Estimation of carbon stocks in Colombian mangroves and associated uncertainties

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Abstract

We estimated carbon (C) stocks in aboveground biomass (AGB) for mangroves in the Caribbean and Pacific coasts of Colombia. Using available data on AGB density and mangrove area for the whole country and each coast independently, we estimated a national carbon stock in AGB for Colombian mangroves as 14.95 ± 2.72 TgC (mean ± SE), with 2.20 ± 0.86 TgC in the Caribbean coast and 9.61 ± 2.78 TgC in the Pacific coast. Uncertainty for total carbon in AGB in Colombian mangroves, reported as SE/mean in percentage, was 18% at the national level, 39% in the Caribbean coast, and 29% in the Pacific coast. This uncertainty was more influenced by uncertainties associated with the estimation of mangrove area for the Caribbean coast, while for the Pacific coast it was more influenced by the uncertainties associated with AGB density. This difference is the result of a contrasting availability of AGB density data for both coasts. Comparison between observed AGB density data and predictions from large-scale models showed that these models underestimate AGB density for Colombian mangroves. We reparameterized these models with our data, but found poor goodness-of-fit statistics for these model structures. We propose therefore three new statistical models to predict AGB density in Colombian mangroves based on climatic and vegetation data. In all cases, the best models included the enhanced vegetation index (EVI) and the mean temperature of driest quarter (BIO9).

Keywords: Blue carbon, uncertainty analysis, aboveground biomass, EVI, national carbon inventory

1. Introduction

Efforts to reduce tropical deforestation have traditionally focused on terrestrial environments; however, recent studies investigating the contribution of coastal ecosystems to mitigate climate change through carbon sequestration and storage suggest that these ecosystems can rival their terrestrial counterparts (Yee, 2010). Coastal vegetated ecosystems, in particular mangroves, salt marshes, and seagrasses conform Earth's 'blue carbon' sinks (Herr et al., 2012). They comprise only 0.05% of the plant biomass on land, but store a comparable amount of carbon per year, and thus rank among the most important carbon sinks on the planet (Nellemann et al., 2009). HOLA

Among these blue carbon ecosystems, mangroves have an enormous capacity for carbon sequestration and storage (Nellemann et al., 2009; Donato et al., 2011; Adame et al., 2013), and may pose serious risks for greenhouse gas (GHG) emissions due to land use change in coastal areas (World Bank, 2010). Unfortunately, there is a large data gap at regional scales about carbon storage in mangroves (Donato et al., 2011), so their inclusion in national climate change mitigation strategies is still limited. This data gap hinders the possibility of mangrove ecosystems to participate in current climate change mitigation schemes such as Reducing Emissions from Deforestation and Forest Degradation (REDD+) as well as Nationally Appropriate Mitigation Actions (NAMAs)(Alongi, 2011; Herr et al., 2012; Murray et al., 2012; Boucher et al., 2014).

Participation in climate change mitigation schemes will require countries to produce accurate estimates of their forest carbon stocks and stocks changes through robust Measurement, Reporting and Verification (MRV) programs (Cohen et al., 2013). To achieve the required quality level, it is important *to assess the quality of measurements taken in field, data compilation and analysis data in order to generate error estimates and improve future measurements* (Maniatis and Mollicone, 2010). Furthermore, the success of blue carbon projects depends to a large degree on the reliability of the scientific information used for their implementation (Alongi 2011, Maniatis and Mollicone, 2010). In this sense, it is necessary to quantify and report uncertainties in estimates of carbon stocks for these ecosystems (Kauffman and Donato, 2012; Alongi, 2011) as well as the main sources that contribute to the uncertainty in the carbon stock estimates.

Two sources of information are necessary for the estimation of temporal changes in GHG emissions or GHG emission reductions in forests: emission factors (i.e. carbon stocks changes) and activity data (i.e. changes in areas under a specific land use). The Intergovernmental Panel on Climate Change (IPCC, 2003, 2006) highlights the necessity to provide estimations for these two sources of information with a level of uncertainty as low as possible (according with the capacity of the country), reporting mean estimates along their 95% confidence limits. In this respect, it is necessary to provide uncertainty estimates for both carbon stocks and area in determining the baseline for climate change mitigation projects (Maniatis and Mollicone, 2010).

Estimates of carbon stocks changes can be obtained using different approaches. The IPCC (2003, 2006) has categorized these approaches in three different levels: Tier 1, Tier 2, and Tier 3; with increasing accuracy and complexity in MRV from Tier 1 to Tier 3 (Maniatis and Mollicone, 2010). For the estimation of forest carbon stocks, particularly in aboveground biomass (AGB), information about mangrove cover areas, forest-plot inventory data as well as statistical models are combined to obtain carbon stock estimates for particular regions. These three different sources of information contain uncertainties that must be propagated to the final estimate. For plot inventory data, uncertainties are generally associated with sampling errors, the use of allometric models, and other systematic errors (Chave et al., 2005; Sierra et al., 2007). For mangrove cover area, uncertainty is related with the ability to detect and delineate accurately areas that correspond to mangroves. Detection of cover area can be done with field-surveys, aerial photographs, or satellite products, and these areas should correspond to the areas or the ecological characteristics where biomass estimates are available. Lastly, a model must be used to scale-up plot-level data to landscape and regional levels. Model predictions also contain uncertainty related to model structure and parameter values (IPCC, 2006). To propagate uncertainty from these different sources, one can either propagate analytically standard deviations or standard errors using known formulas, or use Monte Carlo methods (Chave et al., 2005; Sierra et al., 2007; IPCC, 2006).

In Colombia, estimates of carbon stocks in mangroves are available only for a few locations. Data for these sites was produced for research projects or to establish the baseline of carbon stocks for the future implementation of pilot REDD+ at the project level (Bolivar et al., In preparation; Carbono & Bosques, 2015). Despite the importance of these efforts, C stock estimates for mangroves are not articulated with the mitigation strategy being designed at the national level. For instance, a recent estimation of carbon stocks at the national level (Phillips et al., 2011) did not include mangroves as an independent category, underestimating the capacity of the country to mitigate climate through terrestrial C sinks.

Given that national estimates of carbon stocks are relevant inputs for decision-making and implementation of future climate change mitigation strategies, it is necessary to adjust carbon stocks estimates for mangrove ecosystems reducing current uncertainties. To achieve this goal, it is important to identify sources of uncertainty at regional (different coastlines) and at national scales, and in this way, to prioritize actions to reduce it. Additionally, the development of tools such as

AGB models at national scale could help to identify the relevance of different mangrove areas as carbon sinks, including predictive variables that account for significant levels of spatial variability (Ewel et al., 1998; Kristensen et al., 2008).

