CARBON DYNAMICS AND LAND-USE CHOICES: BUILDING A REGIONAL-SCALE MULTIDISCIPLINARY MODEL

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ABSTRACT

Policy enabling tropical forests to approach their potential contribution to global-climate-change mitigation requires forecasts of land use and carbon storage on a large scale over long periods. In this paper, we present an integrated modeling methodology that addresses these needs. We model the dynamics of the human land-use system and of C pools contained in each ecosystem, as well as their interactions. The model is national scale, and is currently applied in a preliminary way to Costa Rica using data spanning a period of over fifty years. It combines an ecological process model, parameterized using field and other data, with an economic model, estimated using historical data to ensure a close link to actual behavior. These two models are linked so that ecological conditions affect land-use choices and vice versa. The integrated model predicts land use and its consequences for C storage for policy scenarios. These predictions can be used to create baselines, reward sequestration, and estimate the value in both environmental and economic terms of including C sequestration in tropical forests as part of the efforts to mitigate global climate change. The model can also be used to assess the benefits from costly activities to increase accuracy and thus reduce errors and their societal costs.

Keywords: carbon, sequestration, climate change, land use, modelling.

1 INTRODUCTION

The Clean Development Mechanism (CDM) under the Framework Convention on Climate Change is the institutional structure for the sale to developed countries of credits from net C emission reductions in developing countries. Afforestation and reforestation activities carried out since 2000 are eligible for such credits. Avoiding deforestation has been ruled ineligible, however, despite its potentially large contribution to short-run climate-change mitigation and the suite of possible ancillary benefits. The developed countries that demand C credits to satisfy their obligations under the Kyoto Protocol are also constrained. These countries are limited to purchasing CDM credits from C sequestration up to only one per cent of their 'assigned amount' or total allowable net emissions. These constraints limit the global societal gains from C sequestration in the tropics.

One key reason for these limitations is the uncertainty inherent in predictions of land use and C storage and dynamics. Prediction and measurement difficulties raise environmental integrity, efficiency and equity concerns. The difference between accurately measured actual C pools and the 'baseline' level of C storage expected to occur without a CDM is the ideal measure of ‘certified emission reductions’. If C is measured poorly and baselines are inaccurate, trading could lead to increased global net emissions and efforts to sequester C will be misdirected and inefficient. Further, stakeholders must feel that rewards are fair. Over-rewarding additional sequestration would anger environmentalists and the supplier's competitors, while underpaying for honest effort may discourage suppliers. Thus, accurate baseline predictions and C measurements are valuable. For practical reasons, however, the effort put into them should be limited. If we spend excessive time and money on measurement and prediction, we are wasting resources that could be used directly for mitigation.

These concerns highlight the need for high-quality integrated models. This paper describes and illustrates how an integrated model can be built on strong empirical foundations. Our model can be used to generate land-use baseline and C estimates; to simulate policy scenarios; and to assess the benefits of predicting land use and measuring C accurately. We model an international climate policy that rewards all forms of sequestration and avoids deforestation and allows national level 'projects' in developing countries. This is not in line with Kyoto but rather aims to illustrate the potential benefits and the risks from a more comprehensive policy. Our model could be restricted to the Kyoto case as one scenario. We hope models such as ours can be used to inform future policy-makers.

This paper is drawn from work by an interdisciplinary team of ecologists, economists and geographers who are creating such a model for the whole of Costa Rica over a period of over 50 years. For more details see Pfaff et al. (2000). This approach could be replicated in other developing countries, at either a regional or national level.

2 CONCEPTUAL DESIGN OF ICEE (INTEGRATED C ECOLOGY & ECONOMICS) MODEL

2.1 Concepts

Our ICEE model integrates, both spatially and temporally, ecological modeling of C dynamics with economic modeling of land use. To our knowledge, interactions in which land use affects forest ecosystems on this scale have been considered only implicitly through the use of historical land-use and land-cover databases in ecological simulations (Reiners et al., 2002; VEMAP, 1995; Foley et al., 1996; and Houghton et al., 1999). Antle et al., (2001) have created a similar coupled model that focuses on C-sequestration in agricultural soil. Linkages from ecology to land use are often incorporated, in the sense that ecological conditions are understood to constrain economic outcomes. But many analyses have ignored all linkages, and even when linkages have been modeled, the dynamic interactions and feedback mechanisms between ecosystems and land-use changes have largely been ignored.

Our modeling of C pools begins with a dynamic process model of below- and above-ground C. This is calibrated along a range of land-cover types, both natural and intervened, using field data including C and N pools in both vegetation and soils, some collected as part of our project. Then the model is deployed at the local to national level using GIS data on soil types, climatic conditions and land-use/cover types to simulate C dynamics in space and time.

Our economic modeling combines a dynamic model of individual landowner choices with an underlying model of spatial economic development. Individual land-use decisions change over time with economic and physical conditions. Decisions by landowners in turn change local conditions, which affect their own and others' future individual land-use decisions. We estimate the effects of driving factors on forest clearing outcomes, using remotely sensed observations of actual land cover at several points in time as well as socio-economic, biophysical and ecological data. The results, i.e. predicted clearing probabilities for all plots in the country, are applied to GIS data on distributions of the independent variables.

