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A BEHAVIORAL MODEL OF LANDSCAPE CHANGE IN THE AMAZON BASIN: THE COLONIST CASE

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Abstract. This paper presents the prototype of a predictive model capable of describing both magnitudes of deforestation and its spatial articulation into patterns of forest fragmentation. In a departure from other landscape models, it establishes an explicit behavioral foundation for algorithm development, predicated on notions of the peasant economy and on household production theory. It takes a ''bottom-up'' approach, generating the process of land-cover change occurring at lot level together with the geography of a transportation system to describe regional landscape change. In other words, it translates the decentralized decisions of individual households into a collective, spatial impact. In so doing, the model unites the richness of survey research on farm households with the analytical rigor of spatial analysis enabled by geographic information systems (GIS). The paper describes earlier efforts at spatial modeling, provides a critique of the so-called spatially explicit model, and elaborates a behavioral foundation by considering farm practices of colonists in the Amazon basin. It then uses insight from the behavioral statement to motivate a GIS-based model architecture. The model is implemented for a long-standing colonization frontier in the eastern sector of the basin, along the Trans-Amazon Highway in the State of Pará, Brazil. Results are subjected to both sensitivity analysis and error assessment, and suggestions are made about how the model could be improved.

Key words: *Amazon; fragmentation; land-cover and land-use change.*

Introduction

By now, there is general consensus that land-use and land-cover change cause significant environmental impacts at global and local scales (Stern et al. 1992). Although changes in the earth's vegetative cover occur throughout the world, most attention in recent years has focused on tropical deforestation, which releases substantial quantities of carbon to the atmosphere, at the same time as it destroys habitat for innumerable species (Myers 1980). It should come as no surprise that loss of tropical forest has emerged as a major global issue, sparking both public concern and scientific research.

Two broad categories of scientific questions attend the loss of tropical forest. On the one hand are the many environmental impacts that follow in its wake. Since Norman Myers first sounded the alarm of tropical forest loss, ecologists and environmental scientists have written extensively on this subject, and provided the world community with an exhaustive account. By way of contrast to these ecological concerns are questions relating to the social and economic causes of forest loss. These reside largely within the purview of the social sciences, which have spawned an extensive literature addressing the human drivers of tropical deforestation (Geist and Lambin 2001). This paper falls within this latter category by focusing on the land-use and land-cover change dynamics associated with colonization in the Amazon basin. Colonist farmers account for a substantial portion of deforestation both worldwide and in the Amazon region (Walker et al. 2000, Geist and Lambin 2001).

The paper, however, goes one step further than much of the work accomplished to date by social scientists. In particular, it presents a model capable of predicting, in addition to quantities of deforestation, the spatial articulation of human behavior into patterns of forest fragmentation, which is necessary for understanding the biodiversity impacts of land-cover change. Most models from the social sciences have been a-spatial and statistical, attempting to discover, through statistical inference, the main variables driving the process of forest loss in the aggregate (Kaimowitz and Angelsen 1998). So-called spatially explicit models do utilize spatial data in defining independent variables, but the intent usually is to identify the driving variables

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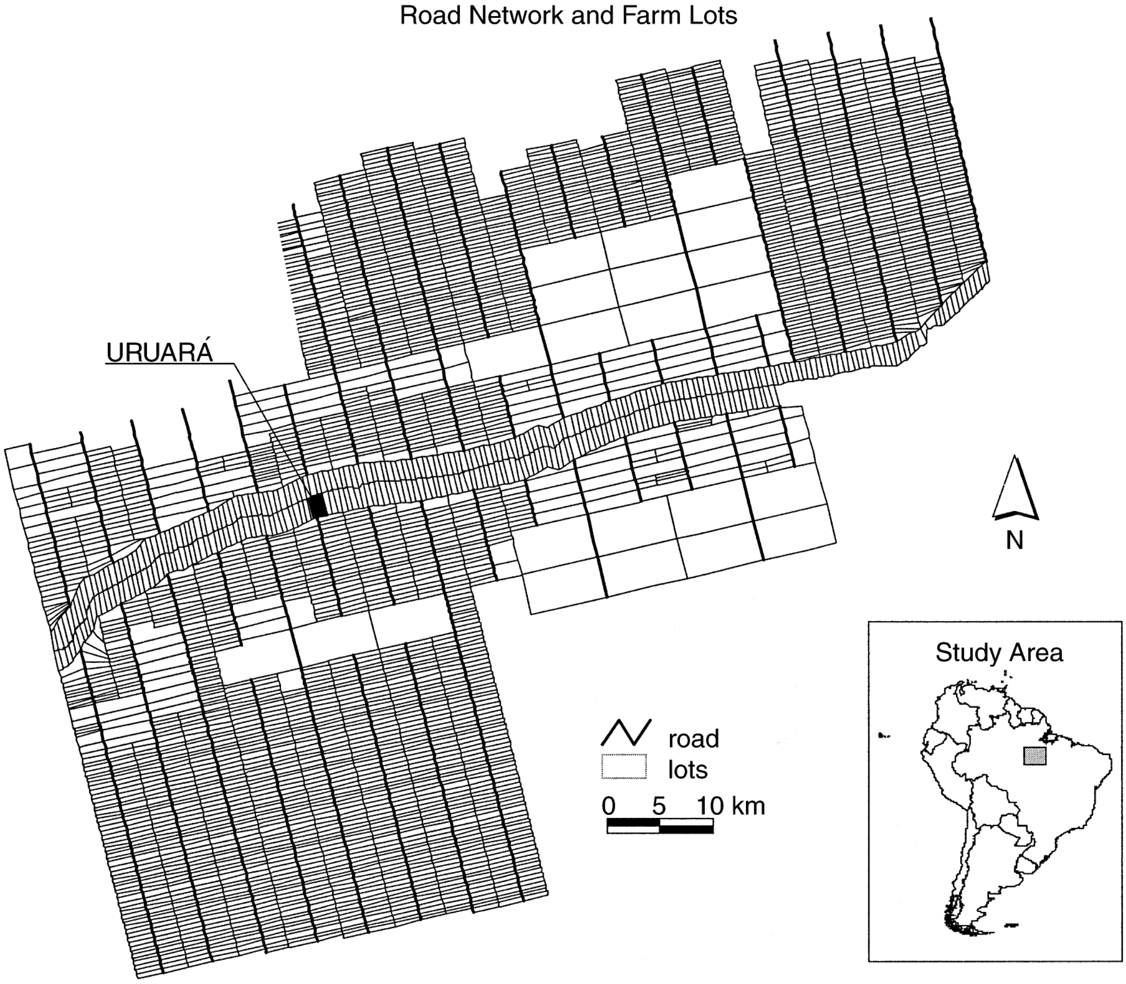

FIG. 1. Map of the study area in Brazil showing road network and farm lots.

through inference, and not to provide a tool for depicting the spatial patterns that result (for an exception, see Mertens and Lambin [2000]).

By way of contrast, the goal of the present model is to predict landscape change, and to do so on the basis of a framework stemming from notions of the peasant economy and household production theory (Singh et al. 1986, Thorner et al. 1986, Ellis 1993). This is accomplished by stating a welfare optimization ''problem'' for colonist households, which provides a rationale for using a parsimonious collection of variables to generate the process of land-cover change occurring at lot level. These processes are then aggregated in a geographic information system to reflect a regional landscape. Hence, the operational model scales up from the farm to the ''colonization'' landscape, translating the decentralized decisions of households into a collective, spatial impact (Brondizio et al. 2002). The model is fit with field data, and executed for an actual site along the Trans-Amazon Highway, in the eastern sector of the basin (State of Pará, Brazil; see Fig. 1). The framework advanced is conceptually related to the DELTA model (Dale et al. 1993, 1994) that has been applied to colonization in the western sector of the Amazon basin (State of Rondônia, Brazil).

The paper is organized as follows. In the next section, *Toward the explicit representation of space,* we consider the development of landscape change models. This involves a discussion of spatial concepts in landscape ecology, and the convergence of work by landscape ecologists, economists, and geographers. In addition, we give a critique of the underlying behavioral theory that motivates a wide range of model applications. This serves as an introduction to *Conceptualizing the behavioral process,* which considers the behavior of the small holders actually engaged in tropical deforestation, and also provides a statement of the maximization problem we take to be representative of colonist households in the Amazon basin. *The GIS model* places this household model into spatial context, and describes a GIS methodology for translating the behavior of households into forest fragmentation patterns. *Implementing the model* discusses model implementation and presents results. A formal demonstration of correspondence between prior modeling efforts and the framework of this paper is provided in the Appendix.

