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# Driving forces of tropical deforestation: The role of remote sensing and spatial models

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Remote sensing technologies are increasingly used to monitor landscape change in many parts of the world. While the availability of extensive and timely imagery from various satellite sensors can aid in identifying the rates and patterns of deforestation, modelling techniques can evaluate the socioeconomic and biophysical forces driving deforestation processes. This paper briefly reviews some emerging spatial methodologies aimed at identifying driving forces of land use change and applies one such methodology to understand deforestation in Mexico. Satellite image classification, change analysis and econometric modelling are used to identify the rates, hotspots and drivers of deforestation in a case study of the southern Yucatán peninsular region, an enumerated global hotspot of biodiversity and tropical deforestation. In particular, the relative roles of biophysical and socioeconomic factors in driving regional deforestation rates are evaluated. Such methodological approaches can be applied to other regions of the forested tropics and contribute insights to conservation planning and policy.

**Keywords:** tropical deforestation, proximate and driving forces, remote sensing, modelling, Mexico

## Introduction

Tropical environments are among the most important locations of global land use and cover change (LUCC). Tropical forests, in particular, play critical roles as repositories of biological diversity and in regulating global biogeochemical and hydrologic cycles (Eltahir & Bras, 1996; Houghton, 1999; Cairns *et al.*, 2000; Myers *et al.*, 2000). The increase in tropical deforestation during the 1990s, offsetting net temperate zone reforestation, contributed to a 9.4 million ha net decrease in global forest cover during 1990–2000 (FAO, 2001). While annual deforestation rates in Africa and Latin America were of the order of 0.36 per cent and 0.33 per cent respectively during 1990–97, Southeast Asia had the highest observed rate of forest loss, at 0.76 per cent of 1990 forest extents (Achard *et al.*, 2002). Conversely, it is also in Southeast Asia that forest regrowth rates are the highest at 0.19 per cent, as compared to 0.04 per cent for Latin America and 0.07 per cent for Africa. These trends indicate the prevalence of complex, multidirectional changes in tropical forests.

The deforestation rates reported above are driven in part by 'natural' disturbance regimes and ecological processes (Dunning *et al.*, 1992). Increasingly, however, human activities are responsible for a permanent loss of forest cover, or at least for leaving long-lasting legacies in altered forest structure and composition, even under conditions of subsequent reforestation (Foster, 1992). The LUCC research programme, a joint initiative of the International Geosphere-Biosphere Programme (IGBP) and the International Human Dimensions Programme (IHDP) has used a 'proximate sources/driving forces' framework to understand the causes of LUCC (Turner *et al.*, 1995; Lambin *et al.*, 1999; Geist & Lambin, 2002). Proximate causes refer to activities that directly result in a transformation of land use/cover, while driving forces indicate the underlying processes that give rise to the proximate actions effecting landscape change. Thus, proximate causes include timber extraction, agricultural and pasture expansion, colonization of formerly inaccessible frontiers, infrastructure development and urbanization (Shukla *et al.*, 1990; Burgess, 1993; Ojima *et al.*, 1994; Lambin *et al.*, 2003). All these have had far-reaching consequences in terms of spatial extent, ecosystem impacts, climate change, food production and local livelihoods in tropical forests (Foley *et al.*, 2005). Underpinning such proximate causes are the fundamental sociopolitical, economic, cultural and biophysical forces that drive LUCC, including population growth, regional agricultural and development policies, and the priorities of local land management institutions (Kasperson *et al.*, 1995; Ostrom *et al.*, 1999; Geist & Lambin, 2002; Leemans *et al.*, 2003). The identification of these driving forces, which is essential to understanding ongoing LUCC processes, constitutes one of the dominant challenges in international LUCC research and in the formulation of regional land/forest management policies.

The LUCC programme and other efforts to monitor tropical landscape increasingly use satellite remote sensing and change analysis as powerful tools in monitoring the rates and patterns of tropical forest change (Iverson *et al.*, 1989; Hansen *et al.*, 2000). High resolution satellite data are now used to monitor deforestation as well as successional regrowth (Baltaxe, 1986; Nelson & Holben, 1986; Woodwell *et al.*, 1987; Malingreau *et al.*, 1989; Berta *et al.*, 1990; Gilruth *et al.*, 1990; Green & Sussman, 1990; Sader *et al.*, 1990; Campbell & Browder, 1992; Kummer, 1992; Mausel *et al.*, 1993). In fact, satellite imagery is considered by some to be the most reliable source of quantitative information about deforestation, shifting or swidden cultivation and other land cover and land use changes in the tropics (Sader *et al.*, 1994). Although much work has focused on the use of NOAA's (National Oceanic and Atmospheric Administration's) AVHRR (Advanced Very High Resolution Radiometer) and NASA's (National Aeronautics and Space Agency) Landsat Thematic Mapper (TM) data, the number of land cover types typically classified from such imagery has been small, with few notable exceptions. While offering relatively lower spatial resolution at 1.1 km, AVHRR data have proven to be rich data sources for the mapping of global land cover at a high temporal resolution, particularly in drier ecoregions. Landsat TM, however, has been more effective at separating evergreen forest types in the humid tropics (DeFries & Townshend, 1994; Hansen *et al.*, 2000).

