

## Research Article

# Land Use Change from Biofuels Derived from Forest Residue: A Case of Washington State

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Received 23 January 2013; Revised 24 March 2013; Accepted 14 May 2013

Academic Editor: Tun-Hsiang Edward Yu

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Biofuel policy in the United States is transitioning away from corn towards second-generation biofuels in part because of the debate over environmental damages from indirect land use change. We combine a spatially explicit parcel level model for land use change in Washington State with simulations for biofuel policy aimed at utilizing forest residue as feedstock. Using a spatially explicit model provides greater precision in measuring net returns to forestland and development and indicates which areas will be most impacted by biofuel policy. The effect of policy is simulated via scenarios of increasing net returns to forestry and of siting feedstock-processing plants. Our results suggest that forestland will increase from such a policy, leading to a net reduction in atmospheric carbon from indirect land use change. This is in contrast to the experience of corn ethanol where the change in carbon emissions is potentially positive and large in magnitude.

## 1. Introduction

Biofuels policy in the United States developed as a plan to move towards energy independence and reduce the environmental externalities associated with fossil fuels. The policy was largely successful at creating a thriving domestic ethanol industry as the combination of high fuel prices and generous subsidies led to significant amounts of corn devoted to ethanol production. The recent spike in food prices starting in 2007, and research on emissions from indirect land use change [1], spurred debate over the net benefits of ethanol policy. The combination of biofuel mandates with high fuel prices, along with economic growth in Asia and a decline of the USA dollar, is thought to have contributed to price increases for several staple food commodities [2]. However, there is no consensus on the extent that price increases are directly due to biofuel mandates. Using an aggregate calorie index, Roberts and Schlenker [3] estimate that the USA ethanol mandate increased food prices by 20–30%, while in a computable general equilibrium model (CGE) Timilsina et al. [4] find small effects of biofuel policy for all crops except for sugar. There is also debate regarding the emissions from

land use change associated with biofuel growth. The widely cited paper by Searchinger et al. [1] suggests that impacts from land use change dominate the environmental effects of biofuel policy. Several studies [5–7] argue that estimates for land use change are sensitive to modeling assumptions, and accounting for crop yield growth substantially ameliorates cropland conversion.

Public discourse over the potentially deleterious secondary effects of conventional corn ethanol catalyzed an evolution of biofuel policy towards second-generation advanced biofuels. Cellulosic biofuel is receiving attention due to the perceived environmental benefits since feedstocks are not derived from food crops and can be cultivated on marginal land. In contrast to conventional ethanol that requires a 20% life cycle greenhouse gas (GHG) reduction, cellulosic ethanol derived from nonfood feedstock such as cellulose, hemicellulose, or lignin require a 50% reduction (the definitions of different fuel categories are available at <http://www.afdc.energy.gov/laws/RFS/>). Since land use impacts are a key component of the life cycle emission from biofuels, it is essential to estimate the expected land use changes from various cellulosic feedstocks. In particular,

a land that is retained, in or converted to, forestland due to cellulosic biofuels will contribute to net GHG reductions as carbon is sequestered while trees mature and deforestation emissions are avoided. This research offers a preliminary assessment of the potential land use changes from ethanol derived from forest residue.

The current market penetration of advanced biofuels is still small, at only 13% of total biofuel production; meanwhile cellulosic ethanol is essentially a rounding error at less than 0.1% of total renewable fuel [8]. Initial academic research supported cellulosic ethanol's competitiveness [9], but more recent research restrains the early optimism [10]. There are several reasons to expect growth in the advanced biofuels industry, despite its current stature. First, the second Renewable Fuel Standard (RFS2) established in 2007 mandates that growth in renewable fuel comes from advanced biofuel. Conventional corn ethanol already exceeds the mandate; and since current production hovers around 10% of total gasoline, its growth is further constrained by the blend wall, whereby many standard cars cannot accept fuel blends with more than 10% ethanol. These two factors and the ability of some cellulosic ethanol to act as a drop-in fuel, or direct replacement, for petroleum-based gasoline suggest that growth in the renewable fuels industry will come from advanced biofuels [11]. Despite the forces that signal a burgeoning cellulosic ethanol industry, costs need to decrease and infrastructure needs to be developed before cellulosic ethanol is a major component of the US energy portfolio.

Washington State is poised to take advantage of a burgeoning cellulosic ethanol industry, particularly from forest residue-derived feedstock. In addition to incentives for biofuels at the state level, since much of the State's agricultural land produces high value crops such as apples, grapes, and hops, there is a drive for feedstock to come from woody biomass consisting primarily of forest residue (see WA state incentives at <http://www.afdc.energy.gov/laws/laws/WA/tech/3251>). The desire to promote this industry is evidenced by \$80 million worth of grant money given to Washington State universities in collaboration with private industry to advance the commercialization of advanced drop-in cellulosic biofuels (details on the grants can be found at <http://www.washington.edu/news/2011/09/28/nw-biofuels-coming-of-age-with-80-million-in-separate-projects-led-by-uw-wsu/>). Given the optimism for second-generation biofuels there is little research investigating the land use change implications from these fuels. While feedstocks for advanced biofuels are assumed to be cultivated on marginal lands, empirical research is necessary to prevent the pitfalls of unintended consequences that marred the first round of ethanol policy. Assessing the land use implications of biofuels from forest residue is crucial in order to meet the criteria for 50% GHG reductions laid out in the RFS2. We build a land use model based on a spatially explicit parcel database for Washington State to assess the potential land use implications from a state biofuel policy targeting forest residue as a feedstock.

Feedstock prices, tax and zoning policy, urban growth pressures, and agricultural productivity are some of the many factors influencing land use decisions. This research will quantify some of the major variables influencing land

use change in Washington State. We pay close attention to variables potentially driven by biofuel policy such as the location of feedstock processing plants and returns to forestry. Estimating an empirical land use model with parcel-level data yields spatially explicit predictions of land use decisions. We find intuitive results from the land use model such as proximity to feedstock processors and net returns to forestry increase the probability of retaining or converting to forestland. Armed with these parameters, we run land use simulations to explore the consequences of a second-generation biofuel policy. The simulations suggest that forestland could increase by 0.1%–1%, depending on our assumptions about the implications of biofuel policy. Although small in percentage terms since forestland makes up a large part of total land use in Washington State, a 1% increase in forestland equates to over 500,000 acres in our sample alone. Since forested land stores carbon as biomass as the trees grow, this suggests that there are actually beneficial secondary environmental impacts from land use change in terms of carbon. There are also important local environmental impacts, such as water quality, associated with land use change that will be left for future research. These results are most informative for Washington State policy for forest residue, and further research can extend the methodology to a national scale and other forms of feedstock.

