

Traditional shifting agriculture: tracking forest carbon stock and biodiversity through time in western Panama

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Abstract

Reducing emissions from deforestation and forest degradation (REDD+) requires developing countries to quantify greenhouse gas emissions and removals from forests in a manner that is robust, transparent, and as accurate as possible. Although shifting cultivation is a dominant practice in several developing countries, there is still very limited information available on how to monitor this land-use practice for REDD+ as little is known about the areas of shifting cultivation or the net carbon balance. In this study, we propose and test a methodology to monitor the effect of the shifting cultivation on above-ground carbon stocks. We combine multiyear remote sensing information, taken from a 12-year period, with an in-depth community forest carbon stock inventory in Palo Seco Forest Reserve, western Panama. Using remote sensing, we were able to separate four forest classes expressing different forest-use intensity and time-since-intervention, which demonstrate expected trends in above-ground carbon stocks. The addition of different interventions observed over time is shown to be a good predictor, with remote sensing variables explaining 64.2% of the variation in forest carbon stocks in cultivated landscapes. Multitemporal and multispectral medium-resolution satellite imagery is shown to be adequate for tracking land-use dynamics of the agriculture-fallow cycle. The results also indicate that, over time, shifting cultivation has a transitory effect on forest carbon stocks in the study area. This is due to the rapid recovery of forest carbon stocks, which results in limited net emissions. Finally, community participation yielded important additional benefits to measuring carbon stocks, including transparency and the valorization of local knowledge for biodiversity monitoring. Our study provides important inputs regarding shifting cultivation, which should be taken into consideration when national forest monitoring systems are created, given the context of REDD+ safeguards.

Keywords: cultivated landscapes, forest intervention, land-use dynamics, reducing emissions from deforestation and forest degradation, remote sensing analysis, shifting cultivation

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Introduction

As a new post-Kyoto climate regime is being negotiated under the United Nations Framework Convention on Climate Change (UNFCCC), countries have agreed to consider the Reduction of Emissions from Deforestation and Forest Degradation (REDD+), and the role of conservation, sustainable management of forests, and enhancement of forest carbon stocks in developing countries (REDD+) as relevant mitigation actions (UNFCCC 2010). Deforestation and forest degradation account for 12–17% of global greenhouse gas emissions (IPCC, 2007; van der Werf *et al.*, 2009). Developing countries that wish to participate in REDD+ have been requested to construct a reference emissions level/reference level, which is a benchmark for estimating emission

reductions that are eventually achieved by REDD+. Participating nations are further requested to establish a national forest monitoring system to quantify emissions and removals from forests in a robust, transparent, and accurate manner.

In his analysis of global forest trends using the Food and Agriculture Organization's Forest Resource Assessment data set, Grainger (2008) has identified forest regrowth as an important source of uncertainty. Using the Republic of Panama as a model country, Pelletier *et al.* (2011) further showed that a poor understanding of land-use dynamics, which are related to the agriculture-fallow cycle or shifting cultivation, may induce up to 20% error in reference emission levels. An important fraction of Panama's territory oscillates between agriculture and fallow and, thus, the net carbon balance of this dynamic over time remains unclear.

DeFries *et al.* (2007) have indicated that the land-use dynamics resulting from shifting cultivation or other

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temporary clearing may not produce net emissions over the long-term. Forest clearing for shifting cultivation releases less carbon than does permanent forest clearing because the fallow period allows some regrowth (Watson *et al.*, 2000). On average, carbon stocks would remain at some intermediate level associated with regrowth (Ramankutty *et al.*, 2007), depending on forest type and the length of fallow (Fearnside, 2000; Watson *et al.*, 2000). Successive interventions or repeated agriculture-fallow cycles, however, can affect species composition, reduce carbon storage capacity, and act as a precursor to the establishment of more permanent nonforest land cover (Eaton & Lawrence, 2009; Peres *et al.*, 2006).

According to IPCC (2003), temporary fallow should be considered as cultivated land, unless it corresponds to classification criteria defining forested land. In the humid tropics where trees grow rapidly, fallow land could effectively be classified as forest after just a few years. Therefore, under shifting cultivation, considering fallows as new deforestation could overestimate related emissions (DeFries *et al.*, 2007), whereas considering them as another type of croplands might underestimate emissions, as carbon density in fallow is higher than in most croplands (Tschakert *et al.*, 2007). To fully capture the dynamics of shifting agriculture, the management unit to be considered when monitoring emissions is the entire forest area rather than individual patches that have been cleared within the forest. Furthermore, we argue that shifting cultivation is akin to degradation rather than deforestation because of the temporary nature of fallow clearing. Of course, the consistency of the approach and the definitions that are used by countries to measure and monitor forests and the impacts of REDD+ activities, together with the importance of accounting for all significant fluxes, are at the root of good measurement and reporting practices.

In the context of REDD+, one common challenge to monitoring emissions that arise from shifting cultivation is the absence of clear guidance. Mertz (2009) showed that shifting cultivation systems are particularly difficult to capture because of the complex spectral signature of fields, fallows of various lengths, and the frequent inclusion of permanent farming. Multiyear assessments using a time series of satellite imagery have been suggested as an adequate means of tracking complex land-cover dynamics that include clearing and regrowth. Such assessments increase the possibility of detecting small-scale intervention (Matricardi *et al.*, 2007; Asner *et al.*, 2005; Stone & Lefebvre, 1998; Broadbent *et al.*, 2006), and using subpixel information (Souza *et al.*, 2003; Brandt & Townsend, 2006; Matricardi *et al.*, 2010). Compelling research on selective logging has made use of methodologies that allow the extent of

these activities to be quantified (Asner *et al.*, 2004b, 2006; Souza *et al.*, 2005a). Forest carbon inventories, together with field information on land-use practices and intervention histories, have been key to understanding the impacts that such activities have on forest carbon stocks (Asner *et al.*, 2004a; Souza, 2005b; Gerwing, 2002) and, consequently, the estimation of selective logging contributions to CO₂ emissions.

In building on advancements made in studies of selective logging, our study provides a new approach to monitor degradation and forest carbon stock enhancement in the context of shifting cultivation, which could be used under REDD+, by combining multiyear remote sensing information gathered over a 12-year period with an in-depth forest carbon stock inventory. Community participatory methods are used alongside remote sensing and forest carbon inventories to obtain comprehensive land-use history and information on the territory under study.

We focused on three aspects of forest intervention in western Panama: (i) forest area dynamics; (ii) the ability to capture forest carbon density with the time series of vegetation indices and fraction images; and (iii) the relationships between forest carbon density, land-use practices and biodiversity. Forest intervention, as it was considered in this research, reflected the multiple use of the study area by local inhabitants, who depend on natural resources for their livelihood, and was predominantly the result of shifting cultivation, but also included the collection of firewood and timber for domestic use. We expected that the combined effects of interventions that were observed over time through remote sensing would enable us to predict forest carbon stocks in cultivated landscapes.

Materials and methods

Study Area

This study was conducted in the eastern part of the Palo Seco Forest Reserve (BPPS, *Bosque Protector de Palo Seco* in Spanish), which is a protected area covering 167 409 ha located on the Atlantic side of western Panama (Fig. 1) at the junction between the Talamanca Mountain Range and the Central Cordillera. Average daily temperature in the region is 26 °C and the mean annual precipitation is >2500 mm, which is evenly distributed throughout the year (ANAM/CBMAP, 2006).

According to ANAM/CBMAP (2006) about 10 000 people, mostly indigenous, presently live within the protected area; half of which overlaps with the indigenous territory *Comarca Ngäbe-Buglé*. Although the BPPS is a multiuse protected area where the collection of firewood and construction timber for domestic use is permitted, together with subsistence agriculture (J. Mosaquites, *personal communication*), the

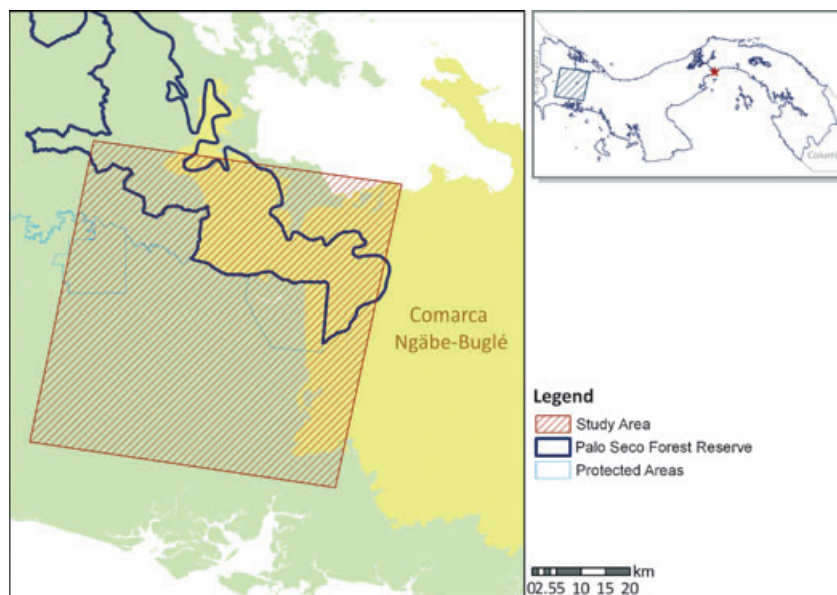


Fig. 1 Regional map presenting the area covered by the remote sensing analysis. Note that part of the Palo Seco Forest Reserve falls within the Ngäbe-Buglé indigenous territory.

