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Title: 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 green-house gas emissions and removals from forests in a manner that is robust, transparent, and as accurate as possible. While 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 the present work, we propose and test a methodology to monitor the effect of the shifting cultivation on above-ground carbon stocks. We combine multi-year 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. With 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. Multi-temporal and multi-spectral 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.

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% to 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 is not clear.

DeFries *et al.* (2007) have indicated that the land-use dynamics resulting from shifting cultivation or other 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 non-forest land cover (Peres *et al.*, 2006; Eaton & Lawrence, 2009).

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 over-estimate related emissions (DeFries *et al*., 2007), while considering them as another type of croplands might underestimate emissions, since 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. Multi-year 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 (Stone & Lefebvre, 1998; Asner *et al.*, 2005; Broadbent *et al.*, 2006; Matricardi *et al.*, 2007), and by using sub-pixel 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; Souza *et al.*, 2005a; Asner *et al.*, 2006). 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 (Gerwing, 2002; Asner *et al.*, 2004a; Souza *et al.*, 2005b) and, consequently, the estimation of selective logging contributions to CO_2 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 multi-year 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: 1) forest area dynamics; 2) the ability to capture forest carbon density with the time series of vegetation indices and fraction images; and 3) 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 ºC 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 multi-use protected area where the collection of firewood and construction timber for domestic use is permitted, together with subsistence agriculture (J. Mosaquites, *personal communication*), the Comarca Ngäbe-Buglé itself experienced the highest annual rate of deforestation (-2.3%) in the country between 1990 and 2000 compared to the other provinces (ANAM/ITTO, 2003).

Previously described as pristine forest (Gaceta Oficial de Panamá, 28 de septiembre de 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. Because of 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 + SD) was 1.7 ± 1.5 y, while that of fallowing was 3.8 ± 2.6 y. Fallow length vary considerably according to the crops that are planted. More than half of the respondents had at least 3.6 ha ± 5.4 ha of land in fallow for more than five years (Pelletier, 2012). Aggregate land use of 45 households that were interviewed consisted of 90 ha of crops, 163 ha of old fallow (> 5 y), and 195.5 ha of young fallow (< 5 y) (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 x 60 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 used 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 with a Garmin Legend HCx GPS device (Garmin International, USA; WAAS system-enabled) and, using the nearest neighbors re-sampling method, images were brought to a 15m pixel resolution (Table 1).

A supervised classification separated each image into five cover classes (cloud, shade, water, forest, agriculture) using maximum likelihood classification. Cloud and shade masks were used to create a forest/non-forest binary map and to mask out non-forest 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 ($MSAVI_{af}$) (Matricardi e*t al.,* 2010) (Details in Appendix).

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 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, non-photosynthetic vegetation (e.g., wood debris), and soil (Details in Appendix).

Temporal change analysis

Each image was classified into Forest, Intervened forest, and Non-Forest[1] 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 MSAVIaf, green vegetation fraction, and soil fraction. The thresholds were chosen by comparing the index values of areas that were clearly identified as non-intervened forest and based on two 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

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

2007 maps, which included the three classes (Forest, Intervened forest, Non-Forest) (Figure 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 y), Deforested land that was revegetated, and Recent intervention (< 6 y). 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 (Figure 3). 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 category fell within the recommendations made to capture C stocks adequately in forested landscapes (Clark & Clark, 2000; Nascimento & Laurance, 2002; Chave *et al.*, 2004). 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 three-day practical measurements training. After working for two 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. 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).

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 sub-plot 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 x 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 < 1cm was harvested in a 50 x 50 cm quadrat (Kirby and Potvin 2007). As these pools were 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 are relatively unaffected by this practice (Tschakert *et al.*, 2007; Bruun *et al.*, 2009).