## 2. Literature Review

*2.1. Land Use and Environmental Outcomes.* The United States pursues one of the world's largest biofuel policies aimed at decreasing emissions from fossil fuel, increasing energy independence, and supporting the domestic agricultural industry. This research focuses on the secondary environmental impacts due to land use change, although the primary carbon benefits of replacing gasoline with corn-based ethanol are also debated. One of the most prominent studies, by Searchinger et al. [1] investigates the impact of ethanol mandates on global greenhouse gas (GHG) emissions. In all scenarios, the loss of carbon sequestration from conversion of forestland and grassland to cropland for either food or biofuels generates a net global increase in GHG. Other research suggests much lower emissions from land use change and argues that Searchinger et al.'s [1] estimates depend on specific modeling assumptions. For example Dumortier et al.'s [5] estimates from a CGE model are as low as 15% of those based on the assumptions employed by Searchinger et al. [1]. Much of the debate rests on the assumption about how crop yields respond to higher food crop prices; and accounting for market-induced yield change greatly ameliorates the land use change and consequent GHG emissions, associated with biofuel policy [5–7]. While GHG emissions are a global pollutant, land use change also affects local environmental outcomes. Several studies [12, 13] estimate that cultivated croplands have deleterious impacts on local water quality, suggesting local as well as global impacts from land use change.

*2.2. Land Use Theory.* In order to determine the environmental costs and benefits of land use change from biofuel

policy, we need to identify the causal factors affecting land use allocations. A review of land use change models by Irwin and Geoghegan [14] advocates for spatially explicit economic models to explain the element of human behavior in land use decisions. While early studies face data and computational limitations in developing a spatially explicit model, currently there are a plethora of publically available spatial data and software packages that facilitate spatial data analysis.

The primary method based on microeconomic foundations for modeling land use is the random utility maximization (RUM) model where an agent chooses between a discrete set of alternatives in order to maximize utility. A common econometric specification for discrete choice analysis is the logit family that estimates the probability of choosing each alternative given some explanatory variables. Various forms of logit are used in estimating land use change. In addition to the conventional multinomial logit nested logit creates wider categories and models the choice of subgroup within each class, while random parameters allow for random heterogeneity in the parameters at the level of the agent. The first spatial models of land use change focus on a subset of possible land use decisions, such as the risk of forested land to be converted to urban development, but more recent research models the full land use decision. Since landowners have multiple options at their disposal when choosing their land use, models must account for the costs and benefits of *all* options in a landowner's choice set. Lubowski et al. [15] focus on the decision to enter the Conservation Reserve Program (CRP), which is the first national scale analysis of land use change in the United States that covers all major land use options available to private landholders. The research emphasizes that net returns to all land uses must be included in an empirical analysis of land use change. The authors create proxies for net return to each land use at the county level combined with parcel-level attributes such as soil quality to predict land use allocations conditional on the initial land use. A more complete overview of the economic and econometric theory, as well as details of the data, is described by Lubowski [16].

A different approach using real option value highlights the dynamic nature of land use decisions. Behan et al. [17] model the decision of when to switch rural land from agriculture to forestry. If the decision is to never switch or immediately switch the model is analogous to a discrete choice model, the interior solution adds richness to the model if the timing of land use decisions is important.

**2.3. Land Use Empirical Applications.** This study focuses on an empirical application of a land use change using microlevel data. Most empirical studies first estimate the parameters in a land use model and then simulate the potential effect of changes to the exogenous variables due to new policies. Lubowski et al. [15] use the estimates of a national land use model to predict the change in land use given changes in private returns, changes in government subsidies, and the elimination of the CRP. The EU helped fund the Irish government to increase hectares of forest as part of a carbon mitigation strategy, though the transition to forestry is far

behind the scheduled goals. Behan et al. [17] employ a land use model to estimate the additional payments necessary to increase the speed of the process. Langpap et al. [13] merge a model for land use with a water quality model to delineate the mechanisms through which land use affects water quality and offers policy advice for cost effective methods to improve watershed health. Polyakov and Zhang [18] analyze how preferential tax laws in Louisiana influence the allocation of rural and urban land, and also the composition of rural land between agricultural and forested land.

### 3. Methodology

**3.1. Theoretical Background.** We employ a discrete choice (RUM) model that is the preferred [12, 13, 15, 18] methodology to estimate spatially explicit micro-level empirical land use models in the literature. First we overview some of the economic theory behind discrete choice models and then discuss the estimation strategy. A dynamic optimization problem determines land use decisions where the land chosen yields the highest discounted sum of expected profits. Since only private landholders can be assumed to be profit maximizers, all public land will be excluded from the analysis. The full theoretical model is outlined in detail in [16], and some of the primary features are presented here. The landowners' problem of how many acres ( $a_{jkt}$ ) to allocate from use  $j$  to use  $k$  at time  $t$  is determined by the stock of land in use  $j$  at time  $t$  ( $S_{jt}$ ), the returns to each use ( $R_{jt}$ ), the costs of converting  $a$  acres from use  $j$  to use  $k$  ( $C_{jkt}(a)$ ), the continuation value of the optimal program ( $V_{t+1}$ ), and the discount rate  $r$ . The dynamic optimization problem is

$$\begin{aligned} \max_{a_{jkt}} \quad & \int_{t=0}^{\infty} \left\{ \sum_{j=1}^J E_t [R_{jt}] S_{jt} e^{-rt} - \sum_{j=1}^J \sum_{k=1}^K E_t [C_{jkt}(a_{jkt})] e^{-rt} \right. \\ & \left. + E_t [V_{t+1}] e^{-rt} \right\} dt \\ \text{s.t.} \quad & \dot{S}_{jt} = \sum_{k=1}^K (a_{kjt} - a_{jkt}), \\ & \sum_{k=1}^K a_{jkt} \leq S_{jt}, \\ & a_{jkt} \geq 0. \end{aligned} \tag{1}$$

There are several simplifying assumptions that help reduce the optimization problem to facilitate estimation. If landowners are risk neutral, they base their decisions on expected value  $E_t[R_{jt}] = R_{jt}$ ;  $E_t[C_{jkt}(a_{jkt})] = C_{jkt}(a_{jkt})$ ;  $E_t[V_{t+1}] = V_{t+1}$ . If land use change is thought to be an irreversible decision, or landowners only plan one conversion at a time, then the continuation value is just equal to the net present value from use  $k$ ,  $V_{t+1} = \sum_{t=0}^{\infty} R_{kt} e^{-rt}$ . With these assumptions

the current value Hamiltonian, with shadow prices  $\mu_j(t)$  for  $j = 1, \dots, J$ , is

$$\begin{aligned} \mathcal{H} = & \sum_{j=1}^J R_{jt} S_{jt} - \sum_{j=1}^J \sum_{k=1}^K a_{jkt}(t) C_{jk}(t) \\ & + \sum_{j=1}^J \mu_j(t) \left\{ \sum_{k=1}^K [a_{kj}(t) - a_{jk}(t)] \right\}. \end{aligned} \quad (2)$$

