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ORIGINAL ARTICLE

Accounting for carbon stocks in models of land-use change: an application to Southern Yucatan

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Abstract To assess the impact of land-use change on carbon stocks, we apply a new methodology, linking ecological and economic modeling, to southern Yucatan, Mexico. A spatial econometric multinomial logit model of ten land-cover classes is estimated (four primary forest categories, three secondary growth categories, an invasive species, and two agricultural land-cover categories), using satellite data on land cover, linked with census socio-economic data and other biophysical spatial data from 2000. The analysis is novel in that it is the first attempt to link detailed satellite data on land use, with on-the-ground estimates of carbon stocks in a spatial econometric model of land use. The estimated multinomial logit model is then used with two scenarios of future economic growth ("low growth" and "high growth" changes in population, agricultural land use, market access, and education levels) in the region to predict land-cover changes resulting from the economic growth. The per hectare carbon (C) stocks in each land-cover class are derived from previously published estimates of biomass from field sampling across the study region. We consider aboveground-only, aboveground plus soil, transient and non-transient pools of carbon. These estimates are scaled up to the total area in each class according to the predictions of the model baseline and the two development scenarios. Subsequently, the changes in carbon stocks resulting from the predicted land-cover changes are calculated. Under the low growth scenario, carbon stocks declined by 5%; under the high growth scenario, losses were 12%. Including soil C, the proportional losses were lower, but the absolute amount lost was more than double (to 6 Tg C under the low and almost 15 Tg C under the high-growth scenario). This methodology could be further developed for applications in global change policy, such as payments for environmental services (PES) or reduction in emissions from deforestation and degradation (REDD).

Keywords Spatially explicit land-use econometric modeling · Carbon stocks · Remote sensing · Mexico · Land-use change · REDD

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Introduction

Tropical forests provide many ecological services. They are the most diverse of the earth's terrestrial biomes and they affect hydrological and biogeochemical cycles globally, influencing the climate system through interactions with the atmosphere. Regulation of atmospheric carbon dioxide through carbon sequestration in biomass is an ecological service of particular policy interest. Under the Kyoto Protocol, the Clean Development Mechanism

(CDM) was established. The CDM set up a process for issuing certified emission reduction credits (CERs) to appropriately authorized afforestation and reforestation projects, but did not recognize avoided deforestation (AD). As current estimates attribute about 15–20% of carbon dioxide emissions to deforestation (Canadell et al. 2007), there has been some research discussion of including policies to reduce emissions from deforestation and degradation (REDD) in discussions for a future global warming treaty (Gullison et al. 2007). Even within the original CDM framework, there were many implementation issues involved concerning the accurate accounting of carbon sequestration credits associated with a proposed project (e.g., Chomitz 1999; Pfaff et al. 2000), which are only exacerbated when considering the carbon "saved" from avoided deforestation for carbon credits. As Kerr et al. (2003) have argued, two calculations are necessary for these policies to be meaningfully implemented: (1) some projection of how much forest would exist in a region without the proposed project and (2) the amount of carbon sequestered as a result of the proposed project.

In this paper, we develop a methodology for calculating the impact on carbon associated with land-use changes, applied to a region of southern Yucatan. This methodology could be used as an initial baseline to assess afforestation, reforestation, or avoided deforestation. This approach is based on a rich, detailed dataset, resulting from field research on forest ecology, analysis of remote sensing data on land-cover types in the study region, and a multinomial logit (MNL) model to explain those land covers. MNL models are used to model the relationship between discrete dependant variables, here, the discrete land-cover categories, and a set of independent variables. Previous research (e.g. Kerr et al. 2003; Pfaff et al. 2000) has used similar econometric methods, and Kerr et al. (2003) link their econometric model with an ecological simulation model and develop a sophisticated feedback mechanism between land use and simulated carbon stocks. We take a different approach by linking the results of a much more detailed (more land-cover classes as well as greater spatial specificity) econometric model with field-derived carbon data for each of the land-cover classes in our region. As far as we are aware, this level of site-specific, detailed modeling of the carbon implications of land use and predictions for future land uses are rare in the global change literature (but see Gaston et al. 1998; Niles et al. 2002; Shongen and Brown 2006 for approaches at different scales and intensities). We use this model as a baseline, calculate the amount of carbon in the current landscape, and then assess the implications for carbon stocks of different potential development scenarios for the region.

Methods

Study area

The older growth vegetation in the Southern Yucatan is a mosaic of forest types with different structural appearances (Lawrence 2005; Schneider 2008; Vester et al. 2007), which reflects primarily the variation in biophysical conditions (soils, topography, and rainfall). A seasonal deciduous forest covers the region with two general classes: upland forest (*Selva Mediana*) and wetland forest (*Selva Baja Inundable* or *Bajo*). Upland forest is characterized by four main types: (1) Selva Baja and Mediana Subcaducifolia, low-medium stature deciduous forest; (2) Selva Mediana, medium-stature forest with a lower level of deciduousness compared to the previous class, (3) Selva Alta, high-stature forest present on more humid areas of the region, and (4) Selva Baja, a transitional short-stature forest between humid and dry regions. Inundated forest, the extent of which has not changed in the last 30 years are of two types: (1) Bajos, seasonally inundated short-stature forest and (2) Tular/Savannas: seasonally inundated grasslands. Land covers showing human disturbance are secondary vegetation, croplands, and large pastures. Finally, a plant invasive (bracken fern) is frequently present in large areas cleared for either agriculture or pastures.

