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Forestland owners' willingness to plant pine on non-forested land for woody bioenergy in Virginia

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ABSTRACT

Woody bioenergy provides an opportunity for new source of revenue, which forestland owners can respond to either by supplying biomass from an existing stand or by establishing feedstock plantations on currently non-forested land. Using survey data sent out to 900 randomly selected participants in Virginia, we assess if forestland owners would allocate parts of their currently non-forested land, such as cropland and pasture/grazing land, to growing loblolly pine for bioenergy production purposes. Using recursive partitioning based logistic regression, we show that the decision to plant pine on non-forested land depends both on economic and non-economic factors, including price, demographic attributes of the forestland owner, mode of land acquisition and their respective threshold values, providing profile types policies encouraging biomass supply can use in tailoring their efforts. Using bid values, expected landowner revenue from growing pine, we also find a mean willingness to accept value of $1424/acre. Our results also show that the choice among land use types follows economies of scale while the choice among land covers for a given land use type follows species diversification.

1. Introduction

Southern states make up a third of the nation's forest cover and contribute up to 60% of the national wood supply, the leading forest type being *Pinus* (McKeand et al., 2003; Sample et al., 2010). With 69% of the region's 214 million acres of forest cover located on their land, southern private forestland owners are important stakeholders who can affect market and broader forest related ecosystem outcomes through their management decisions (Oswalt et al., 2009).

Making up 63% of the state, Virginia has 15.8 million acres of forestland, a value comparable to the thirteen southern states' average forest cover of 16.1 million acres (Hubbard et al., 2007). A large and growing share of the state's biomass based electricity comes from wood waste, making it among the top ten states in its use of biomass based energy (Biomass Research and Development Initiative, 2003; Hubbard et al., 2007). Most of the nearly 2 million dry tons of harvesting residue produced annually in the state are, however, used up either for industrial fuel, fiber byproducts, or other products (USFS, 2003). One of the ways to meet the growing demand for biomass is to convert currently non-forested land - such as cropland, pasture/grazing land - to growing pine such as loblolly pine (*Pinus taeda*), which benefits from being both widely available in the state and from forestland owners being familiar with its needs and yield performance (Schultz, 1997; USGS, 2013).

While we do not estimate the net change in different land use types nor whether any such change leads to beneficial or adverse impacts on the environment, we estimate the likelihood of such land use change and identify what socioeconomic factors and land use features that can be used to predict it. We also infer the pattern respondents' choices follow to identify their underlying strategies and objectives. This is relevant because by better understanding how forestland owners respond to emerging opportunities and by identifying the factors that explain their response to such opportunities, we can anticipate and plan for the resulting economic, social, and environmental outcomes. This can take the form of designing strategies and incentives that sustain beneficial outcomes while mitigating undesirable ones; ensuring that practices meet predefined sustainability targets, and by simulating how forestland owners might respond to different types of policies and market circumstances.

The rest of the paper is organized as follows. Section 2 presents a short review of previous studies and highlights the gap this paper intends to address. Section 3 presents the decision making framework and provides details about the model used to analyze the data. Section 4 describes how the survey was designed, the types of questions it contained, how it was administered, and the response rate. Section 5 presents results and discussions while Section 6 highlights the conclusions, implications, and future research needs.

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2. Literature review

The allocation of land to different land use types is a dynamic process affected by the expected demand for a given product, the monetary and non-monetary costs and benefits associated with different land use options, irreversibility and uncertainty of investment and lost option value, land suitability, land management objectives, relevant public policy, and other factors that determine the production possibility of the different land use options available to the land owner (Alig et al., 1998).

Previous studies on land use change focus either on historic trends or anticipated changes with relevant factors such as population growth, technology, commodity demand, and elasticity of substitution between different land use types. The latter are modeled either exogenously or endogenously to explain the shifting proportions of different land use types in the context of maximizing discounted net return (Lubowski et al., 2008; Drummond and Loveland, 2010). The approaches used in these studies, ranging from spatial allocation models, spatially explicit econometric models, and agent based models, have varying qualities in terms of realism, precision, and replicability (Grimm et al., 2005). Challenges of using these models include how they require regional and intensive data and their relatively large-scale unit of analyses that makes the results irrelevant at a smaller scale (Lal and Alavalapati, 2014). The land use changes of interest in previous studies seldom pertain to bioenergy, and even then the definition of biomass is either too broad or mostly focuses on feedstocks like switchgrass (Timmons, 2014).

