# A Dynamic Model of Land Use Change with Spatially Explicit Data[1]

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**Abstract:**
Most of the economic literature that uses spatially-explicit data to estimate the determinants of land-use change is limited to static models and uses cross-sectional data sets (Chomitz and Gray, (1995), Nelson and Hellerstein, (1995), Deininger and Minten, (2002)). Recently, attempts have been made to move from a static to a dynamic framework using panel data sets (Munroe et al., 2002) and to find alternatives to the widely used limited dependent variable models. With the exception of some experimentation with survival analysis (Boscolo et al. (1999) and Vance and Geoghegan (2002)), no other alternatives have been proposed.

In this study, we use a discrete choice dynamic model of land-use where the agent's choices are regarded as the solution to a dynamic optimization problem. The first result of using of a dynamic framework is that the assumption of observing the system at a stationary state, one that characterizes all earlier studies, is no longer necessary. Secondly, multitemporal analysis makes it possible to better account for the forces that propagate through space and time and are affected by time lags and spatial diffusion processes. Finally, our model introduces more of the complexities that characterize the decision process. Many of these complexities are assumed away in limited dependent variable models and only partially captured in survival analysis models. In particular, the irreversibility of some decisions (e.g. when a primary forest is cleared away, it is not an available choice in the next time period), expectations about future prices, and forward-looking behavior of the land operator are accounted for.
For the estimation of the parameters of interest, we build upon a model proposed by Rust (1987) and use a pseudo-maximum likelihood estimator, the Nested Pseudo-Likelihood (NPL) algorithm as proposed by Aguirregabiria and Mira (2002). We tested our model using satellite images and other ancillary data for an area in Panama. Part of this data set was previously used in land use models that used cross-sectional data (Nelson et al. (2001 and 2004)). We calibrated the model using three time periods (1985, 1987, and 1997) and the parameter estimates were used to predict land use change in the year 2000.

Our results show that this model improves upon the existing literature in several ways. First, prediction accuracy of land use change is superior to any of the existing models. Second, we demonstrate how simpler models of land use change, models that do not account for friction in moving in and out uses, overestimate the effects of changes in transportation costs. Third, the incorporation of output prices and expectations regarding future states of the system allow to simulate the effects of policies that would otherwise remain unexplored.

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## Introduction

The main objective of this study is to develop a dynamic model to estimate the determinants of land use change using data derived from satellite images. Recent research in this area has mostly focused on improving the econometric techniques of estimation using limited dependent variable models, and, with the exception of some experimentation with survival analysis, there are no other attempts to use alternate methods to model land use change. The advantages of using a dynamic model for land use change are many and the method we propose overcomes many of the weaknesses of previous models. When cross-sectional data are used, all the dynamics and interactions that are responsible for the choice of a particular land use are collapsed as if all the forces were interacting simultaneously. Important characteristics of the decision process cannot be captured through static analysis. One example is the forward-looking behavior of the land operator who has expectations about future prices and knowledge regarding the effects that current decisions might have on future options such as irreversibility of particular investments. Disregarding these potentially important components of the decision process might lead to errors in the estimate of the parameters of interest with the risk of formulating wrong normative policy recommendations. Other advantages deriving from using the model proposed here are in the mitigation of one of the undesirable consequences of using the multinomial logit specification namely the Independence from Irrelevant Alternatives assumption discussed below. The model we propose to analyze land use change uses some of the key concepts of dynamic programming in combination with the typical multinomial logit specification. Over the last two decades, there has been considerable progress in the econometrics of discrete choice dynamic programming models and although the computational burden of estimation has somewhat hindered empirical work in this area, the estimation of these models has increased our understanding of individual and firm behavior[2]. As an empirical application of the model, we will use our econometric estimations to simulate the effects of road re-pavement and compare the results with previous studies of the same area (Nelson 2001b). Moreover, since unlike previous studies our model accounts for prices at the central market, we are able to simulate the spatial differential effects of policies that alter output price ratios through time.

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[2] For an extensive survey on the structural estimation of dynamic discrete choice models, see Eckstein and Wolpin (1989).

## Review of the Literature

This section reviews the economic literature that investigates the determinants of land-use choices or land-use change using spatially explicit data. Prior to the use of spatially explicit data, economists analyzed these problems using census data, which could be at different administration levels such as state, county or a province, with no spatial differentiation inside the unit of analysis. These studies provided general indications on the occurrence of the phenomenon under investigation or an estimation of its determinants. However, no information was given on *where* the change was likely to occur. Two modeling techniques characterize the literature. A first group of studies, from Chomitz and Gray (1995) to Munroe, Southworth, Tucker (2001), uses a multinomial logit specification to compute the probabilities of observing each land-use choice at each location. A second group of more recent studies, Boscolo, Pfaff, Kerr, and Sanchez (1999), Irwin and Bockstael (2001), and Vance and Geoghegan (2001), have experimented with survival models in order to overcome some of the limitations and shortcomings of the multinomial logit approach. Most of the economic literature that uses spatially-explicit data to investigate the determinants of land use choices and land use change is limited to static models and uses cross-sectional data sets (Chomitz and Gray, (1995), Nelson and Hellerstein, (1995), Deininger and Minten, (2002)). However, even Chomitz and Gray (1995, pgg. 493-494) acknowledged that some important issues involved in land use change are inherently dynamic and that expectations of future prices and irreversibility of some land use choices needed to be taken into consideration. The first attempt to introduce the time dimension in this type of analysis can be attributed to Mertens and Lambin (2000) but their results were challenged by Munroe, Southworth, and Tucker (2001) who found that a simple "static" multinomial logit preformed better. Recently, attempts have been made to move from a static to a dynamic framework and normally these attempts correspond to using panel data sets (Munroe et al., 2002). However, the use of panel data does not necessarily mean that dynamic processes are introduced in the model. In fact, any link between time periods is missing in Munroe et al., (2002). A different type of approach was proposed by Boscolo et al. (1999) who used a survival model to study deforestation in Costa Rica. Survival models frame the problem in terms of optimal switching time and implicitly take into account the option value of a choice. To our knowledge no attempts have been made so far to compare the performance of all these models in terms of prediction accuracy and no other alternatives have been proposed. Discrete choice models such as logit or probit can accommodate, with adjustments to avoid inconsistent estimates, lagged values that are supposed to include certain types of dynamic processes. It is more difficult to incorporate more complicated dynamics where the choice that an agent makes at one point in time has an effect on the options that are available to him in the future. The procedures for modeling these decisions were first developed for various applications by, for example, Wolpin (1984) on women's fertility, Pakes (1986) on patent options, Wolpin (1987) on job search, Rust (1987) on engine replacement, Berkovec and Stern (1991) on retirement, and others. Sequential decision making under uncertainty can be modeled using dynamic programming, a framework that allows reducing a multidimensional problem to a recursive solution of a sequence of two-period problem. The term dynamic programming was coined by Bellman in his Principle of Optimality (Bellman, 1957) to describe the technique, which he brought together to study a class of optimization problems involving sequences of decisions. Unfortunately, the solution to these problems poses a considerable computational burden and suffers from the curse of dimensionality. Several ways have been proposed to reduce the computational burden (Keane and Wolpin (1994), Rust (1997), Hotz and Miller (1993), and Hotz et al. (1993)). The two contributions that most greatly contributed to the manageability of the estimation process are Rust's assumption on the structure of the stochastic term and Hotz and Miller's assumption on the relationship between valuation function and choice probabilities. Rust (1987) assumes that the factors that the researcher does not observe do not depend on any previous state variables and decisions and that these unobservables are iid extreme value. Under this admittedly restrictive assumption, the choice probabilities take a closed form that is easy to calculate. Hotz and Miller (1993) show that there is a correspondence between the valuation function in each time period and the choice probabilities in future periods. This correspondence allows the valuation functions to be calculated with these probabilities instead of backward recursion. In this study we follow both Rust and Hotz and Miller to model land use change.

***Econometric difficulties using spatial data***

The use of spatially explicit data introduces unique econometric problems. Anselin and Bera (1998) distinguish between two types of specification error: nuisance and substantive spatial dependence. In the case of nuisance spatial dependence, ignoring spatial effects can result in inefficient, but not biased, estimators. Ignoring substantive spatial dependence, econometric estimation will yield biased and inefficient parameter estimates, Anselin (1988). Limited dependent variable models have generally relied on ad-hoc methods to correct for potential spatial effects. However, it was impossible to determine if these methods were effective until the recent Kelejian and Prucha (2001) paper proposed a test for spatial dependence in regression analysis with limited dependent variable models. In the attempt to correct for spatial effects, Nelson and Hellerstein (1995) apply a "coding" scheme, which is the selection of a sample over a regular grid in such a way that two observations are not neighbors. The rationale for this method is that the relationship between observations decays proportionately with the Euclidean distance. Therefore, two observations sufficiently distant do not influence each other. The "coding" method has been subsequently used by Mertens and Lambin (2000), Munroe, Southworth, Tucker (2001), and Nelson et al. (2001b). Nelson and Hellerstein

(1996), and Nelson, Harris, Stone, (2001a) corrected for spatial effects using two additional explanatory variable representing latitude and longitude of each observation. This method would probably be helpful if the problem 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. Nelson et al. (2001a) and Munroe, Southworth, Tucker (2001) use lags of key physio-geographic variables such as soil type and slope for the same purpose. As De Pinto and Nelson (2002) have shown using the Kelejian and Prucha version of Moran's I, the use of this particular type of lag variables appears to be relatively successful in removing spatial error dependence.

