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Assessment of carbon effects from two projects from the Rainforest Foundation Norway's programme portfolio

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Title: Assessment of carbon effects from two projects from the Rainforest Foundation Norway's programme portfolio

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Abstract: The Rainforest Foundation Norway (RFN) has commissioned CICERO to do a project on the carbon effects of two REDD+ projects as a literature study. The two sites are found in Indonesia and Colombia. We have assessed carbon densities and carbon stocks. Further, we have assessed how different hypothetical storylines could lead to different CO2 emissions at the two sites. The last part of the report is an assessment and proposal of methods that RFN can utilize to quantify the greenhouse gas effects of future projects. We have based our carbon stock and potential carbon emission estimates on datasets from Global Forest Watch

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Contents

1 Summary

The Rainforest Foundation Norway (RFN) has commissioned CICERO to do a project on the carbon effects of two REDD+ projects as a literature study. The two sites are found in Indonesia and Colombia. We have assessed carbon densities and carbon stocks specifically for the two projects, but also for tropical forests in general. Further, we have assessed how different hypothetical storylines could lead to different CO_2 emissions at the two sites. The last part of the report is an assessment and proposal of methods that RFN can utilize to quantify the greenhouse gas effects of future projects. The report is written for experts and people working on or interested in the topic.

Several datasets on carbon densities and forest loss are publicly available. We have based our estimates on Global Forest Watch, presented in Zarin et al. (2016), since this dataset is one of the newest and with the highest resolution. Common for all datasets on carbon densities is that they combine input from

- Field measurements of tree biomass at sites
- Satellite-based light detection and ranging (LIDAR)
- Optical sensors from satellites

Our report focuses on aboveground and belowground carbon in biomass as these carbon stocks are most well-known. We also give an indication of soil carbon as soil carbon and peat carbon can potentially be significant carbon stocks.

We estimate that the average carbon densities at the two projects are 162 and 155 Mg C/ha for aboveground biomass and 42 and 40 Mg C/ha for belowground carbon for Indonesia and Colombia, respectively. In addition, some 120 Mg C/ha can also be found as soil carbon. The project area in Colombia is by far the largest of the two areas covered, with a total carbon stock of about 270 Mt C, compared to 1.7 Mt C in Indonesia. These carbon densities are similar to those found in most tropical forests.

We present five storylines as different hypothetical cases that could have happened had these two areas not been protected through REDD+ projects. These are only meant as illustrations, and not as baselines. First, we assume that the development in the projects follow the historic development in the larger surrounding area (case 1) or on a national level (case 2). Second, extreme cases where all the forest is removed for agriculture (case 3) or clear cut (case 4). Finally, we consider projected future pathways (case 5). Both project areas have seen little deforestation in the period 2000-2012 according to the analyzed data from Global Forest Watch. However, we are unable in this report to establish a causal relationship between the protection of the two project areas and small amounts of deforestation, or if other factors are more important for deforestation rates. The area around the project in Colombia has seen little deforestation, while the project in Indonesia is near areas with

significant deforestation. Among the different storylines, clear cut of the project areas would give the largest carbon emissions by far. These storylines consider only carbon stock changes within the project areas, while protecting areas may also cause indirect land-use effects.

We propose four different approaches RFN can use to quantify the future carbon effects of projects:

1. Simple approach using average carbon densities and historical deforestation rates
2. Cost-effective approach based on best publicly available high-resolution data and combined with synthetic reference[1]
3. Similar to 2, but updating dataset with own forest change modelling
4. Include all carbon stocks, which depends on resource demanding fieldwork to complement approach 2

If cost-effectiveness and utilizing state-of-the-art scientific knowledge is preferred, we suggest that RFN should go for approach 2. The most comprehensive analysis would need to combine the findings in approach 2 with approach 3 and 4. The most challenging part of estimating carbon effects of projects is the establishment of a baseline.

[1] Synthetic reference is based on a statistical method called *synthetic control method that* can be used to construct a counterfactual baseline of deforestation rates in the project area had the project not been implemented. Comparing actual developments with the counterfactual gives an estimate of the project’s causal impact.

2 Introduction

The Rainforest Foundation Norway (RFN) has commissioned CICERO to do a project on the carbon effects of two REDD+ projects as a literature study. The two sites are run by KKI Warsi in Indonesia and by Association of Captains and Traditional Indigenous Authorities of the Pirá Paraná (ACAIPI) in Colombia. The site in Indonesia, Bujan Raba, cover an area of 72.91 km^2, of which 53.36 km^2 is to be protected and 19.55 km^2 to be utilized by the local community. The project in Colombia is much larger covering about 7000 km^2. RFN has asked for these four assessments:

- Assess the carbon density and stock for the two project areas, including carbon in the soil, based on literature on type of region and vegetation
- Assess whether these carbon densities are applicable to other tropical forests where RFN have projects
- Assess the greenhouse gas effects of the two projects, based on 3-4 hypothetical cases developed with input from RFN and partners
- Assess and propose methods that can be used to quantify the greenhouse gas effects of future RFN projects in a cost-efficient manner

3 Methods

We have performed a desk study to answer the four research questions. Hence, we have not performed modelling or measurements specific at the two projects. The main part of the project has been to identify and utilize high quality peer-reviewed articles and forest databases relevant for the work. This report is solely based on peer-reviewed articles to ensure quality. We have focused on recent literature and review articles, since they give a good overview of the current understanding. The approach taken to assess the current state of the art on these topics has been to localize recognized and high-level articles in the field and check the articles they cite and the articles that have been citing these articles. Some of these articles are accompanied with freely available datasets on biomass density or carbon density in the tropics. These databases are also updated. We have based our calculations for the two projects on Global Forest Watch[2] since this dataset is one of the newest and with the highest resolution. Other databases are Land Use, Carbon & Emission Data[3] and Global Land Analysis & Discovery[4]. Most of the databases show the data in online maps, but the data can also be downloaded.

The existing literature do not answer the four research questions completely and provide insufficient grounds for assessing the greenhouse gas effect of the two projects. Our estimates are based on changes in carbon stocks only and compared with alternative storylines of what could have had happened. Further, we do not try to quantify carbon leakages or attribute changes to protection of the project areas. We discuss critically these knowledge gaps, the limitations they pose and how they may be addressed in future assessments.

[2] The homepage is https://www.globalforestwatch.org/, and contains data from Zarin et al. (2016). Data on aboveground live woody biomass density in 2000 is here http://data.globalforestwatch.org/datasets/8f93a6f94a414f9588ce4657a39c59ff_1?geometry=-152.666%2C-29.387%2C204.346%2C29.377, tree cover loss for period 2000-2012 https://beta-gfw.opendata.arcgis.com/datasets/63f9425c45404c36a23495ed7bef1314, and tree cover gain for period 2000-2012 https://beta-gfw.opendata.arcgis.com/datasets/6c9f379a362e4926ad24b58444f4ba67. The resolution of the data is 30 x 30 m. Updates prolonging the time series are expected. The data is compatible with GIS, but can be converted to any format desirable for the users after downloading the data. We converted the data into netCDF files and calculated carbon stocks and changes with Matlab.

[3] Data on forest biomass is found here https://www.wur.nl/en/Research-Results/Chair-groups/Environmental-Sciences/Laboratory-of-Geo-information-Science-and-Remote-Sensing/Research/Integrated-land-monitoring/Forest_Biomass.htm. Data for a pan-tropical biomass map is given with a 1 km resolution and for a global forest biomass map at 0.01° resolution. This webpage is linked to the Avitabile et al. (2016) study.

[4] Data on pan tropical forest strata is found here https://glad.umd.edu/dataset/pan-tropical-forest-strata. The Tyukavina et al. (2015) study relates to this dataset.

3.1 Aboveground carbon densities in biomass

We have identified recent articles that estimate aboveground carbon densities in tropical forests. These studies estimate aboveground carbon in live woody vegetation with three steps (e.g., Saatchi et al., 2011; Baccini et al., 2012; Bustamante et al., 2016; Zarin et al., 2016; Mitchard, 2018):

- Field measurements of tree biomass at sites
- Satellite-based light detection and ranging (LIDAR)
- Optical sensors from satellites

See also Figure 1 on schematic differences between these methods and Figure 2 on what parameters these methods measure. From field measurements of tree biomass at several sites, allometric and statistical models can be developed. By applying satellite-based light detection and ranging (LiDAR), a statistical relationship between field measurements and data from LIDAR can be established. This allows for quantification of biomass beyond the sampling sites. Finally, other satellite measurements are used to estimate biomass densities over large areas. Satellite such as MODIS cover the entire tropics. Pan-tropical biomass maps from the satellites are calibrated with the LiDAR data. The combination of these three methods is the most used method to give measured estimate of aboveground biomass.

Estimates of aboveground biomass are converted into aboveground carbon density estimates by simply multiplying with the factor 0.5, which is the average carbon content of trees (e.g., Saatchi et al., 2011; Baccini et al., 2012).

These three different measurement types that are combined are very different in terms of scale and accuracy, see Figure 1. More details on how parameters from these three methods are used to calculate forest carbon densities are given in Figure 2. There is no best method, but these methods are complementary and give decent carbon estimates covering large areas. However, uncertainties are high, and Bustamante et al. (2016) indicate errors of 20-50 % for estimate of aboveground biomass.

Optical sensors from satellites can only detect changes in the upper canopy properties, as spectral indices are often saturated for dense forests, and cannot be used directly to estimate carbon stocks. Active sensors from LiDAR can provide data to estimate biomass volume, but not wood density. Field measurements at different locations give specific data on vegetation which is otherwise is not possible; however, it is impossible to measure the situation over larger areas with only field plots. The strength of these three methods are combined to give good data. For instance, remote sensing measurements must be calibrated to well-sampled and precise field data, and, hence, should not be utilized without this support.

Newer generation of satellites are coming, and they provide finer resolution. The earlier studies on forest carbon density maps had resolution of 1 km with the satellite ICESat (Saatchi et al., 2011) and 500 m with the satellite MODIS (Baccini et al., 2012). Newer studies have provided resolutions down to 30 m, such as by Tyukavina et al. (2015); Zarin et al. (2016) applying the satellite Landsat together with Google Earth and forest models.