Toward the Explicit Representation of Space

Ecological roots

Landscape ecology has long addressed the spatial manifestations of ecosystems, including biotic and abiotic components and their functional relationships. Early research addressed natural forces affecting the history and spatial configuration of patches (Pickett and White 1985) and how such changes affected species (Burgess and Sharpe 1981, Harris 1984). However, difficulty in conducting empirical work soon led to landscape models, which can be grouped into categories by variable definitions and by degree of spatial resolution implemented by the analyst (Baker 1989). Landscape models have grown popular as tools for conducting ecological research (Sklar and Constanza 1991), and for managing natural resources (see, for example, Sklar et al. [2001]).

The discussion here will consider only stochastic spatial landscape approaches (Baker 1989), and within this class, the transition probability model. The ecological versions of this model type evidently have converged with similar formulations from the social sciences, producing the so-called spatially explicit model. The framework to be advanced in this paper is stochastic in nature, and motivated by a critique of the spatially explicit model.

The probabilistic tradition in ecological modeling is extensive. For landscape models, the fundamental concept is Markovian, positing that land possesses a set of possible cover states, and that land-cover change is simply a stochastic transition from one state to another. This may be represented as

$$\mathbf{n}^{t+1} = \mathbf{P}\mathbf{n}^{t}$$

where $\mathbf{n}$ is a vector (superscripted in time) of j land-cover types for a land parcel; and $\mathbf{P}$ is a $j \times j$ matrix of transition probabilities (between covers), over the period, t to $t + 1$. Although the Markovian framework received early criticism due to alleged restrictions on the matrix of transition probabilities (Turner 1987), it was subsequently observed that $\mathbf{P}$ itself could be parameterized (Baker 1989). This led to the basic statement now serving as a conceptual foundation for modeling and estimation, namely

$$\mathbf{n}^{t+1} = \mathbf{P}[t, \mathbf{x}]\mathbf{n}^{t}. \quad (1)$$

Here, $\mathbf{n}$ is as before, but $\mathbf{P}$ has been written in functional form linking probabilities to variables in a vector, $\mathbf{x}$, affecting land-cover change; t is retained to generalize the statement for nonstationary conditions (Baker 1989). One common specification of the functional form is logistic (e.g., Turner et al. 1996):

$$\mathbf{P} = e^{\beta\mathbf{x}}/[1 + e^{\beta\mathbf{x}}]. \quad (2)$$

Although initial formulations were aspatial, treating landscapes as aggregate units, dimensionality can be added by adapting Eq. 1 to a coordinate system (Browder et al. 1985, Franklin and Forman 1987, Gardner et al. 1987, Wilkie and Finn 1988). Thus, states at time $t + 1$ for a parcel with geographic coordinates (i, j) are given as

$$\mathbf{n}_{i,j}^{t+1} = p_{i,j}(t, \mathbf{x})\mathbf{n}_{i,j}^{t}. \quad (3)$$

The specification of Eq. 2 can also be placed in spatial context, and becomes operational once parameters associated with β are determined. Such parameters, in turn, can be estimated through inference in what some social scientists call ''spatially explicit models.''

Spatially explicit land-use models

The spatially explicit models considered in this paper focus on statistical estimation of the probabilities of change (e.g., Eq. 2) occurring at a highly disaggregate level, typically the pixel. Data for the dependent variable is derived through remote sensing, and independent variables, reflecting mainly market access, are generated by manipulating abstractions in geographic information systems. Presently, ecologists, economists, and geographers are engaged in specifications of such models, and applications range across temperate and tropical ecosystems (Ludeke et al. 1990, Bockstael 1996, Turner et al. 1996, Wear et al. 1996, 1998, Chomitz and Gray 1997, Mertens and Lambin 1997, 2000, Nelson and Hellerstein 1997, Geoghegan et al. 2001). Other modeling paradigms have been advanced to account for disaggregate changes in land cover (e.g., cellular automata), but they do not necessarily aim at statistical estimation based on probability theory (Manson 2001).

In a spatially explicit model, land-cover change is essentially a switch in the classification of a pixel of arbitrary dimension. Such switches occur, by the theory stated, on the basis of profit maximization, which leads to reduced form equations that link the probability of land-cover change to variables such as distance from markets or local producer prices for specific commodities. For example, Bockstael (1996) hypothesizes that the probability a parcel, j, will be developed is

$$\text{Prob(develop)} = \text{prob}(Z_{j\text{D}t} > Z_{j\text{N}t}) \quad (4)$$

where Z is present value minus discounted costs, and is taken to consist of a systematic and random component, for both developed (D) or undeveloped (N) states at time t. The implication is that the parcel is developed only if it generates more value in that state, an outcome which presumably would reflect purposeful, economic behavior on part of the decision maker charged with managing the parcel. Similarly, Chomitz and Gray (1996) and Nelson and Hellerstein (1997) hypothesize that a set of i land uses, alternative to undeveloped forest, provide potential rents, R_i, defined on prices for inputs and outputs, and production magnitudes. The observed land use on some arbitrary parcel (and at some time, t) is given as j, when $R_j > R_i$, for all $i \neq j$.

The model of Eq. 2 is meant to reflect socioeconomic impacts on probabilities of land-cover change through variables in the **x** vector, but the behavioral links between variable values and land-cover outcomes remain obscure. This can be rectified by an appeal to discrete choice theory and its explicit bridge between the motivations and consequences of human behavior. To this end, the conditional logit framework of McFadden (McFadden 1974, McFadden and Reid 1975, Maddala 1983, Ben-Akiva and Lerman 1985) can be transformed into a ''logit'' model requiring only data on the **x** vector for the observational unit in question (e.g., a pixel). Following Pfaff (1997), let rents (pure profit) associated with deforestation be R_d, and rents of intact forest, R_f. Let rent, in turn, possess systematic (V) and random (ε) components, or

$$R_i = V_i + \varepsilon_i,\ i = \mathrm{d, f}.$$

Specify V_i as $\boldsymbol{\beta}_i\mathbf{x}$, where $\boldsymbol{\beta}_i$ is a vector of alternative specific coefficients, and **x** is a vector of variables associated with each empirical observation taken on a land parcel of some size (e.g., the pixel). Then deforestation on the parcel is observed with probability,

$$\mathrm{prob}\ (\mathrm{V_d} + \varepsilon_\mathrm{d} > \mathrm{V_f} + \varepsilon_\mathrm{f}). \tag{5}$$

In applications of spatially explicit models, we do not observe discrete choices based on observable attributes of alternative land covers, as would be necessary in a conditional logit model (Maddala 1983). Instead, we observe the outcome only (of some land management decision), namely a discrete measure associated with land classification. We also observe a set of attributes associated with the land parcel, namely the **x** vector. Hence, the only way to operationalize an equation such as Eq. 5 is to posit two **β** vectors, one for deforested land and the other for intact forest. Doing so, we can rewrite Eq. 5 in distribution form using the linear specification of V_i $(= \boldsymbol{\beta}_i\mathbf{x})$:

$$\mathrm{prob}[(\varepsilon_\mathrm{f} - \varepsilon_\mathrm{d}) < (\boldsymbol{\beta}_\mathrm{d} - \boldsymbol{\beta}_\mathrm{f})\mathbf{x}]$$
$$= F[(\boldsymbol{\beta}_\mathrm{d} - \boldsymbol{\beta}_\mathrm{f})\mathbf{x}], \quad \text{or} \quad F[\boldsymbol{\beta}^*\mathbf{x}],$$

where $\boldsymbol{\beta}^* = \boldsymbol{\beta}_\mathrm{d} - \boldsymbol{\beta}_\mathrm{f}$. Assuming that ε_f and ε_d are independent and Gumbell distributed (Ben-Akiva and Lerman 1985:71), we have

$$\mathrm{prob(deforestation)} = e^{\mu\boldsymbol{\beta}^*\mathbf{x}}/(1 + e^{\mu\boldsymbol{\beta}^*\mathbf{x}}).$$

Defining a new **β** vector based on the differences of the underlying ones for the two land covers (i.e., $\boldsymbol{\beta} = \mu\boldsymbol{\beta}^*$) yields Eq. 1.1 in Hosmer and Lemeshow (1989: 6), or

$$\mathrm{prob(deforestation)} = e^{\boldsymbol{\beta}\mathbf{x}}/(1 + e^{\boldsymbol{\beta}\mathbf{x}}). \tag{6}$$

An estimate of this vector can be obtained using the method of maximum likelihood (see Turner et al. [1996], Chomitz and Gray [1997], and Nelson and Hellerstein [1997] for multinomial versions). Note that Eq. 6 is identical to the specification of Eq. 2, in which case the discrete choice model founded on the notion of profit (and utility) maximization provides a behavioral basis for landscape change models.

