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Land Use Change with Spatially Explicit Data: A Dynamic Approach

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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 cross-sectional data sets. Recent attempts to move to a more dynamic analysis include using panel data sets and survival analysis. 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 irreversibility of some decisions, expectations about future prices, and forward-looking behavior of the land operator can all be accounted for. Our results show that a model specification that incorporates some of the complexities of the decision process improves upon results found in the existing literature. First, prediction accuracy of land use change is superior to any of the existing models. Second, we demonstrate that models that do not account for transactions costs tend to overestimate the effects of changes in transportation costs.

Keywords Land use · Deforestation · Discrete choice dynamic optimization · Dynamic optimization

1 Introduction

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 cross-sectional data sets (Chomitz and Gray 1995; Nelson and Hellerstein 1995; Deininger and Minten 2002; Chomitz and Thomas 2003). However, even the original publication by Chomitz and Gray (1995, pp. 493–494) acknowledged that important issues in land use change are inherently dynamic and that expectations of future prices and irreversibility of some land use choices should be considered. When cross-sectional data are used, all the dynamics and interactions responsible

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for the choice of a particular land use are assumed to occur contemporaneously. Disregarding the intertemporal components of the decision process can lead to errors in parameter estimates of interest. Schatzki (2003) finds that land use models that do not accurately incorporate the dynamics involved in the decision process—uncertainty in future payoffs, sunk costs, and cost of conversion—overestimate conversion rates from agriculture to forest in the state of Georgia. Provencher and Bishop (2004) find that static random utility models tend to overstate responses to changes in recreation site quality.

A few attempts have been made to incorporate dynamic mechanisms. Mertens et al. (2000) use land use trajectories to implicitly account for spatio-temporal complexities of land use decisions. Munroe et al. (2004) include time lags of the land use choice to include the intertemporal relationships among choices in the model. 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. The inclusion of temporal lags of the dependent variable is a common practice in discrete choice models to capture "inertia or variety-seeking behavior" (Train 2003). However, this method can cause estimation problems because most of the data (e.g., slope, elevation, distance to roads and villages) used in land use change models as explanatory variables do not change in time. Hence they are likely to be correlated with a lagged endogenous variable causing collinearity problems. Furthermore, land use change models are often used in areas for which only limited data exist so models are often not complete in their specification. A potential consequence is endogeneity and biased estimators. A group of studies (Boscolo et al. 1999; Irwin and Bockstael 2002; Vance and Geoghegan 2002), have experimented with survival analysis, framing the land use change problem in terms of optimal switching time and 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 but assumes irreversibility of any land use change.

In this paper, we develop and implement a dynamic qualitative-dependent-variable model that explicitly incorporates the land operator expectations about future prices and knowledge of the effects of current decisions on future options such as irreversibility of particular investments. Moreover, unlike previous studies, we can account for output prices at the central market so that it becomes possible to simulate the spatial differential effects of policies that alter output price ratios through time. The model uses some of the key concepts of dynamic programming in combination with the standard multinomial logit specification. Previous applications of this modeling technique include studies on women's fertility (Wolpin 1984), patent options (Pakes 1986), job search (Wolpin 1987), engine replacement (Rust 1987) and on changes in recreation site quality (Provencher and Bishop 1997). The computational burden of estimation has somewhat hindered empirical work in this area, but several methods have been proposed to reduce it (Keane and Wolpin 1994; Rust 1997; Hotz and Miller 1993). In this paper we use an estimator, the nested pseudo-likelihood algorithm (NPL) proposed by Aguirregabiria and Mira (2002) which bridges the gap between Rust's computationally burdensome but efficient estimator (nested fixed point estimator, NFXP) and the less efficient but less taxing estimator (the conditional choice probabilities estimator, CCP) proposed by Hotz and Miller (1993).

2 A Dynamic Model of Land Use Change

We assume that the observed land use is the result of an ongoing optimization process; at each point in time the operator chooses a land use with the highest expected net present value.[1] 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. The dynamic optimization process framework allows us to introduce explicitly complexities absent in other models of land use. First, land use choices are based on expectations on prices. Second, the decision made at a certain point in time can affect the future value of one or more explanatory variables, at times with characteristics of irreversibility. For example, when primary forest is cut, it is not an available choice in the next time period. Third, option values enter in the analysis. Option value, learning processes, and sunk costs all require that the expected profit needed to induce land use conversion must be significantly higher than the profit derived from the current use.

3 The Discrete-Choice Dynamic Programming Model

The state of the system faced by the agent[2] can be described by vector X:

$$X'_{lt} = \left\{\boldsymbol{p}_{jlt}, \boldsymbol{w}_{klt}, \boldsymbol{A}_{lt}\right\}, \tag{1}$$

where $j \in \{1, \ldots, J\}$ is an element of a finite set of possible land uses, l indicates the location at which production takes place, t is the time subscript, $\boldsymbol{p}$ is a vector of exogenous prices for j possible outputs, $\boldsymbol{w}$ is a vector of prices for k possible inputs necessary for production, and $\boldsymbol{A}$ is a vector of location specific features that are unchanging, such as soil quality, slope, and elevation, that affect land productivity.

At each time t the land operator makes a decision about the land use on a particular plot of land. Let j_{lt} indicate that alternative $j \in J$ is chosen at time t at location l. Alternatives are defined to be mutually exclusive (i.e. no multiproduct outputs are possible). The farmer knows the state at time t and has expectations on how the system evolves in future time periods. Furthermore, the agent is aware that decisions made at time t can influence the time path of the state variables. The agent's expectations about the evolution of the state variables are described by the following:

$$X'_{lt+1} = H\left(X'_{lt}, j_{lt}, \tau\right), \tag{2}$$

where τ is a parameter that characterizes the distribution H. The use of the Markov structure to model the agent's expectations implies that only the value of the set of the state variables X' at time t, and its law of motion is needed, i.e. the probability distribution H, to characterize how the state changes from one period to the next.

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 the single control variable j_{lt}. The agent behaves according to the following optimal decision rule:

$$\max_{j_{lt}} E\left[\sum_{t=0}^{\infty} \beta^t \Pi(X_{lt}, j_{lt})\right]. \tag{3}$$

[1] We make the assumption that profit maximization is equivalent to utility maximization. This can be an unrealistic assumption particularly when risk-minimization behavior might strongly influence land-use decisions. However, given the categories of land use we use for our analysis—agriculture, forest, and idle—the differences in behavior should not be appreciable.

