Essays on Payments for Ecosystem Services Given Multiple Objectives

A Thesis Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

Moonwon Soh

August 2018

Acknowledgements

This thesis is based on guidance and help from many precious people. First of all, I would like to thank my advisor, Dr. Cho. He gave me great direction in guiding my future career, and his passion and intuition for research always inspired me. Also, Drs. Yu and Boyer helped provide the methodological foundation for this thesis and helped me pursue an academic career. I also thank Dr. English, J. Menard, and B. Wilson for helping me manage the data and providing guidance on further research questions. There was great help from my classmates, K. Campbell, S. Bellingham, B. Kenner, L. McKay, U. Rahman, and V. Siokos. The continuous support and companionship they showed me helped me keep doing my research. I also thank K. Pasaribu and B. Sharma who spent plenty of time with me solving research questions. I gratefully acknowledge the Agriculture and Food Research Initiative Competitive Grant no.11401442 and Multistate Project no. TEN00507 (Multistate no. W4133) from the USDA National Institute of Food and Agriculture through the projects “Developing a Cost-Effective Payment System for Forest Carbon Sequestration” and “Costs and Benefits of Natural Resources on Public and Private Lands: Management, Economic, Valuation, and Integrated Decision-Making” respectively. Finally, special gratitude goes to my parents. They always show unbelievable and unconditional love for me. I could not have made any progress without their endless support.

Abstract

This thesis is built with two essays on payments for ecosystem services under different objectives. The purpose of the first essay is identifying optimal spatial targets for PES under the multiple objectives of maximizing cost efficiency of ecological benefits, represented by per unit cost of the ecological benefit, and maximizing economic impacts, represented by gross domestic product (GDP). 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 impacts. Multi-objective linear programming (MOLP), an optimization tool, was chosen to incorporate these objectives as targeting criteria. Results identifying targeted counties with optimal PES distributions will help conservation agencies anticipate regional (i.e., county-level) budget allocations dependent on the relative importance placed on the two objectives. Similarly, projections of regional forest carbon storage and economic impacts from the optimal distributions of payments will help conservation agencies anticipate regional heterogeneity in forest carbon storage and economic impacts and access their tradeoffs.

The second essay is for identifying spatial targets that optimally allocate a given budget to achieve the multiple objectives of improving cost efficiency and promoting equity and economic development. We evaluate trade-off and synergistic relationships among the three objectives. Our results will help conservation agencies understand how optimal spatial targeting and optimal budget allocations change with different weighting schemes. Specifically, conservation agencies can optimally target and allocate budgets to counties based on their preferences among the different weighting scenarios with regard

to the trade-offs and synergies among the objectives of improving the cost efficiency of carbon storage, decreasing poverty, and increasing economic impact of PES. The case study area in our two essay covers the part of Central and Southern Appalachian Region of the United States.

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Chapter 2: Targeting payments for ecosystem services given ecological and economic objectives

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Chapter 1: Introduction

The global temperature, on average, 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). As global concern mounts around the issue of climate change, increasing and sustaining forest-based carbon sequestration has proven to be a cost-effective way of mitigating atmospheric carbon (Dwyer et al. 1992)

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). Payment systems for ecosystem services (PES), like forest-based carbon sequestration, have received considerable attention recently as a policy tool to internalize the value of ecosystem services into land-use decision making (Engel et al. 2008; Farley and Costanza 2010)

The use of PES is often viewed as a means to achieve conservation goals while promoting social equity and rural economic development (Bremer et al. 2014). However, the potential inclusion of forest carbon in the U.S. carbon market program is controversial, due in no small part to uncomfortably high levels of uncertainty in terms of cost efficiency and potential economic impacts of payments for ecosystem services

(PES). Specifically, asymmetric information with regard to opportunity costs makes it difficult to structure payments capable of differentiating between lands that differ in terms of carbon sequestration opportunity costs and/or landowner willingness-to-accept (WTA) payment to either afforest or refrain from deforesting their land. Likewise, relevant social welfare analyses raise questions about the positive economic impacts of PES since the mechanism involves the government taking wealth away from taxpayers and redistributing it to forest landowners, creating the potential for deadweight loss (Wu and Babcock 1995).

Therefore, there are several studies addressing cost efficiency emphasizes the integration of costs and benefits in PES targeting criteria (Barton et al. 2003; Ferraro 2004; Claassen et al. 2008) and finding 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, economic accounting of ecosystem services, and the use of appropriate spatial targeting (Pagiola et al. 2005; Zilberman et al. 2008; Hyberg et al. 1991; Grêt-Regamey and Kytzia 2007; Milder et al. 2010). Also, the studies focusing on the balance among cost efficiency, social equity, and rural economic development has evolved to help design PES that achieve conservation goals while promoting social equity and rural economic development.

In response to issue around PES, the first essay focuses on identifying optimal spatial targets for PES under the multiple objectives of maximizing cost efficiency of ecological benefits, represented by per unit cost of ecological benefit, and maximizing economic impacts, represented by gross domestic product (GDP). A further purpose is to evaluate the tradeoff between the two objectives. Along the same line with the first essay, the second essay is dealing with identifying spatial targets that optimally allocate a given budget to achieve the multiple objectives of improving cost efficiency and promoting equity and economic development. Then, we evaluate trade-off and synergistic relationships among the three objectives. With the result from two essays will help conservation agency anticipate budget allocations dependent on the relative importance placed on the two several objectives.

References

Barton, D., D. Faith, G. Rusch, J.O. Gjershauf, M. Castro, M. Vega, and E. Vega. 2003. "Spatial prioritization of environmental service payment for biodiversity protection." Report SNR 4746/2003. Norwegian Institute for Water Research, Oslo.

Bremer, L.L., K.A. Farley, and D. Lopez-Carr. 2014. "What factors influence participation in payment for ecosystem services programs? An evaluation of Ecuador's SocioPáramo program." *Land Use Policy* 36: 122-133.

Claassen, R., A. Cattaneo, and R. Johansson. 2008. "Cost-effective design of agri-environmental payment programs: US experience in theory and practice." *Ecological Economics* 65 (4): 737-752.

Dwyer, J.F., E.G. McPherson, H.W. Schroeder, and R.A. Rowntree. 1992. "Assessing the benefits and costs of the urban forest." *Journal of Arboriculture* 18: 227-227.

Engel, S., S. Pagiola, and S. Wunder. 2008. "Designing payment for environmental services in theory and practice: An overview of the issues." *Ecological Economics* 65 (4): 663-674.

Farley, J., and R. Costanza. 2010. "Payments for ecosystem services: From local to global." *Ecological Economics* 69 (11): 2060-2068.

Ferraro, P.J. 2004. "Targeting conservation investments in heterogenous landscapes: a distance function approach and application to watershed management." *American Journal of Agricultural Economics* 86 (4): 905-918.

Garnett, T. 2008. "Cooking up a storm: Food, greenhouse gas emissions and our changing climate." Report. Food Climate Research Network, Centre for

Environmental Strategy, University of Surrey.

Grêt-Regamey, A., and S. Kytzia. 2007. "Integrating the valuation of ecosystem services into the input–output economics of an Alpine region." *Ecological Economics* 63 (4): 786-798.

Hyberg, B.T., M.R. Dicks, and T. Hebert. 1991. "Economic impacts of the conservation reserve program on rural economies." *The Review of Regional Studies* 21 (1): 91-105.

Intergovernmental Panel on Climate Change (IPCC). 2007. *Climate Change 2007: The Physical Science Basis.* S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller, eds. Cambridge University Press, Cambridge, United Kingdom and New York.

Intergovernmental Panel on Climate Change (IPCC). 2014. "Headline statements from the summary for policymakers." Climate change 2014: Synthesis report. IPCC. Available at: https://www.ipcc.ch/news_and_events/docs/ar5/ar5_syr_headlines_en.pdf

Milder, J., S. Scherr, and C. Bracer. 2010. "Trends and future potential of payment for ecosystem services to alleviate rural poverty in developing countries." *Ecology and Society* 15(2).

Pagiola, S., A. Arcenas, and G. Platais. 2005. "Can payments for environmental services help reduce poverty? An exploration of the issues and the evidence to date from Latin America." *World Development* 33 (2): 237-253.

Wünscher, T., S. Engel, and S. Wunder. 2008. "Spatial targeting of payments for environmental services: A tool for boosting conservation benefits." *Ecological Economics* 65 (4): 822-833.

Wu, J., and B.A. Babcock. 1995. "Optimal design of a voluntary green payment program under asymmetric information." *Journal of Agricultural and Resource Economics* 20 (2): 316-327.

Zilberman, D., L. Lipper, and N. McCarthy. 2008. "When could payments for environmental services benefit the poor?" *Environment and Development Economics* 13 (3): 255-278.

Chapter 2: Targeting payments for ecosystem services given ecological and economic objective

Abstract

We identify optimal spatial targets for payments for ecosystem services (PES) under the multiple objectives of maximizing forest carbon storage cost efficiency and maximizing economic impacts. A further purpose is to evaluate the tradeoff between the two objectives. These objectives are used as targeting criteria in our case study of the Central and Southern Appalachian Region of the United States, a heavily forested, low-income region that could benefit from the economic impacts from PES. The concave shaped Pareto optimal frontiers provide evidence that 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. Our projections of county-level forest carbon storage and economic impacts help conservation agencies anticipate regional heterogeneity in forest carbon storage and economic impacts and access their tradeoffs.

1. Introduction

1.1. Background and objective

The global temperature, on average, 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 (Garnett 2008; IPCC 2014). 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 (Wittman and Caron 2009; Latta et al. 2011; Cho et al. 2017). 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 potential economic impacts to rural communities (Miranda et al. 2003; Corbera et al. 2009; Li et al. 2011). 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 uncomfortably high levels of uncertainty in terms of cost efficiency and potential economic impacts of payments for ecosystem services (PES). Specifically, asymmetric information with regard to opportunity costs makes it difficult to structure payments capable of differentiating between lands that differ in terms of carbon sequestration opportunity costs and/or landowner willingness-to-accept (WTA) payment to either afforest or refrain from deforesting their land. Likewise, relevant social welfare analyses raise questions about the positive economic impacts of PES since the mechanism involves the government taking wealth away from taxpayers and redistributing it to forest landowners, creating the potential for deadweight loss (Wu and Babcock 1995).

Two branches of literature on PES have been developed to address these difficulties: one dealing with 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, economic accounting of ecosystem services, and the use of appropriate spatial targeting (Hyberg et al. 1991; Pagiola et al. 2005; Grêt-Regamey and Kytzia 2007; Zilberman et al. 2008; Milder et al. 2010).

Despite the important role of cost efficiency in achieving given levels of ecological benefits and the need to receive positive economic impacts from successfully developed 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) an understanding of the tradeoffs between these objectives is important for successful PES design (Wu and Yu 2017).

The purpose of this research is to fill a gap in the literature by identifying optimal spatial targets for PES under the multiple objectives of maximizing cost efficiency of ecological benefits, represented by per unit cost of ecological benefit, and maximizing economic impacts, represented by gross domestic product (GDP). 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 impacts. Multi-objective linear programming (MOLP), an optimization tool (Savir 1966), was chosen to incorporate these objectives as targeting criteria in our case study of the Central and Southern Appalachian Region of the United States (see Figure 2.1.).

The study area is a significant carbon sink accounting for around 20% of the forested area in the U.S. and is also in need of an economic stimulus since it is one of the most concentrated areas of poverty in the U.S. (Smith et al. 2009; Carl Vinson Institute of Government 2002). Recent, continental-scale carbon budget analyses based on multiple scaling approaches suggest that the region is becoming increasingly important as a significant carbon sink (Hayes et al. 2012). Further, the average poverty rate of the region was around 24% from 1960-2000, while the national average during the same period was around 14% (Deaton and Niman 2012)

Through MOLP, we identify optimal county-level targets with a total conservation budget optimally distributed under 27 alternatives, nine weighting scenarios involving the two core objectives multiplied by three budget scenarios, and identify resulting changes in forest carbon and estimate economic impacts. We then develop three tradeoff frontiers between the two objectives that are created from the targeted PES for the three budget scenarios. Along each frontier, PES is Pareto optimal since forest carbon storage cannot be increased without sacrificing economic impacts and vice versa.

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

1.2. Literature review

In literature concerned 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 between 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 focuses on whether the correlation between costs and benefits has implications for the cost efficiency of protection. Babcock et al. (1997) analyzed how the joint spatial distribution of costs and benefits influences the cost efficiency of different targeting rules. Ferraro (2003) examined the correlation between benefit ranking and cost ranking to identify conditions under which the integration of cost and benefit information is likely important for effective decision making. Chomitz et al. (2006) evaluated cost-targeting criteria by examining the effect of correlation between costs and biodiversity for a targeting rule that includes a low-cost solution. Ando et al. (1998) examined the effect of heterogeneous costs and corresponding biodiversity on efficient conservation. Polasky et al. (2001) investigated the relation between a conservation budget and biological reserves and concluded 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 cost-benefit 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; Curran et al. 2016; Schöttker et al. 2016; Drechsler et al. 2017).

In addition, PES programs have become a flagship approach for conservation organizations to advance rural economic development and reduce poverty (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 (Engel 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 started to focus on understanding the economic impacts of PES (Engel et al. 2008; Zilberman et al. 2008; Zhang and Pagiola 2011). Findings in the literature include the following: 1) PES can be vital for poverty reduction and rural economic development if designed to fit local conditions (Pagiola et al. 2005), 2) the spatial distribution of land and land quality are essential in determining poverty impacts (Zilberman et al. 2008), 3) the economic impacts of PES depend on how effectively the program reaches the targeted beneficiaries (Hyberg et al. 1991; Milder et al. 2010), 4) and the date when the program starts is crucial for successful impacts on economic development and poverty reduction (Randrianarison et al. 2017).

Few studies consider the economic impacts of PES when using the cost efficiency of ecological benefits as the targeting criterion (Pagiola et al. 2005; Milder et al. 2010; Ingram et al. 2014). When estimating the economic impacts of PES, the cost efficiency of ecological benefits is typically ignored. In contrast, a few studies examined 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 involves estimating the values of ecological and economic impacts for given payment distributions. Specifically, since payment distributions are critical elements for multi-objective optimization, simultaneously maximizing both ecological and economic impacts is difficult.

2. Method

In our case study, we employ a framework that estimates forest carbon storage and economic impacts using optimal payment distributions for multiple scenarios with different weights between the two objectives. First, we estimate potential maximum forest carbon benefits available for 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 to forestland change. We then convert forestland changes to forest carbon storage through a carbon simulation model. The maximum county-level economic impacts, represented by GDP, for given payment amounts are estimated using Impact Analysis for Planning (IMPLAN) via analyzing the interdependence of 536 industries based on the North American Industry Classification System (NAICS) throughout the regional economies (AIM-AG 2017). The estimates acquired from the land-use, carbon simulation, and IMPLAN models become inputs for the MOLP model to identify a set of optimal target counties with an optimal budget distribution given different weights between the two objectives and total PES budgets. The results from the integrated empirical framework are used to develop their Pareto optimal frontiers.

2.1. Land-use model

We adopt the conceptual framework developed in earlier works (Capozza and Helsley 1989; Parks and Murray 1994; Barbier and Burgess 1997; Mauldin et al. 1999; Plantinga et al. 1999; Lubowski et al. 2006; Lubowski et al. 2008) to specify a land use model. The model assumes a risk-neutral, utility-maximizing, price-taking landowner who maximizes expected net-present return from the decision to convert forestland to an alternative use or retain forestland for a given time period. Under this conceptual framework, land is retained as forest as long as the discounted marginal net benefit from forestland exceeds the discounted marginal net benefit from competing land uses. Given the conceptual framework, retaining forestland, given a time period, is expected to increase as the discounted marginal net benefit from forestland relative to the discounted marginal net benefit from competing land uses increases.

In our study, we hypothesize that forested area at the end of a period relative to forested area at the beginning of the period is a function of annual forest return relative to annual returns from competing land uses (i.e., crop, pasture, and urban) at the beginning of the period. To test the hypothesis, we estimate the following semi-log model at the county level:

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

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. 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 2001-2006 and 0 otherwise) is included in X to capture temporal differences in the ratios of forested area that are not captured by the difference in relative returns across time. 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 S.1.of the online supplementary material or Cho et al. (2017) for a detailed description of how the four net returns are calculated. The Zonal Statistics tool in ArcGIS 10.1 (ESRI 2012) and a Digital Elevation Model (DEM) (U.S. Geological Survey 2013) are used to estimate county-average slope and elevation. See Table 2.1. for a detailed description of the variables.

Once the land-use model in equation (1) was estimated, we calculated 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 was significant at the 5% level (hereafter referred to as "significant") in our land-use model, and thus we simulated changes in the ratio of forested area by incrementally increasing forest return relative to 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 that payments made at the county level are to discourage deforestation for urbanization.

The simulation is implemented under the assumption that the bid amount by conservation agencies converges to equilibrium, where the bid equals landowners' opportunity costs of providing forest-based carbon storage. As a result, asymmetric information in opportunity costs between landowners and conservation agencies seeking to purchase the ecosystem services is overcome (Latacz-Lohmann and Van der Hamsvoort 1997; Stoneham et al. 2003; Schilizzi and Latacz-Lohmann 2007). We make such an assumption since a portion of landowners may end up receiving payments equaling more than their opportunity costs, should overbidding be allowed without resolving the asymmetry (Ferraro 2008; Persson and Alpízar 2013)

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2.2. Carbon simulation model

The Terrestrial Ecosystem Model (TEM) is used to estimate changes in carbon storage corresponding to changes in the ratio of forested area for 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 for 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, this is done by simulating changes in the ratio of forested area as forest return is incrementally increased relative to return from urban use.

2.3. Impact analysis for planning

IMPLAN (Version 3.0) utilizes a National Trade Flows Model (NTFM) (doubly-constrained gravity model) to estimate a new set of regional purchase coefficients and trade data to estimate local purchases based on a region's characteristics (Lindall et al. 2006). IMPLAN output includes descriptive measures of the economy including total industry output (a measure of economic activity), employment, labor income, and total value-added or gross domestic product (GDP). Total industry output is defined as the value of production by industry per year or a measure of overall economic activity by the industry. Employment represents total wage and salary employees, as well as self-employed jobs in a region, for both full-time and part-time workers. Labor income is defined as employee compensation, including benefits, and proprietary (owner-operator) income. Total value added, or GDP is defined as all income to workers paid by employers; self-employed income; interests; rents, royalties, dividends, and profit payments; and excise and sales taxes paid by individuals to businesses. Not only does the model describe a regional economy, it can be used for predictive purposes by providing multiplier-based estimates. From the economic impact indicators generated by IMPLAN, GDP was selected to represent economic impacts for our study. It is considered the most proper instrument for estimating regional overall economic impact (Weisbrod and Weisbrod 1997).

Multipliers measure the response of the economy to a change in production or demand. Multiplier analysis generally focuses on the impacts of exogenous changes on: a) output of the sectors in the economy, b) income earned by households because of new outputs, and c) employment (in physical terms) that is expected to be generated because of the new outputs. The concept of multipliers rests on the difference between the initial impact of an exogenous change (final demand) and the total impacts of a change. Direct impacts measure the response of a given industry given a change in final demand for that same industry. Indirect impacts represent the response by all local industries that occur as a result of a change in final demand for a specific industry. Induced impacts represent the response by all local industries caused by increased (or decreased) expenditures of new household income and inter-institutional transfers generated (or loss) from the direct and indirect impacts of the change in final demand for a specific industry. Direct, indirect and induced impact were integrated as economic impact in our model

We used Type SAM (Social Accounting Matrix) multipliers in our model. Type SAM multipliers are used to estimate induced impacts and are calculated as (direct + indirect + induced impacts)/direct impacts. The Type SAM multipliers take into account the expenditures resulting from increased incomes of households from payment as well as inter-institutional transfers resulting from economic activity. Therefore, Type SAM multipliers assume that as final demand changes, incomes also increase along with inter-institutional transfers. As consumers and institutions increase expenditures, this leads to increased demands for local industries.

