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How Can Carbon Sequestration in Tropical Forests be Rewarded? Evidence from Costa Rica

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Introduction

As empirical evidence that human activities are affecting the global climate increases, so do efforts to identify and evaluate climate mitigation and adaptation options. Forest managers and policy makers around the world are increasingly participating in and following such efforts, since forestry activities (e.g., reforestation, slowing deforestation, or improved forest management) could in principle play an important role within the set of climate-change mitigation strategies.

According to the last IPCC assessment (Watson et al. 1996), initiatives to slow deforestation, promote natural forest regeneration and create a global forestation program (plantations and agroforestry) have the potential to offset 12–15 percent of global fossil fuel carbon emissions from 1995 and 2050. More than two-thirds of such opportunities exist in the tropics.[1]

While the magnitude of these numbers indicates a potential role for land- and forestry-based projects as carbon sinks, questions have been raised over the feasibility of such projects as mitigation strategies, especially in developing countries. These questions stem from concerns about environmental integrity reflected in the requirements of Article 12 of the Kyoto Protocol, which clarifies the potential role of developing countries in climate-change mitigation. Their key role comes within the Clean Development Mechanism (CDM).[2] Developing countries can contribute carbon offsets through the CDM only if these offsets are "additional" to what would

[1] For opportunities in the seven Central American countries, see Rodriguez, Corrales, and Pratt (1998).

[2] The CDM is an instrument for joint emissions reduction between Annex I (industrialized) and non-Annex I (developing) countries. It rests on the rationale that emissions trading (of which CDM is one vehicle) allows the achievement of a given mitigation target at the lowest cost while promoting sustainable development.

have happened in the absence of the initiative, are real and long-term, and can be accurately measured, monitored, and verified.

For forestry and land-use change projects, the demonstration of additionality and reliable quantification of a project's impacts remains a challenge. How can we predict what the level of deforestation will be *without* projects, in order to assess additionality? How can we estimate GHG release from deforestation when neither the extent of forest cover nor the amount of carbon stored in forest ecosystems is known with precision? How would the accounting for a given project include leakage, i.e., indirect project effects (positive or negative) outside the project's boundaries? How can we address the problem that sequestration offsets are reversible and hence may not be long-lasting? These and other issues have been debated at length (for example, by Andrasko 1997, Brown et al. 1997, Anon. 1998, Chomitz 1998, and Goldemberg 1998).

Dealing with these issues is complicated by the fact that since non-Annex I countries have no quantitative commitments under the Kyoto Protocol, they typically lack national emissions baselines against which additional reductions can be established and traded; this means that additionality is an issue even at a national level. A potential solution is the establishment of national emissions baselines before trading takes place (Panayotou 1998). Lacking these, we must proceed on a case-by-case, project-level basis.

Before the CDM can be used extensively, the international community will need to agree on methodologies to determine baselines and estimate offsets that are reasonably accurate and not subject to manipulation. The scientific bodies of the FCCC are actively working to address these issues. For example, IPCC has set up a working group to report on the appropriate treatment of sinks by the end of 1999.

These challenges to forestry projects as credible mitigation alternatives suggest the value of increased understanding of the process influencing land-use changes, and such understanding is important in any case in light of the importance of forest ecosystems in Central America as tourist destinations, reservoirs of biological diversity, and providers of many environmental services such as water quality and regulation. In this chapter we aim to contribute to such understanding, by addressing the following questions:

1. Can land use be accurately measured at national scales, for instance through interpretation of satellite images? What levels of accuracy can be expected for a Central American country?

2. What are the driving forces behind land-use change that must be taken into account in creating credible, fair, national or regional level baseline projections of deforestation and reforestation?

3. Can carbon stocks be reliably estimated? What are their levels in climax vegetation and on cleared land under different physical and climatic conditions? How do carbon stocks change over time when land is reforested? How does this vary by physical and climatic conditions?

In order to suggest evidence and show ways for future research to improve the answers to these questions, this chapter focuses on Costa Rica as a case study. Costa Rica was chosen for several reasons. First, the country has long engaged in assessment of its land-use and conservation-related research activities; thus, land-use data are available. Second, the country has explicitly embraced the concept of "capturing" global environmental services through innovative financial mechanisms. It has already sold carbon offsets under the Pilot Phase of Joint Implementation, the forerunner to the CDM, and it is likely to be one of the first countries to create sequestration projects under the CDM. Third, Costa Rica contains many significant tropical research stations. Thus, relevant ecological measures are relatively available. Fourth, in attempting to influence changes in land use, the country has experimented with the establishment and strengthening of protected areas and with a series of fiscal incentives aimed at encouraging reforestation and conservation activities.[3] Finally, given the unusual amount of data available in Costa Rica, there are implications for other Central American countries; the level of analytical accuracy attainable in Costa Rica can be taken as an upper bound on what is likely to be feasible elsewhere.

The chapter is structured as follows. First, below, we begin this analysis of the process influencing land changes with a dynamic model of land-use choices. Such models have often been suggested, but crucial features have often been neglected in application. This model generates testable hypotheses regarding factors underlying patterns of land-use changes in tropical areas. The next section describes the data collected for this project and discusses the quality of land-use data. It also outlines the variables used to test the implications of the model. Following that, we present our results and then discuss the linkage from land-use changes to

[3] Additional policy changes that have had an impact on Costa Rican forests include sanctions for deforestation, see the new Forestry Law 7575/1996, summarized in Castro and Arias 1998.

implied carbon sequestration, and the quality of information currently available on carbon sequestration. Finally, we present some conclusions and lessons learned. This paper includes the first results emerging from a larger project on carbon sequestration in Costa Rica by a group of economic, geographic, and ecological researchers (see Kerr et al. 2000).[4]

A Dynamic Model of Land-Use Choices

To create baseline projections of forest and deforestation against which sequestration can be rewarded, we need a model that will predict land-use changes. In chapter 15 we use estimates of agricultural returns to directly estimate the response of forest and hence carbon in response to dollar-valued rewards for sequestration. In this chapter we look at the effects of qualitative factors that are related to agricultural returns and, hence, affect land-use choices. We present a simple dynamic model of deforestation and model reforestation in an analogous way. In our use of a dynamic model we follow Stavins (2000, forthcoming), Parks and Hardie (1995), and Ehui and Hertel (1989). However, borrowing from Kerr, Pfaff, and Sanchez-Azofeifa (1998), we emphasize how the implications of a dynamic view of land-use choices differ from the typical application of land-use models. In particular, we use a new empirical approach based on the dynamic model's implications.

Model and Optimality Conditions

In order to predict the level of deforestation in the presence and absence of carbon rewards, we model the land manager of each hectare *i* as facing the following dynamic optimization problem. The land manager selects *T*, the time when land is cleared, to maximize the present discounted value of returns from the use of hectare *i*,

$$\text{Max}_T \int_0^T (S_{it}) \, e^{-rt} \, dt \; + \int_T^\infty R_{it} \, e^{-rt} \, dt - C_T \, e^{-rt} \tag{1}$$

where:

S_{it} = Potential return (rent) to forest uses of the land

R_{it} = Maximum potential return to non-forest land use

[4] This larger project involves Suzi Kerr, Alex Pfaff, and Arturo Sanchez-Azofeifa, and also Flint Hughes, Shuguang Liu, David Schimel, Joseph Tosi, and Vicente Watson. For more information on this project, contact Suzi Kerr (Suzi.Kerr@motu.org.nz) or Alex Pfaff (ap196@columbia.edu). The larger project is funded in part by the Tinker Foundation, the National Center for Ecological Analysis and Synthesis, and the National Science Foundation.

C_T = Cost of conversion net of obtainable timber value

Two conditions are necessary for clearing to occur. The first is that clearing must be profitable.

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

In other words, for clearing to be worthwhile, present discounted rents from non-forest uses will have to more than compensate the land manager for the lost returns from forestry uses (including the value of carbon offsets sales) and the cost of land conversion.[5]

However, an "arbitrage" condition must also be satisfied. The reason is that even if clearing is profitable at time t, it may be even more profitable to wait and clear at $t + 1$ instead, for instance, because during that time period conversion costs may be expected to fall.[6] Thus:

$$R_{it} - S_{it} - rC_t + \frac{d}{dt} C_t > 0 \tag{3}$$

Equations (2) and (3) are necessary but not sufficient conditions. The second-order condition is satisfied if the net returns to cleared land rise monotonically and the costs of conversion fall in a convex way. We base our empirical method on (3). In the historical period we are considering the sufficient condition almost certain to hold because of the consistent development process. Given the low historical economic value of standing forest (which does *not* necessarily still include the most valuable timber trees), condition (2) is almost certain to hold for most of the relevant period. In very recent years the recreation and ecotourism value of standing forest in a few areas and the potential for conservation incentives will have raised the economic value slightly but not enough to affect national estimates.

Application to Observable Variables

Dynamic Intuition

In static land-use models (such as by Chomitz and Gray 1996 or Pfaff 1999), at every point in time a land manager allocates a parcel of land to the use that will provide the highest returns at that time. Thus, current returns (and thus the factors that affect returns) determine current land uses and, by implication, changes in returns determine changes in land use. A

[5] At the moment we exclude the possibility of reforestation. Later models will incorporate transitions in both directions.