[2] For the rest of the paper we use the terms agent, farmer, and land operator interchangeably.

The solution to the intertemporal optimization problem in Eq. 3 is given recursively by the Bellman equation and called the value function:

$$V\left(X_{lt}\right) = \max_{j_{lt}} \Pi\left(X_{lt}, j_{lt}\right) + \beta E\left[V\left(X_{lt+1}\right)\right], \tag{4}$$

where $\beta \in(0,1)$ is the discount factor. This function is essentially the same as the expected highest net present value. As Rust (1987) shows, under some mild regularity conditions the stochastic control problem takes the form of a deterministic and stationary decision rule given by:

$$j_{lt}^{*} = \operatorname*{arg\,max}_{j\in\{1,\ldots,J\}} \left[\Pi\left(X_{lt}, j_{lt}\right) + \beta E\left[V\left(X_{lt+1}\right)\right]\right]. \tag{5}$$

Note that the decision in Eq. 5 explicitly accounts for the optimal timing of land use change and the option value of an investment. Because the researcher does not observe all state variables, we divide the state variables into an observable and an unobservable component: x_{lt} and ε_{lt} respectively.

We assume that the payoff function is additively separable in the observable and unobservable components: $\Pi\left(X_{lt}, j_{lt}\right) = \pi\left(x_{lt}, j_{lt}\right) + \varepsilon\left(j_{lt}\right)$. Moreover, we assume that the unobservables are identically and independently distributed over time and over choice alternatives.[3] Expectations about the next period's state are conditional on the current state and choice and can be written as: $h_{\tau}\left(x_{lt+1}, \varepsilon_{lt+1}|x_{lt}, \varepsilon_{lt}, j_{lt}\right) = g_{\sigma}\left(\varepsilon_{lt+1}\right) f_{\varphi}\left(x_{lt+1}|x_{lt}, j_{jt}\right)$ where g is the density of ε_{t+1} with variance σ and f is the conditional choice transition probability of x_t with variance φ. The value function in Eq. 4 can be written as follows:

$$V\left(x_{lt}\right) = \int\limits_{\varepsilon} \max_{j_{lt}} \left\{\pi(x_{lt}, j_{lt}) + \varepsilon\left(j_{lt}\right) + \beta \int\limits_{x_{t+1}} V\left(x_{lt+1}\right) df_{\varphi}\left(x_{lt+1}|x_{lt}, j_{lt}\right)\right\} dg_{\sigma}\left(\varepsilon_{lt}\right). \tag{6}$$

Since the payoff depends in part on some unobserved factors, we need to reframe the problem in terms of probabilistic solutions; that is, what is the probability of observing a particular decision j_{lt} conditional on the available information? Assuming that ε are IID type I extreme-value distributions with mean zero, variance σ, and PDF $f\left(\varepsilon_j\right) = \exp\left(-\varepsilon_j\right)\exp\left(-e^{-\varepsilon_i}\right)$, the conditional choice probabilities that a land use i is chosen $\Pr\left(i_{lt}|x_{lt}\right)$ are given by the multinomial logit formula:

$$P\left(i_{lt}|x_{lt}\right) = \frac{\exp\left\{\pi\left(x_{lt}, i_{lt}\right) + \beta E\left[V\left(x_{lt+1}, i_{lt}\right)\right]\right\}}{\sum\limits_{j=J} \exp\left\{\pi\left(x_{lt}, j_{lt}\right) + \beta E\left[V\left(x_{lt+1}, j_{lt}\right)\right]\right\}}. \tag{7}$$

The presence of the term $\beta E\left[V\left(x_{lt+1}, c_{jlt}\right)\right]$, called the continuation value in the dynamic programming literature, is the main departure from 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 (1987) notes that this dynamic version of the multinomial logit does not suffer from the IIA problem. In the dynamic version, the specification of the value function V implies that all alternatives are taken into account at each stage.

[3] In the dynamic programming literature these two assumptions are commonly known as additive separability and conditional independence (Pakes 1986).

4 Specification of the Payoff Function

Assume producers have access to all k available inputs. They can combine these inputs to produce j possible different products.[4] Producers are free to choose any single output j and the output level to maximize profit. Following the existing literature (see Chomitz and Gray 1995; Nelson and Hellerstein 1995; Deininger and Minten 2002, among others), we use an indirect profit function based on a Cobb-Douglas production function to express at each time t the maximum one-period profit as a function of the output and input prices (see Beattie and Taylor 1993):[5]

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

where: α_{kj} are the exponents of the Cobb-Douglas production function and $\gamma = 1 - \sum_k \alpha_k$.

The vector of location specific features A_l functions as a productivity shifter. A is a multiplicative combination of a number of unchanging geophysical features G, such as soil quality, slope, and elevation, that affect land productivity and s_t, a time-dependent variable to capture possible temporary productivity effects that might delay or speed up the process of change. Several studies (Schatzki 2003; Stavins and Jaffe 1990; Plantinga 1996) have documented that moving into or out of a land use is not frictionless and including s allows us to partially capture that effect.

$$A_l = \left(\prod_{n=1}^{N} G^{\phi_n} * S^{\phi} \right), \tag{9}$$

The term s is specified as:

$$s = \frac{1}{1 + e^{\left(-\frac{t}{2}\right)}}$$

where t is the number of years a parcel of land has been in use j.[6] Taking the log of Eq. 8 gives:

$$\ln \Pi_{jl} = \ln \gamma_j + \frac{1}{\gamma_j} \left[\ln p_{jl} + \ln A_l + \sum_k \left(-\alpha_{kj} \ln w_{kjl} + \alpha_{kj} \ln \alpha_{kj} \right) \right]. \tag{10}$$

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

$$\begin{aligned} p_{jl} &= \exp\left\lfloor p_{j0} - \lambda_l D_{jl}^{0} \right\rfloor \\ w_{jl} &= \exp\left\lfloor w_{j0} + \delta_l D_{jl}^{I} \right\rfloor \end{aligned} \tag{11}$$

[4] Since we are assuming a one-to-one correspondence between land uses and outputs there are j possible land uses and j possible outputs.