An important development in recent years has been the extension of satellite remote sensing and ancillary spatial data to move beyond a focus on immediate forest loss (proximate cause) and attempt to understand the human and biophysical drivers of environmental change. Notably, such driving forces have been studied in LUCC and related research, albeit not always in spatially explicit modelling frameworks (using georeferenced data). Drivers of environmental (and forest) change may range from population dynamics (Bilsborrow & Okoth-Ogendo, 1992; Meyer & Turner, 1992; Cropper & Griffiths, 1994; Mather & Needle, 2000) to agricultural policies, economic and market factors (Rudel & Roper, 1997; Mertens *et al.*, 2000; Klepeis & Vance, 2003); land tenure and property regimes (Mendelsohn & Balick, 1995; Angelsen, 1999; Futemma & Brondizio, 2003), technological change (Headrick, 1990; Foray & Grubler, 1996; El-Lakany & Ball, 2001; Røpke, 2001) and cultural dynamics (Bennett & Dahlberg, 1990; Arizpe, 1996; Proctor, 1998; Bürgi *et al.*, 2005). For excellent reviews of economic models of tropical deforestation and meta-analyses of human driving forces revealed in 152 subnational case studies respectively see Kaimowitz and Angelsen (1998) and Geist and Lambin (2002).

Increasingly, researchers recognize the value of merging research on driving forces with spatially referenced data and methods to better understand the explicit spatial patterns and trajectories of land change. This paper discusses some key features of such remote sensing/driving forces research methodologies, particularly those encompassing spatially explicit models. It highlights three common features of such spatial models: the use of spatial data, reliance on economic theories and methods, and a concern with multiple methods and scalar issues. It presents a case study application of the spatially explicit approach to identifying driving forces of tropical deforestation in southern Mexico. In conclusion, the paper looks at the feasibility of applying a similar methodology to modelling deforestation pathways in the Indonesian context.

## Spatial driving forces approach to land use/cover change

Since the 1990s, a number of studies have attempted to explicate the dynamics of land change in local and regional-scale analyses by combining remote sensing data with spatially referenced biophysical, social and economic information. Many of these spatially explicit studies have the ultimate goal of understanding not merely the location and nature (proximate cause) of land change, but also identifying the fundamental driving forces of that change. To this end, such approaches analyse remote sensing and ancillary spatial information with diverse modelling techniques referred to in this paper as focusing on spatial driving forces (SDF) of local and regional LUCC. It may be argued that not all driving forces of a spatially observable LUCC event are spatial in origin or intent; for instance, national trade policies may be characterized by some as 'aspatial'. Nevertheless, such policies clearly exert their influence over particular geographic extents and may have distinct impacts in diverse geographic locations or scales, depending on the local context. This paper focuses on the SDF approach for two fundamental reasons. First, it is expedient to focus on spatially observable LUCC in areas of rapid and widespread changes because remote sensing affords us the means to do so, and because it is often in these rapidly changing areas that we encounter populations that are vulnerable in terms of survival of livelihoods and ecosystems. Second, the SDF approach allows preliminary assessments of exactly which factors matter for what kinds of land use changes and at what scales. Drivers that may appear to be non-varying at local scales (e.g. neoliberal economic policy at the national level) may be traced in certain cases to locally varying outcomes (e.g. different subsidy levels to different producers) that, with the aid of diverse field methods, may sometimes be spatially represented. SDF approaches are effective heuristic devices to reveal spatial regularities between landscape change and its dominant drivers, and make manifest for deeper analysis those changes that cannot be captured by observable spatial data. The following sections highlight three common features of SDF modelling approaches: the use of spatially explicit data; reliance on economic theories and/or econometric techniques; and methodological pluralism and scalar concerns.

### *Spatially explicit datasets*

SDF approaches to LUCC dynamics typically use a wide diversity of spatially referenced data. As indicated by Geoghegan *et al.* (1997; 2001), one of the advantages of modelling with satellite imagery and Geographic Information Systems (GIS) data lies in the possibility of generating relevant, spatially explicit variables for analysis. In regression models of deforestation processes, for instance, the products of satellite image classification yield the dependent variable, such as locations and/or area of deforestation. Image classification may also yield rich ancillary datasets (independent variables) that can be used to test specific hypotheses about deforestation dynamics. For instance, present-day landscape structure may be hypothesized to influence future deforestation, as fragmented forests tend to be more vulnerable to further change. Similarly, access to roads and hydrology may be important considerations in a local agent's decision to deforest a particular patch/pixel of forest (Nelson & Hellerstein, 1997). Classified land cover maps from satellite imagery can be used in GIS to produce additional data, such as indices of landscape structure and distances to particular cover classes (e.g. roads, water or nearest cleared land). Aside from using ancillary spatially referenced data (such as those digitized from roads and soils maps or interpolated from climatological point samples), SDF models of land change frequently use GIS to produce additional variables for analysis. Such techniques are particularly useful in data sparse environments such as the tropics (Nelson & Geoghegan, 2002). An innovative example is provided by Müller and Zeller (2002), using GIS to generate Thiessen polygons as proxy village boundaries in remote highland areas of Vietnam, an area where such administrative/political boundaries are difficult to obtain or generate in the field with a global positioning system (GPS). Driving processes (e.g. market prices) that for a local area may be considered space-invariant and yet time-dependent, can be captured in SDF model runs that test for stationarity in landscape transition probabilities and relationships to hypothesized drivers as represented by chosen variables.

*Economic theories and econometric/statistical techniques*

In the impetus to understand the driving forces of landscape change, many SDF models draw upon various theories and conceptual frameworks of agricultural and land use change. Such theories aim at the causal processes of land use changes and decision making and therefore are often strongly economic or behavioural in orientation (van der Veen & Otter, 2001). Von Thünen and Ricardian theories of land use allocations are among the more frequently used. These theories are predicated on understanding land use allocations as a function of market integration (proxy: distance to markets), environmental factors that determine land/bid rents and, therefore, the choice of particular parcel areas for agricultural use. Among the first examples of land use modelling using an econometric framework was one put forth by Chomitz and Gray (1996), and spatial econometric techniques have been increasingly applied in recent years (Cropper *et al.*, 1999; Pfaff, 1999; Geoghegan *et al.*, 2001; Nelson *et al.*, 2001; Munroe *et al.*, 2004; Walker, 2004).

