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Unveiling spatial variations of high forest live biomass carbon stocks of Gabon using advanced remote sensing techniques

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Supplementary material for this article is available online

Abstract

Gabon is one of 11 high-forest, low-deforestation (HFLD) countries in the world. It has the highest proportion of preserved forests in the Congo Basin and is the first country to create large forest carbon offset credits in the market. However, about 60% of forests in Gabon is allocated to logging concessions, causing concerns for forest degradation and the sustainability of carbon credits. Here, we use a combination of air- and space-borne remote sensing data and the-state-of-the-art gradient boosted regression trees to estimate forest structure and aboveground biomass carbon density (ACD) of trees at 100 m resolution for the year circa 2020. Mapping spatial variations of ACD across floristically diverse landscapes, we estimate average density and total living carbon storage of trees at the national and sub-national levels. The estimated ACD of trees in forestlands within the country was 142.12 $\pm$ 7.3 Mg C ha^{-1} with the highest values found in central Gabon (150.08 $\pm$ 5.8 Mg C ha^{-1}) and on highlands (161.18 $\pm$ 6.7 Mg C ha^{-1}). On average, in every region, ACD of forests found within logging concessions (149.89 $\pm$ 6.1 Mg C ha^{-1}) was higher than unmanaged forests of unprotected areas (122.81 $\pm$ 4.4 Mg C ha^{-1}), indicating the combined effects of logging in carbon-rich forests and increased productivity due to management. The country's total estimated biomass carbon for trees (above and belowground) stored within the forests was 4.14 $\pm$ 0.3 Pg C with 68% found within logging concessions and 14% within protected areas. The map provides high precision and comprehensive assessment of carbon stocks of trees in Gabon's forests, significantly improving the country's prospects to implement climate mitigation policies and to participate in carbon markets.

1. Introduction

The urgency of mitigating climate change has spurred global efforts to harness the role of forests in sequestering atmospheric carbon dioxide (Richard *et al* 2011, Moomaw *et al* 2020, Smith *et al* 2020, Hurteau 2021). This prompted the United Nations Framework Convention on Climate Change (UNFCC 2009, Aniel Bodansky 2010) to set up financial incentives to countries aiming to reduce carbon emissions from deforestation and forest degradation (REDD+; Pachauri and Meyer 2014). Countries intending to achieve this goal must either reduce their national deforestation and degradation rates or maintain them low especially for high-forest, low-deforestation (HFLD) countries (Da Fonseca *et al* 2007). National entities that demonstrate emissions reductions may be able to sell those carbon credits on the international carbon market (Pan *et al* 2022, Sacherer *et al* 2022, Schumacher 2023).

The Republic of Gabon in Central Africa is one of 11 HFLD countries (Da Fonseca *et al* 2007) with extensive tropical rainforest that spans approximately 22 million hectares, representing nearly 88% of its land areas (Sannier *et al* 2014). These forests have one of the highest aboveground biomass (AGB) in the world (Saatchi *et al* 2011, Austin *et al* 2017), with the highest proportion of preserved forests in the Congo Basin (Shapiro *et al* 2021), and the lowest rates of tree cover loss (<0.1% averaged over 30 years, Hansen *et al* 2013). Additionally, forests in Gabon are a substantial asset for the country to develop carbon credits for different international markets, to offset national emissions from other sources, and to drive its progress towards its commitments under international climate agreements. However, like other countries in the Congo Basin, the government has targeted industrial agriculture and logging (covering about 70% of the country) for its economic development, while committing to reduce greenhouse gas emissions and preserve ecosystems and biodiversity. Forests of Gabon are therefore exploited extensively by the timber industry. This introduces a difficulty in accounting for forest exploitation while addressing the trade-off between the promotion of carbon sequestration and conservation of its forests under the REDD+ initiative (Molua 2019). To make informed land-use planning, decision-makers require accurate estimation of the carbon stored within its forests at a relevant spatial scale (Romijn *et al* 2012, Herold *et al* 2019).

Previous efforts to quantify forest carbon stock of trees in Gabon relied on small numbers of field inventory plots (Medjibe *et al* 2011, 2013, Poulsen *et al* 2020), which failed to capture the variability of carbon stocks across its floristically diverse forests (CNC 2021). Developing an accurate map of forest carbon at landscape scales (1 ha) has two advantages: (1) provides spatial distribution carbon stocks to allow for better forest management and conservation, and (2) allows more precise national or jurisdictional level carbon accounting for emissions and removals compared to limited inventory samples (McRoberts Ronald *et al* 2022). Meanwhile remote sensing observations of forest structure and estimates of biomass can be used for a more systematic assessment of forest carbon storage at local to national levels. The venue of laser technology into forest monitoring such as airborne laser scanning (ALS) has shown its potential to extend AGB estimation beyond the limited networks of field inventory plots (Réjou-Méchain *et al* 2019, Duncanson *et al* 2022). ALS measurements provide detailed information of the forest canopy height and have been coupled with carbon estimates from field inventory plots to derive regional AGB maps over few hundreds of hectares in Gabon at 100 m (1 ha) spatial resolution (Mitchard *et al* 2012, Armston *et al* 2016, Fatoyinbo *et al* 2017, Silva *et al* 2017, 2018, Labriere *et al* 2018). Although ALS can be used to extend the analysis to larger areas, it is costly and impractical to use over larger geographic areas. The availability of the new spaceborne laser technology from the NASA Global Ecosystem Dynamics Investigation (GEDI) overcomes this challenge by providing an unprecedented sampling density of the vertical structure of the forest globally at 25 m resolution (Dubayah *et al* 2021, Lahssini *et al* 2022a, 2022b). Several machine learning (ML) algorithms have been developed to extrapolate footprint-level forest canopy height measurements from GEDI by integrating multisource satellite imagery and other geospatial datasets (Hansen *et al* 2013, Lang *et al* 2019, Potapov *et al* 2021, Lahssini *et al* 2022b).

