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Targeting Payments for Ecosystem Services Given Ecological and Economic Objectives

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Abstract

The purpose of this research is to identify optimal spatial targets for payments for ecosystem services under the multiple objectives of maximizing cost efficiencies of ecological services and maximizing economic benefits, and analyzing the tradeoff between them. These objectives are taken as targeting criteria in our case study of the Central and Southern Appalachian Region of the United States using Multi-Objective Linear Programming as the optimization tool. We identify optimal county-level targets, with payment budgets optimally distributed among counties, under 27 combinations of nine weighting scenarios between the two objectives and three budget scenarios, and the resulting changes in forest carbon and economic benefits. Using this information, we develop three Pareto optimal frontiers between the two objectives to evaluate the tradeoff between the objectives for each assumed payment budget. Maps of the county-level payment budget distributions, given the objective weighting scenarios between the two objectives, provide evidence that the greater the weight assigned to maximizing forest carbon benefits relative to maximizing economic impacts, the more widespread the optimal budget is allocated among the counties. The concave shape of each Pareto optimal frontier provides evidence that (1) an increase in the weight assigned to economic impacts and a decrease in the weight assigned to forest carbon benefits increases economic impacts that requires a sacrifice of forest carbon benefits and vice versa, and (2) the increase in economic impacts is relatively higher than the sacrifice in forest carbon benefits when the initial weight assigned to economic impacts is relatively lower than the initial weight assigned to forest carbon benefits and vice versa. Because of the concavity of the Pareto optimal relationship, assigning greater weight to an objective, which is of minimal concern at the initial policy-making stage, makes sense if conservation agencies add that objective to a multiple-objective targeting framework. For example, assigning a positive weight to economic impacts yields higher economic impacts for a smaller sacrifice of forest carbon benefits when the initial optimal spatial target focuses on promoting cost-efficient forest carbon benefits without concern for providing positive economic impacts.

Targeting Payments for Ecosystem Services Given Ecological and Economic Objectives

1. Introduction

1.1. Background and objective

The global temperature on Earth increased between 0.6 and 0.9 degrees Celsius over the 1906-2005 period. The rate of increase almost doubled during the last half decade of that period (IPCC, 2007). Recent climate change has triggered extensive, negative effects on natural and human systems, including loss and damage to ecosystems and environmental resources (IPCC, 2014). Carbon dioxide that comprises the majority of anthropogenic greenhouse gas emissions is one of the major contributing factors to the observed increase in global temperatures since the mid-20th century (IPCC, 2014; Garnett, 2008). In response, worldwide attempts to mitigate atmospheric carbon emissions have been made (Dodman, 2009). Among those efforts, considerable attention has focused on promoting forest carbon sequestration to offset carbon emissions by reducing deforestation and increasing afforestation (Cho et al., 2017; Latta et al., 2011; Wittman and Caron, 2009). These efforts are important, because global forestland has the capacity to sequester 2.4 ± 0.4 peta-grams of carbon emissions annually, which is equivalent to 30% of global carbon emissions from fossil fuels used in 2008 (Le Quéré et al., 2009; Pan et al., 2011).

Despite the vital role of carbon sequestration in mitigating climate change, most forestland owners receive no compensation for their contributions to this service. Incentive payments to forest landowners can internalize the positive externality of carbon sequestration (Engel et al., 2008; Wünscher et al., 2008; Farley and Costanza, 2010) while providing positive economic benefits to rural communities (Li et al., 2011; Miranda et al., 2003; Corbera et al., 2009). The proposed American Clean Energy and Security Act would have included a cap-and-

trade program to generate payments for forest landowners for the carbon sequestered in their forests (USDS, 2010). That said, the potential inclusion of forest carbon in the U.S. carbon market program is controversial, due in no small part to the uncomfortably high levels of uncertainty for obtaining a successful outcome in terms of cost efficiency and economic impacts.

Two branches of literature on payments for ecosystem services (PES) have been developed to address these difficulties: one dealing PES cost efficiency and the other dealing with the economic impacts of PES programs. The literature addressing cost efficiency emphasizes the integration of costs and benefits in PES targeting criteria (Barton et al., 2003; Ferraro, 2004; Claassen et al., 2008). The other branch of literature finds that low-income rural households and communities can potentially benefit from PES programs, but program success depends on factors such as local conditions, the distribution of land and land quality, and the use of appropriate spatial targeting (Pagiola et al., 2005; Zilberman et al., 2008; Hyberg et al., 1991; Milder et al., 2010). Despite the important roles of the cost efficiency of achieving a given levels of ecological benefits as well as the objective of receiving positive economic benefits in developing successful PES programs, few, if any, studies integrate these objectives into PES targeting criteria. This gap in the literature is surprising given that (1) PES often serve multiple objectives, including the promotion of efficient conservation and positive economic impacts (Bulte et al., 2008; McShane et al., 2011; Sims et al., 2014) and (2) understanding the tradeoffs between these objectives is important for successful PES design (Wu and Yu, 2017).

The purpose of this research is to fill the literature gap by identifying optimal spatial targets for PES under the multiple objectives of maximizing the cost efficiency of ecological benefits and maximizing economic benefits. A further purpose is to evaluate the tradeoff between the two objectives. In our case study, the two objectives of a PES program are to

maximize the cost efficiency of forest carbon storage and to maximize the program's economic benefits. The optimization tool, multi-objective linear programming (MOLP) (Savir, 1966), is used with these objectives as the targeting criteria in our case study of the Central and Southern Appalachian Region of the United States (see Figure 1). Through MOLP we identify optimal county-level targets with a total conservation budget optimally distributed among the counties under 27 alternatives, consisting of nine weighting scenarios between the objectives and three budget scenarios, and their resulting changes in forest carbon and economic benefits. We then develop three tradeoff frontiers between the two objectives that are triggered by the targeted PES. Along each frontier, the PES is Pareto optimal in that forest carbon storage cannot be increased without sacrificing economic benefits and vice versa.