[6] In addition, future returns on cleared land may depend on the time of clearing (e.g., land may degrade).

typical empirical application, even if motivated by a dynamic theoretical model, considers unobserved determinants solely in terms of omitted current variables within the estimation.

A dynamic model adds the issue of *when* to change one's land-use allocation, and it takes into account the effect of history on current decisions—and thus a focus on inter-temporal factors. One implication of this is that additional land-use determinants must be included in the model, for example, expectations of future clearing costs. Second, past decisions will affect future decisions and unobservable factors will be correlated over time. Rather than modeling the level of cleared land, as is traditional, we model the conditional probability of clearing land, given that it is not yet cleared.

In our model, the probability of clearing depends not only on changes in returns but also on the level of returns. This occurs because of unobservable variables that change over time and interact with observable returns. One example is "adjustment costs." Once a land manager identifies the best land allocation, shifting to that allocation over time may occur in several steps because of costs that arise in moving to that allocation. For example, suppose a large one-time shift in land-use returns suddenly made a great deal of forest clearing optimal. As the clearing occurs, a lack of local labor might lead to a rising wage on the margin. This additional cost of clearing is a form of adjustment costs, which would imply that even if factors in returns are unchanged after their one-time shift, land allocation would change over time, moving in steps to the optimal outcome.

If the rising marginal wage were observable, it would simply be another observable factor useful for explaining land changes over time. However, many forms of adjustment costs may not be directly observable. An alternative approach to estimation, given unobserved adjustment costs, is to give an explicit role to *time*, because the adjustment story suggests that land shifts over time toward the optimal allocation. This implies, in contrast to standard models, that in our model even if observed determinants of returns from land uses do not change over some period of time, the allocation of land could well change over that period.

In addition, learning over time (which is likely to be unobservable) about how benefits and costs of land uses will shift over time could yield land shifts over time, even conditional on fixed observable factors in returns. The option value of waiting to take fully or partially irreversible actions (such as cutting mature forests, which cannot be immediately restored) will fall as uncertainty is resolved. Unobservable resolution of uncertainty over time could lead to a path of land allocation shifts over time.

Further, land parcels are heterogeneous in unobservable ways. Thus, the returns from parcels (in both forest and non-forest uses) will vary across space even after we control for all observable factors. At least some of this heterogeneity may be observed by local land managers (perhaps learned over a long period of time). As a result, the more favorable parcels of land are likely to be developed first and the less-favorable only later. We can use the history of development on observationally similar land to predict the quality of remaining forest, if we have an idea about the distribution of unobservable quality. In particular, given all observable factors' values, the likelihood that a forested parcel is high-quality land when no others in the area have been cleared will be higher than when land managers have already chosen to clear most similar parcels. They will have left the least desirable land—that is, the land-use history (i.e., what has and has *not* already been developed) may tell us something.[7]

An alternative way to consider the probability that remaining land is lower quality, or that adjustment costs mean that partial adjustment is still happening in response to the existing returns level, is to consider how developed the area is. Development will tend to improve road access and also improve access to credit—and thus lower discount rates—making investment more attractive. A highly developed area is likely to have come close to equilibrium and exploited available opportunities. Costa Rica in general is developing over time, so simple calendar time is one way to consider this. However, different parts of Costa Rica are developing at different rates, depending on the road network and on historical accidents. Recently opened-up areas may still contain valuable land to be cleared. One measure of such development is simply how much land has already been developed. An alternative is the level of urbanization in the area.

Formal Derivation of Econometric Specification

Following Saloner and Shepard (1995), to take account of unobservable heterogeneity, define:

$$\varepsilon_{it} = E[R_{it} - S_{it} \mid X_{it}] - [R_{it} - S_{it}] \quad (4)$$

[7] This distributional issue was also explicit in Stavins and Jaffe (1990) and leads to their use of a logistic distribution. It has a different effect when combined with unobservable dynamic variables such as adjustment costs and uncertainty.

$E[R_{it} - S_{it} \mid X_{it}]$ is the mean per-period return on a cleared land parcel with observable characteristics X_{it}. Land parcels with a lower ε_{it} are more likely to be cleared. Eq. (3) becomes

$$\varepsilon_{it} \leq R_{it} - S_{it} - r\,C_t + \frac{d}{dt}C_t \tag{5}$$

ε^* is the value of ε that satisfies (5) exactly. The probability that land parcel i is cleared in period t, conditional on not having been cleared before t, the hazard rate for parcel i in period t:

$$h_{it} = \frac{F[\varepsilon^*(X_{it+1}, \mathrm{t}+1)] - F[\varepsilon^*(X_{it}, \mathrm{t})]}{1 - F[\varepsilon^*(X_{it}, \mathrm{t})]} \tag{6}$$

where $F(.)$ is the cumulative distribution function for ε.[8] The behavior of the hazard over time depends on $F(.)$, on the way that X_{it} changes over time, and on the rate ε^* changes over time due to common unobserved factors.[9]

Less technically, we can ask: If conversion has not occurred by time t, what is the probability that, in the next time period, conversion will occur? For example, given that plot i was forested in 1986, what is the probability that it will be deforested by 1997? The answer is the conditional probability $prob(1986 < T_i \leq 1997 \mid T_i > 1986)$. At the plot level, this conditional probability is the hazard rate, h_{it}:

$$h_{it} = \frac{prob_{it}\ \text{(plot i cleared between 86 and 97)}}{prob_{it}\ \text{(plot is forest in 1986)}} \tag{7}$$

Using only district-level data, not individual data, we cannot estimate a duration model by maximum likelihood.[10] Instead, we estimate the district-level hazards in each interval and use those as the dependent variable in a regression, relating hazards to observable variables relating to land use returns and time. The deforestation rate for a given district is a simple estimate of the parcel-level hazard rates averaged across a district. $d_{st} = 1$ if the land parcel is cleared during time t; $g = 1$ if it was forested at time t.

$$\hat{h}_t = \frac{\sum_{s=1}^{n} d_{st}}{\sum_{s=1}^{n} g_{st}} = \text{deforestation rate} \tag{8}$$

[8] This is not exactly correct when X is changing over time. The point reached in the cumulative distribution function at any point in time will depend on the historical values of X as well as current values.
[9] For more discussion of duration models and hazard rates see Kiefer (1988) or Greene (1990).
[10] In a separate paper we are using pixel-level data to do this.

The advantage of understanding the relationship between the deforestation rate and the individual plot holder's optimization problem is that the coefficient estimates we derive can be interpreted clearly in the context of a specific model. Economics and other disciplines have often used a class of hazard models called proportional hazard models.[11] In these models, all parcels share a common underlying hazard, h_{0t}, that changes over time, and their hazard is shifted proportionally based on their characteristics x_{it}. The shifter, ϕ, is not time-dependent. β is the vector of coefficients to be estimated.

$$\hat{h}_{it} = \phi(x_i, \beta)\, h_{0t} \tag{9}$$

$\phi(x,\beta)$ could be any functional form. $\phi(x,\beta) = \exp(x'\beta)$ is convenient because it constrains the hazard to be positive without restricting β. Inference is also straightforward with this specification. We can interpret β as the marginal effect of the variable on the log of the probability of deforestation. If we assume that $F(.)$is exponential, the underlying hazard is constant, and taking logs of both sides of (9), we estimate the following equation (the second term is simply the constant):

$$\ln(\hat{h}_{it}) = x_{it}'\beta + \ln(h_0) + \mu_{it} \tag{10}$$

A more general specification of the underlying hazard allows it to be time-dependent. We allow the baseline hazard to be time-dependent; and, including time or time dummies and using time interactions and estimating separate cross-sections allow the independent variables to interact with time. We also include measures of development as well as calendar time.[12]

We estimate (10) with different specification of time-dependent hazards using data on district-level forest cover at different points in time and variables related to returns to different land uses. The return to clearing land in different locations depends on the productivity of the land, the cost of production, the cost of getting goods to market, and the value of those goods when they are sold. Regulatory constraints, such as the existence of parks, may limit clearing directly.

[11] This approach is used heavily in the biomedical literature in studies of mortality, as well as in the labor literature to study unemployment duration and the technology-change literature to study timing of technology adoption.
[12] Some distributional assumptions directly create a time-dependent baseline hazard. For example, if we define $h_{0t} = h_0\alpha t^{\alpha-1}$, which implies a Weibull distribution, the estimating equation becomes: $\ln(h_{it}) = x_{it}'\beta + \ln(h_0) + \ln\alpha + (\alpha - 1)\ln t + \mu_{it.}$. The Weibull allows either an increasing or decreasing hazard over time.

Data and Variables

We estimate the model described in the previous section by using district-level data obtained from the analysis of digital maps and secondary sources. The dependent variable is created from forest cover data. Independent variables are related to physical, geographical and socioeconomic factors and are aggregated to the district level. Geo-referenced features have been assigned to each district by overlaying the thematic maps with a 1996 district map. Sources and characteristics of the data are described in the following paragraphs (see alsoTable 14-1). We also discuss the quality of data available for measuring land use; i.e., our ability to observe forest levels and changes.

