

Regional patterns of agricultural land use and deforestation in Colombia

Andrés Etter^{a,b,c,*}, Clive McAlpine^{a,b}, Kerrie Wilson^a,
Stuart Phinn^b, Hugh Possingham^a

^aThe Ecology Centre, University of Queensland, Brisbane, QLD 4072, Australia

^bCentre for Remote Sensing and Spatial Information Science, School of Geography, Planning and Architecture,
University of Queensland, Brisbane, QLD 4072, Australia

^cFacultad de Estudios Ambientales y Rurales, Universidad Javeriana, Bogotá, Colombia

Received 14 June 2005; received in revised form 11 November 2005; accepted 16 November 2005

Available online 18 January 2006

Abstract

An expanding human population and associated demands for goods and services continues to exert an increasing pressure on ecological systems. Although the rate of expansion of agricultural lands has slowed since 1960, rapid deforestation still occurs in many tropical countries, including Colombia. However, the location and extent of deforestation and associated ecological impacts within tropical countries is often not well known. The primary aim of this study was to obtain an understanding of the spatial patterns of forest conversion for agricultural land uses in Colombia. We modeled native forest conversion in Colombia at regional and national-levels using logistic regression and classification trees. We investigated the impact of ignoring the regional variability of model parameters, and identified biophysical and socioeconomic factors that best explain the current spatial pattern and inter-regional variation in forest cover. We validated our predictions for the Amazon region using MODIS satellite imagery. The regional-level classification tree that accounted for regional heterogeneity had the greatest discrimination ability. Factors related to accessibility (distance to roads and towns) were related to the presence of forest cover, although this relationship varied regionally. In order to identify areas with a high risk of deforestation, we used predictions from the best model, refined by areas with rural population growth rates of >2%. We ranked forest ecosystem types in terms of levels of threat of conversion. Our results provide useful inputs to planning for biodiversity conservation in Colombia, by identifying areas and ecosystem types that are vulnerable to deforestation. Several of the predicted deforestation hotspots coincide with areas that are outstanding in terms of biodiversity value.

© 2005 Elsevier B.V. All rights reserved.

Keywords: Deforestation; Modeling; Regional variability; Agriculture; Spatial footprint; Land cover change; Hotspots; Colombia

1. Introduction

A rapidly expanding human population and associated demands for goods and services is exerting an increasing pressure on ecological systems. Over the past century, the area of agricultural land has doubled worldwide (Houghton, 1994). Since 1960, while the rate of expansion of cropland has only increased by 10%, food production has doubled as a

result of increased agricultural productivity due to intensification of production and an expansion of irrigation agriculture. Indeed, the area of agricultural land per capita halved during the 20th century, from around 0.75 ha/person in 1900 to 0.35 ha/person in 1990 (Ramankutty et al., 2002). These global averages, however, mask active colonization and deforestation processes in countries of Southeast Asia (e.g. Indonesia), tropical Africa (e.g. Cameroon), Latin America (e.g. Brazil, Colombia, Ecuador and Bolivia) (Achard et al., 2002; Lepers et al., 2005), and even northern Australia (McAlpine et al., 2002). In Colombia, for example, tropical forests, especially in the Pacific and Amazon lowlands, continue to be cleared (Instituto Geográfico

* Corresponding author at: School of Geography, Planning and Architecture, Chamberlain Bldg. 35-506, University of Queensland, Saint Lucia, QLD 4072, Australia. Tel.: +61 7 33653535; fax: +61 7 33656899.
E-mail address: andres.etter@uq.edu.au (A. Etter).

Agustín Codazzi, 1992; Chaves and Arango, 1998; Etter et al., 2005a).

One approach to quantifying human impacts on ecological systems is to measure the “ecological footprint”, that is, the environmental resources required to support the consumption of a defined population (Wackernagel and Rees, 1996). The average footprint of the world population in 2002 was estimated to be 2.3 ha/person, with a global deficit of 0.4 ha/person. This deficit was due to an extension beyond our global biological capacity of 1.9 ha/person which commenced in the 1980s (Wackernagel et al., 2002). Some countries still show a “surplus” in their biological capacity relative to their ecological footprint. One such country is Colombia, which is estimated to have an ecological footprint of 1.3 ha/person and a national surplus of 1.2 ha/person. This surplus, however, is unlikely to be an indicator of a more sustainable society, but rather of lower levels of consumption due to a low national population density and a high level of poverty. The spatial expression of the ecological footprint is land cover change and the transformation or degradation of natural ecosystems.

From a planning perspective, it is important to have a spatially explicit understanding of existing and predicted land cover changes, and knowledge of their underlying drivers. The drivers of land cover change are both “proximate” such as soils and accessibility, and “exogenous” such as global commodity markets and national and international policies (Geist and Lambin, 2001). One approach to understanding the

drivers of land cover change and their spatial interaction is to model their influence on the physical landscape using empirical land cover data (e.g. Serneels and Lambin, 2001; Laurance et al., 2002; Nagendra et al., 2003; Mertens et al., 2004; Etter et al., 2005a,b). There are many pathways of land cover change (Lambin et al., 2003). Here we are interested in the conversion of native forests to agricultural land use, otherwise referred to as deforestation.

The main drivers and constraints of deforestation are, in general, well understood (Forman, 1995; Geist and Lambin, 2001), and include proximity to roads and settlements, distance to forest edges, soil fertility, rainfall, slope, and rural population density and growth (e.g. Veldkamp et al., 1992; Mertens and Lambin, 1999; Southworth and Tucker, 2001; Laurance et al., 2002). However, the modeling of deforestation is often constrained by the inability to include all causal factors, or by the uneven quality (scale and precision) of available data.

In addition, many models erroneously assume that the processes of land cover change operate in a spatially homogeneous manner across landscapes (>1000 km²) and regions (>10,000 km²) (McDonald and Urban, 2004). However, often landscapes and regions show contrasting biophysical and socioeconomic characteristics, which differentially affect the likelihood of deforestation. In Colombia, for example, there is a large contrast in the biophysical characteristics and hence land use patterns between the Andean, Caribbean and Amazon regions (Fig. 1a) (Etter,

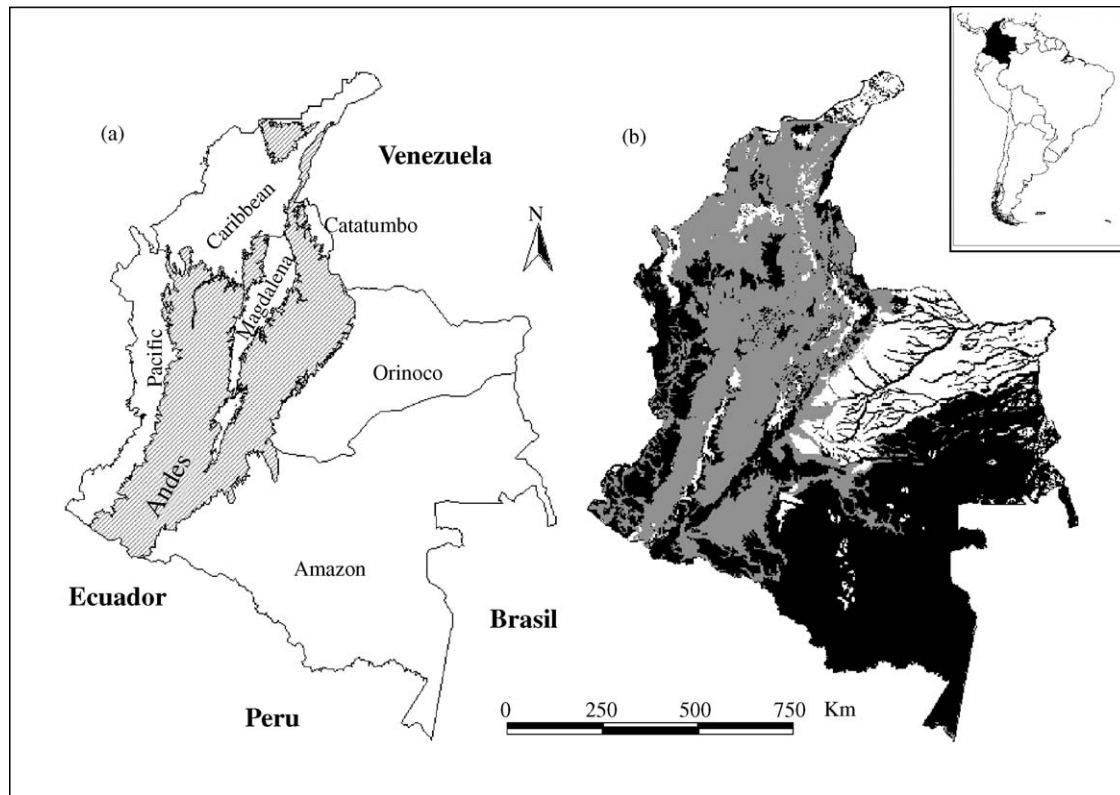


Fig. 1. Location of Colombia showing: (a) the seven regions and (b) the extent of the original (gray + black) and remnant natural forest ecosystems (black), and non-forested ecosystems (white).

1998; Palacios, 2001), and therefore differences in deforestation dynamics are expected. If a model of deforestation is uniformly applied across different regions or landscapes, an averaging of the causal factors occurs and their relative importance will likely be underestimated or overestimated in certain areas (McDonald and Urban, 2004). These problems are amplified when modeling at a national-level where large contrasts can be expected.

In Colombia, studies of land cover change have focused at the landscape-level (Etter and Andrade, 1987; Viña and Cavalier, 1998; Garcia, 2002; Mendoza and Etter, 2002; Etter et al., 2005b), while little is known about the patterns and drivers of land cover changes at regional and national-levels (but see Armenteras et al., 2003 for an analysis of fragmentation in the Andean region). The lack of reliable statistics on land cover change at these levels has limited the integration of such knowledge into land use and conservation planning in Colombia.

The aim of this study was to model deforestation in Colombia at regional and national-levels and use this information to achieve the following objectives: (i) assess, in a spatially explicit manner, the ecological footprint of different agricultural land uses; (ii) identify biophysical and socioeconomic factors that best explain the current spatial pattern of deforestation, and whether these factors vary between regions and (iii) identify native ecosystems with a high probability of conversion to agricultural land uses (cattle and cropping) based on current socioeconomic conditions. We restrict our analyses to land cover changes that involve deforestation and analyze the predicted distribution of forest loss using logistic regression and classification trees. We compare the predictive performance of deforestation models that include and ignore the spatial variation in the effect of explanatory variables, and validate our predictions using recent satellite imagery.