The results identifying optimally targeted counties with optimal PES distributions will help conservation agencies anticipate regional (i.e., county-level) budget allocations that depend on the relative importance they place on the two objectives. Similarly, projections of regional forest carbon storage and economic benefits resulting from the optimal distributions of payments will help conservation agencies anticipate regional heterogeneity in forest carbon storage and economic benefits and their tradeoffs. The regional heterogeneity in the anticipated effects of the two benefits and their tradeoffs can serve as an empirically-informed knowledge base for conservation agencies to utilize in evaluating forest-based carbon incentive payment programs that balance the objectives of providing forest carbon storage and economic benefits.

1.2. Literature review

In the literature dealing with targeting criteria for conservation programs, benefits, costs, and benefit-cost ratios are used as targeting criteria (Babcock et al., 1997). In the benefit-

targeting approach, high-benefit target areas are identified based on differences in the benefits between protected and unprotected lands (Scott et al., 1993; Wright et al., 1994; Powell et al., 2000; Rodrigues et al., 2003). Under this targeting approach, the costs of establishing protected areas are implicitly assumed to be equal. In reality, substantial cost variation exists across potential protected areas, suggesting the need to integrate establishment costs and benefits when selecting areas to target for protection (Ando et al., 1998; Balmford et al., 2000; Polasky et al., 2001; Ferraro, 2003; Moore et al., 2004).

A branch of literature focusses on whether the correlation between costs and benefits has implications for the cost efficiency of protection. Babcock et al. (1997) analyze how the joint spatial distribution of costs and benefits influences the cost efficiency of different targeting rules. Ferraro (2003) examines the correlation between benefit ranking and cost ranking to identify the conditions under which the integration of cost and benefit information is likely important to effective decision making. Chomitz et al. (2006) evaluate cost-targeting criteria by examining the effect of correlation between costs and biodiversity on a targeting rule that includes a low-cost solution. Ando et al. (1998) examine the effect of heterogeneous costs and corresponding biodiversity on efficient conservation. Polasky et al. (2001) investigate the relation between a conservation budget and biological reserves, and conclude that an integrated analysis of biological costs and benefits is needed to make effective conservation decisions.

A large set of literature focuses on improving the cost efficiency of PES through the costbenefit relationship (Antle et al., 2003; Barton et al., 2003; Ferraro, 2004; Lubowski et al., 2006; Claassen et al., 2008; Engel et al., 2008; Gibbons et al., 2011; Lewis et al., 2011; Mason and Plantinga, 2011; Armsworth et al., 2012; Hanley et al., 2012; Polasky et al., 2014).

The literature suggests that increases in cost efficiency are achieved when more finely resolved spatial variations in costs and benefits are used to allocate PES contracts and set payment rates (Babcock et al., 1996; Antle et al., 2003; Zhao et al., 2003; Mason and Plantinga, 2011; Armsworth et al., 2012). Recent literature suggests that contract length and timing have clear implications for the cost efficiency of PES and other conservation programs (Ando and Chen, 2011; Lennox and Armsworth, 2011; Drechsler et al., 2017; Curran et al., 2016; Schöttker et al., 2016).

In addition, PES programs have become the flagship of conservation organizations in advancing rural economic development and poverty reduction (Zilberman et al., 2008). The financial transfers of PES allow landowners to internalize the positive externalities associated with ecosystem services (Grieg-Gran et al., 2005) and, thus, PES programs are a potential tool for generating positive regional economic impacts for participating landowners (Engle et al., 2008; Zilberman et al., 2008; Zhang and Pagiola, 2011). Developing countries have begun to incorporate PES into rural economic development programs (Muradian et al., 2010) and the literature has begun to focus on understanding the economic impacts of PES (Engle et al., 2008; Zilberman et al., 2008; Zhang and Pagiola, 2011). Among the findings in literature are: PES can be vital for poverty reduction and rural economic development if designed to fit local conditions (Pagiola et al., 2005), the spatial distributions of land and land quality are essential in determining poverty impacts (Zilberman et al., 2008), the economic impacts of PES depend on how effectively the program reaches the targeted beneficiaries (Hyberg et al., 1991; Milder et al., 2010), and the date when the program starts is crucial to successful impacts on economic development and poverty reduction (Randrianarison et al., 2017).

Few studies consider the economic impacts of PES when using cost efficiency of ecological benefits as the targeting criterion (Pagiola et al., 2005; Milder et al., 2010; Ingram et al., 2014) and, when estimating the economic impacts of PES, the cost efficiency of ecological benefits is typically ignored. In contrast, a few studies examine the tradeoffs between cost efficiency and distributional equity in analyzing the performance of PES (Alix-Garcia et al., 2003; Wu and Yu, 2017). A major challenge in developing a framework that considers both criteria in the spatial targeting of PES is estimating the values of ecological and economic benefits for given payment distributions. Specifically, because payment distributions are critical elements of multi-objective optimization, simultaneously maximizing both ecological and economic benefits is difficult.

In our case study, we employ a framework that estimates the values of forest carbon storage and economic benefits with optimal payment distributions for multiple scenarios with different weights between the two objectives. First, we estimate the potential maximum forest carbon benefits available to each county in response to alternative PES. This potential carbon benefit is found by estimating the opportunity cost of sequestering forest carbon using a land-use model that links forest-based carbon payments with forestland changes. We then convert the forestland changes to forest carbon storage though a carbon simulation model. The maximum county-level economic impacts for given payment amounts are estimated using the Impact Analysis for Planning (IMPLAN) model by analyzing the interdependence of industries throughout the regional economies (AIM-AG, 2017).

