

Land-Cover-Change Trajectories in Southern Cameroon

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The objective of this study is to better understand the complexity of deforestation processes in southern Cameroon by testing a multivariate, spatial model of land-cover change trajectories associated with deforestation. The spatial model integrates a spectrum of independent variables that characterize land rent on a spatially explicit basis. The use of a time series of high-spatial-resolution remote sensing images (Landsat MSS and SPOT XS), spanning two decades, allows a thorough validation of spatial projections of future deforestation. Remote sensing observations reveal a continuous trend of forest clearing and forest degradation in southern regions of Cameroon, but with a highly fluctuating rate. A significant proportion of the areas subject to a land-cover conversion experienced other changes in the following years. The study also demonstrates that modeling land-cover change trajectories over several observation years allows a better projection of areas with a high probability of change in land-cover than projecting such areas on the basis of observations from the previous time period alone. Statistical results suggest that, in our southern Cameroon study area, roads mostly increased the accessibility of the forest for migrants rather than providing incentives for a transformation of local subsistence agriculture into market-oriented farming systems. The spatial model developed in this study allows simulations of likely impacts of human actions, leading to a transformation of the landscape (e.g., road projects) on key landscape attributes (e.g., biodiversity). Currently, several road projects or major logging concessions exist in southern Cameroon. *Key Words: deforestation, land-use change, Africa, geographic information systems, landscape model.*

Understanding processes of land-use and land-cover change has always been an important research area in geography. This research is receiving renewed interest thanks to a combination of new demands for understanding anthropogenic surface processes (Meyer and Turner 1994) and the maturation of technologies used to collect and analyze large amounts of spatially explicit data on the land surface (Lambin 1997). Enhanced monitoring and modeling abilities allow researchers to improve the detailed spatial modeling of land-use and land-cover changes while still achieving the level of generality that is required for a global perspective on such changes.

Land-cover changes are often conceived as simple and irreversible conversions from one cover type to another. In this idealized representation, deforestation would be a total and permanent change from a dense forest landscape to an area with a low tree cover, and agricultural expansion would mean the transition to perma-

nent cultivation. While such neat schemes would make the monitoring and modeling of land-cover changes a straightforward task, reality is more complex. Land-cover changes are most often noncontinuous in space, leading to complex landscape mosaics and mixtures of cover types. They are also reversible, and often follow time sequences of successive cover types (or mixture of cover types). These sequences can be linear (e.g., from dense forest to smallholder agriculture to large ranches to degraded land) or cyclical, as in the case of long-fallow agriculture. It is necessary to integrate this complexity into the analysis of land-cover-change processes so as to acquire a better understanding of the causes of change and to better predict likely evolutions based on such models.

Most previous statistical analyses of the causes of deforestation have thus far used, as a dependent variable, a simple binary measure such as deforestation versus no deforestation, or forest versus nonforest (see reviews by Brown and

Pearce 1994; Lambin 1994). The assumption in such studies is that deforestation is permanent and that the presence of nonforest at one time implies that forest will remain absent for a long period. A few authors, analyzing time series of remote sensing data, have instead emphasized the reversibility of land-cover conversions, which in theory should lead to complex trajectories of change (Lucas et al. 1993; Alves and Skole 1996). This issue is particularly important in the analysis of secondary forests. Such forests accumulate biomass more rapidly than primary ones and therefore act as a net sink for atmospheric carbon (Brown and Lugo 1990). Another example of the reversibility of land-cover changes is found in semiarid regions that are highly vulnerable to droughts, but that also exhibit considerable resiliency (Tucker et al. 1991).

The concept of *trajectories of change* has attracted some attention from a theoretical viewpoint. These trajectories, defined as trends over time among the relationships between the factors that shape the changing nature of human-environment relations and their effects within a particular region (Kasperson et al. 1995), take widely different forms and depend on circumstances, regional contexts, and government policies. Lambin (1997) suggested that generic paths of change can be identified, such as the typical sequences of land-use changes found across tropical regions. Trajectories of change were also analyzed as part of the long-run processes of agricultural intensification driven by demographic phenomena, as described by Boserup (1965). Such trajectories have been characterized as defined by the stock of environmental resources and human well-being (Karshenas 1994), or as a function of time, in terms of degree of sustainability of human-environment relations (Kasperson et al. 1995). In this study, trajectories of land-cover change refer to successions of land-cover types for a given sampling unit over more than two observation years.

The objective of this study is to better understand the land-use change trajectories associated with different deforestation processes in southern Cameroon. We test a multivariate spatial model of land-cover-change trajectories associated with deforestation. Previous studies have ignored complex sequences of land-cover changes, as they simply measured the conversions from one category to another (Sader and Joyce 1988; Gastellu-Etchegorry and Sinulingga

1988; Ludeke et al. 1990; Brown et al. 1993; Liu et al. 1993; Sader 1995; Mertens and Lambin 1997). Chomitz and Gray (1996) developed a multinomial logit model, with three potential outcomes (i.e., natural vegetation, commercial agriculture, and semisubsistence agriculture). All these previous studies measured changes in land-cover between only two time periods. In this paper, we test whether modeling land-cover-change trajectories over a sequence of observation years allows a better projection of areas with a high probability of change in land-cover than on the basis of observations from only the previous time period. In other words, do we better represent deforestation processes if we consider that land-use changes are not first-order processes—i.e., if the probability of a given land use at any time does not only depend upon the most recent use, but also upon even earlier ones?

After defining the conceptual model on which our analyses are based, this work consists in the following steps: (1) measurement of the dependent variable, which is defined as sequences of land-cover changes, using a time series of high-spatial-resolution remote sensing images, spanning two decades; (2) measurements of independent variables that characterize as realistically as possible the determinants of land-use on a spatially explicit basis; (3) development of multivariate spatial models of land-cover conversions and land-cover change trajectories; and (4) validation of spatial projections of areas at risk of deforestation, using recent remote-sensing data. The major improvements, compared to our previous study on the same region (Mertens and Lambin 1997), consist in the nature of the dependent variable, the integration of a broader spectrum of independent variables, the multivariate model, the validation of the model predictions, and the proposed application of the model's projections to assess potential impacts of land-cover changes.

Background

Economic Models of Deforestation

In econometric approaches to land-use changes, the supply and demand functions of the land market, which is assumed to be competitive, are estimated. Most economic modeling of land-use changes originates from the land-rent theories

of von Thünen and Ricardo. Models of urban and periurban land allocation are much more developed than their rural counterpart (Riebsame et al. 1994). Any parcel of land, given its attributes and location, is assumed to be allocated to the use that earns the highest rent. Deforestation, for example, is driven by choices by land managers among alternative rents. Land conservation depends on investment decisions by land managers, based on comparisons between discounted benefits and costs. Such models allow investigation of the influence of various policy measures on land allocation choices (Lambin 1997).

Microeconomic models usually assume that the agents whose behavior is described within the model have the capacity to make informed predictions and plans, and that they are risk minimizers (Fischer et al. 1996). After exploring all options available to them, individuals make rational decisions based on available information, obligations, and expectations (social as well as economic), so as to balance anticipated returns and risks (Vanclay 1995). Given the inherent unpredictability of some of the socioeconomic forces driving land-use changes, economic models often adopt a normative approach.

Panayotou and Sungsuwan (1989) constructed a theoretically based model of tropical deforestation by introducing three demand functions: the demand for logging, the demand for fuelwood, and the demand for conversion to agricultural land. They then obtained an aggregate deforestation function and empirically estimated a simplified model for northern Thailand. In addition, several partial or general equilibrium models of land use have been developed to describe the trade-off between land clearance for agriculture and resource conservation or maintenance (Walker 1987; Southgate 1990; Jones and O'Neill 1992). Jones and O'Neill (1992) examined the impact of profit maximization decisions modeled at the individual level on region-wide environmental outcomes. Von Thünen land-use models were also applied to describe periurban deforestation at regional scales (Jones and O'Neill 1993; Chomitz and Gray 1996). The spatial model of Chomitz and Gray (1996) applied to Belize indicated that intensification of the road network around market areas provides a better trade-off between spurring development and minimizing deforestation than the extensification of the network. In a review of economic models of deforestation,

Kaimowitz and Angelsen (1997) distinguished between household and firm-level models, regional-level models, and national and macro-level models. Within their typology, this study examines a regional-level spatial regression model. The main contribution of our work, in this substantive and methodological context, is to improve the representation of the processes of deforestation in these economic models—not as simple forest conversions between two time periods but as complex trajectories of changes affected by reversibility and fluctuations over successive observation periods.

Deforestation and Land Rent

Our approach to modeling land-use and land-cover changes assumes that land is devoted to the use that generates the highest potential rent. This rent is a function of the returns and costs of forest conversion. *Returns* to forest conversion depend on:

1. *farmgate price of outputs* (P_O) as a function of the price at the market and the transportation cost; it is computed as:

$$P_O = \text{price at town} - \frac{\sum(\text{distance on road}_i * \text{cost/kg-km on road}_i)}{\quad} \quad (1)$$

2. *farmgate price of inputs* (P_I) as a function of the price at the market and the transportation cost; it is computed as:

$$P_I = \text{price at town} + \frac{\sum(\text{distance on road}_i * \text{cost/kg-km on road}_i)}{\quad} \quad (2)$$

3. *agroclimatic conditions*, which can be represented by classes of land aptitude for agriculture, which describe the influence of soil, climate, and topography on the potential yield of the main crops of the local farming systems.

Costs of forest conversion depend on:

1. *physical accessibility to the forest*, which in turn depends on the road network and the number of openings in the forest cover that facilitate access to the forested areas; this can be measured by the forest-cover fragmentation and by the distance of any forest location to the nearest forest/non-forest edge;

2. *forest-clearing cost*, which is related to the technology used for forest clearing and to the density of the vegetation cover;
3. *social accessibility to forested land*, which is related to human pressure on the land and depends on the population density relative to nonfarm employment opportunities in the region and, as a proxy variable, on the average income level of the local population (low average income level is assumed to generate greater demand for land);
4. *land tenure* and, in particular, the degree of tenure security of the forest occupants.

A forest plot is assumed to be converted to nonforest if it has a positive rent (i.e., if the returns to conversion are positive). The rent is unobserved (Chomitz and Gray 1996), but a reduced-form model can be estimated empirically, as a cross-section, under the assumption of a spatial equilibrium between the supply and demand for agricultural and forest commodities (Panayotou and Sungsuwan 1989). The model is greatly simplified if market prices are made exogenous, and if it is assumed that they remain constant. In this case, land-use decisions leading to changes in total production or consumption of agricultural products cannot affect market prices through, for example, market saturation. It also simplifies the model since we can then assume that decisions on any site are independent of those of other sites (Vanclay 1995).

A problem may arise in the above model when roads are endogenous to agricultural land use. As Chomitz and Gray note: "If roads are preferentially routed through agriculturally suitable areas and if some aspects of suitability are not observed, then the model may overestimate the effect of distance from the road" (1996: 493). This bias can be reduced by explicitly introducing a variable measuring the suitability of land for agriculture. Also, in southern Cameroon, the placement of the road network is generally exogenous to agricultural land use (as it is related to the need to connect distant cities and towns), though it is often endogenous to logging activities.