We identified 7056 individual plants ≥ 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, 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; 4 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 with 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 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 by Redundancy Analysis (RDA). Three biodiversity indices, the richness (number of species per plot), the Shannon diversity number (exp(H), where $H = -\Sigma p_i \ln(p_i)$, and where p_i is the proportional abundance of species i, and Simpson diversity number (1/D, where $D = \Sigma(p_i)^2$), were included to the RDA model. Five spatial variables representing spatial structures at different scales and selected with the use of 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 while the response variables were normalized. Global forward selection was used to obtain a parsimonious RDA model and verify for inflated variance (VIF), in order 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 in order 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 in order 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 with remote sensing, five plots were excluded as they had been cultivated since 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 through time following human intervention. Our ability to fully understand changes in forest area over 1,500 ha during the time period covered by the satellite imagery (12 years) (Figure 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 non-forested areas from the beginning of 1999 to the end of 2000 (Figure 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 to 2004 (Figure 3).

Discriminant Analysis (LDA) 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), while “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 (Figure 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 Mg ha^{-}

[1], 85.1 ± 10.6 Mg ha^{-1}, 65.0 ± 9.2 Mg ha^{-1}, 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 by 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), while 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 superior to the others. Substantial collinearity between some indices/fractions (NDVI, MSAVI, $MSAVI_{af}$) 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 with a regression model based on the NPV Fraction 1999, Soil Fraction 2011 and MSAVIaf 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, while the space had the highest loadings for woody debris (Figure 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 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 (Figure 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 Mg C ha^{-1}; 54.0 ± 6.0 Mg C ha^{-1}) and lowest for Cropland (29.1 ± 6.7 Mg C ha^{-1}; Figure 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 estimates (Pelletier et al., 2011). Our study provides 1) 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, 2) evidence that shifting cultivation may have limited effects on forest C stocks over time, and 3) 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 (Messerli *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). Here, we have shown that our approach using multi-temporal 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 (Stone & Lefebvre, 1998; Asner *et al.*, 2005; Laporte *et al.*, 2007). 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 (>6yrs)→Deforested revegetated→Recent intervention (<6yrs). Forest and Recent intervention (<6yrs) as well as Forest and Deforested devegetated mean aboveground 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 *et al.*, 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 (Figure 9). This difference may be the result of undetected forest use by 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 GOFC-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 one 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. In order 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 (Chazdon, 2003; Robiglio & Sinclair, 2011). 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 are left untouched, as it has been observed on old pasture in the study area, the intervention effect on C stock may be limited (Laurance *et al.*, 2000; Feldpausch *et al.*, 2005).

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 multi-use 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 (Geist & Lambin, 2001; Mertz, 2009; 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 (Toledo *et al.*, 2003; Ickowitz, 2006; Nielsen *et al.*, 2006; Harvey *et al.*, 2008). 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 (Ickowitz, 2006; Fischer *et al.*, 2008; Harvey *et al.*, 2008; DeClerck *et al.*, 2010; Padoch & Pinedo-Vasquez, 2010). Of course, the intensification of land-use practices, including shortening of the fallow period, may change these conditions (Eaton & Lawrence, 2009; Dalle *et al.*, 2011; Robiglio & Sinclair, 2011).

While 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 (Kirby & Potvin, 2007; Ruiz-Jaen & Potvin, 2010) 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 to 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, while 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. Yet, 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 done 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 done by outsiders.

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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[a]	0.56	15 m	19
			SWIR[b]	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[c]	03/01/2011	35%	1-5,7	0.23	30 m	17

[a] VNIR (Visible Near Infrared)

[b] SWIR (Short Wave Infrared)

[c] For the last image of the time series (2011), we ordered imagery to be collected while the fieldwork was performed. However, we had to wait for over six 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.

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 y)	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 y)	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[b] 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[a].
Non-forest	Land that appeared deforested in 2007 and potentially during earlier years. Excluded from the sampling.
Cloud/Shade	Cloud/shade cover during 2007, the time period before the forest inventory, Excluded from the forest carbon inventory.

[a] For the purpose of 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.

[b] In order 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.