The main objectives of this study are: (i) to estimate the current uncertainty in the estimation of the national carbon stock in AGB for mangrove ecosystems in Colombia, identifying sources of uncertainty and proposing possible ways to reduce it; and (ii) to develop a statistical model to predict carbon stocks at the national level. We present estimates not only for the entire country, but also for mangroves in each coast, Caribbean and Pacific.

2. Methods

2.1. Data

We used data from two different sources: (i) scientific articles and/or technical reports from studies developed in mangrove areas located in the Caribbean and Pacific coast of Colombia, in which above ground biomass (AGB) was quantified and; (ii) data from two inventories of carbon stocks in Cispatá bay (Colombian Caribbean coast) and Málaga bay (Colombian Pacific coast) (Bolivar et al., In preparation; Carbono & Bosques, 2015). For the first type of data, we selected only studies which included coordinates or specific location names that can be easily geolocated (INVEMAR, 2007; Lema and Polanía, 2007; De la Peña et al., 2010; Blanco et al., 2012). The main difference between both data types is the scale of the information. The first data type report average AGB per location, while the second data type reports estimates per plot covering the same region (22 permanent plots of 500 m^2 in Cispatá bay and 10 in Málaga bay).

Furthermore, information about mangrove cover area comes from two different sources: global estimations (FAO, 2007; Giri et al., 2010, 2013; Hutchison et al., 2014) and national estimations compiled by the Colombian institute for ocean and coastal research (INVEMAR, 2014) and derived from particular estimations made by the different environmental authorities with jurisdiction in mangrove areas along the country.

2.2. National carbon stocks from available data and associated uncertainties

We pooled the available AGB density data by coast and for the entire country and calculated averages, standard deviations, and standard errors at each level. To report results in units of C, we used a conversion factor of 0.5 as recommended by other authors (MacDicken, 1997; Clark et al., 2001; Fearnside and Laurance, 2004; Chave et al., 2005; Aragão et al., 2009). We also calculated averages from the available data on mangrove areas for each coast and the entire country. Based on the obtained averages and standard errors for each variable, we calculated national and regional carbon stocks using a Monte Carlo procedure in which we sampled 1000 random deviates from a normal distribution with mean equal to the average from the available data and standard deviation from their standard errors. We multiplied both sets of 1000 random deviates (AGB density $\times$ mangrove area) to obtain a set of 1000 random numbers with mean equal to the expected C stock for each region and standard deviation for the mean according to the Central Limit Theorem (see also Sierra et al., 2007). Therefore, we report uncertainties for the mean AGB, mean mangrove area, and mean C stock.

To report uncertainties, we use the coefficient of variation CV calculated as the ratio SE to the mean for sample data, and as SD to mean for Monte Carlo simulated variables.

To identify whether the uncertainty in the regional and national C stocks are mostly contributed by uncertainties in AGB density or mangrove area and the efforts that must be made to reduce it, we developed a sensitivity analysis based on different levels of uncertainty for each contributing variable. We assumed values of uncertainty of 0%, 5%, 10%, 15%, 20%, 30%, 50% and 100% (as CV in percentage) for each variable and calculated the uncertainty in the regional or national C stock for all possible combinations.

2.3. Predictive models

We used available models published in the scientific literature to predict AGB for the locations where we have data and evaluated the possibility of using these models for our regional and national estimations. We evaluated the latitude-based model developed by Twilley et al. (1992) and the climate-based model developed by Hutchison et al. (2014). Given that we obtained very poor performance of these models in predicting our observations (see Results section), we developed our own set of predictive models for AGB with regression analysis.

We evaluated different functional response models to explain the AGB at each location i:

$$AGB_i = a + bX_i + e_i, \tag{1}$$

$$\frac{1}{AGB_i} = a + b\frac{1}{X_i} + e_i, \tag{2}$$

$$\log AGB_i = a + bX_i + e_i, \tag{3}$$

$$\log AGB_i = a + b\log X_i + e_i, \tag{4}$$

$$\log AGB_i = a + b\frac{1}{X_i} + e_i, \tag{5}$$

where X_i represents the value of a predictive variable at the location i, with an error e_i, and coefficients a and b. As predictive variables, we evaluated latitud, the Enhanced Vegetation Index (EVI) from MODIS (Didan et al., 2015), bioclimatic variables form the WorldClim dataset (Hijmans et al., 2005), and possible combinations among all variables. We evaluated in total 48 models. For parameter estimation, we used ordinary least squares using function `lm` in R.

The latitude data were used to calculate distance from the equator, which has been previously linked to mangrove productivity (Twilley et al., 1992; Saenger and Snedaker, 1993; Komiyama et al., 2008; Wang et al., 2013; Alongi, 2014). Working with the assumption that mangrove biomass will be affected by temperature and precipitation (Komiyama et al., 2008; Hutchison et al., 2014), average and extreme bioclimatic variables proposed by Hutchison et al. (2014) were included as well as precipitation and temperature associated to the driest quarter (Table 1). Bioclimatic data were extracted from the WorldClim Bioclim (Hijmans et al., 2005) 30 arc-second data set (http://www.worldclim.org/bioclim). Likewise, global MODIS vegetation indexes provide consistent spatial and temporal comparisons of vegetation conditions; in this sense, EVI values were retrieved from the online data pool, courtesy of the NASA Land Processes Distributed Active Archive Center (LP DAAC) (Didan et al., 2015) (https://lpdaac.usgs.gov/data_access/data_pool). AGB data sources used to develop the predictive model can be consulted in the data base related in supplementary information of this paper.

Model performance was assessed using the adjusted coefficient of determination ($\mathrm{R_a}^2$), which informs about in-sampling predictive power, and the Akaike information criterion with a correction for finite sample sizes (AICc), indicating model generalizability as it relates to model simplicity (Jardine and Siikamäki, 2014).