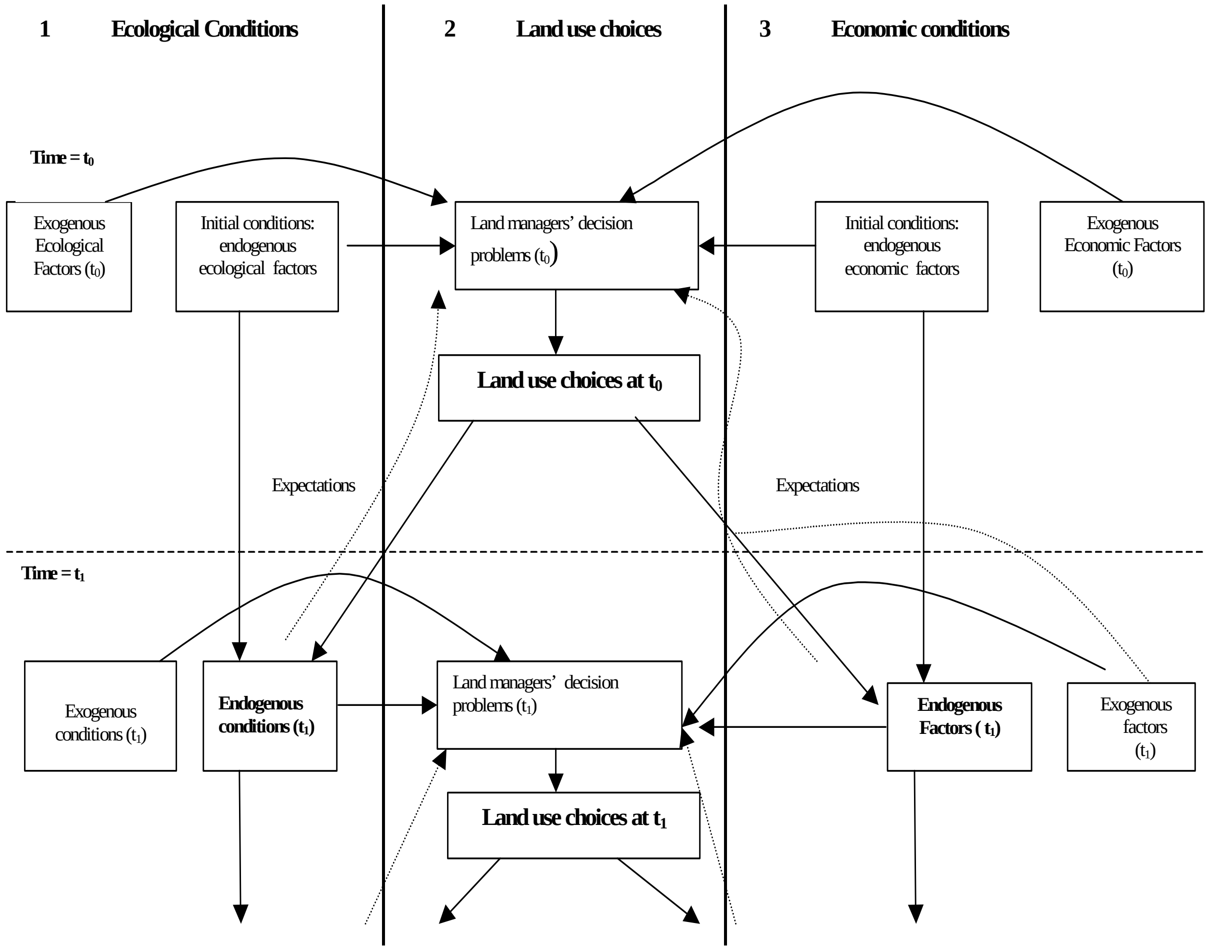
Cross-disciplinary integration of these modeling efforts takes three forms. First, we allow soil fertility, which both influences and is influenced by C stocks, to affect human land-use choices. Second, land-use choices affect C dynamics. Third, any rewards offered for C sequestration that are based on current and potential C storage, will affect land-use choices. These interactions occur in real time and, combined with the non-linear dynamics of each of the individual systems, create a complex set of possible paths of C storage and land use.

Our land-use and C predictions, at local or national scales, are evaluated in terms of both in-sample fit and prediction of out-of-sample data. We also consider economic and environmental costs of inaccuracies in land-use and C predictions. Because baseline and C measures have direct real-world applications, the inaccuracies can be viewed in light of the costs of real-world errors.

2.2 Design

Our Integrated Carbon Ecology and Economics model, ICEE, explicitly models the interactions and feedbacks between ecosystems and human land-use activities using a 3-component integrated model shown in Figure 1.

Figure 1 Diagram showing the interactions among various components of the Integrated Carbon Ecology & Economy (ICEE) model.



The left hand side of the figure (the first component) represents the ecological model that uses climate, soil, and land-use and land-cover information to predict C stocks and soil quality for a range of physical conditions and land uses at time t_0, as well as their evolution over time. The right hand side (the third component) represents the equivalent economic modeling. Exogenous (i.e. determined outside the model) economic factors such as international prices, agricultural technology and C sequestration policy, and endogenous (altered within the system) economic factors, such as the history of land use and the road network in an area, determine the economic conditions for each plot. The endogenous factors evolve over time in response to individual land use choices.

The middle section (the second component) couples the ecological and economic models through the land manager's choice of land use at each point in time. This choice depends on expected economic returns from a range of land uses. The expected economic returns depend on both current and expected future ecological and economic conditions. For example, if landowners expect land to degrade (i.e., lose site crop production potential) under a given use, this will affect their assessment of optimal land use. At the same time, land-use choices alter endogenous ecological and economic conditions in the next period. Land-use choices also affect nearby plots by changing access, market conditions, and ecosystem parameters (for instance, they have effects on seed dispersal dynamics and fire regimes).

The exogenous variables are predicted outside the model as scenario assumptions. Endogenous conditions at the beginning of the prediction period are used as initial conditions from which the model is run forward to predict the endogenous variables and the economic and ecological outputs. These predictions will depend not only on the conditions at each plot but also on the location of the plot and conditions on other plots located nearby. The output of the model includes C stocks and land use for every point in space in every time period. Kerr et al. (2002) use a simplified version of this approach to predict the evolution of C stocks in Costa Rica.

3 DISCIPLINARY MODELING

3.1 Ecological modeling

The ecological component models the dynamics of endogenous ecological and physical conditions, such as C and N stocks and fluxes, in response to changes in exogenous conditions such as climate and to endogenous land use choices. The model can assimilate land-cover/use information from remote sensing, agricultural census statistics, and projected land-cover/use from the economic model. The ecological model provides input to the land-use-choice model through estimates of biomass productivity. It also provides estimates of C stocks at each point in time, which depend on ecosystem conditions and interventions.

About a dozen models can be used to predict the dynamics of soil C in ecosystems (Smith et al., 1997). We have elected to use the well-established ecosystem model CENTURY. This model, developed at Colorado State University (Parton et al., 1987), simulates C, N, P, and S cycles in various ecosystems, including pastures, forests, crops, and savannas, and can model the impacts of management practices such as fertilization, and cultivation, as well as natural disturbances such as fire and hurricane (Parton et al., 1987, 1993). This model has also been tested extensively against field measurements from various ecosystems around the world (e.g., Parton et al., 1993; Schimel et al., 1994; Smith et al.,

1997) and used for biogeochemical simulation purposes at the regional, continental, and global scales (e.g., Schimel et al., 1994; VEMAP, 1995; Schimel et al., 1997). CENTURY has already been adapted for simulating nitrogen and C dynamics in various ecosystems in the Atlantic lowlands of Costa Rica, including primary forests, secondary forests, pastures, and banana plantations (Liu et al. 1999, Liu et al. 2000, Reiners et al. 2002).