Comarca Ngäbe-Buglé itself experienced the highest annual rate of deforestation (-2.3%) in the country between 1990 and 2000 compared with the other provinces (ANAM/ITTO, 2003).

Previously described as pristine forest (Gaceta Oficial, 1983), the area where the field study was conducted was not colonized until 1975 by the Ngäbe, who had migrated from the Cricamola River Delta. At the time of our study, the population was 549 inhabitants. Multiple varieties of bananas, peach palms, and various tuber crops are cultivated within a shifting cultivation system, resulting in a mosaic of fallow plots of different ages. As the absence of a distinct dry season, the vegetation that is cleared in this system for new farms or from fallow land is usually not burned, but is left to decay in the fields (Smith, 2005). According to household interviews in the area, the period of cultivation (mean \pm SD) was 1.7 ± 1.5 years, whereas that of fallowing was 3.8 ± 2.6 years. Fallow length vary considerably according to the crops that are planted. More than half of the respondents had at least $3.6 \text{ ha} \pm 5.4 \text{ ha}$ of land in fallow for more than 5 years (Pelletier, 2012). Aggregate land use of 45 households that were interviewed consisted of 90 ha of crops, 163 ha of old fallow (>5 years), and 195.5 ha of young fallow (<5 years) (J. Pelletier, unpublished data). The use of fire has been limited to the creation of pasture for cattle ranching, which is not a dominant land-use practice, and has even declined in the area, according to local residents (Pelletier, 2012).

Remote sensing analysis

The surface area that was covered by the remote sensing analysis is $60 \times 60 \text{ km}$.

In-depth field information that was collected in this study concentrated on a specific area of over 1500 ha. The effect of forest intervention on forest carbon density was studied using

a time-series of five satellite images taken between 1999 and 2011. The limited availability of cloud-free images determined the study to less than a 4-year temporal resolution and required the use of both ASTER and Landsat TM5 imagery. Figure 2 presents a schema of the remote sensing analysis.

Preprocessing of the images. The images were radiometrically, atmospherically, and geometrically corrected to facilitate detection of change over time. Each image was submitted to atmospheric and radiometric correction using REFLECT software that was based on 6S code routines (Bouroubi *et al.*, 2010). Orthorectification of each image was performed using ground control points (GCP) collected using a Garmin Legend HCx GPS device (Garmin International, USA; WAAS system-enabled) and, using the nearest neighbors resampling method, images were brought to a 15 m pixel resolution (Table 1).

A supervised classification separated each image into five cover classes (cloud, shade, water, forest, and agriculture) using maximum likelihood classification. Cloud and shade masks were used to create a forest/nonforest binary map and to mask out nonforest areas. Forest maps were created for the years 1999, 2000, 2004, 2007, and 2011. These procedures were performed in Geomatica (version 9.1, PCI Geomatics).

Image processing. We applied three vegetation and near-infrared indices to each image: the Normalized Difference Vegetation Index (NDVI); the Modified Soil Adjusted Vegetation Index (MSAVI) (Huete, 1988; Qi *et al.*, 1994); and the Modified Soil Adjusted Vegetation Index-aerosol free (MSAVI_{at}) (Matricardi *et al.*, 2010) (Details in Appendix S1).

We then selected end-members and performed a spectral mixture analysis. Spectral mixture analysis-based classification transforms the pixel reflectance that is obtained from all bands into fractions of reference end-members, which are pure pixels

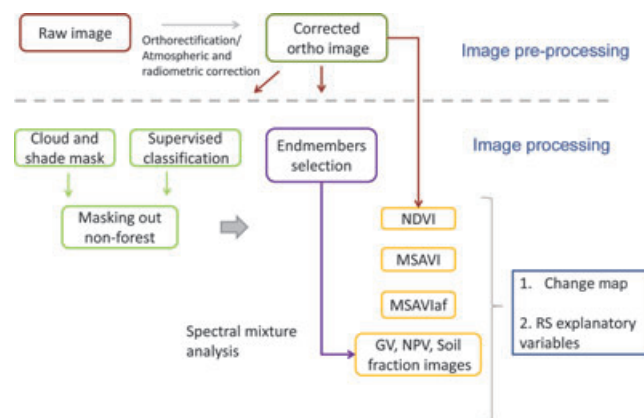


Fig. 2 Schema of remote sensing analysis performed on each of the five images of the time series.

Table 1 Time series of satellite images

| Satellite and sensor | Date of acquisition | Cloud Cover | Bands used | Ortho rms | Grid cell size | Number of GCPs |
|----------------------|---------------------|-------------|------------|-----------|----------------|----------------|
| Landsat 5 TM | 18/01/1999 | 0% | 1–5,7 | 0.26 | 30 m | 19 |
| Landsat 5 TM | 22/12/2000 | 0% | 1–5,7 | 0.28 | 30 m | 19 |
| TERRA ASTER | 02/02/2004 | 3% | VNIR | 0.56 | 15 m | 19 |
| | | | SWIR | 0.28 | 30 m | 19 |
| TERRA ASTER | 14/03/2007 | 11% | VNIR | 0.56 | 15 m | 20 |
| | | | SWIR | 0.28 | 30 m | 20 |
| Landsat 5 TM* | 03/01/2011 | 35% | 1–5,7 | 0.23 | 30 m | 17 |

*For the last image of the time series (2011), we ordered imagery to be collected, whereas the fieldwork was performed. However, we had to wait for over 6 months to obtain a useable image as the rest were covered with clouds. Still, the Landsat image for 2011 is contaminated with clouds, resulting in missing data.

VNIR, Visible near infrared; SWIR, Short wave infrared.

representing observable material on the ground. To select end-members, six image subsets were extracted from each image of the time series. For each image, the selected end-members were those for which the pixels demonstrated the best fit of the linear spectral mixture model. The final model included three end-members: green vegetation, nonphotosynthetic vegetation (e.g. wood debris), and soil (Details in Appendix S1).

Temporal change analysis. Each image was classified into Forest, Intervened forest, and Non-Forest¹ representing the intensity of forest-use practices in terms of canopy cover. Intervened forest was first classified as Forest in the binary map and then, identified using an index threshold on the $MSAVI_{af}$, green vegetation fraction, and soil fraction. The thresholds were chosen by comparing the index values of areas that were clearly identified as nonintervened forest and based on 2 years of field knowledge acquired by JP. In the context of REDD+, pixels classified as Intervened forest or temporarily as Non-Forest would be indicative of forest degradation. The 1999, 2000, 2004, and 2007 maps, which included

the three classes (Forest, Intervened forest, Non-Forest) (Fig. 3), were compared on a per-pixel basis to assess changes through time using map algebra in ArcGIS (ESRI, USA). The resulting forest cover change map revealed a complex land-cover dynamic, resulting in 81 classes. To adequately calibrate C stocks in the field, we simplified this forest cover change map according to the intensity of forest-use practices and time-since-intervention. The resulting map included four categories (Table 2): Forest, Old intervention (>6 years), Deforested land that was revegetated, and Recent intervention (<6 years). Pixels classified as Non-Forest throughout the time series were excluded from the field survey.

Forest carbon inventory

Hawth's Analysis Tools (version 3.27), which is an extension to ArcGIS, were used to generate stratified random sampling points for the four categories of the simplified forest cover change map (Fig. 4). Forty-seven sampling points were chosen using a Garmin Legend HCx GPS device (Garmin International, USA). Each sampling point covered >0.25 ha and a minimum of 11 sampling points were chosen per forest category for a total survey area of 13.3 ha. The area sampled for each

¹The term Non-forest in the image classification does not refer to permanent land-use change.

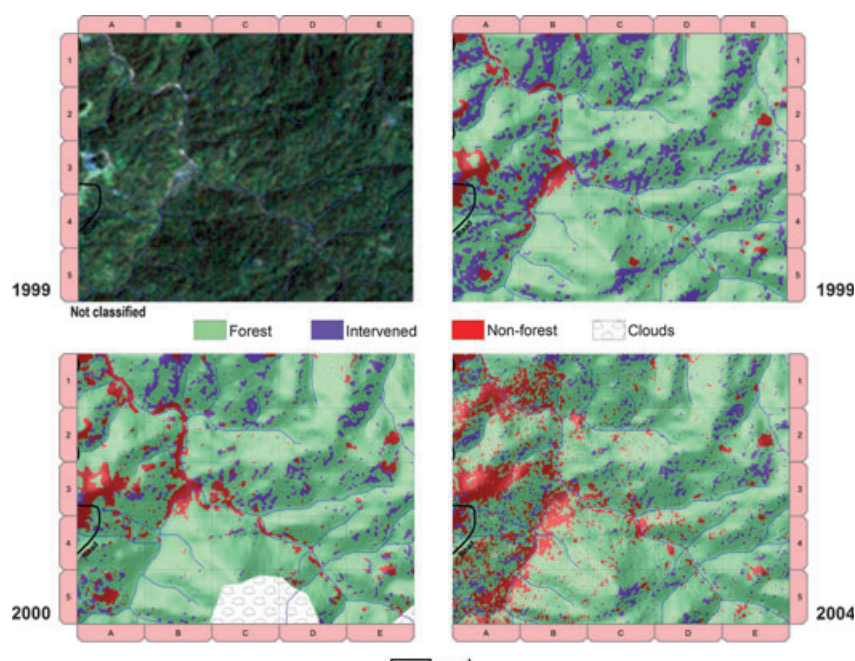


Fig. 3 Map of forest cover change through time in the study area for the period 1999 (with the nonclassified and classified image), 2000, and 2004.