2. Methods

2.1. Study region

Colombia is located in the northwest of South America and has a land area of 1.1 million km². It comprises five major biogeographic regions that have contrasting biophysical and land use characteristics: Andes (278,000 km²), Caribbean (115,400 km²), Pacific Coast (74,600 km²), the Colombian Amazon (455,000 km²), and Orinoco plains (169,200 km²), plus two smaller regions, the Magdalena (37,100 km²) and Catatumbo (7000 km²), which are generally included in the Andean region (Fig. 1a). Across these regions, there are large variations in altitude (0–5800 m), in mean annual rainfall (300–10,000 mm), in length of growing period (60–360 days year⁻¹), and in geological substrates. A salient characteristic of Colombian geography is its high environmental variability relative to its geographic size, with Colombian ecosystems ranging from

desert and tropical savannas, to very humid rainforests and tropical snow-covered mountains. As a consequence of this variability, Colombia has high levels of endemism and species richness and has been classed as a mega-diverse country (Hernández et al., 1992; Chaves and Arango, 1998).

During the 20th century, the population of Colombia increased 10-fold and surpassed 40 million in 2000. Historically, the majority of the Colombian population (65%) has been concentrated in the Andean and Caribbean regions (Colmenares, 1999; Herrera, 2000). These regions currently have an average rural population density of approximately 33 persons/km², while the Pacific, Orinoco and Amazon regions have densities ranging from 5 to 17 persons/km². While 25% of the population still resides in rural areas, since the 1970s, Colombia has become an increasingly urban and industrialized country. Accompanying this transition, the average national population growth rate fell below 2% in the late 1990s when the rural population stabilized. Ethnically, the country has undergone a strong mixing, resulting in a dominant Mestizo (ethnically and biologically mixed) population. However, the cultural diversity is still high, with regionally contrasting rural cultures of 99 ethnic groups with 101 languages, varying from Amerindian to Afro-American and European-American (Loh and Harmon, 2005).

The Colombian economy is based on mining (oil, coal and nickel), agriculture (coffee, flowers) and industrial exports. The expanding globalization of the economy since 1990 severely impacted on the traditional agricultural sector, by increasing foreign agricultural imports. In recent decades, Colombia has experienced considerable social and political unrest, driven by extremist left and right-wing armed forces. This unrest has triggered large internal population movements and economic destabilization. Accompanying this unrest, a pervasive economy of illegal crops (Coca – *Erythroxylum coca* – in the lowlands, and Opium – *Papaver somniferum* – in the highlands) for export has developed in many remote frontier areas and has caused further social and political instability. These internal social and political pressures have important consequences for regional land cover change patterns, including redirection of colonization patterns and land abandonment in certain areas.

2.2. Calculation of the spatial footprint

One of the main components required to calculate the ecological footprint of a country is an understanding of changes in land uses. Here, we focus on the conversion of native forest to agricultural land uses and determine the spatial footprint of agriculture in Colombia. First, we determined the contribution of different agricultural land uses to the spatial footprint using the land use types from the transformed ecosystems of the national ecosystem map at a scale of 1:2,000,000 (Etter, 1998), which used the most detailed information available at the time. We view this map as appropriate for the scale of the analysis presented here

and the objectives of the analysis, which is to distinguish cropping and grazing land uses. This map classifies land uses into: (i) crops (consisting of commercial agriculture, colonist agriculture, smallholder agriculture); (ii) grazing (consisting of grazing on cleared forest lands and grazing on natural grasslands) and (iii) remnant near-natural ecosystems.

Commercial agriculture involves the mechanical cropping of annuals and perennials and occurs on medium to large properties. Common crops include coffee, sugarcane, palm oil, irrigated rice, soybean, cotton, corn, and potato. Smallholder agriculture is a labor intensive land use that combines subsistence and cash crops (such as coffee, corn, potato and beans) with grazing of cattle, sheep and goats. It typically occurs on small properties owned by peasants in the Andean region. Colonist agriculture occurs mainly in agricultural frontier areas in the Amazon and Pacific, where there is restricted access. It is a labor intensive land use that typically involves subsistence crops mixed with cattle grazing, with illegal crops, especially Coca, important in remote areas of the Pacific lowlands and the Amazon. Grazing land uses often involve cattle and ranges from extensive ranches to semi-intensive on introduced pastures. Typical exotic pasture species include *Braquiaria* (*Braquiaria* spp.) in the lowlands, and *Kikuyo* (*Pennisetum clandestinum*) in Andean region above 1500 m. Some grazed areas are for dairy farming.

We calculated the average area required per person for each type of agricultural land use using the total population

of Colombia in the year 2000. This provided the contribution of each land use type to the spatial footprint within each of the seven regions of Colombia (Fig. 1a). To assess the relationship between the spatial footprint of agricultural land uses and biophysical factors and accessibility, we overlaid the maps of land use with a soil fertility map and a distance to roads map using the “intersect” operation in ArcView GIS version 3.3.

2.3. Predictive deforestation models

A national multi-temporal dataset of land cover and land cover change is not available for Colombia and this limits our ability to understand and predict spatial patterns of deforestation at a national-level. One option to overcome this limitation is to generate a model of deforestation based on forest presence–absence data using information of present natural vegetation from a single date, and environmental and socioeconomic data as explanatory variables. A map of present natural forest vegetation shows the historic cumulative change of areas where deforestation for agricultural land uses have occurred. This model then can be used to obtain an understanding of the factors driving this type of land cover change, and to identify the areas vulnerable to future changes.

Since the patterns and processes of land cover change are very different in landscapes that are forested and those that are non-forested, we restricted our analysis to forest ecosystems, and excluded non-forested ecosystems such

Table 1
Data used in the modeling process

Data	Source	Units	Comments
Remnant ecosystems	Etter, 1998; Etter et al., 1999	Categorical: ecosystem type	Re-sampled to a 2 km grid. A mask of the remnant forest ecosystems was derived, binary (1, 0)
Potential ecosystems	Etter, 1998; Etter et al., 1999; Instituto Geográfico Agustín Codazzi, 1985	Categorical: ecosystem type	Re-sampled to a 2 km grid. A mask of the original forest ecosystems was derived, binary (1, 0)
Climate	International Water Management Institute (http://www.iwmi.cgiar.org/Watlas/download.htm)		Re-sampled from 18 to 2 km grid, and smoothed with average on a 5 × 5 moving window
Rain		Continuous: rain days/yr	
Moist		Continuous: annual MAI ^a	
Slope	Map derived from the Shuttle Radar Topography Mission (SRTM) http://edcns17.cr.usgs.gov/srtmbil/	Continuous: %	Re-sampled to the 2 km grid from 90 m data. Slope map in %
Soil	Instituto Geográfico Agustín Codazzi (1983)	Categorical: fertility classes	Re-sampled to the 2 km grid from 1:500,000 maps
Distance to towns, rivers and roads	Instituto Geográfico Agustín Codazzi (2000)	Continuous: km	Re-sampled to the 2 km grid
Rural population growth rates 1985–1993	Departamento Administrativo Nacional de Estadística-DANE (1993)	Continuous: % per annum	From census data of 1985 and 1993 at the municipality-level, a map of rural population growth rate was produced
Protected areas	Ministry of Environment (2000)	Binary (1, 0)	Undifferentiated units of national reserve System. Re-sampled to the 2 km grid from 1: 1,500,000 maps

^a Moisture Availability Index (for calculation refer to source).

as savannas, “Páramos” (high-Andean grasslands), dry scrub, and deserts (Fig. 1b).

2.3.1. Datasets

The datasets described herein were used to: analyze the spatial patterns of deforestation, determine underlying drivers of this process, and predict forested areas with a high probability of conversion in the future. The characteristics and sources of the datasets employed are detailed in Table 1.

We constructed a “potential” ecosystem map using a combination of the ecosystem map of Colombia (Etter, 1998), the ecosystem map of the Andean region of Colombia (Etter et al., 1999), and the agro-ecological map of Colombia (Instituto Geográfico Agustín Codazzi, 1985). First we cross-tabulated the ecosystem and agro-ecological maps and established the major equivalences between map codes, leaving out the smaller (<10%) coincidence values. The potential ecosystems within the transformed areas were then interpreted using the agro-ecological map (Instituto Geográfico Agustín Codazzi, 1985) (Etter, 1998; Etter et al., 1999). A mask of the forested areas of Colombia was derived from the “potential” ecosystems map by excluding the non-forested ecosystems (Table 1).

With the forest mask, a remnant forest ecosystems map was constructed (Etter, 1998; Etter et al., 1999). From it a binary (1, 0) forest/non-forested raster map was resampled to a 2 km grid and used as a response variable in the statistical models. For the explanatory variables the following raster maps (resampled to a 2 km grid) were used: slope (%), soil fertility (ordinally ranked from very low (1) to high (4)), an index of moisture availability, the number of days with rain per year, distance to towns, roads and rivers (km), the presence or absence of protected areas, and regional boundaries (Table 1, Fig. 2).

