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Spatial targeting of payments for ecosystem services under growth uncertainties

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Abstract: Despite the impacts of economic growth fluctuations, few studies have explicitly focused on how payments for ecosystem services (PES) can account for uncertainty in benefits and costs of PES caused by growth fluctuations. The objective of our study was to identify spatial targets for county-level PES by maximizing the expected future cost efficiency of ecological benefits under two growth scenarios and compare them with counties targeted during baseline years (i.e., 2001, 2006, and 2011) without considering growth uncertainty. Empirical results using a case study of forest-based carbon storage in the Central and Southern Appalachian region show that spatial targeting based on estimates of carbon-cost efficiency for the baseline years is significantly different from spatial targeting based on expected future carbon-cost efficiency. The difference arises from the variability in growth conditions that determine future uncertainty in the return to forest relative to the opportunity cost of forest, along with changes in future carbon cost efficiencies. Our county-level map of expected future carbon cost efficiencies will help conservation organizations identify a cost-efficient allocation of incentive payments that is robust to changes in growth fluctuations over time.

Keywords: payments for ecosystem services, carbon cost efficiency, growth uncertainty, spatial targeting

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1. Introduction

Changes in land use are known to impact the status and integrity of ecosystems through habitat loss, degradation, and fragmentation (Defries et al. 2007; Kremen et al. 2007; Magliocca et al. 2015; Rudel et al. 2005). Incentives offered to landowners in exchange for managing their land to supply ecological services (or payments for ecosystem services (PES)) have the potential to counter these land use changes. Recently, attention has focused on improving forest-based ecosystem services through PES to discourage deforestation and encourage afforestation. However, intervening in growth-driven forestland changes is not a simple task because forestland competes with other rent-generating land uses such as urban development (Chomitz 2007; Geist and Lambin 2001; Myers 2008). The major challenge is that the values of forest-based ecosystem services, commonly referred as positive externalities, are not captured in the value of forestland (Brander et al. 2010).

Many researches have focused on internalizing positive externalities into forest management and forestland changes (Bharat 2008; Cho et al. 2017; Ferraro 2008; Fraser 2009; Kim and Cho 2018; Lubowski et al. 2006; Mason and Plantinga 2011; Sims et al. 2013; Wunder 2007). In those literature, land use models have been commonly used to estimate the spatially-varying opportunity costs of supplying forest-based conservation benefits by analyzing the relationship between land use choice and the relative returns from forestry and alternative land uses. The estimated opportunity costs of converting forestland can be used to derive cost function for forest and farm-related conservation benefits, which is critical for internalizing the positive externalities into forestland changes (Lubowski et al. 2006; Lubowski et al. 2008). Those cost functions are commonly used to evaluate the efficiency of PES programs (Armsworth

et al. 2011; Fraser 2009; Gibbons et al. 2011; Hanley et al. 2012; Kim and Langpap 2014; Polasky et al. 2014; Zhao et al. 2004). Along the same token, a few empirical studies have addressed spatial variation in ecological benefits and individual landowners' opportunity costs of providing future ecological benefits (Fraser 2009; Lubowski et al. 2006; Mason and Plantinga 2011; Zhao et al. 2004).

The literature focusing on the efficiency of PES programs often ignores relevant uncertainties (Ando et al. 1998; Naidoo and Ricketts 2006; Polasky et al. 2005; Spies et al. 2007). On the other hand, researchers have developed scenarios incorporating factors such as population growth, economic uncertainty, and conservation policy enactment to examine future land use change (Ahn et al. 2002; Martinuzzi et al. 2015; Radeloff et al. 2012; Schulp et al. 2008; Sleeter et al. 2012). Among them, a few studies have developed econometric models that simulate future land-use change based on the relationship between the projected returns from different land uses (Ahn et al. 2002; Radeloff et al. 2012). Radeloff et al. (2012) developed an econometric land-use change model for the conterminous United States using four future scenarios: business as usual, afforestation, removal of agricultural subsidies, and increased urban rents. The afforestation scenario, for example, examined the effect of new afforestation subsidies and deforestation taxes while the increased urban rents scenario assumed substantial county-level urban rent growth (Radeloff et al., 2012). Ahn et al. (2002) projected land use change in the south-central region of the United States to 2050 using an economic model and two scenarios.