Major inputs for the monthly-time-step version of CENTURY include land-use and land-cover type, monthly average maximum and minimum air temperature, monthly precipitation, lignin content of the plant material, C:N plant tissues, soil texture, initial soil C and N levels, atmospheric N deposition, and management practices such as fertilization. Many of these inputs come from field measurements; others come from existing literature. Past land-use and land-cover changes are interpolated, while future land-use changes are predicted using the economic model of land use described in the next section. The major outputs of CENTURY include net primary productivity, crop yields, C decomposition, C exchange rates between ecosystems and the atmosphere, and C stocks in vegetation and soils.

In order to scale up the plot-level CENTURY model over large areas such as an entire country (even one the size of Costa Rica), a General Ensemble biogeochemical Modeling System (GEMS) GEMS was developed that incorporates spatially and temporally explicit information into the simulations (Liu et al., 2003). In GEMS, the CENTURY model is encapsulated within a data assimilator, through which input files are updated automatically using information from GIS data sets as well as results of the economic model of land use. This GEMS is currently being used to quantify the spatial and temporal dimensions of C dynamics within the coterminous Unites States. A modified prototype was also used for the estimation of the total flux and spatial pattern of nitrous oxide emissions from soils in the Atlantic Zone of Costa Rica (Reiners et al. 2002).

A primary strength of GEMS lies in its ability to make explicit use of the joint frequency distribution (JFD) over space of the critical driving variables such as land cover, soils and climate. Specifically, a fundamental construct of the GEMS is that variances and covariances of given variables in space, information which can be provided in a JFD table, are necessarily incorporated in the simulation process. This is crucial for simulations that aggregate up from plot-level results, as it forces the model to be explicit in beliefs about key distributions. It also permits explicit uncertainty estimates for the results, via ensemble Monte Carlo simulations.

The JFD table gives a discrete partitioning over the relevant space (e.g., Costa Rica) of:

$$E(p) = \int E[p(\mathbf{X})]f(\mathbf{X})dX \quad (1)$$

where p is the process-based environmental model, **X** is a vector of model variables, and f is the joint frequency distribution of **X**. Generally, it is impossible to analytically integrate equation (1) because the models are usually complex. Therefore, using a GIS, the JFD table provides:

$$E(p) = \sum_{i=1}^{n} E[p(\mathbf{X}_i)]F(\mathbf{X}_i) \quad (2)$$

where n is the number of strata or unique homogeneous regions as defined by the GIS overlays of the major inputs, and F is the frequency of cells or the total area of strata i as defined by $\mathbf{X}_i$.

Before GEMS is run, the underlying biogeochemical model CENTURY should be calibrated and validated with field data collected in each dominant life zone in Costa Rica. Our previous modeling efforts using CENTURY indicated the importance of the water cycle in the tropical moist to wet forest life zones to nitrogen trace gas emissions, which is tightly coupled with the C cycle (Liu et al., 2000, Reiners et al., 2002). Few models, including CENTURY, have been tested in all the dominant life zones in Costa Rica. To calibrate and validate our ecological model we use newly collected ecological field data that quantify C and N stocks in soils and aboveground biomass of ecosystems, with systematic sampling of the variation in edaphic, climatic, and land use conditions. Model validation performed so far, using field measurements collected from 13 sites from five dominant life zones (i.e., tropical montane rain forest (TM-rf), tropical pre-montane moist forest (TP-mf), tropical moist forest (T-mf), tropical dry forest (T-df), and tropical wet forest (T-wf)), indicates that simulated results of aboveground live biomass, large woody debris, and fine litter agreed well with field measurements; simulated net primary production values agreed well with data reported from literature (Clark et al., 2001); and total amounts of soil organic carbon (SOC) in the top 20-cm soil layer were well simulated in TM-rf and TP-mf, significantly under-estimated in T-df

(α=0.05), and significantly overestimated in T-mf and T-wf (α=0.05). The overestimation of SOC by the model in T-mf and T-wf was consistent with our previous findings that the default maximum decomposition rates for the slow and passive SOC in CENTURY, originally parameterized for the Great Plains, were too low for the tropical moist and wet forests (Liu et al., 2000). A comprehensive assessment of the performance of the CENTURY in Costa Rica has been planned as we are collecting additional field data in different life zones.

3.2 Economic modeling

Our theoretical modeling of land-use choices generates testable hypotheses about causation, motivating the use of data on real behavior across time and space in a revealed preference approach to estimate coefficients representing causal effects, not simply correlation or trends. Early applications of this approach to analyze deforestation include Stavins and Jaffe (1990), and it has been used to consider C sequestration in the United States (Stavins, 1999; and Plantinga et al., 1998). For tropical settings, applications include Pfaff (1999) in Brazil, and our work in Costa Rica (Kerr et al., 2002).

An alternative approach is to develop models that specify human behavior (see, e.g., Richards et al. 1993). On a larger scale, Sohngen et al. (1999) consider C sequestration in commercial forestry using an optimization model of global timber markets. While these models have value for understanding the effects of economic forces, if used for prediction they are forced to assume that people will behave in exactly the ways they specify – i.e. optimize in a narrowly defined sense. This is extremely problematic when we consider the complexity of the situations and motives real people face. Thus, in generating predictions we prefer to let the data on past human behavior speak for themselves. We use econometric analysis of human responses to ecological and economic conditions to generate the parameters of our predictive simulation model.

The economics has two steps. First, we model the behavior of individual land-users, taking outside conditions as given for a particular location and point in time. This is the basis of the second component in our integrated model (see Figure 1). Second, we explicitly model the interactions among these individuals. We empirically test spatial assumptions about the effects of land use choices of conditions on neighboring plots. Interactions among plots create potentially persistent and non-linear compound effects of shocks such as a new road. This is the basis of the third component in our integrated model.

3.2.1 Individual land-use behavior

The land manager of each plot i faces a dynamic optimization problem that we model with two stages. First, the land manager decides what he would do with the land if he cleared it at time t.

He chooses a crop $x_{t,}$ out of a set of crops X, to maximize the present discounted value of his expected utility (U is a von-Neumann Morgenstern utility function and r is the discount rate) from a combination of short and long run agricultural returns from a range of options. y_t indicates the choice made. The returns and hence choices vary across space and time because of physical and economic factors including productivity, crop prices and access to markets. The exogenous physical and economic conditions on the site are summarized in z_t and the land use history is given by $(y_0 \ldots y_{t-1})$. x_s* are optimal choices from s=t+1 onward given expected future conditions. Current choices will depend on their effect on these future options. Future options depend on previous choices of crop because of degradation of soil or investments in clearing, irrigation or permanent crops.