The behavioral critique

The provision of a behavioral basis to landscape change models represents a prime contribution by social scientists. Nevertheless, the behavioral assumptions that have been advanced may be questionable for several reasons, which has implications for the utility of derivative operational models. Limitations revolve around two issues, namely the type of behavior assumed and the appropriateness of the observation unit used in estimation.

In general, spatially explicit models assume that land owners manage their land to maximize rents (and profits). This may be a reasonable assumption for settings where property rights are never disputed, and where the economic environment is well-organized into markets mostly free from catastrophic shocks. However, tropical deforestation in the Amazon basin occurs in a frontier setting, where the institutions necessary for profit maximization may be lacking, and where income-poor households eke out very difficult lives with few economic resources beyond their own labor power (Dillon and Scandizzo 1978, Ellis 1993, Alston et al. 1997).

Such an empirical reality suggests that behavior may be different than profit maximization, an assumption typical of microeconomic applications. In particular, a household economy framework may be more appropriate, where the consumption and production decisions of households are nonseparable. In this setting, household demography is the main factor affecting land allocation decisions, which is not the case when markets are present and households behave as profit maximizing firms (Nakajima 1969, Singh et al. 1986, Thorner et al. 1986, Ellis 1993). An implication is that statistical applications using only data generated from GIS software, which is common with the spatially explicit model, will be miss-specified in the econometric sense when they omit variables accounting for household demography, information that can only be obtained from fieldwork (Walker et al. 2000, Irwin and Geoghegan 2001). As a consequence, the estimates of the β values will be biased. Another problem can arise by virtue of the unit of observation. The spatially explicitly model generally uses pixel-level data for highly disaggregated land parcels. Such parcels do not conform to the actual management units for which land-cover decisions are made. When information is lacking at pixel level for how an entire property—of which the pixel forms part—is managed, a second problem with specification arises.

Conceptualizing the Behavioral Process

The model presented in this paper circumvents some of these potential problems by developing a household economy framework that theorizes the management of land parcels as an integrated system. It is assumed that households consist of subsistence farmers who practice shifting cultivation, and that farm production is constrained by the productivity of the resource base and by the availability of family labor. Although many have pointed out that farm systems in the Amazon are dynamic, undergoing an evolution from shifting cultivation to ranches, perennials plantations, or some combination (Walker and Homma 1966, McCracken et al. 1999, Perz 2001), model statements for both shifting cultivation and dynamic systems yield the same control variables that serve as the theoretical foundation for the GIS-based model to be presented (Walker 2003). The type of farming system we seek to represent has very wide distribution throughout the Amazon basin (Dale et al. 1993, Browder 1994, Jonas da Veiga et al. 1996, Whitcover and Vosti 1996, Pichón 1997, Walker et al. 1997*a*, Fujisaka and White 1998, Vosti et al. 1998); moreover, colonist farmers are the region's most significant component of rural population (S. Perz, *personal communication*).

As in Walker (1999), the smallholder family is taken to maximize yearly utility, not profits

$$\sum_{t=0}^{\infty} \beta^t U(\mathrm{l}, \mathrm{s}). \tag{7}$$

Here, U is the household's utility function, which is discounted by a factor, β. Leisure is represented by l, and food, or subsistence, by s. The objective function represented by Eq. 7 enables the linking of household attributes to decisions about the nature of production under shifting cultivation, such as fallow length and areas of cleared land. As such, it advances agent-based models of shifting cultivation that are primarily focused on production (Barrett 1991, Dvorak 1992, Krautkraemer 1994, Albers and Goldbach 2000).

In the farming system to be considered, the shifting cultivator first deforests land in order to develop a set of farm plots, and then engages in rotational agriculture, shifting from one plot to the next, and slashing the vegetation that has accumulated during an intervening period of fallow. To maintain focus on the spatial model, assume that plots are used for only one year. This is not a strong assumption, as Boserup's classification of fallow systems (Boserup 1981) suggests that one or two years of cropping on cleared plots is common; moreover, very short cycles (one or two years) are observed in the region (Walker et al. 1997*a*), given that infertile soils and wet climate tend to hasten fertility decline (Barrett 1991:177). Although not essential, the assumption of single year cropping facilitates model development and exposition. As shall soon become apparent, one of the choice variables available to the household in maximizing utility (and welfare) is the age at which secondary regrowth is slashed, symbolized as a. Given a one-year use of plot, this is equal to the number of plots in the rotational system, and also to the number of deforestation events undertaken by the household.

Let household labor endowment be L, and consider two phases of household activity, indexed lc and ag, reflecting land clearance, or deforestation, and agricultural activity, or rotation, respectively. Assuming a labor–leisure trade-off (Ellis 1993), let l_i and w_i be the leisure and work associated with the two phases, $i \in$ (1c, ag). Given the labor endowment L, it must be the case that (Ellis 1993) $w_{1c} + l_{1c} = L$ and $w_{ag} + l_{ag} = L$.

Work requirements are functions of the age of the secondary vegetation used and the amount of land on each plot, which is identical to the deforestation event magnitude, or r (Dvorak 1992:810). (Note that r is the amount of land needed to farm during some arbitrary time period. Because this land is created from primary forest on a yearly basis in the beginning, it also represents the amount of land deforested each year during the farm's deforestation phase.) Hence, total work in the two periods is $w_{lc} = rg(N)$ and $w_{ag} = rg(a)$, where g (unit area cost function) is a function of time. The variable a is as defined, namely age of secondary forest (Pingali and Binswanger 1984, Angelsen 1994). (Note that a represents the age of secondary forest observed as a variable in both biomass recovery and labor requirement functions. The specific a selected by the farmer under optimization is also the number of deforestation events observed.) N is "age" of mature forest. Food production, s, for the two situations (use of secondary forest or mature forest) is given as $s_{lc} = rf(N)$ for mature forest and $s_{ag} = rf(a)$ for secondary forest, where $f(a)$ relates crop output per unit area to age of vegetation, and N and a are as before (Barrett 1991, Dvorak 1992, Angelsen 1994, Walker 1999). This function is predicated on the ecology of forest succession, which shows increased biomass accumulations as a function of recovery (Uhl 1987, Saldarriaga et al. 1988, Brown and Lugo 1990, Lucas et al. 1993, Vieira 1996).

The two-phase problem can now be restated as one of maximizing household welfare, W_s, through the creation of a system of shifting cultivation or

$$W_s = \max \sum_{t=0}^{a-1} \beta^t U(\mathrm{l}_{lc}, \mathrm{s}_{lc}) + \sum_{t=a}^{\infty} \beta^t U(\mathrm{l}_{ag}, \mathrm{s}_{ag}) \tag{8}$$

through choice of l_{lc}, l_{ag}, s_{lc}, and s_{ag}, subject to the following constraints on labor:

$$0 \le l_{lc} = L - [g(N)/f(N)]s_{lc}$$

$$0 \le l_{ag} = L - [g(a)/f(a)]s_{ag}$$

The two budget conditions are given by substituting for work expenditures in the constraints associated with labor endowment, and then eliminating r with a substitution using production relations.

The optimization problem may be reformulated by rewriting both geometric series, and by observing that leisure and subsistence are functions of a and r. Thus, the problem is now given as maximizing the following equation, through the choice of a and r:

$$(1 - \beta^a)U(L, N, r) + \beta^a U(L, a, r) \tag{9}$$

subject to $rg(N) \le L$ and $rg(a) \le L$. This is a nonlinear optimization problem with inequality constraints and two control variables, rotation period (or age of secondary vegetation utilized, a) and single-period land requirement (r). In principle, such a problem can be solved numerically, using the appropriate procedures, and parameterizations for household characteristics, including size of family and household preferences for subsistence goods and leisure (Miller 2000, Walker 2003).

The goal of the paper, however, is not to provide explicit solutions to this particular problem, but to use its theoretical argument to justify a focus on the control variables themselves, namely a and r. The final formulation of Eq. 9 has the effect of transforming household decisions about leisure and subsistence into a simplified choice directly germane to the land-cover dynamic in question, namely the size of the plots cleared (the deforestation event magnitude, r), and the number of deforestation events, a, which is also the same as the age at which secondary forest is slashed under the assumption of a one year crop cycle. These newly derived control variables are empirically observable (Walker et al. 1997*b*).