Remote sensing

The baseline land-cover map was developed through the analysis of Landsat Enhanced Thematic Mapper (ETM +/TM) imagery for 2000. The study region is covered by four scenes path/row 20/47 and 20/48 ETM; 19/47 and19/48 TM, an area of approximately 20,000 km^2. The image processing methods consisted of a supervised classification based on field training sites used in maximum likelihood classifier (Vester et al. 2007; Schmook et al. 2010). Additionally, an in-process classification assessment was performed to determine locations with uncertain results shown in the maximum likelihood classification (for details see Eastman et al. 2005). An accuracy assessment performed after the classification resulted in 88% land class accuracy. The target classes for the classification are those described earlier: four types of upland forest, two types of inundated vegetation, three types of secondary vegetation, one type of invasive species, two types of agricultural areas, urban settlements, and water (see Table 1). The total extent of the area is 18,700 km^2 (Fig. 1). However, this entire spatial extent is not used for the econometric modeling below, as some of the area is forest reserve managed by the biosphere reserve or *ejidos* (community controlled lands), and these areas are legally constrained to remain in forest cover and therefore removed from the change analysis. We included only agricultural *ejidos* where legal constraints on land-use change

Table 1 Land-cover classes in SYPR region

Land-cover class	Total area (ha)	Study area (ha)
1. Upland forest		
Selva Baja/Mediana Subcaducifolia	354,815	62,811
Selva Mediana	601,108	271,270
Selva Alta and Mediana	179,102	99,166
Selva Baja	246,422	82,372
2. Inundated vegetation		
Selva Baja Inundable	260,553	145,954
Tular/Savanna	16,730	10,478
3. Secondary vegetation		
Herbaceous	27,409	23,316
Shrubby	44,824	33,886
Arboreous	92,199	59,345
4. Invasive species		
Bracken Fern	28,095	21,354
5. Cropland		
Crop cultivation (Milpa)	8,088	7,056
Pasture/large-scale agriculture	10,805	9,313
6. Urban settlements	15,999	13,332
7. Water	4,093	3,797

are not so strict. As a result, the area for the econometric modeling is 8,441 km^2, the area in light gray in Fig. 1.

Ecology

Secondary forest

To estimate carbon stocks for each of the secondary forest classes defined for the remote sensing mentioned earlier, we drew upon a study of 36 forests sampled in a stratified-random manner across the major gradients in our study area (rainfall, history of cultivation, and forest age) (Eaton and Lawrence 2009). The ejidos were drawn from a random-stratified sample, and the farmers we worked with were selected from a random sample based on the age of their fields. We used a decade of field experience to assign a range of ages to each remotely sensed class and used a weighted average for the class-based C stock (Table 2). The Herbaceous class was considered to represent the youngest fallows, consisting of vegetation 1–2 years old. The Shrubby class was considered to represent vegetation 3–6 years old, and the Arboreous class was considered to represent vegetation 7–15 years old. Although some secondary forests are undoubtedly older than this, they are difficult to distinguish by remote sensing, most likely because structural differences between old secondary and mature forest are not captured by most sensors; also because leaf area is not very different in old secondary forests and mature forests (Lawrence 2005).

For the Herbaceous and Shrubby classes, we assumed that the landscape held equal proportions of forest in all ages within the class (e.g., 50% age 1 year and 50% age 2 years in Herbaceous). For the Arboreous class, we assumed that 61% of the class was represented by forests less than 9 years old, as mean fallow length is less than 9 years across the region (Schmook, this issue). Our weighted average assumed 20.33% of the landscape in Arboreous was 7 years old, 20.33% was 8 years old, and 20.33% was 9 years old. We assumed that 9% was 10 years old, 9% was 11 years old, and 9% was 12 years old. Vester et al. (2007) showed that 12% of secondary forest reverted to the mature forest category from 1988 to

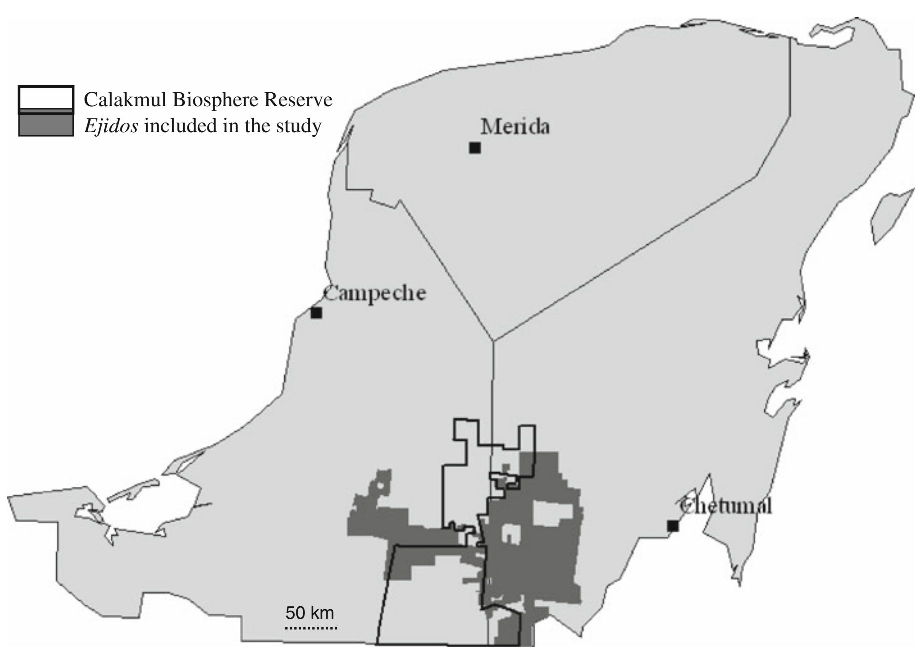

Fig. 1 Yucatán Peninsular Region, Mexico. Area of the ejidos used in the study

Table 2 Carbon stocks for each class (Tg/ha)

	Total stocks (1)		Non-transient stocks (2)	
	Aboveground	Aboveground + soil	Aboveground	Aboveground + soil
Mature forest				
Selva Baja and Mediana Subcaducifolia	77.3	391.3	77.3	391.3
Selva Mediana	86.5	400.5	86.5	400.5
Selva Alta and Mediana	90.9	404.9	90.9	404.9
Selva Baja	77.3	391.3	77.3	391.3
Selva Baja Inundable	61.8	375.8	61.8	375.8
Secondary forest				
Herbaceous	29.6	259.6	10.2	240.2
Shrubby	22.4	252.4	13.8	243.8
Arboreous	19.0	249.0	19.0	249.0
Low-stature vegetation				
Bracken Fern	6.9	236.9	6.9	236.9
Crop cultivation	31.9	290.9	5.5	264.5
Pasture/large-scale Agriculture	7.6	237.6	6.3	236.3
Tular/Savanna	8.7	238.7	8.7	238.7
Other				
Bare soil/settlements-urban	x	x	x	x
Water	x	x	x	x

1. Total stocks include live aboveground biomass, forest floor, fine and coarse woody debris, and soils to 1 m (no roots)

2. Non-transient stocks exclude fine and coarse woody debris in converted land that is above the amount that would recover in the oldest secondary forest class (Arboreous). These pools result from burning rather than being self-generated and they disappear with time

2000. We infer that those forests, prior to reversion, were the oldest secondary forests in the Arboreous category. We divided this proportion equally, such that 4% of the Arboreous category was 13 years old, 4% was 14 years old, and 4% was 15 years old.