## A dynamic model of land use change

Our objective is to create a dynamic model of the land-operator's decision process using information on the actual land use as provided by satellite images and other spatially explicit data such as preexisting topographic and soil maps. We assume that the observed land use is the result of an ongoing optimization process. At each point in time the land operator chooses the land use with the highest expected profit. The discrete nature of the control variable, the land use type, prevents us from obtaining first order conditions by differentiation of the objective function as we would normally do in a dynamic optimization problem. The maximizing decision rule is instead obtained as a solution to a system of inequalities. Applications of discrete choice models that use panel data (Mertens and Lambin (2000), Munroe, Southworth, and Tucker (2002)) did not include the complexities of decision making in several ways. First, the decision made at a certain point in time might affect the future value of one or more explanatory variables. A common assumption of limited dependent models is that the choice set is invariant through time. However, this is not always the case. For example, when a primary forest is cut, it is not an available choice in the next time period. Second, Option values do not enter in the analysis. That is, the option of delaying the change might in itself have a value particularly when choices are irreversible. Third, moving in or out of a land use can be costly. Learning processes might create friction in moving out of a land use. Familiarity with practices related to a particular land use as opposed to an alternative one creates an asymmetry in information that can lead to comparative advantage of the more familiar use. The amount of time a land operator has been involved in a particular use influences his knowledge of the sector and his productivity level[3]. All the above points can cause problems when the researcher wants to simulate the effects of new economic policies or changes in economic variables such as output prices or transportation costs. Due to option value, learning processes, and sunk costs the

[3] An important source of asymmetry between land uses are sunk costs. For a study on the effects of sunk costs on land use choices see Schatzki (2003).

expected profit required to induce a land use conversion needs to be significantly higher than the profit derived from the current use. This issue is well documented in Stavin and Jaffe (1990), Plantiga (1996), and more recently in an article by Schatzki (2003). Not accounting for these sources of friction between alternate uses results in overestimating the effects of changes in output prices, transportation costs, and in general of all those policies that change economic conditions for the land owner. Previous models of land use change that use spatially explicit data generally do not account for these asymmetries. The exception is models that use survival analysis, which by construction account for the option value. In order to overcome these limits we propose to model the agent's decision problem following a dynamic programming framework.

***The discrete-choice dynamic programming model***

The state of the system faced by the agent can be described by the following vector of state variables:

$$X_{lt}^{'} = \{p_{1lt},..., p_{Jlt}, w_{1lt},..., w_{Jlt}, A_{lt}, \varepsilon_{lt}\}, \qquad \textbf{(1)}$$

where

$j \in \{1,...., J\}$ a finite set of possible land uses,

$l$ indicates the location at which production takes place,

$t$ is the time subscript.

$p$ indicates output price, and $w$ input prices.

$A_{lt}$ is a multiplicative combination of $N$ features affecting productivity and is defined as follows:

$$A_{lt} = \left(\prod_{n=1}^{N-1} G_t^{\phi_n} * s_t^{\phi}\right), \qquad \textbf{(2)}$$

In particular, the productivity shifter $A$ is a combination of geophysical features ($G$) affecting productivity and a term ($s$) that captures the temporary productivity disadvantages, or advantages, of changing land use. Geophysical features provide an indication regarding the suitability of land to different uses and include aspects such as slope, altitude, climate, and soil quality. The "friction" term $s$ gauges the learning processes that might create friction in moving out of a land use. When a new activity is undertaken there are investments that need to be made, additional knowledge and information that needs to be acquired. The level of productivity achieved in a land use will be dependent on the time the land operator is involved in that particular land use. The stochastic term $\varepsilon$ captures the unobservable characteristics that influence the system. These characteristics are known to the agent but not to the researcher. We use this error term to reconcile the fact that we are not realistically capable of predicting the behavior of economic agents with certainty. We assume this unobservable error term is dependent on the choice decision made by the agent. At each time $t$ the land operator has to make a decision $c_j$ on what production activity he/she wants to undertake on a plot of land. We assume the decision to be rational in the sense that it is supposed to maximize the expected stream of profits from the use of the plot of land. Let $c_{jlt}$ = 1 indicate that alternative $j \in J$ is chosen at time $t$. Alternatives are defined to be mutually exclusive so that $\sum_{j=1}^{J} c_{jlt} = 1$. The farmer knows the state he/she is in at time $t$ and has expectations on how the system evolves in future time periods. Furthermore, the agent is aware that certain decisions made at time $t$ influence the time path of the state variables. The agent's beliefs on the evolution of the state variables can be described by an agent-specific equation of motion:

$$E[X_{l,t+1}] = f(X_{l,t}, c_{jl\,t}, \theta), \qquad \textbf{(3)}$$

where $E(.)$ is the expectation operator with a Markov structure and $\theta$ is a parameter that characterizes the distribution $f$. The Markov structure implies that the firm does not need to remember the entire previous history to solve its optimization problem, but only a summary statistic belonging to a finite vector space, $X_t \in \boldsymbol{X}$**.** All that is needed in a Markov process is the value of the set of the state variable $X$ at time $t$, and its law of motion, i.e. the probability distribution $f$, which characterizes how the state changes from one period to the next.

Equation 3 stochastically determines next period's state $X_{t+1}$ as a function of the current state vector $X_t$ and the alternative chosen $c_t$ at time $t$. The agent's objective is to maximize the expected discounted value of payoffs $\Pi$ at any time $t$ by choosing the optimal sequence of control variables $\{c_{jlt}\}_{j \in J}$. Agents behave according to the following optimal decision rule:

$$\max_{c_{jt}} E\left[\sum_{t=0}^{T} \beta^t \Pi(X_{lt}, c_{ljt})\right]. \qquad \textbf{(4)}$$

The solution to the intertemporal optimization problem as expressed in Equation 4 is given recursively by the Bellman equation and called the *value function:*

$$V(X_{lt}, c_{jlt}) = \max_{c_{j\in J}} \Pi(X_{lt}, c_{jlt}) + \beta\, E[V(X_{l,t+1}, c_{jl,t+1})], \qquad \textbf{(5)}$$

where

$$EV(X_{l,t+1}) = \max_{c_j} \int_{X_{t+1}} V(X_{t+1}, c_{j,t+1}) f(\partial X_{t+1} \mid X_t, c_{jt}), \qquad \textbf{(6)}$$

and $\beta \in (0,1)$ is the discount factor. As Rust (1987) showed, under some mild regularity conditions the stochastic control problem takes the form of a deterministic and stationary decision rule given by:

$$c^* = \underset{j\in\{1,\dots,J\}}{\arg\max} \left\{ \Pi(X_{lt}, c_{jlt}) + \beta EV(X_{l,t+1}, c_{jl,t+1}) \right\}. \qquad \textbf{(7)}$$

Note that the optimal decision in 7 implies that

$$\Pi(X_t, c_{it}) + \beta V(X_{t+1}, c_{i,t+1}) \geq \Pi(X_t, c_{j,t}) + \beta V(X_{t+1}, c_{j,t+1}) \ \ \forall j \ \text{ where } j \in J \text{ and } i \neq j \quad ,$$

which explicitly accounts for the optimality of the timing of land use change and the option value of an investment.

***Specification of the payoff function***

Assume producers have equal access to all available inputs l. They can combine these inputs so to obtain j different products and $Q_j$ indicates output quantities. Producers are free to choose any output j they want and they will choose $Q_j$ to maximize profit. We account for the location of the production activity by introducing the term *A* as defined in 2 into the production function. The effect of *A* is to limit or enhance the possibility of producing output $j$ at location *l.* Following the existing literature, we use a Cobb-Douglas functional form to represent the production technology and we use the indirect profit function to express at each time t the maximum profit as a function of the output and input prices[4]:

$$\Pi_{jl}(p_{jl}, w_{kjl}, A_l, c_{jl}) = \gamma_j \left[ p_{jl} A_l \prod_k w_{kjl}^{-\alpha_{kj}} \alpha_{kj}^{\alpha_{kj}} \right]^{\frac{1}{\gamma_j}}, \qquad \textbf{(8)}$$

where: $\gamma = 1 - \sum_k \alpha_k$ . Taking the log of equation 8 gives:

4 See Beattie, Bruce R. and C. Robert Taylor. The Economics of Production. Malabar: Krieger Publishing Company, 1993, page 248.

$$\ln \Pi_{jl} = \ln \gamma_j + \frac{1}{\gamma_j}\left[\ln p_{jl} + \ln A_l + \sum_k \left(-\alpha_{kj} \ln w_{kjl} + \alpha_{kj} \ln \alpha_{kj}\right)\right]. \qquad \textbf{(9)}$$

We model location specific prices as a combination of market prices and cost of access prices, with market prices strongly exogenous. They take the following functional form:

$$p_{jl} = \exp[p_{j0} - \lambda_1 D^O_{jl}]$$

$$w_{jl} = \exp[w_{j0} + \delta_1 D^I_{jl}], \qquad \textbf{(10)}$$

where: $p_{j0}$ and $w_{j0}$ are prices at the market, $D^O_{jl}$ and $D^I_{jl}$ are the cost of access measured from the market to location $l$ for output $j$ and inputs respectively. Substituting these proxies into equation 10 and with some other algebraic manipulation, we have:

$$\ln \Pi_{jlt} = \eta_{0jl} + \eta_{1j} P_{0t} + \eta_{2jl} D^O_{jlt} + \eta_{3jl} D^I_{jlt} + \sum_{n=1}^{N-1} \eta_{4njl} \ln G_{nl} + \eta_{5jl} \ln s_l$$

where

$$\eta_{0jl} = \ln \gamma_j + \frac{1}{\gamma_j} \sum_k \left(\alpha_{kj} \ln \alpha_{kj}\right) + \frac{\left(\gamma_j - 1\right)}{\gamma_j} w_{0l}$$

$$\eta_{1il} = \frac{1}{\gamma_j}$$

$$\eta_{2jl} = \frac{\lambda_1}{\gamma_j}$$

$$\eta_{3jl} = \frac{\left(\gamma_j - 1\right)}{\gamma_j}$$

$$\eta_{4njl} = \frac{\phi_n}{\gamma_j}$$

$$\eta_{5jl} = \frac{\phi_N}{\gamma_j}. \qquad \textbf{( 11)}$$

Suppose that there are three possible output $j$ where $J=\{1,2,3\}$, determined by choice $c_{jt}$, the land operator can choose from. The choices are: forestry (1), agricultural activities, i.e. husbandry and farming (2), and hold land idle (3), which returns zero instantaneous profit. The instantaneous profit function $\Pi(.)$ will be equal to:

$$\Pi(.) = \begin{cases} \eta_{01l} + \eta_{11l} P_{1l} + \eta_{21l} D^O_{1l} + \eta_{31l} D^I_{1l} + \sum_{n=1}^{N-1} \eta_{4n1l} \ln G_l + \eta_{51l} \ln s & c_1 = 1 \\ \eta_{02l} + \eta_{12l} P_{2l} + \eta_{22l} D^O_{2l} + \eta_{32l} D^I_{2l} + \sum_{n=1}^{N-1} \eta_{4n2l} \ln G_l + \eta_{52l} \ln s & c_2 = 1 \qquad \textbf{(12)} \\ 0 & c_3 = 1 \end{cases}$$