[5] We assume that, even though technological changes may have occurred during the period under analysis, the Cobb-Douglas production function correctly represents the input–output relationship.

[6] This functional form has a sigmoid shape with one as the asymptotic value. The number of years t is divided by 2 to create sufficient variability in the explanatory variable to carry out the estimation process. Dividing t by different values changes the values of the estimates but not the signs or the number of correct predictions for each land use.

where p_{j0} and w_{j0} are prices at the market, D^0_{jl} and D^I_{jl} are costs of access measured from the market to location l for output j and inputs respectively. The reduced form of the one-period estimable function becomes:[7]

$$\ln \Pi_{jl} = \eta_{0j} + \eta_{1j} p_{j0} + \eta_{2j} D^0_{jl} + \sum_{n=1}^{K} \eta_{3nl} w_n + \eta_{4kl} D^I_l + \sum_{n=1}^{N} \eta_{5n} \ln G_{nl} + \eta_{6jl} \ln s_{jl}. \tag{12}$$

From the perspective of the researcher, the state of the system faced by the agent can be described by the following vector of variables:

$$x'_{lt} = \left\{ \mathrm{p}_{jlt}, w_{jlt}, D^I_{lt}, D^O_{lt}, G_{lt}, s_{lt}, \varepsilon_{lt} \right\}. \tag{13}$$

In our empirical analysis we make the common assumption in the literature (Chomitz and Gray 1995; Munroe et al. 2002; Nelson et al. 2001, among others) that differences in input costs are due only to differences in transportation costs. This means that w_{j0} are all identical. We also assume that transportation costs for both inputs and outputs and the productivity shifter s evolve deterministically and the geophysical characteristics G are constant for the period under analysis. Therefore we limit the system uncertainty to output prices.

If the farmer knew with certainty that a field would be in a particular land use forever, the only relevant information about future prices would the expected price of that output. However, if a field could potentially have multiple land uses, then other factors that influence the likelihood of conversion (conversion costs to the various land uses and other uncertainties) also influence the land use choice today. We use a Markov transition probability matrix to capture these two effects. The first is expectations about the evolution of each output price. The second is a measure to capture expectations about the other factors that influence the switch from one land use to another in the future.

For output price expectations we follow (Taylor and Burt 1984) and assume that they are formed in a simple autoregressive fashion:

$$p_{jt+1} = \alpha_0 + \alpha_1 p_{jt} + \mu_j. \tag{14}$$

The land operator expectation about the next period's price for each output is based on a linear relationship with the current period's price and a random parameter μ. We use Eq. 14 to derive the probability that an output price at time t will take on a range of values at time $t+1$. Once the parameters α_0 and α_0 are estimated, we can calculate the probability π that, given a particular price at time t, the price at time $t+1$ will fall in an interval of width $\pm\,\mu/2$ centered on the realized prices at the different time periods.

The second component of the transition probability matrix, λ_{jt}, can be thought of as the probability that the land use in period $t+1$ is i given a land use j in period t. These probabilities can be estimated non-parametrically using the one time period lag of the actual transition ratios across uses.

The Markov transition probability matrix for the output prices (15) consists of elements ω_{iy}, each of which is the joint probability $f\left(\lambda_{jt+1}, \pi_{jt+1}\right)$. In our empirical analysis we use the transition ratios for the period t to $t+1$ that are given by the transitions that occurred in the period $t-1$ to t[8] so that $\pi_{jt}+1$ and $\lambda_{jt}+1$ can be assumed uncorrelated and therefore

[7] See Nelson et al. (2001) for details on the derivation of a function similar to this.

[8] Lack of data restricted our estimation in two ways. Given that data on land use choices was available only for four years, $t-1$ refers to the *available* time period before time t. For example, for the transition probabilities

$f\left(\lambda_{jt+1}, \pi_{jt+1}\right) = f_1\left(\lambda_{jt+1}\right) f_2\left(\pi_{jt+1}\right).$

$$
\Omega = \begin{array}{c c}
 & \begin{array}{ccccccccccccccc} p_{Ft1} & \cdot & \cdot & \cdot & p_{Ft5} & p_{At1} & \cdot & \cdot & \cdot & p_{At5} & p_{It1} & \cdot & \cdot & \cdot & p_{It5} \end{array} \\
\begin{array}{c} p_{Ft1} \\ \cdot \\ \cdot \\ \cdot \\ p_{Ft5} \\ p_{At1} \\ \cdot \\ \cdot \\ \cdot \\ p_{At5} \\ p_{It1} \\ \cdot \\ \cdot \\ \cdot \\ p_{It5} \end{array} &
\begin{pmatrix}
\omega_{11} & \cdot & \cdot & \cdot & \omega_{1v} & \omega_{1w} & \cdot & \cdot & \cdot & \omega_{1x} & \omega_{1y} & \cdot & \cdot & \cdot & \omega_{1z} \\
\cdot & \cdot & & & & & \cdot & & & & & \cdot & & & \cdot \\
\cdot & & \cdot & & & & & \cdot & & & & & \cdot & & \cdot \\
\cdot & & & \cdot & & & & & \cdot & & & & & \cdot & \cdot \\
\omega_{11} & & & & \omega_{vv} & \omega_{vw} & & & & \omega_{vx} & \omega_{wv} & & & & \omega_{wz} \\
0 & 0 & 0 & 0 & 0 & & & & & & & & & & \cdot \\
0 & 0 & 0 & 0 & 0 & & \cdot & & & & & \cdot & & & \cdot \\
0 & 0 & 0 & 0 & 0 & & & \cdot & & & & & \cdot & & \cdot \\
0 & 0 & 0 & 0 & 0 & & & & \cdot & & & & & \cdot & \cdot \\
0 & 0 & 0 & 0 & 0 & \omega_{xw} & & & & \omega_{xx} & \omega_{xy} & & & & \omega_{xz} \\
\omega_{y1} & & & & \omega_{yv} & \omega_{yw} & & & & \omega_{yx} & \omega_{yy} & & & & \omega_{xz} \\
\cdot & \cdot & & & & & \cdot & & & & & \cdot & & & \cdot \\
\cdot & & \cdot & & & & & \cdot & & & & & \cdot & & \cdot \\
\cdot & & & \cdot & & & & & \cdot & & & & & \cdot & \cdot \\
\omega_{z1} & \cdot & \cdot & \cdot & \omega_{zv} & \omega_{zw} & \cdot & \cdot & \cdot & \omega_{zx} & \omega_{zy} & \cdot & \cdot & \cdot & \omega_{zz}
\end{pmatrix}
\end{array}. \tag{15}
$$

Not all future prices are relevant. For example, if the farmer cuts down trees this period the price of timber in the next period is not relevant. We can incorporate the irreversibility of certain choices into the transition probability matrix. For example, once forest is cleared, it is impossible to benefit from future timber prices for a many years and so λ_{jt}, and therefore ω_{iy}, is zero. In the example Markov transition probability matrix of Eq. 15 with five time periods, 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 t_1.[9] Transition probabilities constructed in this way capture the irreversibility of some decisions.

