Modeling Deforestation and Land Use Change: Sparse Data Environments

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MODELING DEFORESTATION AND LAND USE CHANGE: SPARSE DATA ENVIRONMENTS[1]

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Abstract:

Land use change in developing countries is of great interest to policymakers and researchers from many backgrounds. Concerns about consequences of deforestation for global climate change and biodiversity have received the most publicity, but loss of wetlands, declining land productivity, and watershed management are also problems facing developing countries. In developing countries, analysis is especially constrained by lack of data.

This paper reviews modeling approaches for data-constrained environments that involve methods such as neural nets and dynamic programming and research results that link individual household survey data with satellite images using geographic positioning systems.

JEL Classifications: Q15, Q23, R14

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Introduction

During the past two decades, direct human transformation of terrestrial ecosystems, sometimes referred to as land use change, has been increasingly regarded as a primary source of global environmental change (Millennium Ecosystem Assessment, 2005). Important environmental problems such as desertification, sedimentation of lakes and rivers, biodiversity loss, and climate change caused by greenhouse gasses, are just a sample of local and global phenomena brought about or exacerbated by human activities.

These problems have attracted the interest of many disciplines. In particular, ecologists, economists, and geographers have engaged in the specification of models that attempt to capture the causes and consequences of land-cover and land-use change. Applications of these models range across temperate and tropical ecosystems. Some of these models use spatially-explicit data in the sense that the dependent variable and most or all the independent variables are geographically identified through a system of coordinates. These modeling efforts are also characterized by the use of data derived from remote sensing applications, and handled and manipulated with geographic information system software.

In this article we focus on the recent progress made in the area of behavioral models on land use change in regions where data are particularly scarce. Most of the developing world falls in this category. We review a group of promising new modeling techniques that address some of the limitations of earlier approaches at the cost of increased data needs.

The Bid-rent Model and Static Analysis

Almost all economic models of land use change that use spatially data are based on the bid-rent model introduced by von Thünen in 1826. Johann Heinrich von Thünen used agricultural products to illustrate the importance of location and the resulting transport costs to a central market in determining land use choices at various locations. The basic idea was that of *land rent*, defined as the price paid for the services yielded by land during a specific time period, determines land use. The land use with the highest value product can offer the highest land rents and, thus, *outbids* other uses. The choice of land use at a given location is made by a profit-maximizing "operator" of the land at that location – a single person, household, or group of people in the case of common property ownership. In the simplest von Thünen formulation, with homogeneous land and ownership, the resulting land use pattern is a set of concentric rings around the market center with each ring devoted to growing a particular crop.

Identifying Land Use Determinants Using Comparative Statics Analysis

The earliest of the spatial economics analyses used a single period to identify important land use determinants. Variation across space is the source of information about the causes of change. Chomitz and Gray (1996) provided the first publication of a theoretical basis for the reduced form estimates common in newer land use studies.

The operator is assumed to choose a particular land use by comparing the net present value of the returns to all possible land uses. If we assume that a given land use has a single marketed product, the net present value of the return to that land use (h), its rent (R_{hl}) is given by:

$$R_{hl} = P_{hl}Q_{hl} - C_{hl}X_{hl} \qquad 1$$

where P is the output price, Q is the quantity of output, C is a vector of input costs, X is a vector of inputs under operator control all for each land use h at location l. The operator identifies the X necessary to maximize R for each land use and uses that information to choose the land use with the highest R_{hl} for the parcel. Note that this formulation assumes that the operator starts *tabula rasa*; there are no costs of converting from an existing land use to one that has just become the most profitable.

Using a Cobb-Douglas functional form to represent the production technology and using the indirect profit function to express at each time t the maximum profit as a function of the output and input prices (see Beattie and Taylor, 1993 for more details):

$$R_{hl} = b_h \left(P_{hl} G_l \prod_k C_{khl}^{-\alpha_{kh}} \alpha_{kh}^{kh} \right)^{1/b_h} \qquad 2$$

where the α_ks are the exponents of the Cobb-Douglas production function with k inputs, $b_h = 1 - \sum_k \alpha_k$, and G is a productivity shifter, a multiplicative combination of geophysical features affecting productivity such as slope, altitude, climate, and soil quality.

Since parcel-specific data on prices of outputs and costs of inputs are seldom available it is common to proxy them with access cost to a relevant location such as the nearest village, market or town.

$$\begin{aligned} P_{hl} &= \exp\left[\gamma_{0l} + \gamma_{1l} D_l\right] \\ C_{khl} &= \exp\left[\delta_{0kl} + \delta_{1kl} D_l\right] \end{aligned} \qquad 3$$

After further manipulation and assumptions about production relationships, in particular the use of a Cobb-Douglas functional form, we arrive at the following reduced form (see Nelson and Geoghegan, 2002 for more details):

$$\ln R_{hl} = \alpha_{0h} + \alpha_{1h} D + \sum_n \alpha_{nh} \ln G_l + \varepsilon_{hl} = \beta_h^{'} X_l + \varepsilon_{hl} \qquad 4$$