***Outline of the estimation procedure***

Satellite images provide information on the land use chosen by the land operator in the form of panel data. Ancillary data on soil type, elevation, slope, and temperatures, which form the geophysical characteristics *G* are provided by existing maps of the area. We have a series of observations $\{(c_1, x_1), (c_2, x_2), ..., (c_T, x_T)\}$ and for each location we can form the likelihood $\ell^f \{c_1, x_1), (c_2, x_2), ..., (c_T, x_T) \mid c_0, x_0\}$. We can estimate our parameters of interest maximizing the likelihood function for the optimization process. For a number *L* of locations, with the $l^{th}$ location having observations for T time periods, we have

$$\ell = \prod_{l=1}^{L} \prod_{t=1}^{T} \Pr(c_{jlt} \mid x_t, \theta_1), \qquad \textbf{(13)}$$

where $\Pr(c_{jlt} \mid x_t, \theta_1)$ is the probability of choosing action $c_j$ given the observed vector of state variables $x_t$, a vector of parameters (the object of our estimation) $\theta_l$, and the fact that action $c_{jt}$ is supposed to maximize the expectation of the stream of profits. We acknowledge that the researcher does not observe all state variables (but assume the land operator does), we divide the state variables into observable and unobservable: $X_{lt} = (x_{lt}, \varepsilon_{lt})$. In other words, we assume that the data set cannot provide full information on the state of the system and on those variables that are relevant for the decision making process. We now introduce two assumptions about the structure of observable and unobservable state variables that are necessary to proceed. The two assumptions are: Additive Separability (AS) and Conditional Independence (CI), and are borrowed directly form the static discrete choice literature (McFadden 1981). Additive Separability: The one period payoff function is additively separable in the observable and unobservable components: $\Pi(X_t, c_{jt}) = \pi(x_t, c_{jt}) + \varepsilon(c_{jt})$.

Conditional Independence: The individual's beliefs about the next period's state are conditional on the current state and the choice can be written as: $P(x_{t+1}, \varepsilon_{t+1} \mid x_t, \varepsilon_t, c_{jt}) = g(\varepsilon_{t+1} \mid x_{t+1}) f(x_{t+1} \mid x_t, c_{jt})$ That is, $x_{t+1}$ is a sufficient statistic for $\varepsilon_{t+1}$ which means that any potential serial correlation between $\varepsilon_{t+1}$ and $\varepsilon_t$ is transmitted entirely through the vector $x_t$. The probability density function of $x_{t+1}$ depends entirely on $x_t$ and not on $\varepsilon_t$[5]. The CI assumption is essential to express future payoff differences as a function of observable state variables and choice

[5] In our model this is reasonable since state variables are either exogenous such as prices at the central location and transportation costs, or do not change over time such as geo-physical attributes of land.

decision *j* but not as function of unobservables, and it greatly simplifies the computation of *EV(.)*. Using AS and CI assumptions, the value function in equation 6 can be re-written as follows:

$$V(x_{lt}) = \int_{\varepsilon} \max_{c_j} \left\{ \Pi(x_{lt}, c_{jt}) + \varepsilon(c_j) + \beta \int_{x_{t+1}} V\ (x_{t+1}, c_{j,t+1}) f(x_{t+1} \mid x_t, c_j) \right\} g(\partial\varepsilon \mid x)\,. \qquad \textbf{(14)}$$

In the absence of perfect knowledge of the state variables, the researcher can reframe the problem in terms of probabilistic solutions; what is the probability for the researcher to observe the land operator making a particular decision $c_j$ conditional on the available information?

Assuming that $\varepsilon$ are IID with type I extreme-value distribution whose CDF is $F(\varepsilon_i < \varepsilon) = \exp(-e^{-\varepsilon})$ and PDF is $f(\varepsilon_i) = \exp(-\varepsilon_i - e^{-\varepsilon_i})$, the choice probabilities $\Pr(c_j \mid x_t)$ are given by the multinomial logit formula:

$$P(c_{i,t} \mid x_t) = \frac{\exp(\Pi(x_t, c_{it}) + \varepsilon(c_j) + \beta V\ (x_{t+1}, c_{i,t+1}))}{\sum_{j \in J} \exp(\Pi(x_t, c_{jt}) + \varepsilon(c_j) + \beta V\ (x_{t+1}, c_{j,t+1}))}\,, \qquad \textbf{(15)}$$

The presence of the term $\beta E[V(x_{lt}, c_{jlt})]$, called the continuation value in the dynamic programming literature, constitutes the main departure form the static multinomial logit formula. It captures the effect of current choices on future states of the system. The continuation value can be interpreted as a “shadow price” for the effects of each action on future payoffs, and must be added to the current profit in order to describe the optimizing behavior of the operator. Rust (1994) notes that this dynamic version of the multinomial logit does not suffer from the IIA problem. In the dynamic version, the way the value function V is specified implies that all alternatives are taken into account at each stage. The continuation value poses some problem from an estimation standpoint since it normally requires that the researcher solves the fixed point contraction mapping problem, which involves the use of computationally demanding backward recursive methods. Hotz and Miller (1993) found an alternative method to dealing with the continuation value. Their method avoids the need to repeatedly re-solve the dynamic problem to obtain a solution to the fixed point problem. We follow Hotz and Miller (1993) and write 14 as follow:

$$V(x_{lt}) = \sum_{j=1}^{J} P(c_{jt} \mid x_t) \left\{ \Pi(x_t, c_{jt}) + e(c_{jt}, P) + r \sum_{x} V_\theta(x_{t+1} \mid x_t, c_{jt}) f(x_{t+1} \mid x_t, c_{jt}) \right\}. \qquad \textbf{(16)}$$

[6]

Equation 16 can be solved to directly obtain $V(x_{lt})$ . Re-writing in compact matrix notation:

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[6] Note that the space for the state variable has been discretized $\{x_1, \ldots, x_M\}$ where M is the size of the discretization grid.

$$V(x_{lt}) = (I_M - \beta[\sum_J P(c_{jt}) * F(c_{jt})])^{-1} \left\{ \sum_{j=1}^{J} P(c_{jt}) * \left[ \Pi(x_t, c_{jt}) + e(c_{jt}, P) \right] \right\}, \qquad \textbf{(17)}$$

where $I_M$ is the identity matrix, $P(c_j)$ is an (M(J-1) X 1) vector and $F(c_j)$ is an (M X M) matrix of unconditional transition probabilities induced by $P$, $\Pi(.)$, and $e(.)$ are M X 1 vectors that stack the corresponding elements at all states for choice alternative $c$, and * is the Hadamard (or element-by element) product. This reformulation of the value function exploits the fact that the value function can be expressed in terms of choice probabilities, transition probabilities, and payoff function. Once the transition probabilities $f(x_{lt+1}|x_{lt}, c_{ljt})$ are computed, estimates of the parameters of the payoff function can be obtained using the nested pseudo-likelihood algorithm (NPL) proposed by Aguirregabiria and Mira (2002). Aguirregabiria and Mira build upon Hotz and Miller's work that shows how the researcher need not to repeatedly re-solve the dynamic problem to obtain a solution to the fixed point problem and estimates for the parameter values as in Rust (1986), but can exploit that the value function can be expressed in terms of choice probabilities, transition probabilities, and payoff function. The drawback of Hotz and Miller's estimator (the Conditional Choice Probabilities estimator, CCP) was a loss in efficiency compared to the computationally burdensome but efficient Rust's estimator (Nested Fixed Point Estimator, NFXP). Aguirregabiria and Mira demonstrate that by using a policy iteration operator a two-stage algorithm can be constructed such that starting with a non-parametric estimate of choice probabilities estimates of the structural parameters can be obtained and these estimates can be used to update the choice probabilities estimates, and the process repeated. This new algorithm bridges the gap between Rust's and Hotz and Miller's estimator since the asymptotic distribution of this estimator is the same as the NFXP. We turn now to describe the law of motion for the observed state variable $x_{lt}$ with three possible land uses - forest, agriculture, idle – and where

$$x_{lt}^{'} = \left\{ p_{Ft}, p_{At}, p_{It}, D_{lt}^{I}, D_{lt}^{O}, A_{lt} \right\},^{7} \qquad \textbf{(18)}$$

and $p_{Ft}, p_{At}, p_{It}, D_{lt}^{I}, D_{lt}^{O}, A_{lt}$ are vectors of size M whose values span the space of each variable. These values can be obtained through discretization over a grid of size M, or can be the values that the variables take during the period under consideration. Decisions made by land owners at time $t$ have an effect on the value of the state variable at time $t+1$. For instance, a farmer who clears primary forest to grow a field crop makes reverting to forest the next time period impossible. Moreover, in certain conditions, typically tropical or rain forest, the decision of clearing forest to cultivate the land causes a decrease in soil fertility. We describe how the current choice (which acts as a

[7] Note that, since our payoff function (eq. 3.4.2) accounts for future decisions and possible land use changes, in order to describe the state of the system we also need to incorporate prices for all three possible outputs.