In this study, we use state-of-the-art geospatial modeling techniques to map AGB of forests over Gabon at 1 ha) spatial resolution for the year circa 2020. Our methodology is designed: (1) to generate wall-to-wall layers of forest structure by mapping canopy height measurements derived from GEDI using ML algorithms and satellite imagery as predictors, (2) to convert the height metrics to live AGB of trees using a large number of biomass estimates from airborne lidar data to train additional ML models, and (3) to estimate below ground live biomass (BGB) of roots from AGB and summing the two compartments to get an estimate of the total living carbon of trees in the forest available for the country. We compared the mapped estimates of tree AGB with estimates from the national forest inventory (NFI) plots and GEDI direct estimates of tree AGB (L4B product) available for the country.

2. Methods

2.1. Study area

Gabon is located in the Gulf of Guinea along the Atlantic coast of Central Africa (figure 1) The climate is equatorial, warm and humid with a mean annual temperature (averaged 1901–2015) of 25 °C and a mean annual precipitation of 1800 mm. Gabon is sparsely populated (Zhang *et al* 2002) with almost 90% of the population living in urban areas (World Bank Group 2019) or distributed in small villages along a few main roads that cross the country.

2.2. Mapping forest height metrics

We used Google Earth Engine (GEE) cloud computiong platform (Gorelick *et al* 2017) to combine satellite datasets from Landsat, ALOS PALSAR, Digital Elevation Model from Copernicus and three relative height (RH) metrics from GEDI measurements: RH50, RH75, and RH98 corresponding to the canopy height of 50th, 75th, and 98th percentile of energy returns relative to the ground (see supplementary material for more details). To reduce the systematic

