Spatial and Temporal Heterogeneity of Carbon Storage and Optimal Provision of Carbon Storage

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Dedication

I reserve this page to express my sincere gratitude to my friends, colleagues, faculty, and staff at the Department of Agricultural and Resource Economics, the University of Tennessee. I remember the first day when I arrived at Morgan Hall and met Dr. Bill Park as my undergraduate advisor. I also recall how excited I was to take classes as a freshman in college. My next major meeting was with Dr. Roland Roberts about the graduate committee's decision to accept me in the Master Program. These were just some of moments that reflect critical turning points in my life. I am sure there is a long list of names associated with crucial memories that I ought to include to give full credit for all their support for my success as a graduate student. I dedicate this section to thanking each and all of the faculty and staff members of the Department of Agricultural and Resource Economics, the University of Tennessee.

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Abstract

Human activity, particularly the conversion of natural land cover into human-dominated cover types, is putting increasing pressure on the health of the global ecosystem. Loss of forestland is a major contributor to greenhouse gas (GHG) emissions, which cause climate change because forests can help sequester GHG emission in the atmosphere. However, mitigating climate change by sequestering carbon through reforestation and/or avoiding deforestation is an appealing option because of the potential scale of such sequestration, the possible cost advantages over other mitigation efforts, and the opportunity it provides to incentivize the sustainable use of rural lands. Incentive payments can support forest-based carbon sequestration by internalizing the positive externalities generated by carbon storage in private forests.

In this thesis, we present two essays focusing on the efficiency of different incentive payment approaches that intend to account for the variations in the costs of supplying forest-based carbon storage. The first essay entitled, "Cost Efficiency of Payment Systems for Forest Carbon Sequestration Incorporating Spatial and Temporal Heterogeneities," mainly focuses on assessing the spatial and temporal heterogeneities in the costs of supplying forest-based carbon storage. The spatial distributions of the cost efficiency of carbon storage for each of the three periods are mapped to visually highlight the spatial and temporal variations of the cost efficiency of carbon storage (referred to as "cost-efficiency maps"). The cost-efficiency maps for each of the three periods can be used as a reference for spatial targeting of incentive payments under different periods. Our findings are particularly important and interesting as the growing literature on the cost efficiency of payment programs for ecosystem services has not considered the potential room for improvement in regards to their cost efficiencies using temporal heterogeneity.

The second essay, essay entitled, “Optimal Provision of Forest-Based Carbon Storage and Cost Effectiveness of Incentive Payment Approaches”, deals with estimating how much cost efficiency can be improved by incorporating asymmetric information between landowners and government agencies seeking to purchase forest-based carbon sequestration. Both essays use the U.S. Bureau of Economic Analysis’ (BEA) Economic Area 88, which consists of one Kentucky and 17 Tennessee counties as a case study.

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Chapter 1: Introduction

Introduction

Global climate change is considered to be the biggest threat to human health and to the environment in the 21st century (Kane et al., 2000; Walther et al., 2002; Parry el al., 2004; Patz et al., 2005; McMichael et al., 2006; Costello et al., 2009; Laczko and Aghazarm, 2009). Human induced activities such as land use conversion through the expansion of agriculture and urbanization contribute greatly to climate change (Vitousek et al., 1997; IPCC, 2001; Pielke et al., 2002; Kalnay and Cai, 2003). Changes in land use are known to impact ecosystem services through the loss, modification, and fragmentation of habitats, degradation of soil and water, and overexploitation of native species (Pimm and Raven, 2000; Wu, 2008; Eigenbrod et al., 2011; Sims et al., 2014; Cho et al., 2016). Incentive payments for promoting a range of ecosystem services have the potential to counter these land use changes (Sims, 2013). Much attention has focused on enhancing forest-based ecosystem services through incentive payments to landowners to prevent deforestation and encourage afforestation (Smith and Scherr, 2002; Wunder, 2005; Wünscher et al., 2006; Engel et al., 2008; Jack et al., 2008; Pagiola et al., 2008; Munoz-Pina et al., 2008; Claassen et al., 2008; Baylis et al., 2008; Ferraro, 2008; Wunder and Alban, 2008). One of the most notable incentive programs is the Conservation Reserve Program (CRP). Established in 1985, the CRP aims to protect environmentally sensitive cropland for soil conservation, water quality, and wildlife habitat (US Department of Agriculture Farm Service Agency, 2016).

Incentive payment programs like the CRP tend to be controversial because financial support for the establishment of the incentive payments is in short supply. Spatial heterogeneity in the costs of supplying ecosystem services plays a critical role in incentive payment design (Frimpong et al., 2006; Jandl et al., 2007; Hanley et al., 2012). The more finely public agencies

can resolve spatial variation in costs, use this information to allocate contracts, and set payment rates, the more cost effective payment programs become (Babcock et al., 1997a, 1997b; Antle et al., 2003; Zhao et al., 2004; Mason and Plantinga, 2011; Armsworth et al., 2012). For example, Babcock et al. (1997a, 1997b) shows that targeting rules based on the purchase of maximum land acreage for ecosystem services without consideration of spatial heterogeneity in their costs and benefits results in suboptimal levels of ecosystem services, given a fixed budget. The authors demonstrate that the relative variability of costs and benefits and correlation between the two are the most important determinants of the cost effectiveness of payment schemes.

Although spatial heterogeneity in the costs and benefits of supplying ecosystem services has received much attention, few, if any, studies have explicitly focused on the potential for payment programs for ecosystem services that account for both spatial and temporal heterogeneity to improve cost efficiency. The first essay contributes to the growing literature on the cost effectiveness of supplying ecosystem services using incentive payment programs by accounting for spatial and temporal heterogeneity in ecosystem services and opportunity costs of providing ecosystem services. Such innovation allows us to identify temporal variations in the spatial distribution of cost efficiency of carbon storage.

In the same vein as the first essay, the second essay focuses on estimating how much cost efficiency can be improved by estimating cost-efficient site-specific payments (referred to as "optimal payment scheme") for optimal provision of forest-based carbon storage that incorporates the spatial heterogeneities in forest carbon sequestration and opportunity costs for sequestering carbon, and then by comparing its cost efficiency with fixed-rate payment scheme (i.e., per-hectare carbon value and per-ton carbon value) that disregard the spatial variations. The findings will help policymakers select incentive payment mechanisms, identify would-be

participants, estimate payment amounts, anticipate budget outlays, and better understand and quantify the impacts of land use change on forest carbon sequestration.

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Chapter 2: Cost Efficiency of Payment Systems for Forest Carbon Sequestration Incorporating Spatial and Temporal Heterogeneities

Abstract

Concern is growing about climate change and its threats to human health, the environment, and ecosystems. Establishing new or expanding forest areas through afforestation, reforestation, and mitigation of deforestation by providing incentives can be an effective policy tool for offsetting greenhouse gases. Many studies have focused on the efficiency of different incentive payment approaches intended to account for the spatial variations in the benefits of forest-based ecosystem services and opportunity costs of forestland. Although spatial heterogeneity has received much attention, few, if any, studies have explicitly focused on the potential for payment programs for ecosystem services that account for both spatial and temporal heterogeneity to improve cost efficiency. The objective of this research is to assess the spatial and temporal heterogeneities in the costs of supplying forest-based carbon storage to help identifying spatial targeting of incentive payments under different time periods. Our empirical results for the 18-county case study show that there are spatial and temporal heterogeneities in the cost efficiency of carbon storage. Our findings are triggered by the difference in dynamics of the response of forestland changes to the change in net return of forest land. The different dynamic responses are triggered by the difference in the transition probabilities of forest-related land uses to the change of the payment to forestland owners, which depends on the margin for increasing transition probability of the increase in forestland with the higher payments. The cost-efficiency maps for each of the three periods can be used as a reference for spatial targeting of incentive payments under different periods.

1. Introduction

1.1. Background and objective

Concern is growing about climate change and its threats to human health, the environment, and ecosystems (Stavins, 1999; Canadell et al., 2007). The accumulation of greenhouse gases (GHG) in the atmosphere in the form of carbon dioxide (CO_2) is considered a major cause of climate change. Capturing atmospheric carbon through carbon sequestration can provide substantial GHG mitigation benefits (Silver et al., 2000). Establishing new or expanding forest areas through afforestation, reforestation, and mitigation of deforestation by providing incentives to landowners can be an effective policy tool for offsetting GHG emissions (Schroeder, 1992; Dixon et al., 1993; McCarl and Schneider, 2001; Balmford et al., 2002; Kindermann et al., 2008).

Many studies have focused on the cost efficiency of different incentive payment approaches intended to encourage forest-based carbon sequestration (Zhao et al., 2003; Lubowski et al., 2006; Fraser, 2009; Mason and Plantinga, 2011). The cost efficiency of incentive payment programs providing forest-based carbon sequestration depends on program design. The effectiveness of a program providing incentives to landowners to afforest non-forested land or sustain forests at risk of deforestation is likely related to whether the program accounts for heterogeneity in the land's capacity to sequester carbon and the opportunity cost of maintaining the forestland.

Heterogeneity in the land's capacity to sequester carbon, spatial heterogeneity, mainly stems from its spatial variation in quality, elevation, and geological conditions (Hardie and Parks, 1997; Wear and Bolstad, 1998; Antle et al., 2003; Frimpong et al., 2006; Jandl et al., 2007). On the other hand, heterogeneity in the opportunity cost of retaining forestland results

from spatial and temporal variations in land markets that change the relative returns from forestland and competing land uses (Lubowski et al., 2006). Accounting for these heterogeneities in comparing the cost efficiencies of different incentive payment approaches is important. For example, the cost efficiencies are likely different for a program that bases payments on estimates of the amounts of carbon actually sequestered ("carbon-based payment") and one that bases payments on the amounts of land that are either afforested or retained as forestland ("forest-based payment") (Babcock et al., 1997a, 1997b; Antle et al., 2003; Hanley et al., 2012). Although spatial heterogeneity has received much attention, few, if any, studies have explicitly focused on the potential for payment programs for ecosystem services that account for both spatial and temporal heterogeneity to improve cost efficiency.

The objective of this research is to assess the spatial and temporal heterogeneities in the costs of supplying forest-based carbon storage to help identifying spatial targeting of incentive payments under different time periods. We developed a case study that aimed to achieve the objective based on one of 179 Bureau of Economic Areas (U.S. Department of Commerce 2016), which consists of 17 Tennessee counties and 1 Kentucky county (Figure 2.1) over three time periods (i.e., 1992-2001, 2001-2006, and 2006-2011). This region was chosen to represent the larger Appalachian region that is considered to be the largest carbon sink among the six bioclimatic regions of the conterminous U.S. (Schimel et al., 2000; Tian et al., 2010). The three particular time periods were chosen because land use data we selected to obtain the opportunity cost of the forestland were collected for 1992, 2001, 2006 and 2011 from the National Land-Cover Dataset (NLCD) (see below).

This research contributes to the growing literature on the cost effectiveness of supplying ecosystem services using incentive payment programs by accounting for spatial and temporal

heterogeneity in ecosystem services and opportunity costs of providing ecosystem services. Such innovation allows us to identify temporal variations in the spatial distribution of cost efficiency of carbon storage. In particular, the spatial distributions of the cost efficiency of carbon storage for each of the three periods are mapped to visually highlight the spatial and temporal variations of the cost efficiency of carbon storage (referred to as "cost-efficiency maps"). The cost-efficiency maps for each of the three periods can be used as a reference for spatial targeting of incentive payments under different periods. Our findings are particularly important and interesting as the growing literature on the cost efficiency of payment programs for ecosystem services has not considered the potential room for improvement of their cost efficiencies using temporal heterogeneity.

1.2. Literature review

Despite the potential for ecosystem-service benefits, changes in forest-related land use is a complex issue that contends with deforestation pressures from other land uses such as urban development (Geist and Lambin, 2001; United Nations Framework Convention on Climate Change, 2006; Chomitz, 2006; Myers, 2008). The primary complication is that the value of forest-based ecosystem services is not captured in the market economy (Brander et al., 2010). Economists commonly refer to the value of ecosystem services as a positive externality and the phenomenon of market economy not capturing that value as a market failure. A considerable amount of work has been done to address the impact of internalizing the positive externalities into forest management and land-use decisions (e.g., Stainback and Alavalapati, 2004; Zhao et al., 2003; Silva-Chavez, 2005; Lubowski et al., 2006; Wunder, 2007; Bharrat, 2008; Ferraro, 2008; Fraser, 2009; Mason and Plantinga, 2011; Sims et al., 2013).

Many studies have focused on the efficiency of different incentive payment approaches intended to account for the spatial variations in the benefits of forest-based ecosystem services and opportunity costs of forestland. However, measuring and monitoring the benefits and the opportunity costs involved is challenging and potentially expensive (Richards and Stokes, 2004; Stavins and Richards, 2005; Kim and Langpap, 2014). Researchers have attempted to overcome such challenges by developing an approach that allows estimating the spatial heterogeneity in opportunity costs of supplying conservation benefits (Antle et al.,2003; Zhao et al., 2003; Fraser, 2009; Armsworth et al., 2012; Gibbons et al., 2011; Lewis et al., 2011; Hanley et al., 2012; Kim and Langpap, 2014; Polasky et al., 2014).

Despite abundant literature on their efficiency, the literature focusing on mitigating the financial burden of providing ecosystem services often ignores the temporal heterogeneity (Ando et al., 1998; Polasky et al., 2005; Naidoo and Ricketts, 2006; Spies et al., 2007; Nelson et al., 2008). Temporal heterogeneities in the benefits and costs of such programs come from many sources. Among them, temporal variation in the opportunity cost of forestland is a critical, but hitherto under-studied, source of temporal heterogeneity related to program costs and effectiveness. Because the unprecedented market fluctuations of recent years change the relative returns from forestland and competing land uses, and thus change the opportunity cost of forestland, temporal variation associated with the benefits and costs of a payment program has become increasingly crucial in designing these programs.

2. Methodology

The objective of this research is achieved through the pursuit of the following steps: Step 1. developing a one km^2 pixel-level, land-use model to estimate the site-specific opportunity costs of the forestland by linking land use changes and the relative returns from

different land uses; Step 2. employing a carbon simulation model to project site-specific carbon storage levels for the forest cover based on climate, forest type, disturbance and management history, and other environmental characteristics; Step 3. deriving annual pixel-level supply curves for carbon storage under each of the three periods based on predicted land-use change for an incrementally increasing net return of forestland in each of the three periods from the land use model and their corresponding changes in carbon storage from the carbon simulation model; and Step 4. contrasting and mapping distribution of cost efficiencies that allow each dollar is distributed among the pixels in the most efficient way using the annual pixel-level supply curves for carbon storage for each of the three periods under a hypothetical budget scenario. Below we discuss the details of each of the four steps.

2.1. Step 1. A land use model

Consider a risk-neutral, utility-maximizing, and price-taking landowner who faces the choice of allocationg a parcel of land among a set of alternative uses. Given this assumption, the dynamic character of land-use allocation may be modeled by viewing the land owner's decision on land use allocations over time that stems from the difference between the expected streams of net present returns from different activities (Lambert et al., 2016). Following the notation used in Lambert et al. (2016), a landowner g converts land use from category j to k during a period t for a spatial unit i, when the expected net returns (V_k) from land use k exceed the net returns from land use j, less the discounted cost of conversion from use j to k, ($C_{j,k}$). For example, if a unit of converted land is denoted as q and considering that $C_{j,j} = 0$.

$$q_{t,g(i),j,k} = \begin{cases} 1 \; if \; max_k(V_{t,k} - C_{t,j,k}) > V_{t-1,j} \\ 0 \; otherwise \end{cases}, \forall \, j, k, and \; t \qquad (1)$$

Since the variable q is not often observed we can use the total area corresponding with each land use to proxy q. Aggregating q across all g decision makers in spatial unit i, in period t, the total area (A) converted to each land use category in period t is $A_{t,i,k} = \sum_{j=1}^{K} \sum_{g(i)=1}^{G(i)} q_{t,g(i),j,k}$. The general form of the share of *k* land use during period t for a spatial unit i is $s_{t,i,k} = A_{t,i,k}/\overline{A_i}$, where $\overline{A_i}$ is the total area subject to conversion in i.

Following this framework, we model the land use decisions among five types of land use classification (i.e., cropland, pasture, urban, forest, and other) over three periods (i.e., 1992-2001, 2001-2006, and 2006-2011) at the one km^2 pixel level. It is hypothesized that the shares of five types of land uses are functions of the net returns from the land uses and other factors that affect land use decisions. Because the land use decisions are intertemporally connected, it is important to understand the probabilities of transitioning from one type of land use to another (referred to as "land-use transition probabilities") over each of the three periods. To do so, it was estimated the Multinomial logistic Markov transition probabilities using maximum likelihood (ML) based on similar methods employed in previous studies (MacRae, 1977; Miller and Plantinga, 1999; Ahn et al., 2000; Plantinga and Ahn, 2002; Lambert et al., 2016).

Specifically, and following Lambert et al. (2016) we hypothesize that land-use shares in the last year of each of the three periods (i.e., 2001, 2006, and 2011) are functions of the expected annual returns from each land-use for the same years by estimating the following equation:

$$\pi(t^e, i, j, k) = \frac{exp[(s(t^b, i, j) \sum_h^H \beta(h, k) X(t^e, i, h)]}{\sum_{k=1}^{K} exp[(s(t^b, i, j) \sum_h^H \beta(h, k) X(t^e, i, h]} \quad (2)$$

where $\pi(t^e, i, j, k)$ for spatial unit (i.e., one km^2 pixel level) $i = 1, \ldots, N$ is the probability for land use j transitioning to land use k during time period t^e, $s(t^b, i, j)$ represents the observed

land share in use j at the beginning of each time period t^b, $\beta(h,k)$ is the parameter associated with an explanatory variable h in land-use k, and $X(t^e,i,h)$ is the vector of explanatory variables (i.e. representing forest returns, pasture returns, crop returns, and urban returns, slope, and two years dummy variables) at the end of each time period t^e for the spatial unit i (MacRae,1977; Lambert et al., 2016). In this study we refer to the current period as t^e and to the lag or prior period as t^b, since each period's duration is different (i.e. 1992-2001, 2001-2006, 2006-2011).

The shares of each land use category represented by $s(t,i,j)$ are assumed to be mutually exclusive, such as $\sum_{j=1}^{K} s(t,i,j) = 1$. This implies that each land use allocation is unique (i.e., each land use share is assigned to only one specific land use category or choice). The parameters $\beta(h,k)$ are estimated using the log likelihood of the joint multinomial probability distribution across i spatial units, j land uses in period t^b, and k uses in t^e. Maximizing the following equation yields the maximum likelihood estimates of β (Lambert et al., 2016):

$$\max_{\beta_{h,k}} ln\, L = \sum_t \sum_i \sum_k \sum_h \beta_{h,k} . s_{t^b,i,k} . x_{t^b,i,h} - \sum_t \sum_i \sum_j \left[\Omega_{t^b,i,j}\right] \quad (3)$$

where $\Omega_{t^b,i,j} = \sum_k \exp(s_{t^b,i,j} * \sum_h^H \beta(h,k) * X(t^e,i,h))$ is the denominator from equation (2). A category is omitted to identify the system (e.g. $\beta = 0$ for the other land use category).

The 30 m × 30 m areas were aggregated within each one km^2 pixel for each of the five types of land use classification from the original 21 NLCD classifications (US Geological Survey, 2013).[1] We included the net returns from the four land-use categories (i.e., cropland, pasture, urban, and forest) as major explanatory variables to capture the relationship between land use choices and relative returns (five land use categories were defined, but the model

[1] The 21 NLCD classifications are merged into five land use categories based on the following method: cultivated cropland as "cropland" category, pasture/hay and grassland/herbaceous land cover as "pasture", developed open space, low intensity, medium intensity, and high intensity as "urban land use", deciduous, evergreen, and mixed forest as "forest land", and the rest of the NLCD classifications as "other use".

required the calculation of only four net returns). See supplemental material for the details about the datasets and how the net returns were estimated.

We have also included the mean slope of each pixel, mean elevation of each pixel, and two-time period dummy variables (1 if the allocation of land-use share is made during 2001-2006 and 2006-2011, and 1992-2001 as a reference duration) as other explanatory variables. The mean slope and the mean elevation were included because the study area is hilly and mountainous and the slope and the elevation were found to be major factors of the land use decisions under such geophysical conditions in the previous literature (e.g., Nelson and Geoghegan, 2002). The mean slope and the mean elevation for each one km^2 were measured using raster grids derived from the 30 m × 30 m Digital Elevation Model (DEM) (USGS, 2013) and calculated using the Zonal Statistics tool in ArcGIS 10.1 (ESRI, 2012). In addition, the time period dummy variables were included to control for any unaccounted time trends that was not captured by changes in net returns from the land uses over the three periods. See Table 2.1 for a detailed description of the variables and their simple statistics.

Once the land-use transition probabilities that define the relationship between land use choices and relative returns are estimated using equation (2), we calculate the transition matrices of land-shares by matrix multiplication between the relative land-use transition probabilities (i.e., transpose of the transition probability matrix correspondent to the land use) and the land-use share in the time-lagged period. Specifically, given the land-use shares in 1992, 2001, 2006, we predicted transition matrices of land-share for the period of 1992-2001, 2001-2006, and 2006-2011. The estimated 5 × 5 transition matrices were used to simulate the changes in land shares that were converted to the changes in carbon storage levels based on a carbon simulation model in Step 2 (see below).

