE between TomoSAR RH100 and GEDI RH100.

criteria listed in Table S1 in supplementary material. We used 17 input features for the RF-AGB model, which are from two groups: (1) the TomoSAR RH metrics from RH10 to RH100 in a 10% step (i.e. RH10, RH20, RH30, RH40, RH50, RH60, RH70, RH80, RH90 and RH100) and (2) TomoSAR backscatter $P(h)$ from 0 m to 60 m in a 10 m step (i.e. 0, 10, 20, 30, 40, 50 and 60).

$$AGB = RF(RH, P(h)) \quad (1)$$

A five-fold cross-validation (James et al. 2013) was implemented to test the transferability of the RF-AGB model (Table 2). The data was randomly shuffled and split into five groups, and five models were trained. For each model, four groups (80%) were used as training set and one group (20%) as testing data. The model with highest R^2 between prediction and testing data was selected as the final model, which was then applied to the whole research area. The standard deviation of the predicted AGB from the five individual models in cross-validation was used to quantify the uncertainty of the RF-AGB model. The RF regression model was trained independently in Lopé and Mondah using scikit-learn package (Pedregosa et al. 2011). Default parameters from the RandomForestRegressor function were used. For example, one hundred trees were used and the minimum number of samples for each split is two.

3.4. Estimating AGB profiles from TomoSAR profiles

We applied a profile adaptation – exponential correction (Toraño Caicoya et al. 2015) to derive the TomoSAR AGB profile from backscatter profiles at field plots in Mondah:

$$AGB_{tomo}(h) = \frac{f_{corr}(h)}{\sum f_{corr}(h)} \times AGB \quad (2)$$

Table 2. Five-fold cross-validation to estimate AGB at 50 m resolution. Model with the highest R^2 was selected as the final model and applied to the whole research area.

Sites	Training data size	Testing data size	R^2	RMSE (Mg/ha)
Lopé	745	186	$0.44^{0.51}_{0.3}^*$	103^{131}_{100}
Mondah	314	78	$0.67^{0.75}_{<0}$	74^{104}_{42}

*Median^{Max}_{Min}

where h is the absolute height above ground. $AGB_{tomo}(h)$ is the estimated biomass between h and $h + \Delta h$. The height interval Δh was set to 1 m for keeping consistent with height sampling of TomoSAR. $f_{corr}(h)$ is the corrected TomoSAR backscatter profile (see SI 2 in the supplementary material for the calculation). AGB is the sum of $AGB_{tomo}(h)$. Forest height and AGB were taken from in-situ measurements (Fatoyinbo et al. 2018) to calculate $AGB_{tomo}(h)$ in order to avoid introducing additional errors in the approach by taking TomoSAR-derived forest height and AGB.

The TomoSAR-derived biomass profiles were compared with biomass profiles that were derived from field measurements. To the best of our knowledge, there are no directly measured biomass profiles in our study areas. Therefore we developed and applied a tree allometry model to derive the vertical AGB distribution of individual trees based on a pantropical tree biomass database (Ploton et al. 2016). The model estimates biomass profile from diameter at breast height (DBH) and wood density. The description, calibration, validation and a sensitivity analysis of the tree allometry model are included in the supplementary material (SI 3). Forest height, AGB, DBH and wood density were taken from field data in Mondah (Fatoyinbo et al. 2018). Then, the biomass profile of a field plot $AGB_{plot}(h)$ was computed as the sum of biomass profiles from all trees in this plot:

$$AGB_{plot}(h) = \sum AGB_{tree}(h), \quad (3)$$

where $AGB_{tree}(h)$ is the modelled biomass distribution along height at single tree level.

3.5. Evaluation metrics

Performance metrics including coefficient of determination (R^2), mean absolute error (MAE) and root mean square error (RMSE) were used for evaluation (Janssen and Heuberger 1995).