Table 2 Simplified forest cover change categories

| | Description |
|--------------------------------|--|
| Forest | Forests that have not undergone any observable forest intervention process over the period of the time series |
| Older intervention (>6 years) | Forest intervention (not classified as Non-Forest) observed on the 1999 and/or 2000 satellite images and classified as Forest in 2004 and 2007 |
| Recent intervention (<6 years) | Forest intervention (not classified as Non-Forest) observed on the 2004 and/or 2007 satellite image, but that were classified as forest in 1999 and 2000 |
| Deforested† revegetated | Forest-land that has been classified as Non-Forest on the 1999 and/or 2000 and/or 2004 images and classified as Forest in 2007* |
| Non-forest | Land that appeared deforested in 2007 and potentially during earlier years. |
| Cloud/Shade | Excluded from the sampling Cloud/shade cover during 2007, the time period before the forest inventory, Excluded from the forest carbon inventory |

*For the field survey performed in 2010, we decided that to avoid the risk of arriving in Non-Forest areas by not visiting plots classified as Non-Forest in 2007, as the focus of this survey was on forested areas.

†To be consistent with IPCC terminology, this category should be described as forest land remaining as forest land, but temporarily unstocked. However, for simplification purposes, we called this category Deforested revegetated as we found it more descriptive of the activity taking place.

category fell within the recommendations made to capture C stocks adequately in forested landscapes (Clark & Clark, 2000; Chave *et al.*, 2004; Nascimento & Laurance, 2002). Fieldwork took place in July–August 2010.

Seven men were selected by the local community to inventory forest carbon. The group, including individuals with a comprehensive knowledge of the local flora, was given 3-day practical measurements training. After working for 2 weeks with JP, two teams were formed, one led by the local

coordinator and the other by JP. The local coordinator obtained permission from landowners for the carbon inventory prior to field visits. A short survey of the landowners was conducted to determine land-use history and what products were extracted from the inventory plots.

Circular ground plots were deployed following Dalle & Potvin (2004). For each sampling location, four 15 m radius plots were laid out on a 160 m transect for a total of 188 survey plots (Fig. 4). This transect approach was chosen to account

for forest heterogeneity. The geographic coordinates of each plot, together with its slope, were taken at its centre using a Vertex laser (Vertex IV Hypsometer/Transponder 360 Package; Haglöf Sweden, Långsele).

The diameter at breast height (DBH, 1.3 m) of all trees, palms, lianas, herbaceous plants (banana tree), and tree ferns ≥ 10 cm DBH was measured to the nearest mm following rules detailed by Condit (1998) in each 15 m radius plot; a 6 m radius subplot was established for vegetation 5–10 cm DBH. The height of standing trees that had snapped below the crown was estimated. Downed woody debris ≥ 10 cm were measured following Kirby and Potvin (2007). Following IPCC (2003) guidelines, a key category analysis was performed on 20 plots representing the four forest categories. We established two 3×3 m quadrats to measure basal diameter (BD, 10 cm above ground level) of all saplings, shrubs, palms, and lianas that were < 5 cm and ≥ 1 cm BD. Litter and all vegetation with BD < 1 cm was harvested in a 50×50 cm quadrat (Kirby and Potvin 2007). As these pools remained relatively unimportant, they were not measured in the other 168 plots. Below-ground C stocks and soil organic C (SOC) were not measured, in part because of complications involved in taking direct measurements. SOC dynamics in shifting cultivation systems are variable, with some studies finding that SOC contents remain relatively unaffected by this practice (Bruun *et al.*, 2009; Tschakert *et al.*, 2007).

We identified 7056 individual plants \geq to 5 cm DBH, which corresponded to 167 morphospecies. Local Spanish or Ngäberé names, leaves (flowers and fruits when available) of the most common trees species, and photographs of leaves and trunks were collected to support identification. Leaf specimens were pressed, dried, and identified to genus or family by Professor Mireya D. Correa A., Director of the National Herbarium of Panama and botanist with the Smithsonian Tropical Research Institute (STRI).

Biomass calculation and carbon estimation

Allometric models were used to convert vegetation and woody debris measurements to above-ground biomass (AGB) (Table 3). We first estimated AGB at the plot level (Mg) and scaled the per hectare value by correcting plot size or transect length for the slope (Van Wagner, 1982). AGB was converted to C using a mean 47% C value for the biomass content of trees, palms, and lianas (Kirby & Potvin, 2007), and assuming the same percentage for fern and banana trees. A C fraction equivalent to 50% of the biomass content was used for coarse woody debris.

Statistical analysis

We studied changes in forest carbon stock in relation to (i) the time series of vegetation indices and fractions, as well as (ii) land use and biodiversity.

A spatial correlogram based on Moran's I coefficient detected a slightly significant spatial correlation for forest carbon density in the field at the smallest distance class (< 200 m). We took the residuals to control for the transect effect of the forest carbon stock variable ($n = 188$) or we aggregated the data per transect ($n = 47$; four plots each) by using the mean C value.

For each image of the time series, we extracted the means of six remote sensing variables (including vegetation indices, and Green vegetation, Non-photosynthetic vegetation, and Soil Fractions) that corresponded to each field plot using the polygon zonal statistics available using Hawth's Analysis Tools. These remote sensing variables were used as explanatory variables that conveyed information about past interventions. Forest above-ground carbon stocks were used as the dependent variable.

To evaluate the classification of the four forest categories, we performed a linear discriminant analysis (LDA) on the

Table 3 Allometric models used to convert measures of vegetation and woody debris to AGB

| | Source | Models | Units |
|---------------------------------------|------------------------------------|--|-------|
| Trees and palms ≥ 5 cm DBH | Chave <i>et al.</i> (2005) | $AGB = \text{Exp}\{-1.239 + 1.98 \cdot \text{Log}(\text{DBH}) + 0.207 \times [\text{Log}(\text{DBH})]^2 - 0.0281 \cdot [\text{Log}(\text{DBH})]^3\} \cdot \pi$ | kg |
| Tree snags ≥ 5 cm DBH | Nascimento and Laurance (2002) | $AGB = \pi[BA \cdot (\text{Height}) \cdot 0.78]$ | Mg |
| Dead trees ≥ 5 cm DBH | Delaney <i>et al.</i> (1998) | 90% of total AGB of live trees | kg |
| Lianas ≥ 5 cm DBH | DeWalt and Chave (2004) | $AGB = \text{Exp}[0.298 + 1.027 \ln(BA)]$ | Mg |
| Banana trees ≥ 5 cm DBH | van Noordwijk <i>et al.</i> (2003) | $W = 0.030 \text{DBH}^{2.13}$ | Mg |
| Tree ferns ≥ 5 cm DBH | Stanley <i>et al.</i> (2010) | $1135.3 \text{DBH} - 4814.5$ | g |
| Saplings < 5 cm DBH, ≥ 1 cm BD | Kirby and Potvin (2007) | $\text{Exp}[3.965 + 2.383 \ln(BD)]$ | g |
| Coarse Woody Debris | Van Wagner (1982); Waddell (2002) | $[(\pi^2/8L)\Sigma(d^2)]\rho_{\text{drc}} \cdot \text{Cs}$ | kg |

AGB, Above-ground biomass.

DBH is the diameter at breast height (diameter at 1.3 m above ground level; cm).

BD is the Basal diameter (diameter at 10 cm above ground level; cm); BA, Basal area (m^2) or equation $BA = \pi(\text{DBH})^2/40\,000$.

Pi is the species specific wood density value (g cm^{-3}) of tree (i), or 0.54 when wood density of species or species unknown.

Cs is the slope correction factor $\sqrt{1 + (\% \text{ of slope}/100)^2}$ or $r_{\text{prime}} = r/[\cos(\alpha)]^2$.

ρ_{drc} is the decay class reduction factor; depending if sound $\rho_{\text{drc}} = 0.453 \text{ g cm}^{-3}$ or rotten $\rho_{\text{drc}} = 0.319 \text{ g cm}^{-3}$ (Clark *et al.*, 2002); corrected for slope, not corrected for tilt of individual pieces.

remote sensing variables for the 188 plots that were visited. The indices were normalized using Box–Cox transformation prior to analysis; five outliers were identified as being contaminated by cloud or haze and were removed (Legendre & Legendre, 2012), leaving 183 observations for the LDA.

Two multiple regression models were used to predict total above-ground C (univariate response variable: sum of standing C + down woody debris C) with backward elimination of remote sensing variables from either 1999 to 2007 ($n = 47$) or 1999 to 2011 ($n = 28$; missing data due to cloud contamination of the 2011 image) data series.

