Bayesian Methods to Estimate Urban Growth Potential

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Abstract

Urban growth often influences the production of ecosystem services. The impacts of urbanization on landscapes can subsequently affect landowners' perceptions, values and decisions regarding their land. Within land-use and land-change research, very few models of dynamic landscape-scale processes like urbanization incorporate empirically-grounded landowner decision-making processes. Very little attention has focused on the heterogeneous decision-making processes that aggregate to influence broader-scale patterns of urbanization. We examine the land-use tradeoffs faced by individual landowners' in one of the United States' most rapidly urbanizing regions – the urban area surrounding Charlotte, North Carolina. We focus on the land-use decisions of non-industrial private forest owners located across the region's development gradient. A discrete choice experiment is used to determine the critical factors influencing individual forest owners' intent to sell their undeveloped properties across a series of experimentally varied scenarios of urban growth. Data are analyzed using a hierarchical Bayesian approach. The estimates derived from the survey data are used to modify a spatially-explicit trend-based urban development potential model, derived from remotely-sensed imagery and observed changes in the region's socioeconomic and infrastructural characteristics between 2000 and 2011. This modeling approach combines the theoretical underpinnings of behavioral economics with spatiotemporal data describing a region's historical development patterns. By integrating empirical social preference data into spatially-explicit urban growth models, we begin to more realistically capture processes as well as patterns that drive the location, magnitude and rates of urban growth.

Keywords: stated choice methods; urbanization; land change; Bayesian model

Bayesian Methods to Estimate Urban Growth Potential

Introduction

Across the globe, rapid urban expansion is impacting both the productivity of natural systems and the health of human populations. Globally, recent projections suggest that by 2030 urban land area will be 3 times larger than the extent observed in 2000 (Seto, Güneralp, & Hutya, 2012). Urbanization results in the loss of productive agricultural lands, fragmentation of critical habitats that support biodiversity and a reduction in the amount of carbon the biosphere can sequester from the atmosphere (Seto, Fragkias, Güneralp, & Reilly, 2011). In the United States, recent research has demonstrated that the conversion of forests and farmlands to low-density built environments has compromised local ecosystems and the life-sustaining benefits these ecosystems provide (Alig, Kline, & Lichtenstein, 2004; Brown, Johnson, Loveland, & Theobald, 2005; Hansen et al., 2005a; Maestas, Knight, & Gilgert, 2003; Munn, Barlow, Evans, & Cleaves, 2002; Radeloff, Hammer, & Stewart, 2005). These environmental consequences will become increasingly salient as the global population continues to grow and as greater proportions of the population choose to live in urban areas (Angel, Parent, Civco, Blei, & Potere, 2011).

Despite growing concerns over the environmental consequences of rapidly growing urban areas, very little research has attempted to understand how the decisions of individual landowners affect aggregate urbanization processes. Numerous studies of urban growth have used observational data of historical development patterns (e.g., remote sensing data, property ownership records, etc.) to describe, quantify and project the location, magnitude and rates of urban growth (Seto et al., 2011; Verburg et al., 2016). Historical development trends are frequently used to measure and model urban growth patterns (Brown, Verburg, Pontius Jr, &

Lange, 2013; National Research Council, 2013). However, urbanization at its most fundamental level is the result of individual landowners' decisions to sell or develop their farm- and/or forestland. Urbanization is an emergent process resulting from the aggregate land-use decisions of hundreds or thousands of individual landowners and their interactions with their environments (Alberti, 2010; Verburg et al., 2015).

The land-use decisions of landowners in urbanizing regions are influenced by multiple, often conflicting, factors. Urban development commonly results in an increase in the market value of nearby agricultural and forest lands (Bastian, McLeod, Germino, Reiners, & Blasko, 2002; Delbecq, Kuethe, & Borchers, 2014; Guiling, Brorsen, & Doye, 2009). Consequently, owners of those agricultural and forest lands may welcome nearby urban development, seeing it as a way to expand the value of their properties. However, most small non-industrial agricultural and forest owners in the United States do not manage their properties for financial reasons. Rather they value the aesthetic, cultural, recreational and social benefits provided by owning a working farm or an unmanaged forest stand (Silver, Leahy, Weiskittel, Noblet, & Kittredge, 2015). Nationwide survey data suggest non-industrial private forest owners tend to rate financial objectives for owning woodlands less important than amenity-related objectives such as desirable landscape aesthetics, providing habitat for wildlife or protecting nature (Butler et al., 2016). If landowners place more value on the non-monetary uses of their properties, it is likely they would perceive encroaching development and rising property values as a burden. Nearby development can directly affect landowners' ability to achieve the aesthetic, cultural, recreational and social benefits, which they value most. As development encroaches and property values rise, property taxes also increase which can create a financial burden on landowners who do not manage their properties for income generation (Butler et al., 2012; Greene et al., 2014; Ma et al.,

2014). These are the difficult tradeoffs faced by landowners in rapidly urbanizing regions. These complex and multi-faceted decisions are the most fundamental mechanism of the urbanization process.

It is important to note at this point that not *all* urbanization is driven by the sovereign decisions of landowners. Development can occur through direct state intervention. In the United States for example, eminent domain has allowed city governments to expropriate private property for public use via compensating payments (Epstein, 2013). Similarly, compulsory purchase orders, used in the United Kingdom, Ireland, Taiwan and developing countries are a legal mechanism through which ownership of private property can be transferred if it is deemed to be in the public interest (Adu-Gyamfi, 2012; Denyer-Green, 2013; Lin & Lin, 2006). With these exceptions, the predominant method through which urbanization occurs is via the aggregation of individual landowners' decision to sell their farmland and/or forestland.

In this research, we explicitly examine the factors driving individual landowners' land-use decisions in one of the United States' most rapidly urbanizing regions – the urban area surrounding Charlotte, North Carolina. Our investigation focuses on the land-use decisions made by non-industrial private forest owners spread across the region's development gradient. A discrete choice experiment is used to determine the critical factors influencing individual forest owners' intent to sell their properties across a series of experimentally varied development scenarios. Data are modeled with a Bayesian hierarchical model. The *choice experiment* model yields estimated posterior distributions for each of the experiment's attributes. We use these estimated posterior distributions to inform a subsequent hierarchical spatial model, the *development potential model*, which predicts the potential of each parcel within the study area to be developed based upon historical development patterns and parcel-specific attributes which

match the attributes presented to forest owners in the choice experiment (current distance to development, property value and qualification for a tax-relief program). The linked modeling approach, enabled through the use of Bayesian estimation techniques, allows us to generate spatially-explicit estimates of development potential that are informed by primary data collected from the forest owners whose future land-use decisions will affect how and where urbanization occurs throughout the study area. We show that urban growth is an aggregate product of human decisions, which are themselves a function of how individuals evaluate competing factors associated with encroaching development. Our research demonstrates that carefully developed and rigorously employed social science research can be used to inform projections of the location, magnitude and rates of urban growth.

