Equilibrium Land Use Model

Catherine Kling Cornell University
Benjamin Leard Resources for the Future
Weilun Shi Cornell University
Matthew Wibbenmeyer Resources for the Future

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1 Introduction

Currently human use directly affects more than 70 percent of global ice-free land area (Mbow et al. 2017). How this land is used has profound consequences for a variety of ecosystem services, including carbon storage, water quantity and quality, biodiversity, air quality, and more. Yet individual land owners frequently do not have explicit incentives to manage land in ways that maximize its social benefits. For example, while as much as one-third of the climate mitigation needed by 2030 to stabilize global warming to 2 degrees C could be provided cost-effectively through land management actions (Griscom et al. 2017), land owners typically do not consider these social benefits of their land management.

A variety of incentive-based policies have been implemented or proposed in the US to encourage landowners to choose socially beneficial land uses. California—under Assembly Bill 32—and nine northeastern states—under the Regional Greenhouse Gas Initiative—allow businesses to use carbon offset projects such as forestry or agricultural projects in place of direct carbon emissions reductions. Including offset programs in carbon market schemes can decrease the cost of carbon emissions reductions by providing an alternative pathway for businesses with high costs of emissions abatement to reduce emissions (Dudek and LeBlanc 1990). One of the largest incentive-based land use policies in the US is the Conservation Reserve Program (CRP), through which farmers can receive federal payments to retire land for conservation purposes. The US Department of Agriculture enrolls 22 million acres—approximately the land area of Mainein CRP, with the goal of reducing soil erosion and improving water quality and wildlife habitat (USDA Farm Services Agency 2019). Incentive-based policies have also been used by federal, state, and local governments to encourage watershed protection and biodiversity conservation.

Effectiveness of incentive-based land use policies depends critically on how land-owners respond to policy incentives. For policies in which offsets or government subsidies change the relative returns of a particular land use type, program benefits and costs depend on how responsive land-use choices are to changes in returns. For example, cost-savings from including forest carbon offsets within a carbon tax or trading scheme will depend on the elasticity of land-use choices with respect to offset price. Additionality—the degree to which offset or other incentive payments result in additional land use changes, rather than payments to landowners who would have chosen environmentally-beneficial land uses without them—is another important factor in determining program benefits and costs.

Here, we propose to undertake development of a model that will allow us to assess the costs and benefits of national-scale incentive-based land use policies. Our model will use National Resources Inventory (NRI) data, combined with a panel data set of national county-level land use returns, to estimate a discrete choice model of land use conversion across six broad land use categories. In the past, similar models have been used to study the costs of incentivizing carbon storage in forests (Lubowski et al. 2006), consequences of federal biofuel policy (Scott 2014), effects of land use policies on conservation outcomes (e.g. Lewis and Plantinga 2007, Lewis et al. 2011, Lawler et al. 2014), and the effects of local land use laws on urban development (e.g. Wu and Cho 2007). Our proposed model is most related to that of Lubowski et al. (2006), but builds on the previous study in several important ways. First, while Lubowski et al. (2006) accounted for endogenous price responses in their policy simulation model, their estimation of land use choice elasticities did not account for price endogeneity. As Roberts and Schlenker (2013) show, not accounting for price endogeneity can bias agricultural supply elasticities toward zero, thus underestimating the cost-savings associated with mitigating climate change through the land use sector. Advances in discrete choice modeling now allow econometricians to better account for price endogeneity (Berry et al. 1995; 2004; Train 2009). Second, our policy simulation model will allow endogenous price responses within all land use commodity markets. Third, our model will provide updated results based on new NRI data, including years since 1997.