The pattern of forest cover depicted in the forest cover map was the result of the historical sum of deforestation events, and had the disadvantage of being unable to differentiate where the most recent forest cover changes have occurred. However, since most contemporary deforestation in Colombia is occurring in colonization fronts (Viña et al., 2004; Etter et al., 2005a,b), rural population growth is expected to potentially be the major driver of deforestation. A map of rural population growth rate from 1985 to 1993 was therefore generated at the municipality-level using national census data (Departamento Administrativo Nacional de Estadística-DANE, 1993). However, because rural population growth is continuously changing in time and space, demographic data cannot be averaged

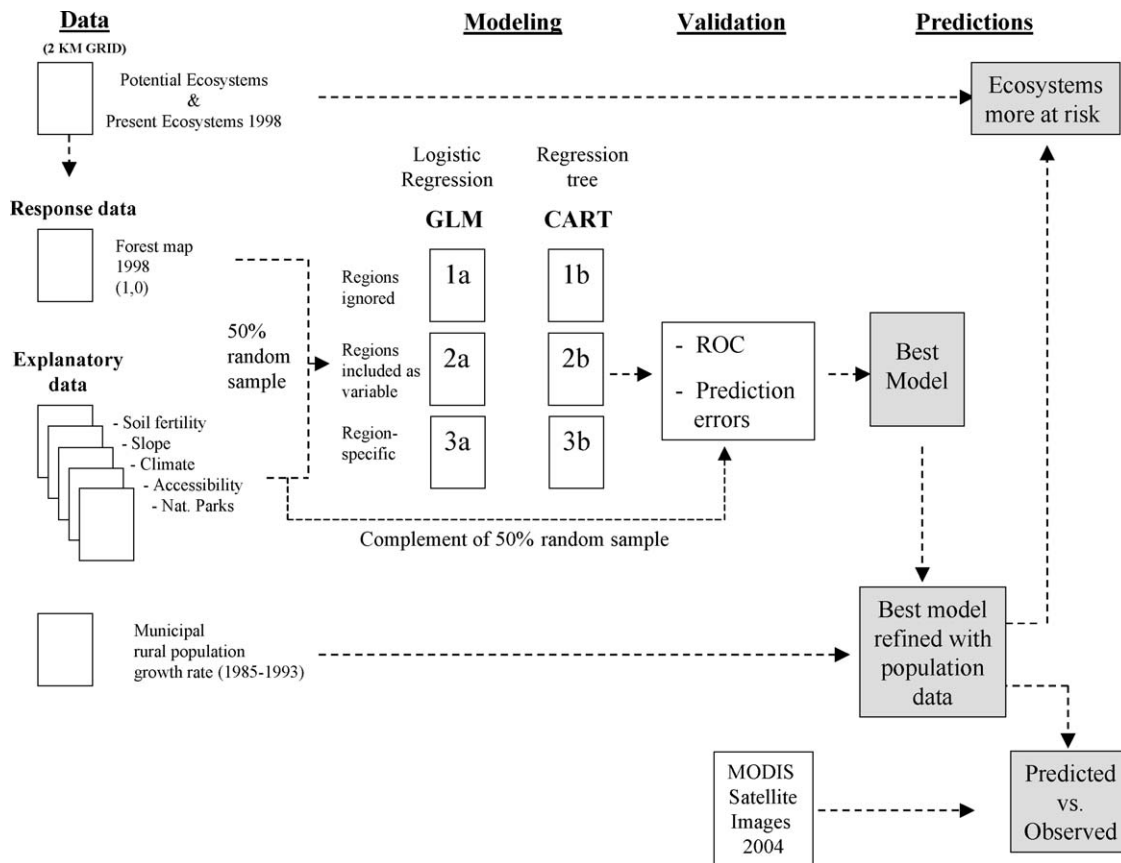


Fig. 2. Schematic diagram showing the methodological sequence describing the input data, the modeling and validation approaches, and the generation of predictions.

over time, thereby precluding its use as an explanatory variable in the statistical models of deforestation. For this reason, this data was used only to refine the predictions from the best-performing model by using high rural population growth (>2%) to filter areas with the highest risk of deforestation.

We employed South American MODIS satellite images (500 m resolution, 32-day mosaics) to qualitatively validate our predictions of forest conversion. Images from two dates (December 2004–February 2005 and December 2003–February 2004) were acquired from the Global Land Cover Facility of the University of Maryland, <http://glcfapp.umd.edu:8080/esdi/index.jsp>. Because several areas of the Andean, Caribbean and Pacific regions had a complex pattern of cloud cover, we concentrated the validation analysis in the Amazon region. An automated classification proved to be difficult due to mixed land cover mosaics of the colonization areas, and therefore a visual interpretation approach that could benefit from pattern recognition of cleared fields based on experience and knowledge of the area was preferred. To enable visual interpretation of forested and cleared areas, a color composite was produced using bands 1 (red = 620–670 nm), 2 (near-infrared = 841–876 nm) and 6 (short wave infrared = 1628–1652 nm). The interpretation was performed visually by overlaying the mask of the cleared areas in 1998 on the satellite image composite (Etter, 1998). Areas cleared after 1998 were delineated to produce a deforestation map from 1998 to 2005.

2.3.2. Statistical modeling

The statistical modeling framework comprised three steps and is shown in Fig. 2: (1) predicting the future spatial location of forest conversion; (2) refining the predictions with the population growth rate data and (3) validating the predictions with MODIS satellite imagery. All analysis was performed using S-PLUS (Insightful-Corporation, 2002).

First, we tested for colinearity between the explanatory variables using Pearson's correlation coefficient. Only three pairs of variables showed a moderate degree of colinearity: number of rain days and moisture index ($r = 0.56$), and distance to roads and distance to towns ($r = 0.53$), which could be expected; and number of rain days and distance to roads ($r = 0.48$). However, as the level of colinearity was below an acceptable level of 0.7 (Green, 1979), all explanatory variables were retained for further analysis.

Second, we developed a classification tree (CART) (Lewis, 2000) and a generalized linear model (GLM) (logistic regression, Hosmer and Lemeshow, 2000) to predict forest conversion at a regional and a national-level. We employed both modeling techniques as they treat the spatial variation in the effect of explanatory variables differently (McDonald and Urban, 2004). Logistic regression treats the effect of variables in a spatially homogeneous manner whereas classification trees treat the effect in a

spatially heterogeneous manner. McDonald and Urban (2004) found classification trees to more accurately predict land cover change than logistic regression when the affect of explanatory variables varies spatially across regions, as is the case in Colombia.

Six types of models were generated (three classification trees and three logistic regression models) (Fig. 2), incorporating three spatial extents of analysis: (1) incorporating the whole country without differentiating regions (Model 1), (2) incorporating the whole country with regions included as an additional explanatory variable (Model 2), and (3) region-specific models (Model 3). The relationship between forest conversion and rainfall was expected to be non-linear with highest deforestation in the more suitable intermediate rainfall areas, and therefore quadratic forms of the variables describing the moisture index and the number of rain days were employed. The general form of the models is expressed as

$$\begin{aligned} \text{Model 1 : } (y) \sim & \beta_0 + \beta_1 \text{moist} + \beta_2 \text{rain} + \beta_3 \text{soil} + \beta_4 \text{slope} \\ & + \beta_5 \text{roads} + \beta_6 \text{rivers} + \beta_7 \text{towns} + \beta_8 \text{parks} \\ & + \beta_9 \text{moist} \times \text{moist} + \beta_{10} \text{rain} \times \text{rain} \end{aligned} \quad (1)$$

$$\begin{aligned} \text{Model 2 : } (y) \sim & \beta_0 + \beta_1 \text{moist} + \beta_2 \text{rain} + \beta_3 \text{soil} + \beta_4 \text{slope} \\ & + \beta_5 \text{roads} + \beta_6 \text{rivers} + \beta_7 \text{towns} + \beta_8 \text{parks} \\ & + \beta_9 \text{moist} \times \text{moist} + \beta_{10} \text{rain} \times \text{rain} \\ & + \beta_{11} \text{region} \end{aligned} \quad (2)$$

$$\begin{aligned} \text{Model 3 : } (y_{\text{region } j}) \sim & \beta_0 + \beta_1 \text{moist} + \beta_2 \text{rain} + \beta_3 \text{soil} \\ & + \beta_4 \text{slope} + \beta_5 \text{roads} + \beta_6 \text{rivers} + \beta_7 \text{towns} \\ & + \beta_8 \text{parks} + \beta_9 \text{moist} \times \text{moist} + \beta_{10} \text{rain} \times \text{rain} \end{aligned} \quad (3)$$

The classification tree was generated using the Recursive Partitioning and Regression Tree (*rpart*) extension for SPLUS (Insightful-Corporation, 2002). Classification tree models partition a dataset recursively into subsets that are increasingly homogeneous with respect to the response variable based on an optimal binary split on one of a set of explanatory variables, defining regions for which the response variable has similar values (McDonald and Urban, 2004). For a detailed explanation of classification tree generation methods, refer to Wilson et al. (2005a). According to Lewis (2000), classification trees have a number of advantages over logistic regression models including being non-parametric and therefore able to handle highly skewed or multi-modal data, and being able to handle categorical explanatory variables with an ordinal or non-ordinal structure. The logistic regression model was applied using the SPLUS statistical software (Insightful-Corporation, 2002). For the logistic regression

models, the explanatory variables were standardized using the SCALE function in SPLUS by dividing values by their root-mean-square to allow comparison of the relative effect of each variable.

Each model was calibrated on a random subset of half of the forest cover data and was validated on the remainder. For each model, the area under the Receiver Operator Characteristic Curve (ROC) (Metz, 1978) was used as a measure of discrimination ability and was calculated by comparing the predictions of deforestation to the actual distribution of forest cover as obtained from the validation dataset (Pontius and Batchu, 2003).

In order to visualize the locations of incorrectly predicted forested and cleared areas (Pontius, 2000), the predicted values of each model were split into two groups from the lowest value upwards according to the number of observed cells with forest absent ($n = 96,086$). These cells were classified as cleared (0), while the remaining cells ($n = 141,901$) were classified as forested (1). The distribution of the cells predicted to be cleared or to remain forested from each model, was then compared to their actual distribution as obtained from the map of forest cover. The location of cells incorrectly predicted to be forested or cleared was then mapped and evaluated to provide an assessment of the best-performing model.

Using the results of the best-performing model, we identified areas with a high probability of conversion as those with a predicted probability of $>70\%$. We overlaid these areas with the $>2\%$ rural population growth rate map using the intersect function in ArcView GIS version 3.3, to identify “deforestation hotspot” areas. In order to qualify and quantify the ecological impact of predicted forest conversion, we cross-tabulated the deforestation hotspot map with the forest ecosystem map, and identified the 10 most threatened forest ecosystems in terms of total area and of proportion of remnant area affected.

Finally, we validated the map of deforestation hotspots using forest cover conversion observed between 1998 and 2004 by comparing the ecosystem map and the map of cleared forest areas interpreted from the MODIS satellite imagery. We concentrated the model validation in the cloud-free Amazon region. To avoid problems associated with uneven clarity due to atmospheric interferences (e.g. humidity, haze and smoke), we cross-validated our interpretation of forested areas using the images acquired for 2004 and 2005. We then assessed the spatial coincidence between the observed conversion of forest between 1998 and 2004 (derived from the ecosystem map and the MODIS images) and the predicted conversion of forest (derived from the map of deforestation hotspots). Because the map of deforestation hotspots lacks a precise temporal framework, our aim was to validate only the approximate location of predicted forest conversion, and not to quantify the change.

3. Results

3.1. The spatial footprint of agricultural land uses

Approximately 35% of the total land area of Colombia was cleared by 1998 (excluding modified but not cleared land such as savannas and some Páramos areas). Some 180,600 km² (69%) of the Andean forests and 203,400 km² (30%) of the lowland forests were cleared by 1998. This is equivalent to 0.96 ha of cleared land per person (Table 2). Cropping accounted for 126,500 km² or 32% of the cleared area, while grazing, mostly extensive grazing of beef cattle, accounted for the remaining 264,500 km² and is the dominant land use across all regions (Tables 2 and 3).