The future land-use changes using the scenario analysis are done under the implicit assumption that economic growth fluctuations are a critical source of program cost uncertainty because the opportunity costs of maintaining farmland and forestland depend on fluctuations of expected returns from competing land uses (Schatzki 2003; Verick and Islam 2010). On the other

hand, studies dealing with the effects of economic growth uncertainty on ecological benefits have represented uncertainty with the option value of postponing the urban development decision in a theoretical framework (Lange and Liu 2014; Langpap and Wu 2004; Shah and Ando 2016; Sims 2011; Smith and Shogren 2002). Despite such efforts on scenario analysis and option value approach, few, if any, studies have addressed the impact on spatially-varying conservation costs of uncertainties involved with explicit market growth conditions. The lack of literature in this issue is surprising given that 1) the dynamic role of growth fluctuations in evaluating incentive payment systems, which, in turn, may affect the efficacy of incentive payment programs (Cho et al. 2018) and 2) incorporating the variability in the returns and opportunity cost of forestland conservation has become increasingly crucial in designing PES programs with the unprecedented growth fluctuations of recent years.

The objective of our research is to fill a gap in the literature by identifying spatial targets for PES that maximize the expected cost efficiency of future ecological benefits across different economic growth scenarios. To achieve the objective, we forecast county-level cost efficiency of forest-based carbon storage in the Central and Southern Appalachian region in the Eastern United States under two future growth scenarios (i.e., high- and low-growth). Then, we calculate and map forecasted county-level expected cost efficiencies of forest-based carbon storage using the two scenarios and their corresponding probabilities of occurrence. We focus on county-level spatial targeting because conservation organizations rarely design PES programs at the individual parcel level when faced with large spatial areas as in our case study (Wunder and Wertz-Kanounnikoff 2009). Instead, they tend to prioritize sub-regions (i.e., administrative units such as counties) and assign different payments to parcels within the prioritized sub-regions (Ando and Mallory 2012). Our analysis is designed to inform sub-region decision making.

We focus our analysis on the effect of future economic growth uncertainty on the opportunity costs of converting forests to competing land uses and the resulting changes in carbon cost efficiencies. A county-level map of expected future carbon cost efficiencies will help conservation organizations identify a cost-efficient allocation of incentive payments that is robust to changes in growth fluctuations over time. Such map provides guidance on how to geographically allocate incentive payments to maximize cost efficiency in the presence of growth uncertainties. Providing a framework to geographically allocate incentive payments in the presence of economic uncertainty could help land managers and conservation organizations more efficiently focus resources toward conservation planning. Further, our comparison of the expected cost efficiencies between two future growth scenarios and the cost efficiencies from historic estimates helps in understanding adjustments in targeted payments needed to account for growth-induced uncertainties.

3. Methods

Three steps are taken to achieve our research objective. First, we model forestland change at the county level as a function of returns from forestland and competing land uses (i.e., crop, pasture, and urban) and other land-use change factors. We estimate a pooled land use model with county-level observations for three periods (i.e., 1992-2001, 2001-2006, and 2006-2011). These periods were chosen because land-use data are available from the National Land Cover Database (NLCD) for 1992, 2001, 2006, and 2011. We estimate the marginal effects of returns from forestland relative to crop, pasture, and urban land to assess the marginal effects of incentive payments on forestland owners. Second, we forecast future returns from forestland and competing land uses for each growth scenario and use them to forecast county-level forestland

areas using the marginal effects obtained from the first step (forecasts from 2021 to 2046). Third, we estimate and map future expected county-level carbon cost efficiencies using forestland areas from the second step in combination with long-run carbon storage estimates for forestland using the dynamic Terrestrial Ecosystem Model (TEM) and the probabilities of occurrence of the growth scenarios based on historical data.

3.1. Step 1: Estimating the pooled land use model

A pooled county-level land use model is specified with the dependent variable being forest share in the last year of a period divided by forest share in the first year of the period (i.e., periods 1992-2001, 2001-2006, and 2006-2011) (referred to as “growth in forest share”). The explanatory variables are returns from forestland relative to crop, pasture, and urban land in the first year of each period, and other explanatory variables including geophysical characteristics such as slope and elevation, and binary variables representing ecoregions, states, and time periods. The returns from forestland relative to competing land uses in the first year of a period are hypothesized to affect the growth in forest share over a period because socioeconomic changes affect land use changes with time lag effects (Kozak et al. 2017). For example, changes in socioeconomic drivers affect subsequent changes in forest cover with time lags of multiple years (Loran et al. 2017).

Areas of forestland and other land uses from the four NLCD datasets for 1992, 2001, 2006, and 2011 at a resolution of $30\text{ m} \times 30\text{ m}$ were used to aggregate forestland share for each county. The NLCD classifications of deciduous forest, evergreen forest, and mixed forest were merged into one forestland category.