The GIS Model

The GIS model to be presented takes as its foundation the behavioral rationale for the variables, a and r, established in the preceding section. In essence, the modeling effort is one of expressing the articulation of a and r as functions of household attributes and site characteristics, and in a two-dimensional colonization space defined by a transportation system and property boundaries. To reflect the empirical setting, the transportation system is taken to consist of a development "highway" intersected by a series of evenly spaced settlement roads (travessões in Pará; linhas in Rondônia). Organized along the highway and between the roads are "lots," mostly 100-ha parcels typically associated with a single owner, and of variable dimension. In the state of Pará, for example, they are 500 × 2000 m on the highway, and 400 × 2500 m on the settlement roads. Fig. 1 shows the colonization plan for the study area, a digitized version of cadastral maps produced by the Brazilian colonization agency, Instituto de Colonização e Reforma Agraria, or INCRA. Other larger dimension lots may be observed also; these were designed originally for occupation by agroindustrial operations, and not smallholder colonization. The geometry of the initial land occupation scheme provided for settlement roads to be spaced approximately every 5 km, which is an exogenous condition of critical importance to the unfolding of the fragmentation pattern.

Building the model

An INFO table of lot attributes (e.g., id, a, r, and counter items to hold temporary calculations) and three ARC/INFO grid data structures are employed to represent different dimensions of the colonization space. The grids were created with the same grain and extent, and with coincident cell centers. Also, all cell sides were set to 20 m because the value 20 is a factor common to typical lot widths and depths, and is approximate to the nominal cell resolution of Landsat TM imagery. The grids are described as follows:

1) An integer lot grid represents the spatial distribution of property ownership via a key of unique lot identification numbers. This data set was created by digitizing the paper map of property boundaries provided by INCRA, and by converting digitized lot polygons into gridded zones. The distribution of lot areas, however, includes a number of large lots that are used mostly for agroindustrial operations and, therefore, are subject to different deforestation processes than those associated with colonist smallholdings. Consequently, a working subset of lots with area values less than 135 ha was selected, thereby restricting the analysis to smallholdings only.

2) A vector data structure represents the transportation system, and was created by selecting arc segments associated with digitized property boundaries coincident with known road features. The original colonization map, field notes, and two Landsat TM images were used as ancillary guides during the selection process. For analysis purposes, the vectorized road network was converted into a binary grid. Cells in the integer lot grid associated with roads in the binary network grid were converted to NODATA in order to maintain crisp cell identities. Ultimately, a derivative of the binary network grid was created containing values at cell locations that represent Euclidean ground distances from the development highway. This derived grid serves as a frictional surface and, in effect, links the spatial colonization process with time, at landscape scale. The development highway is assumed to be the axis from which colonization emanates. Settlement and subsequent deforestation events are modeled to occur sooner at locations closer to the highway, and later at more distant locations.

3) A floating-point grid with cell values representing distances from the front of each lot serves as a second frictional cost surface, this one at lot level. The front of each lot, namely the property edge adjacent to the road network, is taken as the axis from which deforestation processes begin on individual holdings. Thus, deforestation events occur sooner at locations close to the lot front, and later at more distant locations. Rather than expressing distance values in ground units, they are expressed as proportions (between 0 and 1) and calculated by dividing individual cell distance values by the maximum cell distance value associated with each property. By virtue of the rectangular road and lot geometries imposed on the landscape, this calculation serves to transform two-dimensional measures of area into one-dimensional measures of depth (along a unit vector).

Adding attributes to the model

Land-cover evolution is determined at lot level, and is defined on the basis of four attributes, namely the number of deforestation events (a), associated magnitudes (r), distance from the development highway, and distance from the lot front. Two of these attributes, a and r, are random variables generated from a probabilistic model under the assumption that colonists possess only one holding. This assumption allows that processes of land-cover change on individual lots be regarded as independent. Although property concentrations do occur in the study region, this is generally not the case for small holders (Walker et al. 2000, 2002).

The probabilistic model functions as follows. First, the number of deforestation events, a, is determined as a discrete random variable following a uniform distribution, or $a \sim U(1, a_u)$, where the upper bound to the distribution, a_u, is allowed to vary for sensitivity analysis. Next, a prediction of total deforestation is made in regression format as $Y = \beta_0 + \beta_1 X + \xi$, where β_0 and β_1 are parameters, X is a lot-specific variable measuring distance of the lot from the main highway, and ξ is a normal random variable distributed as $N(0, \sigma^2)$. The parameter, β_0, is also allowed to vary for sensitivity analysis, while β_1 is fixed by regression results, as is the variance of the error term, σ^2. Once a and Y have been given for a lot, it is straightforward to calculate the deforestation event magnitude as $r = a/Y$. The parameter values describing the number of deforestation events are consistent with field observation (Dale et al. 1993, 1994, Walker et al. 1997*b*).

The regression analysis was based on a sample of 261 farm households in the study region, undertaken in 1996 (See Walker et al. 2002 and Perz and Walker 2002 for details). Using a sub-sample restricted by satellite coverage, the methods described in Walker et al. (2000) were used in linking household data to amounts of deforestation occurring on individual lots, as measured from remotely sensed data. A bivariate regression was run on this subsample to obtain the value for the β_1 coefficient and the estimate of the error.

The probabilistic model demonstrates how household attributes and site conditions may be introduced into the GIS architecture, thereby incorporating the behavioral imperative of the household optimization problem stated in Eq. 9. A formal treatment showing the nature of the correspondence between the Markovian probabilities of spatial landscape models and the probabilistic representation of this paper is provided in the Appendix. The distributions on a and r represent a simplification of reality, based on incomplete information on the households and sites. Nevertheless, one of the most important variables affecting colonist land-use decisions, namely market access, is taken into account by the regression results for distance to the development highway (Walker et al. 2002).

Implementing the Model

Land-cover change on a lot begins with colonization, which occurs earlier at short distances from the development highway. With colonization—defined as the occupation of a lot—land clearing occurs from front to back in individual deforestation events (Walker 2003). As discussed, a lot possesses a fixed number of events and a fixed event magnitude, and r hectares are cleared every year for a years until the process stops. Lots with the same number of deforestation events may deforest at different times as a function of distance from the development highway, with distant lots possibly starting the process after near properties have finished. Since the deforestation event magnitude is fixed at lot level, the total amount of deforestation occurring on any individual lot is given as the product of the number of events and their magnitude, or $a \times r$. For modeling purposes, this is converted to a proportion of lot size, and maximum deforestation on any given lot may range up to 100%. The process as described is depicted by the cartographic model in Fig. 2 which, for simulation purposes, was translated into the Arc macro language (AML), a software-specific scripting language provided by ESRI for use with ARC/INFO software and data formats.

The simulation design

The simulation is accomplished as follows. First, values of a and r are drawn randomly for each lot and stored in an INFO table, together with the key of unique lot identification numbers, lot area values, and a set of counter items. The a and r values can be linked to gridded lot locations via a one-to-one database relation using the key of unique lot identification numbers.

Given value assignments to individual lots and an average rate of colonization into the forest (e.g., 1200 m/yr), the simulation proceeds through a sequence of iterations (see Fig. 2) until a predetermined maximum iteration number is reached. This sequence explicitly