Land Use and Forest Cover

Land-use and forest-cover data were derived from five maps (1979, 1984, 1986, 1992, 1996/97).

The 1979 and 1992 Data Sets

The 1979 and 1992 data sets were developed in 1994–95 as part of the national inventory of greenhouse gas emissions. The Costa Rican National Meteorological Institute (IMN) (see, i.e., IMN 1994) was responsible for data production. A team consisting of professionals from the Natural Resources Ministry (MINAE) (see, i.e., MINAE 1997) and the Agriculture Ministry (MAG) provided support for the database generation. The IMN work was divided into two phases: visual image interpretation and GIS implementation. Final products were printed at a 1:200,000 scale. They do not report any standard quality controls (national or international); they also do not indicate overall map errors by land-use/cover classes as is regularly done on maps derived from remote sensing (Congalton 1991; Fitzpatrick-Lins 1981).

They used remote sensing from two different sensors: Landsat 4 (Multispectral Scanner, 80 × 80 m of spatial resolution, and 4 spectral bands) and Landsat 5 (Thematic Mapper, 25 × 25 m of spatial resolution, and 7 spectral bands). In general, they visually interpreted data from black and white photographic products and manually extracted fractal boundaries between classes (no image processing). Even though they could implement a digital interpretation of the data set, this was not the objective of the study.

They extracted data for several land-use types. There is a mix of definitions between what can be considered land cover and land use. Land use *involves both the manner in which the biophysical attributes of the land are manipulated and the intent underlying that manipulation—the purpose for which the land is used* (IGBP 1995). On the other side of the spectrum*, land cover is the biophysical state of the earth's surface and immediate subsurface* (IGBP 1995). For example, intervened forest, permanent crops, cattle grazing, and others presented in the map are classes denoting intent or purpose; rocky lands are a class denoting biophysical attributes. Land use and land cover are not clearly differentiated on either the 1979 or the 1992 map.

Because general practice indicates that satellite scenes need to have no more than 20 percent cloud cover, remote-sensing data are generally acquired for Costa Rica during the dry season (January to the end of April). An analysis of the final maps seems to indicate that this criterion was followed, as there was no cloud cover at all on the final products. It is interesting to point out that it is almost impossible to find cloud-free data sets for Costa Rica. An archive search of Landsat MSS and TM scenes for 1979 and 1992 at the Earth Resources (EROS) Data Center indicates that it is impossible to have a wall-to-wall cloud-free data set for Costa Rica for the selected IMN maps. Unfortunately, there is no indication in the proposal, or the original IMN's report, regarding how cloud-cover areas presented on the selected remote-sensing databases were corrected.

In addition to the former problems, the 1979 data present spatial holes at the digital level. Available data sets did not have a GIS coverage for the northern part of Costa Rica, therefore digital information regarding land use/cover for this year and region was not available. An additional problem with the 1992 database is the lack of consistency in the classification scheme and the presence of classification errors. One specific example of this problem is the Braulio Carrillo National Park. In the northern part of the park, where the biological station "La Selva" is located, primary and secondary forest currently present in this region and detected by Sanchez-Azofeifa(1996) was classified as pasture land and agricultural fields. This lack of consistency is present in several sites in the 1992 map. Caution must be taken when the 1986 and 1992 data set is use for land-use and carbon-change estimations. Results using these data sets and the 1986–1997 FONAFIFO data sets indicate important differences in the estimation of total carbon sequestration for the country (Busch, Sathaye, and Sanchez-Azofeifa 1998).

The 1984 Data Set

The 1984 data set is a compilation of land-cover information done by Costa Rica's National Geographic Institute. Data were interpreted from a wall-to-wall coverage of 1:60,000 aerial photographs. They do not indicate quality-control procedures or the methods used to extract the land-cover information. Even though this lack of information limits a comparison with other data sets, a comparison with remote-sensing–derived data for 1986 shows a high degree of correlation between the two data sets. This indicates that this data set can be eventually used to construct deforestation trends for Costa Rica (Sanchez-Azofeifa 1996).

The 1986 and 1997 Data Sets

The National Fund for Forestry Financing (FONAFIFO) contracted the Centro Cientifico Tropical (CCT) and the Research Center for Sustainable Development of the University of Costa Rica (CIEDES-UCR), to conduct a study regarding the change in forest cover in Costa Rica. The selected study period was 1986/87 and 1996/97 (see FONAFIFO 1998). Conservation International certified data and quality-control procedures. For this study FONAFIFO acquired a total of six Landsat TM5 satellite scenes with a maximum cloud cover of 20 percent.

The main objectives of the FONAFIFO study were:

- to estimate the extension and distribution of current forest cover in Costa Rica,
- to consider forest-cover changes during the last ten years,
- to map the distribution of areas under different types of forestry incentives (conservation, management, and forest protection).

It was expected that this study would generate information allowing an analysis regarding the degree of forest fragmentation, as well as quantification of deforestation and forest growth rates.

Since the main goal of FONAFIFO's map was to create a land-cover database, the forest cover was not disaggregated by degree of human intervention (e.g., primary forest, intervened primary forest, secondary forest, "Yoliyales," and plantations are all in one class). However, secondary forest emerging between 1986 and 1997 was produced as the results of subtracting the non-forest present in 1986 to the forest present in 1997. The final product differentiates between forest, non-forest, mangroves, secondary forest (land that was not classified as forest in 1986 but was so in 1996), and area deforested between 1986 and 1997.

Satellite images were classified and interpreted following quality control procedures established by the NASA Pathfinder Tropical Deforestation Project (Landsat Pathfinder) (Chomentowsky, Salas et al. 1994; Skole and Tucker 1993). The final map was produced at 1:250,000 scale; the minimum mapping unit was 3 ha; and 300 control points per scene were used for geo-referencing. The geo-referencing error was estimated to be less than 25 m overall. The Centro Cientifico Tropical selected ground control points to verify the forest/non-forest classification. A total of 456 ground control points were selected for accuracy assessment. Sample selection was not randomly stratified due to accessibility problems in some parts of Costa Rica (e.g., topography and lack of roads). This problem is currently under study for the implementation of Costa Rica's year 2000 forest resource assessment. The point distribution indicates that 42 percent of the sample is in forested areas and 58 percent is in non-forest areas. Total accuracy for the forest class was estimated at 90 percent (with confidence limits of 85–95 percent). This means that 90 percent of the ground control plots located in-forest were correctly classified as forest from the interpretation of the satellite images. Accuracy for the non-forest class was 94 percent (with confidence limits of 91–97 percent). The final map has an overall accuracy of 88 percent. Trends in forest area, by province, are summarized in Table 14-3.

For this paper, before developing deforestation and reforestation data, some preliminary data processing was carried out to obtain a final data set that was as consistent as possible. At this stage we excluded the use of the 1984 and 1992 maps. (The 1984 map used a different classification of land uses from the one used in the 1986–97 maps.) Given the proximity in time between 1984 and 1986, we judged that excluding 1984 would not lose much information. (Subsequent analysis will test whether including 1984 will add valuable information.) The 1992 map was also excluded from the analysis because it contains data inconsistent with the overall land-use trend (see Table 14-2). We attribute this problem to the fact that, for this map, boundaries between land uses had been extracted manually, with no image processing. While this was also the methodology employed with the 1979 map, a significantly higher level of forest fragmentation had occurred by 1992, making more difficult the definition of forest-cover contours. Thus, in an attempt to maintain a consistent time series of land uses, our analysis included the 1979, 1986, and 1997 maps.

Several corrections have also been required. In certain districts, deforestation rates could not be computed because: (1) digital data were not available (a problem for a group of districts in the northern part of the country in 1979); (2) the district was significantly covered by clouds during one or both dates; (3) forest cover was suspiciously low (a problem encountered in comparing 1979 with 1986), an error probably due to the different classification employed in 1979; and (4) seasonality had to be considered in vegetation detection. To partially mitigate the cloud cover issue for the period 1986–97, selected areas have been re-analyzed for this study.

For land-use change analyses, we also paid attention to the deciduous tropical forest primarily covering the Guanacaste region (Costa Rica's Northwest). The Holdridge classification identifies this area as a Tropical Dry forest (Holdridge 1967). Satellite imagery data are generally collected during the dry season when there is not only minimal cloud cover but also few or no leaves in the deciduous forest. The presence of deciduous forest has produced an important error in the 1992 data set: Forest cover was mistaken for either bare soil or pastureland, and areas that were actually covered with secondary or emerging deciduous forest were not labeled accordingly. This error was identified during the 1997 forest-cover assessment (FONAFIFO 1998), when work was conducted during the wet season (April–November), allowing for the identification of a significant extension of deciduous forest never identified before due to errors in the monitoring scheme. The lack of a good monitoring system regarding the 1992 data sets for the Guanacaste Peninsula indicates that all land-cover estimates might be affected by some unknown but significant level of error. Unfortunately, deciduous forest could not be detected in the 1986 map either. This means that deforestation/reforestation rates could not be measured accurately between 1986 and 1997 for the Guanacaste region. Because of the classification issues described above, reforestation rates were computed only for the period 1986–97.