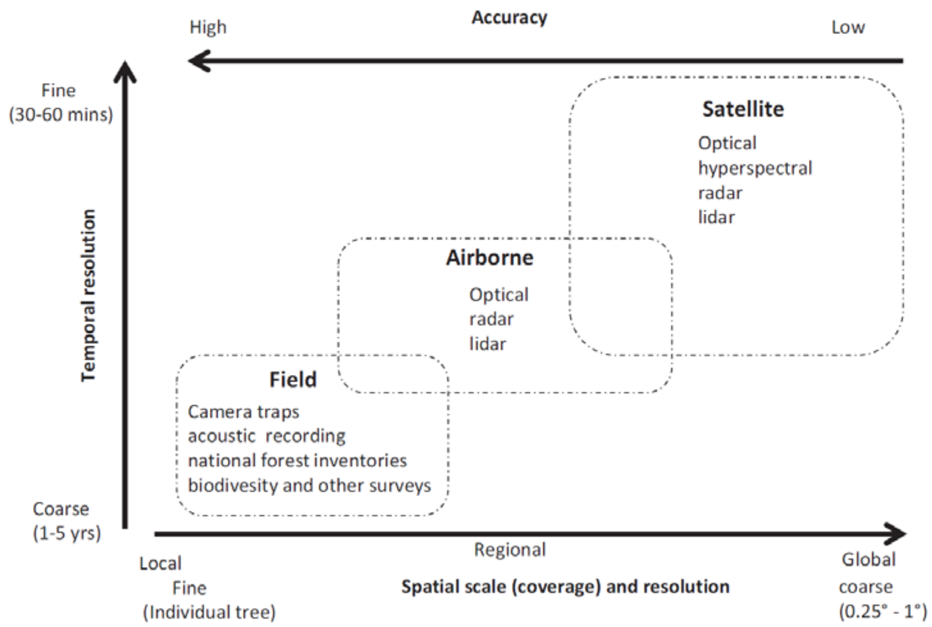

Figure 1: Spatial and temporal resolution of different methods for monitoring forest carbon stocks. A combination of field, LIDAR, and satellite measurements is the best basis to assess the carbon density in tropical forests as the advantages of each type of measurement are utilized. Figure is from Bustamante et al. (2016).

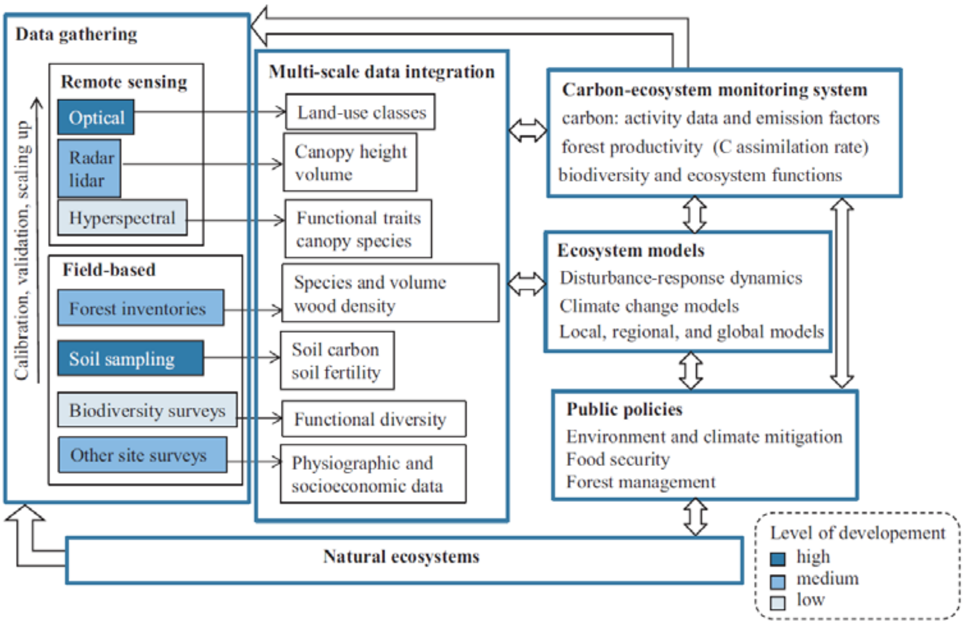

Figure 2: Multiscale integrative framework for spatially monitoring and modeling of carbon stocks. Data can be gathered by either field-based or remote sensing. The middle column shows what parameters these methods look at. Figure is from Bustamante et al. (2016).

The carbon stock of an area has earlier been estimated by multiplying the area with some representative carbon density value. Given the increasing availability of detailed carbon density measurements[5], it is common today to add the carbon stock in each pixel in the area of interest to find the total carbon stock in the area.

Our calculations are based on openly available quality-controlled remote sensing datasets from Global Forest Watch for the year 2000[6], which is also described by Zarin et al. (2016). The resolution of the data is 30 x 30 m. We only include forest with a tree cover greater than 25%, that is a canopy cover threshold of 25%, to be in line with the available dataset. Other threshold values are used, and both FAO and IPCC refer to 10% as a potential cut-off for forest.

3.2 Belowground carbon densities in biomass

The methods described so far are on carbon density for the parts of the tree above the ground. As trees has roots, some carbon is also stored belowground. This belowground carbon is much more difficult to measure. The most common approach is to estimate the belowground carbon based on the extent of the aboveground carbon. Saatchi et al. (2011) estimated belowground biomass (BGB) as

$$BGB = 0.489 * AGB^{0.89}$$

where AGB stand for aboveground biomass. The carbon content is found by multiplying BGB with 0.5. We have used this formulation in this report.

3.3 Soil carbon and peat carbon

Spatially resolved carbon density maps are not available for carbon stored in soil and peat. The main reason is that these carbon stocks have normally been measured with field measurements, with only a few exceptions (e.g., Grinand et al., 2017), thus, making a pan-tropical map extremely demanding to produce. Estimates of the total carbon stock or the average carbon density for soil and peat have been published (e.g., Page et al., 2011; Houghton and Nassikas, 2017), but detailed information for the two projects are not available.

In this report, we have based our estimates on the average carbon density of undisturbed soils in tropical rain forest, 120 Mg C/ha, from Houghton and Nassikas (2017). We assume no significant peat carbon in the projects, but this can be added if found in the areas.

3.4 Carbon stocks

The carbon stocks in the projects have been estimated by adding the carbon stock from each pixel of the project areas. This has been done separately for aboveground carbon, belowground carbon, and soil carbon.

3.5 Carbon emissions and losses

The carbon emissions from deforestation can be estimated by combining datasets on aboveground biomass for a year and time series on tree cover loss. For instance, Global Forest Watch provides datasets on both, and we have used those to estimate carbon emissions in this report.

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[5] Information on different carbon density maps are given in previous footnotes.

[6] The homepage is https://www.globalforestwatch.org/. Data on aboveground live woody biomass density in 2000 is here http://data.globalforestwatch.org/datasets/8f93a6f94a414f9588ce4657a39c59ff_1?geometry=-152.666%2C-29.387%2C204.346%2C29.377

In this report, we have only estimated carbon emissions based on losses of aboveground and belowground biomass given datasets from Global Forest Watch. These emission calculations have been done at a pixel level and summarized to estimate the carbon emissions from the project areas. The share of carbon that is lost is based on carbon loss ratios from Carter et al. (2017), 93% and 85% in Indonesia and Colombia, respectively. Some of the deforestation is based on timber production. Carbon will be stored until the wood products are decomposed or burnt. We have not included this carbon storing effect. Common practice is to assume loss of carbon at the point of harvest; however, we may overestimate the carbon emissions in our modelling with this approach.

Generally, estimating the carbon released from deforestation is more difficult to assess than assessing the spatial extent of deforestation (Mitchard, 2018). Estimates have historically been made by simply multiplying the area deforested by an average carbon density value. Variations in carbon density are now accounted for with pantropical carbon density maps. However, an issue is that the carbon data often have a coarser resolution than the deforestation data, as well as large biases and uncertainties in the carbon data at small scales. By utilizing the Global Forest Watch, we make sure that the resolution of the carbon density and deforestation maps are the same with highly resolved data, but we are still challenged by large biases and uncertainties that may occur at small scales. Hence, carbon densities can be both overestimated and underestimated. These issues should be considered when estimating the carbon emissions from the two projects.

To estimate the carbon loss from forest degradation is even harder (Bustamante et al., 2016; Mitchard, 2018). This is because forest degradation is caused by a variety of processes with different effects (commercial logging, fuelwood extraction, sub-canopy cultivation, grazing, fire, and edge effects caused by nearby deforestation) and that degradation events often are smaller than one pixel. A pixel could contain a mix of deforestation, forest degradation, regrowth from previous disturbed forests, and changes in intact forest. The methods to estimate carbon loss from forest degradation are the same as for deforestation, but studies are rare and often for small areas.

3.6 Alternative storylines

We have also produced several alternative storylines of what could have had happened at the two project sites given different counterfactual worlds where the areas are not protected. These storylines are only meant as illustrations and not as reference scenarios. They are based on findings in the literature and by intention made simple. These alternative storylines are presented in Section 4.3.