The spatial patterns of forest conversion for agriculture in Colombia shows large regional differences, with forest conversion concentrated in the Andean and Caribbean region (Table 3, Fig. 1). The spatial pattern of different agricultural land uses is related to soil fertility, with commercial agriculture and intensive peasant agriculture occurring on more fertile soils, while grazing and colonist agriculture occupies less fertile areas (Fig. 3a). A large proportion of agricultural and grazing lands, except for land used for colonist agriculture, is located within 10 km of roads, which indicates a strong positive relationship between the presence of road infrastructure and forest clearing for agricultural purposes (Fig. 3b). In contrast colonist agriculture is more dispersed, occurring in the Amazon and Pacific regions at distances >50 km from roads. This is because rivers are still an important source of access in these regions (Fig. 3b). Remaining forested areas, are predominantly located on less fertile soils and are distant from roads (Fig. 3a and b).

3.2. Predictions of deforestation

The performance of the six types of models varied considerably (Fig. 4). Regardless of model, the highest probability of forest conversion is in the Andean and Caribbean regions. Models generated using logistic regression showed more spatially detailed predictions compared to the classification tree models; however a comparison of the discrimination ability of the model predictions revealed that

Table 2
Relationship between population and area of transformed ecosystems in Colombia

Land use	Total area (ha)	Area per capita (ha)
All used land (cleared + non-cleared)	520,338	1.28
All cleared land	391,600	0.96
Total crops	126,497	0.31
Total grazing lands	393,270	0.97
Extensive grazing on cleared forest land	264,530	0.65
Extensive grazing on natural grasslands	135,900	0.33
Remnant natural landscapes	620,310	1.52
Total land	1,137,650	2.80

Table 3
Percentage area of different land uses across Colombian regions

	Andes	Catatumbo	Magdalena	Caribbean	Orinoco	Pacific	Amazon
Natural	36.9	40.8	7.1	22.6	20.2	66.5	87.5
Commercial agriculture	7.4	4.4	5.6	3.4	1.7	1.5	0.0
Smallholder agriculture	9.3	2.5	4.2	2.9	0.9	2.9	0.0
Colonist agriculture	4.2	6.2	4.0	3.1	0.7	12.2	5.1
Grazing	42.0	46.0	79.1	68.0	76.5 ^a	17.1	7.4

^a Most grazing lands are in semi-natural savanna ecosystems.

this perceived precision was misleading (Fig. 5). The region-specific classification tree had the highest discrimination ability (ROC = 0.96). In contrast, discrimination ability of the national-level classification tree and logistic regression models was 0.84 and 0.91, respectively. The logistic regression model (ROC = 0.95) that included regions as an additional explanatory variable had a similar discrimination ability to the region-specific classification tree. However, 11.1% of forested cells and 15.7% of cleared cells were misclassified by logistic regression model that included regions as an additional explanatory variable (Fig. 5b). These prediction errors were approximately 20% higher than for the region-specific classification tree, which incorrectly predicted 9.1% of forested and 13.1% of cleared cells (Fig. 5d).

Regardless of model, the majority of erroneously predicted cleared areas were located in the Andean region, while the majority of erroneously predicted forested areas were located in the lowlands of the Amazon and Pacific regions (Fig. 5). In addition, the error in the predictions of

cleared areas was significantly higher (40–50%) than the error associated with the predictions of forested areas (Fig. 5).

At the national-level, the most important variables explaining the presence and absence of forest cover were distance to roads and distance to towns for both the logistic regression and classification tree models (Figs. 6 and 7). However, the effect of the variables on the presence of forest cover varied from region to region as indicated by the coefficients from the logistic regression model (Fig. 6, Appendix A), and the inclusion of variables in the classification trees (Fig. 7). According to the results of the logistic regression models, distance to roads and towns were important explanatory variables at the national-level (Fig. 6a) for most regions (Fig. 6b and e). The effect of other variables such as soil fertility (Andean, Pacific, Orinoco) and number of rain days (Caribbean, Magdalena) were important explanatory variables in only a few regions. Nevertheless, in general, the following relationships between deforestation and the explanatory variables were obtained from the results of all the models: deforestation was predicted to be greater in un-protected areas that have fertile soils, gentle slopes, and are near to settlements, roads and rivers. The relationship between the number of rain days and forest conversion was positive in the Caribbean and Amazon, while negative in the Andean region.

3.3. Predicted deforestation hotspots

The effect of including the rural population growth rate data in the best model (the region-specific classification tree) was the reduction of the overall area predicted to be deforested by 49%. The impact of including rural population growth varied regionally, ranging from a reduction of 60% in the Andean region to 7% in the Amazon region (Fig. 8, Table 4). Increasing the population growth rate from 2 to 3% decreased the predicted area of transformed forest by a further 15%, but had little effect on the general location of deforestation hotspots.

A comparison of the predicted deforestation hotspots in the Amazon region with the observed areas of deforestation identified using the MODIS images showed a reasonable level of agreement (Fig. 9). However, the predictions were spatially more scattered than the observed patterns of deforestation, which occur as more continuous bands along the edges of forest.

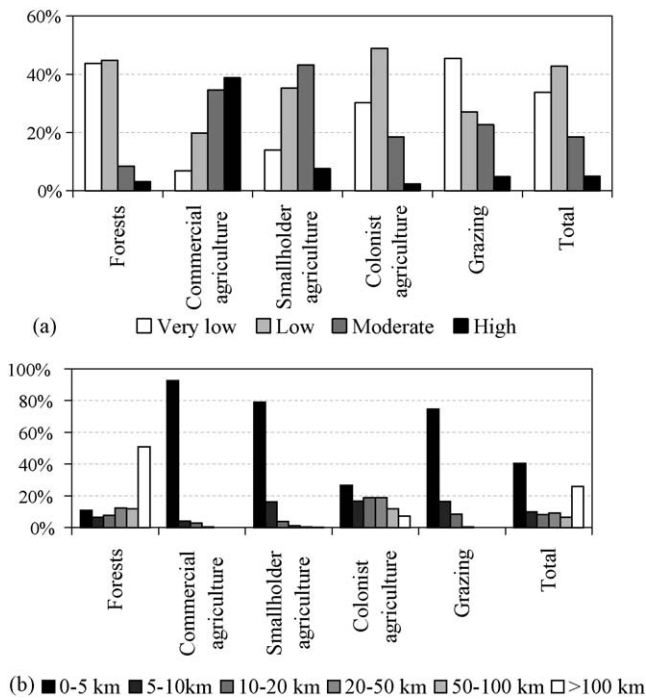


Fig. 3. Relationship between the main types of land use to: (a) soil fertility, and (b) distance to roads.

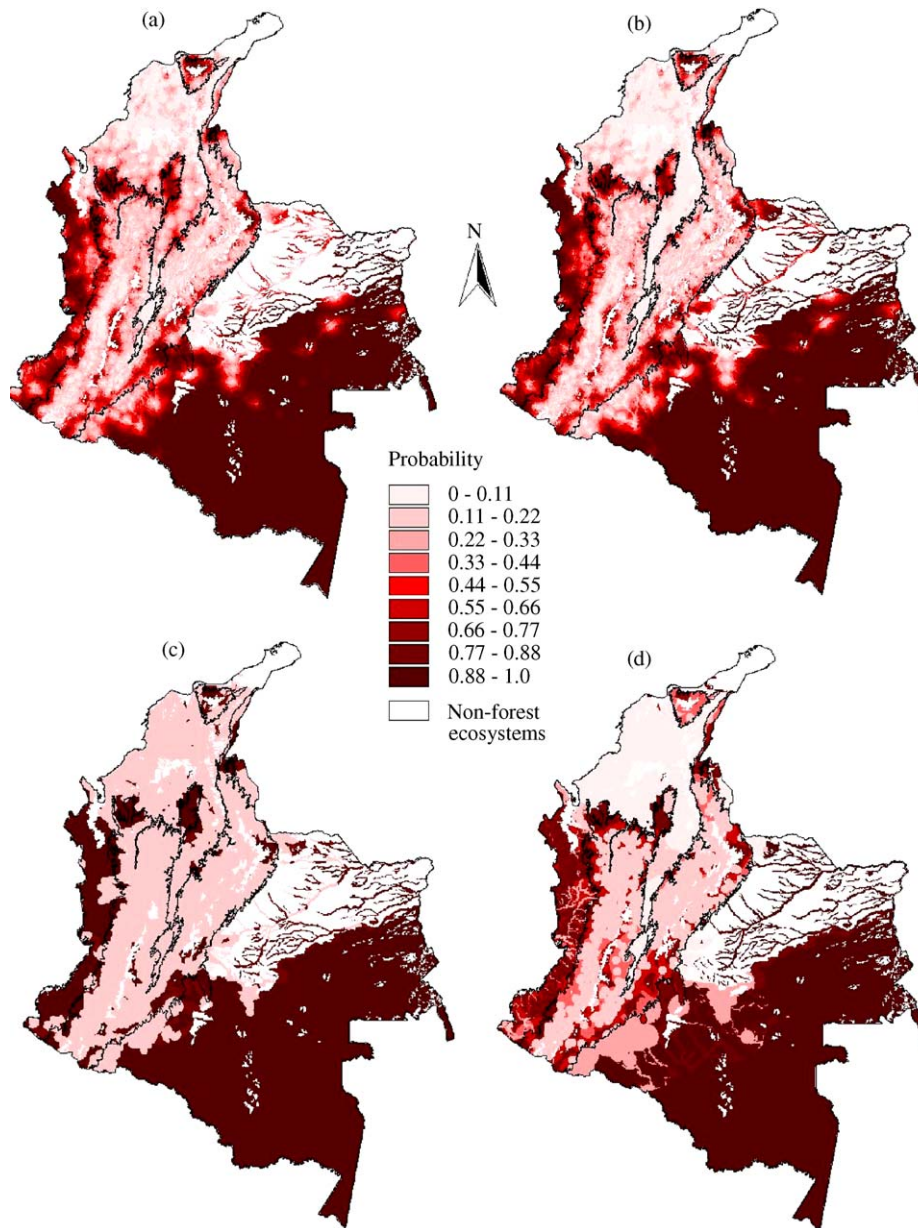


Fig. 4. Predicted forest conversion from the best and worst classification tree and logistic regression models: (a) logistic regression with regions not differentiated; (b) region-specific logistic regression; (c) classification tree with regions not differentiated and (d) region-specific classification tree.

