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# **Spatial and Temporal Variation in the Optimal Provision of Forest-based Carbon Storage**

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# **Spatial and Temporal Variation in the Optimal Provision of Forest-based Carbon Storage**

## **Abstract**

Establishing new or expanding forest areas through afforestation, reforestation, and mitigation of deforestation can be an effective policy tool for offsetting greenhouse gas emissions. Despite the positive perspective, incentive payment approaches intended to encourage forest-based carbon sequestration are deemed to suffer inefficiency primarily due to asymmetric information between landowners and government agencies seeking to purchase environmental benefits. Failing to at least partially resolve this asymmetry may lead to some landowners receiving payments far exceeding their costs, and thus may result in deviation from optimal provision of ecosystem services. The objective of our research is to determine optimal provision of forest-based carbon storage, focusing particularly on how the optimal provision changes over space and time. This analysis occurs through the estimation of site-specific opportunity costs of supplying carbon storage that are used to derive cumulative carbon supply curves and to identify optimal spatial targeting of incentive payments. The empirical results for the 18-county case study show that optimal provision of forest-based carbon storage are 309,000, 435,171, and 356,171 metric tons per year for the periods of 1992-2001, 2001-2006, and 2006-2011, respectively, at the annual costs of about \$5.8 million, \$8.7 million, and \$7.9 million, respectively. We found that the optimal provision of forest-based carbon storage differs across space and time because of the spatial and temporal heterogeneities in the marginal cost of carbon storage and the maximum potential gain of carbon storage. These findings have significant meanings in the literature since few studies, if any, explicitly consider both the temporal and spatial dynamics of the cost efficiency to come up with optimal budget outlays and corresponding carbon storage levels, payment amounts, and would-be participants. Our finding can be used in ways similar to the decision-making guide for Conservation Reserve Program (CRP) enrollment.

**Keywords:** Carbon sequestration, Forest, Spatial heterogeneity, Temporal heterogeneity, Economic efficiency

# **Spatial and Temporal Variation in the Optimal Provision of Forest-based Carbon Storage**

## **1. INTRODUCTION**

### *1.1. Background and objective*

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<sub>2</sub>) is the most abundant and impactful GHG (Schmidt et al. 2010). Thus, capturing atmospheric carbon through carbon sequestration can provide substantial GHG mitigation benefits (Silver, Ostertag and Lugo 2000). Subsidy programs to promote the establishment, expansion, or maintenance of forest areas through afforestation, reforestation, or deforestation mitigation can be an effective policy tool for offsetting GHG emissions (Schroeder, 1992; Dixon, Winjum and Schroeder, 1993).

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). Forest-based carbon sequestration is a type of ecosystem service and a public good, which, once provided, is available to everyone regardless of whether they pay. Given that private landowners may bear the cost of providing this service, it may be “under-provided” absent some form of market intervention to cure the market failure associated with public goods (Daily, 1997; Millennium Ecosystem Assessment, 2005; Polasky et al., 2014).

There is a number of existing payments for ecosystem services (PES) programs around the world (Schomers and Matzdorf, 2013). For example, Costa Rica’s PES program pays private landowners \$64 per hectare per year for 10 years for forest conservation (Pagiola, 2006). China’s Sloping Land Conversion Program is another example that helped to increase China’s

forest area by 10 to 20% by compensating land owners for retiring land and reforestation (Hyde et al., 2003). Despite these successes, designing incentive programs is difficult when the provision of ecosystem services depends on landowners' private information about the costs of providing these services (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 limit the ability of these programs to generate optimal provision of ecosystem services (Ferraro, 2008; Gorte and Ramseur, 2010).

The objective of this research is to determine the optimal provision of forest-based carbon storage focusing particularly on how the optimal level changes over space and time. The hypothesis is that the optimal provision of forest-based carbon storage differs across space and time because of the spatial and temporal heterogeneities in the costs of supplying forest-based carbon storage. This hypothesis is tested by estimating the site-specific opportunity costs of supplying carbon storage and using these estimates to derive cumulative carbon supply curves and identify optimal spatial targeting of incentive payments.

This research provides relevant and important information to help policymakers select an incentive payment mechanism by anticipating optimal budget outlays, estimating payment amounts, and identifying would-be participants. Previous studies on the cost efficiencies of different incentive payment approaches have focused on spatial heterogeneity in the capacity of land to sequester carbon emanating from spatial variation in quality, elevation, and geological conditions and in spatial and temporal variations in climatic conditions (Wear and Bolstad, 1998; Antle et al., 2003; Jandl et al., 2005; Frimpong, Ross-Davis, Lee and Broussard, 2006). This study extends this literature by accounting for spatial heterogeneity in sequestration capacity, and also for spatial and temporal heterogeneity in the site-specific opportunity costs of

retaining forestland by comparing the optimal provision of forest-based carbon storage and the optimal spatial targeting of incentive payments under different time periods.

## *1.2. Literature review*

Three strands of the literature associated with the optimal provision of land-based ecosystem services such as forest-based carbon storage are of particular relevance to this study: (1) examinations of the relationship between land use and net returns from land use, (2) estimates of the opportunity costs of carbon storage through afforestation, reforestation and/or avoiding deforestation, and (3) analyses of the optimal incentive payment and its relation to the optimal provision of ecosystem services.

Land-use change models have been used to estimate the relationship between land-use choices and relative returns in the forestry and agricultural sectors for the purposes of generating carbon-sequestration cost functions (e.g., Stavins 1999; Plantinga et al. 1999; Newell and Stavins 2000; Antle et al. 2003; Kurkalova et al. 2003; Lubowski et al. 2006). Accordingly, 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, Plantinga and Alig, 2001; Cho, Wu and Alig 2005; Broniak, 2007; Sohngen and Brown, 2006; Ahn 2008, and Cho et al. 2014). 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).

Share models can cover a large study area but fail to capture spatial heterogeneity over aggregated areas. In contrast, parcel-level models work on a disaggregated enough scale to capture spatial heterogeneity in costs but are difficult to extend over a large study area. An alternative that can resolve both difficulties is to use a pixel-level land-use 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 GIS databases (Brewer et al. 2012; Myint et al. 2011).

A number of different approaches have been used to assess the opportunity costs of sequestering carbon. The sector model approach uses a spatial and market equilibrium model to assess a wide range of economic, environmental, and policy issues of interest to forestry and agricultural sectors (e.g., the U.S. agricultural sector model (USMP) and the forestry and agricultural sector optimization model (FASOM)). The second approach is to utilize an econometric model derived from a general, random utility model framework. For this approach, discrete choice models (i.e., multinomial logit and nested logit models) have been used to simulate landowner responses to forest-based carbon incentive programs (e.g., Plantinga 1997; Plantinga et al. 1999; Stavins 1999; and Lubowski et al. 2006). Other factors affecting land-use change, such as the cost of acquiring the skills and knowledge needed to manage forested land and non-market benefits, were controlled in the discrete choice models. This spatial resolution (i.e., 1km<sup>2</sup> pixel level, county level) is required as scheme performance depends on the site-specific opportunity costs of supplying an amount of carbon storage.

This research takes advantage of advances in carbon simulation modeling and improved data on forest disturbance, management, and land-use change through a suite of more fully-resolved, process-based biogeochemical models. A subset of these models incorporate

observational and inventory data on forest disturbance, management, and land use conversion to estimate carbon sources and sinks with consideration of a more comprehensive set of the major controlling factors (e.g., Hayes et al. 2011). Comparisons among these main scaling approaches for carbon budget accounting can yield improved constraints on estimates of sources and sinks in regional-scale applications (Hayes and Turner 2012).