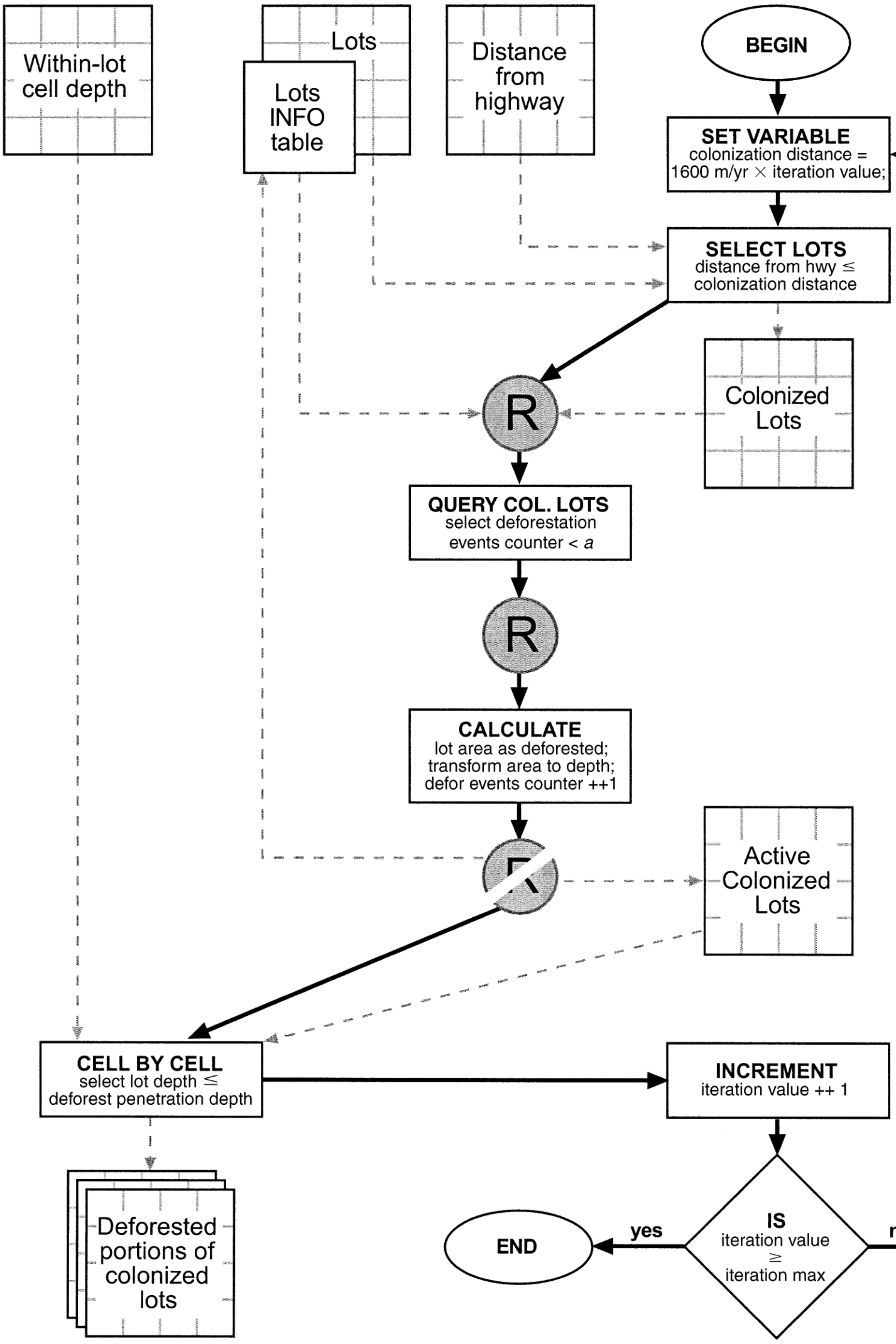

FIG. 2. The cartographic model. Solid lines represent processing flow; dashed lines represent data flow. Shaded circles represent a one-to-one database relation.

TABLE 1. Predicted deforestation after 25 years.

a_u	Colonization rate (m)	b_0	No. cells deforested	Area (ha)	Total area deforested (%)	Producer's accuracy (%)
6	800	40	647 042	25 882	15.16	33.27
6	800	60	932 352	37 294	24.22	47.94
6	800	80	1 114 708	44 588	32.83	57.32
6	1600	40	740 292	29 612	19.22	38.07
6	1600	60	1 134 637	45 385	34.21	58.35
6	1600	80	1 402 915	56 117	49.23	72.14

links time with the spatial processes of colonization and deforestation. In brief, each iteration initiates colonization and deforestation processes farther from the development highway and deeper into individual forest holdings, respectively.

During each iteration (see Fig. 2), a subset of lots is "colonized" by spatially selecting lots having cells with "distance from the highway" values that are less than the colonization distance value (e.g., [1200 m/yr] × iteration value). Next, an ephemeral and one-to-one database relation is created between the INFO table containing lot attributes (e.g., id, *a, r,* and counters) and the colonized lots grid. By virtue of the one-to-one relation, the number of records in the INFO table is effectively reduced to the same subset contained within the colonized lots grid. The subset is reduced further to "activate" only those lots that have experienced a number of deforestation events less than the preassigned and randomly drawn event (a) value. As stated above, the maximum deforestation on any given lot may range up to 100%. The number of time steps for which individual lots have been activated previously is stored in the INFO table as a counter item. For this reduced set only, the amount of lot area deforested is calculated (e.g., r × [deforestation event counter]). This value is important because it simulates the amount of lot area that has been cleared up to a certain time, and not the total amount expected to accrue after the deforestation process has run its course.

The counter values for all colonized and activated lots are then incremented by a value of 1 and the database relation is severed. At this point, the INFO data table is reestablished in its entirety, with the complete history of all lots, activated or not, up to the current time step.

Visualizing patterns of deforestation

A simple mathematical relationship exists between measures of lot area and lot depth by virtue of the rectangular road and lot geometries imposed on the landscape. Consequently, measures of within-lot deforestation extents, which are transformed from two-dimensional measures of deforested area (in ground units) to one-dimensional measures of penetration depth (along a unit vector), can be compared to one-dimensional measures of lot depth (also along a unit vector). Such proportional lot depth values are retained in the lot distance grid. Accordingly, at the end of each iteration and on a cell-by-cell basis, a new grid is created and cells are classified as deforested (1) if the proportional lot depth value for a particular cell location is less than or equal to the proportional penetration depth value for the lot to which it belongs. The balance of non-NODATA grid cells is classified as not deforested (0). This comparison routine generates a sequence of snapshots that represents accumulating effects of the deforestation process. At the end of each time step, the simulation iteration value is incremented by a value of 1 and the program continues until the predetermined maximum iteration value is reached.

An illustrative simulation

The model was implemented for a region in the eastern sector of the Amazon basin as depicted in Fig. 1, a stretch along the Trans-Amazon Highway running about 100 km east and west, and 60 km north and south. Sample results are presented in Table 1, showing the amount of areas deforested as a function of different sets of parameter values. In addition, a measure of model performance is given, so-called producer's accuracy, which has been adapted from the map accuracy literature (Card 1982, Nelson and Hellerstein 1997, Congalton and Green 1999). The parameters varied involve the rate of colonization, and the intercept term on the regression model used to generate the deforestation event magnitudes; the upper bound to the number of deforestation events, a_u, remains fixed. Colonization, or the household penetration of settlement roads, ranges from two lots per year (800 m) to four (1600 m). The simulations reflect an outcome after 25 years.

Model performance and error can be assessed on the basis of its ability to predict the actual aggregate magnitude of deforestation, as well as its spatial pattern, which have been referred to as quantity and locational ability, respectively (Pontius 2000). This was accomplished by comparing model results to actual land cover. To this end, an initial land-cover mosaic was created using four adjacent Landsat 7 enhanced thematic mapper plus (ETM+) scenes for 1999. Locational error was minimized using ground control points along the Trans-Amazon Highway and recognizable features on the settlement roads. The mosaic and original scenes were geographically corrected for axis translation and the vector file of digitized lot boundaries used for the simulations was registered to the processed mosaic using the Trans-Amazon highway as reference, to at most plus or minus four pixels, or ±120 m error.

Six-band composites were derived from the rectified scenes, which were then corrected for atmospheric and bidirectional reflectance effects. The low gain thermal band (band 6a, ETM+) was resampled to 30 × 30 m resolution, and reinserted to derive a seven-band ETM+ composite. Signatures for 14 classes were taken from band 5–4–3 composites, seven-band principal component analysis composites, and a red–near-infrared derivative image was used in supervised classifications to derive five themes. The five-theme images were mosaicked, clipped to the extents of the lot boundary, reclassed to two classes (forested and deforested), and overlain with the simulations to produce the necessary measures for error assessment.

Overall, the mosaic of classified images indicates an aggregate deforestation of 25% for the study area, the target deforestation magnitude for the simulations given colonization began in the early 1970s. As Table 1 shows, the aggregate deforestation magnitudes depicted by the model bracket the actual amount of deforestation measured from the satellite imagery. The percent predicted ranges from a little over 15% to 49%, reflecting the variation in parameter values. As would be expected, an increased colonization rate tends to augment the magnitude of deforestation, as do increments in the regression intercept term. The deforestation rate overall appears more sensitive to the intercept, at least for the magnitudes given. Thus, for a colonization rate of two lots per year, deforestation ranges from 15 to 32% as the intercept doubles from 40 to 80 ha. A similar effect holds for a colonization rate of four lots per year, with deforestation ranging from 19 to 49%. The ability of the model to reflect spatial pattern can be indicated by producer's accuracy, a statistic used in cartographic and remote sensing applications to indicate the ability of a map to indicate an actual feature of the landscape. In the case of a map with land-cover features, producer's accuracy is the probability (conditional) that the map shows some land cover at an arbitrary point, given that that particular land cover is actually observed at the point (Congalton and Green 1999).

In this application, producer's accuracy is used as a measure of model performance, and is taken to be the conditional probability of predicting a deforested pixel given that the pixel is actually deforested (Nelson and Hellerstein 1977, Pontius 2000). Table 1 shows the range associated with the selected parameter values to be from 33 to 72%. While the 72% value is quite high, it is worth noting that the percent deforested predicted by the model is significantly greater than the actual amount for this parameter setting. On the other hand, the parameter setting that produces an aggregate deforestation of 24% shows a producer's accuracy of 48%, considerably lower than the maximum value achieved.