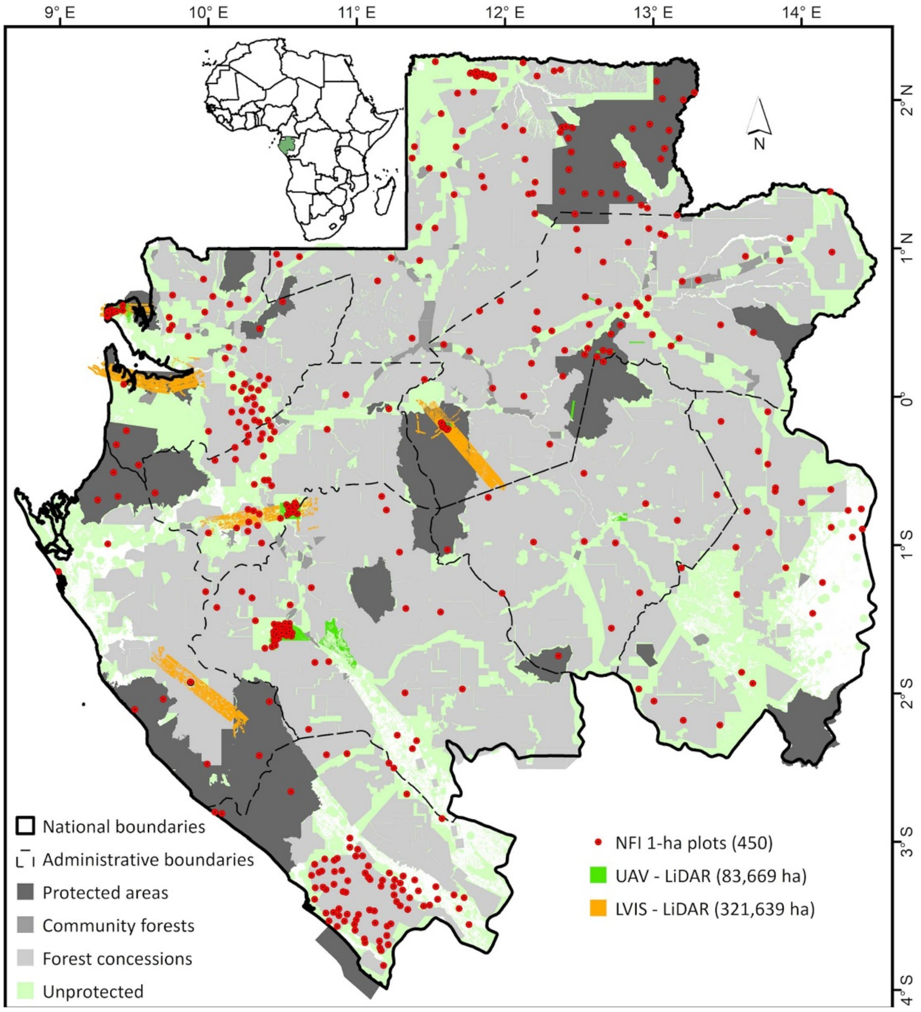

Figure 1. Study area showing the distribution of field and airborne sampling data over the different land cover allocation in Gabon. LVIS: NASA Land Vegetation and Ice Sensor; NFI: national forest inventory; UAV: Unmanned Aerial Vehicle.

geolocation errors observed with GEDI footprints (Tang *et al* 2023), the ~6.2 million GEDI shots at 25 m were aggregated to 100 m grid cells (pixels) and the average value for each height metric was retained as the dependent variable. We filtered aggregated pixels with a minimum of 3 footprints of 25 m, yielding a total of ~1.5 million height metrics at 100 m across the study area. Of these data, 80% were used for model training and 20% for the final model validation. We used Gradient Boosted Regression Trees (GBRT; Friedman 2002) as the machine learning algorithm to predict and map each RH metric across Gabon. GBRT algorithm has become widely popular for remote sensing applications due to the accuracy of its results (Chen and Guestrin 2016, Colin *et al* 2017, Xu *et al* 2021). After being scaled to have an identical mean and standard deviation, the satellite predictors were geographically aligned and stacked with the 100 m GEDI training data and tiled into 20 × 20 km areas with 70% overlap. We applied local GBRT models over each tile considering a minimum of 500 aggregated GEDI pixels available for the respective tile as training. For tiles with fewer GEDI training pixels, we considered those available over neighboring non-overlapping tiles until the condition was met. A wall-to-wall canopy height prediction was obtained by mosaicking estimates from each tile considering the median value of overlapping pixels to minimize discontinuity effects between tiles (figure S1).

2.2.1. Estimating AGB and associated uncertainties

We used the ALS-based AGB estimates for trees available over the country (figure 1) to train a GBRT model with the predicted RH metrics and generate a national scale AGB map. We also developed a pixel-based prediction uncertainty associated with the spatial modeling of AGB by performing a 10-fold cross validation (CV) with 90% training and 10% testing and repeating the procedure 100 times. The pixel level error is assigned by the variance of the 100 times predictions. As height metrics have been used to predict the biomass, we consider the height metrics as predictor layers without any uncertainty and consider the variance of carbon density inference at the national level to include both sampling and the residual variance (see supplementary material). To provide the mean and variance of the regional and national level estimates we followed the error propagation approach that considers the variance associated with the model and the spatial correlation (Xu *et al* 2016, McRoberts Ronald *et al* 2022, Cushman *et al* 2023). The validation of the biomass carbon density was also performed using National Forest Inventory (NFI) and research plots. We used the 450 1 ha plots available over Gabon from NFI and local random or systematic samples to assess the accuracy of the predicted AGB map at the pixel level.

2.2.2. National carbon statistics

We applied the most recent carbon conversion factor for tropical forests of 0.456 (Martin *et al* 2018) adopted by Gabon (CNC 2021) to convert AGB to aboveground carbon density (ACD) of trees. The average national ACD estimate was compared to the ones from the systematic random sampling with NFI and the biomass product from GEDI L4B (Dubayah *et al* 2022). We combined the recent map of floristic types available over the Congo Basin (Réjou-Méchain *et al* 2021) with the forest cover map developed by the Gabonese Studies and Space Observations Agency (AGEOS, CNC 2021) to assess the variation in carbon density within the main forest formations. A similar comparison was made for different landforms in the country based on the landform map available of the region (Viennois *et al* 2022). We used a post-hoc pairwise Tukey test to test for the significant difference between the mean ACD values. We estimated the belowground living carbon density (BCD) from the roots using the root-shoot ratio of 0.235 (Mokany *et al* 2006) and added it to the ACD to get an estimate of the total living carbon density (TCD) of trees. The total carbon in live tree vegetation was obtained by multiplying the TCD with the total forest area available for the year 2020.

3. Results

3.1. Canopy height estimates over Gabon

The performance of the models used to predict different RH metrics varied according to the validation dataset (figure 2). Overall, the model performances showed better agreement when compared to the GEDI validation dataset (figures 2(a)–(c)) in comparison with LVIS data that showed the best agreement with RH75 between 20 and 35 m predictions (figure 2(e)).

3.2. Aboveground carbon prediction

The error associated with ACD predictions over Gabon gave an R^2 of 0.59 with an RMSE of 40.4 Mg C ha^{-1} when compared to ALS-based ACD (figure 3(a)) while the validation with plot data gave a similar R^2 (0.5) and lower RMSE (38.85 Mg C ha^{-1}).