Ability to Observe Land Use

As the discussion above indicates, it is possible to measure forest cover with a high degree of accuracy if analysis is *careful*. Many risks are involved, however. Cloud cover, deciduous forests, and fragmented forests all require careful analysis and documentation, but some measures taken for climate-related purposes have not used the best possible techniques and have led to inaccurate results.

Definition of Dependent Variables

We use three periods of change, 1900–1979, 1980–1986, and 1987–1997. We assume 1900 as our "zero clearing" point, the time before which clearing had taken place in each district.[13] In 1900 we assume that population density was zero, the urbanized population share was zero, and there were no protected areas. The deforestation over each of these periods is converted to an equivalent annual rate to make it comparable. The formula used to annualize is

$$\hat{h}_{it} \text{ between years } t \text{ and } t+1 = 1\text{-}\left(1\text{-}\frac{\text{forest lost}_{\text{t, t+1}}}{\text{forest}_{\text{t}}}\right)^{\frac{1}{year_{t+1}-year_t}} \qquad (11)$$

The dependent variable for the deforestation equations is the log of the annualized estimated hazard rate defined in (11), i.e., the log of the district's annualized deforestation rate.[14]

For the periods before 1986, the deforestation rate used is the net rate, i.e., the sum of the actual deforestation and reforestation rates that occurred within the district but which cannot be separately identified. Although deforestation and reforestation are separate processes with separate drivers, it may be that the net deforestation is quite a good approximation because there was not a great deal of reforestation taking place in earlier periods. For the 1986–97 time period, we used actual deforestation, which for this period is observed separately from reforestation. For the reforestation regressions, we used net reforestation between 1979 and 1986 and actual reforestation between 1986 and 1997.

Local Environmental Conditions

To account for important ecological features of the landscape (such as precipitation, temperature, and elevation), we employed the Holdridge Life Zone System, which divides the country into 12 ecological zones and 11 transition zones. A map of the country based on the Holdridge classification was available from the Tropical Science Center. Local environmental conditions in each district have been quantified by the proportion of the district falling into each one of the 12 main life zones.[15] Humid pre-montane is the omitted dummy. The distribution of

[13] In 1900 there was some level of development, but it was low and had been relatively steady for a long period of time. Historical evidence suggests that major changes occured mostly after 1945. Later work will investigate the effects of these early years on the model.
[14] In periods where there was no clearing, the hazard rate is zero and we cannot take logs. To avoid this problem we add 0.0001 to each hazard rate; this does not affect the coefficients.
[15] For later work we are estimating the percentage of remaining forest in each life zone at each point in time, rather than as the percentage of the district.

the country by life zones is given in Table 14-4. Life zones are potentially important because they relate closely to agricultural productivity. We have omitted the most productive life zone, so we expect all others to have lower deforestation probabilities.

Soil types (measured as ha/ha) are used to indicate fertility. The soil data come from a project by FAO and the Costa Rican Ministry of Agriculture. Three soil types are included: ultisol, entisol, and alfisol. The omitted soil types are better-quality soils: molisol, inceptisol, and vertisol. We would expect the soil measures to have negative coefficients because they are the poorer-quality soils.

We use an estimate of the share of the cleared district land in pasture in 1984 to predict reforestation. These data come from the National Geographic Institute map. Anecdotal evidence suggests that most reforested land was that previously used for pasture, i.e., low-quality or degraded cleared land. Thus we expect that districts with more land in pasture will later have more reforestation.

Population and Development Level

Population data at the district level were available for 1950, 1984, and 1996; these data came from the Ministerio de Economia, Industria y Comercio, Direccion General de Estadistica y Censos (1952, 1986, 1997). Urban and rural population was available for 1950 and 1984. Only total population was available in 1996. Since new districts have been formed over time and others have disappeared, our population data set contains some inaccuracies. For example, approximately a dozen districts reported in the 1950 census are not reported in later censuses. Inconsistencies between 1984 and 1996 were limited to fewer than ten districts.

A common intuition is that population levels are significant determinants of clearing. Although population levels are themselves a function of other factors (i.e., people immigrate to and emigrate from an area when that is beneficial), at any point in time the number of people affects the demand for food and shelter and the supply of labor. A great deal of the early empirical literature on deforestation focused on this factor, tending to find a positive coefficient (e.g., Pfaff 1999). Population density in 1984 (per hectare) was used as one measure of the relative level of development and local market demand and supply in different districts.

The degree of urbanization in 1950 (urban population/total population) was used as another measure of the relative level of development. Greater urbanization may indicate a local economy moving away from extensive agriculture and hence a lower propensity to clear new land. Around urban areas, forest areas that remain may be valuable for recreation, flood control, and air and water quality.

Time since 1900 is included as a development proxy as a quadratic to allow for nonlinear and non-monotonic effects. Also, the share of original forest area previously cleared, as well as its square are included as proxies for development and as indications of the likelihood that remaining land is of high quality.

Roads and Distance to Market

Transport costs are expected to have a significant effect on deforestation because they affect both input costs and farm-gate prices for crops. We use measures of the availability of roads and of distance to proxy for transport costs. Road length (km) and density (km/ha) at the district level come from a map prepared in the mid-1980s. This information must be used with caution because the current road network is dynamic and important changes cannot be detected at the 1:200,000 scale. At the time that this component of the project was developed, no 1:50,000-scale data set at the road level was available in GIS format.[16] Roads are included as a density (km/ha) for each district.

Distance to market is measured as the minimum of the distances from a district's centroid to the centroids of the market centers of San Jose, Limon, and Puntarenas. A conditional GIS was developed to generate this information. The main data source was the National Geographic Institute (IGN) 1:50,000 district map, a map prepared by IGN during 1996. Because we might expect the costs of transport to fall with time, we also included the interaction of distance to market with time.

Protected Areas

Protected areas in Costa Rica can be classified into 7 main groups: National Parks, Wildlife Refuges, Biological Reserves, Forest Reserves, Protection Zones, Wetlands, and other. DeShazo and Monestel) generously provided their number, and the establishment dates were based on compiled information from SINAC (Costa Rican National System of Protected Areas). The data set for this study covers "continental areas" only (i.e., islands were not considered). All Costa Rican national parks and biological reserves were included for analysis, as were wildlife refuges and forest reserves with areas >2,000 ha. Since almost all wildlife refuges and forest reserves established before 1986 were larger than 2,000 ha, our data set almost fully identifies such areas under protection during the time intervals pre-1979, 1979–86, and 1986–1997. Wetlands and protection zones were not disaggregated by time. This is not a problem for wetlands, since they were primarily established after 1986. Protection zones, on the other hand, were established over time. Protection zones amount to approximately 160,000 ha or around 10 percent of protected areas in 1997. The data are summarized in Table 14-5.

The establishment of a protected area would be expected to lower the rate of deforestation within a district. For example, Busch et al. (1998) found evidence that, while not completely protected, national parks and other protected zones suffered very little deforestation after 1986. A forest reserve is not protected, but we would expect it to be better managed than an area of forest with no clear tenure. Land-zoning policy variables are included as densities of different sorts of protected areas (e.g., national parks, forest reserves).[17] A rise in national park or forest reserve density might be expected to reduce deforestation.

It is probable, however, that the Costa Rican government did not randomly choose the location of these protected and managed areas. If policy makers considered those factors and correlated them with past or expected rates of clearing, then estimating the effects of protected areas became more complicated. For instance, if for unobservable reasons the districts in which the parks were located had unusually high historical deforestation rates (conditional on other observable factors), then even if the parks had no effect at all they might *appear* to have a negative estimated effect on deforestation; the good-quality land has already been cleared in that area and deforestation would have slowed even without the park.

Ideally, by understanding the decision rules by which the protected areas are allocated, we can identify factors unrelated to clearing but which determined those allocations. Biodiversity hotspots that a policy maker might wish to protect may provide a possible instrumental variable

[16] We are in the process of creating an historical series of road maps to avoid using roads from the 1980s to explain earlier deforestation. Roads are largely endogenous to the process of development.

[17] In addition, to consider leakage, a dummy variable indicates that such a large area exists in a nearby district. A conditional GIS was used to identifying neighboring districts. These results were insignificant and are not presented.

for future analyses. We use prior protected-area density to explain future deforestation to avoid reverse causality, but results should still be interpreted with caution.

Conservation Incentives

Two main categories of conservation incentives were available for this study: *Deducciones del impuesto sobre la Renta* (tax deductions for reforestation, which started in 1979) and Certificates for Forest Improvements (FONAFIFO 1998). The certificates, initiated in the mid-80s and reaffirmed with the most recent Forestry Law 7575/1996, include reforestation certificates (Certificados de Abono Forestal para Reforestacion or CAF and CAFA), forest management certificates (Certificados de Abono Forestal para Manejo or CAFMA), and forest protection certificates (Certificados para la Proteccion del Bosque or CPB). (Further description of these incentives can be found in Segura, Kaimowitz, and Rodriguez [1997] and FONAFIFO [undated].)