SDF approaches in modelling processes of agricultural change in landscapes undergoing demographic and/or infrastructural transitions also draw upon theories of agricultural intensification (Boserup, 1965; Ruttan & Hayami, 1984; Turner & Brush, 1987; Turner & Ali, 1996; Müller & Zeller, 2002; Laney, 2004). Agricultural intensification theories explicate how demand themes and land pressures resulting from population pressures may drive the need for higher agricultural production. Increased production can occur through agricultural expansion at a constant technological level or through agricultural intensification on already farmed lands by substituting labour and capital for land. Aside from population pressure, exogenous factors such as infrastructure development, market integration and other changes in regional political economy and ecology may change the set of constraints and opportunities for land managers and pave the way for agricultural intensification. SDF models also examine the effects of structural forces that drive and/or constrain deforestation processes, such as the prevalence of multiple property and land tenure regimes, the existence of protected reserves effectively blocking land access and use, and policies such as infrastructure development, colonization programmes, market integration, structural adjustment and agricultural subsidies (Cropper *et al.*, 1999; Seto & Kaufmann, 2003; Walker & Solecki, 2004).

It is important to point out that not all spatial models that investigate the driving forces of land change use economic theories or frameworks aiming to explain the behaviour of land managers. Walker (2004) points out that sociologists and geographers used inferential statistics and spatially referenced regression models to explain the driving forces of deforestation before the debut of spatially explicit economics (Allen & Barnes, 1985; Rudel, 1989; Ludeke *et al.*, 1990). Irwin and Geoghegan (2001) distinguish between empirical LUCC models and spatial economic LUCC models, indicating that while the former may 'fit' observed LUCC patterns reasonably well to spatial processes, they are less successful at explaining the human behaviour driving the observed patterns, even when they incorporate socioeconomic variables. The authors attribute this to an ad hoc choice of economic variables rather than choosing explanatory variables based on pre-existing economic theories of human behaviour (i.e. rational choice or bounded rationality).

*Methodological pluralism and scalar dynamics*

Although SDF approaches use models that are quantitative, spatial (e.g. areal extents) and very often spatially explicit (i.e. georeferenced data), they frequently incorporate data generated through interdisciplinary collaboration and/or using a diversity of research methods. Such methodological diversity extends SDF research beyond satellite image classification and modelling, incorporating regional environmental history (Klepeis & Turner, 2001), political ecological frameworks (Vasquez-Leon & Liverman, 2004), ethnographic methods (Guyer & Lambin, 1993), ecological research (Turner *et al.*, 1996; Smith *et al.*, 1999), or census data compilation, archival and social survey research (Wood & Skole, 1998; Geoghegan *et al.*, 2001; Rindfuss *et al.*, 2003).

The above methodologies contribute in at least two fundamental ways to enriching LUCC research. First, they address LUCC processes and driving forces that operate at a variety of spatial and temporal scales, effectively expanding the scope of analysis beyond what would be permitted by remotely sensed data alone. By its nature, remotely sensed data is suited for analysis at broad spatial scales and relatively recent time periods (early to mid-twentieth century and onwards if aerial photography is included). When combined with ethnographic research, broad-scale analyses can be complemented and strengthened with in-depth knowledge of processes driving local environmental change. Environmental historians and long-term ecological research emphasize the enduring legacies of past land uses and their driving processes on current outcomes, extending the temporal scale of LUCC research (Foster, 1992; Klepeis, 2004).

Another notable advantage of mixing remote sensing with other methodologies lies in enabling an accurate interpretation of model results in relation to a specific area, generating the explanatory tissue that bridges the modelled driving factors and the actual mechanisms of change. In other words, ethnography, interviews, household surveys, field-based community and participatory sketch mapping and other methods afford alternate perspectives and understandings of the transformation being investigated. In so doing, such methods can clarify the differences and connections between observed correlations and chains of causation.

SDF approaches have explicitly investigated the significance of the scale of analysis, including temporal scale, for model analysis and prediction. For instance, Munroe *et al.* (2004) studied land change trajectories in western Honduras between 1987 and 1996 and found fundamental differences between LUCC processes and their drivers in 1987–91 and 1991–96, results that exemplify nonlinearities in driving processes over time. Mertens *et al.* (2004) modelled deforestation in Santa Cruz, Bolivia over distinct spatial scales and time periods, exploring driving forces that included biophysical factors, access to roads and markets, land tenure and zoning policies. They found distinct factors to prevail at the department versus local scales: for instance, better accessibility, higher soil fertility and higher rainfall increased department-wide deforestation, but had either no or the opposite effect in specific local zones. The authors also found that the relationship of driving forces to deforestation processes was generally weaker in 1989–94 as compared with the pre-1989 period.

The magnitude and nature of the role of driving forces on LUCC as identified by SDF models are also subject to a variety of scalar and related problems such as choice of the units of analysis and spatial autocorrelation, reviewed by Anselin (2002) and Openshaw and Taylor (1979) and others. The choice of the pixel as the basic unit of analysis in land cover mapping and modelling is far from sacrosanct. Saura (2004) and others have investigated the impact of pixel sizes and aggregation levels on indices of landscape structure. Landscape patches are an alternate choice of unit of land cover mapping and change analysis (Peroni *et al.*, 2000; Burnett & Blaschke, 2003). Patch units may improve landscape characterization on some counts; however, they may distort other indices of landscape structure (Flamm & Turner, 1994). No one spatial unit necessarily represents the 'perfect' choice, rather, LUCC and landscape ecological research suggest that the relative advantages and drawbacks of pixels versus patches as units of analysis appear to depend upon the chosen mapping/modelling goals, scale of analysis and landscape context (Smith *et al.*, 2003; Crews-Meyer, 2004; Fleming *et al.*, 2004).

