Development and Deforestation: evidence from Costa Rica

Suzi Kerr [Ω] *, Alexander S.P. Pfaff [Ω] **, and Arturo Sanchez***

December 2004
Motu Manuscript

Abstract

We estimate the drivers of deforestation in Costa Rica through the 20th century. Deforestation rates in Costa Rica rise initially and then fall. Our empirical approach and panel data allow us to explore new questions on the dynamics of development and deforestation including early clearing of the most agriculturally productive and accessible lands, national trends in deforestation pressure, gradual adjustment after shocks to local agricultural profitability, and local endogenous development following early clearing. Our results are consistent with previous literature that focuses on forests stocks in that we find that potential agricultural returns and distances to market are important determinants of clearing. The results also highlight the important role of the development of government and market institutions and infrastructure at the local and national levels. Our results can help to predict patterns of agricultural development, to anticipate environmental pressures, and to predict deforestation baselines that could be used in the global climate change mitigation effort.

Keywords: land use, deforestation, development, Costa Rica

We acknowledge financial support from the National Science Foundation Grant No. 9980252, the Tinker Foundation, the Harvard Institute for International Development, the National Center for Environmental Analysis and Synthesis at UC-Santa Barbara, and CERC and CHSS at Columbia University. Many thanks to Antonio Bento, Nancy Bockstael, Richard Eckhaus, Ken Richards, Rob Stavins and other audience participants for useful comments at conferences. Thanks to Ina Porras, Steve Cournane, Joanna Hendy, David Kennedy, Juan Andres Robalino, Jason Timmins, and William Power for research assistance. The Tropical Science Center in San José, Costa Rica kindly hosted us during our research. Joseph Tosi and Vicente Watson at the Center provided valuable help at many points in the project. All opinions are our own, and we are responsible for all errors and omissions.

[Ω] Shares lead authorship.
[*] Motu Economic and Public Policy Research.
[**] Columbia University, School of International & Public Affairs and Department of Economics.
[***] University of Alberta, Earth Observation Systems Laboratory (EOSL).

1 Introduction

Deforestation leads to changed habitat, release of carbon to the atmosphere, soil degradation, and flooding. At the same time it allows agricultural development and the expansion of human settlement. While we have considerable understanding of land-use patterns in developed countries, and even of land use at points in time within some developing countries, relatively little careful empirical work has been done on the nature of deforestation over time along a development path.

One motivation for predicting forest change is the desire to reduce net carbon emissions to limit global climate-change. If we are to reward developing countries for protecting forests to sequester carbon and thus lower global emissions, we want to predict what countries would have done with their forests in the absence of rewards. Otherwise we may simply reward them for things they would have done anyway. Another motivation is to predict where agricultural development pressure might arise. This allows more effective planning for infrastructure and government services. A final motivation is to predict where threats to biodiversity might occur in order to target scarce resources for protection.

We estimate a deforestation equation for Costa Rica using GIS data on forests at five points in time and a partition of the country into over one thousand units of observation (subdistricts). Costa Rica is an excellent country for initiating such analysis of development and deforestation. Not only has it passed through many different development and clearing stages but its spatial forest data go back to the early 1960s. Costa Rica is small enough that it faces clear exogenous shocks from international markets. It features a wide range of observable geophysical conditions that imply exogenous variation in agricultural productivity. Our empirical approach and panel data allow us to explore the dynamics of development and deforestation including: early use of the the most agriculturally productive and accessible lands; common national drivers; gradual adjustment after shocks to local profitability; and local endogenous development following early clearing.

Our work builds on the rapidly growing literature that uses past land-use behaviors to reveal the drivers of land-use change (Stavins and Jaffe 1990 is an early example, Irwin and Bockstael 2002 a more recent one). In the developing country context, Chomitz and Gray 1996, Nelson and Hellerstein 1997, Pfaff 1999, Cropper et al. 2001, and Geoghegan et al. 2001 offer a range of econometric analyses of forest cover. Kaimowitz and Angelson 1998 survey a wide range of approaches to economic modeling of tropical deforestation. Several studies of deforestation have analyzed Costa Rica specifically, notably including regression analysis by Rosero-Bixby and Palloni 1996. Most studies in Costa Rica, though, have taken approaches somewhat different from our microeconomics-based regressions (see, e.g., Sader and Joyce 1988 on rates of deforestation, Harrison 1991's focus on the effects of population, and the rule-based extrapolations in Pontius, Cornell and Hall 2001).

Our results are consistent with the previous literature that focuses on forests stocks in that we find that potential agricultural returns and distances to market are important determinants of clearing. The agricultural suitability of the local climate and the quality of the soil are consistently good indicators of pressure to deforest. Directly estimated agricultural returns that take into account changes in export prices, observed yields and climatic and soil constraints on crops are significant predictors of deforestation pressure. Our work extends previous research by emphasising the effects of these factors on the path of deforestation as well as on forest stocks in equilibrium.

Our work also contributes to the literature on the 'environmental Kuznets curve' where development is hypothesised to initially degrade but later improve environmental quality. Cropper and Griffiths 1994, Panayotou 1995 and Antle and Heidebrink 1995 find mixed results for the relationship between net deforestation rates and income in cross country regressions. In a panel study, Foster and Rosenzweig (2003) use a combination of cross country analysis with a general equilibrium approach, and household analysis using longitudinal datasets within India to conclude that increases in income, at least within India, lead to reforestation as a result of increases in demand for forest products.

The pattern of deforestation in Costa Rica is consistent with the broad ideas of the 'Kuznets curve' with deforestation rates rising initially then falling to nearly zero (see Figure 1). Since the mid 1990s the combination of low deforestation with rising reforestation rates might be leading to improvements in environmental quality. We are able to explore the drivers of these changes at both a national and local scale. We find that better quality agricultural land is cleared earlier and that clearing on that land levels off in later years (see Figure 2). We find that the distance to market strongly discourages clearing before 1963 and when the Costa Rican economy is more mature, after 1986, but that deforestation pressure near the frontier is higher than near cities during Costa Rica's period of rapid development, 1963 – 1986.

Our results also highlight the potentially important role of the development of government and market institutions and infrastructure at the local and national levels. Even after controlling for changes in international prices and the availability of good agricultural land, we find that previous local clearing is a good predictor of future clearing, though this effect reduces at very high levels of clearing. We also find that, conditional on the time paths of other variables, the national pressure to deforest falls with time, and falls particularly steeply after the mid 1980s. This is associated with the development of modern forestry legislation and an extensive national parks system.