Accounting for heterogeneity in the land's capacity to store carbon and heterogeneity in the opportunity cost of retaining forestland is important for the optimal provision of ecosystem services. This is accomplished by achieving optimal cost efficiency of incentive payments. Spatial heterogeneity in the costs of supplying environmental services plays a critical role in incentive payment design (Hanley et al. 2012). The smaller the scale at which 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. 2003; Mason and Plantinga 2011; Armsworth et al. 2012). Although spatial heterogeneity has received much attention, few studies, if any, have explicitly focused on the potential for forest-based payment programs that account for both spatial and temporal heterogeneity to improve cost efficiency, and further, to link the improved cost efficiency to the optimal provision of ecosystem services.

## **2. STUDY REGION**

The study region for this project is Bureau of Economic Analysis (BEA) Economic Area 88 (U.S. Department of Commerce 2016), consisting of 17 Tennessee counties and 1 Kentucky county (Figure 1). The study is divided into three time periods 1992-2001, 2001-2006, and 2006-2011 (referred to as periods 1, 2, and 3, respectively). This region it was chosen to represent the



Appalachian region, which accounts for 20% of U.S. forestland (Smith et al., 2009) and the southeastern United States, which 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., 2010a). 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 (Turner et al., 1995; Wear, 1995; Birdsey et al., 2006; Malmshiemer 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 the disinvestment by timber companies provide an opportunity and an impetus for programs to incentivize forest-based carbon sequestration.

### **3. METHODOLOGY**

The optimal level of provision of forest carbon storage, accounting for spatial and temporal heterogeneities in the ability of the land to store carbon and the opportunity cost of forestland, is estimated by: (1) developing a one km<sup>2</sup> pixel-level land-use model to link forest-based carbon incentive payments with deforestation and afforestation based on maximizing net returns from different land-uses;(2) employing a carbon simulation model to project site-specific carbon storage levels for the forest sector based on climate, forest type, disturbance and management history, and other environmental characteristics; (3) deriving the site-specific annual supply curves for carbon storage for each of the three time periods based on predicted

land-use change and carbon storage for an incrementally increasing net return of forestland; (4) developing payment systems that allow payment allocations to each pixel for the cost-efficient provision of carbon storage for all three periods using the annual supply curves for carbon storage for each pixel for each period; (5) deriving three separate marginal cost curves of cumulative carbon storage using the cost-efficient payment distributions obtained from (4) and determining three separate optimal provisions of carbon storage by identifying equilibrium points between the three marginal cost curves and the U.S. Environmental Protection Agency's (USEPA's) estimate of the marginal benefit of carbon sequestration (USEPA, 2015); and (6) contrasting and mapping cost efficiencies for all three time periods.

### 3.1. *Estimating a land use model*

Suppose a landowner chooses a combination of land-use types that maximizes net returns for the landowner. The shares of land-use types are then functions of net returns from the land-uses and other factors that influence land-use decisions. Following the notation from Miller and Plantinga (1999), the general functional form of the land-share allocated to a particular type of land-use is expressed as:

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

where, at time  $t$  by a landowner  $n_i$  of a parcel  $i$  ( $i = 1, \dots, N$ ),  $s_k(t, n_i)$  is observed land-share using  $k$ ,  $X(t, n_i)$  includes factors that influence land-use decisions (i.e., net returns from alternative land uses and physical characteristics of land such as slope), and  $u_k(t, n_i)$  is the error term.

The net returns from different land-uses are observed after the allocation of land is designated across different time periods, or land-use decisions 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. To accomplish such tasks, a Markov decision process in a logistic form with time-varying transition probabilities (referred to as “maximum entropy model”) can be used to determine the shift of land from one use to another:

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

where  $\pi(j, k, t)$  is the transition probability for land use  $j$  to  $k$  during a time period  $t$ ,  $s(j, t^b)$  represents 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  $X_h(t^e, i)$  is the vector of explanatory variables at the end of each time period  $t^e$  on a parcel  $i$  (MacRae, 1977).

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<sup>2</sup> 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 (i.e., the transition probabilities are all positive, the row sum of the transition probabilities from one land use to the others sums to one, and the land shares in each pixel sum to one for each time period). The transition of land from one use to another must be consistent with the following conditions:

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

By estimating equation (2), we hypothesize that land-use shares in 2001, 2006, and 2011 are functions of expected annual returns from each land-use for the same time period (i.e., net

returns in 2001, 2006 and 2011, respectively).<sup>1</sup> The slope of pixels as physical characteristics of land that influence land-use decisions is included because land-use choices are affected by landscape attributes (e.g., Nelson and Geoghegan, 2002). We also include two dummy variables indicating whether the allocation of land-use share is made in 2001 or 2006 (2011 as a reference year). These time period dummy variables control for trends from one time period to another (see Table 1 for variable names, definitions, and descriptive statistics). Standard errors were adjusted for spatial dependences using a spatial heteroskedastic robust covariance estimator (Lambert, Boyer, and He, 2015).

Once the transition probability of land-use change for each pixel across the three periods is estimated, the transition matrices of land shares are estimated to simulate the effect of hypothetical carbon incentive payments which directly impacts the expected net returns of forestland 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 time-lagged period.

### 3.2. *Estimating a carbon simulation model*

The changes in carbon storage 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. 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

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<sup>1</sup> See S1 in the supplementary materials for details about the net returns.

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. The 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, the total of carbon sequestered is then computed by multiplying the model results by the actual area of each biome.<sup>2</sup> 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  $5 \times 5$  transition matrices of changes in carbon storage in tons per square kilometer ( $ton/km^2$ ) across the three periods. These matrices correspond to the  $5 \times 5$  land use transition matrices of changes for each pixel across the three periods discussed above.

### *3.3. Deriving annual carbon storage supply curves for each pixel for each period*

Carbon storage without payments are estimated using the land-share and associated carbon storage transition matrices as a baseline. Changes in land use transition are then simulated by incrementally increasing forestland return per hectare by from \$1 to \$750 per hectare in each of the three periods in the land-use transition model. These changes are translated into changes in carbon storage by multiplying the simulated land use transition

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<sup>2</sup> Please see S2 in the supplemental material section for more details about the carbon model used in this simulation.

matrices by the carbon storage transition matrices. Using the information, we derive three separate annual supply curves for carbon storage in tons per hectare for each pixel for the three periods where (1) conversion of forestland to crop, pasture, range, and urban uses under the baseline without payment is refrained and (2) crop, pasture, and range lands are afforested, as we incrementally increase the expected net return of forestland in the land-use transition model. By establishing three supply curves for carbon storage, we identify the payment required to reach the maximum potential of additional carbon storage at each pixel for the three periods, which occurs when the maximum forestland area available through afforestation, reforestation, and mitigation of deforestation is reached.

#### *3.4. Developing payment systems for the cost-efficient provision of carbon storage*

Using the three annual supply curves for carbon storage at each pixel for the three time periods, we develop payment systems for the cost-efficient provision of carbon storage under the assumption that (i) the one km<sup>2</sup> pixels represent the spatial structure of the decision-making units, (ii) there is no payment price discrimination between pixels (i.e., A payment will be allocated to each 1km<sup>2</sup> pixel), and (iii) private landowners are all risk averse in the face of uncertainties that influence net returns from alternative land-uses.

The most efficient distribution of each dollar of the payment among the pixels for each of the three time periods separately 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; (4) Allocating payment to the pixel with the highest marginal or average carbon stored per dollar paid until each pixel the marginal carbon stored decreases to zero for each pixel.

### *3.5. Deriving the marginal cost curves of cumulative carbon storage and determining optimal provisions of carbon storage*

Marginal cost curves for the project region are derived for each time period based on the allocation of payments across the pixels described above. To make the interpretation more meaningful, we derive the net present value (NPV) from the annual payment received by the landowner, 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. A discount rate of 3% is used to calculate NPV following examples in the literature (Hope, 2006; Link and Tol 2011; Anthoff and Tol, 2011) based on the 2010 US dollar.