Resources for the Future (RFF) has a deep history and strong reputation for developing economic models to inform climate policy. Given growing recognition that natural climate solutions may be an important and cost-effective channel through which to address climate change, our medium-term goal will be to use our model to study potential cost-savings associated with forest carbon offset programs. This work will add to RFF's existing suite of climate policy analysis models and enhance RFF's ability to evaluate and inform carbon policy. While this alone will be a high impact contribution to RFF's modeling capacity, our proposed work has significant longer-run potential as well. In the future, the model can be built upon to allow consideration of agricultural policy and water and biodiversity conservation policies. This proposal details previous literature, proposed empirical and simulation models, and the data sources required for a study of cost-savings associated with carbon storage in forests. This initial proposal to Sloan Foundation will not fully cover the time required for data collection, model development, and estimation of a national land use model. Therefore, we also discuss the more limited study of agriculture-CRP conversions we will pursue as a proof-of-concept for the broader project. Finally, we will discuss several areas where our model may be of use in the future.

2 Literature Review

This research will build on a long tradition of research in economics on land use and land conversion decisions (e.g. Von Thünen 1826; Muth 1961). Within the U.S., an important thread of this research over the past two decades—beginning with Claassen and Tegene (1999)—has used the National Resource Inventory (NRI), a survey of land use and natural resource conditions on non-federal lands throughout the contiguous U.S., to estimate discrete choice models of land use. An early and important application of such methods was provided by Lubowski et al. (2006), who used the NRI, combined with a national dataset describing county-level returns to various land uses, to estimate a series of land-use choice elasticities. They then used those elasticities within a policy simulation to predict the costs of a policy to incentivize carbon storage in forest. Previous work on cost of carbon sequestration in forest (e.g. Stavins 1999) had used county-level on land use conversions within the southeastern US to estimate revealed preference measures of costs of carbon sequestration through land use. Using the NRI, Lubowski et al. (2006) were able to estimate discrete choice models using micro-level data on land conversion decisions at a national scale. Other papers have made use of NRI data to assess consequences of federal farm policy (e.g. Claassen et al. 2016), conservation outcomes (e.g. Lewis and Plantinga 2007,Lewis et al. 2011,Lawler et al. 2014), and the effects of local land use laws on urban development (e.g. Wu and Cho 2007).

Discrete choice land use studies using the NRI have generally found that land use conversion decisions are inelastic with respect to changes in net returns. Elasticity estimates vary across studies and land use type conversion pairs, but Lubowski et al. (2006) estimate, for example, that the probability of converting from forest to cropland increases by 0.30 percentage points when returns to cropland increase by 1 percent.

While Lubowski et al. (2006) and other studies allow for endogenous adjustments in land use returns within policy simulations, they do not typically account for price endogeneity in estimates of land conversion elasticities. As Roberts and Schlenker (2013) show, not accounting for price endogeneity can bias agricultural supply elasticities toward zero. Price endogeneity can arise due to both cross-sectional and variation in unobserved factors affecting land use returns. For example, counties may vary in unobserved ways that affect the suitability of average parcels for particular land uses. Factors that favor a particular land use are expected to be negatively correlated with returns to that land use. Therefore, we expect omitting these unobserved factors should bias elasticity estimates downward. Similarly, unobserved land supply shocks (e.g. due to changes in production technology) over time are expected to be negatively correlated with net returns, driving elasticity estimates downward. Accounting for price endogeneity is particularly important in national land use models that make use of county-level NRI and land use returns data because most of these studies rely on NRI data in which parcels have been anonymized at the county level, which constrains measurement of parcel-level returns. Price endogeneity may explain why Lubowski et al. (2006) found several negative land conversion elasticities, in which more land is converted to a particular use when relative returns from that use decrease. These elasticity estimates drive results from policy simulations, therefore better accounting for price endogeneity may improve the accuracy of predicted policy outcomes.

We build on this body of literature by incorporating features of modern discrete choice methods that account for price endogeneity. First, we will define county-land condition class groups and estimate the share of parcels within each group undergoing each conversion type. Because for some land use conversion types, many counties may not experience any land use conversions in a given year, we use a Poisson regression. We include county-year-conversion type fixed effects and in the second step, we estimate the fixed effects as a function of county-year returns. Because county level returns are endogenous, we will instrument for them using a Hausman instrument.