Our results can help to predict patterns of agricultural development, to anticipate environmental pressures, and to predict deforestation baselines that could be used in the global climate change mitigation effort.

The rest of the paper proceeds as follows. Section 2 presents a dynamic model of individual land-use choices and forest clearing for agriculture. Section 3 derives our econometric specification, drawing on other literature analyzing transitions. Section 4 discusses the land-use data and explanatory variables that we use. Section 5 presents our results and Section 6 concludes.

2 A Dynamic Model Of Deforestation For Costa Rica

Our use of a dynamic theoretical model and follows the land-use-and-deforestation literature (e.g., Ehui and Hertel 1989, Stavins and Jaffe 1990, and Parks and Hardie 1995) and assumes that land clearing is not reversed at least in the short term. This reflects the Costa Rican experience and the focus of our work on the development period where deforestation is the dominant process. The theoretical reason to separate deforestation from reforestation transitions is that the latter do not result automatically from reduced deforestation pressure.

Deforestation has irreversibilities, since trees take time to grow and incurring the costs of development changes marginal returns. After an export boom causes clearing, even if prices later fall to a level insufficient to induce additional clearing, this price fall may not induce abandonment and reforestation of recently cleared land.

The manager of each forested hectare j faces a dynamic optimization problem. Risk neutral by assumption, the land manager selects T, the time when land is cleared, in order to maximize the expected present discounted value of returns from the use of hectare j:

$$\mathrm{Max}_T \int_0^T S_{jt}\, e^{-rt}\, dt + \int_T^{\infty} R_{jt}\, e^{-rt}\, dt - C_T\, e^{-rt} \tag{1}$$

where:

S_{jt} = expected return to forest uses of the land

R_{jt} = expected return to non-forest land uses

C_T = cost of clearing net of obtainable timber value and including lost option value[1]

r = the interest rate

Two conditions are necessary for clearing to occur at time T. First, clearing must be profitable. For clearing to occur, the present discounted rents from non-forest uses will have to more than compensate the manager for the lost returns from forestry uses and the net cost of land clearing:

$$\int_T^{\infty} (R_{jt} - S_{jt})\, e^{-rt}\, dt - C_T > 0 \tag{2}$$

However, even if clearing is profitable at time t, it may be more profitable to wait and clear at t+1. For example, clearing costs may fall. Thus, the following 'arbitrage' condition must hold:

$$R_{jt} - S_{jt} - r_t\, C_t + \frac{dC_T}{dt} > 0 \tag{3}$$

Both conditions must hold for clearing to be preferred. However, if the second-order condition (4) holds , then either of these necessary conditions is also sufficient for clearing to be chosen.

$$\frac{dR_{jt}}{dt} - \frac{dS_{jt}}{dt} + \frac{d^2}{dt^2} C_t > 0 \tag{4}$$

The forest status for each parcel at each point in time will be determined by whether or not these conditions hold or have held previously. The land that will be deforested in each time interval will be the land that is marginal for agriculture and has not previously been cleared.

Land parcels will have different outcomes across space due to different returns, because land suitability and market access vary. Agricultural returns and costs of clearing will also change over time. National development trends that affect net returns are exogenous to local land use.

---

[1] A more comprehensive model would also include uncertainty, risk aversion, and forward-looking knowledge of the ability to shift back and forth optimally between cleared and uncleared states. Uncertainty combined with the irreversibilities in deforestation and the ability to learn over time implies an option value to waiting to clear, though individual dynamics are not the empirical focus in either the related deforestation literature or in this paper.

As legal and economic institutions improve, tenure security rises, and access to credit and insurance is enhanced making capital investment more attractive and thus increasing expected net returns to clearing when land and capital are complements. Improved infrastructure, such as distribution networks, lowers costs and raises farmgate output prices. Development of locally appropriate technology lowers costs and improves output quality. Increased openness of the country to trade raises the value of export products and may reduce the costs of imported inputs.

On the other hand, development of environmental regulation to protect forests, forestry legislation to efficiently manage and hence raise returns to forestry, development of a modern industrial and service economy that raises agricultural wages, and movement toward capital-intensive farming that is less economic on low quality land may reduce the net returns to clearing on marginal land. We might expect the development process to initially promote clearing but later to deter it. These national development changes may relate to changes in GDP per capita, the environmental Kuznets curve hypothesis.

Other aspects of economic and institutional development may be locally endogenous. These effects are likely to occur at the subdistrict level and be reflected in movements in ▯it. One process exogenous to individual land users but endogenous to regions is that as the forest is cleared and human activity increases, this stimulates further investment in infrastructure such as in credit agencies, transport networks and services, raising returns in unobserved ways.

Some of these changes, such as changes in international prices for key crops or changes in average crop yields, will be observable. Others, such as improvements in infrastructure or market institutions are not directly observable but may be spatially correlated or even locally path dependent and are probably monotonic in calendar time. As land is cleared, the distribution of characteristics on remaining forested land changes so the amount of land that is marginal for clearing changes. Aggregate deforestation rates will depend on how quickly agricultural returns change, how strong the changes in local and national institutions are, and how much potentially agriculturally productive land remains in forest.

3 Econometric Specification

We develop a reduced form specification motivated by intuitions from a structural model. To derive an econometric specification from the model, we assert (4) and work from (3).

Following our model above, we examine parcels' transitions from forest to non-forest only. Our GIS data makes it possible to decompose changes in forest into deforestation and reforestation.

Our model predicts time of clearing, i.e. the timing of a transition. Our intuitions draw on econometric analysis of duration (see Kiefer 1988, Lancaster 1990) and are similar to those in analyses of the probability that a firm adopts a given technology or an individual ends a spell of unemployment by finding a job. Applying (3) to all parcels and years predicts the clearing of individual forest parcels. If (3) has ever been satisfied since the last transition to forest, then the parcel is cleared; if not, then the parcel is forested and a candidate for clearing in the next interval, such that if (3) is satisfied during that interval then the parcel will be cleared.

In the theoretical model, predicted deforestation for any parcel is deterministic. However, we do not perfectly measure the parcels' returns and costs, let alone expected future values. In addition landowner risk aversion, limited access to credit, availability of family labour, non-market motivations and bounded rationality mean that the simple theoretical model is unlikely to be a perfect description of any individual landowner's real behaviour.