In the case of the individual decision, Z_t will include not only truly exogenous characteristics such as initial soil and climate, that affect crop yields, and international crop prices, but also features such as access costs that are exogenous from the point of view of the land manager although they are determined within the wider model. The land manager's discount rate reflects the value of capital and his access to capital. It also reflects his uncertainty about the future. For instance, if he perceives his tenure security to be low, he will have a high discount rate and future options will be less important. The land manager solves this problem at every point in time.0

$$Max_{x_t \in X} \text{ E U}(x_t | (y_0 \ldots y_{t-1}), Z_t) + \int_{s=t+1}^{\infty} \text{E U}(x^*_s \mid (x_0 \ldots x_t \ldots x_{s-1}), Z_t)\, e^{-r(s)}\, ds \qquad (3)$$

R_{it}, or the change in utility from the optimal choice of crop for plot i at time t, is defined as the return from the series of optimal choices now and in the future. It is used as an input to the second stage of the problem.

The first stage of the problem can be estimated using a multinomial logit on crop choice data (McFadden, 1974). This requires estimates of potential crop returns under a range of conditions. We need to make explicit links between ecological characteristics of the land and economic returns. Our earlier analysis of Costa Rica (Kerr et al. 2002) has found that even broad measures of biophysical conditions, lifezone and soil characteristics, have significant explanatory power with respect to land use choices. CENTURY can predict biomass productivity for each plot at each point in time. These predictions can be used to create models of crop yield calibrated with economic data on actual yields. When we combine these with crop prices and transport cost measures, we obtain site-specific measures of economic returns that affect land-use choices and hence future soil quality. This creates a spatially-specific dynamic feedback from land use to land degradation then back to land returns and land use.

This estimation yields predicted probabilities of choices among different crops on land that is cleared. The model is not deterministic because of the many unobservable factors that affect land manager decisions. Land managers facing observationally similar conditions do not in reality all choose the same crop. The estimated optimal return will be a weighted average of estimated returns for different crops based on the predicted probabilities that each is chosen. Our current analysis (Kerr et al., 2002) models land use choices by correlating actual land use with lifezones and assigning probabilities to each major land use in each lifezone. The predicted probabilities are combined with price and yield estimates to create estimates of potential returns if any plot of land were cleared at any time, R_{it}.

In the second stage, given R_{it}, the land manager selects T, the time when the land is cleared (reforestation is treated as a new crop). Below, S_{it} is the potential return (or rent) to forested uses of the land, while C_T is the cost of clearing net of timber value (including lost option value):

$$\mathrm{Max}_T \int_0^T \mathrm{E}\, U_i(S_{it})\, e^{-rt}\, dt + \int_T^\infty \mathrm{E}\, U_i(R_{it})\, e^{-rt}\, dt - C_T\, e^{-rt} \qquad (4)$$

Using the results from the first stage, for transitions data, the second stage of the problem could be estimated using methods developed primarily in labor economics (Lancaster, 1990) and the study of technology adoption (e.g.: Saloner and Shepard 1995, Kerr and Newell, forthcoming) as well as in medical research. Continuous conditional probabilities of transition from forest to cleared land on small plots would be estimated from observed discrete transitions and a range of explanatory variables by maximum likelihood using testable assumptions about the underlying population distribution. Currently, Kerr et al. (2002) estimates this model for Costa Rica using data that groups discrete transitions at the plot level into fractions deforested in larger polygons.

Current decisions by neighboring land managers are likely to be correlated with the land manager's decision because of unobservable conditions such as tenure security that persist across space. To both test and control for spatial correlation in grouped data, Kerr et al. 2002 applies standard spatial error corrections (Anselin 1988). With plot-level data we will initially use a method known as the Gibbs Sampler, in a Bayesian approach (LeSage 1999, Pinkse 1999).

The quality of fit achieved in this model can be assessed by considering the R^2 of the regression that underlies it and by comparisons with out-of-sample data. We also explicitly model the uncertainty in each coefficient and in projections of independent variables to provide distributions of predictions (see Kerr et al., 2003 for more detail).

3.2.2 Evolution of economic conditions & path-dependent spatial development

The returns to forest and different crops and the costs of clearing depend on a combination of exogenous and endogenous forces. Exogenous factors such as national population, international crop prices and global technology change over time. Distances to key locations (ports or major cities) do not change, although the cost and time involved in reaching them will. For econometric modeling, the effects of observable exogenous factors can be included directly. Unobservable but time-varying exogenous factors can be included through testable assumptions on the time dependent error structure. For predictive modeling, these factors are predicted outside the model and entered as scenario assumptions.

In addition, however, when one land manager makes a decision he alters the choices affecting all other land managers; some changes in conditions are endogenous. At this point the system becomes complex and the individual decisions are interactive. In the same way that Krugman's work on economic geography (e.g. Krugman, 1991) suggests that cities will form gradually and that there are multiple equilibria because of path dependence, the pattern of agricultural expansion also will be gradual and path dependent. For example, clearing land may require creating an access path. This improves access for other plots of land nearby and increases the attractiveness of clearing them also. More extensive development may lead to the creation of a road. Increased economic activity in an area increases input supply and output demand for local producers in that area. Widespread production of a specific crop will lead to the provision of services for that crop such as seeds, special fertilizers and equipment, local knowledge networks and a marketing network. As population reaches a critical mass, banks will establish credit facilities. Helpful (if one-dimensional) models of this sort appear in Fujita et al. (1999).

The variable but unobservable state of local and national infrastructure and institutions are particularly important in developing countries where capital scarcity, poor access, poor information, weak property rights and expanding agricultural frontiers are standard features. The costs of rapid development and factors such as restricted capital access and poor institutions mean that an area cannot move directly to develop all of the land that would be profitable in equilibrium. As infrastructure and institutions develop, returns will be higher. This could lead to more clearing as well as allowing land use to reach equilibrium more quickly. High levels of national development may ultimately lead to government development of regulations regarding tenure, forestry development and forest conservation. Increased income, urbanization, education and visible loss of the natural environment, combined with an increase in foreign tourism, may change cultural norms toward conservation.

In the econometric work we can include observations of endogenous conditions such as roads, credit availability, etc. This is a useful approach for identifying historical causality, but for predictive purposes would require direct prediction of all endogenous factors including roads. For predictive modeling, these path-dependent effects can be estimated by including contemporaneous and lagged spatial terms in the 'time of clearing' model. Contemporaneous conditions in neighboring areas reflect activity in past periods; this affects the conditions the land manager faces. Variables representing conditions in neighboring areas, such as level of clearing, road access, population density and crop choices, can be generated using GIS techniques. Kerr et al. (2002a) find evidence suggesting that both local and national endogenous developments are important determinants of land use decisions.