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 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 forest carbon storage O_c and maximum economic impacts O_e as:

$$O_c = \underset{x_i^c}{MAX}(\sum_{i=1}^{n} c_i * x_i^c) \textit{ subject to } \sum_{i=1}^{n} tp_i * x_i^c \leq B,$$

$$O_e = \underset{x_i^e}{MAX}(\sum_{i=1}^{n} e_i * x_i^e) \textit{ subject to } \sum_{i=1}^{n} tp_i * x_i^e \leq B, \qquad (2)$$

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 government's budget for 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:

$$\textit{Min}\ \mathrm{Q}$$

subject to

$$W_c * (O_c - \sum_{i=1}^{n} c_i * x_i) * \frac{1}{O_c} \leq \mathrm{Q}$$

$$W_e * (O_e - \sum_{i=1}^{n} e_i * x_i) * \frac{1}{O_e} \leq \mathrm{Q} \qquad (3)$$

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 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 *fminimax* function in Matlab (MathWorks 2017) is used with necessary modification of the code.

3. Empirical results and discussion

Table 2.2. reports coefficients and corresponding standard errors for the semi-log model in equation (1). The goodness of fit of the model is reflected in an adjusted R^2 of 0.174, suggesting that the explanatory variables explain 17.4% of the variation of the ratio of forested area. The F-statistic value is equal to 8.12 and statistically significant at the 5% level, suggesting that overall estimation of the model is significant.

Forest return relative to urban return is positive and significant, while the other two relative returns are insignificant. 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, not crop or pasture management.

The dummy variables associated with the Cumberlands & Southern Ridge and Valley Ecoregion and the 2001-2006 time period are significant while state dummy variables are not 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, (2) the ratio of forested area decreases more during the 2006-2011 period relative to the 2001-2006 period on average, and (3) the change of the ratio of forest area is not significantly affected by state boundaries. These two findings suggest that loss of forestland differs across ecoregions and time.

Figure 2.2. illustrates simulated forested area for the entire study area that would have been discouraged from 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 a budget of $1,541,578 (Figure 2.2.). The spatial distribution of the maximum allocated budget across counties is shown in Figure 2.3. This figure illustrates how the payment budget would have been allocated if its distribution were based on how much forested area would have been discouraged from urban development without the optimal spatial targeting of payments.

Figure 2.4. 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 at 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 (1) higher carbon storage gains from preventing deforestation (1.85 tonne/hectare higher than the average carbon storage gain of 4.26 tonne/hectare for the entire study area) and (2) relatively lower opportunity costs of preventing deforestation ($86.35/hectare lower than the average opportunity cost of $93.03/hectare).

Figure 2.5. illustrates the spatial distribution across counties of economic-cost efficiency (total county value added divided by the county's maximum allocated budget). 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 that is purchased from local producers (IMPLAN Group LLC 2017).

Table 2.3. shows total carbon storage, gross domestic product, carbon-cost efficiency, and economic-cost efficiency for the nine objective weighting scenarios calculated for each budget scenario. On average, economic-cost efficiency is higher when more weight is placed on maximizing economic impacts compared to maximizing carbon-cost efficiency, while carbon-cost efficiency is higher when more weight is assigned to maximizing carbon-cost efficiency. Figure 2.6. illustrates the payment budget distribution 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 2.6. since the budget level has little effect on the overall pattern of the weighted distributions.

The maps in Figure 2.6. 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 discovery results from a greater dispersion of economic impacts among counties relative to carbon benefits (Figure 2.7.). Specifically, the coefficient of variation of economic impacts with the maximum allocated budget is 3.50. For carbon benefits, the coefficient of variation is 2.50. Results from a two-sample Kolmogorov-Smirnov test (Massey 1951) indicate that the distribution of economic impacts stochastically dominates the distribution of carbon benefits (p-value < 0.05).

Second, under all weighting scenarios, consistently higher optimal budgets occur in the counties of southern Appalachia (i.e. Alabama, Georgia, Tennessee and North Carolina) and the southeastern end of Pennsylvania. The counties with optimal budget allocations in the upper quartile in Figure 2.6. tend to have high economic-cost efficiencies regardless of the weight assigned for 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 among the top 65 counties ranked by highest economic-cost efficiency, while only 21 counties are among the top 65 counties ranked by highest carbon-cost efficiency. These findings suggest that economic-cost 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 to a greater dispersion of economic-cost efficiency relative to carbon-cost efficiency.

Figure 2.8. 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 for each budget scenario. For example, given a weight of 100% assigned to maximizing forest carbon benefits at point A on the 50%-budget frontier (i.e., W_c = 100% and W_e = 0%), the optimal budget distribution among counties yields 296,215 tonnes of carbon storage and $1,360,551 of economic impacts (see Table 2.3.). Reducing the weight on maximizing forest carbon storage to 87.5% and increasing the weight on maximizing economic impacts 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 yields 295,802 tonnes of carbon storage and $1,367,666 in economic impacts (see Table 2.3.). The move from point A to point B implies that economic impacts increase by $7,115 with a sacrifice of 413 tonnes of carbon storage, yielding a tradeoff ratio of 0.058 tonnes/$. 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 benefits and economic impacts is consistent for the three budget scenarios and values for both objectives consistently decrease with tighter budget scenarios.

4. Conclusions

There is clear evidence suggesting that PES can 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 developed an integrated empirical framework for identifying optimal spatial PES targets with optimal payment budget distributions with tradeoffs between ecological and economic impacts. 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 Central and Southern Appalachian Region of the United States. We evaluated the implications of different weighting scenarios between the two objectives for county-level optimal budget distributions. In addition, we developed Pareto optimal frontiers under alternative total budget constraints that assumed the given total budget could not be reallocated among counties without sacrificing one objective for the other.

Maps of PES optimal budget distributions among counties, given different weighting scenarios, 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. This finding occurs since the economic-impact objective is more dominant in the targeting decision than the carbon-cost efficiency objective, on average. This evidence suggests that incorporating economic impacts in the targeting criteria, along with promoting cost-efficient conservation, is 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 economic impacts while reducing 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 economic impacts. The concavity of the Pareto optimal relationship can be explained by the law of increasing opportunity cost, implying that as an increase in the weight assigned to economic impacts (or forest carbon benefits) rises, the opportunity cost of economic growth (or forest carbon benefits) increases (Nicholson and Snyder 2011).

The tradeoff between ecological benefits and economic impacts 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 the dual objectives of promoting efficient ecosystem services and providing economic impacts. This approach takes advantage of multiple models in one framework to estimate values for both objectives and inputs them into an optimization model. Hence, our framework is feasible for PES programs when both ecological and economic impacts 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. The economic impacts of the payments for biodiversity enhancement can then be quantified using an IMPLAN model.

As a final note, it is worth to point out other researchers' claim that integrating distributive impacts may undermine the major purpose of PES, improving the efficiency of conservation of ecosystem services (Engel et al. 2008; TEEB 2010; Kinzig et al. 2011). This argument states that while PES has potential implications for other attributes such as equitability, it is better to address these issues separately. The claim is based on "Tinbergen rule" of the classical theory of economic policy (Tinbergen 1952) which states an equal number of policy instruments should be applied to achieve a certain number of policy targets. In practice, it may be better for local development if the available budget is split and a portion is given to cost efficient forest conservation and another portion to economic development. This contrasts with putting all funds allocated to PES according to the Pareto optimal frontiers and hoping the payments trickle down to local development. Overall, however, we still think it is important to understand spatial targeting for PES as a means to undertake conservation goals while also promoting economic impacts.

References

Agri-Industry Modeling and Analysis Group (AIM-AG). 2017. "Input-output analysis and multipliers. The University of Tennessee." Available at: http://aimag.ag.utk.edu/multipliers.html#

Alix-Garcia, J., A. de Janvry, and E. Sadoulet. 2003. "Targeting Payments for Environmental Services: The Role of Risk." *Agricultural and Resource Economics Update* 7 (4): 9-11.

Ando, A.W., and X. Chen. 2011. "Optimal contract lengths for voluntary ecosystem service provision with varied dynamic benefit functions." *Conservation Letters* 4 (3): 207-218.

Ando, A., J. Camm, S. Polasky, and A. Solow. 1998. "Species distributions, land values, and efficient conservation." *Science* 279 (5359): 2126-2128.

Antle, J., S. Capalbo, S. Mooney, E. Elliott, and K. Paustian. 2003. "Spatial heterogeneity, contract design, and the efficiency of carbon sequestration policies for agriculture." *Journal of Environmental Economics and Management* 46 (2): 231-250.

Armsworth, P.R., S. Acs, M. Dallimer, K.J. Gaston, N.D. Hanley, and P. Wilson. 2012. "The cost of policy simplification in conservation incentive programs." *Ecology Letters* 15 (5): 406-414.

Babcock, B.A., P.G. Lakshminarayan, J. Wu, and D. Zilberman. 1996. "The economics of a public fund for environmental amenities: a study of CRP contracts." *American Journal of Agricultural Economics* 78 (4): 961-971.

Babcock, B.A., P.G. Lakshminarayan, J. Wu, and D. Zilberman. 1997. "Targeting tools for the purchase of environmental amenities.” *Land Economics* 73 (3): 325-339.

Barbier, E.B., and J.C. Burgess. 1997. “The economics of tropical forest land use options.” *Land Economics* 73 (2): 174-195.

Barton, D., D. Faith, G. Rusch, J.O. Gjershauf, M. Castro, M. Vega, and E. Vega. 2003. “Spatial prioritization of environmental service payment for biodiversity protection.” Report SNR 4746/2003. Norwegian Institute for Water Research, Oslo.

Balmford, A., K.J. Gaston, A.S. Rodrigues, and A. James. 2000. “Integrating Costs of Conservation into International Priority Setting.” *Conservation Biology* 14 (3): 597-605.

Bulte, E.H., L. Lipper, R. Stringer, and D. Zilberman. 2008. “Payments for ecosystem services and poverty reduction: concepts, issues, and empirical perspectives.” *Environment and Development Economics* 13 (3): 245-254.

Capozza, D.R., and R.W. Helsley. 1989. “The fundamentals of land prices and urban growth.” *Journal of Urban Economics* 26 (3): 295-306.

Carl Vinson Institute of Government. 2002. “Dismantling Persistent Poverty in the Southeastern United States.” Carl Vinson Institute of Government, University of Georgia, Athens. Available at: http://www.poverty.uga.edu/docs/SE_Report.pdf

Cho, S., J. Lee, R.K. Roberts, B.C. English, E.T. Yu, T. Kim, and P.R. Armsworth. 2017. “Evaluating a tax-based subsidy approach for forest carbon sequestration.” *Environmental Conservation* 43 (3): 234-243.

Chomitz, K., G. Da Fonseca, K. Alger, D. Stoms, M. Honzák, E.C. Landau, T.S.

Thomas, W. Wayt Thomas, and F. Davis. 2006. “Viable reserve networks arise from individual landholder responses to conservation incentives.” *Ecology and Society* 11(2).

Claassen, R., A. Cattaneo, and R. Johansson. 2008. “Cost-effective design of agri-environmental payment programs: US experience in theory and practice.” *Ecological Economics* 65 (4): 737-752.

Corbera, E., C.G. Soberanis, and K. Brown. 2009. “Institutional dimensions of Payments for Ecosystem Services: An analysis of Mexico's carbon forestry programme.” *Ecological Economics* 68 (3): 743-761.

Curran, M., B. Kiteme, T. Wünscher, T. Koellner, and S. Hellweg. 2016. “Pay the farmer, or buy the land? -Cost-effectiveness of payments for ecosystem services versus land purchases or easements in Central Kenya.” *Ecological Economics* 127: 59-67.

Deaton, B.J., and E. Niman. 2012. “An empirical examination of the relationship between mining employment and poverty in the Appalachian region.” *Applied Economics* 44 (3): 303-312.

Dodman, D. 2009. “Blaming cities for climate change? An analysis of urban greenhouse gas emissions inventories.” *Environment and Urbanization* 21 (1): 185-201.

Drechsler, M., K. Johst, and F. Wätzold. 2017.” The cost-effective length of contracts for payments to compensate land owners for biodiversity conservation measures.” *Biological Conservation* 207: 72-79.

Engel, S., S. Pagiola, and S. Wunder. 2008. “Designing payment for environmental services in theory and practice: An overview of the issues.” *Ecological Economics*

65 (4): 663-674.

ESRI. 2012. ArcGIS Help 10.1: Spatial Analyst Toolsets, ArcGIS Resources. Available at: http://www.esri.com/.

Farley, J., and R. Costanza. 2010. "Payments for ecosystem services: From local to global." *Ecological Economics* 69 (11): 2060-2068.

Faustmann, M. 1849. "Calculation of the Value Which Forest Land and Immature Stands Possess for Forstry". In M. Gane, ed. *Martin Faustmann and the Evolution of Discounted Cash Flow*. University of Oxford.

Ferraro, P.J. 2003. "Assigning priority to environmental policy interventions in a heterogeneous world." *Journal of Policy Analysis and Management* 22 (1): 27-43.

Ferraro, P.J. 2004. "Targeting conservation investments in heterogenous landscapes: a distance function approach and application to watershed management." *American Journal of Agricultural Economics* 86 (4): 905-918.

Ferraro, P.J. 2008. "Asymmetric information and contract design for payments for environmental services." *Ecological Economics* 65 (4): 810-821.

Garnett, T. 2008. "Cooking up a storm: Food, greenhouse gas emissions and our changing climate." Report. Food Climate Research Network, Centre for Environmental Strategy, University of Surrey.

Gibbons, J.M., E. Nicholson, E.J. Milner-Gulland, and J.P. Jones. 2011. "Should Payments for Biodiversity Conservation be Based on Action or Results?" *Journal of Applied Ecology* 48 (5): 1218-1226.

Grêt-Regamey, A., and S. Kytzia. 2007. "Integrating the valuation of ecosystem services into the input-output economics of an Alpine region." *Ecological Economics* 63

(4): 786-798.

Grieg-Gran, M., I. Porras, and S. Wunder. 2005. “How can market mechanisms for forest environmental services help the poor? Preliminary lessons from Latin America.” *World Development* 33 (9): 1511-1527.

Hanley, N., S. Banerjee, G.D. Lennox, and P.R. Armsworth. 2012. “How should we incentivize private landowners to ‘produce’ more biodiversity?” *Oxford Review of Economic Policy* 28 (1): 93-113.

Hayes, D.J., A.D. McGuire, D.W. Kicklighter, K.R. Gurney, T.J. Burnside, and J.M. Melillo. 2011. “Is the northern high-latitude land-based CO2 sink weakening?” *Global Biogeochemical Cycles* 25 (3).

Hayes, D.J., D.P. Turner, G. Stinson, A.D. McGuire, Y. Wei, T.O. West, L.S. Heath, B. deJong, B.G. McConkey, R.A. Birdsey, W.A. Kurz, A.R. Jacobson, D.N. Huntzinger, Y. Pan, W.M. Post, and R.B. Cook. 2012. “Reconciling estimates of the contemporary North American carbon balance among terrestrial biosphere models, atmospheric inversions and a new approach for estimating net ecosystem exchange from inventory-based data.” *Global Change Biology* 18 (4): 1282-1289.

Hyberg, B.T., M.R. Dicks, and T. Hebert. 1991. “Economic impacts of the conservation reserve program on rural economies.” *The Review of Regional Studies* 21 (1): 91-105.

IMPLAN Group LLC. 2017. The controlled vocabulary of IMPLAN-specific terms. Available at: http://oldsupport.implan.com/index.php?option=com_glossary&id=198&Itemid=164

Ingram, J.C., D. Wilkie, T. Clements, R.B. McNab, F. Nelson, E.H. Baur, H.T.

Sachedina, D.D. Peterson, and C.H. Foley. 2014. “Evidence of payments for ecosystem services as a mechanism for supporting biodiversity conservation and rural livelihoods.” *Ecosystem Services* 7: 10-21.

Intergovernmental Panel on Climate Change (IPCC). 2007. *Climate Change 2007: The Physical Science Basis.* S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller, eds. Cambridge, United Kingdom and New York, Cambridge University Press.

Intergovernmental Panel on Climate Change (IPCC). 2014. “Headline statements from the summary for policymakers.” Climate change 2014: Synthesis report. IPCC. Available at: https://www.ipcc.ch/news_and_events/docs/ar5/ar5_syr_headlines_en.pdf

Kinzig, A.P., C. Perrings, F.S. Chapin, S. Polasky, V.K. Smith, D. Tilman, and B.L. Turner. 2011. “Paying for Ecosystem Services - Promise and Peril.” *Science* 334: 603-604.

Latacz-Lohmann, U., and C. Van der Hamsvoort. 1997. “Auctioning conservation contracts: a theoretical analysis and an application.” *American Journal of Agricultural Economics* 79 (2): 407-418.

Latta, G., D.M. Adams, R.J. Alig, and E. White. 2011. “Simulated effects of mandatory versus voluntary participation in private forest carbon offset markets in the United States.” *Journal of Forest Economics* 17 (2): 127-141.

Lennox, G.D., and P.R. Armsworth. 2011. “Suitability of short or long conservation contracts under ecological and socio-economic uncertainty.” *Ecological Modelling* 222 (15): 2856-2866.

Le Quéré, C., M.R. Raupach, J.G. Canadell, G. Marland, L. Bopp, P. Ciais, T.J. Conway, S.C. Doney, R.A. Feely, P. Foster, P. Friedlingstein, K. Gurney, R.A. Houghton, J.I. House, C. Huntingford, P.E. Levy, M.R. Lomas, J. Majkut, N. Metzl, J.P. Ometto, G.P. Peters, I.C. Prentice, J.T. Randerson, S.W. Running, J.L. Sarmiento, U. Schuster, S. Sitch, T. Takahashi, N. Viovy, G.R. van der Werf, and F.I. Woodward. 2009. "Trends in the sources and sinks of carbon dioxide." *Nature Geoscience* 2 (12): 831-836.

Lewis, D.J., A.J. Plantinga, E. Nelson, and S. Polasky. 2011." The efficiency of voluntary incentives policies for preventing biodiversity loss." *Resource and Energy Economics* 33 (1): 192- 211.

Li, J., M.W. Feldman, S. Li, and G.C. Daily. 2011. "Rural household income and inequality under the Sloping Land Conversion Program in western China." *Proceedings of the National Academy of Sciences* 108 (19): 7721-7726.

Lindall, S., Olson, and G. Alward. 2006. "Deriving multi-regional models using the IMPLAN national trade flows model." Paper presented at Regional Science Association International meeting, Sante Fe, New Mexico.

Lubowski, R.N., A.J. Plantinga, and R.N. Stavins. 2006. "Land-Use Change and Carbon Sinks: Econometric Estimation of the Carbon Sequestration Supply Function." *Journal of Environmental Economics and Management* 51 (2): 135-152.

Lubowski, R.N., A.J. Plantinga, and R.N. Stavins. 2008. "What drives land-use change in the United States? A national analysis of landowner decisions." *Land Economics* 84 (4): 529-550.

Mason, C.F., and A.J. Plantinga. 2011. "Contracting for Impure Public Goods: Carbon

Offsets and Additionality” (No. w16963). National Bureau of Economic Research.

Massey Jr, F.J. 1951. “The Kolmogorov-Smirnov test for goodness of fit.” *Journal of the American Statistical Association* 46 (253): 68-78.