We used the R package AICcmodavg (Mazerolle, 2015) to compare candidate models that showed

Table 1: Bioclimatic variables used for modeling (see www.worldclim.org/bioclim)

Variable	Name	Type
BIO1	Annual mean temperature (℃)	Average and seasonalities
BIO4	Temperature seasonality: S.D. of monthly mean temperature	Average and seasonalities
BIO12	Annual precipitation (mm)	Average and seasonalities
BIO15	Precipitation seasonality: CV of monthly precipitation	Average and seasonalities
BIO9	Mean Temperature of Driest Quarter (℃)	Extremes
BIO10	Mean Temperature of warmest quarter (℃)	Extremes
BIO11	Mean Temperature of coldest quarter (℃)	Extremes
BIO16	Precipitation of the wettest quarter (mm)	Extremes
BIO17	Precipitation of the driest quarter (mm)	Extremes

the best predictive power and simplicity through a “model selection table” based on the AIC. This table assigns to each model a weight, which could be interpreted as the probability of an i model to be the best of the evaluated group of models. Candidate models can be classified in four categories according to these weights: “substantial weight models”, “some weight models”, “little weight models” and “no weight models”. We selected models classified in the “substantial weight” and “some weight” groups as models to be used in biomass predictions.

To determine the influence of environmental local variability on AGB, we also fitted multilevel models through maximum likelihood estimation using the R package lme4 (Bates et al., 2015). We assumed our data as classified into two subgroups, site and Coastal Environmental Units (CEU). The first subgroup refers to the specific location of the sites, while the CUE refers to an environmental classification of coastal zones in Colombia (CNT MIZC and CCO, 2010). We estimated the initial proposed models including separately each subgroup, but also the interaction of both. The predictive power of the model was analyzed using the Deviance statistic ($D^2\%$), which measures the percentage of the variability explained by the model.

2.4. AGB estimation using the predictive models

We estimated model-average predictions of AGB based on the candidate models classified as “substantial weight models” category according to the results of the “model selection table” describe in the above section. Model-average predictions were carried out weighting each model by its AIC weight.

EVI data base used for the estimation was got from ACA ES NECESARIO TENER CLARA LA FUENTE DE INFORMACIN DE VICTOR. For the same points associated with EVI data, we obtained the WorldClim bioclimatic variables BIO9 and BI016.

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3. Results

3.1. National carbon stock estimation from available data and associated uncertainties

3.1.1. Mangrove areas

Published approaches for the estimation of mangrove areas at the country level vary from one study to another. The methodological spectrum goes from studies using global approaches like those reported by Giri et al. (2013, 2010) and Hutchison et al. (2014) using remote sensing products, to studies focused on regional surveys using land verification (FAO, 2007), and a compilation individual estimates developed at a local scale under different methodologies INVEMAR (2014) (Table 2).

We found that mean mangrove area for the Pacific coast was around four times larger than mean mangrove area for the Caribbean coast. We obtained larger uncertainties in terms of area for the Caribbean than for the Pacific coast. In terms of the total mangrove area of the country, the uncertainty was bigger for area than for AGB density (Table 3).

Table 2: Mangrove areas in Colombia as reported in different sources of information and with different methodological approaches

Source	Year	Caribbean coast (ha)	Pacific coast (ha)	Total country (ha)	Methodological Approach
INVEMAR (2014)	2004-2013	69 894.02	239 239.20	300 133.22	Areas calculated from individual estimates by administrative units (departments) with mangrove cover in Colombia. Methodological approach used for each specific case is not reported in the document. Date of estimation is variable between departments.
Giri et al. (2013, 2010)	2000	47 064.78	165 563.6	212 628.4	Compilation of the extent of mangroves forests from the Global Land Survey and the Landsat archive with hybrid supervised and unsupervised digital image classification techniques. The data are available at 30-m spatial resolution. Area estimated under the assumption that each coordinate in the country represent a raster pixel of 900 m^2.
Giri et al. (2013, 2010)	2000	13 846.07	144 882.74	158 728.21	Compilation of the extent of mangroves forests from the Global Land Survey and the Landsat archive with hybrid supervised and unsupervised digital image classification techniques. The data are available at 30-m spatial resolution. Area estimated using ArcGis version 10.2.2 Software.
FAO (2007)	1997			371 250	Caribbean: interpretation of satellite images. Pacific: aerial photographs, radar and satellite images. Land verification, specifying mangrove areas with help of 1:100 000 scale maps.
Hutchison et al. (2014)	1999 - 2003			410 152	Spatial information extracted from mangrove map developed by Spalding et al. (2010). Landsat images, using a variety of image-processing techniques and with considerable expert review.

3.1.2. Aboveground biomass density

For the case of AGB density, estimates from the literature correspond to different spatial scales, thus, for the case of mangroves in Córdoba department in the Caribbean coast and Valle del Cauca department in the Pacific coast, available AGB density was linked with individual plots while for the rest of the areas the available data correspond to estimation for wider locations (e.g. type of forest, physiographic location, etc.) (see supplementary information).

When AGB for both coasts are compared, the average values do not differ significantly between each other. In terms of uncertainty, larger values of the CV were observed for AGB in the Pacific coast than in the Caribbean coast.

Table 3: mean, standard deviation (SD), standard error (SE) and coefficient of variation (CV) for Area and AGB density for Colombian mangroves.

Region	Area (ha)				AGB density (Mg/ha)			
	mean	SD	SE	CV	mean	SD	SE	CV
Caribbean	43 601.62	28 184.01	16 272.04	0.37	102.20	58.42	9.74	0.09
Pacific	183 228.50	49 596.60	28 634.61	0.16	105.58	83.13	26.29	0.25
Colombia	290 578.40	105 306.40	47 094.44	0.16	102.93	63.55	9.37	0.09

3.1.3. Regional and national AGB carbon stocks

Due to the use of data about mangrove area published for the whole country and every coast independently (Table 2), the sum of total carbon in AGB estimated for both coasts does not correspond to the value reported for the whole country (Table 4).

Total carbon in AGB showed larger values in Pacific mangroves (9.61 ± 2.78 TgC) (mean ± SE) than in Caribbean mangroves (2.20 ± 0.86 TgC). This result is highly influenced by mangrove area, because if the comparison is made in terms of the same area unit (hectare), values of Carbon between both coasts do not show significant differences (Figure 1).