Related Literature

The Effect of Urbanization on Forest Property Values

Economic theory suggests the value of land is determined by the net present value of expected future returns (Chavas & Thomas, 1999). For forested properties, expected future returns can be influenced by the proximity to viable timber markets, accessibility to city centers and future rent increases resulting from an increased demand for land (i.e., population growth) (Capozza & Helsley, 1989). Rising property values resulting from the increased demand for land is most notable near or at the boundaries of urban areas (Delbecq et al., 2014). In a national study measuring the determinants of agricultural land values, Plantinga et al. (2002) found that as much as 80% of a property's market value is attributable to expected development rents. This proportion tends to rise as urban areas expand and the total amount of developable lands diminishes (Bastian et al., 2002; Guiling et al., 2009; Wear & Newman, 2004). Consequently,

forest owners living near rapidly urbanizing regions are facing difficult decisions regarding whether they retain the current use of their forest lands (e.g., harvesting for timber, recreational and/or aesthetic enjoyment, etc.) and pay increasing property taxes, or decide to sell to developers (Butler et al., 2012; Greene et al., 2014; Ma et al., 2014).

While there has been a large body of empirical work examining the factors and effects of urbanization on property values, most of this research has focused on agricultural land values and has used hedonic pricing methods. To our knowledge, only one study has used stated choice experiments to examine the factors influencing forest landowners' decision to sell. Stated choice experiments allow researchers to explore the extent to which forest owners' decisions regarding their properties are influenced by rising property values (if at all) relative to other important factors such as the owners' financial and management objectives. Rozance and Rabotyagov (2014) administered a stated preference survey to small Washington forest landowners in order to gauge their intent to sell their forested properties based on perceptions of existing and future development pressures and the timing of such development. The study concluded that forest owners who managed their land as 'a sound financial investment' were more likely to anticipate developing their forestlands in the near future. Conversely, forest owners who indicated managing their land for either 'aesthetic enjoyment' or as 'a place for wildlife' were less likely to anticipate developing their forestland, even after controlling for the proximity of future development. Additionally, owners of larger forests were significantly more likely to anticipate developing their forestland in the near future. Rozance and Rabotyagov also determined the likelihood of development decreased by 15% for every mile a forest owners' property was from development. Similarly, forest owners living nearer to developed areas were more likely to

indicate developing their properties sooner (for every mile a forest owner's property was from development, the estimated time to development decreased by 2%).

Given the findings of Rozance and Rabotyagov (2014), as well as the large body of literature focused on quantifying the effects of urbanization on property values, we expect increased property values will positively influence the likelihood of forest owners around the Charlotte metropolitan area indicating an intent to sell his/her forest land. This expectation is guided by the assumption that landowners are profit seeking entities who will capitalize on the rising property values that accompany encroaching urban development by selling their own land.

Negative Consequences Associated with Urban Development

In addition to the rising tax burden faced by forest owners whose properties are in urbanizing regions, urbanization also results in a variety of other undesirable environmental consequences which may influence forest owners' decision to retain or sell their property. Some of these impacts include habitat fragmentation, decreased air quality, diminished water quality and quantity as well as the introduction of exotic plant species and reductions in native species richness (Bhatta, 2010; Hansen et al., 2005b). Urban development also commonly results in increased traffic congestion, which can reduce personal time and impact psychological health (Brueckner, 2000; Frumkin, 2002). Urban growth is also associated with degraded landscape aesthetics, which may be particularly salient for forest owners (Erickson, Ryan, & De Young, 2002) and rural residents (Milburn, Brown, & Mulley, 2010) who tend to value and maintain their forest land for aesthetic instead of monetary reasons. The diverse array of evidence suggesting urbanization has negative ecological and social/psychological impacts provides further support that distance to urban development will negatively influence the likelihood of an

individual indicating an intent to sell his/her forest land. That is, the further a forest owner's parcel is from existing development, the less likely they would be to indicate intent to sell it for development.

Given the findings of the large body of literature focused on quantifying the negative consequences of urbanization for existing agricultural and forest landowners, we expect greater distances to urban development will be negatively related to the likelihood of an individual indicating an intent to sell his/her forest land. This expectation is guided by the assumption (and empirical data) that non-industrial forest owners' land-use decisions are influenced by their desire to maintain desirable aesthetic and non-market benefits from their forested lands. As urbanization encroaches and those benefits diminish, these landowners will receive less utility from ownership and subsequently sell their properties.

Alternative Property Tax Mechanisms

While the distance between a forest owners' property and nearby urban development is likely to influence their property values as well as their intent to sell their forest land, the extent of this influence may be mitigated by qualifying for specific tax-relief programs. In North Carolina, property is traditionally assessed at market value. However, agricultural, forest and horticultural lands can also be valued at present use, which is based on their ability to produce income under management (PUV is calculated by dividing net return by the capitalization/discount rate) (North Carolina Department of Revenue, 2015). Present-use values are generally substantially lower than market value, which can offer a significant tax reduction to qualifying private landowners. North Carolina's present-use value program is one of many policies that aim to reduce the negative externalities caused by land-use changes, via slowing

rural land conversion, encouraging reforestation and sustainable management practices (Polyakov & Zhang, 2008). However, several previous studies have concluded that present-use value programs only delay land conversion, because many property owners prefer long-term capital gains (Anderson, 2012; Polyakov & Zhang, 2008). Additionally, landowners may find it beneficial to sell portions of their property when faced with increased tax burdens (Poudyal & Hodges, 2009). Other problems with the efficacy of present-use value programs include low awareness and, subsequently, low enrollment rates (Williams, Gottfried, Brockett, & Evans, 2004). Low enrollment rates are due to a number of factors, including minimum acreage and forest management plan requirements.

Despite the limitations noted in previous examinations and/or reviews of present-use value programs, they do offer a mechanism through which forest owners can mitigate some of the unwanted consequences associated with nearby urban development, namely rising property taxes. Given this, we expect the ability of properties to qualify for the present-use value program will decrease the likelihood that forest owners will intend to develop them.

Collectively, this study examines the influence of: 1) rising property values; 2) distance to new urban development; and 3) the ability of properties to qualify for a tax-relief program on forest owners' intent to sell their properties for development. These influences are examined through the use of a discrete choice experiment delivered via a mail survey to forest owners living in the rapidly growing urban areas surrounding Charlotte, North Carolina, USA. The results from the choice experiment are subsequently integrated into a spatial model predicting development potential across the study region. By linking estimates derived from the choice model to an established model of development potential (Meentemeyer et al., 2013), we are able to develop spatially-explicit maps of development potential that are directly and empirically

informed by a representative sample of the forest owners who will shape the region's future through their land-use decisions.

Materials and Methods

Definitions

Throughout this paper we use the term 'urbanization' to refer to the process of population concentration that occurs through either an increased number of individuals living within one urban area or the increase in the total number of urban areas within a defined geographic extent (Tisdale, 1942). Relatedly, 'urban growth' refers to the spatial expansion of urban areas, occurring most often through the conversion of agricultural or forested areas to residential and commercial land uses (Seto et al., 2014). More generally, 'land-use change' refers to the conversion of a spatial area from one dominant land-use type (e.g., agriculture) to another dominant land use type (e.g., residential development). 'Urban potential' refers to the likelihood that a spatial area (e.g., a parcel or the area within the geographic boundaries of a pixel) will be converted from an agricultural or forested land use to a residential or commercial land use based on historical development patterns and population projections (Meentemeyer et al., 2013).