2.2. Step 2. A carbon simulation model

We estimated the changes in carbon storage that corresponds to the changes in land shares using a Terrestrial Ecosystem Model (TEM) cohort level based on climate, forest type, disturbance and management history, and other environmental characteristics of a particular pixel (Oak Ridge National Laboratory, 2016). Based on monthly fluxes that are provided by the TEM cohort level, we estimated carbon sequestration to account for the net total of carbon uptake through photosynthesis against carbon losses over each of the three periods separately (see supplemental material for the details of the carbon simulation model). Then, we used the total carbon storage estimated for each period in each of the five land use categories for each pixel and the 5 × 5 land use transition matrices of changes for each pixel across the three periods obtained in Step 1 to derive the 5 × 5 transition matrices of changes in carbon storage in tons per square kilometer (ton/km^2) across the three periods. The 5 × 5 transition matrices of changes in carbon storage were used to derive annual pixel-level supply curves for carbon storage in Step 3 by simulating the changes in land shares for an incrementally increasing net return of forestland in each of the three periods (see below).

2.3. Step 3. Annual pixel-level supply curves for carbon storage

We estimated carbon storage for each pixel using the observed land-shares based on 1992, 2001, 2006, and 2011 NLCD data and associated carbon storage transition matrices from Step 2 as a baseline carbon storage. The land-shares observed in each year represent a snap-shot in time, while the three periods are used to demonstrate the temporal variation in the opportunity cost of carbon storage for each pixel. Given the baseline carbon storage with observed net returns of forestland for each pixel in each of the three periods, we simulated

changes in land use transition by incrementally increasing net return of forestland (ranging from $1 to $750 per hectare, with a $1 per hectare increment) in each of the three periods using the pixel-level land use model in Step 1. These changes were converted into changes in carbon storage using the carbon simulation model in Step 2. The relationship between the increase in net return of forestland and corresponding changes in carbon storage for each pixel is developed as an annual pixel-level supply curve for carbon storage in tons per hectare for each of the three periods. Given a 1 km^2 pixel, each incremental increase in net return to forest is associated with a 5 × 5 transition probability matrix, that is used to predict a 5 × 5 transition matrix of land-share. The predicted transition matrix is then multiplied by the 5 × 5 transition matrices of changes in carbon storage. The sum of the product of both matrices equals to the value of additonal annual carbon storage. The process to construct the pixel-level supply curves of carbon is similar across the three periods for the entire set of pixels (i.e., total of 14,680 annual supply curves of carbon in each period).

2.4. Step 4. Cost-efficiency maps

The annual pixel-level supply curves for carbon storage for each of the three periods from Step 3 was used to simulate payments by allowing each dollar to be distributed among the pixels in the most efficient way. This simulation was done under the assumption that (i) the one km^2 pixel represent the spatial structure of the decision-making units and (ii) the decision-makers are risk neutral in the face of uncertainties in net returns from alternative land-uses. For the most efficient allocation of each dollar among the pixels, we implemented the following for each of the three periods separately: (1) we calculated marginal carbon stored per dollar paid at each pixel; (2) we sorted the pixels by the descending order of the maximum average carbon

stored per dollar paid; (3) we allocated each dollar to the pixels with the highest marginal or average carbon stored per dollar paid until the marginal carbon stored in each pixel decreases to zero for each pixel; (4) we calculated average cost effectiveness under the hypothetical budget of $1 million and developed a cost-efficiency map for each of the three periods under the budget (note that the choice of budget constraint does not have much implications other than different layers of payment distributions).

3. Empirical results and discussion

3.1. Step 1. A land use model

We report the model parameter estimates and standard errors of the Multinomial logistic Markov transition probabilities using maximum likelihood (ML) of the land use model in Table 2.2 The estimated empirical model required parametrization of the transition probabilities with the multinomial logistic distribution. The maximum likelihood estimates of Markov transition probability coefficients indicate how the land shares in period t change in response to the change in net returns (i.e., increase in forest net returns in each period). The null hypothesis $\beta(h,k) = 0$ was rejected at the 1% level. The pseudo R-square in our model is 0.045 and the log-likelihood is -300,440. We ought to interpret this statistic with great caution since the pseudo R-square is not an equivalent measure from the R-square of an OLS regression (Menard, 2000). McFadden (1974) suggests that the pseudo R-square be calculated by the formula 1 – Lur/Lr, where Lur is the log-likelihood function for the estimated model, and Lr is the log-likelihood function in the model with only the intercept (Wooldridge, 2015). Therefore, the ratio of the likelihoods suggests the level of improvement over the intercept model offered by the unrestricted model, i.e. the smaller the ratio the larger the improvement.

The coefficients for all the net return and slope variables are statistically significant at the 1% level across the all four land uses and they provide information about the own and cross net returns relationships between the transition of land use j to k. The standard interpretation of the multinomial logit model is that a unit change in the predictor variable, the logit of its outcome, and more specifically the land use choice in our case, is expected to change by its respective parameter estimate. However, this method has a limitation to properly interpret the results of our land use model since the variables interact with more than one category (i.e., there are five possible land use choices: forest, pasture, crop, urban and other). Furthermore, it is worth noting that some of the coefficients have positive and negative signs. For example, the parameter estimates associated with the explanatory variable forest net return are 0.2975, 0.0272, -3.2323, and 0.0510 for forestland, pastureland, cropland, and urban land use respectively. Relying on this information alone may not be sufficient to explain the impact of increasing net returns on land use change. Hence, the interpretation of the model coefficients is not straightforward because they have different signs and magnitudes (Wooldridge, 2010) especially when $K > 2$ (Miller and Plantinga, 2003). We use the transition elasticity to elaborate further on the impact of increase in forest net returns on the transition probabilities and land shares.

The transition elasticities of the Multinomial logistic Markov transition probabilities are presented in Table 2.3. We focus on the discussion about how forest net return affects the probabilities of changes in forest area (i.e., deforestation and afforestation). A 1% increase in forest net return (1) increases the probability of maintaining the forestland as forestland by 0.50%, (2) decreases the probability of deforestation to pasture, crop, urban, and other uses by 2.04%, 32.71%, 1.5%, and 2.30%, respectively, and (3) increases the probability of afforestation

of pasture, crop, urban, and other uses by 0.31%, 0.04%, 0.15%, and 0.09%, respectively. The findings collectively suggest that providing incentives to landowners to afforest non-forested land and to sustain forests at risk of deforestation are both viable approaches, and the latter is a more cost efficient approach than the former. In particular, the large negative effect of the forest net return on the probability of deforestation to cropland suggests that deforestation for cropland is more cost efficient to prevent than other types of deforestation among the various risk of deforestation.

3.2. Step 2. A carbon simulation model

The annual changes in forestland based on the observed land-use change at the pixel level for the three periods (see Figures 2.2, 2.3, and 2.4) and corresponding annual changes in carbon storage estimated from the carbon model are mapped (see Figures 2.5, 2.6, and 2.7). Based on these pixel-level values, net forest gain/loss and corresponding annual average net gain/loss of carbon storage in each county across the three periods are summarized in Table 2.4.

The spatial pattern of the annual change in carbon storage varies across the three time periods with different extents. For example, Morgan County experienced the biggest loss of forestland which consequently resulted in the biggest loss of carbon storage for each of the three periods among the 18 counties. The large degree of deforestation in Morgan County is likely associated with its rapid population growth of 13% between 1990 and 2010, in part related with employment opportunity created by the Tennessee Valley Authority (TVA) (Strickland, 2003; U.S. Census, 2010; Kline and Moretti, 2014; Economic Profile System-Human Dimensions EPS, 2014). On the contrary, 7 counties (i.e., Anderson, Bell, Blount, Claiborne, Campbell, Hamblen, and Monroe Counties) in the study region, gained carbon storage over some of the

time periods. For example, Hamblen County experienced a net gain of forestland (i.e., 698 and 91 hectares for periods 2001-2006 and 2006-2011, respectively), resulting in a net gain in carbon storage (i.e., 1.17 and 2.77 metric tons per hectare per year for periods 2001-2006 and 2006-2011, respectively). Those gains are mostly due to the conversion of pasture to forest (net losses of 962 and 628 hectares of pasture land in Hamblen County for periods 1992-2001 and 2001-2006, respectively). This change might be attributed to natural resource conservation programs conducted in Hamblen and neighboring counties that aimed at, among other objectives, supporting afforestation and erosion control (Tennessee Valley Authority, 2010).

3.3. Step 3. Annual pixel-level supply curves for carbon storage

We derive site-specific annual supply curves for carbon storage for each of the 14,680 pixels for each of the three time periods. Figure 2.8. shows the three supply curves for three representative pixels for period 1992-2001 to illustrate the spatial heterogeneity in the carbon supply curves given a fixed period. The carbon supply curves increase at an increasing rate while approaching maximum carbon-storage capacities of 17.50, 24.10, and 30.09 metric tons per year at $99, $125, and $198 per hectare per year for these three pixels. Figure 2.9. shows the three supply curves for a randomly selected pixel during the three periods to illustrate the temporal heterogeneity in the carbon supply curves given a fixed location. The carbon supply curves approach maximum carbon-storage capacities of 18.11, 37.15, and 39.02 metric tons per year at $125, $200, and $300 per hectare annually, for the periods 1992-2001, 2001-2006 and 2006-2011, respectively.

In both figures, the maximum carbon storage capacities occur when the marginal effect of a $1 increase in forest returns on the likelihood of additional forest acreage approaches zero. These zero convergence points occur when the area available to afforest non-forested land and

to sustain forests at risk of deforestation reaches its maximum. The spatial and temporal heterogeneity shown in the shapes of the supply curves for carbon storage, respectively, in Figures 2.8 and 2.9 suggest that there is a need to account for both heterogeneities to improve cost effectiveness of incentive payment approaches.

3.4. Step 4. Cost-efficiency maps

Figures 2.10, 2.11, and 2.12 show the cost-efficiency map of carbon storage across the three time periods under the assumption that each dollar is distributed among the pixels in the most efficient way. The hypothetical budget of $1 million was used to gain 19,865, 39,503, and 38,552 hectares of additional forest, which generate 18,238, 52,268 and 47,319 metric tons of carbon storage annually, yielding cost efficiency of 54.83, 19.13, and 21.13 in dollars per metric ton of carbon, respectively, for the three periods. Table 2.5 summarizes this information at the county level across the three periods to illustrate spatial heterogeneity across each time period. It shows that the largest area of land (i.e., 2,191, 4,403, and 4,113 hectares for periods 1992-2001, 2001-2006 and 2006-2011, respectively) were selected to participate in payment programs with the highest total payment amounts (i.e., $98,705, $149,285, and $169,710) in Morgan County. In contrast, the least area of land (i.e., 78, 335, and 296 hectares) were selected to participate with the lowest total payment amounts (i.e., $477, $7,020, and $7,045) in Bell County.

The reason behind the differences in area of participation amounts of carbon supply and payments are illustrated by comparing the transition probabilities of forest-related land use changes between a randomly selected pixel in each of Bell County (least participant county) and Morgan County (largest participant county) during 1992-2001 in Figure 2.13. The figure shows

that the transition probability of the forestland for the pixel in Morgan County remained forested during 1992-2001 jumps from 20.7% with the zero payment to 50.41% with the payment of $25 per metric ton. The changes for the pixel during 1992-2001 in Bell County (i.e., 97.13% to 99.73% with payment ranges of $0-$12 for forestland remained as forestland) are drastically less responsive than those of the pixel in Morgan County. The difference in the dynamic responses in transition probability to the change of the payment is mainly because of the difference in the room for increasing the transition probability that forestland remained forested (i.e., 2.87% in Bell County and 79.3% in Morgan County). Other randomly selected pixels between the two counties also show the similar contrasting difference in the patterns. These findings suggest that dynamic responses of forest-related land use changes to the change of the payment to forestland owners depends on room for increasing transition probability of the increase in forestland with the higher payments. Specifically, the higher dynamic responses that are reflected in the higher dynamics in the corresponding transition probabilities result in the higher area of participation of the payment programs.

4. Conclusion

Given the growing literature on the spatial distribution of cost effectiveness of supplying ecosystem services using incentive payment programs and the potential room for improvement of their cost efficiencies using temporal heterogeneity, the spatial and temporal variations of the cost efficiency of carbon storage is imperative. The cost efficient incentive payment program providing forest-based carbon sequestration will require more carefully accounting for heterogeneities on both sides. We examined the spatial and temporal heterogeneities in the costs of supplying forest-based carbon storage using a case study of one of 179 Bureau of Economic

Area, which consists of 17 Tennessee counties and 1 Kentucky county, in the larger Appalachian region.

Our empirical results for the 18-county case study show that there are spatial and temporal heterogeneities in the cost efficiency of carbon storage. Our findings are triggered by the difference in dynamics of the response of forestland changes to the change in net return of forest land. The different dynamic responses are triggered by the difference in the transition probabilities of forest-related land uses to the change of the payment to forestland owners, which depends on how much room there is for increasing transition probability of the increase in forestland with the higher payments. The cost-efficiency maps for each of the three periods can be used as a reference for spatial targeting of incentive payments under different periods. For example, policymakers can anticipate regional budget allocation based on the cost-efficiency maps to predict variations of impact areas under a hypothetical budget scenario under different periods.

Our findings have significant implications because few, if any, studies have explicitly considered both the temporal and spatial dynamics of the cost efficiency to come up with site-specific and time-specific carbon storage levels, payment amounts, and would-be participants. For example, the pixel-level carbon storage rates and pixel-level annualized costs of carbon storage can be used in ways comparable to the Environmental Benefits Index (EBI) – an index to rank farmers' request to enroll land into CRP set by USDA-Farm Service Agency since 1996 (Congressional Research Service, 2014). This information can be easily used at a more spatially granular level (e.g., counties and ecoregions) by taking averages of the estimates from our estimated supply curves and their corresponding values at the pixel level. In addition, the

temporal heterogeneities in the supply curves and their corresponding values caution us of the need to update these values for more efficient implementation of the payment programs.

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Appendix

Table 2. 1. Variable Names, Definitions, and Descriptive Statistics

Variable	Description	Mean
Forest Return	Annual net return from forest-use at the county level ($/ha)	30.29 (17.93)
Pasture Return	Annual net return from pasture-use at the county level ($/ha)	47.75 (6.17)
Crop Return	Annual net return from crop-use at the county level ($/ha)	45.35 (375.22)
Urban Return	Annual net return for urban-use at the census-block group level ($/ha)	1012.55 (1460.91)
Slope	Average slope at pixel-level (degrees)	10.60 (4.62)
2006 Year dummy	1 if the land-use decision was in 2006, 0 otherwise	0.33 (0.47)
2011 Year dummy	1 if the land-use decision was in 2011, 0 otherwise	0.33 (0.47)

Note: Numbers in parentheses are standard deviations.

Table 2. 2. Parameter Estimates and Standard Errors of the Multinomial Logistic Markov Transition Probabilities Using Maximum Likelihood (ML) of the Land Use Model

Variables	Forestland	Pastureland	Cropland	Urban-land
Constant	-10.5893*	-6.0800	-38.9779*	-10.9107
	(0.7039)	(0.7000)	(2.6418)	(0.7654)
Forest Return	0.2975*	0.0272*	-3.2323*	0.0815*
	(0.0128)	(0.0126)	(0.0608)	(0.0135)
Pasture Return	0.2853*	0.2810*	1.8621*	0.3475*
	(0.0318)	(0.0317)	(0.1182)	(0.0345)
Crop Return	-0.0008*	-0.0004*	0.0109*	-0.0031*
	(0.0002)	0.0002)	(0.0005)	(0.0002)
Urban Return	0.0009*	0.0002*	-0.0045*	0.0031*
	(0.0001)	(0.0001)	(0.0004)	(0.0001)
Slope	0.5467*	0.4607*	0.9564*	0.4900*
	(0.0197)	(0.0197)	0.0670)	(0.0210)
Year dummy 06	2.2729*	1.0192	0.7736*	0.6322*
	(0.1267)	(0.1248)	(0.4248)	(0.1356)
Year dummy 11	3.6713*	1.4835	1.2578	1.7043
	(0.1922)	(0.1903)	(0.4916)	(0.2053)

Note: Pseudo R-square is 0.045 and log-likelihood is -300,440, N=44040. The category of other uses was used as the reference group.
* Indicates statistical significance at the 1% level. Numbers in parentheses are standard deviations.

Table 2. 3. Transition Elasticity of the Multinomial Logistic Markov Transition Probabilities Using Maximum Likelihood (ML) of the Land Use Model

Variables		Forest Share	Pasture Share	Crop Share	Urban Share	Other Share
Intercept	Forest	-0.6043	2.1610	-18.0117	-0.8014	5.8889
	Pasture	-0.5295	0.4829	-6.9026	-0.6016	1.8478
	Crop	-0.0147	0.0535	-0.4444	-0.0197	0.1455
	Urban	-0.1592	0.2905	-2.9907	-0.1913	0.8970
	Other	-0.1001	0.1139	-1.4470	-0.1153	0.4023
Forest Returns	Forest	0.5015	-2.0412	-32.7070	-1.5302	-2.2978
	Pasture	0.3130	-0.1587	-5.8473	-0.0639	-0.2063
	Crop	0.0410	0.0124	-0.3294	0.0181	0.0095
	Urban	0.1510	-0.0290	-2.1995	0.0072	-0.0472
	Other	0.0885	-0.0016	-1.0883	0.0165	-0.0107
Pasture Returns	Forest	-0.0140	-0.0653	18.9239	0.7330	-3.4411
	Pasture	-0.0081	-0.0262	6.6856	0.2559	-1.2194
	Crop	-0.0252	-0.0265	0.4650	-0.0058	-0.1139
	Urban	-0.0464	-0.0543	2.8711	0.0687	-0.5743
	Other	-0.0261	-0.0300	1.4022	0.0302	-0.2846
Crop Returns	Forest	-0.0040	-0.0005	0.0876	-0.0217	0.0028
	Pasture	-0.0070	-0.0031	0.0949	-0.0267	0.0005
	Crop	-0.0019	-0.0011	0.0185	-0.0058	-0.0004
	Urban	-0.0043	-0.0050	-0.0236	-0.0005	-0.0057
	Other	-0.0027	-0.0018	0.0198	-0.0070	-0.0010

Table 2. 3. Continued

Variables		Forest Share	Pasture Share	Crop Share	Urban Share	Other Share
Urban Returns	Forest	-0.0378	-0.1688	-1.0542	0.3749	5.8889
	Pasture	-0.0107	-0.0745	-0.5056	0.1902	1.8478
	Crop	0.0016	-0.0034	-0.0373	0.0175	0.1455
	Urban	-0.1322	-0.2052	-0.6980	0.0975	0.8970
	Other	-0.0011	-0.0178	-0.1308	0.0515	0.4023
Slope	Forest	0.1670	-0.4762	3.2282	-0.2564	-2.2978
	Pasture	0.1557	-0.0059	0.9262	0.0494	-0.2063
	Crop	0.0111	0.0019	0.0553	0.005	0.0095
	Urban	0.0725	0.0037	0.4004	0.0272	-0.0472
	Other	0.0360	0.0041	0.1741	0.0142	-0.0107
Year Dummy 06	Forest	0.0700	-0.1645	-0.2105	-0.2369	-3.4411
	Pasture	0.0813	-0.0241	-0.0448	-0.0567	-1.2194
	Crop	0.0034	-0.0001	-0.0008	-0.0011	-0.1139
	Urban	0.0511	-0.0031	-0.0137	-0.0199	-0.5743
	Other	0.0184	-0.0018	-0.0058	-0.008	-0.2846
Year Dummy 11	Forest	0.1133	-0.2864	-0.3276	-0.2460	0.0028
	Pasture	0.1243	-0.0631	-0.0825	-0.0442	0.0005
	Crop	0.0051	-0.0009	-0.0015	-0.0003	-0.0004
	Urban	0.0761	-0.0235	-0.0338	-0.0135	-0.0057
	Other	0.0292	-0.0074	-0.0112	-0.0037	-0.0010

Table 2. 4. Net Gain/Loss of Forestland and Pasture Land and Annual Average Net Gain/Loss of Carbon Storage in each County across the Three Time Periods

County	1992-2001			2001-2006			2006-2011		
	Annual Carbon Storage (MT/ha)	Net Change in Forest (ha/year)	Net Change in Pasture (ha/year)	Annual Carbon Storage (MT/ha)	Net Change in Forest (ha/year)	Net Change in Pasture (ha/year)	Annual Carbon Storage (MT/ha)	Net Change in Forest (ha/year)	Net Change in Pasture (ha/year)
Bell	0.24	54	26	0.02	-489	330	0.18	-148	44
Anderson	-3.19	-1273	798	-0.20	-594	-6	-0.30	-407	-75
Blount	-3.46	-2018	237	-0.13	330	-794	-0.23	-172	-332
Campbell	-1.34	-714	599	0.25	-960	514	0.50	-304	-237
Claiborne	-3.62	-2117	1157	0.29	-774	-166	0.38	-328	-560
Cocke	-3.25	-1091	625	-0.54	-515	-363	-0.64	-225	-270
Grainger	-2.17	-910	367	1.70	-290	-166	1.32	-88	-587
Hamblen	-5.25	-958	374	1.17	698	-962	2.77	91	-628
Hancock	-2.81	-541	717	-1.70	-536	8	-1.26	-185	-255
Jefferson	-3.10	-905	222	1.84	667	-940	2.08	-109	-907
Knox	-4.29	-3185	755	-1.22	-2921	-343	-0.67	-207	-198
Loudon	-4.35	-1330	881	0.35	86	-914	1.88	-58	-407
Monroe	-5.93	-2460	1588	-3.01	246	-530	-0.58	80	-1018
Morgan	-7.45	-3451	3043	-8.25	-3557	113	-6.49	-871	-868
Roane	-3.89	-1793	1172	-0.48	-655	-2	-0.20	-568	-300
Scott	-2.54	-1216	936	-2.30	-1699	777	-2.20	-802	112
Sevier	-2.89	-1518	128	0.77	190	-369	0.32	-592	28
Union	-3.40	-907	740	-2.27	-413	56	-1.33	-267	-383