The estimates acquired from the land-use, carbon simulation, and IMPLAN models become inputs in the MOLP to identify a set of optimal target counties with an optimal budget distribution among the counties that yields a set of optimal forest carbon storage and economic

impacts, given different weights between the two objectives and total PES budgets. The results from the integrated empirical framework are used to develop Pareto optimal frontiers between optimal forest carbon storage and optimal economic impacts. These results are a major contribution to the literature because they help conservation agencies understand optimal county targets with heterogeneity of ecological and economic benefits and their tradeoffs, all under one framework, which has not been done before.

2. Method

2.1. Land-use model

We hypothesize that the forested area at the end of a period relative to the forested area at the beginning of the period is a function of the annual forest return relative to the annual returns from competing land uses (i.e., crop, pasture, and urban) at the beginning of the period. Following Barbier and Burgess (1997)'s optimal allocation of forestland between competing land uses over time, we estimate the following semi-log model at the county level:

$$\log\left(\frac{y_{t+n}}{y_t}\right) = \alpha + \beta_c x_t^c + \beta_p x_t^p + \beta_u x_t^u + X\delta + \varepsilon$$
(1)

where y_t and y_{t+n} are, respectively, forested areas in the first and last years of two five-year periods (i.e., 2001-2006 and 2006-2011); x_t^c , x_t^p , x_t^u are the first year's forest returns relative to the returns from crop, pasture, and urban land uses, respectively, estimated by subtracting returns from competing land uses from forest return; X includes other factors that affect $\frac{y_{t+n}}{y_t}$ (referred to as "ratio of forested area"); α , β_c , β_p , β_u , and δ are corresponding parameters; and ε is an error term. The county-average slope and elevation are included in X to control for the effects of topographical characteristics. The time-period dummy variable (i.e., 1 for observation in 20012006 and 0 otherwise) is included in X to capture temporal differences in the ratios of forested area that are not captured by difference in relative returns across the periods. Ecoregion dummy variables and state dummy variables are included in X to capture regional fixed effects, such as differences in land-use change patterns and land-use policies across ecoregions and states.

Forested areas at the county level are estimated by aggregating 30-m resolution land cover data from National Land Cover Database (NLCD, 2011). The annual forest return at the county level is estimated based on Faustmann's model (1849) using harvest volume data from the Forest Inventory and Analysis database (USDA Forest Service, 2017) and stumpage price data from Timber Mart-South (2006, 2011). The annual return of cropland is estimated based on county-level net cash farm income from cropland and areas of harvest cropland from USDA Census of Agriculture (2012) and National Agricultural Statistical Service (NASS, 2014). The annual return from pastureland is estimated using county-level pastureland rent, county-level cattle numbers, and county-level pastureland area from National Agricultural Statistics Service (2014) and USDA Census of Agriculture (2012). The annual return from urban land is estimated based on parcel-level data for assessed land value and total assessed value from the tax assessors' offices of 25 counties and census-block group data for median housing price (U.S. Census Bureau, 2000; American Community Survey, 2009, 2012). (See Supplementary material in Cho et al. (2017) for a detailed description of how four net returns are calculated.) The Zonal Statistics tool in ArcGIS 10.1 (ESRI, 2012) and the Digital Elevation Model (DEM) (U.S. Geological Survey, 2013) are used to estimate the county-average slope and elevation. See Table 1 for a detailed description of the variables.

Once the land-use model in equation (1) is estimated, we calculate the marginal effects of forest return relative to returns from competing land uses (i.e., crop, pasture, and urban) on the

ratio of forested area for each period. Only the marginal effect of the forest return relative to the return from urban use is significant at the 5% level (hereafter referred to as "significant") in our land-use model, and thus we simulate changes in the ratio of forested area by incrementally increasing the forest return relative to the urban return, holding urban return constant. This simulation implies that all forestland owners receive the same payment amount if they are in the same county and payments made at the county level are to discourage deforestation for urbanization.

The maximum amount of deforested land that could have been prevented from being converted to urban use in a county is used in the carbon simulation model described in section 2.2. to estimate the maximum amount of forest carbon storage for that county. The IMPLAN model is then used to estimate the maximum economic impacts of the payments needed to supply the maximum forest carbon storage in each county (referred to as "the maximum payments") as described in section 2.3. The maximum amounts of forest carbon storage, maximum payments, and maximum economic impacts, all at the county level, are used in the MOLP described in section 2.4.

2.2. Carbon simulation model

The Terrestrial Ecosystem Model (TEM) is used to estimate changes in carbon storage that correspond to changes in the ratio of forested area in each period based on climate, forest type, disturbance and management histories, and other environmental characteristics (Hayes et al., 2011). The TEM enables us to simulate cohort-level monthly carbon fluxes for a period in each of the four land-use categories (crop, pasture, urban, and forest). The simulated carbon fluxes are used to estimate carbon storage in forestland and urban land. The estimated changes in

carbon storage at the cohort level, based on the area of each contiguous vegetation type, are used to aggregate changes in carbon storage to the county level for each period by simulating changes in the ratio of forested area as the forest return is incrementally increased relative to the return from urban use.

