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ASSESSING CARBON STOCKS USING INDIGENOUS PEOPLES' FIELD MEASUREMENTS IN AMAZONIAN GUYANA

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ABSTRACT

Accurate estimations of carbon stocks across large tracts of tropical forests are key for participation in programs promoting avoided deforestation and carbon sequestration, such as the UN REDD+ framework. Trained local technicians can provide such data, and this, combined with satellite imagery, allows robust carbon stock estimation across vegetation classes and large areas. In the first comprehensive survey in Guyana conducted by indigenous people, ground data from 21 study sites in the Rupununi region were used to estimate above ground tree carbon stocks across a diversity of ecosystems and land use types. Carbon stocks varied between village sites from 1 Tg to 22.7 Tg, and these amounts were related to stem counts as well as tree size. This variation was linked to vegetation type across the region, with trees in savannas holding on average 14.5 MgC ha^{-1} and forest 141.9 MgC ha^{-1}. The results indicated that previous estimates based on remotely sensed data for this area may be inaccurate. There were also differences in carbon stocks between the north and south Rupununi regions, as well as between village sites and uninhabited control areas. Differences between north and south probably reflect vegetation type, regional hydrology, geology and topography, while differences between inhabited and uninhabited areas are presumably driven by community use. Recruiting local technicians for field work allowed a) large amounts of ground data to be collected for a wide region otherwise hard to access, and b) ensured that local people were directly involved in Guyana's Low Carbon Development Strategy. This is the first such comprehensive survey of carbon stocks and vegetation types over a large area in Guyana, one of the first countries to develop such a program. The potential inclusion of forests held by indigenous peoples in REDD+ programs is a global issue: we clearly show that indigenous people are capable of assessing and monitoring carbon on their lands, and should therefore be partners in such programs.

Keywords

Tropical forest; tree carbon stocks; indigenous land management; REDD+; Guyana; land cover satellite imagery.

INTRODUCTION

The importance of trees and forests, especially tropical forests, as carbon sinks and stocks is well established, with forests globally sequestering 2.4 ± 0.4 PgC yr^{-1} by one estimate (Pan et al. 2011). Forests are under multiple development pressures, including logging, fragmentation for mining, and clearing for agriculture. The latter is particularly critical in tropical regions, where land conversion accounted for carbon emissions of 1.3 ± 0.7 PgC yr^{-1} between 1990 and 2007 (Pan et al. 2011). In addition to development stressors, climate change itself is a key threat to forests in the Amazon basin (Malhi et al. 2008), and in order to mitigate rapid climate change, it is essential that forests are kept as intact as possible so they can continue as carbon sinks (Gibbs et al. 2007).

Recognition and understanding of the global importance of forest carbon stocks and forest ecosystem functioning has led to the development of several schemes whereby the maintenance of forest cover and carbon sequestration is remunerated, such as the UN REDD/REDD+ program (Reducing Emissions from Deforestation and forest Degradation; http://www.un-redd.org). These schemes, and others, such as national and international carbon trading programs, and voluntary payments for carbon sequestration services, require the measurement of carbon stock baselines, and subsequent monitoring and reporting of carbon pools (Cedgren 2009), through a combination of remote sensing and ground truthing methods. To achieve support for REDD+ schemes and ensure that they fairly compensate forest stewards, it is essential that local stakeholders understand the carbon measurement process. This has been achieved through participatory approaches whereby local, trained, citizen scientists provide useful data across large areas, as has been demonstrated (Butt et al. 2013, Danielsen et al. 2013, Torres 2014).

Guyana was one of the first countries to submit a REDD Readiness Plan for testing national payments for carbon storage to the Forest Carbon Partnership Facility, a global partnership between national governments and other entities focussed on REDD+ (www.forestcarbonpartnership.org/sites/forestcarbonpartnership.org/files/Documents/PDF/Panama_PC_meeting_summary_for_website_clean.pdf), and also one of the first to establish a national REDD program. The Guyana REDD+ Investment Fund (GRIF) was set up as part of Guyana's Low Carbon Development Strategy (LCDS), as a climate finance mechanism by which avoided deforestation could be compensated until an international REDD+ mechanism became operational (http://www.guyanareddfund.org/index.php#). The fund was capitalized by the government of Norway.

In order to become part of a scheme such as REDD/REDD+, Measurement, Reporting and Verification (MRV) activities need to be coordinated and carried out by capable people on the ground, to complement remotely sensed monitoring data. This partnership approach reflects the importance placed on both the rights of indigenous people as stakeholders, and their involvement in the REDD process, by the Guyana-Norway Agreement (Cedergren 2009, Gutman and Aguilar-Amuchastegui 2012). Citizen science and other participatory approaches to monitoring provide an effective method of forest monitoring, and in the Guyana context Amerindian communities manage their resources, inform other community members of carbon stocks on their land, and gain insight and training in forest monitoring, which should enable an informed decision-making process with regard to opting in or out of the REDD program within the LCDS. Transparent and effective multi-stakeholder consultations are ongoing and evolving in Guyana: an audit in July 2012 indicated that only three of the ten verification indicators reviewed by Rainforest Alliance (Donovan et al. 2012) had been fully met, four partially met and three not met. Two of those that were not met ("Protection of the rights of indigenous peoples" and "Transparent and effective multi-stakeholder consultations continue and evolve"), referred specifically to the involvement of indigenous peoples in the process.