The relation between biodiversity measures (biodiversity indices and identity of dominant morphospecies), land-use types, spatial structure as explanatory variables, and Standing C and down Woody debris C, as response variables, was examined using redundancy analysis (RDA). Three biodiversity indices, the richness (number of species per plot), the Shannon diversity number [$\exp(H)$, where $H = -\sum p_i \ln(p_i)$], and where p_i is the proportional abundance of species i , and Simpson diversity number ($1/D$, where $D = \sum(p_i)^2$), were included to the RDA model. Five spatial variables representing spatial structures at different scales and selected using distance-based Moran's eigenvector maps (db MEM) (Borcard *et al.*, 2011) were also included in this RDA model. Prior to analysis, the numeric explanatory variables were normalized and standardized, whereas the response variables were normalized. Global forward selection was used to obtain a parsimonious RDA model and verify for inflated variance (VIF), to minimize the correlation among variables (Borcard *et al.*, 2011). This procedure resulted in a simplified model consisting of the land-use types (categorical), the richness, the identity of the dominant (categorical), and one spatial variable (medium scale).

We used variation partitioning to quantify the various unique and combined fractions of the variation in above-ground C explained by each explanatory variable. Each explanatory dataset was forward selected separately to assess the magnitude of the various fractions, including the combined ones (Borcard *et al.*, 2011). The explanatory datasets included three biodiversity indices, identity of the dominant, land-use, and five spatial variables (db MEM). The categorical variables (land-use types and the Dominant identity) were recoded as dummy binary variables (Legendre & Legendre, 2012). Variation partitioning was performed with the `varpart()` function of the `vegan` package in R (Oksanen *et al.*, 2011).

One-way ANOVA and subsequent multiple means comparisons (*post hoc* Tukey HSD) examined differences in forest carbon stocks among forest-use categories that were derived from the remote sensing analysis and in forest carbon stocks among land-use types observed from the field and verified with the landowners. In both cases, we controlled for the transect effect. For the Forest category that was identified using remote sensing, five plots were excluded as they had been cultivated, as the last image in 2007. Also, Pearson product-moment correlations (r) were calculated between the plant with the greatest DBH in the plots and total above-ground C. All statistical analysis was performed in R (R Development Core Team, 2005).

Results

Tracking changes in forest areas

A major study objective is to develop a better understanding of changes in forest carbon stocks

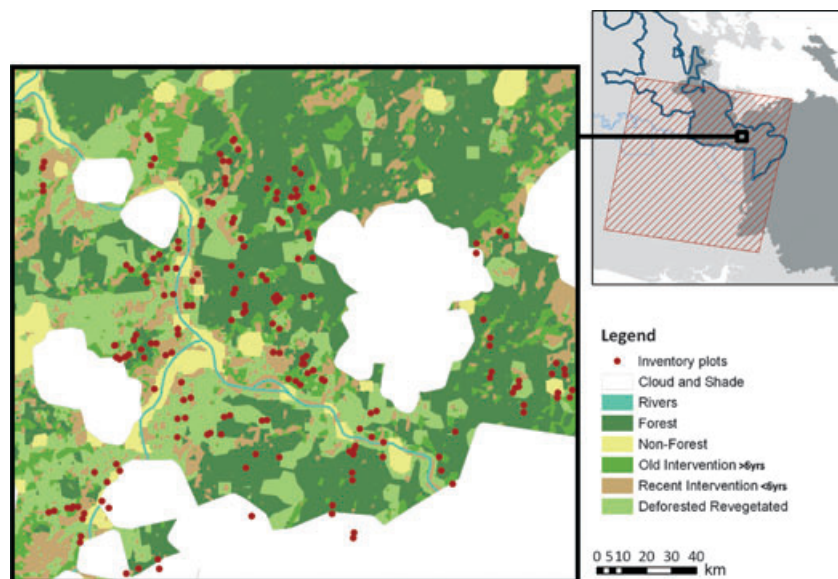


Fig. 4 Forest carbon inventory area located in the Palo Seco Forest Reserve (blue contour) and in the Comarca Ngäbe-Buglé (dark gray). The closeup of the forest carbon inventory area shows the forest classes identified using remote sensing analysis.

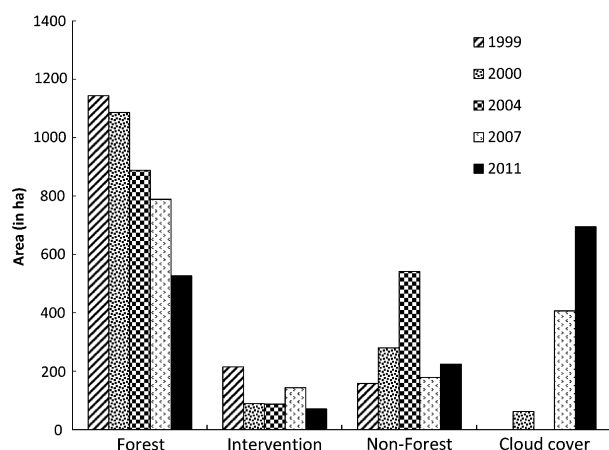


Fig. 5 Forest area change over time from 1999 to 2011. The 2007 and 2011 images had a higher fraction covered by clouds.

through time following human intervention. Our ability to fully understand changes in forest area over 1500 ha during the time period covered by the satellite imagery (12 years) (Fig. 5) was impeded by cloud cover in 2007 and 2011. Forest area diminished from 1999 to 2004, and part of the intervened forest area was reduced, with a corresponding increase in nonforested areas from the beginning of 1999 to the end of 2000 (Fig. 5).

Spatially explicit tracking of Forest pixels shows that a large fraction of the Non-forest or Intervened forest pixels reverted to Forest through time, indicating a cyclical rather than linear pattern of land-use change. This land-use dynamic among the Forest, Intervened forest, the Non-forest land is illustrated for 1999–2004 (Fig. 3).

Discriminant analysis correctly classified 80.7% of the observations. Of the four forest-use categories, the 'Forest' category was most efficiently classified on the basis of remote sensing variables (86.3% correct classification), whereas 'Recent intervention' was least strongly differentiated from the other categories (75.8%) (Table 4). The bi-plot of the discriminant analysis shows the groups' separation among the categories of Forest, Deforested revegetated and Interventions for

the first two axes (Fig. 6). The bi-plot of the second and third axes showed the separation between Old and Recent interventions (Data not shown).

ANOVA was used to compare forest carbon stocks of the four forest categories obtained from remote sensing. The respective mean total above-ground C stocks for the Forest, Old Intervention, Deforested Revegetated, and Recent Intervention groups were 99.1 ± 12.0 , 85.1 ± 10.6 , 65.0 ± 9.2 , and 52.2 ± 7.4 Mg ha⁻¹. Significant difference between categories was found ($F_{3,179} = 5.19$, $P = 0.0019$), specifically between Forest and Recent intervention categories (Tukey HDS; $P = 0.006$), as well as Forest and Deforested Revegetated (Tukey HDS; $P = 0.030$). Old intervention did not differ significantly from the other forest categories.

The Deforested revegetated category that was identified using remote sensing was consistent with the field information in 83% of cases (44 of 53 plots). Four sites that were mis-attributed, had experienced landslides in a section of the plot (3), or were adjacent to a landslide (1), whereas one other site was used to harvest fuel and construction wood (but not deforested) according to the field information. Wood harvesting may have been more intensive in this area at a particular point in the past, which could have resulted in the area exhibiting low above-ground C (50.7 Mg ha⁻¹). Only four plots visited remain inconsistent relative to the remote sensing analysis (8%).

Explaining forest carbon density with the time series of remote sensing variables

Total above-ground C (Standing C + woody debris C) was regressed against the remote sensing variables. Cloud cover in 2011 that obscured sampling plots resulted in a lack of information for some transects. In this first analysis, remote sensing variables for 2011 were excluded for 47 transects (i.e. 188 plots). Multiple linear regression included seven remote sensing variables, which explained 64.2% of the variation in forest carbon density (R^2 – adjusted = 0.578; Table 5). None of the remote sensing variables stood out as indubitably

Table 4 Classification table obtained from the linear discriminant analysis classification function

| Forest Classification | Objects assigned by the classification function | | | | |
|------------------------|---|--------|------------------|---------------------|--------------------|
| | Deforested revegetated | Forest | Old intervention | Recent intervention | Total correct in % |
| Deforested revegetated | 42 | 6 | 4 | 1 | 79.2 |
| Forest | 7 | 56 | 2 | 0 | 86.2 |
| Old intervention | 4 | 2 | 24 | 1 | 77.4 |
| Recent intervention | 2 | 2 | 4 | 25 | 75.8 |
| Total | 53 | 65 | 31 | 33 | 80.7 |

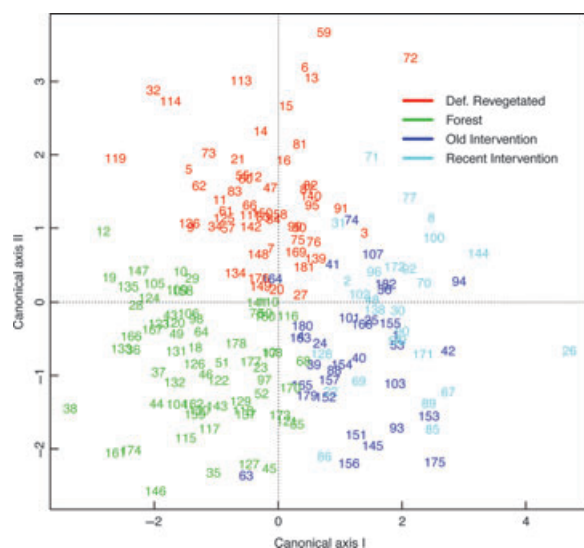


Fig. 6 Ordination diagram of the sites, which are identified by their color group in the canonical discriminant space.