We noticed a general decrease of the error towards higher ACD estimates (figure 3(b)) with less than 22.8 Mg C ha^{-1} of absolute error obtained for ACD ranges between 91.2 and 182.4 Mg C ha^{-1} (representing about 70% of the validation dataset). The predicted ACD map showed no systematic error (bias = 0.01 Mg C ha^{-1}) when compared with ALS-based ACD estimates, whereas the validation with plot-based ACD showed an overall systematic error of 5 Mg C ha^{-1}, caused mostly by the overestimation of ACD within 0–90 Mg C Mg ha^{-1} that can be adjusted in a bias-correction approach.

The spatial distribution of ACD revealed a detailed gradient of forest structure (figure 4) from low ACD of forests along the coast—except for tall mangrove forests in Pongara national park (figure 4(b)); followed by an increase towards the country's interior and a drop within the northeastern flooded forests (figure 4(c)). The map also captured the spatial variability in ACD associated with logging (logging roads and tree harvesting; figure 4(d)) and secondary forests recovering around urban areas (figure 4(e)).

3.3. Regional and national level estimates

The national scale average forest ACD predicted from our map is 142.12 ± 7.3 (95% CI) Mg C ha^{-1} (figure 3(c)) and in close agreement with the value reported from NFI plots (141.7 ± 60.4 Mg C ha^{-1}) and significantly higher than GEDI L4B estimations (104.42 ± 12.6 Mg C ha^{-1}). Note that the precision of the estimate from the Gabon carbon map from our study is significantly better than the NFI and the GEDI L4B estimates due to the large number of pixels and significantly negligible systematic error.

The comparison of the average ACD and its RMSE derived from our map with estimates from NFI plots and GEDI L4B revealed differences within vegetation types and landforms (figure 5). The highest ACD was found within Central forests (150.08 ± 5.8 Mg C ha^{-1}, figure 5(a)); Congolian north-eastern forests (140.25 ± 7.2 Mg C ha^{-1}) and tall mangroves (130.3 ± 6.3 Mg C ha^{-1}) with wetlands (33.63 ± 12.6 Mg C ha^{-1}) and low mangroves (24.2 ± 22.2 Mg C ha^{-1}) having the lowest ACD. Highlands supported forests with the highest ACD (figure 5(b)) within mountains (161.18 ± 6.7 Mg C ha^{-1}) and hills (149.38 ± 5.3 Mg C ha^{-1}). Forests with the lowest ACD of trees were found on coastal plains (92.61 ± 4.2 Mg C ha^{-1}).

3.4. National assessment of carbon storage

The total live carbon (aboveground + belowground) of trees stored within forests in Gabon was estimated to be 4.14 ± 0.3 Pg C (table 1). The highest

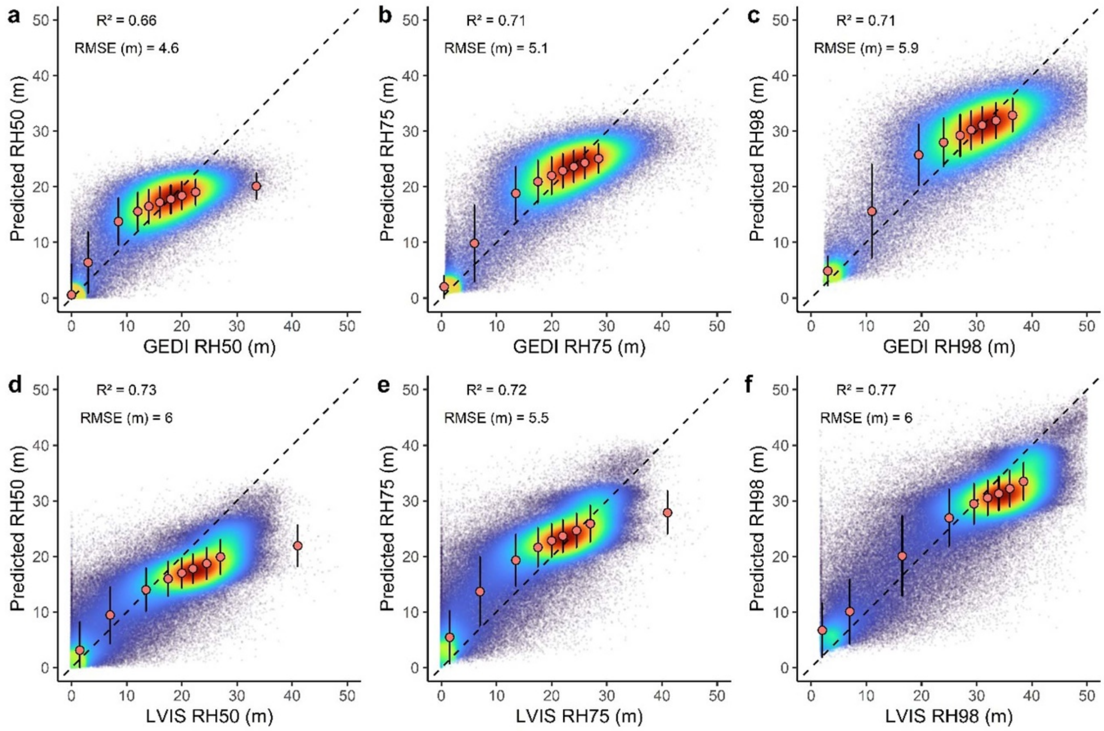

Figure 2. Validation of the modeled relative heights over Gabon. Density plot showing model performances of the different RH models (RH50; RH75 and RH98 as first, second and third columns) from spaceborne GEDI (first row) and airborne LVIS (second row). Filled red points are the average of predicted RH metrics within successive bins of 10% percentiles with associated standard deviation (black vertical bars).