The necessary and sufficient conditions for an optimum are

$$\begin{aligned} -\frac{\partial \mathcal{H}}{\partial S_{jt}} &= \dot{\mu}_{jt} - r\mu_{jt} = -R_{jt}, \\ \frac{\partial \mathcal{H}}{\partial a_{jkt}} &= -C'_{jkt}(a_{jkt}) + \mu_{kt} - \mu_{jt} \leq 0, \\ a_{jkt} \frac{\partial \mathcal{H}}{\partial a_{jkt}} &= a_{jkt} [C'_{jkt}(a_{jkt}) + \mu_{kt} - \mu_{jt}] = 0. \end{aligned} \quad (3)$$

An additional set of assumptions helps clarify the optimality conditions and outline an empirical strategy for modeling land use change. The first is that marginal conversion costs are nonincreasing,  $C'_{jkt}(a_{jkt}) \leq 0$ . In the steady state  $\dot{\mu}_{jt} = 0$ , and therefore  $\mu_{jt} = R_{jt}/r$ . The shadow value of use  $j$ ,  $\mu_{jt}$ , represents the net present value of future returns for that use and provides the basis for the decision rule of how much acreage to switch from use  $j$  to use  $k$  at time  $t$  ( $a_{jkt}$ ). If  $a_{jkt} = 0$  landowners retain all land in current use  $j$  because the gain in future payments from switching to use  $k$  does not outweigh the conversion costs. Likewise, if  $a_{jkt} = a_{jkt}^{\max}$  the decision is to switch all possible land from use  $j$  to use  $k$ . This may be equal to the total stock of land, or some maximum feasible acres to switch. Lastly, if  $a_{jkt} = a_{jkt}^*$  landowners convert a distinct amount of land to use  $k$ , where the landowner is indifferent to converting one more acre from  $j$  to  $k$ . This corresponds to an interior solution. If the return to use  $i = j, k$  does not vary with  $a_{jkt}$ , this means that marginal conversion costs are not constant, or that the landowner is indifferent between all allocations of  $j$  and  $k$ . Note that this will be difficult to distinguish empirically from  $a_{jkt}^{\max}$  because the researcher in general does not observe when a feasibility constraint on the maximum number of acres is obtained. If expectations about future returns are static, then the decision to switch all available land from use  $j$  to use  $k$  at time  $t$  depends on the single period returns and conversion costs

$$R_{kt} - C'_{jkt}(a_{jkt}) > R_{jt}. \quad (4)$$

Equation (4) allows us to estimate an empirical model to determine land use change.

**3.2. Econometric Model.** The most common model for estimating land use change is a form of the logit model. In order to overcome the independence of irrelevant alternatives (IIAs) property of the traditional logit, researchers estimate a nested logit [15] or a random parameter logit [18]. The model conditions on the initial use of land because land conversion

costs will depend on the current land use. Studies use one period [13, 15] or current value of all future [18] returns conditional on the initial use. Land is converted to a use  $k$  if  $R_{nkt} - C_{nkt|j} > R_{nit} - C_{nit|j}$  for all  $i$  where  $R_{nit}$  is the return on parcel  $n$  for use  $i$  at time  $t$ ,  $C_{nit|j}$  is the cost of converting land from on plot  $n$  to use  $i$  at time  $t$  given current use  $j$ , and  $C_{nit|j} = 0$  for  $i = j$ . Utility from converting land on plot  $n$  from use  $j$  to use  $k$  is represented  $U_{nkt+1|j} = R_{nkt} - R_{njt} - C_{nkt|j}$ . Though utility is not directly observable, it can be separated into a systematic component  $V_{nkt+1|j}$  and a random element  $\epsilon_{nkt}$ . Systematic utility is separated into a section on use-specific  $x_{nkt}$  and general attributes  $p_{nt}$  of plot  $n$  affecting the returns and conversion costs at time  $t$ . Since returns from all uses are relevant to the landowner's decision,  $V_{nkt+1|j} = (x_{nit}, p_{nt})$ . The probability of converting land from use  $j$  to use  $k$  at time  $t$  is

$$\begin{aligned} P_{nkt+1|j} &= \text{Prob}(V_{nkt+1|j} + \epsilon_{nkt} > V_{nit+1|j} + \epsilon_{nit}) \\ &= \text{Prob}(\epsilon_{nkt} - \epsilon_{nit} > V_{nit+1|j} - V_{nkt+1|j}). \end{aligned} \quad (5)$$

Assuming the random elements of utility are independent and identically distributed with a type I extreme value distribution, the probabilities can be estimated with a multinomial logit model [19] with estimated probabilities

$$\begin{aligned} P_{nkt+1|j} &= \frac{\exp(\alpha_{kj} + \tau_{kt} + \beta' x_{nkt} - \beta' x_{njt} + \gamma'_k s_{nt} - \gamma'_j s_{nt})}{\sum_{i=1}^J \exp(\alpha_{ij} + \tau_{it} + \beta' x_{nit} - \beta' x_{njt} + \gamma'_i s_{nt} - \gamma'_j s_{nt})}, \end{aligned} \quad (6)$$

where  $\alpha_{ij}$  is a conversion specific constant,  $\tau_{it}$  is a year fixed effect,  $\beta$  is a vector of coefficients on parcel-use specific variables, and  $\gamma_i$  is a vector of coefficient on the parcel-specific variables. The  $\beta' x_{njt}$  and  $\gamma'_j s_{nt}$  terms appear in the numerator and denominator, and they cancel out producing the model to estimate

$$P_{nkt+1|j} = \frac{\exp(\alpha_{kj} + \tau_{kt} + \beta' x_{nkt} + \gamma'_k s_{nt})}{\sum_{i=1}^J \exp(\alpha_{ij} + \tau_{it} + \beta' x_{nit} + \gamma'_i s_{nt})}. \quad (7)$$

## 4. Data

The primary data sources are the Washington State Parcel and Forestland databases hosted by the University of Washington Geographic Information Service (WAGIS). Rogers and Cooke [20] provide a detailed description of the database development. Figure 1 shows a map of Washington State with the data coverage for the Parcel and Forestland data. Previous studies use the National Resource Inventory (NRI), a national panel survey dataset containing information on land use, soil and water quality, conservation practices, and land ownership, and merge the plot-level NRI data with proxies for net returns collected at the county level [13, 15, 18]. The advantage of the WAGIS data lies in the richness of data available at the parcel level. Returns to forestry and urban uses can be calculated at the parcel level through observed biomass