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

	Source	Models	Units
Trees and palms >= 5cm DBH	Chave et al. (2005)	AGB= Exp[-1.239+1.98*Log(DBH)+0.207*(Log(DBH))^2-0.0281*(Log(DBH))^3]*ρi	Kg
Tree snags >=5 cm DBH	Nascimento and Laurance (2002)	AGB= ρi[BA*(Height)*0.78]	Mg
Dead trees >=5 cm DBH	Delaney et al. (1998)	90% of total AGB of live trees	Kg
Lianas >= 5cm DBH	DeWalt and Chave (2004)	AGB= Exp[0.298+1.027Ln(BA)]	Mg
Banana trees >=5cm DBH	van Noordwijk et al.(2003)	W=0.030DBH^2.13	Mg
Tree ferns >= 5cm DBH	Standley et al. (2010)	1135.3DBH-4814.5	g
Saplings < 5 cm DBH, >=1cm BD	Kirby and Potvin (2007)	Exp[3.965 + 2.383 ln(BD)]	g
Coarse Woody Debris	Van Wagner (1982); Waddell (2002)	[(π^2/8L)Σ(d^2)]ρdrc*Cs	Kg

AGB: Above Ground Biomass

DBH: Diameter at Breast Height (diameter at 1.3m above ground level; cm)

BD: Basal Diameter (diameter at 10 cm above ground level; cm)

BA: Basal Area (m2) or equation BA = pi(DBH)^2/40000

ρi = species specific wood density value (g cm -3) of tree (i), or 0.54 when wood density of species or species unknown

Cs: Slope correction factor sqrt(1+(%of slope/100)^2) or rprime=r/(cos(alpha))^2

ρdrc: Decay Class Reduction Factor; depending if sound ρdrc=0.453 g cm-3) or rotten ρdrc=0.319 g cm-3 (Clark et al., 2002); corrected for slope, not corrected for tilt of individual pieces

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

	Objects assigned by the Classification function				Total correct in %
Forest Classification	Deforested Revegetated	Forest	Old Intervention	Recent Intervention	
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**

Table 5. Parsimonious multiple regression model of total aboveground carbon stocks in relation to vegetation indices/fractional components after backward elimination and reduction of collinearity (n = 47).

Variables	**Coefficient**	**Std. Error**	**t value**	**Pr(>|t|)**
(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

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

Land-use classes	diff	lwr	upr	p 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**

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

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

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

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

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

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

Figure 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 (4 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 biplot 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, while the second axis (related to woody debris) explained 22.8% of the total variation explained.

Figure 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.

Figure 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).