MathWorks. 2017. fminimax Documentation. Available at: https://www.mathworks.com/help/optim/ug/fminimax.html

Mauldin, T., A.J. Plantinga, and R.J. Alig. 1999. *Land Use in the Lake States Region: Analysis of Past Trends and Projections of Future Changes*. US Department of Agriculture, Forest Service, Pacific Northwest Research Station.

McShane, T.O., H.D. Paul, C.T. Tran, N.S. Alexander, K. Ann, M. Bruno, M. David, V.T. Hoang, L.D. Juan, P. Manuel, W. Meredith, B. Peter, C. Peter, and M. Welch-Devine. 2011. “Hard choices: making trade-offs between biodiversity conservation and human well-being.” *Biological Conservation* 144 (3): 966-972.

Milder, J., S. Scherr, and C. Bracer. 2010. “Trends and future potential of payment for ecosystem services to alleviate rural poverty in developing countries.” *Ecology and Society* 15(2).

Miranda, M., I.T. Porras, and M.L. Moreno. 2003. *The Social Impacts of Payments for Environmental Services in Costa Rica: A Quantitative Field Survey and Analysis of the Virilla Watershed. Markets for Environmental Services No.1*. London, UK: International Institute for Environment and Development (IIED)

Moore, J., A. Balmford, T. Allnutt, and N. Burgess. 2004. “Integrating costs into conservation planning across Africa.” *Biological Conservation* 117 (3): 343-350.

Muradian, R., E. Corbera, U. Pascual, N. Kosoy, and P.H. May. 2010. “Reconciling theory and practice: An alternative conceptual framework for understanding payments for environmental services." *Ecological Economics* 69 (6): 1202-1208.

National Agricultural Statistics Service (NASS). 2014. Available at: http://quickstats.nass.usda.gov/

National Land Cover Database (NLCD). 2011. Product Data Downloads. Available at: http://www.mrlc.gov/nlcd11_data.php

Nicholson, W., and C. Snyder. 2011. *Microeconomic Theory: Basic Principles and Extensions*. Nelson Education.

Pagiola, S., A. Arcenas, and G. Platais. 2005. "Can payments for environmental services help reduce poverty? An exploration of the issues and the evidence to date from Latin America." *World Development* 33 (2): 237-253.

Pan, Y., R.A. Birdsey, J. Fang, R. Houghton, P.E. Kauppi, W.A. Kurz, O.L. Phillips, A. Shvidenko, S.L. Lewis, J.G. Canadell, P. Ciais, R.B. Jackson, S.W. Pacala, A.D. McGuire, S. Piao, A. Rautiainen, S. Sitch, and D. Hayes. 2011. "A large and persistent carbon sink in the world's forests." *Science* 333 (6045): 988-993.

Parks, P.J., and B.C. Murray. 1994. "Land attributes and land allocation: Nonindustrial forest use in the Pacific Northwest." *Forest Science* 40 (3): 558–575.

Persson, U. M., and F. Alpízar. 2013. "Conditional cash transfers and payments for environmental services-a conceptual framework for explaining and judging differences in outcomes." *World Development* 43: 124-137.

Plantinga, A.J., T. Mauldin, and D.J. Miller. 1999. "An Econometric Analysis of the Costs of Sequestering Carbon in Forests." *American Journal of Agricultural Economics.* 81: 812-824.

Polasky, S., D.J. Lewis, A.J. Plantinga, and E. Nelson. 2014. “Implementing the optimal provision of ecosystem services.” *Proceedings of the National Academy of Sciences* 111 (17): 6248-6253.

Polasky, S., J.D. Camm, and B. Garber-Yonts. 2001.” Selecting biological reserves cost-effectively: an application to terrestrial vertebrate conservation in Oregon.” *Land Economics* 77 (1): 68-78.

Powell, G.V., J. Barborak, and M. Rodriguez. 2000. “Assessing representativeness of protected natural areas in Costa Rica for protecting biodiversity: a preliminary gab analysis.” *Biological Conservation* 93 (1): 35-41.

Ragsdale, C. 2014. *Spreadsheet Modeling and Decision Analysis: A Practical Introduction to Business Analytics*. Nelson Education.

Randrianarison, H., J. Ramiaramanana, and F. Wätzold. 2017. “When to Pay? Adjusting the Timing of Payments in PES Design to the Needs of Poor Land-users.” *Ecological Economics* 138: 168-177.

Rodrigues, A.S.L., S.J. Andelman, M.I. Bakarr, L. Boitani, T.M. Brooks, R.M. Cowling, L.D.C. Fishpool, G.A.B. Fonseca, K.J. Gaston, M. Hoffman, J. Long, P.A. Marquet, J.D. Pilgrim, R.L. Pressey, J. Schipper, W. Sechrest, S.N. Stuart, L.G. Underhill, R.W. Waller, M.E.J. Watts, and Y. Xie. 2003. “Global gap analysis: towards a representative network of protected areas.” *Advances in Applied Biodiversity Science* 5: 73-74.

Savir, D. 1966. “Multi Objective Linear Programming” (No. ORC-66-21). California Univ Berkeley Operations Research Center.

Schilizzi, S., and U. Latacz-Lohmann. 2007. “Assessing the performance of conservation auctions: an experimental study.” *Land Economics* 83 (4): 497-515.

Schöttker, O., K. Jost, M. Drechsler, and F. Wätzold. 2016. “Land for Biodiversity Conservation–To buy or borrow?” *Ecological Economics* 129: 94-103.

Scott, J.M., F. Davis, B. Csuti, R. Noss, B. Butterield, C. Groves, H. Anderson, S. Caicco, F. D'erchia, T.C. Edwards Jr., J. Ulliman, and R.G. Wright. 1993. “Gap analysis: a geographic approach to protection of biological diversity.” *Wildlife Monographs* 3-41.

Sims, K.R., J.M. Alix-garcia, E. Shapiro-garza, L.R. Fine, V.C. Radeloff, G. Aronson, S. Castillo, C. Ramirez-reyes, and P. Yanez-pagans. 2014. “Improving environmental and social targeting through adaptive management in Mexico's payments for hydrological services program.” *Conservation Biology* 28 (5): 1151-1159.

Smith, W.B., P.D. Miles, C.H. Perry, and S.A. Pugh. 2009. *Forest Resources of the United States, 2007.* Gen. Tech. Rep. WO-78. Washington, DC: U.S. Department of Agriculture, Forest Service, Washington Office.

Stoneham, G., V. Chaudhri, A. Ha, and L. Strappazzon. 2003. “Auctions for conservation contracts: an empirical examination of Victoria's BushTender trial.” *Australian Journal of Agricultural and Resource Economics* 47 (4): 477-500.

TEEB. 2010. *The Economics of Ecosystems and Biodiversity for Local and Regional Policy Makers.* H. Gundimeda, and H. Wittmer, eds. Abingdon, United Kingdom: Routledge.

Timber Mart-South (TMS). 2006, 2011. Product and Services.

Available at: http://www.timbermart-south.com./products.html

Tinbergen, J., ed. 1952. *On the Theory of Economic Policy*. Amsterdam: North-Holland.

U.S. Census Bureau. 2000. Census 2000 Gateway.
Available at: https://www.census.gov/main/www/cen2000.html

U.S. Census Bureau; American Community Survey (ACS). 2009, 2012. Available at: https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2015/

U.S. Department of Agriculture (USDA), Census of Agriculture. 2012. 2012 Census Publications. Available at: https://www.agcensus.usda.gov/Publications/2012/

U.S. Department of Agriculture (USDA) Forest Service. 2017. FIA Data and Tools. Available at: https://www.fia.fs.fed.us/tools-data/index.php

U.S. Department of State (USDS). 2010. U.S. Climate Action Report 2010. Washington: Global Publishing Services.

U.S. Geological Survey (USGS). 2013. Data and Tools.
Available at: https://www.usgs.gov/products/data-and-tools/gis-data

Weisbrod, G., and B. Weisbrod.1997. "Measuring economic impacts of projects and programs." *Economic Development Research Group* 10: 1-11.

Wittman, H.K., and C. Caron. 2009. "Carbon offsets and inequality: social costs and co-benefits in Guatemala and Sri Lanka." *Society and Natural Resources* 22 (8): 710-726.

Wright, R.G., J.G. MacCracken, and J. Hall. 1994. "An ecological evaluation of proposed new conservation areas in Idaho: evaluating proposed Idaho national parks." *Conservation Biology* 8 (1): 207-216.

Wu, J., and B.A. Babcock. 1995. "Optimal design of a voluntary green payment program under asymmetric information." *Journal of Agricultural and Resource Economics* 20 (2): 316-327.

Wu, J., and J. Yu. 2017. "Efficiency-Equity Tradeoffs in Targeting Payments for Ecosystem Services." *American Journal of Agricultural Economics* 99 (4): 894-913.

Wünscher, T., S. Engel, and S. Wunder. 2008. "Spatial targeting of payments for environmental services: A tool for boosting conservation benefits." *Ecological Economics* 65 (4): 822-833.

Zhang, W., and S. Pagiola. 2011. "Assessing the potential for synergies in the implementation of payments for environmental services programmes: an empirical analysis of Costa Rica." *Environmental Conservation* 38 (4): 406-416.

Zhao, J., C.L. Kling, and L.A. Kurkalova. 2003. "Alternative Green Payment Policies under Heterogeneity When Multiple Benefits Matter." Working Paper 03-WP341, Center for Agricultural and Rural Development (CARD), Iowa State University.

Zilberman, D., L. Lipper, and N. McCarthy. 2008. "When could payments for environmental services benefit the poor?" *Environment and Development Economics* 13 (3): 255-278.

Appendix

Table 2.1. Variable definitions and descriptive statistics

Variables	Definition	Mean (Std Dev)
Dependent variable		
Change in forest share	Ratio of forested area between the beginning and the end of a given period (i.e., 2001-2006 and 2006-2011)	0.991 (0.023)
Economic variables		
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	First year's annual forest return relative to annual return from urban use ($/hectare)	-53.017 (1,603.387)
Geophysical variables		
Average elevation	Average elevation (meter)	71.063 (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 ridge and valley ecoregion	1 if county is in Cumberlands and Southern Ridge and Valley ecoregion, 0 otherwise	0.479 (0.500)
Alabama	1 if county is in Alabama, 0 otherwise	0.097 (0.296)
Georgia	1 if county is in Georgia, 0 otherwise	0.079 (0.271)
Kentucky	1 if county is in Kentucky, 0 otherwise	0.121 (0.327)
Maryland	1 if county is in Maryland, 0 otherwise	0.013 (0.117)
North Carolina	1 if county is in North Carolina, 0 otherwise	0.083 (0.276)
Pennsylvania	1 if county is in Pennsylvania, 0 otherwise	0.131 (0.338)
Tennessee	1 if county is in Tennessee, 0 otherwise	0.152 (0.360)
Virginia	1 if county is in Virginia, 0 otherwise	0.190 (0.393)
West Virginia	1 if county is in West Virginia, 0 otherwise	0.118 (0.322)
Year variable		
Period dummy variable	1 if period is 2006-2011, 0 otherwise	0.500 (0.500)

Table 2.2. Parameter estimates from log-linear model (n = 576)

Variables	Coefficient (Std Dev)
Constant	-0.004
	(0.011)
Economic variables	
Forest return relative to crop return (× 0.00001)	0.005
	(0.131)
Forest return relative to pasture return (× 0.001)	0.048
	(0.067)
Forest return relative to urban return (× 0.00001)	0.629*
	(0.068)
Geophysical variables	
Average elevation (× 0.00001)	0.378
	(0.751)
Average slope (× 0.01)	-0.049
	(0.114)
Appalachian forest ecoregion	-0.009
	(0.005)
Cumberlands and southern ridge and valley ecoregion	-0.012*
	(0.004)
Alabama (× 0.1)	-0.004
	(0.105)
Georgia	0.001
	(0.010)
Kentucky	0.001
	(0.010)
Maryland	0.013
	(0.013)
North Carolina (× 0.1)	0.008
	(0.099)
Pennsylvania	0.012
	(0.010)
Tennessee (× 0.1)	-0.005
	(0.101)
Virginia	0.006
	(0.010)
West Virginia	0.004
	(0.010)
Year variable	
Period dummy variable	0.005*
	(0.002)

Note: * denotes significance at the 5% level.

Table 2.3. 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

Weight combinations (W_c/ W_e)	75% of total budget				50% of total budget				25% of total budget			
	TC (tonne)	GDP ($)	CCE (tonne/$)	ECE ($/$)	TC (tonne)	GDP ($)	CCE (tonne/$)	ECE ($/$)	TC (tonne)	GDP ($)	CCE (tonne/$)	ECE ($/$)
100.0 / 0.0	304,706	2,009,310	0.2635	1.737	296,215	1,360,552	0.384	1.765	225,685	674,178	0.585	1.749
87.5 / 12.5	304,362	2,020,011	0.2632	1.747	295,802	1,367,666	0.383	1.774	224,093	684,703	0.581	1.776
75.0 / 25.0	304,105	2,024,047	0.2630	1.750	294,948	1,369,845	0.382	1.777	222,502	689,837	0.577	1.789
62.5 / 37.5	303,847	2,026,536	0.2628	1.752	293,850	1,371,336	0.381	1.779	220,721	693,912	0.572	1.800
50.0 / 50.0	303,599	2,028,704	0.2625	1.754	292,291	1,372,491	0.379	1.780	218,320	696,821	0.566	1.808
37.5 / 62.5	303,318	2,030,540	0.2623	1.756	289,838	1,373,595	0.376	1.782	214,840	699,566	0.557	1.815
25.0 / 75.0	302,879	2,032,036	0.2619	1.757	285,937	1,375,901	0.371	1.785	209,650	703,277	0.543	1.824
12.5 / 87.5	301,461	2,033,010	0.2607	1.758	277,059	1,379,444	0.359	1.789	199,608	708,448	0.517	1.838
0.0 / 100.0	271,817	2,036,105	0.2350	1.761	191,186	1,392,523	0.248	1.806	133,754	720,335	0.347	1.869

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

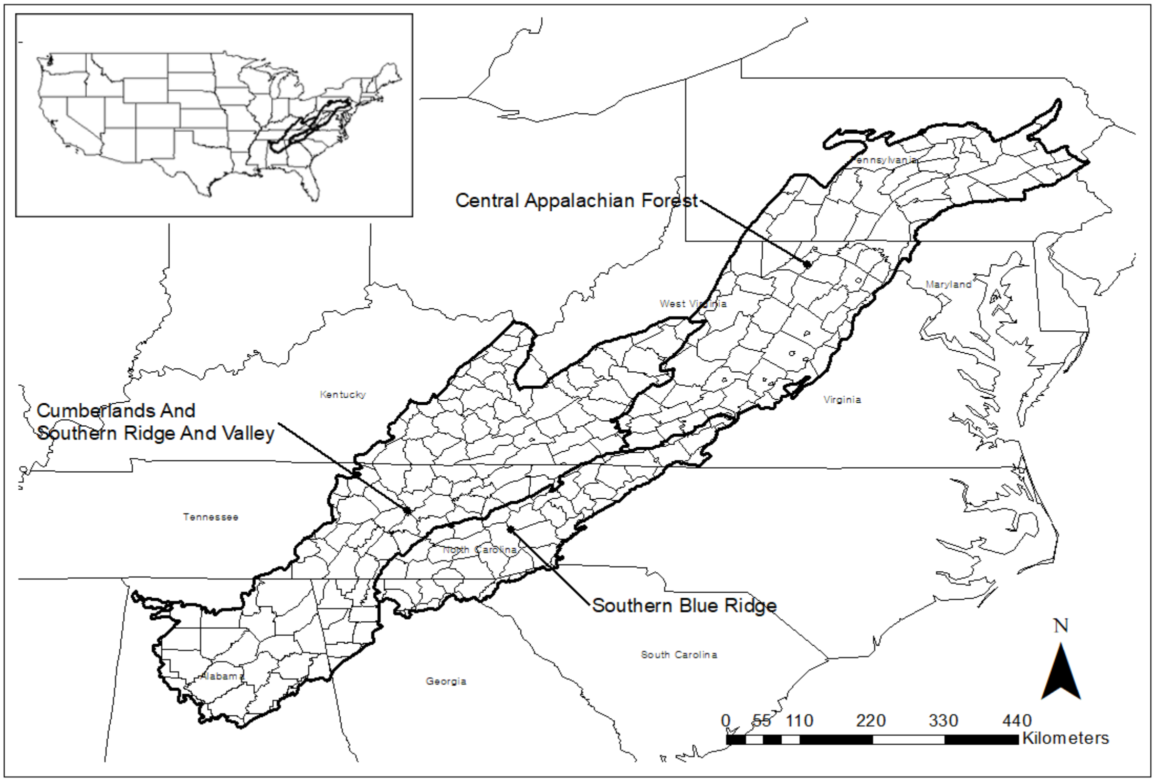


Figure 2.1. Overview of study area

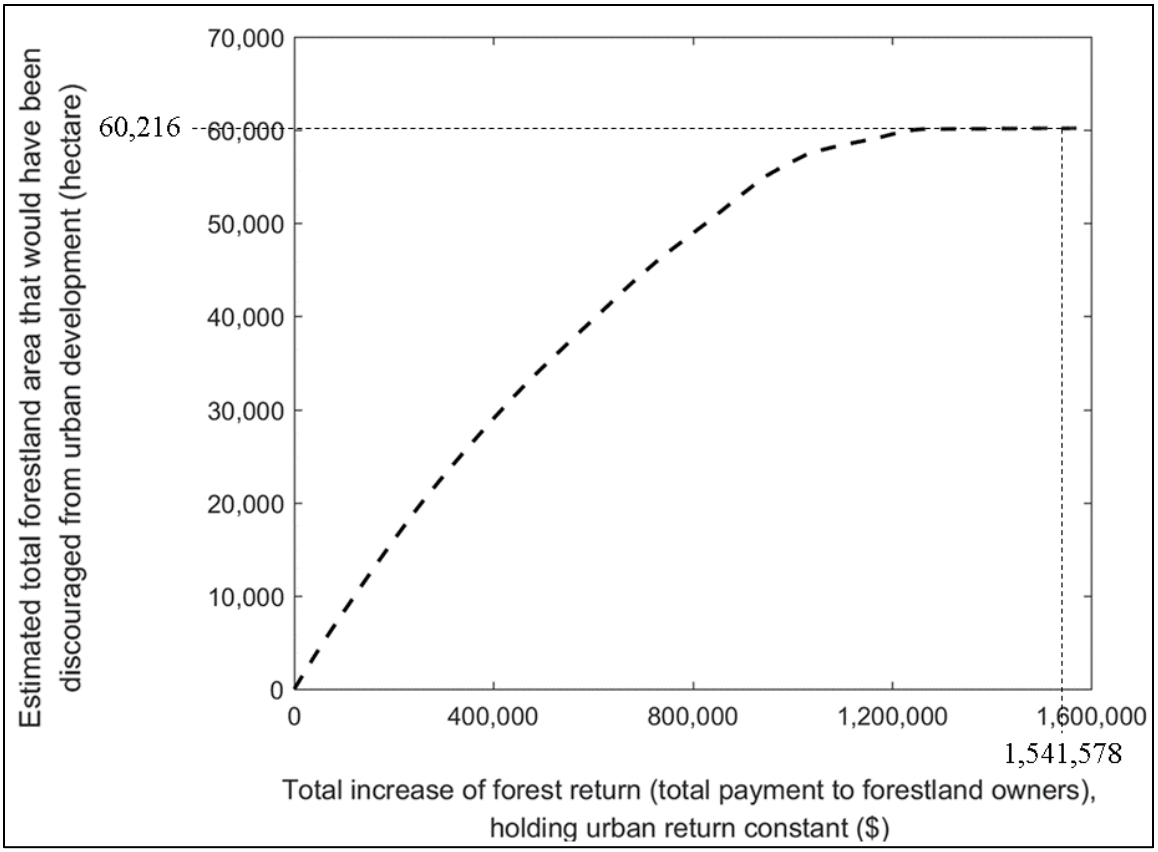


Figure 2.2. Estimated total forestland area that would have been discouraged from urban development subsequent to total increase of forest return (total payment to forestland owners), holding urban return constant, for entire study area