Actual returns and changes in costs vary across parcels for which the observable factors in benefits and costs yield the same estimated net benefits from clearing. Thus, we assume that clearing occurs if:

$$R_{jt} - S_{jt} - r_t\, C_t + \frac{dC_T}{dt} \;=\; X_{jt}\beta - \gamma_t - \varepsilon_{jt} > 0 \qquad (5)$$

where j refers to a specific parcel, Xjt is a matrix of observable measure of the benefits and costs of clearing, t is a common national error that varies with time and has a xero mean, and jt is a parcel-year-specific term to account for unobserved heterogeneity in net returns to current clearing.

Our data are not for parcels, however, but for larger subdistricts, i. We observe deforestation in subdistricts not discrete clearing of parcels. In our aggregated data, each parcel in a subdistrict has the same measured net benefits. The difference between parcel level returns and observed subdistrict variables makes it useful to decompose the error. Thus jt = it +j where it is the common error for the subdistrict andj is the deviation of returns on parcel j from the mean for the parcels in its subdistrict i. Initially, when all land is forested, i, j, and hence j for all forested parcels are distributed with mean zero. As local clearing leads to endogenous development of local institutions and infrastructure that change local returns at the subdistrict level, the distribution of it changes. As land is cleared in a non-random way, the distribution of agricultural productivity and types of landowners on forested parcels is selectively truncated. More productive subdistricts and more productive parcels with each subdistrict are more likely to be cleared early and thus drop out of the distribution of forested land. We assume that the mean of the jt distribution shifts with the percentage of land previously cleared in the subdistrict i around the parcel to account for both the endogenous development and selection effects.

For each subdistrict i with parcels j = 1…Ii, the clearing or deforestation rate is predicted to be the number of parcels that satisfy (5) during this interval but not before, and so are cleared during the interval, divided by the number that had never previously satisfied (5), i.e. were not previously cleared. Thus, our predicted deforestation rate within larger subdistricts is analogous to a 'hazard rate' as defined in the transitions literature. We define this as

$$h_{it} = \mathrm{f}(X_{it}\beta)/(1-\mathrm{F}(X_{it}\beta)) \qquad (6)$$

The predicted clearing rates depend upon the Xit as well as on the assumed distribution of the it and jt. We now include in Xit time effects to control for t as well as a variable, percentage of forest in subdistrict i already cleared, to proxy for the shift in the mean of jt. These time effects and distribution shifters have a purely econometric role but the parameters that are estimated can also be interpreted in relation to development. In some models we include fixed effects for each subdistrict to account for i. We then assume that the cumulative distribution of the remaining error is logistic at each point in time. Thus we have a logit model for each parcel:

$$\mathrm{F}(X_{it}\beta) \;=\; \frac{1}{1+\exp(X_{it}\beta)} \qquad (7)$$

For our grouped data, we estimate this model using the minimum logit chi-square method also known as 'grouped logit'. If is a subdistrict's measured rate of forest loss, then we estimate:

$$\log \frac{\hat{h}_{it}}{1-\hat{h}_{it}} = X_{it}\beta + \mu_{it} \qquad (8)$$

The variance of the can be estimated by , where Iit represents the number of forested parcels within subdistrict i at the beginning of interval t, and the estimator is consistent and asymptotically normal. (8) is estimated by weighted least squares.

3.1 Spatial Correlation

The jt in (5) and in (8) may not be independent over space. Contiguous land parcels and subdistricts may share productive soil qualities or slope characteristics that are unobserved, or demand or supply conditions that are unobserved may be correlated across neighbouring subdistricts. If the are spatially autocorrelated, the regressions in (8) will provide consistent but inefficient coefficient estimates.

Using the distances among the subdistricts' centroids, we test for spatial autocorrelation at each point in time. First we use a spatial-weight matrix to compute the Moran I statistic. This requires a judgement about which observations may be related to others and how. We assume that within a cutoff distance (we try 5, 10, 30 and 50 km) of a given subdistrict, each subdistrict 'nearby' (within the cutoff distance) exerts an equal potential influence on the given subdistrict. As the number of such influential observations varies over sub-districts, we row-standardize the matrix so that the influence weights always sum to one, i.e. we divide a fixed total influence upon each subdistrict equally among those observations assumed to potentially have influence. In order to go beyond magnitudes of the Moran I statistics in considering what distance might be the best cutoff to use, without assuming a particular spatial-weight matrix we also apply Conley and Topa 2002's non-parametric estimate of spatial covariance as a function of distance.

We correct for spatial autocorrelation in two ways. First we use the spatial-weight matrix following Anselin 1988's EGLS approach to obtain more efficient estimates; second we compute robust standard errors. For the coefficients from the weighted OLS we apply, for a 40km cutoff, a covariance matrix estimator from Conley 1999 shown to be consistent when effective distances are not precisely observed.

3.2 Interpreting the Dynamics Of Development

Local endogenous development suggests that past clearing may stimulate current clearing.

In contrast, the selection effect that affects the distribution of jt on the forested land that remains suggests the opposite prior for past clearing. Which dominates is an empirical question. We might expect the endogenous local development effect to dominate when levels of clearing and hence local institutions and infractructure are low and not all good land is likely to be exploited. In contrast, we might expect that the selection effect will have a large influence when past clearing levels are high and only poor quality land remains in forest. At this point local institutions and infrastructure may also approach a level where increased clearing does not lead to significant endogenous development. To allow for tradeoffs between these two effects we include a polynomial for past clearing.

Finally, a process endogenous even to individual land users is that whenever agricultural returns shift, adjustment to the new equilibrium level of cleared land may not be instantaneous. Costs may rise with adjustment due to limited local labor, labor mobility and access to credit. Partial adjustment implies that past changes in returns can have ongoing effects, which suggests persistence in rates of forest clearing. This is not explicitly in our error structure but we include lagged clearing as a proxy for such effects. We do this only in later cross-sectional regressions since for early intervals this is the same as past clearing.

4 Data

Table 1 gives the means and standard deviations of the variables used, weighted by the forested area per observation. The following sections describe the data sources and variable definitions.

4.1 Forest Cover and Dependent Variable

We observe forest cover at five points in time: 1963, 1979, 1986, 1997 and 2000. We first separate the country into 436 political districts. Second, within each district we have one observation for each 'life zone' that is present. The Holdridge Life Zone System (Holdridge 1967) divides Costa Rica into twelve ecological life zones reflecting levels of precipitation and temperature. On average about three life zones are present in a district and we have up to 1229 observations per year. Our dependent variable is the annualised deforestation rate within the subdistrict in each time interval. As some subdistricts become fully deforested the number of observations falls.