Determining the economically efficient level of carbon storage requires both marginal cost and marginal benefit curves. As estimating the benefits of sequestering carbon is beyond the scope of this research, the U.S. government's estimate of the annual social cost of carbon is used. The social cost of carbon is an estimate of the economic damages incurred (avoided) with an increase (decrease) of one metric ton of CO<sub>2</sub> emissions (USEPA, 2010). Thus, the social cost of carbon can be interpreted as an estimate of the marginal benefits of sequestering or storing (avoiding release) of a metric ton of CO<sub>2</sub> in a forest-based system. The social benefit of carbon storage that is capable of reducing CO<sub>2</sub> emissions annually. Given the interpretation, we first convert the social price of carbon from 2010 dollars per metric ton of CO<sub>2</sub> to 2010 dollars per

metric ton of carbon using the price of \$69 per metric ton at the 3% discount rate in the 2050 emission year. We use the marginal benefit of carbon storage in dollars per metric ton of carbon stored to determine the optimal point, the equilibrium level for the provision of carbon storage in each period on our three separate marginal cost curves at 3% discount rate based on the 2010 US \$. We convert social costs of carbon in dollar per metric tons of CO<sub>2</sub> to dollar per metric tons of carbon storage (i.e., \$253) using a simple conversion factor: one ton of stored carbon in forestland removes 3.67 tons of CO<sub>2</sub> from the atmosphere (IPCC, 2010). We interpret the converted value as an annual marginal benefit of cumulative carbon storage. Using this value and our estimates of annual marginal cost curves, we obtain equilibrium points that identify optimal prices and optimal provisions of carbon storage for three different periods. The marginal benefit of cumulative carbon storage is kept constant across the three periods to test the temporal heterogeneity of optimal carbon storage.

### *3.6. Contrasting and mapping cost efficiencies for the three time periods*

Once the optimal price and cumulative carbon storage are identified for each time period, the budget needed to reach the equilibrium levels (referred to as “optimal budgets”) can be determined. Given the optimal budgets, we test for differences in spatial heterogeneity of the relative cost efficiency of the payment systems across different periods. Here, we calculate average cost efficiency for each pixel from the total assigned dollars divided by the total additional carbon generated for each selected pixel (\$ per metric ton) following the payment rule described above separately for the three periods where the average cost efficiency is mapped to visually highlight spatial variations between the three periods. The cost-efficiency



maps will help identify optimal spatial targeting of incentive payments for forest-based carbon storage for different periods.

#### **4. DATA**

A variety of datasets are needed for the land-use and carbon-simulation models. 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<sup>2</sup> 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 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. 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.

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). 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<sup>2</sup> 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).<sup>3</sup>

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<sup>3</sup> Additional information on the calculation of returns to the four land uses can be found in the supplementary material.

## **5. EMPIRICAL RESULTS AND DISCUSSION**

### **5.1. Land-use model**

The estimated coefficients and goodness-of-fit information from the maximum entropy model are reported in Table 2. The estimated coefficients of the net returns of the four land-uses and slope were significant at the 5% level (hereafter, referred to as “significant”) across all four land-uses, while four of eight estimated coefficients of the time dummy variables were significant. The results suggest that economic incentives, reflected in the net returns for the land-uses, and physical characteristics of land, represented by slope, influence land-use allocations. In addition, at least half of the time trends captured through two-year dummy variables (i.e., 2006 and 2011 year dummy variables) were found to influence land-use decisions.

We use the transition elasticities of the non-stationary Markov transition probabilities reported in Table 3 to analyze the impact of the change in explanatory variables since the interpretation of the signs and magnitudes of the estimated coefficients is difficult when more than two transition states are involved in the decision choices. The transition elasticities are reported in averages over the three time periods, and then over the spatial units while using the marginal effects, following Miller and Plantinga (1999). In the discussion of the transition elasticities, we focus on the role of forest net return on the land-use transition probabilities. An increase in the forest net return by 1% increases the probability of retaining the forestland as forestland by 0.50% and also increases the transition probability from pasture, cropland, urban land, and other land to forestland by 0.31%, 0.04%, 0.15%, and 0.09%, respectively. Likewise, an increase in forest net return by 1% decreases the transition probability from forestland to

pasture, cropland, urban land, and other land by 2.04%, 32.71%, 1.53%, and 2.30%, respectively.

The differences in the elasticity of different land-use returns may be related to differences in the flexibility of land-use conversions. For example, the larger magnitude of the negative effect of forest net return on the transition probability from forestland to cropland may be related to the conversion of forestland to cropland being more preventable than the conversion of forestland to the other land-uses. This is an interesting finding in a sense that forest-based carbon payment is likely more effective for reversing the decision of deforestation for cropland than the decision of deforestation for any other land-uses. Collectively, these findings suggest that an increase in the forest return increases the probability of forestland being chosen, implying forest-based carbon payment is a viable approach for promoting carbon storage in forest in the study region.

## **5.2. Carbon simulation model**

The annual changes in forestland based on the observed land-use change and the annual changes in carbon storage estimated from the carbon model (referred to as “baseline scenarios”) at the pixel level are mapped in each of the three time periods (see Figures 2 and 3). 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 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 carbon storage for each of the three periods among the 18 counties. The loss of carbon storage is a direct result of the loss of forestland. In contrast to the other counties from the BEA 88 area,

the large degree of deforestation in Morgan County is likely associated with its rapid population growth of 13% between 1990 and 2010 (U.S. Census, 2010). The county's population growth has been credited to the creation of manufacturing facilities and solar power farms in the area, thus, significantly increasing manufacturing employment in the region (Kline and Moretti, 2014).

Some 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 2 and 3, respectively), resulting in a net gain in carbon storage (i.e., 1.17 and 2.77 metric tons per hectare per year for periods 2 and 3, 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 1 and 2, 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).

### **5.3. Site-specific annual supply curve**

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 4 shows the three supply curves for three randomly selected pixels for period 1 (i.e., 1992-2001) to illustrate the spatial heterogeneity in the carbon supply curves given a fixed period. The carbon supply curves increase at increasing rates and become vertical at the 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 5 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 increase at increasing rates and become vertical at the 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 1, 2, and 3, respectively. The maximum carbon storage capacities occur when the maximum amount of forestland that would not be converted to other uses and non-forestland that would have been converted to forestland if the incentive payment program were implemented.

#### **5.4. Optimal provision of the forest-based carbon storage**

Figure 6 shows the socially optimal provision of carbon storage at 309,000, 435,171, and 356,171 metric tons per year for periods 1, 2, and 3, respectively, at the annual costs of \$5.8 million, \$8.7 million, and \$7.9 million, respectively. The total cost in each period reflects the sum of the annual NPV of each payment made at the socially optimal provision level of carbon storage. The equilibrium points were identified given the annual marginal cost curves based on the cumulative carbon storage across different payment levels for the entire study area and the annual marginal benefit of carbon storage (i.e., \$253.22 per metric ton of carbon stored) borrowed from USEPA (2010), all at the 3% discount rate based on the 2010 US dollar.

The different socially optimal provision levels of carbon storage for periods 1, 2, and 3 stem from the differences in the marginal cost of metric ton of carbon storage. Figure 6 shows that marginal costs are lowest in period 2 and highest in period 1. If marginal benefits remain constant over the three periods, then the efficient level of storage will be highest in period 2 and lowest in period 1. This finding suggests that payment systems for a given target level of carbon storage can improve their cost efficiencies if they incorporate temporal heterogeneity. This

finding is 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.