Project Fauna was a Guyana-based initiative developed by a team of researchers from various research institutions and local indigenous leaders to examine the connected nature of indigenous people and their environment (Fragoso et al. 2005, Luzar et al. 2011). The main goal of the project was an assessment of how biodiversity influences and is influenced by changes in indigenous human culture, and of how land use change influences these elements of coupled human natural systems (Luzar and Fragoso 2013, Read et al. 2010, Luzar et al. 2011). Socioeconomic and biodiversity variables were measured on titled lands using a participatory approach. The project also measured above ground vegetation carbon to 1) address the issue of links between carbon and biodiversity and contribute to the discussion of bundled ecosystem services, and 2) advance indigenous community understanding of carbon, carbon politics and REDD+ programs, thus enabling their participation in the national discussion on carbon value and payments.

From 2007 to 2010, Project Fauna trained 335 indigenous technicians across 30 Amerindian communities in the Rupununi region (Figure 1) to monitor wildlife populations and hunting patterns, and to describe vegetation structure. The success of this program (Luzar and Fragoso 2013, Luzar et al. 2011, Read et al. 2010) led Project Fauna to initiate a vegetation and carbon assessment pilot study (Epps 2010; http://www.stanford.edu/group/fragoso/), which aimed to: 1) build the scientific capacity of local communities in understanding the sources and stocks of carbon in the environment, and how to measure carbon in above ground vegetation (AGV); 2) estimate the carbon stocks in distinct vegetation types and on titled lands, and; 3) compare tree carbon around villages to that in areas unused by people. Here we describe the results of the tree measurement/carbon assessment program carried out in the Rupununi region of south western Guyana, and outline the implications for the inclusion of indigenous people in monitoring their own carbon stocks in REDD+ schemes globally.

METHODS

Study area

The Rupununi region is classed as 'moist tropical forest' by the IPCC (2003), with 2000 to 4000 mm yr^{-1} rainfall, and is dominated by savannas and forests (Read et al. 2010, Hammond 2005). Ten types of vegetation were described in the study area (Cummings 2013; Levi et al. 2013), and these were grouped into eight categories to maintain adequate sample sizes: High Forest Flooded, High Forest Upland, Ite Swamp, Low Forest Flooded, Low Forest Upland, Muri Shrub Upland, Savanna Flooded and Savanna Upland (Table 1). The 2006 Amerindian Act establishes land rights for Guyana's indigenous people (Fig. 1), who may claim title of their community lands. Indigenous communities that have received 'titled lands' have rights to forest and above ground resources within their boundaries (Cummings 2013). Although rights to carbon stocks have not been defined, the government has acknowledged this right by giving Amerindian communities the choice of opt in or out of enrolling their lands in

Guyana's national REDD program and to receive compensation from government under a REDD+ agreement (http://www.lcds.gov.gy March 2013 report).

Of the 23 villages in the larger study (Luzar et al. 2011), members of 17 communities carried out the tree measuring work in the 20 sites: 15 'village' sites and 5 'control' sites Records from one village were omitted, due to inexplicable tree size discrepancies between this site and both the literature and data from our study for the local forest types (see Discussion for more detail). (Table 2; Figure 1). Transects 4 km long were randomly placed around the villages and in five control areas identified as regions where no hunting, logging or gathering occurs (see Luzar et al. 2011). There were up to eight 10 m x 10 m (0.01 ha) plots per transect, with 111 transects and 604 plots of 0.01 ha sampled overall (Table 2). This provided 6.04 hectares of AGV (tree) data. The frequency of vegetation types varied widely by site and by region, with High Forest Upland and Low Forest Upland the most common types. Ite Swamp and Savanna Flooded were the least common vegetation types (only two plots for each of these types) (Table 2).

Training & data collection

Three-day training sessions were held in three locations across the region over a two-week period (villages 6, 14, 19; Fig. 1), and comprised both classroom instruction and field demonstrations and practise. Common sampling protocols for major carbon pools were used, in line with other forest assessment projects, such as IPCC (2003), and RAINFOR (Metcalfe et al. 2009, Marthews et al. 2012): tree diameters were standardly measured in cm at breast height (1.3 m). On average, 14 volunteers were trained at each of the three training sessions. The first part of the workshop focussed on carbon definitions, the carbon cycle and the measurement of carbon in the field. Two field workers per site sampled trees > 10 cm DBH in the plots in their transects, and met with Project Fauna staff monthly to hand over data sheets and resolve any technical problems which might have arisen.

Data analysis

To reflect the fact that the Rupununi region covers two distinct geographic and political regions, separated by the Kanuku Mountains (Fig. 1), plot data were divided into 'north' and 'south', based on differences in coarse vegetation types (Huber et al. 1995) and geology. The north Rupununi is dominated by continental sands and silts, the south Rupununi by younger granites and volcanic formations (Government of Guyana 2001). Thus, in addition to the eight categories of vegetation types, and a comparison between village and control sites, we also consider difference between the north and south region (Table 2). The distinction between north and south is also important politically, as the north is inhabited by the Makushi people and the south by the Wapishana, whose language, cultural practices and occupation patterns differ (Luzar and Fragoso 2013). Based on the regional rainfall regime, the allometric equation for 'moist tropical forest' was used to calculate biomass (IPCC 2003), and multiplied by 0.5 to derive above ground tree carbon:

$$Y = 0.5 \bullet \exp[-2.289 + 2.649 \bullet \ln(DBH) - 0.021 \bullet (\ln(DBH))^2]$$

Where Y = kgC.