The choice of land use is determined by three sets of variables. The first set is the location's geophysical characteristics. These might be vegetative (type of forest cover, soil quality), mineral, or even atmospheric (rainfall, evapotranspiration). A second set of characteristics is socioeconomic — location-specific attributes such as prices of inputs and outputs; degree of operator control over the parcel; and household characteristics. Finally, geophysical and socioeconomic variables combine with a set of production technologies that relate inputs and outputs. The decision variable, either profit or utility, is unobserved. Hence the need to use latent-variable techniques to link land use determinants with outcomes. This situation is similar to the discrete choice problem, where maximization of (unobserved) utility leads to an observed choice among discrete alternatives. We can reformulate this problem as finding the probability of choosing land use *k* at location *l*:

$$\Pr[choice\, h] = \Pr\left[\ln R_{hl} > \ln R_{\ln}\right]; \qquad 5$$

where $h \in \{1, \ldots N\}$ a finite set of available choices; and $h \neq m$

Substituting from equation 4 leads to:

$$\Pr\left[choice\, h\right] = \Pr\left[\varepsilon_{hl} - \varepsilon_{1l} < \left(\boldsymbol{\beta}_h - \boldsymbol{\beta}_1\right)\mathbf{X}_l, \ldots, \varepsilon_{hl} - \varepsilon_{Nl} < \left(\boldsymbol{\beta}_h - \boldsymbol{\beta}_\mathbf{N}\right)\mathbf{X}_l\right] \qquad 6$$

The choice of estimation techniques depends upon the distribution of the error term. If it is extreme value and the errors are uncorrelated across land uses, McFadden (1973) has shown that:

$$\Pr(choice\, m) = \frac{e^{\boldsymbol{\beta}_m{}'\mathbf{X}_\mathbf{l}}}{\sum_{h=1}^{N} e^{\boldsymbol{\beta}_h{}'\mathbf{X}_\mathbf{l}}} \qquad 7$$

The β_hs are estimated using maximum likelihood techniques.

We use the estimated β_hs to generate probability predictions for each land use at every location in the area under investigation. For example, with 4 land use choices, we might find the following land use probabilities at a location – forest type A – 70%, forest type B – 15%, agriculture – 5%, urban areas – 10%. The sum of probabilities for all four categories is 100%. To convert probabilities to predicted choices, the winner-takes-all rule is typically used; that is, the land use with the highest probability is the 'predicted' land use. Other rules have been proposed but seldom implemented.

Assumptions, Problems, and Shortcomings

Several assumptions are necessary to estimate the model described in equation 4. Some of these assumptions are dictated by the availability of data. For example, the absence of information on actual transportation costs has meant that most authors use a proxy for the actual costs of moving other goods, both inputs and outputs.

While there are a few examples of research using georeferenced survey data (Vance and Geoghegan, 2006; Geogheagan et al., 2001), most studies rely on data derived from satellite images and make the assumption of a one-to-one correspondence between the unit of observation and the unit of decision making.

There are other assumptions that are a direct consequence of the model specification of equation 4 have potentially severe consequences for usefulness of this model.

Stationary state and dynamic processes

Models that use cross-sectional data assume that information on land use is collected from a stationary state. This means that at the time data are collected all the dynamic forces and interactions responsible for land use choices have taken place and exhausted their effect. There are several potential problems with this assumption. For example, building a road changes transportation costs; lowering a tariff on imported corn reduces the profitability of corn farming. Since responses to these changes are not instantaneous, not all changes might be observable in a time period close to when the policy changes are implemented or infrastructure investment is completed. Furthermore, the costs associated with the process of change from one land use to another affect the speed of change, which may be faster for some conversions than others. Chomitz and Gray (1995, pg. 493-494) stress the potential significance of price expectations and irreversibility of some land use choices. Ignoring the time dimension also corresponds to ignoring the possible option value of certain choices, learning processes, and sunk costs (Schatzki, 2003). All these factors imply that the expected profit needed to induce land use conversion is likely to be significantly higher than the profit derived from the current use.

Property rights

The operator of a parcel of land is assumed to have effective property rights and perfect information, and principal-agent problems do not exist.

In fact, the likelihood and the type of change in land use also depends on the existence and enforceability of property rights. When property rights are poorly defined the competitive bidding process on which the von Thünen model relies breaks down.

Spatial effects and interdependent behavior

Modeling land use choices in the context of equation 7 assumes independence of behavior of the decision-maker and no spatial interactions, either socioeconomic or biological. In fact, an agent's behavior might be the result of interactions among several decision makers rather than the profit maximization decision of an individual who acts in isolation. Second, eco-biological processes can transcend parcel boundaries and create interdependence across locations. All these interactions may involve both spatial and temporal dimensions.

The potential for spatial interdependence translates into econometric difficulties. Ignoring spatial effects – local, global, and in-errors following Anselin's taxonomy – can result in biased and/or inefficient parameter estimates (Anselin, 2003).

Nonlinearity in the objective function

The specification of equation 4 forces the relationship between dependent and independent variables to be linear. The independent variables in the estimation can be nonlinearly transformed versions of the true underlying variables (e.g. including distance and distance squared) but the estimating relationship is linear. However, there are some situations when a linear specification is incorrect. Robertson (2005) presents two examples, reproduced in Figure 1.