We derived relationships between age and C for each of five components: live aboveground biomass (Eqs. 1 and 2), fine woody debris (Eq. 3), coarse woody debris (Eq. 4), forest floor litter (Eq. 5), and soil organic carbon to 1 m, using data for forests in the first cycle only (from Eaton and Lawrence 2009). The calculation for live aboveground biomass C (LAB-C) in the first cultivation cycle is:

$$\begin{aligned} y &= 1.3353(\text{age}) + 4.3465 \\ r^2 &= 0.793\,(n = 13\,\text{forest, aged}\,2{-}25\,\text{years}) \end{aligned} \tag{1}$$

The equation for determining the amount of C in each subsequent cycle using a relationship describing the decline in LAB-C with cycles is:

$$\begin{aligned} y &= 33.657e^{(-0.4183*\text{age})} \\ r^2 &= 0.99\,(n = 28\,\text{forests, aged}\,2{-}28\,\text{years}) \end{aligned} \tag{2}$$

From this relationship, we generated a multiplier for forests in the first cycle (1.0), second cycle (0.66), third cycle (0.44), and fourth cycle (0.29).

The calculation for fine woody debris C in all cultivation-fallow cycles is:

$$\begin{aligned} y &= 0.0373(\text{age})^2 - 0.9048(\text{age}) + 6.4349 \\ r^2 &= 0.60\,(n = 22\,\text{forests, aged}\,2{-}16\,\text{years}) \end{aligned} \tag{3}$$

Coarse woody debris (CWD-C) in the first cultivation-fallow cycle was calculated as:

$$\begin{aligned} y &= 0.2375(\text{age})^2 - 5.2369(\text{age}) + 30.831 \\ r^2 &= 0.80\,(n = 12\,\text{forests, aged}\,2{-}16\,\text{years}) \end{aligned} \tag{4}$$

Eaton and Lawrence (2009) found a non-linear decline in CWD-C with each cycle. CWD-C did not differ significantly from the first to the second cycle, but dropped significantly, by 85%, in the third or fourth cycle. We used a multiplier of 1.0 for forests in the first and second cycle and 0.15 for forests in the third or fourth cycles.

Finally, the equation used to estimate forest floor litter C in all cultivation-fallow cycles is:

$$\begin{aligned} y &= 0.6172\ln(\text{age}) + 1.1264 \\ r^2 &= 0.24\,(n = 28\,\text{forests, aged}\,2{-}25\,\text{years}) \end{aligned} \tag{5}$$

Using the weighted average age per class, we determined the amount of C in each component for each class. Eaton and Lawrence (2009) found no significant change in soil C with forest age among secondary forests, but a significant difference between mature forest soil C (314 Mg/ha; $n = 8$) and secondary forest soil C (230 Mg/ha C; $n = 27$, aged 2–25 years). Thus, we used these soil C values for unconverted and converted land, respectively. The depth used (1 m) allows for comparison with many other carbon assessments, and in most cases, it agrees with the depth of the soil over bedrock in the region.

Next, we considered the fact that the landscape consists of patches with different cultivation histories. Some patches have experienced up to four crop-fallow cycles. Carbon stocks in the forest floor, fine woody debris, and soils do not decline significantly with each cycle of cultivation (Eaton and Lawrence 2009). However, C in live aboveground biomass and coarse woody debris does decline significantly with each cycle. We used the relationship between C stocks and number of cycles to determine the per cycle reduction in C for each component. Our experience with informants while sampling forests led us to estimate that 35% of the land currently in secondary forest had been through one cultivation-fallow cycle, 40% had been through two cycles, 20% had been through three cycles, and 5% had been through four cycles. We have rarely encountered a forest that has gone through more than four cycles in recent history. We adjusted the amount of C in live aboveground biomass and coarse woody debris to reflect the proportion of the landscape that had been through various numbers of cycles.

Mature forest

Stocks for Selva Baja and Selva Baja/Mediana Subcaducifolia are based on published values for mature forests in the north of the region in the *ejido* of El Refugio (Eaton and Lawrence 2009; Table 2). Selva Mediana stocks are the average of values from El Refugio and Nicolas Bravo, and Selva Alta stocks are the average of values from Nicolas Bravo and Arroyo Negro in the south of the region. Selva Baja Inundable values are estimated as 80% of the values in Selva Baja to reflect the low stature of these inundated forests.

For the non-inundated forest types, we recognize that a portion of the class is actually old secondary forest that is indistinguishable by remote sensing. The 12% of secondary forest in 1988 that reverted to mature forest accounts for about 240 ha. This represents 1.7% of the mature forest in our study area. We added a third again as much to represent the amount of secondary forest that reverted to the mature forest category prior to 1988. The total area of old secondary forest misidentified as mature forest was estimated at 2.3%. We used C stocks from 25-year-old forest for this portion of the landscape and created a weighted average for stocks in the mature forest classes. Values were only reduced by 0.2% (for total stocks) to 1% (aboveground only). Therefore, we did not adjust mature forest values. At this point in history, the failure to differentiate old secondary forest from mature forest does not have a great effect on estimated C stocks for mature forest in the Southern Yucatan. This will change as a greater proportion of the landscape is converted to secondary forest and then reverts back to a forest indistinguishable, remotely, from mature forest.

Low-stature vegetation

Carbon stocks in crops are derived from data on aboveground biomass in adjacent chile and maize fields along the north–south road that bisects our study area (see Table 2). Twelve circular plots were sampled in 18 chile and 18 maize fields (plot area per field of 59 and 84 m^2, respectively; Irving and Lawrence, unpublished data). Woody debris stocks were calculated as for secondary forests mentioned earlier, with an age of zero (maize fields were sampled in the original study and assigned an age of 0). Pasture values were derived from data on aboveground biomass in 13 pastures, all well managed and thus relatively free of trees, sampled in a parallel fashion to the crop fields above. Woody debris values were estimated as those resulting after four cycles of use, assuming that pastures are burned more frequently than crop fields and fallows. Stocks of aboveground biomass C for the class of bracken fern were determined from 60 1-m^2 samples in 20 invaded fields in the *ejido* of Nicolas Bravo, east of the study region (Schneider 2006). This number includes both live and dead plant material. Little woody debris was present because bracken patches burn so frequently, so C stocks in that pool were ignored for this analysis. The Tular/Savanna class was defined as having the same aboveground biomass stocks as the Herbaceous class, absent 73 and 93% of the woody debris C (FWD and CWD, respectively). Soil C for Bracken, Tular/Savanna, and Pasture was assigned as equal to that of secondary forest (230 Mg/ha C). Crop land was assigned a weighted mean of 259 Mg/ha C, assuming that 65% of the crop fields are derived from secondary forest and 35% are derived from mature forest (after Schmook 2008). We assume those converted from mature forest have not yet had time to lose substantial amounts of C.