The conceptual model described above guided the selection of independent variables to be entered in the model. Unfortunately, no spatially explicit information was available on land tenure or land pressure. On the latter, the demographic data collected by local administrators were either too spatially aggregated or too sparse to be ex-

ploited in a spatial model. These two variables were therefore ignored in the analyses that follow; the forest-clearing technique is assumed to be primitive (fire and hand-cutting of trees), and to be identical throughout the study area.

Study Area

The Institutional Context in Cameroon

Evergreen and semideciduous forests cover approximately 44 percent of the area of Cameroon (FAO 1995), mostly in the southern part of the country. In the past several decades, a forestry code has regulated the management of forests in Cameroon. Recent degradation of the forests and international concerns about environmental issues have encouraged the country to revise its forest policy so as to promote a sustainable use of forest resources. This has resulted in the recent creation of the Office National de Développement des Forêts (ONADEF) in 1990 and the Ministry of Environment and Forest (MINEF) in 1992. Regulations governing the entire forestry sector have been significantly modified with the creation in 1995 of the National Forestry Action Program (NFAP). Its objectives (MINEF 1996) are to: (1) ensure the protection of the forest heritage and participate in safeguarding the environment and preserving biodiversity; (2) increase participation of local populations in forest conservation and management, so as to raise living standards; (3) develop forest resources with a view to increasing GDP while conserving production potential of fuelwood, timber, nontimber products, and wildlife resources; (4) ensure resource renewal through regeneration and reforestation, with a view to sustaining land potential; (5) revitalize the forestry sector by setting up an efficient institutional system that involves all parties concerned with the management of the sector.

A land-use plan, consisting of a zoning of the territory into large land-management units, has also been adopted. According to this plan, the southern part of Cameroon, which contains most of the nation's forest resources, is divided into two domains: (1) the *permanent forest domain*, composed of forest zones owned by the State [*forêts domaniales*] or public collectives [*forêts communales*]; and (2) the *nonpermanent forest domain*, composed of land likely to be diverted to agro-sylvo-pastoral uses.

It is interesting to monitor whether these new institutional tools have alleviated some of the problems of forest degradation in Cameroon. In its latest Forest Resource Assessment report, the Food and Agriculture Organization of the U.N. (FAO 1995) reported that Cameroon loses a net 0.6 percent of its forest every year. It is difficult, however, to produce accurate deforestation figures since, in Cameroon, most forest-cover changes take place as degradation due to fires, agricultural encroachment, and selective logging activities (Sayer et al. 1992).

The Bertoua Region

The study area is around the town of Bertoua, in the East Province of Cameroon. Located on the northeastern part of the southern Cameroon plateau (Figure 1), it is dominated by semideciduous forests with forest-savanna transition zone and savanna woodlands in the northern part of the province. The East province still has the lowest population density of Cameroon (4.1 inhabitants/km² in 1987) and the highest rate of rural population (70.1 percent). Slash-and-burn



Figure 1. Cameroon with the location of the study area. Only the main towns of interest are shown. The approximate spatial extent of the actual forest area is shaded in light grey. The Dja reserve area is shaded in dark grey.

agriculture is widespread. The low population density in southern Cameroon provinces has led to high rates of immigration, mostly of workers into agricultural and forest logging sectors. All provinces in the forest zone of Cameroon have a large positive migratory balance, except for the South Province (Pokam 1996). In-migration into the East Province is related to agricultural land availability, the presence of logging companies, and improvements in road and railway infrastructures. The road network, which, in this region, the logging companies often built and maintained for wood transport, facilitates access to forest areas by shifting cultivators in search of new agricultural land (Karsenty et al. 1993). Most of these landless migrants originate from the adjacent provinces or from the Central African Republic.

The East Province is a sensitive zone in terms of deforestation and biodiversity. Large areas defined in the new zoning plan as belonging to the forest domains have already been cleared or degraded. Numerous logging concessions have been granted to citizens as well as to foreign companies, in small, one-year-lease concessions referred to as *ventes de coupes*. A large faunal reserve, the Dja reservation, lies just south of the study area (Figure 1). It is one of the largest conservation areas in Cameroon (5,260 km²) and is a major biodiversity reserve both for fauna and vegetation.¹ Due to the growth of the rural population in the region, it is threatened by poaching and rapid encroachment of cocoa, coffee, and subsistence plots, particularly on the northern and western borders. Several roads in the province, including at the border of the Dja reservation, have been rehabilitated or built through funding by international agencies. This raises worries that the road developments will lead to further deforestation at the edge or within the reservation for wood extraction, commercial hunting, and agricultural encroachment. For all these reasons, and in order to better manage potential ecological impacts of future road projects, it is useful to develop predictive models for areas likely to be affected by future forest conversion. This can best be achieved by calibrating a spatial model of deforestation on adjacent areas in the province, where the process of forest-cover change is more advanced.

Data

A time series of four high-spatial-resolution satellite images was acquired for the years 1973,

1986, 1991, and 1996. Two Landsat MSS images (at a nominal spatial resolution of 50 × 70 m) were obtained at thirteen-year intervals (1973 and 1986), as were two SPOT XS (at a nominal spatial resolution of 20 × 20 m) at five-year intervals (1991 and 1996). The Landsat MSS and SPOT data from the four years were geometrically rectified and registered to a common UTM projection based on 1:200,000-scale topographic maps of Cameroon, and were further re-sampled, using the nearest-neighbor technique, to the spatial resolution of Landsat MSS. The best fit was provided using a second-order polynomial based on more than one hundred ground control points (root mean square error below the MSS pixel size). The area used to calibrate the model corresponds to the common zone between the two Landsat MSS and the 1991 SPOT images. It covers approximately 110,000 ha. The area used for model validation is the common zone between the area used for model calibration and the 1996 SPOT image. It covers 50,000 ha. We applied radiometric corrections, taking into account sensor parameters and solar illumination conditions, to transform the digital numbers into reflectances (using the formulas provided in Markham and Barker 1987). Vertical panchromatic aerial photographs from 1979 (at a 1:20,000 scale) and 1993 (at a 1:10,000 scale) were also assembled to support the interpretation of the satellite data.

Digital maps of road networks and towns were produced by manual digitization of the 1:200,000-scale topographic maps of Cameroon (Centre Géographique National 1978) and the more recent aerial photographs and remote sensing data for an update. Based on field observations, we characterized each road segment by its surface material. Population data from the 1976 and 1987 censuses, as well as agricultural data from 1984 to 1991, were compiled from agricultural census and surveys at the level of "arrondissements," administrative units with an average size of 5,700 km².

During three successive field excursions in 1993, 1994, and 1997, we assembled detailed ground observations of vegetation cover, agricultural practices, wood exploitation activities, surface material of roads, crop prices at different markets in the region, distribution systems, and qualitative information on land-use conflicts. We collected landscape observations along the main and secondary roads to cover all the accessible parts of the study area. All field observa-

tions were georeferenced (with an accuracy around 100 m) using a global positioning system (GPS). We used these field data, and the aerial photographs for the most remote areas, for validation of the remote sensing-based land-cover and land-cover change maps, and to support the interpretation of the statistical results. These observations were represented with a minimum mapping unit of 50×50 m (i.e., the MSS pixel).

The spatial resolution of the modeling experiment is determined by the coarser spatial resolution of the data used to compute the dependent variable (the Landsat MSS at 50×50 m, in this case). This resolution is therefore the basis for measuring all independent variables. As for any geographical study, the spatial resolution may have an impact on results (Arbia 1989)—for example, a finer spatial resolution could have led to the detection of finer-scale forest clearings and could, therefore, have altered the statistical results. The spatial resolution used here, however, is consistent with the spatial extent of the study, and the mapping unit more or less corresponds to the size of fields in small-holder agriculture.

Variables and Procedures

Measurement of the Dependent Variables

Below, two models with two different dependent variables are tested and compared. First, the dependent variable is defined as the presence or absence of deforestation between two observation years. Second, it is defined as a set of land-cover change trajectories over three observation years. In both cases, it is measured in the steps described below, using the time series of high-spatial-resolution remote sensing images.

Land-Cover Classifications. Land-cover maps of the study area for 1973, 1986, 1991, and 1996 were derived for each individual image, using a supervised classification procedure, based on a maximum likelihood classifier. The training areas were derived from the field observations in combination with an interpretation of the aerial photographs at the closest date. Training areas were only selected within the areas that did not change between the dates of acquisition of remote sensing data and the period of field observations. We estimated classification accuracy for all years, using an independent sample of 262

observations from the field campaigns and the low-altitude aerial photographs. Contingency tables between the reference data and remote sensing-based classification were produced, and the overall accuracy and Kappa index were computed (Congalton 1991). The population of pixels was first stratified by land-cover class, and an equal number of pixel observations was randomly selected in each class, with a minimum of 50 observations per class (as recommended by Congalton 1991).

Land-Cover-Change Analysis. Changes in land-cover between the successive dates were detected by combining two techniques in a multistage approach (after Pilon et al. 1988; Sader 1995; Macleod and Congalton 1998): (1) post-classification comparison—that is, overlaying and comparing the two successive land-cover classifications—and (2) band differencing—that is, subtracting reflectances (in this case, from the near-infrared Landsat MSS band 0.8–1.1 μm and SPOT band 0.79–0.89 μm) measured at the successive dates. The postclassification comparison leads to a categorical map that indicates, for every pixel, the land-cover classes at the two successive observation years (Jakubauskas 1990; Sader 1995). The ability to characterize “from” and “to” identifiers is essential for the definition of land-cover change trajectories. The disadvantage of this method is its dependence upon the classification accuracy of the maps compared.² We reduced this problem here thanks to an aggregation of the land-cover classes into a binary map: forest versus nonforest before change detection. This simple classification scheme results in a much-improved classification accuracy at the successive dates.

In addition, the second change-detection technique used in combination with the post-classification comparison further increases the reliability of the final land-cover change map. The band differencing method leads to a measure of change along a continuum of change intensity. It indicates the degree to which the change has modified the vegetation cover, using the surface reflectance as a proxy. While a direct evaluation of change areas is not possible with this latter method, it allows for the detection of forest degradation and thinning as well as of forest-cover conversion. Several recent studies have demonstrated the utility of the band differencing method for land-cover change detection (Murchoney and Haack 1994; Coppin and Bauer

1996; Milchener and Houhoulis 1997; Macleod and Congalton 1998).

We have combined the advantage of the two methods using the following procedure. The unchanged areas identified, based on the image differencing map, were labeled based on the first-date land-cover map. The changed areas identified based on image differencing were labeled using the result of the postclassification comparison method. This allows us to reduce the misclassifications on the final land-cover change map by reducing the area for which the results of the postclassification method are retained. In other words, the results of the postclassification method are only applied to the areas that have been identified as being affected by change based on the image differencing method, which is more reliable for change detection but fails to characterize the “from” and “to” land-cover classes. To avoid any overestimation of deforestation based on the image differencing method, a threshold value of change intensity was defined to highlight only the areas that have experienced the highest change intensity. This threshold was defined on the basis of field observations and corresponds to ± 1.5 standard deviations from the mean change intensity for the study area. Note that, as the Landsat MSS and SPOT data were resampled to the same spatial resolution (50×50 m) before they were classified, the combination of data from different sensors does not affect the estimates of land-cover change over time. Note also that great care was taken to avoid any bias related to climate variation, first by working with remote-sensing data from the same season, and second, by adapting the change thresholds to the phenological condition of semideciduous forest.