### **5.5. Optimal spatial targeting of incentive payments**

Figure 7 shows the spatial distribution of cost efficiency of carbon storage across the three time periods at the optimal levels of carbon storage. At the optimum level, annual program payments of \$5.8 million, \$8.7 million, and \$7.9 million are made generating 102,767, 203,963, and 202,348 hectares of additional forest, which generate 309,000, 435,171, and 356,171 metric tons of carbon storage annually, yielding cost efficiency of 21.93, 20.29, and 23.45 in dollars per metric ton of carbon, respectively, for the three periods. Table 5 summarizes this information at the county level to illustrate spatial heterogeneity across the study region. It shows that the largest area of land (i.e., 11,700, 24,464, and 24,810 hectares for periods 1, 2, and 3, respectively) were selected to participate with the highest total payment amounts (i.e., \$0.7 million, \$1.1 million, and \$1.0 million) in Knox County. In contrast, the least area of land (i.e., 413, 1,698, and 2,130 hectares) were selected to participate with the lowest total payment amounts (i.e., \$39,933, \$75,967, and \$68,567) in Bell County.

The reason behind the differences in area of participation amounts of carbon supply, and payments are illustrated by comparing the county-level supply curves for carbon storage of Knox and Bell Counties for period 1 in Figure 8. The different shapes of the county-level supply curves for carbon storage between the two counties in Figure 8 are derived from the following reasons: (1) lower costs per metric ton for any given level of carbon storage for Knox County (i.e., \$20.67) than for Bell County (i.e., \$40.46) and (2) higher maximum carbon storage for

Knox County (i.e., 55,000 metric tons per year) than for Bell County (i.e., 1,500 metric tons per year).

## **6. CONCLUSION**

The empirical results for the 18-county case study show that optimal provision of forest-based carbon storage are 309,000, 435,171, and 356,171 metric tons per year for periods 1, 2, and 3, respectively, with annual costs of about \$5.8 million, \$8.7 million, and \$7.9 million, respectively. We found that the optimal provision of forest-based carbon storage differs across space and time because of the spatial and temporal heterogeneities in the marginal cost of carbon storage. These 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 optimal budget outlays and corresponding carbon storage levels, payment amounts, and would-be participants.

In process of achieving our objective, we derived 14,680 site-specific annual supply curves for carbon storage for each of the three time periods at the one km<sup>2</sup> pixel level. These site-specific annual supply curves can be used in ways similar to the decision-making guide for Conservation Reserve Program (CRP) enrollment. For example, maximum annual payment per hectare corresponding to the maximum potential gain of carbon storage at the pixel level can be used in ways comparable to the maximum ceiling on acceptable bid prices for CRP set by the USDA-Farm Service Agency (Hellerstein et al., 2015). Similarly, 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.

Despite the clear implication of our study, it is important to understand its caveat as well. Our land-use model is static and, therefore, is not able to accommodate dynamic processes of nature (e.g., climate shifts, and natural disturbances). Dynamic processes of these types are increasingly important to incorporate when spatially targeting investments for ecosystem services as climate changes and natural disturbances pose an increasingly imminent threat to ecosystem services. Future analyses connecting this dynamic nature of land-use changes to the costs of a payment program for forest-based carbon sequestration would be useful in improving the cost efficiency of payment programs.

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**Table 1. Variable names, definitions, and descriptive statistics**

Variable	Description	Mean
Return from forestland	Expected annual net return from forest-use at the county level (\$ per hectare)	50.15 (-12.15)
Return from pastureland	Expected annual net return from pasture-use at the county level (\$ per hectare)	49.54 (-3.13)
Return from cropland	Expected annual net return from crop-use at the county level (\$ per hectare)	54.31 (-383.52)
Return from urban land	Expected annual net return for urban-use at the census-block group level (\$ per hectare)	1059.35 (-1541.02)
Slope	Average slope at pixel-level (degrees)	10.6 (-4.62)
Elevation	Average elevation at pixel-level (meters)	392.08 (-107.43)
2006 Year dummy	1 if the land-use decision was in 2006, 0 otherwise	0.5 (-0.5)
2011 Year dummy	1 if the land-use decision was in 2011, 0 otherwise	0.5 (-0.5)

Note: Numbers in parentheses are standard deviations.



**Table 2. Parameter estimates (PE) from the Maximum Entropy model for land-use allocations**

Variables	Forestland	Pastureland	Cropland	Urban-land
	Parameter estimates	Parameter estimates	Parameter estimates	Parameter estimates
Constant	-10.5893* (0.7039)	-6.0800 (0.7000)	-38.9779* (2.6418)	-10.9107 (0.7654)
Forest Return	0.2975* (0.0128)	0.0272* (0.0126)	-3.2323* (0.0608)	0.0815* (0.0135*)
Pasture Return	0.2853* (0.0318)	0.2810* (0.0317)	1.8621* (0.1182)	0.3475* (0.0345)
Crop Return	-0.0008* (0.0002)	-0.00042* (0.0002)	0.0109* (0.0005)	-0.0031* (0.0002)
Urban Return	0.0009* (0.0001)	0.0002* (0.0001)	-0.00452* (0.0004)	0.0031* (0.0001)
Slope	0.5467* (0.0197)	0.4607* (0.0197)	0.9564* (0.0670)	0.4900* (0.0210)
Year dummy 06	2.2729* (0.1267)	1.0192 (0.1248)	0.7736* (0.4248)	0.6322* (0.1356)
Year dummy 11	3.6713* (0.1922)	1.4835 (0.1903)	1.2578 (0.4916)	1.7043 (0.2053)

Note: Adjusted R-square is 0.045 and log-likelihood is -300,440. The category of other uses was used as the reference group.

\* Indicates statistical significance at the 5% level. Numbers in parentheses are standard errors.

**Table 3. Transition elasticity of the non-stationary Markov transition probabilities for the land-use model**

Variables		Forest Share	Pasture Share	Crop Share	Urban Share	Other Share
Intercept	Forest	-0.6043	2.161	-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	0.897
	Other	-0.1001	0.1139	-1.447	-0.1153	0.4023
Forest Returns	Forest	0.5015	-2.0412	-32.707	-1.5302	-2.2978
	Pasture	0.313	-0.1587	-5.8473	-0.0639	-0.2063
	Crop	0.041	0.0124	-0.3294	0.0181	0.0095
	Urban	0.151	-0.029	-2.1995	0.0072	-0.0472
	Other	0.0885	-0.0016	-1.0883	0.0165	-0.0107
Pasture Returns	Forest	-0.014	-0.0653	18.9239	0.733	-3.4411
	Pasture	-0.0081	-0.0262	6.6856	0.2559	-1.2194
	Crop	-0.0252	-0.0265	0.465	-0.0058	-0.1139
	Urban	-0.0464	-0.0543	2.8711	0.0687	-0.5743
	Other	-0.0261	-0.03	1.4022	0.0302	-0.2846
Crop Returns	Forest	-0.004	-0.0005	0.0876	-0.0217	0.0028
	Pasture	-0.007	-0.0031	0.0949	-0.0267	0.0005
	Crop	-0.0019	-0.0011	0.0185	-0.0058	-0.0004
	Urban	-0.0043	-0.005	-0.0236	-0.0005	-0.0057
	Other	-0.0027	-0.0018	0.0198	-0.007	-0.001

**Table 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	0.167	-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	0.036	0.0041	0.1741	0.0142	-0.0107
Year Dummy 06	Forest	0.07	-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	-0.246	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