Table 2. 5. Selected Area of Participation, Net Present Value of Payment, Cost Efficiency (CE) across the Three Time Periods

County	1992-2001				2001-2006				2006-2011			
	Total Area (ha)	Net Present Value of Payment ($/year)	Total Carbon Storage (MT/year)	CE	Total Area (ha)	Net Present Value of Payment ($/year)	Total Carbon Storage (MT/year)	CE	Total Area (ha)	Net Present Value of Payment ($/year)	Total Carbon Storage (MT/year)	CE
Bell	78	477	10	64.03	335	7,020	256.73	27.34	296	7,045	220	32.05
Anderson	922	40,401	818	49.37	1778	46,400	2,344.65	19.79	1490	47,575	2137	22.26
Blount	1851	93,474	1035	90.29	3381	85,985	3,976.01	21.63	3119	84,285	3045	27.68
Campbell	312	18,801	339	55.48	1477	36,820	2,276.41	16.17	1506	33,305	1791	18.60
Claiborne	1400	64,602	1355	47.67	3273	68,920	3,667.34	18.79	2903	66,730	2059	32.42
Cocke	733	29,979	579	51.75	1418	35,465	2,402.60	14.76	1450	32,990	1870	17.64
Grainger	920	50,625	812	62.34	1691	48,030	2,976.78	16.13	1690	46,035	2721	16.92
Hamblen	902	75,366	870	86.61	1384	45,445	2,581.27	17.61	1393	46,760	2779	16.83
Hancock	735	15,660	310	50.48	1543	29,605	2,138.81	13.84	1489	20,545	1012	20.31
Jefferson	1558	93,834	1340	70.04	2577	65,365	3,143.81	20.79	2548	67,955	4042	16.81
Knox	1835	78,910	1463	71.69	3388	64,975	2,522.09	25.76	3351	48,865	2093	23.35
Loudon	1353	76,770	1450	52.93	2207	62,000	3,075.93	20.16	2225	64,575	2719	23.75
Monroe	1407	85,950	1295	66.37	2911	67,500	3,158.84	21.37	2721	66,640	3392	19.65
Morgan	2191	98,705	2983	33.09	4403	149,285	7,531.49	20.31	4113	169,710	6332	26.80
Roane	1522	66,879	1388	48.19	2603	64,145	3,861.08	16.61	2840	71,445	4018	17.78
Scott	823	22,662	643	35.22	1783	37,350	2,301.74	16.23	1661	42,200	2685	15.72
Sevier	659	64,305	1073	59.91	1879	50,290	2,178.28	23.09	2259	53,935	3151	17.12
Union	664	22,608	475	47.55	1472	35,400	1,874.87	18.88	1498	29,405	1253	23.46



Figure 2. 1. Overview of Study Area

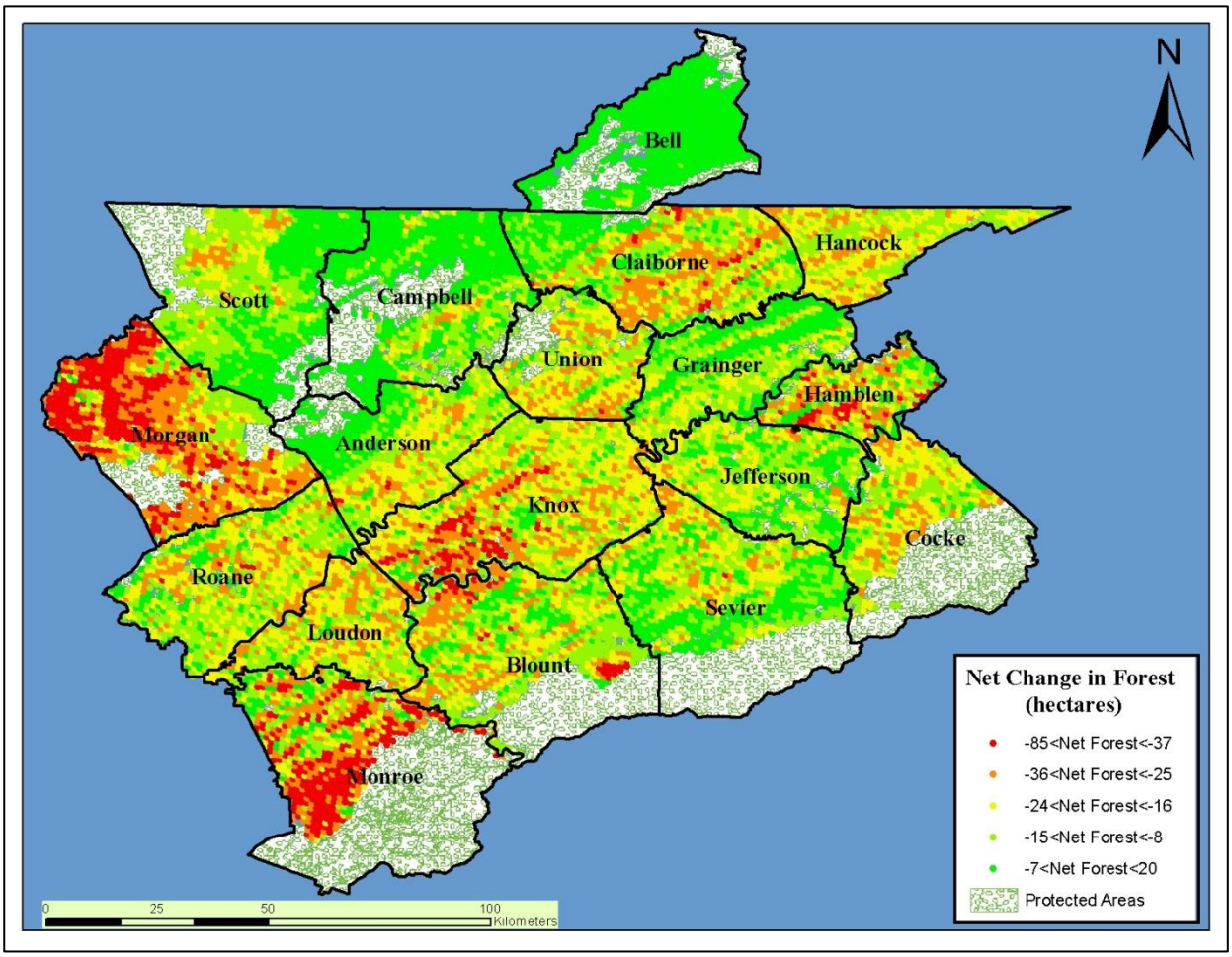


Figure 2. 2. Net change in forestland during 1992-2001

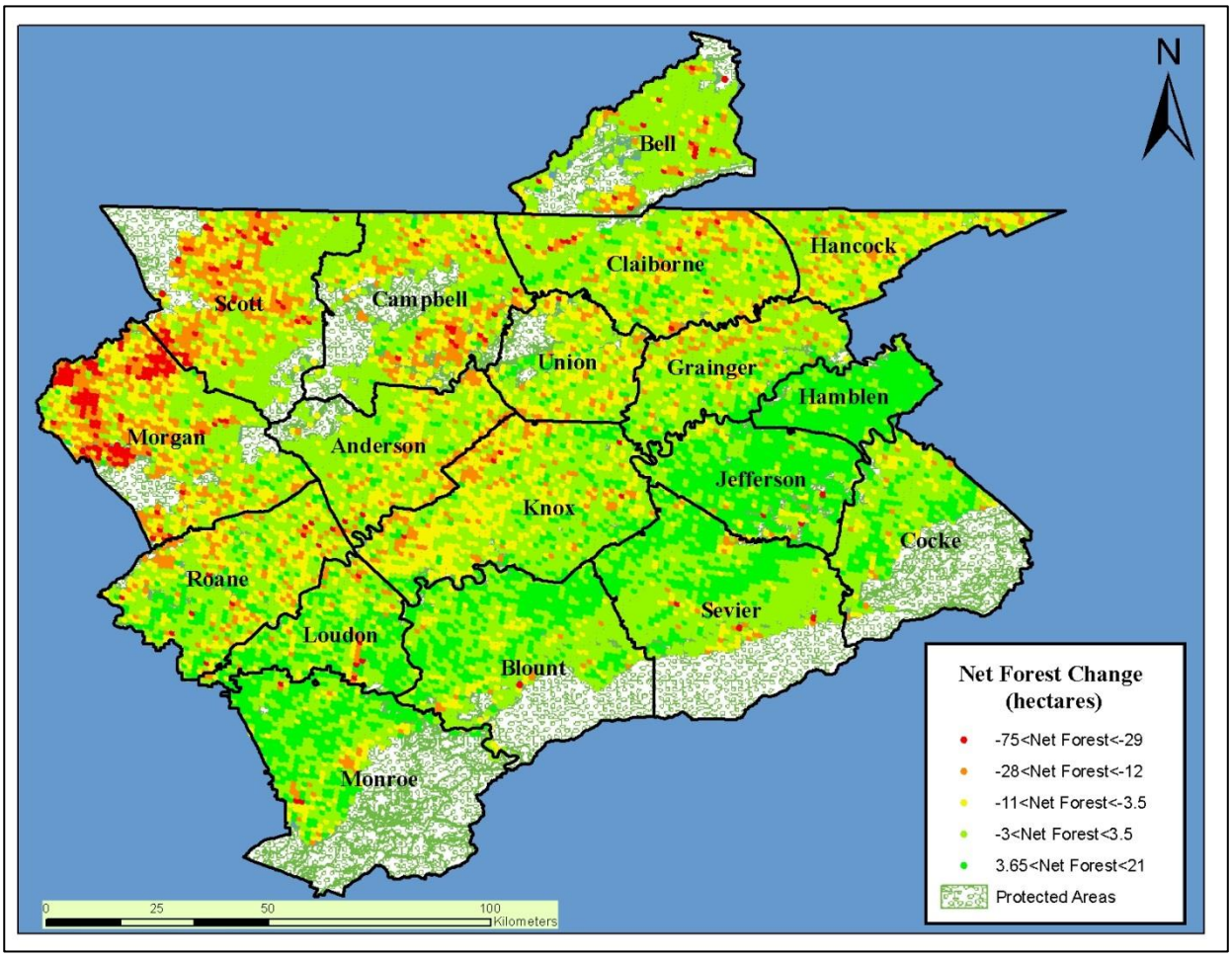


Figure 2. 3. Net change in forestland during 2001-2006

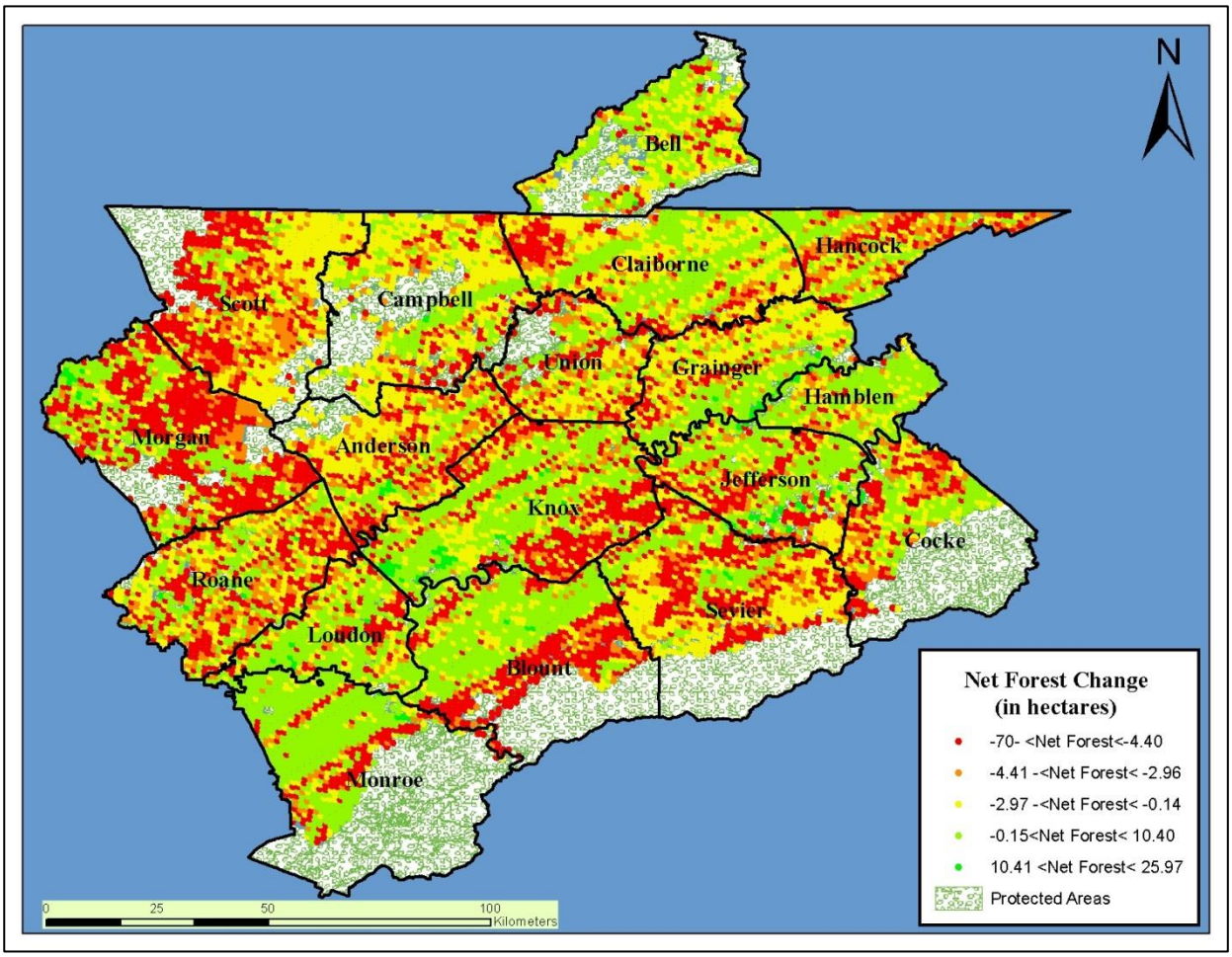


Figure 2. 4. Net change in forestland during 2006-2011

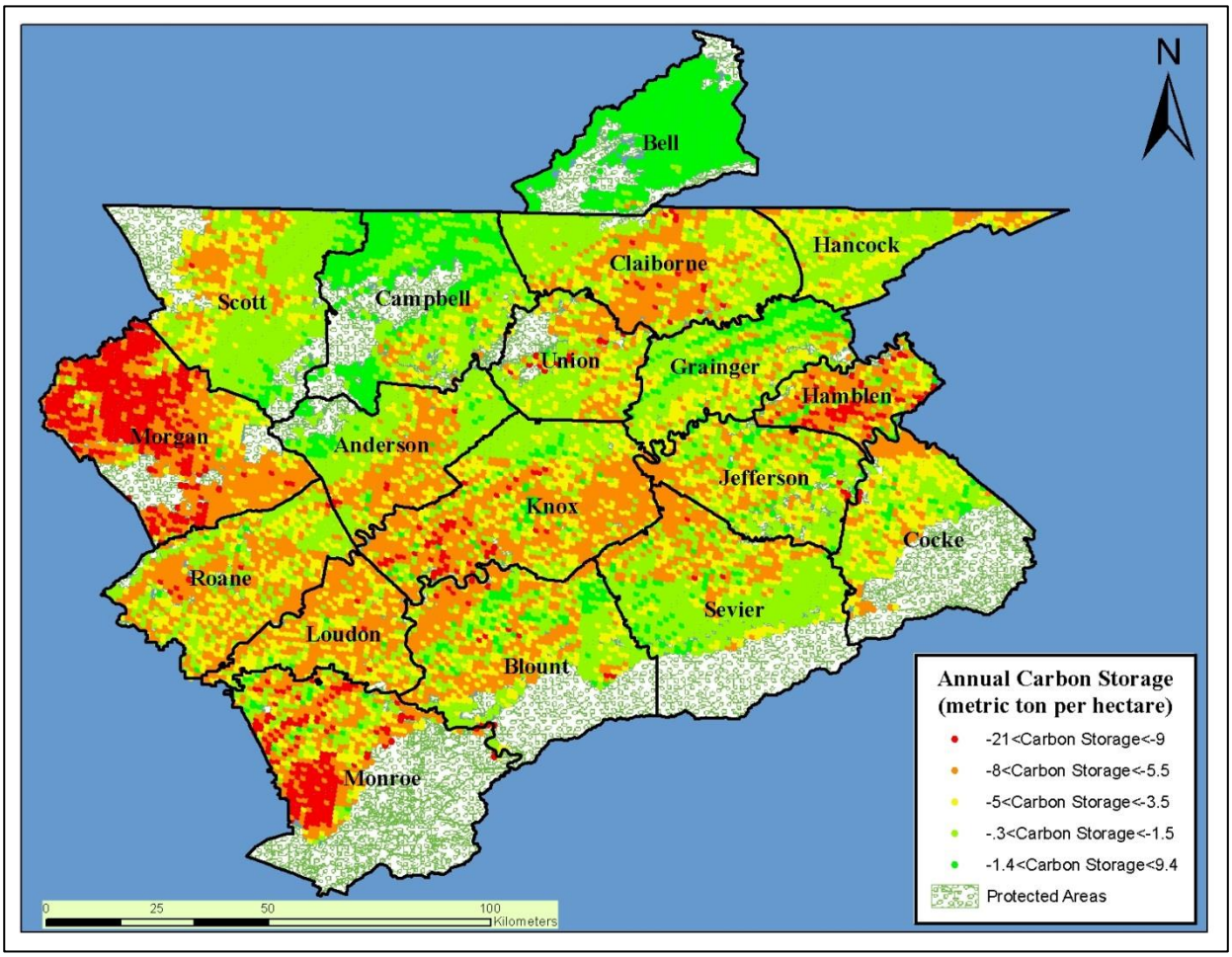


Figure 2. 5. Annual carbon storage based on net change in forestland during 1992-2001

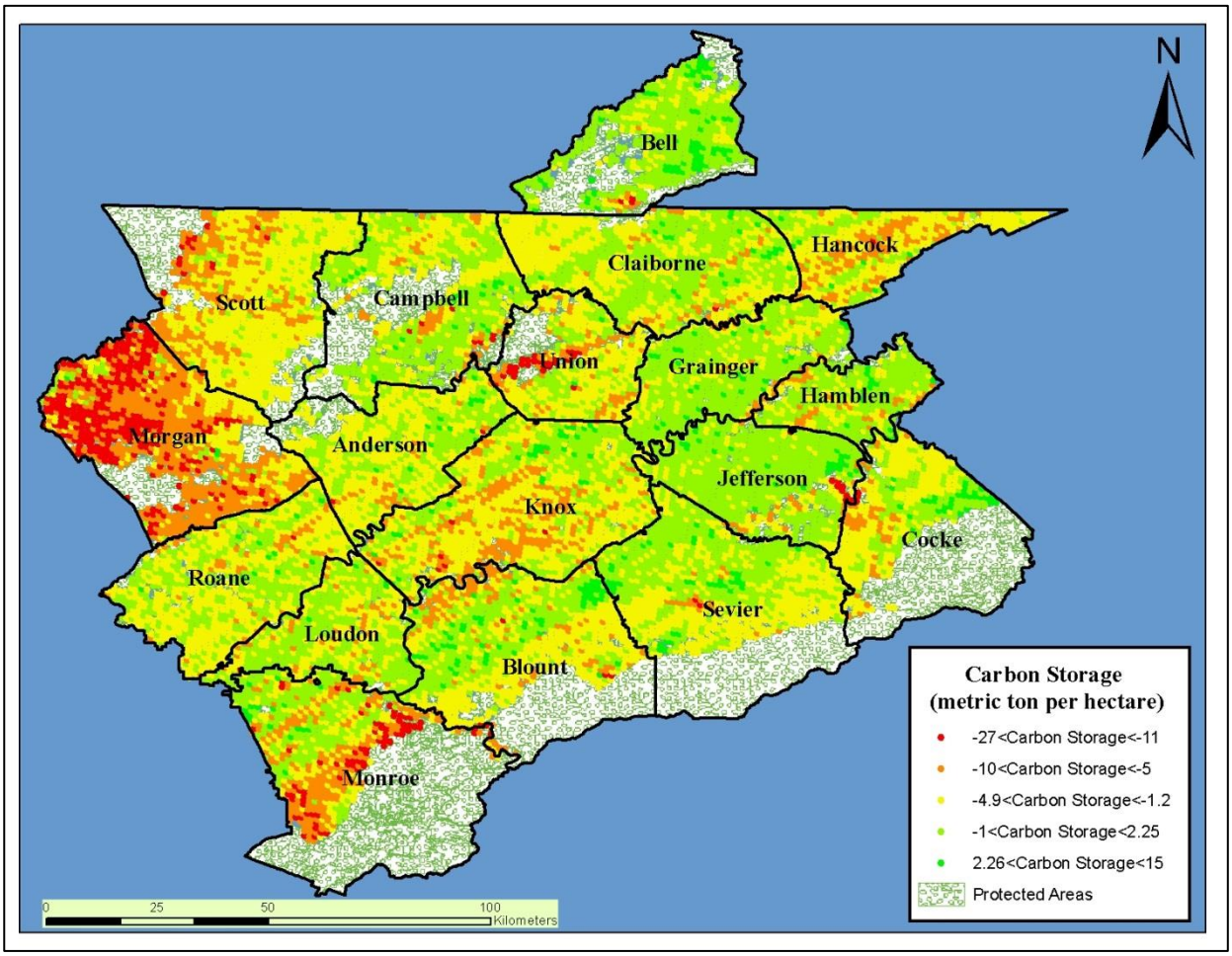


Figure 2. 6. Annual carbon storage based on net change in forestland during 2001-2006