3.3 ICEE integration

The previous sections have described the construction of the model components. Here we discuss how they are combined into an integrated ecological and economic model and used to create simulations for validation and policy purposes. The model illustrated in Figure 1 can be summarized in two equations. The first equation predicts endogenous ecological and economic conditions, ω_t. The process-based model predicts ecological conditions based on exogenous ecological conditions, such as climate, elevation, and soil type, and on the history of land use. Z_t is a matrix of observable exogenous characteristics of the plot and the economy at time t. y_{it} is the actual land use on plot i at t so ($y_{i0,}\ldots y_{it-1}$) is the land use history. The land uses on neighboring plots, y_{jt-1}, summarize the endogenous development of the economic conditions. The dynamic spatial economic model predicts these endogenous economic conditions as a function of individual plot-level decisions.

$$\omega_{it} = \omega_{it}(y_{it}, (y_{i0}, \ldots, y_{it-1}), Z_t,\ y_{jt}) \tag{5}$$

The second equation predicts these individual plot-level decisions. $\gamma_{x_{st}, y_t}(i)$ is a transition probability from the current land use, y_{it}, to each of n potential land uses $x_{s,t+1}$, s = 1,…, n for plot i during time t. These transition probabilities sum to 1. The economic model predicts the transition probabilities by multiplying the probability of clearing by the conditional probability of choosing each particular crop. Although the model predicts that expectations of future ecological and economic conditions affect current decisions, we assume that these expectations are based on current information and conditions and are hence captured indirectly.

$$\overline{\gamma}_{it} = \begin{pmatrix} \gamma_{x_{1t+1}, y_t}(i) \\ \vdots \\ \gamma_{x_{1nt+1}, y_t}(i) \end{pmatrix} = \overline{\gamma}(Z_{it}, \omega_{it}, y_{i0}, \ldots, y_{it}) \tag{6}$$

The next period's land use, y_{it+1}, is a discrete random draw from the distribution of land uses with probabilities defined by the vector $\overline{\gamma}_{it}$. These two equations are simulated simultaneously.

In order to realize the seamless integration, the output of the economic model on each simulation unit (an administrative district or a land parcel) at each time step (i.e., each year) can be injected into the ecological model; the output from the ecological model at each time step can then be fed back to the economic model. Time synchronization between those models is very important in the integrated model. It ensures that the feedbacks between ecosystems and economic systems we see in the real world are appropriately represented in the integrated model. Several techniques can be used to realize the parallel simulation (Tanenbaum, 1987). The key outputs from the integrated model are land use and C stocks (changes) on each plot in each year as well as at the national level.

4 DATA USED IN COSTA RICAN ILLUSTRATION

4.1 Ecological data

Systematic datasets that quantify C and N pools in ecosystems of tropical countries are rare. For example, numerous field studies have examined soil C and N dynamics in Costa Rica (e.g., Ewel at al., 1981; Matson et al., 1987; Marrs et al., 1988; Motavalli et al., 1994, 1995; Reiners et al., 1994; Veldkamp, 1994; Fernandes and Sanford, 1995). However, no studies have yet been conducted to quantify C and N pools at the ecosystem scale in a manner that explicitly quantifies soil and aboveground pools along the range of climatic, edaphic, and land use characteristics encountered in Costa Rica. Without detailed, region-specific measures of aboveground and soil C and N pools, regional estimates of the dynamics of such pools will be superficial at best, and inaccurate and misleading at worst, because the distribution of both C and N pools among tropical forest ecosystems varies substantially as a function of soil type, climate, and land use and land cover conditions (Detwiler, 1986; Schlesinger, 1986; Brown et al., 1993; Hughes et al., 1999; Hughes et al., 2000). While the numerous studies relevant to C and N dynamics conducted to date in Costa Rica aid the construction of C and N budgets in ecosystems across the nation, these studies are not sufficient to accurately estimate regional C and N stocks in vegetation and soils. The paucity of relevant data regarding terrestrial C and N pools and dynamics poses a challenge for accurate national-scale accounting of C sequestration in Costa Rica. Further, this challenge must be addressed by any other country facing the task of determining C stocks within ecosystems that span elevational, latitudinal, and precipitation gradients. Indeed, this challenge may be less daunting in Costa Rica than in other countries because of the relatively small size of that nation and the relatively large amount of ecological studies that have been conducted there.

Our research team is currently conducting a field research program designed to quantify, in an extensive and intensive manner, aboveground biomass, C, and N pools in forest and agriculture ecosystems across Costa Rica. The objectives are to carry out systematic and comprehensive field measurements of aboveground biomass and C at 120 study sites within Costa Rican forests ranging from tropical-wet to tropical-dry Life Zones (6 different zones), and to quantify C dynamics along land use gradients that exist within of each of those life zones. Sites include mature forest vegetation, the dominant forms of managed sites (e.g., pastures, banana and coffee crops), and secondary forests of various ages. Mature forest values will be used as the hypothesized maxima for aboveground C sequestration. Actively managed sites (e.g., pastures and croplands) will be used as the hypothesized minima for sequestration, and secondary forests will provide information regarding potential rates of accumulation following abandonment. In this way we will determine the influence of edaphic and climatic variables on aboveground biomass and C dynamics as well as the interplay between land use change and those environmental variables.

If our modeling efforts are to be applied to other countries, ecosystem classification components of GEMS can be based on climate and topographic data of the given country or separately derived. In the Costa Rican case, we use the World Life-Zone System of Ecological Classification (Holdridge, 1967). Ground observations and climate data have been combined to create a GIS map of the 12 Life zones and 11 transition zones in Costa Rica. This map, provided by the Tropical Science Center, is used as a layer of spatial framework (together with GIS maps of soils and climate) to generate a JFD table defining the heterogeneities of ecosystems types and biophysical conditions in Costa Rica. The life zone map also provides common spatial units for field sampling design, biogeochemical and economic modeling and analysis.

4.2 Land use and land-use history

National scale land use / land cover data for tropical countries is primarily available from remote sensing. In developed countries, census data provides relatively accurate time series data. Developing country census data collection is usually infrequent and also done for relatively large political units. Satellite images are available since the late 1970s. With careful analysis these provide high quality data at a fine level of detail. They can relatively easily distinguish forest and non-forest, as well as land cover categories such as rocky areas, lakes, and mangroves.