Trajectories of Land-Cover Change. The trajectories of land-cover change are defined by the successive transitions between land-cover categories over the observation years. Only three observation years were retained for the definition of these trajectories, since the fourth observation year was reserved for validation purposes. All possible land-cover trajectories were reduced to eight major sequences based upon the forest and nonforest categories. The latter class includes agriculture, heavily degraded forest, and savanna. These sequences and their interpretation are shown in Table 1.

These sequences are defined from a limited temporal sample of observations. Therefore, expressions such as “permanent forest regrowth” or “old forest clearing” only have meaning relative to the timing of observations—for example, a new clearing could take place anytime after the last observation of forest regrowth. The sequences that involve successions of clearings and regrowths (numbers 4 and 5) are likely to be associated with fallow agriculture.

Measurement of the Independent Variables

Several spatially explicit variables, generated using standard GIS analysis tools,³ were evaluated as determinants of the land rent and, therefore, as influencing decisions on forest clearing. These are described below.

Weighted distance to the nearest road. This variable was calculated as a series of 50-m-wide buffers expanding from each arc of the road network. The distance from any point to the nearest road was weighted by the average transportation cost on each road segment. Transport cost was based

Table 1. Land-Cover-Change Trajectories between 1973 and 1991 with Area, Proportion of Total Area Affected by Each Trajectory (%)

	Change Trajectory			Description	Coverage	
	1973	1986	1991		(ha)	(%)
1	Forest	Forest	Forest	Stable primary or secondary forest	92,451.25	81.10
2	Forest	Forest	Nonforest	Recent forest clearing	4,143.75	3.64
3	Forest	Nonforest	Nonforest	Old and permanent forest clearing	4,535.00	3.97
4	Forest	Nonforest	Forest	Old forest clearing with regrowth	264.50	0.23
5	Nonforest	Forest	Nonforest	Forest regrowth with new clearing	430.50	0.37
6	Nonforest	Forest	Forest	Old and permanent forest regrowth	650.00	0.57
7	Nonforest	Nonforest	Forest	Recent forest regrowth	562.50	0.49
8	Nonforest	Nonforest	Nonforest	Stable savanna or permanent agriculture	10,954.00	9.60

on the surface material of the road and was measured by the hourly-average traveling speed, following Chomitz and Gray (1996). A parcel of land located at one km from an asphalt road passable throughout the year has a higher estimated rent than a parcel of land at the same distance from a narrow dirt road usable only in the dry season. Four categories of roads were considered, based on the hourly-average traveling speed (from 20 to 80 km/h). The accessibility of any point was described as a function of the shortest distance to the road multiplied by a weight varying from 1 (for principal, permanent roads with an average speed of 80 km/h) to 4 (for tracks, which can only be used seasonally, with an average speed of 20 km/h), with values of 2 and 3 for, respectively, secondary roads (with an average speed of 60 km/h) and permanent tracks (with an average speed of 40 km/h). Detailed studies in Central Africa (Finifter and Verna 1996) and in the Brazilian Amazon (Stone 1998) have estimated the transportation cost for timber (in monetary units) for different road types. These studies have demonstrated that the actual transportation cost on principal roads, secondary roads, and permanent tracks varies by a factor proportional to the average traveling speed (1–3). They did not consider seasonal tracks. Field surveys suggest that the transportation costs for agricultural products and timber vary in a similar way for different road types (Forni, personal communication).

Weighted distance to the nearest market town along the road network. This variable was calculated as the sum of the distance from each location to the nearest road and the distance, along the road, to the nearest town. The distance on the road to the nearest town was weighted according to: (1) the transportation cost, by weighting the distances traveled respectively on different sections of the road by a factor varying from 1 to 4 according to the road quality (see above), and (2) the type of town market, by weighting the total distance to the town by a factor inversely proportional to the price level of agricultural products at the market. Actually, the attractivity of a town for a farmer settled in the surrounding area depends not only on its accessibility but also on the average retail price of agricultural products at its market. High output prices at a given market increase the land rent of parcels of surrounding land. Three types of markets were considered: urban, semirural, and rural (Atayi and Knipscheer 1980). At rural markets,

producers sell their goods directly. At semirural markets, there is a mix of producers and retailers selling agricultural products. At urban markets, there is a higher proportion of retailers, and retail prices are higher. Producers benefit from these higher retail prices if they sell their products directly at the market, which is the case for farmers living at a reasonable distance from the town or if the retailers do not capture most of the price difference between rural and urban markets. The weights assigned to the three categories of market types in the distance calculation were based on the average retail price of the agricultural products at the market under consideration, as observed by Atayi and Knipscheer (1980). The values are 1 for rural markets, 1.08 for semirural markets, and 1.59 for urban markets. Thus:

$$\text{Distance to town}_j = \frac{[\text{distance to the nearest road} + \sum_i (\text{distance on road segment}_i \times \text{surface material of road}_i)]}{\text{index of average retail price at town}_j} \quad (3)$$

Only towns with more than 5,000 inhabitants and with a permanent market were taken into account. The towns just outside the study area were also included in this calculation.

Soil aptitude for agriculture. This variable was determined from a combination of data on the 1:1,000,000-scale ORSTOM soil map (Martin and Segalen 1966), and the 1:200,000-scale soil map included in the zoning plan of the East Province (Ministry of Forestry and Environment 1995). Even though the scales of the maps differ, the level of generalization of both is roughly equivalent. The latter map provides slightly more accurate information for the southern part of the study area. Five classes of soil aptitude for agriculture were distinguished with, in decreasing order of quality: (1) brown-red, ferralitic soils, (2) red soils with sesquioxides, (3) hydromorphic soils, (4) hardened soils, and (5) lateritic duricrusts. This information was introduced as a categorical variable in the statistical model. The cartographic information on soil aptitude is the least detailed and reliable of all the variables included in the model.

Shortest distance to the nearest forest/nonforest edge at the initial time period. This variable was selected as a measure of the physical accessibility to the forest cover for farmers and/or loggers, and is hypothesized to influence forest-clearing costs. It was calculated as a series of 50-m-wide

buffers expanding from all interfaces between pixels classified as forest and those classified as nonforest. To remove the influence of isolated pixels on this distance calculation, the land-cover map was first smoothed using a five-by-five pixel low pass filter. For this smoothing, the most frequently occurring class in the window was assigned to the central pixel of a moving window (i.e., a modal filter).

Spatial fragmentation of the forest cover in the immediate surroundings of each location. This variable was calculated in nine-by-nine pixels windows using the Matheron (1970) index:

$$M = \frac{\text{Number of edges between forest and other cover types pixels}}{\sqrt{\text{no. of forest pixels}} \times \sqrt{\text{total no. of pixels}}} \quad (4)$$

The numerator measures the number of pairs of adjacent pixels classified as forest and other cover types (i.e., number of forest/nonforest interfaces included within the window), while the denominator normalizes this count by the size of the forest and the total area. The index characterizes the length of the perimeter line of forest pixels exposed to nonforest cover types. This variable, and the previous one, are taken as proxies for the accessibility of the forest cover. They should indirectly influence forest-clearing costs.

Logistic Multiple Regression Models

Background. Many of the previous spatial, statistical analyses of deforestation have concentrated on univariate relationships (Sader and Joyce 1988; Gastellu-Etchegorry and Sinulingga 1988; Brown et al. 1993; Liu et al. 1993; Sader 1995; Mertens and Lambin 1997). These authors attempted to identify predictors of areas with the greatest propensity for deforestation. Developing a multivariate model of the proximate causes of deforestation allows us to account for the interactions between independent variables and to rank explanatory variables according to their degree of importance in explaining the spatial-variation deforestation.

The technique used in this study is logistic multiple regression (LMR). It is designed to estimate the parameters of a multivariate explanatory model in situations in which the dependent variable is categorical, and the independent variables are continuous or categorical. LMR is

more appropriate than discriminant analysis if some independent variables are qualitative in nature (Press and Wilson 1978). Our objective is to predict the probability of the presence or absence of deforestation (or any other land-cover change trajectory), based on a series of environmental and locational descriptor variables. The LMR technique yields coefficients for each independent variable based on a sample of data. These coefficients are interpreted as weights in an algorithm that generates a map depicting the probability of a specific category of land-cover change for all sampling units. LMR has already been successfully used in wildlife habitat studies (Pereira and Itami 1991; Narumalani et al. 1997; Bian and West 1997) and deforestation analyses (Ludeke et al. 1990; Chomitz and Gray 1996).

Statistical Procedure. LMR identifies the role and intensity of explanatory variables X_n in the prediction of the probability of one state of the dependent variable, which is defined as a categorical variable Y . Suppose X is a vector of explanatory variables and p is the response probability to be modeled with, in the case of a dichotomous dependent variable, $p = \Pr(Y = 1 | X)$, with $Y = 0$ meaning the absence of deforestation and $Y = 1$ meaning the presence of deforestation. The linear logistic model has the form:

$$\text{logit}(p) = \log\left[\frac{p}{1-p}\right] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \quad (5)$$

where α is the intercept and β_n are slope parameters. The probability values can thus be quantitatively expressed in terms of explanatory variables by:

$$p = \frac{e^{(\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}}{1 + e^{(\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}} \quad (6)$$

Odds ratios can also be used to facilitate model interpretation (Stokes et al. 1995; Menard 1995). The odds ratio is a measure of association that approximates how much more likely (or unlikely) it is for the outcome to be present for a set of values of independent variables (Hosmer and Lemeshow 1989). The probability, the odds, and the logit are three different ways of expressing the same thing (Menard 1995). The estimated odds values are computed as the exponential of

the parameter estimate values (Hosmer and Lemeshow 1989; Agresti 1990):

$$\text{odds}(p) = e^{(\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)} \quad (7)$$

In this study, LMR was performed using the CATMOD functions in the SAS/STAT software. The predictive ability of a logistic regression model is evaluated from the table of maximum likelihood estimate (MLE), which contains the maximum likelihood estimate of the parameter, the estimated standard error of the parameter estimate, the Wald chi-square statistic, and the significance probability for the parameter estimate. In the case of logistic models, the goodness-of-fit measure is defined as the ratio of maximized log likelihood. This pseudo R^2 or ρ^2 is defined as (Wrigley 1985):

$$\rho^2 = 1 - \frac{\log[\beta]}{\log[C]} \quad (8)$$

or one minus the ratio of the maximized log likelihood values of the fitted ($\log[\beta]$) and constant-term-only ($\log[C]$) models. Although ρ^2 ranges in value from 0 to 1, its value tends to be considerably lower than the value of the coefficient of determination R^2 of conventional regression analysis. It should not be judged by the standards of what is normally considered a "good fit" in conventional regression analysis (Wrigley 1985). Values between 0.2 and 0.4 should be taken to represent a very good fit of the model (Domencich and McFadden 1975).