3.4. Ecosystem vulnerability

Overlaying the predicted deforestation hotspots with the ecosystem map provided a qualitative assessment of the relative risk of forest conversion for the remnant natural ecosystems. The five forested ecosystems predicted to be most vulnerable to forest conversion, ranked according to predicted area transformed were (Fig. 10a): the Humid tropical forests of the undulating plains of the northern Amazon, the Humid sub-Andean forests; the Humid high-Andean forests; the Humid mid-altitude Andean forests and the Humid tropical forests of the undulating plains in the Magdalena. However, when risk was measured in terms of the

proportion of the remnant ecosystem area predicted to be transformed the ranking of risk changed to (Fig. 10b): very dry tropical forests in the Caribbean; humid tropical forests of the rolling landscapes in the Magdalena; the tropical dry forests of the hills; and the lowland Swamp forests of the Caribbean.

4. Discussion

The aim of this study was to predict national and regional-level patterns of deforestation for agricultural land uses in Colombia and understand the underlying drivers and constraints.

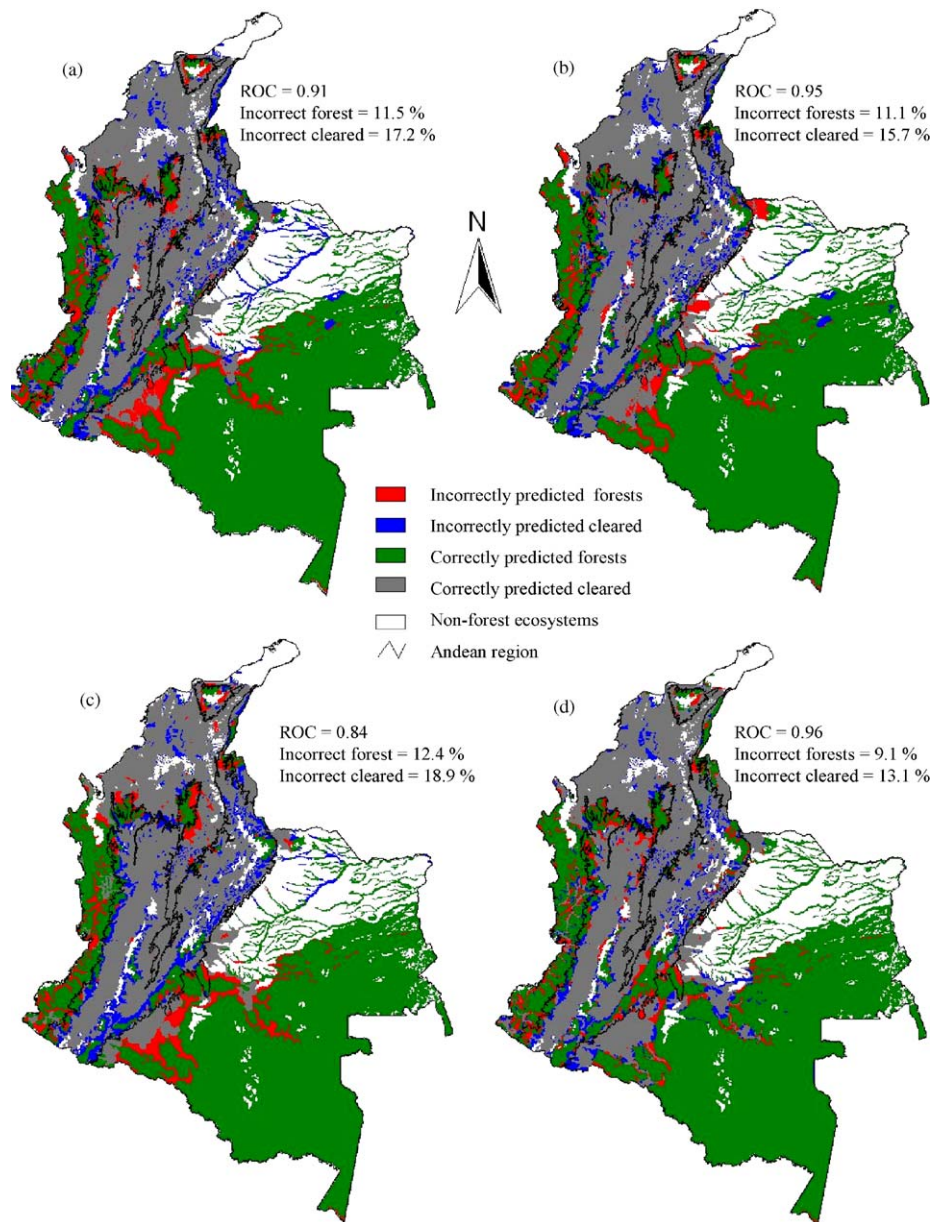


Fig. 5. Maps showing the location and percentage of incorrectly predicted forested and cleared land and the ROC values for the best and worst logistic regression and classification tree models: (a) logistic regression with regions not differentiated; (b) region-specific logistic regression; (c) classification tree with regions not differentiated and (d) region-specific classification tree.

4.1. The spatial footprint and deforestation modeling

The “ecological footprint” concept (Wackernagel et al., 2002) can be linked to measures of vulnerability, in particular to measures of the risk of exposure of areas to threatening processes (Wilson et al., 2005b). Such assessments have potential applications in land use and conservation planning. However, in order to link scientific research and policy and inform planning, we need to provide spatially explicit calculations of the “ecological footprint” of land uses, and analyze their impact on a region-specific basis. We therefore argue that models of land cover change be integrated into the footprint concept to allow the

prediction of changes in ecological footprints in a spatially explicit manner.

Our results show that the beef cattle industry is the largest contributor to the spatial footprint of agricultural land uses in Colombia at both a national and a regional-level (Table 3). As a result of this land use, biologically diverse and complex tropical forests have been mostly transformed into ecologically simplified introduced grasslands and cropping areas. Grazing lands derived from cleared forests have a low population density, and at a national-level, a spatial footprint of 0.65 ha/person (occupying 68% of cleared land) (Table 2). However, this measure does not account for the large areas of “semi-natural” savannas and high-Andean

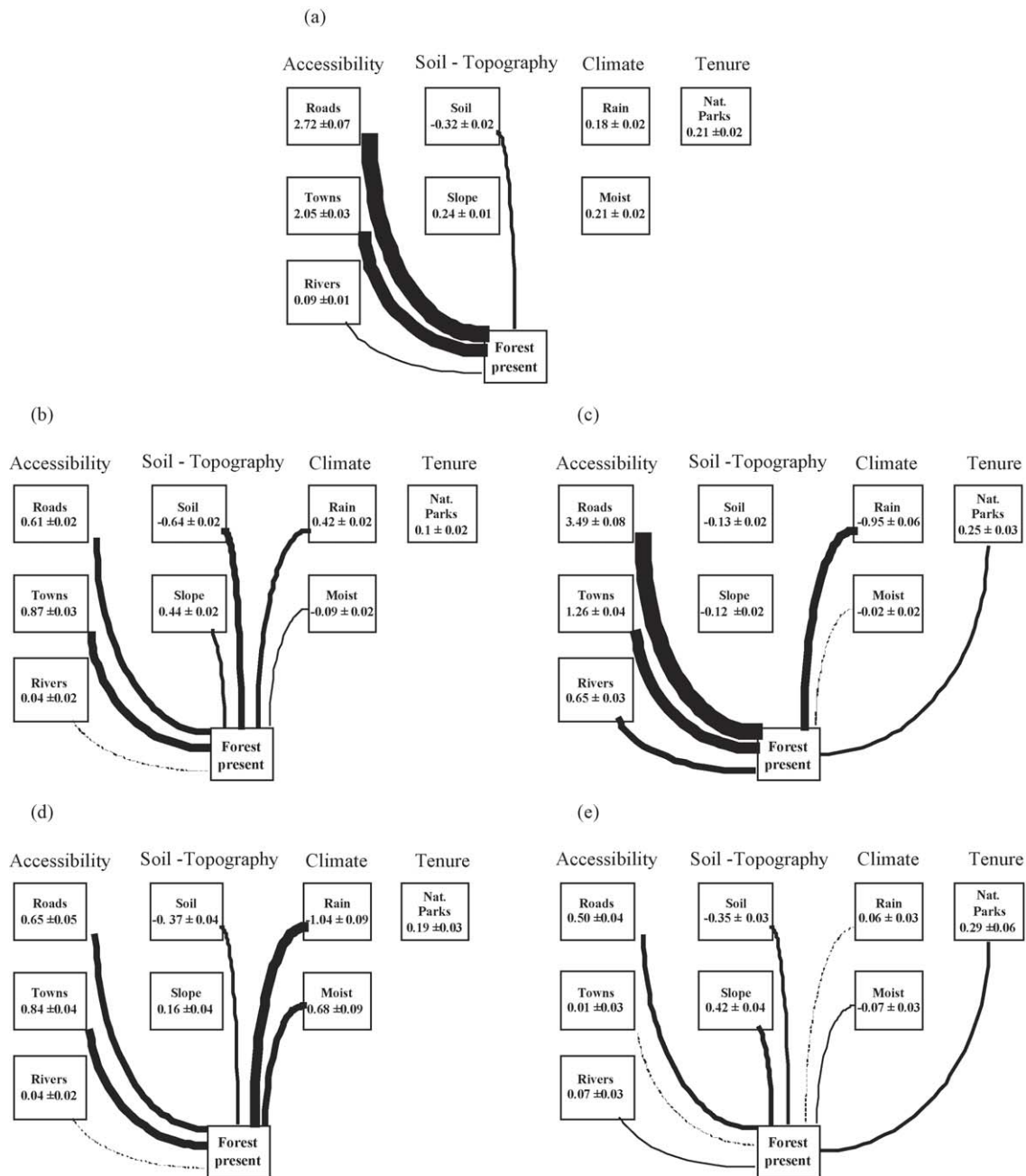


Fig. 6. Comparative effect of the explanatory variables in the logistic regression models: (a) national model with regions as variable, (b) Andean region model, (c) Amazon region model, (d) Caribbean region model, and (e) Pacific region model. Thickness of arrows is proportional to the effect of variable; dotted lines indicate non-significant relationships. Numbers in boxes indicate coefficients and S.E.

grasslands and shrublands (Páramos), whose composition and structure has also been modified by centuries of grazing pressure. If all areas subject to grazing land use are considered, the spatial footprint of the cattle industry increases to 0.97 ha/person (Table 2). The majority of cattle in Colombia are produced for the national market, with exports restricted due to foot and mouth disease. Hence, this footprint represents the internal consumption of beef products. A historical analysis by Etter and van Wyngaarden (2000) also found recently cleared areas in Colombia to be

increasingly dominated by pastures as compared to cropped areas. Despite its large area of impact, little is known about the long-term effects of cattle grazing on biodiversity and ecosystem processes in Colombia.