5 Estimation Procedure

Equations 6 and 7 are the building blocks of the econometric model. Let the vector $\theta \equiv \left\{\theta_\eta, \theta_\sigma, \theta_\varphi\right\}$ indicate the unknown parameters in the payoff function, the density of the unobservables, and the conditional transition probabilities function. The solution of Eq. 6 provides the vector of optimal values V, the payoff values. Given these values, it is possible to obtain the choice probabilities using Eq. 7.

We are here only concerned with the estimation of the parameters in θ_η since the variance of the unobservables is normalized to 1 and the conditional transition probabilities for the state variables are estimated non-parametrically. Furthermore, the discount factor β is assumed to be known. Aguirregabiria and Mira (2002) show that the nested pseudo-likelihood algorithm (NPL) exploits several properties of a policy iteration operator associated with the integrand in Eq. 6.

Let $P = \left\{P^j\left(x_{lt}\right) : x_{lt} \in X'; j \in J\right\}$ be an arbitrary vector of conditional choice probabilities where X' is a vector of state variables and J is the vector of all possible land

Footnote 8 continued
for the period 1987–1997 we used the actual transitions occurred during the period 1985–1987. Secondly, we did not have land use data for periods that precede the year 1985 Rather than discard the observations for the year 1985, we assume that the land use transition probabilities are constant for the time period before 1985.

9 In the language of Markov chains, the state *forest* is not accessible from state *agriculture*. Topologically these states are said not to communicate.

use choices. Let $\Psi_\theta(P) \equiv \left\{\Psi_\theta^j(x_{lt}; P) : x_{lt} \in X'; j \in J\right\}$ be the policy iteration operator, which is a fixed point mapping in the space of P. When unobservables have an extreme value distribution this operator has the following closed form:

$$\Psi_\theta^j(x_{lt}; P) = \frac{\exp\left\{\left[\Pi(x_{lt}) + \beta \sum\limits_{x_{lt+1}} f(x_{lt+1}|x_{lt}, i_{lt}) V_\Pi\right]\frac{\theta}{\sigma} + \frac{\beta}{\sigma}\sum\limits_{x_{lt+1}} f(x_{lt+1}|x_{lt}, i_{lt}) V_\varepsilon\right\}}{\sum\limits_{j=1}^{J}\exp\left\{\left[\Pi(x_{lt}) + \beta \sum_{x_{lt+1}} f(x_{lt+1}|x_{lt}, j_{lt}) V_\Pi\right]\frac{\theta}{\sigma} + \frac{\beta}{\sigma}\sum\limits_{x_{lt+1}} f(x_{lt+1}|x_{lt}, j_{lt}) V_\varepsilon\right\}} \tag{16}$$

This equation uses Hotz and Miller (1993) results showing that the value function can be expressed in terms of choice probabilities, transition probabilities, and payoff function:[10]

$$V_\Pi = \left(I_M - \beta\left[\sum_{j=1}^{J} P(j_{lt})^* F(j_{lt})\right]\right)^{-1}\left\{\sum_{j=1}^{J} P(j_{lt})^* \Pi(x_{lt}, j_{lt})\right\} \tag{17}$$

and

$$V_\tau = \left\{I_M - \beta\left[\sum_{j=1}^{J} P(j_{lt})^* F(j_{lt})\right]\right\}^{-1}\left\{\sum_{j=1}^{J} P(j_{lt})^* \left[Euler - \ln(P(j_{lt}))\right]\right\}. \tag{18}$$

I_M is the identity matrix, $P(j)$ is an $(M(J-1) \times 1)$ vector, $F(j)$ is an $(\mathrm{M}\times\mathrm{M})$ matrix of unconditional transition probabilities induced by P. $\Pi(\cdot)$ and $\mathrm{e}(\cdot)$ are $\mathrm{M}\times 1$ vectors that stack the corresponding elements at all states for choice alternative j, and $*$ is the Hadamard (or element-by element) product. Once the conditional transition probabilities $h(x_{lt+1}|x_{lt}, j_{lt})$ are computed, estimates of the parameters of the payoff function can be obtained using the NPL algorithm. For each location l we have a series of observations of the land use choice and the observable state variables $\{(j_1, x_1), (j_2, x_2), \ldots, (j_T, x_T)\}$. We can estimate our parameters of interest by maximizing the likelihood function for the optimization process. With L locations, and each location having observations for T time periods, the likelihood for this model is given by:

$$l(j) = \sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{j=1}^{J} I\{j\} \ln P_\theta^j(x_{lt}),$$

where for any vector of parameters θ, $P_\theta = \left\{P_\theta^j(x) : j \in J; x \in X\right\}$ is the unique fixed point of the mapping Ψ_θ. For an arbitrary vector of probabilities P, the following pseudo-likelihood function can be defined:

$$\widetilde{l}(j; P) = \sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{j=1}^{J} I\{j\} \ln \Psi_\theta^j(x_{lt}; P).$$

[10] Given that the error term has an independent across alternative extreme value distribution, the conditional expectation function $e_\sigma(j_{lt}, P)$ is given by the closed form $\sigma(Euler - \ln P(j_{lt}))$ where $Euler$ is the Euler constant 0.5771.