Statistical analyses (two-sample t-tests assuming unequal variance) were carried out for different vegetation types, control vs village tree carbon, on the north/south data overall and for each vegetation type.

The data were error-checked and 'cleaned' before analysis by a scientist in the field, including cross-checking with tree size data available from another project for the same transects (Cummings 2013). Data from this work were available for trees larger than 25 cm DBH for 12 control and village sites in common with our dataset. The DBH values did not differ significantly between the two datasets ($0.2<P<1$).

Estimation of carbon biomass within village titled lands

An important part of the project's engagement with local indigenous communities was the provision of estimates, for their own use, of carbon stocks within their titled lands. As the spatial distribution of vegetation types within titled land boundaries varied from that of the sample plots, the tree carbon stock measurements for each vegetation type were applied to an area-wide vegetation map in order to calculate titled land carbon stocks. A land cover classification map was constructed based on the Landsat TM imageries (Path 231, Row 57 and 58) and the ground truth data (Figure S1; Levi et al. 2013, Cummings 2013). Titled land estimations of carbon stocks were calculated by applying the carbon value per hectare for each vegetation type (from the plot-based calculations) to the land cover Landsat vegetation classes (Table S1). These values were then summed for the area within the border of a village's titled land.

RESULTS

Above ground tree carbon

The mean DBH of the trees across all the sample plots ranged from 10 cm to 153.4 cm, and varied by vegetation type (Figure 2). High and Low Forest Upland and Ite swamp had the largest trees, and Muri Shrub Upland and Savanna Flooded the smallest. Mean carbon per hectare ranged from 20.3 MgC ha^{-1} to 220.1 MgC ha^{-1}, a function of vegetation type and type of site ('village' or 'control'). The mean value was 123.7 MgC ha^{-1}. Grouped by broad vegetation type, mean 'forest' carbon per hectare was 145.5 MgC ha^{-1} and 'savanna' carbon per hectare was 28.2 MgC ha^{-1}.

The Upland High and Low Forest (175.7 MgC ha^{-1}; 130.4 MgC ha^{-1}) and Flooded High and Low Forest (118.4 and 109.7 MgC ha^{-1}) had the highest carbon per unit area, and both Savanna types had the least tree carbon (4.5 MgC ha^{-1}; 28.3 MgC ha^{-1}) (Figure 3). Comparison of carbon stocks by vegetation type revealed significant differences between all types apart from High Forest Flooded and Low Forest Flooded/Upland, Low Forest Flooded and Low Forest Upland, and Muri Shrub Upland and Savanna Upland (Table 3a).

The north-south analysis showed that the northern forests had significantly ($P < 0.05$) greater carbon than the southern forests (150.1 MgC ha^{-1} and 118.4 MgC ha^{-1}), and this was driven primarily by the Low Forest Upland vegetation group (Table 3b). Stem numbers per vegetation type differed significantly between north and south regions for Low Forest Upland (495 ha^{-1} and 323 ha^{-1}, respectively), and this was reflected in the differences in carbon between the two regions (Table 3b). High Forest Upland carbon was also markedly different between regions. The 'control' sites had larger carbon stocks than the village sites (172.4 MgC ha^{-1} and 127.4 MgC ha^{-1}) ($P=0.05$) and a greater mean number of stems per site (182 stems and 122 stems).

Above ground carbon stocks of titled lands

Estimation of carbon stocks for each village's titled land based on technicians' ground data and satellite images reveals that the total carbon stock per titled land varies significantly (Table 4). The village titled lands with the greatest mean tree carbon MgC ha^{-1} were 7N and 9N, and the sites with the smallest mean tree carbon per hectare were 12N and 14S (Figure 4). The variance clearly reflects the extent of the different vegetation types in each titled land and the differences in size of titled land area. The lowest titled land carbon estimate, for site 12N - 37 MgC/ha, derives from an area of mainly grassland (Fig. 1).

DISCUSSION

This first comprehensive assessment of carbon stocks and vegetation types across a large region in Guyana showed the value and efficiency of using Amerindian stakeholders in REDD+ work. The implications for the LCDS and REDD+ for Guyana and indigenous people have not previously elucidated with an underpinning of observed forest data.

Vegetation type & regional variation

The indigenous field technicians working with Project Fauna collected and provided sufficiently accurate data to enable the estimation and assessment of their carbon stocks, as reported in other studies employing participatory methods (Butt et al. 2013, Danielsen et al. 2013). The data collected by one of the 21 communities were unfortunately too problematic to be used in our analyses – the reasons remain unclear and the data were unable to be salvaged due to a break in the research chain. Importantly, it was easy to detect when a problem had occurred with data quality as the diameter measurements were so different to those of other sites. Overall, local technicians were motivated to be as accurate as possible as they had a vested interest in knowing how much carbon is held on their titled lands, now that it has value through the climate finance mechanism. While this is a positive step, it will be important to ensure that human bias in terms of potential conflicts of interest (i.e., reporting larger carbon stocks than actually exist through provision of erroneously large diameter measurements) should be avoided. There are several possible ways of achieving this, including cross-checking measurements for the same site using different teams; re-measuring plots where diameter values are systematically higher than the overall mean, and; informing of potential penalties from deliberate over-estimates, such as disqualification from payment schemes.