Spatial interaction in data may be represented in SDF models through a variety of methods, such as spatially lagged dependent variables as an independent variable in regression equations, or geostatistical techniques for analysing spatial error autocorrelation, or spatial autoregressive models (Anselin, 2002). The related modifiable areal unit problem relates to how units of analysis are spatially aggregated, while ecological fallacy relates to erroneous conclusions emerging from cross-level inference, for example, when inferring behaviour or driving forces at local levels based on model estimation at a more aggregate level (Robinson, 1950; Stoker, 1993). The spatial scale-dependence of driving forces has also been investigated in relation to both top-down and bottom-up processes in SDF and other models (Wiens, 1989; Levin, 1992; Verburg *et al.*, 1999; Nelson, 2001). Walsh *et al.* (2001) used canonical correlation to investigate systematically the scale-dependence of relationships between environmental and socioeconomic variables in northeast Thailand, concluding that variations in biomass were explained by population factors at fine spatial scales, and biophysical factors at coarser scales. Geoghegan *et al.* (2001) evaluated the biophysical and socioeconomic driving forces of regional and local (parcel) scale land use change in a large study area in the southern Yucatán. The next sections of this paper present a regional-scale SDF model of deforestation processes in a subset of the region, focusing specifically on the most dynamic area of landscape transformations in the vicinity of the Calakmul Biosphere Reserve (CBR).

## Case study: Southern Yucatán peninsular region, Mexico

### *Study area*

The southern Yucatán peninsular region (SYPR) of Mexico is one of 35 enumerated global hotspots of biodiversity, as well as of tropical deforestation (Achard *et al.*, 1998). Home to the largest remaining stretch of contiguous forest in the southern Mexico-Central American region as well as Mexico's largest protected area, the 723.128 ha CBR, the region encompasses diverse tropical and subtropical ecosystems and lies within the Mesoamerican Biological Corridor, a multilateral conservation programme seeking to link established reserves from southern Mexico down to Panama (Miller *et al.*, 2001; Turner *et al.*, 2004). Calakmul has experienced episodic waves of transformation, including several centuries of land use by the ancient Mayan civilization that declined after CE 900, thus permitting the re-establishment of forest (Turner, 1983; Whitmore & Turner, 2001; Turner *et al.*, 2003). Recent increases in deforestation rates have been driven primarily by peasant farmers in communal land grants (*ejidos*) involved in a mix of subsistence and market production (Vance, 2004). Intensifying concerns for environmental protection at the national and international levels led to the establishment of CBR in 1989 and its entry into the United Nations (UN) Man and the Biosphere (MAB) programme in 1992. The reserve boundaries include a mixture of state, private and communal property regimes, with *ejido* lands constituting the majority (>50 per cent) of its area. Despite the establishment of the CBR, however, LUCC changes continue to unfold, prompting various policy and local action focused on local development and/or forest and soil conservation.

### *Land use/cover change: classification and modelling methodology*

The classification of the Landsat TM imagery (see Roy Chowdhury & Schneider, 2004), which was conducted in collaboration with the interdisciplinary project on Land Cover and Land Use Change–southern Yucatán peninsular region (LCLUC-SYPR) at Clark University (Turner *et al.*, 2004), can be summarized into four phases: (i) image georeferencing and noise removal through Tasseled Cap transformations and principal components analyses; (ii) texture analysis and calculation of normalized difference of vegetation index (NDVI) to produce additional bands for image classification; (iii) signature development using training sets for prevalent land cover classes obtained through numerous field visits; and (iv) a maximum likelihood supervized classification to derive composite land cover maps for 1987, 1992 and 1996. The classification produced a total of 10 land cover classes: water; seasonally flooded; short-stature forests (locally, *baja* forest); well-drained, mid-tall stature upland forests (locally, *mediana* forest); seasonally inundated savannas; herbaceous wetlands; three stages of upland successional growth (herbaceous, shrub-dominated, arboreal); cropland; pasture; and one significant invasive species (bracken fern). These classes were aggregated to six classes for regional-scale change detection and modelling: wetland forest, upland forest, intermediate and late successional growth (7–15 years), savanna and wetlands, agriculture (cropland, pasture and young fallow or early successional regrowth) and bracken fern.

A regional, spatially explicit model explored the proximate and driving forces behind the observed landscape change during 1987–96 in an area of 7400 km$^2$ located centrally in the Calakmul municipality (Figure 1). This area, encompassing the CBR buffer zone's eastern flank, includes Calakmul's most recently opened southern frontier and is one of the region's hotspots of landscape change. The model focused particularly on the conversion of mature wetland or upland forests (in 1987) to the aggregate agricultural cover class (cropland, pasture and young fallow) by 1996, and on areas under the predominant communal land tenure (*ejidal*). The results presented exemplify an approach referred to occasionally in land change studies as 'socialising the pixel' and 'pixelizing the social' (Geoghegan *et al.*, 1998; Turner, 2002).

### *Model formulation, dependent and independent variables*

The transitions detailed in Figure 1 provided the requisite dependent variable for the regional deforestation model. The regional model of deforestation uses a binomial logit formulation with the classification derived dependent variable (forest persistence versus deforestation during 1987–96) and ancillary biophysical, locational, landscape and socioeconomic GIS layers as independent variables, and produces a predicted probability of deforestation as well as parameter estimates as follows:

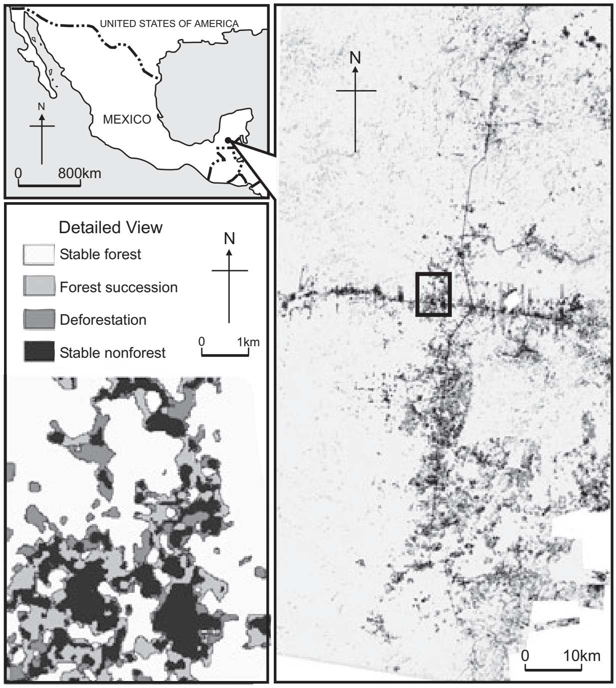


**Figure 1.** *Forest–agriculture transitions in eastern Calakmul, 1987–96, showing detailed spatial patterns of change.*

$$\Pr(y_j \neq 0 \mid x_j) = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2\cdots}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2\cdots}}$$

where

$y_j$ = 0 if pixel *j* was forest in 1987 and remained forested in 1996 (base case), 1 if pixel *j* was forest in 1987 and was deforested in 1996,

$x_j$ = value of independent (explanatory) variable at pixel *j*,

$\beta s$ = estimated parameters for each independent variable.

Among the biophysical variables considered were slope, elevation, soil type, rainfall and type of mature forest: seasonally flooded *baja* forest versus well-drained upland *mediana* forest. Slope and elevation information were derived from a Digital Elevation Model (DEM) of the region obtained from Mexico's National Institute for Statistics and Geographic Information (INEGI). Lower elevations and slopes were hypothesized to be preferred for agriculture (and hence agricultural deforestation), owing to potentially higher land preparation and management costs in rugged terrain. Soils were digitized by LCLUC-SYPR project personnel from a 1 : 250 000 scale INEGI-produced soils map. Two types of soils prevail in the region: mollisols (redzinas) in upland areas, and vertisols in seasonally inundated depressions (Turner *et al.*, 2001; Pérez-Salicrup, 2004); most farmers in the region prefer the well-drained mollisols or the transitional zone between lowland and upland soils. Rainfall in the region follows a marked north-south gradient and increases southwards, with strong implications for forest structure and function as well as agricultural productivity (Lawrence & Foster, 2002; Read & Lawrence, 2003). Rainfall maps were produced by the LCLUC-SYPR project by kriging data obtained from 20 rainfall stations located in and around SYPR. All else being equal, higher rainfall can lead to higher agricultural yields; regions that experience higher rainfall may, thus, be hypothesized to have potentially higher land rents and, therefore, higher probabilities of agricultural deforestation. The type of mature forest present was derived from the land cover classification for the 1987 image date – and it was hypothesized, based on local observations of agricultural sites, that deforestation would be more likely on upland *mediana* forests than seasonally flooding *baja* forests.

Several aspects of a forest pixel's location were critical independent variables in the deforestation model. Distances to roads and markets determine pixel/parcel accessibility, and can be significant in determining land rents. The GIS layers were produced through simple GIS distance analyses using digitized roads layers and the municipality seat, Xpujil, as the main market location. The model also explored spatially contiguous processes of deforestation by including, as an independent variable, a forest pixel's distance to nearest existing agriculture. Indices of forest fragmentation, land cover diversity and dominance were calculated for each pixel based on its immediate $3 \times 3$ pixel neighbourhood. The variables, along with the number of agricultural pixels within a $5 \times 5$ neighbourhood, capture aspects of landscape structure that may influence spatial deforestation processes.

The model presented here uses census data to select demographic and socioeconomic variables that may influence deforestation probability. These data were linked in a GIS to a map of *ejido* (village) boundaries and the census derived variables uniformly distributed across each individual village. For instance, if the census reported 29 per cent of all houses in village A had running water, the 'per cent houses with running water' GIS layer would have a value of 29 for each pixel within the boundaries of village A. Although this method fails to capture socioeconomic differentiation *within* villages, aggregate village-level census data often constitute the only regionally comprehensive information source. The village-level census data used in this deforestation model include: total male and female populations, number of school-going children from 6–15 years of age, number of individuals at age 15 with some post-elementary education, and indicators of community wealth such as number of private houses with running water and electricity. Wealth and education can reflect higher quality of life, made feasible in part by deforestation and agricultural production. Alternatively, wealth and education may be the result of off-farm opportunities that reduce deforestation pressures. This study also uses a spatially explicit database of state investment in the infrastructure, agriculture and forestry sectors in the region's *ejidos* during 1990–99. Such investments, compiled through a comprehensive review of records of government secretariats, local nongovernmental organizations (NGOs), and community organizations, yielded two variables: (i) total state investment, a proxy variable for *ejido*-level sociopolitical capital; and (ii) investment specific to agricultural intensification and conservation. In general, overall *ejido*-level sociopolitical capital (the total state investment variable) is hypothesized to increase deforestation, attracting and diverting more subsidies and inputs for agricultural livelihoods. The latter variable represents potential for agricultural intensification and forest preservation, reducing overall agricultural extensification and deforestation. Of course, such a release on deforestation pressure can only be expected to occur in *ejidos* where conservation outcomes and non-agricultural opportunities outweigh increases in capital applicable towards agricultural expansion.