2.3. Impact Analysis for Planning

The IMPLAN model is used to estimate the economic impacts triggered by payments at the county level. IMPLAN provides a number of economic indicators such as total industry output (TIO), total value added (TVA) or Gross Domestic Product (GDP), employment (EMP), and taxes. Out of these economic impact indicators that IMPLAN generates, GDP is selected to represent the economic impacts in our study. It is considered the most proper instrument for estimating regional overall economic impact (Weisbrod and Weisbrod, 1997). Using the interrelationships between industries, households, and government, a multiplier is generated that shows how a dollar is spent and re-spent for the direct, indirect, and induced economic impacts of the total value added from the maximum payments within each of the counties (Mulholland et al., 2011). The datasets used to obtain the multiplier in the IMPLAN model are from the U.S. Bureau of Economic Analysis, U.S. Bureau of Labor Statistics, and U.S. Census Bureau (IMPLAN Group LLC, 2017a).

2.4. Multi-objective linear programming

The multiple objectives of maximizing both forest carbon benefits and economic impacts triggered by payments are the targeting criteria we use in MOLP. Following Ragsdale (2014), the MINIMAX method, which searches for optimal solutions with the minimal deviation from the target value for each objective, is utilized to determine optimal target counties in two steps. The first step determines the optimal objective values of each individual objective, i.e. maximum of forest carbon storage O_c and maximum of economic impacts O_e as:

$$O_{c} = \underset{x_{i}^{c}}{MAX} \left(\sum_{i=1}^{n} c_{i} * x_{i}^{c} \right) \text{ subject to } \sum_{i=1}^{n} tp_{i} * x_{i}^{c} \leq B,$$

$$O_{e} = \underset{x_{i}^{e}}{MAX} \left(\sum_{i=1}^{n} e_{i} * x_{i}^{e} \right) \text{ subject to } \sum_{i=1}^{n} tp_{i} * x_{i}^{e} \leq B,$$
(2)

where c_i and e_i are total forest carbon storage and total economic impact for county *i*; x_i^c and x_i^e are the optimal decision variables (continuous numbers between 0 as the lower bound and 1 as the upper bound) representing the share for county *i* that is optimal for the respective objectives; tp_i is the total payment that is needed to obtain the total forest carbon storage at county *i*; and *B* is the budget government one of three budget scenarios (i.e., 75%, 50%, and 25% of budget needed to reach maximum carbon storage capacity).

Using the optimal values of the two individual objectives from the first step, the second set of optimal decision variables x_i (continuous numbers between 0 as the lower bound and 1 as the upper bound) for county *i* that minimizes the largest weighted deviation from the optimal values of the two objectives (O_c and O_e), with two constraints simultaneously is estimated as:

Min Q

subject to

$$W_{c} * (O_{c} - \sum_{i=1}^{n} c_{i} * x_{i}) * \frac{1}{o_{c}} \leq Q$$

$$W_{e} * (O_{e} - \sum_{i=1}^{n} e_{i} * x_{i}) * \frac{1}{o_{e}} \leq Q$$
(3)

where W_c , is a hypothetical weight for forest carbon storage and W_e is a hypothetical weight associated with economic impact. Nine weight combinations between the two objectives (i.e., W_c -100% and W_e -0%, W_c -87.5% and W_e -12.5%, W_c -75% and W_e -25%, W_c -62.5% and W_e - 37.5%, W_c -50% and W_e -50%, W_c -37.5% and W_e -62.5%, W_c -25% and W_e -75%, W_c -12.5% and W_e -87.5%, and W_c -0% and W_e -100%) are used to reflect relative importance between the two objectives. Once the optimal decision variable x_i is obtained, it is considered as the proportion of the area that is included in PES from the maximum candidate area in the county *i*. The budget allocated to the county *i* is estimated by multiplying the proportion of the county, the optimal decision variable x_i , by maximum payment tp_i . To solve the MOLP, the *fininimax* function in Matlab (MathWorks, 2017) is used with necessary modification of the code.

3. Empirical results and discussion

Table 2 reports coefficients and corresponding standard errors of the semi-log model in equation (1). The goodness of fit of the model is reflected in adjusted R^2 of 0.174. Forest return relative to urban return is positive and significant, while the other two relative returns are not significant. Thus, the results suggest that forest return affects the ratio of forested area only if it is valued relative to urban return. Specifically, an increase of \$1/hectare/year in forest return relative to urban return in the first year increases the average ratio of forested area by 0.0006% during the two periods. This finding suggests that incentive payments to boost forest return work towards sustaining and/or increasing forestland only if the competing land use is urban development, and not crop or pasture.

The dummy variables for the Cumberlands & Southern Ridge and Valley Ecoregion and for the 2001-2006 period are significant. The signs of the coefficients imply that (1) the ratio of forested area decreases more in the Cumberlands & Southern Ridge and Valley Ecoregion than in the Southern Blue Ridge Ecoregion on average, and (2) the ratio of forested area decreases

more during the 2006-2011 period relative to the 2001-2006 period on average. These two findings suggest that the loss of forestland differs across ecoregions and time.

Figure 2 illustrates simulated forested area in the entire study area that would have been prevented from deforestation for urban development at different values of forest return relative to urban return. The simulated prevention of deforested area increases at a decreasing rate until it reaches 60,216 hectares with the budget of \$1,541,578 (Figure 2). The spatial distribution of the maximum allocated budget across counties is shown in Figure 3. This figure illustrates how the payment budget would have been distributed if its distribution were based on how much forested area would have been deforested for urbanization without the optimal spatial targeting of payments.

Figure 4 illustrates the spatial distribution of carbon-cost efficiency across counties. The distribution ranges from 0.01 tonne/\$ to 1.97 tonne/\$ when the payment budget is not constrained. Carbon-cost efficiency is higher in the border area between West Virginia and Virginia, southwest Pennsylvania, southwest North Carolina, and the southern tip of Appalachia in Alabama. Counties in the highest carbon-cost efficiency range (0.68–1.97 tonne/\$) tend to have (i) higher carbon storage gains from preventing deforestation for urban use (1.85 tonne/hectare higher than the average carbon storage gain of 4.26 tonne/hectare for the entire study area) and (ii) relatively lower opportunity costs of preventing deforestation for urban use (\$86.35/hectare lower than the average opportunity cost of \$93.03/hectare).