Although Guyana does not allow independent trading of carbon by individual land title holders, it would provide pro-rated payments to villages that ‘opt in’ to the LCDS mechanism and sign a REDD+ agreement with government (http://www.lcds.gov.gy, March 2013 report). Knowledge of amounts and patterns of carbon content on the land would facilitate negotiation and decision making by Amerindian communities choosing to opt in or out of the national REDD program. It would also increase national and international understanding of the contribution of Amerindian titled lands to carbon stocks and carbon loss relative to other land use types in the country.

Carbon stocks vary across the eight different vegetation types found in the Rupununi forest-savanna region. Differences also occurred amongst forest categories, for example upland high forest supported more carbon than flooded high forest (175.7 MgC/ha; 118.4 MgC/ha). This suggests that carbon stock baselines, such as for REDD and REDD+ programs, originating from generalized forest data from remote sensing, and correlated with national and international data bases, may not reflect local and regional level carbon stocks (Mitchard et al. 2014). This will have implications for measuring carbon emission changes from the baseline under carbon payment programs where inaccurate generalizations may result in incorrect values. By vegetation type, Upland High Forest had > 25% more carbon than Upland Low Forest, and > 35% more carbon than both types of Flooded Forest: this amount of difference in carbon stock between forest is policy relevant, as it can inform both the UN/ program bodies, and developing countries, on the value of investing in expensive 'Tier III' assessments (satellite imagery and ground measurements).

While the village sites differed as to the extent of dominance of each vegetation type, overall the most frequent vegetation types across the whole area were High Forest Upland - which generally includes taller trees and denser forest - and Low Forest Upland. Muri shrub was only found in the northern sites, while there were more upland savanna sites in the south. This variation in dominance of vegetation types from village site to village site means that carbon stocks also vary between villages, as this is a function of stem density and tree size. The size of carbon stock for each village therefore depends on the local vegetation type, which has implications for the potential contribution of the titled land to the national REDD Program, and the pro-rated compensation a village might receive once it opts in to the LCDS program.

The north-south analysis showed that the northern forests had significantly larger carbon stocks than the southern forests, driven by Upland Low Forest. In addition to rainfall variation between the two areas, they differ in coarse vegetation type and extent (Huber et al

1995, ter Steege 2001), and their geology (Government of Guyana 2001), which drives variation in geomorphology, hydrology and soils. These differences will affect the amount of above ground vegetation that can be supported, and thus the size of the carbon stock (Baraloto et al. 2011).

Human resource use impacts on carbon stocks

The 'control' sites had larger carbon stocks per hectare than the village sites (for the four vegetation types that occurred in the control sites: High Forest Flooded and Upland and Low Forest Flooded and Upland), and greater stem density (~50%) in these sites. Although there was no significant difference in tree diameter size between the control and village sites, the large variation in stem density may reflect the impact of local forest resource use: sites near villages have probably been subject to greater extraction intensity than those farther away. This indicates that the carbon values for undisturbed forests should not be simply applied to forest areas of titled community lands, but rather that this difference in land use impact should be explicitly acknowledged in carbon stock evaluations.

Volunteer-collected data applied to carbon stock estimations have been shown to be accurate within a range of ±10% (Butt et al. 2013, and see Danielsen et al. 2013): we can state with reasonable confidence that trees > 10 cm DBH in the forests of the Rupununi region hold between 111 MgC ha^{-1} and 136 MgC ha^{-1} on average. The northern part of the region had between 135 MgC ha^{-1} and 165 MgC ha^{-1}, and the southern part between 106 MgC ha^{-1} and 130 MgC ha^{-1}. The estimates derived from this project are in line with AGV carbon in other areas and other tropical forests globally and regionally, as derived from a combination of on-the-ground and remotely-sensed data (Saatchi et al. 2011). ter Steege (2001) gave an estimation of 150 MgC ha^{-1}, which included (standing) dead trees, while Conservation International (CI) estimated around 180 MgC ha^{-1} (Cedergren 2009), and the FRA gave a South American average of 110 MgC ha^{-1} for Guyana forests (FAO 2006). The Guyana UN REDD+ project uses Alder and Kuijk (2009) Forestry Commission study values for their baseline estimates of forest carbon biomass (Cedergren 2009). These were reported as tCO_2, including roots, equating to 167 MgC ha^{-1}. The large variation amongst carbon stock estimates for similar forest types and regions could be the result of a number of factors, and strongly suggests the need for a standardized approach to carbon assessments.

Ours is the first forest inventory of the Rupununi region of Amazonian Guyana beyond the nine sample units surveyed from 1968-73 for trees >30 cm DBH (Alder and Kuijk 2009), and the first to sample in savannah and forest, where tropical carbon stocks in general are not well established (Houghton 2005). A comprehensive carbon stock assessment from Colombia gave 112 MgC ha^{-1} for primary forest in the region, and 21 MgC ha^{-1} for secondary forest (Sierra 2007), and cite lack of clear distinction between these forest types as one of the problems related to carbon stock estimation in tropical forests.