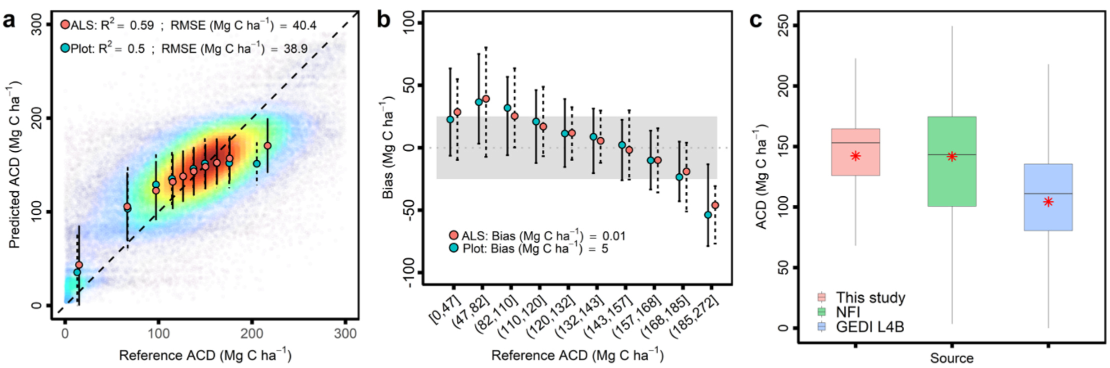

Figure 3. Validation of the modeled aboveground carbon density (ACD) over Gabon. Relationship between predicted and reference ACD with colors of the point cloud showing a gradient of increasing point density from blue to red (a). Filled points are the average of predicted ACD within 10 percentiles intervals and associated standard deviation (black vertical bars). Uncertainties associated with ACD estimates within 10 percentile intervals and associated standard deviation (b). The gray ribbon highlights bins with less than 20 Mg C ha^{-1} of absolute error. National scale averages of ACD from different data sources (c).

total carbon was stored within logging concessions (2.82 ± 0.1 Pg C) representing 68% of the total carbon of the country, with only 14% (0.58 ± 0.2 Pg C) stored within protected areas and 17% (0.73 ± 0.3 Pg C) stored within unprotected forests. Community forests with their low surface area (∼0.27 million ha) had the lowest carbon stocks (0.04 ± 0.2 Pg C). Minkébé and Lopé were the two national parks with the highest carbon storage (∼0.1 Pg C each) while Ogooué-Ivindo was the province with the highest forest carbon storage (0.77 ± 0.3 Pg C).