4. Results

4.1. Vertical distribution of TomoSAR backscatter

The transect of TomoSAR backscatter represents forests with different vertical structure (Figures 4, 5). Scattering is visible from both canopy and ground, and the difference of volume peak's location indicates the difference of forest height. The TomoSAR backscatter shows different spatial pattern at 0 m, 15 m, 30 m and 45 m layers, as shown in Figure 4(b–e) and Figure 5(b–e). In comparison with LVIS RH100, only areas with RH100 larger than around 40 m shows relatively strong backscatter at 45 m layer (Figure 2). TomoSAR backscatter profiles grouped by LVIS RH100 (i.e. 0–15 m, 15–30 m, 30–45 m, and 45–60 m) and LVIS AGB (i.e. 0–200 Mg/ha, 200–400 Mg/ha, 400–600 Mg/ha and 600–800 Mg/ha) at 50 m spatial resolution were presented in Figure 4(f–g) and Figure 5(f–g). The vertical profile of each group was calculated by taking the median value of TomoSAR backscatter at each height. In both sites, the ground scattering is dominant for forests below 30 m. For forests between 30 and 40 m height, the canopy scattering appears and it is stronger in Lopé than Mondah. For forests above 40 m, the maximum intensity of

canopy scattering slightly grows and the ground scattering still exists. The TomoSAR profiles with AGB larger than 200 Mg/ha have similar shapes in Lopé but different shapes in Mondah. Generally, profiles from forests with high AGB have the volume peak at higher levels and smaller backscatter at the ground.

4.2. TomoSAR-derived forest height

The derived forest height (RH100) from GEDI and TomoSAR and the validation with height from airborne LVIS observations are presented in Figure 6. In Lopé, most GEDI footprints cover forests with height between 40 m and 50 m. TomoSAR RH100 overestimates LVIS RH100 around 5 m for most forests between 40 m and 50 m height but it underestimates in some mountainous areas in the east of the Lopé site. Forests covered by GEDI in Mondah ranges from 10 m to 50 m high. For forests between 40 m and 50 m, TomoSAR RH100 matches with LVIS RH100. However, forests between 10 m and 30 m are systematically underestimated in TomoSAR RH100. The performance in estimating RH100 from TomoSAR slightly differs between sites ($R^2 = 0.34$ Lopé, 0.39 Mondah; MAE = 5.7 m Lopé, 7.1 m Mondah; and RMSE = 8.2 m Lopé, 9.8 m Mondah). Those results confirm that TomoSAR can be used to estimate regional spatial gradients of forest canopy height, however, local errors can be substantial.

4.3. TomoSAR-derived above-ground biomass

Above-ground biomass from GEDI, AGB derived from TomoSAR and the comparison with AGB from LVIS are presented in Figure 7. In Lopé, GEDI AGB in forests ranges from 300 Mg/