Implementation for Southern Cameroon.

Based on our data, spatial LMR models were built with specific categories of land-cover change as the dependent variable and, as described above, independent variables for road proximity, town proximity, forest-cover fragmentation, proximity to a forest/nonforest edge, and soil aptitude for agriculture (a categorical variable). We tested the existence of collinearity between the independent variables and developed and compared two types of models. We first defined the dependent variable as the presence or absence of deforestation between two observation years, referred to as the *forest conversion model*. Second, we defined a set of land-cover-change trajectories over three observation years as the *land-cover trajectories model*. These changes in land-cover were derived from the change-detection analysis performed on the time series of remote sensing data.

For the land-cover trajectories model, the dependent variable is categorical. All land-cover trajectories that start with a forest cover in the initial period (1973) need to be modeled together, using a single multinomial logistic regression model. The results of this model are therefore conditional to the initial land-cover. These trajectories include stable forest, permanent deforestation (at the early or later period), and deforestation followed by reforestation. A multinomial model accounts for the fact that these trajectories are not independent from each other, as the sum of the areas affected by all these trajectories needs to be equal to the total area under forest in 1973. The same is true for all trajectories starting with nonforest in 1973.

The statistical procedure specifies that the response function consists of generalized logits of the marginal probabilities for the dependent variable. The generalized logits are obtained by taking the logarithms of the ratios of two probabilities. The denominator of each ratio is the marginal probability corresponding to the last observed level of the variable—the *baseline category* (Agresti 1990) or *reference group* (Hosmer and Lemeshow 1989), noted as P_b . The numerator is the marginal probability corresponding to the trajectory under consideration, noted as P_c :

$$\text{logit } P_c = \log \left[\frac{P_c}{P_b} \right] \quad (9)$$

For continuous explanatory variables, positive values of the parameters β indicate that larger values of the variable increase the likelihood of categories other than the baseline category and, inversely, negative values of the parameters β indicate that larger values of the explanatory variables decrease the likelihood of categories other than the baseline category (Jobson 1992). For categorical explanatory variables (i.e., soil aptitude), positive values of the parameter estimates indicate higher probability of observing the considered trajectory rather than the baseline trajectory for the considered level of the variable. For categorical variable (n categories), parameter estimates are computed for the $n - 1$ levels of the variable (differential effect for the $n - 1$ levels of the variable for the considered logit). The parameter estimate (P) for the last level (in the case of $n = 3$) can be obtained by:

$$P_3 = -P_1 - P_2 \quad (10)$$

If r is the number of response levels (i.e., trajectories) of the dependent variable, the procedure computes $r - 1$ equations giving the likelihood of observing a considered trajectory rather than the baseline trajectory for the set of independent variables. The logit for comparing two nonbaseline trajectories is the difference between the logit of these two trajectories obtained with the baseline trajectory model (Hosmer and Lemeshow 1989).

To perform the LMR, a random sampling procedure was used to select N observations points distributed in the study area. Sampling of observations was used due to the presence of spatial autocorrelation in the data. Selecting random observations decreases the probability of selecting adjacent, and therefore spatially autocorrelated, observations. For every sample observation, the values of the dependent and independent variables were recorded. For the forest-conversion model, a random sample of around 10,000 observations was selected. For the land-cover trajectories model, the sample size was approximately 30,000 observations. This ensures that the sample size of each response level of the dependent variable ($r = 4$ as there are four trajectories for the model) is at least 75, that is, at least 25 observations for each response function ($r - 1$).⁴ In reality, there are many more sample observations for most trajectories but the least represented land-cover trajectory determines the total sample size, given the random nature of the sampling.

Mapping the Probability of Land-Cover Changes

Applying LMR results to updated values of the independent variables allows us to generate an image representing the surface probability of future land-cover changes using equation (6). A probability surface for the trajectory associated with recent deforestation can be generated, as deforestation in the near-future is more likely to be controlled by the same factors that controlled the most recent deforestation. This image can then be overlaid on the land-cover map corresponding to the year 1991 (the probability of deforestation was only retained for those pixels that were still forest in 1991). Forest locations characterized by a high probability concentrate spatial attributes that, in the recent past, have been associated with a high frequency of deforestation. This map will therefore predict the forest areas that are most likely to be affected by deforestation. It will

contain no indication as to when these land-cover changes might take place, but it does suggest where future changes will occur if similar recent causal processes observed are maintained. The *predicted probabilities* of land-cover changes only become *projections* of future land-cover changes if a dynamic model predicts future rates of land-cover conversion. Such a dynamic model could be based on the assumption that, in the short-term, changes will continue to take place in the same way they did in the recent past and that the processes of land-cover change, as estimated by the model's coefficients, are stationary. Longer-term projections should incorporate the actual driving forces, as opposed to the proximate causes, of the process. The deforestation probability map (shown below) allows for a rigorous validation of the models since it can be compared to the actual deforestation taking place between the last observation year used in the model calibration, and any subsequent observation years.

Simulation of the Impacts of Land-Cover Changes

The simulation of the potential impacts of land-cover changes can be performed in two ways: first, by assessing the impacts on specific landscape attributes of the changes predicted to occur in the *dependent* variable and, second, by simulating anticipated changes in one or several of the *independent* variables and assessing their predicted impacts on specific landscape attributes through changes in the dependent variable.

For the first case, the overlay of the land-cover-change probability maps on cartographic layers allows us to evaluate what will be the likely consequences of predicted changes on important issues such as agricultural sustainability, measured by the sensitivity to soil erosion of areas that have been cleared for agricultural purposes; biodiversity conservation, measured through the loss of important habitats; and the role of tropical forests and secondary growths on the carbon cycle. In this approach, we take into account only the impacts ensuing from a continuation of current land-use practices.

For the second case, it is quite likely that before investing in infrastructure development projects (e.g., road construction, rehabilitation, or upgrading, or the attribution of a logging concession), an institution will be willing to conduct a detailed assessment of the possible ecological impacts of the project. This simply requires that, after calibrating

the spatial model on past observations, the planned developments (e.g., a road project) are integrated in the cartographic layer(s) representing the independent variable(s) that will be altered by the project (e.g., distance to road and distance to market towns). A new projection of deforestation risk zones can then be produced with these modified variables, based on the calibrated model. The output map displaying the new probabilities of land-cover changes can then be overlaid on maps displaying specific landscape attributes (e.g., biodiversity reserves) to assess the impact of the road project on the resource of interest (as in the first case). To demonstrate the feasibility and usefulness of this approach, we conducted a simulation of the impact of a fictitious road project on a biodiversity reserve in our study area.

Results

Land-Cover Classifications

Five main land-cover classes were discriminated with a high level of accuracy using the re-

mote sensing data: dense forest, fragmented forest, agriculture, savanna, and bare soils. The dense forest class corresponds to evergreen or moist deciduous forest zones, dominated by trees of at least 5 m high and with a forest-cover proportion of 70 percent or more (i.e., closed canopy). The fragmented forest class is a landscape mosaic with between 30 to 70 percent of forest mixed with other classes. The agriculture class corresponds to areas that are at least partially covered by fields or recent fallows (i.e., in the early successional stages), with a forest-cover proportion lower than 30 percent. Only forest fallows of less than 10 years are spectrally separable from forests. Older fallows are thus included in the forest class. The savanna class corresponds to areas dominated by an herbaceous cover and shrubs. The bare soils also include roads and built-up areas. The accuracy of the classifications, before merging of classes, are satisfactory (see Table 2 for the 1991 classification, as an example). After merging of the classes into a binary forest/nonforest map, the accuracies are much improved: overall accuracy and Kappa coefficients of, respectively, 97 percent and 0.95

Table 2. Contingency Table and Accuracy Indicators for the Original (a) and the Binary Recoded (b) Classification of the Spot XS Image of 1991 Aggregated at a 50 × 50 m Resolution

(a) Original Classification

	Field Observations					Total	Accuracy
	Bare Soils	Savanna	Fallow Agriculture	Fragmented Forest	Dense Forest		
Bare soils	44	4	1	1	0	50	0.88
Savanna	2	44	3	1	0	50	0.88
Fallow/agriculture	1	3	47	1	0	52	0.90
Fragmented forest	0	1	2	51	2	56	0.91
Dense forest	0	0	0	3	51	54	0.94
Total	47	52	53	57	53	262	
Producer accuracy	0.94	0.85	0.89	0.89	0.96		
Overall accuracy		0.90					
Kappa		0.88					

(b) Binary Recoded (Forest/ Nonforest) Classification

	Field Observations			Accuracy
	Nonforest	Forest	Total	
Nonforest	149	3	152	0.98
Forest	3	107	110	0.97
Total	152	110	262	
Producer accuracy	0.98	0.97		
Overall accuracy		0.98		
Kappa		0.95		

Table 3. Land-Cover Changes, Transition Probabilities, and Deforestation Rate, 1973–1986^a

			1986	
			Forest	Nonforest
1973	Forest	Area (ha)	96,620.5	4,800.75
		Annual transition probability (%)	99.61	0.39
	Nonforest	Area (ha)	1,081.5	11,488.75
		Annual transition probability (%)	0.70	99.30
Gross deforestation (ha)				4,800.75
Net deforestation (ha)				3,719.25
Net annual deforestation rate (%)				0.28

^aThe top number in row class is the area in hectares; the bottom number is the transition probability on an annual basis (%).

for 1973, 97 percent and 0.93 for 1986, and 98 percent and 0.95 for 1991.

Land-Cover-Change Analysis

Results of the change detection analysis indicate a net reduction in forest cover area throughout the study period. The change matrices shown in Tables 3, 4, and 5 represent the transfer of area (in hectares) among land-cover categories for pairs of successive observation years. The transition probabilities are computed as:

$$p_{ij} = a_{ij} / \sum_j a_{ij} \quad (11)$$

where a_{ij} is the area under the land-cover i at the initial period that was converted to land-cover j at the subsequent period. As the matrices were computed over a different number of years, the transition probabilities have been recomputed on an annual basis, using:

$$\mathbf{T}_{i,j}^1 = \expm^n \frac{1}{\log m} \mathbf{T}_{i,j}^n \quad (12)$$

where $\mathbf{T}_{i,j}^1$ is the transition probability matrix on an annual basis, \expm is the matrix exponential, n is the number of years for the considered period, $\log m$ is matrix logarithm, and $\mathbf{T}_{i,j}^n$ is the transition probability matrix for the considered period.

Tables 3, 4, and 5 show that the net deforestation rate as measured by the ratio between, on one hand, the difference between deforested areas and areas affected by forest regrowth and, on the other hand, the forest-cover area at the initial period, is 7.36 percent between 1973 and 1991. If we only take into account the rate of destruction of forest areas at the initial period—ignoring, therefore, the regrowth of secondary forests that takes place either on the deforested area, a few years later, or elsewhere—the accumulated rate of deforestation from 1973 to 1991 is 9.24 percent. This latter rate is a better indication of potential impacts of deforestation on habitats and, therefore, biodiversity, while the former rate is more relevant to establish a carbon budget or to monitor the availability of wood resources. These tables also show that most forest clearings

Table 4. Land-Cover Changes, Transition Probabilities, and Deforestation Rate, 1986–1991^a

			1991	
			Forest	Nonforest
1986	Forest	Area (ha)	93,101.25	4,574.25
		Annual transition probability (%)	99.03	0.97
	Nonforest	Area (ha)	827	15,489
		Annual transition probability (%)	1.06	98.94
Gross deforestation (ha)				4,574.25
Net deforestation (ha)				3,747.25
Net annual deforestation rate (%)				0.77

^aThe top number in row class is the area in hectares; the bottom number is the transition probability on an annual basis (%).