control variable) affects future values of the state variable as: $x_{t+1} = \Omega * c_{jt} \bullet x_t$, where * is the Hadamard (or element-by element) product and $\bullet$ is the inner product of two matrices, $\Omega$ is a transition probability matrix (Markov matrix) which defines the probability that $x_t$ might take on a range of possible values at time *t+1,* and $c_{jt}$ is a conformable matrix which modifies the transition probability matrix according to the choice. In this study we assume that transportation costs *D*, for both inputs and outputs, and productivity shifter characteristics *A* are constant for the period under analysis and that only output prices change with time. No new roads were built during the time period considered so that any change in transportation cost would affect all parcels equally. We do assume that transportation cost ratios for different outputs stay constant throughout the whole period. Some geophysical characteristics might have changed during the 12 year used to calibrate the model. In particular, soil quality and its suitability to different uses might have varied with time. However, we would need more accurate information on soil fertility in order to introduce this process in our model. Therefore, our law of motion is only a first approximation of how the state variable truly evolves in time, and is limited to changes in output prices. It is important to point out however that, as new information becomes available, the model can be extended to account for changes to other explanatory variables (i.e. changes in transportation costs, changes in soil fertility caused by continuous cultivation). Our law of motion requires that we define a transition probability matrix which defines probabilistically the evolution of the system. In this study we take the land operator perspective and the transition probability matrix will be a representation of his expectations about the evolution of the system. For this the transition probability matrix has two components. The first component we use for our transition probability matrix looks at the "spatially aggregated[8]" likelihood for a parcel to stay in the same use or to change land use in the next time period and is estimated nonparametrically using cross-tabulation. These estimates provide for each time period t the spatially aggregated probability λ for a plot l to stay in the same use *j* at time *t+1* or to switch to any other use $j_t \neq j_{t+1}$ $j \in \{1,....,J\}$. We consider these probabilities to be a measure of how favorably a land owner considers switching to an alternative land use in the future. The likelihood (λ) for a parcel to stay involved in the same use or to switch to other uses is also an estimate of the probability that the price that determines the profit generated by a parcel will follow the evolution of the price for output j as opposed to one of its alternatives: $\lambda = \Pr\{c_{j,t+1} \mid c_{jt}\} = \Pr\{p_{j,t+1} \mid c_{jt}\}, j \in \{1,....,J\}$. The second component of our transition probability matrix

[8] We call it spatially aggregate likelihood since the probability of changing land use is derived from the whole population of observations and it is not a good measure of the probability that a parcel, with specific geophysical and locational characteristics, has to change land use.

incorporates a measure of product price expectations. For each possible output the land operator will have some expectations about future output prices. We follow Taylor and Burt (1984) and assume that these expectations are formed in a simple Markovian fashion:

$$p_{jt+1} = \alpha_1 p_{jt} + \sigma_{jt+1} \quad . \qquad \textbf{(19)}$$

That is, the land operator knows what future prices for each output in the next time period will be up to a random parameter σ. From equation 19 we derive, from the land-user's perspective, the probability that an output price at time *t* might take on a certain range of values at time *t+1*. These probabilities are calculated by finding the probability of a price to be within the upper and lower bound of an interval identified as:

$$\pi \; = \Pr\left\{ p_{j,t+1} \pm {}^{\sigma_{j,t+1}}\!/_{2} \mid p_{j,t}, c_{j,t} \right\} j \in \{1,....,J\} .$$

For each use *j* the Markov transition probability matrix $\Omega$ will have N x N elements where each element $\omega_{iy}$ is the joint probability $f(\lambda,\pi)$. In our empirical analysis we will assume that spatially aggregated probability and the land operator's price expectations are uncorrelated and therefore $f(\lambda,\pi) = f_1(\lambda) f_2(\pi)$[9]. We use the equation of motion for our state variable to incorporate the irreversibility of certain choices in our model. For example, once forest is cleared, it is impossible to benefit from prices for logs for a certain number of future time periods. We use a proper form of $c_{jt}$ to capture the irreversibility process: zeros are injected in $\Omega$ so that prices of unattainable uses do not enter in the expectation formation. For example:

$$\begin{array}{cc}
 & \begin{array}{cccccccccccc} p_{Ft1} & \cdot & \cdot & p_{Ft5} & p_{At1} & \cdot & \cdot & p_{At5} & p_{It1} & \cdot & \cdot & p_{It5} \end{array} \\
\begin{array}{c} p_{Ft1} \\ \cdot \\ \cdot \\ p_{Ft5} \\ p_{At1} \\ \cdot \\ \cdot \\ p_{At5} \\ p_{It1} \\ \cdot \\ \cdot \\ p_{It5} \end{array} &
\left( \begin{array}{cccccccccccc}
\varpi_{11} & \cdot & \cdot & \varpi_{1v} & \varpi_{1w} & \cdot & \cdot & \varpi_{1x} & \varpi_{1y} & \cdot & \cdot & \varpi_{1z} \\
\cdot & \cdot & & \cdot & \cdot & \cdot & & \cdot & \cdot & \cdot & & \cdot \\
\cdot & & \cdot & \cdot & \cdot & & \cdot & \cdot & \cdot & & \cdot & \cdot \\
\varpi_{v1} & & & \varpi_{vv} & \varpi_{vw} & \cdot & \cdot & \varpi_{vx} & \varpi_{vy} & \cdot & \cdot & \varpi_{vz} \\
0 & 0 & 0 & 0 & \varpi_{ww} & \cdot & \cdot & \varpi_{wx} & \varpi_{wy} & \cdot & \cdot & \varpi_{wz} \\
0 & 0 & 0 & 0 & \cdot & \cdot & & \cdot & \cdot & \cdot & & \cdot \\
0 & 0 & 0 & 0 & \cdot & & \cdot & \cdot & \cdot & & \cdot & \cdot \\
0 & 0 & 0 & 0 & \varpi_{xw} & \cdot & \cdot & \varpi_{xx} & \varpi_{xy} & \cdot & \cdot & \varpi_{xz} \\
\varpi_{y1} & \cdot & \cdot & \varpi_{yv} & \varpi_{yw} & \cdot & \cdot & \varpi_{yx} & \varpi_{yy} & \cdot & \cdot & \varpi_{yz} \\
\cdot & \cdot & & \cdot & \cdot & \cdot & & \cdot & \cdot & \cdot & & \cdot \\
\cdot & & \cdot & \cdot & \cdot & & \cdot & \cdot & \cdot & & \cdot & \cdot \\
\varpi_{z1} & \cdot & \cdot & \varpi_{zv} & \varpi_{zw} & \cdot & \cdot & \varpi_{zx} & \varpi_{zy} & \cdot & \cdot & \varpi_{zz}
\end{array} \right)
\end{array} \qquad \textbf{(20)}$$

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[9] While this assumption might not hold in the long run, expectations on future prices in the short run have an effect on land use decisions that might be of both speeding up the switching process or delaying it due to sunk costs, irreversibility of investments, and option value.

in a Markov Transition Probability matrix, with five time periods, constructed as 20, Forest prices ($p_{Ft1} - p_{Ft5}$) do not become part of the expectation for a land owner who is involved in agricultural production at time *t1*.

Transition probabilities so constructed capture the fact that once a particular decision has been made at time *t* certain uses might not be available at time *t+1*. The idea that certain choices restrict the future choice set is similar to the "terminal states" introduced by Holtz and Miller (1993) in the sense that we assume that there are states, agricultural uses in this case, in which land users get "locked in" once they are chosen. The difference is that we build in irreversibility in the Markov transition probability matrix.

***Correcting for Spatial Lag Effects***

The variables in this analysis are derived from data where potentially important spatial relationships exist. For example, all else equal, it seems plausible to expect that a location is more likely to have human intervention if the neighboring locations have human intervention. In addition, some of the data handling procedures introduce the potential for spatial effects. These include various aggregation effects (e.g., reducing the number of land uses and resampling elevation and slope grids from 92 meters to 500 meters), border effects from the conversion of polygons to grids (a cell might fall on the border between two polygons), and the use of cost of access as a proxy for all input and output prices. There is also a potential spatial bias if the unit of observation (the 500 meter square cell) differs systematically from the unit of decision-making. We use two procedures to reduce potential spatial correlation. First, following Besag (1974) as described in Haining (1994) (pp. 131-133) we use a coding scheme, selecting a sample from the full data set so no two sites in the sample are neighbors (neighboring cells in the sample are 5 pixels (2.5 km) apart in the full data set. Once the estimates for the coefficients are obtained they can be used for a simulation of land use choices on the full data set. Second, we include spatial lags of two right hand side variables – slope and the soil index. This approach assumes that substantive spatial effects are primarily associated with soil type and slope. Each lag variable is the average of the values of the original variable in the eight cells surrounding the location. To evaluate how successful these methods are, a version of the Moran's I applicable to limited dependent variables proposed by Kelejian and Prucha (2001) to test for spatial autocorrelation was used.

## Data Sources, Data Handling, and Explanatory Variables.

In this section we describe the data set used for this research, how the data have been manipulated, and what explanatory variables were used and how they were created. The area of study is the Darién province of Panama, a remote and environmentally important region located at the southeastern end of Panama. A sustainable development project financed by the Inter-American Development Bank (IDB) in 1998 collected spatially explicit data on land use, property rights and culture of the area. The principal source of data was a spatial data set prepared by the engineering firm Dames and Moore as part of an Interamerican Development Bank project. The data consist of over 80 coverages stored in Arc Info and Arc View file formats. Variables include land use, location of population centers by ethnic group, temperature, elevation, soil type, elevation, and political boundaries. This data set was integrated with two satellite images, Landsat 5 for the year 1985 and Landsat 7 TM for the year 2000. Sensors carried by satellites record the radiation reflected by the earth surface and the smallest unit, called pixel, varies according to the type of sensor mounted on the satellite. Most of these studies use images recorded by a sensor called Thematic Mapper (TM) that has a pixel size of approximately 30 x 30 meters. However, before the econometric estimation is undertaken pixels are aggregated[10] into units of larger size. In this study we used a unit of size 500 meters by 500 meters. Data on land use choices represent our dependent variable. Land use maps were obtained from Landsat 5 and 7 TM images for the years 1985, 1987, 1997, and 2000. Geometric rectification was carried out using nearest-neighbor resampling algorithm, with a root mean square (RMS) error of less than 0.5 pixels (< 15 m). Existing Dames and Moore land use maps for 1987 and 1997 were also used. Land use is a categorical (qualitative) variable. Previous land use studies of the same area (Nelson et al. 2001a and 2001b) have used a more disaggregated categorization that included several categories forest and crop land. The more detailed categorization was based on the original land use categories as defined by Dames and Moore land use maps. For this study, the land use maps for the year 1985 and 2000 are derived exclusively from photo-interpretation done by the author using satellite images for those two years. We felt that without verification on the ground of the photo-interpretation quality we could only discern between very broad categories of land use. Therefore, for our land use categorization we use three classes: Forest, Agricultural Uses, and Idle Land. These three categories have a spectral signature[11] characteristic enough to allow the interpreter to confidently discern between categories. For this study the category forest includes all types of forested land, agricultural uses includes pasture and crop land, and idle land encompasses all those land use categories that do not have a profit generating output.