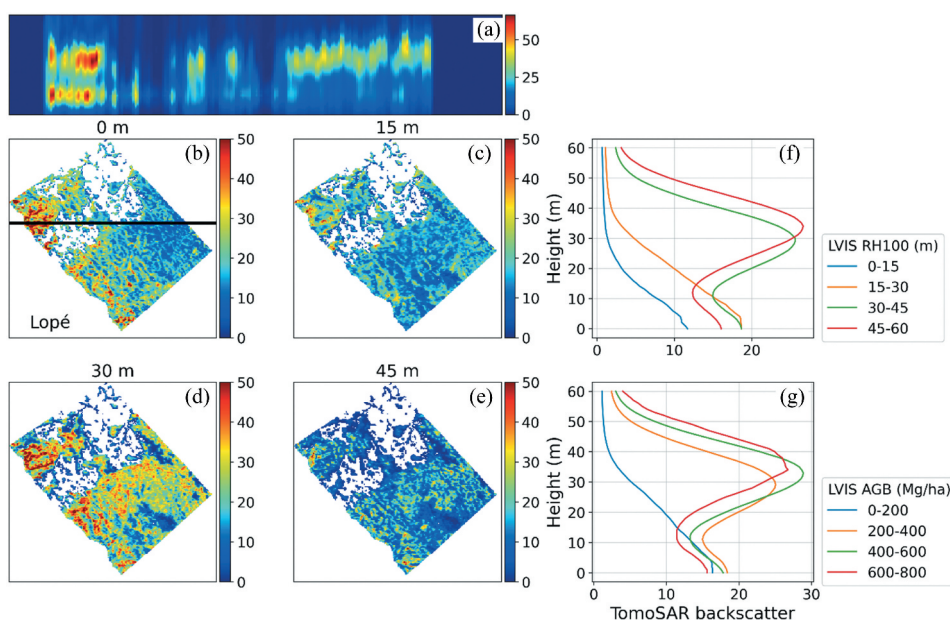


Figure 4. TomoSAR backscatter in Lopé. (a) TomoSAR backscatter along a transect, which is plotted as a black line in (b). (b–e) HV TomoSAR backscatter at 0 m, 15 m, 30 m and 45 m above ground. (f) Median TomoSAR backscatter profiles grouped by LVIS RH100 at 50 m spatial resolution. (g) Median TomoSAR backscatter profiles grouped by LVIS AGB at 50 m spatial resolution.

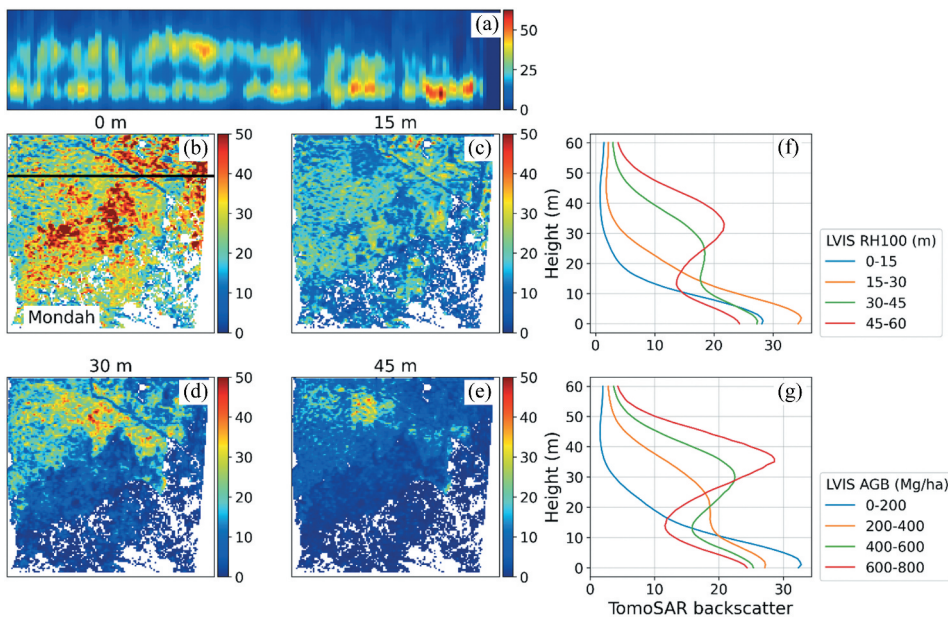


Figure 5. As Figure 4 but for Mondah.

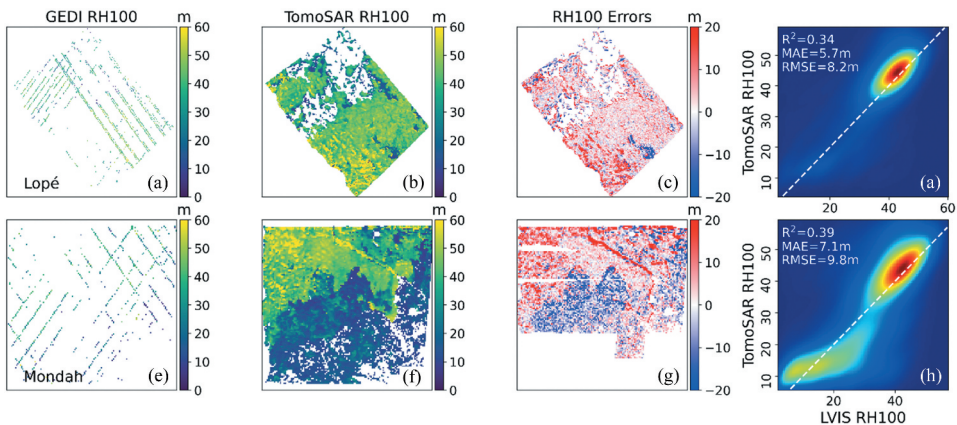


Figure 6. RH100 estimated from TomoSAR with using GEDI RH100 as reference. RH100 errors is the difference between TomoSAR RH100 and LVIS RH100. Plots (d) and (h) are the density map of RH100, where red indicates higher point density and the grey dashed line is 1:1 reference line.