Table 5 Parsimonious multiple regression model of total above-ground carbon stocks in relation with vegetation indices/fractional components after backward elimination and reduction in collinearity ($n = 47$)

| Variables | Coefficient | Std. Error | <i>t</i> value | Pr(> <i>t</i>) |
|---------------|-------------|------------|----------------|-------------------|
| (Intercept) | 1.36E-14 | 2.32E-01 | 0 | 1 |
| NDVI_2000 | 2.40E + 00 | 5.09E-01 | 4.726 | 2.96E-05 |
| MSAVIaf_2000 | -1.82E + 00 | 5.54E-01 | -3.286 | 0.002157 |
| FracGV_2007 | -1.13E + 00 | 3.13E-01 | -3.601 | 0.000883 |
| FracNPV_1999 | -1.34E + 00 | 2.92E-01 | -4.61 | 4.25E-05 |
| NDVI_2004 | 1.61E + 00 | 4.24E-01 | 3.788 | 0.000513 |
| FracSoil_1999 | 1.41E + 00 | 3.86E-01 | 3.659 | 0.000748 |
| FracSoil_2004 | 1.45E + 00 | 3.92E-01 | 3.697 | 0.000669 |

Residual standard error: 1.592 on 39 degrees of freedom.
Multiple *R*-square: 0.6421, Adjusted *R*-square: 0.5779.
F-statistic: 9.995, on 7 and 39 DF, *P*-value: 4.399E-07.

superior to the others. Substantial collinearity between some indices/fractions (NDVI, MSAVI, and MSAVI_{af}) of the same year is evidence that some remote sensing variables from the same year could be interchanged with only small changes in explanatory power. Every year of the time series was represented in the multiple regression models, suggesting that the cumulative effect of intervention on forest explains carbon stock density better than simple examination of the results from any single year.

A second multiple regression, with reduced sampling size including 2011 ($n = 28$) explained 47.1% (R^2 – adjusted = 0.401) of the variation in standing above-ground C and woody debris C using a regression

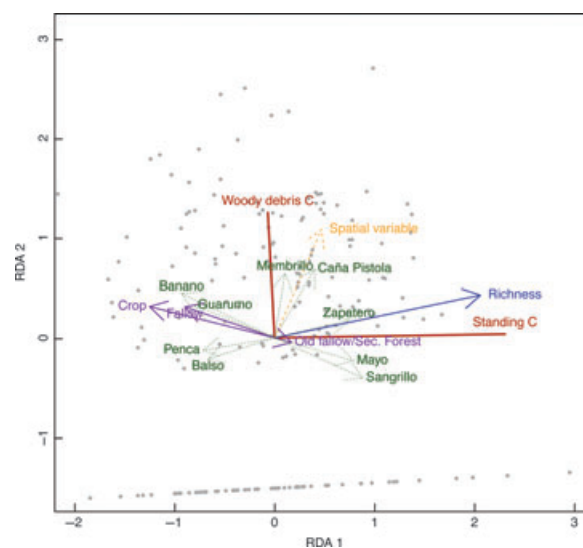


Fig. 7 RDA ordination triplot of the above-ground standing carbon stock density (Above-ground trees, palms, lianas, fern trees (Standing C); and Above-ground woody debris (Woody debris C) explained by the species richness, land-use (four factors, $k-1$ are displayed), the identity of the dominant tree species (58 factors, main ones are displayed), and the db MEM variable (Spatial variable), scaling type 1. The pointed arrows represent the bi-plot scores of the explanatory variables. The red arrows represent the response variables. The linear pattern observed at the bottom of the figure is explained by the absence of woody debris in the plots sampled. Both canonical axes are significant at $P < 0.001$. The first axis (related to standing C) explained 77.2% of the variance, whereas the second axis (related to woody debris) explained 22.8% of the total variation explained.

model based on the NPV Fraction 1999, Soil Fraction 2011 and MSAVI_{af} 2007.

Explaining forest carbon density with the land-use practices and biodiversity

The effect of land use and biodiversity on forest carbon stocks was explored using RDA, which demonstrated that 61.4% of the variation in above-ground standing carbon stocks and woody C is predicted by the explanatory matrix including land use, dominant species identity, plot species richness, and space from db MEM (R^2 – adjusted = 0.422).

The RDA ordination triplot shows that the explanatory variable most closely related to standing C is species richness, whereas the space had the highest loadings for woody debris (Fig. 7). Not surprisingly, Crop and Fallow land-uses are negatively related to Standing C, but slightly positively related to Woody debris C. The presence of *Sangrillo*, *Mayo*, or *Zapatero* trees as dominant species is associated with high levels of Standing C. Conversely, the *banano*, which is one of the main plants that

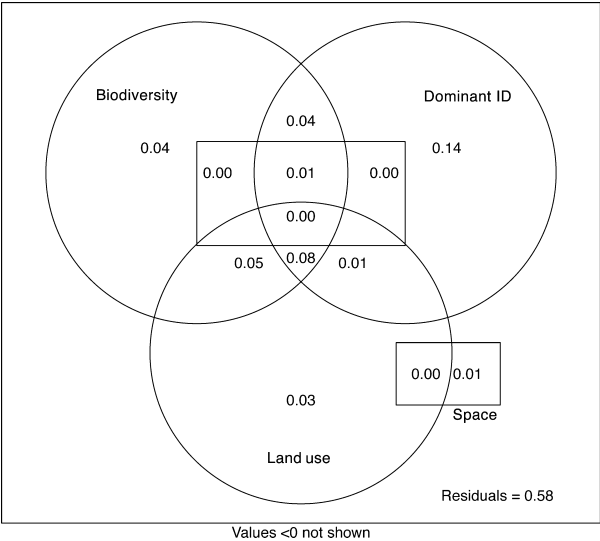


Fig. 8 Venn diagram of the variation partitioning following the rda model using four variables (Land Use, Dominant Identity, Richness and Spatial variable) to explain the variation in the above-ground standing C and woody debris C. The rectangles represent the spatial variable.

is cultivated in croplands, is associated with low levels of Standing C, together with *Guarumo*, *Penca* and *Balso*, which are abundant in fallow lands.

Variance partitioning shows that dominant morphospecies identity alone explained 26.2% of Standing

C plus woody debris (Fig. 8). Together the land-use variables and the biodiversity indices explained 7.1% of the variance. Land use has an effect on both biodiversity and the identity of the dominant species. The combination of these three variables explains 14.2% of the variation. Spatial components alone play a minor role in explaining variation (i.e. 2.4%). Last, the Pearson's correlation between the DBH of the dominant tree in each plot and total above-ground C is positive with $r = 0.897$, $n = 186$, $P < 2.2e-16$.

ANOVA compared the carbon stocks of four land-use classes that were identified in the field. Mean total above-ground C (and associated standard errors) differ significantly among land-use classes ($F_{3,184} = 24.59$, $P < 0.0001$). Stocks were highest for Forest (112.5 ± 10.8 Mg C ha⁻¹), intermediate for Old fallow/Secondary forest and Fallow land (78.4 ± 12.2 and 54.0 ± 6.0 Mg C ha⁻¹), and lowest for Cropland (29.1 ± 6.7 Mg C ha⁻¹; Fig. 9). Forest above-ground C does not differ from Old Fallow/Secondary forest, but does differ from that of Fallow and Croplands, which in turn differs significantly from Fallow and Old fallow/Secondary forest (Table 6).

Discussion

The lack of knowledge of the land-use dynamics that are associated with the agriculture-fallow cycle has been shown to affect the accuracy of forest emission

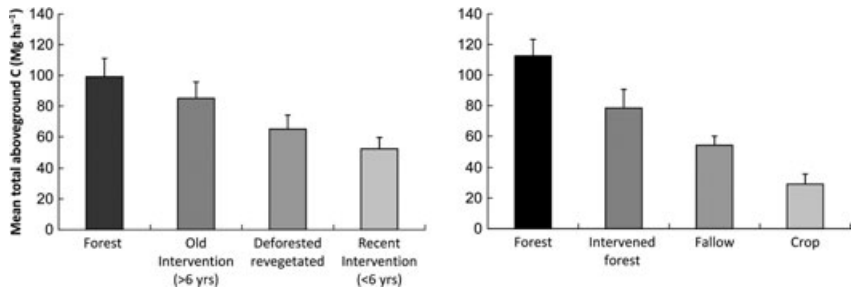


Fig. 9 Mean total above-ground C stock (Standing C and Woody debris C) and standard error of the forest categories based on remote sensing (Left panel) and of the land-use classes based on ground survey (Right panel).

