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Consequences of the Armed Conflict, Forced Human Displacement, and Land Abandonment on Forest Cover Change in Colombia: A Multi-scaled Analysis

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Abstract

Most studies of land change have focused on patterns, rates, and drivers of deforestation, but much less is known about the dynamics associated with agricultural abandonment and ecosystem recovery. Furthermore, most studies are conducted at a single spatial scale, and few have included variables related with internal socio-political conflicts. Here we evaluated the effect of environmental, demographic, and socio-economic variables on woody cover change in Colombia between 2001 and 2010 at the country, biome, and ecoregion scales. We also incorporated factors that reflect the unique history of Colombia such as the presence of illegal-armed groups and forced human displacement. Environmental variables explained the patterns of deforestation and forest regrowth at all scales because they can restrict or encourage different land uses across multiple spatial scales. Demographic variables were important at the biome and ecoregion scales and appear to be a consequence of the armed conflict, particularly through forced human displacement (for example, rural–urban migration), which in some areas has resulted in forest regrowth. In other areas, the impact of illegal armed groups has reduced forest cover, particularly in areas rich in gold and lands appropriate for cattle grazing. This multi-scale and multivariate approach provides a new insight into the complex relationship between woody cover change and land abandonment triggered mainly by armed conflict.

Key words: forest change; land abandonment; armed conflict; forced displacement; multiple spatial scales; multivariate approach.

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Introduction

Land change is a key component of global environmental change, and it has direct and indirect impacts on climate, biodiversity, and natural and human systems (Sala and others 2000; Geist and Lambin 2002; Lambin and others 2003; Thuiller and others 2005). Land change is driven by the complex interaction between multiple factors that act from global (for example, climate change, international markets) to local scales (for example, topography, soil fertility) (Lambin and others 2001; Geist and Lambin 2002; Aide and Grau 2004). Most land-change research has focused on drivers, patterns, and rates of deforestation (Achard and others 2002; Lambin and others 2003) because it is the prevailing process of forest cover change; however, others have suggested that there is a global reforestation trend (Rudel and others 2005; Kauppi and others 2006). Spontaneous forest regeneration on abandoned agricultural lands can potentially diminish the ecological damage of deforestation and degradation (Guariguata and Ostertag 2001; Chazdon 2008). Thus, forest cover change (that is, deforestation and reforestation) needs to be investigated because both processes have repercussions for biodiversity, soil conservation, carbon sequestration, and carbon emission.

Furthermore, it is important to determine the causes of deforestation and reforestation to improve management and conservation activities. In addition, these causes should be analyzed at multiple spatial scales because they are likely to vary depending on the location, resolution, and extent of the analysis (Veldkamp and Lambin 2001; Redo and others 2012). Forest cover change has been related to environmental factors because they can restrict or enhance the expansion of economic activities. For example, areas with favorable environmental conditions will be more economically attractive; therefore, more likely to be deforested. In contrast, areas with harsh environmental conditions located in less productive lands may experience agricultural abandonment and subsequent forest regrowth (Aide and Grau 2004; Wright and Muller-Landau 2006; Meyerson and others 2007). These recovery patterns have been documented in developed countries (Rudel and others 2005), and in many developing countries, including Colombia, Costa Rica, Ecuador, Mexico, and Puerto Rico (Rudel and others 2002; Céspedes and others 2003; Grau and others 2003; Klooster 2003; Sanchez-Cuervo and others 2012).

Several studies have shown that forest cover change is also affected by demographic dynamics, where deforestation is often associated with population growth (Geist and Lambin 2002; Carr 2004), whereas forest regrowth is mainly associated with a decline in local population (Aide and Grau 2004; Rudel and others 2005). For example, rural–urban migration could promote ecosystem recovery due to the reduction of human pressure on natural resources (Aide and Grau 2004; Wright and Muller-Landau 2006; Meyerson and others 2007). Industrialization and urbanization patterns have contributed to the rural–urban migration and abandonment of farming and grazing on marginal lands giving way to forest regrowth (Aide and Grau 2004). Other studies have stressed that forest cover change could also be triggered by armed conflict (Aide and Grau 2004). These conflicts can have mixed environmental effects, either promoting deforestation through overuse and empowerment of natural resources by the armed groups (Etter and others 2006a) or stimulating forest regrowth as agricultural fields are abandon and wood extraction is hindered (Witmer and O'Loughlin 2009; Stevens and others 2011). Some studies have shown that after the conflict deforestation increases because people resettled and expanded agricultural lands (Stevens and others 2011). These examples illustrate the complexity of land change during and following civil strife. Consequently, it is essential to understand the direct and indirect impacts of armed conflict on ecosystems and global biodiversity conservation (Sutherland and others 2009).

Colombia has had a long history of armed conflict and socio-political instability, and thus provides an excellent opportunity to incorporate armed conflict variables in a multivariate analysis of patterns of deforestation and reforestation. In Colombia, studies of land change have mainly focused on deforestation of lowland areas, particularly in the Amazon and Orinoco regions. Most of these studies in the Amazon have been conducted in the Caquetá river basin (Etter and others 2006a, b) and other lowland forest areas (Armenteras and others 2006), whereas in the Orinoco region studies have been conducted in the foothills (Viña and Cavelier 1999), in the lowlands (Etter and others 2006c) or in the entire region (Romero-Ruiz and others 2011). Only a few studies have been conducted in montane forests (Etter and van Wyngaarden 2000), and dry forest dynamics have been virtually ignored. The few studies that have included both reforestation and deforestation were conducted in specific areas located in both lowlands and highlands throughout Colombia (Etter and others 2006c; Dávalos and others 2011), and in a historical analysis (1,500–2,000) at the country scale (Etter and others 2008).

Typically, the factors explaining deforestation in Colombia have been related with accessibility, slope, climate, soils, demography, and land use (Armenteras and others 2006; Etter and others 2006c; Dávalos and others 2011). Nevertheless, these models have not taken into account multiple spatial scales or non-traditional variables such as armed conflict, gold production, poverty, and forced human displacement. The relative importance of the Colombian armed conflict on forest cover change has been debated (Etter and others 2006a; Dávalos and others 2011; Sanchez-Cuervo and others 2012), but no study has included armed conflict variables in a formal analysis. In a country with over 50 years of internal conflict, contrasting political decisions (for example, Plan Colombia), social instability, poverty, and the active presence of illegal armed groups, one could expect impacts on natural resources. These issues are particularly worrisome given that Colombia has been identified as a mega-diverse country (Chaves and Arango 1998) and that its biodiversity and natural resources are at risk. Therefore, it is essential to identify the variables that influence forest cover change at multiple scales to predict the future trajectory of forest dynamics, and to understand the causes of habitat and biodiversity loss.

In this study, we analyzed woody vegetation change (deforestation and reforestation) between 2001 and 2010 for all municipalities at the country, biome, and ecoregion scales. In addition to incorporating traditional environmental and socioeconomic variables, we also incorporated variables that reflected the unique history of Colombia (for example, variables related to armed conflict). The simultaneous analysis of deforestation and reforestation patterns coupled with the analysis of the factors explaining these changes can provide important insights for land change science and the development of appropriate conservation strategies.

Methods

Study Area

Colombia is rich in natural and mineral resources; half of the country is covered by forest and there are large deposits of metals, oil, and natural gas. Colombia also has remarkable differences in elevation (0–5800 m), precipitation (350–12,000 mm/y), and annual mean temperature (over 27°C in the lowlands and between 13 and 17°C in the highlands), which have promoted high diversity of habitats and species, making Colombia one of the most biodiverse countries on earth (Chaves and Arango 1998).

Even though Colombia has vast amounts of natural resources, a long history of social disparity, unequal distribution of land and wealth, coupled with high levels of poverty promoted the rise of several guerrilla groups during the 1960s. Since the 1980s, the armed conflict expanded as these groups shifted from political motives to the control of natural and mineral resources to accumulate wealth and power (Cotte 2010). Since the 1990s, the principal illegal-armed groups are the Fuerzas Armadas Revolucionarias de Colombia (FARC-left-wing) and the Autodefensas Unidas de Colombia or paramilitaries (AUC-right-wing). The FARC is financed partially from the drug trade and devotes about one-third of its soldiers to indirect or direct coca-related activities (Echandía 1999). This illegal economy (stimulated by the increase of international demand) had a gross value of about US$517 million in 2008, and the total area under illicit crops increased from approximately 250 km^2 in 1985 to approximately 1,600 km^2 in 1999 (UNODC 2008). The paramilitary groups are mainly financed by drug traffickers, landowners with extensive properties, and even security officers for petroleum companies (Gillard and others 1998). The paramilitaries typically cause forced displacement of rural populations (for example, peasants) by seizing the land and resources for their clients. Therefore, landowners and traffickers are able to expand their holdings and increase the size of their cattle-ranching farms (Cubides 1999). The government response to overcome the drug economy was the implementation of Plan Colombia during the term of President Andrés Pastrana (1998–2002). Under President Alvaro Uribe (2002–2010), Plan Colombia continued with the coca crop eradication program, but expanded to include the ‘‘Democratic Security’’ program. This program is based on the premise that the major socio-economic problems of Colombia are caused by violence and insecurity; therefore, the program focused on reducing the presence and power of guerrilla groups, particularly the FARC (Acevedo and others 2008). These socio-political issues represent important factors that may influence land change in Colombia.

In this study, municipalities (second administrative scale) were the main unit of analysis. We included 1,097 municipalities and 20 *areas no municipalizadas* or *corregimientos* (name of the third administrative scale in Colombia) because these areas occupied almost 190,000 km^2 in the Amazonas, Guainía, and Vaupes departments.

Land-Use Mapping

Our LULC classification methodology follows the methods described in Clark and others (2012) and Sanchez-Cuervo and others (2012). Here, we summarize the three main steps used to produce the maps analyzed in this study.