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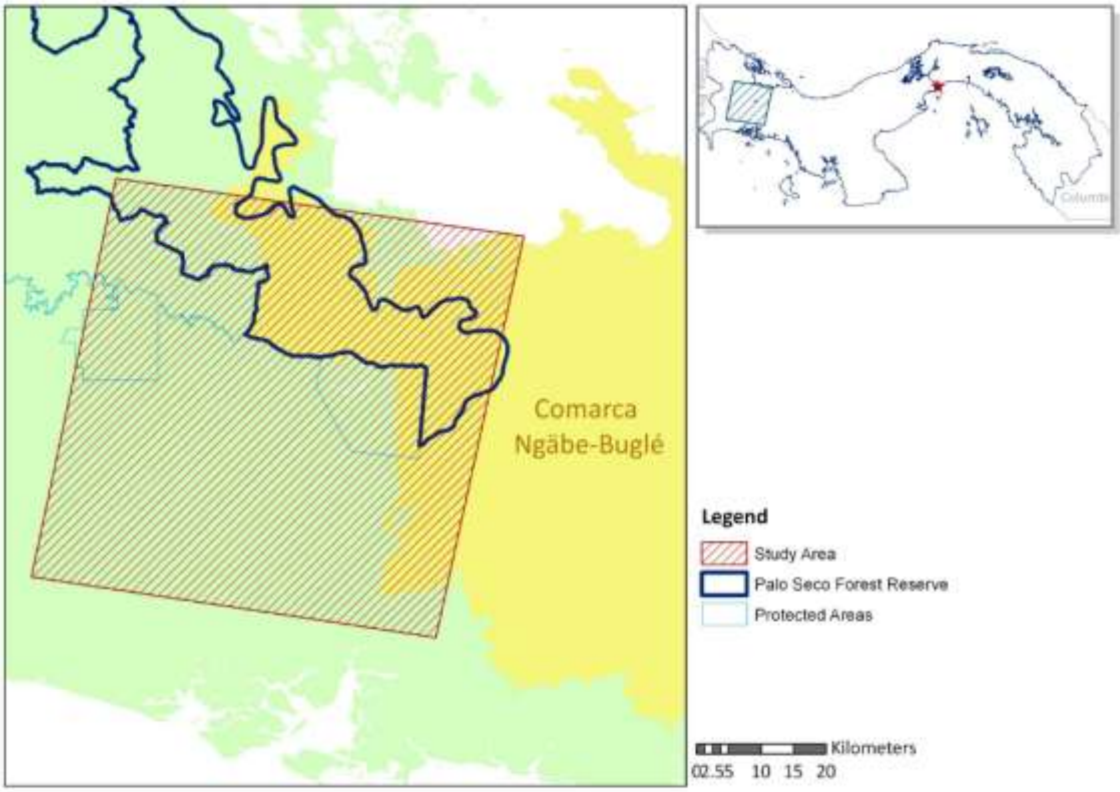