The ratio between the SE and the mean total carbon stock showed larger uncertainty for Caribbean mangroves than for Pacific mangroves. For the case of the total area of mangroves in Colombia, the uncertainty was lower than for every coast analyzed independently (Table 4). Connecting this result with findings related to CV estimated for mangrove areas and AGB density independently (Table 3), it is possible to conclude that uncertainties of total carbon stock in AGB

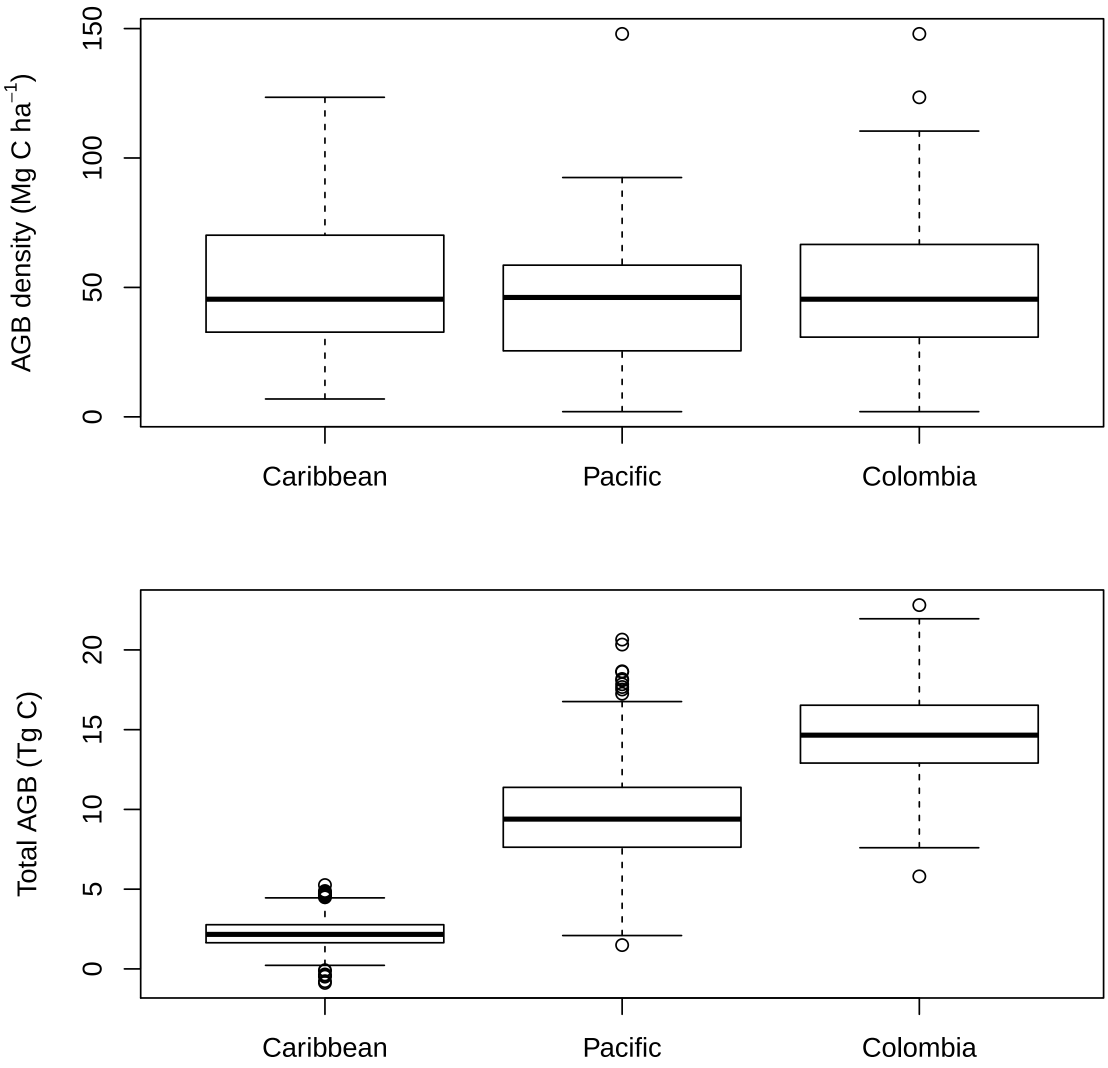

Figure 1: Aboveground biomass (AGB) density (Mg C ha^{-1}) and total carbon stock in AGB for Colombian mangroves (Tg C).

for mangroves located in the Caribbean coast are more influenced by uncertainties associated with mangrove area estimation, while for mangroves located in the Pacific coast this uncertainty in total AGB carbon stock is more influenced by uncertainties in AGB density. At the country level, total uncertainty is more influenced by current uncertainty in mangrove area.

Table 4: Mean of total C in AGB (Tg), standard error (SE), coefficient of variation (CV) and quantiles 10% and 90% for Colombian mangroves.

Region	mean	SE	CV	quantiles	
				10%	90%
Caribbean	2.20	0.86	0.39	1.14	3.31
Pacific	9.61	2.78	0.29	6.26	13.79
Colombia	14.95	2.72	0.18	11.51	18.52

3.1.4. Sensitivity of total uncertainty to uncertainty in mangrove area and AGB density

The sensitivity analysis allowed us to determine the effort necessary to reduce uncertainty in AGB density and/or mangrove area and achieve a desirable level of uncertainty for total AGB carbon stock estimations. Under different levels of uncertainty we projected different levels of CV of total AGB carbon stocks for both coast as well as for whole country (Tables 5, 6 and 7).

Reducing current total AGB carbon stock uncertainty to 10% can be achieved under different combinations of reductions in AGB density uncertainty and mangrove area uncertainty. Achieving this level of uncertainty implies one of two options: (i) reduce uncertainty in area to 5% and maintain the current uncertainty in AGB density (9%) (in the case of the Caribbean coast and the whole country) or reducing it at 10% (in the case of Pacific coast); or (ii) reduce uncertainty in mangrove area to 10% and simultaneously reduce uncertainty in AGB density to 5%.

Both alternatives to achieve 10% uncertainty level for total AGB C stock imply different efforts according with the current uncertainties associated to every input data (AGB density and mangrove area) for each coast. For instance, reduction in terms of mangrove area implies more effort for the Caribbean mangroves (current level of uncertainty 37%), while for the Pacific more effort is needed to reduce current uncertainty associated with AGB density (25%).