We use annual average returns from forestland minus annual average returns from

competing land uses (crop, pasture, and urban uses) since the differences represent the return to forestland relative to its opportunity cost. Annual return from cropland was estimated using county-level net-farm income from cropland and harvested cropland data from USDA Census of Agriculture (2012) and National Agricultural Statistical Service (NASS 2014). Annual return from pastureland was estimated using county-level pastureland rent, cattle numbers, and pastureland data from National Agricultural Statistics Service (2014) and USDA Census of Agriculture (2012).

Other explanatory variables include a county's mean slope and mean elevation because these geophysical characteristics influence forestland conversion costs and are primary drivers of forestland conversion (Nelson and Geoghegan 2002). The slope and elevation variables were calculated using the Zonal Statistics tool in ArcGIS 10.1 (ESRI 2012) and a Digital Elevation Model (DEM) (U.S. Geological Survey 2013). Ecoregion dummy variables (i.e., dummy variables representing the Central Appalachian Forest ecoregion and the Cumberlands and Southern Ridge and Valley ecoregion, with the Southern Blue Ridge ecoregion as the reference), state dummy variables (i.e., dummy variables representing AL, GA, NC, SC, KY, VA, and WV, with TN as the reference), and time-period dummy variables (i.e. dummy variables representing the 2001-2006 and 2006-2011 periods, with 1992-2001 as the reference) were added to control for differences in growth in forest share across ecoregions, states, and periods. Descriptions and summary statistics associated with the variables used in the land use model are found in Table 1.

3.2. Step 2: Forecasting future returns from forestland and competing land uses

We forecast future returns from forestland and competing land uses for two future growth scenarios loosely based on 2010 Resource Planning Act (RPA) storylines (USDA Forest Service

2012) and Southern Forest Futures Project (Wear & Greis 2013) Cornerstone Futures. Linked to IPCC (Intergovernmental Panel on Climate Change) assumptions and projections of population growth, economic growth, and climate, RPA storylines were developed to explore a range of scenarios for natural resources in the future (Nakicenovic et al. 2000), while Cornerstone Futures expanded on RPA storylines to specifically analyze future forest conditions in 13 southeastern US states (Wear and Greis 2013). For our study, population projections from RPA storylines were used to estimate future urban return while the Cornerstone Futures were adopted to estimate future forest return.

The future growth scenarios for our study developed from the abovementioned studies are a high-growth scenario with significant population growth and increasing timber prices and a low-growth scenario with marginal population growth and decreasing timber prices due to decreased demand for timber during slow growth. RPA population projections were based on IPCC SRES (Special Report on Emission Scenarios) global projections that were updated and downscaled based on national data (Nakicenovic et al. 2000; Zarnoch et al. 2010). Population projections range from rapid growth peaking in the mid-21st century (referred to as “A1 storyline”) to continuously increasing growth, but at a low rate (referred to as “B2 storyline”). (See below for a more detailed description of future population growth and forest return assumptions.) We forecasted future returns for the return variables that were statistically significant in the land use model and used them in the estimated land use model to predict future forest-share changes at the county level for each scenario.

The first step in forecasting future urban return involved forecasting median housing values for each census block group (CBG) in the study area from 2021 to 2046 based on a time series model using median housing value data from 1990 to 2016. Annual median housing value

data at the CBG level were only available from the decennial US Census for 1990 and 2000 (US Census Bureau 1990; 2000). Thus, using 1990 as the baseline year, we estimated median housing values from 1991 to 1999 for each CBG by multiplying the previous year's housing value by the percentage change from the previous year's inflation-adjusted housing price index (HPI) to the current year's HPI. The same procedure was implemented to estimate median housing values from 2001 to 2016 using 2000 Census data and 2001-2016 HPI values. The HPI data at the core-based statistical area (CBSA) level were provided by researchers associated with the Federal Housing Finance Agency (Bogin et al. 2016). All median housing values (i.e., 1991-1999 and 2001-2016 estimates and 1990 and 2010 Census values) were deflated to 2010 dollars by the CPI index (BLS 2018).

We chose the autoregressive distributed lag (ARDL) framework to forecast median housing values. The ARDL model has been applied extensively to dynamic single-equation regressions and is used to analyze long-run relationships between economic time series (Hassler and Wolters 2006; Pesaran and Shin 1998). Like other time series modeling approaches, ARDL modeling considers lags of the dependent variable but also allows for lags of the independent variables. A general ARDL model, without a constant term, of lag orders p and q , $ARDL(p, q)$, can be defined for a scalar variable y_t as:

$$y_t = \sum_{i=1}^p a_i y_{t-i} + \sum_{j=0}^q c'_j x_{t-j} + \varepsilon_t, \quad (1)$$

where t is the year, x_{t-j} is a K -dimensional column vector process of lag order q , a_i and c'_j are parameters, $i = 1, \dots, p$, $j = 0, \dots, q$, and ε_t is a zero mean error term (Hassler and Wolters 2006; Kripfganz and Schneider 2016). Optimal lags are selected based on Bayesian Information Criterion (BIC) (Kripfganz and Schneider 2016).