4 Results

4.1 Carbon densities at the two projects

4.1.1 General overview

Globally, living tropical trees store about a third as much carbon as the total amount of carbon held in the atmosphere (Mitchard, 2018). The importance of the tropical forests is clearly seen in Figure 3, as the carbon densities are highest in those areas. Biomass store carbon aboveground and belowground. In addition, significant amounts of carbon can also be found in the soil. Soil organic carbon may stand for 50-75% of the total forest carbon stock (Navarrete-Segueda et al., 2018). Finally, very large amounts of carbon is found in peat layers in peat tropical forests. Peat is carbon-rich, partially decayed organic matter often associated with waterlogged and acidic conditions and found in layers up to 20 m thick. Only 5 % of the tropical forests overlay peat, but this fraction of tropical forests alone store about half as much carbon as the living trees in all tropical forests (Mitchard, 2018). The spatial variability is large and carbon densities at different locations are difficult to uncover as this is dependent on fieldwork at point locations. Existing literature show that of the two regions considered here, Indonesia is the country with the most or second most peat carbon, while Colombia has much smaller amounts (Page et al., 2011; Dargie et al., 2017; Gumbricht et al., 2017). Peatland occupy about 11% of Indonesia's land (Page et al., 2011). Deforestation and forest degradation will also influence these different carbon storages, not only the carbon stored in aboveground and belowground biomass. However, most assessments of carbon in tropical forests focus on the aboveground carbon stored in biomass, with some studies including proxies for belowground carbon of living biomass (e.g., Saatchi et al., 2011).

The variability in carbon densities is large (e.g., Saatchi et al., 2011). Navarrete-Segueda et al. (2018) point out that the variability in aboveground carbon is driven by landscape variations, such as topography and geology, and soil properties. Tropical forests have high biotic and abiotic heterogeneity. Soil properties and forest structure and functionality will vary with space and time. As tropical forest has dense canopy, remote sensing cannot easily measure soil carbon or soil properties, soil bulk density, percentage of coarse fragments and soil depth. Studies provide different carbon density estimates for aboveground biomass depending on different definitions of what the minimum canopy cover of a tropical forest is, for instance Saatchi et al. (2011) provide a table with carbon values given canopy cover threshold of 10, 25, and 30%. Many studies take 25% canopy cover threshold as the cut-off.

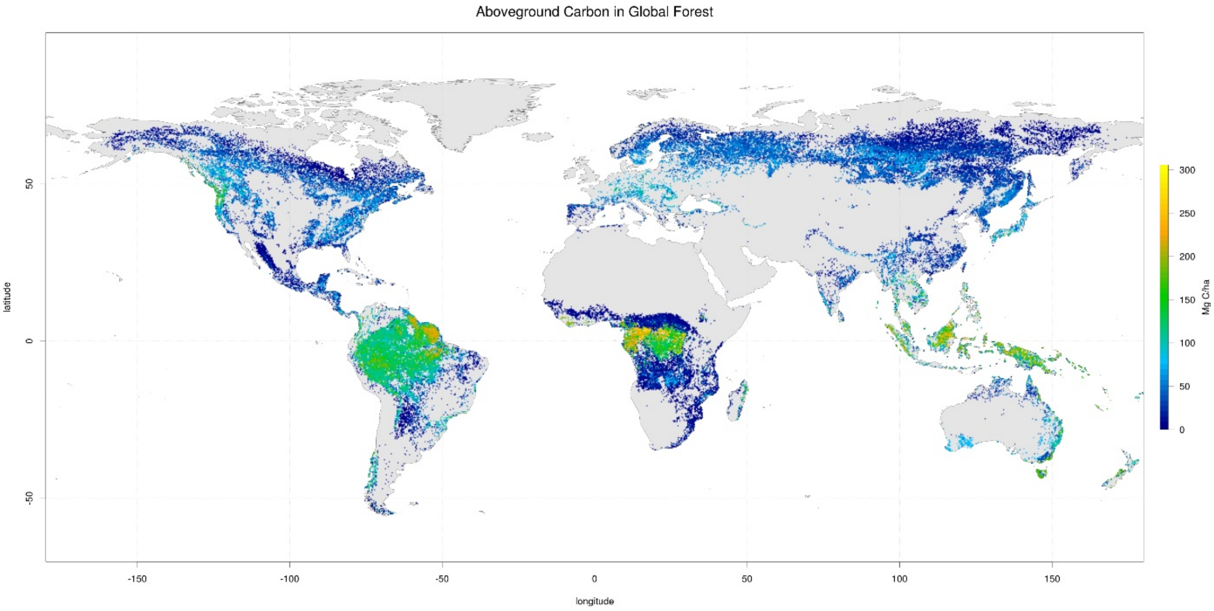

Figure 3: Aboveground carbon in global forests[7] at a resolution of 0.01°. The tropical forests have the largest carbon densities. The dataset is based on Avitabile et al. (2016) on tropical forest and based on Santoro et al. (2015) for boreal forest.

4.1.2 Current carbon densities at the two project sites

Average carbon densities for the two projects are given in Table 1 and total carbon stock in Table 2. These estimates are based on the coordinates provided by RFN. As we have not received the exact coordinates for the project in Colombia, our calculations are based on a larger area. However, we see that carbon densities are similar in areas we believe are within and outside of the project area. For Indonesia, we have the exact coordinates for the village forest, but not for the protected zone, which covers 73% of the village forest area. Maps of aboveground carbon in and around the projects are presented in Figure 4 and Figure 5.

Table 1: Average carbon densities at the projects and the size of the projects. All carbon values are given in C. These can be converted to CO_2 by multiplying with 3.664.

Average carbon densities	Aboveground carbon (Mg C/ha)	Belowground carbon (Mg C/ha)	Soil carbon (Mg C /ha)	Area of project (ha)
Project in Indonesia[8]	162	42	120	5,336
Project in Colombia[9]	155	40	120	700,000

[7] Data downloaded from Land Use, Carbon & Emission Data, https://www.wur.nl/en/Research-Results/Chair-groups/Environmental-Sciences/Laboratory-of-Geo-information-Science-and-Remote-Sensing/Research/Integrated-land-monitoring/Forest_Biomass.htm.

[8] The average aboveground and belowground carbon densities are based on both the protected zone and utilized zone due to lack of data. The average is therefore somewhat lower than for the protected area.

[9] We do not have the exact location of the project; hence, the carbon densities must be seen as approximations.

Table 2: Carbon stock at the projects. All carbon values are given in C. These can be converted to CO_2 by multiplying with 3.664.

Carbon stock	Aboveground carbon (Mt C)	Belowground carbon (Mt C)	Soil carbon (Mt C)
Project in Indonesia	0.86	0.22	0.64
Project in Colombia	108	28	84

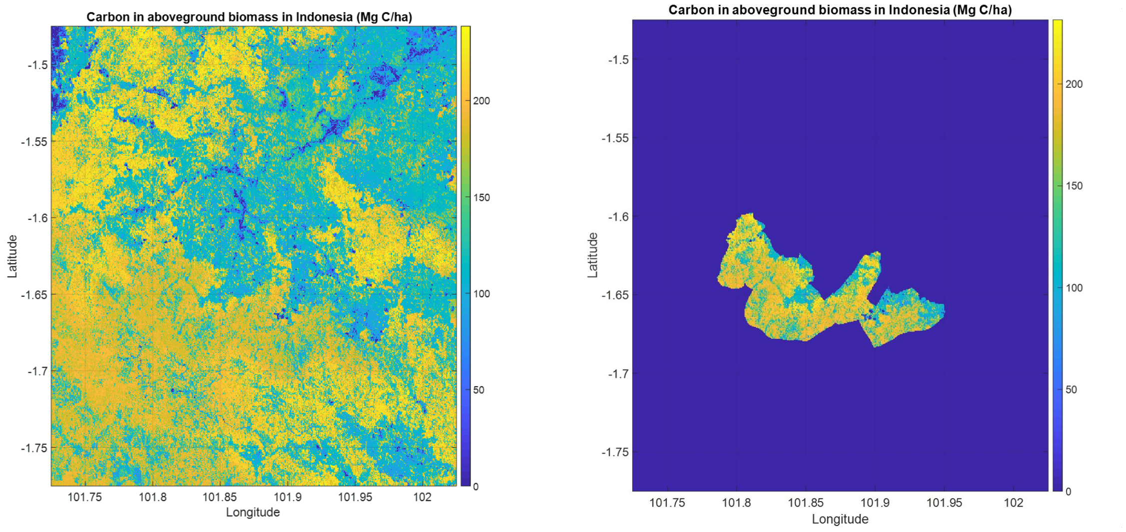

Figure 4: Carbon density in aboveground biomass around the project in Indonesia in the year 2000. Yellow indicate high carbon densities. The size of each pixel is 30x30 m. The source of this dataset is Global Forest Watch. The two panels show the same are, but in the right figure we have removed all data outside of the village forest. The area outside is then given in blue. The village forest shown in the right figure includes both the protected zone and utilized zone. The areas in light blue, areas with the lowest carbon densities, are mostly in the utilized zone.

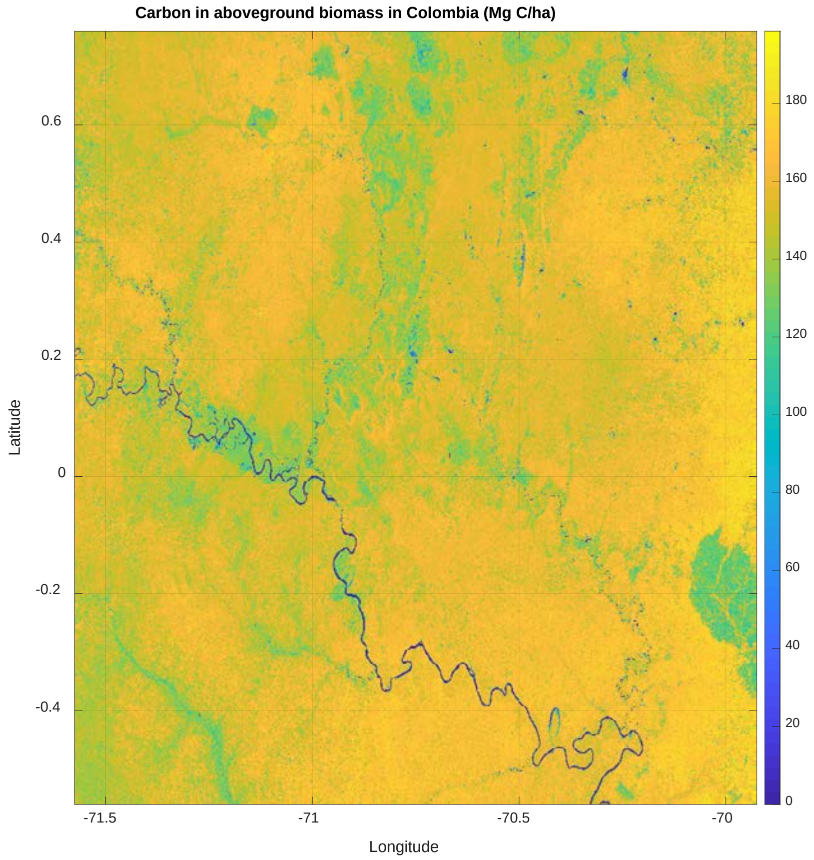

Figure 5: Carbon density in aboveground biomass within and around the project in Colombia. The project covers most of the area shown in the map. The size of each pixel is 30x30 m. The source of this dataset is Global Forest Watch.