In a situation like that of von Thünen's featureless plain but with nonlinear transportation costs, land use can switch from vegetables to wheat and then back (top of Figure 1). Another example is shown in the bottom of Figure 1. Suppose an improved rice variety is particularly sensitive to optimum amounts of water. For either greater or lesser amounts of rainfall, a traditional variety has higher yields. In this situation the relationship between water and land use (in this case variety choice) is nonlinear.

Profit/Utility-maximizing operator

The bid-rent paradigm requires that each land use choice is made by a profit- or utility-maximizing operator. This is often an unrealistic assumption in developing countries where risk-minimization behavior might strongly influence land use decisions. Furthermore, transaction costs may be so high that households make production decisions based on self sufficiency needs rather than market opportunities.

Some, but not all, of the above listed assumptions and shortcomings have been addressed by researchers. In the next section we report some of the new modeling techniques that have been proposed to overcome some of the limitations.

Progress in the Literature

Dynamic processes

Since much of this literature is concerned with deforestation, the temporal dimension has received much attention. While annual crops can often be analyzed adequately using cross section data, many forestry land uses require multiple years to generate an output. In addition, swidden land uses shift from agriculture to forest and back, potentially confounding any analysis based on a single cross section (Dvorak 1992). Once a temporal component is added to production, decision-making under uncertainty becomes an issue since future prices are not known.

The gradually increasing availability of land use/land cover observations has allowed researchers to incorporate the time dimension in their analysis. Some attempts have been made to incorporate dynamic mechanisms using the framework provided by equation 7. Mertens and Lambin (2000) use land use trajectories to implicitly account for spatio-temporal complexities of land use decisions. The land use trajectories specification might capture heuristically the forces that shape land use choices but it does not shed any more light than the previous models on the decision process followed by the land operator. Munroe et al. (2004) include time lags to include the intertemporal relationships among choices in the model. However, this method can cause estimation problems with most of the data sets used in land use change models because explanatory variables such as slope, elevation, distance to roads and villages do not change in time. As a consequence, significant correlation can exist between the unobserved factors contributing to both the independent variable and the dependent variable, which results in biased estimators. Two alternate modeling techniques have been proposed: hazard (also known as survival) analysis and limited dependent variable dynamic optimization.

Survival analysis

A group of studies (Boscolo et al. 1999; Irwin and Bockstael 2001; Vance and Geoghegan 2002), have experimented with survival analysis, framing the land use change problem in terms of optimal time to switch away from an existing land use. These studies implicitly take into account the option value of a choice. This technique overcomes some of the conceptual and technical shortcomings of the discrete choice approach such as the independence from irrelevant alternatives assumption and makes explicit use of the time dimension. Equation 8 lays out the behavioral model underlying the survival analysis technique. The agent chooses the optimum conversion date such that:

$$\max_T \int_0^T \Pi_F e^{-it} dt + \int_T^\infty \Pi_A e^{-it} dt - Ce^{-it} \qquad 8$$

The first term in equation 8 is the net present value of keeping a parcel in its current use *F* from the present to period *T*. The second term is the net present value of converting the parcel to an alternative use after *T*, and the third term is the discounted cost of converting the land use. *i* is the discount rate. With some manipulation, the probability that parcel *l* will be converted in period *t*, its hazard rate, is:

$$h_{lt} = \frac{F\left[\varepsilon^\bullet\left(X_{l,t+1,} t+1\right)\right] - F\left[\varepsilon^\bullet\left(X_{l,t}, t\right)\right]}{1 - F\left[\varepsilon^\bullet\left(X_{l,t}, t\right)\right]} \qquad 9$$

were *F[]* is the cumulative distribution function for ε, X is a set of observable characteristics, and ε^* is the value that satisfies the following arbitrage condition exactly.

$$\Pi_A - \Pi_F + \frac{d}{dt} C \geq \varepsilon \qquad 10$$

Although survival analysis includes the time dimension explicitly and addresses, at least in principle, the cost of conversion issues and the option value of certain choices, it has several problems. In particular, it cannot deal with the possibility of multiple transitions (e.g. forest to agricultural land and back to forest) and the irreversibility of some decisions but not others.

Limited dependent variable dynamic optimization

De Pinto (2004) frames the land user's choice problem as a solution to a dynamic optimization problem. The agent makes a series of choices over time and the alternative that is chosen in one period affects the attributes and availability of alternatives in the future. The agent's objective is to maximize the expected discounted value of payoffs Π at any time t by choosing the optimal time sequence of control variables $\{c_{jlt}\}$, $j \in J$ where the control variable in this case is land use. Agents behave according to the following optimal decision rule:

$$\max_{c_{jlt}} E\left[\sum_{t=0}^{\infty} i^t \Pi(X_{lt}, c_{jlt})\right] \quad 11$$

where $i \in (0,1)$ is the discount factor and X is a vector of variables (i.e. output prices, soil quality, slope, elevation, etc.) that describe the state of the system faced by the agent. The solution to the intertemporal optimization problem in equation 9 is given recursively by the Bellman equation and called the value function:

$$V(X_{lt}) = \max_{c_{jlt}} \Pi(X_{lt}, c_{jlt}) + E\left[V(X_{l,t+1}, c_{jlt})\right] \quad 12$$

The term $E\left[V(X_{l,t+1}, c_{jlt})\right]$, called the continuation value in the dynamic programming literature, captures the effect of current choices on future states of the system. It is like a "shadow price" for the effects of each action on future payoffs.