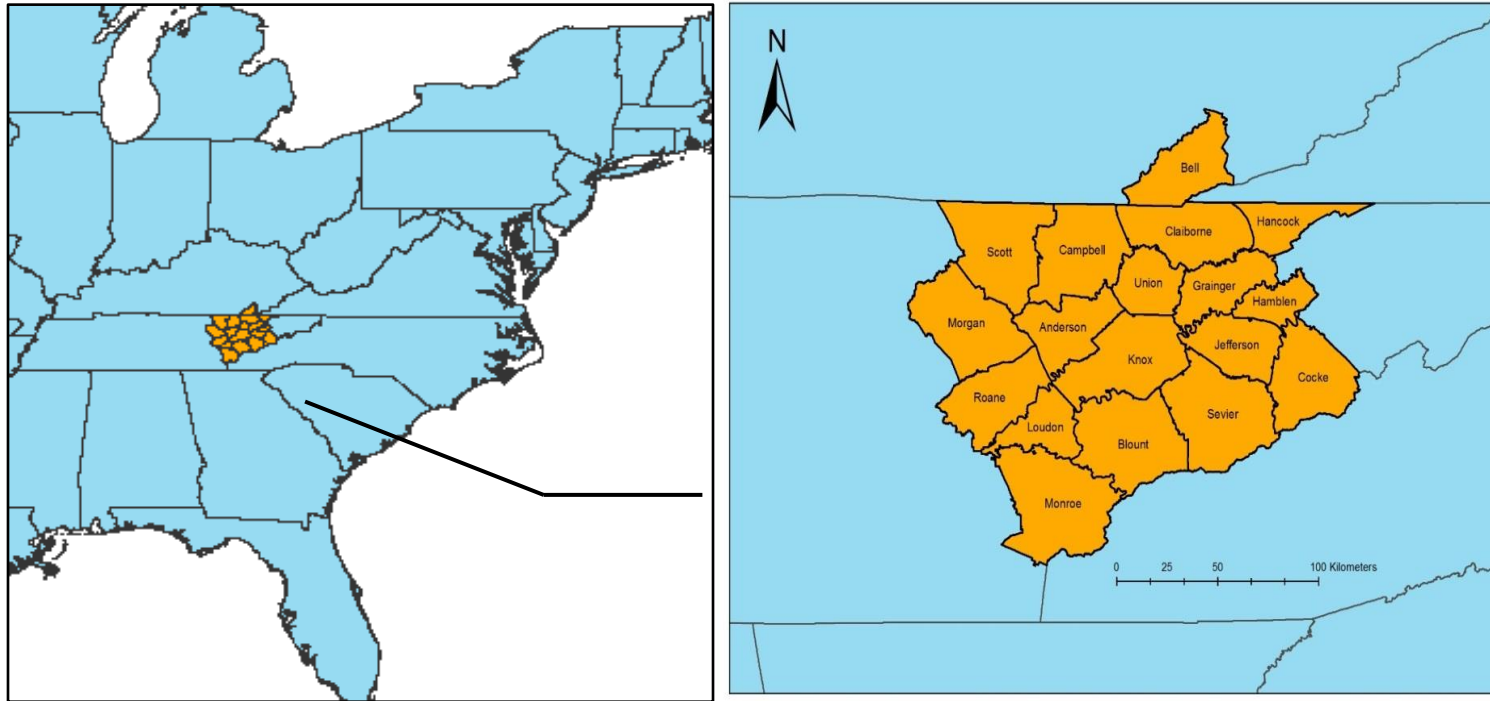
**Table 4. Net gain/loss of forestland and pasture land and annual average net gain/loss of carbon storage in each county across the three time periods**

County	Period 1 (1992-2001)			Period 2 (2001-2006)			Period 3 (2006-2011)		
	Annual Carbon Storage (Metric ton/ha)	Net Change in Forest (ha/year)	Net Change in Pasture (ha/year)	Annual Carbon Storage (Metric ton/ha)	Net Change in Forest (ha/year)	Net Change in Pasture (ha/year)	Annual Carbon Storage (Metric ton/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	-0.2	-594	-6	-0.3	-407	-75
Blount	-3.46	-2018	237	-0.13	330	-794	-0.23	-172	-332
Campbell	-1.34	-714	599	0.25	-960	514	0.5	-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	1.7	-290	-166	1.32	-88	-587
Hamblen	-5.25	-958	374	1.17	698	-962	2.77	91	-628
Hancock	-2.81	-541	717	-1.7	-536	8	-1.26	-185	-255
Jefferson	-3.1	-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	-0.2	-568	-300
Scott	-2.54	-1216	936	-2.3	-1699	777	-2.2	-802	112
Sevier	-2.89	-1518	128	0.77	190	-369	0.32	-592	28
Union	-3.4	-907	740	-2.27	-413	56	-1.33	-267	-383

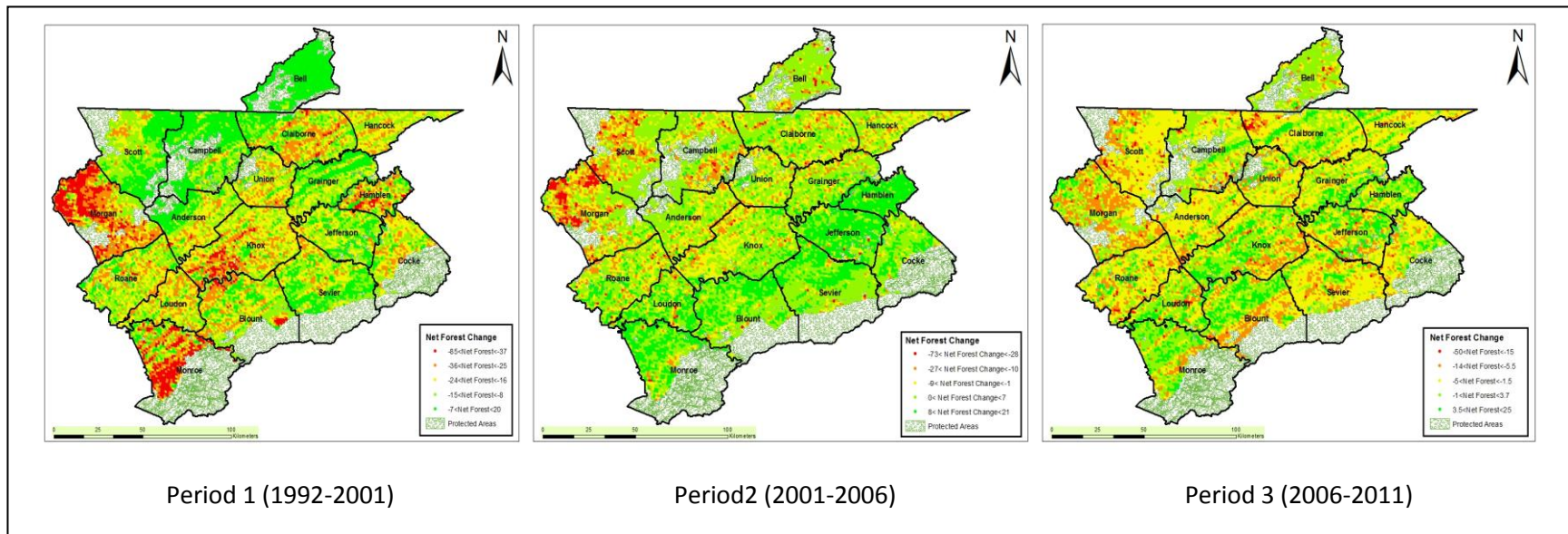
**Table 5. Selected area of participation, net present value of payment, cost efficiency across the three time periods**