Caution should be applied when using these pan-tropical carbon maps for small areas. Saatchi et al. (2011) state that the uncertainty is reduced by increasing the sample area, such as for national- and project-scale assessments (>10 000 ha). For a single pixel, the uncertainty is large. According to Bustamante et al. (2016), estimates of carbon stocks can vary up to 100% in some regions between different biomass maps.

Different carbon datasets also give different estimates. Avitabile et al. (2016) compared the datasets in Saatchi et al. (2011); Baccini et al. (2012) with their own calculations. They found lower levels of about 9-18 %, with higher carbon density values in dense forest areas.

The carbon densities we have estimated for the two projects can be compared to national estimates from different studies, which also give an indication of the uncertainty. For the project in Colombia, we find an average aboveground and belowground carbon density of 155 and 40 Mg C/ha, respectively. Saatchi et al. (2011) estimate the sum of aboveground and belowground carbon density to 122-141 Mg C/ha for Colombia depending on the cutoff for canopy cover threshold (between 10 and 30%). For a canopy cover threshold of 25%, the same as in our calculations, the average value is 138 Mg C/ha, which is the value used in Harris et al. (2012). For Indonesia, Saatchi et al. (2011) give a range of 142-158 Mg C/ha, with 155 Mg C/ha for a canopy cover threshold of 25%, also used in Harris et al. (2012).

Some of the variability in carbon densities may be explained by variations in vegetation. Different types of vegetation, including different types of tropical forest, show a wide range in carbon densities. Baccini et al. (2012) measure an aboveground carbon density of above 100 Mg C/ha for tropical high forest, but only 3 Mg C/ha for grassland. For the tropical forest category with the highest carbon density, closed tropical high forest (>50% canopy closure, trees taller than 15m), the estimate is 139 Mg C/ha. For the category evergreen broadleaf forest, the average for tropical America is 130 Mg C/ha and for tropical Asia 120 Mg C/ha. Tyukavina et al. (2015) divided the forest cover into seven different categories. The aboveground carbon density of the most carbon rich forest (dense cover, tall, and intact forest) is estimated to 147 Mg C/ha for Latin America and 177 Mg C/ha for Asia. Houghton and Nassikas (2017) estimate that the aboveground and belowground carbon density in primary tropical rain forest is 190 Mg C/ha. The variability in carbon densities in the two project areas can therefore be partly explained by variations in vegetation.

4.2 Carbon densities at other potential project sites

Most of the studies that provide carbon density values for Indonesia and Colombia are pan-tropical, thus, also providing values for most countries with tropical forests. All the three carbon and forest datasets introduced in Section 3 are pan-tropical, but our calculations are only based on the Global Forest Watch datasets. The analysis we have done in this report on two projects can be replicated to any other area with tropical forest given the freely available datasets.

The values found for Indonesia and Colombia are representative for the tropical regions in general, however, the carbon density is somewhat larger than the tropical average according to Saatchi et al. (2011) (see Table 3). Saatchi et al. (2011) estimate a tropical average aboveground and belowground carbon density of 115 Mg C/ha with a 25% canopy cover threshold, with Angola having the lowest average of 66 Mg C/ha and Malaysia having the highest average of 179 Mg C/ha. Tyukavina et al. (2015) find that the most carbon-rich tropical forest category (dense cover, tall, intact) has the highest value for Asia, followed by Africa and Latin America. For another REDD+ project in Brazil, a flat level of 100 t C per ha was applied when calculating reduced carbon emissions from deforestation (Angelsen, 2017).

Carbon estimates for other tropical areas should consider with care if the area contain peat. Peat is very heterogeneously distributed, but if an area considered happens to be situated over peat, the total carbon densities are significantly higher.

In conclusion, our estimates of the projects in Colombia and Indonesia give some indication on the carbon densities for other potential projects, but specific assessments should be done when considering other areas.

Table 3: Estimates of forest carbon stocks in different countries with tropical forests by Saatchi et al. (2011). The total carbon values given here is the sum of aboveground carbon and belowground carbon in living biomass. These values are estimated with different threshold of canopy cover as minimum value for forest. In our calculations, we have used a canopy cover threshold of 25%, which is a parameter for forest cover.

	Canopy cover threshold					
	10%		**25%**		**30%**	
Country	**Total C (Gt C)**	**C density (Mg C/ha)**	**Total C (Gt C)**	**C density (Mg C/ha)**	**Total C (Gt C)**	**C density (Mg C/ha)**
Democratic Republic of Congo	24	118	23	128	22	134
Cameroon	5	129	4	142	4	151
Republic of Congo	4	144	4	160	4	162
Gabon	4	160	4	164	4	165

	Canopy cover threshold					
	10%		25%		30%	
Country	**Total C (Gt C)**	**C density (Mg C/ha)**	**Total C (Gt C)**	**C density (Mg C/ha)**	**Total C (Gt C)**	**C density (Mg C/ha)**
Angola	3	44	3	66	2	70
Total sub-Saharan Africa	62	80	50	93	48	106
Brazil	61	102	56	116	54	123
Peru	12	153	12	158	12	160
Colombia	10	122	9	138	9	141
Venezuela	7	118	7	134	7	139
Bolivia	6	84	6	90	6	94
Total Latin America	120	99	110	112	107	119
Indonesia	23	142	20	155	19	158
Myanmar	7	146	6	155	6	157
Papua New Guinea	6	147	6	152	6	153
India	6	89	4	104	4	112
Malaysia	5	172	5	179	4	180
Total Asia and Oceania	65	137	56	155	54	159
Total study region	246	100	215	115	208	124

4.3 CO2 emissions

We have not quantified to what degree the two projects have contributed to avoided carbon emissions or additional emission mitigation, as this depends on establishing a baseline scenario in a counterfactual world where the areas are not protected, as well as an assessment of indirect effects beyond the project boundaries. However, we will present some alternative storylines on what could have happened and how that would have impacted the carbon stocks. Note that these estimates consider only changes in aboveground and belowground biomass, not changes in soil carbon and peat carbon, and only the total changes between 2000 and 2012, not with a temporal resolution. These emissions may occur over a time span, which would be especially true for soil carbon and peat carbon after land use change.

We will not assess which storyline is suitable as a reference scenario. The actual development:

- Base case: Historical observed evolution in the two projects for the period 2000-2012 based on data from Global Forest Watch

Our alternative storylines for alternative development in the project areas

- Case 1: The project areas follow development in a larger area around the projects for the period 2000-2012 based on data from Global Forest Watch
- Case 2: National deforestation rates given quantifications from Zarin et al. (2016) for 2001-2013 are applied to the project sites.
- Case 3: Clear cutting for agricultural use (plantation) over the period 2000-2012
- Case 4: Clear cutting of the area and no regrowth over the period 2000-2012

- Case 5: Assume that the historical deforestation is similar to future scenarios, our main case is the Shared Socio-economic Pathway 2 (SSP2, “Middle of the Road”) with business as usual emissions

> C versus CO_2:
>
> All emissions are given in C in this report, except for some figures from the literature that provide emissions in CO_2. However, emissions are most often given in units of CO_2. All numbers in C can be converted to CO_2 by multiplying with 3.664.

We focus on how the carbon stock change within the project areas. However, protecting areas may also cause indirect land-use effects. We do not include quantifications on this but discuss it further in Section 4.3.9.

We do not indicate any spatial differences in the storylines; however, we acknowledge that deforestation can be heterogenous. Tropical deforestation occurs in “hotspots” (Harris et al., 2017), as Hansen et al. (2008) found that 55% of global deforestation took place in only 6% of the tropical biome. Forest degradation is likely an even larger carbon source that deforestation, since almost 70% of carbon emissions in the tropics are caused by forest degradation and disturbance (Baccini et al., 2017). The relative share is higher in tropical America than in Asia. Both deforestation and forest degradation reduce the carbon density. A schematic view of different processes related to deforestation and reforestation is shown in Figure 6. Untouched forests can become disturbed, degraded or removed, while secondary forest and mature forest can also regrow.

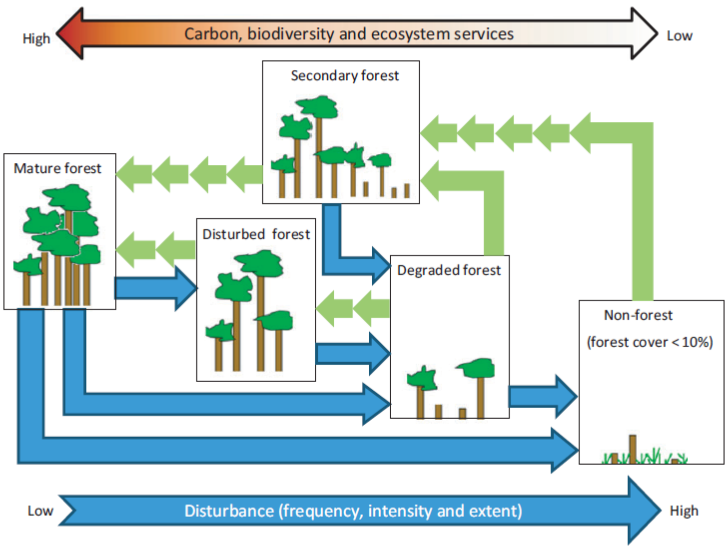

Figure 6: A schematic view of carbon density and biodiversity for tropical forests under different levels of disturbance, from intact forest on the left to non-forest to the right. Figure is from Bustamante et al. (2016).