Study Region

The city of Charlotte, North Carolina and its surrounding metropolitan areas are located in the middle of the United States' third largest "mega-region" (Florida, Mellander, & Stolarick, 2008). Our study area consisted of the six counties within North Carolina surrounding the city (Figure 1). The region is currently home to more than 1.6 million people (U.S. Census Bureau, 2015). However, that number is expected to increase by nearly 40% over the next 20 years with

207 2035 population projections at nearly 2.3 million (NCOSBM, 2015). Most development within
208 the region over the past 30 years has occurred through disjunct, low-density development leading
209 to a loss of both agricultural and forest lands. Region-wide projections suggest that under current
210 growth trajectories, over 200,000 ha of agricultural and forest land will be converted to
211 development by the year 2030 (Meentemeyer et al., 2013).

212
213 [FIGURE 1]
214

215 The land-use decisions made by small-scale non-industrial private forest owners play a
216 large role in shaping what the region's landscapes will look like in the future, since the majority
217 of undeveloped land throughout the region is held by these forest owners (Figure 2b). Most
218 forest owners throughout the region do not manage their properties for income generation, which
219 leaves many of them struggling to find the financial resources needed to meet growing property
220 tax burdens; less than 30% of the non-industrial private forest owners within the study area
221 qualify for the North Carolina present-use value program (Figure 2b). The landscapes of the
222 Southern Piedmont are also historically and culturally important, being some of the first non-
223 coastal landscapes settled in the early 1700s (Blythe & Brockmann, 1961). Many forest owners
224 living throughout the region today attach strong emotional and psychological meanings to the
225 landscapes they and their families have lived on for centuries (BenDor, Shoemaker, Thill,
226 Dorning, & Meentemeyer, 2014). These strong emotional and psychological meanings may
227 cause forest owners to hold on to their properties, even if it is not financially logical to do so. To
228 explicitly and experimentally evaluate how forest owners weigh the tradeoffs associated with

encroaching development pressure, we designed and administered a discrete choice experiment to a representative sample of forest owners living around Charlotte's urban fringe.

[FIGURE 2]

Discrete Choice Experimental Design

Econometric Model of Forest Owners' Intent to Sell. There are a variety of methods to quantify the value forest owners ascribe to their properties; some of which rely on revealed preferences (i.e., their observed behaviors such as selling or leasing their forest land (e.g., Adams & Turner, 2012)) and others which rely on forest owner's stated preferences to alternative hypothetical scenarios. Stated preference studies are particularly appealing to economists studying land use planning issues because they provide the opportunity to measure forest owners' preferences to a variety of future policy and land use scenarios. Stated preference methods are grounded in the idea that if changes in forest ecosystems can be represented by a set of attributes, choices by forest owners among sets of alternatives can yield insightful information about which potential policies or land use patterns would yield the most benefit to forest owners (Holmes & Boyle, 2003). The stated preference method we employed here was a relatively simple discrete choice experiment (Louviere, Hensher, & Swait, 2000)

The discrete choice experiment involved presenting forest owners with a series of hypothetical scenario pairs, asking them to carefully consider the conditions described in each scenario and then make a decision about under which scenario they would most likely sell their property. Given land-use change within our study area is dominated by the development of

agricultural and forest land (BenDor et al., 2014; Singh, Vogler, Shoemaker, & Meentemeyer, 2012), we assume an intent to sell will result in the conversion of the property to either a residential or commercial land use. Each scenario presented three attributes:

- 1) a change in the forest owner's current property value ($\Delta property_value$);
- 2) the distance from the forest owner's property to a new development ($distance_to_development$); and
- 3) whether or not the forest owner's property qualified for a present use value program ($puv_qualify$).

Stated preference methods are consistent with random utility theory (McFadden, 1973), which allows us to estimate the benefits (i.e., utility) associated with changes in the attributes presented to forest owners. Random utility theory involves linking the utility to forest owner's actual choices via a random utility function. The random utility function assumes an individual's preferences j across choice set t are the sum of systematic (V_{ijt}) and random components (ε_{ijt}) such that

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}. \quad (\text{Equation 1})$$

In Equation 1 U_{ijt} is the true albeit unobservable utility individual i associates with alternative j across choice set t . V_{ijt} are a vector of attributes describing hypothetical future scenarios and ε_{ijt} is the unobserved or random component of utility. It is important to note here the design of our discrete choice experiment is relatively simple. It does not account for the

different types of development that might be encroaching upon a forest- or farm-owner's property. Development can range from low-density residential development to mixed-use residential/commercial space to high-density commercial construction. Rather than being a limitation, we feel this ambiguity allowed respondents to determine for themselves, what type of development would most likely occur near their property. Additionally, given the context of our study we were focused exclusively on individuals' intent to sell their property *for development*. Other research has quantified the probability of landowners' managing their land for a variety of different land uses (e.g., agricultural production, pasture, forest, rangeland and urban development) (Lubowski, Plantinga, & Stavins, 2006, 2008). Quantifying conversion functions for *multiple* land-use types, as opposed to the undeveloped/developed dichotomy that we focus on here, and then coupling those empirically-grounded functions with an urban growth model capable of handling them would be a significant advancement to land change science.

Experimental Design, Attributes and Levels. The experimental design involved varying two of the attributes $\Delta property_value$ and $distance_to_development$ across three levels and varying the third attribute $puv_qualify$ across two levels (Table 1). Consequently, there were $3^2 \times 2^1 = 18$ total possible hypothetical scenarios. We deemed it too burdensome to have forest owners respond to 9 scenario pairs, subsequently opting for a fractional factorial design including 6 scenario pairs. The choice of which scenarios to include in the final experimental design were guided by the strategies presented by Louviere et al. (2000).

[TABLE 1]

Immediately prior to the presentation of the discrete choice pairs, forest owners were informed that we were “interested in the factors that influence individuals’ decision to sell or hold their wooded land, including how property values, proximity to new development and present-use value programs affect woodland owners’ decisions, if at all.” Respondents were then provided with a brief narrative of what “new development” referred to and what present-use value programs are; the full instrument is shown in Figure 3.

[FIGURE 3]

Data Collection

Data were collected via two self-administered mail-back surveys sent to a sample of small-scale non-industrial private forest owners living within the study area (Figure 2a). To be included in the sample, forest owners must have owned more than 2 ha of contiguous forest (determined via analysis of 2011 Landsat and LiDAR data (Singh et al., 2012)). The first survey was focused explicitly on forest owners’ beliefs (e.g., their sense of place), their past behaviors and their sociodemographic characteristics. The second survey only delivered the discrete choice experiment. The first survey was administered between November 2011 and April 2012 to 143 forest owners while the second survey was administered in November 2013 to the 126 forest owners who completed the first survey. Both survey packets mailed to respondents included a personalized map showing the forest owner’s property. A cover letter was also attached asking forest owners to respond to the questions in reference to their individual wooded land (excluding other forested land they might have owned). We included these explicit instructions to help ensure respondents felt they had a vested interest in the outcome of the choice question.

Of the 126 forest owners who received the discrete choice experiment, 64 completed and returned the instrument. This 49.6% response rate is acceptable for mail surveys administered to the general public or landowners (Dillman, Smyth, & Christian, 2008). Five forest owners indicated their property had been sold since they responded to the first mail-back survey two years earlier. All analyses were completed on data collected from the remaining 59 forest owners.

Sample Characteristics

Characteristics of Forest Owners and their Properties. Summary statistics describing the sample's sociodemographic characteristics and the characteristics of their properties are shown in Table 2 for reference. Although our sample of landowners had similar characteristics to those of the broader population of private forest owners nationwide, they do appear to be more educated (Butler et al., 2016).