Modeling different carbon dynamics

We have considered four different assessments of carbon dynamics to be used in the land-use scenarios described in the following paragraph. First, we considered alternatives to represent non-soil carbon (‘Aboveground’ in the tables) and total carbon, including soil C (‘Aboveground + soil’).

Next, we modified these to reflect the fact that some pools in the aboveground component are transient. Woody debris in secondary forests and low-statured vegetation is primarily a result of incomplete burning during forest conversion. Although the C stock is present during sampling, it will disappear through time as the woody debris decomposes naturally. For the most part, land that has been converted will never regain the stature at which substantial amounts of woody debris are generated within the stand. Thus, any C stock beyond that found in the oldest secondary forest class is ephemeral. For land that has been converted, 'Non-transient aboveground' includes no woody debris in excess of that found in the 'Arboreous' class. Because woody debris is self-generating in mature forest, these stocks are not considered transient.

Econometrics

The remote sensing work, described earlier, led to the classification of 14 land-cover classes. Of these 14 land-cover classes, four were not included in the econometric analysis. Field research and experience suggested that Selva Baja Inundable and Tular/Savanna were highly unlikely to ever be used for agriculture, because of their characteristics described earlier (Klepeis and Turner 2001). In addition, we excluded water from the analysis as well as the urban class. While clearly there could potentially be urban encroachment into forest or agricultural areas, a model of urban expansion was beyond the scope of this paper.

For the remaining ten land-cover classes, a multinomial logit model was developed to model the factors that affect the probability that a particular pixel is in one of those ten land-cover classes as a function of government census data and other biophysical spatial data. From the study region, a random sample of 10% was drawn for parameter estimation purposes. The unit of observation for the model is the TM pixel, an admittedly arbitrary unit of analysis but one that is about one-tenth the size of an average agricultural plot in the region. The data for the dependent variable are the land-cover classes from the satellite data described earlier.

Independent variables

The independent variables include elevation (ELEVATION, meters above sea level), slope (SLOPE, measured in degrees), aspect (ASPECT, four categories: slopes facing NE, SE, SW and NW) from a digital elevation model; digitized road network from INEGI 1:50,000 topographic maps; rainfall data (interpolated to cover the region) from the Mexican government (Secretary of Agricultural and Hydrological Resources); and socio-demographic data from the Mexican government 1990 and 2000 population census.

Other independent variables, including distance from each individual pixel to roads and markets, were calculated using digitized layers developed for previous analysis (Geoghegan et al. 2004) (D_ROADS, D_MARKET, measured in meters). Using a GIS map of *ejido* boundaries, the census data were linked with the pixels associated with each of the *ejidos* via a uniform distribution, so that each pixel in the *ejido* was assigned the value of the variable from the census data for that *ejido*. The data include information on population in 2000 (POP_00), percent change in population between 1990 and 2000 (POP_CHANGE), language (the number of people per *ejido* that speak SPANISH as their primary language), education (SCHOOL, measured as the percent of the population at age 5 that is in school), and structural characteristics of houses, measured by the number of houses with electricity (ELECTRIC). We also control for areas that are forest reserves and therefore theoretically unavailable for agricultural expansion (RESERVE or not), and in order to control for the amount of local agricultural activity in an area, using the land-cover maps, a variable that measures the number of pixels in a 5 by 5 window surrounding each pixel is calculated (NEAR_AG). Summary statistics for each of the variables can be found in Table 3.

Empirical model

The MNL model has been extensively used throughout applied statistics. We will briefly outline the method here, but further detail can be found in Greene (200X). In our application, the model is used to estimate the probability P that a particular pixel, i, belongs to a particular land-cover class, j (of m land-cover classes). The probability is estimated as:

$$P_{ij} = \frac{\exp(x_i'\beta_j)}{\sum_{h\in J}\exp(x_i'\beta_h)} \tag{6}$$

As the sum of all probabilities equals one $\sum_{j=1}^{m} p_{ij} = 1$, in order to identify the model, the model is restricted ("normalized") so that one set of coefficients is set equal to zero (i.e., the 'base case outcome"). Assuming for exposition purposes that the base case is alternative 1, then $\beta_1 = 0$. As a result, the interpretation of the estimated coefficients for the jth alternative is the relative risk of choosing alternative j instead of the base case alternative, that is:

$$\frac{P[y_i = j]}{P[y_i = 1]} = \exp(x_i'\beta_j) \tag{7}$$

There is an extensive literature on econometric models of land use that has had a number of excellent reviews

Table 3 Summary statistics for MNL model variables

Independent variables (823,833 observations)	Mean	SD	Min	Max
Census 2000				
Total population	681.81	796.67	2.00	3,668.00
Education	27.48	22.67	0.00	100.00
Language	91.56	114.32	0.00	477.00
Electricity	115.53	163.30	0.00	732.00
Population change	0.99	1.53	−1.98	7.07
Slope (%)	3.32	3.64	0.00	50.56
Soils	1.16	0.40	0.00	2.00
Aspect (4 directions)	1.59	1.21	0.00	4.00
Distance from roads (m)	2,545	2,153	0.00	13,528
Forest reserve	0.22	0.42	0.00	1.00
Distance from markets (m)	16,307	7,906	122.59	39,195
Elevation	181.69	67.10	0.00	345.00
Agricultural pattern (5 by 5 window)	1.09	5.73	0.00	50.00
Precipitation (per pixel)	1,115.03	84.64	0.00	1,315.00

(e.g., Barbier and Burgess 2001; Verburg et al. 2004; Holloway et al. 2007). Multinomial logit models, specifically, of land have been widely used, and we give a few examples here. In one of the first spatial economic models of land use in econometrics, Chomitz and Gray (1996) use a MNL to estimate the probability of three land covers: commercial agriculture, subsistence agriculture, and "natural" vegetation (i.e., an aggregation of all other undisturbed land covers) for a region in Belize. Nelson and Hellerstein (1997) estimate a MNL model for an area of Mexico for seven land-use categories. Müller and Zeller (2002) use a MNL model of two temporal cross sections to estimate a model of five land classes in an area of Vietnam. Each of the ten land-cover choices in the multinomial logit model generates estimated coefficients for each of the 14 independent variables. Similar to other researchers using such models, instead of focusing on the 140+ estimated coefficients to test hypotheses concerning the impact of particular variables on particular land-cover choices, we focus instead on our ultimate purpose of developing such a model: to use such a model to estimate carbon stocks in the region and to predict the change in carbon associated with changes in the values of these variables, although we note here that most of the variables have the intuitive sign, such as closeness to road and population levels increase the probability of agricultural land use.