First, reference data (over 10,000 samples) for classifier training and accuracy assessment were collected with human interpretation (authors) using a custom web-based application: the Virtual Interpretation of Earth Web-Interface Tool (VIEW-IT) that overlays MODIS pixel (250 × 250 m) on high-resolution imagery in Google Earth (Clark and Aide 2011). Each sample was assigned the year of the image and the percent cover of seven cover classes: woody (woody vegetation including trees and shrubs), herbaceous vegetation, agriculture, plantations, built-up areas, bare areas, and water. Samples were assigned to a class if the cover in this class was 80% or more. Samples with 20–80% woody, with a bare soil, herbaceous vegetation or agriculture components were assigned to a mixed-woody class.

Second, we used the MODIS MOD13Q1 Vegetation Indices 250 m product (Collection 5) for LULC classification (Clark and others 2010; Clark and others 2012). The product is a 16-day composite of the highest-quality pixels from daily images and includes the Enhanced Vegetation Index (EVI), red, near infrared (NIR), and mid-infrared (MIR) reflectance and pixel reliability with 23 scenes per year available from 2001 to present (Huete and others 2002). For each pixel, we calculated the mean, standard deviation, minimum, maximum, and range for EVI, and red, NIR and MIR reflectance values for calendar years 2001 to 2010. Statistics were calculated for all 12 months, 2 six-month periods, and 3 four-month periods. The MOD13Q1 pixel reliability layer was used to remove all unreliable samples (value = 3) prior to calculating statistics.

Third, we mapped LULC with the Random Forests (RF) tree-based classifier (Breiman 2001) following methods in Clark and others (2012). The RF classifier was implemented using R (v. 2.12.2; (R 2011) and the *randomForest* package (v. 4.6-2; (Liaw and Wiener 2002)). Predictor variables were MODIS-based 4-, 6- and 12-month statistics for EVI, red, NIR and MIR, and were extracted for the year corresponding to the QuickBird image year (2001 to 2010; Clark and Aide, 2011) for each GE reference sample. We trained four separate RF based on samples in separate biomes (that is, Tropical and Subtropical Moist Broadleaf Forests, Tropical and Subtropical Dry Forests, and Tropical and Subtropical Tropical Grasslands, Savannas and Shrublands) with boundaries defined by municipalities (see Sanchez-Cuervo and others 2012). We used R and the RGDAL library to apply the RF objects to every pixel in MODIS tiles covering the zone-biome region for each year, 2001 to 2010. The four separate maps were then mosaicked and reclassified (post-classification) by grouping agriculture and herbaceous, mixed-woody and plantations, and built-up and bare. The combining of classes into a five-class scheme helped reduce inter-class confusion and increase map accuracy while still allowing us to focus on major trajectories of change in woody vegetation. The final five-class maps had an average overall accuracy of 87.4% (±4.3%), with non-water average producer's accuracies ranging from 36.3% (mixed-woody/plantations) to 96.9% (woody) and user's accuracies ranging from 72.5% (mixed-woody/plantations) to 89.4% (woody) (see Sanchez-Cuervo and others 2012). The five-class LULC map was summarized for the 1,117 municipalities or study units.

Explanatory Variables

We collected data for 52 variables at the municipality scale (n = 1,117) to evaluate their effect on woody cover change. These variables were grouped into six categories: (1) Accessibility: density of rivers, paved roads, unpaved roads, and dirt roads; (2) Land-use data: change in coca crops area (2001–2010) and the change in crop area (2006–2010) for cotton, corn, mechanized rice, irrigated rice, plantains, potatoes, and sugarcane. We also included the extent of coffee plantations (2007); (3) socio-economic: poverty (1993 and 2005), head of cattle (2006), and total gold production (2008); (4) armed conflict: forced human displacement (1996 and 2009), and its change (1996 to 2009), paramilitary-AUC presence (2001 and 2005), and guerilla-FARC presence (2001 and 2005); (5) demographic: total population size (1993, 2005, and 2010), total population density (1993, 2005, and 2010), total population change (1993–2005 and 2005–2010), and total population density change (1993–2005 and 2005–2010); (6) environmental: biome, ecoregion, topographic index, elevation, precipitation, and temperature. See Table 1 and supplementary material Appendix A for detailed descriptions of these variables and their sources.

Woody Cover Dynamics

To evaluate the patterns of woody cover change within each municipality, we analyzed the trends performing a linear regression of woody cover area (dependent variable) against time (independent variable, the 10 years of the study—2001 to 2010). If more than 1% of the total municipality area had pixels mapped as No Data for a given year, the land cover data for that year were removed from the regression. To determine the strength of this linear relationship (area vs. time) we used Pearson's correlation coefficient (R), where positive values of

Table 1. Description and Data Sources of Independent Variables for Each Municipality in Colombia

Category	Code	Variable description	Source
Accessibility	RiverDen	River density: calculated as the total river length divided by municipality area (km^2)	SIGOT-IGAC[1]
	PavroadDen	Paved road density: calculated as the total road length divided by municipality area (km^2)	SIGOT-IGAC
	UnpavroadDen	Unpaved road density: calculated as the total unpaved road length divided by municipality area (km^2)	SIGOT-IGAC
	DirtroadDen	Dirt road density: calculated as the total dirt road length divided by municipality area (km^2)	SIGOT-IGAC
Land use	CocaChange0110	Difference between extent of coca crop area in 2001 and 2010 (km^2)	SIMCI-UNODC[2]
	CottonChange0610	Difference between extent of cotton crop area in 2006 and 2010 (km^2)	SIGOT-IGAC
	CornChange0610	Difference between extent of corn crop area in 2006 and 2010 (km^2)	SIGOT-IGAC
	MechRiceChange0610	Difference between extent of mechanized rice crop area in 2006 and 2010 (km^2)	SIGOT-IGAC
	IrrigatedRiceChange0610	Difference between extent of irrigated rice crop area in 2001 and 2010 (km^2)	SIGOT-IGAC
	PlantainChange0610	Difference between extent of plantain plantations area in 2006 and 2010 (km^2)	SIGOT-IGAC
	PotatoesChange0610	Difference between extent of potatoes crop area in 2006 and 2010 (km^2)	SIGOT-IGAC
	SugarcaneChange0610	Difference between extent of sugarcane crop area in 2006 and 2010 (km^2)	SIGOT-IGAC
	Coffee07	Extent of coffee crop area in 2007 (km^2)	SIGOT-IGAC
Socio-economic	Poverty93	Unsatisfied basic needs (%) in 1993	DANE[3]
	Poverty05	Unsatisfied basic needs (%) in 2005	DANE
	HeadCattle06	The number of head of cattle in 2006	SIGOT-IGAC
	Gold08	Total gold production in 2008 (gr)	SIGOT-IGAC
Armed conflict	Displacement96	Number of displace people registered in 1996	SIPOD[4]
	Displacement09	Number of displace people registered in 2009	SIPOD
	DisplacementChange9609	Difference between displace people in 1996 and 2009	SIPOD
	AUC01	Paramilitaries active presence: calculated as density level in 2001	Derechos Humanos[5]
	AUC05	Paramilitaries active presence: calculated as density level in 2005	Derechos Humanos
	FARC01	Guerrilla active presence: calculated as the number of confrontations against national army in 2001	Derechos Humanos
	FARC05	Guerrilla active presence: calculated as the number of confrontations against national army in 2005	Derechos Humanos

Table 1. continued

Category	Code	Variable description	Source
Demographic	Population93	Total population registered in 1993 census	DANE
	PopulationDen93	Population density: total population per km^2 in 1993	DANE
	Population05	Total population registered in 2005 census	DANE
	PopulationDen05	Population density: total population per km^2 in 2005	DANE
	PopulationChange9305	Difference between total population registered in 1993 and 2005	DANE
	PopulationDenChange9305	Difference between total population density in 1993 and 2005	DANE
	Population10	Projection of population for 2010 calculated from registered population between 1993 and 2005	DANE
	PopulationDen10	Population density: total population per km^2 in 2010	DANE
	PopulationChange0510	Difference between total population registered in 2005 and 2010	DANE
	PopulationDenChange0510	Difference between total population density in 2005 and 2010	DANE
	UrbanChange9305	Difference between urban population in 1993 and 2005	DANE
	Rural93	Number of people registered in rural areas in 1993	DANE
	Rural05	Number of people registered in rural areas in 2005	DANE
	Rural10	Number of people registered in rural areas in 2010	DANE
	RuralChange9305	Difference between rural population in 1993 and 2005	DANE
	RuralChange0510	Difference between rural population in 2005 and 2010	DANE
Environmental	Biome	World Wildlife Fund biome classification	Olson and others (2001)
	Ecoregion	Thirteen ecoregions following World Wildlife Fund ecoregion classification	Olson and others (2001)
	TopoInd	Topography index: standard deviation derived from SRTM (90 m): larger values represented complex topography (e.g., mountains)	CGIAR-CSI[6]
	DEMMinimum	Minimum elevation derived from SRTM (90 m)	CGIAR-CSI
	DEMMaximum	Maximum elevation derived from SRTM (90 m)	CGIAR-CSI
	DEMMean	Mean elevation derived from SRTM (90 m)	CGIAR-CSI
	PrecipStdMeanMonthly	Standard deviation of mean monthly precipitation (1990–2005)	CRUD[7]
	PrecipMeanAnnual	Mean annual precipitation (1990–2005)	CRUD
	PrecipStdAnnual	Standard deviation of annual precipitation (1990–2005)	CRUD
	TempStdMeanMonthly	Standard deviation of mean monthly temperature (1990–2005)	CRUD
	TempMeanAnnual	Mean annual temperature (1990–2005)	CRUD
	TempStdAnnual	Standard deviation of annual temperature (1990–2005)	CRUD

[1] *SIGOT-IGAC: Geoportal of the Agustin Codazzi Geographic Institute (Sistema de Información Geográfica para la Planeación y el Ordenamiento Territorial Nacional.*
[2] *SIMCI-UNODC: United Nations Office on Drugs and Crime through the Colombian Integrated System for Illicit Crops Monitoring project.*
[3] *DANE: National Administrative Department of Statistics.*
[4] *SIPOD: Sistema de Información para la Población Desplazada in the Agencia Presidencial para la Acción Social y la Cooperación Internacional (http://www.dps.gov.co/EstadisticasDesplazados/GeneralesPD.aspx?idRpt=3).*
[5] *Derechos Humanos: Programa Presidencial de Derechos Humanos y Derecho Internacional Humanitario.*
[6] *CGIAR-CSI: Consultative Group on International Agriculture Research-Consortium for Spatial Research. SRTM (Shuttle Radar Topography Mission) 90 m Database (http://srtm.csi.cgiar.org).*
[7] *CRUD: Climatic Research Unit Datasets, University of East Anglia (2008).*

R represent an increase in woody cover and negative values of R represent a decrease. We used this approach to standardize woody cover change through time due to outliers or missing data in any given year, and the use of R for trends allows us to compare municipalities, which can vary in size from 17,6 to 65,568 km^2. In addition, this trend analysis takes advantage of the 10 years of data, and it is not based on just two points in time. Although with MODIS we cannot detect changes at the sub pixel level (250 m), the accumulative change from the small scale conversion can be captured by the trend analysis based on the aggregation of all pixels within a municipality (see Sanchez-Cuervo and others 2012; Clark and others 2012). Municipalities with significant changes in woody vegetation had $P \leq 0.05$. All analyses incorporating absolute area were performed using estimates based on each municipality's regression model, rather than the raw area data used to fit the model. We calculated the net change in cover (km^2) of the woody cover class between 2001 and 2010 considering the six biomes and 13 ecoregions.