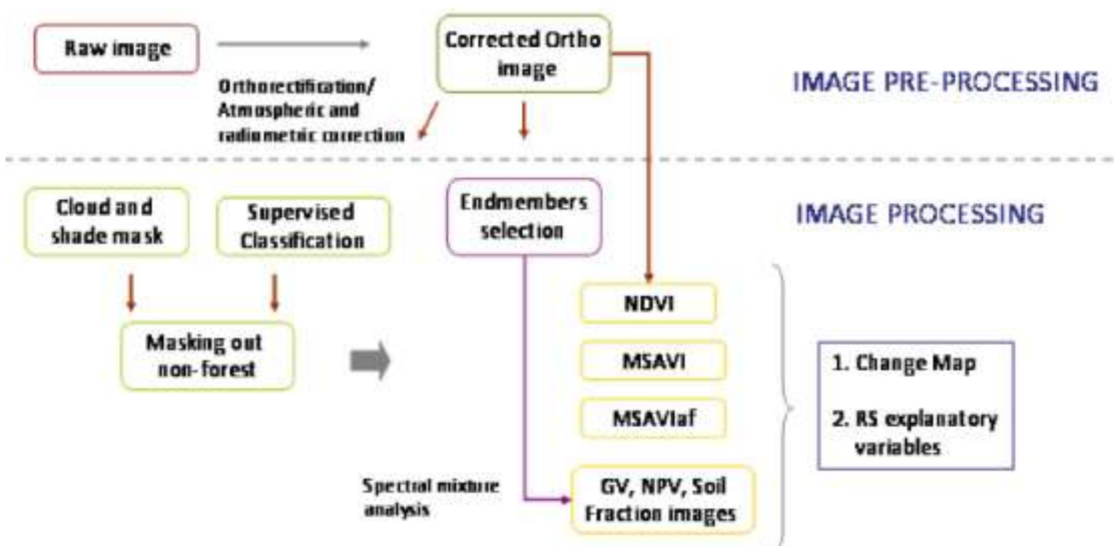