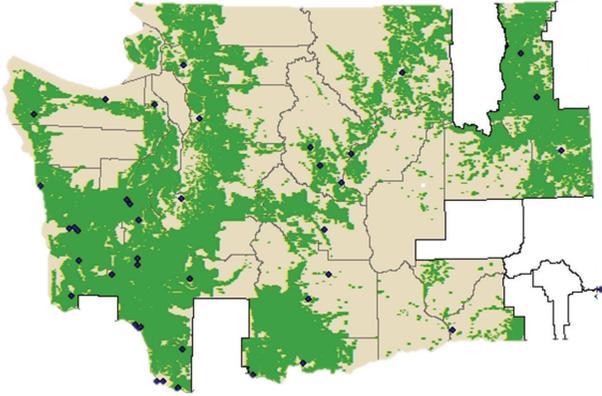


FIGURE 1: Map of Washington State and feedstock processors. Note: the green area is composed of points for a 1000 ft sample grid and represents the location of parcels in our sample. Blue dots are existing, proposed, or hypothetical facilities that process forest residue feedstock. The white areas are counties that did not comply with data requests for the parcel and forestland data projects.

combined with a simple harvesting rule and the assessed values, respectively.

No study, to the best of our knowledge, compiles all the data at the parcel level, so this will provide new depth to the land use change literature. One variable missing in the WAGIS dataset is the soil quality, which we spatially merge from the Soil Survey Geographic Database (SSURGO) maintained by the United States Department of Agriculture's (USDA) Natural Resources Conservation Services (NRCS) division. We use the Land Capability Class (LCC) as our measure of soil quality, and similar to [15] we condense the 8 discrete soil classes to four classes (we define our soil classes, with lower classes representing higher quality soil, as follows: Class 1 is LCC I-II, Class 2 is LCC I-IV, Class 3 is LCC V-VI, and Class 4 is LCC VII-VIII). The WAGIS parcel data contains the assessed value of the land for each parcel, which we use as a proxy to returns to development, and the 2007 Forestland database has returns to forestry at the parcel level. We construct returns to agriculture from county level data obtained from the Bureau of Economic Analysis using the same methodology as Lubowski [16] to generate net returns from total farm income minus production costs. Distance to feedstock facilities, which are displayed in Figure 1, is obtained through the WAGIS group.

We observe land use over two periods: 2007 and 2010. Since some parcels do not match up exactly over time (mostly due to small errors in GIS parcel boundaries), we take a fine scale grid of sample points every 1000 feet throughout the state to obtain our estimation sample. Only private land is included in the study, since we are modeling a landowner's maximization problem and the government may have a different objective function. The gaps from the sample grid within compliant counties seen in Figure 1 consist primarily of federal, state, and local government-owned land. This ensures that we are observing land use at a given location over time. Table 1 displays a matrix of observed land use changes from 2007 to 2010 by acreage. While most of the land stays in

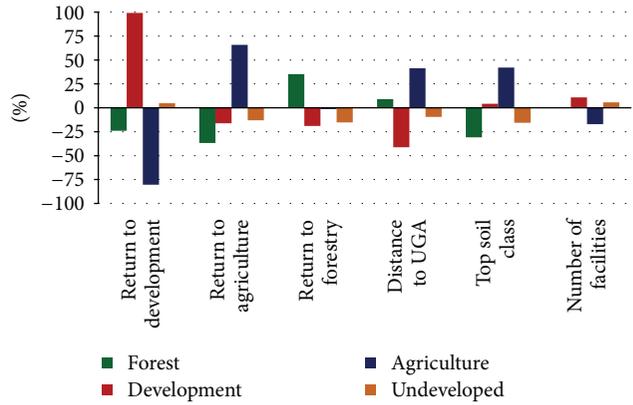


FIGURE 2: Summary statistics. Note: statistics are sample average of key variables by land class. The values shown are percentage deviations for each land use from the sample average. A positive value designates a land use that has a higher than average mean for that variable. All values are per acre and are annualized using a 5% discount rate. Distance to UGA is in miles. Soil class is categorical. The number of facilities is the number of feedstock facilities within 200 miles of a parcel.

its initial use, there are significant changes over time. There are net declines in developed, forest, and undeveloped land and net increases in agricultural land. Looking at some of the major categorical conversions, we see that 41,018 acres of undeveloped land switched to agriculture and 34,537 acres of forestland switched to undeveloped. Figure 2 shows the summary statistics for 2007 by land use class in a graphical format by mean deviations over the whole sample in order to highlight the differences in the covariates across land uses. Not surprisingly, each land use class for which we have returns has above average returns to the currently employed land use. This is particularly apparent for developed and agricultural land. The Top Soil Class is the percentage of parcels with the highest quality soil in our sample (this is equal to LCC I-II from SSURGO), and predictably the best soil is most often used for agriculture.

## 5. Empirical Results

*5.1. Parameter Estimates.* Land use is modeled as a discrete choice, and a multinomial logit model is estimated. Though there are drawbacks to this specification, it is a commonly used model and provides a good starting point for the analysis. The empirical model uses data in 2007 to predict land use for four classes in 2010: developed, agriculture, forest, and undeveloped. The parameters in Table 2 are estimates of the marginal effect of exogenous variables on the probability of a parcel being in each of the four land uses. Since most of the land stays in the same use, we also estimate four separate equations conditional on the land use in 2007.

An advantage of our dataset is that parcels are geo-referenced allowing explicit treatment of the spatial component of land use as advocated in Brady and Irwin [21]. Developing a spatial model adds richness to the empirical analysis, but it also raises many challenges. Spatial models

TABLE 1: Observed land use changes.