Table 1 Mean values for explanatory variables, 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	0.99	0.93	0.95	0.98	$Switch = \frac{1}{1+e^{\left(-\frac{t}{2}\right)}}$

Source: Own calculations using Dames and Moore data set

One starts by making an initial guess of the conditional choice probabilities $P^0 \in [0, 1]^{MJ}$. Each iteration has the following three steps. First, obtain the matrix $V_\Pi\left(P^{k-1}\right)$ and the vector $V_\varepsilon(P^{k-1})$ from Eqs. 17 and 18. Second, for each sample value of x_{lt} obtain estimates for the vector of parameters θ using the logit model in Eq. 16 and call these estimates θ^k. Third, use θ^k from step 2 to obtain new estimates for P and iterate these three steps until convergence in θ is reached.

6 Data Sources, Data Handling, and Explanatory Variables

The area of study is in the Darién province of Panama, a remote and environmentally important region located at the southeastern end of Panama, which includes the Darién National Park, Central America's largest national park and a UNESCO biosphere reserve and World Heritage Site. 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 the project. We augmented this data set with land use estimates derived from two satellite images, Landsat 5 TM for the year 1985 and Landsat 7 TM for the year 2000. Before the econometric estimation is undertaken pixels were sampled every 500 m. Land use maps were generated for the years 1985, 1987, 1997, and 2000.

Previous land use studies of the same area (Nelson et al. 2001, 2004) have used a more disaggregated categorization that included several categories forest and crop land. For this study, the land use maps for the year 1985 and 2000 are derived exclusively from photo-interpretation done by the lead author using satellite images for those two years and three land use classes—forest, agricultural uses, and idle land. The forest category includes all types of forested land, agricultural uses includes pasture and crop land, and idle land indicates all other land use categories such as brush, mangroves, and swamps.

6.1 Geophysical Data

We used the following geophysical explanatory variables—temperature, elevation, slope, soil quality and spatial lags of slope and soil quality. Summary statistics are provided in Table 1.

The temperature data set has values ranging from 21.5 to 27.0° average annual temperature. The highest elevation in the province is 1,800 m but much of the province is close to sea level. The average elevation for the whole area is 291 m. The average elevation of a forest pixel is 356 m. The averages for agriculture and idle pixels are 108 m and 71 m respectively. There is a considerable difference between the average slope of forest (13.51°) and agriculture pixels (3.14°). Lower slope values, below 5°, are particularly suitable for agriculture. The digital soil map identifies seven broad soil categories. These categories are used to create an index (SOILINDX) that ranks the various soil types according to their suitability to agricultural uses with zero for least productive soils to six for most productive soils. The spatial lag variables are the average of the values of the original variable in the eight cells surrounding the location.

6.2 Socioeconomic Data

We use the average prices of several possible outputs to create our explanatory variable output price (PRICE). For forested land the outputs considered are industrial roundwood, sandwood, and wood-based panels. For agricultural uses the possible outputs are rice, corn, cow milk, cattle meat and chicken meat. We use prices per metric ton of output at the country level as reported by FAO for the years 1985, 1987, 1997, 2000, and 2003. For the period under consideration, prices for forest products show a greater variability than prices for agricultural products. All prices are deflated using 1990 as reference year. We assume that location-specific differences in farmgate input prices (w_{jl}) are related exclusively to transportation costs from a central market. We follow previous studies (Nelson et al. 2001, 2004; Munroe et al. 2002), and assume that transport costs for timber are a good proxy for transport costs for all outputs. 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, areas with human intervention, \$0.2–0.5; marsh, \$3.00. These costs are then adjusted to reflect the higher cost of moving over sloping ground. We constructed the friction surface with two destinations—villages and towns in the area (COSTVBAS) and Panama City (COSTNBAS). The average cost of access to different land use categories varies quite dramatically (Table 1). 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.

We also account for the productivity changes that derive from keeping a parcel of land continuously in a certain use. These changes might be related to a greater familiarity with the production processes and a reduced uncertainty regarding costs and revenues generation, but also to changes in soil fertility caused by continuous cultivation. Since we do not have any data on changes of productivity through time we include a variable that keeps track of the number of years that a plot of land is known to have been in the same use. This explanatory variable (SWITCH), which corresponds to s_i in Eq. 9 above averages 0.99 (equivalent to 9.5 years) for pixels classified as forest and 0.93 and 0.95 (equivalent to 5.18 and 5.91 years) for pixels classified as agriculture or idle respectively.

6.3 Correcting for Spatial Correlation

Although there are no well-established methods to incorporate spatial effects in limited dependent variable models, a series of ad-hoc techniques have been widely applied in the spatial literature that are supposed to eliminate or at least mitigate the undesirable effects of spatial autocorrelation (Nelson and Hellerstein 1995; Munroe et al. 2002, among others). For this paper we used two of the techniques that appear to be the most effective in removing spatial autocorrelation: regular sampling from a grid and spatially lagged geophysical variables.[11]

7 Results

7.1 The Transition Probability Matrix

The first step is to construct the Markov transition probability matrix. The first order autoregressive model in Eq. 14 was estimated using yearly output prices from the FAO statistical database for the period 1963–2003.

$$p_{(\text{forest})t+1} = \underset{(2.014)}{226.63} - \underset{(4.773)}{0.10}\; p_t R^2 = 0.49\; \mu = 76.15$$

$$p_{(\text{agriculture})t+1} = \underset{(7.205)}{155.75} + \underset{(2.863)}{0.87}\; p_t R^2 = 0.76\; \mu = 34.38$$

where p_t is the price of the commodity at time t and μ is the standard error of the estimate. The t-statistics are in parenthesis. Using a numerical integration routine,[12] 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 $\pm\mu/2$ centered on the realized prices at the different time periods.[13] Cross-tabulation was used to determine non-parametrically the spatially aggregated land use transition probabilities (see Table 2). Most of the change occurs at the expense of forested land and to a lesser extent of idle land. Two percent of all pixels classified as forest in 1985 were classified as agricultural land in 1987. This percentage grows to 20% for the periods 1987 to 1997 and to 22% for 1997 to 2000 respectively. The share of idle land pixels that change to agricultural land grows from 3% from 1985 to 1987 to 42% in the 1997 to 2000 period. Much less transition occurs from agricultural land to other uses—7% transitions to forest and 6% to idle land in the period 1987–1997, and 1% becomes idle land in the period 1997–2000. We used the spatially aggregated transition probabilities in Table 2 and the land operator's expectations of output prices estimated from the regressions above to derive each element ω_{ij} of the Markov transition probability matrix. The Markov transition probability matrix used for estimation is shown in Table 3.