[TABLE 2]

Sense of Place. Jorgensen and Stedman's (2006) 12-item psychometric scale was included in the first survey to measure forest owners' psychological connections to wooded areas on their property. On average, forest owners indicated they hold strong personal meanings towards their wooded land as responses to the statement items, which were measured on a 5-point Likert scale, ranged from 2.53 to 3.92 (Table S1). We analyzed data obtained via the scale for reliability (Cronbach's $\alpha > 0.70$; Nunnally & Bernstein, 1994) and adequate factor loadings ($\lambda > 0.60$; Hair, Black, Babin, & Anderson, 2009). With these psychometric properties satisfied

(reported in Table S1), we calculated a single *sense_of_place* factor score for inclusion in subsequent regression analyses.

Analysis

Bayesian Analysis. We populated the design matrix V in Equation 1 with the three variables directly included in the discrete choice experiment as attributes ($\Delta\text{property_value}$, $\text{distance_to_development}$ and puv_qualify). We also populated the matrix with the *age* and *income* of the forest owner, the *sense_of_place* construct and the total size of the wooded areas on their property. Age and income were included as controls, given previous analyses of these data has revealed age to be a significant predictor of both forest owners' willingness to allow woody biomass to be harvested from their properties (Dorning, Smith, Shoemaker, & Meentemeyer, 2015) and their willingness to opt into a voluntary payments for carbon storage program (Smith et al., 2016).

We fit the inferential model using a Bayesian hierarchical mixed effects regression model. Bayesian analysis assumes all unknown parameters of interest are random, and can consequently be informed and updated through prior information (Bernardo & Smith, 2000). This assumption contrasts frequentist analysis in which unknown parameters are assumed to be fixed. Bayesian analysis utilizes the Bayes rule to generate posterior distributions of unknown parameters by updating observed data with prior information or assumptions about the distribution of those parameters (Tanner & Wong, 1987). The posterior distributions are proportional to a combination of the observed data and some prior knowledge (posterior $\propto$ likelihood $\times$ prior). Estimates of the posterior distribution are updated through Markov chain Monte Carlo (MCMC) sampling of the prior distribution. MCMC sampling is required because

Bayesian estimators (e.g., posterior means and standard deviations) cannot be simultaneously derived through closed form integration (Bernardo & Smith, 2000). Parameters describing posterior distributions (e.g., means and interval estimates) are updated at each MCMC simulation. Once the MCMC sampling converges, typically after several thousand simulations, the parameters describing the posterior distribution can be assumed stable. Formal hypotheses are tested in Bayesian analysis through interval-hypothesis testing where the probability that an estimated parameter of the posterior distribution fits within an particular interval range is evaluated (Carlin & Louis, 2008).

Choice Experiment Model Specification. Our inferential logistic regression model, grounded in random utility theory and the estimation of the random utility function (Equation 1) is formally specified as:

$$U_{ijt} = a_{ij} + \sum_j^3 \beta v_{it} + \beta z_i + \varepsilon_{ijt}. \quad (\text{Equation 2})$$

In Equation 2, U_{ijt} is the utility individual i receives from choosing j (a preference to sell their forested property) in scenario t . a_{ij} is the respondent specific intercept for alternative j arising from individual i 's unobserved preferences. The β 's are the vectors of estimated coefficients, which do not vary over individuals or choice occasions, related to the vectors of v . These vectors are simply the levels corresponding to the three attributes j ($\Delta property_value$, $distance_to_development$ and $puv_qualify$). We also include a set of individual-level vectors z (age , $income$, $sense_of_place$ and $forested_acres$) as controls; each of these are associated with an estimated coefficient β .

Using a Bayesian approach, we must assume a distribution for all of the coefficients of interest (β s). We assume prior distributions for all fixed effects coefficients are normally distributed, centered on zero ($\mu = 0$) with large variance $\sigma^2 = 10e^{10}$; this is common in Bayesian applications (Hadfield, 2010). The prior for the variance structure was drawn from an Inverse-Wishart distribution with expected (co-)variances set to one and the degree of belief parameter set to zero. We also fit a hierarchical logistic regression using a frequentist approach for comparison.

Development Potential Model Specification. Our primary motivation for adopting a Bayesian approach is that it provides an opportunity to use parameter estimates derived from the choice experiment as informative priors in a subsequent spatial model which predicts the potential of each parcel within the study area to be developed based upon historical development patterns and parcel-specific attributes which match the attributes presented to forest owners in the choice experiment. The *development potential* model is a geospatial hierarchical statistical model with a binary response variable corresponding to lands that transitioned between undeveloped and developed between 2000 and 2011 (0 = developable land that did not develop during the 11-year time period; 1 = developable land that did develop during the 11-year time period). This response variable was constructed using National Land Cover Database datasets and was fit using a stratified random sample of 1,724 grid cells (866 transition cells, 862 no change cells), distributed across the six county study area. The development potential model for this region was originally introduced by Meentemeyer et al. (2013) and fit to a stratified-random sample of 1,450 grid cells distributed across the 11 counties surrounding the Charlotte urban area for the years 1996-2006. There were five predictors of development in the original development potential model; these are described in Table 3.

[TABLE 3]

In this paper, we update the original development potential model by: 1) fitting it to parcel data (as opposed to pixel data); 2) introducing additional independent variables believed to influence forest owners' decisions regarding whether or not they will sell their property for development; and 3) informing those additional variables (via prior distributions) with the parameters estimated by the choice experiment model described above.

The additional independent variables introduced into the development potential model are distance to new development (*distance_to_development*), property value (*property_value*) and qualification for the North Carolina present-use value program (*puv_qualify*). These variables are described, and their data sources are detailed, in Table 3.

To examine and illustrate the influence of informing the development potential model with informative priors generated by a choice experiment, we re-estimated the pixel-based model introduced in Meentemeyer et al. (2013) with the additional independent variables believed to affect forest owners' decisions. Next, we fit the model to parcel data acquired for the same temporal span (2000 to 2011) as the data used to fit the pixel-based model. The model was fit with a hierarchical Bayesian mixed-effects logistic regression estimation procedure. All parameters were estimated using noninformative priors (explained in the Choice Experiment Model Specification section). Finally, we fit the development potential model to just those parcels that comprised the survey's sampling frame (Figure 2b). We used the same hierarchical Bayesian mixed-effects logistic regression estimation procedure. This model, however, used prior distributions generated from the choice experiment model on a subset of the fixed effects

predictor variables (the spatial analogues of the scenario attributes in the choice experiment). Specifically, the priors were: *Δproperty_value* ($\bar{\mu} = 1.719$); *distance_to_development* ($\bar{\mu} = -0.446$) and *puv_qualify* ($\bar{\mu} = -0.251$). Following Bayes' rule, the posterior distribution of all β s is estimated by combining the assumed prior distributions and the observed parcel data y ; this is expressed as:

$$f(\beta|y) = \frac{f(\beta)f(y|\beta)}{f(y)}. \quad (\text{Equation 3})$$

The numerator is the joint density of the observed data and the prior distribution and the denominator is the distribution of the observed data (Hosmer, Lemeshow, & Sturdivant, 2013). The posterior distribution was estimated using the Metropolis-Hastings algorithm and Gibbs sampling, a common and efficient method of MCMC sampling (Casella & George, 1992). All statistical analyses were performed using the MCMCglmm package in R (Hadfield, 2010; Knudson, 2015).