***Geophysical data***

Geophysical variables determine the potential productivity of different land uses at each location. The temperature data set provided by Dames and Moore has values ranging from 21.5 to 27.0 degrees average annual temperature.

[10] This operation was performed using the nearest neighbor interpolation option in ArcView. The nearest neighbor interpolation calculates the value for an output pixel from the values of the four nearest pixels in the input image based on the weighted distance to these pixels.
[11] For any given material, the amount of solar radiation that reflects, absorbs, or transmits varies with wavelength. This important property of matter makes it possible to identify different substances or classes and separate them by their spectral signatures.

As might be expected the lower temperatures are found at higher elevations. The correlation coefficient between temperature and rainfall is 0.99; hence we exclude the rainfall variable from our analysis. Average temperature is 25.71 C°, 26.47 C°, and 26.74 C° for pixels classified as Forest, Agriculture, and Idle respectively. Elevation values were derived from a radarsat raster image with pixel size of 92 meters and then resampled to 500-meter cells. The highest point in the province is 1,800 meters but much of the province is close to sea level. The average elevation for the whole area is 291 meters. However, some land use categories have very different average values. The average elevation of a forested plot of land is 356 meters above sea level (asl) and much lower for land classified as Agriculture and Idle: 108 meter asl and 71 meter asl respectively. To avoid convergence problems during the estimation due to great differences in number magnitudes all values were divided by 100. We assume that slope inside a single pixel is constant. The average slope for each pixel was calculated from the original data on elevation and the average slope for the area is 6.7 degrees. There is a considerable difference between the average slope of pixels classified as Forested land (13.51 degrees) and the average slope of pixels classified as Agricultural land (3.14 degrees). Lower values of slope, below 5 degrees, are considered particularly suitable for agriculture. Digital soil maps prepared by Dames & Moore identify seven broad soil categories in the area of study. These categories are used to create an index (SOILINDX) that ranks the various soil types according to their suitability to agricultural uses. This index ranges from zero for least productive soils for annual crop production to six for most productive soils. We include spatial lags of two right hand side variables: LSLOPE for slope and LSOIL for the soil index. This approach assumes that substantive spatial effects are primarily associated with soil type a slope. Each lag variable is the average of the values of the original variable in the eight cells surrounding the location.

***Socioeconomic Data***

The following variables are chosen to reflect the effect of socioeconomic variables on the payoff function. Agricultural activities for the area are described as mainly based on forest exploitation, cattle rising, and some field crops. Cattle meat, milk, corn, rice, ñame, and beans are mostly sold at the local markets (OEA (1978)). Some of the production of the area is also exported to Panama City and Costa Rica. Total exported production is estimated to be some a total of 166,000 tons, 71,000 of which are wood products and 95,000 tons of harvested crops (Lavial (1998)). The functional form we have chosen to represent input and output prices (equation 10) assumes that prices as experienced by farmers have two components. The first component ($p_{j0}$, $w_{j0}$) is the market price for an input or an output, or its price at a hypothetical central location, and the second component ( $D_{jl}^{O}$ , $D_{jl}^{I}$ ) represent the cost of shipping a product to the market or an input from the market to the farm. Ideally, we would construct the relevant prices at each location using information regarding input and output flows to and from various markets and information regarding prices at the different markets. Unfortunately we do not posses this information. We therefore assume that there is no spatial differentiation in market prices: the price of an input or an output is the same at all markets. As we do not have information regarding what is actually produced at each location, we use the average price of several possible outputs to create our explanatory variable output price (PRICE). If a plot of land is classified as forested land the possible outputs considered are industrial roundwood, sandwood, and wood-based panels. If a parcel is classified as agricultural uses the possible outputs are rice, corn, cow milk, cattle meat and chicken meat. We used data on output prices at the country level as reported by FAO in its statistical database available online at http://www.fao.org/waicent/portal/statistics_en.asp. This data set reports yearly national average prices of individual commodities received by farmers when they sell their own products at the farm gate or first-point-of-sale. With all its limits, limits that mostly restrict its use when a comparison between countries is necessary, this dataset is capable to capture general upward or downward trends in prices. Over the period under consideration, from 1985 to 2000, prices for forest products show a greater variability than prices for agricultural products and while prices for agricultural products show an upward trend, prices for forest products seem to be stationary or exhibit a downward trend in time. Average values for agricultural products range from 880.87 (PAB/MT) in 1985 to 1375.27 (PAB/MT) in 2000 and average values for forest products from 300.73 (PAB/CM) in 1985 to 260.95 (PAB/CM)[12] in 2000. All prices have been deflated using 1990 as reference year and divided by 10 to avoid variables of very different magnitudes which could cause convergence problems during the estimation process. We do not have data on input prices at the market ($w_{j0}$) we assume that differences in farmgate input prices ($w_{jl}$) are related exclusively to transportation costs. This assumption is tenable for bulk inputs such as fertilizers, but less clear for labor inputs. As these data are unavailable, we follow a method used in previous studies (Nelson et el. (1999, 2001a, 2001b), Munroe et al. (2002)) and use timber as a proxy for all transported outputs. In a study of logging in Brazil, Stone estimated the costs of transporting a cubic meter of wood over various land surfaces and navigable waters (Stone (1998)). We calibrated these cost estimates to reflect local conditions based on information gathered in the field and in consultation with project staff. Our per-metric-ton cost estimates of traversing a kilometer with the following land uses are: primary road, \$0.10; secondary road, \$0.15; navigable river, \$0.08, forest, \$3.00, human intervention, \$0.2–0.5; marsh, \$3.00. These costs are then adjusted to reflect the higher cost of moving over sloping ground. The CostDistance module in ArcView calculates the least cost route to the nearest

[12] PAB = Panamanian Balboa interchangeable with the dollar one-to-one; MT = Metric Tonnes; CM = Cubic Meters.

feature (eg. road) by traversing a friction surface. We constructed the friction surface considering that the final destinations of products can be villages and towns in the area (COSTVBAS) or products can be shipped to Panama City (COSTNBAS). The average cost of access to different land use categories varies quite dramatically (Table 5) and is indicative of their locational rents. The average cost from a forest pixel to the northern destination outside the province (COSTNBAS) is $89.58/mt because these locations are both remote and have a high slope. The average cost from an Agricultural pixel is only $30.32/mt because these are located on relatively flat ground in the northern part of the province. All transportation costs values were divided by 10 to avoid variables of very different magnitudes which could cause convergence problems during the estimation process. Moving in or out of a land use is not frictionless and the process of switching to a new land use requires investments and acquisition of new knowledge. It might also result in a greater uncertainty regarding costs and revenues generation, and there are sunk costs involved in a land use change. We focus here solely on the temporary productivity changes that derive from switching from one land use to another. The underlying assumption is that there is a difference between the productivity of two landowners who have been engaged in the same type of production for different lengths of time. The difference between productivity levels might be due to learning processes involved in a production activity, and these learning processes reward a producer who stays involved in the same activity for a longer period. We also assume that the economic agent is aware of these differences and acts accordingly. Since we do not have any data on changes of productivity through time we have added to the other productivity shifters (i.e. geophysical characteristics) a variable that keeps track of the number of years that a plot of land has been continuously involved in the same use. This explanatory variable (SWITCH) averages 9.52 years for pixels classified as forest and 5.18 and 5.91 years for pixels classified as agriculture or idle respectively.

## Results

In order to proceed with our analysis we need to construct the Markov transition probability matrix. The Markov transition probability matrix is a representation of the expectations that the land operator has regarding the evolution of the system and it is formed by two components: one, estimated non-parametrically, is a measure of how favorably a land owner considers switching to an alternative land use in the future. The second component, estimated using simple ordinary least square regression, is a measure of the land operator expectations regarding future output prices. Simple cross-tabulation was used to determine non-parametrically the spatially aggregated land use transition probabilities. Table 2 shows the results of cross-tabulation. We use these aggregated transition probabilities as a measure of how favorably the average land owner looks at a land use change in the next time period and as an indication of the weight the land owner puts on the prices of the alternative land uses. We assume that expectations regarding future output prices are formed following equation 20 which assumes that the land operator will only look at the price of a product at time *t* to forecast its value at time *t+1*.

The first order autoregressive model expressed in equation 20 was estimated using yearly output prices provided by the FAO statistical database for the period 1963 – 2000. The estimation based on 38 observations returned the following results:

$$p_{(forest)t+1} = \underset{(3.457)}{0.77}\, p_t \quad R^2 = 0.57 \quad \sigma_e = 92.12$$

$$p_{(agriculture)t+1} = \underset{(100.7)}{1.02}\, p_t \quad R^2 = 0.80 \quad \sigma_e = 32.93$$

where $\sigma_e$ is the standard error of the estimate and t-statistics are in parenthesis. Since all the other state variables are assumed constant during the period under consideration, all the uncertainty regarding future states of the system is concentrated in the evolution of output prices. Using a numerical integration routine,[13] the results of the first order autoregressive model were used to compute for each land use the probability that, given a particular price at time *t*, the price at time *t+1* will fall in an interval of width $\pm \sigma_{/2}$ centered on the possible states of the system, which are the realized prices at the different time periods. We used the spatially aggregated transition probabilities and the land operator's expectations to derive each element $\omega_{ij}$ of the Markov transition probability matrix. We don't have any data on land use and output prices after the year 2000, but we need one more time period to construct the land operator's expectations in the year 2000. We therefore assumed that the aggregated transition probabilities for the period 2000 – 2003 are the same as the period 1997 – 2000 and that prices in the year 2003 correspond exactly to prices predicted by ordinary least square regression following equation 20. In the Markov transition probability matrix the year 2003 becomes an absorbing state, which is a state that is not exited once it is entered. We need therefore to turn our attention to decisions that might alter the set of possible choices in the future. In particular, the choice of clearing forest to grow field crops has some of the characteristics of an irreversible choice and this is particularly true when the valuable trees on a plot of land are part of the primary forest. The land operator takes into consideration the effects of his choices, a model of land use choice and land use change needs to have a mechanism that equally accounts for that. In our equation of motion, $x_{t+1} = \Omega * c_{jt} \bullet x_t$, the land use choice acts as a control variable modifying the Markov transition probability matrix in such a way that once agricultural uses are chosen it is not possible to revert to forest in the future. More formally, while $c_{2t}$ and $c_{3t}$ that represent agriculture and idle

[13] We used a modified version of Aguirregabiria's Transprob code available at: http://people.bu.edu/vaguirre/programs/programs.html

choices live the Markov matrix unaltered, $c_{1t}$, the choice forest, injects a series of zeros in the Markov matrix so that the probability of moving from agriculture to forest is zero. The result of the Hadamard multiplication between the Markov matrix and $c_{1t}$ is shown in table 3.