To achieve a 10% uncertainty in AGB density for the Pacific coast, it is necessary to increase the number of sampling units by 47, and a 5% uncertainty may not be possible to achieve with less than

Table 5: Sensitivity analysis of uncertainty in total AGB C stock associated to interactions between uncertainty in AGB density and mangrove area for Caribbean coast

		Levels of uncertainty mangrove area							
		0%	5%	10%	15%	20%	30%	50%	100%
Levels of uncertainty AGB	0%	0.00	0.05	0.10	0.15	0.19	0.31	0.48	0.99
	5%	0.05	0.07	0.11	0.16	0.20	0.31	0.48	1.00
	10%	0.10	0.11	0.14	0.18	0.22	0.32	0.49	1.00
	15%	0.16	0.17	0.19	0.22	0.25	0.35	0.51	1.02
	20%	0.19	0.20	0.22	0.24	0.27	0.37	0.53	1.02
	30%	0.30	0.30	0.32	0.33	0.35	0.42	0.59	1.05
	50%	0.48	0.49	0.50	0.51	0.52	0.58	0.71	1.20
	100%	0.95	0.95	0.95	0.97	0.98	1.09	1.16	1.59

Table 6: Sensitivity analysis of uncertainty in total AGB C stock associated to interactions between uncertainty in AGB density and mangrove area for Pacific coast

		Levels of uncertainty mangrove area							
		0%	5%	10%	15%	20%	30%	50%	100%
Levels of uncertainty AGB	0%	0.00	0.05	0.10	0.15	0.20	0.31	0.51	1.03
	5%	0.05	0.07	0.11	0.16	0.20	0.31	0.51	1.03
	10%	0.10	0.11	0.14	0.18	0.22	0.32	0.32	1.00
	15%	0.15	0.16	0.18	0.22	0.25	0.35	0.53	1.06
	20%	0.25	0.21	0.23	0.24	0.28	0.37	0.55	1.06
	30%	0.31	0.31	0.33	0.34	0.36	0.44	0.62	1.12
	50%	0.50	0.50	0.51	0.52	0.56	0.62	0.75	1.31
	100%	1.00	1.00	1.01	1.02	1.03	1.09	1.21	1.84

Table 7: Sensitivity analysis of uncertainty in total AGB C stock associated to interactions between uncertainty in AGB density and mangrove area for Colombian mangroves

		Levels of uncertainty mangrove area							
		0%	5%	10%	15%	20%	30%	50%	100%
Levels of uncertainty AGB	0%	0.00	0.05	0.10	0.15	0.20	0.30	0.47	1.02
	5%	0.05	0.07	0.11	0.16	0.20	0.31	0.48	1.02
	10%	0.10	0.11	0.14	0.18	0.22	0.32	0.49	1.03
	15%	0.15	0.16	0.18	0.21	0.26	0.35	0.50	1.04
	20%	0.24	0.20	0.22	0.24	0.28	0.37	0.51	1.07
	30%	0.31	0.31	0.32	0.35	0.37	0.43	0.57	1.10
	50%	0.51	0.51	0.48	0.53	0.55	0.61	0.74	1.28
	100%	1.00	1.00	1.02	1.02	1.04	1.08	1.20	1.75

200 sampling units (Figure 2). For the Caribbean coast the situation is less critical; it is possible to achieve a 5% uncertainty in AGB density by adding 73 additional sampling units. Combined or the entire country, 81 additional sampling units are required to achieve 5% uncertainty in AGB density. In all cases, we assume that these additional sampling units must follows the principles of random sampling.

3.2. Predictive models

We tested the ability of the models proposed by Twilley et al. (1992) and Hutchison et al. (2014) in predicting our AGB density data. For both models, we found important overestimations of AGB density for the majority of the observations, although in some cases the models underestimated observed AGB density, particularly for values larger than 150-200 Mg ha^{-1} (Figure 3).

A new parameterization of these models with our data set provided a set of parameter values that can potential help in estimating AGB density for our study area. However, the performance of the models as assessed by the R^2_a statistic provided little confidence in these model structures in predicting accurately AGB density (Table 8).