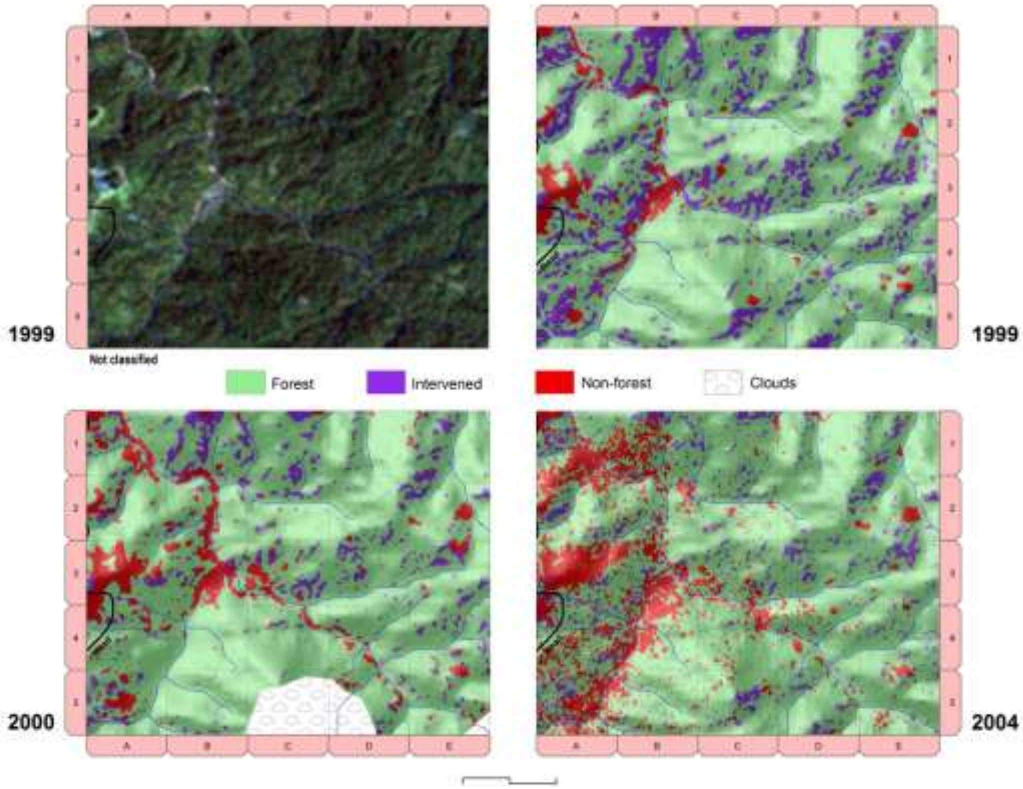
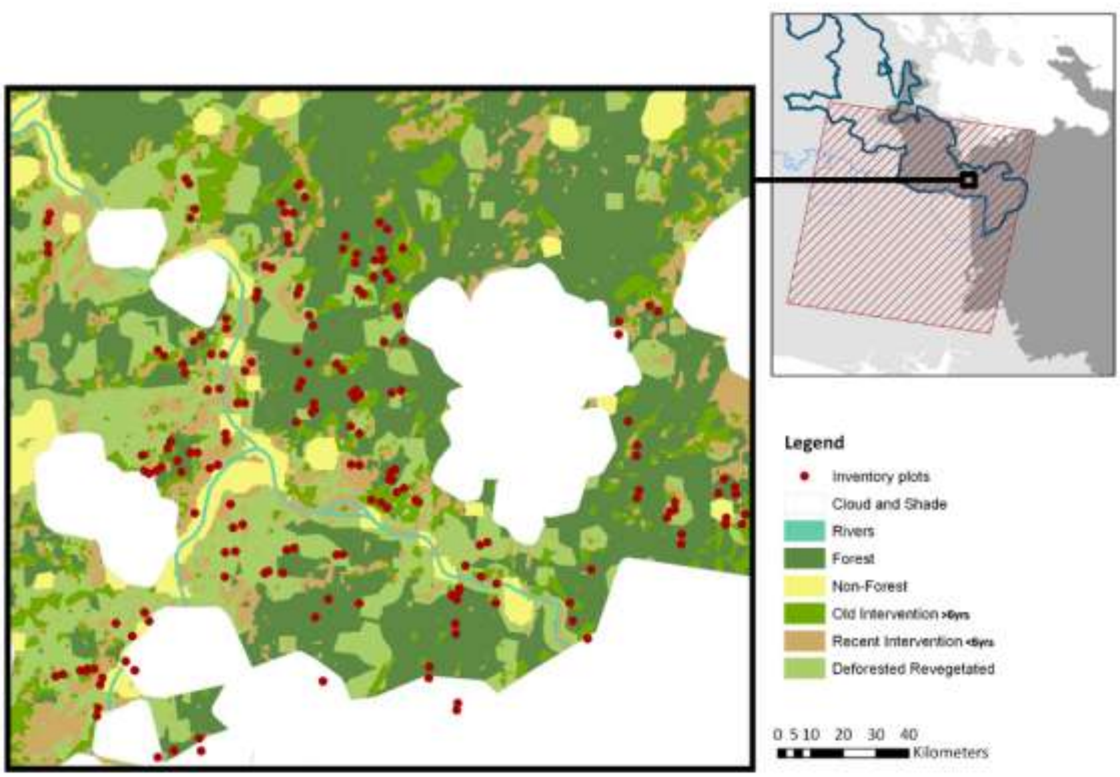