Results

Choice Experiment Model

Before moving to inference, we assessed the convergence of the MCMC simulations by visually inspecting the movement of each coefficient of interest throughout the 200,000 MCMC iterations (the plots are illustrated in Figure 4). Across all estimated coefficients, the trace plots exhibited no evidence of non-stationarity (trend). Additionally, the between-run autocorrelations (not shown) trailed off quickly, suggesting good mixing of the chain.

[FIGURE 4]

The results of fitting Equation 2 with a hierarchical Bayesian mixed-effects logistic regression specification are shown in Table 4. The results of the Bayesian specification revealed changes in each of the choice experiments attributes resulted in notable effects on forest owners' intent to sell their properties. When a scenario described an increase in property values, the estimated posterior mean was 1.719; the odds of a forest owner selling their property are nearly 6 times higher if their property value were to increase by at least 10% from its current value (Odds ratio = $\exp^{1.719} = 5.58$).

[TABLE 4]

Forest owners were less motivated by encroaching development, as shown by the smaller absolute value of the estimated coefficients for the *distance_to_development* variable compared to the *Δproperty_value* variable. The sign of the estimated *distance_to_development* coefficient was negative, suggesting development closer to a forest owner's property is positively correlated with the probability of indicating an intent to sell their property. Effect size measures for the *distance_to_development* variable was -0.446, suggesting nearer development actually has a positive and linear effect on individuals' intent to sell their properties.

Qualifying for a present-use value program does not appear to have any meaningful influence on forest owners' intent to sell their properties. The mean of the posterior distribution of the *puv_qualify* variable was -0.251 with 0 within the 95% credible interval.

The emotional and psychological meanings individuals hold towards their forested property (*sense_of_place*) does not appear to influence their intent to sell their properties. The mean of the posterior distribution was -0.692 with 0 within the 95% credible interval. The results also suggested neither age, income or the number of forested acres on individuals' properties significantly influenced the probability of forest owners' indicating an intent to sell their property; zero was within the 95% credible interval for all three of these predictor variables.

Development Potential Model

All results presented below are for the updated development potential model, which includes the additional independent variables believed to influence forest owners' decisions regarding whether or not they will sell their property for development (*distance_to_development*, *property_value*, *puv_qualify*). Our first estimation was fit to all pixels (i.e., undeveloped in 2000) distributed across the six-county study region; the results of this model are presented in Table 5. The results revealed a negative correlation between the probability of a cell becoming developed and the distance to roads variable and a positive correlation between development and the development pressure variable (i.e., the number of neighboring developed cells within a search distance weighted by distance). Cells closer to roads existing in 2000 were more likely to be developed. Similarly, undeveloped cells with more development nearby were more likely to be developed. The results also revealed that the distance between an undeveloped cell and new development (i.e., new development in 2000) was negatively correlated with the probability of that cell becoming developed. Finally, the model revealed grid cells that fell within parcels which qualified for the North Carolina present-use value program were less likely to be developed in 2011 relative to those which did not qualify. The predicted probabilities of

development for all qualifying pixels within the study region are shown in Figure 5c. For comparison, the predicted probabilities of development estimated with the original Meentemeyer et al. (2013) model (i.e., minus the three additional explanatory variables), is shown in Figure 5b.

[TABLE 5]

[FIGURE 5]

Our second estimation was fit to all parcels (i.e., those that were undeveloped in 2000) distributed across the six-county study region; the results of this model are presented in Table 6. The results were similar to the model fit to all pixels. Specifically, we noted a negative correlation between the probability of a parcel becoming developed and the distance to roads variable, and a positive correlation between development probability and the development pressure variable. Similarly, the model revealed a negative relationship between the distance to newly developed parcels and a property becoming developed by 2011. Parcels that qualified for the present-use value program in 2000 were also less likely to be developed by 2011. Predicted probabilities of development for all qualifying parcels within the study region are shown in Figure 5d.

[TABLE 6]

Our third and final estimation was fit to just those parcels that comprised the survey's sampling frame (shown in Figure 2b); these were non-industrial private forest owners who had at

least 2 ha of forested area on their properties. This estimation used the parameter estimates derived from the choice experiment model as informative priors. The results, shown in Table 7, were similar to both the pixel based model and the parcel based model fit to all properties within the study region. Distance to roads showed a negative correlation with development probability and development pressure showed a positive relationship with development probability. Non-industrial private forestlands further away from new development as well as those which did not qualify for the present-use value program were less likely to be developed.

[TABLE 7]

Figure 6b shows a close-up of the predicted probabilities of derived from the *parcel-based* development potential model fit with non-informative priors. Figure 6c shows a close-up of the predicted probabilities of derived from the *parcel-based* development potential model fit with informative priors for all qualifying parcels owned by non-industrial private forest owners. Finally, Figure 6d shows the difference between the parcel-based surface derived using non-informative priors and the parcel-based surface derived using informative priors for all qualifying parcels owned by non-industrial private forest owners. A simple subtraction between the two surfaces (the development potential surface estimated with informative priors for all qualifying parcels owned by non-industrial private forest owners minus the development potential surface estimated for all parcels using non-informative priors) illustrates the differences obtained through the use of the linked modeling approach. Warmer colors represent qualifying parcels owned by non-industrial private forest owners that were mapped as having higher development potential when informative priors were used and cooler colors represent parcels

owned by non-industrial private forest owners that were mapped as having lower development potential when informative priors were used. Though the differences are small, by using parcel-level information in addition to choice experiment data informed by respondent preferences, we see more heterogeneity than in the pixel-based models of development potential. In areas with high property values, as well as in areas that are closer to development, we start to see divergence in development potential between parcels owned by non-industrial private forest owners and parcels owned by other types of landowners.

[FIGURE 6]

Discussion

The first objective of this research was to empirically quantify how forest owners in a rapidly urbanizing region make decisions when faced with encroaching development. To date, relatively little research has attempted to address this question. There undoubtedly has been a large body of empirical research focused on quantifying the effects of urbanization on property values using revealed preference data such as property transaction data and public tax records (most of this work comes from the fields of agricultural and natural resource economics). This research however, fails to acknowledge that forest owners' decisions are driven by a variety of factors besides the well-documented rise in property values (and taxes) that accompany urban encroachment. These factors can include the heterogeneity in forest owners' perceptions of encroaching development, as many may not perceive, understand or value the impacts that urban expansion has on the production of ecosystem services. These factors can also include the availability of land-use policies, such as alternative property tax mechanisms, designed to

alleviate the rising financial burdens faced by individuals who may not want to sell their forested properties. Logically, these factors can also include forest owners' sociodemographic characteristics (household income being foremost among them) as well as the psychological attachments they hold towards their properties. To measure each of these characteristics, and more importantly quantify their influence on forest owners' land-use decisions, a broader suite of social science methodologies needs to be employed. Recent research has begun to utilize stated preference data, collected through surveys administered to forest owners, to develop a more holistic understanding of what drives forest owners' land-use decisions when faced with nearby urban development (Rozance & Rabotyagov, 2014). Our research builds upon this emerging body of knowledge through the application of a discrete choice experiment delivered explicitly to the non-industrial private forest owners whose individual decisions will shape the trajectory and spatial patterns of urban growth within one of the United States' most rapidly growing mega-regions, the areas surrounding Charlotte, North Carolina.