Figure 5 illustrates the spatial distribution across counties of the economic-cost efficiency (total county value added divided by the county's maximum allocated budget). The economic-cost efficiency is higher in a cluster of counties in Pennsylvania and in other counties dispersed within the rest of the study area. The counties in the highest economic-cost efficiency range

(\$1.75–2.00/\$) tend to have higher regional purchase coefficients, the proportion of each dollar of local demand for a given commodity is purchased from local producers (IMPLAN, 2017b).

Table 3 shows total carbon storage, gross domestic product, carbon-cost efficiency, and economic-cost efficiency for the nine objective weighting scenarios and the three budget scenarios. On average, economic-cost efficiency is higher when more weight is placed on maximizing economic impacts than on maximizing carbon-cost efficiency, while carbon-cost efficiency is higher when more weight is assigned to maximizing carbon-cost efficiency. Figure 6 illustrates the distribution of the payment budget among counties for the nine weighting scenarios when the annual-payment budget is 50% of the budget required to achieve maximum carbon storage capacity. This budget constraint is used in Figure 6, because the budget level has little effect on the overall patterns of the distributions.

The maps in Figure 6 can be characterized by three points. First, the greater the weight assigned to maximizing forest carbon storage relative to maximizing economic impacts, the more the optimal budget allocation is dispersed among the counties. For example, if a weight of 100% were assigned to maximizing the forest carbon benefit, the total budget would be distributed optimally to 202 of the 288 counties. Most (64 counties) of the 86 counties not receiving payments lost no forestland over the two periods. The number of optimally targeted counties gradually declines as the weight assigned to maximizing forest carbon benefits declines and the weight assigned to maximizing economic impacts increases. When a weight of 100% is assigned to maximizing economic impacts, the number of optimally targeted counties falls to 72. This phenomenon results from the greater dispersion of the economic impacts among the counties relative to the carbon benefits (Figure 7). Specifically, the coefficient of variation of economic impacts with the maximum allocated budget is 3.50, while it is 2.50 for carbon benefits. Result

from a two-sample Kolmogorov-Smirnov test (Massey, 1951) indicate that the distribution of economic impact stochastically dominates the distribution of carbon benefit (p-value < 0.05).

Second, under all weighting scenarios, consistently higher optimal budgets occur in the counties of southern Appalachia in Alabama, Georgia, Tennessee and North Carolina, and at the southeast end of Pennsylvania. The counties with optimal budget allocations in the upper quartile in Figure 6 tend to have high economic-cost efficiency regardless of the weight assigned to that objective. This finding implies that economic-cost efficiency is important in allocating the optimal budget.

Third, assuming 50% of the maximum budget, 65 of 288 counties are consistently chosen for optimal spatial targeting regardless of the weighting scenario. Of those counties, 59 counties are in the top 65 counties ranked by high economic-cost efficiency, while only 21 counties are in the top 65 counties ranked by high carbon-cost efficiency. These findings suggest that economiccost efficiency is a relatively more dominant objective in the targeting decision than the objective of carbon-cost efficiency. Again, this pattern of optimization is likely related with greater dispersion of the economic-cost efficiency relative to carbon-cost efficiency.

Figure 8 illustrates three carbon-economic impact frontiers that reflect different tradeoffs between forest carbon storage and economic impacts, given different weights imposed between the two objectives and three budget scenarios. For example, given a weight of 100% assigned to maximizing forest carbon benefit at point A on the 50%-budget frontier (i.e., $W_c = 100\%$ and W_e = 0%), the optimal budget distribution among counties would yield 296,215 tonnes of carbon storage and \$1,360,551 of economic impact (see Table 3). Reducing the weight on maximizing forest carbon storage to 87.5% and increasing the weight on maximizing economic impact to 12.5% (i.e., $W_c = 87.5\%$ and $W_e = 12.5\%$) at point B on the 50%-budget frontier, the optimal

budget distribution would yield 295,802 tonnes of carbon storage and \$1,367,666 of economic impact (see Table 3). The move from point A to point B implies that the economic impact improves by \$7,115 with a sacrifice of 413 tonnes of carbon storage, yielding the tradeoff ratio of 0.058 tonnes/\$. This tradeoff ratio suggests a sacrifice of 0.058 tonnes of forest carbon storage for a conservation agency wanting to achieve an additional \$1 of economic impact. This tradeoff ratio increases (or the amount of forest carbon storage forgone increases for an additional \$1 of economic impact) as the weight assigned to maximizing economic impacts increases (e.g., tradeoff ratio of 6.566 tonnes/\$ from the move of point C for the scenario of W_c -12.5% and W_e -87.5% to point D for the scenario of W_c -0% and W_e -100%). This concave relationship between optimal carbon benefit and economic impacts is consistently for the three budget scenarios and the values of both objectives consistently decrease with tighter budget scenarios.

4. Conclusions

There is strong evidence that PES often serve the multiple objectives of promoting efficient ecosystem services and providing positive economic impacts (Miranda et al., 2003; Bulte et al., 2008; Sims et al., 2014). Nevertheless, PES targeting criteria have mostly focused on promoting efficient conservation without concern for providing positive economic impacts (Babcock et al., 1997; Ando et al., 1998; Barton et al., 2003; Ferraro, 2004). Research is lacking on PES programs that serve both objectives. Thus, it is critically important to understand optimal spatial PES targets and the tradeoffs between the two objectives.