ha to 400 Mg/ha and there are almost no forests with AGB between 100 Mg/ha and 300 Mg/ha. TomoSAR AGB follows the 1:1 reference line against LVIS AGB, but locally large differences can exist. In Mondah, GEDI mainly covers forests with AGB below 400 Mg/ha. There are only few GEDI samples in the centre-northern area which have AGB above 300 Mg/ha. TomoSAR AGB shows similar spatial pattern as LVIS AGB while it is generally underestimated. We also found that the uncertainty in TomoSAR-derived AGB estimates increases at larger AGB (Figure S5 a-b in the supplementary material). Performance

metrics are similar at both sites ($R^2 = 0.45$ Lopé, 0.6 Mondah; MAE = 89.6 Mg/ha Lopé, 87.2 Mg/ha Mondah; RMSE = 115.3 Mg/ha Lopé, 117.8 Mg/ha Mondah).

4.4. TomoSAR-derived biomass profiles at field plots in Mondah

For the in-situ plots in Mondah, we derived the AGB profiles $AGB_{tomo}(h)$ from TomoSAR backscatter $P(h)$ and compared them with AGB profiles derived from field measurements using the tree allometry model. All profiles are presented coloured by field AGB in Figure 8. Estimating AGB vertical distribution from TomoSAR backscatter at field plots in Mondah. While TomoSAR backscatter profiles at low total AGB are dominated by ground scattering, profiles at higher total AGB show less ground scattering and more canopy scattering (Figure 8. Estimating AGB vertical distribution from TomoSAR backscatter at field plots in Mondah. a). Those patterns of TomoSAR backscatter profiles do not necessarily represent the vertical AGB distribution, which show much more biomass close to the ground than in higher levels in both the TomoSAR-derived and field-modelled AGB profiles (Figure 8. Estimating AGB vertical distribution from TomoSAR backscatter at field plots in Mondah. b, c). This pattern is caused by the increasing amount of woody biomass at the base of tree stems than at higher levels and is supported by terrestrial laser scanning of individual trees in Ghana (Figure S7). The TomoSAR-derived and field-modelled AGB profiles show overall moderate to high similarity ($R^2 = 0.41$, MAE = 0.95 Mg/ha, and RMSE = 3.08 Mg/ha, Figure 8(d)). However, the TomoSAR-derived AGB profiles fail to capture the biomass variations in the canopy, even for the plot with AGB larger than 400 Mg/ha. Those results indicate that the backscatter variation along TomoSAR height profiles do not directly represent the vertical variability of AGB but moreover the vertical variability of scattering elements and their interactions but can be used to derive AGB profiles.

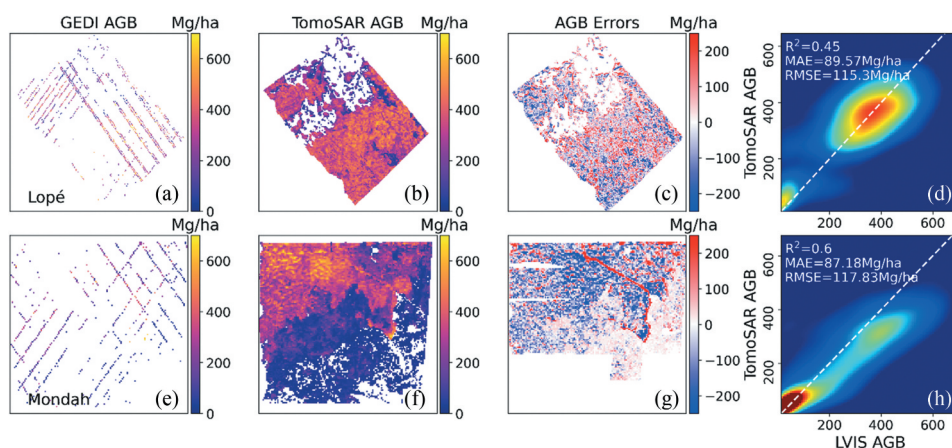


Figure 7. TomoSAR AGB trained with GEDI AGB. AGB errors is the difference between TomoSAR AGB and LVIS AGB. Plots (d) and (h) are the density map of AGB, where red indicates higher point density and the grey dashed line is 1:1 reference line.