By being aware of what carbon stocks are, and how to measure them in their local areas, indigenous groups in Guyana can better participate in national and international carbon market discussions and programs, and more efficiently monitor any compensation to which they are entitled through results-based carbon payments, such as those being implemented by Norway in Guyana, and in the REDD+ programs in general. Indigenous people in Guyana believe that their participation in the national REDD program and LCDS must be informed by self-assessment of carbon stocks (North Rupununi District Development Board and the Deep South Toshao's Council, Fragoso pers. comm.), and this work provides an example of communities who have demonstrated they can effectively measure and monitor their regional carbon stocks, and thus play a key role in the ongoing LCDS and MRV activities necessary for REDD+.

Carbon stock estimate per titled land

Applying the ground-measured carbon data to the satellite land cover classes (Table A1.1) enabled the estimation of carbon stocks for each of the titled land areas in the region. This provided the participating villages and groups with detailed carbon estimates of their lands. It is crucial to engage local indigenous communities in the 'ground-truthing' of forest carbon data as they otherwise often miss the opportunity to receive their share of carbon payment due to the lack of information (Vitel et al. 2013, Jildal et al. 2008, Corbera et al. 2008). Our results revealed that there is a large variance in the average carbon stock among village titled lands (Table 4), which, apart from titled land area, probably reflects the non-homogenous distribution of vegetation type. For each village area, the extent of land cover classes within the titled land was calculated from the satellite imagery (Table A1.2), and this gave landscape-scale information, and provided an understanding of the differences in carbon stocks between different vegetation types in their areas, and how satellite data can contribute to carbon assessments at large scales. This emphasizes the need for freely available higher-resolution remotely sensed imagery in the tropics.

Future work

Forest types need clear identification and characterization in all regions where local measurements are to be used to estimate carbon stocks. Lack of clarity can not only result in large uncertainty in carbon estimates, but may also confound comparisons with satellite imagery forest data, which are important for coherent mapping of aboveground carbon (Goetz 2009).

We suggest a standard protocol for undertaking large-scale carbon stock estimates, combining satellite imagery and ground measurements, as follows: 1) use the highest-resolution satellite imagery available and establish which vegetation types can be definitively identified; 2) select multiple (GPS) locations in each vegetation type and assess its carbon with tree measurements. This would provide a carbon value and range for each forest type identifiable on highest resolution satellite imagery, which can then be applied to any area of forest or titled land. This method, by establishing whether forest types differ significantly in terms of carbon stock, would determine whether or not this level of satellite imagery would need to be used in all assessments. The level of accuracy of lower-resolution (cheaper) satellite imagery for vegetation type identification can be tested using the results from 2, and thus establish the level of detail the lower-resolution imagery can provide (it may not be able to distinguish between all vegetation types). Where different vegetation types have the same per hectare carbon, it will not be necessary to distinguish between them and thus lower-resolution imagery could be used to assess carbon stocks. This approach addresses uncertainty in our knowledge of carbon levels in different vegetation types, providing accurate data that can usefully inform programs such as REDD+ on equitable price per hectare.

Conclusion

We distinguish between three types of uncertainty/variation associated with carbon stock assessments: differences between forest/vegetation types, including differences between managed and unmanaged forest, in different areas; the spatial extent of forest/vegetation types, and; measurement error. These factors will influence remuneration levels and the first two should be incorporated into payment calculations. Effective training and management of local field technicians is crucial to reduce measurement error and should be included in baseline-setting MRV schemes. The field work and analysis carried out in the Rupununi region demonstrates that on-the-ground forest measurements done by well-trained local workers can make valuable contributions to carbon stock estimation across large areas.

The results and findings of this project are of global importance, for example with regard to the potential inclusion of forests on land held by indigenous peoples in REDD+ programs. These programs are bilateral or international in nature, while it is unclear who owns the carbon on indigenous lands. As we demonstrate here, indigenous people are capable of assessing and monitoring carbon on their lands, and should therefore be partners in REDD+, and similar, schemes.

ACKNOWLEDGEMENTS

Dedicated to the memory of Dr Kimberley (Kye) Epps, Stanford University, 1969-2011. We thank the Guyana Environmental Protection Agency and the Ministry of Amerindian Affairs for authorizing Project Fauna. The Gordon and Betty Moore Foundation, the National Science Foundation (NSF; Grant BE/CNH 05 08094), and Stanford University School of Earth Sciences provided funding. The Iwokrama International Centre for Rainforest Conservation, the North Rupununi District Development Board, and the Deep South Toshaos Council, acted as in-country collaborators and provided invaluable logistical support. We are grateful to Mike Williams and Wilson Lorentino for invaluable help in negotiations. We thank the Makushi, Wapishana and Wai-wai technicians whose hard work and dedication made the research possible, as well as the leaders and members of all of our partner communities for their participation, trust, push back, and innumerable contributions to the project. We thank the graduate students, post- docs, data transcribers, and volunteers who are not authors on this article but who contributed essential work and ideas to the project. We are grateful to Kirsten Mariana Silvius, Peter Vitousek and Jeff Luzar for their helpful comments on the manuscript.

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Table 1: Description of vegetation types occurring along transects within the study region. (Meter measurement refers to tree height).

Habitat type	**Description**
High Forest Flooded	Seasonally flooded forest (20 m – 30 m)
High Forest Upland	Terra firme forest (20 m – 35 m)
Ite Swamp	*Mauritia flexuosa* palm (≤ 20 m) dominated seasonal wetland
Low Forest Flooded	Seasonally flooded forest (≤ 15 m)
Low Forest Upland	Terra firme forest (≤ 15 m)
Muri Shrub Upland	Terra firme scrub on white sand soils (≤ 10 m)
Savanna Flooded	Seasonally flooded grassland with occasional small trees (≤ 5 m)
Savanna Upland	Terra firme scrub with occasional small trees (≤ 5 m)

Table 2: Number of plots of each vegetation type, per site and region ('N'=North Rupununi and South Pakaraimas, 'S'=South Rupununi), and total number of sampled transects and plots by site.