County	Period 1 (1992-2001)				Period 2 (2001-2006)				Period 3 (2006-2011)			
	Total Area (ha)	Net Present Value of Payment (\$/year)	Total Carbon Storage (metric ton/year)	CE	Total Area (ha)	Net Present Value of Payment (\$/year)	Total Carbon Storage (metric ton/year)	CE	Total Area (ha)	Net Present Value of Payment (\$/year)	Total Carbon Storage (metric ton/year)	CE
Knox	11,700	687,971	33,289	20.67	24,464	1,012,500	54,286	18.65	24,810	1,003,100	47,670	21.04
Blount	9,282	597,676	29,300	20.4	16,929	728,400	36,640	19.88	15,652	658,700	30,409	21.66
Jefferson	7,815	472,000	28,079	16.81	12,911	554,533	30,827	17.99	12,796	526,033	26,798	19.63
Monroe	7,058	439,667	26,521	16.58	14,581	616,300	27,290	22.58	13,661	547,133	22,984	23.81
Loudon	6,789	381,700	22,130	17.25	11,061	539,233	25,215	21.39	11,180	505,800	22,335	22.65
Morgan	9,478	362,200	29,052	12.47	20,540	672,733	38,627	17.42	20,620	622,833	31,166	19.98
Grainger	4,625	359,756	14,655	24.55	8,479	419,400	22,025	19.04	8,506	369,500	16,650	22.19
Hamblen	4,534	359,633	21,903	16.42	6,944	375,300	21,296	17.62	7,022	355,800	19,517	18.23
Claiborne	7,023	347,867	20,291	17.14	16,390	604,333	31,542	19.16	14,569	539,267	23,909	22.55
Roane	7,637	344,300	20,436	16.85	13,041	584,167	26,783	21.81	14,253	575,133	24,338	23.63
Sevier	5,311	339,167	19,757	17.17	9,422	450,567	21,971	20.51	11,350	438,600	19,932	22.01
Anderson	4,636	334,113	12,404	26.94	8,914	418,133	19,276	21.69	7,503	388,967	16,334	23.81
Cocke	3,691	197,033	7,965	24.74	7,113	313,900	15,542	20.2	7,307	267,733	10,499	25.5
Union	3,346	184,773	6,541	28.25	7,387	311,900	15,151	20.59	7,543	246,967	9,432	26.18
Scott	4,142	156,071	5,337	29.24	8,938	350,200	16,433	21.31	8,359	348,967	14,668	23.79
Campbell	1,583	122,367	5,327	22.97	7,411	338,100	15,954	21.19	7,584	282,167	11,158	25.29
Hancock	3,702	109,400	4,228	25.88	7,740	264,367	13,168	20.08	7,502	190,500	6,157	30.94
Bell	413	39,933	987	40.46	1,698	75,967	3,146	24.15	2,130	68,567	2,355	29.12

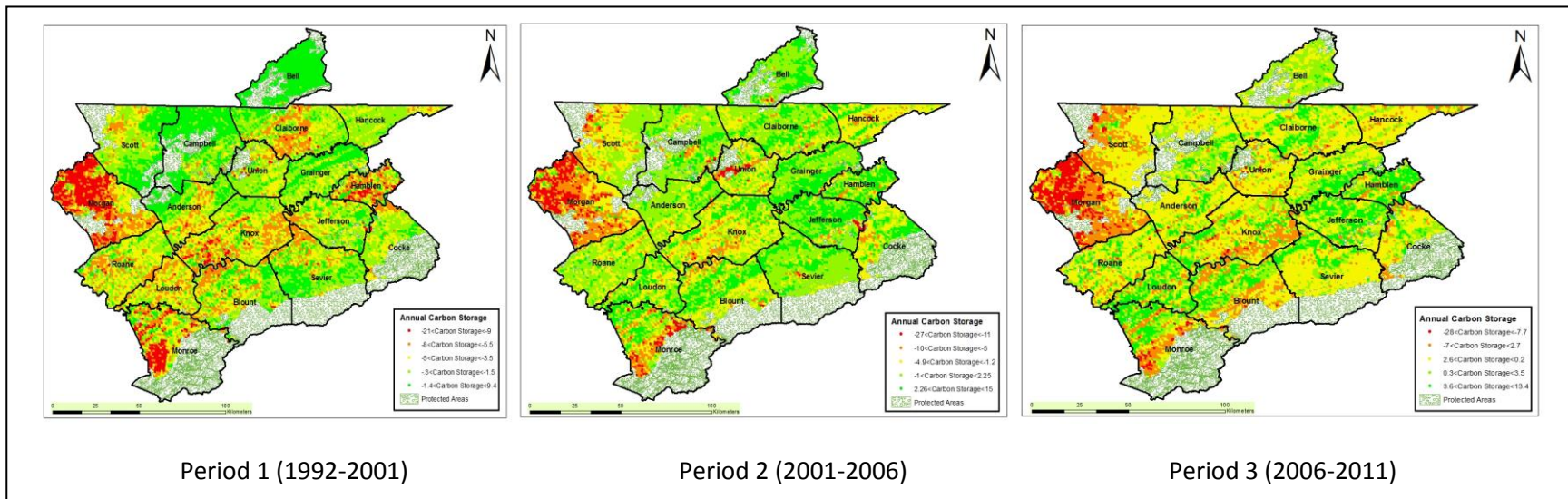
Note: CE denotes annualized cost efficiency in dollar per metric ton.