Table 5. Land-Cover Changes, Transition Probabilities, and Deforestation Rate, 1991–1996^a

			1996	
			Forest	Nonforest
1991	Forest	Area (ha)	34,308.5	3,105
		Annual transition probability (%)	98.18	1.82
	Nonforest	Area (ha)	1,702.5	12,061
		Annual transition probability (%)	2.70	97.29
Gross deforestation (ha)				3,105
Net deforestation (ha)				1,402.5
Net annual deforestation rate (%)				0.75

^aThe top number in row class is the area in hectares; the bottom number is the transition probability on an annual basis (%).

take place for agricultural purposes. There is also some proportion of the agricultural areas affected by forest regrowth. This is part of the long fallow farming system of the region.

The analysis of these tables also reveals two other important elements. First, the rates of deforestation fluctuates through time (from 0.28 percent to 0.77 percent per year between 1973 to 1986, and 1986 to 1991). Note that the net deforestation rate between 1986 to 1991, and 1991 to 1996 is similar (0.77 and 0.75 percent), while the transition probabilities of forest conversion and reforestation are double in 1991–1996 compared to 1986–1991. Therefore, we cannot assume deforestation to be a process that takes place at a constant rate in time. It is strongly controlled by exogenous socioeconomic forces that vary over time, as demonstrated through household surveys in Mertens et al. (2000). Second, the transition probabilities between pairs of land-cover classes vary also through time. Most notable is the probability of a transition from forest to nonforest, which increases from 0.39 for the first period to 0.97 for the second period. Thus, the transition matrix is nonstationary. This has important consequences since the stationarity of the transition matrix is a major assumption of Markov-based models of land-cover change (Lambin 1994). When dealing with nonstationary processes, these models lose any predictive ability unless one modifies the transition probabilities through time according to some complex model design or based on the knowledge that a different land-use change process is taking place at a given time.

Land-Cover-Change Trajectories

The analysis of the percentage of the total area affected by each land-cover change trajec-

tory reveals that the stable trajectories—that is, continuously forest or nonforest for the three observation years—account for 90.70 percent of the study area (see Table 1). Thus, nearly 10 percent of the landscape has changed at least once over the observation period. In the areas that changed, 90 percent did so just once over the period while 10 percent have changed twice in an eighteen-year period.

The analysis of the spatial pattern of the different land-cover trajectories is also interesting. The forest clearings that appear to be permanent are mostly located around towns or near roads. Trajectories characterized by successive transitions between forest and nonforest correspond to short-fallow areas, mostly located along new roads at a greater distance from towns. In general, the spatial pattern of deforestation clearly follows a process of expansion diffusion, as illustrated for the area of Dimako, southeast of our study area (Figure 2). There is a clear centrifugal expansion of deforestation around the town and along the road network in the logged-over area west of Dimako.

Spatial Regression Models of Deforestation

Preliminary Statistical Analyses. Following the results of univariate relationships between the dependent and independent variables (Mertens and Lambin 1997), the logarithm of the distance from roads, towns and forest/nonforest edges was used in the multivariate models. Also, low levels of collinearity were found between the independent variables, with values of the coefficients of determination (R^2) of the multivariate relationships between one independent variable against all the others ranging

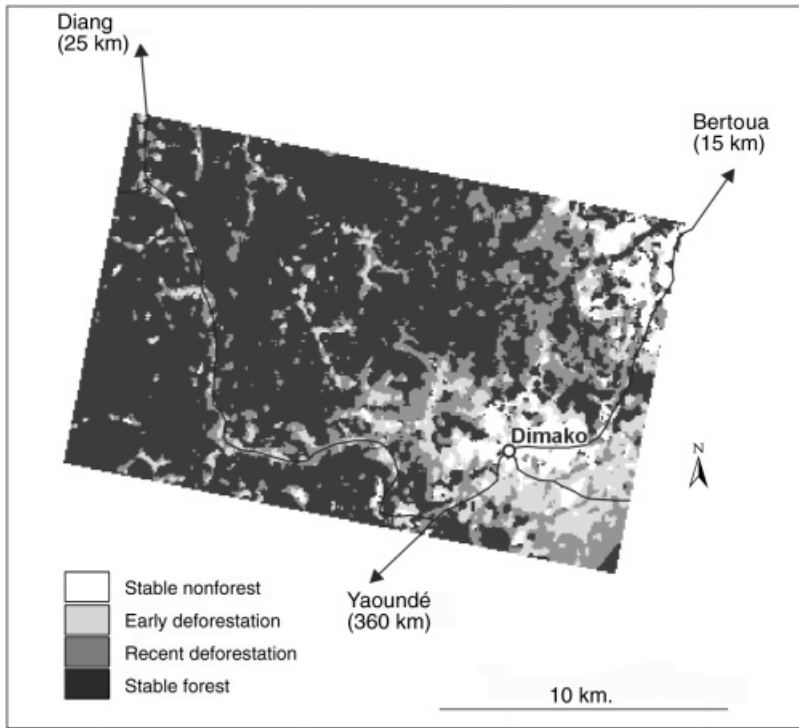


Figure 2. The land-cover-change trajectories around the town of Dimako, southeast of the study area, illustrating the process of expansion diffusion of deforestation away from the town and along the road network.

between 0.45 and 0.52. It is only with R^2 larger than 0.80 for at least one of the independent variables that the collinearity is considered as being problematic for LMR (Menard 1995). So, even though there is some dependence between the explanatory variables, it is not to a level that should pose a problem for the logistic regression. The R^2 of the univariate relationships between variables that were expected to be related, such as distance to roads and distance to forest/nonforest edges, was in fact low (0.26 in that case).

Forest-Cover Conversion Model. The results of the two separate LMR models of deforestation for the periods from 1973 to 1986, and from 1986 to 1991, are given in Tables 6 and 7. These tables present the values of the parameter estimates with their corresponding standard error, chi-square statistics, and significance probability. Positive values of parameters indicate that larger values of the explanatory variables increase the likelihood of deforestation, while negative values indicate the opposite. The resulting equation allows us to calculate the prob-

ability of deforestation. The chi-square statistics indicate the relative weight of the explanatory variables in the model and allow us to assess the role of each variable in the prediction of deforestation.

The overall explanatory power of the models for both periods was satisfactory, with values of ρ^2 of 0.26 for the first period and 0.29 for the second period, which represents a good fit of the model. The significance level and the relative explanatory power of the independent variables varied between the two periods. For both periods, the distance to forest/nonforest edges is the most important explanatory variable. In both cases, the probability associated with the presence of deforestation increases as the distances from forest edges decreases. Forest areas near a forest edge are more accessible and, therefore, more likely to be cleared. The estimated odds of observing deforestation is $\exp(-1.0007) = 0.37$ times higher for each additional unit of distance to forest/nonforest edge. As it is the logarithm of the variable, distance to forest edges, which was used in the model, and as the distance unit was

Table 6. Forest Conversion LMR Model for the First Period (1973–1986)

	Parameter Estimates	Std. Error	Chi-Square	Significance Probability
Distance from roads ^l	-0.0664	0.0717	0.86	0.3544
Distance from towns ^l	-0.7631*	0.0830	84.43	0.0000
Distance from forest/nonforest edge ^l	-1.0007*	0.0746	179.70	0.0000
Forest fragmentation	0.0001	0.0013	0.01	0.9056
High soil aptitude ^c	0.6481*	0.1967	10.86	0.0010
Medium soil aptitude ^c	0.5298	0.2904	3.33	0.0681
Number of Obs: 9,905 ρ^2 : 0.26				

*Denotes parameter estimates significant at the 0.01 level of confidence.

^cCategorical variable: differential effect of $n - 1$ levels of the variable.

^lThe logarithm of the variable is employed.

50 m, areas at 0.5 km from forest edges are $(1/0.37) = 2.72$ times more likely to be cleared than areas at 5 km from forest edges.

For the first period, the role of proximity to towns is important in explaining the probability of deforestation. Areas at 0.5 km from towns are 2.14 times more likely to be cleared than areas at 5 km. Accessibility to towns is therefore an important factor in deforestation, either through the commercialization of agricultural outputs, or through attempts to gain access to inputs. The proximity to a town may also be related to the presence of services in small urban centers or because towns act as centers of diffusion for migrants. Surprisingly, for the second period, the explanatory power of the distance to towns is not statistically significant at the 0.05 probability level. The inverse situation is observed for the variable "distance to roads," which is insignificant for the first period, but highly significant for the next period. The roads in the second period are nearly as important for deforestation as the towns are in the first period.

Areas at 0.5 km from roads are 1.62 times more likely to be cleared than areas 5 km. These results can be explained by the fact that between 1973 and 1986, forest colonization was at an initial stage and mostly affected the immediate surroundings of towns. It is only in the mid-1980s that migrants have started to move farther along the road, at a greater distance from towns.

Deforestation is taking place mostly on good soils during the first period while, in the second period, the explanatory effect of good soils becomes negligible. This suggests that, after the areas around towns have been cleared, roadside locations are the dominant factor in determining deforestation (for accessibility reasons), and migrants do not make incursions into the forest, away from roads, to search for the best soils. This conclusion, however, is tempered by the fact that the soil variable is the one most prone to error in our database. Note also that a high level of forest fragmentation is not significant in explaining the location of deforestation for either period.

Table 7. Forest Conversion LMR Model for the Second Period (1986–1991)

	Parameter Estimates	Std. Error	Chi-Square	Significance Probability
Distance from roads ^l	-0.4823*	0.0653	54.60	0.0000
Distance from towns ^l	-0.0379	0.0877	0.19	0.6654
Distance from forest/nonforest edge ^l	-1.2367*	0.0788	246.03	0.0000
Forest fragmentation	0.0015	0.0012	1.53	0.2155
High soil aptitude ^c	0.3220	0.1763	3.34	0.0677
Medium soil aptitude ^c	-0.4663	0.3128	2.22	0.1361
Number of Obs: 9,917 ρ^2 : 0.29				

*Denotes parameter estimates significant at the 0.01 level of confidence.

^cCategorical variable: differential effect are computed for $n - 1$ levels of the variable.

^lThe logarithm of the variable is employed.