The data used to create the dependent variable come from several different sources. The 1963 data are from aerial photos (translated into maps) digitized by the University of Alberta to distinguish forest and non-forest. For calculating 1900-1963 transitions, we assume that before 1900 all the area that could potentially be forested (not rocks, water or mangroves) is in forest. The 1979 data were produced from Landsat satellite images by the National Meteorological Institute of Costa Rica (IMN 1994), with final products printed at a 1:200,000 scale. Within potentially forested areas, they distinguish 'forest' and other land-uses we group as 'non-forest'. The 1986 and 1997 data were also derived from Landsat satellite images (see FONAFIFO 1998) and distinguish forest, non-forest, and mangroves, while also indicating secondary forest (land classified as forest in 1997 but not 1986) with final maps at 1:250,000 scale. The 2000 Landsat images were processed by the University of Alberta EOSL to be consistent with 1986 and 1997.

The 1986 and 1997 data are thought to mis-classify forest in areas where there is deciduous tropical forest, i.e. primarily in the Guanacaste region, depending on when the data were collected. Satellite images are generally collected during the dry season, when there are few clouds, but at those times often there are also no leaves in the deciduous forest, which can be mistaken for bare soil or pasture. This introduces measurement error in the dependent variable.

For each subdistrict for each time interval, we calculate the area deforested. The 1986, 1997 and 2000 maps all have clouds so we calculate these areas deforested (and thus also rates of loss) from the visible portions of each observation, using pairs of images with consistent visible areas. For intervals before 1986-1997 we cannot distinguish gross from net transitions, and assume gross deforestation equals net. If the measured net deforestation is negative, since we are analyzing deforestation we use a value of zero. After 1986, we know the gross deforestation.

The deforestation rate, is the area deforested during an interval divided by the area within the subdistrict of the forest "at risk" at the start of the interval. Areas with no forest at the start of an interval are dropped, as there is no risk of deforestation. We assume that forest in national parks and biological reserves is not at risk of deforestation (it was not in fact cleared). This yields 4343 observations. Finally, because our time intervals are of varying lengths, for comparability we use the annualised rate of deforestation and assume it is constant throughout the interval. If it is the cumulative deforestation rate in interval t and n is the number of years in that interval, our annualised deforestation rate dependent variable is:

$$\hat{h}_{it} = 1 - (1 - \lambda_{it})^{\frac{1}{n}} \tag{9}$$

4.2 Explanatory Variables

Most observable variation in the components of (3) comes in Rit agricultural returns. In Costa Rica returns to forest are low. Merchantable timber has often been removed before the deforestation decision takes place and regrowth is slow. We do not directly include forest returns or conversion costs though they will affect the interpretation of some variables.

4.2.1 Direct Measure of Agricultural Returns

The annual return rjkt to a given hectare j in crop k at time t is the crop price pkt times the annual yield per hectare yjkt minus the costs of production costjkt. For each year, we estimate the returns for the four major export crops: coffee, bananas, sugar and beef. We have data from 1950 onward. Its quality is very mixed. It improves significantly after 1985. For each interval, returns are averaged across the years for an average return (in 1997 US$) to crop k on one hectare of cleared land during that interval (see Appendix for data and techniques).

Each parcel is used for one crop at a time. We define sjk as the probability of a crop being chosen as the use of newly cleared land. We assume that these probabilities are constant within subdistricts and equal to shares of existing crops.

$$\text{AGRETURN}_{it} = E(r_{it}) = \sum_{k} s_{ik} r_{ikt} \tag{10}$$

We calculate the sik using data on production patterns in the 1970s and 1980s and information on the suitability of different lifezones for different crops. For example, in a humid, lower-montane area we represent the land-manager's choices by assuming that cleared land will be used for coffee or something with a similar return. We expect higher returns to predict higher clearing.

4.2.2 Proxies for Transport Costs and Market access

AGRETURN measures returns at the market, not farmgate returns. Lacking a dollar measure of transport costs, we use the minimum linear distance in kilometers to a major market, DISTCITY, i.e. the shortest of the distances from an observation's center to San José, Puntarenas and Limon as a proxy. We also interact this with time since we expect transport costs to diminish with time as roads and vehicles improve. In cross-sectional regressions for recent years (1986-2000), we also use road density (ROADSDEN), i.e. total length of roads in a district in the mid-1980s divided by the district's area, as an additional proxy for market access.

To control for local market size, we include district-level population density POPDEN and its square POPDEN2. The measure is from census data at the district level, for 1950 and 1984, and is simply divided by the area of the district. Because population is potentially endogenous to other factors that lead to economic activity and deforestation, we use lagged population densities.

4.2.3 Geophysical Proxies for Returns

Given the difficulty of measuring agricultural returns, we also consider spatially specific proxies for returns to clearing. Our geophysical variables proxy for agricultural productivity. More productive land should have higher clearing rates. We create dummies for three groups of lifezones: GOODLZ includes all humid (medium precipitation) areas, which have moderate temperatures; MEDLZ includes very humid areas (higher precipitation) in moderate to mountain elevations (and hence moderate temperature); BADLZ includes very humid areas with high temperatures (tropical), very dry hot areas, and rainy lifezones, all of which are less productive. We also have data on seven different soil types for land outside national parks, another proxy for agricultural productivity. We create a BADSOIL measure, i.e. the proportion of a subdistrict with low-productivity entisol soil.

4.2.4 Proxies for changes in returns over time

As discussed in section 3, we control for the effects of calendar time with either a quadratic in time (measured at the midpoint of the interval) or a set of time dummies for each interval; to account for unobservable local changes in returns and the selection effect we include a quadratic in the cumulative previous clearing in the subdistrict (%CLEARED and (%CLEARED2); and to allow partial adjustment, for cross-sectional regressions after 1986 we include the subdistrict clearing rate in the previous interval (PREVCLEAR).

5 Results

Figure 1 shows that Costa Rican deforestation rates start relatively low, rise to a peak during 1979-1986, and fall to almost zero by 2000. This is due in part to changes in the explanatory factors that we measure, in part to the distribution of land quality, and in part to unobserved processes affecting economic returns. The regressions help to separate these effects.