Explanatory variables such as mortgage rate, unemployment rate, vacancy rate, real

mortgage rate, population growth, and per capita income were considered based on previous studies for which housing price growth was forecasted using time series modeling such as ARDL (Rapach and Strauss 2007; 2009). Ultimately, three variables (i.e., unemployment rate, housing vacancy rate, and real mortgage rate), which were significant and did not display multicollinearity, were chosen as independent variables in the general ARDL model using 1990-2016 data. Unemployment rate was available at the county level (Bureau of Labor Statistics 2018) while homeowner vacancy rate was available at the state level (US Census Bureau 2018). The real mortgage rates were derived by deflating fixed 30-year mortgage rates (FRED 2018) by the CPI index to account for inflation (BLS 2018). Using the ARDL module “ardl” in Stata 15 (StataCorp 2017), ARDL models with optimal lags were estimated for each CBG. The modeling and forecasting procedure for each of the 8,295 CBGs in the study area was facilitated by incorporating a coding loop in Stata. (Sample output from the ARDL procedure can be provided upon request.)

To forecast median housing values for the two growth scenarios discussed above, representative growth conditions were identified based on the most recent real estate growth cycle (Agnello et al. 2015; Cohen et al. 2012). Specifically, the 1998-2006 period was identified as a high-growth scenario and the 2007-2012 period as a low-growth scenario. Assuming the growth conditions during these time periods, average values for each of the three explanatory variables were calculated for each CBG. For example, representative unemployment rates during the low-growth period (2007-2012) were calculated for the respective CBG by averaging unemployment rates from 2007-2012. The average values for the three explanatory variables during the 1998-2006 and 2007-2012 periods were used to simulate future conditions for high-growth and low-growth scenarios, respectively.

The future values of the independent variables were used to develop median-housing-value-dynamic (recursive) forecasts for each CBG using the ARDL model estimates (Baum 2004). The ARDL and forecasting procedures generated median housing value forecasts for each CBG from 2017-2050 for the two future growth scenarios. In turn, these forecasts were used to forecast future urban land return for each scenario.

The forecast procedure starts with estimating the ratio of land value to the forecast of median housing value (referred to as “land value ratios”) for each CBG. Historical parcel-level land value ratios were obtained for counties for which parcel-level data were available by dividing assessed land value by total assessed housing value for single-family houses. Next, OLS regression was performed with the land value ratio as the dependent variable and projected population density and a vector of distance variables (i.e. distance to nearest park, hospital, golf course, school, highway, and city) as explanatory variables. The regression model was specified under the premise that (i) the value of a parcel’s land increases relative to the value of its single-family house in urbanized areas that are more densely populated and closer to the city center (Albouy and Ehrlich 2012) and (ii) the land value ratio does not fluctuate over time (Bourassa et al. 2011).

County-level population forecasts based on 2010 RPA storylines (Zarnoch et al. 2010) were used to estimate future population densities based on growth condition. The RPA population growth scenarios are tied to global future scenarios developed by the Fourth Assessment of the Intergovernmental Panel on Climate Change (IPCC) (Zarnoch et al. 2010). Adopted by the IPCC 3rd and 4th assessments, the Special Report on Emissions Scenarios (SRES) developed scenario families to analyze and make projections on future climate change. These scenarios described futures that vary in terms of economic growth, population growth,

globalization, regionalization, and sustainability (Nakicenovic et al. 2000). For example, the A1 storyline describes a future of rapid economic growth and population growth that peaks in the mid-21st century due to low mortality but declines afterward due to low fertility while the B2 storyline describes a future of less rapid economic growth and slow, but continual population growth that peaks at the end of the 21st century (Nakicenovic et al. 2000; USDA Forest Service 2012). For our study, population growth associated with the A1B storyline was chosen for our high-growth scenario while population growth associated with the B2 storyline was chosen for the low-growth scenario (Zarnoch et al. 2010).