The probabilities are given by:

$$P(c_{hlt} \mid x_{lt}) = \frac{\exp\left[\pi(x_{lt}, c_{hlt}) + iE[V(x_{l,t+1}, c_{hlt})]\right]}{\sum_{j \in J} \exp\left[\pi(x_{lt}, c_{jlt}) + iE[V(x_{l,t+1}, c_{jlt})]\right]} \quad 13$$

The estimator is the nested pseudo-likelihood algorithm (NPL) proposed by Aguirregabiria and Mira (2002). The advantages of this approach are that it can account for the option value of choices, selective irreversibility, and expectations about future prices. The disadvantages are that it requires a relatively complex modeling and it requires data on output prices in order to form the agent expectations.

Property Rights

Nelson and Hellerstein (1996) provided the theoretical background to incorporate property rights in the static Chomitz and Gray framework. In a study on road building and land use change in Mexico the authors introduced the net present value of each land use as the operator's maximand. The land operator now chooses among the possible utilizations the one that generates the highest stream of returns through time.

The net present rent at time t is given by

$$R_{hl} = \int_{t=0}^{\infty} \left(P_{hl} Q_{hl} - \mathbf{C}_{hl} \mathbf{X}_{hl} \right) e^{-i_l t} dt \qquad 14$$

where i_l is the location-specific discount rate.

The version of equation 4 for estimation becomes:

$$\ln R_{hl} = \alpha_{0h} + \alpha_{1h} D + \sum_n \alpha_{nh} \ln G_l + \ln i_l + \varepsilon_{hl} = \beta_h^{'} X_l + \varepsilon_{hl} \qquad 15$$

Nelson, Harris, Stone, (2001) exploited this model specification to assess the potential effects of property rights and a proposed road paving project in the Darién province of Panama on land use. The province has three types of land tenure regimes – private land (with uncertain degree of legal ownership), reserves for indigenous populations, and the Darién National Park. Darién National Park is located on the southern border of the province and makes up about one third of the provincial area.

The mechanism for modeling different property right settings is to include a dummy variable for the different tenure regimes existent in a certain area. If a pixel is in an area with a particular regime, the variable is set to one; outside the area, the variable's value is zero.

It is important to note that while the modified specification makes it possible to test for differences in effectiveness of property rights, it assumes that the agent is maximizing the stream of returns through time. It does not allow for the possibility that in the absence of property rights agents might follow a different decision process.

Spatial Effects

A theoretically rigorous treatment of spatial effects for discrete choice models is still under development (Fleming 2004; Parker and Munroe, forthcoming). In its absence, the land use literature has proposed several ad hoc procedures mitigate the potential negative effects on estimates and predictions. Three types of ad-hoc corrections can be found in the land use literature:

Spatial sampling

Nelson and Hellerstein (1997), following Besag (1974) as described in Haining (1994), applied a “coding” scheme (Besag's terminology) that selects samples over a regular grid in such a way that two observations are not physical neighbors. The rationale for this method is that many spatial relationships between observations decay with Euclidean distance. Observations ‘sufficiently’ distant do not influence each other. See Robertson and Nelson (2006) for more discussion of the issues with spatial sampling.

Latitude and longitude as exogenous variables

Nelson, et al. (2001) corrected for spatial effects using two additional explanatory variable representing latitude and longitude of each observation. This method is equivalent to the spatial expansion technique (Cassetti, 1992). This type of correction is likely to be helpful when the spatial effect is caused by an unobserved variable that varies linearly over the area. However, this is a very special case and does not account for all the other possible spatial relationships.

Spatially lagged geophysical variables

Nelson, et al. (2001) and Munroe, et al. (2002) use spatial lags (weighted averages of values in neighboring locations) of geophysical variables such as soil type, slope, vegetation index used as exogenous variables. The reason for using these types of variables is to account for the direct influence that the surrounding environment might have on land use decisions made in a particular location.

Nonlinear estimation

It turns out there are close parallels between neural net and econometric estimation. Figure 2 presents a diagram of a feed forward neural net with a single hidden layer. In the figure, arrows are called synapses and represent weights in a calculation. Circles are called neurons and they are where the calculations are done. The bottom layer (N0 to N3) is where exogenous variables enter the calculation. The output layer (N7 to N9) includes a neuron for each land use category; in the diagram there are just 3. If there were no hidden layer, the values of the exogenous variables, along with a constant term (called a bias in the neural network literature), would be passed to the top layer where the calculation called a softmax in the neural network literature) for output neuron *m* would be:

$$\Pr(category\, m) = \frac{e^{\boldsymbol{\beta}_m'\mathbf{X}_1}}{\sum_{h=1}^{3} e^{\boldsymbol{\beta}_h'\mathbf{X}_1}} \qquad 16$$

Note that this calculation is identical to that of equation 7. The feed forward neural net has the desirable characteristic that if it has no hidden layers, it is identical to a multinomial logit. The synapse weights are found by minimizing cross-entropy, which is identical to maximizing the log likelihood function.