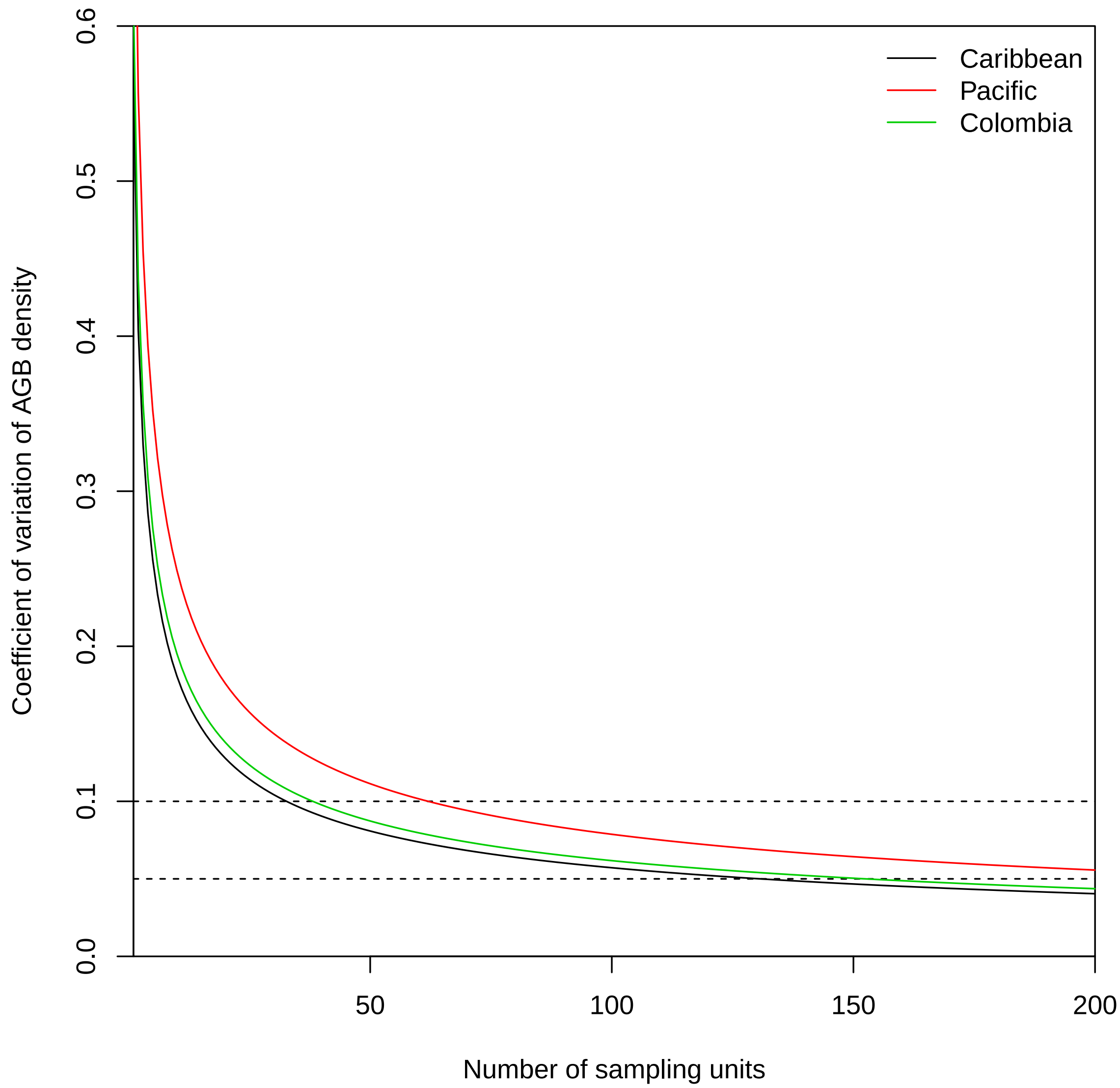

Figure 2: Number of necessary sampling units of AGB density required to reduce current uncertainties at 10% and 5% level for Caribbean, Pacific and total Colombian mangroves.

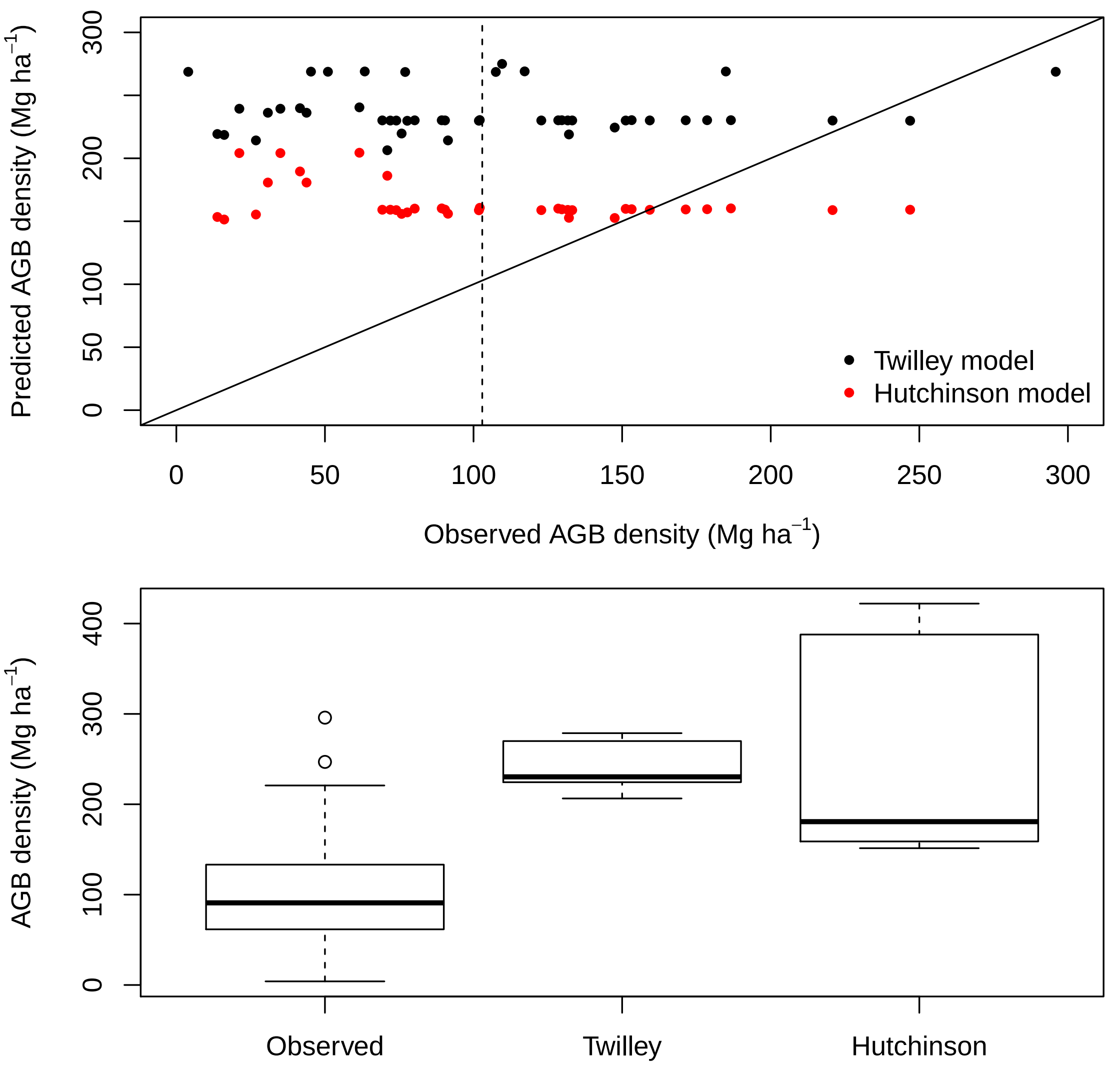

Figure 3: Observed vs. predicted AGB density (Mg ha^{-1}). Predicted values: using global models (Twilley et al., 1992; Hutchison et al., 2014) and observed data: current data available for mangrove areas in Colombia

Table 8: Original models proposed by (1) Twilley et al. (1992) and (2) Hutchison et al. (2014) and the new parameterization obtained with our data. AGB represents above ground biomass density (Mg/ha); Lat latitude (decimal degrees); BIO10 mean temperature of warmest quarter (°C); BIO11 mean temperature of coldest quarter (°C); BIO16 precipitation of the wettest quarter (mm); BIO17 precipitation of the driest quarter (mm) and $R_a{}^2$ adjusted coefficient of determination.

Original model	Reparameterized model	$R_a{}^2$
(1) AGB = -7.921·Lat+298.5	AGB = -1.266·Lat+113.475	-0.020
(2) AGB = 0.295·BIO10 + 0.658·BIO11 + 0.023·BIO16 + 0.195·BIO17 - 120.3	AGB = -0.2546·BIO10 + 3.4824·BIO11 + 0.2435·BIO16 - 0.4056·BIO17 - 875.7776	0.023

We tested 48 new model structures to predict AGB density with our data based on different combinations of the response functions in equations (1) to (5) applied to the bioclimatic variables of Table 1 as well as the values of latitude and EVI (see list of all models in appendix). From this group, six models were selected as candidate models due to their performance (Table 9).