We also gain useful data from aerial photos taken during several different periods. For the whole of Costa Rica, this data is available back to 1963. For some key areas of the country, data is available back to 1945. It can roughly separate forest and non-forest. Together, these images provide the dependent variable for the economic modeling of land use and also the raw data on land use history for the ecological modeling.

Identifying specific land uses, such as coffee relative to sugar plantations is much more difficult but the technology is improving rapidly even there. For example, in Costa Rica some data differentiates pasture, and seasonal and permanent crops. Although it is technically possible to discriminate land uses to a very fine level, current data derived from remote sensing of Costa Rica does not do so. Census data also provides some information, as does industry association data on production. We combine these three sources to get the best possible estimates for major crops.

4.3 Socioeconomic data

The first use of socioeconomic data is to combine it with ecological data to estimate agricultural returns. We collect export prices for key crops. In the Costa Rican case this is sufficient as a measure of price because large amounts of crops are exported to world markets where Costa Rica has no influence. In larger countries, or where much of the production is for domestic use, prices depend on the levels of production; the demand for crops must be modeled separately. We also use data on observed yields for key crops. Later we will complement them with biomass productivity estimates from CENTURY. We have found limited data on production costs and costs of establishment for new crops. For example some crops require irrigation and permanent crops such as coffee involve considerable initial investment.

Transport costs are the final data needed to estimate returns. These are estimated directly (Roebeling et al., 1999) or as a function of travel distances and speeds based on a GIS road network. The latter allows transport costs to vary over time as the network develops. The different types of data are complementary.

If we had georeferenced land-price data, we could estimate returns in an alternative way, using ecological conditions and data on the returns to crops that can be grown as characteristics in a hedonic regression. Land price is usually collected by local or central governments, as the basis of land or property taxes. It will tend to be biased because people want to minimize their tax, but may show a reasonably consistent pattern across space. These two approaches are complementary in choosing the best agricultural return estimates for the final model.

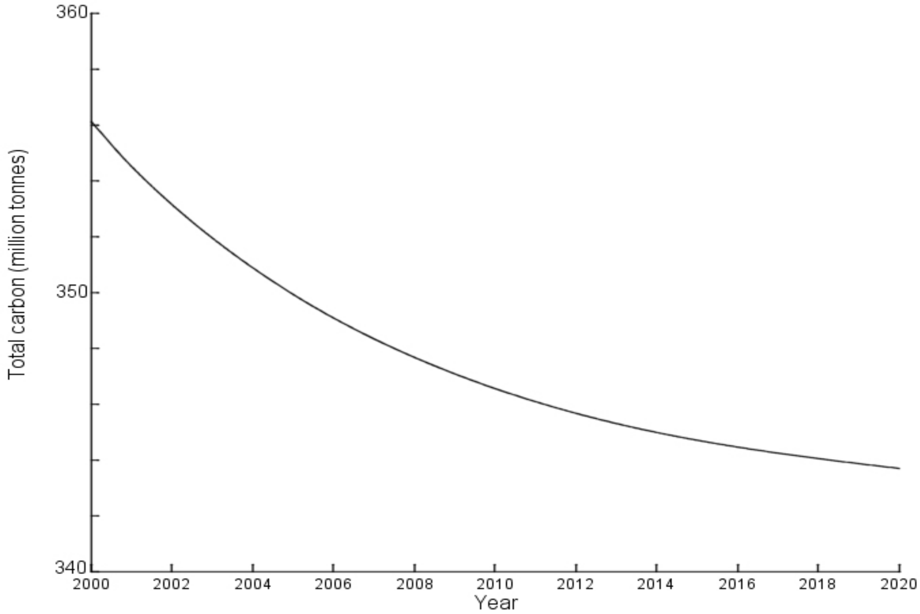
Finally, in order to control for the process of development, which includes exogenous changes in infrastructure, institutions and markets that raise the general level of returns, we require data on characteristics of the economy such as Gross Domestic Product per capita as an estimate of the level of development, and openness ((exports + imports)/GDP) as an estimate of landowners' access to international markets. These types of data are readily available from census data and the World Tables published by the International Monetary Fund.

5 POLICY ANALYSIS AND UNCERTAINTY

5.1 Model predictions

The first products from these integrated modeling efforts are estimates of C baselines and accompanying uncertainty bounds on those baselines. These can be used to create baselines for CDM projects or as the basis for negotiation on the part of new countries that want to enter the Kyoto Protocol on a similar basis to Annex I countries. For example, Figure 2 shows a baseline estimate for Costa Rica going forward from 2000 (from Pfaff, 2002). This was generated from our preliminary integrated model.