7.2 Estimation Results

We used 3 years, 1985, 1987, and 1997, to calibrate the model. The initial data set had 63,894 observations. After using spatial sampling (every 5th pixel in every 5th row) to reduce spatial effects and removing locations with some missing data, the sample size for each year used in

[11] We experimented with several sampling grids and results showed that spatial autocorrelation in the error term decreases as distance between observations increases. We chose to sample every 5th pixel in every 5th row which corresponds to a distance between observations of 2.0 km. Increasing the distance between observations to 2.5 km does not reject the hypothesis of no spatial autocorrelation but reduces the overall predictive power of the model from 0.887 to 0.687.

[12] We used a modified version of Aguirregabiria's Transprob code available at: http://individual.utoronto.ca/vaguirre/software/library_procedures.html accessed 2/02/07.

[13] $\mu/2$ creates an interval (admittedly of arbitrary width) around the estimates for future prices for which the probability of a realized price to be part of the expectations is not zero.

Table 2 Spatially aggregated land use transition probabilities for three periods between 1985 and 2000 (percent of category in original year in final year category)

Land use category	1985–1987		
	Forest (1987)	Agriculture (1987)	Idle (1987)
Forest (1985)	98	2	0
Agriculture (1985)	0	100	0
Idle (1985)	0	3	97
Land use category	1987–1997		
	Forest (1997)	Agriculture (1997)	Idle (1997)
Forest (1987)	69	20	11
Agriculture (1987)	7	87	6
Idle (1987)	4	6	90
Land use category	1997–2000		
	Forest (2000)	Agriculture (2000)	Idle (2000)
Forest (1997)	73	22	5
Agriculture (1997)	3	96	1
Idle (1997)	1	42	57

estimation was 1,976. Table 4 shows the parameter estimates for each explanatory variable. The signs of these estimates are in line with expectations and similar to results obtained in previous studies (Chomitz and Gray 1995; Nelson and Hellerstein 1995; Munroe et al. 2004, among others). For example, as slope increases and as transportation costs to and from local markets (COSTVBAS) and to the region outlet (COSTNBAS) increase, we expect the profitability of agriculture to be reduced and therefore the probability of agriculture to be smaller. The signs of coefficients on cost of access are negative as expected. Higher market prices for agricultural outputs and better soil quality increase the profitability of agriculture.

An important result is the sign and value for the estimate for the variable SWITCH. Our results indicate that the amount of time a plot is kept in agricultural production positively affects the probability that the agricultural land use is chosen in the next time period. Unfortunately we don't have enough information, and the estimates alone are insufficient to tell what factors influence farmers' decisions in this case. Information asymmetry that derives from familiarity with current agricultural practices, better understanding of the market for a certain output, as well as declining natural productivity could all be at play. Our estimates only indicate that overall the time effect is positive for agricultural uses.

7.3 Predictive Power of the Dynamic Discrete Choice Model

Table 5 presents the prediction matrix for the dynamic model. The model was estimated with the reduced set of data and the estimated parameters were then used to generate probability values for each use and for each one of the 63,894 pixels. The predicted land use at a location is the land use category with the highest probability (the winner-take-all rule). 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 high for forest and agriculture categories: forest 0.870, agriculture 0.903. The misclassification occurs mostly between forest and agriculture, with 6,217 pixels erroneously classified as agriculture, and partially

Table 3 Markov transition probability matrix

	Forest uses					Agricultural uses					Idle land				
	P_{t1}	P_{t2}	P_{t3}	P_{t4}	P_{t5}	P_{t1}	P_{t2}	P_{t3}	P_{t4}	P_{t5}	P_{t1}	P_{t2}	P_{t3}	P_{t4}	P_{t5}
Forest uses															
P_{t1}(1985)	0.240	0.339	0.350	0.051	0	0.005	0.015	0	0	0	0	0	0	0	0
P_{t2}(1987)	0	0.169	0.223	0.224	0.074	0	0.040	0.078	0.050	0.032	0	0.110	0	0	0
P_{t3}(1997)	0	0.011	0.113	0.301	0.305	0	0	0.109	0.104	0.007	0	0	0.050	0	0
P_{t4}(2000)	0	0	0.096	0.311	0.323	0	0	0.080	0.121	0.019	0	0	0	0.050	0
P_{t5}(2003)	0	0	0	0	0.730	0	0	0	0	0.220	0	0	0	0	0.050
Agricultural uses															
P_{t1}(1985)	0	0	0	0	0	0.250	0.750	0	0	0	0	0	0	0	0
P_{t2}(1987)	0	0	0	0	0	0	0.189	0.354	0.233	0.154	0	0.070	0	0	0
P_{t3}(1997)	0	0	0	0	0	0	0	0.496	0.463	0.031	0	0	0.010	0	0
P_{t4}(2000)	0	0	0	0	0	0	0	0.356	0.549	0.085	0	0	0	0.010	0
P_{t5}(2003)	0	0	0	0	0	0	0	0	0	0.990	0	0	0	0	0.010
Idle land															
P_{t1}(1985)	0	0	0	0	0	0.008	0.023	0	0	0	0.970	0	0	0	0
P_{t2}(1987)	0	0.010	0.013	0.013	0.004	0	0.012	0.023	0.015	0.010	0	0.900	0	0	0
P_{t3}(1997)	0	0	0.002	0.004	0.004	0	0	0.208	0.199	0.013	0	0	0.570	0	0
P_{t4}(2000)	0	0	0.001	0.004	0.004	0	0	0.153	0.231	0.036	0	0	0	0.570	0
P_{t5}(2003)	0	0	0	0	0.010	0	0	0	0	0.420	0	0	0	0	0.570

Note: Each cell indicates the probability that the relevant price at time $t + 1$ is p_j (the column land use) given that it was p_i (the row land use) at time t. Assume for example that the land use in time period 1 is forest. The probability that the relevant prices at time period 2 are the once relative to forest products and equal to the realized price in 1987 is 0.339. The probability that the relevant prices are the prices of agricultural products and equal to the realized prices in time period 2 is 0.015