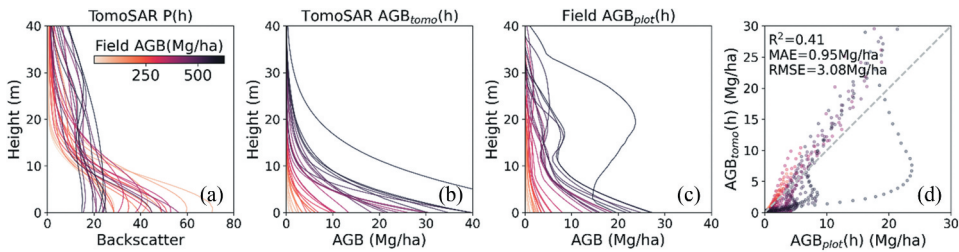


Figure 8. Estimating AGB vertical distribution from TomoSAR backscatter at field plots in Mondah. (a) TomoSAR backscatter profiles. (b) TomoSAR-derived AGB profiles $AGB_{tomo}(h)$. (c) Field measurement-based modelled AGB profiles $AGB_{plot}(h)$. (d) Comparison between all pairs of TomoSAR-derived AGB profiles and the field-modelled AGB profiles. This scatterplot was generated by plotting the TomoSAR-derived AGB profile against the field-modelled AGB profile at each field site. Each point represents the TomoSAR-derived AGB and field-modelled AGB at same field site and same height level. The grey dashed line is 1:1 reference line.

5. Discussion

5.1. Estimating TomoSAR RH100 from GEDI

Despite reproducing the regional spatial gradient of canopy height, the locally substantial errors of the TomoSAR-derived RH100 in comparison with LVIS, points that either the used GEDI reference data, or the TomoSAR data or both have limitations. On the one hand, the accuracy of GEDI RH100 decreases in dense tropical forests because of errors in geolocation (Roy, Kashongwe, and Armston 2021) and detecting ground (Urbazaev et al. 2022). Compared with LVIS RH100, GEDI RH100 shows significant discrepancy in Lopé (RMSE: 8.3 m) and Mondah (RMSE: 9.9 m), especially for forests below 30 m in Mondah (see Figure S1 a and b in the supplementary material). In order to test the effect of using GEDI on the underestimation of TomoSAR RH100 in Mondah, we alternatively used LVIS RH100 at the location of GEDI footprints to determine the TomoSAR reference threshold. However, the estimated TomoSAR RH100 was not improved (Figure S2 in the supplementary material) because the LVIS-derived optimal threshold slightly increased in Lopé (55%) and did not change in Mondah (40%). This points that the errors are more caused by the use of TomoSAR data.

The error in estimating TomoSAR RH100 could come from the assumption that the relationship between volume peak position and height is spatially invariant. Although a constant RH100 threshold was estimated using a cumulative optimization for each study site, the relationship between volume peak positions with forest height may depend on the forest structure and vary across space. In order to test how a spatially varying relationship between volume peak position and height might affect the estimate canopy height, we classified the research area in four groups according to the volume peak position (i.e. 0–15 m, 15–30 m, 30–45 m and 45–60 m) and estimated a threshold for each group. This approach mitigated the underestimation of TomoSAR RH100 for forests with height between 15–30 m but TomoSAR RH100 was still overestimated for forests below 15 m, which is related with the limited TomoSAR resolution (Figure S3 in the supplementary material). However, the performance of this multi-thresholds method depends on the division of groups and the number of available GEDI samples in each group.