4.3.1 Base case: Historical deforestation in the project areas

Times series from Global Forest Watch allows us to follow the actual development in forest cover at the two project sites. In areas where forest is lost, we have assumed that 93% and 85% of corresponding aboveground and belowground biomass carbon is lost in Indonesia and Colombia, respectively (Carter et al., 2017). Soil from disturbed areas will also likely emit carbon over time: See further discussion on quantification of carbon emissions from areas with land use change in Section 4.3.4.

Figures 7 and 8 show the change in forest cover. At the project in Indonesia, most of the historical deforestation occurred in the utilized zone, and not in the protected forest, which indicates that the projected area has been mostly spared from deforestation for the time period we have data for. Carbon will slowly be recaptured in areas with forest gain, but we have not included that in these simple carbon emission estimates. We have estimated the carbon loss pixel by pixel. For pixels with no detected forest loss, we assume no changes in carbon density. Where forest loss was detected, we assume a fraction of the carbon density modelled in 2000 is lost based on values from Carter et al. (2017) and lead to carbon emissions. For the project site in Indonesia, the carbon emissions for the period 2000-2012 is estimated to 0.031 Mt C. For the project site in Colombia, deforestation occurred in 0.4% of the area between 2000 and 2012 (Figure 8). The areas with forest loss are scattered, which may also be an indication of natural events or unrelated to human-induced deforestation. The estimated carbon emissions from the project site is 0.47 Mt C.

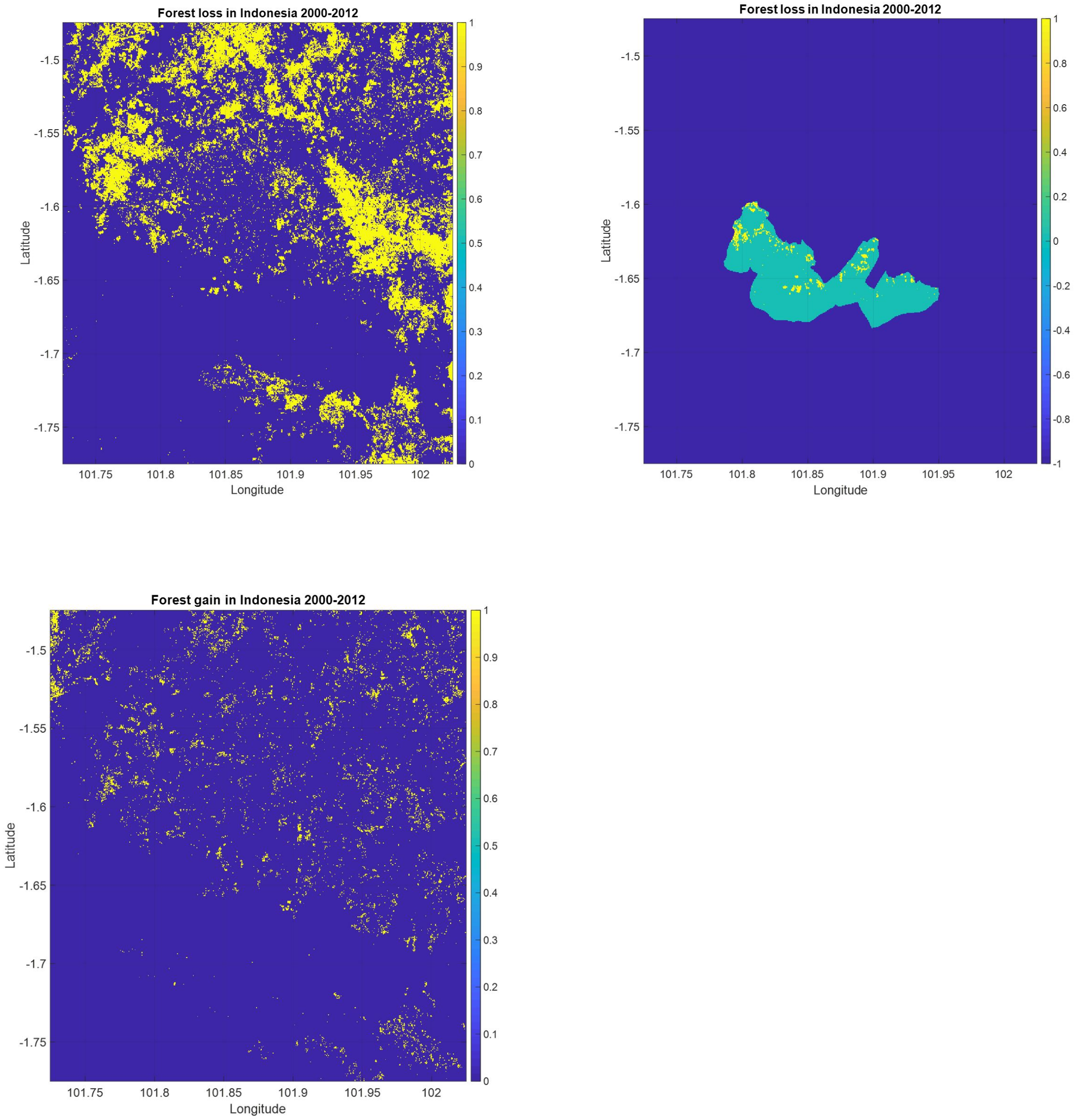

Figure 7: Forest loss (yellow) within and around the project area in Indonesia in the period 2000-2012 (upper figures). The source of this dataset is Global Forest Watch. Each pixel is either unchanged, deforested, or regrown. Left: Forest loss in the project and surrounding area. Right: Only forest loss within the village forest. Both the protected zone and utilized zone are included. Most of the deforestation within the forest village occur in the utilized zone. Lower figure: Forest gain (yellow) within and around the project area in Indonesia in the period 2000-2012. No change is given in blue.

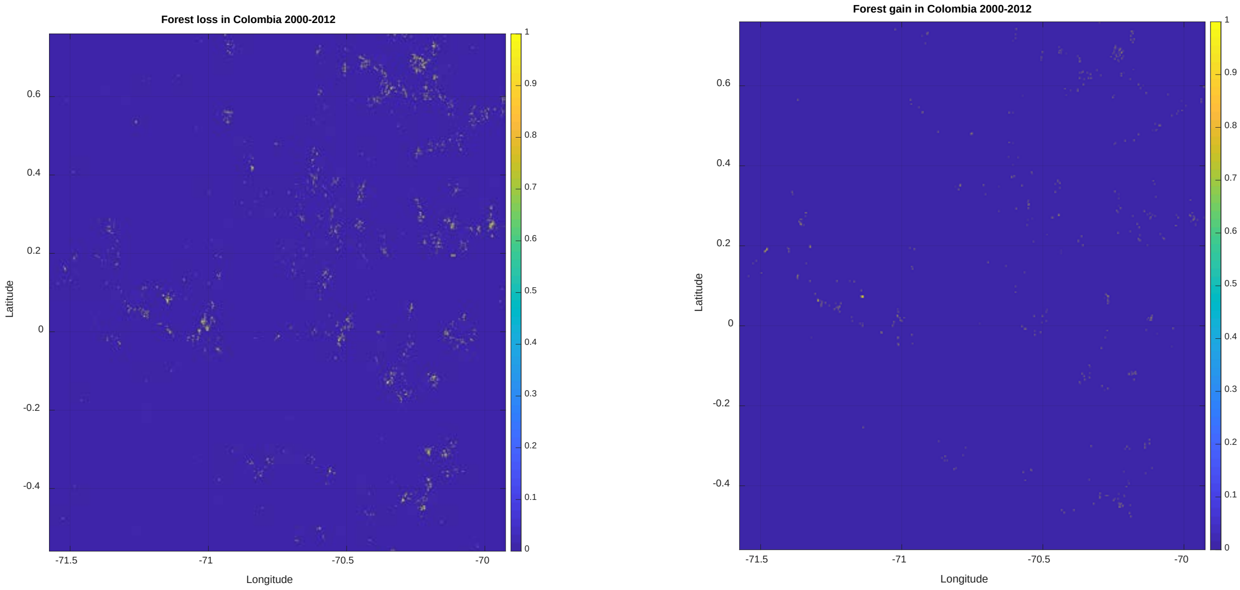

Figure 8: Forest loss (left) and forest gain (right) within and around the project area in Colombia in the period 2000-2012. The source of this dataset is Global Forest Watch. Each pixel is either unchanged, deforested, or regrown.

4.3.2 Case 1: Historical deforestation in surrounding area

For Indonesia, we have looked at deforestation in areas surrounding the project (1.925 °S-0.825 °N and 100.9 °E-103.1 °E), a total area of several million hectares corresponding to the project in Colombia. For the period 2000-2012, 31% of the forest was lost in this larger area, compared to 5.7% in the village forest, i.e., the protected forest and utilized zone at the project site. Applying the same high deforestation rate also to the project area following the method in Section 4.3.1, we estimate a total carbon emissions of 0.21 Mt C over the period. Compared to this hypothetical case, the emission reduction in the project area would in other words be (0.21-0.031) Mt C.

For Colombia, the project is located in an in an area with little deforestation and deforestation rates for the period 2000-2012 seemingly not significantly different inside and outside of the project area. We therefore do not estimate deforestation based on what happened in the surrounding area.

4.3.3 Case 2: National historical deforestation rates

The advantage of comparing to historical deforestation on a national level is that several studies are available. However, there is no scientific consensus on a global dataset for gross deforestation rates, and thus carbon emissions, which is also the case for most countries (Zarin et al., 2016). Zarin et al. (2016) have estimated the gross deforestation rates in primary forests for the period 2001-2013 (see Figure 9). This study looked only at aboveground carbon in living biomass and forests with a canopy cover of minimum 25%. They find that the gross deforestation in Indonesia led to an average emission of 0.394 Gt CO_2 per year when considering forest in general, reduced to 0.198 Gt CO_2 per year for only primary forest. Deforestation peaked in 2012 followed a reduction probably linked to a combination of price and policy signals. The carbon loss in Colombia from deforestation is about 0.07-0.08 Gt CO_2 per year in the period 2001-2013.