Table 4 Estimated parameters by land-use category for the dynamic discrete choice, multinomial logit, mixed logit, and survival models

Variable name	Dynamic discrete choice model[a]		Static multinomial logit model[a]		Mixed logit model[a,c]		Survival model[b]
	Agriculture	Idle	Agriculture	Idle	Agriculture	Idle	
ELEVATION	−1.222**	0.098**	−0.635***	−1.305***	−0.722***(0.582**)	−2.377***(0.489**)	−0.037
TEMPERATURE	−1.963**	−1.160**	−0.818***	−0.267	−0.941**(0.037)	−0.681(0.092)	0.020***
SLOPE	−0.031*	0.0009*	−0.024	−0.040	0.056(0.231***)	0.247(0.188)	−0.010**
SOILINDX	0.296*	−0.020**	0.172	−0.792***	2.155*(0.725*)	−0.110***(0.020*)	0.103***
LSOIL	0.202	−0.006	0.135***	0.115**	0.360***(0.473*)	0.292**(0.411**)	−0.076**
LSLOPE	0.202	−0.006	−0.244**	−0.855***	0.123**(0.054)	0.029***(0.002*)	0.006
COSTNBAS	−1.269*	−0.004	−0.051**	−0.026	−1.209**(0.971*)	−0.223(0.025*)	0.005***
COSTVBAS	−0.654*	−0.042*	−2.417***	−1.227***	−1.125***(0.176***)	−0.033***(0.021***)	0.264**
PRICE	0.068**	−0.212*	–	–	0.022**(–)	−0.415**(–)	0.105***
SWITCH	11.735***	0.022*	–	–	6.918**(0.631***)	0.038*(0.293**)	–

** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level

[a] These models are underidentified unless the parameters for one of the categories are known. We chose Forest as the base category. The values of the estimated betas are relative to the betas in the base category

[b] The survival model estimates the effects of the explanatory variables on the probability of observing change in the next time period

[c] The numbers in parenthesis are the derived standard deviations of the parameter distributions

Table 5 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

Note: Columns are land use predictions for the year 2000; rows are actual land use in the year 2000. Values in bold indicate correct predictions

between agriculture and idle with 855 pixels of agricultural land misclassified as idle. The model performs remarkably well with respect to idle land with 100% of correct predictions. A considerable share of land classified as idle is affected by factors that strongly limit the possibility of bringing the land into production such as recurrent floods and poor soil quality. It is conceivable that in these cases the more complex dynamics related to prices expectations and option values play a less important role. The model seems to fully capture the effects of the physiogeographic factors on the decision process.

7.4 The Value of the Discount Factor β

Unlike Rust's Nested Fixed Point algorithm, the Nested Pseudo-Likelihood algorithm does not provide an estimate for the discount factor β. It is assumed to be known by the researcher Sanchez-Mangas (2003). Given the characteristics of our problem we do not know the value for the discount factor and myopic behavior ($\beta = 0$) and forward-looking behavior ($\beta > 0$) are a priori equally plausible. We chose the β that maximizes the log-likelihood function 0.885, equivalent to an interest rate of 12.9%.

7.5 Comparing the 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—multinomial logit with cross-sectional data, mixed logit model with panel data, and a survival model with panel data.

7.5.1 Static Multinomial Logit with Cross-Sectional Data

This modeling technique has been used to gain insights into the determinants of deforestation and make predictions about changes in land use as a result of road paving (Chomitz and Gray

1995; Nelson and Hellerstein 1995; Munroe et al. 2002). The one-period profit function used for the multinomial logit is the same as the one used for the dynamic model and the estimating function has the same set of explanatory variables, geophysical characteristics and transportation cost variables used in the dynamic discrete choice model with the exceptions of PRICE and SWITCH.[14]

7.5.2 Mixed Logit Model

The mixed logit (also known as the random parameters logit) is a very flexible model that approximates any random utility model and overcomes the major limitation of a multinomial logit applied to panel data set; that is, accounting for the correlation over time in unobserved utility that arises when there are repeated choices by a given agent (McFadden and Train 2000). The one-period profit function used for the mixed logit is the same as the one used for the dynamic model and the estimating function has the same number of explanatory variables, geophysical characteristics and transportation cost variables used in the dynamic discrete choice model. Although this model uses the same panel data set as the dynamic model, no dynamic processes are explicitly included in the specification. The specification takes a random-effect form [15] (see Train 2003 for more details) and for our estimation we assume that all parameters, except for PRICE,[16] are normally distributed with a mean and standard deviation to be estimated. Simulation was performed using 1,000 random draws for each observation.

7.5.3 Survival Model

Models of land use change that use survival analysis frame the problem in terms of optimal switching time. With a survival models it is possible to compute the probability that each land use at location l changes in period t conditional on it not having changed before.[17] For our comparison, we use a fully parametric model, the complementary log linear model that can handle time-varying covariates and assume a type I extreme value distribution[18] for the error term. This specification assumes that the underlying process generating the data is continuous, and data are grouped into discrete time intervals. In our case we used years 1985, 1987, 1997, and 2000, to create three time intervals and calibrate the model. The estimating function has the explanatory variables used in the dynamic discrete choice model with the

[14] The introduction of the variable price causes problems of convergence due to the extremely low variability among observations (there is only one value for each output in one year). The variable SWITCH can only be constructed when one has multiple observations through time of the study area and, by definition, the static model uses only one time period.

[15] We experimented with other models, most notably the random parameters with the random effect following an AR(1) process, but we did not obtain any significant autocorrelation in the parameters and therefore we opted for the random effect model.

[16] When we allowed this parameter to be random the model did not converge, so we restricted it to be fixed.

[17] The land use change literature traditionally has looked at deforestation and the determinants of deforestation. Similarly, empirical applications of the survival model concentrate on deforestation. Since our main objective is to compare the performance of the two models for this study we use the models to predict a change in land use. This means that even transitions from idle land to forest or from agricultural land to forest are accounted for.

[18] There are several other distributions that could be used in a survival model (e.g. exponential, normal, logistic, gamma) we chose type I extreme value since it is the most commonly used in previous studies of land use change.