The regression parameters from the land value ratio model and respective CBG data were used to estimate the average land value ratio for each CBG. Next, a Tobit regression was performed with CBG average lot size as the dependent variable and projected population density and a vector of distance variables as explanatory variables. Tobit regression was deemed appropriate considering the non-negative nature of the dependent variable (Amemiya 1984). The Tobit regression parameters and CBG data were used to estimate average lot size for each CBG. The average land value ratio for each CBG was then divided by average lot size for each CBG to attain an average land value ratio per hectare. Finally, based on growth condition, the average land value ratio per hectare for each CBG was multiplied by the respective forecasted median housing prices to obtain an estimate of median assessed land value per hectare, which was used as a proxy for the expected return per hectare of urban land for each CBG. The estimates were then averaged at the county level and annualized assuming a 100-year period and a 5% discount rate.

Expected annual return per hectare of forestland (i.e., deciduous forestland and evergreen forestland) was estimated using Soil Expectation Value (SEV), which represents the present

discounted value of rents earned by an infinite series of homogeneous timber management activities including harvest rotation length (Bettinger et al 2009). SEV was estimated historically for NLCD years (e.g. 1992, 2001, 2006, and 2011) using past timber price, volume, and area estimates. We also projected future SEV through 2046 based on Cornerstone Futures scenario projections and assumptions related to timber price, volume, and area (Wear and Greis 2013). Regional projections involving timber volume and area from Wear and Greis (2013) were applied to historical county-level data from our study area to create future county-level projections for volume and area. In addition, Wear and Greis' (2013) assumptions related to future timber prices were applied to historical state-level timber price data. Historical and forecasted SEV for forestland f (f = deciduous forestland or evergreen forestland) per hectare for county i for a given year was estimated as:

$$SEV_{fl} = \frac{P_{fl} \cdot Q_{fl}}{(1+r)^{\tau-1}}, \quad (2)$$

where P_{fl} is the stumpage price for forestland f in county l , Q_{fl} is the sawtimber volume per hectare for forestland f in county l , τ is harvest rotation length ($\tau = 50$ years for evergreen forest and 75 years for deciduous forest based on Smith et al. (2006)), and r is the discount rate of 5%.

Stumpage price is the price received by the landowner for sawtimber after all costs of cutting, snigging and haulage have been paid. Historical sawtimber stumpage price data for six southern states (AL, GA, NC, SC, TN, and VA) were obtained from Timber Mart-South (2015), which is a quarterly market price survey report of major timber products. Historical stumpage prices for Kentucky and West Virginia were collected from the Kentucky Division of Forestry (Kentucky Division of Forestry 2015) and West Virginia Division of Forestry respectively (West Virginia Division of Forestry 2015). Estimates of historical timber volume per hectare were obtained by dividing forestland type (i.e. deciduous, evergreen) standing timber volume for

county l based on Forest Inventory and Analysis (FIA) data (USDA-FS 2018) by forestland type area in county l . Area of forestland by forestland type was estimated from NLCD data using ArcGIS (ESRI 2012).

Future forestland return was forecasted following scenario assumptions similar to the 2013 Southern Forest Futures Project (Wear and Greis 2013). Our study's high-growth scenario was based on the "A" Cornerstone Future while the low-growth scenario was based on the "D" Cornerstone Future (Wear and Greis 2013). The "A" Cornerstone Future represents future high economic growth, moderate population growth, increasing timber prices, and baseline tree planting rates while the "D" Cornerstone Future represents future low economic growth, low population growth, decreasing timber prices, and baseline tree planting rates (Wear and Greis 2013). Future timber prices for our high-growth scenario were assumed to increase 1 percent per year while future timber prices were assumed to decrease 1 percent per year for the low-growth scenario (Wear and Greis 2013). Southern Forest Futures Project projections for forest area and volume were applied to county-level observed data to obtain future values for volume per hectare for each county. Specifically, forest area and volume projections associated with Cornerstone Futures "A" and "D" were applied to our study's high-growth and low-growth scenarios respectively.

Like urban return, forestland return was annualized assuming a 100-year period and a 5% discount rate. Weighted averages of annualized forest return for each county l for year t , W_FR_{lt} , were calculated based on shares of the two forestland types as:

$$W_FR_{lt} = \sum_{f=1}^2 w_{flt} \cdot FR_{flt} , \quad (3)$$

where w_{flt} is the ratio of each forestland type f (i.e. deciduous, evergreen) in county l for year t and FR_{flt} is forest return for forestland type f in county l for year t .