	Land use in 2010				Total
	Agriculture	Development	Forest	Undeveloped	
Land use 2007					
Agriculture	492,032	9,703	10,265	11,890	523,890
Development	9,793	1,186,729	20,788	16,953	1,234,263
Forest	16,714	6,387	5,415,103	34,537	5,472,740
Undeveloped	41,018	9,861	20,622	516,097	587,599
Total	559,557	1,212,681	5,466,778	579,476	7,818,492

Matrix represents acres of land in 2010 in each use based on land use in 2007. The diagonal terms are acreage totals for land that stayed in the same use, and the off-diagonal terms are the acreage values for parcels that switched use.

impose a lot of structure on the error term that relies on the researcher's choice of spatial weight matrix. Robertson et al. [22] provide an excellent review of econometric issues in estimating discrete choice spatial models and provide a series of workarounds when a structural spatial model is unwarranted or infeasible. For large samples the spatial error model (SER) is often intractable due to the need to invert an  $N \times N$  matrix. A spatial autoregressive model (SAR) is not appropriate in a setting where the goal is to make predictions because it requires the spatially lagged values of the dependent variable. Discrete data adds a host of other problems in analyzing the likelihood function in the presence of spatial effects. Some recent advances [23, 24] employ Bayesian Markov Chain Monte Carlo simulation methods to estimate the joint posterior distributions with discrete data, but the computational power limits the potential sample size. We select the second workaround of Robertson et al. [22] that adds spatial variables as additional covariates since we have a large dataset, a discrete dependent variable, and aim to generate predictions for land use in response to several policy scenarios. This workaround also performs well relative to structural spatial models that capture the true underlying spatial data generating process in Monte Carlo simulations by Robertson et al. [22].

In addition to the variables described above, we include the averages of neighbors' net returns to forestry and development as well as the proportion of neighbors in each of the four land use categories in 2007 (returns to agriculture are not included because they are only available at the county level). Using these variables we capture some of the unobserved heterogeneity due to spatial proximity inherent in modeling land use. We use five specifications for the spatial weight matrix (SWM) to define neighbors for each parcel: 5, 10, and 20 nearest parcels, as well as all parcels within 5,000 and 10,000 feet. In order to select a preferred model we perform a series of specification tests based on the Bayesian Information Criteria (BIC) (while we do not include all the specifications in the paper, interested readers can contact the authors for additional results). The five specifications derived from the unique SWMs are estimated for both the full model and the model that conditions on 2007 land use. Based on the BIC the spatial variables strongly improve model fit compared to the nonspatial model. While the conditional model also benefits from the spatial variables, the gain in fit is much

less significant. This is likely due to the fact that land use in 2007 captures a significant portion of the unobserved heterogeneity.

The model produces intuitive results with returns to a given use consistently increasing the probability of land ending up in that use. Additionally, returns to alternate uses generally reduce the probability of being in a given use; for example, returns to development reduce the probability of land being used for agriculture and forestry. There are several results that are particularly relevant in examining the potential effects of biofuel policy using forest residue as a feedstock. In our dataset, we observe the location of facilities that processes forest residue; these are primarily pulp and paper mills, and no facility currently generates ethanol from forest residue. Regulatory uncertainty for ethanol's tax breaks and subsidies, challenges for integrating within the fuel blending industry, and large initial capital costs are some of the reasons why we do not observe an active cellulosic ethanol industry despite the abundance of cheap feedstock (some of the regulatory uncertainty hinges on the government's acceptance of the life cycle analysis for carbon in order to qualify as advanced biofuels under RFS2). However, the implications of utilizing forest residue from a landowner's perspective are similar regardless of the end use of the forest residue. Therefore, we use the number of current feedstock processing facilities to proxy for the land use implications of the creation of ethanol plant that utilizes forest residue. The distance a landowner is willing to haul forest residue depends on the price received and the costs associated with collecting and hauling the biomass. In a biomass assessment for WA State Perez-Garcia et al. [25] find that for some price and cost specifications, landowners will send residue to facilities more than 100 miles away, a finding confirmed in other research as well (Johansson et al. [26] examine hauling distance for forest bundles up to 200 km, and Tahvanainen and Anttila [27] look at hauling distance up to 200 km for road and over 300 km for barge). In our data we observe the number of facilities within radii of 50, 100, and 200 miles, and we choose 200 miles in order to capture the effects in all harvest scenarios. As seen in Table 2 an additional feedstock facility has a strong positive impact on the probability of land being in forestry but has negative and insignificant impacts for other land uses or switches signs based on the land use in 2007 ([25] describes the current state of the industry for forest biomass

TABLE 2: Marginal effect of land use model.

Land use in 2007	(1)	(2)	(3)	(4)	(5)
	Any	Development	Agriculture	Forest	Undeveloped
	Development (2010)				
Returns to development	8.53e - 05*** (2.44e - 06)	6.66e - 06*** (6.24e - 07)	5.08e - 06*** (1.87e - 06)	3.43e - 07 (4.24e - 07)	4.26e - 06*** (7.83e - 07)
Returns to agriculture	-2.24e - 05*** (4.63e - 06)	3.90e - 06* (2.04e - 06)	1.15e - 06 (2.17e - 06)	3.37e - 07 (6.71e - 07)	-3.13e - 05*** (4.66e - 06)
Returns to forestry	-0.00262*** (9.47e - 05)	-3.84e - 05* (2.22e - 05)	6.86e - 05** (2.67e - 05)	-1.22e - 05 (7.72e - 06)	0.000446*** (4.99e - 05)
Distance to urban growth Area	-0.00115*** (0.000211)	0.000146 (9.00e - 05)	-0.000209** (9.49e - 05)	2.26e - 05 (2.94e - 05)	0.000232 (0.000166)
No. of feedstock processors (w/i 200 miles)	-0.00662*** (0.00106)	-0.00213*** (0.000371)	0.000338 (0.000463)	-7.72e - 05 (0.000138)	0.00219** (0.000882)
Soil Class 1	0.0623*** (0.00742)	0.00311 (0.00230)	-0.00319 (0.00254)	0.000393 (0.00101)	-0.00864 (0.00612)
Soil Class 2	0.0359*** (0.00545)	0.00591** (0.00234)	-0.00495** (0.00228)	-0.000263 (0.000674)	0.00192 (0.00489)
Soil Class 3	0.0152** (0.00744)	0.00487** (0.00210)	-0.00518** (0.00252)	-0.000592 (0.000881)	0.00156 (0.00645)
Property tax	-0.0103 (0.0149)	0.000958 (0.00531)	-0.00357 (0.00716)	-0.00223 (0.00225)	-0.0306** (0.0124)
% Neighbors in agriculture	0.497*** (0.0116)	0.0242*** (0.00452)	0.0314*** (0.00827)	0.00944*** (0.00234)	0.106*** (0.0107)
% Neighbors in development	0.0505*** (0.0147)	0.0138** (0.00570)	-0.00697 (0.00687)	-0.00270 (0.00317)	0.0950*** (0.0130)
% Neighbors in forestry	-0.490*** (0.0103)	0.0245*** (0.00437)	0.0156** (0.00715)	-0.00241 (0.00192)	0.0515*** (0.00984)
Neighbors returns to development	0.00285*** (0.000117)				
Neighbors returns to forestry	-1.28e - 05*** (3.39e - 06)				
	Agriculture (2010)				
Returns to development	-8.51e - 05*** (1.49e - 06)	-1.55e - 06*** (1.97e - 07)	-3.65e - 06 (5.47e - 06)	-1.18e - 06*** (3.68e - 07)	-3.79e - 06*** (5.91e - 07)
Returns to agriculture	9.41e - 06*** (9.09e - 07)	1.99e - 06*** (3.10e - 07)	1.43e - 05*** (4.44e - 06)	-4.60e - 07 (4.49e - 07)	8.21e - 06*** (8.68e - 07)
Returns to forestry	-0.000321*** (1.91e - 05)	-6.15e - 06*** (2.12e - 06)	-0.000355*** (4.88e - 05)	-3.15e - 06 (4.05e - 06)	-2.13e - 05** (1.03e - 05)
Distance to urban growth Area	-0.000164*** (3.36e - 05)	-4.42e - 05*** (1.51e - 05)	0.000607*** (0.000170)	-3.06e - 05* (1.60e - 05)	-0.000131*** (4.67e - 05)
No. of feedstock processors (w/i 200 miles)	0.000661*** (0.000200)	0.000228*** (5.38e - 05)	-0.00367*** (0.000840)	9.81e - 06 (6.86e - 05)	0.000417* (0.000215)
Soil Class 1	0.0198*** (0.00192)	0.00346** (0.00137)	0.00352 (0.00565)	0.00474** (0.00193)	0.0206*** (0.00655)
Soil Class 2	0.0105*** (0.00104)	0.000838*** (0.000263)	0.00245 (0.00466)	0.00171*** (0.000560)	0.00526*** (0.00130)
Soil Class 3	-0.00187 (0.00122)	0.000277 (0.000568)	-0.0200*** (0.00677)	6.50e - 06 (0.000691)	0.000230 (0.00194)
Property tax	-0.00541* (0.00320)	-0.00144* (0.000763)	-0.0205 (0.0135)	-0.00226* (0.00137)	-0.00589* (0.00333)
% Neighbors in agriculture	0.0129*** (0.00245)	-0.00113*** (0.000436)	-0.0141 (0.0149)	-0.00185 (0.00148)	0.00244 (0.00206)