The selected models showed relatively similar values of $R_a{}^2$. In all cases, the independent variables explained less than 47% of total variability, but between the whole group of models, they were between the best in terms of predictive power. Likewise, these six candidate models showed the lowest Mean Squared Error (MSE) values and higher values for the F-statistic. Additionally, independent variables were significant, Goldfeld-Quant test showed that candidate models do not present heterocedasticity problems, and according to the Durbin Watson test there was not autocorrelation in the residuals. Cooks distance test did not evidence remote observations for any candidate model.

Model 6 showed the lower value of AIC, indicating that this is the model with the best goodness of fit and higher simplicity of all compared models. Nevertheless, when AIC differences are very small, as in our case, the acceptance of one single model may lead to a false sense of confidence. In these cases, Akaike weights provide a straightforward interpretation as the probabilities of each model's being the best in the AIC sense. Using the AICcmodavg R package (Mazerolle, 2015), we identified three model groups according with their weight: models (3), (4) and (6) were classified as models with "substantial weight"; model (5) was classified as model with "some weight"; while models (1) and (2) were classified as models with "little weight". The cumulative AIC weight of models (3), (4) and (6) represents 97% of total, the remaining 3% belonging to models (1) and (5).

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Table 9: Candidate statistical regression models for AGB. When log is the natural logarithm; AGB is the above ground biomass (Mg/ha); BIO9 is the mean temperature of driest quarter (℃); BIO11 mean temperature of coldest quarter (℃); BIO16 is the precipitation of the wettest quarter (mm); EVI is the enhanced vegetation index; Lat latitude (decimal degrees); n is the number of observations; $R_a{}^2$ is the adjusted coefficient of determination; MSE is the mean squared error; F is the F-statistic calculated; AICc is the akaike information criterion with a correction for finite sample sizes; AICcWt is the Akaike weight

Model	n	$R_a{}^2$	MSE	F	AICc	AICcWt
(1) $\log AGB = -94.7756 + 21.9228 \log BIO9 - 3.2190 \log BIO16 + 0.8363 \log EVI - 1.1157 \log \lvert Lat \rvert$	40	0.3586	0.489	6.452	94.12	0.01
(2) $\log AGB = -18.7623 + 39.9688 \log BIO9 - 3.0771 \log BIO16 + 0.7138 \log EVI - 0.8834 \lvert Lat \rvert - 32.0563 \log BIO11$	40	0.353	0.493	5.256	96.26	0.00
(3) $\log AGB = -68.661 + 21.023 \log BIO9 - 5.397 \log BIO16 + 1.842 \log EVI - 11.790 \log \lvert Lat \rvert$	40	0.4507	0.419	9.00	87.92	0.19
(4) $\log AGB = 32.57 - 8256.48 \frac{1}{BIO9} + 572.76 \frac{1}{BIO16} - 6457.22 \frac{1}{EVI} + 21.75 \frac{1}{\lvert Lat \rvert}$	40	0.4675	0.406	9.561	86.68	0.35
(5) $\log AGB = -183.922 + 32.655 \log BIO9 + 1.201 \log EVI - 2.282 \log \lvert Lat \rvert$	40	0.3572	0.490	8.224	92.55	0.02
(6) $\log AGB = 36.25 - 8845.59 \frac{1}{BIO9} - 5303.93 \frac{1}{EVI} + 15.13 \frac{1}{\lvert Lat \rvert}$	40	0.4507	0.419	11.67	86.27	0.43

Even though the evidence ratio between models with "substantial weight" indicates that model (6) is 1.23 times more likely than the next-best model (4), we decided not to accept model (6) as the unique model recomended to predict carbon stocks in Colombian mangroves due to the results from the AIC weights that indicate there is not enough evidence to chose only one model. Instead, we propose the biomass estimation through the use of weighted estimations of each of the three candidate models classified as models with "substantial weight" (models 6, 4 and 3).

Our candidate models included as predictive variables bioclimatology and a satellite-derived vegetation index, information that is easily accessible for all mangrove areas in Colombia. Nevertheless, models built with these variables did not show a very high predictive power. On the contrary, when a location variable such as "site" or "CEU" was included in the models, the predictive power of all of them improved significantly, showing D^2% around 86%-87% for all candidate models in the case of "site" and D^2% around 46%-65% in the case of "CEU" . The interaction site:CEU did not contribute to explain of the variability in our data (Table 10).

4. Discussion

Using error propagation techniques, we were able to calculate the level of uncertainty that can be achieved with existing information for estimating aboveground C stocks for Colombian mangroves. This analysis showed that if Colombia wants to decrease the level of uncertainty in these estimations and include mangroves in its national GHG mitigation strategy, additional efforts are necessary to reduce uncertainty in both AGB density and mangrove area. We discuss here potential strategies to reduce these uncertainties and increase the quality of the estimates to the Tier 3 level as proposed by the IPCC (IPCC, 2003, 2006).

4.1. Uncertainty and Tier 3 level estimates of national carbon stocks

Currently, it is possible to estimate C stocks for Colombian mangroves at a Tier 2 level because there is available data on AGB density and mangrove area at a local level (IPCC, 2003, 2006). However, we found poor quality in the data for mangrove area and had to rely on external sources for area estimation (e.g. Giri et al., 2010); for this reason our best possible estimate of mangrove area is a combination of data classified as Tier 2 (national sources) as well as Tier 1 (global and regional sources).