3.3. *Step 3: Estimating future county-level carbon cost efficiencies*

Future estimates of forestland share for each county under the two future growth scenarios were used to estimate future carbon storage using a long-run dynamic ecological process called the dynamic Terrestrial Ecosystem Model (TEM), a framework developed by researchers at the Oak Ridge National Laboratory (ORNL) (2016). The TEM isolates the change in long-term stored carbon resulting from land use change by focusing on a comparison of relative forestland shares over the years. The TEM uses spatially-related information (i.e. climate, elevation, soils and vegetation) to estimate carbon, nitrogen and water fluxes for each vegetation cohort, with cohorts aggregated within each county to conform to the resolution of the land use model (ORNL 2016). The number of cohorts in a county varies according to vegetation types and their area within each grid cell (Gutman and Reissell 2011). Carbon storage is calculated using monthly estimates provided by the TEM cohort-level carbon pools for each year and grid cell, based on integrating monthly fluxes to account for net total carbon uptake through photosynthesis against carbon losses. Carbon storage efficiency for each county was calculated as opportunity cost divided by carbon storage in tonnes per US dollar.

4. **Results and Discussion**

Table 2 reports parameter estimates and associated standard errors of the pooled land use model. The dependent variable was specified as the natural log of the ratio of forested area at the beginning of a given period to the forested area at the end of the period. The F-test statistic for the land use model was significant at the 5% level. (Hereafter, “significant” refers to the 5% significance level). This finding suggests that the overall fit of the model was reasonably good. This result is complemented by an adjusted R-squared of 0.215. The parameter estimate of forest

return relative to urban return is positive and significant, while the parameter estimates of forest return relative to crop and pasture returns are both insignificant. These findings suggest that an increase in forest return relative to urban return increases growth in forest share, while no such relationship is found for forest return relative to crop or pasture return. Similarly, Cho et al. (2018) found that an increase in net return from forestland conversion to urban use had a positive effect on the ratio of forestland conversion to urban use from 2001 to 2006 during an upturn market period. This result indicates that landowners responded to an increase in forest return by selling less land for development purposes. Specifically, our study shows that an increase of forest net return by \$1/hectare in the beginning of each period, holding urban return constant (or decreasing urban return by \$1/hectare, holding forest return constant), results in a gain in forest share by 0.00197% over a period or by 0.00031% per year. (Per year marginal effects were obtained by dividing period marginal effects by the average duration of each period (i.e., 6.333 years).)

In terms of geophysical explanatory variables, the parameter estimate for average elevation was not significant while average slope was positive and significant. The positive sign of the average slope parameter suggests that counties with steeper slopes tend to have greater growth in forest share over a period. This finding suggests that forestland with steeper slopes likely has lower development potential and opportunity costs due to higher development costs (Barclay and Heath 2015). Parameter estimates associated with the Central and Southern Appalachian ecoregions were not significant suggesting that the topographic characteristics of these ecoregions did not significantly affect forest-share change. The state dummy variables were not significant except for the one for West Virginia. Compared to Tennessee, the reference state, forest share was significantly higher for counties in West Virginia. Both period dummy

variables were positive and significant indicating that growth in forest share was significantly higher during the 2001-2006 and 2006-2011 periods compared to the 1992-2001 period. As a result, growth in forest share increased during the upturn and downturn periods compared to a period of moderate economic growth.

Fig. 1 shows the pattern of average carbon-cost efficiency estimates in tonne/\$ based on our future growth assumptions from 2021 to 2046. Average carbon-cost efficiency estimates remain nearly stable from 2021-2046 under the low-growth scenario but decrease steeply under the high-growth scenario (see Fig. 1). This pattern can be attributed mainly to increases in the difference between forest return and forestland opportunity costs under future high-growth assumptions. Fig. 2 shows forest return relative to forest's opportunity cost (represented by return from forestland minus return from urban land) increasing in future years under high-growth assumptions but remaining fairly stable under low-growth assumptions. As a result of the cumulative changes from 2021-2046, future carbon cost-efficiencies in 2046 are greater when a low-growth scenario is assumed than when a high-growth scenario is assumed.

Fig. 3 illustrates the spatial distributions of carbon-cost efficiency in tonne/\$ across counties in the last year of each baseline period (i.e., 2001, 2006, and 2011) (referred to as "baseline years") and the equivalent forecasted spatial distributions in 2046 from the high-growth and low-growth scenarios. Gradual coloring helps visualize changes in carbon-cost efficiency for comparisons among the maps, which have the same carbon-cost efficiency intervals. In the baseline years, counties in the highest carbon-cost efficiency interval (darkest coloring; > 0.17 tonne/\$) are generally clustered in eastern Kentucky, the border area between West Virginia and Virginia, and the Cumberland Plateau region of Tennessee with some differences. Although the clusters are similar to the baseline years for the 2046 low-growth

scenario, some of the clusters dissipate (e.g., Cumberland Plateau region of Tennessee). On the other hand, the number of counties in the lowest carbon-cost efficiency interval (lightest coloring; ≤ 0.02 tonne/\$) is largest for the 2046 high-growth scenario (81 of 246 counties) than for any of the baseline years (49, 64, and 72 of 246 counties in 2001, 2006, and 2011, respectively). These maps show that areas where forestland can be more efficiently conserved are in similar locations despite economic conditions. However, due to high opportunity costs associated with future upturn conditions, the number of counties in the highest carbon-cost efficiency decreases for the scenario. Conservation planners would likely be inclined to focus on areas where carbon-cost efficiency is highest for both future economic scenarios.