3 Empirical Modeling

3.1 Land use transition choice model

Landowners maximize net returns by choosing to transition their land to one of six broad land use types in the NRI: crops, pasture, range, forests, urban, and CRP. Owner of parcel i obtains net returns V_{ijkt} by choosing to transition its land parcel from use j to use k in year t. Owner of parcel i obtains a net return of V_{ijjt} if it decides to keep the land parcel in use j. Net returns are defined by:

$$V_{ijkt} = U_{ijkt} + \varepsilon_{ijkt} = \alpha_{jkt} LCC_{it} + \beta_{jkt} LCC_{it} R_{kct} + \delta_{jkct} + \varepsilon_{ijkt}. \tag{1}$$

The term LCC_{it} represents parcel i's land capability class (LCC) in year t. The lower the class number, the fewer restrictions the land has for crops. The term R_{kct} denotes the revenue from converting a parcel to land use type k in county c in year t. The term ε_{ijkt} is parcel i's unobserved net return for converting from use j to use k that is unexplained by the observed attributes.

The term δ_{jkct} measures the average net return from converting a parcel of land in county c from use j to use k in year t. We express this as:

$$\delta_{jkct} = \overline{\alpha}_{jkt} + \overline{\beta} R_{kct} + \xi_{jkct}. \tag{2}$$

The term $\overline{\alpha}_{jkt}$ represents the average net return from converting a parcel of land from use j to use k in year t. The term $\overline{\beta}$ represents the average response of net returns to changes in revenues earned by use k in county c and year t. The term ξ_{jkct} includes all unobserved net returns at the county level for converting from use j to use k that is unexplained by the county-level characteristics.

Under the assumption that the error term ε_{ijkt} has a type 1 extreme value distribution, the probability that parcel i in use j is converted to use k in year t is:

$$Pr_{ijkt} = \frac{e^{U_{ijkt}}}{\sum\limits_{m} e^{U_{ijmt}}}. \tag{3}$$

We assign parcels to distinct groups differentiated by LCC, county, and initial land use. We denote a group differentiated by LCC and county by g. For each parcel group, we assign as the outside option the decision to keep the parcel in the same land use, and we normalize the net return from this option to zero, so that $U_{gjjt} = 0$ for all g, j, t. Based on this assumption, Equation (3) can be converted to a linear equation linking observed transition shares and components of net returns:

$$\ln(s_{gjkt}) - \ln(s_{gjjt}) = \alpha_{jkt} LCC_{it} + \beta_{jkt} LCC_{it} R_{kct} + \delta_{jkct}. \tag{4}$$

The left-hand side of Equation (4) is the difference between the log share of parcel group g conversions of initial land use j to use k in year t and the log share of parcel group g initial land use j remaining in land use j in year t.

A concern for estimating the parameters of the model is that the shares could be zero for some of the transition categories. To circumvent this issue, we convert Equation (4) to a Poisson regression. Combining the terms on the left-hand-side, cancelling like terms, and exponentiating both sides yields:

$$\frac{COUNT_{gjkt}}{COUNT_{gjjt}} = exp(\alpha_{jkt}LCC_{it} + \beta_{jkt}LCC_{it}R_{kct} + \delta_{jkct}). \tag{5}$$

The $COUNT$ terms represent counts of the conversions. This equation is defined as long as $COUNT_{gjjt}$ is not zero. For our setting, this is likely to be the case since parcel transitions are relatively uncommon. This equation can be estimated with a fixed effects Poisson regression. The fixed effects are δ_{jkct}.

The fixed effects are obtained post-estimation and are used as the dependent variable in a second stage regression:

$$\widehat{\delta}_{jkct} = \overline{\alpha}_{jkst} + \overline{\beta}R_{kct} + \xi_{jkct}. \tag{6}$$

The per-acre revenue variable R_{kct} is equal to the per-acre equivalent equilibrium price, P_{kct},of the commodity associated with each land use category. Prices are endogenously determined in equilibrium by supply and demand of each commodity. We assume that demand is defined as

$$D_{kct} = d_{kt} + \delta(P_{kct}) + \varepsilon^{D}_{kct} \tag{7}$$

The term d_{kt} represents a commodity demand shock common to all counties in year t. This term represents changes in the demand for the commodity over time, such as changes in consumer preferences for meat products or wood furniture. The function δ defines the demand price sensitivity. The third term, ε^{D}_{kct}, is a demand shock that is specific to land category k in county c in year t.