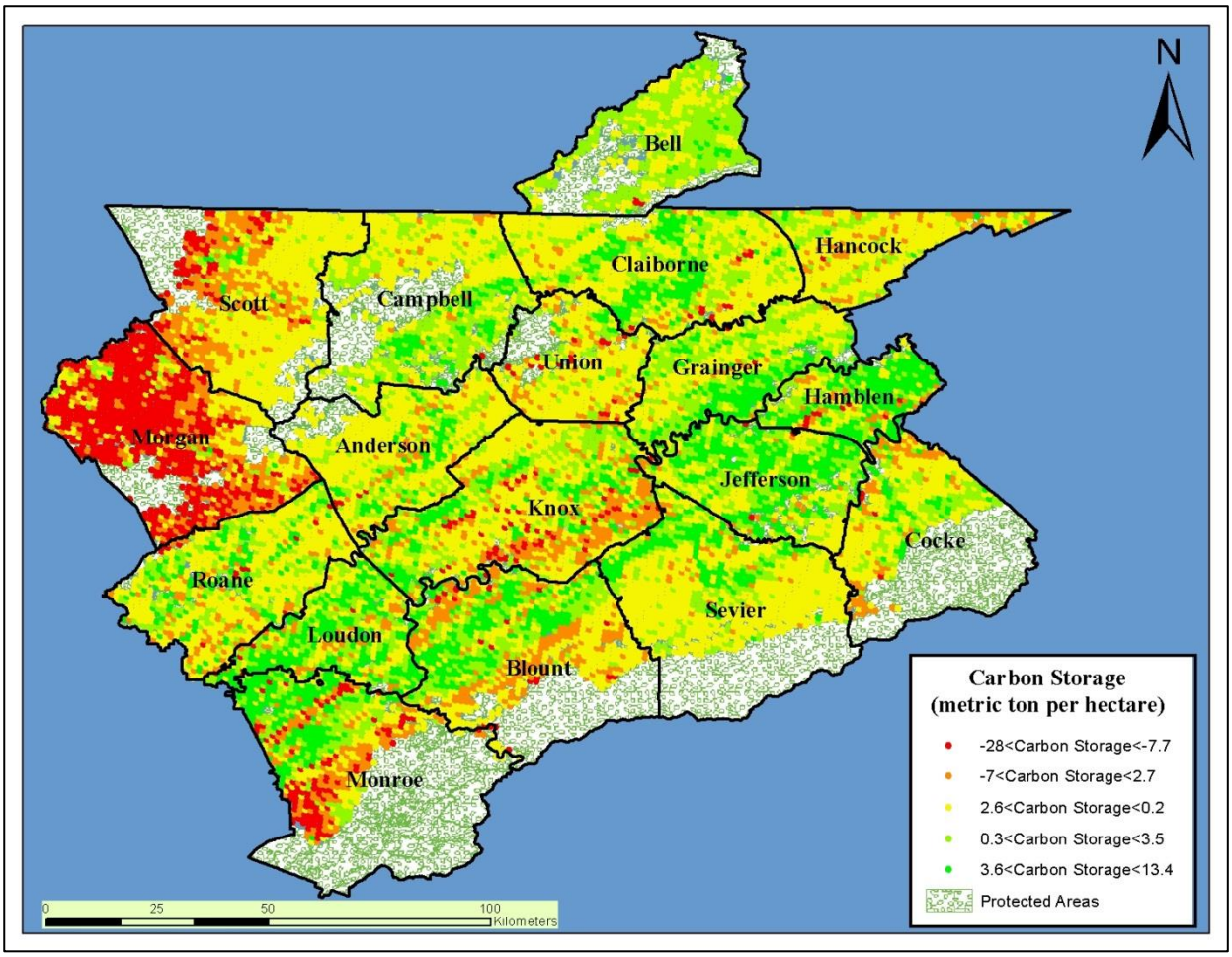


Figure 2. 7. Annual carbon storage based on net change in forestland during 2006-2011

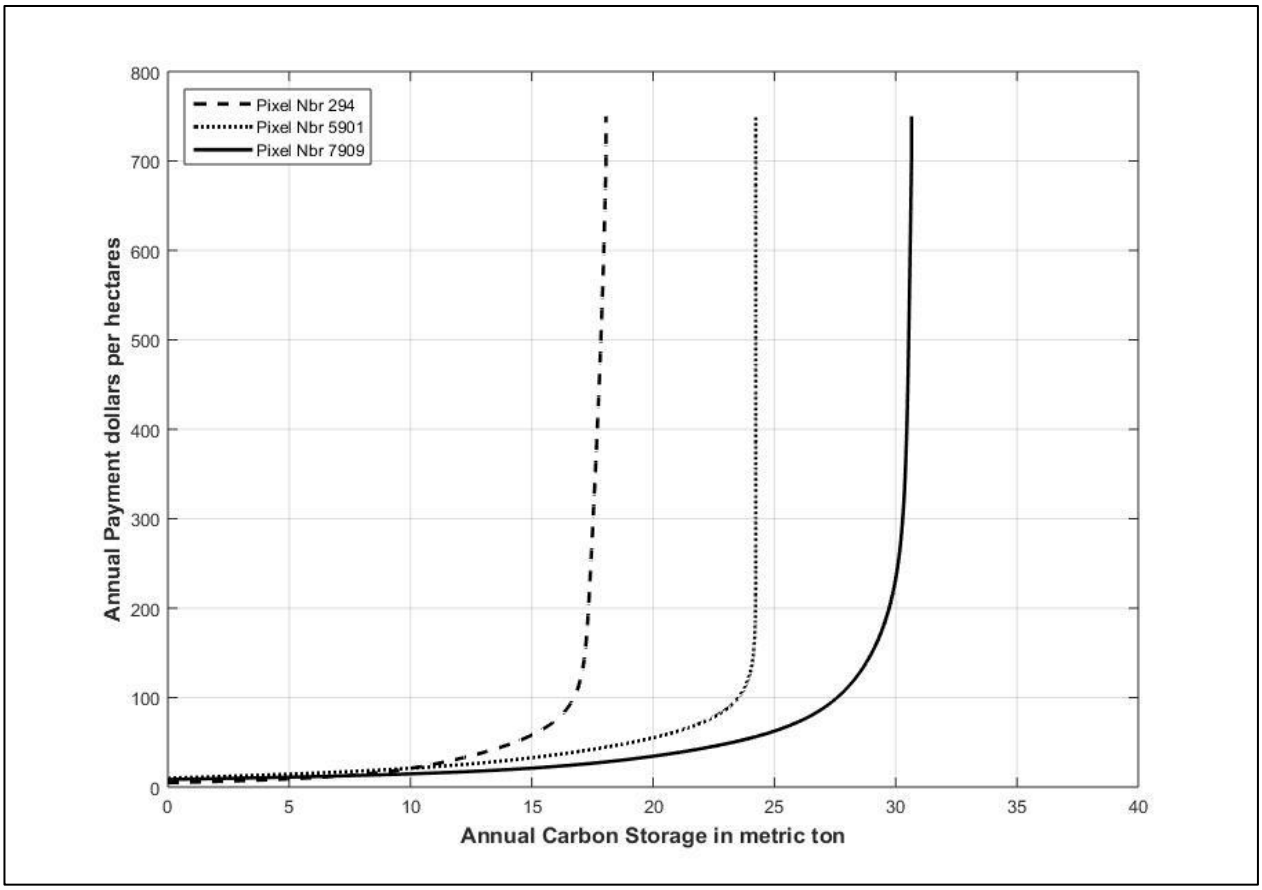


Figure 2. 8. Three supply curves for carbon storage for three randomly selected pixels for a given period (i.e., 1992-2001)

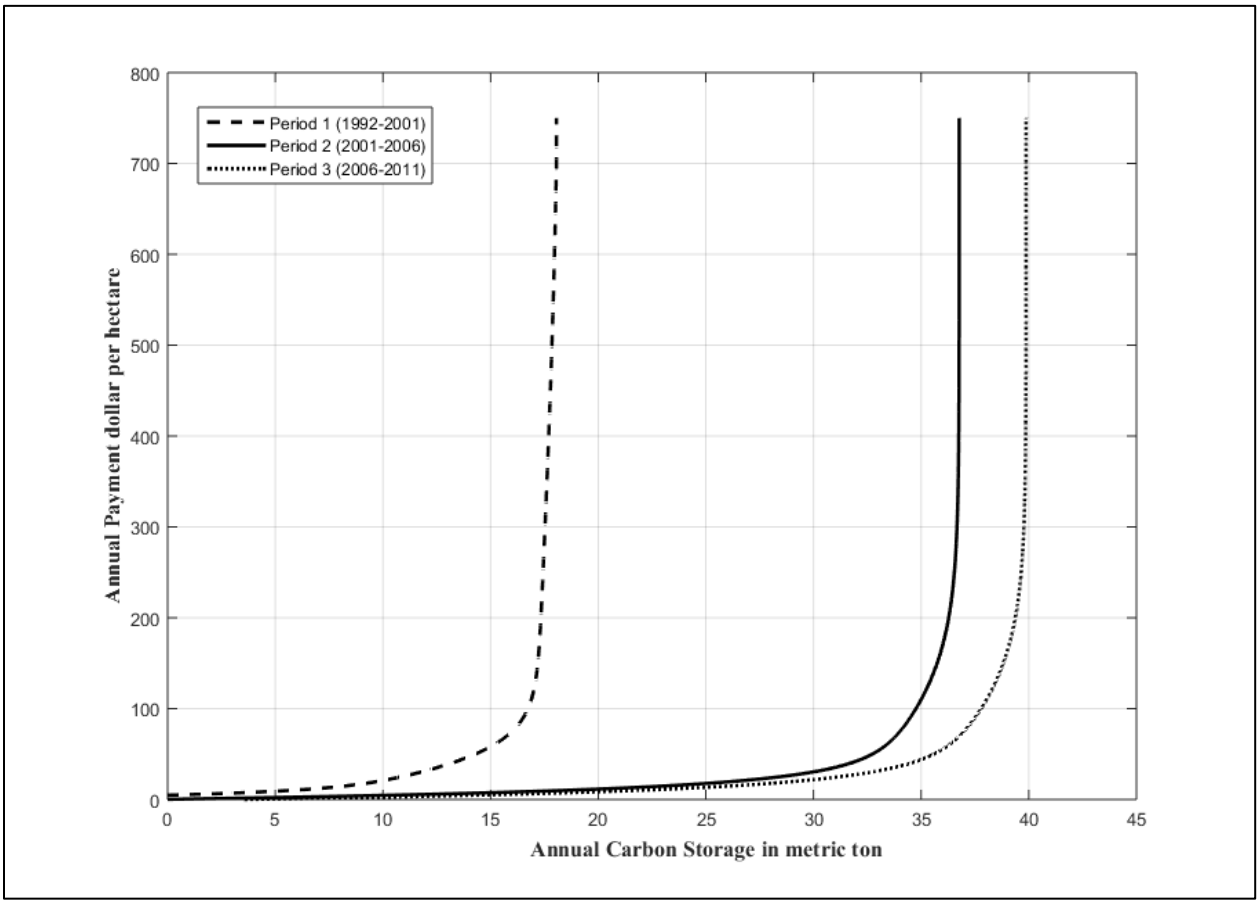


Figure 2. 9. Three supply curves for carbon storage for a randomly selected pixel during the three time periods

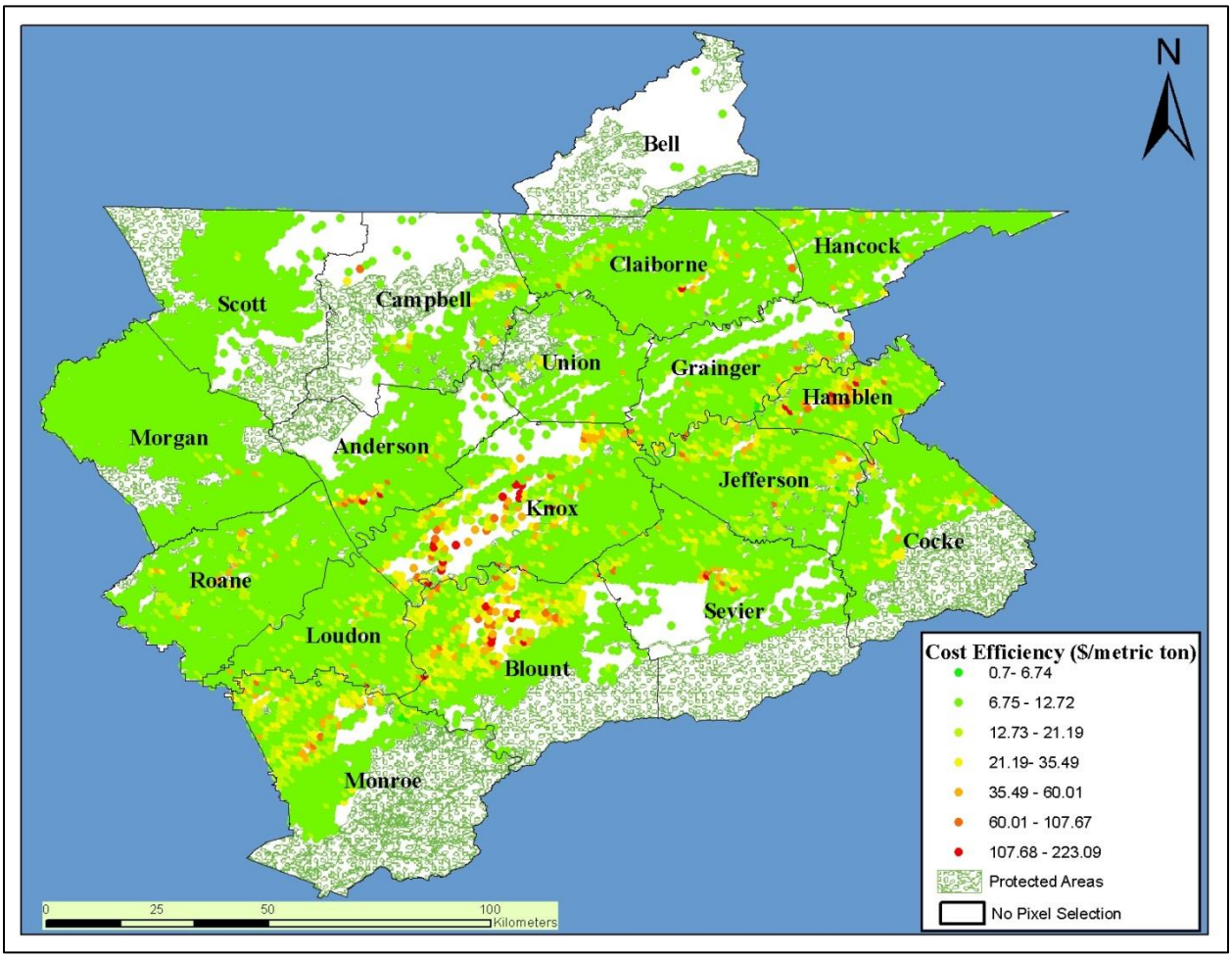


Figure 2. 10. Cost efficiency of carbon storage (dollar/metric ton) based on net change in forestland during 1992-2001

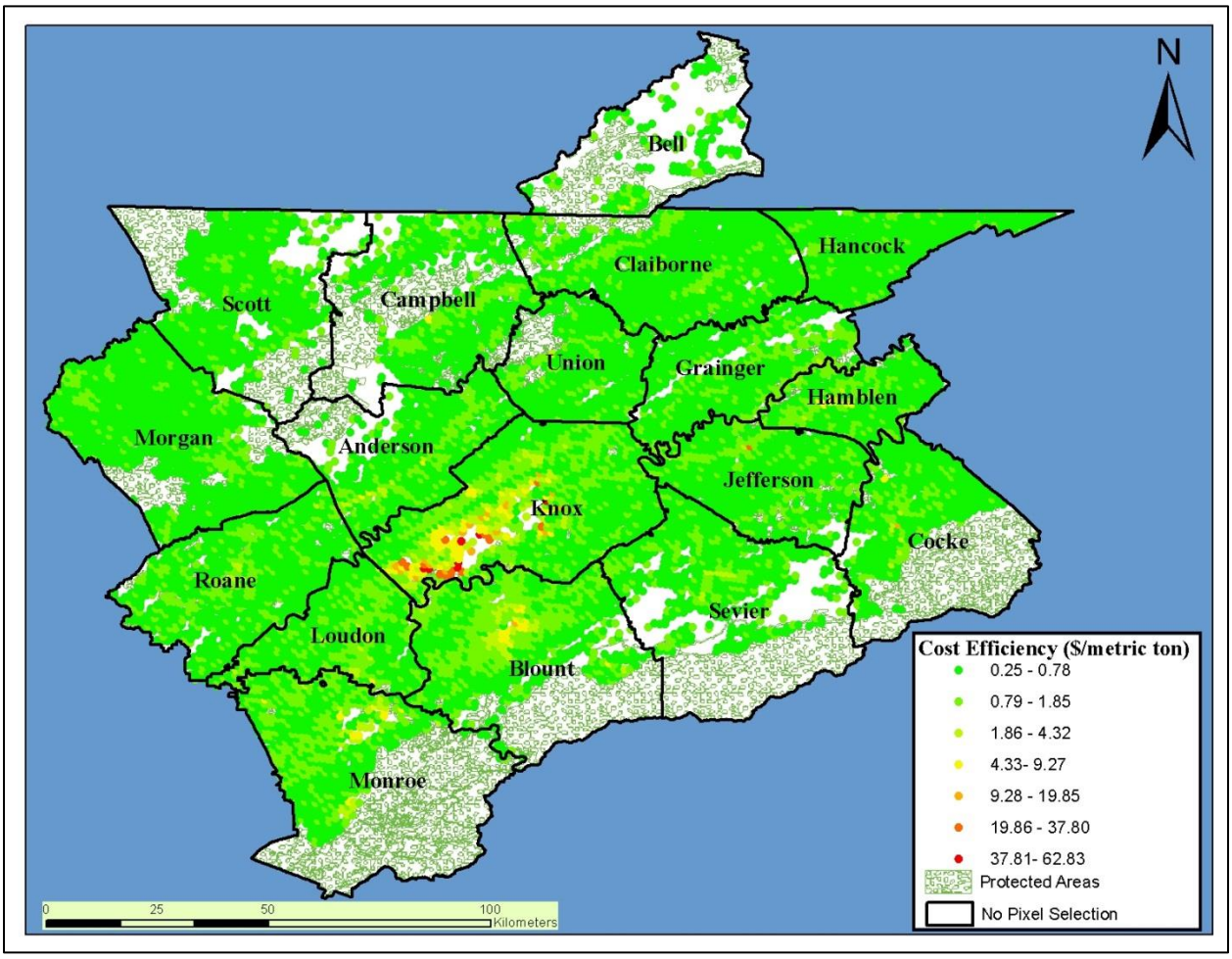


Figure 2. 11. Cost efficiency of carbon storage (dollar/metric ton) based on net change in forestland during 2001-2006

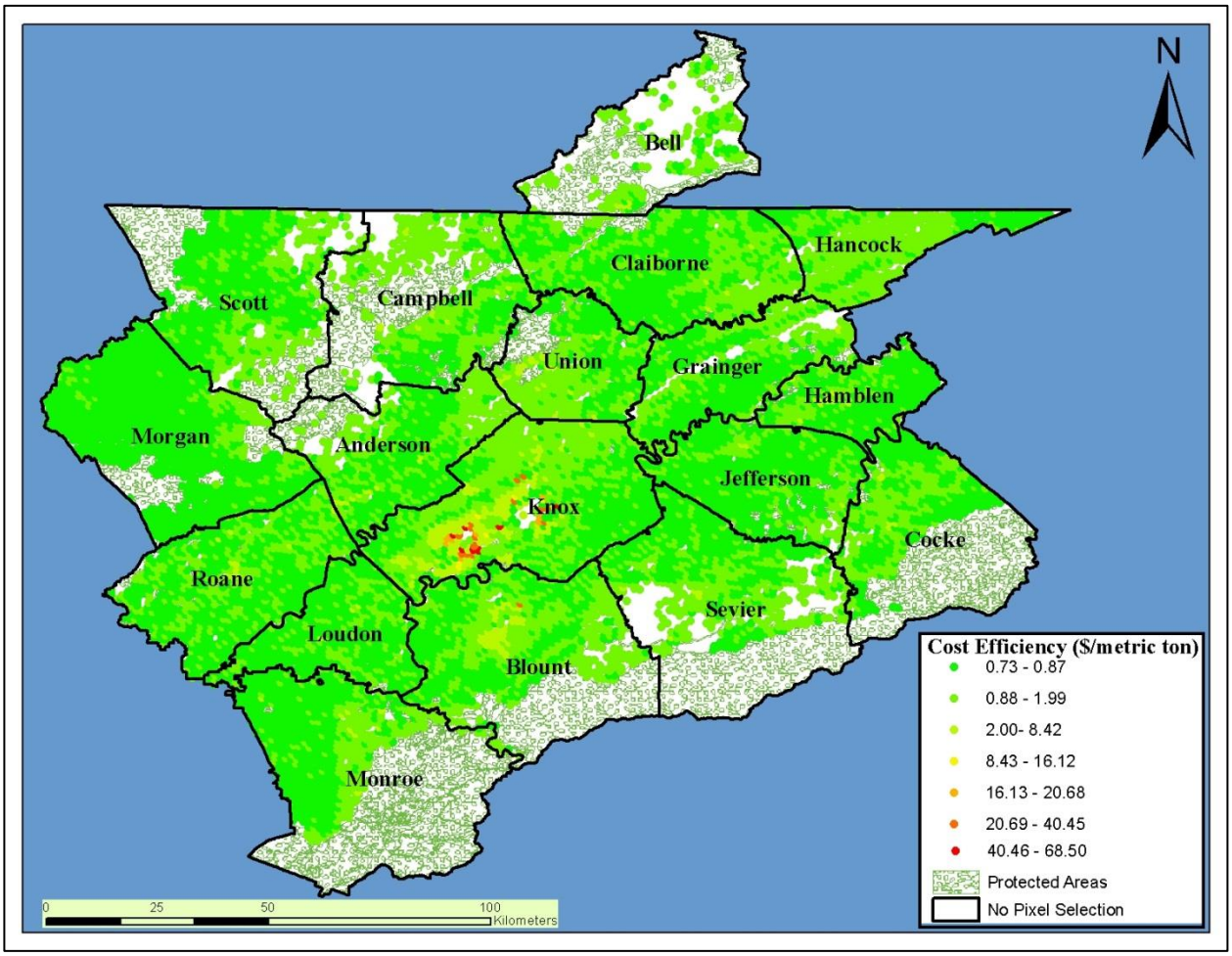


Figure 2. 12. Cost efficiency of carbon storage (dollar/metric ton) based on net change in forestland during 2006-2011