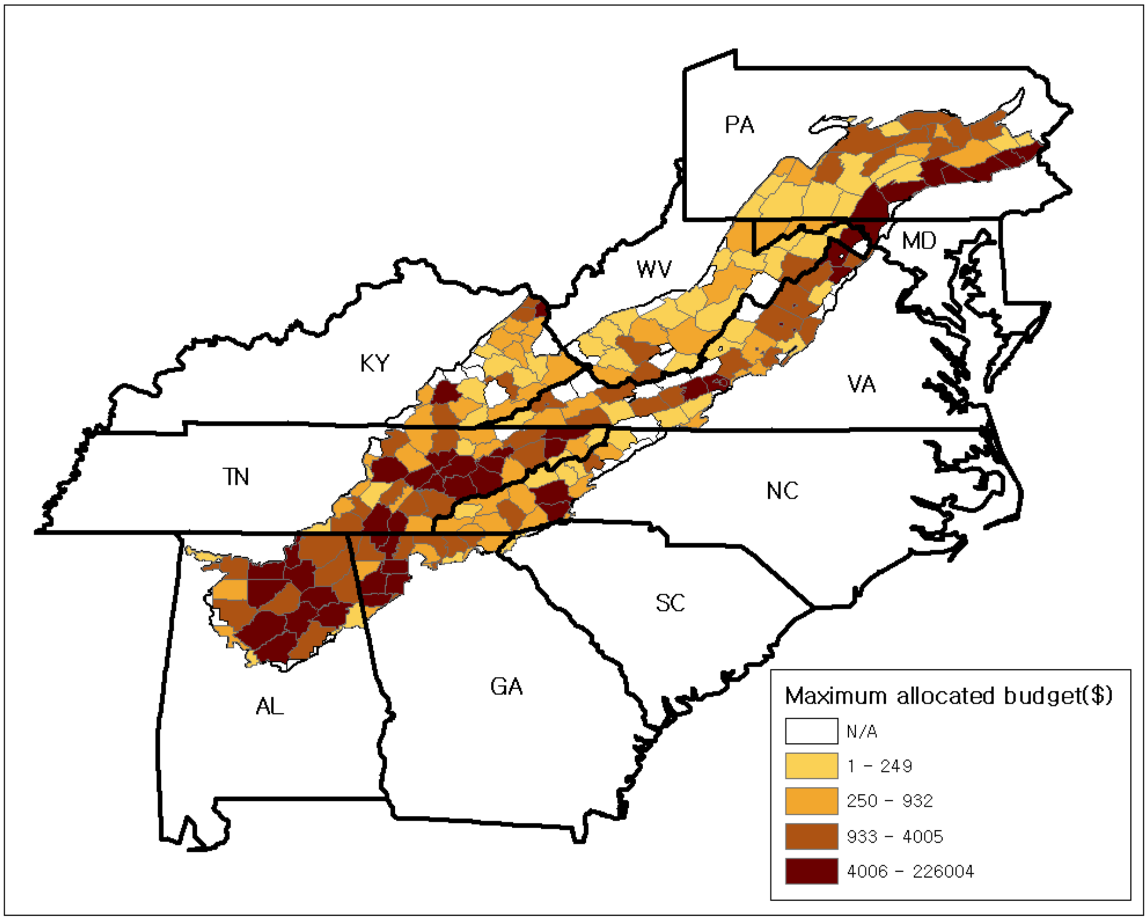


Figure 2.3. Spatial distribution of maximum allocated budget

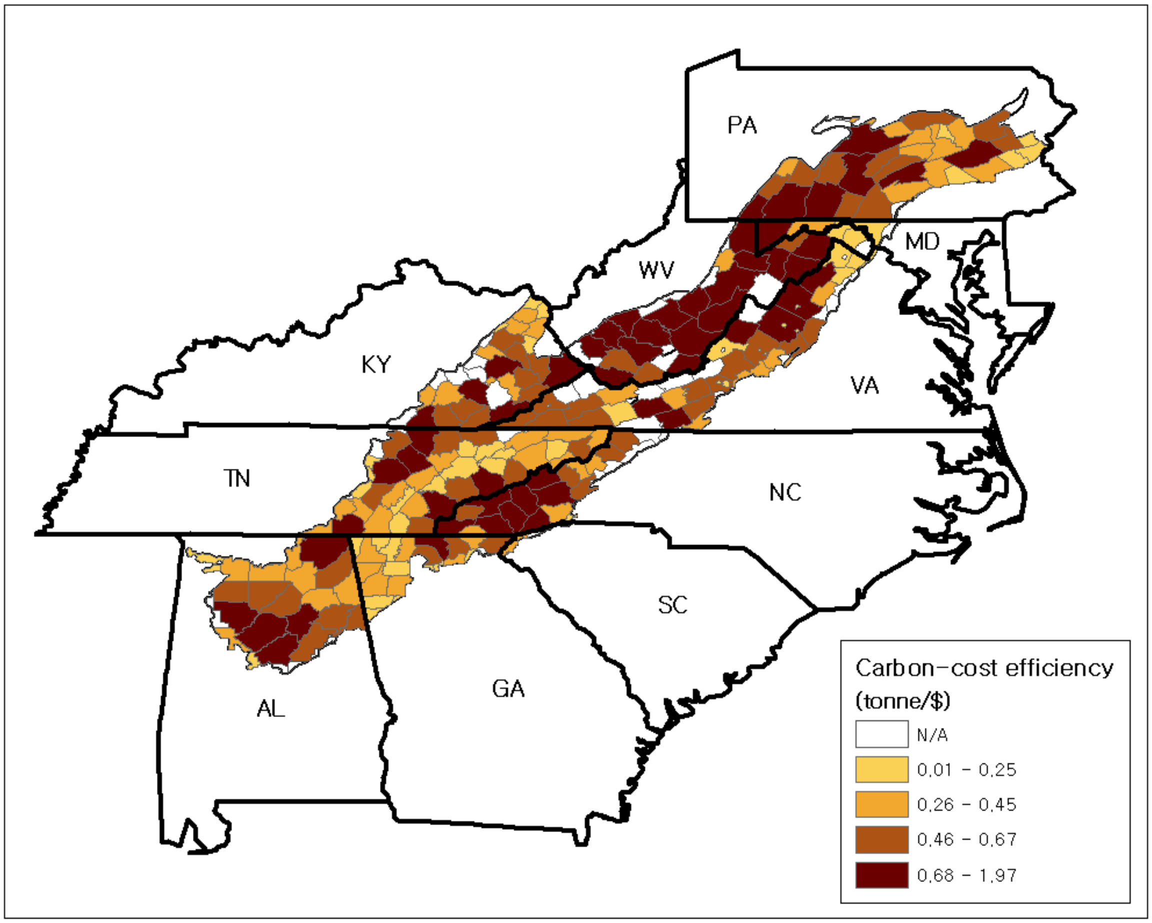


Figure 2.4. Spatial distribution of carbon-cost efficiency

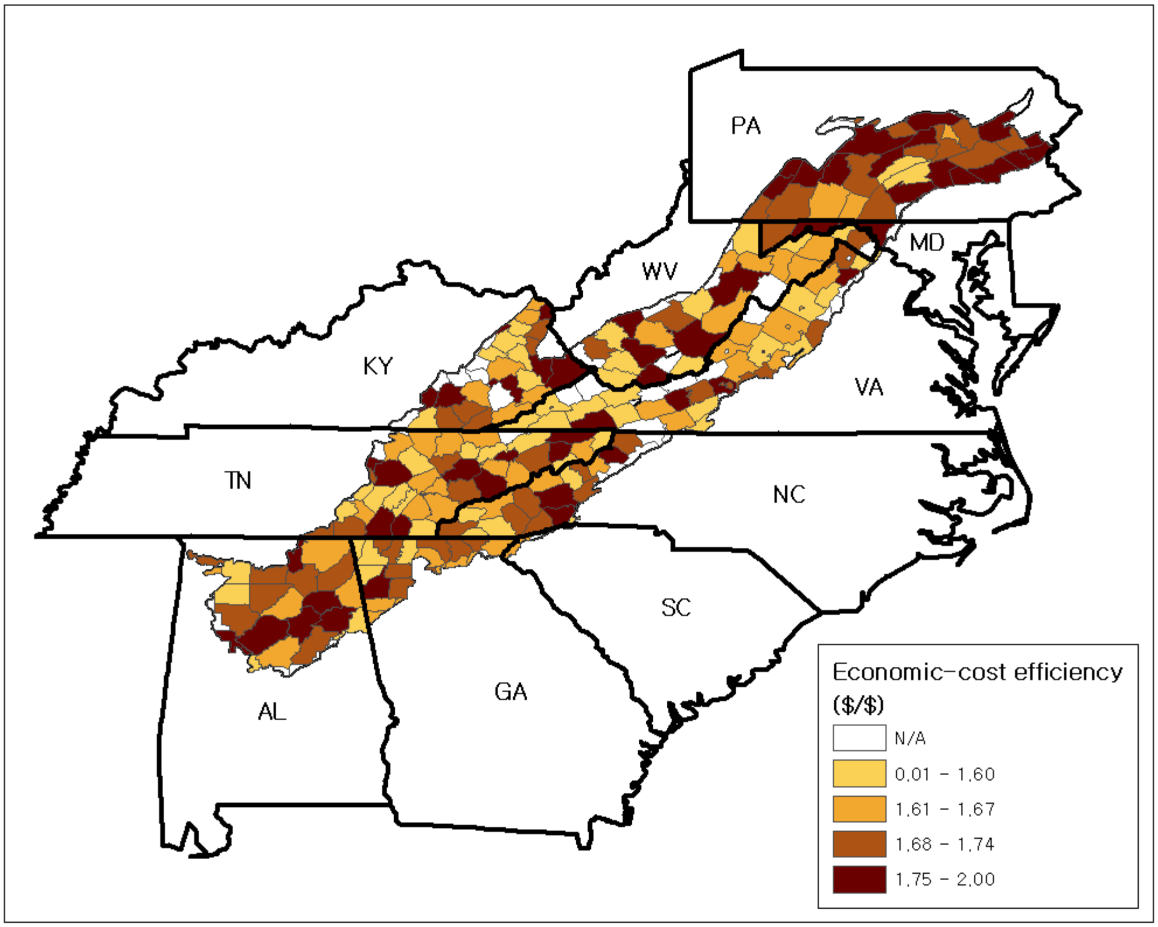


Figure 2.5. Spatial distribution of economic-cost efficiency

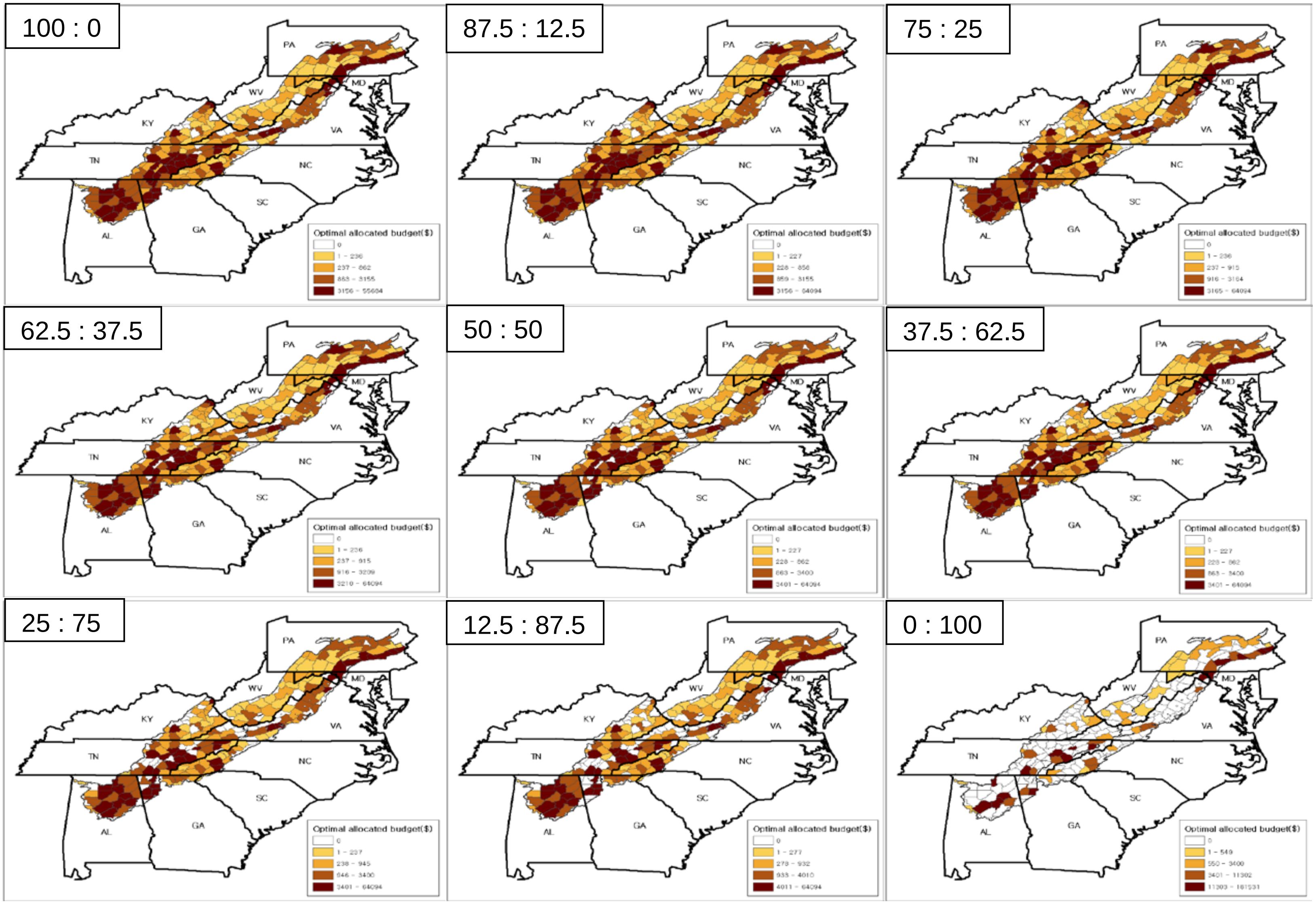


Figure 2.6. Optimal allocated payment budget spatial distribution under the 50% budget scenario with nine weighting scenarios involving the objectives of maximizing forest carbon storage and maximizing economic impacts (W_c : W_e)

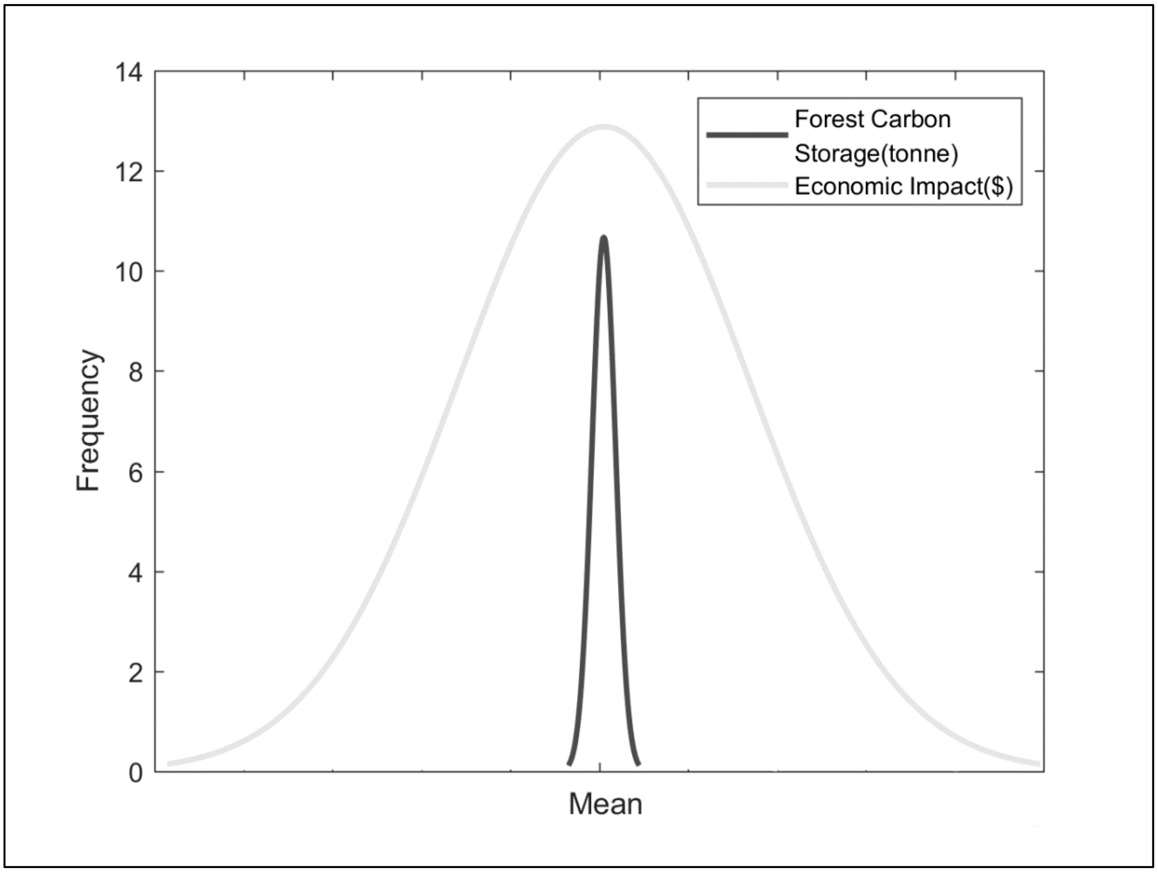


Figure 2.7. Probability density distributions of forest carbon storage and economic impacts