We develop an integrated empirical framework for identifying optimal spatial PES targets with optimal payment budget distributions and tradeoffs between ecological and economic benefits. Our case study deals with the two objectives of maximizing forest carbon

sequestration and the economic impact of PES at the county level in the southern Appalachian Region in the United States. We evaluate the implications of different weighting scenarios between the two objectives for county-level optimal budget distributions. We develop Pareto optimal frontiers under alternative total budget constraints along which the given total budget cannot be reallocated among counties to advance one objective without sacrificing the other.

Maps of PES optimal budget distributions among counties, given different weighting scenarios between the two objectives, provide evidence that, the greater the weight assigned to maximizing forest carbon benefits relative to maximizing economic impacts, the more widespread the optimal budget would be allocated among the counties. This finding occurs because the economic-impact objective is more dominant in the targeting decision than the carbon-cost efficiency objective, on average. This evidence suggests that incorporating positive economic impacts in the targeting criteria, along with promoting cost-efficient conservation, is necessary and a viable option. Our projections of county-level forest carbon storage and economic impacts, given different weighting scenarios, help target optimal county-level PES budget distributions and evaluate their effects on both objectives.

The Pareto optimal frontiers provide evidence that the optimal relationship between forest carbon benefits and economic impacts is concave. Along a given Pareto optimal frontier (i.e., a given PES total budget), (1) an increase in the weight assigned to economic impacts with a corresponding decrease in the weight assigned to forest carbon benefits increases the economic impacts while reducing the forest carbon benefits and vice versa, and (2) the increase in economic impacts is relatively higher than the sacrifice in forest carbon benefits when the initial weight assigned to economic impacts is relatively lower than the initial weight assigned to forest carbon benefits and vice versa. Because of the concavity of the Pareto optimal relationship,

assigning greater weight to an objective, which is of minimal concern at the initial policy-making stage, makes sense if conservation agencies add that objective to a multiple-objective targeting framework. For example, assigning a positive weight to economic impacts yields higher economic impacts for a lower sacrifice of forest carbon benefits when the initial optimal spatial target focuses on promoting cost-efficient forest carbon benefits without concern for providing positive economic impacts.

The tradeoff between ecological benefits and economic benefits is not unique to forest carbon storage and many PES programs face the same issue. Our empirical framework can be applied to other PES programs that have promoting efficient ecosystem services and providing positive economic impacts as their objectives. This approach takes advantage of multiple models in one framework to estimate values for both objectives and feds them into the optimization model. Hence, our framework is feasible for PES programs when both ecological and economic benefits are available. For example, our framework for spatial PES targeting can be used for the multiple objectives of maximizing both biodiversity and economic impacts, if a model can estimate changes in regional biodiversity (e.g., species distribution model) that correspond with land-use changes triggered by payments for biodiversity enhancement that also can be used to estimate economic impacts through IMPLAN.

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Variables	Definition	Mean (Std Dev)	
Dependent variables			
Change in forest share	Ratio of forested area between the beginning and the end of a given period (i.e., 2001-2006	0.991 (0.023)	
Socioeconomic variables	and 2006-2011)		
Forest return relative to crop return	First year's annual forest return relative to annual return from crops (\$/hectare)	-246.686 (915.712)	
Forest return relative to pasture return	First year's annual forest return relative to annual return from pasture (\$/hectare)	14.226 (21.020)	
Forest return relative to urban return Geophysical variables	First year's annual forest return relative to annual return from urban use (\$/hectare)	-653.017 (1603.387)	
Average elevation	Average elevation (meter)	471.063 (216.703)	
Average slope	Average slope (degree)	2.485 (1.335)	
Appalachian forest ecoregion	1 if county is in central Appalachian forest ecoregion, 0 otherwise	0.340 (0.474)	
Cumberlands and southern	1 if county is in Cumberlands and Southern	0.479	
ridge and valley ecoregion Year variable	Ridge and Valley ecoregion, 0 otherwise	(0.500)	
Period dummy variable	1 if period is 2006-2011, 0 otherwise	0.500 (0.500)	

Table 1. Variable definitions and descriptive statistics

Variables	Mean				
	(Std Dev)				
Constant	-0.004				
	(0.011)				
Socioeconomic variables					
Forest return relative to	0.005				
crop return ($\times 0.00001$)	(0.131)				
Forest return relative to	0.048				
pasture return (\times 0.001)	(0.067)				
Forest return relative to	0.629*				
urban return (\times 0.00001)	(0.068)				
Geophysical variables					
Average elevation (\times 0.00001)	0.378				
	(0.751)				
Average slope ($\times 0.01$)	-0.049				
	(0.114)				
Appalachian forest ecoregion	-0.009				
	(0.005)				
Cumberlands and southern	-0.012*				
ridge and valley ecoregion	(0.004)				
State dummy variable	Yes				
Year variable					
Period dummy variable	0.005*				
-	(0.002)				

Table 2. Parameter estimates from log-linear model (n = 576)

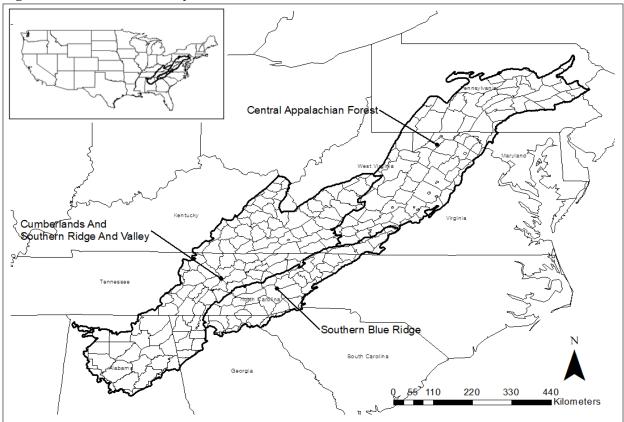
Note: Adjusted $R^2 = 0.174$, Numbers in parentheses are standard errors, and * denotes significance at the 5% level.