Using data collected from a sample of forest owners living throughout the region, our choice experiment model revealed rising property values positively influenced the probability of a forest owner indicating he/she would sell his/her property. This result was expected given most non-industrial private forest owners in the United States do not manage their properties for income generation (Butler, 2008), making them especially vulnerable to fluctuations in property values and property tax rates (Butler et al., 2012; Greene et al., 2014; Ma et al., 2014). Our sample of forest owners were similar to the broader population of forest owners throughout the nation in that the vast majority (71%) indicated they did not manage their property for income-generating purposes (Butler et al., 2016). This result is also consistent with Rozance and

593 Robotyagov's study of forest owners' intent to develop their forested properties in the Pacific
594 Northwest (2014).

595 Our choice experiment model also revealed the closer that development occurred to an
596 undeveloped and forested property, the more likely the owners of that property would be to sell.
597 This result was also expected given our assumption and previous empirical research (Bengston,
598 Asah, & Butler, 2010; Kilgore et al., 2015; Majumdar, Laband, Teeter, & Butler, 2009) which
599 suggests non-industrial private forest owners highly value the more 'rural' and 'natural'
600 landscapes which surround their properties. While our data do not allow us to explicitly state that
601 forest owners associate nearby development with a loss of valued ecosystem services, the
602 random utility framework which grounds our model's specification enables us to infer that new
603 development closer to a forest owner's property results in a substantial and negative impact on
604 the value (or more explicitly put, utility) which he/she derives from owning his/her property.
605 More focused research is needed to explicitly determine which ecosystem services (e.g., carbon
606 sequestration, wildlife habitat, clean water, etc.) forest owners in urbanizing regions value most.
607 This work would enable the development of focused policies, specifically payments for
608 *individual* ecosystem services that would tap into forest owners' motivations for owning their
609 land while simultaneously providing them with some monetary relief from the rising property
610 values.

611 Our choice experiment model also revealed qualifying for the North Carolina present-use
612 value program did not have a substantial influence on forest owners' intent to sell their
613 properties. This result may not be particularly surprising given the program was not explicitly
614 designed as a mechanism to limit urban growth. Rather, the program provides the opportunity to
615 ease the tax burden of forest owners *if* they agree to and implement a forest management plan for

the woodlands on their property. These management plans often involve harvesting operations that, while providing an additional revenue stream for forest owners, do not align with the values they attach to their lands and their motivations for ownership. Tax-relief programs like the North Carolina present-use value program may be effective at achieving their intended goal of reducing the property taxes paid by forest owners while simultaneously bolstering the state's forestry industry, however our results indicate they are not effective at influencing the decision-making process related to selling private forestlands for development. In rapidly urbanizing regions, like our study area, progressive land-use policies are needed that meet all three objectives: reducing the burden of rising taxes faced by private forest owners; supporting local and regional forestry industries which tend to stagnate or decline as urban areas consume harvestable woodlands (Stein et al., 2005); and providing flexibility in allowing forest owners to choose how their forest lands are managed (i.e., not explicitly requiring harvesting). To our knowledge, no current land-use policies exist that satisfy all three of these desirable objectives. However, the growing interest in payments for ecosystem services provided by forests in urban areas (Patterson & Coelho, 2009) may lead to the implementation of effective and novel policy mechanisms.

The second objective of this research was to illustrate how stated preference data related to forest owners' land-use decisions could be used to inform spatially explicit projections of potential future urban growth. We accomplished this by applying a Bayesian statistical specification to an established geospatial model designed to predict the potential for future urban development based upon historical development patterns. The Bayesian specification allowed us to incorporate prior knowledge about forest owners' decision-making behavior (i.e., what we learned from the choice experiment model) into the spatially explicit development potential model. The development potential model introduces other important contextual variables such as

development pressure, distance to roads and county-level effects likely to influence *where* urban growth occurs in the future. By empirically-linking the choice experiment model to the development potential model using a Bayesian approach, we were able to generate spatially-explicit estimates of development potential that, importantly, are informed by primary data collected from the forest owners whose future land-use decisions will affect how and where urbanization occurs throughout the study area. As shown in Figure 6 and described in the results section, the Bayesian parcel-based development potential model fit with informative priors allowed us to better discern heterogeneity and variation across the development potential surface. We were able to fit the parcel-based development potential model to just those forested parcels that could be developed; doing so allowed us to produce more valid estimates of development potential. More explicitly stated, the use of informative priors resulted in a model more finely tuned to the decision-making factors affecting land-use transitions throughout the region. More research on the incorporation of stated preference data into spatially explicit models of development potential is needed. The selective use of informative priors to parameterize urban growth models can be used in a variety of ways. For example, it could be used to better capture the heterogeneity in tastes and preferences among landowners. It could also be used to quantify behavioral responses to specific drivers/inhibitors of urban growth that only occur at specific locations across the urban gradient (e.g., behavioral responses to the development inhibiting invasive plant Japanese knotweed). Future research along these lines would provide a deeper understanding of the dynamic feedbacks that human decision-making processes have on the location and timing of future urban growth.

Urban areas are expanding in size and density across the globe, a trend that shows no signs of slowing (Seto et al., 2011, 2012). Consequently, the ecosystem services produced by

662 agricultural and forested landscapes near urban areas are threatened. Planning for future growth
663 in a sustainable manner will require progressive land-use policies that are both responsive to, and
664 explicitly targeted at, the factors driving individuals' land-use decisions. We have been able
665 develop an understanding of the important factors affecting the land-use decisions of forest
666 owners living around one of the United States' most rapidly growing regions. By linking the
667 results derived from this experiment to a model estimating the potential of land transitions from
668 undeveloped to developed, we have created a more robust conceptualization of the urbanization
669 process. This conceptualization acknowledges urban growth is an aggregate product of human
670 decisions, which are themselves a function of how individuals evaluate competing factors
671 associated with encroaching development. Our research demonstrates rigorously employed social
672 science research can be used to inform spatially explicit projections of where urban growth is
673 most likely to occur in the future.

Table 1

Attributes and levels used in experimental design.

Attribute	Levels
Change in the forest owner's current property value (<i>Δproperty_value</i>)	No change Increase 10% Increase 20%
Distance from the forest owner's property to a new development (<i>distance_to_development</i>)	1000 feet (304.8 m) 1 mile (1.61 km) 2 miles (3.22 km)
Whether or not the forest owner's property qualified for a present use value program (<i>puv_qualify</i>)	Do not qualify Qualify

Table 2Characteristics of forest owners and their properties ($n = 59$).

	Percent	Mean	S.D.	Range	
				Min.	Max.
Characteristics of forest owner					
Age		64.3	11.4	47	91
Education					
High school degree or equivalent	15.3				
Some college (no degree)	17.0				
College degree	40.7				
Some graduate school	5.1				
Graduate degree or higher	22.0				
Gender (female)	28.8				
Income					
Less than \$24,999	13.6				
\$25,000 - \$49,999	10.2				
\$50,000 - \$74,999	23.7				
\$75,000 - \$99,999	17.0				
\$100,000 - \$149,000	15.3				
\$150,000 - \$199,999	13.6				
More than \$200,000	10.2				
Unsure/Don't Know	6.8				
Sense of place		0.0	1.0	-2.3	1.4
Characteristics of forest owners' property					
Forest size (ha)		6.9	8.5	1.0	51.0
Management plan present	32.7				
Timber harvested for income generation	23.7				
Economic value (thousands \$US) ¹		399.1	400.5	34.3	2553.0

¹ Tax assessed value of entire parcel.