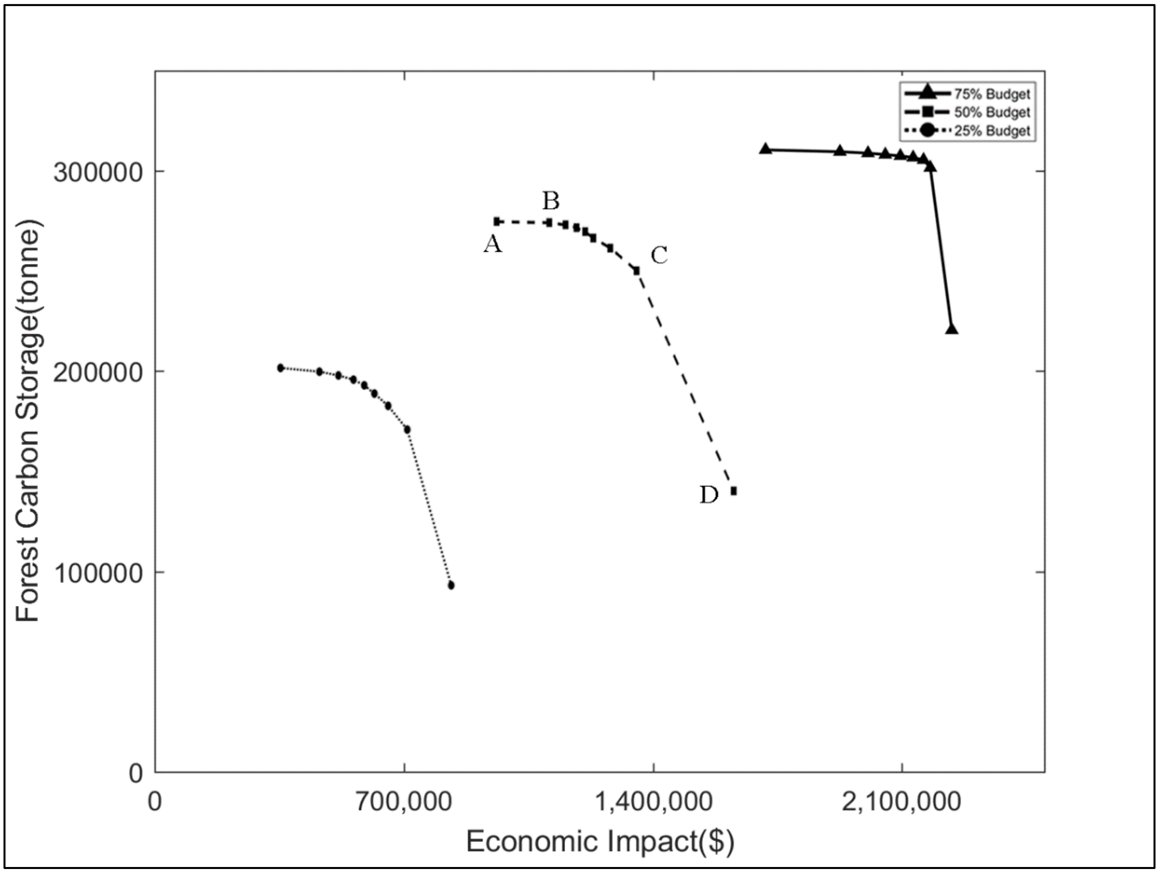


Figure 2.8. Pareto optimal frontiers between optimal forest carbon storage and economic impacts under three budget scenarios

Chapter 3: Spatial targeting of payments for ecosystem services to achieve conservation goals and promote social equity and economic impact

Abstract

The objective of this research is to identify optimal spatial targets and optimally distributed budgets that achieve the multiple objectives of improving cost efficiency of payment systems for ecosystem services (PES) and promoting equity and economic development through PES. Using multi-objective linear programming with three objective functions obtained from four modeling frameworks (i.e., land-use model, carbon simulation model, poverty alleviation model, and Impact Analysis for Planning model), we derive optimal spatial distributions of payment budgets for four priority scenarios. The results show that the optimal budgets are more geographically widespread under the multiple-objective priority scenarios than under the single-objective of maximizing carbon cost efficiency, and the optimal spatial distributions of the four priority scenarios do not change appreciably across priority scenarios. By aggregating the three objective values under the four priority scenarios, the relationships between the three objectives are quantified. Changing the priority weights from 100% on carbon cost efficiency to weights of 50% on carbon cost efficiency and 50% on poverty alleviation efficiency or 50% on carbon cost efficiency and 50% on economic impact demonstrates competitive trade-off between the objective of carbon cost efficiency and the objectives of poverty alleviation and economic impact, and a synergistic relationship between poverty alleviation and economic impact. Our findings can be used as a benchmark for conservation agencies to distribute spatially targeted budgets depending on their priorities.

1. Introduction

1.1. Background and objective

As global concern mounts around the issue of climate change, increasing and sustaining forest-based carbon sequestration has proven to be a cost-effective way of mitigating atmospheric carbon (Dwyer et al. 1992). Despite its potential for climate change mitigation, landowners do not consider the value of forest-based carbon sequestration when making market-based land-use decisions. Payment systems for ecosystem services (PES), like forest-based carbon sequestration, have received considerable attention recently as a policy tool to internalize the value of ecosystem services into land-use decision making (Engel et al. 2008; Farley and Costanza 2010). Notwithstanding the recent popularity of PES, command and control government engagement to improve ecosystem services is controversial due to cost ineffectiveness (Harrington and Morgenstern 2004). Still, payments for forest-based carbon sequestration have become more appealing with growing opportunities for private landowners to participate in the forestry sector (Landell-Mills and Porras 2002; Kroeger and Casey 2007).

The use of PES is often viewed as a means to achieve conservation goals while promoting social equity and rural economic development (Bremer et al. 2014). The literature focusing on conservation goals has dealt with improving the cost efficiency of PES related to return-on-investment (ROI) and spatial targeting (Babcock et al. 1997; Antle et al. 2003; Barton et al. 2003; Ferraro 2004; Claassen et al. 2008; Engel et al. 2008; Gibbons et al. 2011; Armsworth et al. 2012; Hanley et al. 2012). These studies commonly find that the cost efficiency of PES depends on the optimization of scarce financial resources by accounting for the spatial distributions of the costs and benefits of ecosystem services and their relationship (Antle et al. 2003).

The literature focusing on the balance among cost efficiency, social equity, and rural economic development has evolved to help design PES that achieve conservation goals while promoting social equity and rural economic development. Nevertheless, their relationships are complex and include both trade-offs and synergies (Pascual et al. 2010; Gross-Camp et al. 2012). The trade-off between cost efficiency and social equity in the rural economic development framework is often quantified by developing an efficiency-equity frontier (Pascual et al. 2009; Pascual et al. 2010; Wu and Yu 2017). Likewise, a synergistic relationship can be developed between achieving environmental objectives through PES and improving social equity for a rural community (Zhang and Pagiola 2011; Barrett et al. 2013; Pascual et al. 2014; Kearney et al. 2017).

The literature emphasizes the need for PES design to integrate equity into efficiency-driven spatial targeting (Pascual et al. 2014). Despite the need, few, if any, studies that focus on improving cost efficiency of PES have integrated equity into the spatial targeting decision-making process. Another gap in the literature is the lack of studies that include both optimal spatial targeting and the economic impact of PES.

The objective of this research is to fill the gap in the PES literature by identifying spatial targets that optimally allocate a given budget to achieve the multiple objectives of improving cost efficiency and promoting equity and economic development. We evaluate trade-off and synergistic relationships among the three objectives. We use the Central and Southern Appalachian Region of the United States (see Figure 3.1.) as a case study to develop a county-level framework to identify optimal county targets and optimal budget allocations for forest-based carbon sequestration that address the three objectives.

We implement the case study by using multi-objective linear programming (MOLP) (Lieberman 2014) based on three objective functions: (i) maximizing forest-based carbon storage for improving cost efficiency, (ii) alleviating maximum poverty for promoting equity, and (iii) promoting economic impact for economic development. The MOLP is applied under multiple weighting scenarios among the three objectives, given a fixed payment budget. By comparing the optimal solutions under the multiple weighting scenarios, we evaluate trade-off and synergistic relationships among the objectives.

Our results will help conservation agencies understand how optimal spatial targeting and optimal budget allocations change with different weighting schemes. Specifically, conservation agencies can optimally target and allocate budgets to counties based on their preferences among the different weighting scenarios with regard to the trade-offs and synergies among the objectives of improving the cost efficiency of carbon storage, decreasing poverty, and increasing economic impact of PES.

1.2. Literature review

Improving the cost efficiency of PES requires accounting for spatial variations in the benefits and opportunity costs of ecosystem services. However, measuring and monitoring their benefits and costs is challenging and potentially expensive (Richards and Stokes 2004; Kim and Langpap 2015). Researchers have attempted to overcome these challenges through an approach that allows estimating the spatial heterogeneity in the conservation benefits and opportunity costs (Antle 2003; Fraser 2009; Armsworth et al.

2011; Gibbons et al. 2011; Lewis et al. 2011; Hanley et al. 2012; Polasky et al. 2014; Kim and Langpap 2015). Despite abundant literature on the efficiency of incentive payment approaches, the literature focusing on mitigating the financial burden of providing ecosystem services often ignores the social equity and economic impacts of the payments (Antle 2003; Barton et al. 2003; Montagnini and Nair 2004; Classen et al. 2008; Gibbons et al. 2011; Mason and Plantinga 2011; Armsworth et al. 2012; Cho et al. 2017).

A body of literature has evolved around the balance between cost efficiency and social equity in a rural economic development framework mainly because PES are often designed to meet environmental goals at the expense of equity (Pascual et al. 2014). An important question motivating the literature deals with the balance between cost efficiency and social equity in designing PES (Dietz and Atkinson 2010; Muradian et al. 2010; García-Amado et al. 2011; Narloch et al. 2011; Gross-Camp et al. 2012; Mahanty 2013; Kolinjivadi et al. 2015). An efficiency-equity frontier has been used to quantify this trade-off (or synergistic) relationship to facilitate PES disign (e.g., Pascual et al. 2009; Pascual et al. 2010; Wu and Yu 2017). The poverty rate or an equity indicator, such as the Gini Coefficient, typically has been used to measure equity improvements through PES (Zilberman et al. 2008; Pascual et al. 2010; Garcia-Amado et al. 2011; McDermott et al. 2013; Wu and Yu 2017).

Although the literature has been successful in analyzing the relationship between cost efficiency and social equity, few, if any, of those studies provide spatial targeting information about how to geographically allocate a conservation budget. In addition, the literature dealing with optimal spatial targeting downplays the economic impacts of PES

(Mundell 2002). Thus, developing a framework that simultaneously addresses cost efficiency, equity and economic development objectives is critical in evaluating optimal spatial targeting of PES budgets.

2. Method

We use four modeling frameworks, all at the county level, to establish the three objective functions in the MOLP. For objective function (i), we develop a land-use model (see subsection 2.1. for details) to determine the amount of forestland not converted to other uses when the return to forestland increases due to forest-based carbon incentive payments. We then use a carbon simulation model (see subsection 2.2. for details) to determine the maximum forest-based carbon storage that can be supplied from the forestland changes simulated by the land-use model. For objective function (ii), we develop a poverty alleviation model to estimate the reduction in poverty resulting from the incentive payments (see subsection 2.3. for details). For objective function (iii), we use the Impact Analysis for Planning (IMPLAN) model to estimate the economic impact per dollar invested through incentive payments (see subsection 2.4. for details). The estimates obtained from the four models are the parameters and variables for the three objective functions in the MOLP (see subsection 2.5. for details).

Our discussion focusses on the maps and relationships developed from the MOLP and the results from the land-use and poverty alleviation models, which we developed for this study. To simplify and to save space, we briefly discuss the carbon simulation and IMPLAN models but do not report their results directly, although they are available upon request. The MOLP uses the outputs from all four models, and thus we indirectly discuss the results from the carbon simulation and IMPLAN models. In addition, the parameters of the carbon simulation and IMPLAN models come from available models developed and estimated by the authors for other studies (Cho et al. 2018a, 2018b).

2.1. Land-use model

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 linking opportunity costs of forest and farmland with deforestation and farmland loss, and they have been used to derive cost functions for forest- and farm-based carbon storage (Lubowski et al. 2006; Lubowski et al. 2008). Aggregate land-use data, such as our county-level data, have been used to explain how the share of land in counties or larger geographic areas shifts from one land use to another over a transition period (referred to as "land-use share model") (e.g., Ahn et al. 2000; Hardie et al. 2000; Cho et al. 2005; Sohngen and Brown 2006; Ahn 2008). Following the general framework of the land-use share model, we specify the expected shares as a logistic function of a linear combination of decision variables:

$$s_i^t(k) = \frac{exp(\beta_k' X_i^t)}{\sum_{k=1}^{K} \exp(\beta_k' X_i^t)}, \tag{1}$$

where $s_i^t(k)$ is the expected share of land allocated to land-use k in year *t* in county *i*, X_i^t is a set of decision variables in year *t* in county i, and β_k' is a vector of unknown parameters.

If we assume forestland and non-forestland are the only two land uses and divide the share of forestland by the share of non-forestland (referred to as "relative forestland share"), the logistic transformation of equation (1) yields:

$$\ln\left(y_i^t(k=1)/y_i^t(k\neq 1)\right) = \beta'_{k=1}X_i^t - \beta'_{k\neq 1}X_i^t, \tag{2}$$

where $y_i^t(k=1)$ and $y_i^t(k\neq 1)$ are, respectively, the share of forestland and the share of non-forestland (crop, pasture, and urban land) in year *t* in county *i*. All variables that explain spatial correlation among relative forestland shares cannot be included in equation (2), which leads to biased estimates and spatially correlated errors (Cho and Newman 2005; Carrión-Flores et al. 2009).

These problems are frequently handled by *ad hoc* specification using a spatial weight matrix (Anselin 1988). Following the *ad hoc* approach, we hypothesize that the natural log of relative forestland share for county *i* in year *t* is a function of forest return, average return of non-forested land uses, and the relative forestland shares within the neighboring counties defined by the weight matrix, $\sum_{j=1}^{N} w_{ij} y_{ij-1}^t(k=1)/y_{ij-1}^t(k\neq 1)$, where w_{ij} is element (*i*, *j*) of the *N* × *N* spatial weight matrix *W*:

$$\ln\left(y_i^t(k=1)/y_i^t(k\neq 1)\right) = \alpha_y + \sum_{j=1}^{N} w_{ij} y_{ij-1}^t \delta_y + X_i^t \beta_y + \mu_i^y + \lambda_y^t + \epsilon_i^t \tag{3}$$

where *j* represents the *j*th neighboring county, *X* is a vector of explanatory variables including annual forest return and annual average return of non-forested land uses (weighted average of returns from crop, pasture, and urban lands, with land shares as weights), α_y is a scaler parameter, δ_y is a parameter for spatially lagged relative forestland share, β_y is a parameter vector, μ^y and λ_y respectively denote unobserved spatial and time specific effects, and ϵ is an error term.

Annual forest return is included in X because it is the baseline return for sustaining forestland, while the weighted annual average return of non-forested land uses controls for the effects of returns from other land uses on relative forestland share. Slope and elevation variables control for the effects of topographic characteristics on relative forestland share. Year dummy variables, indicating the years in which the relative forestland shares are observed (i.e., 1992 and 2001 dummy variables and 2011 as a reference year), capture the time specific effects. Ecoregion dummy variables (i.e., dummy variables for the Central Appalachian Forest Ecoregion and the Cumberlands and Southern Ridge and Valley Ecoregion, with the Southern Blue Ridge Ecoregion as the reference ecoregion) are included in X to capture the spatial specific effects.

We aggregate data at a $30m \times 30m$ resolution to the county level in 1992, 2001, and 2011 from the National Land-Cover Dataset (NLCD) (U.S. Geological Survey 2016) to construct county-level areas of forestland and non-forested land. We merge the NLCD classifications of deciduous forest, evergreen forest, and mixed forest for forestland. Non-forested land includes the classifications of cultivated cropland, pasture/hay, grass/herbaceous land, developed open space, developed low intensity, developed medium intensity, developed high intensity, and other NLCD classifications.

We use Faustmann's model (1849) to estimate forest return using the harvest timber volume data from the Forest Inventory and Analysis database (U.S. Department of Agriculture Forest Service 2017) and stumpage price data from Timber Mart-South (2006, 2011). The average return of non-forested land uses is calculated by taking the weighted average of crop, pasture, and urban returns, with land shares as weights, at the county level for each of the three years. The details of how the four returns are calculated are provided in the supplementary materials in Cho et al. (2017). Average slope and elevation at the county level are estimated using Zonal Statistics tool in ArcGIS 10.1 (ESRI 2012) and a Digital Elevation Model (DEM) (U.S. Geological Survey 2013).

We adopt the spatial panel model with an instrumental variable (IV) to deal with the endogeneity of the forest return and average return of non-forested land uses that can be caused by the error term being correlated with the return variables (See Table S.2. in Appendix for the IV test and S.3. for the 1st stage land-use model). We estimate the spatial panel IV model with Maximum Likelihood Spatial Autocorrelation (SAC) Panel Regression using the STATA module of SPREGSACXT (Shehata and Mickaiel 2013). See Table 3.1. for a detailed description of the variables used in the estimation.

2.2. Carbon simulation model

We estimate changes in carbon storage from changes in relative forestland shares at the county level in each year using a long-run dynamic ecological process called the Terrestrial Ecosystem Model (TEM), housed at the Oak Ridge National Laboratory (ORNL) (2016). The TEM isolates changes in long-term stored carbon that would result from changes in land use by focusing on a comparison between relative forestland shares with and without payments. The TEM uses spatially-related information (i.e. climate, elevation, soils and vegetation) to estimate the carbon, nitrogen and water fluxes for each vegetation cohort, with cohorts aggregated within each county to conform with the resolution of the land-use model (ORNL 2016). The number of cohorts in a county varies according to vegetation types and their areas within each 1 km^2 grid cell (Gutman and Reissell 2011). Carbon storage is calculated using monthly estimates provided by the

TEM cohort-level carbon pools for each of the four years and grid cells, based on integrating the monthly fluxes to account for the net total of carbon uptake through photosynthesis against carbon losses.

2.3. Poverty alleviation model

While PES do not target poverty alleviation exclusively, incentive payments are assumed to be similar to subsidy programs that target poverty alleviation. Numerous studies deal with the consequences of subsidy programs that focus on various aspects of poverty, such as health care, housing, education, and public welfare (Rosen 1985; Smeeding et al. 1993; Besley and Kanbur 1998; Santiago et al. 2001; Schultz 2004; Fan et al. 2008; Mehmood and Sadiq 2010; Jung et al. 2015; Remler et al. 2017). Those studies quantify the impacts on poverty reduction by assuming that assistance to the poor through subsidy programs positively affect reducing poverty (Fan et al. 2000; Afonso and St Aubyn 2004; Smeeding 2006). In addition, those studies have demonstrated the spatial nature of poverty (Friedman and Lichter 1998; Blank 2005; Partridge and Rickman 2005; DeNavas-Walt 2010).

Given evidence from the poverty literature, spatially persistent poverty rates are expected to decline over time as annual forest returns increase through incentive payments. Thus, we hypothesize that the poverty rate in county *i*, in year *t*+*n* minus poverty rate in year *t* ($P_i^{t+n\sim t}$, referred to as "poverty rate mitigation") is a function of forest return and average return of non-forested land uses (i.e., urban, pasture, and crop) and poverty rates in year *t* within the neighboring counties defined by the weight matrix, $\sum_{j=1}^{N} w_{ij} P_{ij-1}^{t}$, where w_{ij} is element (i, j) of the $N \times N$ spatial weight matrix *W*. We test the hypothesis by estimating the following spatial panel model similar to Jung et al. (2015):

$$(P_i^{t+n\sim t}) = \alpha + \sum_{j=1}^{N} w_{ij} P_{ij-1}^{t} \delta + X_i^t \beta + \mu_i + \lambda^t + \varepsilon_i^t, \tag{4}$$

where *j* represents the *j*th county, *X* is a vector of explanatory variables including forest return and average return of non-forested land uses, demographic and employment characteristics, and the time-period dummy variable (i.e., 1 for observation in $t+n$ = 2001 and t = 1992, 0 for observation in $t+n$ = 2011 and t = 2001), α is a constant parameter, δ is a parameter for the spatially lagged poverty rate, β is a parameter vector, μ and λ respectively denote unobserved spatial and time specific effects, and ε is an error term. Note that the poverty rate is the percentage of individuals with incomes below the US Census Bureau poverty threshold based on the family size and the age of its member (U.S. Census Bureau 2017a).