To assess the effect of the 52 explanatory variables on woody cover change we used Random Forest (RF) regression analysis using the package randomForest (Liaw and Wiener 2002) for R software (R, 2011). We used RF regression analysis instead of classic regression models (for example, ordinary least squares) due to RF's ability to handle complex data distributions, non-linear relationships, and spatial autocorrelation (Segal 2004). The random forest model has two parameters: n_{tree} (overall number of trees in the forest) and m_{try} (randomly preselected predictors for each split). It is important to set n_{tree} and m_{try} because these parameters control variable selection and variable importance are unbiased (Strobl and others 2007). The square root of the number of variables is recommended as a m_{try} value to guarantee stable results (Strobl and others 2007). Therefore, we grew 2,000 trees and we set m_{try} to seven because we incorporated 52 explanatory variables. RF for regression analysis determines the most predictive variables reporting a percentage increase in mean square error (%IncMSE) instead of coefficient of multiple determination (R^2). Our random forest model included woody cover trends (Pearson's correlation coefficient R) as the dependent variable and the 52 explanatory variables as the independent variables (see Table 1 for more details). We performed separate random forest models for: (a) all municipalities in Colombia, (b) five biomes (excluding the Mangroves biome due to the small number of municipalities; $n = 6$) and (c) 13 ecoregions. Finally, to visualize the relationship between woody cover change (R) and the explanatory variable with the highest predictive power we created a scatterplot overlaid by a partial dependence plot. The partial dependence plot shows the directionality and range of values of the predictor variable where there are important changes in forest cover.

Results

Patterns of Woody Cover Change Between 2001 and 2010

There was a clear geographical pattern of woody cover change between 2001 and 2010 (Figure 1): municipalities with significant gains were concentrated in the Andes, whereas municipalities that lost woody cover occurred mainly in the lowlands. Overall, woody cover increased from 580,420 km^2 in 2001 to 597,383 km^2 in 2010, with a net gain of 16,963 km^2 for the entire country. At the biome scale, the net gain in woody vegetation was located mainly in the Moist Forest biome (16,077 km^2) followed by the Desert (1,629 km^2) and the Dry Forest (688 km^2) biomes (Figure 2A). In contrast, woody cover showed a net loss only in the Grassland biome (−1,636 km^2). At the ecoregion scale, woody cover increased in eleven ecoregions, particularly in the Montane Forest ecoregions with a net gain that varied from 4,535 km^2 in the Northern Andean to 891 km^2 in the Cordillera Oriental ecoregions (Figure 2B). The Moist Forest ecoregions also showed an increase in woody cover from 2,955 in the Magdalena-Urabá Moist to only 144 km^2 in the Caquetá Moist which is the largest ecoregion in Colombia (472,066 km^2). The Dry Forest ecoregions had a net gain in woody cover, particularly in the Sinú Valley (1,290 km^2) and in the Magdalena Valley (164 km^2), whereas the Apure-Villavicencio had a net loss of 691 km^2. The Guajira Xeric and the Northern Andean Páramo ecoregions also showed an increase of woody cover of 1,778 and 63 km^2, respectively. The Llanos ecoregion had the greatest net loss (−1,636 km^2) of all ecoregions.

Factors Explaining Woody Cover Change at Multiple Scales

At the national scale, the random forest regression analysis explained 36.8% of the variation in woody vegetation change. This analysis showed that environmental variables were the most important predictors (Table 2). For example, the standard deviation of mean monthly temperature, minimum

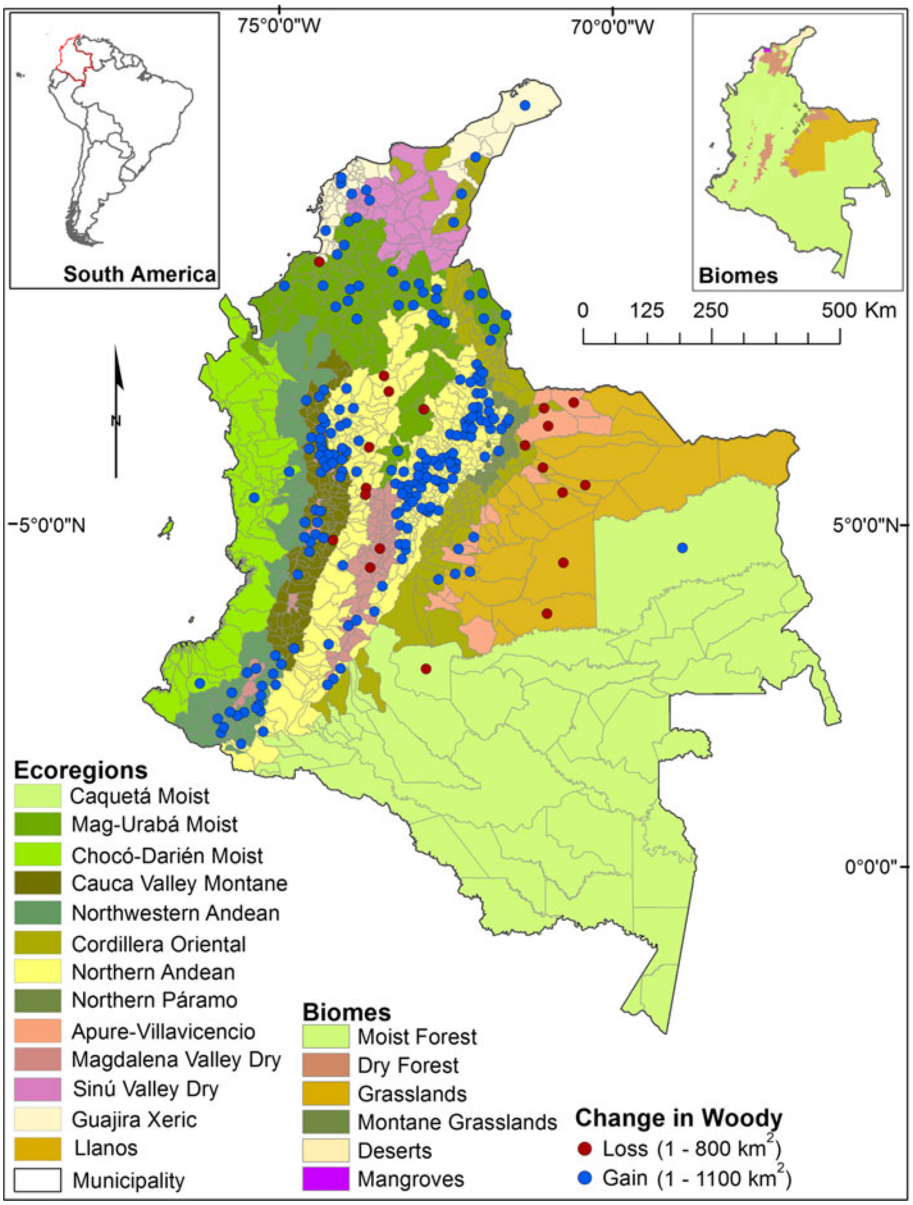

Figure 1. Map of the 13 ecoregions. *Red* and *blue* dots represent municipalities with significant loss or gain in woody cover, respectively. *Inset* shows the distribution of the six biomes (Color figure online).

elevation, and mean annual temperature were the three most important variables explaining deforestation and reforestation patterns. The partial dependency plots showed that woody cover decreased in municipalities with a higher standard deviation of mean monthly temperature (>0.6°C), at lower elevations (<250 m; Figure 3A, B), and higher temperatures (>25°C) in the Grassland biome but also in other municipalities scattered throughout the Moist Forest biome. In contrast, woody cover increased in municipalities with a lower standard deviation of mean monthly temperature, in the highlands, and lower temperatures particularly in the Moist Forest biome.