Adding a hidden layer (called hidden because it doesn't connect to the outside either to receive inputs or to generate final values), allows for nonlinear combinations of the exogenous variables. Unfortunately for estimation, it also allows for the possibility of local minima. This means that the estimation process cannot guarantee a global solution and the computation time is typically much larger. In comparing the predictive power of multinomial logit and a neural net for land use in southern Sumatra, Robertson found that the neural net results were somewhat better but with significantly higher computation time and effort.

Profit Maximization

Vance and Geoghegan (2004) point out that in some areas some farmers may be fully engaged in the local markets while others do not participate. Therefore, the two behaviors should be modeled separately. For this purpose they use a two-stage switching regression with endogenous switching. The first stage defines a dichotomous variable identifying the regime into which each farmer falls:

$$S \text{ (Seller)} = 1 \text{ if } \tau' Z \geq u$$
$$S \text{ (Nonseller)} = 0 \text{ otherwise,}$$

where Z is a vector of variables that determine the seller or non-seller regime and τ is a vector of parameters. Among the variables that determine the seller status are: an index that captures the quantity of in-house consumption, labor availability, age and education of the head-household, distance to markets, and availability of credit. Once the regime is identified the second stage of the regression is implemented:

Sellers: $y_i = \beta_1 X_{1i} + u_{1i}$ if $\tau' Z_i \geq u_i$
Nonsellers: $y_i = \beta_2 X_{2i} + u_{2i}$ if $\tau' Z_i < u_i$,

where the dependent variable y is the number of hectares dedicated to a crop, and $\beta_1 X_1$ and $\beta_2 X_2$ are the associated parameters and explanatory variables for the two different regimes.

This modeling technique makes it possible to distinguish the determinants of land use according to the household's relationship with the market and also to test for the presence of two different behaviors in the same area. One of the drawbacks is that the model is data intensive as it relies heavily on household data.

An Empirical Application

Do these new modeling techniques actually help researcher in making better predictions or better policy recommendations? The answer to this question is not a trivial; two recent papers (Robertson and Nelson, 2006; De Pinto and Nelson, 2006) demonstrate this point. As mentioned earlier, researchers have adopted a series of techniques to mitigate the potential negative consequences of spatial effects under the assumption that if spatial effects are correctly modeled the model performance would improve. Robertson and Nelson (2006) use a Monte Carlo simulation to investigate the consequences of various kinds of spatial effects on predictive ability. Their results show that leaving spatial effects unmodeled does not have serious effects on predictive ability. They argue that the information content in a limited dependent variable model is so limited that only extreme spatial effects are likely to affect predictions and simulations.

One of the problems of using the multinomial logit specification is the independence from irrelevant alternatives assumption. The implications of this assumption in the land use context is that, for example, given two initial land uses that farmers can choose from (i.e. forest and agriculture), the introduction of a third choice (i.e. pasture) should draw equal proportions of resources from the previous two options. This is highly unlikely since considering the costs involved in moving from one utilization to the other, we would expect that farmers would switch more easily from agriculture to pasture than from forest to pasture. Researchers have tried to overcome this problem using alternative specifications such as multinomial probit, nested logit, or randome parameters logit. Nelson et al. (2004) compared the performance of three model specifications – multinomial logit, nested logit, and random parameters logit – and found that the nested logit was superior to the others in terms of correct predictions. However, De Pinto and Nelson (2006) revisit this previous study and compare model performance using a measure of uncertainty present in the predictions of each model. According to this measure there is no statistically significant difference between the performance of nested and multinomial logit.

It is therefore not clear which of these modeling techniques truly improve the usefulness of these models.

We now report in more detail the results of another study that demonstrate the potential value of adopting more advanced modeling techniques. De Pinto (2004) compares the performance of a dynamic discrete choice model against the performance of other models of land use that are common in the literature – multinomial logit, random parameters logit, and a survival model. The dynamic discrete choice model, the random parameters logit, and the survival model are used over three time periods – 1985, 1987, 1997 – and the estimated parameters are used to predict land use in the year 2000. The multinomial logit is used with the year 2000 and the estimated parameters are used to predict the land use for the same year.

We review two sets of results – for land use and land use *change* predictions. The land use results presented in Table 1 and Table 2 show that the dynamic discrete choice model outperforms all alternative models in terms of correct predictions for the year 2000. The overall predictive power of is 0.792 for the multinomial logit, 0.765 for the mixed logit and 0.887 for the dynamic discrete choice. In order to compare the performance of the dynamic discrete choice and survival models, the two are used to predict land use change in the year 2000. The survival model correctly predicts some 66 percent of pixels that actually undergo a change in the year 2000 while the dynamic discrete choice model returns a perfect score with 100 percent of the change correctly predicted (Table 2). Both models over-predict land use change, 27 percent of the pixels that are predicted to change by the dynamic discrete choice do not undergo any change while the survival model overestimates land use change by some 53 percent.