Previous literature shows that income derived from natural-resource use plays a significant role in mitigating poverty (Cavendish 1999; Reddy and Chakravarty 1999; Adhikari 2003; Fisher 2004; Narain et al. 2008; Nielsen et al. 2012; Fonta and Ayuk 2013). The forest return captures the effect of forest return on poverty mitigation and can be used to simulate the effect on poverty mitigation of hypothetical carbon incentive payments. The average return of non-forested land uses captures the effect on the poverty rate of the returns from other land uses as alternatives income sources. We hypothesize that both the forest return and the average return of non-forested land in year *t* are positively related to poverty mitigation between years *t* and $t+n$.

The demographic variables include racial composition (i.e., population percentages of White, Asia-Pacific Islanders, and other races) with the population percentage of Blacks as the reference category; age distribution (i.e., population percentages below 18 years of age, between 18 and 24 years, 65 years of age or older) with the population percentage between 25 and 64 years of age as the reference category; and socioeconomic status (i.e., population percentages with difficulty speaking English, female household heads, at least some college education, living in multiple-worker households) with the population percentages not in these respective categories as the reference categories. The employment variables include percentages of total employment in different industries (i.e., agriculture, manufacture, public, finance, and leisure) with the information, professional, scientific, management, administrative, and waste management service industries (referred to as "other employment percentage") as the reference category. The demographic and employment variables are control variables that influence changes in the poverty rate (e.g., House 1989; Fujiura and Yamaki 2000; Aassve et al. 2006; Hoynes et al. 2006; Engster 2012; Jung et al. 2015). The demographic and employment data are collected from the U.S. Bureau of Labor Statistics (1990) and the U.S. Census Bureau (2000, 2010).

We failed to reject the null hypothesis of exogeneity of the forest return and the average return of non-forested land uses at the 5% significance level. Thus, we estimated the spatial panel model without IV with Maximum Likelihood Estimation Spatial Autocorrelation (SAC) Panel Regression using the STATA module of SPREGSACXT (Shehata and Mickaiel 2013). See Table 3.2. for a detailed description of the variables used in the estimation.

2.4. Impact analysis for planning

The IMPLAN model uses a regional social accounting system and generates a set of balanced economic/social accounts and multipliers. The social accounting system is an extension of input-output analysis. Input-output analysis can provide important and timely information on the interrelationships in a regional economy and the impacts of changes on that economy. To estimate the economic impacts of payments for ecosystem services, expenditures on various inputs were incorporated into IMPLAN. Input-output models analyze the interdependence of industries in an economy through market-based transactions. The model describes the transfer of money between industries and institutions and contains both market and non-market financial flows, such as inter institutional transfers. Output from the model includes descriptive measures of the economy including total industry output (i.e., economic activity), total value-added, state and local taxes, and employment for 536 industries in the study region's economy. We used the total value-added to represent the economic impact from the PES because total value-added is considered gross domestic product and usually represents overall development (Anríquez and Stamoulis 2007). The IMPLAN model utilizes a National Trade Flows Model (NTFM) (doubly-constrained gravity model) to estimate a new set of regional purchase coefficients and other trade data that predict local purchases based on a region’s characteristics (Lindall et al. 2006). Not only can the model be used to describe a regional economy, but the model also can be used for predictive purposes, by providing estimates of multipliers. This analysis uses the local purchase percentages option available in the IMPLAN modeling. These percentages affect the impact values applied to the multipliers. The multiplier impacts can be used to evaluate, measure, and compare results of different economic scenarios.

2.5. Multi-objective linear programming

We use MOLP for the three objectives of maximizing forest-based carbon storage, alleviating maximum poverty, and promoting maximum economic impacts. Following Lieberman (2014)'s two-step optimization procedure, we use a single-objective optimization problem for each of the three objectives in the first step using a Matlab module called *fmincon* and a multi-objective optimization problem in the second step using a Matlab module called *fminimax* (MathWorks 2017a, 2017b).

In the first step, decision variables (i.e., a continuous decimal number from 0 to 1 with 0 defining zero share and 1 full share of forestland in each county) are determined by satisfying each of the three objectives separately under a hypothetical annual budget of $5 million (50% of budget needed to reach maximum carbon storage capacity). In the second step, new decision variables that satisfy all three objectives at the same time are determined by minimizing the maximum percentage gap between the three single target values (i.e., sum of products of the decision variables from the first step and the total quantity of their respective objective values) and their corresponding multi-objective optimal values (i.e., sum of products of the new decision variables and the total quantity of their respective objective values) for each county under the budget constraint. The three percentage gaps are multiplied by four types of hypothetical weight values (i.e., 1 type of single objective of 100% weight on maximizing forest carbon storage; 2 types of dual objectives of 50% weight on maximizing forest carbon storage and 50% weight on alleviating maximum poverty for promoting equity and 50% weight on maximizing forest carbon storage and 50% on promoting economic impact for economic development; 1 type of triple objectives of 33% weight on maximizing forest carbon storage, 33% weight on alleviating maximum poverty for promoting equity, 33% weight on promoting economic impact for economic development) to represent policy priority scenarios between the three objectives.

3. Empirical results and discussion

Table 3.3. reports the parameter estimates and standard errors from the land-use model in equation (3) based on an inverse-distance weight matrix. Our choice of that model is based the model with the minimum log-likelihood ratio (LLR). (See Table S.4. in Appendix for the full report of LLR for the all candidate models.) The overall performance of the model is reflected in its adjusted R^2 of 0.526. The F-test statistics of 233.784 indicates that the overall estimation of the model is significant at the 5% level. The parameter estimates and lack of statistical significance of the spatial lag dependent variable and the spatial error variable imply that the problem of spatially correlated missing variables is not as extensive as is suggested in the literature, which is likely due to the use county-level data (Chou 1991).

The significant (5% level) estimate of the forest return variable (0.03) suggests that an increase of forest return by $1/hectare increases the relative forestland share in each county by 0.03%. This result is crucial to our analysis because it indicates that supplying forest-based carbon storage is feasible through a carbon incentive payment system, and that the impacts on the county-level amounts of forest-carbon storage supplied can be estimated using the carbon simulation model.

As for the geophysical variables, parameter estimates for the average elevation, slope and ecoregion dummy variables are significant at the 5% level, suggesting the importance of these control variables in estimating parameter of the forest return variable. The estimation suggests that counties with higher elevations and steeper slopes tend to have greater relative forestland share. Also, signs of the two ecoregion dummy variables suggest that relative forestland shares are lower in the Cumberlands and Southern Ridge and Valley Ecoregion, and in the Central Appalachian Forest Ecoregion than in the Southern Blue Ridge Ecoregion. These findings reflect that topographic characteristics of the Southern and Central Appalachian Region are such that more forest cover tends to be in landscape regions with high elevation and steep slope and more dense forest cover exist in Southern Blue Ridge Ecoregion than in the other two ecoregions. The more dense forest cover in Sothern Blue Ridge Ecoregion may be relevant to the fact that this ecoregion has the third highest number of hardwood and conifer endemics in North America (Ricketts et al. 1999).

The parameter estimates for the 1992 and 2001 year dummy variables suggest that the relative forestland share in 1992 was greater than in 2011, but the relative forestland share in 2001 was smaller than in 2011. These findings suggest that afforestation and reforestation efforts between 2001 and 2011 may have been successful and/or that deforestation diminished during that period perhaps partially due to the great recession of 2007-2009, although forestland decreased on average over the 19-year study period.

Table 3.4. reports parameter estimates and corresponding standard errors of the poverty model in equation (4) using the 9-nearest neighbor weight matrix (KNN=9). The KNN=9 model has the minimum LLR (see Table S.4. in Appendix for the full report). The adjusted R^2 of the model is 0.773 and the F-statistics of 257.402 is significant at the 5% level, suggesting that the model performs relatively well in terms of explanatory power. The spatial lag and error variables are not significant at the 5% level.

The parameter estimate for the forest return variable in the poverty model is -0.016 and significant at the 5% level, implying that an increase of forest return by $1/hectare yields an average poverty rate reduction of 1.6% annually over the 19-year period. This finding suggests that forest return has a significant effect on mitigating poverty, and thus forest-based carbon incentive payments that trigger an increase in forest return would not only increase carbon storage, but also mitigate poverty. Thus, dollars expended on incentive payments to prevent forestland conversion to other land uses would mitigate poverty as well.

The parameter estimates for three variables (i.e., population percentages between 18 and 24 years of age, living in households with two or more workers, and employment in manufacture) are significant at the 5% level. The positive sign on the percentage of population between 18 and 24 years of age suggests that an increase in this variable, relative to the population percentage between 25 and 64 years of age at the beginning of each period, increases the poverty rate at the end of each period. The negative sign on the population percentage living in households with two or more workers suggests that an increase in this variable at the beginning of each period prompts a reduction in the poverty rate at the end of each period. The positive sign on the percentage of employment in the manufacturing sector suggests that higher employment in manufacturing, relative to the employment percentage in other sectors at the beginning of each period, increases the poverty rate at the end of each period. This finding is explained by the fact that manufacturing employment increased in 27% of counties (76 out of 285 counties), and in all of these counties, the employment percentage in other sectors decreased during the study period. Thus, the finding is logical considering other sectors generally have higher wages than the manufacturing sector. The parameter estimate of 1992-2001 dummy variable suggests that the poverty rate during the 1992-2001 period was lower than during the 2001-2011 period. This finding makes sense given the poverty rate increased in the United States by 1.3 percentage points from 13 percent to 14.3 percent during the great recession of 2007-2009 (U.S. Census Bureau 2017b).

Figures 3.2.-a, 3.2.-b, 3.2.-c, and 3.2.-d show optimal spatial distributions of payment budgets for a single objective weight, two types of dual objective weights, and triple objective weights, respectively, reflecting different priorities between the three objectives (referred to as priority scenarios I, II, III, and IV). Figure 3.2.-a illustrates the spatial distribution of an optimally allocated budget among counties for 100% priority on cost efficiency of carbon storage. The spatial distribution of this optimally allocated budget follows the patterns of the spatial distribution of annual average carbon cost efficiencies during the 2001-2011 period shown in Appendix S.5. This visual assessment is reinforced for priority scenario I in Table 3.5., which presents the quantities of forest carbon sequestration per dollar spent for the four quartiles of the optimally allocated budget (Q_1, Q_2, Q_3, Q_4) shown in Figure 3.2.-a. The general pattern shows that larger budgets are allocated to the counties with higher carbon quantities per dollar spent when the payment priority is 100% on maximizing carbon cost efficiency.

The panels of Figure 3.2. illustrate spatial distributions of optimally allocated budgets when the priority weights are 50% on carbon cost efficiency and 50% on poverty alleviation (Figure 3.2.-b); the priority weights are 50% on carbon cost efficiency and 50% on economic impact (Figure 3.2.-c); and the priority weights are divided equally among the three objectives of carbon cost efficiency, poverty alleviation, and economic impact (Figure 3.2.-d). Table 3.5. shows that the spatial patterns of the optimal budget allocations for priority scenarios II, III, and IV are difficult generalize from the efficiencies of the objectives in the multiple-objective cases, because more than one objective is satisfied in deciding how to optimally allocation the payment budget.

Figures 3.2.-a, 3.2.-b, 3.2.-c, and 3.2.-d illustrate that 63% of counties (or 181 of 285 counties) are selected for optimal spatial targeting under priority scenario I, while 74%, 70%, and 73% of counties are selected for optimal spatial targeting under priority scenarios II, III, and IV for multiple-objective budget allocations. These findings suggest that the spatial targeting of the optimal budget is more widespread among the counties under the multiple-objective priority scenarios than under the single-objective of maximizing carbon cost efficiency. The results also indicate that the optimal spatial distributions do not change appreciably among the four priority scenarios. For example, 79% of counties (or 44 of 56 counties) remained consistently in the upper quartile of the optimal budget allocations of the four priority scenarios. Those targeted counties are in a cluster of counties in Pennsylvania, in a cluster of counties in Alabama, and in counties more widely dispersed within the study area.

Table 3.6. shows trade-off and synergistic relationships among the three objectives for the four priority scenarios. In going from priority scenario I (100% priority on carbon cost efficiency) to priority scenario II (50% priority on carbon cost efficiency and 50% priority on poverty alleviation), 228 persons (or 9.8% increase) are lifted from poverty and economic activity increases by $126,967 (or 1.1% increase), for a sacrifice of 5,866 tonnes of carbon storage (or 2.7% decrease). Likewise, in going from priority scenario I to III (50% priority on carbon cost efficiency and 50% priority on economic impact), the economic impact increases by $150,181 (or 1.2% increase) and 667 persons (or 28.6% increase) are lifted from poverty, for a sacrifice of 9,923 tonnes of carbon storage (or 4.6% decrease). These examples demonstrate the competitive relationships between the objective of carbon cost efficiency and the objectives of poverty alleviation and economic impact, and a synergistic relationship between poverty alleviation and economic impact. The synergic effects in both examples suggest that, regardless of whether the 50% weight is placed on poverty alleviation or on economic impact, placing some priority on either objective reduces poverty and increases economic activity through optimal budget reallocations. The synergic effects likely occur likely because counties with higher poverty alleviation efficiency and counties with higher economic impact efficiency tend to overlap. For example, 69.6% (39 of 56) counties are in the upper quartiles (i.e., Q_1) of both poverty alleviation efficiency and economic impact efficiency (Appendix S.5).

4. Conclusions

The literature on spatial targeting of conservation investments like PES has extensively focused on improving cost efficiency as measured by ROI (e.g., Barton et al. 2013). The results help conservation agencies allocate scarce financial resources by accounting for the spatial distributions of the conservation costs and benefits of ecosystem services and their relationships. Although such efforts are important in improving PES cost efficiency, they neglect other important PES objectives, namely promoting social equity and rural economic development (Mundell 2002; Pascual et al. 2009). To fill the gap, our research addresses the need to identify optimal spatial targeting and distributions of a fixed PES budget that achieve the three objectives of maximizing forest-based carbon storage to improve cost efficiency, maximizing poverty alleviation to promote equity, and maximizing economic impact to encourage economic development using the Central and Southern Appalachian Region of the United States as a case study. We also evaluate the trade-off and synergistic relationships using four scenarios with different priority weights among the three objectives.

Using MOLP with three objective functions obtained from four modeling frameworks (i.e., land-use model, carbon simulation model, poverty alleviation model, and IMPLAN), we derive the optimal spatial distributions of payment budgets for the four priority scenarios. The maps of the optimal spatial distributions show that the targeting of the optimal budget is more widespread among the counties under the multiple-objective priority scenarios than under the single-objective of maximizing carbon cost efficiency, and that the optimal spatial budget distributions of the four priority scenarios do not change appreciably.

The relationships among the objectives are quantified by aggregating and comparing the three objective values under the four priority scenarios. The quantified relationships reveal that different priority weights among the priority scenarios yield both competitive trade-offs and synergistic relationships between the objectives. Changing the priority weights from 100% on carbon cost efficiency to weights of 50% on carbon cost efficiency and 50% on poverty alleviation efficiency or 50% on carbon cost efficiency and 50% on economic impact demonstrates competitive trade-off between the objective of carbon cost efficiency and the objectives of poverty alleviation and economic impact, and a synergistic relationship between poverty alleviation and economic impact. We believe the synergic relationship likely occurs because higher poverty alleviation efficiency and higher economic impact efficiency tend to occur in the same counties.

The optimal spatial budget distributions under different priority scenarios can be used to spatially target PES budgets to encourage forest-based carbon storage, or other conservation goals, while also promoting social equity through poverty alleviation and rural economic development through increased economic activity. Although the optimally allocated budget with the single objective of carbon-cost efficiency is not substantially different from the solutions for the multiple-objective optimization problems, adjustments can be made in spatial targeting and spatially allocated budget amounts based on our results. Further, the quantified trade-off and synergistic relationships among the three objectives can be used by conservation agencies to assess the costs (trade-offs) or benefits (synergies) of the priorities they place on the objectives. Thus, our modeling framework can help conservation agencies adjust their priorities to address other objectives when they view the cost of achieving a single conservation too high in terms of other objectives sacrificed.

References

Aassve, A., M. Iacovou, and L. Mencarini. 2006. “Youth poverty and transition to adulthood in Europe.” *Demographic Research* 15 (2): 21-50.

Adhikari, B. 2003. *Property Rights and Natural Resources: Socio-Economic Heterogeneity and Distributional Implications of Common Property Resource Management*. Kathmandu, Nepal: SANDEE.

Afonso, A., and M. St Aubyn. 2004. “Non-parametric approaches to education and health expenditure efficiency in OECD countries.” *Journal of Applied Economics* 8: 227-246.

Ahn, S. 2008. “How feasible is carbon sequestration in Korea? A study on the costs of sequestering carbon in forest.” *Environmental and Resource Economics* 41 (1): 89-109.

Ahn, S., A.J. Plantinga, and R.J. Alig. 2000. “Predicting future forestland area: a comparison of econometric approaches.” *Forest Science* 46 (3): 363-376.

Anríquez, G., and K. Stamoulis. 2007. “Rural development and poverty reduction: is agriculture still the key?” *Journal of Agricultural and Development Economics* 4 (1): 5-46.

Anselin, L. 1988. “Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity.” *Geographical Analysis* 20 (1): 1-17.

Antle, J., S. Capalbo, S. Mooney, E. Elliott, and K. Paustian. 2003. “Spatial heterogeneity, contract design, and the efficiency of carbon sequestration policies for agriculture.” *Journal of Environmental Economics and Management* 46 (2): 231-250.

Armsworth, P.R., L. Cantú-Salazar, M. Parnell, Z.G. Davies, and R. Stoneman. 2011. “Management costs for small protected areas and economies of scale in habitat conservation.” *Biological Conservation* 144 (1): 423-429.

Armsworth, P.R., S. Acs, M. Dallimer, K.J. Gaston, N.D. Hanley, and P. Wilson. 2012. “The cost of policy simplification in conservation incentive programs.” *Ecology Letters* 15 (5): 406-414.

Babcock, B.A., P.G. Lakshminarayan, J. Wu, and D. Zilberman. 1997. “Targeting tools for the purchase of environmental amenities.” *Land Economics* 325-339.

Barrett, C.B., E.H. Bulte, P. Ferraro, and S. Wunder. 2013. “Economic instruments for nature conservation.” *Key Topics in Conservation Biology* 2 (2013): 59-73.

Barton, D., D. Faith, G. Rusch, J.O. Gjershaug, M. Castro, M. Vega, and E. Vega. 2003. “Spatial prioritisation of environmental service payments for biodiversity protection.” Report SNR 4746/ 2003. Norsk Institutt for vannforskning, Oslo.

Barton, D., S. Blumentrath, and G. Rusch. 2013. “Policyscape-a spatially explicit evaluation of voluntary conservation in a policy mix for biodiversity conservation in Norway.” *Society & Natural Resources* 26 (10): 1185-1201.

Besley, T., and R. Kanbur. 1988. “Food subsidies and poverty alleviation.” *The Economic Journal* 98 (392): 701-719.

Blank, R.M. 2005. “Poverty, policy, and place: How poverty and policies to alleviate poverty are shaped by local characteristics.” *International Regional Science Review* 28 (4): 441-464.

Bremer, L.L., K.A. Farley, and D. Lopez-Carr. 2014. “What factors influence participation in payment for ecosystem services programs? An evaluation of

Ecuador's SocioPáramo program.” *Land Use Policy* 36: 122-133.

Carrión-Flores, C.E., A. Flores-Lagunes, and L. Guci. 2009. “Land use change: a spatial multinomial choice analysis.” Paper presented at Agricultural and Applied Economics Association 2009 Annual Meeting.

Cavendish, W. 1999. *Poverty, Inequality and Environmental Resources: Quantitative Analysis of Rural Households.* Oxford: Centre for the Study of African Economies, Institute of Economics and Statistics, University of Oxford.