Table 6 *Post hoc* multiple comparison tests with Tukey HSD. Significant differences are identified in bold

| Land-use classes | Diff | Lower | Upper | <i>P</i> adj |
|------------------------------------|-----------------|-----------------|-----------------|-----------------|
| Old fallow/Secondary forest-Forest | -0.28771 | -0.6507 | 0.075287 | 0.172004 |
| Crop-Forest | -0.98456 | -1.31776 | -0.65136 | 0 |
| Fallow-Forest | -0.58079 | -0.82184 | -0.33975 | 0 |
| Crop-Old fallow/secondary forest | -0.69685 | -1.12896 | -0.26475 | 0.00026 |
| Fallow-Old fallow/secondary forest | -0.29309 | -0.65887 | 0.072698 | 0.164379 |
| Fallow-Crop | 0.403766 | 0.067535 | 0.739997 | 0.011428 |

estimates (Pelletier *et al.*, 2011). Our study provides (i) a new methodological approach to tracking the dynamics of shifting cultivation areas using affordable medium-resolution imagery and to help predict forest carbon stock changes, (ii) evidence that shifting cultivation may have limited effects on forest C stocks over time, and (iii) support for community monitoring to evaluate related forest carbon changes, with a variety of side benefits. The findings that are presented below are relevant to the monitoring of forest degradation and C stock enhancement for REDD+ in shifting cultivation areas.

Methodology for assessing impacts of shifting cultivation

Shifting cultivation landscapes are characterized by a mosaic of different land-use types that change through time (Mertz, 2009; Padoch & Pinedo-Vasquez, 2010). There is a general lack of knowledge regarding shifting cultivation and fallow area (Fearnside, 2000; Houghton, 2010), location, and intensity of this practice (Hett *et al.*, 2011b). New ways to look at these shifting cultivation landscape mosaics have been proposed and could be very useful in spatially delineating these areas (Messler *et al.*, 2009; Hett *et al.*, 2011b; Hett *et al.*, 2011a). In the context of REDD+, quantifying C emissions and removals from forests in these complex land-use systems is challenging and requires insights into their temporal dynamics. In effect, shifting cultivation may involve a change in carbon stocks without a change in forest area, making it more difficult to detect these activities through satellite imagery (Houghton, 2005). Herein, we have shown that our approach using multitemporal analysis of satellite images can effectively capture complex land-use dynamic of small-scale land-use processes that would not be traceable using only one point in time. Spatially explicit information on pixel transitions over time allows clearings that are temporary to be differentiated from those that remain deforested. We propose that, in the REDD+ context, those temporary clearings should be considered as degradation. We argue that, by monitoring these shifting cultivation areas adequately, we can avoid possible errors of inflating deforestation rates (DeFries *et al.*, 2007) or of omitting the effect of fallow clearings.

In effect, the monitoring of shifting cultivation brings with it quite different technical problems than selective logging, because of its patchy spatial structure. When monitoring selective logging, visible patterns that are associated with log decks, roads, and skid marks facilitate its detectability (Asner *et al.*, 2005; Laporte *et al.*, 2007; Stone & Lefebvre, 1998). For small-scale shifting cultivation, interventions near villages and rivers or road networks are more likely to be identified,

but may still require ground verification. The type of crops that are planted and the use of fire in shifting cultivation systems may influence the detectability of planted plots; burned areas being more easily detected.

On the basis of the remote sensing analysis performed, we were able to discriminate between different intensities of forest-use and time-since-intervention, both of which have consequences on forest C stock with the following trend: Forest→Old intervention (>6 years)→Deforested revegetated→Recent intervention (<6 years). Forest and Recent intervention (<6 years) as well as Forest and Deforested revegetated mean above-ground C presented a significant difference. These results are consistent with research that has been conducted in Amazonia, where more intense intervention categories (logged and burned forests) present significant differences from intact forest in terms of biomass (Souza, 2005b). The mean C density of plots that were classified as Forest by remote sensing is 13.4 Mg C ha⁻¹ lower than for the Forest class that was identified in the field survey (Fig. 9). This difference may be the result of undetected forest-use using remote sensing. It is possible, for example, that the Forest category might have been subject to intervention prior to our time series, i.e. prior to 1999, which would explain why it contains lower carbon stocks than intact forest. This limitation might be overcome with the use of longer time series.

Furthermore, the results of multiple regression indicate that the tracking of land-use dynamics over time can help quantify forest carbon stocks in a human-intervened landscape. In this shifting mosaic, we show that cumulating (multiple) interventions over time can be a good predictor of forest C stock changes. Effectively, in shifting cultivation areas, detecting intervention over time could act as an adequate indicator, which could be integrated into a forest monitoring system for tracking carbon stock changes.

In a GOF-C-GOLD (2010) report, it was suggested that images that were separated by sufficiently long periods of time should be used for forest monitoring to avoid erroneous conclusions with respect to increases in forest areas. In contrast, we propose that understanding of a periodic process that is associated with shifting cultivation requires periodic analysis notions. Statistical theory states that the observational window for periodic events in a series must have a minimum length of two cycles, and its minimum frequency must be at least half a cycle (Legendre & Legendre, 2012). Clearings for shifting cultivation that are used for 1 year before abandonment and may be recultivated after 5 years (1 cycle = 6 years); therefore, the length of the time series should be 12 years with a frequency of observation at least every three years. To detect

possible agricultural intensification that would be indicated by shortened fallow length, which would produce more C emissions, having adequate temporal resolution is important.

This research gives a positive result by providing a low-cost option for countries that are interested in monitoring shifting cultivation areas in terms of forest degradation and C stock enhancement for REDD+. In effect, only affordable and largely available medium-resolution images are required to perform this analysis.

Impacts of shifting cultivation on carbon stocks

One of the objectives of this study is to understand the role of shifting cultivation in terms of its impact on greenhouse gas emissions. The results obtained for the land-use classes as identified in the field suggest a continuum indicative of forest regrowth with carbon stock replenishment, as observed by a C increase from Cultivation → Fallow → Old fallow/Secondary forest → Forest. Moreover, differences in mean above-ground C among classes diminish with time. It also signals that substantial above-ground C stocks can be held within fallow vegetation. These results are consistent with the idea that this shifting mosaic of temporary cleared areas would have limited long-term net emissions, as vegetation regrowth during the fallow period balances the emissions produced by vegetation clearing (DeFries *et al.*, 2007). It is important to reiterate that cloud cover limited our ability to determine the net balance in forest areas; we do not know whether the deforested area is increasing or not.

The short time frame and capacity for forest to restore C stocks can be explained by the nature of the interventions in the landscape where we worked. The prevalence of agroforestry, the small scale of agricultural plots, the proximity to mature forest (seeds), short-lived interventions, and the forest-dominated landscape matrix are characteristics that may have contributed to rapid C stock recovery (Robiglio & Sinclair, 2011; Chazdon, 2003). The residual living vegetation, which affects the succession process (Turner *et al.*, 1998), may explain why there is no difference between the Forest and Old fallow/Secondary forest classes in terms of carbon stock density, the latter having a larger within-group variance. Also, if big trees remain left untouched, as it has been observed on old pasture in the study area, the intervention effect on C stock may be limited (Feldpausch *et al.*, 2005; Laurance *et al.*, 2000).

The rapid recovery of forest carbon stocks following shifting cultivation supports the view that forest and land uses can maintain important ecosystem services,

while they also fulfill a fundamental activity in the economy of local communities as a multiuse system (Noble & Dirzo, 1997). Shifting cultivation has been singled-out as an environmentally destructive and primitive practice and perceived until recently as one of the main drivers of deforestation in the tropics (Mertz, 2009; Geist & Lambin, 2001; Padoch & Pinedo-Vasquez, 2010). This perception is being challenged by numerous studies, which show that shifting cultivation in many situations can be a rational economic and environmental choice for poor farmers in the tropics (Harvey *et al.*, 2008; Souza *et al.*, 2003; Ickowitz, 2006; Nielsen *et al.*, 2006). Our results support the view that shifting cultivation can have a transitory impact on forest carbon stocks and may contribute to the maintenance of ecosystem services, such as carbon reservoirs in human-modified landscapes (DeClerck *et al.*, 2010; Harvey *et al.*, 2008; Ickowitz, 2006; Padoch & Pinedo-Vasquez, 2010; Fischer *et al.*, 2008). Of course, the intensification of land-use practices, including shortening of the fallow period, may change these conditions (Robiglio & Sinclair, 2009; Dalle *et al.*, 2011; Eaton & Lawrence, 2009).

Although land use has a direct effect on forest C stocks, the identity of the dominant species on C alone stands out as the most important factor in explaining variation in above-ground C stocks. On one hand, this information is consistent with other observations (Ruiz-Jaen & Potvin, 2010; Kirby & Potvin, 2007) and perhaps, could be explored further for its use as a proxy measure of forest C stocks. On the other hand, land-use practices that negatively affect dominant tree species (including *Zapatero*, *Sangrillo*, and *Mayo*, which are timber species) may reduce carbon storage in the ecosystem (Kirby & Potvin, 2007). However, the landscape configurations that connect forest patches, maintain a diverse array of habitats, and retain high structural and floristic complexity as found in our study area, may help maintain biodiversity (Harvey *et al.*, 2008; Chazdon *et al.*, 2009).