***Estimation results***

We used 3 years, 1985, 1987, and 1997, to calibrate the model. The initial data set had 63,894 observations. After applying the coding scheme (selecting every 5th pixel in every 5th row) and removing locations with some missing data, the sample size for each year used in estimation was 1,976. We have 3 land use categories and the 9 explanatory variables listed in Table 1 plus a constant. The first two columns in Table 4 show the parameter estimates for each explanatory variable. These estimates, their signs, are in line with our expectations and similar to results obtained in previous studies. An increase in slope or elevation reduces the probability of agriculture to be chosen, and increases in transportation costs to and from local markets (COSTVBAS) and to the region outlet (COSTNBAS) have similar effects. It is important to observe how the effect of prices and soil quality differs between agriculture and idle land choices. Higher market prices for agricultural outputs increase the probability of choosing agriculture while decreasing the probability of letting land idle. Similarly, the better the soil quality the higher the probability of observing agriculture, while the probability of letting land idle increases as the soil quality decreases. Another interesting result is the positive effect that the time spent in agriculture has on the probability of agriculture to be chosen in the next time period. According to our results the longer the time spent in agricultural activities the higher the probability that agriculture is the land utilization that returns the highest payoff. The parameter estimate seems to suggest that the transition from agriculture to other uses penalizes, comparatively, the payoff of the alternatives. The functional form of the profit function we have used for our analysis hypothesizes that the penalty is due to a loss in potential productivity. As we mentioned earlier this loss of productivity might be due to learning processes involved in a particular use and general knowledge of the sector necessary to reach a competitive productivity level. We can use the ratio of the estimated coefficients for the SWITCH and the PRICE variables to gain an insight on the value of each additional year of involvement in Agriculture. Taking the total derivative of our estimated function in 11 with respect to the variables $P$ and $s$ we obtain:

$d \ln \Pi_{jlt} = \eta_{1j} dP_{0t} + \eta_{5jl} d \ln s_l$. Equating $d \ln \Pi_{jlt} = 0$ we have $\dfrac{dP_{0t}}{d \ln s_l} = -\dfrac{\eta_{5jl}}{\eta_{1j}}$ and this gives us the magnitude of a change in price that compensates for one more year of experience farming land. For Agricultural uses we estimated 0.0667 for $\eta_{1j}$ and 0.1315 for $\eta_{5jl}$ and their ratio returns 1.97. Considering that during the estimation process all prices were divided by 10, we can say that one more year of experience in Agricultural production can compensate for a drop in output prices of 19.7 Balboas (the Panamanian currency).

It must be noted that this is an "average" effect. It is reasonable to think that a farmer is penalized by the lack of knowledge during the first few years of farming and that as time progresses the situation stabilizes. It is also important to observe that the investment costs of moving from one land use to an alternative are not considered and that therefore an advantage of staying in the same use derives from avoiding the cost of changing utilization.

***Predictive power of the Dynamic Discrete Choice Model***

In this section we analyze the predictive power of the dynamic discrete choice model using three methods: a pseudo-$R^2$, a ratio of total correct prediction to total number of observations, and a normalized prediction success index proposed by McFadden (1977). For the regression as a whole, a pseudo-$R^2$ measure for limited dependent variable regression is $1- \ln L/\ln L^*$ where L is the likelihood function value for the full model and $L^*$ is the value with only constants on the RHS. The value for this measure was 0.834. Table 4 presents the prediction matrix for the dynamic model. The model was estimated with the reduced set of data following the coding scheme described above. Then the estimated parameters were used to generate probability values for each location. The predicted land use at a location is the land use category with the highest probability. The prediction matrix in Table 4 compares the number of predictions (in the columns) with the actual categories (in the rows) for all observations. The overall predictive power computed as the ratio of the sum of correct predictions in the three categories to total number of cells is 0.887. The predictive power is consistently high for all three categories: Forested Land 0.870, Agricultural Land 0.903, and Idle Land 1.00. The misclassification occurs mostly between Forest and Agriculture, with 6,217 pixels erroneously classified as Agricultural land, and partially between Agriculture and Idle land, 855 pixels of the Idle Land pixels were misclassified as Agriculture.

***The value of the Discount Factor β***

The Nested Pseudo-Likelihood algorithm we used for our model, unlike the Nested Fixed Point algorithm by Rust, does not provide an estimate for the discount factor $\beta$ and $\beta$ is assumed to be known by the researcher. In recent studies that have used the NPL algorithm $\beta$ is fixed by the researcher at a value considered reasonable for the problem analyzed (Sanchez-Mangas (2002), Aguirregabiria and Alonso (2002)). Given the characteristics of our problem we do not know the value for the discount factor and as far as we know myopic behavior ($\beta = 0$) and forward-looking behavior ($\beta>0$) are a priori equally plausible. We experimented with different values of $\beta$ (0.60 –

0.95, with increments of 0.005[14]) and these return similar results but we have chosen the one that generates the highest overall prediction success index for the year 2000. This value is 0.885. Figure 2 shows how the overall prediction success index varies as different values of discount factor are adopted in the estimation.

***Measuring Spatial Correlation***

The variables in this analysis are derived from data where potentially important spatial relationships exist; as a result, the estimates obtained using spatially explicit data might be affected by spatial correlation. Although there are no well-established methods to incorporate spatial effects in limited dependent variable models there is a series of ad-hoc techniques, widely applied in the spatial literature, that are supposed to eliminate or at least mitigate the undesirable effects of spatial autocorrelation. In a previous study this author has investigated the effectiveness of these techniques (De Pinto and Nelson 2002), for this exercise we have decided to use two of the techniques that appear to be the more effective in removing spatial autocorrelation: regular sampling from a grid and spatially lagged geophysical variables. To check the effectiveness of this approach we used a version of the Moran's *I* test statistic suitable for a wide range of discrete choice models developed by Kelejian and Prucha (2001). Figure 3 shows the results when sampling is used. The significance of that statistic is given by a *t*-test, since the statistic is asymptotically normally distributed. The value of the statistic ranged from 122.32 with the full data set to 5.75 when the distance between observations increases to 2 kilometers. Therefore, according to this statistic, sampling our data set spatially reduced significantly the magnitude of spatial autocorrelation, but did not eliminate it completely. The cost of sampling is a reduced number of observations, but if the original sample size is large, which is often the case with this type of data, then the cost is not large. However, while the predictive power of the model is almost invariant as the sampling progresses (from 0.862 with the full data set of 63,894 observations to 0.887 with 1,976 observations) there is a considerable drop in predictive power when the distance between observations increases to 2.5 kilometers which causes the number of observations to decrease to 1,282. This is why we decided to use a sampling distance of 2 kilometers in the final analysis equivalent to selecting every 5$^{th}$ pixel in every 5$^{th}$ row.

## Comparison Dynamic Discrete Choice Model and Other Common Models of Land Use

In this section we compare the performance of the dynamic discrete choice model against the performance of other models of land use that are common in the literature. In particular, we performed a similar analysis of land use using a model that uses cross-sectional data and two models that use the entire panel data set. The models used are a multinomial logit model for the cross-sectional data, a mixed logit model that uses panel data, and a survival model

[14] For $\beta$ values below 0.6 the estimation process did not converge due to matrix singularity problems.

that uses panel data. With the static multinomial logit is impossible to predict what future land use choices will be when changes in output price ratios occur as result of agricultural policies or changes in world prices. The mixed logit model is static in the sense that there no connection between one time period and the previous or next, but can be used to predict future changes in land use. The survival model can be used to predict future changes in land use and accounts for some dynamics present in the system since it implicitly accounts for the option value of a choice. The estimating function used for these alternative models of land use is similar to the one used in the dynamic discrete choice model. However, the multinomial logit does not include output prices (PRICE) and the variable that keeps track of the number of years that a plot of land has been continuously involved in the same utilization (SWITCH), while mixed logit and survival model do include output prices but do not account for possible asymmetries between uses through the variable SWITCH.

***Results***

Table 4 shows that there very little difference among static and dynamic models as far as capturing the effects of the explanatory variables on land use. The signs of the estimated parameters are similar across all the different models. Interesting differences can instead be noted in the explanatory power of the different models. The dynamic discrete choice model appears to be superior in terms of explanatory power (Tables 5 and 6). The overall predictive power for the static multinomial logit is 0.861, which is lower than the overall predictive power obtained for the year 1997 using the dynamic discrete choice model: 0.901. The performance of the mixed logit is inferior to the performance of our model. When both models, mixed logit and dynamic discrete choice, are calibrated over three years 1985, 1987, and 1997 to predict the probability of a change in land use occurring in the year 2000, the overall predictive power of the mixed logit is 0.765 while for the dynamic discrete choice is 0.887. Noticeably, multinomial logit and mixed logit show a similar predictive power for land allocated to agriculture, 0.772 and 0.781 respectively. The transition to and from agriculture is where most of the land use change occur and consequently where the dynamic processes matter the most. The predictive power of the dynamic discrete choice model for agricultural land is 0.903. We believe this result corroborates our contention that dynamic processes need to be explicitly incorporated in the model. Lastly, we used a survival model calibrated on three years 1985, 1987, and 1997 to predict the probability of a change in land use occurring in the year 2000. The survival model correctly predicts some 68% of the change in land use in the year 2000 while the dynamic discrete choice model returns a perfect score with 100% of the change correctly predicted (Table 6).