Figure 2 Predicted baseline C stock in mature forest in Costa Rica



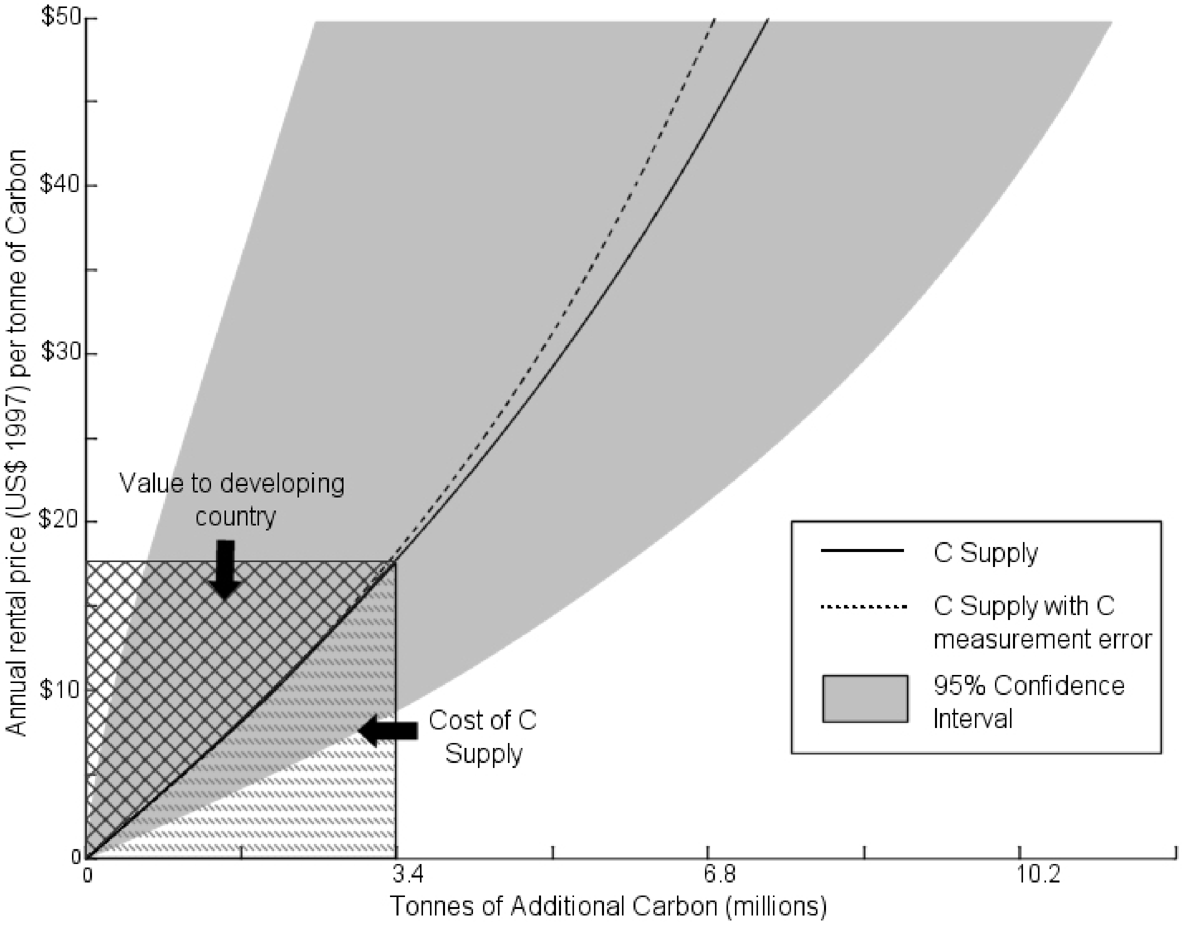
This figure shows a forecast of the total carbon stored in mature forests in Costa Rica from 2000 forward. It is calculated by interacting C estimates in mature forest in each lifezone with predictions of the forest remaining in each lifezone at each point in time. Introducing uncertainty into the carbon measurements gives a 95% confidence interval of approximately $\pm$ 140 million tonnes.

The figure suggests that forest levels will continue to fall slowly and at a decreasing rate. Second, we can predict how much forest will be protected, and hence C will continue to be stored, in response to any given monetary reward for C sequestration. By varying the reward we can develop a supply or, equivalently, cost function for C sequestration (i.e., a relationship between the C reward and the C sequestration supplied by land users). Figure 3 shows an example of a supply function produced from our preliminary model. It predicts that by 2020, if the annual payment for C storage from 2000 onward is $18.50 per tonne C then about 3.4 million tonnes or 1% more carbon will be stored than in the baseline.[3] We use annual payments to reward ongoing storage to avoid the problems associated with the temporary nature of forests. If the annual payment exceeds $50, almost no deforestation would occur. This allows us to assess the value of incorporating C sequestration in the climate-change mitigation effort.

[3] This is the amount of carbon supply that would accumulate after 20 years of a $20 annual carbon rental-price.

The total cost of sequestering C is the integral under the curve.[4] The value of producing these credits is the difference between the cost of producing them and their value to the Annex I countries that will buy them. This is the area above the curve up to the international carbon price (here represented as an annual payment equivalent). The international price reflects the marginal cost of reducing net emissions in other ways or places.

Figure 3 The supply of additional carbon from avoided deforestation between 2000 and 2020 at different levels of annual payment per tonne of C



This is produced by comparing a baseline simulation (Figure 2) with simulations where forest returns per ha are raised by the estimated level of C in that lifezone multiplied by the annual C payment. The shaded area represents a 95% confidence interval on the simulation. The dotted upper curve represents the lower level of supply (higher cost) when C is measured with error and thus carbon payments are poorly targeted. The construction of these curves is described in detail in Kerr et al. (2003) and Kerr and Hendy (2003).

[4] This is the cost in 2020 of continuing to store that much carbon.

Uncertainties in predictions of future scenarios arise from several factors, including the predictions of exogenous variables (e.g., population, economic growth, C reward), historical input data, estimated model coefficients and assumed parameters, as well as potential model misspecification. To model uncertainty, values for certain critical variables including precipitation, temperature, soil texture, and initial soil C content can be drawn from spatially-explicit GIS databases according to the empirical distributions as defined by the databases. Economic values such as population, GNP, and international prices can be varied across ranges based on long-term external forecasts. Coefficients can be varied based on their estimated variance-covariance matrix.

In addition, the economic model is inherently uncertain because land-use choices contain a probabilistic element. Each land-use choice has effects on future choices in the neighborhood and possibly region. Depending on the strengths of positive and negative feedbacks, these changes could disappear so that land use in many simulations converges to a common deterministic pattern, or could be amplified in the surrounding area. Small difference in land managers' choices early in the land use path could lead to significantly different paths of land use and C sequestration. Successive predictive runs with identical inputs will lead to different paths of development depending on the probabilistic path taken in each run. We provide confidence limits or uncertainty bounds for the predicted baselines and C supply functions based on Monte Carlo simulations. We test the sensitivity of environmental and economic outcomes to different policies and can thus contribute to more effective design of the rules that allow C sequestration to replace emissions reductions in developed countries.

5.2 Evaluation of alternative models -- economic and environmental costs

When used predictively, the model generates point forecasts of land-use baselines and C stocks at each point in time, on each plot, under different scenarios. These could be used to define rules for rewarding C sequestration (i.e., baselines and C stock measurements). Rather than measure C directly on each plot where C sequestration is being rewarded, a very costly process, the model would allow C numbers to be based on the climatic and ecological conditions on the plot and the land use history known from GIS databases. When climatic and ecological GIS databases are available, baseline forecasts and C estimates could be made from anywhere in the world and crosschecked by other analysts without the need to actually visit the regions in question.

If C predictions from models such as ours are compared to careful on-site measurements, we will observe forecast / measurement errors. The land-use baseline predictions also will be incorrect relative to true counterfactuals, although those cannot be observed. By definition we cannot observe what would have happened without the reward if the land managers did in fact receive the reward. Thus, when land managers are rewarded for C sequestration, their rewards will be incorrect by an unobservable amount. These errors in baseline predictions and C measurement have real social costs even when we cannot observe them.