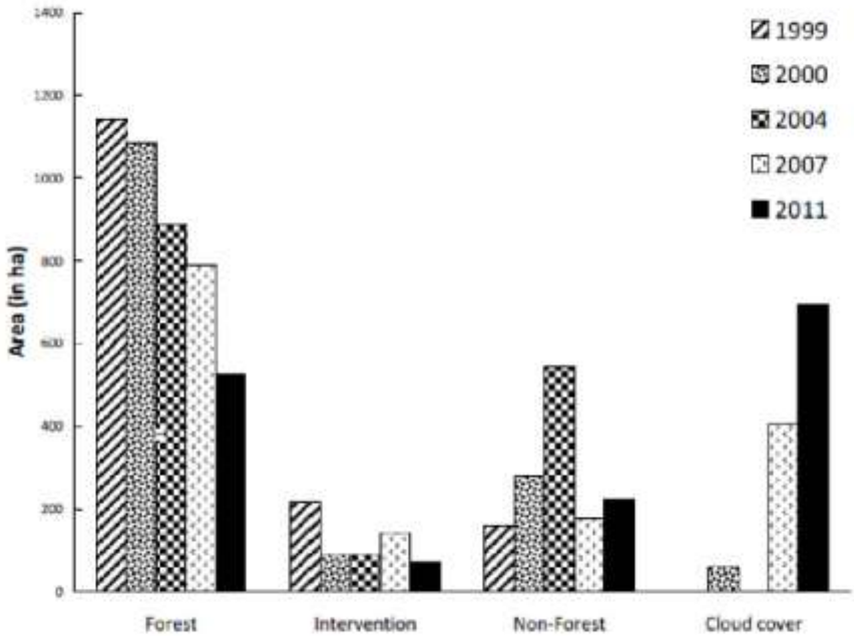
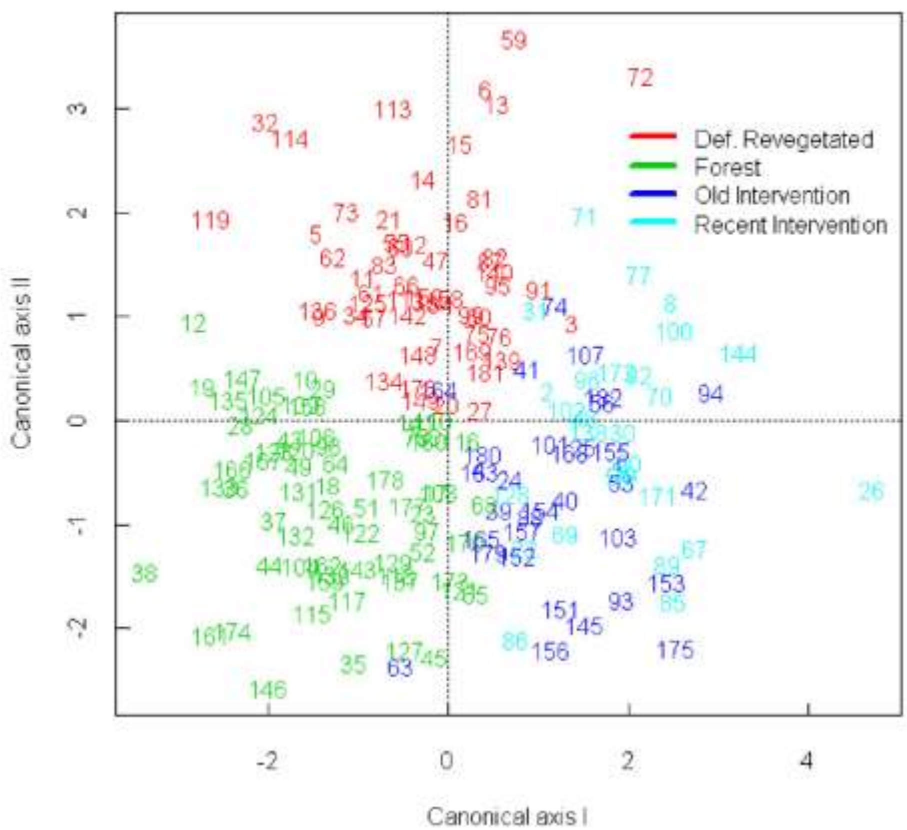