### *Simulation of Change in the Socioeconomic Variables*

Earlier we hypothesized that disregarding important processes such as conversion costs between uses, option values, and expectations regarding the evolution of the system might cause a model to over predict land use change. Our results seem to support this hypothesis. The parameter estimates $\eta$s, can be used to simulate changes in the socioeconomic variables. We follow Nelson et al. (2001b) and simulated resurfacing the road by replacing the original cost variables with updated variables that reflect the reduced cost. We assume the resurfacing reduces the transport cost per cubic meter from \$0.10 to \$0.05 per kilometer; the total saving from a point that uses the entire road for transportation is approximately \$4 per cubic meter. Tables 7 and 8 show the results of the simulation using different estimation methods. These changes are calculated by comparing the predicted base values with the simulated values. Static multinomial logit and static mixed logit predicts a land use change for a total of 11,900 and 41,075 hectares respectively. The same simulation using the survival model predicts a change for 8,800 hectares. When road resurfacing is simulated with the dynamic discrete choice model, land use change occurs only for 6,600 hectares. Unfortunately, road resurfacing has not been undertaken in the area and our hypothesis is not testable against reality. We can only speculate that since the discrete dynamic model shows a higher overall prediction accuracy than all other models and since the introduction of dynamic processes, survival and dynamic discrete choice models, results in a smaller 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.

Interestingly, the differences between models are mostly in the number of hectares but not in the location of change. Most of the change occurs at the frontier between land uses (Figure 4).

## Conclusions

Models of land use change can be used to address a number of policy questions such as the effects on protected areas of changes in output price ratios or changes in the quality and extension of a road network. Time is thought to be an essential component for this type of analysis since most of the phenomena that determine land use decisions are not instantaneous but evolve through time. Disregarding the time dimension might lead to unreliable estimates for the determinants of land use and consequently to the formulation of wrong normative recommendations. Although the trend in the existing literature is to move from a static to dynamic models, the existing models that undertake intertemporal analysis are limited in the way they incorporate dynamic processes. We believe that the discrepancy in performance between our dynamic discrete choice model and the alternatives investigated in this study demonstrate how important it is for a model to approximate as much as possible the complexities of the decision process. The introduction in the model of, admittedly naïve, expectations regarding future output prices and a mechanism that causes friction between uses considerably increase the overall predictive power of the model. The results of our analysis also show that using panel data sets without creating a true dynamic mechanism does not add much insight compared to the static version of the model. Although in the model presented in this study we have created a link between economic conditions at the country level and land use choices, namely output prices, the model does not address other outside forces that can alter the incentives for land use in the Darien region. Specifically, the model does not address directly issues such as population growth or migration into the province from other parts of Panama. Spillover effects from Colombia, a worsening economic situation in other parts of the country, could all alter the incentives to in or out-migrate. These and other changes in macroeconomic conditions can be causes of substantial conversion of forest to human intervention areas and is material for further research. With regard to technology, further advances in remote sensing will serve to increase the sensitivity and accuracy of the biophysical data. It is important to consider that the predictive power of the model is already very high and that to further this type of analysis what is necessary is to improve the quality of our data. First, we need to have some verification on the quality of the data set and specifically the correspondence between land use as interpreted from satellite images and the ground truth. Without this information, we cannot make correct claims on the true predictive power. Secondly, we need to gather information on input prices. Researchers need to experiment with different functional forms but the absence of data on input prices has limited the researcher to the use of the Cobb-Douglas. Moreover, in order to further improve the predictive capability of the model we need more accurate data on soil quality and costs of access. The model we have proposed in this study is flexible enough to accommodate this additional information.


***Figure1:*** *Darién province overview.*

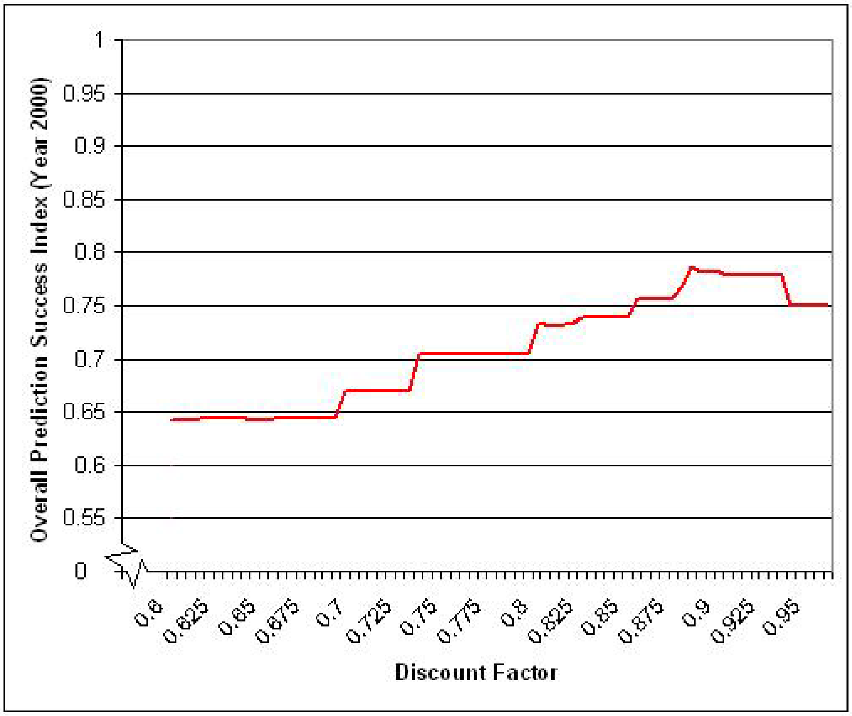


**Figure 2:** Effects of Changes in Discount Factor on Overall Prediction Success Index

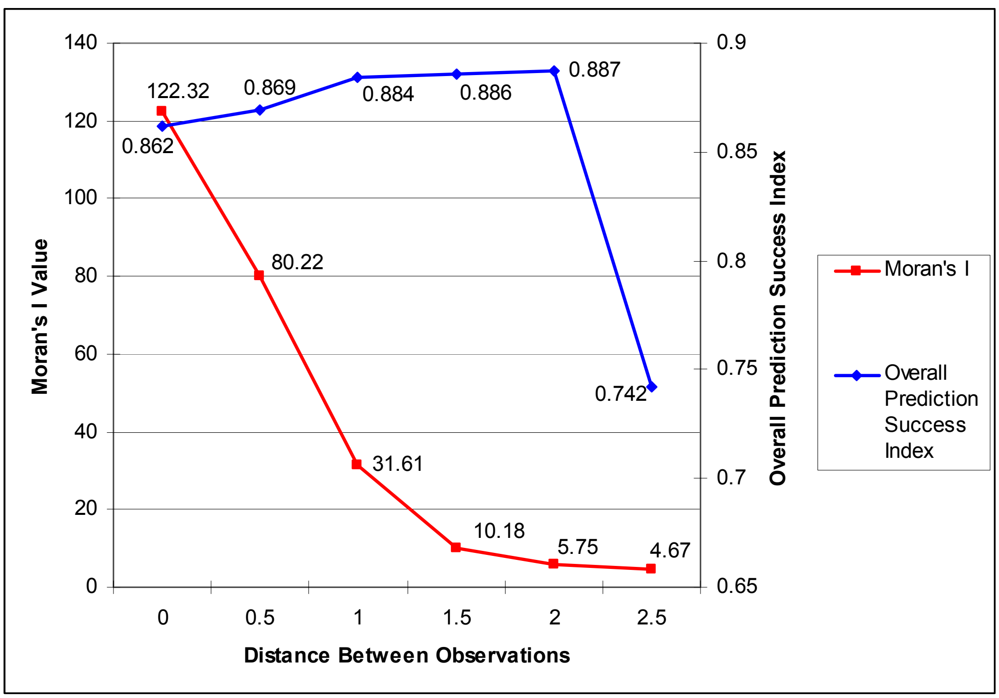


**Figure 3:** Significance of the Kelejian-Prucha Moran's *I* Statistic and Overall Prediction Success Index at Different Sampling Distances.

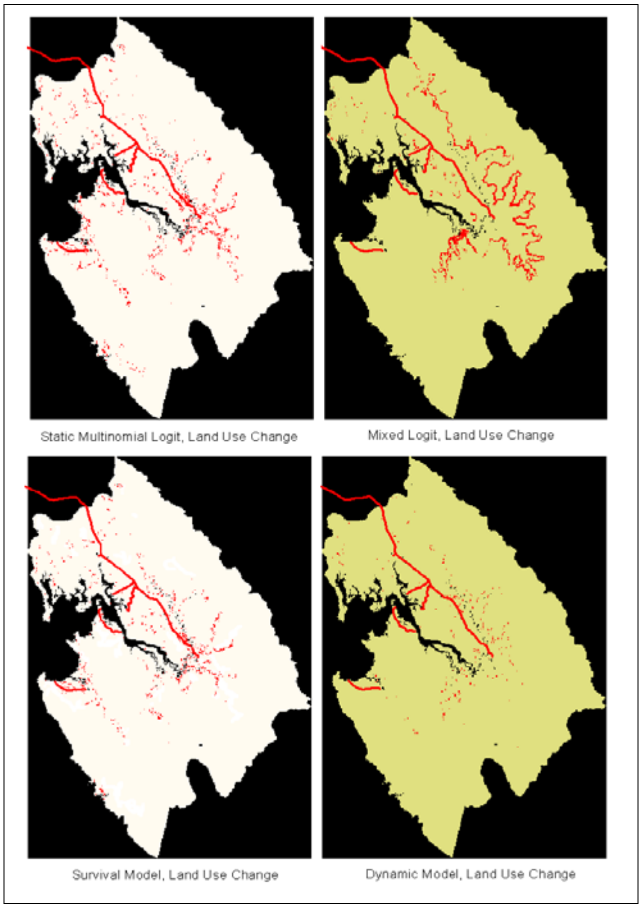


**Figure 4:** Land Use Change Caused by Road Resurfacing with Different Estimation Methods

**Table 1:** Mean values for explanatory variables for the province and within each land use category, year 2000.

| Variable Name | Forest | Agriculture | Idle | Whole Image | Units |
|---|---|---|---|---|---|
| *Geophysical variables* | | | | | |
| ELEVATION | 355.51 | 108.32 | 71.14 | 290.92 | Meters asl |
| TEMPERATURE | 25.71 | 26.47 | 26.74 | 25.93 | Degrees Celsius |
| SLOPE | 13.51 | 3.14 | 2.18 | 6.69 | Degrees |
| SOILINDX | 4.59 | 4.07 | 5.17 | 4.58 | 0 is lowest quality; 7 is highest |
| *Spatial Lag Variables* | | | | | |
| LSOIL | 4.61 | 4.14 | 4.94 | 4.58 | Ave. of SOILINDX in 8 neighboring pixels |
| LSLOPE | 7.95 | 3.27 | 2.26 | 6.69 | Ave. of SLOPE in 8 neighboring pixels |
| *Socioeconomic Variables* | | | | | |
| COSTNBAS | 89.58 | 30.32 | 35.13 | 75.61 | $/mt cost to nearest of northern border |
| COSTVBAS | 37.34 | 1.17 | 3.83 | 28.78 | $/mt cost to nearest inhabited village |
| SWITCH | 9.52 | 5.18 | 5.91 | 8.54 | Number of years in same use |

Source: Own calculations using Dames and Moore data set.