Scenarios

The two scenarios are developed to measure the predicted impact on each individual pixel of the subsequent exogenously imposed increase in the value of each independent variable. The two scenarios that we use for illustrative purposes could be considered as a "high growth" example and a "low growth" example, with the "high growth" scenario having much larger increases in population and other measures of development. The former consists of population increasing at twice the original rate, a doubling of the amount of nearby agricultural use, and childhood school attendance rates doubling. The distance to roads and markets is decreased by 50% while keeping all the other variables at their mean values. For the "low growth" scenario, population growth rate, nearby agriculture and childhood school attendance rates increase by 50%, while the distance to roads and markets is decreased by 25%. While we acknowledge that our scenarios are simplistic due to our data limitations, they provide a useful methodological illustration of the problem.

With these scenario-based changes in the values of the specific explanatory variables in Eq. 2, the estimated coefficients from the multinomial logit model are used to predict a new probability for each land-cover type. The predicted probability of each land-cover type is a non-linear function of each pixel's location and other individual pixel-level characteristics. These new predicted probabilities are subsequently translated into total number of pixels in each land cover. Using the information from the remote sensing of actual amounts of land in each land-cover class, and the carbon calculations described earlier, the total amount of carbon was calculated for the entire study region. We calculated total carbon stocks ('Aboveground' and "Aboveground + soils') as well as non-transient carbon stocks (also 'Aboveground' and "Aboveground + soils') by multiplying the total amount of land in each land-cover class by its associated carbon stock values. A similar calculation was performed for the baseline model prediction and for the two scenarios. For the two land-cover classes excluded from the econometric analysis, the Selva Baja Inundable and the Tular/Savanna, we included the "actual" amount of current land cover in these two classes, kept constant under the two scenarios, for the calculations of carbon stocks, while still excluding the bare soil/urban as well as water class from this part of the analysis.

Results and discussion

Econometric estimation and predictions

The total area in each land-cover class and the in-sample prediction from the baseline model can be found in Table 4. The first column of numbers gives the area in each land cover from the satellite data. As a reminder, a modeling decision was made to not include four of the land-cover classes in the MNL model, as these were land-cover types that are not currently changing in the region (the Selva Baja Inundable, the Tular/Savanna, and the water classes) or for the urban areas for the reasons noted earlier. However, given that current urban areas consist of less than 2% of the current land cover in the region, this omission likely has a small impact on the carbon calculations. We do note that any scenario that includes an increase in population would likely lead to some amount of urban expansion, most likely into previously disturbed lands.

In analyzing the results presented in Table 4, we compare the predicted baseline total area in each land-cover category to the actual extent. The relative accuracy of the baseline model ranges from a very close prediction for crop cultivation (baseline prediction only 0.07% less than actual) to the most inaccurate prediction of 2.51% over-prediction for the pasture/large-scale agriculture. One potential explanation for the relative imprecision for pasture is the dynamic aspect of pasture that our cross-sectional model does not capture. That is, the region has had a dramatic increase in pasture that our static model is inadequate for capturing (see Busch and Geoghegan, this journal). However, this range of accuracy over all the land-cover classes leads to some confidence in using the baseline model for prediction purposes for the scenarios.

The next set of results, found in Table 5, compares the predictions of total amount of reach in each land cover modeled for the two scenarios to the baseline prediction, a calculation of the difference in total pixels for each land class between the scenario and baseline prediction, followed by the percent change in each land-cover class associated with each scenario, compared to the baseline prediction. Both sets of calculations are given, as for the calculation on carbon stocks. The total amount in each land class is important, but there is also some understanding to be gained by discussing some of the changes in percentage terms. For example, the largest change in absolute terms is the loss associated with Selva Baja/Mediana Subcaducifolia, while in percentage terms, the largest predicted change is in the Herbaceous class. Not surprisingly, all the absolute and percent changes associated with the "high" scenario are much larger than the "low" scenario, although as the MNL is a non-linear model, the "high" increases are not a simple linear relationship of the different values associated with the scenarios.

In both scenarios, compared to the baseline model, the predictions lead to a relatively modest increase in crop

Table 4 Actual and baseline land-cover classes

Land–cover classes	Complete study region area (ha)	Baseline model prediction area (ha)	Percent of baseline area to actual area
Selva Baja and Mediana Subcaducifolia	62,812	64,110	2.07
Selva Mediana	271,270	272,209	0.35
Selva Alta and Mediana	99,167	97,714	−1.46
Selva Baja	82,373	82,780	0.49
Selva Baja Inundable	145,955	*	*
Tular/Savanna	10,479	*	*
Herbaceous	23,316	23,272	−0.19
Shrubby	33,887	33,746	−0.42
Arboreous	59,346	58,689	−1.11
Bracken Fern	21,355	20,776	−2.71
Crop cultivation	7,057	7,051	−0.07
Pasture/large-scale agriculture	9,313	9,547	2.51
Bare Soil/settlements-urban	13,333	*	*
Water	3,798	*	*