Site	High Forest Flooded	High Forest Upland	Ite Swamp	Low Forest Flooded	Low Forest Upland	Muri Shrub Upand	Savanna Flooded	Savanna Upland	Number of transects	Number of plots
1N	8	22		6	12				8	48
2N		31							8	31
3N		15		1	6			1	6	26
4N		12			15				5	27
5N		3			8			4	3	15
6N	3	8	1	6	19	3		2	8	42
7N	10	16		9	6				8	41
8N	2	13		15	13	8			7	51
9N	4	9		17	14	4			7	48
10N	2	14		3	11	1			5	31
11N	8	33		3	12				8	56
12N	1	5		6	9				3	21
N total	38	181	1	66	125	16	0	7	76	437
14S	3	3		1	14			6	7	27
15S		6		2				1	3	9
16S	5	12			6				3	20
17S	5	13							3	18
18S	1	13		1	16		2	2	6	35
19S		5			1			1	4	7
20S			1		1			3	3	5
21S	10	36							6	46
S total	24	88	1	4	38	0	2	13	35	167
Total	62	269	2	70	163	16	2	20	111	604

Table 3a: T-test results for comparison of mean plot carbon biomass, by vegetation type. P values are reported for significant differences.

	HFF	HFU	LFF	LFU	MSU	SU
HFF		*	~	~	**	***
HFU			**	*	***	***
LFF				~	**	***
LFU					***	***
MSU						~
SU						

*P < 0.05
**P < 0.01
***P < 0.001
~ = no significant difference

Table 3b: T-test results for mean plot biomass, by vegetation type, north-south comparison.

vegetation type	**one-tail P**	**two-tail P**
All plots (North-South)	****0.029**	***0.059**
for veg types with more than two plots in each region		
High Forest Flooded	0.207	0.414
High Forest Upland	0.12	0.241
Low Forest Flooded	0.331	0.652
Low Forest Upland	****0.019**	****0.037**
Savanna Upland	***0.074**	0.148

* P<0.1
**P<0.05

Table 4: Extent and total above ground carbon estimates of titled lands. Titled lands 3N and 5N fall within one large communal land title. 6N also shares its titled land with other villages (not shown here).

titled land	million MgC	area (ha)
1N	3.01	21,925
3N	22.71	171, 275
5N	22.71	171, 275
6N	6.73	61,989
7N	7.24	48,502
8N	5.47	48,586
9N	7.00	48,658
10N	6.71	54,022
12N	0.90	24,442
14S	3.08	38,287
15S	4.25	36,183
16S	4.72	42,802
18S	4.30	34,599
19S	5.12	56,416
20S	5.88	53,544