This deforestation can only occur in forested areas. According to Harris et al. (2012), Indonesia and Colombia had forest areas of 107 and 63 Mha, respectively, in 2000. In Indonesia, 98.4 Mha of this was primary forest in 2000 (Margono et al., 2014). The share of primary forest is much smaller in Colombia, with as little as 8.5 Mha of primary forest.

If we assume that the historic deforestation rates estimated by Zarin et al. (2016) occurred in primary forest, this gives carbon emissions of 1.1 and 1.6 Mg CO_2 per ha primary forest per year in Indonesia and Colombia, respectively. If we assume these average carbon emissions are representative for the 2000-2012 period, the carbon emissions for the period is 14 and 21 Mg CO_2 per ha primary forest in Indonesia and Colombia, respectively. If this had occurred in the two projects. This would lead to carbon emissions of 0.021 and 4.0 Mt C in Indonesia and Colombia, respectively. The estimated carbon loss in Indonesia is much smaller based on a national deforestation rate that the deforestation in areas surrounding the project. The reason is that there has been a high deforestation pressure in those areas of Sumatra compared to other areas of Indonesia. Using national average deforestation rates in other words mask potentially large regional variabilities.

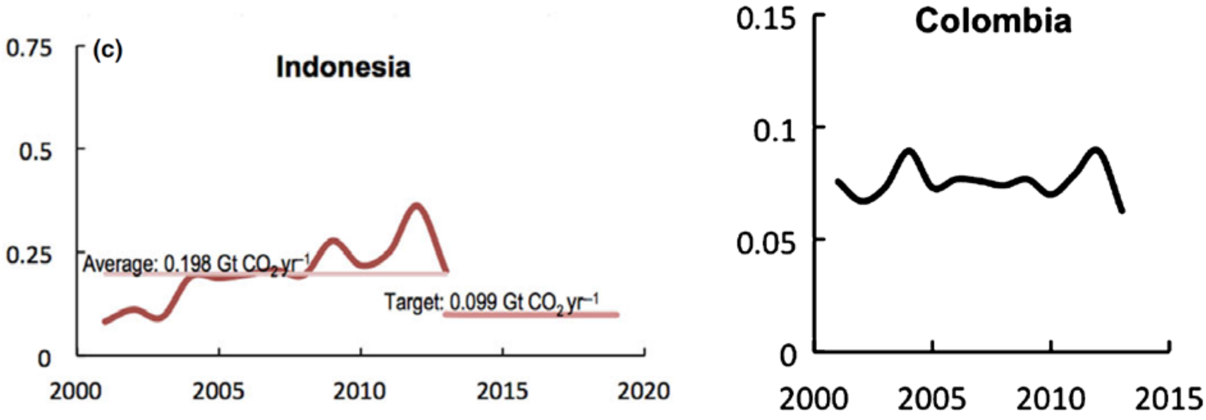

Figure 9: Estimates of gross deforestation in Indonesia (left) and Colombia (right) in the period 2001-2013 according to Zarin et al. (2016). The numbers for Indonesia are on primary forests and for Colombia national statistics for Colombian Amazon combined with deforestation estimates from the literature.

4.3.4 Case 3: Clear cutting for agricultural use

One extreme hypothetical case is that the forest at both projects is clear cut leading for agricultural use. Carter et al. (2017) estimate that agriculture stood for 52 and 76% of the deforestation in Indonesia and Colombia, respectively, in the period 2000-2005.

Bonini et al. (2018) investigated the impact of converting forest in Amazon-Cerrado to soybean plantation. They found a carbon loss of 130.5 Mg C per ha. What type of crop is used will have an influence. Perennial and annual monocrops have very different impacts on the carbon cycle. Even with optimizing the farming the soil carbon stocks may never be restored after deforestation. The reduction in carbon stocks will mainly be due to reduction of aboveground biomass, but also in addition to a continuous decrease of the carbon content in the soil and biomass losses of fine root material. Bonini et al. (2018) state that other studies have shown reductions in soil organic carbon stocks of 16 to 79%. The establishment of a soybean plantation reduced the amount of aboveground carbon by about 98%.

Carter et al. (2017) estimated emissions from agriculture-driven deforestation in the tropics. In this study, they estimated the carbon content in aboveground and belowground biomass in forest before deforestation to be 98 tC per ha in Colombia and 130 tC per ha in Indonesia. Further, they found that the fraction of biomass lost was 83% due to agriculture and 85% for land-use change in general for Colombia and 92% due to agriculture and 93% for land-use change in general for Indonesia. The estimated fraction biomass lost is based on deforestation in the period 1990-2015.

In our estimate we use the fraction of carbon lost from aboveground and belowground biomass from Carter et al. (2017). With a loss of 83% in Colombia, our estimate gives carbon emissions of 113 Mt C. Further, a loss of 92% in Indonesia results in emissions of 1.0 Mt C. Carbon emissions from the soil will also probably contribute, but we have not quantified this. This carbon loss process will also occur over a longer time scale. Some carbon will be stored by the crops, but according to the numbers from Carter et al. (2017), this carbon storage is small compared to the carbon lost from deforestation.

4.3.5 Case 4: Clear cutting and no regrowth

Similar to case 3, we make an estimate of the forest be converted to grassland, which would lead to large carbon emissions. According to carbon estimates from Baccini et al. (2012), the aboveground carbon density in grassland is only 3 Mg C/ha or 3% of the value seen for tropical forest. If we assume that 97% of the carbon from aboveground and belowground biomass is lost, we estimate carbon emissions of 1.1 and 132 Mt C in Indonesia and Colombia, respectively. In these estimates, we have assumed that all carbon removed from the forests will lead to carbon emissions. However, some of the timber may be used in different long-lasting products, such as furniture and building material, and, thus, store carbon.

4.3.6 Case 5: Following SSPs

All the cases have so far looked at historical trends, while the last case is a possible future under given socioeconomic development. The newest generation of widely used scenarios in the climate science community are the shared socio-economic pathways (SSPs). They indicate possible futures given different socio-economic conditions and extent of climate change for the period 2005-2100. The SSPs are divided into five different stories of the future. These SSPs have been examined by several studies, with special attention to tropical forests, deforestation, and REDD+ in Popp et al. (2017); Doelman et al. (2018). Figure 10 shows how emissions from global cumulative land-use change are given in the five SSPs under three different climate change outcomes given Representative Concentration Pathways (RCPs) (Popp et al., 2017), baseline with no further climate policies, RCP4.5, and RCP2.6, where the last one is consistent with a global warming of 2 °C. Today, these emissions are mainly caused by conversion of tropical forests to agricultural land. SSP2 is called the “Middle of the Road” pathway as the world follows a path in which social, economic, and technological trends do not shift markedly from historical patterns. This pathway can potentially be a starting point, while the other SSPs are also possible futures. Given SSP2, we see that global deforestation in the next decades will closely follow historic deforestation rates, at least in pathways that follow the current global fossil emissions trend. In almost all potential pathways the deforestation is stopped or reversed in the second half of the 21st century as many of them include afforestation and reforestation as mitigation measures.

If RFN is going to use SSPs to quantify future deforestation, some choices must be made, such as what SSP and RCP to follow. Different perspectives may lead to different choices. Further, this global deforestation pathway must be downscaled to a national or local level. These pathways have no information on what may happen on such small scales as the two project sites in Indonesia and Colombia. Some assumptions must be made to use these pathways on the project areas we discuss in this report. We would be careful to apply these global trends at such local level; however, we indicate the results if we do. For simplicity, we assume that the historic national deforestation rates continue at a constant level in the next couple of decades, in line with the global trend in the baseline of SSP2 in Figure 10. Our estimate on potential deforestation for the next 13 years period is therefore put simply to the national average deforestation rate for the period 2000-2012. More complex analysis is possible and something RFN can explore if SSPs are seen as useful to predict potential future deforestation.

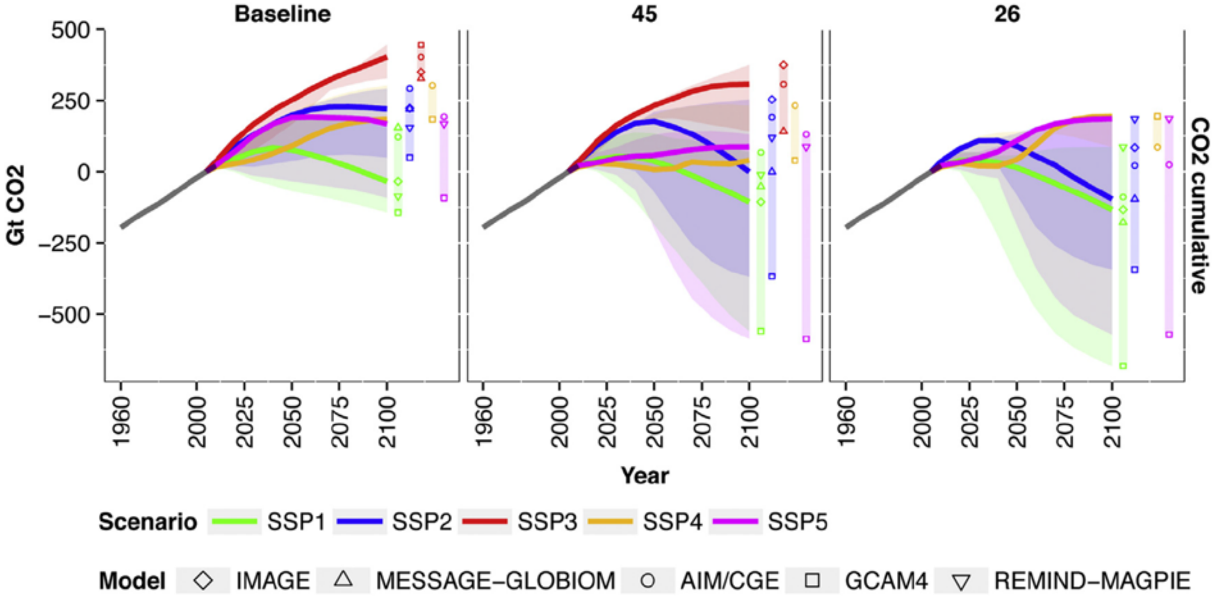

Figure 10: Future emissions from global cumulative land-use change, mainly driven by the conversion of tropical forests to agricultural land as estimated by Popp et al. (2017). Pathways are given for the five SSPs for the baseline (left), RCP4.5 (middle), and RCP2.6 (right).