At the biome scale, the random forest regression analysis explained more than 28% of the variation in woody vegetation in the Moist Forest, Dry Forest, and the Grassland biomes, whereas in the Montane Grassland and the Desert biomes the analysis explained less than 20% (Table 2). Environmental variables explained most of the variation in woody cover, particularly in the Moist Forest, the Dry Forest, and the Deserts biomes, whereas socio-economic and armed conflict variables were the most important factors in the Grassland and the Montane Grassland biomes. The partial dependency plots for the Moist Forest biome showed that woody cover increased in municipalities with mean annual temperature above16°C, high population density (>30 people/km^2 in 2005), and low seasonality (<0.6°C), particularly in the Northern and the Northwestern Andean ecoregions (Table 2;

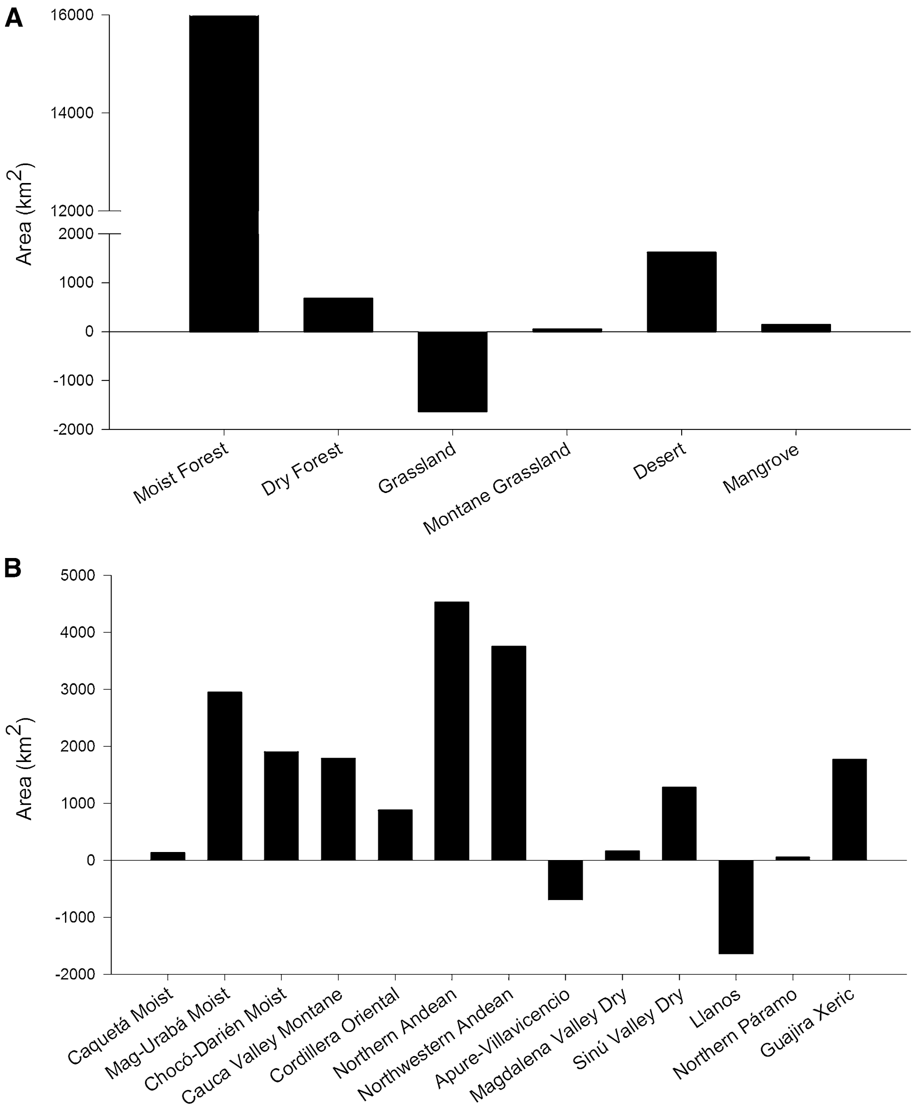

Figure 2. Net change of woody cover from 2001 to 2010 by biome (**A**) and ecoregion (**B**) scales.

Figure 4). In contrast, woody cover decreased in municipalities with high mean annual temperature (>25°C), low population density (<30 people/km^2 in 2005), and high seasonality (>0.6°C) mostly in the Caquetá Moist Forest and Northern Andean Montane Forest ecoregions. In the Dry Forest biome, woody cover increased in municipalities with annual precipitation below 1,500 mm, at elevations above 200 m, and with low unpaved road density, mainly in the Sinú Valley ecoregion (Table 2; Figure 4). In contrast, woody cover decreased in municipalities located in wetter areas, at lower elevations, and where there was a higher density of unpaved roads, mainly in the Apure-Villavicencio and the Magdalena Valley ecoregions. In the Desert biome, woody cover increased mostly when topographic variation increased, at higher elevations (>100 m), and where there were low densities of rivers (Table 2; Figure 4). In the Grassland biome, woody cover decreased as forced displacement increased in 1996, in municipalities with larger populations in 1993 (>5000people), and in municipalities with a lower unpaved road density. In the Montane Grassland biome, woody cover decreased in the poorest municipalities in 1993 and 2005 (UBN > 30%) and in those with higher population density (>30 people/km^2 in 2005).

At the ecoregion scale, the random forest regression analysis explained more than 20% of the variation in woody vegetation in six of the 13 ecoregions (Table 2). The woody cover change in the Moist Forest ecoregions (that is, lowlands) within the Moist Forest biome was explained mostly by environmental variables followed by demographic variables. The partial dependency plots in the Moist Forest ecoregions illustrated that in the Caquetá Moist Forest, woody cover decreased mostly in municipalities with high seasonality (>0.20°C) and

Table 2. Random Forest Results at the Country, Biome, and Ecoregion Scales

Random forest models (% Var)	Important variables	IncMSE %	Trends in woody cover change
Country scale % Var = 36.8	TempStdMeanMonthly	32.2	Decreased as standard deviation increased (>0.6°C)
	DEMMinimum	30.1	Increased as elevation increased (>250 m)
	TempMeanAnnual	29.0	Decreased as mean temperature increased (>25°C)
Biome scale Moist Forest % Var = 28.2	TempMeanAnnual	27.0	Decreased as mean temperature increased (>25°C)
	PopulationDen05	26.0	Increased as pop density increased (>30 people/km^2)
	TempStdMeanMonthly	24.3	Decreased as standard deviation increased (>0.6°C)
Ecoregion scale Caquetá Moist % Var = 16.2	TempStdAnnual	13.3	Decreased as standard deviation increased (>0.20°C)
	PopulationDen05	12.7	Decreased as pop density increased (>10 people/km^2)
	PopulationDen10	12.6	Decreased as pop density increased (>10 people/km^2)
Mag-Urabá Moist % Var = 22.2	TempStdMeanMonthly	16.8	Increased as standard deviation increased (>0.45°C)
	PrecipMeanAnnual	11.5	Decreased at higher precipitation (>2,500 mm)
	PrecipStdAnnual	11.3	Increased as standard deviation increased (>350 mm)
Chocó-Darién Moist % Var = 13.9	PopulationChange0510	10.5	Increased as pop change from lost to gain people
	Poverty93	8.9	Increased as poverty in 1993 increased (>70%)
	PrecipStdAnnual	7.9	Increased as standard deviation increased (>600 mm)
Cauca-Valley Montane % Var = 25.0	DisplacementChange9609	18.0	Decreased as displacement change from lost to gain
	DEMMean	15.0	Decreased at higher elevation (>3,000 m)
	AUC05	10.7	Increased as AUC presence increased
Cordillera Oriental Montane % Var = 24.0	AUC01	23.4	Increased as AUC presence increased
	DEMMean	17.0	Decreased at higher elevation (>1,000 m)
	HeadCattle06	12.0	Decreased as head cattle increased

Table 2. continued

Random forest models (% Var)		Important variables	IncMSE %	Trends in woody cover change
	Northern Andean Montane % Var = 27.1	AUC05	20.5	Decreased as AUC presence increased
		Gold08	19.8	Decreased as gold production increased
		TempStdMeanMonthly	16.1	Increased as standard deviation increased (>0.40°C)
	Northwest Andean Montane % Var = 3.4	PopulationDen05	13.0	Increased as pop density increased (>20 people/km^2)
		PopulationDen10	10.1	Increased as pop density increased (>15 people/km^2)
		HeadCattle06	9.0	Decreased as head cattle increased
Dry Forest % Var = 40.3		PrecipMeanAnnual	23.2	Decreased at higher precipitation (>1,500 mm)
		DEMMinimum	22.4	Increased as elevation increased (>200 m)
		DirtroadDen	22.2	Decreased with higher unpaved road density
	Apure-Villavicencio % Var = 14.2	DEMMin	13.0	Increased at higher elevation (>160 m)
		DEMMean	8.3	Increased at higher elevation (>200 m)
		TempStdMeanMonthly	6.0	Decreased as standard deviation increased (>0.75°C)
	Magdalena Valley Dry % Var = 48.6	TempStdAnnual	25.6	Increased as standard deviation increased (>0.35°C)
		DEMMin	22.1	Increased at higher elevation (>300 m)
		PrecipMeanAnnual	18.0	Decreased at higher precipitation (>1500 mm)
	Sinú-Valley Dry % Var = 26.0	TempStdMeanMonthly	11.8	Decreased as standard deviation increased (>0.50°C)
		PrecipMeanAnnual	10.8	Decreased at higher precipitation (>1,500 mm)
		Rural05	9.0	Decreased as rural population increased
Grassland % Var = 43.9	Llanos	Displacement96	13.3	Decreased as displacement in 1996 increased
		Population93	10.3	Decreased as population in 1993 increased (>5,000 people)
		UnpavroadDen	10.1	Increased with higher unpaved road density
Montane Grassland % Var = 17.5	Northern Páramo	Poverty05	15.2	Decreased as poverty in 2005 increased (>30%)
		PopulationDen05	9.4	Increased as pop density increased (>70 people/km^2)
		Poverty93	8.5	Decreased as poverty in 1993 increased (>30%)
Desert % Var = 13.0	Guajira Xeric	TopoInd	13.5	Increased as standard deviation increased
		DEMMax	10.0	Increased at high elevations (>100 m)
		RiverDen	7.5	Decreased as river density increased

The results include the percent of variation explained by each model, the percent increase of mean square error (IncMSE%) when the variable was excluded, and the effect of the three most important variables on woody cover change.