Fig. 4 illustrates the spatial distribution of expected (considering uncertainty) carbon-cost efficiency in 2046, given the probability of occurrence for each future growth condition (i.e., 0.5 for high-growth scenario and 0.5 for low-growth scenario) based on historical housing price peak and trough patterns (Bracke 2013). Overall, the figure shows that the clusters of counties in the upper 20th percentile of expected future carbon-cost efficiency are in eastern Kentucky, along the border between West Virginia and Virginia, in Virginia near the North Carolina border, and along the Cumberland Plateau in Tennessee. Counties in the lowest 20th percentile of expected future carbon-cost efficiency are in parts of northern Alabama, northwestern Georgia, northern Virginia near the Maryland border, and areas in close proximity to large cities (i.e. Birmingham, AL, Huntsville, AL, Chattanooga, TN, Knoxville, TN, and Asheville, NC). As a result, after taking account the likelihood of both future growth scenarios, conservation planners would be more effective by focusing conservation efforts in areas where carbon-cost efficiencies are highest.

Although some similarities exist, the above comparison suggests differences in the spatial

distributions between the expected carbon-cost efficiencies and the carbon-cost efficiencies in the baseline years and in the 2046 high-growth and low-growth scenarios. The differences are large enough to reject the null hypothesis that expected carbon-cost efficiencies in 2046 equal the carbon-cost efficiencies in all three baseline years ($p\text{-values} \leq 0.05$ for two-tailed paired t -tests). As a result, estimated carbon-cost efficiencies were significantly different under future scenarios compared to estimates from baseline scenarios. This suggests that conservation planners cannot simply rely on historical patterns when identifying areas for conservation.

5. Conclusion

The objective of our study was to identify spatial targets for PES at the county level by maximizing the expected cost efficiency (i.e., considering growth uncertainty) of ecological benefits in 2046 under two future growth scenarios and compare them with the counties targeted without considering growth uncertainty in three baseline years (i.e., 2001, 2006, and 2011). The empirical results from a case study using forest-based carbon storage in the Central and Southern Appalachian region show that spatial targeting based on carbon-cost efficiency estimates for baseline years is significantly different from spatial targeting based on expected future carbon-cost efficiency. The differences are triggered by variability in growth conditions that determines future uncertainty in the returns to forestland and the opportunity cost of holding forestland (sacrificed return from not using the land for urban development), combined with future changes in carbon cost efficiencies. Spatial targeting based on expected future carbon-cost efficiency is particularly important, because past literature has not considered the potential difference in spatial heterogeneity in growth uncertainties to minimize growth-induced risk. Thus, our results show that incentive payment programs can be designed to anticipate potential risks associated

with growth-induced uncertainties affecting the returns from alternative land uses.

Our study contributes to the existing literature on cost efficiency of PES programs. Using expected future carbon-cost efficiency, instead of the cost efficiencies from historic estimates for each scenario, we examine how conservation agencies can identify a cost-efficient allocation of incentive payments that are robust to changes in growth conditions over time. The finding that growth conditions affect the opportunity cost of forestry (return from urban use), and consequently affect carbon cost efficiencies, has valuable inference for designing PES programs. By anticipating expected future carbon-cost efficiencies, conservation agencies can avoid misleading inferences that might affect cost-effective conservation planning by accounting for potential risks associated with growth-induced uncertainties from alternative land uses.

Our study is the first to identify spatial targets for PES that are robust to changes in growth fluctuations over time. Although a first step, our approach suggests the value in considering the dynamic role of growth fluctuations in evaluating PES. It provides motivation for future studies that assess spatial targeting based on forecasting future opportunity costs of providing ecological benefits, conditioned by uncertainty involved with explicit growth conditions. Our work leads to an intriguing question about the direction of research on spatial targeting of conservation investments including PES, namely, whether future research should be framed in the context of cost-efficiency forecasts of ecological benefits, instead of historic estimates that do not account for growth-induced uncertainty.