4.3.7 Summary on storylines

Our quantifications of the storylines should only be seen as crude estimates. The different cases are summarized in Table 4. As the project area in Colombia is much greater than in Indonesia, the potential emissions are that project is by the far largest. However, the two projects have similar emission potentials per unit area. Unsurprisingly, the emissions are by far the largest if the project areas are clear cut. The deforestation rate has been much larger in the area surrounding the project in Indonesia than the project in Colombia.

Table 4: Crude carbon emissions in total and per unit area from the two projects given different hypothetical cases. These estimates include only changes in aboveground and belowground biomass, not changes in carbon soil and peat soil. Most of cases are for the period 2000-2012. All carbon emissions are given in C. These can be converted to CO_2 by multiplying with 3.664.

Carbon emissions in project areas	**Colombia**		**Indonesia**	
	In total (Mt C)	**Per unit area (Mg C/ha)**	**In total (Mt C)**	**Per unit area (Mg C/ha)**
Base case: Historic deforestation	0.47	0.67	0.031	5.8
Case 1: Local deforestation rates	0.47	0.67	0.21	40
Case 2: National deforestation rates	4.0	5.7	0.021	3.9
Case 3: Clear cutting and agriculture	120	160	1.0	190
Case 4: Clear cutting	130	190	1.1	200
Case 5: SSP2 baseline	4.0	5.7	0.021	3.9

4.3.8 What is a useful reference level?

We have given some different storylines of what could hypothetically happen at the two project sites if the projects were not part of REDD+. We will discuss some issues on this topic based on recent scientific literature, while RFN should also be aware of what is common practice today. Guidance is given by Forest Carbon Partnership Facility (2016) and UNFCCC[10]. The most difficult part of assessing the greenhouse gas mitigation effects of the two projects is to define a reference level or baseline that is robust, that is, what the situation would have been if these two cases in Indonesia and Columbia did not exist. Angelsen (2017) discusses how a reference level should be set in REDD+ projects. The core of the issue is attribution, that is whether an outcome is a result of the intervention or other external factors. In this project, we are not able to give a clear answer on what the actual carbon emission savings are. The different hypothetical scenarios described here are given as illustrations of potential carbon effects given different choices.

The typical assumption used is a baseline of “no policy reforms” (Angelsen, 2017). Then, past deforestation can be applied, such as average deforestation in the past 10 years and updated every 3 or 5 years. Among the uncertainties, we find that the future drivers of deforestation and degradation are not known, such as the price of palm oil and soybeans, and the future relationship between such drivers and agricultural land expansion into forests. The level of deforestation will also fluctuate. According to forest transition theory (Mather, 1992), in the early stages of deforestation forest cover is high and deforestation rates low. The forest cover becomes reduced as more forest is removed at higher deforestation rates. At the end, less forest is available for deforestation, leading to reduced deforestation rates.

One issue of quantification is the lack of datasets that can be trusted. Bustamante et al. (2016) state that developing countries often lack consistent historical monitoring and land-cover data. They are forced to rely on remote-sensing approaches mixed with current field assessments of carbon stock changes. Estimates on forest degradation are even harder to set than for deforestation, and Mitchard (2018) write that no country has reliable baseline figures on their rate of forest degradation.

When there is a lack of historical biomass data for appropriate benchmarks and limited capability for monitoring forest degradation using remote sensing, one practical solution is to say that the reference level is a local benchmark that represents areas of low or no degradation and sharing comparable biophysical characteristics (Bustamante et al., 2016).

4.3.9 Leakage effects of REDD+ projects

We have not quantified the displacement or leakage effects of the two projects, but will here briefly discuss the topic. While we find it difficult to assess the carbon effects at the site of the projects, this work is even more challenging when considering that the REDD+ projects may have indirect effects that also leads to CO_2 emissions, which could be labelled “carbon leakage”. Concerns about leakage have been prevalent in REDD+ discussions since the concept was introduced. These concerns were the major reason why REDD+ was initially seen as an initiative to be implemented primarily at a national level, and not through standalone projects – although focus gradually shifted towards project implementation (Angelsen and McNeill, 2012).

An alternative to protection could be to utilize the forest by harvesting the same amount as the natural growth, such that the stock is kept constant. Then, the total effect depends on how the harvested products are utilized if the forest is not protected. Leakage may entail the shifting of deforestation or forest degradation to adjacent forest areas. It may also entail shifting emissions from one sector to another. A study of forest protection in Tanzania (Aaheim et al., 2016) points out that the initial effect is abandonment of charcoal production, which smallholders use to sell to nearby cities. Stopping this trade will not only remove an important source of income from these

[10] Fact sheet on forest reference emission levels: https://redd.unfccc.int/fact-sheets/forest-reference-emission-levels.html

people, but those who buy the charcoal will have to find alternatives. Their most likely choice is kerosene, and the net effect on CO_2 can be questioned. The study shows that if evaluated over decades, it may turn negative. In general, the effect of REDD+ on carbon uptake depends partly on how the products from the protected forests are replaced when protected, and partly on the storage capacity for carbon in the products delivered from the forest.

A more comprehensive study was done in a model experiment for India to assess the impact on carbon uptake of protecting ten percent of the forests in selected states (Aaheim et al., 2018). The immediate effect was a switch in the demand for the products delivered from the protected forests to other forests, with a resulting reduction in carbon uptake from these forests. Protection led to lower total demand for the forest products, but with a permanent increase in the demand from the non-protected forests. As the carbon uptake in protected forests saturates over time, the total uptake from all forests turned out lowest if the forests were protected.

4.3.10 Synthetic reference

Even when data is available on deforestation rates (or other variables of interest) before and after a project is implemented, this is insufficient for estimating the project's impact, because deforestation rates could change due to external drivers. However, a relatively new statistical method called *synthetic control method* (SCM) can be used to construct a counterfactual baseline of deforestation rates in the project area had the project not been implemented. Comparing actual developments with the counterfactual gives an estimate of the project's causal impact.

The counterfactual baseline is constructed as a weighted average of developments in areas not affected by the project, called control units. The idea is that a combination of control units gives a better counterfactual than a single unit. SCM thus requires that data is available for geographical areas that are reasonably comparable to the project area. Compared to other statistical methods, the required number of control units is quite low, 5-10 might suffice. SCM provides a data-driven and objective approach to assigning weights to control units. Typically, the weights are determined so that the baseline deforestation trajectory most closely resembles the pre-project developments in the project area. This procedure can be completed before post-implementation data is available, thus safeguarding against cherry-picking control units. Unlike traditional regression methods, SCM makes explicit the weight given to each control unit and shows how well the baseline trajectory resembles pre-project developments in the project area.

Say that the SCM estimates that the project reduces deforestation by 5%. How confident can we be that the project actually caused the effect? To provide a measure of statistical confidence (p-values), a series of placebo tests can be performed. Each control unit is assigned as a "placebo" project, and the effect on deforestation of this "placebo" treatment is estimated. If there are 10 control units, and no placebo test results in effects $\geq$5%, then we can say that the probability of estimating a 5% project effect purely by chance is less than 10%.

SCM has been used to estimate the effect on deforestation of a local policy initiative launched in 2008 in Paragominas in the Brazilian Amazon (Sills et al., 2015). Other applications include estimating the economic cost of conflict in the Basque county (Abadie and Gardeazabal, 2003), the effect of California's tobacco control program (Abadie et al., 2010), the economic impact of Norway's petroleum endowment (Mideksa, 2013), the effect of energy labels displaying appliances' operating costs (Kallbekken et al., 2013), and the economic cost of German reunification (Abadie et al., 2015).

4.4 Methods to quantify the greenhouse gas effects in the future

How much carbon emissions are these two projects saving in the future? Given the limitations discussed above, in this section we will assess and propose methods that RFN can apply. All these methods can utilize the most recent literature and measurements. It is important to underline that all of these methods are based on important simplifications, such as the omission of any attempt to account for potential leakage.

The suggestions on methods are first introduced in Table 2. This part of the report is rounded up with what are expected method improvements in Section 4.4.5.

Table 5: An overview of the proposed methods to quantify the future carbon effects of projects. Details on the methods are given in the text. Disadvantages are ranked from few and small (+) to many and large (+++).

Method	Level of post-processing	Cost	Disadvantages
1: Average and historic	Very low	Very low	- - -
2: Based on best available data	High	Medium	-
3: Updating best available data	Very high	High	-
4: Fieldwork and produce own datasets	Very high	Very high	- -

4.4.1 Method 1: Average and historic

A first and simple estimate is to base calculations on historic deforestation rates and standard carbon density values. We assume that the carbon density in tropical forest is on average 100 t C/ha and that this forest is protected from clear cutting by REDD+. The reference level is given as the average deforestation rate of the past 10 years and updated every three to five years. This method has several disadvantages, such as not accounting for the actual carbon densities and no deep analysis of what is a reasonable baseline. This method is similar to the one described by Angelsen (2017) and a method that has been used in settling criteria for payment scheme of REDD+ funding in some of the bilateral REDD+ agreements Norway has entered into.

4.4.2 Method 2: Based on best available data

The strategy for this method is to use what are seen as the best, most recent, or most practical publicly available datasets on carbon densities and deforestation. These datasets combine state-of-the-art field measurements and satellite measurements, which RFN can build on. That has been the approach in this report. We have used the datasets from Global Forest Watch, presented by Zarin et al. (2016). This dataset will likely be updated. The database combines existing datasets on carbon densities and loss/gains in forest for the period 2000-2012 and is expected to be expanded to 2000-2014.