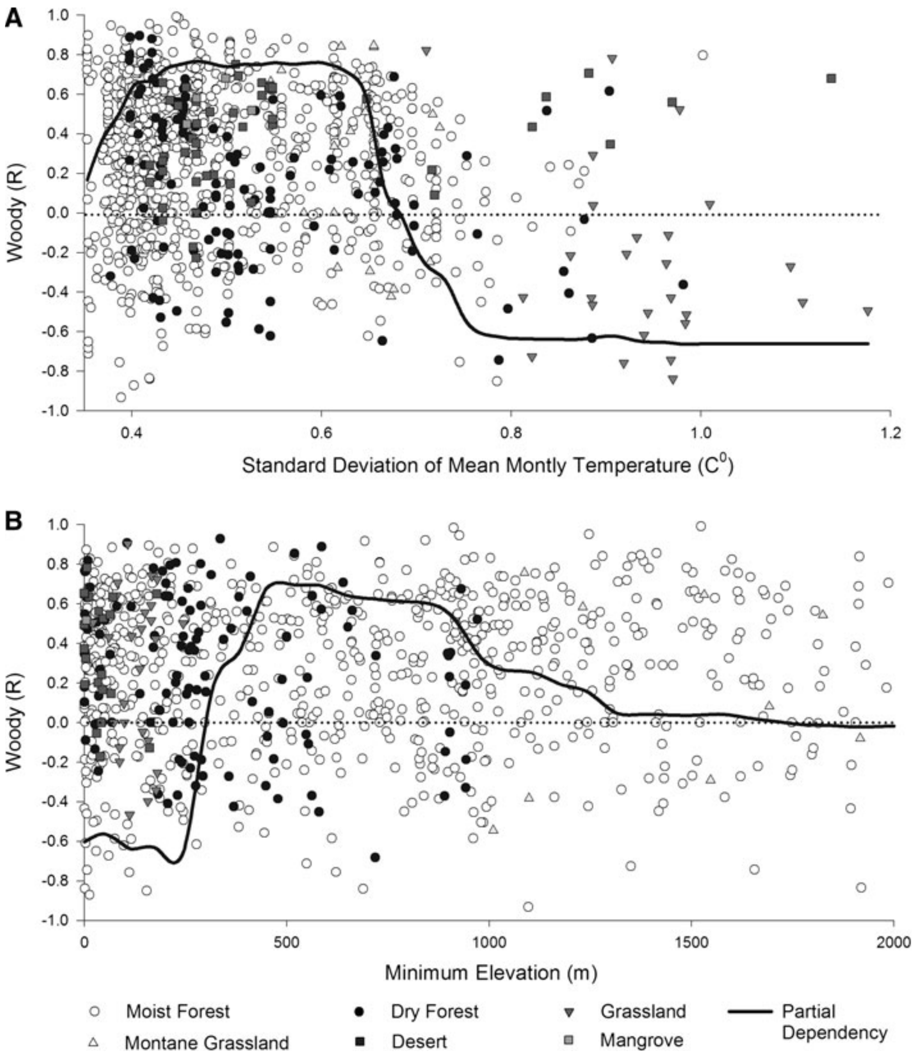

Figure 3. Scatterplots of the standard deviation of mean monthly temperature (**A**) and minimum elevation (**B**) and woody vegetation change (R) for all municipalities in Colombia. A partial dependency plot was added to show directional effect.

with high population density (>10 people/km^2 in 2005 and 2010; Table 2; Figure 5A). In the Magdalena-Urabá Moist Forest, woody cover increased in municipalities with high seasonality (>0.45°C), lower precipitation (<2500 mm), and high standard deviation in precipitation (>350 mm). In the Chocó-Darién Moist Forest, woody were increased in municipalities that gained population between 2005 and 2010, in the poorest municipalities in 1993 (UBN > 70%), in municipalities with high standard deviation in precipitation (>600 m).

In all Montane Forest ecoregions (that is, highlands) within the Moist Forest biome, woody cover change was mostly explained by demographic, armed conflict, socio-economic, and environmental variables (Table 2). The partial dependency plots in the Montane Forest ecoregions showed that in the Cauca Valley Montane Forest, woody vegetation increased mostly in municipalities that showed a reduction in forced displacement between 1996 and 2009, at elevations below 3000 m, and with a high density of paramilitary groups in 2005 (Table 2; Figure 5C). Likewise, in the Cordillera Occidental woody vegetation increased in places with a high density of paramilitary groups in 2001, at elevations below 1,000 m, and low numbers of cattle. In the Northern Andean, the largest Montane Forest ecoregion, the effect of the paramilitary groups seems to be opposite compared with the previous ecoregions because woody cover decreased in municipalities with a high density of paramilitary groups in 2005. Woody cover also decreased in areas with high gold production and with low seasonality (<0.40°C). In the Northwestern Andean, woody cover gains occurred in municipalities with a high population density (>20 people/km^2 in 2005 and 2010) and a low number of cattle.

In the three Dry Forest ecoregions within the Dry Forest biome, woody vegetation change was explained mainly by environmental variables (Table 2). The partial dependency plots in the Dry

Forest ecoregions showed that in the Apure-Villavicencio ecoregion, woody cover loss occurred in municipalities at elevations below 200 m and with high seasonality (>0.75°C; Table 2; Figure 5B). In contrast, in the Magdalena Valley Dry Forest, woody cover decreased mostly in municipalities with low seasonality (<0.35°C), at elevations above 300 m, and with precipitation above 1,500 mm. In the Sinú Valley Dry Forest, woody cover gains were located in municipalities with low seasonality (<0.50°C), low precipitation, and low rural population. Finally, the Grassland, the Montane Grassland, and the Desert biomes only included the Llanos, the Northern Andean Páramo, and the Guajira Xeric ecoregions, respectively; therefore, we did not make partial dependency plots for these ecoregions.

Discussion

Colombia experienced a net gain in woody cover between 2001 and 2010. This is a positive trend for biodiversity, soil conservation, and carbon sequestration, but gaining a hectare of early successional species is not the same as losing a hectare of intact forest and its accompanying fauna (Gibson and others 2011). But, if these areas are allowed to continue recovering, secondary forest can recover forest structure, function, and diversity, and provide habitat for a large proportion of the fauna (Bowen and others 2007; Chazdon 2008). Analyses at the biome and ecoregion scales showed that woody cover change increased mostly in the Moist Forest biome, particularly in the Montane Forest ecoregions. In contrast, woody cover change decreased in the Grassland and in the Dry Forest

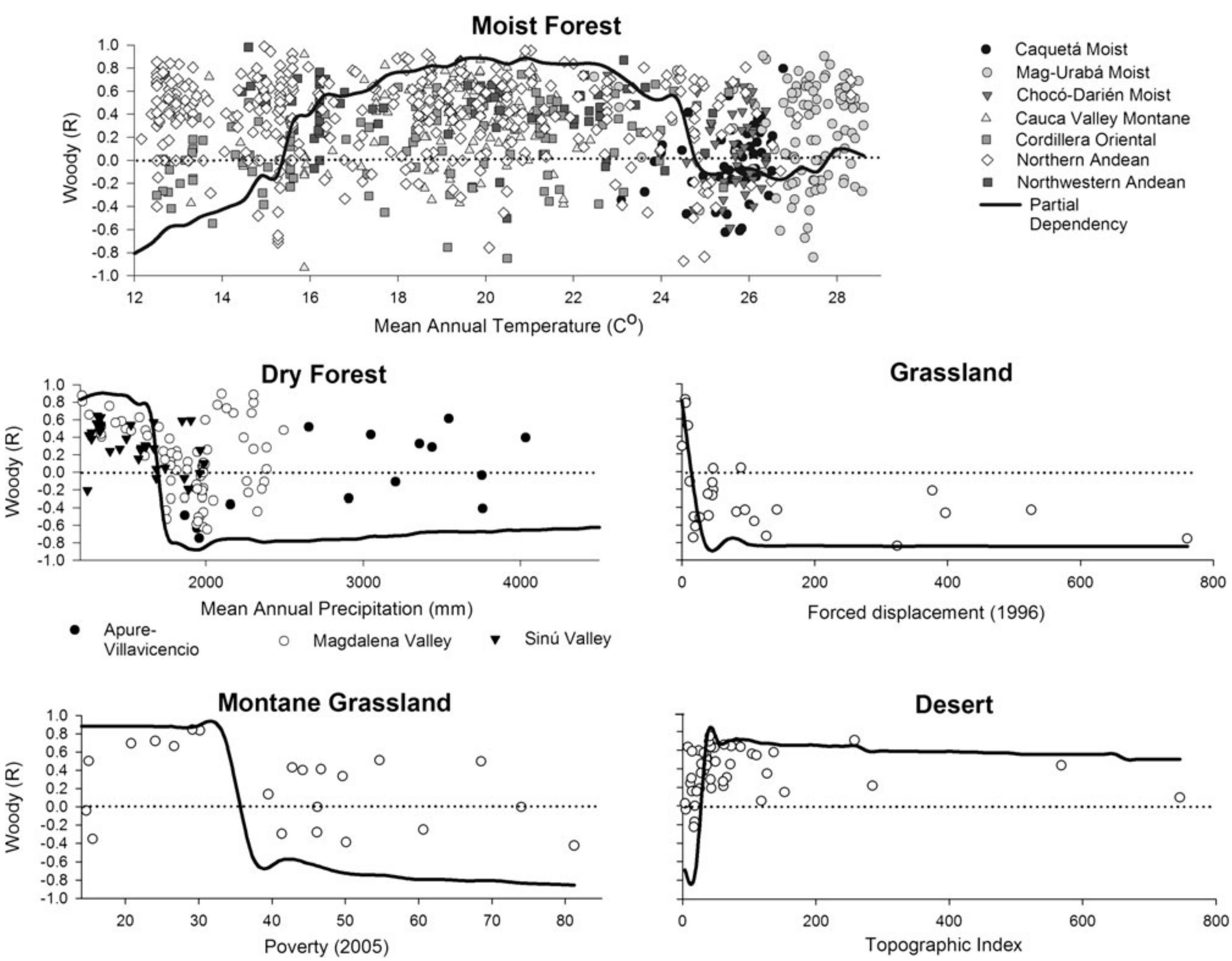

Figure 4. Scatterplots of the mean annual temperature, mean annual precipitation, forced displacement (1996), poverty (2005), and topographic index and woody vegetation change (R) by biome. A partial dependency plot was added to show directional effect.

biomes, particularly in the Llanos and Apure-Villavicencio Dry Forest ecoregions. At the national scale, environmental variables were the most important explaining the patterns of reforestation and deforestation. At the biome and ecoregion scale, environmental variables were important, but demographic, armed conflict, accessibility, and socio-economic variables also helped to explain the variation in woody cover change.