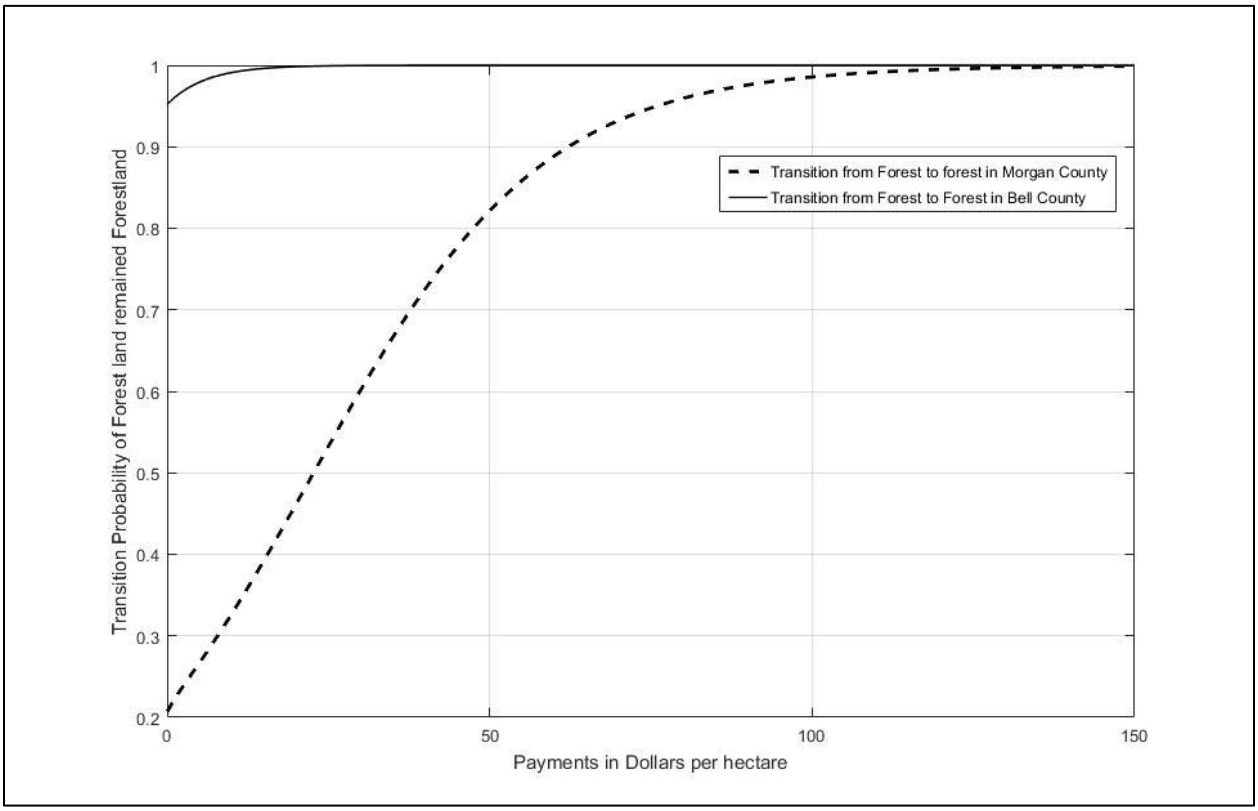


Figure 2. 13. Transition probability of the forestland remained forested in a random pixel of Bell and Morgan counties during 1992-2001

Chapter 3: Optimal Provision of Forest-Based Carbon Storage and Cost Effectiveness of Incentive Payment Approaches

Abstract

Mitigating climate change by sequestering carbon through reforestation and/or avoiding deforestation is an appealing option to offset greenhouse gas (GHG) emissions mainly because of the possible cost advantages over other mitigation efforts. That said, financial support for the establishment of the incentive payments for ecosystem services such as carbon sequestration is in short supply, and thus much attention has focused on the importance of their efficiency. The objective of this research is to estimate how much cost efficiency can be improved by incorporating asymmetric information between landowners and government agencies seeking to purchase forest-based carbon sequestration. The objective is achieved by estimating cost-efficient site-specific payments for optimal provision of forest-based carbon storage that incorporates the spatial heterogeneities in forest carbon sequestration and opportunity costs for sequestering carbon, and then by comparing its cost efficiency with fixed-rate payment scheme that disregard the spatial variations. Our empirical results for the 18-county case study show that optimal provision of forest-based carbon storage is 309,000 metric tons per year with annual costs of $5.8 million, yielding cost efficiency of $21.93 per metric ton in average. We found that the cost efficiency at the optimal provision is almost eight times better than fixed-rate per-hectare payments and is almost four times better than fixed-rate per metric ton payments. Our findings will help policymakers select incentive payment mechanisms, identify would-be participants, estimate payment amounts, anticipate budget outlays, and better understand and quantify the impacts of land use change on forest carbon sequestration.

1. Introduction

Evidence of the role of human activity on the global climate and of the impacts of climate change on people and ecosystems is clear and growing, as are the benefits of mitigating the effects of climate change by reducing the accumulation of greenhouse gases (GHG) in the atmosphere (IPCC, 2013). After water vapor, carbon dioxide (CO_2) is the most abundant and impactful GHG (Schmidt et al., 2010). Thus, capturing atmospheric carbon through carbon sequestration of forests can provide substantial GHG mitigation benefits (Silver et al., 2000). Most private landowners managing forests receive no compensation for their contribution to this service. However, mitigating climate change by sequestering carbon through reforestation and/or avoiding deforestation is an appealing option to offset GHG emissions mainly because of the possible cost advantages over other mitigation efforts (Schroeder, 1992; Dixon et al., 1993; Plantinga et al., 1999; Richards and Stokes, 2004; Figueroa et al., 2008; Jindal et al., 2008; Mason and Plantinga, 2011; USDA, 2011; Kling et al., 2012).

Programs promoting these ecosystem services have the potential to contribute to the sustainability of forested land by conserving or restoring the resources on which these ecosystems depend. For example, in 2009, the U.S. House of Representatives passed the American Clean Energy and Security Act with the goal of reducing net GHG emissions to 17% below 2005 levels in 2020 and 83% below 2005 levels by 2050 (USDS, 2010). Among other measures, the bill plans included the establishment of a cap-and-trade program that to generate payments to forest landowners for the carbon sequestration provided by their forests.

That said, financial support for the establishment of the incentive payments for ecosystem services such as carbon sequestration is in short supply (Ferraro, 2008; Gorte and Ramseur, 2010), and thus much attention has focused on the importance of their efficiency

(Hanley et al., 2012). For example, when designing incentive payment programs, one key distinction is between payment by results (referred to as "performance-based contracts") and payment by actions (referred to as "practice-based contracts") (Gibbons et al., 2011). Practice-based contracts are much more commonly implemented. However, Antle et al. (2003) showed that performance-based contracts for carbon sequestration (per ton based payments) in cropland soils are more cost effective than practice-based contracts (per hectare based payments).

Designing cost-efficient incentive payment programs for forest-based carbon sequestration is difficult because of asymmetric information in opportunity costs between lands that differ in the opportunity costs of carbon sequestration and/or between landowners who differ in their willingness-to-accept (WTA) payment to either afforest or refrain from deforesting their land (Pagiola, 2005; Bennet, 2008; Engel et al., 2008; Polasky et al., 2014). Failing to, at least partially, resolve this information asymmetry may lead to some landowners receiving payments far exceeding their costs, and thus limiting the ability of these programs to generate cost-efficient provision of ecosystem services (Ferraro, 2008; Gorte and Ramseur, 2010).

The objective of this research is to estimate how much cost efficiency can be improved by incorporating asymmetric information between landowners and government agencies seeking to purchase forest-based carbon sequestration. The objective is achieved by estimating cost-efficient site-specific payments (referred to as "optimal payment scheme") for optimal provision of forest-based carbon storage that incorporates the spatial heterogeneities in forest carbon sequestration and opportunity costs for sequestering carbon, and then by comparing its cost efficiency with fixed-rate payment scheme (i.e., per-hectare carbon value and per-ton carbon value) that disregard the spatial variations.

Land use models that reveal the relationship between land use choices and relative returns in the forestry and agricultural sectors have been used to resolve the aforementioned asymmetric information problem (e.g., Stavins, 1999; Plantinga et al., 1999; Newell and Stavins, 2000; Antle et al., 2003; Kurkalova et al., 2004; Lubowski et al., 2006). Two types of land use models are commonly used. One model estimates the share of land for counties or larger geographic areas shifting from one type of land use to another over some transition period (e.g., Hardie et al., 2000; Ahn, et al., 2001; Cho et al., 2005; Broniak, 2007; Sohngen and Brown, 2006; Ahn, 2008). Alternatively, discrete choice models have commonly been used for modeling land-use transitions at the parcel level (e.g., Bockstael, 1996; Bockstael and Bell, 1998; Miller and Plantinga, 1999; Bell and Irwin, 2002; Irwin and Bockstael, 2002, 2004; Irwin et al., 2003; Cho and Newman, 2005; Lubowski et al., 2006; Cho et al., 2008; Langpap and Wu, 2008, 2011).

Parcel-level models work on a disaggregated enough scale to capture spatial heterogeneity in land use choices but are difficult to extend either (a) over a large study area due to heterogeneity in how different counties store and manage parcel level data or (b) over extensive time periods due to the difficulty in tracking land-use changes at the parcel level because of continuous fragmentation of parcels of land into smaller units with each unit put to different use (Igbozurike, 1987). The challenges of estimating multi-scale temporal and spatial modeling of land use changes mainly lie in the difficulties of integrating a land use model at a geographic level disaggregated enough to capture site-specific land use choices over broad enough temporal and spatial scales to quantify key drivers and their effects.

An alternative that can resolve both difficulties is to use a pixel-level land use change model. Pixel-level land use models, which are based on satellite imagery and other raster type

data (e.g., 30 m × 30 m resolution land cover change data), have gained popularity as a result of the development of remote sensing capabilities and geographic information system (GIS) databases (Brewer et al., 2012; Myint et al., 2011). One of the most common pixel-level datasets used to parameterize land use models is the National Land Cover Data (NLCD) (Fry et al., 2011; Jin et al., 2013; Lewis et al., 2011; Sexton et al., 2013; Lister et al., 2014). NLCD is commonly used, because it is considered accurate relative to other land-classification data (Hollister et al., 2004; McMahon, 2007; Jin et al., 2013); it is appropriate for large extent land cover change work; and it is freely available through Multi-Resolution Land Characteristics (MRLC) consortium for the lower 48 States for the years of 1992, 2001, 2006, and 2011 (MRLC 2014).

We used pixel-level land use models based on 1992, 2001, 2006, and 2011 NLCD to account for spatial heterogeneity in sequestration capacity and the site-specific opportunity costs of retaining forestland to estimate site-specific marginal cost curves of supplying carbon storage. By evaluating fixed-rate payment scheme against the optimal payment scheme for optimal provision of forest-based carbon storage that account for aforementioned spatial heterogeneities, we provide information critical to the development and implementation of a cost-effective payment system for carbon sequestration on forested land.

2. Methodology

We estimated the cost-efficient site-specific payments that accounted for spatial heterogeneities in the ability of the land to store carbon and the opportunity cost of forestland by: (1) developing a one km^2 pixel-level, land-use model to link forest-based carbon incentive payments with land use change, including deforestation and afforestation, based on the

assumption that landowners maximize net returns from different land-uses (see section 2.1.); (2) employing a carbon simulation model to project site-specific carbon storage (i.e., the annual carbon changes at the one km^2 in metric ton per year) levels for the forest cover based on climate, forest type, disturbance and management history, and other environmental characteristics (see section 2.2.); (3) deriving site-specific annual supply curve for carbon storage based on predicted land-use change and changes in carbon storage for an incrementally increasing net return of forestland (see section 2.3.); and (4) estimating cost-efficient site-specific payment distributions that allowed cost-efficient provision of carbon storage (see section 2.4.).

We derived the relationship between cumulative carbon storage and annual payment per metric ton under the cost-efficient site-specific payment distributions (referred to as "aggregate marginal cost curve"). Then, we determined the optimal provision of forest-based carbon storage by identifying the equilibrium point between the aggregate marginal cost curve and a proxy for the marginal benefit of carbon sequestration that is based on the U.S. Environmental Protection Agency's (USEPA's) estimate of the social costs of carbon (USEPA, 2015) (see section 2.5.). Finally, we compared the cost efficiency between the optimal payment scheme and the two fixed-rate payment scheme and mapped cost-efficient site-specific payment distributions to visually highlight optimal spatial targeting of payments for forest-based carbon storage (see section 2.6.).

2.1. A land use model

Suppose a landowner chooses a combination of land-use types that maximizes his net returns. The shares of land-use types are then functions of the net returns from the land-uses and

other factors that influence land-use decisions. See Section S.1. of the Supplementary material for the details about the net returns from different land uses. Following the notation from Miller and Plantinga (1999), the general functional form of the land-share allocated to a particular type of land-use (k) is expressed as:

$$s_k(t,i,n) = f_k(X(t,i,n),t,n) + u_k(t,i,n) \quad (1)$$

where, at time periods t (i.e., 1992-2001, 2001-2006, and 2006-2011) by a landowner n of a parcel i $(i = 1, \dots, N)$, $s_k(t,i,n)$ is the observed share of land-use type k, $X(t,i,n)$ includes factors that influence land-use decisions (i.e., net returns from alternative land uses and physical characteristics of land, such as the slope), and $u_k(t,i,n)$ is the error term. The three time periods were chosen according to the land-use data that we used. This land-use data were obtained for the years 1992, 2001, 2006 and 2011 from the National Land-Cover Dataset (NLCD).

The net returns from different land-uses are observed after the allocation of land is designated across different time periods, and thus, land-use decisions across the periods have intertemporal linkages. To accommodate these temporal dynamics in converting the general functional form (Equation 1) to an empirical framework, it is essential to understand the factors affecting land-use change and the land-use transition probabilities among land-use categories over different time periods. Parametrizing the transition probabilities with a multinomial logistic distribution can be convenient (Lambert et al., 2016). To accomplish such tasks, the Multinomial logistic Markov transition probabilities were estimated using maximum likelihood (ML) based on similar methods employed in previous studies (MacRae, 1977; Miller and Plantinga, 1999; Plantinga and Ahn, 2002; Ahn et al., 2000). The multinomial logistic of the

first order of the Markov decision process that is expressed in a logistic form with time-varying transition probabilities can be used to determine the shift of land from one use to another one:

$$\pi(t^e, i, j, k) = \frac{exp[(s(t^b, i, j) \sum_h^H \beta(h, k) X(t^e, i, h)]}{\sum_{k=1}^K exp[(s(t^b, i, j) \sum_h^H \beta(h, k) X(t^e, i, h]} \quad (2)$$

where $\pi(t^e, i, j, k)$ for the spatial unit (i.e., one km^2 pixel level) $i = 1, \dots, N$ is the probability for land use j transitioning to land use k during time period t^e, $s(t^b, i, j)$ represents the observed land share in use j at the beginning of each time period t^b, $\beta(h, k)$ is the parameter associated with an explanatory variable h in land-use k, and $X(t^e, i, h)$ is the vector of explanatory variables at the end of each time period t^e for the spatial unit $i = 1, \dots, N$ (MacRae,1977; Lambert et al., 2016). In this study we refer to the current period as t^e and to the lag or prior period as t^b, since each period's duration is different (i.e. 1992-2001, 2001-2006, 2006-2011).

The multinomial logistic form is used to estimate the transition probabilities (Equation 2) for five land-use categories (i.e., crop, pasture, urban, forest, and other uses) at the one km^2 pixel level, which represents the spatial structure of the decision-making units, over the three periods with the constraints of non-stationary Markov transition probabilities. The first condition that has to be met is that the transition probabilities must be all positive, and the predicted land share s in period t^e is a function of the transition probability π and the land share from the prior period t^b. The second condition is that the land shares in each pixel sum to one for each time period. Lastly, the row sum of the transition probabilities from one land use to the others sum to one. Therefore, the transition of land from one use to another must be consistent with the following conditions:

$$s_{t^e,i,k} = \sum_{j=1}^K \pi_{t^e,i,j,k} * s_{t^b,i,j}\ ,\ \sum_{j=1}^K s_{t,i,j} = 1\ \ , and\ \sum_{k=1}^K \pi_{t^e,i,j,k} = 1\quad \forall\, i, t \quad (3)$$

Following Lambert et al. (2016), the parameters $\beta(h,k)$ are estimated using the log likelihood of the joint multinomial probability distribution across i spatial units, j land uses in period t^b, and k uses in t^e. Maximizing the following equation yields the maximum likelihood estimates of β:

$$\max_{\beta_{h,k}} ln\, L = \sum_t \sum_i \sum_k \sum_h \beta_{h,k}.\, s_{t^b,i,k}.\, x_{t^b,i,h} - \sum_t \sum_i \sum_j \left[\Omega_{t^b,i,j}\right] \quad (4)$$

where $\Omega_{t^b,i,j} = \sum_k \exp(s_{t^b,i,j}.\sum_h^H \beta(h,k).X(t^e,i,h))$ is the denominator from equation (2). A category is omitted to identify the system (e.g. $\beta = 0$ for the other land use category).

By estimating Equation (2), we hypothesize that land-use shares at the end of each time period (i.e., 2001, 2006, and 2011) are functions of expected annual returns from each land-use for the same years (i.e., net returns in 2001, 2006 and 2011, respectively).[2] The average slope of pixels is included as a physical characteristic because land-use choices are affected by landscape attributes (e.g., Nelson and Geoghegan, 2002). We also included two dummy variables indicating whether the allocation of land-use share is made in 1992-2001 or 2001-2006 (1992-2001 as a reference year). These time period dummy variables control for trends from one time period to another (see Table 3.1 for variable names, definitions, and descriptive statistics). Standard errors were adjusted for spatial dependences using a spatial heteroskedastic robust covariance estimator referred to as the "spectral density" matrix since there were time fixed effects included on the right hand side of the model. Following Lambert et al. (2016), robust standard errors are estimated as $V = H^{-1}BH^{-1}$, where H is the hessian of the log likelihood function and B is:

$$B_{j-1,k-1} = \sum_t \sum_n \sum_{m \in d_{m,n} \le d_{max}} K(z) \cdot x'_{t,n,h} \cdot u_{t,n,j-1} \cdot u_{t,m,k-1} \cdot x_{t,m,h} \quad (5)$$

[2] See S.1 in the supplementary materials for details about the net returns.

for the j , k^{th} position of the parameters associated with land use k; $d_{m,n}$ is the Euclidean distance between locations m and n; and d_{max} is a threshold where after neighbor effects are zero. The kernel $K(.)$ mediates the impacts of neighborhood shocks through the Barlett function $z = 1 - \frac{d_{m,n}}{d_{max}}$. The parameter d_{max} is determined by the plug-in bandwidth (Kelejian and Prucha, 2007) of $14{,}680^{0.25}$ = 11 neighbors (14,680 is the number of spatial units in this analysis that correspond to the 1 km by 1 km pixel).

Once the transition probabilities for each pixel across the three periods are estimated, the 5 × 5 transition matrices of land shares are estimated to simulate the effect of changes in expected net returns to forestland associated with hypothetical carbon incentive payments on carbon storage. Specifically, the transition matrices of land-shares are calculated by matrix multiplication between the relative transition probability matrices (i.e., transpose of the transition probability matrix correspondent to the land-use) and the land-use share in the time-lagged period.

2.2. A carbon simulation model

The changes in carbon storage (i.e., positive changes in carbon storage represent carbon sequestration, while negative changes represent carbon emissions) are estimated for three periods: 1992-2001, 2001-2006, and 2006-2011 at a Terrestrial Ecosystem Model (TEM) cohort level based on climate, forest type, disturbance and management history, and other environmental characteristics of a particular pixel (Oak Ridge National Laboratory, 2016). This process-based ecosystem model uses spatially-related information (i.e. climate, elevation, soils and vegetation) to make estimates of carbon, nitrogen and water fluxes (Hayes et al., 2011). The choice of the model was based on its precise implementation of cohort structure which allows for spatially- and temporally-explicit simulation of carbon dynamics by tracking the TEM

cohort heterogeneity in different forest types, along with any disturbance histories (i.e. change in land-use) (Hayes et al., 2011).

Carbon storage is calculated using monthly estimates provided by the TEM cohort level carbon pools over the three time periods, separately. Carbon sequestration is reported for each of the three time periods in grams of carbon per square meter (C/m^2) for different biomes in each grid cell, based on integrating the monthly fluxes to account for the net total of carbon uptake through photosynthesis against carbon losses. The area of each biome is consistent with our pixel spatial resolution, which is also measured in one km^2. Once the annual estimates for the three periods are derived, total carbon sequestrated is computed by multiplying the model results by the actual area of each biome.[3] The total carbon storage estimated for each period in each land-use category (forest, pasture, crop, urban and other land uses) is then used to derive the 5×5 transition matrices of changes in carbon storage in tons per square kilometer (ton/km^2) across the three periods. These matrices correspond to the 5×5 land use transition matrices of changes for each pixel across the three periods discussed above.