4.2. Predictions of deforestation

The scale of analysis (2 km grid) of this study implies that the modeling results presented here should not be seen as spatially precise probabilistic and quantitative forecasts of

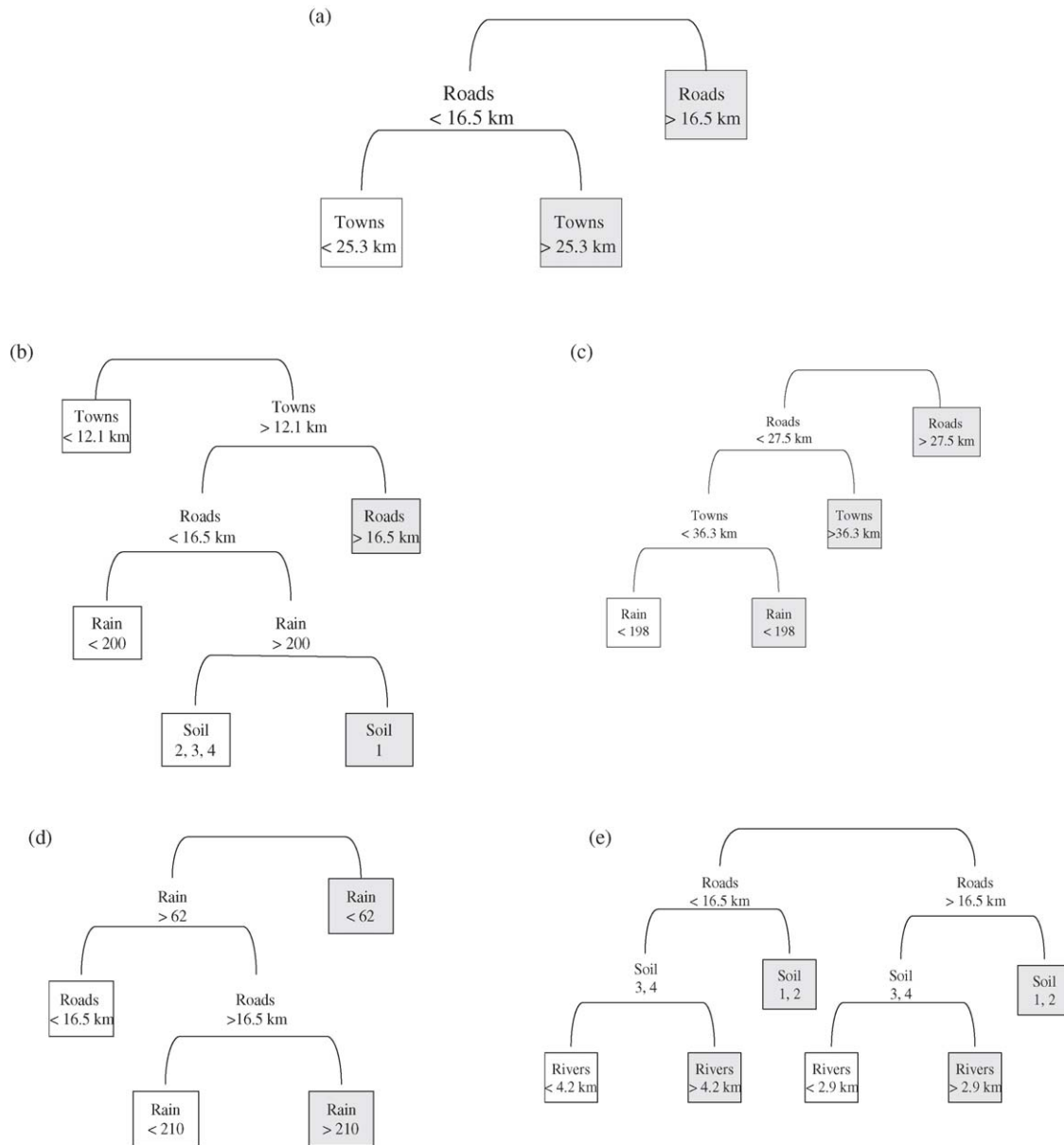


Fig. 7. Comparative effect of the explanatory variables in the classification tree models: (a) national model with regions as variable, (b) Andean region model, (c) Amazon region model, (d) Caribbean region model, and (e) Pacific region model. Shaded boxes indicate terminal nodes with forest present, and white boxes indicate cleared land. Numbers indicate cut-off levels for the explanatory variables in order to determine the tree-splits.

forest conversion, but rather as a planning tool indicating where conversion of forested ecosystems are more likely to occur in the near future. Although our predictions need to be refined as improved data becomes available, the general pattern of areas predicted as most vulnerable to forest conversion is consistent with the actual patterns of colonization and deforestation in Colombia (circled areas in Fig. 8). Our refined ‘best’ model identified the currently observed hotspots of deforestation in the Andean region: Fragua-Patascóy (4), Alto Guayabero (5) and Perijá (8) and in the lowlands of the Pacific region: Quibdó-Tribugá (1) and Patía-Mira (3). At a finer scale, the qualitative validation

using MODIS satellite imagery showed that the predictions of deforestation for the two main colonization fronts in the Amazon did not entirely concur with the observed patterns: for the Caquetá colonization front the predictions did not reflect the observed extent and continuity of deforestation in this area, while excess deforestation was predicted in the Guaviare colonization front (Fig. 9).

A limitation of our study is an inability to assign precise temporal frameworks to our predictions of forest conversion. This is because our models are based on static forest cover data (one snapshot representing the condition of 1998), rather than multi-temporal data that would allow analyzing spatio-

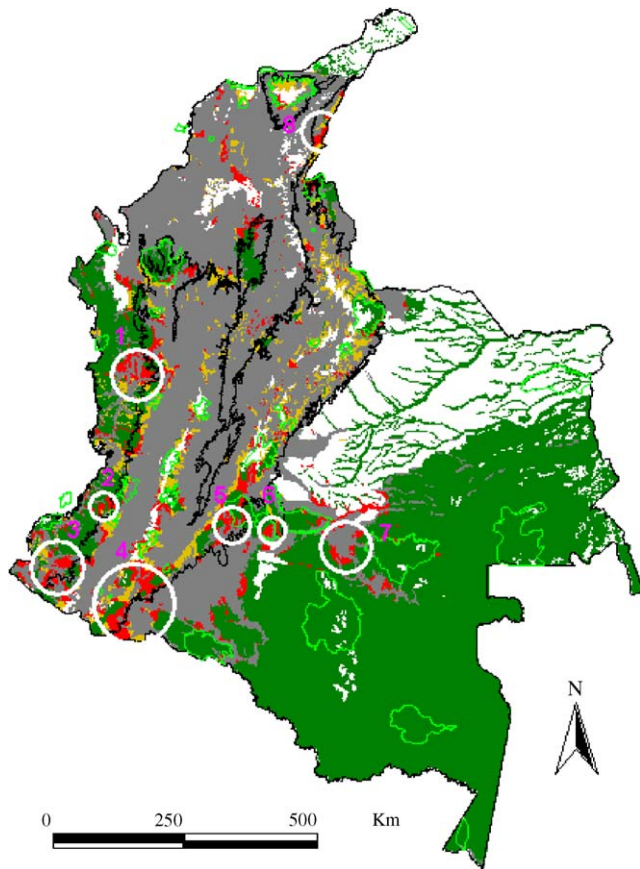


Fig. 8. Predicted deforestation hotspots obtained by combining areas predicted to have the highest probability of forest conversion (>70%) from the best model (the region-specific classification tree) with the areas with >2% rural population growth rate (1985–1993). Red depicts the deforestation hotspots (areas with >70% probability of forest conversion and >2% rural population growth). Orange and red depicts areas with >70% probability of forest conversion. Green depicts forested areas, gray represents cleared forested areas and white represents non-forested areas. White circled areas indicate current hotspots of deforestation, which are also areas of high-value biodiversity value: (1) Quibdó-Tribugá, (2) Farallones-Micay, (3) Patía-Mira, (4) Fragua-Patascoy, (5) Alto Duda-Guayabero, (6) Macarena, (7) Guaviare, and (8) Perijá. Black line is the Andean region, and light-green lines are national parks.

temporal variability of deforestation and regrowth. Furthermore, our models may not reflect the contemporary factors that drive forest conversion, as the present distribution of forest cover represented in our forest cover map is the result of the cumulative impact of past clearing events, and in some areas spanning several hundred years. As a result, our models underestimated lowland forest conversion, especially in the eastern Amazon region such as in Caquetá, where there are active colonization fronts (Viña et al., 2004; Etter et al., 2005a). This result was confirmed by the validation against the satellite images (Fig. 9). This underestimation could possibly be explained by the recent upsurge of the illegal plantations of Coca in this region. This illegal crop is mostly constrained to remote or low government control areas and therefore identifying variables to explain this form of land use change is problematic. Conversely, our models overestimated

forest conversion in the Andean region, as historically, this is where most forest conversion has occurred, but is currently confined to areas in the low-altitude belts, such as San Lucas and La Fragua-Patascoy. To overcome this historical bias, comparable multi-temporal datasets of forest cover and explanatory variables (e.g. roads, population) are required (Wilson et al., 2005b), and temporally explicit models such as CLUE (Verburg et al., 1999) and GEOMOD2 (Pontius et al., 2001) could be employed.

The relationships between the predictions of deforestation and the explanatory variables of our results, reflect the findings of other deforestation assessments. For example, forest conversion was predicted to be greater in areas of high soil fertility, on gentle slopes, close to roads, and with low precipitation (Sader and Joyce, 1988; Ludeke et al., 1990; Veldkamp et al., 1992; Laurance et al., 2002; Linkie et al., 2004). However, the importance of these explanatory variables varies regionally. For example, in the Andean region, distance to towns, soil fertility and distance to roads were most important, while in the Amazon region, the most important variables were distance to roads, distance to towns and the number of rain days (Fig. 6). In regions with more contrasting climate (such as the Caribbean), factors such as number of rain days and moisture availability are important in explaining forest conversion. These results show the major role of accessibility in explaining forest conversion in all regions, but especially in areas of recent deforestation such as the Amazon. It also is consistent with studies in the Brazilian Amazon, where Laurance et al. (2002) found a high correlation between the distance to roads and the amount of cleared land. In Colombia, variables such as distance to rivers are only important in the Amazon where they serve as transport routes.