Cho, S., J. Lee, R.K. Roberts, B.C. English, E.T. Yu, T. Kim, and P.R. Armsworth. 2017. “Evaluating a tax-based subsidy approach for forest carbon sequestration.” *Environmental Conservation* 44 (3): 234-243. Available at: https://www.cambridge .org/core/journals/environmental-conservation/article/evaluating-a-taxbased-subsidy-approach-for-forest-carbon-sequestration/A80E3AEC30570E77A40D966F 8654EE49#fndtn-supplementary-materials

Cho, S., and D.H. Newman. 2005. “Spatial analysis of rural land development.” *Forest Policy and Economics* 7 (5): 732-744.

Cho, S., J. Lee, R.K. Roberts, T.E. Yu, and P.R. Armsworth. 2018a. “Impact of market conditions on the effectiveness of payments for forest-based carbon sequestration.” *Forest Policy and Economics* 92: 33-42.

Cho, S., M. Soh, B.C. English, T.E. Yu, and C. Boyer. 2018b. “Targeting payments for ecosystem services given ecological and economic objectives.” Unpublished, University of Tennessee.

Cho, S., J. Wu, and R. Alig. 2005. “Land development under regulation: Comparison between the east and west sides of the Cascade Range in Oregon, Washington, and California." *Review of Urban & Regional Development Studies* 17 (1): 1-17.

Chou, Y.H. 1991. "Map resolution and spatial autocorrelation." *Geographical Analysis* 23 (3): 228-246.

Claassen, R., A. Cattaneo, and R. Johansson. 2008. "Cost-effective design of agri-environmental payment programs: US experience in theory and practice." *Ecological Economics* 65 (4): 737-752.

DeNavas-Walt, C., B.D. Proctor, and C.H. Lee. 2006. *Income, Poverty and Health Insurance Coverage in the United States: 2005*. Current Population Reports, Washington, D.C.: U.S. Government Printing Office.

Dietz, S., and G. Atkinson. 2010. "The equity-efficiency trade-off in environmental policy: Evidence from stated preferences." *Land Economics* 86 (3): 423-443.

Dwyer, J.F., E.G. McPherson, H.W. Schroeder, and R.A. Rowntree. 1992. "Assessing the benefits and costs of the urban forest." *Journal of Arboriculture* 18: 227-227.

Engel, S., S. Pagiola, and S. Wunder. 2008. "Designing payment for environmental services in theory and practice: An overview of the issues." *Ecological Economics* 65 (4): 663-674.

Engster, D. 2012. "Child poverty and family policies across eighteen wealthy Western democracies." *Journal of Children and Poverty* 18 (2): 121-139.

ESRI. 2012. ArcGIS Help 10.1: Spatial Analyst Toolsets, ArcGIS Resources. Available at: http://www.esri.com/

Fan, S., A. Gulati, and S. Thorat. 2008. "Investment, subsidies, and pro-poor growth in rural India." *Agricultural Economics* 39 (2): 163-170.

Fan, S., P. Hazell, and S. Thorat. 2000. "Government spending, growth and poverty in rural India." *American Journal of Agricultural Economics* 82 (4): 1038-1051.

Farley, J., and R. Costanza. 2010. "Payments for ecosystem services: From local to global." *Ecological Economics* 69 (11): 2060-2068.

Faustmann, M. 1849. Calculation of the Value Which Forest Land and Immature Stands Possess for Forestry. In M. Gane, ed, *Martin Faustmann and the Evolution of Discounted Cash Flow*. University of Oxford.

Ferraro, P.J. 2004. "Targeting conservation investments in heterogenous landscapes: a distance function approach and application to watershed management." *American Journal of Agricultural Economics* 86 (4): 905-918.

Fisher, M. 2004. "Household welfare and forest dependence in Southern Malawi." *Environment and Development Economics* 9 (2): 135-154.

Fonta, W.M., and E.T. Ayuk. 2013. "Measuring the role of forest income in mitigating poverty and inequality: evidence from south-eastern Nigeria." *Forests, Trees and Livelihoods* 22 (2): 86-105.

Fraser, R. 2009. "Land heterogeneity, agricultural income forgone and environmental benefit: An assessment of incentive compatibility problems in environmental stewardship schemes." *Journal of Agricultural Economics* 60 (1): 190-201.

Friedman, S., and D.T. Lichter. 1998. "Spatial inequality and poverty among American children." *Population Research and Policy Review* 17 (2): 91-109.

Fujiura, G.T., and K. Yamaki. 2000. "Trends in demography of childhood poverty and disability." *Exceptional Children* 66 (2): 187-199.

García-Amado, L.R., M.R. Pérez, F.R. Escutia, S.B. García, and E.C. Mejía. 2011.

“Efficiency of payments for environmental services: equity and additionality in a case study from a biosphere reserve in Chiapas, Mexico.” *Ecological Economics* 70 (12): 2361-2368.

Gibbons, J.M., E. Nicholson, E.J. Milner-Gulland, and J.P. Jones. 2011. “Should Payments for 22 Biodiversity Conservation be Based on Action or Results?” *Journal of Applied Ecology* 48 (5): 1218–1226.

Gross-Camp, N.D., A. Martin, S. McGuire, B. Kebede, and J. Munyarukaza. 2012. “Payments for ecosystem services in an African protected area: exploring issues of legitimacy, fairness, equity and effectiveness.” *Oryx* 46 (1): 24-33.

Gutman, G., and A. Reissell, eds. 2011. *Eurasian Arctic Land Cover and Land Use in a Changing Climate*. Springer.

Hanley, N., S. Banerjee, G.D. Lennox, and P.R. Armsworth. 2012. “How should we incentivize private landowners to ‘produce’ more biodiversity?” *Oxford Review of Economic Policy* 28 (1): 93-113.

Harrington, W., and R.D. Morgenstern. 2004. “Economic Incentives versus Command and Control: What’s the Best Approach for Solving Environmental Problems?” *Resources* 152: 13-17. Available at: http://www.rff.org/files/sharepoint/WorkImages/Download/RFF_Resources_152_ecoincentives.pdf

Hardie, I., P. Parks, P. Gottleib, and D. Wear. 2000. “Responsiveness of rural and urban land uses to land rent determinants in the US South.” *Land Economics* 659-673.

House, W.J. 1989. “Demography employment and poverty at the household level in urban Juba Southern Sudan.” WEP Working Paper No 168, Geneva: International Labour Office.

Hoynes, H.W., M.E. Page, and A.H. Stevens. 2006. “Poverty in America: Trends and explanations.” *Journal of Economic Perspectives* 20 (1): 47-68.

Jung, S., S. Cho, and R.K. Roberts. 2015. “The impact of government funding of poverty reduction programmes.” *Papers in Regional Science* 94 (3): 653-675.

Kearney, S.P., S.J. Fonte, E. García, P. Siles, K.M.A. Chan, and S.M. Smukler. 2017. “Evaluating ecosystem service trade-offs and synergies from slash-and-mulch agroforestry systems in El Salvador.” *Ecological Indicators*. Available at: https://doi.org/10.1016/j.ecolind.2017.08.032

Kim, T., and C. Langpap. 2015. “Incentives for carbon sequestration using forest management.” *Environmental and Resource Economics* 62 (3): 491-520.

Kolinjivadi, V., A. Grant, J. Adamowski, and N. Kosoy. 2015. “Juggling multiple dimensions in a complex socio-ecosystem: The issue of targeting in payments for ecosystem services.” *Geoforum* 58: 1-13.

Kroeger, T., and F. Casey. 2007. “An assessment of market-based approaches to providing ecosystem services on agricultural lands.” *Ecological Economics* 64 (2): 321-332.

Landell-Mills, N., and I.T. Porras. 2002. *Silver Bullet or Fools' Gold: a Global Review of Markets for Forest Environmental Services and Their Impact on the Poor*. London: International Institute for Environment and Development.

Lewis, D.J., A.J. Plantinga, E. Nelson, and S. Polasky. 2011. “The efficiency of voluntary incentives policies for preventing biodiversity loss.” *Resource and Energy Economics* 33 (1): 192- 211.

Lieberman, E.R. 2014. *Multi-objective Programming in the USSR*. G.J. Lieberman, and I. Olkin, eds. Academic Press.

Lindall, S., Olson, and G. Alward. 2006. “Deriving multi-regional models using the IMPLAN national trade flows model.” Paper presented at Regional Science Association International meeting, Sante Fe, New Mexico.

Lubowski, R.N., A.J. Plantinga, and R.N. Stavins. 2006. “Land-Use Change and Carbon Sinks: Econometric Estimation of the Carbon Sequestration Supply Function.” *Journal of Environmental Economics and Management* 51 (2): 135-152.

Lubowski, R.N., A.J. Plantinga, and R.N. Stavins. 2008. “What drives land-use change in the United States? A national analysis of landowner decisions.” *Land Economics* 84 (4): 529-550.

Mahanty, S., H. Suich, and L. Tacconi. 2013. “Access and benefits in payments for environmental services and implications for REDD+: Lessons from seven PES schemes.” *Land Use Policy* 31: 38-47.

Mason, C.F., and A.J. Plantinga. 2011. *Contracting for Impure Public Goods: Carbon Offsets and Additionality* (No. w16963). National Bureau of Economic Research.

MathWorks. 2017a. fmincon Documentation.
Available at: https://www.mathworks.com/help/optim/ug/fmincon.html

MathWorks. 2017b. fminimax Documentation.
Available at: https://www.mathworks.com/help/optim/ug/fminimax.html

McDermott, M., S. Mahanty, and K. Schreckenberg. 2013. “Examining equity: a multidimensional framework for assessing equity in payments for ecosystem services.” *Environmental Science & Policy* 33: 416-427.

Mehmood, R., and S. Sadiq. 2010. “The relationship between government expenditure and poverty: a cointegration analysis." *Romanian Journal of Fiscal Policy* 1 (1): 29-37.

Montagnini, F., and P.K.R. Nair. 2004. "Carbon sequestration: an underexploited environmental benefit of agroforestry systems." *Agroforestry Systems* 61: 285-295.

Mundell, M. 2002. "The Economic Impacts of the CRP & CREP Programs in the Long Branch Watershed." Report S-2002-02. The Community Policy Analysis Center (CPAC). University of Missouri Columbia.

Muradian, R., E. Corbera, U. Pascual, N. Kosoy, and P.H. May. 2010. "Reconciling theory and practice: an alternative conceptual framework for understanding payments for environmental services." *Ecological Economics* 69: 1202-1208.

Narain, U., S. Gupta, and K. Van't Veld. 2008. "Poverty and the environment: exploring the relationship between household incomes, private assets, and natural assets." *Land Economics* 84 (1): 148-167.

Narloch, U., U. Pascual, and A.G. Drucker. 2011. "Cost-effectiveness targeting under multiple conservation goals and equity considerations in the Andes." *Environmental Conservation* 38 (4): 417-425.

Nielsen, M.R., M. Pouliot, and R.K. Bakkegaard. 2012. "Combining income and assets measures to include the transitory nature of poverty in assessments of forest dependence: Evidence from the Democratic Republic of Congo." *Ecological Economics* 78: 37-46.

Oak Ridge National Laboratory (ORNL). 2016., Daily Surface Weather and Climatological Summaries (Daymet) weather dataset. Available at: http://daymet.ornl.gov/singlepixel.html

Pascual, U., J. Phelps, E. Garmendia, K. Brown, E. Corbera, A. Martin, E. Gomez-Baggethun, and R. Muradian. 2014. “Social equity matters in payments for ecosystem services.” *Bioscience* 64 (11): 1027-1036.

Pascual, U., R. Muradian, L.C. Rodriguez, and A. Duraiappah. 2009. “Revisiting the relationship between equity and efficiency in payments for environmental services.” Working Paper Series, 1, Ecosystem Services Economics (ESE).

Pascual, U., R. Muradian, L.C. Rodríguez, and A. Duraiappah. 2010. “Exploring the links between equity and efficiency in payments for environmental services: A conceptual approach.” *Ecological Economics* 69 (6): 1237-1244.

Pascual, U., J. Phelps, E. Garmendia, K. Brown, E. Corbera, A. Martin, E. Gomez-Baggethun, and R. Muradian. 2014. “Social equity matters in payments for ecosystem services.” *Bioscience* 64 (11): 1027-1036.

Partridge, M.D., and D.S. Rickman. 2005. “High-poverty nonmetropolitan counties in America: Can economic development help?” *International Regional Science Review* 28 (4): 415-440.

Polasky, S., D.J. Lewis, A.J. Plantinga, and E. Nelson. 2014. “Implementing the optimal provision of ecosystem services.” *Proceedings of the National Academy of Sciences* 111 (17): 6248-6253.

Reddy, S.R.C., and S.P. Chakravarty. 1999. “Forest dependence and income distribution in a subsistence economy: evidence from India.” *World development* 27 (7): 1141-1149.

Remler, D.K., S.D. Korenman, and R.T. Hyson. 2017. “Estimating the Effects of Health Insurance and Other Social Programs on Poverty Under the Affordable Care

Act." *Health Affairs* 36 (10): 1828-1837.

Richards, K.R., and C. Stokes. 2004. "A review of forest carbon sequestration cost studies: a dozen years of research." *Climatic Change* 63 (1-2): 1-48.

Ricketts, T., E. Dinerstein, D.M. Oldson, C. Loucks, W. Eichbaum, D.A. DellaSala, K. Kavanagh, P. Hedao, P. Hurley, K. Carney, R. Abell, and S. Walters. 1999. *Terrestrial Ecoregions of North America: A Conservation Assessment*. T.H Ricketts, ed. New York: Island Press.

Rosen, H.S. 1985. Housing subsidies: "Effects on housing decisions, efficiency, and equity." In A. Auerbach and M. Feldstein, eds. *Handbook of Public Economics* Vol. 1, Elsevier, pp 375-420.

Santiago, A.M., G.C. Galster, and P. Tatian. 2001. "Assessing the Property Value Impacts of the Dispersed Hounsing Subsidy Program in Denver." *Journal of Policy Analysis and Management* 20 (1): 65-88.

Schultz, T.P. 2004. "School subsidies for the poor: evaluating the Mexican Progresa poverty program." *Journal of Development Economics* 74 (1): 199-250.

Shehata, E., and S. Mickaiel. 2013. "SPREGSACXT: Stata module to Estimate Maximum Likelihood Estimation Spatial Auto Correlation (SAC) Panel Regression." Statistical Software Components S457761, Boston College Department of Economics.

Smeeding, T. 2006. "Poor people in rich nations: The United States in comparative perspective." *Journal of Economic Perspectives* 20(1): 69-90.

Smeeding, T.M., P. Saunders, J. Coder, S. Jenkins, J. Fritzell, A.J. Hagenaars, R. Hauser, and M. Wolfson. 1993. Poverty, inequality, and family living standards impacts across seven nations: "The effect of noncash subsidies for health, education and housing." *Review of Income and Wealth* 39 (3): 229-256.

Sohngen, B., and S. Brown. 2006. "The influence of conversion of forest types on carbon sequestration and other ecosystem services in the South Central United States." *Ecological Economics* 57 (4): 698-708.

Timber Mart-South (TMS). 2006, 2011. Product and Services. Available at: http://www.timbermart-south.com./products.html

U.S. Bureau of Labor Statistics. 1990. Data bases, tables, and calculators by subject: Employment. Available at: http://www.bls.gov/data/#employment

U.S. Census Bureau. 2000. Census 2000 Gateway. Available at: https://www.census.gov/main/www/cen2000.html

U.S. Census Bureau. 2010. Data tools. Available at: https://www.census.gov/programs-surveys/decennial-census/data/tools.html

U.S. Census Bureau. 2017a. Poverty: How the Census Bureau Measures Poverty. Available at: https://www.census.gov/topics/income-poverty/poverty/guidance/poverty-measures.html

U.S. Census Bureau. 2017b. Small Area Income and Poverty Estimates (SAIPE) Program. Available at: https://www.census.gov/data-tools/demo/saipe/saipe.html?s_appName=saipe&map_yearSelector=2016&map_geoSelector=aa_c

U.S. Department of Agriculture Forest Service. 2017. FIA Data and Tools. Available at: https://www.fia.fs.fed.us/tools-data/index.php

U.S. Geological Survey (USGS). 2013. Data and Tools.

Available at: https://www.usgs.gov/products/data-and-tools/gis-data

U.S. Geological Survey (USGS). 2016. Multi-Resolution Land Characteristics Consortium(MRLC): National Land Cover Database (NLCD). Available at: http://www.mrlc.gov/finddata.php

Wu, J., and J. Yu. 2017. "Efficiency-Equity Tradeoffs in Targeting Payments for Ecosystem Services." *American Journal of Agricultural Economics* 99 (4): 894-913.

Zhang, W., and S. Pagiola. 2011. "Assessing the potential for synergies in the implementation of payments for environmental services programmes: an empirical analysis of Costa Rica." *Environmental Conservation* 38 (4): 406-416.

Zilberman, D., L. Lipper, and N. McCarthy. 2008. "When could payments for environmental services benefit the poor?" *Environment and Development Economics* 13 (3): 255-278.

Appendix

Table 3.1. Variable definitions and descriptive statistics for the land-use model

Variables	Definition	Mean (Std Dev)
Dependent variables		
Share of forest area relative to non-forest area	Ratio of forested area to non-forested area in years, 1992, 2001, and 2011	3.489 (8.679)
Socioeconomic variables		
Forest return	Annual forest return in years 1992, 2001, and 2011 ($/hectare)	53.778 (18.485)
Average return of non-forested land	Annual weighted average return of non-forested land, with land shares as weights (i.e., crop, pasture, and urban) in years, 1992, 2001, and 2011 ($/hectare)	333.052 (507.480)
Geophysical variables		
Average elevation	Average elevation (meter)	446.756 (204.931)
Average slope	Average slope (degree)	2.156 (1.148)
Appalachian forest ecoregion	1 if county is in Central Appalachian Forest Ecoregion, 0 otherwise	0.336 (0.472)
Cumberlands and southern ridge and valley ecoregion	1 if county is in Cumberlands and Southern Ridge and Valley Ecoregion, 0 otherwise	0.480 (0.499)
Year variable		
Year 1992 dummy variable	1 if year is 1992, 0 otherwise	0.333 (0.471)
Year 2001 dummy variable	1 if year is 2001, 0 otherwise	0.333 (0.471)

Note: All variables are at the county level.

Table 3.2. Variable definitions and descriptive statistics for the poverty alleviation model

Variables	Definition	Mean (Std Dev)
Poverty variable		
Poverty rate mitigation	Poverty rate at the end of the period minus poverty rate at the beginning of the period (i.e., 1992-2001 and 2001-2011)	0.471 (4.656)
Socioeconomic variables (at the beginning of the period, 1992 and 2001)		
Forest return	Annual forest return ($/hectare)	57.955 (20.236)
Average return of non-forested land	Annual weighted average return of non-forested land (i.e., crop, pasture, and urban) with land shares as weights ($/hectare)	28.823 (407.503)
Demographic variable (at the beginning of the period, 1992 and 2001)		
White	White population divided by total population (%)	94.184 (6.395)
Asia-Pacific	Asia-Pacific population divided by total population (%)	0.411 (0.561)
Other races	Native Americans and other races excluding white, Asian-Pacific, and Black population divided by total population (%)	2.034 (3.211)
Age under 17 years	Population aged below 18 years divided by total population (%)	23.822 (2.649)
Age between 18 - 24 years	Population aged between 18 and 24 divided by total population (%)	21.516 (11.567)
Age over 65 years	Population aged 65 or older divided by total population (%)	14.335 (2.906)
English Speaking	Population aged between 16 and 64 with difficulty speaking English divided by total population (%)	3.219 (2.323)
Female-headed household	Population living in female-headed households divided by total population (%)	24.361 (3.439)
Some college education	Population with at least some college education divided by total population aged 25 or older (%)	31.185 (10.493)
Two or more workers	Population living in households with two or more workers divided by total population (%)	18.574 (3.355)
Employment variable (at the beginning of the period, 1992 and 2001)		
Agriculture	Employment in agriculture, forestry, fishing, hunting, and mining divided by total employment (%)	3.301 (6.602)

Table 3.2. Continued

Variables	Definition	Mean (Std Dev)
Manufacture	Employment in manufacturing and construction divided by total employment (%)	6.120 (14.623)
Public	Employment in transportation, warehousing, and other public utilities divided by total employment (%)	8.571 (9.988)
Finance	Employment in Finance, insurance, real estate, rental, and leasing divided by total employment (%)	3.237 (1.637)
Leisure	Employment in arts, entertainment, recreation, accommodation, and food services divided by total employment (%)	7.987 (4.820)
Year variable		
Period dummy variable	1 if year is 1992, 0 otherwise	0.500 (0.500)

Note: All variables are at the county level.