2.3. Annual pixel-level carbon storage supply curves

Carbon storage is estimated using the observed land-shares and associated carbon storage transition matrices as a baseline. Changes in land use are then simulated by increasing forestland return per hectare in $1 increments from $1 to $750 per hectare in 2001 in the land-use transition model (the land use information collected in each period represent a snap-shot in time, and thus the simulation could be done for all three periods). These changes are translated into changes in carbon storage using the carbon simulation model described above. Using this information, annual pixel-level supply curves for carbon storage in tons per hectare are derived

[3] See S.2 in the supplemental material section for more detailed information on the carbon model.

by incrementally increasing the net returns in 2001 to forestland in the land use transition model reduces the extent to which forestland is converted to crop, pasture, range, and urban uses and increases the conversion of crop, pasture, and range lands to forest in the land-use transition model.

2.4. Cost-efficient site-specific payment distributions

Using the annual pixel-level supply curves for carbon storage, we estimated cost-efficient site-specific payment distributions under the assumption that (i) one km^2 pixel represents the spatial structure of the decision-making units, (ii) each dollar is distributed among the pixels in the most efficient way so there is payment price discrimination between pixels, and (iii) landowners are risk neutral in the face of uncertainties in net returns from alternative land-uses.

The cost-efficient site-specific payment distributions among the pixels is found by: (1) calculating marginal carbon stored per dollar paid for each payment level (i.e., payment from $1 to $750 per hectare from the annual supply curves for carbon storage) at each pixel; (2) calculating average carbon stored per dollar paid for each payment level and identifying the payment level for each pixel with the maximum average carbon stored per dollar paid from all the payment levels; (3) sorting the pixels by the descending order of the maximum average carbon stored per dollar paid; and (4) allocating payment to the pixels with the highest marginal or average carbon stored per dollar paid until the marginal carbon stored decreases to zero for each pixel. Since the cost curve describes the minimum cost at which landowners of a particular 1 km^2 parcel is paid for various amounts of carbon storage that it can generate, the task is to

determine the amount of payment necessary to generate the highest additional carbon storage (see section S.3 and Figure S.1 for details in the supplementary material).

2.5. Optimal provision of forest-based carbon storage

The optimal provision of forest-based carbon storage is identified at the equilibrium point between aggregate marginal cost curve we established and the net present value (NPV) of the marginal benefit of carbon sequestration that is based on the U.S. Environmental Protection Agency's (USEPA's) estimate of the social costs of carbon (USEPA, 2015).[4] We first converted the social cost of carbon from 2010 dollars per metric ton of CO_2 to 2010 dollars per metric ton of carbon using the price of $69 per metric ton in the 2050 emission year at the 3% discount rate following examples in the literature (Hope, 2008; Anthoff and Tol, 2011; Link and Tol, 2011). The year 2050 was chosen because this year has been commonly referred to in climate stabilization calculations (Mumovic and Santamouris, 2013). The social cost of carbon $69 per metric ton of CO_2 was converted to $253 per metric ton of carbon storage using a simple conversion factor: one ton of stored carbon in trees removes 3.67 tons of CO_2 from the atmosphere (IPCC, 2010). To be comparable to USEPA's social cost of carbon, we derived the NPV from the annual payment received by the landowner at the discount rate of 3%, assuming the annual payments were to continue in perpetuity, essentially assuming that the program would continue indefinitely and that landowners would not convert covered forest to any other uses, or harvest timber from the forest.

[4] Since our study can only permit us to identify the relationship between the cost effectiveness of different additional carbon storage options (i.e., additional carbon given a level of payment) and the total potential carbon in metric tons, estimating the benefits of sequestering carbon is beyond the scope of this research. Thus, we use USEPA's estimate of the annual social cost of carbon ($253 per metric ton of carbon) as a proxy value for the marginal benefits of sequestering or storing (avoiding release) of a metric ton of CO_2 because the social cost of carbon is an estimate of the economic damages incurred (avoided) with an increase (decrease) of one metric ton of Co_2 emissions (USEPA, 2015).

2.6. Cost efficiency between the optimal payment and the two fixed-rate payments

Once the optimal provision of forest-based carbon storage was identified, the budget needed to reach that level (referred to as "optimal budget") was determined. Given the optimal budget, we identified fixed-rate payments per-hectare and per-ton using simple optimization procedures to ensure that the difference between the optimal budget and the budget needed for each of the fixed-rate payments per-hectare and per-ton carbon value was minimized. (The fixed-rate payments were determined using the simple optimization procedures to ensure the cost efficiency was compared under a comparable budget constraint.) Then, we compared the cost efficiency between the optimal payment scheme and the two fixed-rate payment scheme. We also mapped cost-efficient site-specific payment distributions under the optimal budget to visually highlight optimal spatial targeting.

3. Study area and data

We focus on the U.S. Bureau of Economic Analysis' (BEA) Economic Area 88 (U.S. Department of Commerce, 2016), which consists of one Kentucky and 17 Tennessee counties as a case study (Figure 3.1). This region was chosen to represent the larger Appalachian region which accounts for 20% of U.S. forestland and is considered to be the largest carbon sink among the six bioclimatic regions of the conterminous U.S. (Schimel et al., 2000; Smith et al., 2009; Tian et al., 2010). Furthermore, the large stock of young pine trees in Southern forests provide an opportunity to continuously function as a carbon sink in the future and make the region the most productive in terms of timber production (Wear, 1995; Turner et al., 2005; Birdsey et al., 2006; Malmsheimer et al., 2008). In addition, the majority of the region's forest land is owned by private entities, and the region's timber industry has lately experienced

substantial disinvestment in landholdings. For example, around 88% of the relevant timberland in the Appalachian region is owned by private entities while, in 2004, six of the nine largest timberland transactions in the Southeastern US featured industrial sellers (Clutter et al., 2005; Smith et al., 2009). Privately held forestland and extensive disinvestment by timber companies provide both an opportunity and an impetus for programs to incentivize forest-based carbon sequestration.

A variety of datasets are needed for the land-use and carbon-simulation models (See Section S.2 of the Supplementary material for the details of the dataset for the carbon-simulation model). The land-use model uses the following datasets: land-use data, data used for the estimation of annual returns for specific land-uses, and other socio-economic and geophysical data. Land-use data at a 30 m × 30 m resolution for all five land-use categories in 1992, 2001, 2006, and 2011 are from the National Land-Cover Dataset (NLCD) (US Department of the Interior and US Geological Survey, 2016). The 21 NLCD classifications were merged into five land-use categories as follows: cultivated cropland as "cropland" category; pasture/hay and grassland/herbaceous land-cover as "pasture land-use"; developed open space, developed low intensity, developed medium intensity, and developed high intensity classifications as "urban land-use" category; deciduous forest, evergreen forest, and mixed forest as "forestland" category, and the rest of NLCD classifications (i.e., open water, barren land rock/sand/clay, dwarf scrub, shrub/scrub, woody wetlands, and emergent herbaceous wetlands) as "other use" category. The 30 m × 30 m areas were aggregated within each one km^2 pixel for each land use category.

The expected annual return per hectare of cropland at the county level was estimated based on total county net cash farm income (gross cash farm income and less all cash expenses)

and harvested hectares of cropland for 2001 and 2006 from the USDA Census of Agriculture (2012) and the National Agricultural Statistical Service (NASS, 2014). County-level rent per hectare of pastureland was used as the expected return per hectare of pastureland using the pasture rent data from National Agricultural Statistical Service (National Agricultural Statistics Service, 2014) and data on cattle inventories from the USDA Census of Agriculture (2012). The expected urban return at the census-block group level was estimated using census-block group data for median housing price (U.S. Census Bureau, 2000) and parcel-level data for assessed land value (excluding structures), total assessed value (land and structures), and lot size from the tax assessors' offices of two counties of the study area (i.e., Blount and Roane counties in Tennessee) and five counties. (i.e., Franklin, Fentress, Morgan, Monroe, and Pickett) adjacent to the study area. Data on stumpage price, timber harvest volume, and timber harvest age were used to estimate net returns to forestland. The stumpage price data for Tennessee was obtained from Timber Mart-South (TMS, 2001, 2006) while the stumpage price data for Kentucky was collected from Growing Gold (KDF, 2001, 2006). The timber harvest volume data came from the Forest Inventory and Analysis (FIA) database (FIA; Gray et al., 2012; Woudenberg et al., 2010) and the timber harvest age data came from Smith et al. (2006).

Distance variables were created using ArcGIS 10.1 (ESRI, 2012). These variables represent the distance between parcel centroids and either the centroids of the nearest park, golf course, hospital, or school or the nearest point of a polyline representing a highway. Other socio-economic and geophysical data include data for distance of a forestland parcel to the nearest protected area, mean slope, mean elevation, and other data, including vacancy rate and median household income. Protected area boundaries (including those for federal, state and privately protected areas within the study region) were obtained from the Protected Areas

Database of the United States (PAD-US) (USGS, 2013). Mean slope and mean elevation for each one km^2 were measured using raster grids derived from the 30 m × 30 m Digital Elevation Model (DEM) (USGS, 2013) and calculated using the Zonal Statistics tool in ArcGIS 10.1 (ESRI, 2012). We report the variable names, definition, and descriptive statics associated with the land use model in Table 3.1.

4. Empirical results

The maximum likelihood parameter estimates of the Multinomial logistic Markov transition probabilities form of the land use model are reported in Table 3.2. The parameter estimates for the all four net returns on the shares of all four land uses were significant at the 1% level (hereafter, referred to as "significant"). However, the interpretation of the parameter estimates is not straightforward because the variables interact with more than one category of the dependent variable (i.e., four possible land use choices excluding other use as a reference category) (Miller and Plantinga, 2003; Wooldridge, 2010). Hence, we refer to the elasticities of the Multinomial logistic Markov transition probabilities to elaborate further on their interpretation, focusing on the role of forest net return on the land-use transition probabilities.

The transition elasticities at mean values over the three time periods (Table 3.3) suggest that a 1% increase in the forest net return increases the probability of retaining the forestland by 0.50%. The same increase of the forest net return also causes to decrease conversion probabilities of forestland to pasture, crop, urban, and other uses by 2.04%, 32.71%, 1.53%, and 2.30%, respectively. The same increase of the forest net return also increases the conversion probabilities of pasture, crop, urban, and other uses to forestland, respectively, by 0.31%, 0.04%, 0.15%, and 0.09%. These findings jointly imply that offering incentive payments to

landowners to afforest non-forested land and to retain forests at risk of conversion to non-forest uses are both feasible approaches. It is worth noting that while the transition from urban use to forest may be perceived as an unlikely event, development and extension of urban forest (e.g., urban forest restoration programs) is suspected to be the main cause of the transition (Nowak et al., 2010). The annual changes in carbon storage (see Figure 3.2) based on the observed land-use changes (see Figure 3.3) at the pixel level during the period of 1992-2011 are summarized at the county level in Table 3.4. The annual carbon storage was changed over the range between -18.3 and 9 metric ton per hectare during the 19 years of the period time. As anticipated, the loss of carbon storage occurred more at the pixels with relatively high forestland loss (e.g., pixels at Knox County) while the pixels with carbon storage gain also gained forestland (e.g., pixels at Bell County). The large degree of forestland loss is mainly associated with the large degree of urbanization. For example, 53,979 of 132,933 hectares (or 41%) of deforestation in Knox County during the 19 years of period was for urbanization. In contrast, the majority of forest gain in Bell County during the same period (30,063 of 57,835 hectares or 52%) was due to the conversion of pasture to forestland.

We derived the annual pixel-level carbon storage supply curves for each of the 14,680 pixels using the predicted land-use change and changes in carbon storage for an incrementally increasing net return of forestland. Three supply curves for three representative pixels based on simulated changes in land use by incrementally increasing forestland return per hectare in 2001 are shown in Figure 3.4. The annual pixel-level carbon storage supply curves increase at an increasing rate while approaching maximum carbon-storage capacities of 17, 24, and 31 metric tons per year, respectively, at $98, $149, and $250 per hectare per year. The different shapes of

the supply curves as illustrated as an example in Figure 3.4 are the evidence of the spatial heterogeneity in opportunity costs for sequestrating carbon.

By accumulating the annual pixel-level carbon storage supply curves across the entire area, we derived the aggregate marginal cost curve as shown in Figure 3.5. Following the shapes of the pixel-level curves, the aggregate marginal cost curve increases at an increasing rate while approaching maximum carbon-storage capacity of 451,505 metric tons per year. The aggregate marginal cost curve intersects with USEPA's (2015) marginal benefit of carbon storage (i.e., $253 per metric ton of carbon stored at the 3% discount rate based on the 2010 US dollar) (see Figure 3.5). The equilibrium point identified 309,000 metric tons of annual carbon storage at the total annual cost of $5.8 million as optimal provision, yielding cost efficiency of $21.93 per metric ton in average. This cost efficiency at the optimal provision is almost eight times better than fixed-rate per-hectare payments ($163.94 per metric ton in average) and is almost four times better than fixed-rate per metric ton payments ($81.00 per metric ton in average), assuming the same discount rate in 2010 US dollar.

The cost-efficiency based on the cost-efficient site-specific payment distributions was mapped under the optimal budget to visually highlight optimal spatial targeting (Figure 3.6). 1,222,900 of 1,972,100 hectares (or 62%) of the entire study area, excluding protected area were identified as optimal spatial targeting of payments. Among the optimal target areas, 49% was to afforest pasture land and 41% was to sustain forests at risk of deforestation. If we scrutinize the distributions of the optimal spatial targets more closely, the selected target pixel was highest in Morgan County (83.79% of the entire county's area, excluding protected area) and was lowest in Bell County (9.13% of the entire county's area, excluding protected area). The reason behind this difference is in the transition probabilities of forest-related land use changes. The predicted

probability of choosing forestland increases more for Morgan County than for Bell County in average at any given payment levels, because the increase of transition probability of afforesting non-forested land and of retaining forests at risk of conversion to non-forest uses in average given any payment levels is greater in Morgan County than in Bell County. This difference is reflected in the lower marginal costs for sequestering carbon in Morgan County than in Bell County in average given any payment levels (Figure 3.7).

5. Conclusion

In designing cost-efficient incentive payment programs for forest-based carbon sequestration, spatial targeting under the optimal provision of forest-based carbon storage that incorporates the spatial heterogeneities in forest carbon sequestration and opportunity costs for sequestering carbon is imperative. To account for the spatial heterogeneities, we estimated the site specific annual pixel-level carbon storage supply curves. Then, those curves were aggregated to identify optimal provision of forest-based carbon storage. Subsequently, we compared the cost efficiency between optimal payment schemes and fixed-rate payment schemes that disregard the spatial variations, and we also created a cost-efficiency map based on the cost-efficient site-specific payment distributions under the optimal budget. Our sequential analysis extends the current literature of spatial heterogeneity in the supply of ecosystem services by estimating cost-efficient site-specific payments for optimal provision of ecosystem services.

Our empirical results for the 18-county case study show that optimal provision of forest-based carbon storage is 309,000 metric tons per year with annual costs of $5.8 million, yielding cost efficiency of $21.93 per metric ton in average. We found that the cost efficiency at the

optimal provision is almost eight times better than fixed-rate per-hectare payments and is almost four times better than fixed-rate per metric ton payments. The better cost efficiency of the optimal payment scheme is in the ability to make payments according to the annual pixel-level carbon storage supply curves that collectively incorporates the spatial heterogeneities in forest carbon sequestration and opportunity costs for sequestering carbon. The cost-efficiency map based on the cost-efficient site-specific payment distributions reflects such ability to differentiate the payments.

Our findings will help policymakers select incentive payment mechanisms, identify would-be participants, estimate payment amounts, anticipate budget outlays, and better understand and quantify the impacts of land use change on forest carbon sequestration. Despite the clear implication of our study, it is important to understand its caveat as well. Incentive payment programs tend to be controversial due to what are often uncomfortably high levels of uncertainty about their benefits and costs (Ferraro and Pattanayak, 2006). For example, climate shifts mean the future geographic ranges of different ecosystem services may shift in unpredictable ways. Uncertainty caused by climate shifts is important to incorporate when designing payments for ecosystem services as climate change poses an increasingly imminent threat to ecosystem services (Dale et al., 2001; Logan et al., 2003; Westerling et al., 2011; Woollings et al., 2012). Thus, future analyses incorporating the climate changes in the current empirical framework would be highly valuable to assess the direct impact of environmental conditions for the development of cost-effective incentive payment approach for forest-based carbon storage.

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Appendix

Table 3. 1. Variable Names, Definitions, and Descriptive Statistics

Variable	Description	Mean
Forest Return	Annual net return from forest-use at the county level ($/ha)	30.29 (17.93)
Pasture Return	Annual net return from pasture-use at the county level ($/ha)	47.75 (6.17)
Crop Return	Annual net return from crop-use at the county level ($/ha)	45.35 (375.22)
Urban Return	Annual net return for urban-use at the census-block group level ($/ha)	1012.55 (1460.91)
Slope	Average slope at pixel-level (degrees)	10.60 (4.62)
2006 Year dummy	1 if the land-use decision was in 2006, 0 otherwise	0.33 (0.47)
2011 Year dummy	1 if the land-use decision was in 2011, 0 otherwise	0.33 (0.47)

Note: Numbers in parentheses are standard deviations.

Table 3. 2. Maximum Likelihood Parameter Estimates of the Multinomial Logistic Markov Transition Probabilities from the Land Use Model

Variables	Forestland	Pastureland	Cropland	Urban-land
Constant	-10.5893*	-6.0800	-38.9779*	-10.9107
	(0.7039)	(0.7000)	(2.6418)	(0.7654)
Forest Returns	0.2975*	0.0272*	-3.2323*	0.0815*
	(0.0128)	(0.0126)	(0.0608)	(0.0135*)
Pasture Returns	0.2853*	0.2810*	1.8621*	0.3475*
	(0.0318)	(0.0317)	(0.1182)	(0.0345)
Crop Returns	-0.0008*	-0.0004*	0.0109*	-0.0031*
	(0.0002)	(0.0002)	(0.0005)	(0.0002)
Urban Returns	0.0009*	0.0002*	-0.0045*	0.0031*
	(0.0001)	(0.0001)	(0.0004)	(0.0001)
Slope	0.5467*	0.4607*	0.9564*	0.4900*
	(0.0197)	(0.0197)	0.0670)	(0.0210)
2006 Year dummy	2.2729*	1.0192	0.7736*	0.6322*
	(0.1267)	(0.1248)	(0.4248)	(0.1356)
2011 Year dummy	3.6713*	1.4835	1.2578	1.7043
	(0.1922)	(0.1903)	(0.4916)	(0.2053)

Note: Pseudo R-square is 0.045 and log-likelihood is -300,440, N=44040. The category of other uses was used as the reference group.
* Indicates statistical significance at the 1% level. Numbers in parentheses are standard errors.