Our tests for spatial interactions in the errors suggest that they are important. With the Moran statistics, for each cutoff distance (5-50km) we reject spatial independence. With Conley and Topa 2002's non-parametric estimate of spatial covariance as a function of distance estimated covariance is above the range for accepting spatial independence until about 40km. With the covariance matrix estimator from Conley 1999 the estimated standard errors double on average. Therefore we report only spatially corrected standard errors. In contrast the EGLS estimates are sensitive to spatial cut off distance so we do not include these.

5.1 Returns: Direct and spatial measures

5.1.1 Directly measured returns

Table 2 presents results from the grouped logit with all five time intervals combined. In regressions that control for subdistrict fixed effects, the returns coefficients are positive and generally significant. Our direct measure of returns contributes little when we control for returns using our spatial proxy measures. The coefficient on returns is insignificant and the magnitude of returns' marginal effect is small.

For three of the five cross section regressions in Table 3 we find a positive significant effect of returns that is quite robust. We do not feel that we have strong returns data for the earliest interval (1900-1963) so exclude returns from that cross section. For 1979-1986 a surprisingly significant negative effect is found.

5.1.2 Access To Markets

Transport costs and access to markets appear to play an important role in deforestation. In Table 2, we see that the further land is from a market center the less likely it is to be cleared in the earlier intervals. However, this negative effect abates with time suggesting that distances become less of a barrier to development.

In Table 3, we see that the effect of distance over time may be more complex than supposed. More remote areas initially face significantly lower deforestation pressure. Between 1963 and 1979, and maybe up until 1986, more isolated places appear to face more deforestation pressure. This shift in coefficients may reflect the 'frontier' nature of deforestation as new agricultural areas were opening rapidly in part as a result of development policies. Because Costa Rica is so small, no area is extremely remote. In the later intervals, distance to markets is again a slight deterrent to deforestation.

The density of roads (not in the combined regressions because it is measured only in the mid-1980s), has the hypothesized positive effect but is significant only in the interval 1997-2000. More roads reduce travel costs. Our other measure related to markets is local population density. Before 1986, higher population density leads to more deforestation, although a negative quadratic term suggests that it is the initial populating of an area rather than increasing the density that is most significant. In recent years, the effect becomes insignificant and the sign may even reverse. Roads density, population density, distance to markets and percentage of forest cleared are all correlated and the inclusion of different sets of variables does alter the other coefficients. These interactions do not change the essential nature of the results presented here.

5.1.3 Geophysical Factors in Productivity

Our geophysical proxies for agricultural productivity are generally significant and have the expected signs in Tables 2 and 3. Good and medium life zones are significantly more likely to be cleared than are the bad life zones (including with robust standard errors), and these are large effects, as indicated by the marginal calculations in Table 2. The only important exception to the value of a good lifezone is that in the most recent interval the effect of a good life zone diminishes and in some runs reverses. It may be that new technologies such as irrigation are making climatic conditions less critical. Areas with bad soil are significantly less likely to be cleared in both the pooled and cross section runs. These results provide support for findings within the related literature. The size of these effects is large and the effects of climatic conditions is much larger than that of soils.

5.2 Proxies For Dynamics Of Development

5.2.1 National development trends

We find that time has an initially positive but concave and hence ultimately negative effect on deforestation rates. This significant concave shape remains in fixed-effect regressions with either a quadratic in time or a dummy variable for each time interval. The significant fall in baseline hazard after 1986 is robust to a wide range of specifications. Further, the unobserved changes that this proxy represents are important trends within relative returns to clearing, as shown by the marginal effect in Table 2.

5.2.2 Previous Clearing

The cumulative percentage of forest cleared has a consistent and robust significant positive effect on deforestation. Its square has a significant negative effect. This concavity holds in the fixed-effect regression but not in all the cross sections. The marginal effect given in Table 2 is positive, and has a sizeable impact on deforestation rates.

5.2.3 Partial Adjustment

In the cross-section regressions for recent years higher previous-interval clearing significantly increases current clearing. This suggests partial adjustment, i.e. that the adjustment to land-use equilibrium may not always be reached during an interval, i.e. some shocks to agricultural profitability have impacts across the intervals. It could also reflect serially correlated shocks.

6 Summary and Conclusions

Overall, our results conform well with theory and we can explain a significant percentage of the variation in deforestation, including in the cross-section regressions. Deforestation pressures change significantly over time as development occurs. For both a five-interval common specification involving only the variables in the first column of Table 3 as well as a four-interval common specification involving the variables in the second column of Table 3 other than population density, we reject the null hypothesis of no structural change.

Consistent with previous literature we find that spatially varying market access and natural productivity are important determinants of forest clearing.

Also, the long interval covered by our data allows us to examine development and deforestation. We find significant trends and that proxies for dynamics of development have significant effects. This suggests a dynamic process in which early forest clearing affects later deforestation patterns and may even help to trigger the processes causing the effects of explanatory factors to change.

The constraint on deforestation in early years appears to be the accessibility of high quality land (conditional deforestation rate is higher than actual). In later years it is probably the shortage of high quality land combined with pressures to intensify agriculture rather than extensify. Environmental and forestry regulation may also play a role.

Appendix – direct measure of returns from beef, coffee, sugar and bananas

Units: crop price is in $/kg; yield is in kg/ha; production cost is in $/ha; transport cost is in $/ha.

Observations: 436 districts in Costa Rica from 1900-1997 in principle, but 1950-1997 in fact. The limitations on historical data mean that we do not have good measures for years before 1950 and more generally even within 1950-1997 the quality of the data is higher for the later intervals.

Prices: though some production is sold domestically most is exported. Costa Rica is a small country and we use exogenous export prices (in 1997 US$). Price data are taken from two sources, the Costa Rican Ministry of Planning (Vargas and Saenz 1994) and the Central Bank of Costa Rica website.

Yields: crop yields vary over time because of technological change, and across space because of differences in general productivity and in suitability for particular crops. While lifezones and soils proxy for this variability, here we estimate yield. For instance, in some areas the yield for a particular crop is effectively zero since it would never be grown there. Our data is of two types.

For some crops we have data on yield per hectare: for bananas, county level for 1977-1997, and given no obvious trend we assume this to be constant before 1977; for sugar, province level for several years between 1950 and 1977 and for county level in 1998, and we apply the province-level trends to extrapolate the yields for all counties within a province before 1998.