These conservation incentive data potentially offer a unique opportunity to estimate the costs of carbon sequestration through land-use change projects because a direct linkage between monetary compensations and land-use changes could be estimated. Unfortunately, although the mapping effort supported by FONAFIFO did incorporate the type and location of monetary disbursements, it did not record the year of the transaction; only national data is recorded by year. This lack may be corrected soon, to the extent that paper records are complete.

In addition, it is possible that the impact of these policies on reforestation has not yet been "captured" by the satellite images. As can be seen in Table 14-6, for example, the over 100,000 hectares that benefited from reforestation incentives were reforested primarily after 1988. It is possible, therefore, that their impact will not be detected by satellite images until the early 2000s. The allocation of incentives is also not random, nor a completely open process. Incentives may not be an exogenous variable but could have been allocated in response to pressure from land managers interested in reforestation.

Finally, we include dummies for each province to capture unobserved spatial heterogeneity between regions. All variables except the province dummy variables are logged to avoid bias from extreme outliers. The variables are not expressed as deviations from the mean so cannot be interpreted as marginal effects at the mean. Coefficients indicate direction and significance.[18]

Results

Our preliminary results are from application of the dynamic model of land use, using the district-level data described earlier. The deforestation regressions in Tables 14-7, 14-8, and 14-9 correspond to equation (10), with the addition of time-varying baseline measures (time, time squared, urbanization, and population density). Table 14-7 presents results from pooled data, while Tables 14-8 and 14-9 show results of cross-section analyses. Tables 14-8 and 14-9 include the protected areas policy variables, which are not included in Table 14-7. Tables 14-10 and 14-11 present cross-section reforestation regressions.

Ecological Factors

On the whole, the results are consistent with the intuition that climatic conditions have significant effect on land-use choices and land cover. The implicit normalization relative to the life zone missing from the regression, humid pre-montane, drives the magnitudes and signs of the coefficients. They are roughly ordered from most productive agricultural climate to least. Most coefficients are negative and, with the exception of dry tropical (and rainy sub-alpine, which represents only 0.1 percent of Costa Rica) insignificant where they are positive. This is consistent with the omitted category being the most valuable agricultural land.[19]

The other measure of ecological constraints, soil quality, produced inconsistent results. This variable may be rather poorly measured; thus, this may not reflect the importance of soil quality to decisions.

Economic Factors

Tables 14-7, 14-8, and 14-9 all support the theory suggesting that falling transport costs significantly affect the net input and output prices faced by a producer and, hence, raise

[18] Among the similar life zone variables, they should also indicate the degree of effect.
[19] At present the measure is poor because it measures life zones in the district as a whole, not in the forest area under threat of deforestation. Future work is correcting this problem.

deforestation. In Tables 14-7 to 14-9, greater road density is associated with a higher rate of deforestation. The minimum distance-to-major-markets (San Jose, Limon, and Puntarenas) measure is also negative and significant in Table 14-7, suggesting that deforestation is higher where land parcels are closer to markets, as predicted. Over time, this effect of distance diminishes as transport costs fall, and more isolated areas are more likely to be developed.

Here, in the pooled (Table 14-7) and first cross-sectional (Table 14-8) results, we find that population density is positively related to deforestation. However, we are using 1984 population density to predict earlier deforestation in part of the pooled regression and in the first cross-section, so the causality may well be reversed; people may be migrating to areas for the same reasons that they are clearing forests in those areas. 1984 population density does not significantly relate to deforestation after 1986 and in fact has a negative coefficient in Table 14-9.

Time and Development

As is apparent in the above discussion, some effect of time and/or development has implicitly been revealed, as the results in the 1979–86 and 1986–97 cross-sections are not the same. The pooled (Table 14-7) results are a mixture of the two, as well as including the deforestation during the time period from zero clearing until 1979 For instance, road density and the minimum-distance variables have a smaller effect in the later cross-section. The effect of distance to market also diminishes with time in Table 14-7, which might suggest that access is no longer a constraining factor.

We directly consider the effect of time in Table 14-7. Its estimated effect is concave; that is, as time progresses the deforestation hazard rate first rises and then falls. This shows the danger of linear extrapolation for predictions even over a relatively short period of time. The urbanized share of population has a negative effect on deforestation, except in Table 14-8 where it is close to zero, but it is never significant. The sign of the coefficient is what we expect if urbanization is a measure of development.

For the percentage cleared, our expectation was that greater previous clearing would reflect more economic development in the area, possibly leading to better infrastructure and larger local markets—but also, that better pieces of land had already been developed. Further, we thought that the effect of historical clearing might lead initially to more deforestation but eventually to less deforestation (i.e., a higher cleared percentage would eventually lead to a lower deforestation hazard rate). In Tables 14-7 and 14-8 we see evidence that supports this with a positive coefficient on the percentage cleared and a negative coefficient on its square. By the last change (Table 14-8) this variable has lost significance, possibly indicating that Costa Rica is reaching its equilibrium level of clearing in all districts.

Effects of Protected Areas Policies

In Tables 14-8 and 14-9 we include the densities of the national park and forest reserve areas within districts (these are the policies affecting the greatest area, including the greatest shares of any given district being protected). The existence and relative extent of area under protection or management have tended to reduce deforestation up until 1986. Even though forest reserves are cut, they are managed for forestry so are more likely to managed sustainably. After 1986, national parks seem to continue to be protected and are more significant, possibly because the areas around them are under greater threat from increased development. In contrast, forest reserves seem to be associated with higher deforestation between 1986 and 1997 (see Table 14-9), possibly because they are available for commercial timber cutting and were not cut previously because of certain management practices.[20]

To test the importance of the effect of endogenous park placement, we questioned the correlations between past and future deforestation and protected-areas creation: When locating these areas, did policy makers look for areas with *low* deforestation rates—such that are "safe" and easy to reserve because there was little desire to clear the land. Or, did they look to reserve areas with *high* deforestation rates in order to slow those rates? While these results are not presented here, we find that regressing the changes in national park and forest reserve area densities on the forest stock at the beginning of the period and the deforestation rate in the period

[20] We also considered indirect effects of the establishment of protected areas. The protection of a particular area could displace the production activities planned for that area, such that these activities would then take place on an unprotected area that would otherwise have been left in forest. If so, that would be "leakage," i.e., an indirect effect of the direct protection of the forest within the specified area, which reduces the net protective effect of the establishment of that area. The ideal way to test for such leakage would be with pixel data, where one could test for whether areas adjacent to protected areas have higher deforestation rates than would be expected given the other conditions in the area (such as roads, soil quality, etc.). At the district level, we created two dummy variables, one for districts whose centers are within 20 km of any district that has a national park occupying over half the district's area, and an analogous one for being near to a district with a big forest reserve. If leakage occurs, these variables should have positive effects on the deforestation hazard rate. In a 1979–1986 deforestation cross-section, the near-forest-reserve variable has a significant positive effect, but that for national parks has a significant negative one, while in a 1986–1997 deforestation cross-section, these signs are reversed.

before yields no significance of previous deforestation and some positive effect of higher forest stock. This suggests that our regressions of deforestation on already-established areas may not have large biases.

Reforestation

Finally, we consider reforestation. The least-productive, most-degraded land is usually used for pasture. We expect, then, that cleared areas in use as pastureland are most likely to be reforested. Table 14-10 most closely uses the actual reforestation information available for the 1986–1997 period. In Table 14-10 pastureland has a significant positive effect on reforestation, as expected.

For the period before the 1986–1997 change, our information is quite limited because we can observe only the net deforestation rate, so for most districts the reforestation rate is zero. The share of the district with alfisol soils has a negative effect. More urbanized areas may be less likely to reforest. The effect of 1950 urbanization levels is insignificant, though of the correct sign in 1986–1997 and significant in 1979–1986. In the later period, more heavily-cleared areas are less likely to be reforested, while in the earlier period, more likely to be reforested.

Measuring Carbon Sequestration and Storage in Forests

Estimates of deforestation rates can be used to estimate rates of loss from carbon sinks for Costa Rica (see Chapter 15). Policies to retard deforestation would reduce these losses, thus creating offsets. However, not all forest protection has equal value for carbon sequestration. Our results suggest that forests in different life zones face different levels of threat; they also contain different amounts of carbon.

We assign to each life zone a certain level of potential carbon storage (the carbon stored in the above-ground biomass of a primary or lowly-intervened forest) and accumulation, according to Table 14-4. Basic information for the calculation of the potential carbon storage (in tons of carbon per hectare or tC/ha) and accumulation (tC/ha/yr) was obtained from MINAE

(1997) and compared with other sources.[21] MINAE reports extensively on the volume, and average wood density of 46 sites established by Holdridge et al. (1971) across the country.[22] Data from the Holdridge sites were further complemented with measurements from commercial forestry inventories (MINAE 1997). Inventory data were then translated into biomass figures by using Brown et al. (1989) and then to carbon estimates by using the IPCC guidelines.