TABLE 2: Continued.

Land use in 2007	(1)	(2)	(3)	(4)	(5)
	Any	Development	Agriculture	Forest	Undeveloped
% Neighbors in development	0.147*** (0.00478)	-0.000403 -0.000483	0.0445*** -0.0114	0.00461*** -0.00127	0.0105*** -0.00216
% Neighbors in forestry	-0.0261*** (0.00223)	-0.00250*** -0.000566	-0.00553 -0.0126	-0.00193* -0.00107	-0.00147 -0.00202
Neighbors returns to development	0.000185*** (2.21e - 05)				
Neighbors returns to forestry	1.14e - 05*** (6.27e - 07)				
Forestry (2010)					
Returns to development	5.82e - 05*** (3.33e - 06)	-3.48e - 06*** (2.89e - 07)	-9.30e - 06** (4.65e - 06)	-1.03e - 06 (8.89e - 07)	-8.27e - 06*** (9.86e - 07)
Returns to agriculture	2.72e - 05*** (5.61e - 06)	4.26e - 06*** (5.44e - 07)	-1.77e - 05*** (2.81e - 06)	-2.95e - 06** (1.35e - 06)	1.77e - 05*** (1.29e - 06)
Returns to forestry	0.00452*** (0.000105)	1.09e - 05** (4.97e - 06)	0.000188*** (2.54e - 05)	4.11e - 06 (1.53e - 05)	8.60e - 05*** (1.56e - 05)
Distance to urban growth Area	-3.13e - 06 (0.000222)	-4.99e - 05** (2.23e - 05)	-0.000226** (8.96e - 05)	-8.25e - 05 (5.39e - 05)	-0.000244*** (6.15e - 05)
No. of feedstock processors (w/i 200 miles)	0.0137*** (0.00119)	0.000612*** (0.000105)	-0.000329 (0.000446)	-4.52e - 05 (0.000280)	0.00124*** (0.000294)
Soil Class 1	-0.0666*** (0.00744)	-0.000687 (0.000495)	0.00701* (0.00382)	-0.00967*** (0.00311)	0.00224 (0.00263)
Soil Class 2	-0.0423*** (0.00576)	0.000400 (0.000404)	-0.00169 (0.00221)	-0.00469*** (0.00150)	0.00543*** (0.00146)
Soil Class 3	-0.0253*** (0.00769)	-0.000365 (0.000597)	0.00446 (0.00320)	0.000914 (0.00198)	0.00451* (0.00272)
Property tax	-0.0475*** (0.0181)	-0.00546*** (0.00157)	0.0482*** (0.00796)	0.00295 (0.00479)	-0.0104* (0.00530)
% Neighbors in agriculture	-0.0405*** (0.0144)	-0.00143 (0.00110)	0.00284 (0.00794)	0.00717 (0.00444)	0.00151 (0.00338)
% Neighbors in development	0.243*** (0.0171)	-0.00620*** (0.00177)	-0.0134** (0.00595)	0.0199*** (0.00556)	-0.0134*** (0.00484)
% Neighbors in forestry	1.243*** (0.0122)	0.00146 (0.000937)	0.0267*** (0.00630)	0.0325*** (0.00330)	0.0128*** (0.00269)
Neighbors returns to development	-0.00400*** (0.000130)				
Neighbors returns to forestry	-7.36e - 05*** (5.03e - 06)				
Undeveloped (2010)					
Returns to development	-5.84e - 05*** (2.43e - 06)	-1.63e - 06*** (5.20e - 07)	7.87e - 06*** (2.11e - 06)	1.87e - 06*** (6.87e - 07)	7.80e - 06*** (1.33e - 06)
Returns to agriculture	-1.42e - 05*** (3.88e - 06)	-1.02e - 05*** (1.94e - 06)	2.22e - 06 (2.76e - 06)	3.07e - 06*** (1.09e - 06)	5.42e - 06 (4.86e - 06)
Returns to forestry	-0.00158*** (7.99e - 05)	3.37e - 05 (2.15e - 05)	9.88e - 05*** (3.24e - 05)	1.12e - 05 (1.26e - 05)	-0.000510*** (5.30e - 05)
Distance to urban growth Area	0.00131*** (0.000162)	-5.17e - 05 (8.60e - 05)	-0.000171 (0.000113)	9.05e - 05** (4.24e - 05)	0.000143 (0.000181)
No. of feedstock processors (w/i 200 miles)	-0.00777*** (0.000902)	0.00129*** (0.000352)	0.00366*** (0.000548)	0.000113 (0.000234)	-0.00385*** (0.000948)
Soil Class 1	-0.0155*** (0.00581)	-0.00588*** (0.00179)	-0.00734** (0.00336)	0.00454** (0.00225)	-0.0142 (0.00900)

TABLE 2: Continued.