Else we observe production (kg) and area in production (ha) and divide to get the yields. For coffee we have production from 1974-1992 and 1996 at county level and area at county level from the census for 1950, 1955, 1963, 1973, and 1986. We assume production is fixed pre-1974 and area is fixed post-1986, and then interpolate the coffee areas before calculating yield ratios. For pasture we use national production from 1950 to 1995 and divide by census estimates of area for a national yield estimate. We create county-level variation by utilizing the ratio of number of cattle to pasture in the census data, assuming this variation is related to productivity. In locations where the yields for particular crops are undefined within our data, we assume that they are zero.

Costs: we estimate operating costs on an annual basis, although the data are sparse. For coffee, we observe costs only in 1979 and 1981 by coffee zone. For beef we have a single reliable estimate from 1974 at the national level. For sugar, data is better although still at national level, with estimates from Barboza, Aguilar, and León 1982 and Chaves-Solera 1994 for 1963, 1966, 1972, 1977, 1979 and 1994–96. For bananas we have a technical estimate from Hengsdijk (personal communication, Wageningen Agricultural University) for 1997, but no previous data. These are assumed constant outside the interval within which they are observed and interpolated. For transport costs, lacking direct measures, we rely upon the proxy described above.

Crop Shares: to predict how likely each of the four crops is to be chosen, we use a combination of census and satellite land-use data to estimate the share of each crop in each district. While the satellite data are more precise, they distinguish not crops but simply land uses (permanent crops, pasture, and forest). The data is from 1973 and 1984, and our shares do not change over time.

We combine the district shares with the crop returns for expected annual return per district-year, following (10) above. Then we average the returns across intervals to generate mean returns to which we assume our estimated constant annual interval deforestation rate will have responded.