### *Model results: proximate and distal drivers of regional deforestation*

The spatially explicit logit model estimates the significance, nature and magnitude of influence of each biophysical, locational and socioeconomic factor on regional

**Table 1. Results of regional deforestation model (N = 2905337, pseudo $R^2$ = 0.1768).**

| Variable | Mean | SD | Min | Max | Coefficient | Z |
|---|---|---|---|---|---|---|
| Dependent (forest persistence vs. deforestation) | 0.1260409 | 0.3318955 | 0 | 1 | – | – |
| Elevation (m) | 222.995 | 44.6215 | 70 | 320 | −0.0010792 | −16.52 |
| Slope (degrees) | 1.255094 | 2.1156 | 0 | 62.31 | 0.0260908 | 35.1 |
| Upland soil (dummy) | 0.7966198 | 0.402513 | 0 | 1 | 0.2420602 | 46.85 |
| Rainfall (mm) | 1 071.887 | 66.82922 | 924 | 1206 | 0.0048158 | 101.45 |
| *Mediana* forest (dummy) | 0.9072127 | 0.2901341 | 0 | 1 | 1.920266 | 108.81 |
| Distance to roads (m) | 571.4853 | 416.1939 | 0 | 1 889.464 | −0.001084 | −147.24 |
| Distance to market (Xpujil) (m) | 2 904.357 | 1305.798 | 27.659 | 6 786.79 | 0.0000523 | 18.55 |
| Distance to nearest agriculture 1987 (m) | 60.15593 | 57.74215 | 3 | 483.2 | −0.0146489 | −213.34 |
| Fragmentation Index 1987 | 0.0232651 | 0.0516763 | 0 | 0.5 | 2.942852 | 9.94 |
| Diversity Index 1987 | 0.0957892 | 0.2170787 | 0 | 1.581 | −1.982886 | −32.54 |
| Dominance Index 1987 | 0.0302836 | 0.0861094 | 0 | 0.414 | −0.1495137 | −2.54* |
| Frequency of agricultural pixels in neighbourhood | 0.485981 | 1.789588 | 0 | 20 | 0.214473 | 158.87 |
| Increase in population 1990–2000 (%) | 61.31751 | 98.42871 | −98.97 | 353.57 | −0.0025568 | −58.58 |
| Population male 1990 | 158.2846 | 149.5036 | 9 | 1 529 | −0.0130341 | −88.19 |
| Population females 1990 | 134.3213 | 119.4939 | 11 | 1 387 | 0.010851 | 64.01 |
| Households with running water (%) | 10.12212 | 32.07755 | 0 | 486 | 0.0034567 | 14.79 |
| Households with electricity (%) | 32.62524 | 48.61987 | 0 | 509 | −0.0350148 | −74.46 |
| No. students 6–15 years in 1990 | 59.6512 | 56.67615 | 0 | 235 | 0.0074607 | 32.65 |
| No. with post elementary education at 15 years in 1990 | 13.7401 | 22.57644 | 0 | 109 | −1.59E-07 | −15.88 |
| *Ejido* sociopolitical capital (MNX) | 2 795 005 | 4 989 349 | 6000 | 3.09E+07 | 0.0125893 | 59.45 |
| *Ejido* agriconservation capital (MNX) | 643 941.2 | 583 826.8 | 0 | 2 381 075 | 1.19E-07 | 69.98 |
| Constant term | – | – | – | – | −7.791757 | −151.4 |

All variables (except *significant at 0.05 level) are significant at the 0.001 level.

deforestation. Table 1 summarizes the variable summary statistics and model results. The regional deforestation model produces parameter estimates (coefficients) for each independent variable, which were then used to predict in-sample deforestation probabilities with the GIS datasets (Figure 2).

As hypothesized, biophysical and locational factors are strong determinants of regional deforestation in southern Yucatán: specifically, lower elevation, well-drained upland soils under *mediana* forest are more likely to be deforested during the time period modelled, results that are supported by other LCLUC-SYPR studies (Geoghegan *et al.*, 2004). Fieldwork indicates that most land managers in the region tend to choose lower slopes for cultivation. The positive coefficient for slope in the model is counterintuitive, suggesting higher deforestation probability on steeper slopes. These results may reflect local-scale variations in topography and agricultural suitability of *ejido* lands that are not captured by the insufficiently precise DEM. Topographic data of higher spatial resolution and accuracy, such as those derived from the Shuttle Radar Topography Mission (2000), may improve future model runs. Mean annual precipitation varies from 927 mm to 1206 mm in the modelled region and, as hypothesized, is a significant and positive driver

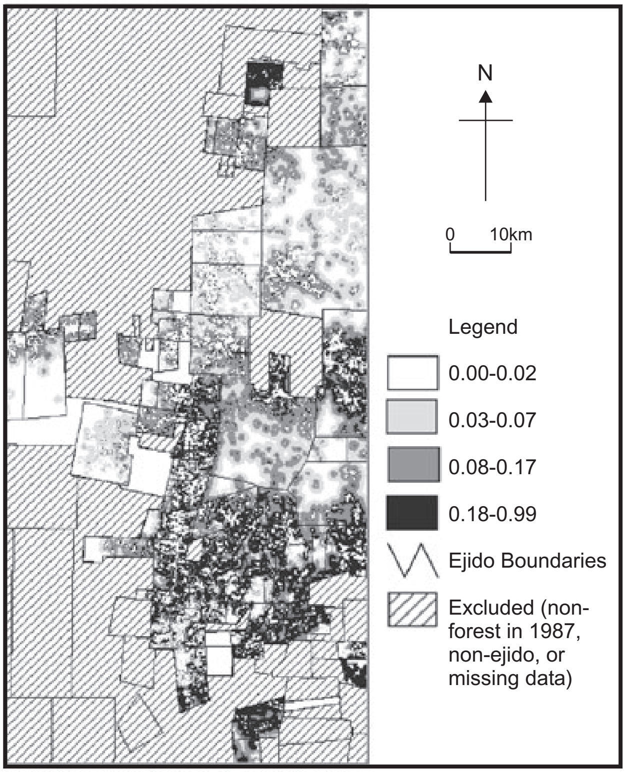


**Figure 2.** *Predicted probabilities of deforestation, 1987–96 (adapted from Roy Chowdhury, 2003); the grey-scale legend depicts continuous deforestation probability collapsed into quartiles.*

of regional deforestation. The southern region receives higher annual rainfall on average, and experienced higher rates of deforestation during the modelled time period.