Variables Driving Woody Cover Change at Multiple Scales

At the national scale, the random forest analysis showed that environmental variables were the most important factors explaining woody vegetation change. Our results suggest that reforestation is occurring mostly in areas with low seasonality and low temperatures in the highlands of the Moist

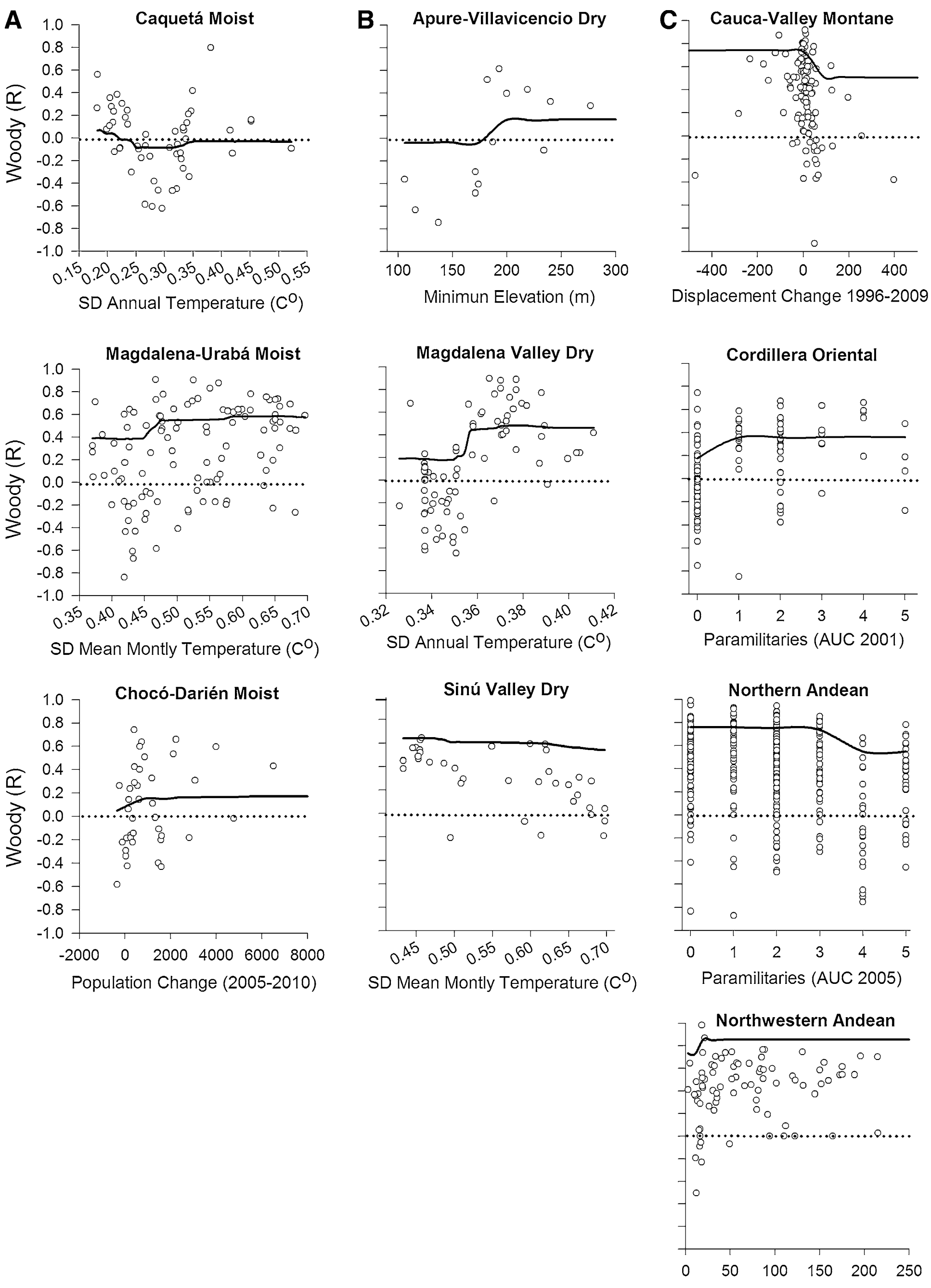

Figure 5. Scatterplots of the most important variables explaining woody cover change for the Moist Forest (**A**), the Dry Forest (**B**), and the Montane Forest (**C**) ecoregions. A partial dependency plot was added to show directional effect.

Forest biome. In contrast, deforestation occurred mainly in the Grassland biome and in municipalities scattered throughout the Moist Forest biome, particularly at low elevations in areas with high temperatures and high seasonality. This pattern of reforestation concentrated in the highlands and deforestation in the lowlands suggests that at the country scale the environmental conditions associated with these regions play an important role in determining land use decisions. These results also reflect the contrasting historical settlement patterns of the country, where most of the population is concentrated in the highlands (Andean region), and where today there has been high levels of rural–urban migration (Etter and others 2008). Although similar results have been described in other Latin American countries (Thomlinson and others 1996; Aide and others 2012; Bonilla-Moheno and others 2012; Redo and others 2012), given the biogeographic, socio-cultural, economic, and demographic differences across Colombia, it is not surprising that other factors (for example, precipitation, illegal-armed groups, poverty) are important for land change at more local spatial scales.

In the Moist Forest biome, factors that explain woody cover change were similar to the predictors (for example, temperature) found at the country scale because this biome covers almost 80% of the national territory. Nevertheless, demographic variables were important in this biome because the random forest model took into account the variation in population density within the Moist Forest (that is, Amazon region-low) and the Montane Forest ecoregions (that is, Andes region-high). Although some studies have shown that demographic factors do not explain vegetation change at broader scales (Aide and others 2012; Bonilla-Moheno and others 2012; Redo and others 2012), others show that these factors can have a major impact on land change (Keys and McConnell 2005; Hazell and Wood 2008). Overall, our results in the largest Colombian biome support the conclusion that reforestation often occurs in areas with high population density (Hecht and Saatchi 2007; Aide and others 2012) mainly in the Andes region (for example, Northwestern Andean ecoregion). This pattern is probably the consequence of urbanization or changes in local economies that promote agricultural intensification in productive areas and woody regrowth in others (Grau and others 2003; Aide and Grau 2004; Rudel and others 2005; Meyfroidt and Lambin 2008). Nevertheless, in the Caquetá Moist Forest ecoregion woody cover decreased as population density increased and the majority of deforestation occurred in the Alto Caquetá and Alto Putumayo regions. This could be the result of cattle ranching given that the agriculture/herbaceous class increased by 2,200 km^2, whereas the woody cover decreased by 1,800 km^2 in these two regions. Our results concur with previous studies in the western Amazon (Sierra 2000; Armenteras and others 2006; Etter and others 2006c).

In the Dry Forest biome, reforestation took place mainly in municipalities with low precipitation, at high elevations, and where there were low densities of dirt roads. These non-optimal environmental conditions appear to have promoted the abandonment of marginal agricultural activities in the Sinú Valley and Magdalena Valley Dry Forest ecoregions. In addition, the cotton industry has declined greatly in these areas due to a shift in cotton production to other countries (Sanchez-Cuervo and others 2012). In contrast, municipalities with higher precipitation, at low elevations, and with high densities of dirt roads tended to be deforested for the expansion of croplands and cattle ranching, particularly in the Apure-Villavicencio (mainly the foothills of the Arauca department) and in the Magdalena Valley Dry Forest. In these municipalities woody cover decreased by approximately 1,300 km^2, whereas the agriculture/herbaceous class increased by 1,400 km^2. The conversion of Dry Forest into agriculture and pastures in our study is similar to that documented across Latin America (Brannstrom 2009), particularly in the Argentine Chaco (Grau and others 2005; Gasparri and Grau 2009), Brazilian Cerrado (Brannstrom and others 2008; Galford and others 2008) and Bolivian lowlands (Killeen and others 2008; Redo and others 2012).

In the Northern Andean Paramo, the only ecoregion in the Montane Grassland biome, the slight net gain in woody cover occurred mainly in municipalities with high population density and decreasing levels of poverty. It is possible that these municipalities are in the early stages of forest transition; however, the total increase in woody cover was only 63 km^2 compared with an increase of 188 km^2 in the agriculture/herbaceous class. Woody cover decreased in municipalities with lower population densities and higher levels of poverty, supporting the idea that impoverished communities with few economic opportunities can be important players in deforestation (Rudel and Roper 1997).

In the Desert biome, woody cover increased mostly in municipalities with low topographic variation and at lower elevations. These municipalities (for example, Uribia, Riohacha, Maicao) are located in the Guajira peninsula where environmental conditions are not optimal for agriculture because this is the driest region in Colombia. The gain of woody cover (that is, shrublands) in these marginal lands could be related to a precipitation anomalies (for example, high precipitation in 2009) or possibly to issues in the classification because the Desert biome was classified as part of the Dry Forest biome (Sanchez-Cuervo and others 2012).