The results of a sample model run are depicted in Fig. 3. Note that the masked-out part of the map contains lands held by agroindustrial interests, which are not covered by the conceptual framework describing land use of small holders. The color codes indicate correct predictions (both deforestation and persistent forest cover) as well as over predictions (deforestation predicted where none occurs) and under predictions (deforestation occurs where none predicted). Overall, the basic structure of deforestation is captured, although the results do show error patterns with substantial over prediction in settlement roads to the northeast, under prediction along the lots located on the Trans-Amazon Highway to the north, and considerable under prediction on one of the deeply penetrating settlement roads to the southwest.

Concluding Remarks

These results demonstrate the feasibility of modeling the deforestation process in two dimensions and producing a visual pattern of forest fragmentation. Although not undertaken in this application, fragmentation metrics could be calculated for artificial landscapes generated by the model, adding additional output of potential utility to landscape ecologists. The model is a prototype with obvious directions for extension and adaptation. Important among these is the development of more realistic distributions for the key variables, a and r, and in particular better empirical representation of their links to household attributes and site conditions. In addition, there is accumulating evidence of cross-generational dynamics, whereby secondary deforestation processes evidently unfold as colonist children expand on the early efforts of their parents (Perry and Walker 2002). Such effects, and alterations of distributions, are entirely tractable within the GIS model architecture. The errors observable in Fig. 3 also indicate the need to introduce into the model structure sensitivity to topography and road quality. Hilly relief to the northeast probably inhibits agricultural development, while well-maintained roads, such as the one to the southwest with excessive under prediction, are likely to be cleared quickly and intensively farmed.

Perhaps of greater importance on conceptual grounds is the recognition that the model presented remains mute on an important piece of the forest fragmentation story, namely the process of road building that penetrates the forest in the first place. Under colonization, government bureaucrats typically build roads on a fixed pattern. Along the Trans-Amazon Highway, for example, federal government built settlement roads every 5 km, north and south, to a distance of 6 km on average (Simmons 2002). However, once farmers began arriving, these initial spurs were extended in search of wood and also to make room for late arrivals. The framework

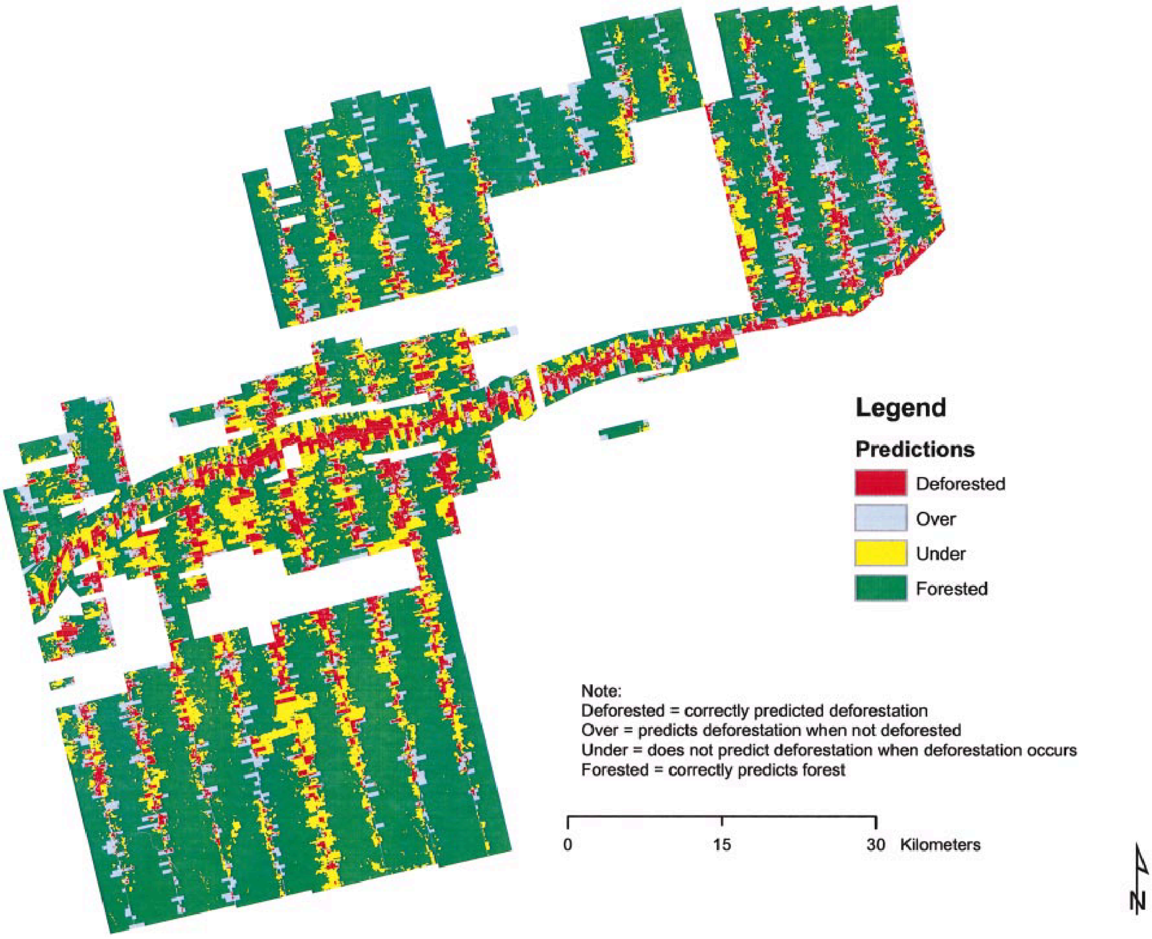

FIG. 3. Sample simulation result. ''Deforested'' means deforestation was correctly predicted; ''over'' means the model predicts deforestation when none occurred; ''under'' means the model does not predict deforestation when it did occur; and ''forested'' means the model correctly predicts forest.

as elaborated here has taken the road system to be exogenous, but road building is clearly a dynamic process, as are road extensions beyond a government's initial effort. In the study area, the extension of roads—in this case by government—did continue beyond the government's original plan to about twenty kilometers on both north and south sides of the Trans-Amazon Highway, in response to growing demand for land by migrants. Then, loggers engaged in road building in select areas with rich trees stands. The current system of transportation, however, mainly reflects the desires and actions of in-migrating small holders who insisted that extension continue in straight lines according to the original plan, in order to facilitate regularization of holdings. The maps of Figs. 1 and 2 represent this extension process, although the model has taken its spatial articulation as given.

Landscape models of tropical forest loss and fragmentation will remain only partially complete until they conceptualize and implement road building as an outcome of human behavior. The model presented in this paper does provide an approach that treats an important component of the overall process, namely the land-use and land-cover change associated with colonist agriculture. With current plans by the Brazilian government to pursue its efforts at road-building and infrastructure improvements (de Cassia 1997, Laurance and Fearnside 1999), land-cover change precipitated by colonists can be expected to intensify. Landscape models such as the one presented in this paper could serve as useful policy tools for assessing the impacts of such government initiatives.

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Literature Cited

Albers, H. J., and M. J. Goldbach. 2000. Irreversible ecosystem change, species competition, and shifting cultivation. Resource and Energy Economics **22**:261–280.

Alston, L. J., G. D. Libecap, and B. Mueller. 1997. Violence and the development of property rights to land in the Brazilian Amazon. Pages 145–163 *in* John, N. Drobak, and John V. C. Nye, editors. The frontiers of the new institutional economics. Academic Press, San Diego, California, USA.

Angelsen, A. 1994. Shifting cultivation expansion and intensity of production: the open economy case. Working Paper (1994:3). Chr. Michelsen Institute of Development Studies and Human Rights, Bergen, Norway.

Baker, W. 1989. A review of models of landscape change. Landscape Ecology **2**:111–133.

Barrett, S. 1991. Optimal soil conservation and the reform of agricultural pricing policies. Journal of Development Economies **36**:167–187.

Ben-Akiva, M., and S. R. Lerman. 1985. Discrete choice analysis: theory and application to travel demand. MIT Press, Cambridge, Massachusetts, USA.

Bockstael, N. E. 1996. Modeling economics and ecology: the importance of a spatial perspective. American Journal of Agricultural Economics **78**:1168–1180.

Boserup, E. 1981. Population and technological change. A study of long-term trends. University of Chicago Press, Chicago, Illinois, USA.

Brondizio, E. S., S. D. McCracken, E. F. Moran, A. D. Siqueira, D. N. Nelson, and C. Rodriguez-Pedraza. 2002. The colonist footprint: towards a conceptual framework of land use and deforestation trajectories among small farmers in Frontier Amazonia. Pages 133–161 *in* C. Wood and R. Porro, editors. Land use and deforestation in the Amazon. University of Florida Press, Gainesville, Florida, USA.