Table 3

Predictor variables in the development potential model.

Meentemeyer et al.'s (2013) <i>pixel-based</i> development potential model					The <i>parcel-based</i> development potential model estimated in this paper				
Variable	Description	Base data	Year(s)	Data source	Variable	Description	Base data	Year(s)	Data source
Development pressure	Number of neighboring developed cells within set search distance weighted by distance	Historical development patterns	1996, 2006	Remote sensing	Development pressure	Number of neighboring developed parcels within set search distance weighted by distance	Historical development patterns	2000, 2011	National Land Cover Database (NLCD)
Distance to interchanges	Distance from cell center to nearest interchange	Primary and secondary road networks	1996	North Carolina Dept. of Transportation	Distance to roads	Distance from cell center to nearest road	Primary and secondary road networks	1996	North Carolina Dept. of Transportation
Distance to roads	Distance from cell center to nearest road	Primary and secondary road networks	1996	North Carolina Dept. of Transportation	Distance to new development	Distance from cell center to new development	Historical development patterns	2000, 2011	NLCD
Land cover	Lands designated as forest or farmland	LiDAR vegetation height; Landsat TM imagery	1996, 2006	Charlotte-Mecklenburg County Storm Water Services; US Geological Survey	Property value	Property values from parcel data	North Carolina County parcel data	2015	North Carolina County parcel data (NC Onemap)
Development pressure $\times$ land cover	Interaction between development pressure and land cover	n/a	1996, 2006	n/a	Qualification for North Carolina's present-use value program	Parcels of contiguously forested land that is greater or equal to the minimum required to qualify for the present-use value program (20 acres)	Land Cover data identified as forested	2011	NLCD

Table 4

Results of hierarchical Bayesian logistic regression.

Independent variables (fixed-effects)	Posterior mean	95% Cred. Interval		Effective sample size	pMCMC ^a
		L.B.	U.B.		
Choice attributes					
Increased Property value (<i>Δproperty_value</i>)					
Levels					
No change	1.719	1.340	2.090	1482	5.0e ⁻⁵
+10% increase					
+25% increase					
New development nearby (<i>distance_to_development</i>)					
Levels					
1000 ft (305 m)	-0.446	-0.814	-0.099	3344	0.013
One mile (1.6 km)					
Two miles (3.2 km)					
Qualify for present-use value program (<i>puv_qualify</i>)					
Levels					
Do not qualify	-0.251	-0.799	0.286	3410	0.357
Qualify					
Characteristics of the forest owner or their property					
Age	-0.074	-0.158	0.003	1577	0.062
Income	0.053	-0.312	0.419	2267	0.763
Sense of place	-0.692	-1.628	0.193	1568	0.117
Forested acres	-0.202	-1.266	0.852	2883	0.699
Hierarchical (random) effects					
Respondent	7.795	2.955	13.710	207	n/a

n = 59 (354 discrete choices)

MCMC iterations = 200,000

Burn-in = 10,000

^a Probability the posterior mean is different from zero.

Table 5Results of hierarchical development potential model fit to data derived from *pixels*.

Independent variables (random-effects)	Posterior mean	Standard Error	Effective sample size	pMCMC ^a	Coef.
~idh (Development pressure: County)	0.004	—	871.4	—	0.004
Development pressure: Cabarrus	-0.009	—	—	—	-0.009
Development pressure: Iredell	-0.017	—	—	—	-0.017
Development pressure: Mecklenburg	-0.019	—	—	—	-0.019
Development pressure: Rowan	0.007	—	—	—	0.007
Development pressure: Stanley	0.043	—	—	—	0.043
Development pressure: Union	-0.006	—	—	—	-0.006
Independent variables (fixed-effects)					
County-specific intercepts					
Intercept (Cabarrus county)	-0.051	0.003	4526	0.842	-0.051
Iredell county	-0.624	0.004	4952	0.032*	-0.675
Mecklenburg county	1.377	0.004	4508	<6e ^{-05***}	1.326
Rowan county	-1.662	0.005	3545	<6e ^{-05***}	-1.713
Stanley county	-3.126	0.017	951	<6e ^{-05***}	-3.177
Union county	-0.335	0.003	5104	0.200	-0.386
Landscape variables					
Distance to roads	-0.298	0.002	3326	0.019*	-0.298
Landcover (Forest = 1/Farmland = 0)	0.264	0.002	4002	0.094	0.264
Development pressure	0.185	0.001	4449	0.001**	0.185
Variables affecting forest owners' decisions					
Distance to new development	-9.120	0.101	3484	0.124	-9.120
Property value	0.030	0.001	927	0.004**	0.030
Qualify for present-use value program	-3.140	0.012	1074	<6e ^{-05***}	-3.140

 $n = 1,724$

MCMC iterations = 200,000

Burn-in = 20,000

^a Probability the posterior mean is different from zero.

Table 6

Results of hierarchical development potential model fit to data derived from *parcels* (using non-informative priors and applied spatially to all parcels).

Independent variables (random-effects)	Posterior mean	Standard Error	Effective sample size	pMCMC ^a	Coef.
~idh (Development pressure: County)	0.006	—	1416	—	0.004
Development pressure: Cabarrus	-0.015	—	—	—	0.118
Development pressure: Iredell	0.007	—	—	—	0.140
Development pressure: Mecklenburg	-0.055	—	—	—	0.078
Development pressure: Rowan	0.013	—	—	—	0.146
Development pressure: Stanley	0.053	—	—	—	0.186
Development pressure: Union	-0.001	—	—	—	0.132
Independent variables (fixed-effects)					
County-specific intercepts					
Intercept (Cabarrus county)	0.648	0.004	4477	0.011*	0.648
Iredell county	-0.822	0.004	4984	0.005*	-0.174
Mecklenburg county	1.646	0.004	4094	<6e-05***	2.294
Rowan county	-1.667	0.600	3769	<6e-05***	-1.019
Stanley county	-3.272	0.015	1190	<6e-05***	-2.624
Union county	-0.346	0.004	5004	0.182	0.302
Landscape variables					
Distance to roads	-0.498	0.002	3648	<6e-05***	-0.498
Landcover (Forest = 1/Farmland = 0)	-0.087	0.003	4108	0.644	-0.087
Development pressure	0.133	0.002	8395	0.004**	0.133
Variables affecting forest owners' decisions					
Distance to new development	-1.889	0.010	3769	0.004**	-1.889
Property value	0.033	0.001	1037	0.002**	0.033
Qualify for present-use value program	-3.208	0.015	842	<6e-05***	-3.208

$n = 1,724$

MCMC iterations = 200,000

Burn-in = 20,000

^a Probability the posterior mean is different from zero.

Table 7

Results of hierarchical development potential model fit to data derived from *parcels* (using priors informed by the choice experiment and applied spatially to only qualifying non-industrial private forest parcels).