**Figure 1. Overview of study area**

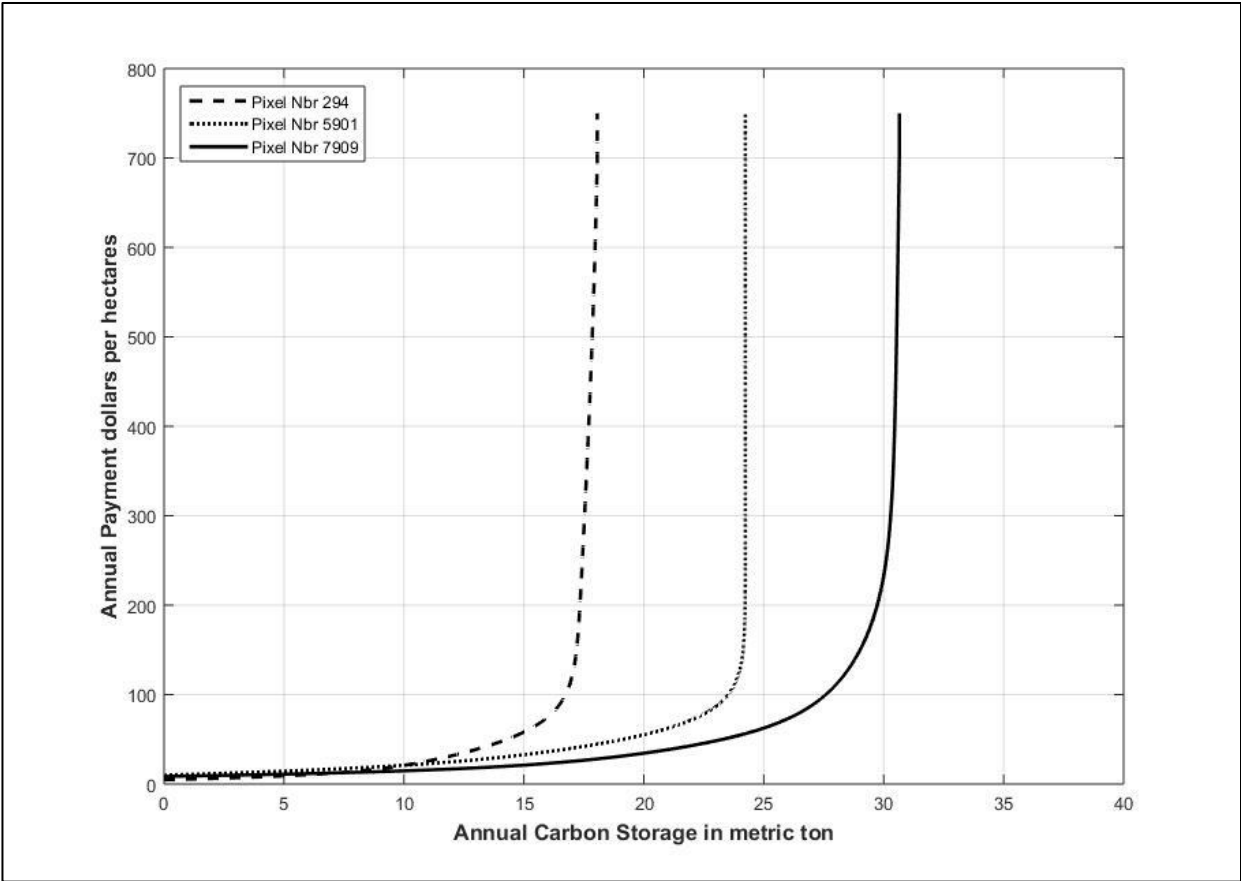


**Figure 2. Annual changes in forestland based on the observed land-use changes**

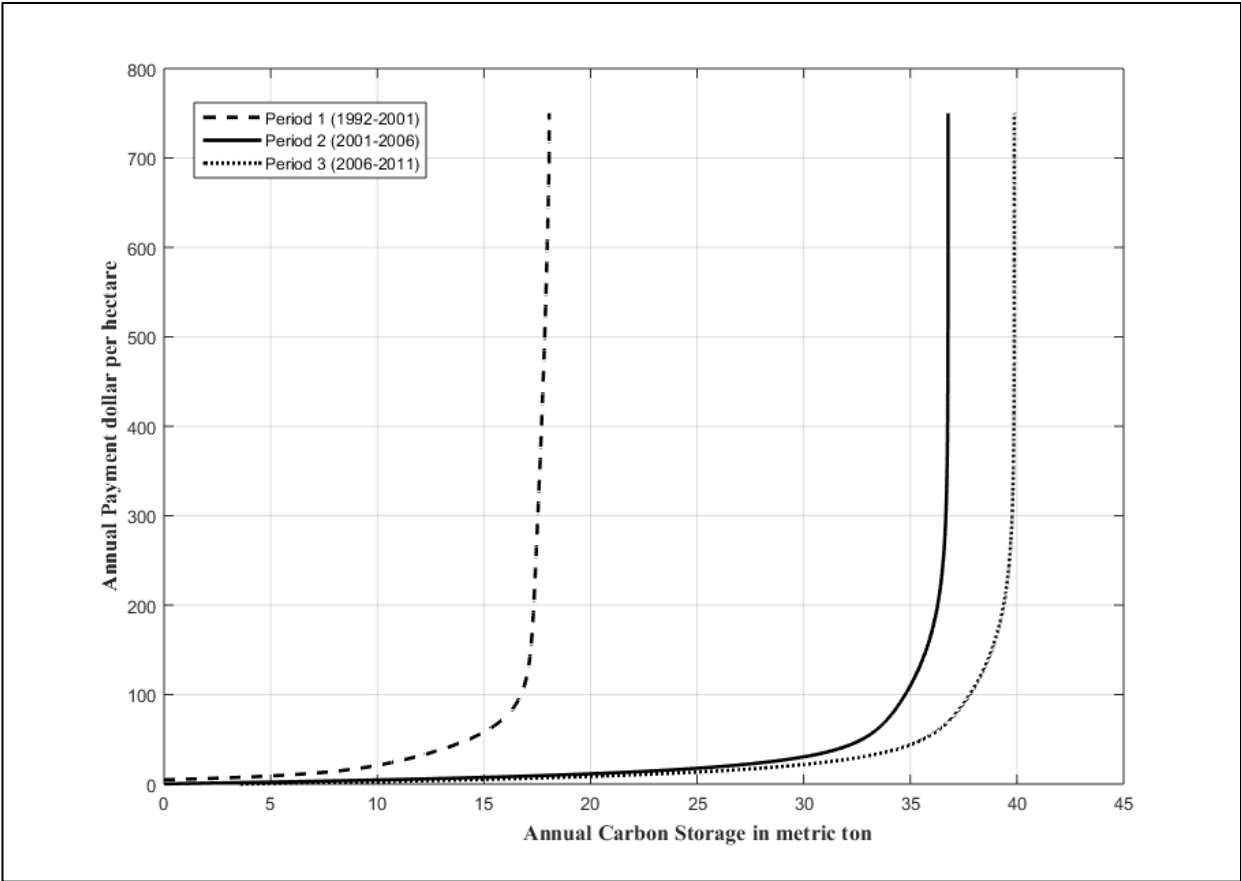


**Figure 3. Annual changes in carbon storage estimated from the carbon model**





**Figure 4. Three supply curves for carbon storage for three randomly selected pixels for a given period (i.e., 1992-2001)**