Land use in 2007	(1)	(2)	(3)	(4)	(5)
	Any	Development	Agriculture	Forest	Undeveloped
Soil Class 2	-0.00415 (0.00457)	-0.00715*** (0.00229)	0.00420 (0.00346)	0.00324*** (0.00122)	-0.0126** (0.00523)
Soil Class 3	0.0119** (0.00602)	-0.00478** (0.00193)	0.0207*** (0.00553)	-0.000329 (0.00164)	-0.00630 (0.00716)
Property tax	0.0632*** (0.0126)	0.00594 (0.00502)	-0.0241*** (0.00824)	0.00155 (0.00400)	0.0469*** (0.0137)
% Neighbors in agriculture	-0.469*** (0.00925)	-0.0216*** (0.00436)	-0.0202** (0.00962)	-0.0148*** (0.00347)	-0.110*** (0.0113)
% Neighbors in development	-0.441*** (0.0112)	-0.00721 (0.00540)	-0.0241*** (0.00695)	-0.0218*** (0.00440)	-0.0921*** (0.0139)
% Neighbors in forestry	-0.728*** (0.00771)	-0.0234*** (0.00423)	-0.0367*** (0.00829)	-0.0282*** (0.00247)	-0.0628*** (0.0103)
Neighbors returns to development	0.000970*** (9.90e - 05)				
Neighbors returns to forestry	7.50e - 05*** (2.67e - 06)				
Pseudo-R <sup>2</sup>	0.3454	0.1297	0.0792	0.0556	0.0714
Observations	113,953	33,380	14,229	43,740	22,609

Reading across the column within a section displays the marginal effects on that section's predicted land use in 2010, given the 2007 land use shown in the column. For example, the agriculture section in column (3) reports the marginal effects on the probability of being in agriculture in 2007 given that the parcel was in forestry in 2007. Standard errors in parentheses; \*\*\*  $P < 0.01$ , \*\*  $P < 0.05$ , \*  $P < 0.1$ .

and concludes that a binding supply side constraint is not likely).

We also perform robustness checks using radii of 50 and 100 miles that can be seen in Table 3. The results are similar in sign but smaller in magnitude and level of significance, most likely because there is not much variation in the number of facilities in the smaller radii. Using facilities within 50 miles significantly dampens the effect of a facility. There is also the potential that the location of feedstock processors is endogenous since they will likely choose to locate near forestland. While we cannot refute this claim outright, we believe that potential endogeneity of facilities is not too problematic since the average number of facilities within 200 miles is greater for developed and undeveloped land than for forestland (average number of facilities within 200 miles is 8.97 for developed land, 7.23 for agriculture, 8.42 for forestland, and 8.65 for undeveloped land). Using the models of land use change alleviates these concerns because all the processors were in place in 2007 and we condition on land use in 2007. Therefore, while feedstock processors may have chosen to locate in areas with high concentration of forestland, once they are built by definition land use cannot dictate their location.

**5.2. Simulation.** Unfortunately there is no state-wide large-scale forest residue biofuel policy in WA that provides us with data to estimate the effects on land use. Therefore, we must postulate the impact the policy may have using our existing historical data. One potential mechanism through which a burgeoning biofuel industry using woody feedstock impacts land use is by increasing the returns to forestry.

Currently demand for forest residue consists primarily of pulp and paper mills; ethanol plants using forest biomass as a feedstock will add an additional consumer of forest residue thus increasing demand for the biomass. Increased demand for forest biomass will raise the price and, in addition to increasing profits for landowners currently harvesting forest residue, will make harvesting residue profitable for landowners who currently do not sell their timber debris. The question remains whether the extra revenue would cause greater forest retention or actually generate conversion to forestland. Since we do not observe the increase in returns to forestry, we assume three scenarios where increased biomass prices generate additional forest returns of 1%, 5%, and 10%.

Another way to proxy for the impact of a biofuel policy is to explore the influence of proximity to a feedstock processor on land use decisions. In the spirit of the Von Thünen rent gradient, forestland close to processor plants has lower transportation costs, and therefore profits from harvesting forest residue are higher than forestland far away from a processing plant. A new plant that processes forest residue for biofuels will make it economically viable to sell forest residue for parcels close to the facility. Therefore, lands surrounding processing plants can proxy for a biofuel policy targeting forest residue.

Armed with the estimates from the land use model, we are able to simulate the land use impacts of biofuel-policy scenarios. First we estimate the model conditioning on initial land use (columns (2)–(5) in Table 2) since we are interested in land use *change*. Next we generate a base prediction of land use given the current variables. Finally, we change a specific

TABLE 3: Robustness checks for proximity to feedstock processing facilities.

Distance—Classification	Development	Agriculture	Forest	Undeveloped
200—All	-0.0311*** (0.00727)	0.0124*** (0.00139)	0.0870*** (0.00829)	-0.0683*** (0.00609)
200—Existing	-0.0464*** (0.00896)	0.0104*** (0.00173)	0.103*** (0.0100)	-0.0674*** (0.00761)
200—Proposed	-0.0187*** (0.00564)	0.00713*** (0.00111)	0.0589*** (0.00650)	-0.0473*** (0.00471)
200—Hypothetical	-0.0281*** (0.00671)	0.0154*** (0.00125)	0.0818*** (0.00775)	-0.0690*** (0.00558)
100—All	-0.00739* (0.00400)	0.000499 (0.000792)	0.0329*** (0.00445)	-0.0260*** (0.00340)
100—Existing	-0.0202*** (0.00557)	0.0102*** (0.00120)	0.0223*** (0.00665)	-0.0122*** (0.00461)
100—Proposed	-0.00140 (0.00284)	0.000544 (0.000562)	0.0215*** (0.00312)	-0.0206*** (0.00244)
100—Hypothetical	-0.00421 (0.00263)	-0.00202*** (0.000539)	0.0216*** (0.00299)	-0.0154*** (0.00222)
50—All	0.0202*** (0.00293)	-0.00334*** (0.000616)	0.00571* (0.00329)	-0.0225*** (0.00251)
50—Existing	0.0119*** (0.00293)	-0.00247*** (0.000640)	-0.00494 (0.00326)	-0.00448* (0.00246)
50—Proposed	0.00844*** (0.00178)	-0.00313*** (0.000413)	-6.54e - 05 (0.00204)	-0.00525*** (0.00149)
50—Hypothetical	0.00894*** (0.00164)	-0.000213 (0.000327)	0.00716*** (0.00180)	-0.0159*** (0.00143)

The values reported are the marginal effects for the number of facilities within different radii and for different classifications. In the first column the radius in miles is given followed by whether the facilities are existing, proposed, hypothetical or any of the three categories. The last four columns represent the impact of the variable on land in that use. All control variables in the regressions reported in Table 2 column (1) are included. Standard errors in parentheses, \*\*\*  $P < 0.01$ , \*\*  $P < 0.05$ , \*  $P < 0.1$ .

variable and then repredict land uses given the new variables and compare acreage to the base prediction. Our policy scenarios are to increase returns to forestland by 1%, 5%, and 10% and to add facilities at three potential locations: Centralia, Aberdeen, and Spokane. Our selected facility locations are identified as promising by a preliminary feasibility analysis and offer good geographic coverage for the state. In order to obtain inference for our simulation results we use a bootstrap approach to draw with replacement from our sample and reestimate the simulated land use changes. This produces bootstrap standard deviations and confidence intervals.