One of the major themes in woody bioenergy related studies is the identification of factors that explain respondents' choice regarding a given forest management decision. Factors like socioeconomic and demographic heterogeneity, different forest management objectives, environmental attitudes and beliefs, extension experience, availability of forest management technical assistance, and policy incentives such as tax credits can be used to explain respondents' willingness to supply biomass for bioenergy from existing forestland (Bliss and Martin, 1989; Becker et al., 2010; Joshi and Arano, 2009). Paula et al. (2011) also found that the size of forestland, active management and bid price affected forestland owners' willingness to harvest biomass in the southern state of Alabama. Shivan and Mehmood (2010) report that species composition of the forestland as well as respondents' educational level and age affect the willingness to supply timber for biofuels. Such factors can be used to delineate purpose of forest management in terms of timber and non-timber priorities (Majumdar et al., 2008). It can also be used to identify different motivators such as financial and non-financial (Koontz, 2001) or internal and external motivators (Bliss and Martin, 1989) that influence forestland owners' behavior. While these factors and their policy implications relate to supplying biomass from existing forestland, little is known about the direction of relationship and significance of these and other factors in explaining forestland owners' decisions to allocate non-forested land to growing pine for bioenergy. This is important in estimating the availability of reliable biomass supply to the industry and because such change can have biophysical, economic, social, and climatic impacts both in the short and long term (Searchinger et al., 2008; Borrion et al., 2012).

Species specific studies also are better suited for a more precise projection of demand, supply, and ecosystem impacts given the different use, value, market, and yield of biomass associated with each species. Using landowner surveys also allow us to capture ground level reality and prove to be a viable option in studying potential land use change, especially when the relevant information for an emerging industry, such as woody bioenergy, is either incomplete or non-existent.

3. Analytical framework

A respondent's choice of whether or not to plant currently non-forested land with pine in response to the emergence of woody bioenergy can be considered under the general framework of the random utility maximization model. This model is composed of systematic and random components, which accounts for idiosyncratic attributes that allow for heterogeneity and stochastic choice resulting from unobserved factors, situational constraints, measurement and sampling error (Corstjens and Gautschi, 1983).

Two choices j and k and their respective objective function, U_j and U_k can be specified as:

$$U_j = \beta_j X_i + \varepsilon_j \text{ and } U_k = \beta_k X_i + \varepsilon_k \tag{1}$$

where j represents the choice to plant pine while k represents the choice not to plant pine; X is the vector of variables that explain the objective function; β_j and β_k are estimated parameters; and ε_j and ε_k are error terms assumed to be independently and identically distributed (Greene, 2003). The choice of j over k, implying that the objective function is better maximized by j than by k, can be specified as:

$$U_j(\beta_j X_i + \varepsilon_j) > U_k(\beta_k X_i + \varepsilon_k), k \neq j \tag{2}$$

The probability that a respondent chooses to plant (j) or not plant (k) pine on their currently non-forested land can then be defined as:

$$P(Y = 1 \mid X) = P(U_j > U_k) \tag{3}$$

$$P(\beta_j X_i + \varepsilon_j - \beta_k X_i - \varepsilon_k > 0 \mid X) \tag{4}$$

$$P(\beta_j X_i - \beta_k X_i + \varepsilon^* > 0 \mid X) \tag{5}$$

$$P(X^* X + \varepsilon > 0 \mid X) = F(\beta^* X_i) \tag{6}$$

where P is a probability function, $\varepsilon^* = \varepsilon_j - \varepsilon_k$ is a random disturbance term and F $(\beta^* X_j)$ is its cumulative distribution function evaluated at $\beta^* X_i$. The distribution of F depends on the assumed distribution of ε^*.

For a logistic cumulative distribution with the *s* shape of logistic function, the logit model can be used to identify the variables that significantly explain respondents' choice. The probability of getting a 'yes' response for the explaining variables as given by

$$P(Y = 1 \mid X_1, X_2, X_3, X_4, \ldots X_k) \tag{7}$$

will have as logit form

$$\text{logit}P(X) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \tag{8}$$

and ranges from positive to negative infinity. The logistic function of the same is:

$$P(X) = 1/\left(1 + e^{-(\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4)}\right) \tag{9}$$

For a composite index of all relevant variables

$$Z = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \tag{10}$$

the mathematical form of the logistic model can be summarized as:

$$F(z) = 1/(1 + e^{-z}) \tag{11}$$

Given the estimation results, the odds ratio (OR) capturing the risk of getting a 'yes' response compared to not getting it between forestland owners with the different attributes of a given variable can be estimated as:

$$OR = e^{\beta},$$

where β is the coefficient of that variable.

Given the dichotomous nature of the dependent variable, the binary logit regression is used in this study. The logit is a widely used model for discrete and probabilistic choice and is preferable to alternative models