The parameter estimates can be used to simulate the effects of changes in the socioeconomic variables. De Pinto (2004) simulated the paving of a major highway in the Darien province by replacing the original cost variables with simulated values that reflect the reduced cost. Table 3 compares the results obtained with the dynamic discrete choice, multinomial logit, and mixed logit models. The dynamic discrete choice model predicts a more modest change than either the multinomial logit or mixed logit models. Table 4 compares the results of the dynamic discrete choice and survival models. The survival model predictions are similar to those of the dynamic discrete choice: 352 and 264 respectively.

Road resurfacing in the area has not been completed yet. We can speculate though that, given the better performance of the dynamic discrete choice model in terms of prediction accuracy and given that both survival and dynamic discrete choice models return similar results in term of land use change caused by a variation in transportation costs, the inclusion of dynamic processes is a necessary component in a model that is to correctly predict change. The results of our simulation suggest that road resurfacing would only cause a modest change in land use and that additional encroachment of forested land by agricultural uses is strongly limited by geophysical factors and transition costs. Interestingly, the differences between models are mostly in the number of hectares but not in the location of change as can be observed in Figure 3. Most of the land use change occurs at the frontier between land uses. The results of the simulation of road resurfacing support the hypothesis that static models tend to overestimate land use changes.

Concluding Remarks

One of the advantages of the static analysis techniques is their relatively low cost. The analysis relies mostly on remotely sensed data and other relatively inexpensive ancillary data such as roads and rivers networks or slope and altitude. As modeling techniques become more sophisticated data requirements increase. First of all, introducing the temporal dimension requires the availability of time series data, which in tropical countries can be a problem due to cloud cover. Relaxing the assumption on profit maximization behavior means that more refined data on household become necessary. It is also important to point out that some of the new data requirements derive from the fact that some assumptions that were perhaps acceptable in static analysis become more problematic in a dynamic setting. For instance, assuming equal inputs for all land use categories is a common practice in static analysis and the differentiation in production costs is due only to transportation costs. However, when time series are used, the unmodeled input prices become part of the error term and the error terms become correlated through time.

The modeling techniques reviewed in this article address some important theoretical shortcomings of earlier models. It is still not clear though if the benefits of using these new methods outweigh the costs, both data and computational. This is an area that researchers have recently started to explore. However, several problems stand in the way. First, it is still difficult to develop rich data sets that make it possible to implement new models. Clearly cloud cover, access to and cost of images are a problem, but also turning satellite images into land use maps and manipulating large data sets are important constraints. Second, some modeling challenges are difficult to solve. For example, researchers have been searching for a statistically sound limited dependent variable estimator that incorporates spatial effects for almost a decade. Third, and possibly more important, a method to compare model performances is not in place and relying on log-likelihood, pseudo R^2, or predictive power measures can be misleading (see De Pinto and Nelson, 2006 for more details). We believe that developing useful economic models capable of explaining land use change processes relies on overcoming these problems.