The equilibrium price P_{kct} is defined by the intersection of supply and demand. Given our definitions of demand and supply, we can express equilibrium returns and prices as:

$$R_{kct} = P_{kct} = f(\Omega, d_{kt}, \varepsilon^{D}_{kct}, \xi_{jkct}), \tag{8}$$

where Ω contains all supply and demand parameters besides d_{kt} (such as $\overline{\alpha}_{jkt}$ and $\overline{\beta}$). We assume that the functional form for $f()$ is approximated as:

$$R_{kct} = P_{kct} = d_{kt} + \widetilde{f}(\Omega) + \varepsilon^{p}_{kct}(\varepsilon^{D}_{kct}, \xi_{jkct}). \tag{9}$$

We assume that the parametrized error term $\varepsilon^{p}_{kct}(\varepsilon^{D}_{kct}, \xi_{jkct})$, which represents shocks to demand or supply, is idependent across counties. From equation (9), we see that returns and the error term, ξ_{jkct}, are correlated. Therefore, estimating equation (6) with ordinary least squares will lead to biased estimates for $\overline{\beta}$. Our assumptions imply that prices for commodity type k in year t are correlated only due to the common demand shock d_{kt}. Therefore, average prices of the same commodity and time period in different counties can be used as an instrument for returns. Formally, we construct an instrument for land use k returns in county c in year t as:

$$R^{IV}_{kct} = \frac{1}{N_{cs} - 1} \sum_{c'} R_{kc't}, \tag{10}$$

where N_{cs} is the number of counties in state s where county c is located and where c' denotes counties in state s besides county c.

This identification approach is a well-known strategy in the industrial organization literature for dealing with price endogeniety (Hausman et al. 1994, Hausman 1996, Nevo 2000). It also is well understood that the assumptions underlying this strategy could be violated in some circumstances. For example, suppose there is a national supply shock, such as the discovery of a technology that increases crop yields per unit of input. This discovery would lower production costs per unit of crops, shifting out the crop supply curve in all counties. This would violate the assumption that the error terms ε^{p}_{kct} are independent across counties. We attempt to control for this possibility by including a rich set of fixed effects, including $\overline{\alpha}_{jkst}$, which absorb all unobserved supply shocks that are common to transitions from land use j to land use k in state m in year t.

3.2 Commodity Equilibrium Model

We integrate land use transition choices in an equilibrium of commodity supply and demand. We extend the approach taken in Lubowski et al. (2006) by allowing commodity prices to be endogenously determined by supply and demand factors. Following Lubowski et al. (2006) , we convert land use transitions to changes in corresponding commodities. The corresponding commodities include timber from forests, raw, non-meat food inputs from crops, housing from urban, beef, chicken, and pork from range and pasture. In contrast to Lubowski et al., we assume that commodities of all land use types besides CRP have prices that are endogenously determined. We aggregate beef, chicken, and pork into a single meat market. In summary, we model endogenous prices and quantities for timber, non-meat food inputs, meat, and housing.

We calibrate demand curves for each of the commodities. Following Lubowski et al. (2006), we use demand elasticities for seven timber production regions — Pacific Northwest (-0.300), Pacific Southwest (-0.497), Rocky Mountains (-0.054), North Central (-0.141), Northeast (-0.029), South Central (-0.193), Southeast (-0.285). We assume a national market for non-meat food inputs and assume a demand elasticity equal to -0.661. We assume a national market for meat and assume an aggregate elasticity of demand equal to -0.71 (Gallet 2010). We calibrate separate housing demand curves for each county assuming a demand elasticity of -0.8 (Albouy et al. 2016).

With supply and demand for each commodity specified, we are able to solve for equilibrium prices of each commodity and region that equates supply and demand in each region. Since supply and demand are non-linear functions of all commodity prices, we use root-finding methods (such as Newton's method) to obtain an equilibrium.