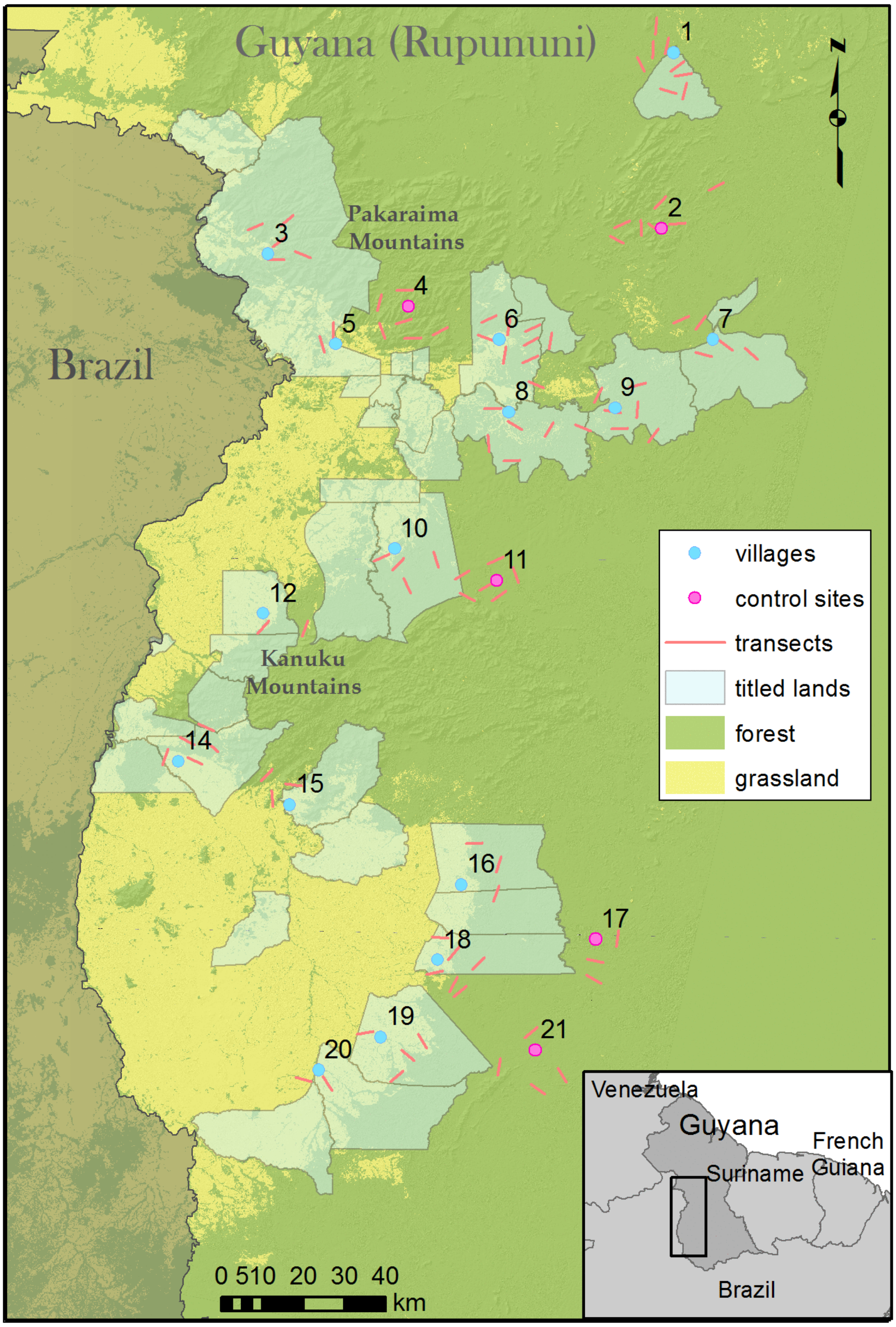
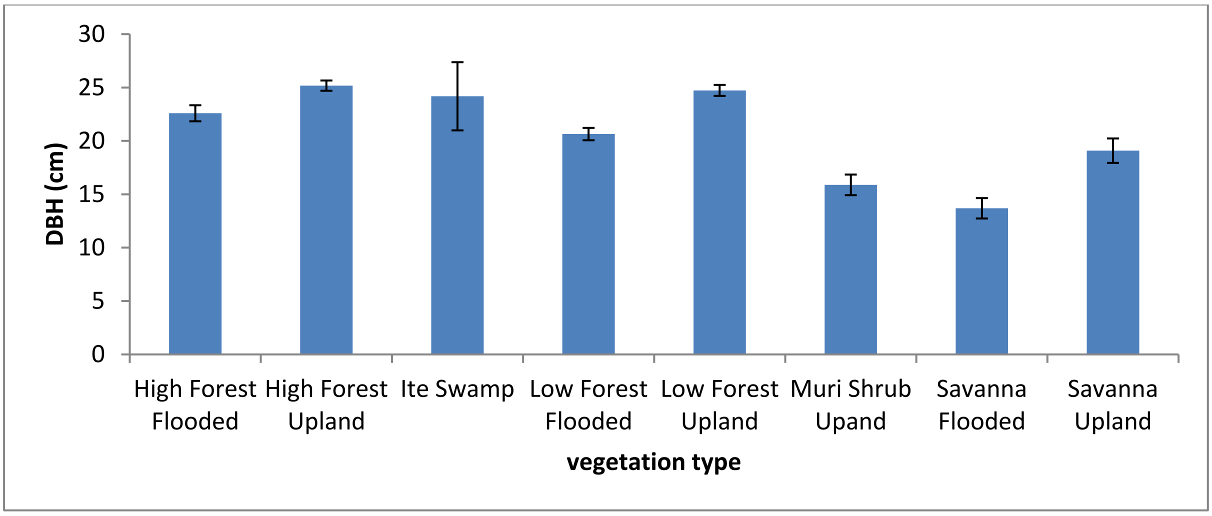


Figure 1: Map of the Rupununi study region in Guyana.



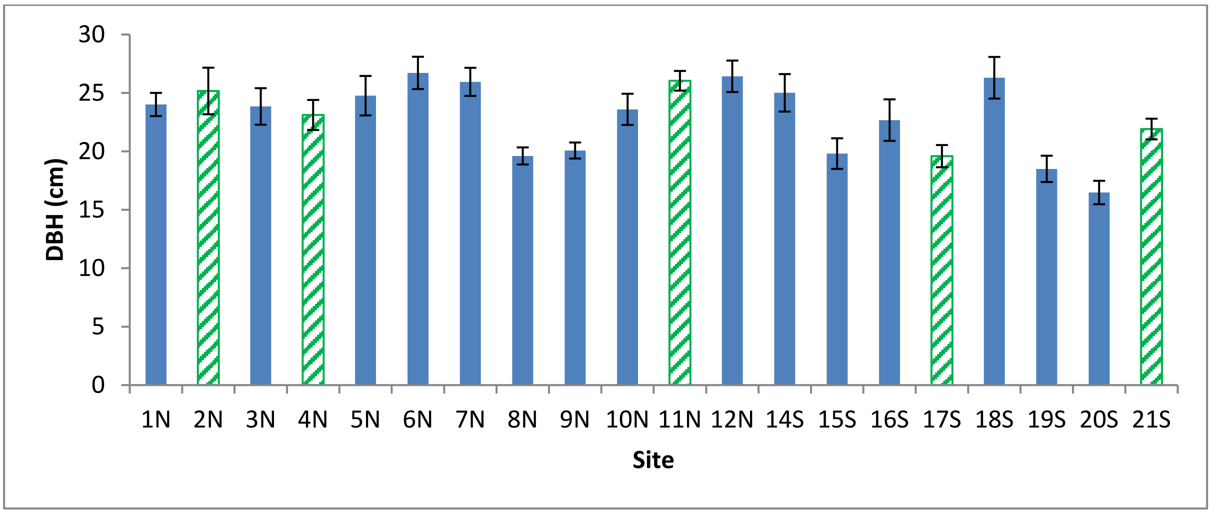


Figure 2: Mean DBH by vegetation type (above) and sample site (below). N = north and S = south. The control sites are represented by striped bars. Error bars represent standard error.