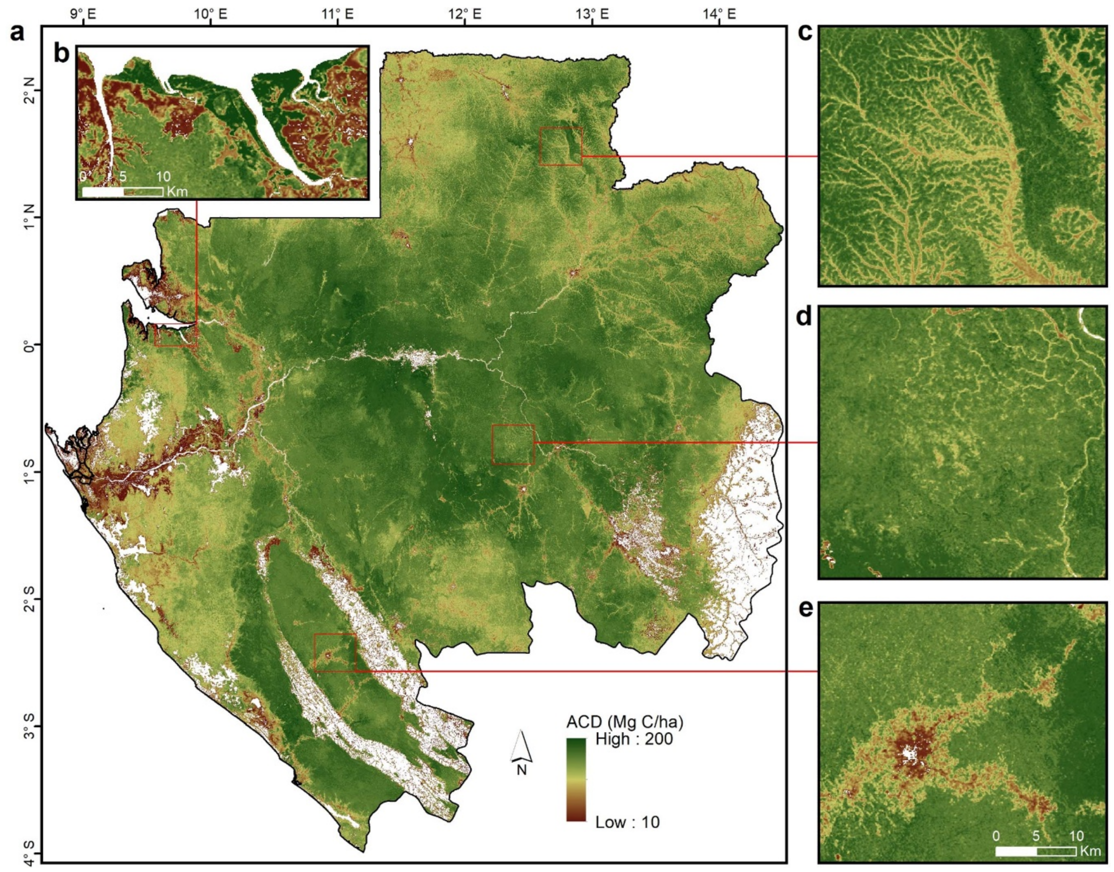

Figure 4. Spatial distribution of the aboveground carbon density (Mg C ha^{-1}) of Gabon's forests at 1 ha resolution for the year circa 2019 (a). Zoom-in subsets highlighting carbon variability within tall mangrove forests of Pongara National Park (b), flooded forests (c), degraded forests within logging concessions (d), and secondary forests along urban areas (e).

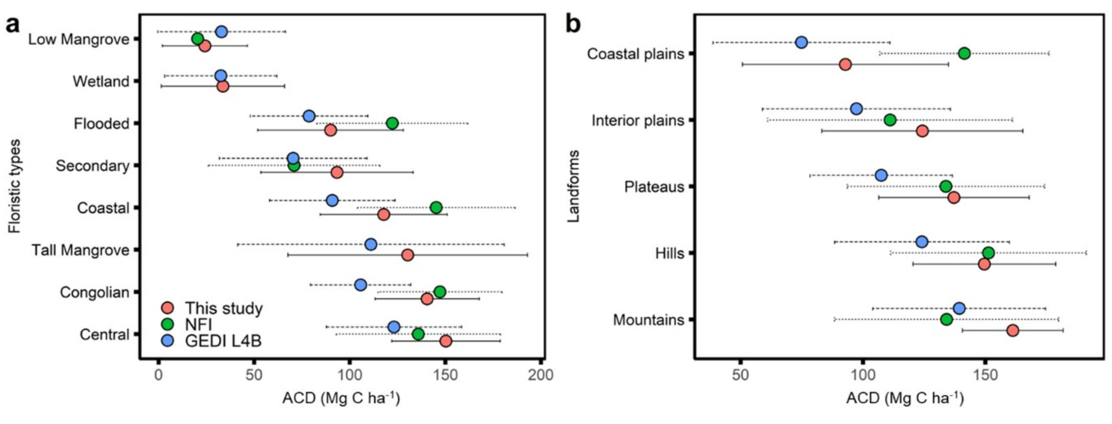

Figure 5. Average aboveground carbon density (ACD) for trees and its variation calculated for each vegetation type (a) and landforms (b). Colors are estimates derived from this study (pink), 450–1 ha NFI plots (green) and GEDI L4B biomass product (blue) with bars corresponding to their associated standard deviation.

4. Discussion

High resolution mapping of forest structure in Gabon is constrained by its dense and complex canopy (Mitchard *et al* 2012, Hansen *et al* 2013, Labriere *et al* 2018, Silva *et al* 2018, Lang *et al* 2019, Mohammad *et al* 2019). The localized ML approach implemented in this study, helped to improve the precision of predicted canopy height metrics (RMSE $\sim$ 6 m on average) as compared to existing global products from Lang *et al* (2019; RMSE = 8.2 m with RH98) and Potapov *et al* (2021, RMSE = 7 m with RH95). Above 35 m the model precision was mainly limited by the saturation of the relationship between the canopy structure and the satellite predictors (Simard *et al* 2011, Fayad *et al* 2014, Wang *et al* 2016, Potapov *et al* 2021). All height metrics showed a slight dilution error by overestimating the height of shorter forests

Table 1. Tree carbon statistics over Gabon within different forest management categories, and jurisdictions with their respective relative proportions to the national total. The forest area estimates are based on the land cover map provided by the Gabonese Studies and Space Observations Agency (AGEOS) for 2020 at 30 m resolution. Total living forest carbon density (TCD) includes above ground (ACD ±95% CI) and below ground (BCD) from root biomass.