**Table 2:** Spatially Aggregated Land Use Transition Probabilities;
Years 1985 – 1987 – 1997 - 2000

| **Land Use Category** | Forest (1987) | Agriculture (1987) | Idle (1987) |
|---|---|---|---|
| Forest (1985) | 98% | 2% | 0% |
| Agriculture (1985) | 0% | 100% | 0% |
| Idle (1985) | 0% | 3% | 97% |
| | Forest (1997) | Agriculture (1997) | Idle (1997) |
| Forest (1987) | 69% | 20% | 11% |
| Agriculture (1987) | 7% | 87% | 6% |
| Idle (1987) | 4% | 6% | 90% |
| | Forest (2000) | Agriculture (2000) | Idle (2000) |
| Forest (1997) | 73% | 22% | 5% |
| Agriculture (1997) | 3% | 96% | 1% |
| Idle (1997) | 1% | 42% | 57% |

**Table 3:** Markov Transition Probability Matrix After Interaction with the Control Variable $c_{1t}$

| | | Forest Uses | | | | | Agricultural Uses | | | | | Idle Land | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $P_{t1}(1985)$ | $P_{t2}(1987)$ | $P_{t3}(1997)$ | $P_{t4}(2000)$ | $P_{t5}(2003)$ | $P_{t1}(1985)$ | $P_{t2}(1987)$ | $P_{t3}(1997)$ | $P_{t4}(2000)$ | $P_{t5}(2003)$ | $P_{t1}(1985)$ | $P_{t2}(1987)$ | $P_{t3}(1997)$ | $P_{t4}(2000)$ | $P_{t5}(2003)$ |
| **Forest Uses** | $P_{t1}(1985)$ | 0.240 | 0.339 | 0.350 | 0.051 | 0.000 | 0.005 | 0.015 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | $P_{t2}(1987)$ | 0.000 | 0.169 | 0.223 | 0.224 | 0.074 | 0.000 | 0.040 | 0.078 | 0.050 | 0.032 | 0.000 | 0.110 | 0.000 | 0.000 | 0.000 |
| | $P_{t3}(1997)$ | 0.000 | 0.011 | 0.113 | 0.301 | 0.305 | 0.000 | 0.000 | 0.109 | 0.104 | 0.007 | 0.000 | 0.000 | 0.050 | 0.000 | 0.000 |
| | $P_{t4}(2000)$ | 0.000 | 0.000 | 0.096 | 0.311 | 0.323 | 0.000 | 0.000 | 0.080 | 0.121 | 0.019 | 0.000 | 0.000 | 0.000 | 0.050 | 0.000 |
| | $P_{t5}(2003)$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.730 | 0.000 | 0.000 | 0.000 | 0.000 | 0.220 | 0.000 | 0.000 | 0.000 | 0.000 | 0.050 |
| **Agricultural Uses** | $P_{t1}(1985)$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.250 | 0.750 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | $P_{t2}(1987)$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.189 | 0.354 | 0.233 | 0.154 | 0.000 | 0.070 | 0.000 | 0.000 | 0.000 |
| | $P_{t3}(1997)$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.496 | 0.463 | 0.031 | 0.000 | 0.000 | 0.010 | 0.000 | 0.000 |
| | $P_{t4}(2000)$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.356 | 0.549 | 0.085 | 0.000 | 0.000 | 0.000 | 0.010 | 0.000 |
| | $P_{t5}(2003)$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.990 | 0.000 | 0.000 | 0.000 | 0.000 | 0.010 |
| **Idle Land** | $P_{t1}(1985)$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.008 | 0.023 | 0.000 | 0.000 | 0.000 | 0.970 | 0.000 | 0.000 | 0.000 | 0.000 |
| | $P_{t2}(1987)$ | 0.000 | 0.010 | 0.013 | 0.013 | 0.004 | 0.000 | 0.012 | 0.023 | 0.015 | 0.010 | 0.000 | 0.900 | 0.000 | 0.000 | 0.000 |
| | $P_{t3}(1997)$ | 0.000 | 0.000 | 0.002 | 0.004 | 0.004 | 0.000 | 0.000 | 0.208 | 0.199 | 0.013 | 0.000 | 0.000 | 0.570 | 0.000 | 0.000 |
| | $P_{t4}(2000)$ | 0.000 | 0.000 | 0.001 | 0.004 | 0.004 | 0.000 | 0.000 | 0.153 | 0.231 | 0.036 | 0.000 | 0.000 | 0.000 | 0.570 | 0.000 |
| | $P_{t5}(2003)$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.010 | 0.000 | 0.000 | 0.000 | 0.000 | 0.420 | 0.000 | 0.000 | 0.000 | 0.000 | 0.570 |

**Table 4:** Estimated Parameters by Land-Use Category Obtained Using Dynamic Discrete Choice Model, Multinomial Logit Model, Mixed Logit Model, and Survival Model

| | **Dynamic Discrete Choice Model¥** | | **Static Multinomial Logit Model¥** | | **Mixed Logit Model¥** | | **Survival Model¥¥** |
|---|---|---|---|---|---|---|---|
| **Variable Name** | Agriculture | Idle | Agriculture | Idle | Agriculture | Idle | |
| *Geophysical variables* | | | | | | | |
| ELEVATION | -1.222** | 0.098** | -0.635*** | -1.305*** | -0.822*** | -0.377*** | -0.03717 |
| TEMPERATURE | -1.963** | -1.160** | -0.818*** | -0.267 | -0.208* | -0.097 | 0.02009*** |
| SLOPE | -0.031* | 0.0009* | -0.024 | -0.040 | 0.008 | 0.001 | -0.01006** |
| SOILINDX | 0.296* | -0.020** | 0.172 | -0.792*** | 0.143* | -0.023*** | 0.10301*** |
| *Spatial Lag Variables* | | | | | | | |
| LSOIL | 0.202 | -0.006 | 0.135*** | 0.115** | 0.242*** | 0.075** | -0.07689** |
| LSLOPE | 0.202 | -0.006 | -0.244** | -0.855*** | 0.123** | 0.029*** | 0.00650 |
| *Socioeconomic Variables* | | | | | | | |
| COSTNBAS | -1.269* | -0.004 | -0.051** | -0.026 | -1.209** | -0.223 | 0.0051*** |
| COSTVBAS | -0.654* | -0.042* | -2.417*** | -1.227*** | -1.125*** | -0.033*** | 0.26477** |
| PRICE | 0.066** | -0.211** | - | - | 0.025** | -0.413** | 0.10721*** |
| SWITCH | 0.131** | -0.485* | - | - | - | - | - |

** Significant at the 1% level
* Significant at the 5% level
¥ These models are underidentified unless the parameters for one of the categories are known. It is standard practice to choose one category as the base and set its betas to zero (Greene, 2003, p 721). This means that the values of the estimated betas are relative to the betas in the base category. In our case we have chosen the base category to be Forest.
¥¥ The survival model estimates the effects of the explanatory variables on the probability of observing change in the next time period.

**Table 5:** Prediction matrix, (Number of 0.25 Km cells; columns are land use predictions, rows are actual land use)

| | Land Use | Forest | Agriculture | Idle | Total (True) | Ratio Correct Predictions to Total |
|---|---|---|---|---|---|---|
| **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 | **45,850** | 1,838 | 589 | 48,277 | 0.949 |
| | Agriculture | 1,525 | **6,618** | 423 | 8,566 | 0.772 |
| | Idle | 1,824 | 2,656 | **2,571** | 7,051 | 0.364 |
| | Total (Predicted) | 49,199 | 11,112 | 3,583 | 63,894 | 0.861 |
| **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 |

*Actual land use and predictions are for the year 2000
**Actual land use and predictions are for the year 1997

**Table 6:** Prediction matrix for Survival Model:
(Number of 0.25 Km cells; columns are predictions of change for year 2000, rows are actual change in the year 2000)

| | Land Use | No-Change | Change | Total (True) | Ratio Correct Predictions to Total |
|---|---|---|---|---|---|
| **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 | 0.951 |
| **Dynamic Discrete Choice Model** | No-Change | **58,511** | 1,549 | 60,060 | 0.974 |
| | Change | 0 | **3,834** | 3,834 | 1.000 |
| | Total (Predicted) | 58,511 | 5,383 | 68,394 | 0.991 |

**Table 7:** Effects of Road Resurfacing for the year 1997, Dynamic Discrete Choice Model vs. Multinomial Logit and Mixed Logit (Number of 0.25 Km cells*)

| | Forest | Agriculture | Idle |
|---|---|---|---|
| **Dynamic Model** | | | |
| Before Resurfacing | 41,890 | 14,935 | 7,069 |
| After Resurfacing | 41,654 | 15,171 | 7,069 |
| Net Change | - 236 | + 236 | 0 |
| **Multinomial Logit** | | | |
| Before Resurfacing | 49,199 | 11,112 | 7,063 |
| After Resurfacing | 48,723 | 11,486 | 7,165 |
| Net Change | - 476 | + 374 | + 102 |
| **Mixed Logit** | | | |
| Before Resurfacing | 35,752 | 20,376 | 7,069 |
| After Resurfacing | 34,109 | 22,019 | 7,069 |
| Net Change | - 1,643 | + 1,643 | 0 |

*Each cell is equivalent to 25 hectares

**Table 8:** Effects of Road Resurfacing on forecasted change for the year 2000, Dynamic Discrete Choice Model vs. Survival Model (Number of 0.25 Km cells*)

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

*Each cell is equivalent to 25 hectares

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