Figure 1 -- Costa Rican Annualised Deforestation Rates By Time Interval

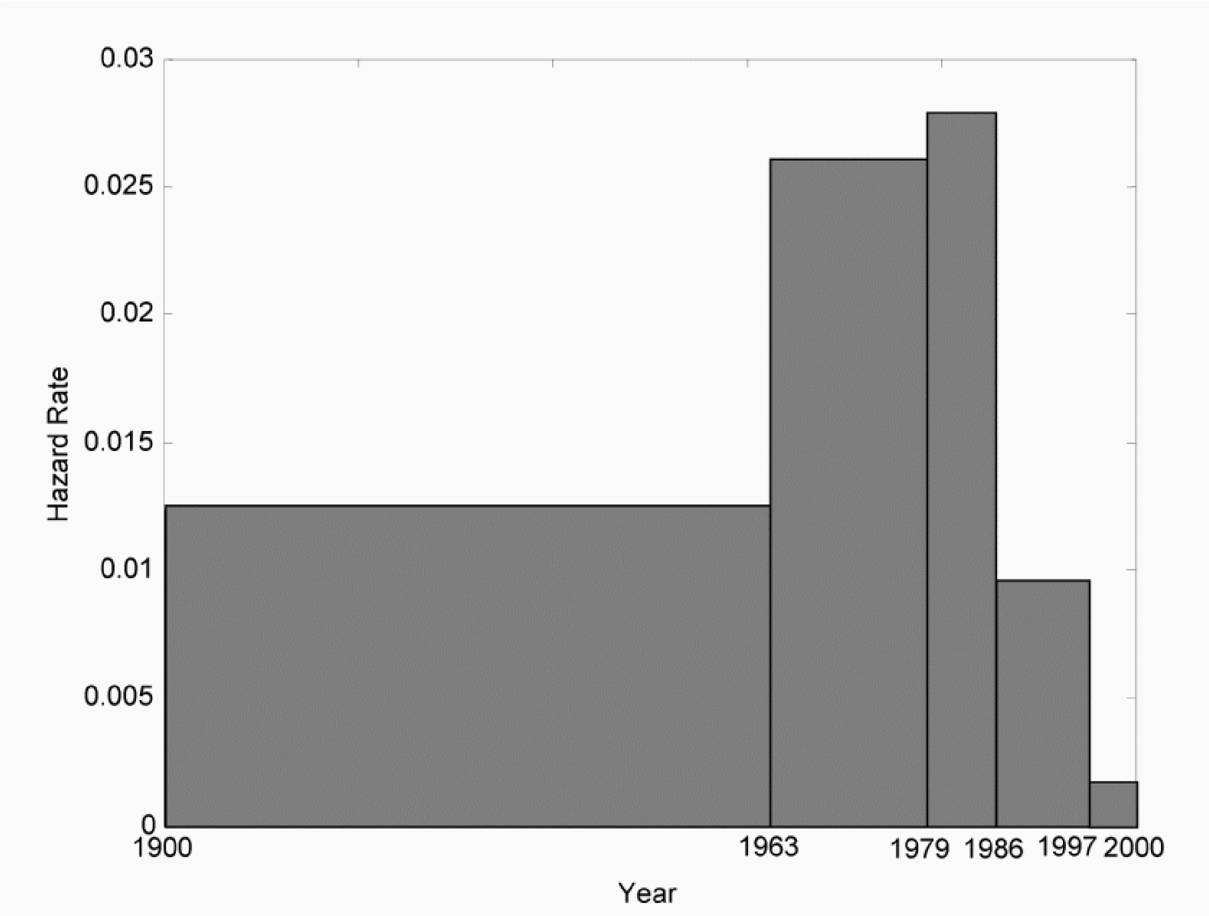

Figure 2 Different dynamics of deforestation depending on land productivity

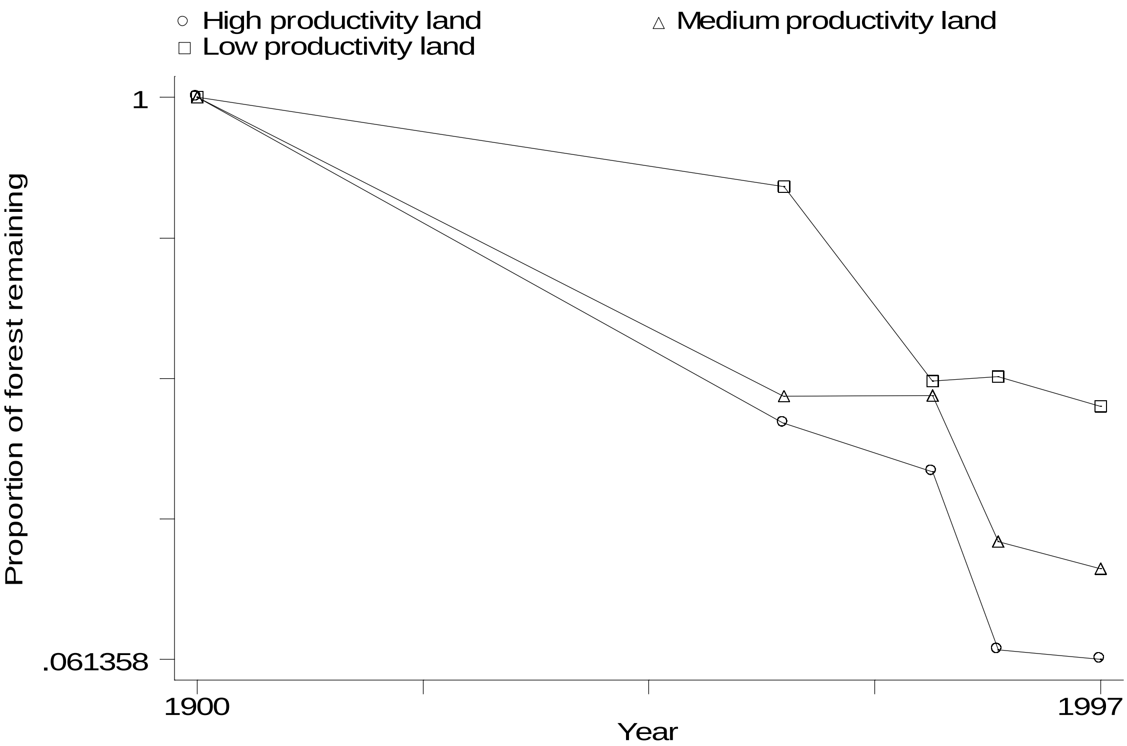

Table 1 -- Variable Definitions and Descriptive Statistics (weighted by forest area)

Variable	**Name**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
<u>Annualised Deforestation Rate</u>		0.016	0.048	0.00001	1
<u>Returns</u>					
Agric.Returns/ha (US$ 1997)	AgReturn	659	1154	0	5047
Distance to major markets (km)	DistCity	73	38	0	186
Roads density	RoadsDen	0.0026	0.0022	0	0.049
Population density (#/ha)	PopDen	0.089	0.38	0	107
<u>Geophysical Characteristics</u>					
Dummy for humid lifezones	GoodLZ	0.24	0.43	0	1
Dummy for very humid (pre montane, lower montane) and	MedLZ	0.23	0.42	0	1
Dummy for very humid (tropical), dry (tropical), and rainy lifezones	BadLZ	0.54	0.50	0	1
Proportion of known soil types that are entisol	BadSoil	0.11	0.23	0	1
<u>Dynamics</u>					
Time at midpoint of interval	Time	66	26	33	100
Proportion of forest cleared	% Cleared	0.21	0.26	0	0.99996
Lagged Defor. Rate (1979 onward)	PrevClear	0.0080	0.017	0	0.46

Table 2 -- Pooled Regression Results

	Grouped Logit uncorrected results (spatial correlation in section 3.3)			
Years	1900 – 2000, pooled transitions			
Dep.Variable	annualized deforestation probability			
Explanatory Variables	**Coefficients** (t statistics)	**Defaults &**	**Marginal Δs**	**1986 Marginal Effects**
AGRETURN	4.7 E-06 (0.26)	1232	1685	0.00036 (< 1% of default)
DISTCITY	-0.020 (-16)	71km	38 km	0.011 (23%)
DISTCITY*TIME	3.0 E-04 (16)	(implied	by the above)	(joint with above)
GOODLZ	0.21 (6.0)	0	1	0.011 (23%)
BADLZ	-0.46 (-11)	0	1	-0.017 (35%)
BADSOIL	-0.13 (-1.9)	0	1	-0.0057 (12%)
TIME	0.13 (21)	86	10	-0.026 (54%)
$TIME^2$	-0.0012 (-25)	(implied	by the above)	(joint with above)
% CLEARED	1.8 (7.4)	37%	28%	0.019 (40%)
% $CLEARED^2$	-0.71 (-2.6)	(implied	by the above)	(joint with above)
_CONS	-6.1 (-36)			
R^2	0.36			
N	4343			

Table 3 -- Cross-section Regression Results

		Grouped Logit uncorrected results (spatial correlation in section 3.3)			
Years	1900-1963	1963-1979	1979-1986	1986-1997	1997-2000
Dependent Variable	annualized def. prob.	annualized def. prob.	annualized def. prob.	annualized def. prob.	annualized def. prob.
Explanatory Variables			**Coefficients** (t statistics)		
AGRETURN		2.8 E-04 (2.4)	-1.3 E-04 (-4.3)	2.7 E-04 (13)	2.5 E-04 (5.6)
DISTCITY	-0.011 (-17)	0.0034 (3.6)	0.0018 (1.4)	-0.0043 (-4.5)	-0.0016 (-1.1)
POPDEN		0.46 (2.7)	1.0 (3.5)	-0.068 (-0.41)	-0.11 (-1.5)
POPDEN^2		-0.030 (-2.1)	-0.068 (-2.8)	0.0065 (0.36)	0.0038 (1.8)
ROADSDEN				18 (0.79)	80 (3.3)
GOODLZ	0.22 (4.2)	0.080 (0.93)	0.20 (2.2)	0.15 (1.7)	0.035 (0.23)
BADLZ	-0.68 (-8.5)	-0.41 (-4.4)	-0.60 (-5.8)	-0.60 (-8.1)	-0.65 (-4.6)
BADSOIL	-0.055 (-0.52)	-0.37 (-2.2)	-0.17 (-0.97)	-0.91 (-5.3)	-0.48 (-1.7)
% CLEARED		2.4 (5.0)	2.0 (3.7)	3.0 (7.4)	0.41 (0.58)
% CLEARED^2		-0.61 (-1.1)	-1.8 (-3.0)	-1.1 (-2.6)	1.26 (1.8)
PREVCLEAR				2.4 (2.6)	14 (7.1)
_CONS	-3.0 (-57)	-3.8 (29)	-2.9 (-16)	-5.1 (-33)	-5.9 (-25)
R^2	0.31	0.29	0.29	0.51	0.39
N	1128	799	638	649	782

References

Anselin, L. (1988). Spatial Econometrics: Methods and Models. Studies in Operational Regional Science, Kluwer Academic Publishers, Dordrecht, 284p.