Table 10: Deviance analysis for candidate multilevel models through maximum likelihood estimation for AGB. When Site and CEU (Coastal Environmental Unit) are location variables; AIC is the akaike information criterion; $D^2\%$ is the Deviance

Model	Model modifications	AIC	Null deviance	Residual deviance	$D^2\%$
(1)	Original model	91.57	29.75	17.12	44.42
(1)	Site	60.01	29.75	3.86	87.02
(1)	CEU	85.55	29.75	12.06	59.46
(1)	Site:CEU	60.01	29.75	3.86	87.02
(2)	Original model	92.76	29.75	16.78	43.60
(2)	Site	61.85	29.75	3.847	87.07
(2)	CEU	84.18	29.75	11.09	62.17
(2)	Site:CEU	61.85	29.75	3.847	87.07
(3)	Original model	85.38	29.75	14.66	50.72
(3)	Site	61.16	29.75	3.97	86.64
(3)	CEU	87.05	29.75	12.52	57.92
(3)	Site:CEU	61.16	29.75	3.97	86.64
(4)	Original model	84.13	29.75	14.21	52.24
(4)	Site	62.65	29.75	4.13	86.13
(4)	CEU	79.77	29.75	10.43	64.94
(4)	Site:CEU	62.65	29.75	4.13	86.13
(5)	Original model	90.97	29.75	17.65	40.67
(5)	Site	65.15	29.75	4.62	84.48
(5)	CEU	94.85	29.75	15.99	46.25
(5)	Site:CEU	65.15	29.75	4.62	84.48
(6)	Original model	84.50	29.75	15.08	49.31
(6)	Site	64.56	29.75	4.55	84.71
(6)	CEU	88.05	29.75	13.49	54.66
(6)	Site:CEU	64.56	29.75	4.55	84.71

For REDD+ projects, it is appropriate to use Tier 2 data in the calculation of C stocks and avoided emissions (Maniatis and Mollicone, 2010), and our results suggest that it is currently possible to estimate C stocks in Colombian mangroves with a level of uncertainty that ranges between 18 to 39% of the mean (Table 4). Nevertheless, Colombia is in a transition to Tier 3 for the overall GHG national inventory, and to achieve this level the country is working on the firsts steps concerning the estimates of emissions factors for the AFOLU sector. The country is already working on a first phase of its national forest inventory (IDEAM, 2015), where mangroves should be treated as a separate ecosystem type for monitoring AGB density and area.

To achieve this Tier 3 level in mangrove ecosystems, it is important to increase the number of sampling units for AGB density and develop local assessments of mangrove area that are verified through field surveys. Our uncertainty analysis showed that more sampling units are required in both the Caribbean and the Pacific coasts to achieve a 10% uncertainty of the mean AGB density. These sampling units should represent well the local level of variability within sites as suggested by the multilevel models (Table 10), and the estimation of areas should characterize these local level of variability as well if these models are to be used for prediction. There is already good evidence for a gradient of increased seasonality of precipitation and salinity from west to east in the Caribbean (Polanía et al., 2015), and these ecological gradients must be captured both by the classification of areas in different groups and the AGB density that would correspond to each group.

4.2. Sensitivity of total uncertainty to uncertainty in mangrove area and AGB density

Although there is not a level of uncertainty that is required or even recommended for monitoring of C stocks in the AFOLU sector, we chose 10% as a desired level to achieve. In this regard, the IPCC (2003) mentions *there is not a predetermined level of precision; uncertainty is assessed to help to prioritize efforts to improve accuracy in the future and guide decisions on methodological choice*. In this sense, a 10% level of uncertainty as a goal can help in determining where to focus future monitoring efforts. Our sensitivity analysis showed that this 10% level can only be achieved by reducing uncertainty in both mangrove area and AGB density, and keeping the current level of uncertainty in any of these two components is not an option to reduce overall uncertainty to 10%.

In the estimation of areas using remote sensing products, it is possible to achieve between 10 to 15% uncertainty (IPCC, 2003), a level that is much lower than our current uncertainties in mangrove areas (16-37%). We believe this level of uncertainty can be achieved with much less effort than that required to reduce uncertainties for AGB density. With a 10% uncertainty in area it is therefore necessary to reduce uncertainty in AGB density to 5% (Table 7), which implies a large effort in terms of costs and logistics (to move from a level of 10% to a level of 5% almost three times more sampling units are needed). This is particularly difficult for mangroves in the Pacific coast where the current level of uncertainty in AGB density is 25%.

Based on these results, we recommend to develop a national assessment of mangrove areas using remote sensing products to achieve 10% uncertainties and establish an additional set of monitoring plots in both coasts to reduce uncertainties to 5-10%, with special focus on the Pacific where the mangroves are underrepresented.

4.3. Predictive models

Predictive models of carbon stocks in mangrove ecosystem are an important tool for managers and decision makers because they provide a general idea about the potential as carbon sinks of different mangrove areas along the country, and help to prioritize efforts in terms of investment in research and development of pilot projects. They can also help to identify potential emissions due to land use change and design climate change mitigation projects.

We found that previously published pantropical models for predicting carbon in mangroves fail at predicting our local observations of AGB density. Although these models are based on climatic variables known to predict well mangrove distributions worldwide, the models fail at predicting spatial heterogeneity at smaller scales, a limitation already recognized by model developers (Hutchison et al., 2014).

Despite these limitations, we found that it is possible to develop accurate models using remote sensing information. In our case, models including EVI (enhanced vegetation index), Latitude and BIO9 (mean temperature of driest quarter) provided the best statistics in all cases. Some of the models also included the bioclimatic variable BIO16 (precipitation in the wettest quarter), consistent with previous studies that found good predictive power for these variables (Hutchison et al., 2014; Herz, 1999; Anaya et al., 2009).

We identified model structure as an additional source of uncertainty in estimating C stocks (cf IPCC, 2006), and for this reason we do not recommend one particular model but a set of three models that should be used together. We recommend to weigh the predictions from each of these three models according to the AIC and calculate prediction uncertainty accordingly. If additional information is available in terms of stratified areas for different sites, we recommend the use of multilevel models that account for spatial heterogeneity.

5. Conclusions

Two main sources of uncertainty contribute to the overall uncertainty in total carbon stocks in aboveground biomass for Colombian mangroves: uncertainty in mangrove area and uncertainty in AGB density. Area is the main source of uncertainty for total carbon stocks in mangroves of the Caribbean coast, while AGB density is the main source of uncertainty for mangroves in the Pacific coast of Colombia.

To reduce the current levels of uncertainty in carbon stocks for Colombian mangroves (from 18% to 10% of the mean) and achieve a Tier 3 level in accuracy as recommended by the IPCC, it is necessary to reduce uncertainty in mangrove area from 16 to 10% and uncertainty in AGB density from 9 to 5%. This could be achieved by increasing the amount of sampling units along both coasts for AGB inventories, with particular emphasis on the Pacific. Detailed estimations of mangrove areas with stratifications by mangrove type are also required to achieve this 10% in overall uncertainty.

Models based on remote sensing information such as EVI and bioclimatic variables from WorldClim offer good opportunities to increase the level of detail and accuracy in predictions of mangrove carbon stocks, but these predictions need to account for model-structure uncertainty as well as local scale variability. We propose here a set of models that account for these sources of uncertainty, which could help in future assessments of aboveground C stocks in Colombian mangroves.

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