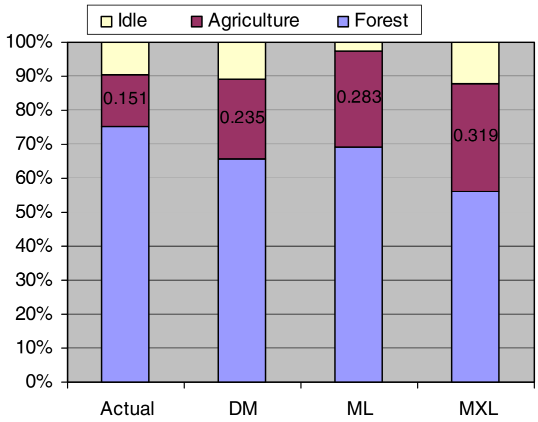

Fig. 1 Actual and projected land use for the year 2000. *Note*: DM, ML, and MXL indicate dynamic model, multinomial logit, and mixed logit respectively

exception of the variable SWITCH that, by construction, would have a perfect correlation with the dependent variable.

7.6 Results of Model Comparisons

The results in Table 4 suggest that there is very little difference among models as far as capturing the effects of the explanatory variables on land use choices at this location. The signs of the estimated parameters are, with few exceptions, similar across all the estimation methods and consistent with the existing literature. The estimates for the survival model cannot be compared to the ones obtained with the other two models: they measure the effect of the explanatory variables on the probability of observing change in the next time period. However, the parameter estimates for this model also have the expected signs. The probability of observing a land use change increases as slope decreases, soil quality increases, and as output prices increase. The positive signs for the explanatory variables distance from villages and towns (COSTNBAS) and distance from the region outlet (COSTVBAS) seem to capture the fact that change is mostly occurring at locations at the frontier between agriculture and forest.

Interesting differences can be noted in the explanatory power of the different models shown in Table 5 . The dynamic model outperforms multinomial and mixed logit in terms of correct predictions for the year 2000: the overall predictive power of the multinomial logit is 0.792, for the mixed logit is 0.765 while for the dynamic discrete choice is 0.887. For the agriculture category, where most of the land use change occurs and consequently where the dynamic processes matter the most, the predictive power of the dynamic discrete choice model (0.903) is higher than multinomial (0.844) and mixed logit (0.781). Only 45% and 37% of all pixels predicted as agriculture in the year 2000 by the multinomial and mixed logit are correct, while this percentage climbs to 58% using the dynamic model.

As can be seen in Fig. 1: Actual and Projected Land Use for the year 2000, all three models tend to overestimate the amount of land in agriculture. However, the predictions of the dynamic model are closer to the true land use than the other two models. The percentage of land in agriculture in the year 2000 is 15% of the whole area while it is projected to be 23.5%, 28.3%, and 31.9% by the dynamic model, multinomial logit and mixed logit respectively. Most of the change in the area is due to the conversion of forested or idle land to agricultural uses (see Table 2); this is where the dynamics involved in the decision process matter the most.

Table 6 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

Note: Columns are land use predictions for the year 2000; rows are actual land use in the year 2000. Values in bold indicate correct predictions

Our results indicate that the models that do not include any dynamic processes overestimate land use conversion.

Finally, when a survival model is used to predict the probability of a land use change in the year 2000, the survival model correctly predicts some 66% 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). Both models over predict land use change, however 72% of the predicted chance is correct for the dynamic discrete choice model while only 46% is correct for the survival model.

7.7 Simulation of Changes in the Socioeconomic Variables

The estimates of the ηs from Eq. 12 can also be used to simulate the effects of changes in the socioeconomic variables. Following an example in the literature (Nelson and Hellerstein 1995; Nelson et al. 2004), we simulated the paving of the Pan American highway (see Fig. 2) in the Darien province. The original cost variables were replaced with simulated values that reflect the reduced cost. We assumed the paving reduces the transport cost per cubic meter from \$0.10 to \$0.05 per kilometer along the road; the total saving from a point that uses the entire road for transportation is approximately \$4 per cubic meter. Table 7 compares the results obtained with the dynamic discrete choice, multinomial logit, and mixed logit models. These changes are calculated by comparing the predicted base values with the simulated values. The change occurs at the expenses of forested land for all three models but the magnitude of the change varies substantially among models. The dynamic model predicts a reduction in forested land equivalent to 6,600 ha. This is a relatively modest change when compared to the 88,575 and 30,075 ha predicted by the multinomial logit and mixed logit models respectively.

Table 8 compares the results of the dynamic discrete choice and survival models. The total number of hectares that are predicted to undergo some form of land use change due to a reduction of transportation costs by the survival model is 8,800. The two models that incorporate the option value of choices return similar predictions in terms of change due to the resurfacing.

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

Fig. 2 Darién province overview

in land use and that additional encroachment of forested land by agricultural uses is strongly limited by geophysical factors and transition costs.

8 Conclusions

Although the trend in the existing literature is from a static to dynamic models, the existing models that undertake intertemporal analysis are limited in the way they incorporate dynamic

Table 7 Effects of road resurfacing for the year 2000, dynamic discrete choice model vs. multinomial logit (number of 0.25 km cells)

	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

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
Survival model		
Before resurfacing	5,453	58,441
After resurfacing	5,775	58,119
Net change	+352	−352

processes. In this article we have used a dynamic optimization framework to introduce many of the missing dynamics. The introduction of output prices, expectations about future prices, irreversibility of choices, and a mechanism that accounts for asymmetries between uses, provides valuable empirical insights into the decision process and improves upon the existing models in terms of prediction accuracy. Our estimates suggest that familiarity facilitates efficiency. The positive sign and the value of the parameter estimate suggests that for most of the parcels used in agriculture, fertility loss due to continuous cultivation is not an issue. From a practical standpoint this means that policies that favor one land use over others, for example, reforestation policies, need to account for the advantage that current land use has over potential alternatives if they are to be successful in shaping land use choices. Disregarding these potentially important components of the decision process might lead to incorrect normative policy recommendations. Although the models compared have similar results for the determinants of land use choices (i.e. the signs of the estimated parameters) the effect of changes in the value of some explanatory variables vary greatly in magnitude according to the model. In particular, the results of the simulation of road resurfacing support our hypothesis that static models tend to overestimate land use changes.

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