Weight	75% of total budget				50% of total budget			25% of total budget				
combinations	TC	TVA	CCE	ECE	TC	TVA	CCE	ECE	TC	TVA	CCE	ECE
(W_c/W_e)	(tonne)	(\$)	(tonne/\$)	(\$/\$)	(tonne)	(\$)	(tonne/\$)	(\$/\$)	(tonne)	(\$)	(tonne/\$)	(\$/\$)
100.0 / 00.0	304,706	2,009,310	0.2635	1.7378	296,215	1,360,552	0.3843	1.7651	225,685	674,178	0.5855	1.7493
87.5 / 12.5	304,362	2,020,011	0.2632	1.7471	295,802	1,367,666	0.3838	1.7744	224,093	684,703	0.5814	1.7766
75.0 / 25.0	304,105	2,024,047	0.2630	1.7506	294,948	1,369,845	0.3827	1.7772	222,502	689,837	0.5773	1.7899
62.5 / 37.5	303,847	2,026,536	0.2628	1.7527	293,850	1,371,336	0.3812	1.7791	220,721	693,912	0.5727	1.8005
50.0 / 50.0	303,599	2,028,704	0.2625	1.7546	292,291	1,372,491	0.3792	1.7806	218,320	696,821	0.5664	1.8080
37.5 / 62.5	303,318	2,030,540	0.2623	1.7562	289,838	1,373,595	0.3760	1.7821	214,840	699,566	0.5574	1.8151
25.0 / 75.0	302,879	2,032,036	0.2619	1.7575	285,937	1,375,901	0.3710	1.7850	209,650	703,277	0.5439	1.8248
12.5 / 87.5	301,461	2,033,010	0.2607	1.7583	277,059	1,379,444	0.3594	1.7896	199,608	708,448	0.5179	1.8382
00.0 / 100.0	271,817	2,036,105	0.2350	1.7610	191,186	1,39,2523	0.2480	1.8066	133,754	720,335	0.3470	1.8690

Table 3. Total carbon storage (TC), gross domestic product (GDP), carbon-cost efficiency (CCE), and economic-cost efficiency (ECE) across nine weighting scenarios for three budget scenarios

Note: W_c is the assigned weight for maximizing forest carbon storage and W_e is the assigned weight for maximize economic impacts.





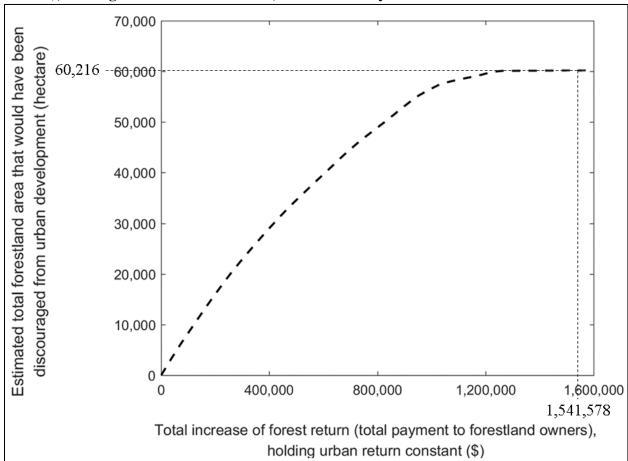


Figure 2. Estimated total forestland area that would have been discouraged from urban development subsequent to total increase of forest return (total payment to forestland owners), holding urban return constant, for entire study area