These findings cannot necessarily be generalized to the overall protected area or to other area where different land-use practices may prevail. Shifting cultivation, as performed by Ngäbe people, is part of a social-ecological system that will differ substantially if compared with Latino colonists' slash-and-burn practices. Also, C recovery from shifting cultivation in another forest type, such as the tropical dry forest for instance, would be expected to be slower (Brown & Lugo, 1990).

The value of community monitoring

Annex I of the Cancun Agreement adopted some of the guidelines and safeguards that should surround

REDD+ activities (UNFCCC, 2010). These safeguards indicate that the full and effective participation of relevant stakeholders, in particular, indigenous peoples and local communities, should be promoted and supported when undertaking REDD+, including for monitoring activities. Skutsch *et al.* (2009) signals that, whereas several studies have looked at the capacity of local people to assess forest biodiversity or disturbance, only a few projects have trained local people to make detailed measurements of carbon stocks. However, community measurements can be a winning approach for assessments of carbon stocks and biodiversity, fulfilling important biodiversity monitoring, which is well-aligned with the safeguards (CIGA-REDD, 2011). Our study provides further evidence to support not only the feasibility, but also the advantage of this approach. Working with local people has been particularly efficient for locating the randomly selected sampling points because of their knowledge of the territory. The workers, most of whom had primary education, were quick to learn the techniques and how to use the tools after capacity-building and field practice as observed by Skutsch (2005) and also probably resulted in more cost-effective study than if it had been performed by professional foresters. In effect, Danielsen *et al.* (2011) conclude that, when examining the reliability and comparing the cost of community monitoring with forester-led measurements, local people can collect forest condition data of quality comparable to those collected by trained scientists, at half the cost.

Working with local people has brought more added-value than the strict measurement of carbon stocks alone. An additional advantage is incurred when the measurement of local biodiversity is facilitated through the application of traditional knowledge. Moreover, the complementary information provided by local experts and landowners on land-use history and practices is of great value in explaining carbon stock variation in the landscape. Finally, community member participation in carbon stock measurement contributed to the transparency of the process, which would have certainly generated much distrust if it had been performed by outsiders.

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References

- ANAM/CBMAP (2006) *Plan de Manejo Actualizado: Bosque Protector de Palo Seco*. Autoridad Nacional del Ambiente y Corredor Biológico Mesoamericano del Atlántico Panameno, Panama, Republica de Panama.
- ANAM/ITTO (2003) *Informe final de resultados de la cobertura boscosa y uso del suelo de la Republica de Panama: 1992–2000*. Autoridad Nacional del Ambiente, Panama, Republica de Panama.
- Asner GP, Keller M, Pereira R, Zweede JC, Silva JNM (2004a) Canopy damage and recovery after selective logging in Amazonia: field and satellite studies. *Ecological Applications*, **14**, S280–S298.
- Asner GP, Keller M, Silva JNM (2004b) Spatial and temporal dynamics of forest canopy gaps following selective logging in the eastern Amazon. *Global Change Biology*, **10**, 765–783.
- Asner GP, Knapp DE, Broadbent EN, Oliveira PJC, Keller M, Silva JN (2005) Selective logging in the Brazilian Amazon. *Science*, **310**, 480–482.
- Asner GP, Broadbent EN, Oliveira PJC, Keller M, Knapp DE, Silva JNM (2006) Condition and fate of logged forests in the Brazilian Amazon. *Proceedings of the National Academy of Sciences USA*, **103**, 12947–12950.
- Borcard D, Gillet F, Legendre P. (2011) *Numerical Ecology with R*. Springer, New York, USA.
- Bouroubi Y, Cavayas F, Tremblay N (2010) *Les corrections radiométriques des images multispectrales et leur importance pour la fiabilité des applications de la télédétection*. Sarrebruck, Germany.
- Brandt JS, Townsend PA (2006) Land use-land cover conversion, regeneration and degradation in the high elevation Bolivian Andes. *Landscape Ecology*, **21**, 607–623.
- Broadbent EN, Zarin DJ, Asner GP, Pena-Claros M, Cooper A, Littell R (2006) Recovery of forest structure and spectral properties after selective logging in lowland Bolivia. *Ecological Applications*, **16**, 1148–1163.
- Brown S, Lugo AE (1990) Tropical secondary forests. *Journal of Tropical Ecology*, **6**, 1–32.
- Bruun TB, de Neergaard A, Lawrence D, Ziegler AD (2009) Environmental consequences of the demise of swidden cultivation in Southeast Asia: carbon storage and soil quality. *Human Ecology*, **37**, 375–388.
- Chave J, Condit R, Aguilar S, Hernandez A, Lao S, Perez R (2004) Error propagation and scaling for tropical forest biomass estimates. *Philosophical Transactions of the Royal Society of London Series B-Biological Sciences*, **359**, 409–420.
- Chave J, Andalo C, Brown S *et al.* (2005) Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia*, **145**, 87–99.
- Chazdon RL (2003) Tropical forest recovery: legacies of human impact and natural disturbances. *Perspectives in Plant Ecology Evolution and Systematics*, **6**, 51–71.
- Chazdon RL, Peres CA, Dent D *et al.* (2009) The potential for species conservation in tropical secondary forests. *Conservation Biology*, **23**, 1406–1417.
- CIGA-REDD (2011) *Report on the FCPF Workshop "Linking Community Monitoring with National MRV for REDD+"*. CIGA-REDD, UNAM, Mexico City, 12–14 September 2011.
- Clark DB, Clark DA (2000) Landscape-scale variation in forest structure and biomass in a tropical rain forest. *Forest Ecology and Management*, **137**, 185–198.
- Clark DB, Clark DA, Brown S, Oberbauer SF, Veldkamp E (2002) Stocks and flows of coarse woody debris across a tropical rain forest nutrient and topography gradient. *Forest Ecology and Management*, **164**, 237–248.
- Condit R (1998) *Tropical Forest Census Plots*. Springer-Verlag, Berlin.
- Dalle SP, Potvin C (2004) Conservation of useful plants: an evaluation of local priorities from two indigenous communities in eastern Panama. *Economic Botany*, **58**, 38–57.
- Dalle SP, Pulido MT, de Blois S (2011) Balancing shifting cultivation and forest conservation: lessons from a "sustainable landscape" in southeastern Mexico. *Ecological Applications*, **21**, 1557–1572.
- Danielsen F, Skutsch M, Burgess ND *et al.* (2011) At the heart of REDD+: a role for local people in monitoring forests? *Conservation Letters*, **4**, 158–167.
- DeClerck FAJ, Chazdon R, Holl KD *et al.* (2010) Biodiversity conservation in human-modified landscapes of Mesoamerica: past, present and future. *Biological Conservation*, **143**, 2301–2313.