Impact of the Armed Conflict

The armed conflict has mainly impacted woody change in three areas: Montane Forest ecoregions, Llanos ecoregion, and Chocó-Darién and Magdalena-Urabá Moist Forest ecoregions. The Montane Forest ecoregions were characterized by a complex dynamic between woody vegetation change and armed conflict, demographic, and socio-economic variables. This is not surprising because the Andes and its inter-Andean valleys have had a long history of colonization (Etter and others 2008), contain 65% of the total population, and have the strongest economic growth in the country. We found that the presence of paramilitary groups (that is, AUC) was among the top three variables explaining woody cover change in three of the four Montane Forest ecoregions and their presence was associated either with reforestation or deforestation, depending on the particular ecoregion. The effect of the paramilitary groups either promoting reforestation or deforestation seems to be dependent of the physical properties of the landscape, availability of natural and mineral resources (for example, gold, oil), and the control of strategic areas for illegal activities. For example, reforestation tended to occur in municipalities with a high density of paramilitary groups at lower elevations (<3000 m) in the Cordillera Oriental and to the north of the Cauca Valley Montane Forest. It is possible that paramilitary groups used these mountainous areas as corridors to transport drugs and weapons from the Andes to the Pacific Ocean and from the Andes to the Orinoco region (Defensoria del Pueblo 2001; López 2010). On the other hand, deforestation trends occurred mostly in municipalities with a high density of paramilitary groups and high gold production mainly in the Northern Andean Montane ecoregion, the third largest ecoregion in Colombia. Furthermore, there was a dramatic increase in gold production (2001–13 to 2008–28 tons) in the entire Northern Andean Montane ecoregion (SIMCO 2012). In addition, in the Magdalena Medio and several municipalities in the coffee growing region, paramilitary groups caused the forced displacement of thousands of peasants, and much of these areas (>2000 km^2) were converted into the agriculture/herbaceous class, that is, cattle ranches (Defensoria del Pueblo 2001; Molano 2005).

Another area with strong influences from illegal armed groups is the Llanos, the only ecoregion in the Grassland biome. In the Llanos, land clearing was evident in municipalities with high forced displacement in 1996, a large population in 1993, and low unpaved road density. Demographic changes started in the late 1980s to middle 1990s when five petroleum fields were discovered in Arauca, Casanare, and Meta departments (Rausch 2009). Following the discoveries, economic development increased rapidly, promoting a strong migration of Andean peasants, which lead to high rates of land conversion toward mechanized agriculture (for example, rice) and cattle grazing (Romero-Ruiz and others 2011). The economic growth and the geographic location of the Llanos represented an important source of funding for illegal armed groups as well as an essential strategic corridor between the Venezuelan border and central Colombia (Rausch 2009; López 2010). The presence of illegal-armed groups (for example, guerilla-FARC, paramilitaries-AUC) caused the displacement of over 6,500 peasants from rural to urban areas in 1996 (SIPOD 2010). It is possible that these abandoned areas have been transformed into cropland and pasturelands and presently are expanding because the agriculture/herbaceous class increased by approximately 100% in the region. This trend is likely to continue given that the Llanos is considered the new agricultural frontier of Colombia.

In the Chocó-Darién and Magdalena-Urabá Moist Forest ecoregions the armed conflict has resulted in a high level of forced displacement from poor rural areas to urban areas (Molano 2005) and an increase in forest cover. In the Magdalena-Urabá Moist Forest woody cover change was explained by environmental factors, but population change also played a key role through forced displacement of almost 31,000 peasants in the 1990s (SIPOD 2010); therefore, the variable displacement in 1996 was among the top five variables in this ecoregion. The combination of a high level of rural–urban migration, low economic growth, and the presence of the armed groups has contributed to forest regrowth in several areas of these Moist Forest ecoregions.

Surprisingly, even though the FARC have had a key role in the forced displacement of rural communities and subsequent land abandonment since the 1990s (López 2010; Defensoria del Pueblo 2001), their presence was not an important variable explaining woody change in our analyses. It is possible that the Plan Colombia and its Democratic Security policies reduced guerrilla presence between 2002 and 2010 across the country (Acevedo and others 2008) and diminished their effect on forest cover change.

Conclusions

Our results illustrate the complexity of forest change, especially when analyzed at multiple spatial scales and provide new perspectives about the causes of forest change in Colombia. First, we determined that environmental variables were important for explaining woody cover change from the country to the ecoregion scales because environment conditions can either restrict or encourage different land uses (for example, agriculture or pastures expansion) at all scales. Second, given that Colombia has high environmental heterogeneity coupled with remarkable socio-cultural, economic, and demographic differences across its regions, demography and socio-economy factors are important in explaining woody cover change at the biome and ecoregion scales. Nevertheless, in Colombia, the importance of demographic variables appear to mainly be a consequence of the armed conflict, particularly through forced human displacement (for example, rural–urban migration) in areas where there was a high presence of armed illegal groups. These factors promoted land abandonment, reducing forest pressure, and leading to forest regrowth mainly in rural areas. Third, armed conflict variables (that is, paramilitary groups) were the most important variables in some ecoregions, suggesting that their presence can have large impacts on local patterns of forest cover change. The direction of their impact (that is, deforestation or reforestation) depends on: (1) physical properties of the landscape (for example, lowlands—more deforestation); (2) availability of areas rich in natural and mineral resources to accumulate and generate wealth as well as a source of funding (that is, Magdalena Medio, Llanos—more deforestation); and (3) the strategic value of the areas for illegal activities (for example, corridors to transport weapons and drugs), which favor reforestation. In summary, this multi-scale/multivariate approach provides a new insight into the complex relationship between forest cover change and land abandonment triggered mainly by armed conflict in Colombia.

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References

Acevedo B, Bewley-Taylor D, Youngers C. 2008. Ten years of plan Colombia: an analytical assessment. Briefing paper sixteen. The Beckley Foundation. Drug Policy Programme, Washington. 13 p.

Achard F, Eva HD, Stibig HJ, Mayaux P, Gallego J, Richards T, Malingreau JP. 2002. Determination of deforestation rates of the world's humid tropical forests. Science 297:999–1002.

Aide TM, Clark ML, Grau HR, López-Carr D, Levy MA, Redo D, Bonilla-Moheno M, Riner G, Andrade-Núñez MJ, Muñiz M. 2012. Deforestation and Reforestation of Latin America and the Caribbean (2001–2010). Biotropica. p 1–10. doi:10.1111/j.1744-7429.2012.00908.x

Aide TM, Grau HR. 2004. Globalization, migration, and Latin American ecosystems. Science 305:1915–16.

Armenteras D, Rudas G, Rodriguez N, Sua S, Romero M. 2006. Patterns and causes of deforestation in the Colombian Amazon. Ecol Indic 6:353–68.

Bonilla-Moheno M, Aide TM, Clark M. 2012. The influence of socioeconomic, environmental, and demographic factors on municipality-scale land-cover change in Mexico. Reg Environ Chang 12(3):543–57. doi:10.1007/s10113-011-0268-z.

Bowen ME, McAlpine CA, House APN, Smith GC. 2007. Regrowth forests on abandoned agricultural land: a review of their habitat values for recovering forest fauna. Biol Conserv 140:273–96.

Brannstrom C. 2009. South America's neoliberal agricultural frontiers: places of environmental sacrifice or conservation opportunity? AMBIO 38:141–9.

Brannstrom C, Jepson W, Filippi AM, Redo D, Xu Z, Ganesh S. 2008. Land change in the Brazilian Savanna (Cerrado), 1986–2002: comparative analysis and implications for land-use policy. Land Use Policy 25:579–95.

Breiman L. 2001. Random forest. Mach Learn 45:5–32.

Carr DL. 2004. Proximate population factors and deforestation in tropical agricultural frontiers. Popul Environ 25:585–612.

Céspedes M, Gutierrez MV, Holbrook NM, Rocha OJ. 2003. Restoration of genetic diversity in the dry forest tree *Swietenia macrophylla* (Meliaceae) after pasture abandonment in Costa Rica. Molecular Ecology 12:3201–12.

Chaves ME, Arango N. 1998. Informe Nacional sobre el estado de la Biodiversidad en Colombia 1997. Bogotá, DC, Colombia: Instituto de Investigación de Recursos Biológicos Alexander von Humboldt.

Chazdon RL. 2008. Beyond deforestation: restoring forests and ecosystem services on degraded lands. Science 320:1458–60.

Clark ML, Aide TM. 2011. Virtual interpretation of Earth Web-Interface Tool (VIEW-IT) for collecting land-use/land-cover reference data. Remote Sens 3:601–20.

Clark ML, Aide TM, Grau HR, Riner G. 2010. A scalable approach to mapping annual land-cover at 250 m using MODIS time-series data: a case study in the Dry Chaco ecoregion of South America. Remote Sens Environ 114:2816–32.

Clark ML, Aide TM, Riner G. 2012. Land change for all municipalities in Latin America and the Caribbean assessed from 250-m MODIS imagery (2001–2010). Remote Sens Environ 126:84–103.

Cotte A (2010) Poverty, armed conflict, and human rights: an analysis of the objective causes of violence in Colombia. Investigation Group on Violence, Institutions and Economic Development. Universidad de La Salle, Bogotá, DC, Colombia. 50 p.

Cubides F. 1999. Los paramilitares y su estrategia. Llorente, MV, Deas, Ms, Reconocer la guerra para construir la paz. Editorial Norma, Bogotá, DC, Colombia. 151–199 pp.

Dávalos LM, Bejarano AC, Hall M, Correa HL, Corthals A, Espejo O. 2011. Forest and drugs: coca-driven deforestation in tropical biodiversity hotspots. Environ Sci Technol 45:1219–27.

del Pueblo Defensoria. 2001. Informe Defensorial sobre el Desplazamiento Forzado por la Violencia en Colombia. Bogotá, DC, Colombia: Defensoría del Pueblo. 59 p

Echandía C. 1999. El Conflicto Armado y las Manifestaciones de Violencia en las Regiones de Colombia. Presidencia de la República, Observatorio de Violencia de la Oficina del Alto Comisionado para la Paz, Bogotá, DC, Colombia. 263 p.

Etter A, McAlpine C, Phinn S, Pullar D, Possingham H. 2006a. Characterizing a tropical deforestation wave: the Caquetá colonization front in the Colombian Amazon. Glob Chang Biol 12:1409–20.

Etter A, McAlpine C, Phinn S, Pullar D, Possingham H. 2006b. Unplanned land clearing of Colombian rainforests: spreading like disease? Landsc Urban Plan 77:240–54.

Etter A, McAlpine C, Possingham H. 2008. Historical patterns and drivers of landscape change in Colombia since 1500: a regionalized spatial approach. Ann Assoc Am Geogr 98:2–23.