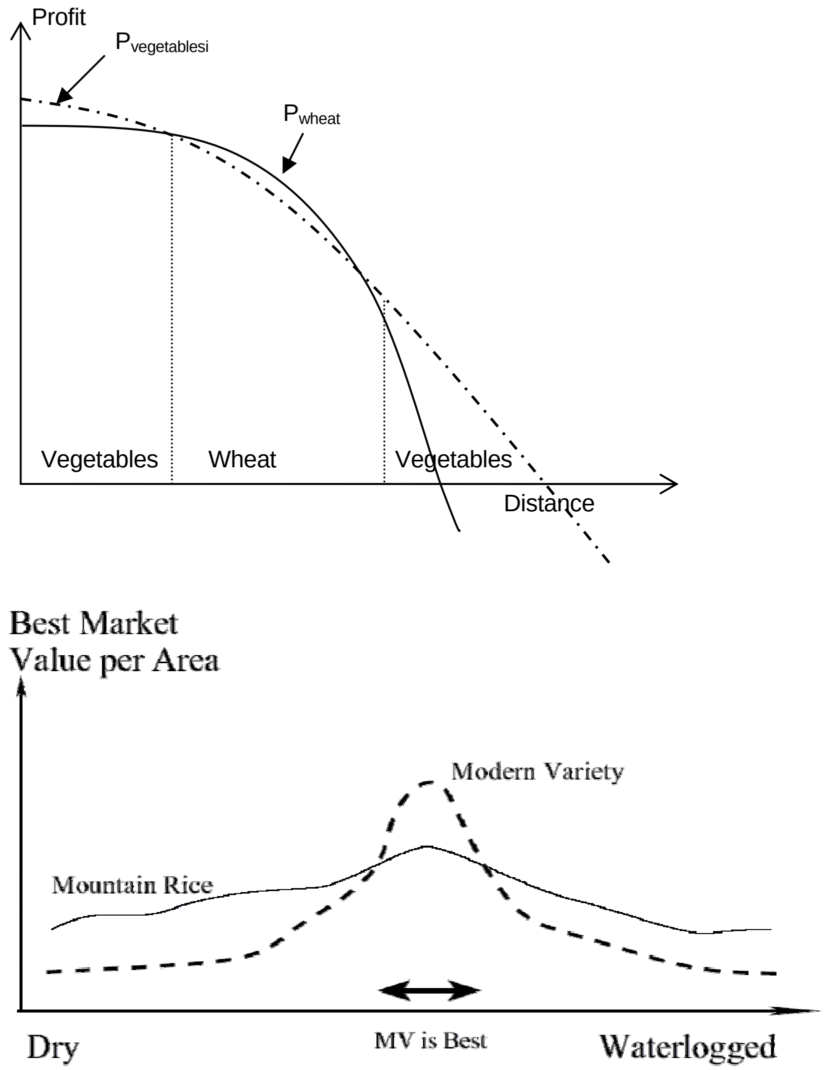

Figure 1: Examples of Nonlinearity in the Objective Function
Source: Robertson, 2005.

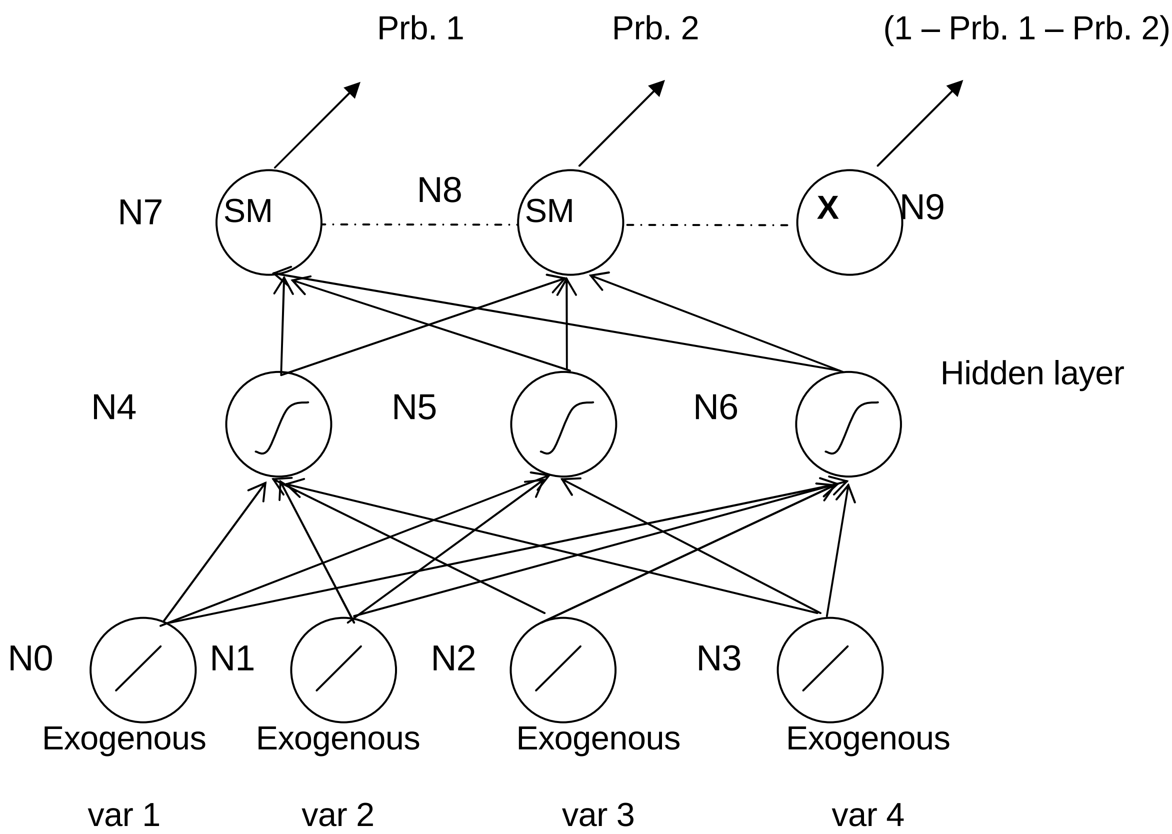

Figure 2: Neural Net with Single Hidden Layer
Source: Based on Robertson,2005.