Table 5 Comparison of econometric predictions of land covers from scenarios

Land-cover classes	Scenario "Low" model prediction area (ha)	Scenario "High" model prediction area (ha)	Percent change of scenario "Low" from baseline	Percent change of scenario "High" from baseline
Selva Baja and Mediana Subcaducifolia	38,344	23,160	−40.19	−63.87
Selva Mediana	296,263	290,778	6.82	8.84
Selva Alta and Mediana	73,698	53,728	−24.58	−45.01
Selva baja	68,357	55,597	−17.42	−32.84
Selva Baja Inundable	*	*	*	*
Tular/Savanna	*	*	*	*
Herbaceous	45,784	79,169	96.73	240.18
Shrubby	50,660	71,010	50.12	110.43
Arboreous	56,134	53,855	−4.35	−8.24
Bracken Fern	19,073	17,677	−8.20	−14.92
Crop cultivation	7,894	7,750	9.90	11.96
Pasture/large-scale agriculture	13,687	17,171	43.36	79.85
Bare soil/settlements-urban	38,344	23,160	*	*
Water	*	*	*	*

cultivation, ranging from 10% for the "low" scenario to 12% for the "high" scenario, and given the relative low total amount of land currently in agriculture in the region, this class also has the smallest predicted absolute amount of change as well. For the pasture/large-scale agriculture class, however, this predicted range of increase is 43% for the "low" and 80% for the "high" scenarios, with associated larger increases in absolute amount of land as well. The differences between these two predictions are a result of the difference in the size of the estimated parameters from the baseline model for the population variable, education variable, and market access variable, as all three had smaller magnitudes for the crop outcome, so therefore the aggregation of all three changes in the scenarios led to a much smaller impact on crop than pasture/large-scale agriculture.

The largest percent increases in land-cover class areas are in the Herbaceous and Shrubby classes, reflecting the likelihood that any increase in agricultural land uses will have a "multiplier" effect on the potential fallow land-cover classes. This result must be interpreted cautiously, as the current approach does not explicitly model fallow cycle dynamics. In absolute terms, the predicted changes are large as well, on the order of the absolute amount of change predicted for each of mature forest classes as well.

Most of these predicted percent increases in land-cover classes "come" from the different forest cover types. That is, most of the forest-cover classes have a concurrent decrease in the amount of area. In increasing amounts, these are: Selva Baja (17% loss under the low scenario and 33% loss under the 'high'), Selva Alta and Mediana (25 to 45%), and Selva Baja/Mediana Subcaducifolia (40 and 64%). However, there is a predicted modest increase in the percent of Selva Mediana (7 and 9%) and a modest decrease in the percent of arboreous (4 and 8%). One possible explanation for these small, non-intuitive changes is that these land covers are active parts of a fallow cycle dynamic that the econometric model cannot capture correctly.

Counter intuitively, the predictions from the two scenarios result in a decrease in the extent of bracken fern. As in the case of fallow, the current model does not incorporate the dynamic nature of the bracken fern invasion, and as a result, the model likely predicts that these locations are "good" for agriculture and pasture, based on their other locational characteristics, and does not account for the reality that bracken fern often spreads to nearby invaded areas, usually where land has been cleared and subjected to frequent fire events that impede the recovery of those areas to forest. We could have excluded bracken fern from the analysis, as we did for urban land cover, but we wanted to allow for bracken fern to expand under the scenarios, as that was our maintained hypothesis. Clearly, the current static, cross-sectional model fails significantly in this regard.

Carbon storage under current land use

Not surprisingly, most of the carbon in the system is stored in the soil. For the baseline scenario, considering soil to 1 m as well as aboveground stocks increases the total pool almost fivefold over the total for aboveground stocks alone, from 55.9 Tg C to 301.7 Tg C (Table 6). Across the baseline landscape, all mature forests account for 94.5% of

Table 6 Total carbon stocks (Tg/ha) as predicted by the model and from measured field data

Tg	Actual		Baseline model prediction		Scenario "Low" model prediction		Scenario "High" model prediction	
Land-cover classes	Above ground	Above ground + Soils	Above ground	Above ground + Soils	Above ground	Above ground + soils	Above ground	Above ground + soils
Mature forest								
Selva Baja and Mediana Subcaducifolia	4.85	24.57	4.95	25.08	2.96	15.00	1.79	9.06
Selva Mediana	23.45	108.59	23.53	108.97	25.61	118.60	25.13	116.40
Selva Alta and Mediana	9.01	40.14	8.88	39.55	6.70	29.83	4.88	21.75
Selva Baja	6.37	32.22	6.40	32.38	5.28	26.74	4.30	21.75
Selva Baja Inundable	9.02	54.83	9.02	54.83	9.02	54.83	9.02	54.83
Secondary forest								
Herbaceous	0.69	6.05	0.69	6.04	1.36	11.88	2.34	20.55
Shrubby	0.76	8.55	0.75	8.51	1.13	12.78	1.59	17.91
Arboreous	1.13	14.77	1.12	14.61	1.07	13.97	1.02	13.41
Low-stature vegetation								
Bracken fern	0.15	5.06	0.14	4.92	0.13	4.52	0.12	4.19
Crop cultivation	0.23	2.05	0.22	2.05	0.25	2.30	0.25	2.25
Pasture/Large-scale agriculture	0.07	2.21	0.07	2.27	0.10	3.25	0.13	4.08
Tular/Savanna	0.09	2.50	0.09	2.50	0.09	2.50	0.09	2.50
Total carbon	55.87	301.54	55.89	301.71	53.71	296.19	50.67	288.67

the aboveground carbon, whereas all secondary forests account for 4.6% and all open lands, including cultivated land, invaded land, and Tular/Savannah, account for 1.0% of all C stored (Fig. 1). This is not proportional to the amount of land in each category. Excluding land in water or urban areas, the baseline scenario includes 80.2% mature forest, 14.0% secondary forest, and 5.8% open land (see Table 1). The make-up of the baseline sample differs somewhat from the original landscape, because we only sampled the agricultural ejidos—in the original landscape, 87.8% of the area is mature forest, 8.8% is secondary forest, and 3.4% is open (Table 1). Distinguishing land with a recent human imprint (open or in fallow) from 'mature vegetation' (not disturbed in recent history) reveals that only 5.4% of the C stored is in human-dominated areas under the baseline scenario.

Including both aboveground and soil C, the proportion of carbon held in mature forests is 86.4% of C stored under the baseline scenario. Secondary forest holds 9.7% and open lands hold 3.9% (Fig. 2b). These numbers better match the distribution of land covers. Nevertheless, mature forest still accounts for more of the carbon stored than expected given its dominance by area, and both secondary forest and open lands account for less than expected (about 30% less than expected based on their areal extent). Because of the large soil stocks remaining in lands with a recent human imprint, almost 13% of regional carbon is stored in human-dominated areas when soil C is included.