Browder, J. A., H. A. Bartley, and K. S. Davis. 1985. A probabilistic model of the relationship between marshland–water interface and marsh disintegration. Ecological Modelling **29**:245–260.

Brown, S., and A. Lugo. 1990. Tropical secondary forests. Journal of Tropical Ecology **6**:1–32.

Burgess, R. L., and D. M. Sharpe. 1981. Forest island dynamics in man-dominated landscapes. Springer-Verlag, New York, New York, USA.

Card, D. H. 1982. Using known map category marginal frequencies to improve estimates of thematic map accuracy. Photogrammetric Engineering and Remote Sensing **48**(3): 431–439.

Chomitz, K. M., and D. A. Gray. 1996. Roads, land use, and deforestation: a spatial model applied to Belize. World Bank Economic Review **10**(3):487–512.

Congalton, R. G., and K. Green. 1999. Assessing the accuracy of remotely sensed data: principles and practices. Lewis Publishers, Boca Raton, Florida, USA.

Dale, V. H., R. V. O'Neill, M. Pedlowski, and F. Southworth. 1993. Causes and effects of land-use change in central Rondônia, Brazil. Photogrammetric Engineering and Remote Sensing **59**(6):997–1005.

Dale, V. H., R. V. O'Neill, F. Southworth, and M. Pedlowski. 1994. Modeling effects of land management in the Brazilian Amazonian settlement of Rondônia. Conservation Biology **8**(1):196–206.

de Cassia, R. 1997. BR-174: FHC anuncia abertura de nova frontiera agricola no norte. Amazonas em Tempo, Manaus, Brazil, A4, 25 June 1997.

Dillon, J. L., and P. L. Scandizzo. 1978. Risk attitudes of subsistence farmers in northeast Brazil: a sampling approach. American Journal of Agricultural Economics **60**(3): 425–435.

Dvorak, K. A. 1992. Resource management by West African farmers and the economics of shifting cultivation. American Journal of Agricultural Economics **74**(3):809–815.

Ellis, F. 1993. Peasant economics: farm households and agrarian development. Second edition. Cambridge University Press, Cambridge, UK.

Franklin, J. F., and R. T. T. Forman. 1987. Creating landscape patterns by forest cutting: ecological consequences and principles. Landscape Ecology **1**:5–18.

Fujitska, S., and D. White. 1998. Pasture or permanent crops after slash-and-burn cultivation? Land-use choice in three Amazon colonies. Agroforestry Systems **42**:45–59.

Gardner, R. H., B. T. Milne, M. G. Turner, and R. V. O'Neill. 1987. Neutral models for the analysis of broad-scale landscape pattern. Landscape Ecology **1**:19–28.

Geist, H. J., and E. F. Lambin. 2001. What drives tropical deforestation? LUCC Report Series No. 4. LLUC International Office, University of Louvain, Louvain-la-Neuve, Belgium.

Geoghegan, J., S. C. Villar, P. Klepeis, P. M. Mendoza, Y. Ogneva-Himmelberger, R. R. Chowdhury, B. L. Turner, and C. Vance. 2001. Modeling tropical deforestation in the southern Yucatán peninsular region: comparing survey and satellite data. Agriculture, Ecosystems and Environment **1765**:1–22.

Harris, L. D. 1984. The fragmented forest. University of Chicago Press, Chicago, USA.

Hosmer, D. W., and S. Lemeshow. 1989. Applied logistic regression. John Wiley and Sons, New York, New York, USA.

Irwin, E. G., and J. Geoghegan. 2001. Theory, data, methods: developing spatially explicit economic models of land use change. Agriculture, Ecosystems and Environment **1764**: 1–18.

Jonas da Veiga, J., J. Tourrand, and D. Quanz. 1996. A pecuária na fronteira agrícola a Amazônia: o caso do municipio de Uruará, PA, na Região da Transamazônica. Documentos No 87. EMBRAPA/CPATU, Belém, Brazil.

Kaimowitz, D., and A. Angelsen. 1998. Economic models of tropical deforestation: a review. Center for International Forestry Research, Bogor, Indonesia.

Krautkraemer, J. A. 1994. Population growth, soil fertility, and agricultural intensification. Journal of Development Economics **44**:403–428.

Laurance, W. F., and P. M. Fearnside. 1999. Amazon burning. Trends in Ecology and Evolution **14**:457.

Lucas, R. M., M. Honzak, G. M. Foody, P. J. Curran, and C. Corves. 1993. Characterizing tropical secondary forests using multi-temporal Landsat sensor imagery. International Journal of Remote Sensing **14**(16):3061–3067.

Ludeke, A. K., R. C. Magio, and L. M. Reid. 1990. An analysis of anthropogenic deforestation using logistic regression and GIS. Journal of Environmental Management **32**:247–259.

Maddala, G. S. 1983. Limited-dependent and qualitative variables in econometrics. Cambridge University Press, Cambridge, UK.

Manson, S. M. 2001. Simplifying complexity: a review of complexity theory. Geoforum **32**:405–414.

McCracken, S. D., E. Brondizio, D. Nelson, E. Moran, A. Siqueira, and C. Rodriguez Pedraza. 1999. Remote sensing

and GIS at farm property level: demography and deforestation in the Brazilian Amazon. Photogrammetric Engineering and Remote Sensing **65**(11):1311–320.
McFadden, D. 1974. The measurement of urban travel demand. Journal of Public Economics **3**:303–328.
McFadden, D., and F. Reid. 1975. Aggregate travel demand forecasting from disaggregated behavioral models. No. 534. Transportation Research Board Record, Washington, D.C., USA.
Mertens, B., and E. Lambin. 1997. Spatial modelling of deforestation in southern Cameroon: spatial disaggregation of diverse deforestation processes. Applied Geography **17**(2):143–162.
Mertens, B., and E. Lambin. 2000. Land-cover-change trajectories in southern Cameroon. Annals of the Association of American Geographers **90**(3):467–494.
Miller, R. E. 2000. Optimization: foundations and applications. John Wiley and Sons, New York, New York, USA.
Myers, N. 1980. The present status and future prospects of the tropical moist forest. Environmental Conservation **7**: 101–114.
Nakajima, C. 1969. Subsistence and commercial family farms: some theoretical models of subjective equilibrium. Pages 165–185 *in* C. R. Wharton, editor. Subsistence agriculture and economic development. Aldine Publishing Company, Chicago, Illinois, USA.
Nelson, G. C., and D. Hellerstein. 1997. Do roads cause deforestation? Using satellite images in econometric analysis of land use. American Journal of Agricultural Economics **79**:80–88.
Perz, S. 2001. Household demographic factors as life cycle determinants of land use in the Amazon. Population Research and Policy Review **20**:159–186.
Perz, S., and R. T. Walker. 2002. Household life cycles and secondary forest cover among smallholders in the Amazon. World Development **30**(6):1009–1027.
Pfaff, A. S. P. 1999. What drives deforestation in the Brazilian Amazon? Journal of Environmental Economics and Management **37**:26–43.
Pichón, F. J. 1997. Settler households and land-use patterns in the Amazon frontier: farm-level evidence from Ecuador. World Development **25**(1):67–91.
Pickett, S. T. A., and P. S. White, editors. 1985. The ecology of natural disturbance and patch dynamics. Academic Press, New York, New York, USA.
Pingali, P., and H. Binswanger. 1984. Population density and farming systems: the changing locus of innovations and technical change. Pages 51–76 *in* R. Lee, editor. Population, food, and rural development. Clarendon Press, Oxford, UK.
Pontius, R. G. 2000. Quantification error verses location error in comparison of categorical maps. Photogrammetric Engineering and Remote Sensing **66**(8):1011–1016.
Saldarriaga, J. G., D. C. West, M. L. Tharp, and C. Uhl. 1988. Long-term chronosequence of forest succession in the Upper Rio Negro of Colombia and Venezuela. Journal of Ecology **76**:938–958.
Simmons, C. S. 2002. The local articulation of land use conflict: economic development, environment, and Amerindian rights. Professional Geographer **54**(2):241–258.
Singh, I., L. Squire, and J. Strauss. 1986. The basic model: theory, empirical results and policy considerations. Pages 17–47 *in* I. Singh, L. Squire, and J. Strauss, editors. Agricultural household models. Johns Hopkins University Press, Baltimore, Maryland, USA.
Sklar, F., and R. Constanza. 1991. The development of dynamic spatial models for landscape ecology: a review and prognosis. Pages 239–288 *in* M. G. Turner and R. H. Gardner, editors. Quantitative methods in landscape ecology. Springer-Verlag, New York, New York, USA.
Sklar, F. H., H. C. Fitz, Y. Wu, R. Van Zee, and C. McVoy. 2001. The design of ecological landscape models for Everglades restoration. Ecological Economics **37**(3):379–401.
Stern, P. C., O. R. Young, and D. Druckman, editors. 1992. Global environmental change: understanding the human dimensions. National Academy Press, Washington, D.C., USA.
Thorner, D., B. Kerblay, and R. E. F. Smith. 1986. A. V. Chayanov on the theory of peasant economy. University of Wisconsin Press, Madison, Wisconsin, USA.
Turner, M. G. 1987. Spatial simulation of landscape changes in Georgia: a comparison of three transition models. Landscape Ecology **1**:29–36.
Turner, M. G., D. N. Wear, and R. O. Flamm. 1996. Land ownership and land-cover change in the Southern Appalachian Highlands and the Olympic Peninsula. Ecological Applications **6**:1150–1172.
Uhl, C. 1987. Factors controlling succession following slash-and-burn agriculture in Amazonia. Journal of Ecology **75**: 377–407.
Vieira, I., R. Salomão, N. Rosa, D. Nepstad, and J. Roma. 1996. O Renascimento do Floresta no Rastro da Agricultura. Ciência Hoje **21**:119.
Vosti, S. A., J. Witcover, and C. L. Carpentier. 1998. Arresting deforestation and resource degradation in the forest margins of the humid tropics: policy, technology, and institutional options for western Brazil. Final report. International Food Policy Research Institute, Washington, D.C., USA.
Walker, R. 1999. The structure of uncultivated wilderness: land use beyond the extensive margin. Journal of Regional Science **33**:387–410.
Walker, R. T. 2003. Mapping process to pattern in the landscape change of the Amazonian frontier. Annals of the Association of American Geographers **93**:376–398.
Walker, R. T., and A. Homma. 1996. Land use and land cover dynamics in the Brazilian Amazon: an overview. Ecological Economics **18**(1):67–80.
Walker, R. T., A. Homma, A. Conto, R. Carvalho, C. Ferreira, A. Santos, P. Oliveira, and C. Rodriguez. 1997*a*. As Contradições do Processo de Desenvolvimento Agrícolo na Transamazon—contradictions in the process of agricultural development along the Transamazon Highway. EMBRAPA Document # 93. EMBRAPA/CPATU, Belém, Brazil.
Walker, R. T., A. Homma, F. Scatena, A. Conto, C. Rodriquez, C. Ferreira, P. Mourão, and R. Carvalho. 1997*b*. Land cover evolution of small properties on the Transamazon Highway. Revista de Economia e Sociologia Rural **35**(2):115–126.
Walker, R. T., E. Moran, and L. Anselin. 2000. Deforestation and cattle ranching in the Brazilian Amazon: external capital and household processes. World Development **28**(4): 683–698.
Walker, R. T., S. Perz, M. Caldas, and L. G. Texeira da Silva. 2002. Land use and land cover change in forest frontiers: the role of household life cycles. International Regional Science Review **25**(2):169–199.
Wear, D. N., and P. Bolstad. 1998. Land-use change in Southern Appalachian landscapes: spatial analysis and forecast evaluation. Ecosystems **1**:575–594.
Wear, D. N., M. G. Turner, and R. O. Flamm. 1996. Ecosystem management with multiple owners: landscape dynamics in a Southern Appalachian watershed. Ecological Applications **6**:1173–1188.
Wear, D. N., M. G. Turner, and R. J. Naiman. 1998. Land cover along an urban–rural gradient: implications for water quality. Ecological Applications **8**:619–630.
Whitcover, J., and S. A. Vosti. 1996. Alternatives to slash-and-burn agriculture (ASB): a characterization of Brazilian