Independent variables (random-effects)	Posterior mean	Standard Error	Effective sample size	pMCMC ^a	Coef.
~idh (Development pressure: County)	0.006	—	1416	—	0.006
Development pressure: Cabarrus	-0.015	—	—	—	0.117
Development pressure: Iredell	0.008	—	—	—	0.140
Development pressure: Mecklenburg	-0.056	—	—	—	0.076
Development pressure: Rowan	0.012	—	—	—	0.144
Development pressure: Stanley	0.053	—	—	—	0.185
Development pressure: Union	-0.001	—	—	—	0.131
Independent variables (fixed-effects)					
County-specific intercepts					
Intercept (Cabarrus county)	0.667	0.003	5442	0.003**	0.667
Iredell county	-0.835	0.004	5243	0.001*	-0.168
Mecklenburg county	1.640	0.004	4266	<6e-05***	2.307
Rowan county	-1.675	0.005	3936	<6e-05***	-1.008
Stanley county	-3.273	0.011	1587	<6e-05***	-2.606
Union county	-0.349	0.003	5855	0.144	0.318
Landscape variables					
Distance to roads	-0.491	0.002	3785	<6e-05***	-0.491
Landcover (Forest = 1/Farmland = 0)	-0.079	0.003	4485	0.658	-0.079
Development pressure	0.132	0.001	8869	0.005**	0.132
Variables affecting forest owners' decisions					
Distance to new development	-2.019	0.008	5168	<6e-05***	-2.019
Property value	0.034	0.001	965	0.004**	0.034
Qualify for present-use value program	-3.228	0.012	1084	<6e-05***	-3.228

$n = 1,724$

MCMC iterations = 200,000

Burn-in = 20,000

^a Probability the posterior mean is different from zero.

Table S1

Forest owners' responses to the 12-item sense of place scale.

Statement item	Completely disagree (%)	Somewhat disagree (%)	Neither agree nor disagree (%)	Somewhat agree (%)	Completely agree (%)	Mean	S.D.	Factor Loading
Everything about my wooded land is a reflection of me	9 (16.7)	9 (16.7)	15 (27.8)	7 (13.0)	14 (25.9)	2.83	1.65	0.68
My wooded land says very little about who I am (reverse coded)	19 (36.5)	10 (19.2)	15 (28.8)	1 (1.9)	7 (13.5)	2.05	1.50	— ^a
I feel that I can really be myself when I am on my wooded land	5 (8.9)	1 (1.8)	16 (28.6)	10 (17.9)	24 (42.9)	3.58	1.56	0.73
My wooded land reflects the type of person I am	6 (11.1)	8 (14.8)	13 (24.1)	15 (27.8)	12 (22.2)	3.02	1.59	0.81
I feel relaxed when I am on on my wooded land	2 (3.5)	4 (7.0)	7 (12.3)	16 (28.1)	28 (49.1)	3.92	1.41	0.68
I feel happiest when I am on my wooded land	4 (7.1)	5 (8.9)	12 (21.4)	15 (26.8)	20 (35.7)	3.50	1.52	0.85
My wooded land is my favorite place to be	5 (8.9)	6 (10.7)	16 (28.6)	11 (19.6)	18 (32.1)	3.32	1.54	0.80
I really miss my wooded land when I am away from it for too long	8 (16.0)	5 (10.0)	16 (32.0)	10 (20.0)	11 (22.0)	2.68	1.72	0.76
My wooded land is the best place for doing the things that I enjoy most	5 (9.3)	10 (18.5)	18 (33.3)	9 (16.7)	12 (22.2)	2.92	1.54	0.89
For doing the things that I enjoy most, no other place can compare to my wooded land	9 (16.7)	14 (25.9)	16 (29.6)	8 (14.8)	7 (13.0)	2.53	1.47	0.71
My wooded land is not a good place to do the things I most like to do (reverse coded)	27 (50.0)	16 (29.6)	5 (9.3)	4 (7.4)	2 (3.7)	1.67	1.19	— ^a
As far as I'm concerned, there are better places to be than on my wooded land (reverse coded)	22 (40.7)	14 (25.9)	9 (16.7)	5 (9.3)	4 (7.4)	1.95	1.37	— ^a

Overall scale $\alpha = 0.93$ ^a Item dropped due to poor factor loading before assessment of measurement model fit and calculation of *sense_of_place* factor score.

Figure 1. Study area.

Figure 2. (a) The study area with land cover and survey points. (b) Parcels that comprise the study's sampling frame of forest owners classified by whether or not the parcel qualifies for the present-use value program.

Part 1. Likelihood of Selling Your Property
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We are interested in the factors that influence individuals' decision to sell or hold their wooded land, including how **property values**, **proximity to new development**, and **present-use value programs** affect woodland owners' decisions, if at all. Here, "new development" refers to clearing of previously undeveloped woodland or farmland in order to build structures or infrastructure. Qualifying for a present-use value program would allow the value of your land to be based on current use as agricultural or forested land, resulting in a substantial reduction in taxes. Note that we are not examining whether or not your land actually qualifies, therefore please ignore your actual present use value status.

To help us understand the importance of these factors, consider each pair of hypothetical conditions below. **For each pair please provide two responses: 1) which set of conditions would make you more likely to sell your wooded land shown in the attached map and 2) how likely you would be to sell your property under those conditions.** *Example: In the first pair choose between the first scenario where your property value has increased by 25%, new developments have been started within 1000 feet of your property and your wooded land does not qualify for the present-use value policy AND the second scenario where your property value has increased by 10%, new developments have started within one mile of your property and your wooded land does not qualify for present use value policy.*

Pair	Change in your current property value	Distance from your property to a new development	Availability of a present use value program	Under which of these two conditions, would you be most likely to sell your property?	Likelihood of selling
1	Increase 25%	1000 feet	Do not qualify	☐	____%
	Increase 10%	One mile	Do not qualify	☐	
2	Increase 10%	One mile	Do not qualify	☐	____%
	No Change	Two miles	Do not qualify	☐	
3	Increase 10%	1000 feet	Do not qualify	☐	____%
	No Change	One mile	Qualify	☐	
4	Increase 25%	One mile	Qualify	☐	____%
	No Change	1000 feet	Qualify	☐	
5	No Change	One mile	Do not qualify	☐	____%
	Increase 10%	1000 feet	Qualify	☐	
6	No Change	1000 feet	Do not qualify	☐	____%
	Increase 10%	Two miles	Do not qualify	☐	

☐ I would not sell my wooded land under any of these circumstances

Figure 3. Survey question

Figure 4. Diagnostic plots for posterior distributions generated from Bayesian estimation of the choice experiment eliciting forest owners' intent to sell their properties.

Figure 5. (a) The six county study area in North Carolina with a zoom-in on the focus area. (b) The *pixel-based* model with the same model and variables used in Meentemeyer et al. (2013). (c) The *pixel-based* model with the additional predictor variables related to the choice experiment (i.e., property values, distance to new development and qualification for the present use value program). (d) The *parcel-based* model with the additional predictor variables related to the choice experiment. All models utilized a Bayesian approach with non-informative priors (i.e., for fixed effects this equates to a mean of zero and very large variance, see methods for additional details).

Figure 6. (a) Six county study area with qualifying parcels owned by non-industrial private forest owners shown in green. (b) Results of the *parcel-based* development potential model fit with non-informative priors (see methods for more details). (c) Results of the *parcel-based* development potential model fit to only qualifying parcels owned by non-industrial private forest owners – modeled using priors generated by the choice experiment model (see methods for more details). (d) The difference between estimated development potential derived from the *parcel-based* model fit with non-informative priors and the *parcel-based* model fit with informative priors generated by the choice experiment model. Warmer colors represent qualifying parcels owned by non-industrial private forest owners that were mapped as having higher development potential when informative priors were used and cooler colors represent parcels owned by non-industrial private forest owners that were mapped as having lower development potential when informative priors were used.

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