**Figure 5. Three supply curves for carbon storage for a randomly selected pixel during the three time periods**

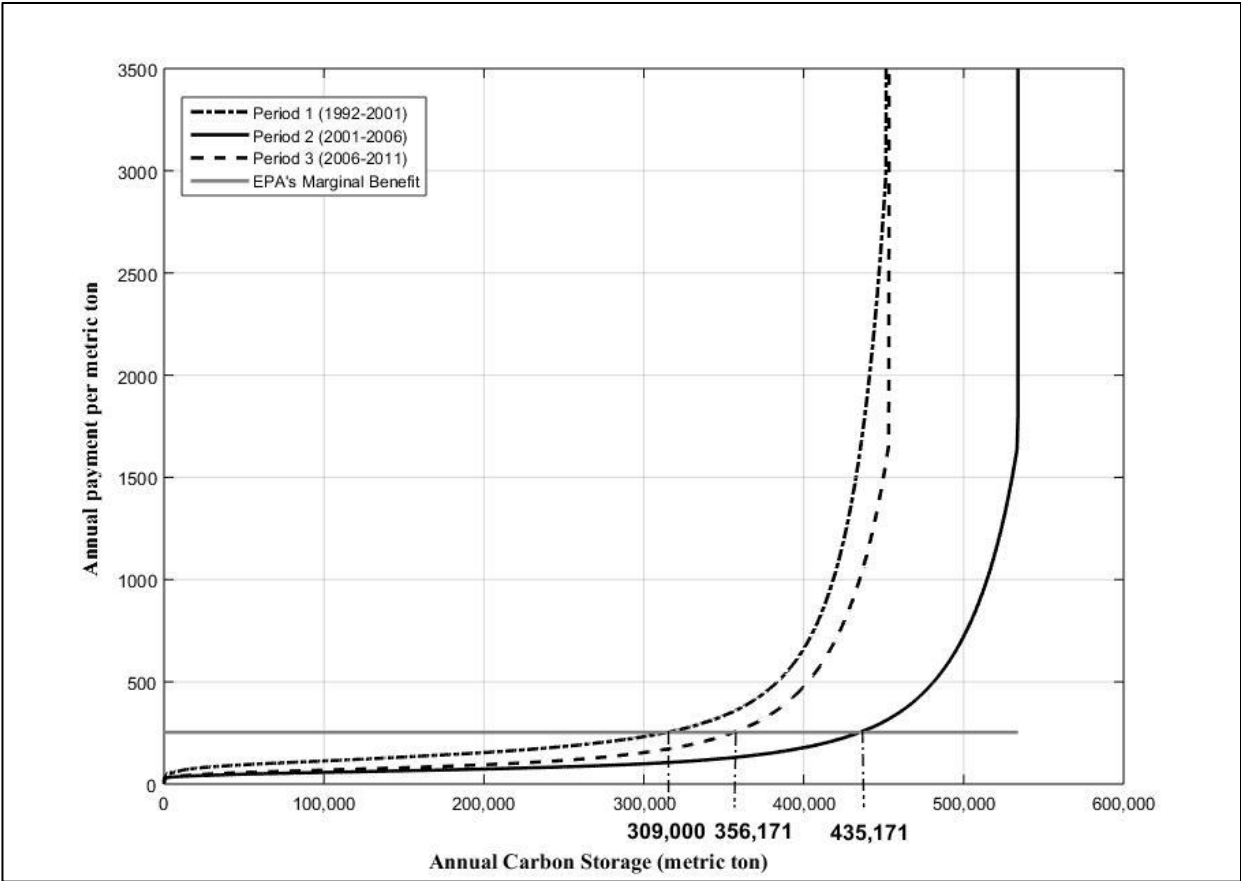
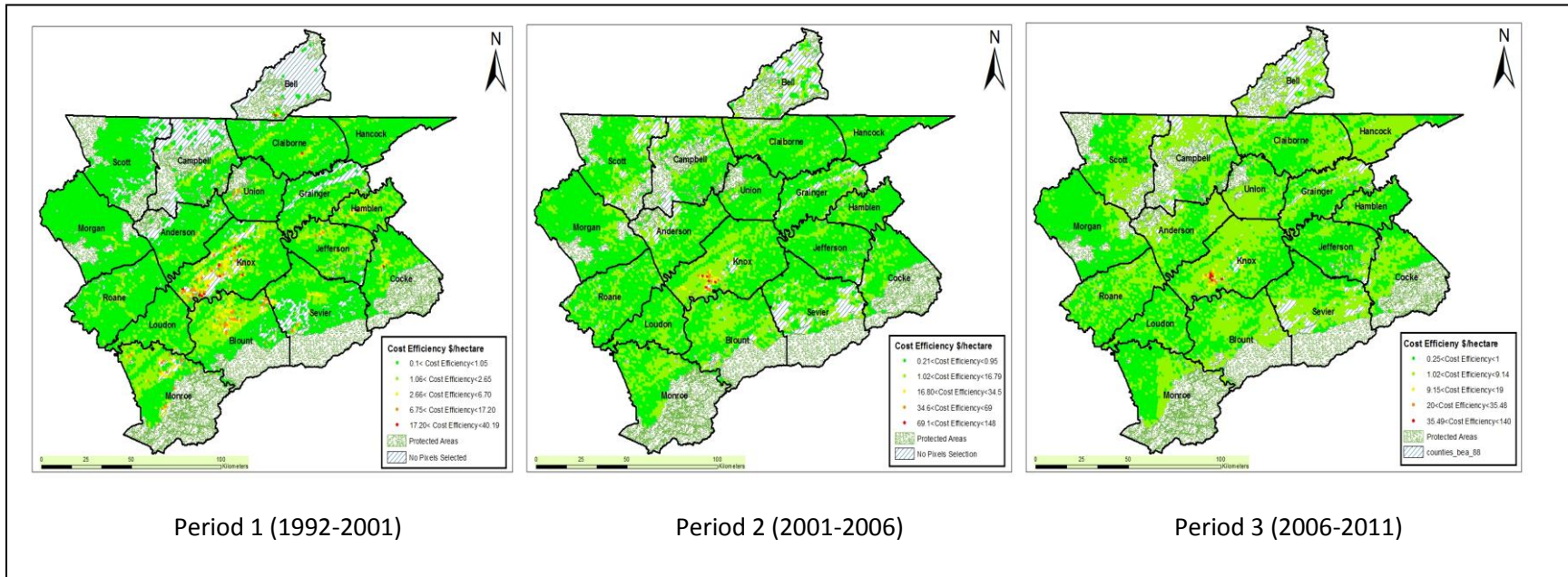
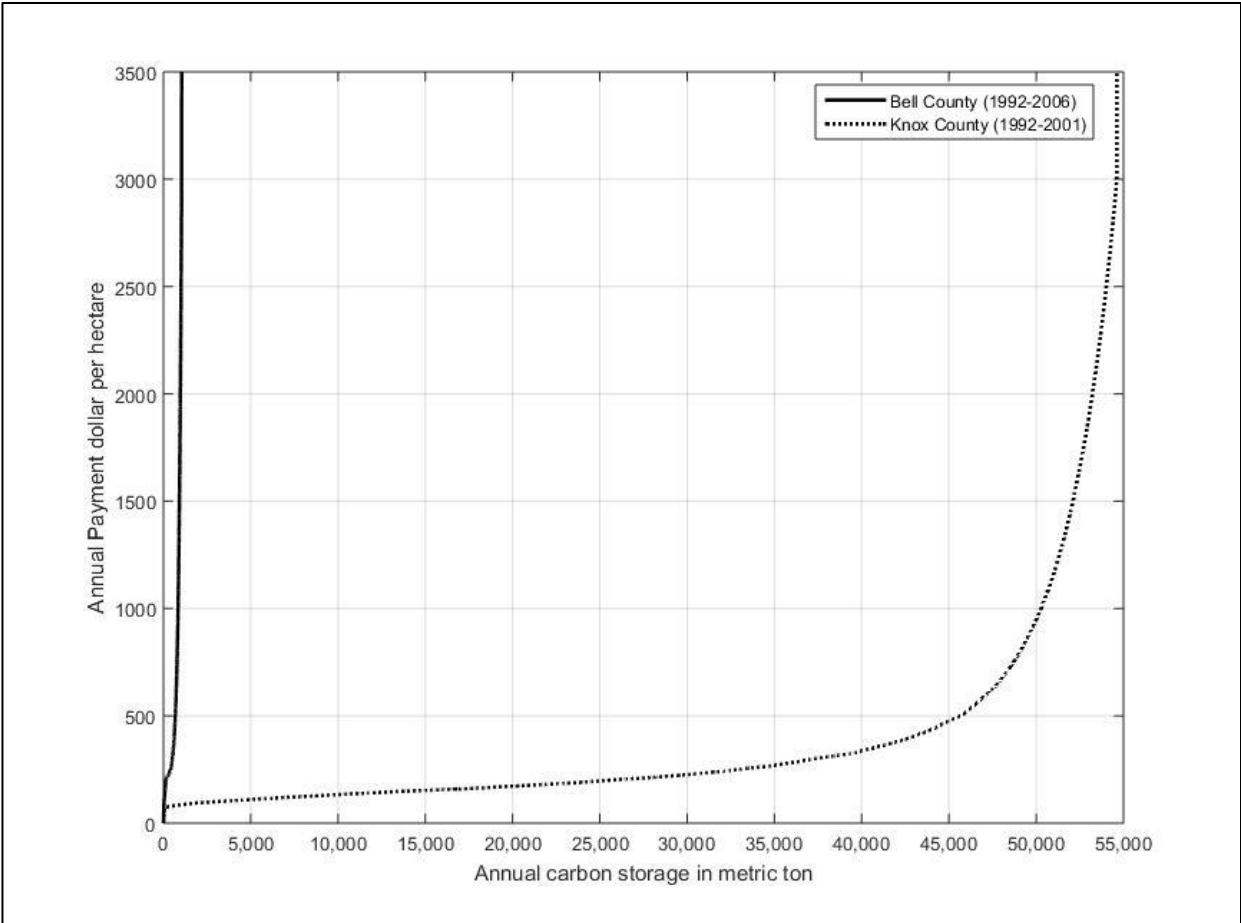


Figure 6. Socially optimal provisions of carbon storage across three time periods



**Figure 7. Spatial distribution of cost efficiency of carbon storage across the three time periods at the socially optimal levels of carbon**



**Figure 8. County-level supply curves for carbon storage between two counties (Knox and Bell) for period 1**

## SUPPLEMENTARY MATERIAL

### S1. 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.

## S2. 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<sub>2</sub> 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., McGuire et al. 1992, 1993, 2001; Raich et al. 1991; Pan et al. 1996; Schimel et al. 2000; Melillo et al. 1993; Tian et al. 1998; Hayes et al. 2011; Yuan et al. 2012; Zhuang et al. 2002; Felzer et al. 2009; Yi et al. 2009).

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<sub>2</sub> 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  $0.25^{\circ} \times 0.25^{\circ}$  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  $0.25^{\circ}$  land use data, while the  $0.25^{\circ}$  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  $0.25^{\circ}$  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  $0.25^{\circ}$  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 design 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<sub>2</sub> concentration in 1860, and no ozone) was used to run TEM and obtain a 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.