The baseline can be settled by using synthetic reference as a method. The synthetic reference needs data points (carbon densities and deforestation) from other areas in the countries, not just project specific. However, if such data is available, this method is relatively simple.

A visual schematic of method 2 is given in Figure 11. This method delivers the most bang for the buck, or being the most cost-effective, as the work is moderate in extent, but builds on highly complex datasets. Among the disadvantages are the reliance on others updating the datasets, always some years behind (currently last year is 2012/2014), and no spatial information on soil carbon and peat carbon.

4.4.3 Method 3: Updating best available data

The disadvantage of method 2 is the reliance on forest datasets updates and always not having data for the most recent years. Method 3 builds on the available, but expand with own calculations on forest loss, with focus on most recent years, in order to have more updated estimates. This approach will depend on independent work with recent satellite data and ground-based measurements.

4.4.4 Method 4: Fieldwork and produce own datasets

The publicly available datasets are on aboveground carbon densities and not on soil carbon and peat carbon. To make an estimate of all carbon stocks and emissions, field work at the projects are needed in addition to the findings from method 2. Additional fieldwork is especially important in areas with peat. In addition, datasets on aboveground carbon densities may also have large biases and errors on small scales. Fieldwork by RFN can be a quality check of the pan-tropical carbon maps at specific localities. Field work is difficult and resource demanding.

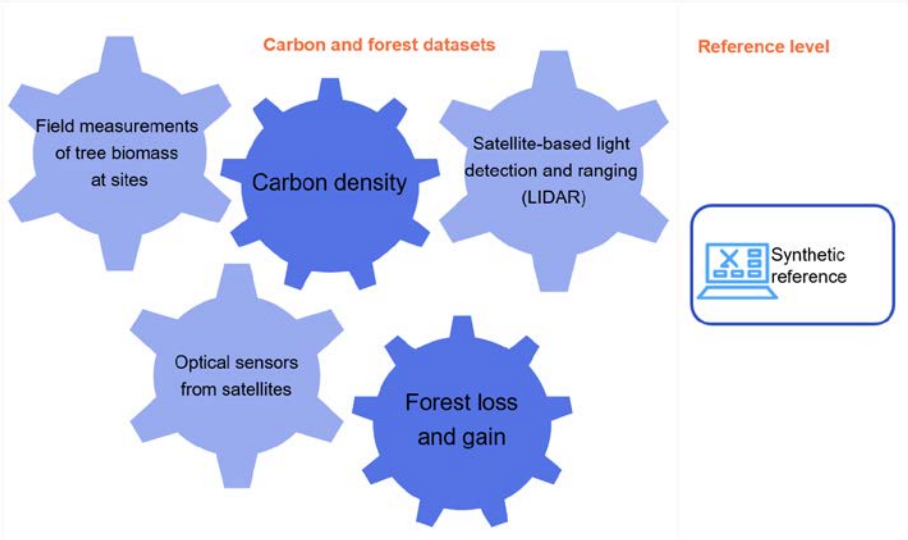

Figure 11: A schematic view of method 2, which utilizes datasets of carbon densities. That dataset is based on field measurements, LIDAR measurements, and optical measurements from satellites. Forest gain and loss is also measured with satellites. Changes in forest cover in an area can be compared to a reference or baseline by producing a synthetic reference based on the same datasets for other areas.

4.4.5 Improving measurement methods

The methods of quantifying carbon densities and changes in the tropical forest are improving. In this section, we present some newer trends discussed in the recent scientific literature.

The standard setup of estimating carbon densities is to combine remote sensing from satellites and LiDAR with robust field-based datasets. New and upcoming satellites with higher resolution can improve this method. Mitchard (2018) mention the new satellite missions GEDI, OCO-3, and BIOMASS, the latter expected launched in 2021. Bustamante et al. (2016) mention the Sentinel 2 satellites launched in 2015/2016 and ESA satellite LiDAR to be launched in 2020.

Even though most studies combine remote sensing analyses with field plots, Bustamante et al. (2016) find that the biomass maps in the literature diverge. Estimates of aboveground carbon stocks vary by over 100% in African forests and by 60% in Amazonian forests. The estimates can improve with higher resolution and the inclusion of variability given differences in topography and soils. Making sure of compatibility of sources used for forest area and carbon stocks will also be essential in improving estimates.

Mitchard (2018) presents also other options to assess the tropical forest carbon balance. At small scales, forest inventory plots are useful. Tree diameters are measured, and species recorded, in order to estimate tree mass. Revisiting networks of such plots every five years gives precise estimates of how carbon stocks are changing. Another option is measurements of the air by network of towers and marine measurement sites supplemented with ship and aircraft data. When these measurements are combined with atmospheric transport models, we can estimate net flows of CO_2 into or out of an area at a broad and regional scale. As directly measuring forest responses is difficult, Mitchard (2018) presents also dynamic vegetation models as mean to predict changes. Satellites can be used not only to help measures forest area and carbon stocks, but also greenhouse gas concentrations. The breathing in and out of the forest can be measured directly. All these methods are suitable in different forms to assess changes in the forest carbon, but not necessarily useful to assess whether changes are caused by REDD+ projects or similar.

Carbon emission from forest degradation is even more difficult to assess than from deforestation. Bustamante et al. (2016) argue that the carbon effects (and biodiversity) of forest degradation and recovery can be evaluated by combining ecosystem models, multiscale remote sensing, and networks of field plots, to some extent similar to assessing deforestation. The uncertainty on degradation can be reduced by combining these different methods. However, uncertainties are still high, and Bustamante et al. (2016) state that the combination of errors can be 20-50% for aboveground-biomass estimates, while this does not consider the significant uncertainties from forest degradation and soil carbon estimates.

Uncertainties can be reduced, but at a cost, as schematic shown in Figure 12. The costs of precise assessment increases both with precision and landscape heterogeneity. Bustamante et al. (2016) indicate that field work should focus on the largest stems and describing plant species, especially in secondary forests. Remote-sensing techniques can be cost-effective on nation scale to assess forest carbon stocks. However, satellites are best on changes in canopy properties, not on what happens in the understory.

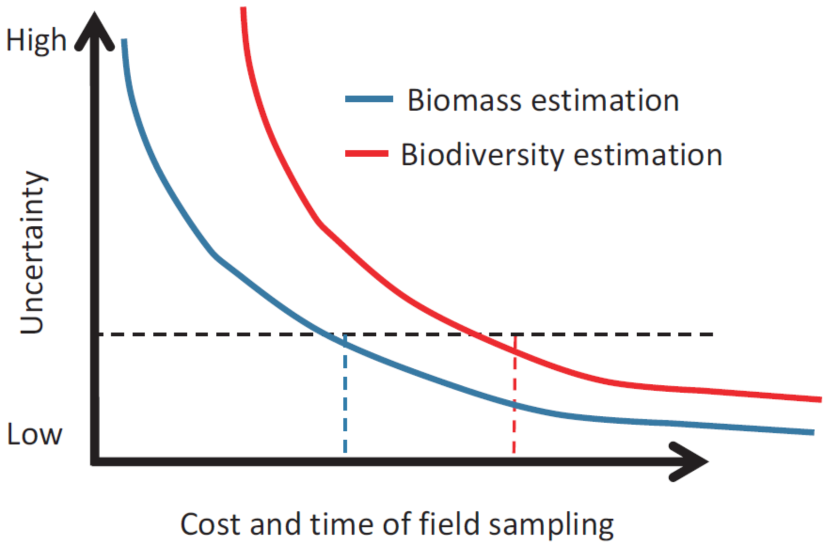

Figure 12: A schematic relationship between accuracy and costs and time of measuring forest carbon stocks (Bustamante et al., 2016). Uncertainty can easily be reduced with some initial field sampling, but reducing the uncertainty further is more demanding.

The forest dynamics must be better understood to better grasp deforestation and forest degradation. Bustamante et al. (2016) point to better process-oriented description of forest dynamics (recruitment, mortality, growth dynamics, and species composition), how these processes are modified by anthropogenic disturbances (such as fire, logging, edge effects, and land conversion) and climate change and events. There are issues on scaling from plot-scale studies to landscapes. Scaling could be better facilitated using remote sensing variables, such as leaf area index. Major limitations for all model types are the lack of data for parameterization and the cost to run models at high spatial resolution. Models on forest dynamics have typically spatial scales of 5 km resolution (Bustamante et al., 2016).

Longo et al. (2016) find that for Brazilian Amazon regional and pantropical products consistently overestimate aboveground carbon density in degraded forests, underestimate aboveground carbon density in intact forests, when comparing detailed airborne LiDAR with previous and cruder estimates.

5 Conclusion

This report is a desk study that have investigated carbon stocks and potential carbon emissions from two REDD+ projects, one in Indonesia and one in Colombia. Further research and more in-depth studies are needed to quantify the carbon emissions potentially reduced by these projects. The carbon densities at both projects are similar to in large part of pan-tropical forests.

We have presented five storylines of what could have happened if not these two areas were not protected as REDD+ projects. These are only meant as illustrations, and not as baselines. In addition, protection of the forest may also cause indirect land-use effects.

Not surprisingly, the largest carbon emissions by far will occur by clear cut. Both project areas saw little deforestation in the period 2000-2012. We do not establish a causal relationship between protecting the two project areas and avoiding deforestation; however, our analysis finds little deforestation within those two projects in the period 2000-2012. Other factors are probably also contributing to these areas not being deforested, such that the surrounding area in Colombia has not yet seen a significant deforestation pressure.

We also propose four different approaches RFN can use to quantify the future carbon effects of projects, while acknowledging the shortcomings / knowledge gaps in currently available approaches. If cost-effectiveness and utilizing state-of-the-art scientific knowledge is preferred, we suggest that RFN goes for combining best publicly available high-resolution data with synthetic reference. More resources could be added to improve estimates on more recent years and on carbon densities in soil and peat at the locations.

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