Anselin, L. and G.M. Florax, eds. (1995). New Directions in Spatial Econometrics. Advanced in Spatial Science, Springer Verlag, 420p.

Antle, John M. and Gregg Heidebrink (1995) "Environment and Development: Theory and International Evidence" Economic Development and Cultural Change XLIII, pp. 604-625

Barboza, C.V., J.F. Aguilar and J.S. León (1982). Desarollo tecnologico en el cultivo de la caña de azucar . Consejo Nacional de Investigaciones Cientificos y Tecnologicas, Costa Rica.

Castro-Salazar, R. and G. Arias-Murillo (1998). Costa Rica: toward the sustainability of its forest resources. Technical Report, FONAFIFO, San José, Costa Rica.

Chaves-Solera, M. A. 1994. Organizacion de la agroindustria azucarera costarricense y costos de produccion agricola de la caña de Azucar. DIECA 59p. San Jose, Costa Rica.

Chomitz, K.M. and D.A. Gray (1996). "Roads, Land Use and Deforestation: A Spatial Model Applied to Belize". World Bank Economic Review 10(3):487-512.

Conley, T.G. (1999). "GMM estimation with cross sectional dependence". Journal of Econometrics 92:1-45.

Conley, T.G. and G. Topa (2002). "Socio-economic Distance and Spatial Patterns in Unemployment". Journal of Applied Econometrics 17:303-327.

Cropper, M. and C. Griffiths (1994). "The Interaction of Population Growth and Environmental Quality". American Economics Review: Papers and Proceedings 84(2):250-254.

Cropper, M., J. Puri and C. Griffiths (2001). "Predicting the Location of Deforestation". Land Economics 77(2):172-186.

FONAFIFO (1998). Mapa de Cobertura Forestal de Costa Rica. San José, Costa Rica.

Geoghegan, J., S.C. Villar, P. Klepeis, P.M. Mendoza, Y. Ogneva-Himmelberger, R.R. Chowdhury, B.L. Turner II and C. Vance (2001). "Modeling tropical deforestation in the southern Yucatan peninsular region: comparing survey and satellite data". Agriculture Ecosystems & Environment 85:25-46.

Grossman, Gene M., and Alan B. Krueger, (1995) "Economic Growth and the Environment" Quarterly Journal of Economics, CX:353-377

Harrison, Susan (1991). "Population Growth, Land Use and Deforestation in Costa Rica, 1950-1984." Interciencia 16(2):83-93.

Holdridge, L. 1967. Life zone ecology. Tropical Science Center, San José, Costa Rica.

Instituto Meteorologico Nacional (1994). Mapa de Uso de la Tierra de Costa Rica. San José.

Irwin, E.G. and N.E. Bockstael (2002). "Interacting Agents, Spatial Externalities, and the Endogenous Evolution of Residential Land Use Pattern". Journal of Economic Geography 2(1):31-54.

Kaimowitz D. and A. Angelsen (1998). Economic Models of Tropical Deforestation: A Review. CIFOR, Indonesia.

Kiefer, N.M. (1988). "Economic Duration Data and Hazard Functions" Journal of Economic Literature XXVI(June):646-679.

Lancaster, T. (1990). The Econometric Analysis of Transition Data. Econometric Society Monograph No. 17. Cambridge: Cambridge University Press.

Maddala, G. (1983). Limited-Dependent and Qualitative Variables in Econometrics. Cambridge: Cambridge University Press.

Nelson, G.C. and D. Hellerstein (1997). "Do Roads Cause Deforestation? Using Satellite Images in Econometric Analysis of Land Use" American J. of Agricultural Economics 79: 80-88.

Panayotou, T. (1995) "Environmental degradation at different stages of economic development" in I. Ahmed and J. A. Doeleman, Eds. Beyond Rio: The Environmental Crisis and Sustainable Livelihoods in the Third World (London: Macmillan Press) pp. 13-36

Pfaff, A. S. P and Suzi Kerr. 2007 “What Would Have Happened: Reviewing and improving estimated baselines for tropical forests and sequestered carbon” Motu manuscript. www.motu.org.nz

Pfaff, A.S.P (1999). “What Drives Deforestation in the Brazilian Amazon? Evidence from Satellite and Socioeconomic Data”. J. of Environmental Economics and Mgmt 37(1):26.

Pontius, R.G. Jr., J.D. Cornell and C.A.S. Hall (2001). “Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica”. Agriculture Ecosystems & Environment 85:191-203.

Rosero-Bixby L. and A. Palloni (1996). Population and Deforestation in Costa Rica. Paper presented at the Annual Meeting of the Population Association of America in New Orleans.

Sader, S.A. and Joyce, A. T. (1988) "Deforestation rates and trends in Costa Rica" Biotropica 20: 11-19

Saloner, G. and A. Shepard (1995). “Adoption of Technologies with Network Effects: An Empirical Examination of the Adoption of Automated Teller Machines”. RAND Journal of Economics 26(3):479–501.

Sanchez-Azofeifa, G.A., G.C. Daily, A.S.P. Pfaff, and C. Busch (2003). “Integrity and Isolation of Costa Rica’s national parks and biological reserves: examining the dynamics of land-cover change”. Biological Conservation 109:123-135.

Stavins, R.N., A. Jaffe (1990). "Unintended Impacts of Public Investments on Private Decisions: The Depletion of Forested Wetlands". American Economic Review, 80(3):337-352.

Vargas, J.R. and O. Saenz (1994). Costa Rica en cifras 1950–1992. MIDEPLAN PNUD.

http://www.naturvardsverket.se/dokument/press/2004/juni/postkyoto/brazil1.pdf and brazil2.pdf

http://www.conserveonline.org/2004/07/s/en/Tropical_Deforestation_and_Kyoto_Protocol.pdf

Heckman, James. 1979. "Sample Selection Bias as a Specification Error," Econometrica, 47, pp. 153-161.

Kerr, Suzi, Joanna Hendy, Shuguang Liu and Alexander S P Pfaff. 2003. "Uncertainty and Carbon Policy Integrity," Motu Working Paper 04-03, Motu Economic and Public Policy Research, Wellington, New Zealand.

Pfaff, Alexander S. P. and Arturo Azofeifa Sanchez. 2004. "Deforestation Pressure and Biological Reserve Planning: A Conceptual Approach and an Illustrative Application for Costa Rica," Resource and Energy Economics, 26, pp. 237-254.