Land-Cover Trajectories Model. We only present the results of the multinomial model developed for all the areas that were forest at the initial time period (1973), as forest clearing is by far the dominant land-cover change process in the region. Table 8 presents the values of the parameter estimates, with their corresponding standard error, chi-square statistics, and significance probability. Positive values of parameters indicate that larger values of the explanatory variables increase the likelihood of observing the land-cover trajectory under consideration rather than the baseline trajectory (stable forest throughout the study period in this case). The overall explanatory power of the model was high, with a $\rho^2 = 0.36$. Thus, sequences of land-cover changes are indeed controlled by the spatial determinants of land rent that were introduced in this model. Table 8 shows also the odds values between all trajectories. For all the deforestation trajectories, parameter estimates are

negative for all three distance variables. Thus, the probabilities of trajectories associated with deforestation decrease, by reference to the stable trajectory, with increasing distances from roads, towns, and forest edges. By contrast, the probability of occurrence of stable trajectories is higher at greater distances from forest edges, roads, and towns, and for low levels of fragmentation of the forest-cover. The best protection against forest clearing in conservation areas (such as the neighboring Dja faunal reserve) is therefore a buffer of closed forest. No such buffer zone currently exists around this reserve.

As observed above, the distance from towns is only important for predicting early deforestation, while distance to roads has a greater effect on the recent deforestation. As the deforestation in the region progresses, farmers have to move further from towns, along the road network, to find new agricultural areas. More recent deforestation is therefore less influenced by prox-

Table 8. Multinomial Logit Model for the Land-Cover-Change Trajectories Beginning with Forest Cover in 1973, Using the Stable Forest Trajectory (Forest-Forest-Forest) as the Baseline Category

	Parameter Estimates	Std. Error	Chi-Square	Significance Probability	Odds
Early deforestation trajectory (forest/nonforest/nonforest)					
Distance from roads ¹	-0.1702*	0.0438	15.11	0.0001	0.843
Distance from towns ¹	-0.8477*	0.0555	232.98	0.0000	0.428
Distance from forest/nonforest edge ¹	-0.9586*	0.0462	430.71	0.0000	0.383
Forest fragmentation	0.0029*	0.0007	13.49	0.0002	1.002
High soil aptitude ^c	1.0825*	0.1535	49.76	0.0000	2.952
Medium soil aptitude ^c	-0.2213	0.2628	0.71	0.3996	0.801
Recent deforestation trajectory (forest/forest/nonforest)					
Distance from roads ¹	-0.4160*	0.0413	101.28	0.0000	0.659
Distance from towns ¹	-0.0925	0.0578	2.65	0.1034	0.911
Distance from forest/nonforest edge ¹	-1.0610*	0.0485	477.84	0.0000	0.346
Forest fragmentation	0.0042*	0.0008	30.50	0.0000	1.004
High soil aptitude ^c	0.6032*	0.1360	19.67	0.0000	1.827
Medium soil aptitude ^c	-1.0065*	0.2521	15.93	0.0001	0.365
Fallow agriculture trajectory (forest/nonforest/forest)					
Distance from roads ¹	-0.1747	0.1602	1.19	0.2756	0.839
Distance from towns ¹	-0.8464*	0.1862	20.67	0.0000	0.428
Distance from forest/nonforest edge ¹	-0.9548*	0.1779	28.82	0.0000	0.384
Forest fragmentation	0.0054	0.0027	3.80	0.0514	1.005
High soil aptitude ^c	0.5001	0.3925	1.62	0.2026	1.64
Medium soil aptitude ^c	1.1006	0.4964	4.92	0.0266	3.005
Number of Obs: 29,757 ρ^2 : 0.36					

* Denotes parameter estimates significant at the 0.01 level of confidence.

^c Categorical variable: differential effect are computed for $n - 1$ levels of the variable.

¹ The logarithm of the variable is employed.

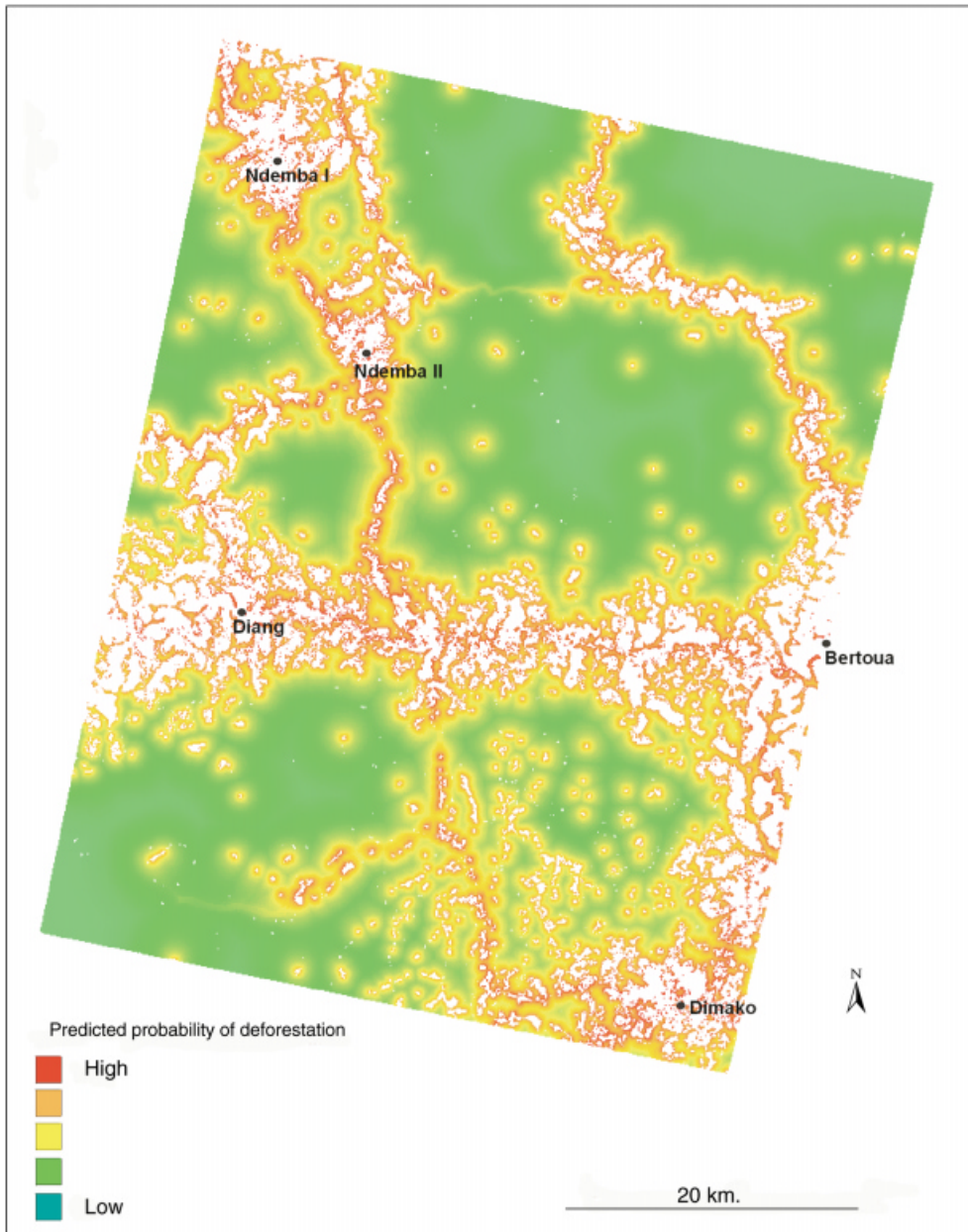


Figure 3. The predicted probabilities of the land-cover-change trajectories associated with deforestation (“deforestation risk zones”). The predicted values are based on the model calibrated for the period 1973–1986–1991 (land-cover trajectories model). Each location still forest in 1991 was assigned a probability (between 0 and 1) of being cleared, given its landscape attributes. The areas predicted as having the highest probability of deforestation are mainly located at short distances from forest/nonforest edges, towns and roads.

imity to towns. The decreasing explanatory power of the distance to towns, as the deforestation progresses, suggests that the role of roads in the deforestation process is mostly to increase the ac-

cessibility of the forest for migrants (i.e., a colonization process) rather than to spur the transformation of local subsistence agriculture into market-oriented farming systems (i.e., a process

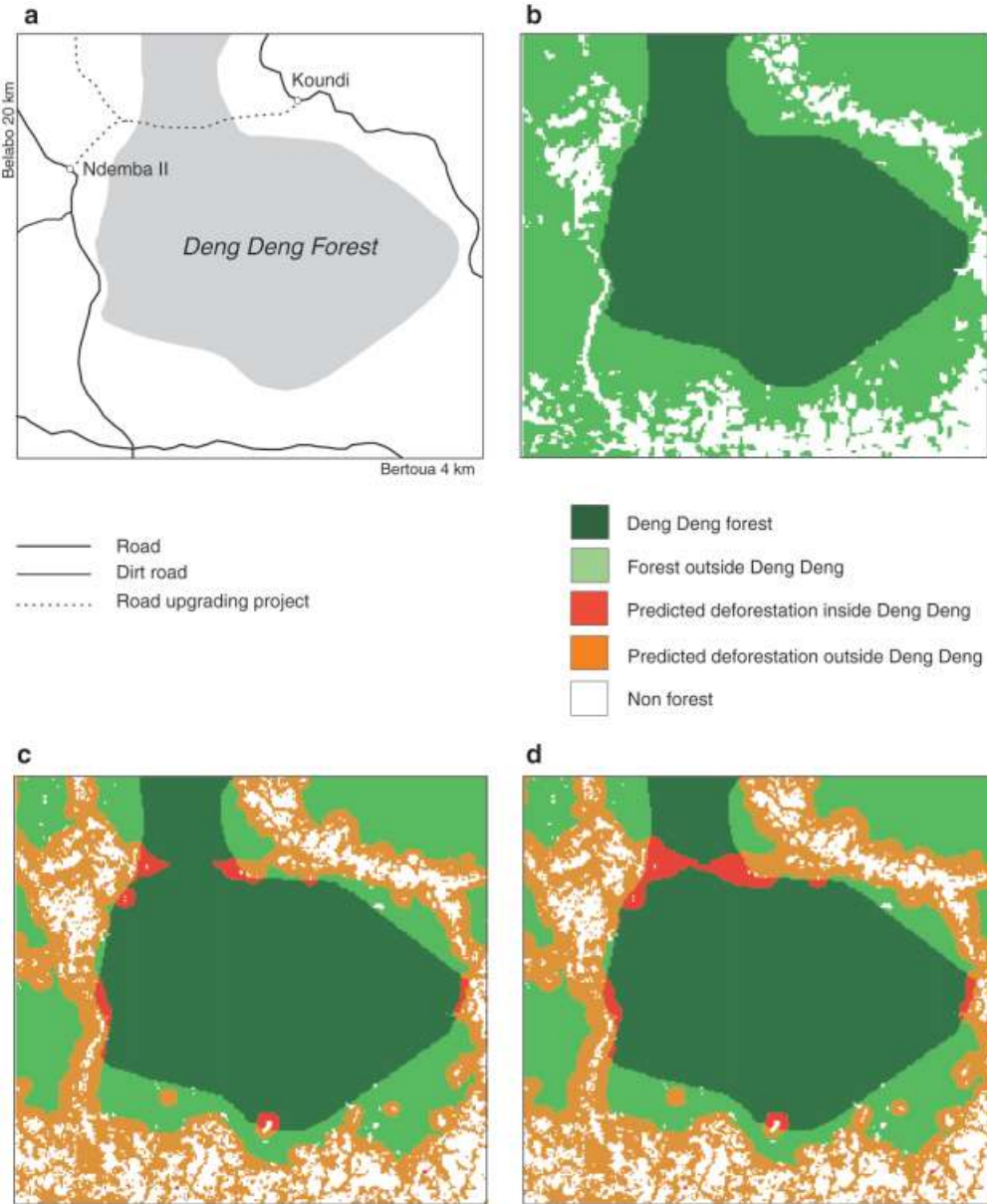


Figure 4. Simulation of the impact of a fictitious road-upgrading project on the deforestation in the Deng Deng in situ conservation area: (a) map of the road network of the area and limits of the Deng Deng forest, (b) land-cover classification of the area, (c) areas with a predicted probability of deforestation >0.8 based on the current situation of the road network, and (d) areas with a predicted probability of deforestation >0.8 based on the road network after upgrading of the road north of the forest. It is clearly visible that the road-upgrading project would lead to an increase of the area at risk of deforestation within the forest reserve. It would therefore have a quantifiable impact on biodiversity.

of development of local agriculture in response to incentives from distant markets). And if roads do indeed facilitate the commercialization of agricultural products to the markets, it seems to be

mostly the case for new migrants who have settled along these roads rather than for farmers involved in shifting cultivation around towns.