3.3 Carbon Model

We are interested in the impact of policies such as carbon offset programs on carbon sequestration, through changes in land use. To link changes in the land market to changes in carbon sequestration, we will apply estimates from the scientific literature describing carbon stocks per acre by land use type (e.g. Heath et al. 2011) and how carbon stock changes upon land conversion (Conant et al. 2001). Where possible, we will use regionally varying estimates of carbon stock by land use type, to reflect regional differences in the per acre carbon stock associated with regionally-varying forest types, for example.

4 Data

4.1 Land use data

The outcome variable for our econometric model comes from the National Resources Inventory. The National Resources Inventory (NRI) is a statistical survey of land use and natural resource conditions on non-Federal lands throughout the contiguous US, Hawaii, Puerto Rico, and the Virgin Islands. In each NRI, site visits and—more recently—satellite remote sensing are used to measure land use and natural resource conditions at each of more than 800,000 NRI sample points. The precise locations of sample points are anonymized to the county-level by the NRCS, but they are measured repeatedly across NRI waves, providing a panel data set of land use changes within parcels across the US. Between 1977 and 1997, the NRI was conducted every 5 years, though significant changes were made to the survey between 1977 and 1982, invalidating comparisons between 1977 data and later years. After 1997, NRCS transitioned to a continuous NRI in which a subset of the NRI are sampled every year.

An alternative to the NRI would be to use satellite data or a data product derived from satellite data, like the National Land Cover Database (NLCD). An advantage of the NLCD is that it provides complete geographic coverage, and that observations' locations are precisely known. However, while the NLCD is well-suited to studies of *land cover*, measurements of land cover frequently diverge from *land use*, for example in forested exurban residential areas (Irwin et al. 2007). Therefore, because of its use of survey methods and site visits to precisely measure land use, and because of its consistency over such a long a time-span, the NRI is considered the "gold-standard" for national-scale studies of land use change within the US.

We have obtained from the NRCS their point-level data set from 2015, with locations of points known to the county-level. The 2015 NRI data contains consistent measures of land use and land use change across from 1982 to 2015. In addition to land use, the data set includes data on a variety of point-level characteristics, including measures of soil characteristics and erodability, suitability for agriculture ("Land Capability Class"), double-cropping, conservation practices, and forest type.

4.2 Land use returns data

The primary explanatory variables within the econometric model are county-level measures of average net returns for each land use type. We will follow Lubowski et al. (2006) in constructing these measures, updating the returns data set for years after 1997 and using improved data sources where possible. Construction of a county-level data set describing net returns to each land use will be the primary data task as we implement this project. For most land use types, national county-level data sources are available. For example, average county-level returns from cropland can be constructed from the USDA National Agricultural Statistics Service (NASS) Census of Agriculture. The Census of Agriculture provides county-level data on acreage by crop, county-level measures of per acre yield by crop, and state-level measures of crop price and production expenses. From these data, we can construct county-level average returns to cropland. While similar measures can be constructed from national data sources for most other land use types (range, pasture, urban, and CRP), net returns from forestland rely on stumpage price data, which is not collected at a national level. Because stumpage price data must be collected for each state and assembled with data on forest types and timber yields, forest returns will be the most time-consuming component of the net returns data set.

5 Applications

5.1 Carbon sequestration subsidy policies and asymmetric information

Reducing greenhouse gas emissions through land use change often involves a subsidy payment to landowners. Carbon offset programs, such as those in the California AB 32 program, the Regional Greenhouse Gas program, and the proposed offset provision as part of the Waxman-Markey federal cap and trade program, are designed in this manner. A common concern with these programs is that the payments are for activities that would have been done without the subsidy. This problem of "additionality" has significant distributional and efficiency implications for policy design (Bento et al. 2015). Additionality arises because of asymmetric information between landowners and policy makers: landowners know more about their future decisions than policy makers. This leads to adverse selection: landowners that would have reduced carbon emissions anyway are more likely to opt in to the voluntary program than landowners that have to experience a costly transition to obtain the subsidy. At worst, a subsidy program could be transferring significant rents from capped to uncapped sectors with little to no emissions reductions taking place.