As seen in Figure 3 both policy scenarios predict increases in forestland leading to environmental benefits from land use change. Since we are using a sample of a 1000 foot grid over WA State, we present percentage changes in land use as opposed to total acreage. The increase in forestland due to higher forest returns ranges from 0.1–1% depending on the assumptions of the increase in forest net returns. The facility simulations depend on where the facilities are located. Facilities in Centralia and Aberdeen both produce a 0.5% increase in forestland, while the increase for a facility in Spokane is only 0.1%, with some repetitions of the simulation producing small decreases in forestland. The spatially explicit data allow us to estimate the specific parcels most likely to be experience

land use change due to biofuel policy. This information can be used for the overall life cycle assessment to analyze the carbon footprint of a forest residue biofuel policy in WA and to assess whether cellulosic biofuels meet the federal carbon reduction requirements for second-generation biofuels.

## 6. Conclusions

The land use model helps to understand some of the secondary effects of biofuel policy in WA State. Researchers tend to focus on the negative environmental consequence of converting land to grow crops for biofuels such as loss of carbon sequestration [1] and pollution due to agricultural runoff [13]. However, the biofuel policy in question is one relating to harvesting forest residue and has much different implications for land use. We find that biofuel policy targeting forest residue will increase land in forestry, leading to a reduction in GHG emissions due to the carbon sequestration. A key limitation is that our simulations are based on assumptions of how a biofuel policy will affect variables that impact land use. We also cannot determine whether the underlying relationship between these variables and land use will remain constant after a biofuel policy is established. Nonetheless, these results produce an empirical

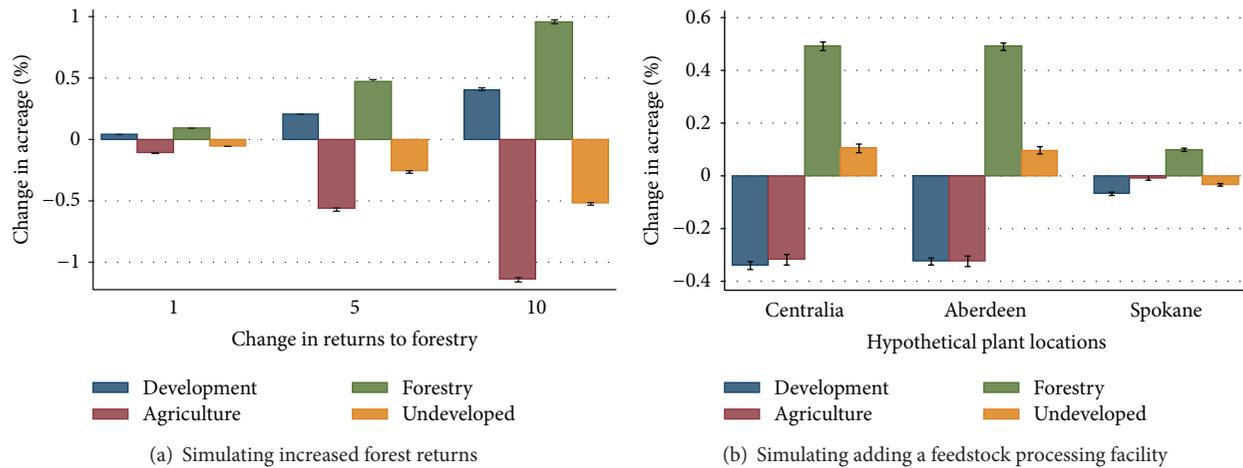


FIGURE 3: Land use change from policy simulations. Note: simulations are run on land use models conditional on land use in 2007 and correspond to columns (2)–(5) in Table 2. One thousand bootstrap simulations are performed to generate out of sample predictions. The average percentage change in each land use is shown with numerical bootstrap standard errors used to create confidence intervals.

and quantitative exploration of the potential indirect effects of a biofuel policy in Washington State. The next steps are to link the land use model to local water quality. While carbon emissions are a global pollutant, impacts of water quality will be felt locally and therefore warrant further analysis.

## Appendix

Table 3 shows results dependent on the designation of the facility and the threshold distance for proximity to feedstock processing facilities. Each row is the estimate of the marginal effect of the variable for the number of facilities within a given radii on the probability of land being in each of the four uses. Each row represents a separate regression that contains all the control variables from the regression in Table 2. These regressions are on the pooled data as opposed to conditioning on the initial land use. In our dataset, we have the number of facilities within 50, 100, and 200 miles of each parcel for existing facilities, as well as formally proposed facilities and locations mentioned in news and reports but without the formal paperwork.

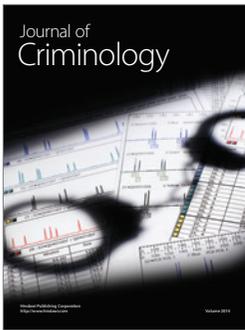
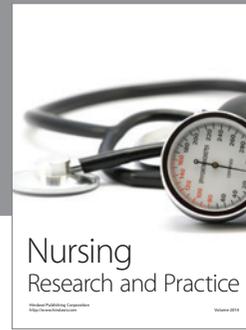
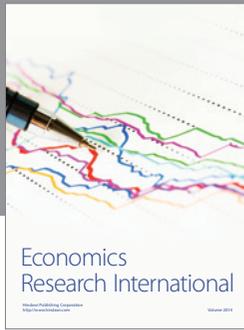
## Acknowledgments

The authors would like to thank Luke Rogers and Andrew Cooke for assistance with, and insight into, the Parcel and Forestland databases, as well as Rick Gustafson for helpful comments and suggestions. This research was supported in part by the McIntire-Stennis Cooperative Forestry Research Program (Public Law 87-788), funded through the United States Department of Agriculture (USDA), National Institute for Food and Agriculture (NIFA).

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