	Area (Mha)	ACD mean (Mg C ha^{-1})	BCD mean (Mg C ha^{-1})	TCD mean (Mg C ha^{-1})	Total C (Pg C)	Total C (%)
Management						
Logging	15.234	149.89 ± 6.1	35.22 ± 8.47	185.11 ± 14.57	2.8201	**68.11**
Protected	3.252	144.40 ± 8.7	33.93 ± 9.81	178.34 ± 18.51	0.5801	**14.01**
Unprotected	4.831	122.81 ± 4.4	28.86 ± 10.3	151.67 ± 14.7	0.7328	**17.7**
Community	0.272	137.77 ± 4.1	32.38 ± 9.71	170.15 ± 13.81	0.0463	**1.12**
National Parks						
Akanda	0.028	32.80 ± 7	7.71 ± 3.5	40.51 ± 10.5	0.0011	**0.03**
Birougou	0.069	136.92 ± 5.4	32.18 ± 6.94	169.10 ± 12.34	0.0117	**0.28**
Ivindo	0.297	162.99 ± 5.22	38.30 ± 6.43	201.29 ± 11.65	0.0597	**1.44**
Loango	0.123	111.30 ± 6.32	26.16 ± 9.39	137.46 ± 15.71	0.0169	**0.41**
Lopé	0.466	173.57 ± 6.8	40.79 ± 10.84	214.36 ± 17.64	0.1000	**2.42**
Mayumba	0.005	83.08 ± 6.9	19.52 ± 10.55	102.61 ± 17.41	0.0005	**0.01**
Minkébé	0.758	144.84 ± 6.2	34.04 ± 8.96	178.88 ± 15.16	0.1356	**3.28**
Monts de Cristal	0.120	156.84 ± 4.6	36.86 ± 5.06	193.69 ± 9.66	0.0232	**0.56**
Moukalaba-Doudou	0.416	156.12 ± 6.4	36.69 ± 9.66	192.81 ± 16.06	0.0802	**1.94**
Mwagna	0.115	150.19 ± 5.9	35.30 ± 8.09	185.49 ± 13.99	0.0215	**0.52**
Plateaux Batéké	0.057	81.62 ± 6.6	19.18 ± 10.18	100.80 ± 16.78	0.0058	**0.14**
Pongara	0.072	92.63 ± 12.7	21.77 ± 6.18	114.40 ± 18.88	0.0082	**0.20**
Waka	0.107	161.63 ± 4.7	37.98 ± 5.17	199.62 ± 9.87	0.0214	**0.52**
Provinces						
Estuaire	1.876	136.74 ± 8.6	32.13 ± 17.38	168.87 ± 24.98	0.3168	**7.65**
Haut-Ogooué	2.305	131.28 ± 6.5	30.85 ± 9.85	162.14 ± 16.35	0.3737	**9.03**
Moyen-Ogooué	1.573	149.50 ± 6.5	35.13 ± 10.02	184.64 ± 16.52	0.2904	**7.01**
Ngounié	3.500	146.45 ± 6	34.42 ± 8.38	180.87 ± 14.38	0.6332	**15.29**
Nyanga	1.607	144.34 ± 6.5	33.92 ± 9.91	178.25 ± 16.41	0.2864	**6.92**
Ogooué-Ivindo	4.273	146.47 ± 6.1	34.42 ± 8.89	180.89 ± 14.99	0.7729	**18.67**
Ogooué-Lolo	2.872	161.37 ± 6	37.92 ± 8.09	199.30 ± 14.09	0.5724	**13.82**
Ogooué-Maritime	1.875	111.60 ± 6.5	26.23 ± 10.06	137.83 ± 16.56	0.2584	**6.24**
Wouleu-Ntem	3.708	138.81 ± 6.4	32.62 ± 9.51	171.43 ± 14.91	0.6357	**15.35**
Total	**23.592**	**142.12 ± 8.2**	**33.40 ± 4**	**175.52 ± 12.2**	**4.1408 ± 0.332**	

and underestimating the height of tallest forests. This effect is partially due to the lack of sample data at the lower and higher end of the distribution forcing the machine learning model to overfit the prediction towards the main part of the distribution. As these areas are relatively small over the country, their impact on the overall carbon density estimation likely remains small. The 1-ha resolution ACD map of forest trees generated from this study is the first available product calibrated for the Republic of Gabon using state-of-the-art techniques in geospatial modeling. The map reveals large-scale spatial variability of the carbon stored within its forests with low uncertainty (95% CI = 0.03). The average ACD obtained over Gabon's forests (142.12 ± 7.3 Mg C ha^{-1}) is consistent with previous estimates from NFI plots (141.7 ± 60.4 Mg C ha^{-1}; Poulsen *et al* 2020) but with significantly better uncertainty due to the large number of map pixels. Considering the recent global biomass product from GEDI L4B led to ∼30% underestimation of national scale average ACD. This highlights the importance of calibrating local biomass models to improve the accuracy of biomass maps at regional to national scales (Næsset *et al* 2020).