The land-cover-change trajectory that corre-

sponds to fallow agriculture (forest, nonforest, forest) is mostly predicted by proximity to forest edges and to towns. Interestingly, fallow agriculture is positively associated with the presence of medium aptitude soils while the more permanent deforestation, which is likely to be associated with more intensive, market-oriented agriculture, is associated with the presence of soil with a high aptitude for agriculture. The estimated odds of observing the fallow agriculture trajectory rather than the early deforestation trajectory on medium-aptitude soil is $\exp[1.01 - (-0.22)] = 3.41$ times higher. The estimated odds of observing the early deforestation trajectory rather than the fallow agriculture trajectory on high-aptitude soil is $\exp(1.08 - 0.50) = 1.79$ times higher.

Distance to forest/nonforest edges is the dominant variable to explain all land-cover change trajectories. This indicates the “spatial inertia” of land-cover change processes: changes recur where they have already taken place in the recent past. The rationale behind this spatial process is related to the importance of the accessibility of the forest cover, which is increased by the existence of openings in the forest cover. There is therefore a strong “spatial spread” effect of land-cover changes, whether these are permanent conversions or temporary changes.

Mapping the Probability of Land-Cover Changes: Validation and Model Comparison

The probability of deforestation was first predicted based on the model calibrated on two observation years (1986–1991). On the predicted map, each location that was still forest in 1991 was assigned a certain probability (between 0 and 1) of being cleared, given its landscape attributes. Due to the high explanatory power of the variables measuring distances to forest/nonforest edges, towns, and roads, the areas predicted as having the highest probability of deforestation are primarily located at small distances from these features.

Second, the probability of deforestation was predicted based on the land-cover trajectories model calibrated over the period 1973–1986–1991, for locations forested in 1973. Figure 3 represents the predicted probability of deforestation using the equation corresponding to the trajectory of recent deforestation. The areas with the highest risk of deforestation (in red-orange) are concentrated around the main towns, on the forest edges and along roads. Ev-

ery small opening in the forest cover is also associated with a higher risk of deforestation.⁵ (For a simulation of the impact of a fictitious project on deforestation, see Figure 4, discussed below.)

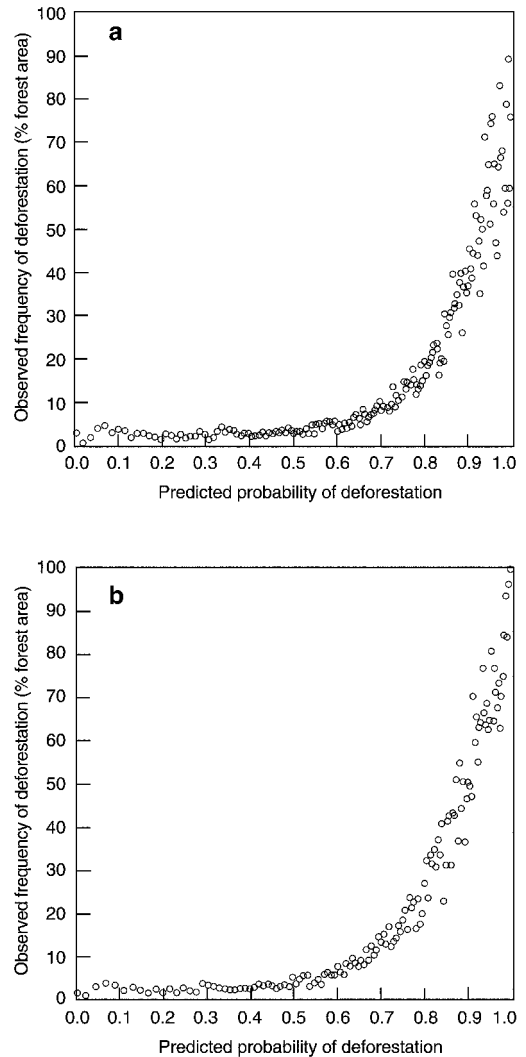


Figure 5. Actual deforestation between 1991 and 1996 in areas with different ranges of predicted probabilities of deforestation using: (a) the forest-conversion model (1986–1973), and (b) the land-cover trajectories model (1973–1986–1991). In both cases, high rates of deforestation have been observed in areas predicted to have a very high probability of deforestation. The observed deforestation decreases sharply with the predicted probabilities of deforestation, since the validation period is only the five subsequent years. The model based on land-cover-change trajectories yields better predictions.

Table 9. Proportion of Observed Deforested Areas (1991–1996) within Predicted Probability of Deforestation Zones Using Forest-Conversion Model and Land-Cover Trajectories Model

Predicted Probability of Deforestation	Proportion of Observed Deforested Area (%)	
	Based on the 1986–1991 Forest-Conversion Model	Based on the 1973–1986–1991 Land-Cover Trajectories Model
>0.98	63.57	89.08
>0.95	61.85	74.46
>0.90	51.87	62.91

To validate these predictions of land-cover change risk-zones, the predicted probabilities of change, based on models calibrated on observations up to 1991, were compared to the observed land-cover changes between 1991 and 1996 (Figure 5). This validation—and the comparison of the performances of the two-periods model versus the land-cover change trajectory model—were performed in two ways: (1) by quantifying the proportion of areas with a high predicted probability of deforestation that have actually been deforested, as measured by:

$$\frac{\text{area with a high probability of deforestation and deforested in 1991–96}}{\text{total area with a high probability of deforestation}}$$

and (2) by quantifying the proportion of the observed deforestation taking place in areas that were predicted to have a high probability of deforestation, as measured by:

$$\frac{\text{area with a high probability of deforestation and deforested in 1991–96}}{\text{total area deforested in 1991–96}}$$

In general, high rates of deforestation have been observed in areas predicted to have a very high probability of deforestation. The observed deforestation decreases sharply with the predicted probabilities of deforestation, since the validation period is short (just the five subsequent years). Concerning the first measure (Table 9 and Figure 5), 89.08 percent of the forest areas predicted to have a probability of deforestation larger than 0.98, with the model cali-

brated on land-cover change trajectories between 1973, 1986 and 1991, have actually been cleared in the five following years. For the two-dates model (1986–1991), this percentage is only 63.57 percent. Thus, analyzing successive land-cover changes rather than only conversions over a short time period does improve model performance. The difference between the two models is quickly attenuated as we examine areas with a slightly lower predicted probability of deforestation. Concerning the second measure (Table 10), for all intervals of predicted probabilities of deforestation, there is a higher percentage of observed deforestation if the land-cover-change trajectories model is used, rather than the two-periods model. Again, the difference between the two models is attenuated for areas with a lower predicted probability of deforestation. We can therefore conclude that the modeling of land-cover-change trajectories over more than two observation years leads to a better prediction of the probabilities of land-cover change than the modeling of simple land-cover conversions over just two periods of time.

More fundamentally, Table 10 reveals that there is an important trade-off between the size of the area a policy-maker is willing to consider as being “at risk” and the amount of deforestation that will be found in that area. Areas at very high risk (e.g., predicted probability of deforestation of 0.80 or more) based on the trajec-

Table 10. Proportion of Observed Deforested Areas (1991–1996) versus Predicted Probability of Deforestation Using the Land-Cover Trajectories Model^a

Predicted Probability of Deforestation	Observed Deforested and Forested Area (%)	
	Based on the 1986–1991 Forest-Conversion Model	Based on the 1973–1986–1991 Land-Cover Trajectories Model
>0.90	20.42 1.74	24.57 1.86
>0.80	48.97 8.97	50.18 8.61
>0.50	80.34 50.76	81.12 45.65

^a The top number in row class is the proportion of observed deforested areas (%); the bottom number is the proportion of forested area (%) affected by a given range of probability of deforestation in 1991.

tory model, cover only about 8 percent of the total forest area and concentrate around 50 percent of the total deforestation of the area. On one hand, it is feasible to monitor this territory

at frequent time intervals and to plan interventions to mitigate undesirable patterns or effects of forest conversion. On the other hand, these very high-risk zones only include half of the to-