benchmark sites of Pedro Peixoto and Theobroma. MP-8 Working Paper No. US 96–003. International Food Policy Research Institute, Washington, D.C., USA.

Wilkie, D. S., and J. T. Finn. 1988. A spatial model of land use and forest regeneration in the Ituri Forest of northeastern Zaire. Ecological Modelling **41**:307–323.

APPENDIX

A relationship between the Markovian probability of deforestation occurring on some pixel, as modeled by the spatially explicit model, and the framework developed in this paper can be established as follows. Note that these probabilities of necessity are nonstationary, since whether or not a particular pixel is deforested in the GIS model depends, in part, on the time of colonization. Let the deforestation probability be given as $P_{ij}(D)$ for some arbitrary pixel, where i is its x coordinate (in meters), j is its y coordinate (in meters), and D is the binary event affecting the pixel, deforestation. Assume, further, that all pixel locations have been normalized to individual lots. From the assumption regarding spatial evolution on a property, $P_{iv}(D) = P_{iw}(D)$, $w \neq v$. Define some integer, t_t, as the ''tier'' number indicating distance from the development highway. All pixels associated with some lot possess the same tier number, which represents whether or not colonization has reached it. So long as the deforestation process has not begun, or so long as $t < t_t$, the probability of deforestation at tier t is 0, or $P_{it_t}(D) = 0$ for $t < t_t$.

Now consider a non-negative integer k such that as $t_t \leq t_t + k \leq t_t + (a_u - 1)$, or $0 \leq k \leq a_u - 1$. Times $t = t_t + k$ define a period of active deforestation on lots at tier t_t. Let a be uniform, or $a \sim U_a(1, a_u)$, and let r possess a density function, $f_r(r)$. Note that in the GIS model, r is given as Y/a, where Y is total deforestation predicted to occur on some lot. To facilitate the exposition, we assume the unconditional distribution. Define Ω as the sample space of a, or $\Omega = 1 \cup 2 \cup \ldots \cup a_u$. Intersecting deforestation event, D, with the universe of possible a values yields $P_{it_t}(D/t) = P_{it_t}[(D \cap \Omega)/t]$ for some $t = t_t + k$. Expanding the intersection event and applying Bayes' Rule gives $P_{it_t}[\{[(D/a = 1) \cap a = 1] \cup [(D/a = 2) \cap a = 2] \cup \ldots [(D/a = a_u) \cap a = a_u]\}/t = t_t + k]$. The individual intersection probabilities are $1/a_u P_{it_t}(ar > 400i)$ for realizations of a less than or equal to the number of deforestation events that have actually taken place, which is $(k + 1)$. Recall that 400 is the width of the lot in meters, in which case $400i$ is the area cleared, given i. Here, area (ar) is measured in square meters. For realizations of $a > k + 1$, the deforestation process has not run its course, and the probability of deforestation is the same as for the realization $a = k + 1$. For such upper-tail values of a (relative to the value of k), the probabilities of deforestation are identical, or $P_{it_t}[(D/a > k + 1)] = P_{it_t}[(k + 1)r > 400i]$. Note that deforestation given $a > k + 1$ is composed of the union of all deforestation conditional on earlier times in the process. However, since the event, $[jr > 400i] \subset [(k + 1)r > 400i]$, for $j < k + 1$, the probability of the union becomes $P_{it_t}[(k + 1)r > 400i]$.

Combining terms, the overall probability of deforestation at time t, unconditional on the a value, is

$$\left(\frac{1}{a_u}\right)\left[\sum_{a=1}^{k} P_{it_t}(ar > 400i)\right] + \left(\frac{a_u - k}{a_u}\right)P_{it_t}[(k + 1)r > 400i].$$

Thus, the nonstationary Markovian probability for $t = t_t + k$ is

$$P_{it_t}\left(\frac{D}{t}\right) = P_{it_t} = \left(\frac{1}{a_u}\right)\sum_{a=1}^{k}\left[1 - f_r\left(\frac{400i}{a}\right)\right] + \left(\frac{a_u - k}{a_u}\right)\left[1 - f_r\left(\frac{400i}{k + 1}\right)\right].$$

Consider now the situation as $t \rightarrow \infty$. The possibility for additional deforestation expires once $t_t + (a_u - 1) \leq t$. At this point, the probability of deforestation becomes invariant in time, or stationary, and can be written as

$$P_{it_t}(D) = \frac{P_{it_t}(r > 400_i)}{a_u} + \frac{P_{it_t}\left(r > \dfrac{400i}{2}\right)}{a_u} + \cdots + \frac{P_{it_t}\left(r > \dfrac{400i}{a_u}\right)}{a_u}$$

or

$$P_{it_t}(D/\infty) = \left(\frac{1}{a_u}\right)\sum_{k=1}^{a_u}\left[1 - f_r\left(\frac{400i}{k}\right)\right].$$

These relationships demonstrate the formal correspondence between Markovian probabilities of change common in spatial landscape models and the behavioral factors considered in this paper. In particular, household characteristics are reflected through the distributions on the land-cover change parameters, a and r, which in turn are derived from behavioral theory. As mentioned in the text, greater realism would be possible by considering the nature of the assumed distributions on a and r.