Comarca
Ngäbe-Buglé
Legend
Study Area
Palo Seco Forest Reserve
Protected Areas
Kilometers
0 2.5 5 10 15 20

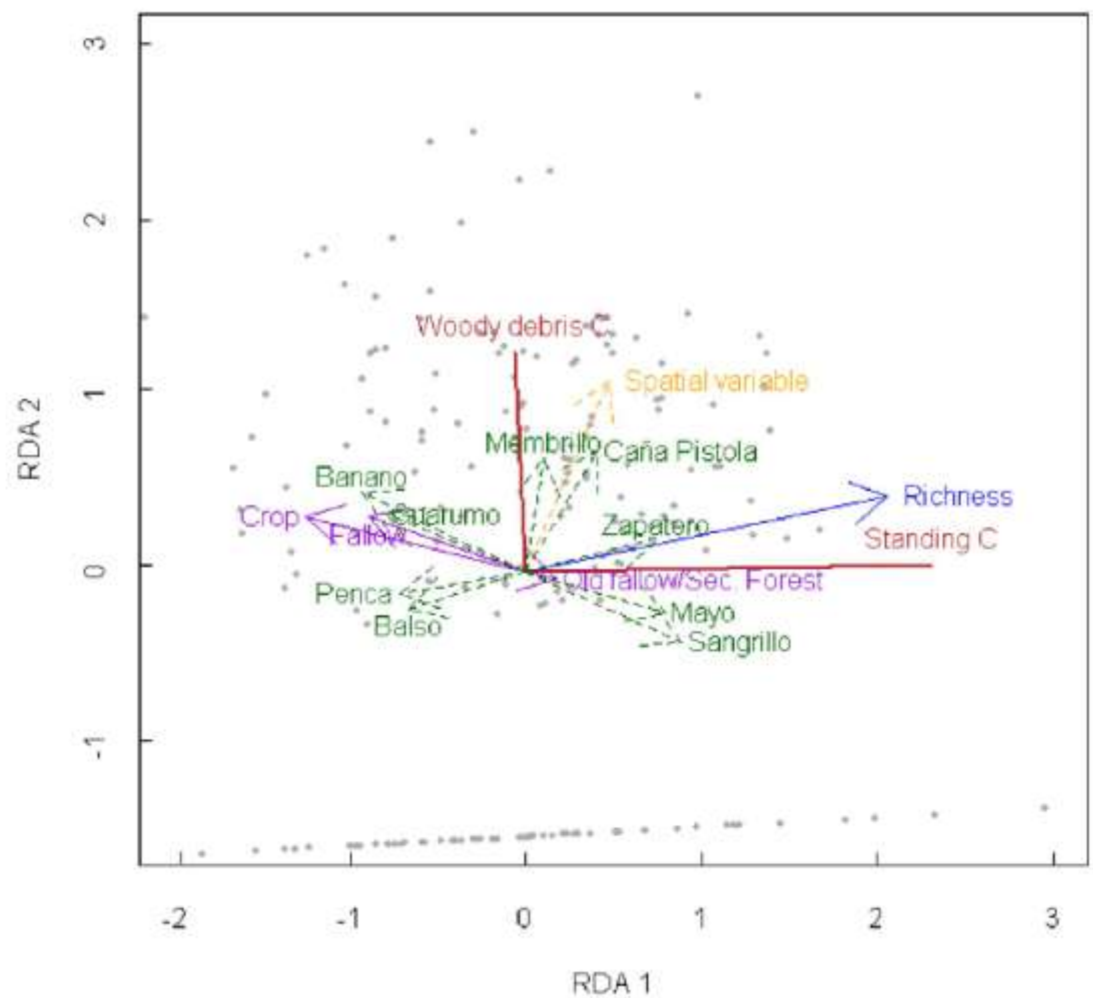

Raw image
Orthorectification/
Atmospheric and
radiometric correction
Corrected Ortho
image
IMAGE PRE-PROCESSING
Cloud and
shade mask
Supervised
Classification
Endmembers
selection
IMAGE PROCESSING
Masking out
non-forest
NDVI
MSAVI
MSAVIaf
Spectral mixture
analysis
GV, NPV, Soil
Fraction images
1. Change Map
2. RS explanatory
variables

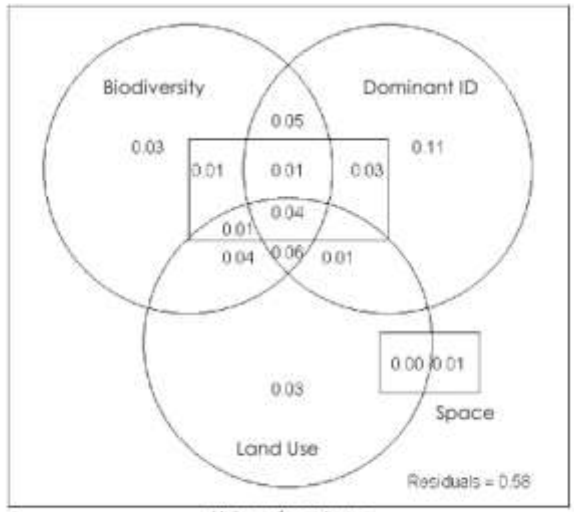

1999
1999
Not classified
Forest
Intervened
Non-forest
Clouds
2000
2004


Legend
Inventory plots
Cloud and Shade
Rivers
Forest
Non-Forest
Old Intervention
Recent Intervention
Deforested Revegetated
0 5 10 20 30 40
Kilometers


1999
2000
2004
2007
2011
Area (in ha)
Forest
Intervention
Non-Forest
Cloud cover


Def. Revegetated
Forest
Old Intervention
Recent Intervention
Canonical axis II
Canonical axis I


Woody debris C
Spatial variable
Membrillo
Caña Pistola
Banano
Richness
Crop
Guarumo
Fallow
Zapatero
Standing C
Old fallow/Sec. Forest
Penca
Balso
Mayo
Sangrillo
RDA 2
RDA 1
3
2
1
0
-1
-2
-1
0
1
2
3



Values <0 not shown