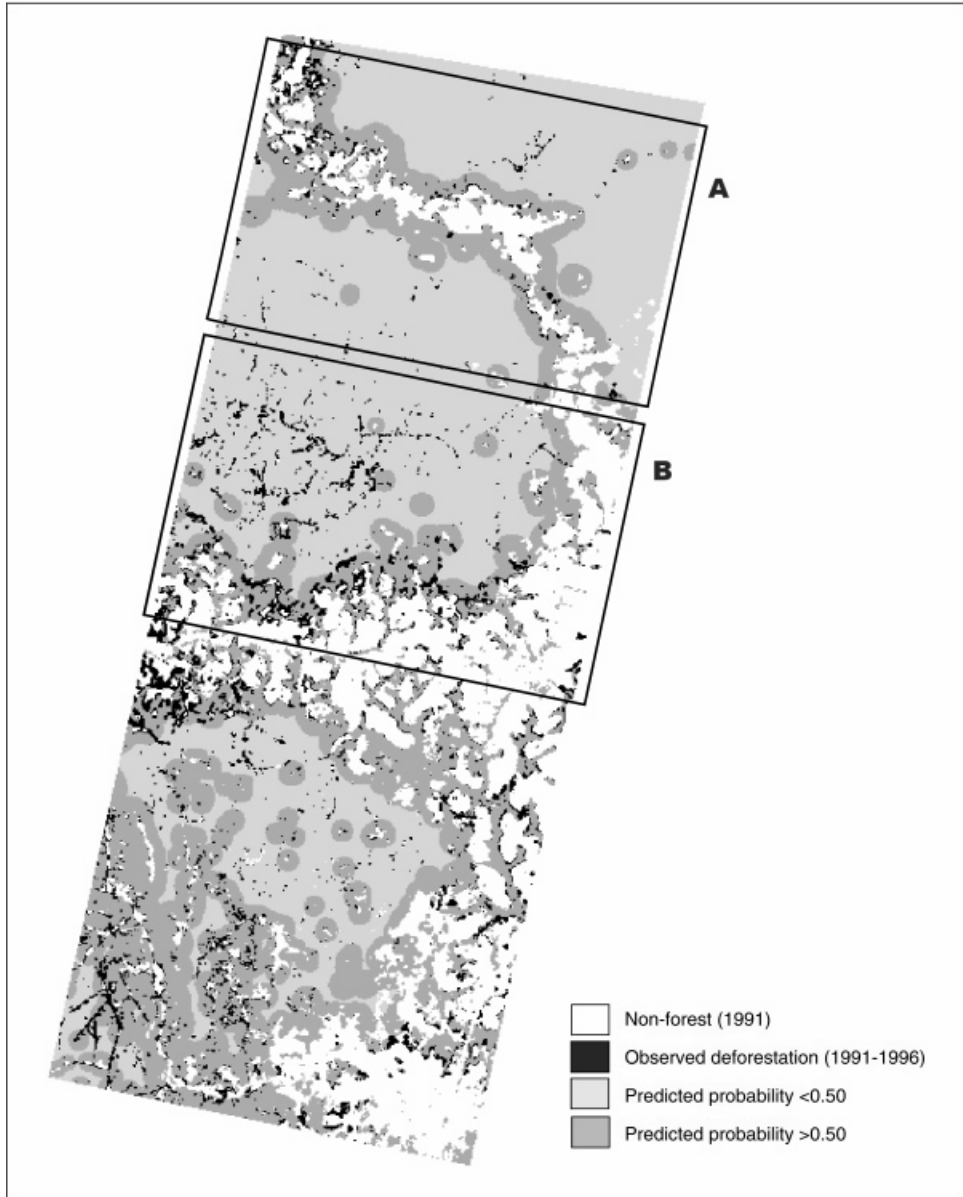


Figure 6. Observed deforestation between 1991 and 1996 within and outside areas with a predicted probability of deforestation >0.5 . Most deforestation is concentrated in the areas predicted to be at risk of deforestation, except the linear patterns of deforestation associated with recent logging activities and diffuse patterns associated with shifting cultivation (zone B). Similar linear patterns of deforestation are also observed in the southwestern part on the study area. These patterns appear in areas with high values of predicted probability of deforestation as they correspond to older logging concessions already taken over by shifting cultivators.

tal deforestation. To control a much larger share of the total deforestation (e.g., 80 percent of the total deforestation actually taking place), one would have to consider all areas with a predicted probability of deforestation of 0.50 or more, which represents 45 percent of the total forest area (Table 10)—a much larger territory to cover. The optimal trade-off between the size of the territory to be monitored and the amount of deforestation taking place in that territory depends on each application.

Figure 6 displays a map of actual deforested areas during the validation period (1991–1996) in relation to the areas predicted to have a high and low probability of deforestation. It is particularly interesting to analyze the location of areas with a weak correspondence between observed and predicted deforestation. These areas are characterized by a linear or a diffuse pattern of forest clearing. The linear pattern is particularly visible in the northwestern corner of zone B (Figure 6). These areas correspond to deforestation along the logging roads. The diffuse pattern corresponds to areas of slash-and-burn agriculture. In both cases, the processes of deforestation are weakly linked to the market and are less determined by accessibility constraints. Rather, the location of such activities are strongly controlled by the land-tenure system, either for the granting of logging concessions by the government or in the selection by farmers of the areas to be cleared for shifting cultivation. Since land tenure was not represented in the model, it does not predict well the location of logging and shifting cultivation activities. As seen in Table 11, the model performances on an area without any logging activity (zone A, Figure 6) is superior to the model performances on an area with logging activity (zone B, Figure 6).

Impacts of Deforestation Processes

For illustrative purposes, we conducted a simulation of the potential impact of a fictitious road-upgrading project on a biodiversity reserve. The Deng Deng forest is located northwest of Bertoua. It is a primary forest that the FAO (1996) identified as an area of “in situ conservation of forest genetic resources.” It is surrounded west, east, and south by permanent roads that are attracting an important migration flux and have led to significant roadside deforestation over the last decades (Figure 4a, b). North of the forest,

Table 11. Proportion of Observed Deforested Areas (1996) versus Predicted Probability of Deforestation Using the Land-Cover Trajectories Model, for Zones with and without Logging Concessions^a

Predicted Probability of Deforestation	Observed Deforested and Forested Area (%)	
	In Zone without Logging (A)	In Zone with Logging (B)
>0.90	31.20 1.91	17.12 1.96
>0.80	63.54 8.95	38.29 9.12
>0.50	85.79 44.51	82.98 70.12

^a The top number in row class is the proportion of observed deforested areas (%); the bottom number is the proportion of forested area (%) affected by a given range of probability of deforestation in 1991.

the road connecting Ndemba II and Koundi is still a poor dirt road, barely passable during the rainy season. For this simulation, we assumed that there was a project to upgrade this dirt road into an asphalt road that would be permanently passable.

Our impact assessment of this improved road was performed by changing the weight of the road north of the forest from a value of 4 (seasonal road with an average speed of 20 km/h) to a value of 1 (permanent roads with an average speed of 80 km/h). A new map of deforestation risk zones was then produced, using the model calibrated on the past observations. The result of this spatial projection (Figure 4d) can be compared to the map of deforestation risk zone based on the current situation of the road network (Figure 4c). The upgrading of the road would lead to an increase of the areas at risk of deforestation in the Deng Deng forest (from 1.2 percent to 2.5 percent having a probability of being cleared larger than 0.80, which means a difference of 406 ha of forest at high risk of being cleared). Outside the forest reserve, the increase in the forest area at risk is much smaller (from 28.3 percent to 28.5 percent, having a probability of being cleared larger than 0.80, which means a difference of 65 ha of forest at high risk of being cleared) (compare Figures 4c, d). The potential impact of this road project within the biodiversity reserve would thus be large in the absence of measures to enforce the reserve boundaries.

Conclusion

Remote-sensing observations revealed a continuous trend of forest clearing and forest degradation in southern regions of Cameroon, but with a highly fluctuating rate. The rates of deforestation have sharply increased in the area of Bertoua in the mid-1980s, followed by a slight decline in the early 1990s. This study also reveals that the new institutional tools for forest management and land-use planning in Cameroon have not yet provided a sustainable answer to the problems of degradation of the forests.

Successive observations highlight the dynamic character of land-cover changes. A significant proportion of the areas subject to a land-cover conversion are subject to another change in the following years. The matrix of transition probabilities between different land-cover types is nonstationary. Also, there are clear trajectories of land-cover changes that display a spatial pattern suggesting a centrifugal expansion of deforestation around towns and along the road network. The spatial distribution of land-cover-change trajectories can be modeled on the basis of cultural and natural landscape attributes that describe the land rent of forest areas. These spatial models indicate the "spatial inertia" of land-cover-change processes: changes take place around locations of recent previous changes. Openings in the forest cover increase accessibility into the forest. There is therefore a strong "spatial spread" effect of land-cover changes. Taking into account land-cover trajectories (i.e., succession of land-covers over more than two dates) allows for more reliable spatial projections of areas at risk of being deforested than taking into consideration only the previous observation. Land-cover changes are therefore best described as multiple-order processes, as there are generic and predictable trajectories of land-cover changes.

The spatial relationships analyzed in this study allowed us to better understand the process of deforestation in this region and, in particular, to formulate a hypothesis on the role of roads with respect to deforestation. Statistical results suggested that roads mostly increased the accessibility of the forest for migrants rather than provided incentives for a transformation of local subsistence agriculture into market-oriented farming systems. The process is therefore more a colonization of forest areas by migrants than the development of local agriculture in response to

an expansion of distant urban markets. An alternative hypothesis could be that, once the areas surrounding towns had been cleared, the attraction of roads is simply a new manifestation of the attraction of towns. At the end of the observation period, however, the rate of deforestation far from towns (but along the roads) is as high as the rate in the vicinity of towns at the beginning of the observation period. The fact that forest clearing for fallow agriculture takes place on medium rather than high-aptitude soils suggests that deforestation is more strongly influenced by accessibility variables than by soil suitability.

The main weaknesses of the modeling approach adopted in this study are that: (1) it is difficult to separate correlation from causality or to determine the direction of causality (Kaimowitz and Angelsen 1997); (2) only measurable, location-specific variables influencing the decision to convert land-cover have been integrated into the model, while underlying and more distant driving forces are ignored; and (3) the model assumes that cultural and sociopolitical factors have a minor influence on the selection of sites to be cleared. This study therefore only provides a representation of reality from one specific angle, which is due to be complemented by other disciplinary vantage points before a comprehensive understanding of the land-cover change processes in the region can be acquired. This study, however, generates several research questions to be addressed by other disciplines and approaches. For example, the patterns of land-use change revealed by this study have been related to household survey data that illuminate the macroeconomic factors driving some of these changes (Mertens et al. 2000).

The spatial model developed in this study allows us to conduct simulations of likely impacts of human actions leading to a transformation of the landscape (e.g., road projects) on key landscape attributes (e.g., biodiversity). Currently, several road projects or major logging concessions exist in southern Cameroon. They lead to heated debates, notably from nature conservation nongovernmental organizations, yet at present there is no objective way to conduct regional-scale environmental impact assessments. The modeling framework developed in this study provides a most suitable basis to perform such simulations. The spatial-model design developed here can lead to a decision support system that can be used as a policy tool to conduct en-

vironmental-impact assessment studies during the approval process of any project affecting the landscape. It generates spatially explicit projections that allows us to better understand the interaction between development projects and nature-conservation imperatives.

This research showed that land-cover changes associated with the granting of logging concessions and with shifting cultivation not oriented toward the market were not well predicted by the current model design. Other variables (e.g., land tenure) need to be integrated. Also, it is likely that the modeling of these activities needs to adopt a broader perspective (i.e., not exclusively spatial) and, in the case of logging, to integrate more remote driving forces such as national or international demand for timber.

Acknowledgments

This work was performed in the research program on satellite remote sensing for the Belgian State, Services of the Prime Minister, Office for Scientific, Technical and Cultural Affairs (contract T4/DD/001). We are grateful to D. Margot for programming work done for this study, to D. Peeters for advice on the statistical analyses, and to four anonymous reviewers who greatly helped in improving an earlier version of the manuscript.

Notes

1. It was recognized as Biosphere Reserve under UNESCO's Man and the Biosphere Program in 1981 and was inscribed on the World Heritage list in 1984 (Sayer et al. 1992).
2. The change map derived from a comparison of two classifications exhibits accuracies similar to the product of multiplying the accuracies of each individual classification (Stow et al. 1980).
3. The image processing and GIS analyses were performed with the Modular GIS Environment software package of Intergraph corporation.
4. Because the dependent variable of each model contains four trajectories, and the standard response function is used to compute three generalized logits for each population (SAS 1989).
5. By contrast, a map of the predicted probabilities of fallow agriculture (not displayed on the figure) shows that the higher probabilities of occurrence are less related to roads and are more concentrated around the small forest openings.

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