A potential solution for improving TomoSAR-based forest height is using TomoSAR profiles to parameterize the reflectivity profile in polarimetric interferometric SAR (PolInSAR) model, and then estimate forest height with PolInSAR methods (Guliaev et al. 2021). In addition, the accuracy of detecting ground is affected by negative slopes (Pardini et al. 2018), which also affect height estimates.

5.2. Estimating TomoSAR AGB

Similar as for the RH100, differences between TomoSAR-derived AGB and LVIS reference AGB can be caused by the use of TomoSAR data or by the use of GEDI AGB as reference. GEDI AGB and LVIS AGB show clear differences in Lopé (RMSE: 137.6 Mg/ha) and Mondah (RMSE: 144.6 Mg/ha), which are even slightly higher than between TomoSAR AGB and LVIS AGB (Figure 7). In Mondah, GEDI AGB is underestimated when LVIS AGB is larger than 200 Mg/ha (see Figure S1 d in the supplementary material). We checked the effect of errors in GEDI AGB on estimating TomoSAR AGB by training the RF-AGB model with LVIS AGB located at GEDI footprints. The cross validation results are listed in Table S2 in supplementary material. The results show no systematic underestimation anymore (RMSE: 105.3 Mg/ha, Figure S4 h in the supplementary material) and also the uncertainty of AGB estimates decrease in both sites (Figure S5). Therefore, the quality of GEDI AGB is the main reason for the underestimation of TomoSAR AGB at Mondah and our results demonstrate the potential of using TomoSAR backscatter from multiple layers to derive total AGB.

5.3. Estimating TomoSAR AGB profiles

We assumed that stronger TomoSAR backscatter corresponds to more scattering elements such as stems and branches. An exponential correction method was applied here for relating TomoSAR vertical profile with AGB vertical profile. This approach originally uses L-band Capon-derived TomoSAR profiles (Toraño Caicoya et al. 2015). Although it is adapted to each TomoSAR profile through forest height and ratio $A_{max_pic}/A_{first_pic}$, the adaption method may also depend on the SAR wavelength and the selection of TomoSAR algorithms. The exponential correction method shows limited capability to compensate the bias introduced by ground scattering since the variation of TomoSAR backscattered power in the crown is almost missing after the correction. The ground scattering mainly concentrates at the terrain level and is sensitive to terrain slope (Smith-Jonforsen, Ulander, and Luo 2005), which includes terrain backscattering, trunk-ground double-bounce scattering and canopy-ground double-bounce scattering (Freeman and Durden 1998; Tebaldini et al. 2019). Double-bounce scattering can be mitigated through extracting volume-only contribution based on fully polarization data (Pardini et al. 2018; Tebaldini and Rocca 2012). While our results indicate the potential to further apply approaches to derive vertical AGB profiles from TomoSAR profiles, such efforts require targeted field observations with forest mensuration techniques and terrestrial laser scanning in order to develop sufficient reference data for the description of biomass at the surface (grasses), in understory (shrub layer) and overstory (tree crowns).

6. Conclusions

Here we assessed the sensitivity of P-band TomoSAR backscatter to forest height, AGB and the vertical distribution of biomass by using spaceborne lidar observations from GEDI as reference in two tropical forest sites in Lopé and Mondah, Gabon, Africa. The TomoSAR-derived forest height (RH100) shows moderate agreement in terms of regional spatial gradients in comparison with airborne derived canopy height but local errors are substantial which is mainly caused by the cumulative optimizing method we used for relating volume peak position with forest height. This method needs to be adapted locally.

We then estimated total AGB from multiple TomoSAR height layers by using the GEDI AGB product as reference in a random forest regression model. The underestimation of TomoSAR AGB in comparison to LVIS-derived AGB is mainly caused by the underestimation in the GEDI AGB reference data and hence our results demonstrate that multiple TomoSAR-layers can be used to estimate total AGB.

Finally, we investigated the possibility of retrieving the vertical distribution of biomass from TomoSAR backscatter profiles. TomoSAR-derived biomass profiles are linearly related with the biomass profiles that were modelled from field measurements but cannot describe the biomass changes in canopy. While our results indicate the possibility of estimating the vertical distribution of biomass from TomoSAR profiles, we highlight the need for more field observations to quantify the vertical structure and biomass distribution in tropical forests.

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No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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