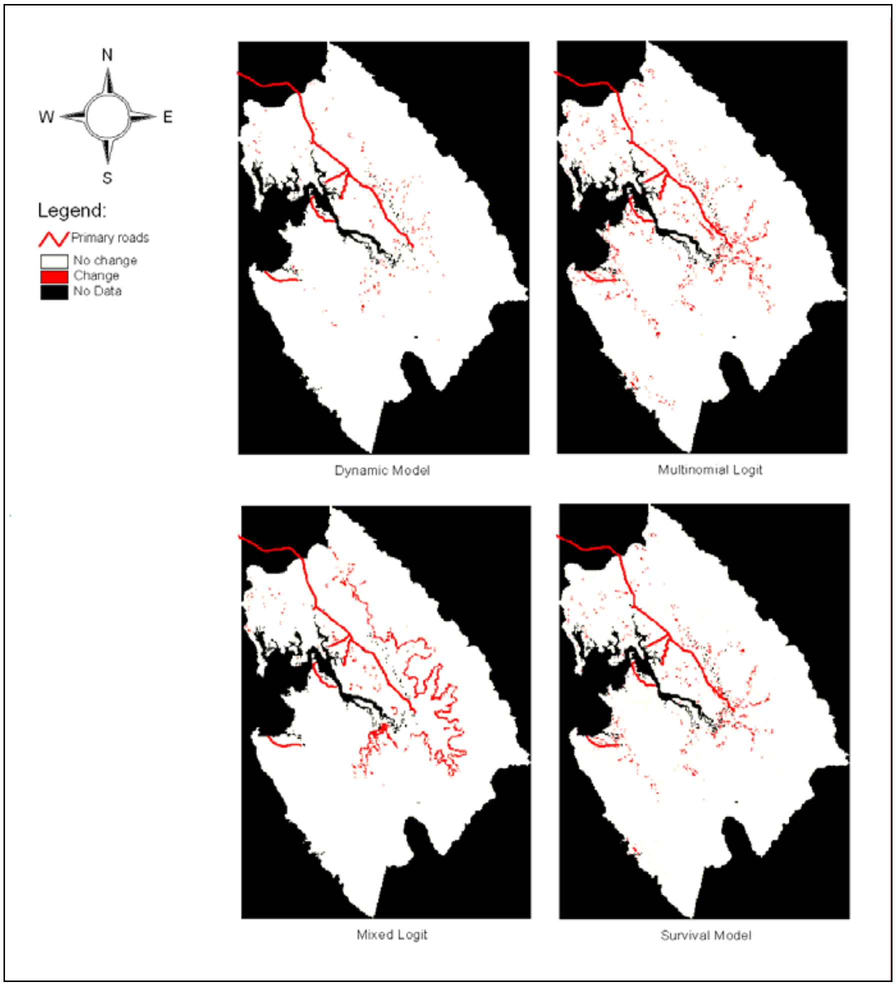

Figure 3: Land Use Change Caused by Road Resurfacing with Different Estimation Methods.
Source: De Pinto, 2004.

Table 1: Prediction matrix for the Dynamic Discrete Choice, Multinomial Logit, and Mixed Logit Models, (Number of 0.25 Km cells)

	Land Use	Forest	Agriculture	Idle	Total (True)	Ratio Correct to Total Predictions
Dynamic Discrete Choice Model	Forest	**41,817**	6,217	19	48,053	0.870
	Agriculture	73	**8,718**	855	9,646	0.903
	Idle	0	0	**6,195**	6,195	1.000
	Total (Predicted)	41,890	14,935	7,069	63,894	0.887
Multinomial Logit	Forest	**40,950**	7,002	101	48,053	0.852
	Agriculture	1,431	**8,148**	67	9,646	0.844
	Idle	1,725	2,951	**1,519**	6,195	0.245
	Total (Predicted)	44,106	18,101	1,687	63,894	0.792
Mixed Logit	Forest	**35,157**	12,842	54	48,053	0.731
	Agriculture	595	**7,534**	1,517	9,646	0.781
	Idle	0	0	**6,195**	6,195	1.000
	Total (Predicted)	35,752	20,376	7,766	63,894	0.765

Source: De Pinto, 2004.

Note: Columns are predictions of change for year 2000; rows are actual change in the year 2000)

Table 2: Prediction matrix for Survival Model and Dynamic Discrete Choice Model (Number of 0.25 Km cells)

	Land Use	No-Change	Change	Total (True)	Ratio Correct Predictions to Total
Dynamic Discrete Choice Model	No-Change	**58,621**	1,439	60,060	0.976
	Change	0	**3,834**	3,834	1.000
	Total (Predicted)	58,621	5,273	63,894	0.977
Survival Model	No-Change	**57,143**	2,917	60,060	0.951
	Change	1,298	**2,536**	3,834	0.66
	Total (Predicted)	58,441	5,453	63,894	0.934

Source: De Pinto, 2004.

Note: Columns are predictions of change for year 2000; rows are actual change in the year 2000)

Table 3: Effects of Road Resurfacing for the Year 2000, Dynamic Discrete Choice Model vs. Multinomial Logit

	Forest	Agriculture	Idle
Dynamic Model			
Before Resurfacing	41,890	14,935	7,069
After Resurfacing	41,626	15,199	7,069
Net Change	- 264	+ 264	0
Multinomial Logit			
Before Resurfacing	44,106	18,101	1,687
After Resurfacing	40,653	20,558	2,773
Net Change	- 3,543	+ 2,457	+ 1,086
Mixed Logit			
Before Resurfacing	36,107	19,660	7,659
After Resurfacing	34,904	20,863	7,659
Net Change	- 1,203	+ 1,203	0

Source: De Pinto, 2004.

Note: Number of 0.25 Km cells.

Table 4: Effects of road resurfacing on forecasted change for the year 2000, Dynamic Discrete Choice Model vs. Survival Model (number of .25 km cells)

	Change	No-Change
Dynamic Model		
Before Resurfacing	5,383	58,511
After Resurfacing	5,647	58,247
Net Change	+264	- 264
Survival Model		
Before Resurfacing	5,453	58,441
After Resurfacing	5,775	58,119
Net Change	+352	-352

Source: De Pinto, 2004.

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