Locational factors and landscape structure are significant predictors of deforestation in the region, findings that highlight the spatially contiguous nature of deforestation processes in many regions worldwide. Forests located close to roads and existing agriculture, or those with higher frequency of agricultural pixels in their neighbourhoods are at greatest risk of deforestation. Less important in magnitude but also significant are distance to markets and indices of landscape structure. The model suggests that forests closer to the regional market in Xpujil are less likely to undergo deforestation, a counterintuitive result that could have several explanations: (i) the method used to calculate distances was shortest linear distance rather than along existing road networks; (ii) only one major market centre (Xpujil) was included in the analysis, whereas several lesser markets may function effectively at the local level; and (iii) the modelled subregion includes the *zona chilera*, villages known for their investment in the dominant commercial crop, jalapeno chilli. Chilli is bought from farmers/producers by middlemen who literally come to the 'farmgate', making distances to markets less important than accessibility to roads. The standardized coefficient for distance to market is of the same order of magnitude as those for landscape structure indices. Forest pixels in highly fragmented landscapes (range 0–0.5) appear to face a higher likelihood of deforestation. Nevertheless, the negative signs of the coefficients for landscape diversity (range 0–1.58) and dominance (range 0–0.41) suggest further complexities in the relationship between deforestation probability and landscape configuration. Pixels in neighbourhoods of more even distribution of land cover types (lower dominance) and lower diversity are more likely to be deforested.

Demographic and socioeconomic factors are related to deforestation probability in significant but complex ways. All else being equal, a higher per cent increase in total *ejido* population over the decade 1990–2000 could be expected to increase the likelihood of deforestation, yet model results suggest the reverse. Similarly, more males and fewer females in 1990 translate into lower deforestation probabilities – an unexpected result given that most agricultural deforestation is for subsistence or market crops and generally linked to male farmers. The significance may lie in investigating whether or not more males begin to engage in off-farm activities, releasing pressure on forests; also, standardizing demographic variables by *ejido* land area may revise some of these results. The village-scale, census-derived education variables had interesting implications for deforestation probability. Village-level education, as represented by the number of school-going children 6–15 years of age, increases deforestation likelihood, reflecting how consumption demand can drive deforestation even in the face of a reduced labour supply as children devote time to school. Another village-scale metric of education, population older than 15 with post-elementary education, decreases deforestation probabilities, suggesting that educated adults in many villages are involved in increased off-farm livelihood alternatives. Indicators of wealth, as represented by proportion of households in a village with access to water and electricity, are positively related to probability of deforestation, indicating that relative affluence does not relieve dependence on the land. In fact, field studies in the region indicate that greater relative wealth is likely to increase capital-intensive agricultural uses such as pasture or chilli. Higher sociopolitical capital is directly linked to higher deforestation, demonstrating that the increased access to subsidies, projects and better integration within the regional political economy leads to greater agricultural expansion. Government investment, specifically in agricultural intensification and forest conservation (*ejido* agri-conservation capital), appears to reduce deforestation.

The spatial model described in this case study exemplifies the SDF approach to understanding land change in a local area. In this case, the model results reveal the dominant biophysical, locational and socioeconomic factors that drive deforestation in the most dynamic region of the CBR. In this region, deforestation is most strongly driven by ease of access from existing roads and agricultural plots, followed by the type of mature forest in question, and biophysical variables such as rainfall. While landscape structure is a significant predictor of deforestation probability, socioeconomic factors such as demography, wealth and village sociopolitical capital can exert far greater influence on the fate of local forests, as evident from the magnitude of estimated parameters in Table 1.

### *'Hardening' predictions and model validation*

To validate the regional deforestation model, the continuous prediction map in Figure 2 was classified into a binary change/no change map following the methodology developed earlier by LCLUC-SYPR project researchers (Geoghegan *et al.*, 2001; 2004). For this regional deforestation model, the actual number (N) of pixels that underwent deforestation during 1987–96 was determined and the N pixels in the continuous probability map that had the highest predicted likelihood of change were selected. These were assigned a value of 1 in a new categorical map of predicted change for the deforestation model, with all other pixels assigned a value of 0. This binary map is compared to the map of actual regional deforestation for 1987–96, to evaluate model performance (Figure 3).

The model correctly predicts the vast majority (91 per cent) of forest pixels that remained unchanged over the decade examined, comparable to the 96 per cent correct

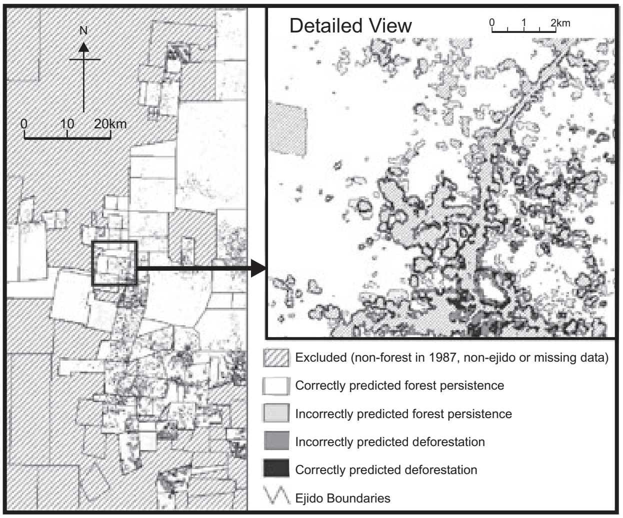


**Figure 3.** *'Hardening' deforestation probabilities and model validation (adapted from Roy Chowdhury, 2003) showing detailed spatial patterns of correct and incorrect predictions.*