The level of details achieved at finer scales helps us to accurately describe carbon allocation at the national level. The low carbon density recorded within coastal forests on plains is a consequence of a heavy historical harvesting that occurred in the area during slave trade (16th–19th century) and colonialism (Collomb *et al* 2000, CNC 2021). Ever since, most of the forests have been sustainably managed either for timber production within logging concessions or protected for biodiversity conservation. Logging concessions represent about 60% of the total forest cover of the county (CNC 2021) and store the highest amount of ACD on average (149.89 Mg C ha^{-1} ± 6.1) as compared to unmanaged forests found within unprotected areas (122.81 Mg C ha^{-1} ± 4.4) which agrees with Poulsen *et al* (2020). The higher ACD observed within logging concessions is most likely a consequence of direct selection of forests with a high abundance of large trees suitable for logging. Except for forests dominated by Okoumé, most of the industrial logging in Gabon is selective and focused on high-value tree species (White 1994, 2020) leading to a low biomass loss (Medjibe *et al* 2011, 2013). In addition, the higher rates of carbon sequestration from post-harvest activities (Gourlet-Fleury *et al* 2013, Medjibe 2020) and the longer rotation cycles to at least 20 years implemented in Gabon (République Gabonaise 2001, Pérez *et al* 2005) provides more time for the forest to recover after disturbance, supporting the maintenance of high carbon storage. This positive effect of management on carbon storage can be exacerbated in areas with fertile soils, as soil fertility has been identified to be the only environmental variable positively influencing ACD in Gabon from plot data (Poulsen *et al* 2020).

The national scale carbon estimates provided in this study constitute a baseline for future forest management or emission reduction projects. The country's total estimated carbon stock (above and belowground) is 4.14 Pg C, with a country-scale error of less than 1%. About 68% of the total carbon stock is found within logging concessions (2.82 Pg C) given their spatial extent and the high ACD in these forests. The 13 national parks in the country store 14% of the total carbon, equivalent to 0.58 Pg C. Among these parks, four (Ivindo, Lopé, Minkébé and Moukalaba-Doudou) stand out for having the largest forest cover and the highest ACD on average and 65% of the carbon stock in national parks is found within them. Most of these parks have their forest structure vulnerable to global change (Réjou-Méchain *et al* 2021) except for Akanda, Monts de Cristal, Plateaux Batéké and Pongara, where only 7% (0.03 Pg C) of the total carbon is found. The four coastal provinces (Estuaire, Moyen-Ogooué, Nyanga, Ogooué-Maritime) with the less dense forests store a total of 1.15 Pg C representing 28% of the total carbon storage of the country. The remaining carbon storage is similarly distributed within the five other provinces found at the interior, except for Haut-Ogooué, which stores only 9% of the total carbon due to the dominance of savanna vegetation and forests impacted by long term human disturbances related to mining (CNC 2021).

Most of the forests in Gabon are found in areas that were historically villages spread across the country before colonial occupation forced their clearance in favor of coerced settlement of the population along the major roads (CNC 2021). In addition, the impact of slave trade in the coastal area led to a reduction in its human population which resulted in the regeneration of vast swathes of forest which today are 150–500 years old (CNC 2021). Further back still, a population crash that affected much of West Central Africa between about 1200–800 years ago, reduced the human influence on the forests in Gabon (Oslisly *et al* 2013). As a result, most of the current forests in Gabon, like elsewhere in Central Africa, are actively progressing towards later successional stages and more old growth vegetation types, partially explaining their tendency toward a long-term stable carbon sink (Lewis *et al* 2009, Hubau *et al* 2020).

5. Conclusion

We provided the first systematic and accurate assessment of the forest carbon density and storage at landscape scales for the second largest forested country in the world. This map not only reveals the extensive spatial variability of carbon stored within Gabon's forests but also does so with low uncertainty, providing reliable data for decision-making. Considering the spatial extent of logging concessions across Gabon, improved quantification, and characterization of the influence of management practices on the forest structure would enable a more informed accounting of carbon fluxes, providing a foundation for an improved set of incentives for conserving forest carbon stocks and sinks. The map we generate can be used as input into calculations of baseline carbon stocks and emissions in the context of REDD+ at regional to national scales. We expect significant improvements of Gabon's forest biomass mapping in future with the launch of NISAR (L-band) and BIOMASS (P-band) radar missions in early 2024.

Data availability statement

The NFI plot data used in this study are the properties of Le Ministère des Eaux, de la Forest, de la Mer, de l'Environnement of the Republic of Gabon and are subject to third party restrictions. All the GEDI and satellite data are freely available from the Google Earth Engine repositories via these links: https://developers.google.com/earth-engine/datasets/catalog/LARSE_GEDI_GEDI02_A_002_MONTHLY#description and https://developers.google.com/earth-engine/datasets/catalog. The AfriSAR gridded forest biomass and canopy metrics derived from LVIS over Gabon are freely available at the NASA ORNL DAAC https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1775. The additional UAV-ALS data are now available from Rodda *et al* (2024) https://doi.org/10.23708/H2MHXF.

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Conflict of interest

The authors declare no conflict of interest.

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