Carbon Storage

To compute the average carbon storage of a forest stand in a given life zone, we referred to the potential carbon per hectare of 27 protected areas included in the MINAE proposal. The 27 areas are dispersed throughout the country and, thus, provide a first approximation to the level of carbon storage that may be found in different forest areas. Since a certain variation in carbon storage levels was observed within the same life zone, we computed the potential carbon per hectare as the average carbon storage of the available plots. The results are in Table 14-4.

Of course, the carbon storage estimates reported in Table 14-4 are rather crude and should be considered with caution; other ecologists in Costa Rica contest them.[23] First, they do not reflect Costa Rica's extreme variety of microclimatic conditions. Second, they refer to potential carbon storage, while many forested areas have been heavily intervened in the past and may, in practice, contain lower carbon.[24]

Keeping these caveats in mind, comparison with other studies suggests that if an upward bias exists, it is not large. For example, Rodriguez (1998) estimates that, 20 years after selective logging, a forest in the bmh-T/bmh-P life zones stores approximately 95 tC/ha in the above-ground biomass.[25] Assuming that, in the absence of additional harvests, biomass accumulation continues (she estimates harvests every twenty years), her figure closely approximates the ones in Table 14-4.

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[21] The study reported by MINAE focused on mature forests, and sites were selected on well-drained upland sites in each life zone. Site selection ignored two life zones, bp-SA and bp-MB, the first because it comprises only scrubby vegetation, the second because it contained no remaining mature vegetation.

[22] The document consists of a detailed project proposal that was submitted to and approved by the U.S. Initiative on Joint Implementation. All elements of the proposal were independently verified by SGS, which is now certifying the amount of carbon offsets generated by this project.

[23] As part of our wider project, Flint Hughes, Vicente Watson, and Joseph Tosi are collecting new field data on carbon stocks in Costa Rica and they, together with Shuguang Liu, are working to calibrate the Lifezone and CENTURY models to yield improved carbon stock and accumulation estimates across life zones.

[24] Holdridge et al. (1971) characterize the site selection as focusing on mature forests on well-drained and upland slopes. Thus, the site selection process was not intended to be representative of the life zone.

[25] It is assumed that the carbon-to-biomass ratio is 0.5.

Carbon Accumulation

The rates of carbon accumulation in secondary forests were also based on the estimates reported by MINAE. These estimates had been derived with the Tosi (1980) formula (cited in Mora 1995), which links annual net above-ground primary productivity (and carbon fixation in plant biomass) to real evapotranspiration. (Estimates by life zone are summarized in Table 14-4.) We compared such growth estimates with the data reported by Ortiz et al. (1998), which refer to secondary forests of different ages in selected environments. At age 33, a stand in the bmh-P/bmh-T life zone exhibited levels of carbon storage of 86 tC/ha).[26] At age 44, a stand in the bh-P life zone had a storage level of 85 tC/ha, while a third stand at age 33 in the bh-T life zone stored 67 tC/ha. These data translate into annual estimates of carbon accumulation more conservative than those obtained from the Tosi formula. Observed rates of carbon accumulation in plantations, however, far exceed the rates estimated for secondary forests. For example, Ramirez and Gomez (1998) compared the rates of growth of several plantations (with different species) in Costa Rica and estimated an average sequestration rate of 7.7 tC/ha/yr. It should also be noted that, although Table 14-4 reports constant carbon accumulation rates, biomass growth in forest stands is likely to slow down as forests mature.

Table 14-4 suggests that total above-ground biomass peaks at the lowest and middle altitudes and then decreases as we move to pre-montane or high mountain levels. On the other hand, biomass accumulation rates (see below) seem to decrease as we move from lowland levels to higher altitudes; this may have implications for carbon offsets. If these data are confirmed by further investigations, more credits should be given per hectare for the protection of existing forests at *higher* altitudes because they store higher amounts of carbon. (Life zones with suffixes –MB and –M stand for lower mountain and mountain.) On the other hand, more credits should be given for secondary regeneration at very humid lower elevations, where biomass accumulation is particularly high, than at high elevations where forest recovery and, hence, accumulation is slow.[27]

[26] These are our estimates since Ortiz et al. (1998) only present figures (and not numbers) of storage levels at different ages.

[27] This is, of course, holding other things equal. For example, cleared land may contain different levels of carbon in different areas.

Carbon dynamics vary dramatically across ecological conditions. In contrast to the relatively good information on plantation forestry, relatively little is known about carbon stocks or accumulation in natural tropical forests. It is impossible to assess the quality of existing estimates without more data and good quality modeling. If we can establish relatively unbiased carbon estimates across broad ecosystem types such as life zones and by length of regeneration we may be able to create a system that is correct on average and does not lead to too much manipulation. It is always possible to directly measure aboveground carbon on a specific site, and even soil carbon, but the process is costly.[28] More research is urgently needed to find more robust estimates and to test whether we need detailed estimates on a site-by-site basis rather than using broad estimates based on life zone.

Summary and Conclusions

The main results from this study can be summarized as follows. In our chapter introduction our #1 question was how "accurately" we can measure land use. With proper geographic information systems and remote-sensing methodologies (such as the ones followed in the production of the 1986–97 forest-cover maps) it is possible to produce an accurate assessment of the forested area of a country. The mapping effort produced for FONAFIFO reported, at a national level, an attribution of forested and non-forested land with accuracy levels of 90 and 94 percent respectively. This relies on very careful analysis by highly qualified people; poor-quality work can still lead to very misleading estimates. Any policy based on remote-sensing data would have to implement very careful quality control and auditing.

Estimating with accuracy how land uses have changed in the past is complicated by differing mapping efforts using different methodologies and classifications, by the presence of cloud cover, by the seasonality of vegetation detection, and by lack of metadata information for the land-cover databases. For example, the 1992 map was deemed inadequate for this analysis. By comparing the 1992 with the 1986 map, we found that the 1992 map overestimated forest cover by about 400,000 hectares (Table 14-2). Thus, initiatives such as the Protected Area Project (MINAE 1997), which evaluated the rate of deforestation in the proximity of 27 protected areas by comparing forest covers in 1979 and 1992, likely underestimated deforestation for that period. Classification issues arose in our analysis when we compared the

[28] This approach has been taken in the Nature Conservancy project in Bolivia.

1979 with the 1986 data set. For the period 1986–97, the presence of cloud cover prevented the estimation of land-use changes on 670,369 ha (13.1 percent of Costa Rica). Because images were chosen from different seasons, no change detection was possible on 976,535 ha (19.1 percent of the country). These facts may limit the possibility of accurately measuring historical changes in forest cover on a national scale.

Concerning the question about the factors driving deforestation and reforestation, regression results suggest that deforestation is more likely in highly productive agricultural areas and areas with low transport costs to markets. These results are consistent with previous observations in Costa Rica (e.g., Rosero-Bixby and Palloni 1996) and elsewhere (Pfaff 1999; and Kaimowitz and Angelsen 1998).

The deforestation rates that Costa Rica experienced in the ’80s did not continue into the ’90s. A suggestion that tropical deforestation has slowed in the early 1990s had already been made by Sanchez-Azofeifa (1996). The change-detection analysis employed in this study shows that deforestation rates in Costa Rica have slowed down dramatically, even in those regions where very high deforestation rates were observed between 1979 and 1986. Thus, the deforestation rates observed in one period appear to be poor predictors of future deforestation. Our results suggest that deforestation rates will at first rise with development as access improves and markets for crops develop, but ultimately deforestation will fall as the best land is developed and the economy makes a transition toward more intensive agriculture, manufacturing, and tourism. Policy reform in Costa Rica (in particular, the removal of agricultural subsidies and the establishment of protected areas) might have contributed significantly to a decrease in recent deforestation rates.

The implication for carbon markets is that the establishment of baselines based uniquely on past land-use changes is likely to be inaccurate. Projections of deforestation should take into account an area’s ecological, geographic, and socioeconomic characteristics. They should also take into account the pressure of population, the existing level of clearing and the level of development in the country. Incorporating these factors allows for more accurate prediction than simple extrapolation of past deforestation rates. And it should be reasonably unbiased on a national level, even while acknowledging that, plot-by-plot or even national-level projections are never perfect. Baselines will never be purely scientific and ultimately will include purely negotiated elements.

Understanding the process and determinants of land-use changes is crucial, not only to inform policies directed at climate-change issues, but also to address broader issues related to forest management, biodiversity conservation, rural development, and regulation of environmental services. Since the study of these processes is virtually impossible without adequate information, we recommend that existing databases concerning land uses be improved. Particularly lacking is information on many policy and socio-economic variables that we would expect to be quite important, including both land tenure security and land returns.

Finally, concerning the #3 question of earlier: carbon storage and accumulation appear to vary, based on geographic variables identified by the various life zones—high carbon storage and low carbon accumulation seem to occur at mid-altitudes, while biomass accumulates at very humid lower elevations. Thus, mid-altitude areas should receive greater rewards for forest protection, while very humid lower elevations should receive high rewards for secondary regeneration. The evidence on carbon dynamics is limited at present and needs to be a focus of significant research attention before credible estimates can be provided.