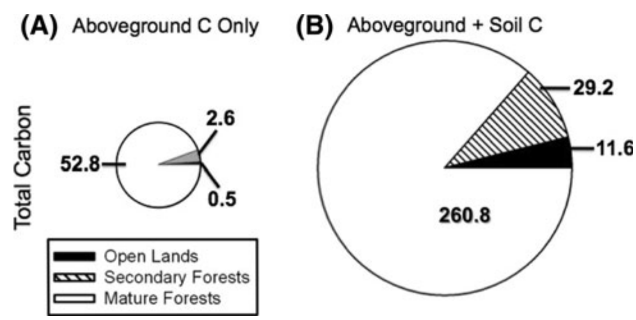

Fig. 2 Carbon (Tg) stored in (**a**) aboveground biomass, living and dead, and (**b**) aboveground biomass and soil to 1 m in different land-use types under baseline conditions. Pie chart size is proportional to total C stocks

As stated in the methods, the non-transient pool may be a better indicator of terrestrial carbon storage through time because pools (such as coarse woody debris) that will disappear through decomposition are not counted. The proportions do not differ substantially from the proportions derived from the total C pools, but more of the C is held in mature forest. This difference stems from the fact that in mature forest, all of the pools are non-transient, whereas the substantial pools of woody debris in open lands and young secondary forests are transient, and thus excluded, in this analysis. In the baseline scenario, 96.1% of the non-transient aboveground C is held in mature forest, 3.3% is in secondary forest, and 0.6% is in open lands. If soil C is

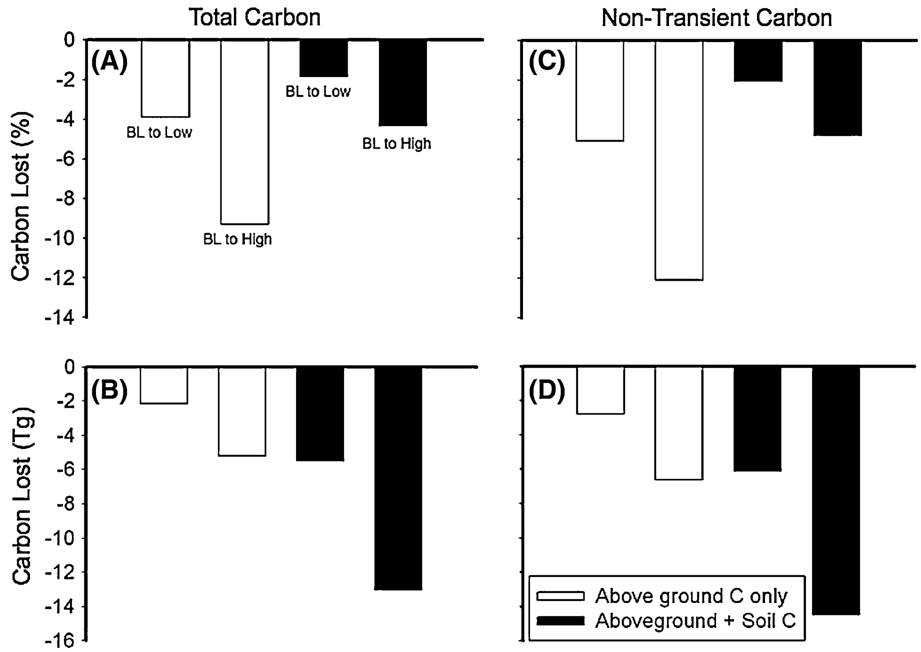

Fig. 3 Percent (**a**, **c**) and teragrams (Tg) (**b**, **d**) of carbon lost with modeled low and high land-use intensification. Changes from the baseline (BL) are shown in aboveground C (*clear bars*) and aboveground plus soil C (*dark bars*) in the total pool (**a**, **b**) and in the non-transient (**c**, **d**) pool

considered as well, the numbers are virtually identical to those for the total pool: 86.7% of non-transient C is in mature forest, 9.4% is in secondary forest, and 3.8% in open lands. What these results demonstrate is that the decision to exclude transient stocks in assessments of the total pool is much less important than the decision to include soil carbon in an analysis of changing carbon stocks in the landscape.

Carbon impact of intensification

Both scenarios yield losses in the total amount of C stored (Table 6). The 'low' scenario holds 3.9% (2.2 Tg) less total, aboveground C than the baseline (Fig. 3a and b, respectively). The 'high' scenario holds 9.3% (5.2 Tg) less total, aboveground C. If we include soil carbon, losses are more muted as a proportion, but the total amount lost is greater. In the 'low' scenario, only 1.8% of total aboveground plus soil C is lost, but this represents 5.5 Tg of C. Similarly, in the 'high' scenario, proportional losses appear to be half as great as those of aboveground C (4.3%). However, this number represents 13.0 Tg C, more than twice as much C as lost from aboveground pools alone (Fig. 3b).

Considering only non-transient pools results in modestly more severe C losses from the landscape (Table 7). For aboveground only, the 'low' scenario loses 2.8 Tg or 5.1% of the baseline amount (Fig. 3c and d). The 'high' scenario loses 6.6 Tg or 12.1% of the baseline stored C. These losses are about 27–30% greater than estimates that include transient pools. The difference between total (including transient pools) and non-transient pools in response to the land-use intensification scenarios is less substantial when soil C is included. Under the 'low' scenario, non-transient aboveground plus soil C declines by 2% (6.1 Tg) versus 1.8% (for the aboveground total including transient pools). Non-transient aboveground plus soil C declines by 4.8% (14.5 Tg), rather than 4.3% (for total), under the 'high' scenario (Fig. 3a, c, and d). The absolute magnitude of losses is also less different between non-transient and total when soil carbon is included (about 11% higher for non-transient).

With agricultural intensification, less of the carbon is stored in mature forests. Whereas mature forests hold about 95% of the aboveground carbon in the baseline, with modest intensification they hold only 94% (taking the average for total and non-transient pools). Further intensification reduces mature forest carbon to only 91% of the regional total. The percentage of carbon held in secondary forests increases from about 4% in the baseline to 5.5% in the low intensification scenario and almost 8% in the high-intensification scenario. If soil carbon is included, the shift is more dramatic still. The carbon held in mature forests, aboveground plus soil, drops from about 87 to 83% of the regional total with modest intensification and to 78% with further intensification. The percentage held in secondary forest increases from over 9% for the baseline to 13% with low intensification and almost 18% with high intensification.