The differences between the logistic regression and classification tree models in terms of their prediction errors and their discrimination ability was of the same order of magnitude as that observed by McDonald and Urban (2004). An advantage of classification trees over logistic regression is that they offer additional information for interpreting the relative importance of explanatory variables by ranking them and providing information on thresholds. However, logistic regression models provide estimates of coefficients and a measure of the significance of variables. We concur with McDonald and Urban (2004) and Wilson et al. (2005a) that classification trees and logistic regression models should be used in a complementary manner to model land cover changes. Our results show the usefulness of using additional data to refine model predictions. For example, our use of population growth data removed large areas of the Andean region that were incorrectly predicted to be cleared (Fig. 5d, blue and Fig. 8, orange). Other ancillary data, such as legal and illegal crops or political conflicts, could also be used to further refine our predictions.

An assessment of fragmentation in the Andean region by (Armenteras et al., 2003) identified the Andean oak

Table 4

Forest area predicted to be cleared by the 'region-specific classification tree ($p > 70\%$)' (CART), and municipalities with annual population growth $>2\%$ (CART and POP 2%)

Region	CART		CART and POP 2%		Difference (%)
	ha	%	ha	%	
Andes	5,511,600	62.9	2,265,600	50.8	60.2
Catatumbo	20,400	0.2	5,600	0.1	72.1
Magdalena	185,200	2.1	68,400	1.5	61.3
Caribbean	684,400	7.8	342,400	7.7	49.2
Orinoco	97,200	1.1	78,000	1.7	19.3
Pacific	1,276,000	14.6	780,800	17.5	39.1
Amazon	988,400	11.3	920,000	20.6	7.0
Total	8,763,200	100.0	4,460,800	100.0	49.1

(*Quercus* spp.) forests as the most threatened ecosystem. Our results assigned an intermediate threat level to these forests, but ranked other ecosystems such as the humid mid-Andean and the humid and sub-humid high-Andean forests, as vulnerable to clearing. These results illustrate how different analytical approaches can lead to different conclusions. In order to provide information that is useful for policy makers, an assessment of the certainty of the predictions of vulnerability is required (Wilson et al, 2005).

4.3. Implications for conservation planning

In addition to information on biological and ecological values, information on the vulnerability of areas to threats such as land clearing, has been identified as important for prioritizing conservation action (Pressey et al., 1993; Wilson

et al., 2005b). Our results provide a ranking of the risk of exposure of remnant forested ecosystems to agricultural conversion. However, the limited knowledge concerning the vulnerability of Colombian ecosystems is alarming, given the vast opportunities for analysis offered by remote sensing technology and the global importance of the environmental resources and biodiversity of Colombia (Chaves and Arango, 1998). In addition, our predicted deforestation hotspots coincide with areas that are outstanding in terms of their biodiversity value (Hernández et al., 1992), such as the Quibdó-Tribugá, Patía-Mira, Fragua-Patascoy and Perijá areas (Fig. 6). The consequences of these results for conservation planning in Colombia is an important aspect of our planned future research.

We argue that an ecosystem monitoring protocol for Colombia is urgently required to allow information on

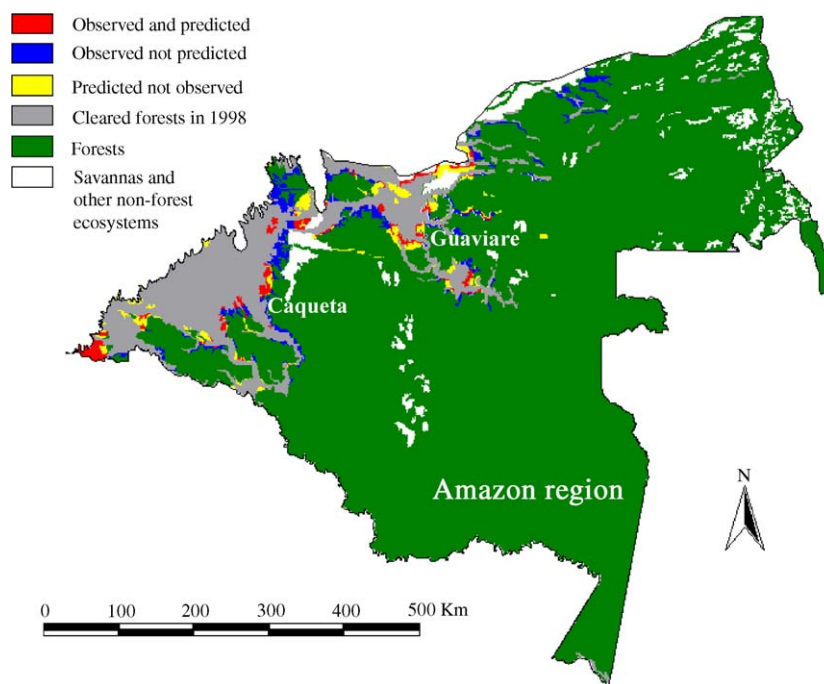


Fig. 9. Map of the Amazon region of Colombia, showing the agreement and disagreement between the predicted deforestation hotspots (Fig. 8) and the observed forest conversion. The latter was interpreted using the ecosystem map and the MODIS satellite images of 1998 and 2004, respectively.

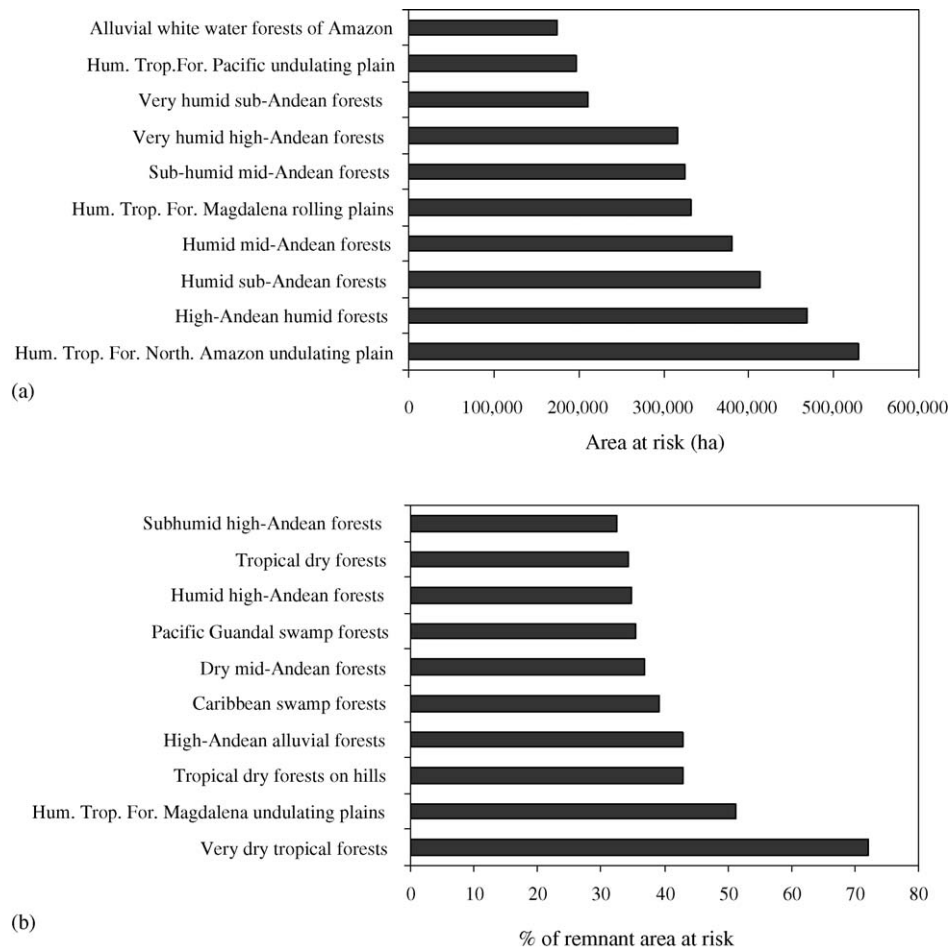


Fig. 10. Remnant forested ecosystems predicted to be at risk according to the refined deforestation hotspot model. (a) Most vulnerable forested ecosystems in terms of total area at risk, and (b) most affected forested ecosystems in terms of proportion of remnant area at risk.

threats to and vulnerability of ecosystems to be incorporated into conservation planning. Because of important regional differences in the patterns and drivers of deforestation, monitoring and planning are required at a regional or sub-regional levels, rather than at a national-level. This will ensure that a thorough understanding and monitoring of threatening processes in Colombia is obtained, and that conservation actions are targeted.

5. Conclusions

This study fulfilled its aims by providing new knowledge about the primary factors influencing deforestation in Colombia and their variability across regions. It also provided predictions of the probable expansion of the spatial footprint of agricultural land uses and of deforestation hotspots. Accessibility was found to be an important variable for explaining the patterns of deforestation observed in Colombia at both the regional and the national-level. We also showed the utility of a combination

of statistical modeling approaches to analyze and predict deforestation. Accounting for the regional heterogeneity of Colombia when modeling deforestation increased accuracy of predictions. Colombia is a country where the biological natural resources are an important asset, and the gains and losses from inappropriate land cover change are very high. However, land use planning in Colombia is in its infancy and would benefit greatly from the use of improved data and monitoring programs. In order to safeguard the biological assets of Colombia, more needs to be done to measure, in a systematic way, changes in the “ecological footprint” of different agricultural land uses and their impacts.

Acknowledgements

We thank the Universidad Javeriana and the University of Queensland for financial support to AE. Constructive comments of two anonymous reviewers helped improve the paper.