Etter A, McAlpine C, Pullar D, Possingham H. 2006c. Modelling the conversion of Colombian lowland ecosystems since 1940: drivers, patterns and rates. J Environ Manage 79:74–87.

Etter A, van Wyngaarden W. 2000. Patterns of landscape transformation in Colombia, with emphasis in the Andean region. AMBIO 29:432–9.

Galford GL, Mustard JF, Melillo J, Gendrin A, Cerri CC, Cerri CEP. 2008. Wavelet analysis of MODIS time series to detect expansion and intensification of row-crop agriculture in Brazil. Remote Sens Environ 112:576–87.

Gasparri NI, Grau HR. 2009. Deforestation and fragmentation of Chaco dry forest in NW Argentina (1972–2007). Forest Ecol Manag 258:913–21.

Geist HJ, Lambin EF. 2002. Proximate causes and underlying driving forces of tropical deforestation. Bioscience 52:143–50.

Gibson L, Lee TM, Koh LP, Brook BW, Gardner TA, Barlow J, Peres CA, Bradshaw CJA, Laurance WF, Lovejoy TE, Sodhi NS. 2011. Primary forests are irreplaceable for sustaining tropical biodiversity. Nature 478(7369):378–81. doi:10.1038/nature10425.

Gillard M, Gomez I, Jones. M. 1998. BP sacks security chief over arms deal. Inquiry into arms and spy scandal. The Guardian London.

Grau HR, Aide TM, Gasparri NI. 2005. Globalization and soybean expansion into semiarid ecosystems of Argentina. AMBIO 34:265–6.

Grau HR, Aide TM, Zimmerman JK, Thomlinson JR, Helmer E, Zou X. 2003. The ecological consequences of socioeconomic and land-use changes in postagriculture Puerto Rico. Bioscience 53:1159–68.

Guariguata MR, Ostertag R. 2001. Neotropical secondary forest succession: changes in structural and functional characteristics. Forest Ecol Manage 148:185–206.

Hazell P, Wood S. 2008. Drivers of change in global agriculture. Philos Trans R Soc B 363:495–515.

Hecht SB, Saatchi SS. 2007. Globalization and forest resurgence: changes in forest cover in El Salvador. Bioscience 57:663–72.

Huete A, Didan K, Miura T, Rodriguez E, Gao X, Ferreira L. 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens Environ 83:195–213.

Kauppi PE, Ausubel JH, Fang JY, Mather AS, Sedjo RA, Waggoner PE. 2006. Returning forests analyzed with the forest identity. P Natl Acad Sci USA 103:17574–9.

Keys E, McConnell WJ. 2005. Global change and the intensification of agriculture in the tropics. Glob Environ Chang 15:320–37.

Killeen TJ, Guerra A, Calzada M, Correa L, Calderon V, Soria L, Quezada B, Steininger MK. 2008. Total historical land-use change in eastern Bolivia: who, where, when, and how much? Ecol Soc 13(1):36.

Klooster D. 2003. Regional forest transitions in highland Mexico? The importance of local institutions in a globalized countryside. Prof Geographer 55:227–37.

Lambin EF, Geist HJ, Lepers E. 2003. Dynamics of land-use and land-cover change in tropical regions. Annu Rev Env Resour 28:205–41.

Lambin EF, Turner BL, Geist HJ, Agbola SB, Angelsen A, Bruce JW, Coomes OT, Dirzo R, Fischer G, Folke C, George PS, Homewood K, Imbernon J, Leemans R, Li XB, Moran EF, Mortimore M, Ramakrishnan PS, Richards JF, Skanes H, Steffen W, Stone GD, Svedin U, Veldkamp TA, Vogel C, Xu JC. 2001. The causes of land-use and land-cover change: moving beyond the myths. Glob Environ Chang 11:261–9.

Liaw A, Wiener M. 2002. Classification and regression by randomForest. R News 2:18–22.

López P. 2010. Análisis de la influencia de las FARC y ELN en los procesos electorales en el departamento de Arauca en el periodo comprendido entre 1998–2004. Facultad de Ciencias Políticas y Relaciones Internacionales. Pontificia Universidad Javeriana, Bogotá, DC, Colombia.

Meyerson FAB, Merino L, Durand J. 2007. Migration and environment in the context of globalization. Front Ecol Environ 5:182–90.

Meyfroidt P, Lambin EF. 2008. The causes of the reforestation in Vietnam. Land Use Policy 25:182–97.

Molano A. 2005. Control and exploitation of natural resources: principal objectives of paramilitary expansion. Paramilitarism in Colombia: are demobilisation and peace compatible with justice and human rights? Uppsala University, Uppsala, Sweden.

Olson DM, Dinerstein E, Wikramanayake ED, Burgess ND, Powell GVN, Underwood EC, D'Amico JA, Itoua I, Strand HE, Morrison JC, Loucks CJ, Allnutt TF, Ricketts TH, Kura Y, Lamoreux JF, Wettengel WW, Hedao P, Kassem KR. 2001. Terrestrial ecoregions of the worlds: a new map of life on Earth. Bioscience 51: 933–938.

R. 2011. A language and environment for statistical computing. R Foundation for Statistical Computing. http://www.R-project.org.

Rausch JM. 2009. Petroleum and the transformation of the Llanos Frontier in Colombia: 1980 to the present. Latin Americanist 53:113–36.

Redo D, Aide TM, Clark ML. 2012. The relative importance of socio-economic and environmental variables in explaining land change in Bolivia, 2001–2009. Ann Assoc Am Geogr 102:778–807.

Romero-Ruiz MH, Flantua SGA, Tansey K, Berrio JC. 2011. Landscape transformations in savannas of northern South America: land use/cover changes since 1987 in the Llanos Orientales of Colombia. Appl Geogr 32:766–76.

Rudel T, Roper J. 1997. The paths to rain forest destruction: crossnational patterns of tropical deforestation, 1975–1990. World Dev 25:53–65.

Rudel TK, Bates D, Machinguiashi R. 2002. A tropical forest transition? Agricultural change, out-migration, and secondary forests in the Ecuadorian Amazon. Ann Assoc Am Geogr 92:87–102.

Rudel TK, Coomes OT, Moran E, Achard F, Angelsen A, Xu JC, Lambin E. 2005. Forest transitions: towards a global understanding of land use change. Glob Environ Chang 15:23–31.

Sala OE, Chapin FS, Armesto JJ, Berlow E, Bloomfield J, Dirzo R, Huber-Sanwald E, Huenneke LF, Jackson RB, Kinzig A, Leemans R, Lodge DM, Mooney HA, Oesterheld M, Poff NL, Sykes MT, Walker BH, Walker M, Wall DH. 2000. Biodiversity: global biodiversity scenarios for the year 2100. Science 287:1770–4.

Sanchez-Cuervo AM, Aide TM, Clark ML, Etter A. 2012. Land cover change in Colombia: surprising forest recovery trends between 2001 and 2010. PLoS ONE 7:e43943.

Segal MR. 2004. Machine learning benchmarks and random forest regression. Center for bioinformatics and molecular biostatistics. University of California, San Francisco, CA.

Sierra R. 2000. Dynamics and patterns of deforestation in the western Amazon: the Napo deforestation front, 1986–1996. Appl Geogr 20:1–16.

SIMCO. 2012. Sistema de Información Minero Colombiano. http://www.simco.gov.co.

SIPOD. 2010. Sistema de información para la población desplazada. Agencia Presidencial para la Acción Social y la Cooperación Internacional. http://www.dps.gov.co.

Stevens K, Campbell L, Urquhart G, Kramer D, Qi JG. 2011. Examining complexities of forest cover change during armed conflict on Nicaragua's Atlantic Coast. Biodivers Conserv 20:2597–613.

Strobl C, Boulesteix AL, Zeileis A, Hothorn T. 2007. Bias in random forest variable importance measures: illustrations, sources and a solution. BMC Bioinformatics 8:25.

Sutherland WJ, Adams WM, Aronson RB, Aveling R, Blackburn TM, Broad S, Ceballos G, Cote IM, Cowling RM, Da Fonseca GAB, Dinerstein E, Ferraro PJ, Fleishman E, Gascon C, Hunter M, Hutton J, Kareiva P, Kuria A, MacDonald DW, MacKinnon K, Madgwick FJ, Mascia MB, McNeely J, Milner-Gulland EJ, Moon S, Morley CG, Nelson S, Osborn D, Pai M, Parsons ECM, Peck LS, Possingham H, Prior SV, Pullin AS, Rands MRW, Ranganathan J, Redford KH, Rodriguez JP, Seymour F, Sobel J, Sodhi NS, Stott A, Vance-Borland K, Watkinson AR. 2009. One hundred questions of importance to the conservation of global biological diversity. Conserv Biol 23:557–67.

Thomlinson JR, Serrano MI, Lopez TD, Aide TM, Zimmerman JK. 1996. Land-use dynamics in a post-agricultural Puerto Rican landscape (1936–1988). Biotropica 28:525–36.

Thuiller W, Lavorel S, Araujo MB, Sykes MT, Prentice IC. 2005. Climate change threats to plant diversity in Europe. Proc Natl Acad Sci USA 102:8245–50.

UNODC. 2008. Monitoreo de cultivos de coca 2008. United Nations Office for Drug and Crime, Bogotá, DC, Colombia. 107 p.

Veldkamp A, Lambin EF. 2001. Predicting land-use change. Agr Ecosyst Environ 85:1–6.

Viña A, Cavelier J. 1999. Deforestation rates (1938–1988) of tropical lowlands forest on the Andean foothills of Colombia. Biotropica 31:31–6.

Witmer FDW, O'Loughlin J. 2009. Satellite data methods and application in the evaluation of war outcomes: abandoned agricultural land in Bosnia-Herzegovina after the 1992–1995 conflict. Ann Assoc Am Geogr 99:1033–44.

Wright SJ, Muller-Landau HC. 2006. The future of tropical forest species. Biotropica 38:287–301.