Although we evaluated cost-side growth uncertainty in this study, benefit-side uncertainty may also exist. For example, climate change can affect biomass growth of forests and thus affect carbon sinks (e.g., Houghton 2005) and the benefits of PES programs. Accounting for uncertainty in benefits is important when designing PES as climate change poses an increasing

risk to the benefits of ecosystem services. Future analyses that accommodate both opportunity cost (e.g., growth uncertainty) and benefits (e.g., climate change) uncertainties would be useful in generating better inferences for designing PES programs.

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Table 1 Variable definitions and descriptive statistics for the land use model (n=738)

Variable	Definition	Mean (Std Dev)
<i>Dependent variable</i>		
Change in forest share	Ratio of forested area in a period's beginning year to forested area in the last year of the period (i.e., 1992-2001, 2001-2006 and 2006-2011)	0.981 (0.037)
<i>Economic variables</i>		
Forest return relative to crop return	First year's annual average forest return minus annual average crop return (\$/hectare)	-375.720 (862.996)
Forest return relative to pasture return	First year's annual average forest return minus annual average pasture return (\$/hectare)	-44.588 (8.229)
Forest return relative to urban return	First year's annual average forest return minus annual average urban return (\$/hectare)	-281.314 (422.307)
<i>Geophysical variables</i>		
Average elevation	County average elevation (meter)	488.750 (221.307)
Average slope	County average slope (degree)	2.513 (1.414)
Cumberlands and Southern Ridge and Valley ecoregion	1 if county is in Cumberlands and Southern Ridge and Valley ecoregion, 0 otherwise	0.508 (0.500)
Central Appalachian Forest ecoregion	1 if county is in Central Appalachian Forest ecoregion, 0 otherwise	0.232 (0.422)
Alabama	1 if county is in Alabama, 0 otherwise	0.114 (0.318)
Georgia	1 if county is in Georgia, 0 otherwise	0.093 (0.291)
North Carolina	1 if county is in North Carolina, 0 otherwise	0.097 (0.297)
South Carolina	1 if county is in South Carolina, 0 otherwise	0.012 (0.110)
Kentucky	1 if county is in Kentucky, 0 otherwise	0.142 (0.350)
Virginia	1 if county is in Virginia, 0 otherwise	0.223 (0.417)
West Virginia	1 if county is in West Virginia, 0 otherwise	0.138 (0.345)
<i>Time variables</i>		
2001-2006 period dummy	1 if observation took place during 2001- 2006, 0 otherwise	0.333 (0.472)
2006-2011 period dummy	1 if observation took place during 2006-2011, 0 otherwise	0.333 (0.472)

Table 2 Parameter estimates from forest share model (n = 738)

Variable	Parameter Estimates (Std Error)
Constant	-0.070* (0.315)
<i>Economic variables</i>	
Forest return relative to crop return ($\times 0.00001$)	-0.185 (0.191)
Forest return relative to pasture return ($\times 0.001$)	-0.420 (0.227)
Forest return relative to urban return ($\times 0.0001$)	0.197* (0.038)
<i>Geophysical variables</i>	
Average elevation ($\times 0.0001$)	-0.118 (0.120)
Average slope	0.008* (0.002)
Cumberlands and Southern Ridge and Valley ecoregion	-0.009 (0.005)
Central Appalachian Forest ecoregion	-0.008 (0.006)
Alabama	0.003 (0.006)
Georgia	0.002 (0.006)
North Carolina	-0.005 (0.007)
South Carolina	0.008 (0.014)
Kentucky	0.010 (0.005)
Virginia	0.001 (0.006)
West Virginia	0.025* (0.007)
<i>Time variables</i>	
2001-2006 period dummy	0.029* (0.004)
2006-2011 period dummy	0.036* (0.004)
F-test statistic	13.640*
Adjusted R-squared	0.215

Note: * denotes significance at the 5% level. Dependent variable is the natural log of growth in forest share (forest share in the last year of a period divided by forest share in the first year of the period).

Fig. 1 Pattern of average carbon-cost efficiency estimates in tonne/\$ based on different future growth assumptions from 2021 to 2046

Fig. 2 Patterns of return to forest relative to the opportunity cost of forest (i.e. return from forestland minus return from urban land) for future years under high-growth assumptions

Fig. 3 Spatial distribution of carbon-cost efficiency in tonne/\$ across counties in the last year of each baseline period (i.e. 2001, 2006, and 2011) and the equivalent forecasted spatial distribution in 2046 for the high-growth and low-growth scenarios

Fig. 4 Spatial distribution of expected carbon-cost efficiency in 2046 given probabilities of occurrence for each growth condition (50% high-growth, 50% low-growth)