The model presented in this paper will be refined as analyses make use of pixel-level information and as better data become available. However, this exercise provides some indication of specific factors deserving of special consideration in the development of sectoral baselines—which, hopefully, can facilitate better design of future forest protection and regeneration policy and programs. We have also provided some evidence on our current ability to measure forest cover and carbon dynamics on a large scale. This evidence suggests that it is possible to measure land use with careful remote-sensing work but that carbon measures require more fieldwork and analysis.

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Appendix: Modeling Land-Use Changes and Carbon Sequestration—A Selected Review of Others' Studies

Over the past ten years, several studies have attempted to estimate the potential for carbon sequestration through forestry and land-use change programs.[29] Most of these studies used a "least cost" or "engineering" approach to estimate the potential supply of carbon offsets from a particular region.[30] Such approach essentially quantifies the difference in economic returns between forestry and alternative uses of the land. The cost of carbon sequestration is then computed as the monetary amount that would make forestry a more attractive option than land clearing and agricultural production.

Such analyses identify potential land areas suitable for reforestation, conservation, or improved forest management and match each area with an alternative treatment (e.g., reforestation, pasture).[31] For each they estimate the land rent from the current use and predict the rent from the alternative use (e.g., from pasture if the land is currently forested) and the conversion costs. They then compute the amount of carbon storage or accumulation implied by protecting forest or reforesting. From a comparison of carbon storage rates with the costs of the program, a summary statistic, "dollars spent per ton of carbon sequestered," is obtained. The costs of converting agricultural land into forests increases with the relative profitability of agricultural land. The lowest-cost offsets will be created first and increased offsets can only be attained at increased unit carbon sequestration costs. By ordering the carbon sequestration potential by its unit costs, a carbon supply schedule is derived (see, e.g., Richards et al. 1993). This approach has been widely used and, to date, still provides the basis to assess the economic desirability of alternative carbon offset projects.

The use of least-cost estimates for this type of analysis is perhaps the only feasible approach in most developing countries. This approach, however, has been recently criticized on the following basis (Stavins, 2000): (1) land-use changes may involve irreversible investments in the face of uncertainties (Parks, 1993); (2) land users may receive non-pecuniary returns from current uses of the land; (3) land users may face liquidity constraints; and (4) the analyst may be unaware of some market benefits and costs. It is extremely difficult for an analyst to predict what a farmer will actually do on his land and what his real returns will be.

As a consequence, least-cost estimates are said to be likely to underestimate the "true" costs of inducing changes in land uses. For example, in a study focused in the United States, Moulton and Richards (1990) found that average annual payments of $72, $65, and $51 per acre would be required to enroll a certain amount of land into a reforestation program in the states of Maine, South Carolina, and Wisconsin. More recently, Plantinga et al. (1998), using an econometric approach, found that the above payments would only be sufficient to enroll 8 percent, 82 percent, and 26 percent of the acreage estimated by Moulton and Richards in the three states.

Since no econometric analysis similar to Stavins (2000) or Plantinga (1998) has been carried out in developing countries, we can only speculate whether or not least-cost estimates adequately reflect the real costs of inducing changes in land uses (e.g., to promote reforestation) in developing countries. Our feeling is that, due to a variety of uncertainties (often difficult to quantify) and a generally poor capital market, we might expect that the above issues will play a

[29] See, for example, Trexler and Haugen 1994, the 1995 special issue on Forestry and Climate Change of the journal *Biomass and Bioenergy*, or chapter 9 of IPCC 1996

[30] For example, Moulton and Richards 1990.

[31] Areas are often disaggregated according to relevant variables, e.g., soil productivity and climate.

significant role in many developing countries even more than they do in the United States, thus making the case for an econometric approach even stronger. On the other hand, initiatives to slow deforestation do not require irreversible investments of the kind expected in the establishment of a plantation, and non-pecuniary returns from current uses of the land may well play in favor of keeping forest cover.

Our attempt is to estimate the cost of carbon sequestration by evaluating, over time, how land users have responded to changing environmental and economic conditions. We will use this knowledge to directly estimate land managers' responses to change in relative land-use returns and, hence, the opportunity cost of changing that behavior. Focusing on deforestation, several studies have preceded us in this quest. For example, Pfaff (1999), econometrically analyzes factors that drive deforestation in the Brazilian Amazon, including road and river access, soil fertility, credit availability, and government policies. Rosero-Bixby and Palloni (1996) analyze the correlation between population and deforestation in Costa Rica controlling for factors such as accessibility and ecological features. Kaimowitz and Angelsen (1998) review other studies, in Central America and elsewhere.

Table 14-1. Sources of Geographic Data

Thematic map	Source	Scale	Year
Land use & forest cover	National Meteorologic Institute (IMN)	1:200,000	1979
Land use & forest cover	National Geographic Institute (IGN)	1:200,000	1984
Land use & forest cover	National Meteorologic Institute (IMN)	1:200,000	1992
Forest cover	FONAFIFO	1:250,000	1986
Forest cover	FONAFIFO	1:250,000	1997
District areas	National Geographic Institute (IGN)	1:50,000	1996
Soil fertility	FAO – MAG	1:200,000	1994
Soil types	FAO – MAG	1:200,000	1994
Life zones	Tropical Science Center	1:200,000	1995
Road network/density	Transportation and Public Works Ministry	1:200,000	1985
National parks	SINAC		1997
Biological reserves	SINAC		1997
Forest reserves	SINAC		1997
Wildlife refuges	SINAC		1997
Incentives for reforestation, conservation and management	FONAFIFO		1997

Table 14-2. Forest Area (ha) in Costa Rica by Province (1979–1997)

				Forest area			Deforestation	Regeneration
Province	**Total area**	(1979)	(1984)	(1986)	(1992)	(1997)	(1986–97)	(1986–97)
San José	497,220	326,552	180,089	150,270	206,274	171,564	9,691	30,984
Alajuela	977,000	343,760	419,191	252,372	507,460	246,132	31,996	25,757
Cartago	309,256	237,864	201,963	205,751	223,099	205,470	10,090	9,809
Heredia	266,445	124,867	163,256	165,927	176,687	149,656	25,333	9,062
Guanacaste	1,019,295	509,759	216,591	344,487	290,003	338,621	14,014	8,148
Puntarenas	1,122,948	631,797	440,482	381,757	490,092	388,043	17,984	24,270
Limón	917,871	665,395	584,511	548,891	560,268	512,740	54,829	18,678
Total	**5,110,035**	**2,839,994**	**2,206,083**	**2,049,455**	**2,453,883**	**2,012,226**	**163,937**	**126,707**

Note: A comparison of forest-cover data across years should consider that different maps had different cloud cover. The problem is most evident in the 1979 map where large sections of the northern region could not be interpreted. The apparent increase in forest area, for example in the province of Heredia, is due to this problem. Also, the 1986 map is a “derived” map. It is obtained from the 1997 map and corrected for deforestation and reforestation. Data strengths and limitation with regards to each of the data sources is described in the text.

Table 14-3. Changes in Forest Cover in Costa Rica by Province (1979–1997)

Province	Total area	Share of land under forest cover (1979)	(1986)	(1997)	Annual deforestation rate[a] (1979–86)	(1986–97)	Annual regeneration (1986–97)
San José	0.10	0.66	0.30	0.35	10.5%	0.6%	2.1%
Alajuela	0.19	0.35	0.26	0.25	4.3%	1.2%	1.0%
Cartago	0.06	0.77	0.67	0.66	2.1%	0.5%	0.4%
Heredia	0.05	0.47	0.62	0.56	-4.1%	1.5%	0.5%
Guanacaste	0.20	0.50	0.34	0.33	5.4%	0.4%	0.2%
Puntarenas	0.22	0.56	0.34	0.35	6.9%	0.4%	0.6%
Limón	0.18	0.72	0.60	0.56	2.7%	1.0%	0.3%
Total	**1.00**	**0.56**	**0.40**	**0.39**	**4.6%**	**0.8%[b]**	**0.6%**

Notes: [a]A comparison of forest cover data across years should consider that different maps had different cloud cover (see, e.g., the 1979 map where large sections of the northern region could not be interpreted). This error is reflected in the negative deforestation of Heredia province where the increase in forest cover is due to lack of data in 1979. [b]This deforestation rate is obtained by comparing the forest area loss 1986–97 with the forest area in 1986. Since the 1986–97 deforestation was measurable only in part of the country (most noticeably, it could not be measured in Guanacaste), this rate assumes that where data was not available, no deforestation took place. If forest loss were measured where both forest area and deforestation data are available, the rate would be closer to 1 percent.