Table 3. 3. Transition Elasticities of the Non-stationary Markov Transition Probabilities for the Land-use Model at Mean Values over the Three Time Periods

Variables		Forest Share	Pasture Share	Crop Share	Urban Share	Other Share
Intercept	Forest	-0.6043	2.1610	-18.0117	-0.8014	5.8889
	Pasture	-0.5295	0.4829	-6.9026	-0.6016	1.8478
	Crop	-0.0147	0.0535	-0.4444	-0.0197	0.1455
	Urban	-0.1592	0.2905	-2.9907	-0.1913	0.8970
	Other	-0.1001	0.1139	-1.4470	-0.1153	0.4023
Forest Returns	Forest	0.5015	-2.0412	-32.7070	-1.5302	-2.2978
	Pasture	0.3130	-0.1587	-5.8473	-0.0639	-0.2063
	Crop	0.0410	0.0124	-0.3294	0.0181	0.0095
	Urban	0.1510	-0.0290	-2.1995	0.0072	-0.0472
	Other	0.0885	-0.0016	-1.0883	0.0165	-0.0107
Pasture Returns	Forest	-0.0140	-0.0653	18.9239	0.7330	-3.4411
	Pasture	-0.0081	-0.0262	6.6856	0.2559	-1.2194
	Crop	-0.0252	-0.0265	0.4650	-0.0058	-0.1139
	Urban	-0.0464	-0.0543	2.8711	0.0687	-0.5743
	Other	-0.0261	-0.0300	1.4022	0.0302	-0.2846
Crop Returns	Forest	-0.0040	-0.0005	0.0876	-0.0217	0.0028
	Pasture	-0.0070	-0.0031	0.0949	-0.0267	0.0005
	Crop	-0.0019	-0.0011	0.0185	-0.0058	-0.0004
	Urban	-0.0043	-0.0050	-0.0236	-0.0005	-0.0057
	Other	-0.0027	-0.0018	0.0198	-0.0070	-0.0010

Table 3. 3. Continued

Variables		Forest Share	Pasture Share	Crop Share	Urban Share	Other Share
Urban Returns	Forest	-0.0378	-0.1688	-1.0542	0.3749	5.8889
	Pasture	-0.0107	-0.0745	-0.5056	0.1902	1.8478
	Crop	0.0016	-0.0034	-0.0373	0.0175	0.1455
	Urban	-0.1322	-0.2052	-0.6980	0.0975	0.8970
	Other	-0.0011	-0.0178	-0.1308	0.0515	0.4023
Slope	Forest	0.1670	-0.4762	3.2282	-0.2564	-2.2978
	Pasture	0.1557	-0.0059	0.9262	0.0494	-0.2063
	Crop	0.0111	0.0019	0.0553	0.0050	0.0095
	Urban	0.0725	0.0037	0.4004	0.0272	-0.0472
	Other	0.0360	0.0041	0.1741	0.0142	-0.0107
Year dummy 06	Forest	0.0700	-0.1645	-0.2105	-0.2369	-3.4411
	Pasture	0.0813	-0.0241	-0.0448	-0.0567	-1.2194
	Crop	0.0034	-0.0001	-0.0008	-0.0011	-0.1139
	Urban	0.0511	-0.0031	-0.0137	-0.0199	-0.5743
	Other	0.0184	-0.0018	-0.0058	-0.0080	-0.2846
Year dummy 11	Forest	0.1133	-0.2864	-0.3276	-0.2460	0.0028
	Pasture	0.1243	-0.0631	-0.0825	-0.0442	0.0005
	Crop	0.0051	-0.0009	-0.0015	-0.0003	-0.0004
	Urban	0.0761	-0.0235	-0.0338	-0.0135	-0.0057
	Other	0.0292	-0.0074	-0.0112	-0.0037	-0.0010

Table 3. 4. Annual Changes in Carbon Storage Based on the Observed Land-Use Changes during the Period 1992-2001, Summarized at County Level

County	Annual Carbon Storage (MT/ha)	Net Change in Forest (hectare)
Bell	0.86	335
Anderson	-1.65	-611
Blount	-1.69	-1034
Campbell	-0.44	-120
Claiborne	-1.54	-896
Cocke	-1.85	-545
Grainger	-0.23	-116
Hamblen	-1.45	-264
Hancock	-2.11	-743
Jefferson	-0.44	-106
Knox	-2.53	-1667
Loudon	-1.47	-386
Monroe	-3.76	-1424
Morgan	-7.41	-3600
Roane	-2.02	-836
Scott	-2.39	-1048
Sevier	-1.08	-565
Union	-2.56	-633



Figure 3. 1. Overview of study area

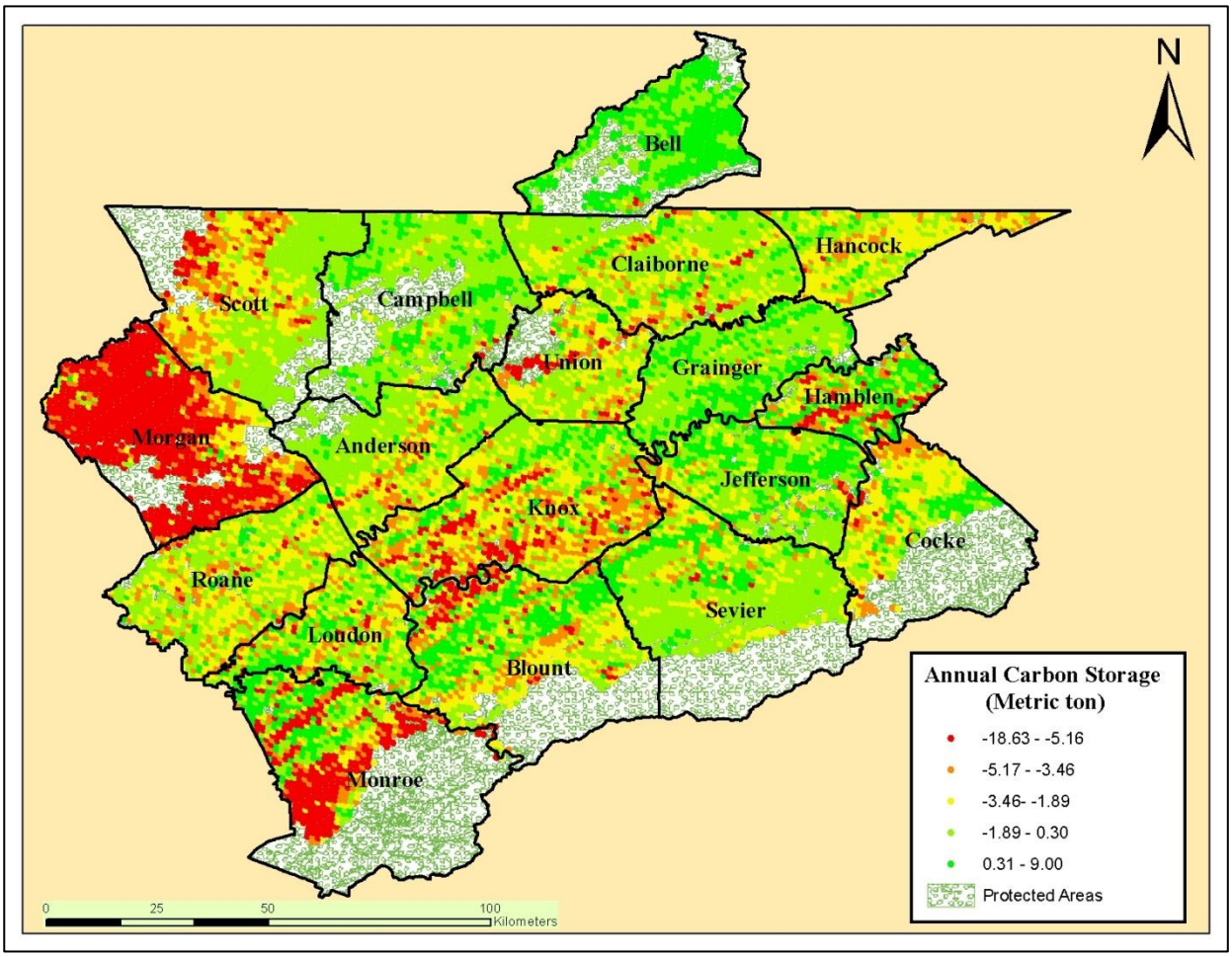


Figure 3. 2. Annual changes in carbon storage in metric ton estimated from the carbon model

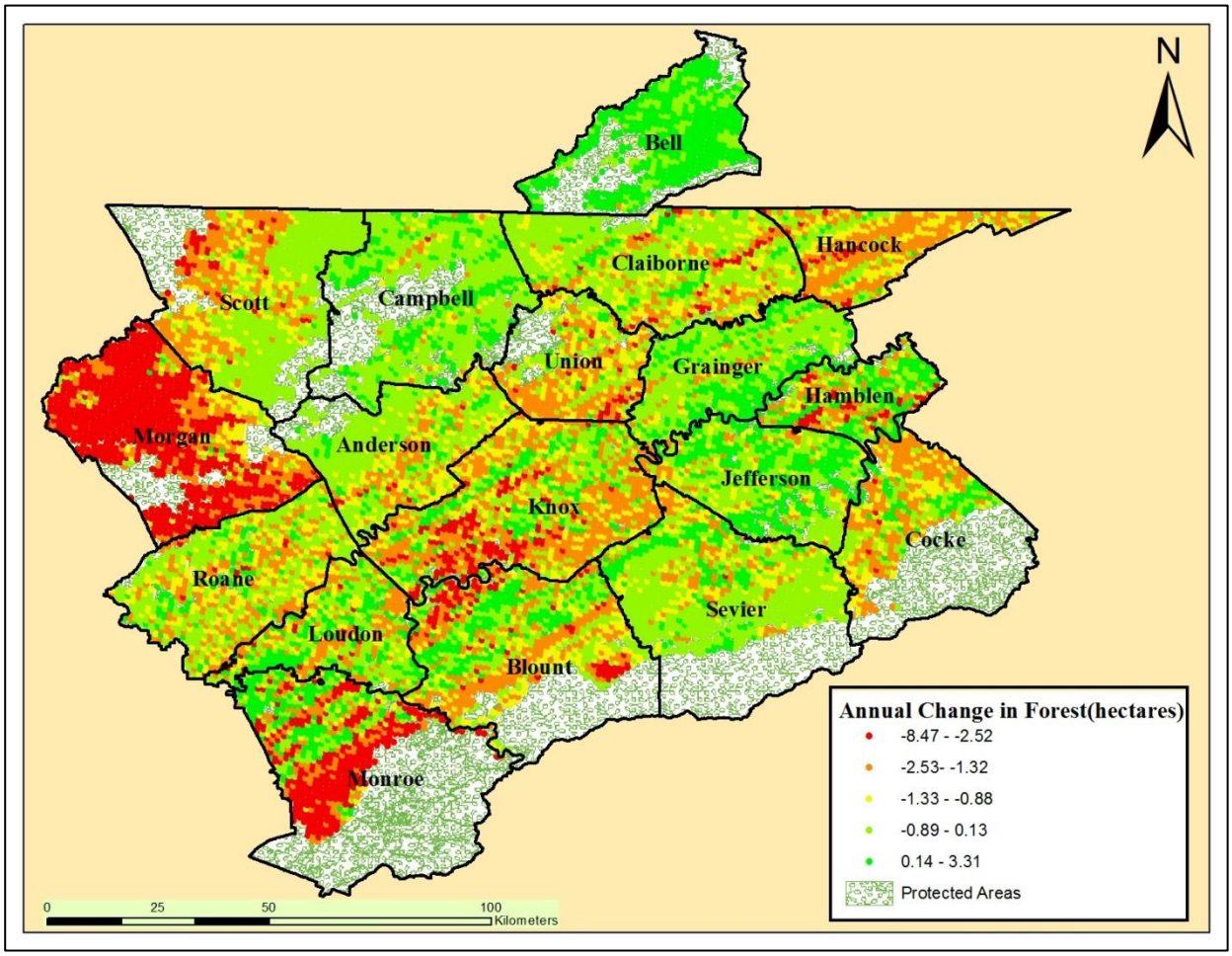


Figure 3. 3. Annual changes in forestland

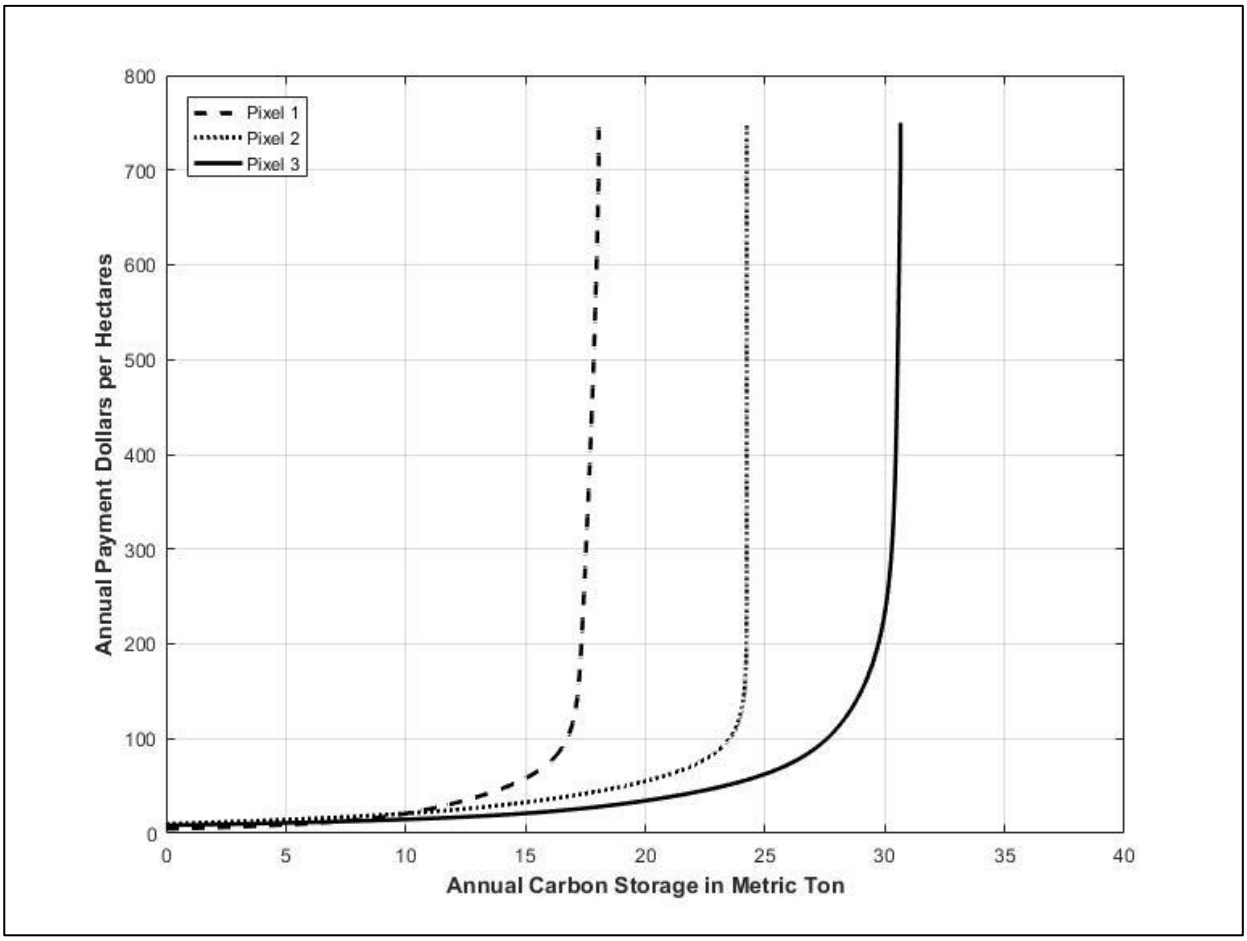


Figure 3. 4. Three supply curves for three representative pixels based on simulated changes in land use by incrementally increasing forestland return per hectare in 2001

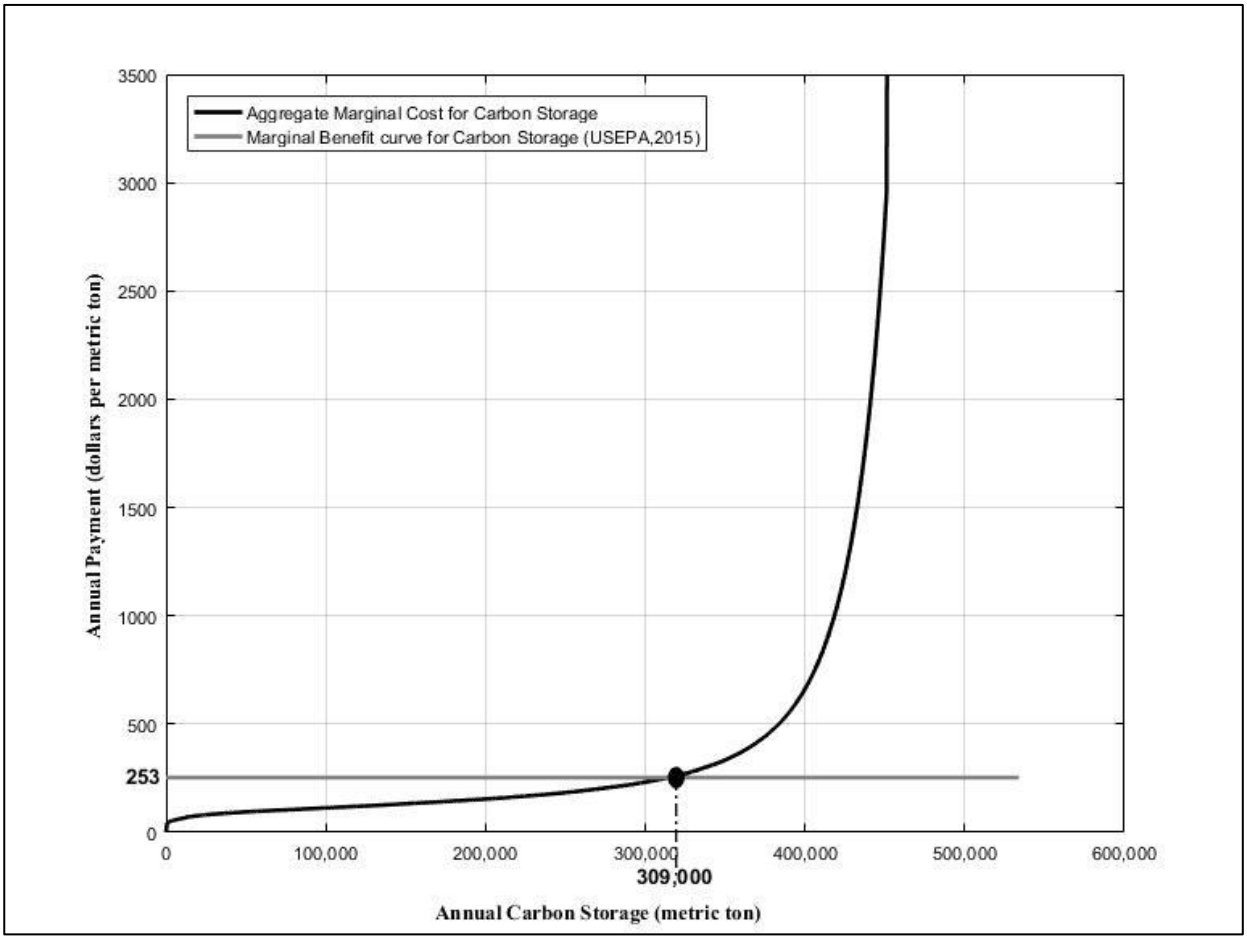


Figure 3. 5. Optimal provision of carbon storage

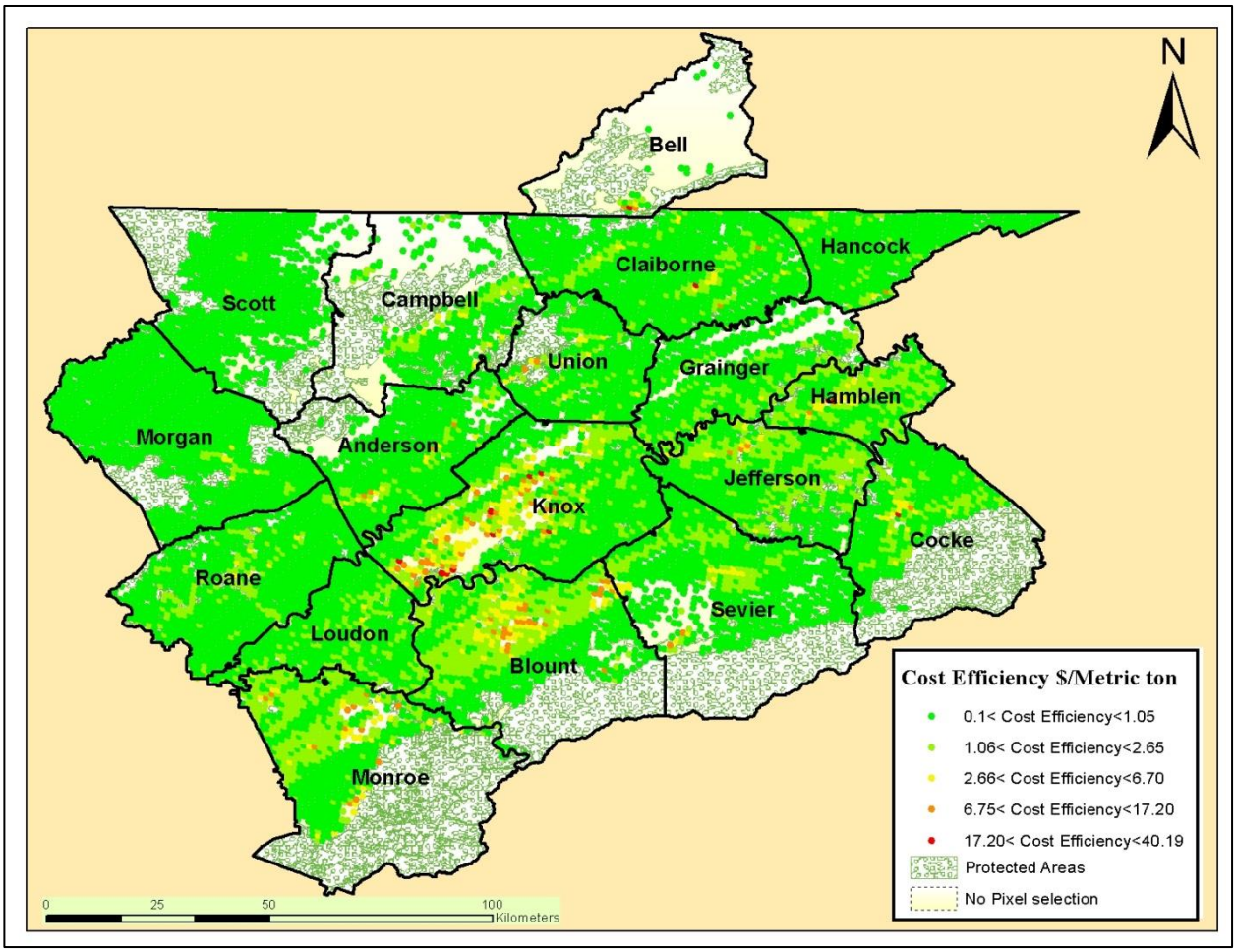


Figure 3. 6. Map of cost-efficient site-specific payment distributions under the optimal budget

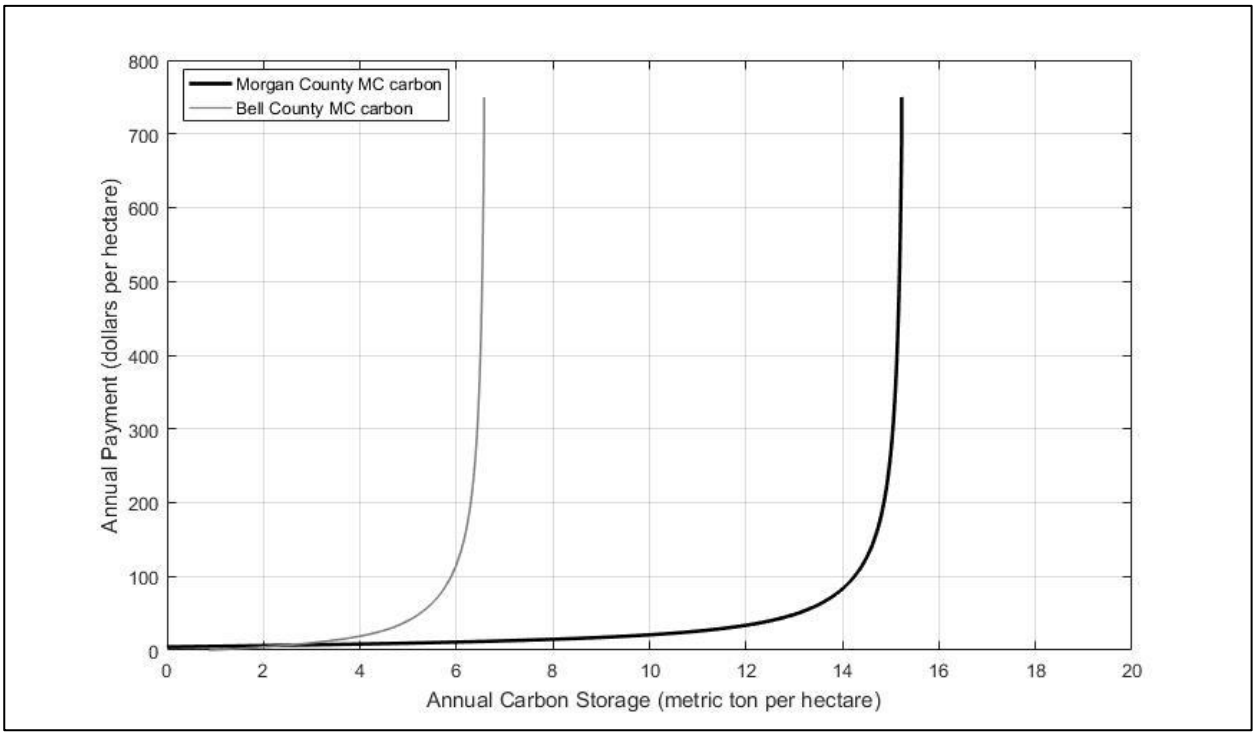


Figure 3. 7. Marginal cost of carbon storage in Morgan and Bell county

Chapter 4: Summary

Summary

This study examines the effects of incentive payments through increasing economic decision variables (i.e., Annual net returns from different land use categories to private landowners) on the land use decisions and choices. While both essays focus on the impact of payments on land use conversion in the Bureau of Economic Analysis, BEA 88 area in the southern Appalachian region of the United States, and on how the opportunity cost for the provision of ecosystem service (i.e., carbon sequestration, and carbon storage) varies among different parcels, the objectives and the empirical results are unique to each case. The two essays in this thesis evaluate the efficiency of different incentive payment approaches that intend to account for the variations in the costs of supplying forest-based carbon storage. The first essay mainly focuses on assessing the spatial and temporal heterogeneities in the costs of supplying forest-based carbon storage to help identifying spatial targeting of incentive payments under different time periods. The second essay deals with estimating how much cost efficiency can be improved by incorporating asymmetric information between landowners and government agencies seeking to purchase forest-based carbon sequestration. Both essays use the U.S. Bureau of Economic Analysis' (BEA) Economic Area 88, which consists of one Kentucky and 17 Tennessee counties as a case study.