When regulatory rewards are based on incorrect measures and forecasts, there are three costs. First, the inaccurate rewards will lead to aggregate environmental outcomes that differ from those desired. Overstated measurements of sequestration would lead to real increases in global net emissions when the sequestration credits are sold to a developed country and they use them to increase their own net greenhouse gas emissions. What matters here are errors in aggregate additional sequestration relative to baseline for the whole country (or the globe). The cost will depend on how far, under the inaccurate rewards, the aggregate actual additional sequestration differs from the aggregate credits generated for sale. The global cost of each excess credit could be measured as marginal environmental damage minus avoided marginal abatement cost. Producing too many credits is likely to be perceived as a greater cost than producing too few, although if global targets were chosen efficiently both would be concerns.

Second, land managers would have faced inappropriate and hence inefficient incentives to sequester C. The cost of the sequestration that did in fact occur would be higher than necessary. Some will sequester too much and others too little. Our model can estimate these costs in dollar terms. With accurate C rewards, the average cost per tonne in the year 2020 of continuing to store 1% of baseline carbon, given by the area under the solid curve in Figure 3, is $7.90.[5] The marginal cost of additional carbon storage over the period 2000 to 2020 is $18.50 per tonne per year. The dotted line in Figure 3 shows the cost curve for

[5] The modeling of the impacts of carbon errors into our simulations is described in detail in Kerr and Hendy (2003).

sequestering when there is error in our carbon measurements.[6] Introducing variance in carbon measurement increases the cost of storing this carbon by approximately 3%.

Third, land managers who sequester equal amounts of C will be rewarded differently, thereby creating equity concerns. This could affect the acceptability of the system. Unacceptability is immeasurable but the marginal costs will increase with the size of errors, whether those errors are positive or negative.

Both of these costs, efficiency and equity, depend on errors in plot-level rewards. Efficiency costs simply depend on errors relative to reality. Equity costs depend on how forecasts vary across plots that are perceived to be identical. Even if the forecasts provide the correct number of credits for aggregate sequestration, inefficiency and inequity could be problems.

We can evaluate predictions using assumptions about each of these types of cost and a combination of costs. The use of social costs to evaluate errors takes us beyond standard validation approaches where errors vary only by size, not by direction or relationship to other variables. Once we have specified our cost function for errors, standard validation approaches could be used to analyze the distribution of the cost of errors rather than the distribution of the errors themselves.

5.3 How much accuracy is sufficient?

Our general modeling approach allows us to produce forecasts based on remotely sensed and exogenous data, reducing the costs of creating baselines and measuring C. Simplifying that model still further would save on the need to collect so much data and / or the need for so much modeling complexity. For most developing countries, ecological data is not as readily available as in the Costa Rican example. The more site-specific data a modeling approach needs the more expensive it will be to calibrate and validate, because the costs of collecting ecological field data, new socio-economic data and land-cover data is high. Historical socio-economic data may not exist. Can we generate simplified versions of the integrated model that reach a reasonable degree of accuracy in prediction?

[6] Details of the derivation of this line are given in Kerr and Hendy (2003).

We can simulate a variety of models that are based directly on our basic model but simplified in terms of both data input and model complexity. We can then compare their forecast errors to our full model. Simpler, partially linearized versions of our models could be created using statistical analysis such as step-wise regression analysis or non-linear regression analysis (Johnson and Wichern, 1988). Meta-modeling techniques have been used to evaluate the impact of agricultural policy on soil degradation (Lakshminarayan et al., 1997). In the same way, meta-models could be developed to define forecasting models, with different degrees of complexity, based on the simulated results of the integrated model.

After developing the simpler meta-models from a subset of data, we can test their accuracy on the out-of-sample locations and time periods against both the existing GIS databases and simulated results based on the integrated model. The importance of variables and the accuracy of different models can be determined by considering the economic implications of models using different levels of complexity and variables and the errors they create, as discussed above. Based on this analysis, we can pinpoint the variables, types of locations and time periods where field data and remote sensing data should be collected to estimate baselines and C stocks most effectively. Preliminary analysis of this type is reported in Kerr et al (2003). The results could facilitate more effective monitoring of C sequestration projects; these sensitive variables and locations should be monitored with highest priority (Post et al., 1999).

Such comparisons also will suggest whether the simplified meta-models maintain sufficient accuracy. Accuracy can be measured in terms of the estimated models' abilities to ensure the sequestration outcomes envisioned and their implications for economic efficiency and equity. These gains can be contrasted with the qualitative value of greater model simplicity. Simplicity translates to lower costs of participation in trading and, potentially, lower corruption through greater transparency and verifiability in the application of crediting rules. If sufficient accuracy is possible at reasonable cost, the sequestration outcomes envisioned could be approximately achieved and reasonable efficiency and equity would be attained. Greater simplicity would stimulate further participation in climate-change mitigation thereby lowering costs and raising the global efficiency of implementation of the Kyoto emissions limitations.

6 CONCLUSION

To predict the evolution of an ecosystem as accurately as possible, the interactions between ecosystem dynamics and human land-use need to be modeled. The methodology developed in this paper involves a three-component approach that models the development of the ecological system, the human land-use system and the dynamic interactions between the two. The ecological component uses methods that combine ecological process-modeling and GIS to scale plot-level results up to landscapes and regions. This maintains the benefits of detailed process modeling while allowing for heterogeneity in the landscape. The economic component advances empirical modeling of land-use change in circumstances where markets and institutions are in the process of rapid development so that more standard models of equilibrium land use cannot be applied readily. We are able to analyze the economic and environmental costs of uncertainty.

When predicting baselines and C dynamics for quantifying C rewards, the cost associated with collection of a comprehensive dataset should be weighed against the benefits gained from the high-quality data. Simpler models with coarser datasets will result in less costly baseline and C predictions. In this paper we have proposed assessing the relative benefits of models with varying degrees of complexity by comparing the environmental, economic efficiency, and equity costs associated with errors in baselines and C measures. The distributions of the costs of the errors can be used to compare models.

These methods all will be applicable to future models of coupled natural and human land-use systems. The primary motivation for our research is to develop models and generate insights that will allow researchers and policy analysts to model land-use and C interactions in other countries and regions. It is our ultimate goal to generalize and apply the integrated modeling system to other regions, including non-tropical regions. The selection of Costa Rica to perform the model development was deliberate. Costa Rica offers rich databases, and a range of economic conditions and tropical life zones that cover most of the economic and ecological conditions represented in Latin America today. If models are to be widely used to implement climate-change mitigation policies such as the CDM, however, they need to be simpler, with reduced input variables and less complex modeling structures. Testing simplified versions of our model to find a simpler model that maintains accuracy will help us to suggest a modeling system or methodology that is more easily applied to regions where data are not as rich as in Costa Rica.

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