Table 14-4. Potential Carbon Storage and Accumulation by Life Zone

Life zone	Potential carbon stored in above ground biomass (tC/ha) (1)	(2)	Potential carbon accumulation (tC/ha/yr) (1)	Proportion of total area (%)
Dry tropical (bs-T)	34	7–94	3.3	2.8
Humid–Tropical (bh-T)	117	259	3.8	20.9
Very humid–Tropical (bmh-T)	138	182	4.4	22.5
Humid Pre-montane (bh-P)	70	104	3.4	10.9
Very humid–Pre-montane (bmh-P)	111	153	3.9	23.5
Rainy–Pre-montane (bp-P)	94	159	3.6	7.3
Humid–Lower montane (bh-MB)	289	159	2.3	0.5
Very humid–Lower montane (bmh-MB)	174	210	2.9	2.2
Rainy–Lower montane (bp-MB)	—	162	2.5	6.8
Very humid–montane (bmh-M)	154	—	—	0.0
Rainy–montane (bp-M)	139	154	1.9	2.5
Rainy–Sub-alpine (bp-SA)	10	—	—	0.1

Source: MINAE (1997); Helmer and Brown (1998).
Note: Sources (1) and (2) used many of the same plots to derive the carbon estimates. Discrepancies between them are primarily due to the height of the forest stand considered for the calculations. In MINAE (1997) stand volume of a tree was measured only up to the height of the first branch. It is assumed that carbon content in dry biomass is 50% (Brown 1997).

Table 14-5. National Parks and Other Protected Areas

Type	Number				Hectares
	Before 1979	1979–86	1986–97	Total	
National park	12	2	8	22	552,775
Wildlife refuge	—	6	27	33	170,450
Biological reserve	6	1	3	10	26,581
Forest reserve	8	1	3	12	283,944
Wetland	—	1	12	13	28,031
Protection zone	10	10	10	30	165,025
Other				1	231
Total				**121**	**1,227,037**

Source: DeShazo and Monestel (1997); FONAFIFO/SINAC, digitized by the Tropical Science Center, Costa Rica.

Table 14-6. Hectares Reforested, Managed, and Protected with Selected Forestry Incentives in Costa Rica (1979–1995)

Year	Renta	CAF	CAFA	CAFMA	CPB	Total
1979	633					633
1980	1,074					1,074
1981	1,402					1,402
1982	877					877
1983	1,748					1,748
1984	1,194					1,194
1985	1,479					1,479
1986	3,796					3,796
1987	4,754					4,754
1988	7,261	29	761			8,051
1989	5,668	943	1,269			7,880
1990	4,510	3,180	2,375			10,065
1991	978	4,616	3,217			8,811
1992	145	5,603	4,230	74		10,052
1993		5,788	4,135	75		9,998
1994	78	6,413	5,332	9,971		21,794
1995		11,515	12,499	12,000*	22,200	46,214
Total	**35,597**	**38,087**	**33,818**	**10,120**	**22,200**	**139,822**

Source: FONAFIFO-MINAE 1996. Explanation of codes: see text.

Table 14-7. Hazard Regression with Time Factors (equation 10)

Variables	Coefficients (std errors)	
Cartago Province	−.82[c]	(.24)
Guanacaste Province	.34	(.27)
Heredia Province	.051	(.30)
Limón Province	−.12	(.22)
puntarenas province	.80[c]	(.22)
San José Province	.13	(.21)
Humid – Lower montane	.034	(.04)
Humid – Tropical	−.012	(.015)
Very humid – Pre-montane	−.0053	(.021)
Very humid – Lower montane	−.085[c]	(.022)
Very humid – Montane	.081	(.081)
Very humid – Tropical	−.014	(.017)
Dry tropical	.069[c]	(.027)
Rainy – Pre-montane	−.031[a]	(.018)
Rainy – Lower montane	−.040[b]	(.019)
Rainy – Montane	−.019	(.021)
Rainy – Sub-alpine	.13[c]	(.039)
Ultisol	.028	(.017)
Entisol	.042[c]	(.014)
Alfisol	.047[b]	(.020)
Road density (km/ha)	.56[c]	(.10)
Minimum distance to market (km)	−1.0E-05[c]	(2.2E-06)
Minimum distance to market * Time	8.4E-08[c]	(3.0E-08)
1984 Population density (#/ha)	.14[c]	(.030)
1950 Urban population/Total population	−.014	(.022)
Time (year-1899)	.24[c]	(.031)
Time Squared	−.0025[c]	(.0003)
Share of district cleared	.35[b]	(.15)
Share of district cleared squared	−.48[c]	(.097)
Constant	−.83	(1.6)
Adjusted R^2	.51	
Number of observations	922	

Omitted province is Alajuela; omitted life zone is humid pre-montane, which is high productivity.
All variables are logged, except province dummies, and variables containing distances and time.
[a] = significant at 90%; [b] at 95%; [c] at 99%.

Table 14-8. Deforestation CS (1979–1986) with Two Protected Area Variables

Variables	Coefficients (std errors)	
Cartago Province	−1.4[b]	(.56)
Guanacaste Province	.17	(.65)
Heredia Province	.26	(.65)
Limón Province	−.62	(.44)
Puntarenas Province	1.2[b]	(.48)
San José Province	1.1[b]	(.44)
Humid – Lower montane	.19[b]	(.07)
Humid – Tropical	.013	(.032)
Very humid – Pre-montane	.018	(.056)
Very humid – Lower montane	−.039	(.044)
Very humid – Montane	.033	(.15)
Very humid – Tropical	.11[c]	(.036)
Dry tropical	Dropped	
Rainy – Pre-montane	−.068[a]	(.038)
Rainy – Lower montane	.011	(.038)
Rainy – Montane	−.023	(.042)
Rainy – Sub-alpine	.21[c]	(.080)
Ultisol	−.0041	(.037)
Entisol	.0040	(.031)
Alfisol	.038	(.064)
Road density (km/ha)	.33	(.23)
Minimum distance to market (km)	.0002	(.090)
1984 Population density (#/ha)	.21[c]	(.074)
1950 Urban population/Total population	−.042	(.041)
Share of district cleared	.34[b]	(.17)
Share of district cleared squared	−.43[c]	(.12)
National park density	−.0090	(.031)
Forest reserve density	−.13[c]	(.034)
Constant	1.4	(3.0)
Adjusted R^2	.44	
Number of observations	251	

Omitted province is Alajuela; omitted life zone is humid pre-montane, which is high productivity.
All variables are logged, except province dummies.
[a] = significant at 90%; [b] at 95%; and [c] at 99%.

Table 14-9. Deforestation CS (1986–1997) with Two Protected Area Variables

Variables	Coefficients (std errors)	
Cartago Province	1.7[c]	(.39)
Guanacaste Province	1.5[c]	(.43)
Heredia Province	1.4[c]	(.35)
Limón Province	1.1[c]	(.27)
Puntarenas Province	−.16	(.28)
San José Province	.38	(.32)
Humid – Lower montane	.020	(.054)
Humid – Tropical	.024	(.020)
Very humid – Pre-montane	−.043	(.037)
Very humid – Lower montane	−.017	(.033)
Very humid – Montane	−.10	(.10)
Very humid – Tropical	.084[c]	(.024)
Dry tropical	Dropped	
Rainy – Pre-montane	.044[a]	(.024)
Rainy – Lower montane	−.080[c]	(.024)
Rainy – Montane	.0062	(.028)
Rainy – Sub-alpine	−.013	(.049)
Ultisol	.074[c]	(.024)
Entisol	−.088[c]	(.021)
Alfisol	−.046	(.046)
Road density (km/ha)	.27[a]	(.15)
Minimum distance to market (km)	−.088	(.056)
1984 Population density (#/ha)	−.063	(.041)
1950 Urban population/Total population	.0082	(.021)
Share of district cleared	133	(757)
Share of district cleared squared	−66	(379)
National park density	−.061[c]	(.019)
Forest reserve density	.086[c]	(.020)
Constant	−3.9[b]	(1.9)
Adjusted R^2	.52	
Number of observations	271	

Omitted province is Alajuela; omitted life zone is humid pre-montane, which is high productivity.
All variables are logged, except province dummies.
[a] = significant at 90%; [b] at 95%; and [c] at 99%.

Table 14-10. Reforestation Regression (CSs) with Pasture (1986–1997)

Variables	Coefficients (std errors)	
Road density (km/ha)	−0.62	(0.41)
Ultisol	−0.044	(0.049)
Entisol	0.011	(0.82)
Alfisol	−0.16[c]	(0.045)
Minimum distance to market (km)	−0.15	(0.15)
1984 Population density (#/ha)	0.16	(0.23)
1950 Urban population/Total population	−0.015	(0.046)
Share of district cleared	−29[c]	(7.1)
Share of cleared land in pasture	0.080[b]	(0.28)
Constant	−14[b]	(2.8)
Adjusted R^2	.23	
Number of observations	111	

All variables are logged.
[a] = significant at 90%; [b] at 95%; and [c] at 99%.

Table 14-11. Reforestation Regression (CSs) with Pasture (1979–1986)

Variables	Coefficients (std errors)	
Road density (km/ha)	0.36	(0.24)
Ultisol	0.011	(0.036)
Entisol	0.010	(0.041)
Alfisol	−0.14[b]	(0.059)
Minimum distance to market	−0.13	(0.18)
1984 Population density (#/ha)	−0.097	(0.20)
1950 Urban population/Total population	−0.098[b]	(0.043)
Share of district cleared	1.1[c]	(0.31)
Share of cleared land in pasture	0.027	(0.032)
Constant	−12[c]	(2.5)
Adjusted R^2	0.14	
Number of Observations	162	

All variables are logged.
[a] = significant at 90%; [b] at 95%; and [c] at 99%.