prediction for forest persistence calculated by the LCLUC-SYPR project using the larger SYPR region (Geoghegan *et al.*, 2004). Of all the forest pixels that were actually deforested during 1987–96, the model presented here successfully predicts about 40 per cent of actually deforested pixels, also within the same range as the larger SYPR region (33 per cent correct predictions of deforestation reported in Geoghegan *et al.*, 2004). Most correctly predicted deforestation involved pixels located close to areas that were already deforested in 1987 to begin with, indicating that the model successfully captures the spatial contagion of local deforestation processes. The model overestimates this contagion, however, because it over predicts deforestation in areas adjoining the correctly predicted deforestation pixels. The variable capturing distance to nearest agriculture has the highest standardized estimated coefficient (z-score = –213.34), and may be responsible for the over prediction.

The spatial pattern of pixels where the regional model over predicts forest persistence is not random, but does not appear to fit a simple distance-based criterion. Variables not captured in the model may account for some of this error, including new distributions of parcels to *ejido* members, as would be suggested by the clumped pattern of larger areas of under predicted deforestation (Figure 3). In other areas, such as to the north of the modelled area, this error assumes a spatially dispersed form that could indicate artifacts of image classification errors described elsewhere (Roy Chowdhury, 2003; Roy Chowdhury & Schneider, 2004). The other alternative is that there are further spatial processes occurring in these areas that the model does not currently explain, such as farmers establishing new agricultural fields farther from older plots for pest control or on account of local variations in soil suitability.

## Conclusions

Accurate assessments of forest cover and rates of forest loss, and a clear identification of its proximate sources should comprize the first step to analysing deforestation. Designing policy responses to address deforestation and make forest protection more effective, however, further requires a deeper understanding of the primary mechanisms and driving factors behind forest change. Proximate assessments of landscape change enabled by remote sensing can be enriched by in-depth analyses of the underlying driving forces at play. The social sciences and spatial modelling approaches reviewed and illustrated in this paper can contribute to this project.

A focus on spatial and spatially explicit modelling, analysis of multiple variables chosen for their relevance to local deforestation outcomes and/or economic causal theories, and a focus on diverse methodological traditions and scalar dynamics are key features of what this paper describes as the SDF approach to land use change. A case study in southern Mexico demonstrates such an approach to understanding the dominant drivers of deforestation for agricultural expansion. In Indonesia, proximate causes of forest change also include smallholder agricultural expansion (World Bank, 1990; Indrabudi *et al.*, 1998) but in addition to tree crop production, oil palm estates (Dove, 1993; Osgood, 1994; Chomitz & Griffiths, 1996; Casson, 2000) timber extraction and conversion to industrial plantations (Angelsen, 1995; Fuller & Fulk, 2001; Dennis & Colfer, 2006). The SDF approach may be applied to identify the dominant socioeconomic drivers of such changes, which include population pressures, transmigration, land tenure status, levels of affluence, technology and education, differing perceptions of protected forest status, international timber prices and state policies that favour logging concessions (Secrett, 1986; Whitten, 1987; Osgood, 1994; Sunderlin & Resosudarmo, 1994; Thiele, 1994; Indrabudi *et al.*, 1998; Dennis & Colfer, 2006). In extending SDF methodologies, it would be wise to heed some cautionary notes that have been sounded in recent literature.

First, SDF studies must adequately characterize local agents of deforestation in order to understand diverse rationales in land management (Sunderlin & Resosudarmo, 1994; Paudel & Thapa, 2004). While the model presented in this paper does not focus on land management decisions at the scale of the individual household parcel, parcel-scale analysis was also conducted in a separate SDF model in order to understand how diverse land use allocations and deforestation trends are affected by household socioeconomics, ethnicity, land tenure, demography and interaction with social and political-economic institutions (Roy Chowdhury, 2006), as will the implication of scalar dynamics for discrepancies between land cover outcomes and statistical relationships at the regional and parcel levels.

Second, SDF models must attempt to account for the legacies of longstanding and broad socioeconomic processes, thus incorporating structural factors in the analysis of driving forces. In the Indonesian case, this would entail examining the residual spatial legacies of the land tenure law in the post-New Order *reformasi* period, as well as understanding the implications of current land reform, administration and policy (Thorburn, 2004). Modelling structural effects is a challenging task, but essential to understanding both broad-scale determinants of landscape change as well as constraints on local-scale decision making. For an analysis of policy institutions influencing land management in southern Mexico, see Geoghegan *et al.* (2001). Roy Chowdhury and Turner (2006) provide a spatial analysis of how smallholder agency and broad structural institutional factors interact to influence household land use portfolios in the southern Yucatán.

Third, SDF approaches must continue the move away from monistic explanations of land change to careful, comparative assessments of the multiple driving forces of change (Sunderlin & Resosudarmo, 1994; Geist & Lambin, 2002). While empirical SDF approaches may not be as effective as economic SDF models at explicating the causal chains of deforestation, all SDF analysis that include multiple, carefully chosen variables, rigorous hypothesis testing and on-ground (or equivalent) study of the local mechanisms of change processes can help shift the focus from incidental correlations to understanding causal connections. Perhaps most importantly, SDF models should continue to draw from, collaborate with and on occasion defer to other disciplinary and methodological traditions to strengthen understanding of the processes of human-environment transformations and, in doing so, identify important interactions between and among causes and agents of land change (Sunderlin & Resosudarmo, 1994; Geist & Lambin, 2002; Rindfuss *et al.*, 2003). Only then will such approaches produce solid scientific analysis that can inform policy reform required to effectively protect the world's remaining forests and the livelihoods that depend upon them.

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