References

- Achard, F., Eva, H., Stibig, H.-J., Mayaux, P., Gallego, J., Richards, T., Malingreau, J.-P., 2002. Determination of deforestation rates of the World's humid tropical forests. *Science* 297 (9 August), 999–1002.
- Armenteras, D., Gast, F., Villareal, H., 2003. Andean forest fragmentation and the representativeness of protected natural areas in the eastern Andes. *Colombia Biol. Conserv.* 113 (2), 245–256.
- Chaves, M.E., Arango, N. (Eds.), 1998. Informe Nacional Sobre el Estado de la Biodiversidad en Colombia-1997. I.A. von Humboldt, Bogota.
- Colmenares, G., 1999. Historia Economica y Social de Colombia I. TM Editores, Bogota.
- Departamento Administrativo Nacional de Estadística-DANE, 1993. Censo Nacional de Poblacion. http://www.dane.gov.co/inf_est/poblacion.
- Etter, A., Andrade, A., 1987. Seguimiento al proceso de colonizacion en la Amazonia Colombiana. In: Proceedings of the IV Latin American Remote Sensing Symposium (Memorias del IV Simposio Latinoamericano de Sensores Remotos), IGAC, Bogotá, pp. 84–92.
- Etter, A., 1998. Mapa general de ecosistemas de Colombia (1:2,000,000). In: Chaves, M.E., Arango, N. (Eds.), Informe Nacional Sobre el Estado de la Biodiversidad en Colombia-1997. Instituto Alexander von Humboldt, Bogotá.
- Etter, A., Fandino, M.T., Van Wyngaarden, W., 1999. Mapa de ecosistemas originales. In: Analysis de la Representatividad de los Ecosistemas de la region Andina en Colombia (Informe Final), Javeriana University-UNDP-Instituto A. von Humboldt, Bogotá.
- Etter, A., van Wyngaarden, W., 2000. Patterns of landscape transformation in Colombia with emphasis in the Andean region. *Ambio* 29 (7), 432–439.
- Etter, A., McAlpine, C., Phinn, S., Pullar, D., Possingham, H., 2005a. Unplanned land clearing of Colombian rainforests: spreading like disease? *Landscape Urban Plann.* (doi:10.1016/j.landurbplan.2005.03.002), in press.
- Etter, A., McAlpine, C., Pullar, D., Possingham, H., 2005b. Modeling the conversion of Colombian lowland ecosystems since 1940: drivers, patterns and rates. *J. Environ. Manage.* (doi:10.1016/j.jenvman.2005.05.017), in press.
- Forman, R.T.T., 1995. Land Mosaics: The Ecology of Landscapes and Regions. Cambridge U.P., N.Y.
- García, J., 2002. Estudio de la transformacion de los ecosistemas secos de la baja Guajira (1940–1997), Colombia. BSc Thesis, PUJ, Bogota.
- Geist, H.J., Lambin, E.F., 2001. What drives tropical deforestation? A meta-analysis of proximate and underlying causes of deforestation based on subnational case study evidence (<http://www.geo.ucl.ac.be/LUCC/lucc.html>). LUCC Report Series, 4. CIACO, Louvain-la-Neuve.
- Green, R.H., 1979. Sampling Design and Statistical Methods for Environmental Biologists. Wiley, New York.
- Hernández, J., Ortiz, R., Walschburger, T., Hurtado, A., 1992. Estado de la Biodiversidad en Colombia. La Diversidad Biológica de Iberoamérica. I. CYTED, Mexico, DF, 146 pp.
- Herrera, M., 2000. Ordenamiento territorial y control politico en las Llanuras del Caribe y en los Andes Centrales Neogranadinos, Siglo XVIII. PhD Thesis, U. of Syracuse, N.Y.
- Hosmer, D.W., Lemeshow, S., 2000. Applied Logistic Regression. John Wiley & Sons Inc., New York, 373 pp.
- Houghton, R.A., 1994. The worldwide extent of land-use change: in the last few centuries, and particularly in the last several decades, effects of land-use change have become global. *Bioscience* 44 (5), 305–313.
- Insightful-Corporation, 2002. S-Plus 6.1 for Windows, Seattle, Washington.
- Instituto Geográfico Agustín Codazzi, 1992. La Poblacion en el proceso de formacion del Pais. IGAC, Bogota.
- Instituto Geográfico Agustín Codazzi, 1983. Mapa general de suelos de Colombia (1:1 500 000). IGAC, Bogotá.
- Instituto Geográfico Agustín Codazzi, 2000. Mapas topopgráficos (1:1 500 000). IGAC, Bogotá.
- Instituto Geográfico Agustín Codazzi, 1985. Mapa Agroecologico de Colombia. IGAC, Bogotá.
- Lambin, E.F., Geist, H.J., Lepers, E., 2003. Dynamics of land-use and land-cover change in tropical regions. *Annu. Rev. Environ. Resour.* 28 (205–241).
- Laurance, W.F., Albernaz, A.K., Schroth, G., Fearnside, P.M., Bergen, S., Venticinque, E.M., Da Costa, C., 2002. Predictors of deforestation in the Brazilian Amazon. *J. Biogeogr.* 29, 737–748.
- Lepers, E., Lambin, E.F., Janetos, A.C., Defries, R., Achard, F., Ramankutty, N., Scholes, R.J., 2005. A synthesis of information on rapid land-cover change for the period 1981–2000. *Bioscience* 55 (2), 115–124.
- Lewis, R.J., 2000. An Introduction to Classification and Regression Tree (CART) Analysis, 2000 Annual Meeting of the Society for Academic Emergency Medicine. (<http://www.saem.org/download/lewis1.pdf>). San Francisco, California.
- Linkie, M., Smith, R.J., Leader-Williams, N., 2004. Mapping and predicting deforestation patterns in the lowlands of Sumatra. *Biodivers. Conserv.* 13 (10), 1809–1818.
- Loh, J., Harmon, D., 2005. A global index of biocultural diversity. *Ecol. Indicators* 5 (3), 231–241.
- Ludeke, A.K., Maggio, R.C., Reid, L.M., 1990. An analysis of anthropogenic deforestation using logistic regression and GIS. *J. Environ. Manage.* 31, 247–259.
- McAlpine, C., Fensham, R.J., Temple-Smith, D.E., 2002. Biodiversity conservation and vegetation clearing in Queensland: principles and thresholds. *Rangeland J.* 24 (1), 36–55.
- McDonald, R.I., Urban, D.L., 2004. Spatially varying rules of landscape change: lessons from a case study. *Landscape Urban Plann.*, corrected proof, in press.
- Mendoza, J.E., Etter, A., 2002. Multitemporal analysis (1940–1996) of land cover changes in the south-western Bogota highplain (Colombia). *Landscape Urban Plann.* 59, 147–158.
- Mertens, B., Lambin, E., 1999. Modelling land cover dynamics: integration of fine-scale land cover data with landscape attributes. *Int. J. Appl. Earth Observ. Geoinform.* 1 (1), 48–52.
- Mertens, B., Kaimowitz, D., Puntodewo, A., Vanclay, J., Mendez, 2004. Modelling deforestation at distinct geographic scales and time periods in Santa Cruz, Bolivia. *Int. Region. Sci. Rev.* 27 (3), 271–296.
- Metz, C.E., 1978. Basic principles of ROC analysis. *Semin. Nucl. Med.* 8, 283–298.
- Ministry of Environment (Colombia), 2000. Mapas de las areas protegidas de Colombia (1:1 500 000). Bogotá.
- Nagendra, H., Southworth, J., Tucker, C.J., 2003. Accessibility as a determinant of landscape transformation in western Honduras: linking pattern and process. *Landscape Ecol.* 18 (2), 141–158.
- Palacios, G. (Ed.), 2001. La Naturaleza en Disputa: Historia Ambiental de Colombia 1850–2000. Ediciones Universidad Nacional-Colciencias, Bogota.
- Pontius Jr., R.G., 2000. Quantification error versus location error in comparison of categorical maps. *Photogramm. Eng. Rem. Sens.* 66 (8), 1011–1016.
- Pontius Jr., R.G., Cornell, J.D., Hall, C.A.S., 2001. Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica. *Agric. Ecosyst. Environ.* 85 (1–3), 191–203.
- Pontius Jr., R.G., Batchu, K., 2003. Using the relative operating characteristic to quantify certainty in prediction of location of land cover change in India. *Trans. GIS* 7 (4), 467–484.
- Pressey, R.L., Humphries, C.J., Margules, C.R., Vane-Wright, R.I., Williams, P.H., 1993. Beyond opportunism: key principles for systematic reserve selection. *Trends Ecol. Evol.* 8 (4), 124–128.
- Ramankutty, N., Foley, J.A., Olejniczak, N.J., 2002. People on the land: changes in global population and croplands during the 20th century. *Ambio* 31 (3), 251–257.
- Sader, S.A., Joyce, A.T., 1988. Deforestation rates and trends in Costa Rica 1940–1983. *Biotropica* 20 (1), 11–19.

- Serneels, S., Lambin, E.F., 2001. Proximate causes of land-use change in Narok District, Kenya: a spatial statistical model. *Agric. Ecosyst. Environ.* 85 (1–3), 65–81.
- Southworth, J., Tucker, C.J., 2001. The influence of accessibility, local institutions and socioeconomic factors on forest cover change in the mountains of western Honduras. *Mt. Res. Dev.* 21 (3), 276–283.
- Veldkamp, E., Weitz, A.M., Staritsky, I.G., Huising, E.J., 1992. Deforestation trends in the Atlantic zone of Costa Rica: a case study. *Land Degrad. Rehab.* 3, 71–84.
- Verburg, P.H., de K.G.H.J., Kok, K., Veldkamp, A., Bouma, J., 1999. A spatial explicit allocation procedure for modelling the pattern of land use change based upon actual land use. *Ecol. Model.* 116 (1), 45–61.
- Viña, A., Cavelier, J., 1998. Deforestación en el piedemonte llanero (1940–1990). *Biotropica* 30 (1), 37–48.
- Viña, A., Echavarría, F., Rundquist, D.C., 2004. Satellite change detection analysis of deforestation rates and patterns along the Colombia–Ecuador border. *Ambio* 33 (3), 118–125.
- Wackernagel, M., Rees, W.E., 1996. *Our Ecological Footprint: Reducing Human Impact on the Earth*. New Society, Gabriola Island, BC.
- Wackernagel, M., Schulz, N.B., Deumling, D., Linares, A.C., Jenkins, M., Kapos, V., Monfreda, C., Loh, J., Myers, N., Norgaard, R., Randers, J., 2002. Tracking the ecological overshoot of the human economy. *PNAS* 99 (14), 9266–9271.
- Wilson, K., Newton, A., Echeverría, C., Weston, C., Burgman, M., 2005a. A vulnerability analysis of the temperate forests of south central Chile. *Biol. Conserv.* 122, 9–21.
- Wilson, K., Pressey, R.L., Newton, A., Burgman, M., Possingham, H., Weston, C., 2005b. Measuring and incorporating vulnerability into conservation planning. *Environ. Manage.* 35 (5), 527–543.