Our model is well-suited to quantify these issues for carbon mitigation programs in the US. We model the decision of landowners based on observed and unobserved characteristics. The unobserved characteristics, which are represented by landowner-specific error terms, represent asymmetric information (Mason and Plantinga 2013). Therefore, with our model, we will be able to quantify the distribution of additional versus non-additional emissions reductions being credited by a subsidy program, and how this distribution is affected by changing subsidy amounts and altering other policy design features. With our model, we will be able to quantify the efficiency and distributional costs of alternative policy options that address additionality, including setting stringent baselines, discounting, and limiting the use of offsets.

Assessing the costs of carbon sequestration through carbon offset subsidy programs is the medium-term goal of this project. Doing so will require assembling a data set of county-level returns for all land uses, including forestland, so that we can consider effects of policies on changes between all land use pairs. It will require implementing our empirical and simulation models. Finally, it will require application of a carbon model, in order to estimate the consequences of land use change simulations for carbon sequestration. This proposal to the Sloan Foundation will not allow us to complete all the steps necessary to implement this study. Instead, we propose to use funding from the Sloan Foundation to begin building toward this medium-term goal by implementing our empirical model in a more limited study of the Conservation Reserve Program.

5.2 Evaluating changes to the Conservation Reserve Program

The Conservation Reserve Program (CRP) is a subsidy for landowners to transition their land out of crops to improve soil, water quality, and provide other environmental benefits. Subsidy payments are based on the productivity of soils within a county and average returns to cropland. The 2018 Farm Bill limits the amount of payments available for landowners to 85 percent of the average county rental rate and 90 percent of that estimated rate for continuous enrollments.

The CRP faces similar concerns to carbon offset programs, in that landowners have private information about their land. In theory, this creates adverse selction, where landowners that would have transitioned their land out of crops without a payment are more likely to opt in to the program. The CRP addresses this issue in several ways, including basing the subsidy on county-level characteristics and limiting the total amount of subsidy paid. Nevertheless, evaluating the cost-effectiveness of the CRP requires accounting for adverse selection. Our model is capable of accounting for adverse selection by incorporating landowner decisions that are a function of a private error term for each land use type. Landowners that have a low value for their crop error term would have transitioned their land out of crops with only a small subsidy payment. These transitions represent "non-additional" transitions and do not create environmental benefits.

We will use funding from the Sloan Foundation to apply our proposed empirical model to the study of CRP enrollment. We will collect national county-level data on net returns for only two land use types, agriculture and CRP, limiting up-front data collection costs. We will then pilot estimation of our proposed empirical model, and application of our proposed simulation model. This analysis will serve as a proof-of-concept for our medium-run goal of developing a broader model for the purposes of analyzing carbon offset programs and may result in publishable research in own right.

5.3 Ecosystem services

Land use choices impact a variety of ecosystem services in addition to carbon storage. Previous studies have used national economic models of land use change to estimate the consequences of land use change for ecosystem services(e.g. Lawler et al. 2014), but because these studies frequently rely on county-level NRI data, they may not always accurately capture changes in ecosystem services for which production processes are highly spatially variable. To better understand the consequences of county-level land conversion rates on ecosystem services, historical county-level conversions observed within the NRI can be paired with NLCD satellite data to predict areas within counties in which the probability of each land conversion type is highest.

Within county conversion probabilities can then be used within a spatial ecosystem services model to estimate changes to ecosystem services. For example, a model such as InVEST can be used to estimate effects of simulated land use changes for a broad suite of ecosystem services, including habitat quality, recreation, and water quantity and quality. Land use change may be particularly important for water quality and water quantity; therefore, future work could also focus expressly on investigating consequences of land use change for water. With hydrologists, we could integrate simulated land use change with a model that predicts consequences for water. Because water is an important input for agricultural production, water availability and price could then be coupled to the economic land use change model, as a component of returns to agricultural land. An important application of this model would be examining causes and consequences of water availability for land use under climate change.

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