- DeFries R, Achard F, Brown S, Herold M, Murdiyarso D, Schlamadinger B, de Souza C (2007) Earth observations for estimating greenhouse gas emissions from deforestation in developing countries. *Environmental Science & Policy*, **10**, 385–394.
- Delaney M, Brown S, Lugo AE, Torres-Lezama A, Quintero NB (1998) The quantity and turnover of dead wood in permanent forest plots in six life zones of Venezuela. *Biotropica*, **30**, 2–11.
- DeWalt SJ, Chave J (2004) Structure and biomass of four lowland Neotropical forests. *Biotropica*, **36**, 7–19.
- Eaton JM, Lawrence D (2009) Loss of carbon sequestration potential after several decades of shifting cultivation in the Southern Yucatan. *Forest Ecology and Management*, **258**, 949–958.
- Fearnside PM (2000) Global warming and tropical land-use change: greenhouse gas emissions from biomass burning, decomposition and soils in forest conversion, shifting cultivation and secondary vegetation. *Climatic Change*, **46**, 115–158.
- Feldpausch TR, Jirka S, Passos CAM, Jasper F, Riha SJ (2005) When big trees fall: damage and carbon export by reduced impact logging in southern Amazonia. *Forest Ecology and Management*, **219**, 199–215.
- Fischer J, Brosi B, Daily GC *et al.* (2008) Should agricultural policies encourage land sparing or wildlife-friendly farming? *Frontiers in Ecology and the Environment*, **6**, 382–387.
- Gaceta Oficial (1983) Decreto Ejecutivo N° 25 "Por el cual se declara y se describe el Bosque Protector de Palo Seco en los Distritos de Chiriquí Grande y Changuinola, Provincia de Bocas del Toro". Gobierno Nacional de Panamá, República de Panamá.
- Geist HJ, Lambin E (2001) *What Drives Tropical Deforestation? A Meta-Analysis of Proximate and Underlying Causes of Deforestation Based on Subnational Case Study Evidence*. LUCC Report Series 4. International Human Dimensions Programme on Global Environmental Change (IHDP), International Geosphere-Biosphere Programme (IGBP), Louvain-la-Neuve, Belgium.
- Gerwing JJ (2002) Degradation of forests through logging and fire in the eastern Brazilian Amazon. *Forest Ecology and Management*, **157**, 131–141.
- GOFC-GOLD (2010) *A Sourcebook of Methods and Procedures for Monitoring and Reporting Anthropogenic Greenhouse Gas Emissions and Removals Caused by Deforestation, Gains and Losses of Carbon Stocks in Forests Remaining Forests, and Forestation*. GOFC-GOLD Report version COP16-1. GOFC-GOLD Project Office, Natural Resources Canada, Edmonton Alberta, Canada.
- Grainger A (2008) Difficulties in tracking the long-term global trend in tropical forest area. *Proceedings of the National Academy of Sciences USA*, **105**, 818–823.
- Harvey CA, Komar O, Chazdon R *et al.* (2008) Integrating agricultural landscapes with biodiversity conservation in the Mesoamerican hotspot. *Conservation Biology*, **22**, 8–15.
- Hett C, Heinemann A, Messerli P (2011a) Spatial Assessment of carbon stocks of living vegetation at the national level in Lao PDR. *Geografisk Tidsskrift*, **111**, 11–26.
- Hett C, Castella JC, Heinemann A, Messerli P, Pfund JL (2011b) A landscape mosaics approach for characterizing swidden systems from a REDD+ perspective. *Applied Geography*, **32**, 608–618.
- Houghton RA (2005) Aboveground forest biomass and the global carbon balance. *Global Change Biology*, **11**, 945–958.
- Houghton RA (2010) How well do we know the flux of CO₂ from land-use change? *Tellus Series B Chemical and Physical Meteorology*, **62**, 337–351.
- Huete AR (1988) A soil-adjust vegetation index (SAVI). *Remote Sensing of Environment*, **25**, 295–309.
- Ickowitz A (2006) Shifting cultivation and deforestation in tropical Africa: critical reflections. *Development and Change*, **37**, 599–626.
- IPCC (2003) *Good Practice Guidance for Land Use*. Land-Use Change and Forestry, Institute for Global Environmental Strategies (IGES), Japan.
- IPCC (2007) *IPCC Fourth Assessment Report: Climate Change 2007*. Intergovernmental Panel on Climate Change, Geneva, Switzerland.
- Kirby KR, Potvin C (2007) Variation in carbon storage among tree species: implications for the management of a small-scale carbon sink project. *Forest Ecology and Management*, **246**, 208–221.
- Laporte NT, Stabach JA, Grosch R, Lin TS, Goetz SJ (2007) Expansion of industrial logging in Central Africa. *Science*, **316**, 1451–1451.
- Laurance WF, Delamonica P, Laurance SG, Vasconcelos HL, Lovejoy TE (2000) Conservation - Rainforest fragmentation kills big trees. *Nature*, **404**, 836–836.
- Legendre P, Legendre L (2012) *Numerical Ecology*, 3rd English ed. Elsevier Science BV, Amsterdam.
- Matricardi EAT, Skole DL, Cochrane MA, Pedlowski M, Chomentowski W (2007) Multi-temporal assessment of selective logging in the Brazilian Amazon using Landsat data. *International Journal of Remote Sensing*, **28**, 63–82.
- Matricardi EAT, Skole DL, Pedlowski MA, Chomentowski W, Fernandes LC (2010) Assessment of tropical forest degradation by selective logging and fire using Landsat imagery. *Remote Sensing of Environment*, **114**, 1117–1129.
- Mertz O (2009) Trends in shifting cultivation and the REDD mechanism. *Current Opinion in Environmental Sustainability*, **1**, 156–160.
- Messerli P, Heinemann A, Epprecht M (2009) Finding homogeneity in heterogeneity – a new approach to quantifying landscape mosaics developed for the Lao PDR. *Human Ecology*, **37**, 291–304.
- Nascimento HEM, Laurance WF (2002) Total aboveground biomass in central Amazonian rainforests: a landscape-scale study. *Forest Ecology and Management*, **168**, 311–321.
- Nielsen U, Mertz O, Noweg GT (2006) The rationality of shifting cultivation systems: labor productivity revisited. *Human Ecology*, **34**, 210–218.
- Noble IR, Dirzo R (1997) Forests as human-dominated ecosystems. *Science*, **277**, 522–525.
- van Noordwijk M, Rahayu S, Hairiah K, Wulan YC, Farida C, Verbist B (2003) Carbon stock assessment for a forest-to-coffee conversion landscape in Sumber-Jaya (Lampung, Indonesia): from allometric equations to land use change analysis. *Science in China, Series C-Life Sciences*, **45**, 75–86.
- Oksanen JF, Blanchet G, Kindt R *et al.* (2011) *vegan: Community Ecology Package*. R package version 1.17-9. Available at: <http://CRAN.R-project.org/package=vegan> (accessed 30 July 2012).
- Padoch C, Pinedo-Vasquez M (2010) Saving slash-and-burn to save biodiversity. *Biotropica*, **42**, 550–552.
- Pelletier J (2012) *Emissions from Land-Cover Change in Panama: Uncertainty, Dynamics, and Perceptions*. Doctoral Thesis, McGill University, Montreal, QC.
- Pelletier J, Ramankutty N, Potvin C (2011) Diagnosing the uncertainty and detectability of emission reductions for REDD+ under current capabilities: an example for Panama. *Environmental Research Letters*, **6**, 024005.
- Peres CA, Barlow J, Laurance WF (2006) Detecting anthropogenic disturbance in tropical forests. *Trends in Ecology & Evolution*, **21**, 227–229.
- Qi J, Chehbouni A, Huete AR, Kerr YH, Sorooshian S (1994) A modified soil adjusted vegetation index. *Remote Sensing of Environment*, **48**, 119–126.
- R Development Core Team (2005) *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.
- Ramankutty N, Gibbs HK, Achard F, Defries R, Foley JA, Houghton RA (2007) Challenges to estimating carbon emissions from deforestation. *Global Change Biology*, **13**, 51–66.
- Robiglio V, Sinclair F (2011) Maintaining the conservation value of shifting cultivation landscapes requires spatially explicit interventions. *Environmental Management*, **48**, 289–306.
- Ruiz-Jaen MC, Potvin C (2010) Tree diversity explains variation in ecosystem function in a Neotropical forest in Panama. *Biotropica*, **42**, 638–646.
- Skutsch MM (2005) Reducing carbon transaction costs in community based forest management. *Climate Policy*, **5**, 433–443.
- Skutsch M, Van Laake P, Zahabu E, Karky B, Phartiyal P (2009) Community monitoring in REDD+. *Realising REDD+: National Strategy and Policy Options* (ed. Angelsen A), pp. 101–112, Bogor, Indonesia.
- Smith DA (2005) Garden game: shifting cultivation, indigenous hunting and wildlife ecology in western Panama. *Human Ecology*, **33**, 505–537.
- Souza CM Jr, Firestone L, Silva LM, Roberts D (2003) Mapping forest degradation in the Eastern Amazon from SPOT 4 through spectral mixture models. *Remote Sensing of Environment*, **87**, 494–506.
- Souza CM Jr, Roberts DA, Cochrane MA (2005a) Combining spectral and spatial information to map canopy damage from selective logging and forest fires. *Remote Sensing of Environment*, **98**, 329–343.
- Souza CM Jr, Roberts DA, Monteiro A (2005b) Multi-temporal analysis of degraded forests in the southern Brazilian Amazon. *Earth Interactions*, **9**, 1–25.
- Stanley W, Brown S, Kant Z, Calmon M, Tiepolo G, Boucher T (2010) *The Climate Action Project Research Initiative*. The Nature Conservancy, Arlington, VA.
- Stone TA, Lefebvre P (1998) Using multi-temporal satellite data to evaluate selective logging in Para, Brazil. *International Journal of Remote Sensing*, **19**, 2517–2526.
- Tschakert P, Coomes OT, Potvin C (2007) Indigenous livelihoods, slash-and-burn agriculture, and carbon stocks in Eastern Panama. *Ecological Economics*, **60**, 807–820.
- Turner MG, Baker WL, Peterson CJ, Peet PK (1998) Factors Influencing Succession: Lessons from Large, Infrequent Natural Disturbances. *Ecosystems*, **1**, 511–523.

- UNFCCC (2010) The Cancun Agreements: Outcome of the work of the Ad Hoc Working Group on Long-term Cooperative Action under the Convention. Decision 1/CP.16, FCCC/CP/2010/7/Add.1, FCCC/CP/2010/7/Add.1. United Nations Framework Convention on Climate Change, <http://unfccc.int/resource/docs/2010/cop16/eng/07a01.pdf#page=2>.
- Van Wagner CE (1982) *Practical Aspects of the Line Intercept Method*. Petawawa National Forestry Institute Information Report PI-X-12. Canadian Forestry Service, Chalk River, Ontario.
- Waddell KL (2002) Sampling coarse woody debris for multiple attributes in extensive resource inventories. *Ecological Indicators*, **1**, 139–153.
- Watson RT, Noble IR, Bolin B, Ravindranath NH, Verardo DJ, Dokken DJ (eds) (2000) *Land Use, Land-Use Change and Forestry*. Cambridge University Press, Cambridge, UK.
- van der Werf GR, Morton DC, DeFries RS *et al.* (2009) CO₂ emissions from forest loss. *Nature Geoscience*, **2**, 737–738.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Vegetation and Near-Infrared indices.

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