In analyzing the results presented in Tables 6 and 7, the "actual" calculated total aboveground carbon stocks match the baseline predicted amount very well, reflecting the relative overall close match between the predicted land covers from the baseline model. Again, both the "low" and

Table 7 Non-transient carbon stocks (Tg/ha) as predicted by the model and from measured field data

Tg	Actual		Baseline model prediction		Scenario "Low" model prediction		Scenario "High" model prediction	
Land-cover classes	Above ground	Above ground + soils	Above ground	Above ground + soils	Above ground	Above ground + soils	Above ground	Above ground + soils
Mature forest								
Selva Baja and Mediana Subcaducifolia	4.85	24.57	4.95	25.08	2.96	15.00	1.79	9.06
Selva Mediana	23.45	108.59	23.53	108.97	25.61	118.60	25.13	116.40
Selva Alta and Mediana	9.01	40.14	8.88	39.55	6.70	29.83	4.88	21.75
Selva Baja	6.37	32.22	6.40	32.38	5.28	26.74	4.30	21.75
Selva Baja Inundable	9.02	54.83	9.02	54.83	9.02	54.83	9.02	54.83
Secondary forest								
Herbaceous	0.24	5.60	0.24	5.59	0.47	10.99	0.81	19.01
Shrubby	0.47	8.26	0.46	8.22	0.70	12.32	0.98	17.30
Arboreous	1.13	14.77	1.12	14.61	1.07	13.97	1.02	13.41
Low-stature vegetation								
Bracken fern	0.15	5.06	0.14	4.92	0.13	4.52	0.12	4.19
Crop cultivation	0.04	1.87	0.04	1.86	0.04	2.09	0.04	2.05
Pasture/Large-scale agriculture	0.06	2.20	0.06	2.26	0.09	3.23	0.11	4.06
Tular/Savanna	0.09	2.50	0.09	2.50	0.09	2.50	0.09	2.50
Total carbon	54.87	300.60	54.94	300.77	52.16	294.64	48.30	286.29

high scenarios predicted declines in aboveground carbon stocks from baseline conditions. Interestingly, area predicted to change under the "low" scenario is 136,927 ha, which is 16.6% of all of the area included in the model. Clearly, while there are losses associated with high carbon stock land-cover classes, (e.g., mature forest), the total amount of carbon loss, in this analysis, is one-quarter of the amount of land-cover change in percentage terms. That is, less carbon is lost than might be expected based solely on the amount of land-cover change.

Limitations

The econometric modeling approach presented in this paper is based on a single cross section. Clearly, a richer and more accurate model would be a dynamic model based on a time series of actual land-cover changes with the appropriate time-varying explanatory variables, areas for future research. In addition, while urban land cover still only consists of about 2% in the region, in any sort of future scenario, there could potentially be urban encroachment into forest or agricultural areas, without a detailed understanding of urban expansion in the region, this dynamic was beyond the scope of this paper. Similarly, a dynamic model that incorporated fallow cycle and bracken fern interactions would also more closely reflect reality, as would a carbon stock model that incorporated spatial dynamics. In addition, for policy analysis, these baseline methodology would have to be further validated and developed through uncertainty propagation for a more detailed understanding of the robustness of the approach and potential range in variation in modeling results.

The land-cover map used in the model is the result of a thematic classification. This means that areas that contain different types of vegetation are usually defined as a discrete class, depending on how close the value of reflectance of a pixel is to the mean value for the class in question. Most of the remote sensed data comes at resolutions that aggregate landscape attributes; for example, a 30-m pixel could contain different types of vegetation and could result in ambiguous characterizations. This is of particular importance in our study because it may affect the areas estimated under secondary vegetation or mixed areas such bracken and secondary growth (Schneider and Fernando, forthcoming).

Finally, the carbon estimates are subject to some error. The confidence intervals for estimates of aboveground biomass carbon stocks are proportionally larger than those of soil + aboveground stocks, but in absolute terms are substantially less. On average, the confidence interval for a given age-class is almost ±24% for aboveground biomass C and ±8% for aboveground + soil C, or 5–9 Tg/ha and 22–25 Tg/ha, respectively, for total stocks (derived from data in Table 3, Eaton and Lawrence 2009). In fact, because we specified the number of prior cycles and used weighted averaging, our model estimates are substantially better constrained. Estimates for mature forest, those 'lost' or those representing emissions, are better than the estimates for younger forest, those representing ‘recovery’ or sequestration.

Conclusions

This paper has demonstrated a methodology for linking “on the ground” ecological data on carbon stocks with satellite data on land cover and an economic model to understand the effect of potential development scenarios on landscape-wide carbon storage. The satellite data were used in a multinomial logit model to estimate the probability of different land-cover types in the future, based on their individual specific characteristics. This estimated model was subsequently used to develop a baseline and two scenarios of different development paths to predict the impact on carbon stocks of the forest of these two scenarios. We found that including transient carbon stocks that will continue to decompose without replacement underestimates carbon losses by up to 30%. Furthermore, including soil carbon dampens the proportional change, though it increases the absolute losses. In both our scenarios, absolute losses more than doubled when soil carbon was included. The policy implications of this include a further understanding of the potential trade-offs involved between using more aggregate but less accurate forest cover classes and data and the more detailed approach taken here. For example, carbon stocks vary by a factor of four from the least carbon stock content forest type to the greatest carbon stock. Therefore, an aggregation into simple primary forest and secondary forest classes could lead to inaccurate predictions. The econometric modeling demonstrated, as previous research has also shown, the importance of the location of forested land from road networks for deforestation modeling. The implication of this for REDD and PES is that forested areas far from roads are much less likely to be deforested in the near future, so less in need of PES to keep in forest cover.

This approach, modified and expanded, could be used to simulate the carbon impact of different potential policy options, such as those proposed to reduce deforestation via the payment for environmental services, in order to calculate the amount of payment required for avoided deforestation to achieve a certain level of reduced carbon emitted. Clearly, the actual policy intervention proposed to reduce deforestation would have to be accurately portrayed in the scenario development. For example, if a program is put in place to intensify agricultural land use through a reduction in the fallow cycle with an associated increase in chemical inputs, fallow cycle dynamics must be incorporated into the modeling framework as well as the incentives necessary to achieve such an outcome, such as the subsidies of chemical inputs. More generally, whatever the policy “levers” that are being considered to affect individual land-use decision making are, they must be incorporated into the modeling framework.

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