Our empirical results for the 18-county case study in the first essay generated the cost-efficiency maps for each of the three periods that can be used as a reference for spatial targeting of incentive payments under different periods. The different dynamic responses are triggered by the difference in the transition probabilities of forest-related land uses to the change of the payment to forestland owners, which depends on the margin for increasing transition probability of the increase in forestland with the higher payments. The findings have significant implications

because few, if any, studies have explicitly considered both the temporal and spatial dynamics of the cost efficiency to come up with site-specific and time-specific carbon storage levels, payment amounts, and would-be participants.

Using the same land use model and carbon simulation outputs from the 18 county as the first essay, the second essay estimated cost-efficient site-specific payments for optimal provision of forest-based carbon storage that incorporates the spatial heterogeneities in forest carbon sequestration and opportunity costs for sequestering carbon, and then compared its cost efficiency with a fixed-rate payment scheme that disregards the spatial variations. The empirical results show that optimal provision of forest-based carbon storage is 309,000 metric tons per year with annual costs of $5.8 million, yielding cost efficiency of $21.93 per metric ton in average. The results also found that the cost efficiency at the optimal provision is almost eight times better than fixed-rate per-hectare payments and is almost four times better than fixed-rate per metric ton payments. The findings will help policymakers select incentive payment mechanisms, identify would-be participants, estimate payment amounts, anticipate budget outlays, and better understand and quantify the impacts of land use change on forest carbon sequestration.

Payment for ecosystem services are often government ran and uniform across participants or landowners (i.e., one size fits all approach of payment schemes). The challenge always remains in finding way to create smaller scales payment programs that can account for both spatial and temporal dynamics of benefits and costs of improving an environmental amenity such as carbon sequestration and carbon storage (Wunder and Alban, 2008). Our case study is unique yet can be a prominent asset in providing a reference or a benchmark if a payment scheme is designed to target larger area or greater number of participants.

Appendix: Supplemental Material

S.1. Expected annual return of four land uses

We use Soil Expectation Value (SEV) to estimate the expected annual return per hectare of forestland. In the SEV estimation, the harvest age is determined by setting the average stumpage value equal to the annual incremental change in stumpage value. The harvest volume data is obtained from the Forest Inventory and Analysis (FIA) database (USDA Forest Service, 2015). The stumpage price for Tennessee is obtained from Timber Mart-South (Timber Mart-South, 2015), and the stumpage price for Kentucky is collected from Growing Gold (Kentucky Division of Forestry, 2015).

We use county-level rent per hectare of pastureland as the expected return per hectare of pastureland. County-level data for 2001 and 2006 is not available. The data is predicted by regressing county-level pastureland rent on state-level pastureland rent and county-level cattle numbers and pastureland area for the 2008-2012 period. The pastureland rent data is from National Agricultural Statistical Service (National Agricultural Statistics Service, 2014) and cattle number data is from the USDA Census of Agriculture (2012).

The expected annual return per hectare of cropland at the county level is estimated using the following *ad hoc* procedure. First, the ratio of livestock and poultry cash expenses to total farm production expenses is derived. Second, this ratio is multiplied by total county net farm cash farm income to arrive at an estimate of net farm cash income from livestock and poultry. Third, the estimated net cash farm income from livestock and poultry is subtracted from total net cash farm income, resulting in an estimate of net cash farm income from cropland. Fourth, county-level net cash farm income from cropland is divided by hectares of harvested cropland in the county.

The expected annual net return per hectare of urban land is calculated using the following *ad hoc* procedure. First, parcel-level land value ratios are obtained for counties for which parcel-level data is available by dividing assessed land value by total assessed value. Second, the parcels' land value ratios are divided by their respective plot sizes to obtain land value ratios per hectare. Third, the land value ratios per hectare is regressed against population density and a vector of distance variables (i.e., distances between the census-block groups and the nearest city center with population greater than 10,000, park, golf course, hospital, school, and highway). Fourth, the regression coefficients and the respective census-block group data are used to estimate the average land value ratio per hectare for each census-block group. Fifth, the average land value ratio per hectare for each census-block group is multiplied by the respective median housing price to obtain an estimate of the median assessed land value per hectare, which is used as a proxy for the expected net return per hectare of urban land at the census-block group level.

S.2. Terrestrial Ecosystem Model

The Terrestrial Ecosystem Model (TEM) is a process-based ecosystem model that simulates carbon, nitrogen, and water dynamics of vegetation and soils in terrestrial ecosystems at multiple spatial scales. The TEM uses spatially referenced information for climate, land-use and land-cover, land-disturbance (i.e., fire, insect & disease, forest harvest, hurricane & storm), atmospheric composition (e.g., nitrogen deposition, tropospheric ozone and atmospheric CO_2 concentration), elevation, soil, and vegetation properties to make estimates of important carbon, nitrogen, and water fluxes and pool sizes, as well as soil thermal conditions of terrestrial ecosystems. The TEM normally operates on a monthly time step, but extends to daily and sub-daily time steps with recent improvements. TEM has extensively applied to explore the spatial and temporal change patterns of net primary productivity, net ecosystem carbon balance, and

carbon stocks at site, regional, and global scales as influenced by multiple environmental factors (e.g., Raich et al., 1991; McGuire et al., 1992, 1993, 2001; Melillo et al., 1993; Pan et al., 1996; Tian et al., 1998; Schimel et al., 2000; Zhuang et al., 2002; Felzer et al., 2009; Yi et al., 2009; Hayes et al., 2011; Yuan et al., 2012).

In TEM, the net ecosystem carbon balance (NECB) is estimated as (McGuire et al., 2001):

$$NECB = GPP - Ra - Rh - Ec - Ep - Ed - El$$

Where, *GPP* is the gross primary productivity, *Ra* is plant autotrophic respiration, *Rh* is heterotrophic respiration, *Ec* is carbon emission during the conversion of natural ecosystems to agriculture, *Ep* is the sum of carbon emission from the decomposition of agricultural and wood product, *Ed* is direct carbon emission from disturbance, and *El* is carbon leaching from terrestrial ecosystem to aquatic system. NECB represents the change in total carbon storage across all pools, or the sum of all carbon fluxes into (sink, positive) and out of (source, negative) the ecosystem over a given time step. The net ecosystem productivity (NPP) is calculated as the difference between *GPP* and *Ra* (*GPP - Ra*).

Since its emergence, many branches of the TEM versions have been developed to meet specific requirements of research tasks. The TEM development and application history was described in detail at the website: http://ecosystems.mbl.edu/TEM/. In this study, the TEM6.1 version, which was improved based on the TEM6.0 version (Hayes et al., 2011), was applied. As compared to its previous versions, TEM6.1 is characterized by several improvements as follows 1) Land-use and stand age cohorts are dynamically tracked in the model simulation. This version has no vegetation dynamic module to track vegetation succession after land disturbance. The application of large numbers of cohorts are able to more realistically mimic the complex plant

functional type (PFT) and age-dependent responses of plants to disturbance and changing environmental factors, and thus, greatly reduce the simulation uncertainty resulted from lack of vegetation dynamic sub-model; 2) The vegetation has been divided into four components: leaf, stem, coarse root, and fine root; 3) the soil carbon pool was partitioned into four pools: aboveground fine litter, coarse woody debris, belowground litter, and soil organic matter. Within each pool, three decomposition conditions are further partitioned: fast, slow, and resistant decomposition rates; 4) A standing dead wood pool is added. The standing dead wood is a very important pool under the impacts of extreme climate events and land-disturbance.

Model input data description

Two types (static and dynamic variables) of model input data are used to drive the TEM. The static variables include soil texture (percent of sand, clay and loam), soil drainage condition (wet or dry), soil topography information (elevation, slope, aspect), and potential vegetation map (assumed vegetation types in 1700 with no human activities). The dynamic variables include atmospheric CO_2 concentration (annual), annual historical land-use data (i.e., cropland, urban, pasture, and deforestation proportion) before 1992, monthly transient climate data (precipitation, air temperature, and short-wave radiation), monthly tropospheric ozone, and annual nitrogen deposition data. The data source and generation methods for static data and for monthly climate data, land-use data, nitrogen deposition are described in Wei et al. (2014). All of the data have a spatial resolution of $0.25^{o} \times 0.25^{o}$ by latitude and longitude. We specifically mask these data out for our study region. The land use-data after 1992 is replaced with the classified 30 m Landsat TM/ETM remote sensing images at four time periods (i.e., 1992, 2001, 2006, and 2011). To fit the TEM model plant functional types (PFTs), we regrouped the classified Landsat TM/ETM land-use categories into six types: cropland, pasture, urban, temperate evergreen forest, temperate deciduous forest, and shrub-land. This dynamic approach for generating vegetation

and age cohorts based on the land-use data has been described in Hayes et al. (2011). In this study, land-use cohorts before 1992 are directly based on the 0.25^{o} land use data, while the 0.25^{o} cohort data for the four time periods after 1992 is rescaled from the 30 m Landsat data. The total 30 m grid cell numbers and area within each 0.25^{o} grid cells for each specific PFT are summed to form a PFT cohort. Due to different disturbance history for each PFT cohort is further divided into several age-structure cohorts. Finally, for each 0.25^{o} grid cell, we obtain a series of cohorts with different PFTs and stand age-structure. Therefore, we generate the land-use cohorts for the four time periods. The tropospheric ozone concentration data (AOT40 ozone exposure index: the accumulated hourly ozone concentration over a threshold of 40 ppb-hr) was from Felzer et al. (2005).

Carbon sequestration rate under a specific land-use condition could be significantly influenced by the time since land-use change and by variations in other environmental factors. Therefore, in this study, we applied the potential carbon sequestration rate (i.e., the maximum carbon stocks under a specific environmental and land-use condition) to represent the influences of land-use change effects on carbon sequestration rate under the four land-use scenarios (1992, 2001, 2006, 2011). To analyze the land-use change effects, we designed the following model simulation experiments: 1) equilibrium experiment: the environmental and land-use data 1700 (represented by potential vegetation map, mean climate data during 1979-2008, nitrogen deposition and atmospheric CO_2 concentration in 1860, and no ozone) was used to run TEM and obtain an equilibrium model output for experiment 2; 2) baseline experiment: the environmental and land-use data during 1700-1991 are used. The equilibrium outputs from experiment 1 are used as the starting carbon, nitrogen, and water stocks to run TEM and obtain baseline model outputs for model further uses; 3) 1992 land-use experiment: the land-use in 1992 (generated

based on the Landsat satellite data), nitrogen deposition, ozone concentration, and atmospheric in 1992, as well as the mean climate for the period (1979-2008) are used to run TEM. The baseline data from experiment 2 is used as the starting carbon, nitrogen, and water stocks, then the model runs for 500 years to arrive at the model equilibrium status and gets the potential carbon stocks for each land-use type in each grid cell; 4) 2001 land-use experiment: the model driving data is the same as that in experiment 3 except that the 1992 land-use data is replaced by 2001 land-use data; 5) 2006 land-use experiment: the model driving data is the same as that in experiment 3 except that the 1992 land-use data is replaced by 2006 land-use data; 6) 2011 land-use experiment: the model driving data is the same as that in scenario 3 except that the 1992 land-use data is replaced by 2011 land-use data.

To ensure the accuracy of ecosystem carbon, nitrogen, and water dynamics, the model parameters have to be recalibrated first against field observation and regional inventory data at or around the study region. We find one observational site and collect carbon related data for each land-use category (i.e., cropland, evergreen needle leaf forest, deciduous broadleaf forest, pasture/grassland, and deciduous shrub land) in the study region. The selected calibration sites are mostly from the AmeriFlux sites: Chestnut Ridge (US-ChR; deciduous broadleaf forest), Canaan Valley (US-CaV, grassland), Duke Forest Loblolly Pine (US-Dk3, evergreen needle leaf forest), and Alabama's Old Rotation site (corn, soybean and cotton cropland). The collected target variables for calibration include monthly GPP, NPP, leaf, stem and root biomass, leaf area index, soil organic carbon, soil available nitrogen, nitrogen uptake rate, aboveground and belowground litter carbon, coarse woody debris, evapotranspiration, etc.

S.3. Details of Allocating Payment to the Pixels with the Highest Marginal or Average Carbon Stored per Dollar

Choosing the pixel with the lowest marginal cost curve to pay first will not necessarily minimize the total cost at each dollar increment because the shapes of some of the pixels' marginal cost curves (i.e., marginal cost curves for some of the parcels are not monotonically increasing) violate the assumptions needed to apply the Equi-Marginal principle (e.g., a sufficient condition must be met to ensure that marginal cost curves are continuously differentiable; Marginal cost curves are always upward sloping (McKitrick, 1999). Furthermore, because the annual supply curves of carbon storage for some of the 1 km^2 are not monotonically increasing we cannot derive the marginal cost curve for the entire BEA88 area by just summing the supply curves. This violates the equi-marginal principal that states that the total value can be maximized when the marginal values per unit of resource are equated across all areas (Odean et al., 2007). Hence if the objective was only to minimize costs, then we get a discontinuous function that is due to the fact that the optimal path or allocation of abatement across candidate parcels depends upon the total amount of dollars paid. Our method, which is described in the next section, eliminates this path dependency.

The construction of the marginal abatement cost curve for the entire BEA88 area is done based on a computational simulation in Matlab comprised of the following steps:

1. The marginal cost curve for carbon storage for each 1 km^2 pixel is derived.
2. The cumulative carbon storage is calculated using (1) output at each incremental payment of one dollar by adding up the total carbon generated.

3. The average level of carbon storage at each payment level, or the ratio of the cumulative carbon storage (2) over the cumulative payment, for each pixel and each payment level is calculated.
4. The highest average level of carbon storage for each pixel is identified.
5. We rank the pixel level output from step (3) based on highest average level of carbon storage from highest to lowest. The averages of cumulative carbon storage per given payment are ranked based on the highest average in descending order.
6. Once all the pixels are ordered based on their maximum averages, the pixel with the highest average is paid first (Step 1. of Flow Chart of Payment Simulation in Figure S.1 in the supplemental material section). This payment is equal to the amount of the cumulative payments used to compute the average.

The next step is to determine whether to allocate the marginal or additional dollar to the same pixel or to allocate it to another pixel (Step 2. in Figure S.1). The next pixel, in terms of maximum average carbon, will be paid as long as its highest average is greater than the prior pixel's marginal carbon storage for an additional dollar (Steps 6 and 7 in Figure S.1). Otherwise the first pixel will be allocated an additional dollar (Step 3. in Figure S.1). Meanwhile, the second process is implemented by replacing the marginal carbon storage for the selected pixel by its next marginal carbon storage (Step 4. in Figure S.1), and the following pixel is not paid unless the first constraint is met again (Step 5. in Figure S.1). This process of replacement and re-ranking continues until all of the highest averages have been paid. At that point, payments are simply allocated to the pixel with the highest marginal. The simulation will continue until all pixels are paid.

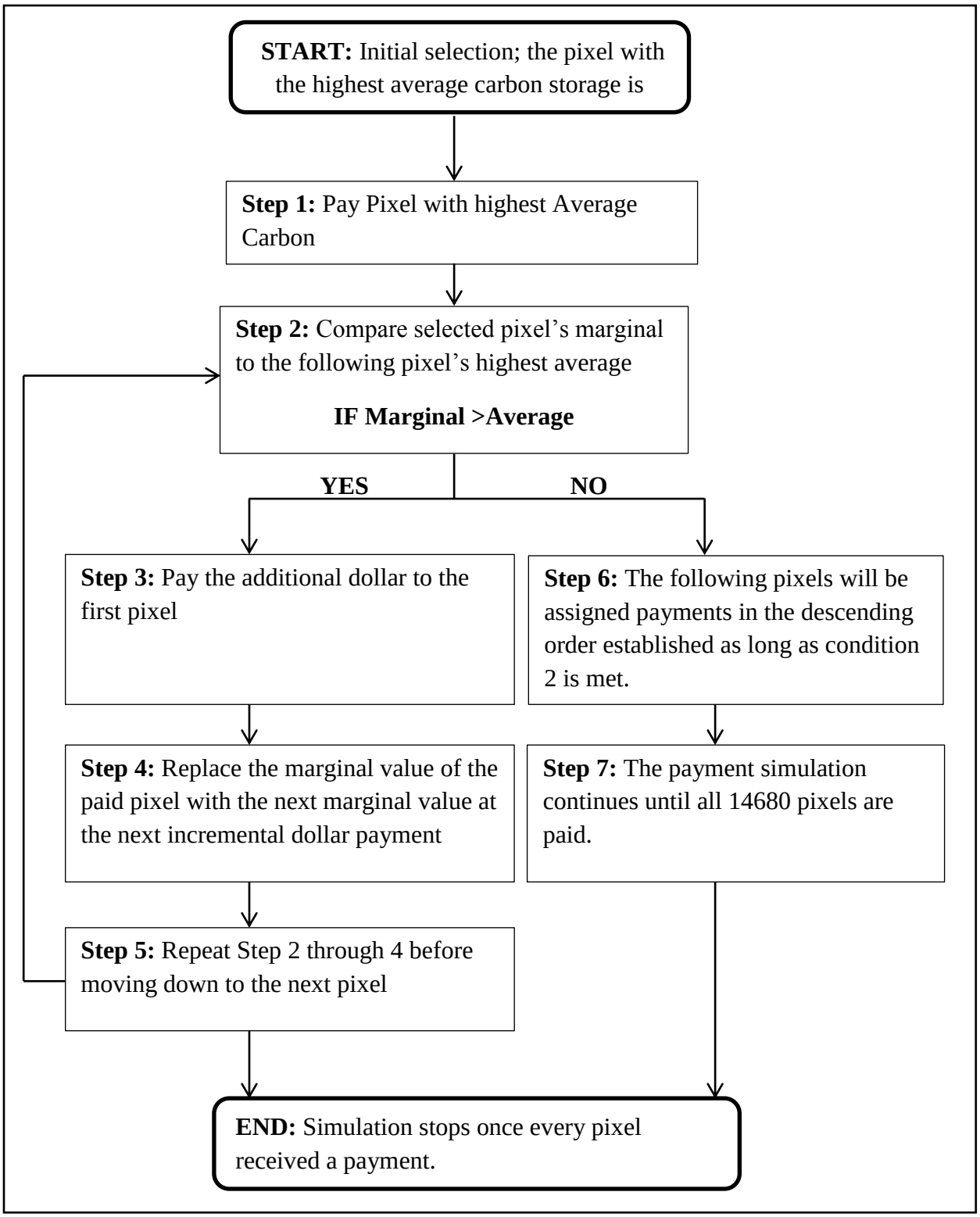


Figure S. 1. Flow Chart of Payment Simulation

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