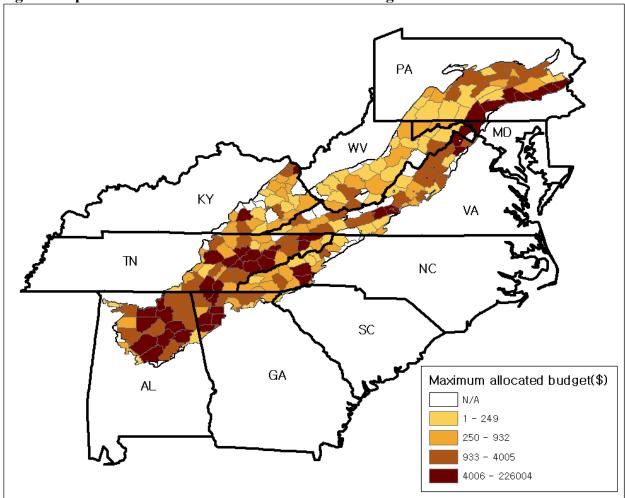


Figure 3. Spatial distribution of maximum allocated budget

Note: N/A represent counties that did not lose any forestland over the periods

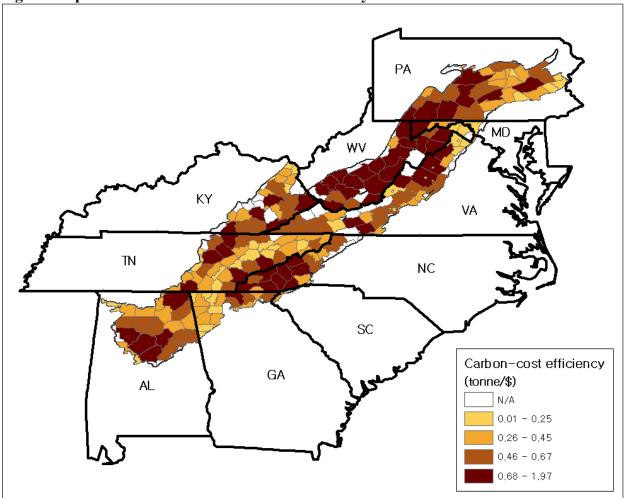


Figure 4. Spatial distribution of carbon-cost efficiency

Note: N/A represent counties that did not lose any forestland over the periods

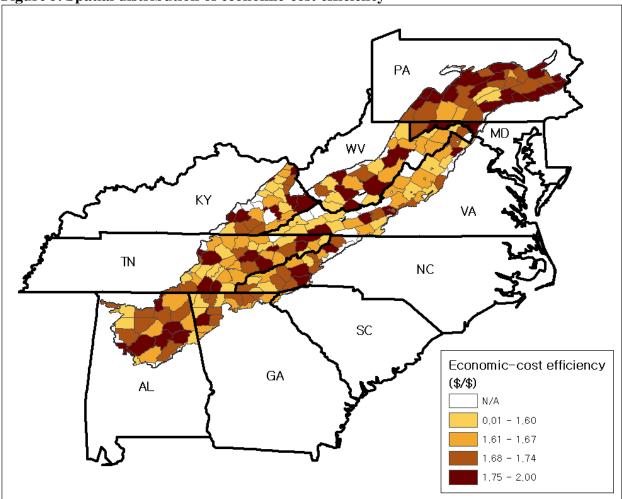
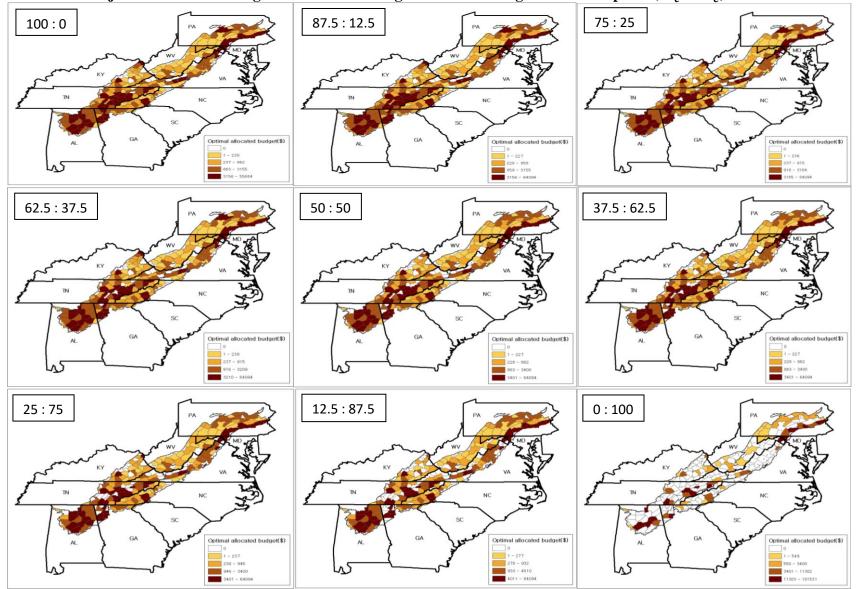


Figure 5. Spatial distribution of economic-cost efficiency

Note: N/A represent counties that did not lose any forestland over the periods

Figure 6. Optimal spatial distribution of payment budget under the 50% budget scenario with nine weighting scenarios between the objectives of maximizing forest carbon storage and maximizing economic impacts (W_c : W_e)



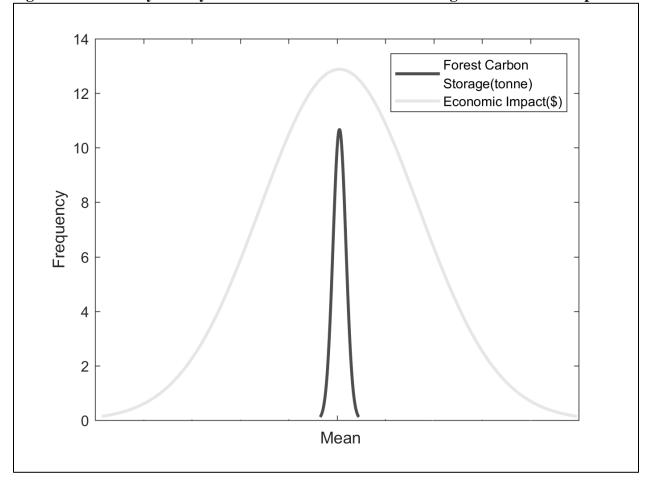


Figure 7. Probability density distributions of forest carbon storage and economic impacts

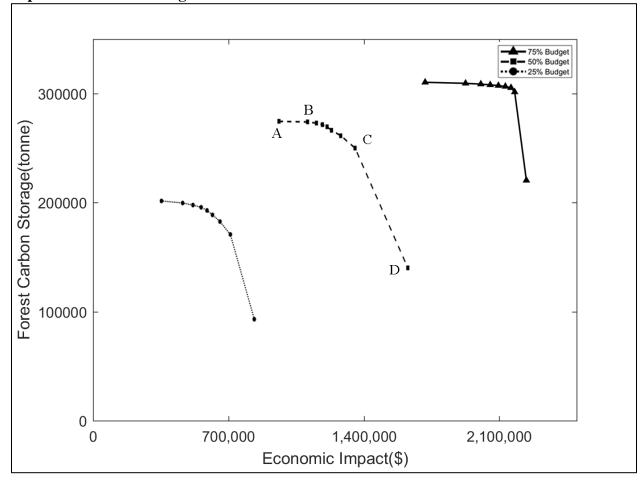


Figure 8. Pareto optimal frontiers between optimal forest carbon storage and economic impacts under three budget scenarios