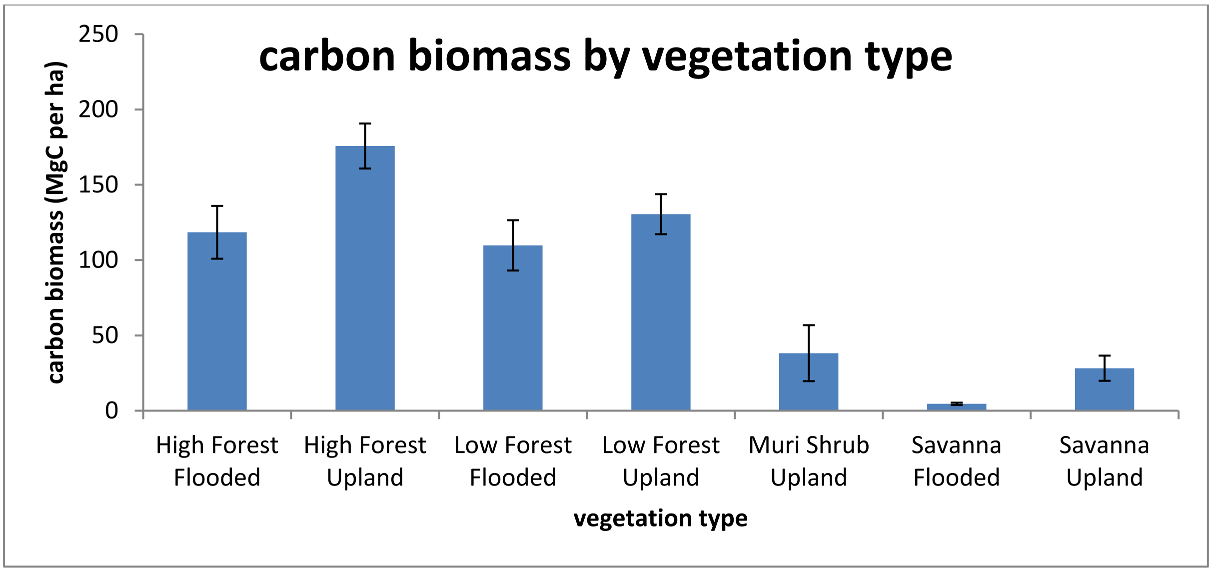


Figure 3: Mean carbon biomass (MgC per hectare) by vegetation type. Error bars represent standard error.

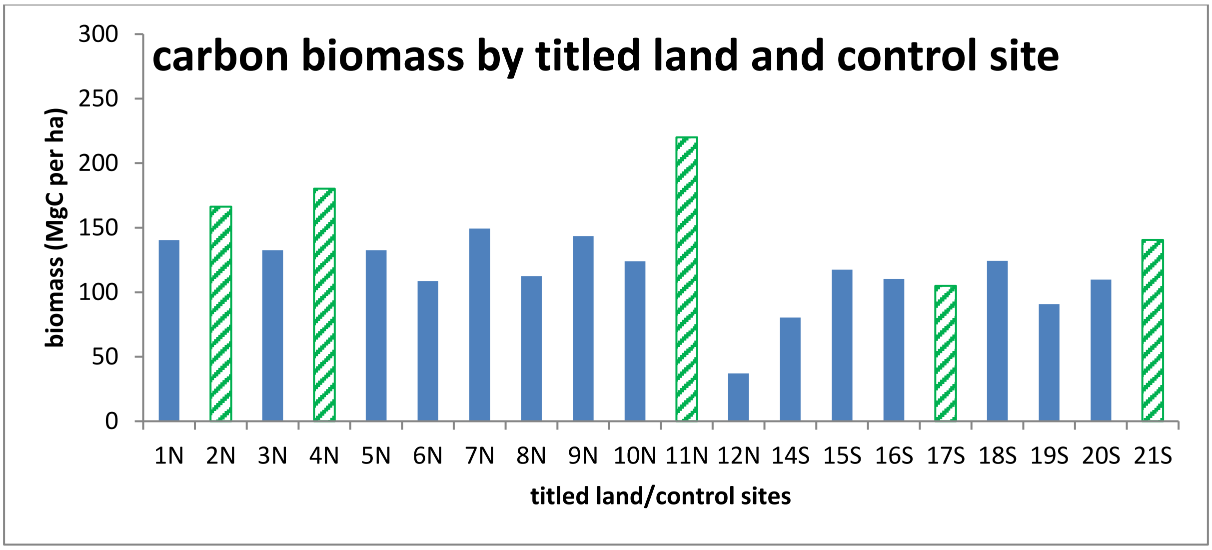


Figure 4: Average carbon biomass (MgC per hectare) by village titled land. The areas encompassing control sites, included for comparison, are represented by striped bars.