Table 3.3. Parameter estimates of the land-use model from the spatial panel model with IV

Variables	Coefficient (Std Dev)
Socioeconomic variables	
Forest return	0.030*
	(0.015)
Average return of non-forested land (× 0.1)	-0.004
	(0.003)
Geophysical variables	
Average elevation (× 0.1)	0.003*
	(0.001)
Average slope	0.172*
	(0.053)
Appalachian forest ecoregion	-0.476*
	(0.130)
Cumberlands and southern ridge and valley ecoregion	-0.069
	(0.158)
Year variable	
Year 1992 dummy variable	0.160*
	(0.069)
Year 2001 dummy variable	-0.667*
	(0.372)
Spatial dependence variable	
Spatial lag	-0.263
	(0.306)
Spatial error	0.333
	(0.244)

Note: Adjusted R^2 = 0.526, Numbers in parentheses are standard errors, and * denotes significance at the 5% level.

Table 3.4. Parameter estimates of the poverty alleviation model from the spatial panel model without IV

Variables	Coefficient (Std Dev)
Socioeconomic variables	
Forest return	-0.016*
	(0.008)
Average return of non-forested land (× 0.01)	-0.007
	(0.032)
Demographic variable	
White	0.005
	(0.027)
Asia-Pacific	0.186
	(0.375)
Other races	0.042
	(0.064)
Age under 17 years	-0.052
	(0.090)
Age between 18 - 24 years	0.124*
	(0.056)
Age over 65 years	-0.024
	(0.085)
English Speaking	0.052
	(0.120)
Female-headed householder	0.099
	(0.052)
Some college education	-0.005
	(0.023)
Two or more workers	-0.205*
	(0.085)
Agriculture	-0.016
	(0.029)
Manufacture	0.055*
	(0.015)
Public	-0.068
	(0.041)
Finance	0.060
	(0.083)
Leisure	0.019
	(0.030)

Table 3.4. Continued

Variables	Coefficient (Std Dev)
Year variable	
Period dummy variable	-2.631*
	(1.242)
Spatial dependence variable	
Spatial lag	0.004
	(0.102)
Spatial error	0.041
	(0.157)

Note: Adjusted $R^2 = 0.773$, Numbers in parentheses are standard errors, and * denotes significance at the 5% level.

Table 3.5. Carbon cost, poverty alleviation, and economic impact cost efficiencies under four priority scenarios by quartile of the optimal allocated budget distributions

Scenarios	Quartiles	Optimal budget distribution ($)	Optimal carbon storage (tonne)	Carbon cost efficiency (tonne/$)	Total poverty alleviation (population)	Poverty alleviation efficiency (population/$)	Total Economic impact ($)	Economic Impact efficiency ($/$)
I	Q_1	19,218 – 737,116	190,710.68	0.047	-	-	-	-
	Q_2	3,953 – 19,217	16,600.83	0.042	-	-	-	-
	Q_3	1,710 – 3,952	4,189.46	0.035	-	-	-	-
	Q_4	1 – 1,709	1,179.44	0.033	-	-	-	-
II	Q_1	15,211 – 737,719	180,321.51	0.046	2,157	0.044	-	-
	Q_2	5,384 – 15,210	19,736.73	0.036	135	0.023	-	-
	Q_3	2,149 – 5,383	5,139.84	0.033	237	0.106	-	-
	Q_4	1 – 2,148	1,617.06	0.034	25	0.024	-	-
III	Q_1	16,695 – 737,119	177,065.79	0.047	-	-	10,634,567	0.050
	Q_2	6,374 – 16,694	16,859.71	0.040	-	-	970,578	0.050
	Q_3	2,176 – 6,373	7,198.08	0.033	-	-	497,349	0.037
	Q_4	1 – 2,175	1,634.38	0.034	-	-	103,358	0.042
IV	Q_1	16,888 – 737,119	171,916.51	0.046	2,553	0.010	10,294,469	0.046
	Q_2	6,551 – 16,887	21,371.71	0.037	169	0.003	1,303,491	0.039
	Q_3	2,198 – 6,550	6,138.97	0.033	228	0.012	436,486	0.044
	Q_4	1 - 2197	1,740.69	0.035	18	0.003	107,645	0.041

Note: I, II, III, and IV are single objective of maximizing forest-based carbon storage for improving cost efficiency (100% weight), dual objectives of maximizing forest-based carbon storage for improving cost efficiency (50%) and alleviating maximum poverty for promoting equity (50%), dual objectives of maximizing forest-based carbon storage for improving cost efficiency (50%) and promoting economic impact for economic development (50%), and triple objectives of maximizing forest-based carbon storage for improving cost efficiency (33%), alleviating maximum poverty for promoting equity (33%), and promoting economic impact for economic development (33%), respectively.

Table 3.6. Total carbon storage, poverty alleviation, and economic impact under a hypothetical budget of $5 million (50% of budget needed to reach maximum carbon storage capacity) with four weight scenarios

Scenarios	Carbon storage (tonne)	Poverty alleviation (population)	Economic impact ($)
I	212,681	2,326	12,055,671
II	206,815	2,554	12,182,638
III	202,758	2,993	12,205,852
IV	201,171	2,970	12,142,209

Note: I, II, III, and IV are single objective of maximizing forest-based carbon storage for improving cost efficiency ($100% weight), dual objectives of maximizing forest-based carbon storage for improving cost efficiency (50%) and alleviating maximum poverty for promoting equity (50%), dual objectives of maximizing forest-based carbon storage for improving cost efficiency (50%) and promoting economic impact for economic development (50%), and triple objectives of maximizing forest-based carbon storage for improving cost efficiency (33%), alleviating maximum poverty for promoting equity (33%), and promoting economic impact for economic development (33%), respectively.

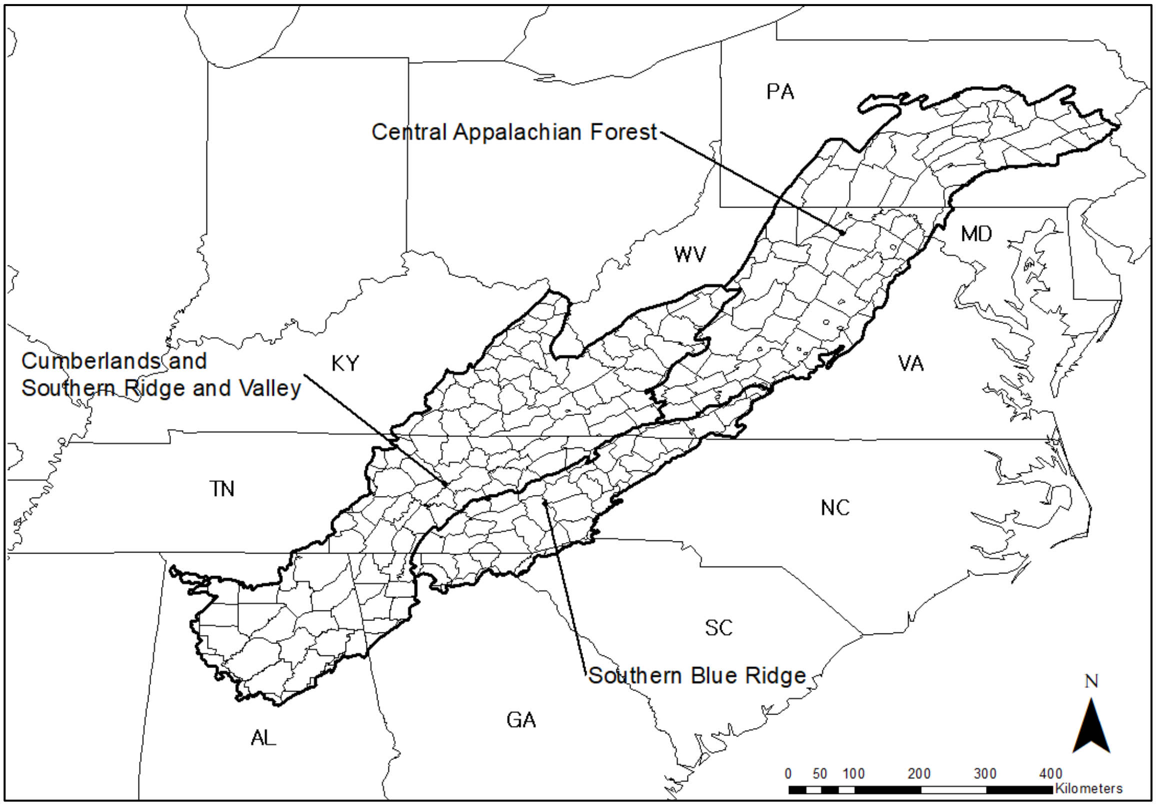


Figure 3.1. Overview of case study area

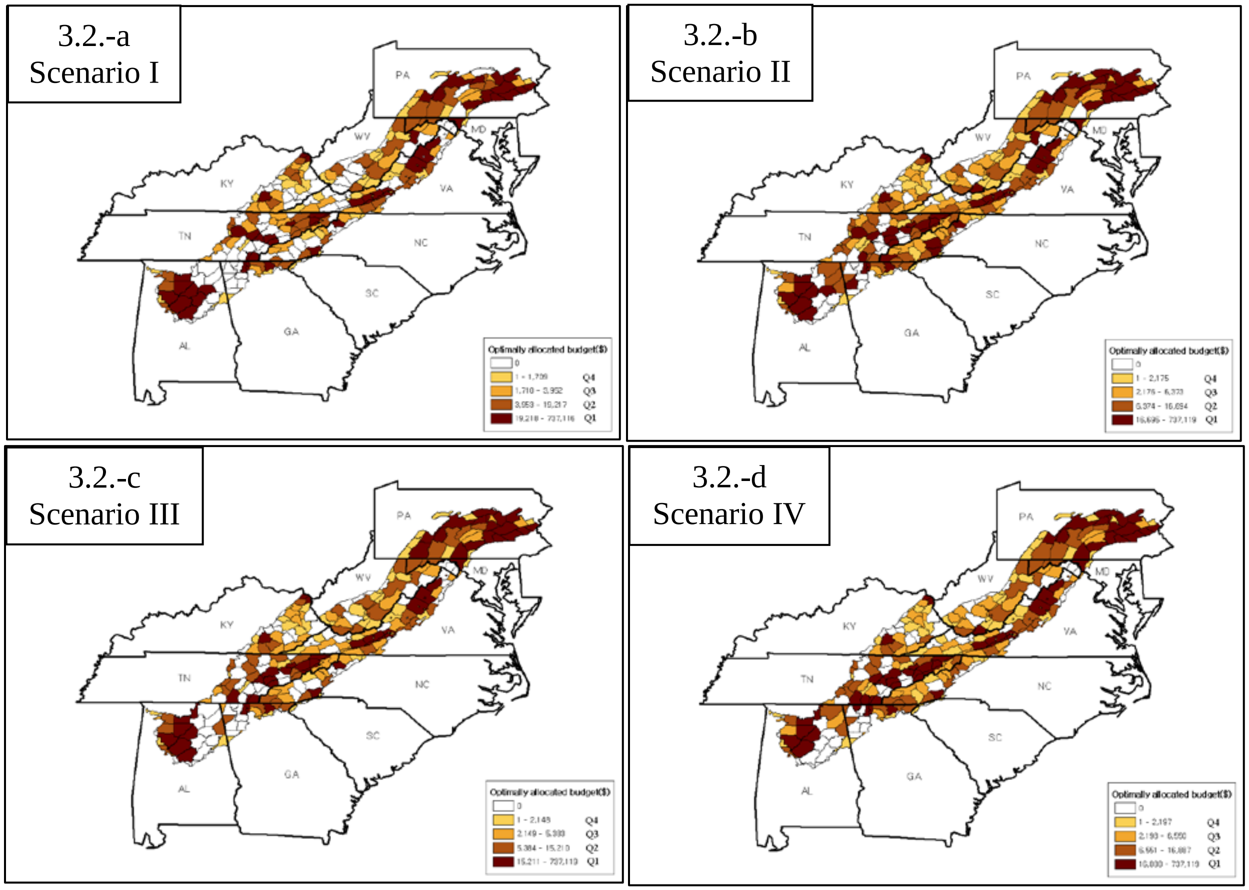


Figure 3.2. Optimal spatial distribution of payment budget scenario focusing on single, dual, and triple objectives (I, II, III, and IV)

Note: I, II, III, and IV are single objective of maximizing forest-based carbon storage for improving cost efficiency (100% weight), dual objectives of maximizing forest-based carbon storage for improving cost efficiency (50%) and alleviating maximum poverty for promoting equity (50%), dual objectives of maximizing forest-based carbon storage for improving cost efficiency (50%) and promoting economic impact for economic development (50%), and triple objectives of maximizing forest-based carbon storage for improving cost efficiency (33%), alleviating maximum poverty for promoting equity (33%), and promoting economic impact for economic development (33%), respectively.

Chapter 4: Summary

The two essays examine the optimal spatial targeting of PES under several objectives. Through MOLP in the first essay, we identify optimal county-level targets with a total conservation budget optimally distributed under 27 alternatives, nine weighting scenarios involving the two core objectives multiplied by three budget scenarios and identify resulting changes in forest carbon and estimate economic impacts. We then develop three tradeoff frontiers between the two objectives that are created from the targeted PES for the three budget scenarios. Along each frontier, PES is Pareto optimal since forest carbon storage cannot be increased without sacrificing economic impacts and vice versa**.** In the second essay, we implement the case study by using MOLP based on three objective functions: (i) maximizing forest-based carbon storage for improving cost efficiency, (ii) alleviating maximum poverty for promoting equity, and (iii) promoting economic impact for economic development. By comparing the optimal solutions under the multiple weighting scenarios, we evaluate trade-off and synergistic relationships among the objectives.

In the empirical result from the first essay, maps of PES optimal budget distributions among counties, given different weighting scenarios, 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. This finding occurs since the economic-impact objective is more dominant in the targeting decision than the carbon-cost efficiency objective, on average. Also, 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 economic impacts while reducing 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. The concavity of the Pareto optimal relationship can be explained by the law of increasing opportunity cost, implying that as an increase in the weight assigned to economic impacts (or forest carbon benefits) rises, the opportunity cost of economic growth (or forest carbon benefits) increases.

Considering additional poverty alleviation as social equity in the second essay, the relationships among the objectives are quantified by aggregating and comparing the three objective values under the four priority scenarios. The quantified relationships reveal that different priority weights among the priority scenarios yield both competitive trade-offs and synergistic relationships between the objectives. Changing the priority weights from 100% on carbon cost efficiency to weights of 50% on carbon cost efficiency and 50% on poverty alleviation efficiency or 50% on carbon cost efficiency and 50% on economic impact demonstrates competitive trade-off between the objective of carbon cost efficiency and the objectives of poverty alleviation and economic impact, and a synergistic relationship between poverty alleviation and economic impact. We believe the synergic relationship likely occurs because higher poverty alleviation efficiency and higher economic impact efficiency tend to occur in the same counties. The optimal spatial budget distributions under different priority scenarios can be used to spatially target PES budgets to encourage forest-based carbon storage, or other conservation goals, while also promoting social equity through poverty alleviation and rural economic development through increased economic activity. Further, the quantified trade-off and synergistic relationships among the multi objectives can be used by conservation agencies to assess the costs (trade-offs) or benefits (synergies) of the priorities they place on the objectives. Thus, our modeling framework can help conservation agencies adjust their priorities to address other objectives when they view the cost of achieving a single conservation too high in terms of other objectives sacrificed.

Appendix: Supplemental Material

S.1. Expected annual return per hectare of four land uses

The 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 the rents earned by an infinite series of identical rotations with the same timber management activities (Bettinger et al. 2009). The SEV for forestland f (f = deciduous forestland or evergreen forestland) per hectare for county j in 2001, for example, was estimated as:

$$SEV_{fjt} = \frac{P_f \cdot Q_{fjt}}{(1+r)^t - 1},$$

where P_f is the stumpage price for forestland f in 2001, Q_{fjt} is the harvest volume per hectare for forestland f in county j at harvest age t, and r is the discount rate of 5%. Here, the stumpage price is the price received by the landholder for the forest products after all costs of cutting, snigging and haulage have been paid. Following the conventional timber-harvesting decision rule, the harvest age t was determined by setting the average stumpage value equal to the annual incremental change in stumpage value for forestland in county j. Then, Q_{fjt} was obtained by taking the average of the plot-level harvest volume per hectare for county j based on the Forest Inventory and Analysis (FIA) database (USDA Forest Service 2015).

The stumpage price for Tennessee was obtained from Timber Mart-South (2015), which is a quarterly market price survey report of the major timber products. The stumpage price for Kentucky was collected from Growing Gold (Kentucky Division of Forestry 2015). The information on harvest volume and rotation age at the county-level for deciduous forestland and evergreen forestland was from Smith et al. (2006).

Weighted averages in 2001 and 2006 of the SEVs for a county were calculated with the shares of the two forestland types in the county as weights. Then, the annualized weighted-average SEV per hectare for the county was calculated for each year. The SEV is annualized for the following reason: Forestland provides non-annual periodic income based on the timber harvest cycle and expected returns from the other three land uses are estimated as annual values. The expected returns from the four land uses must be in the same unit (i.e., annual US $ per hectare) because they are included as regressors for competing land uses in the multinomial logit model.

Weighted averages of the SEVs for each county j for year t (t = 2001 and 2006), $WSEV_{jt}$, were calculated based on shares of the two forestland types as:

$$WSEV_{jt} = \sum_{f=1}^{2} w_f \cdot SEV_{fjt} .$$

where w_f is the ratio of each tree type in the county and SEV_{fjt} is the SEV for forestland type f in county j for year t. Then, the annualized weighted-average SEV per hectare ($A_{WSEV_{jt}}$) for each forestland type in each county in year t was calculated as:

$$A_{WSEV_{jt}} = WSEV_{jt} \Bigg/ \left(\frac{\left[1-(1/(1+i)^n)\right]}{r} \right) ,$$

where r is the discount rate and n represent a period of 100 years, which can be flexible, but should be adequately long. Then, the property tax amounts, which vary by county, were subtracted from A_{WSEV} to estimate the expected annual return per hectare of forestland after tax.

County-level rent per hectare of pastureland was used as the expected net return per hectare of pastureland. County-level data for 2001 and 2006 were not available. The data were predicted using a fixed-effect model with panel data by regressing county-level pastureland rent on state-level pastureland rent and county-level cattle numbers and pastureland area for the period of 2008–2012. The latter variables were included under the premise that pastureland rent is positively related with the size of the cattle herd and the area of pastureland within a county. The pastureland rent data were from National Agricultural Statistical Service (NASS 2014) and cattle number data were from Census of Agriculture (USDA Census of Agriculture 2012). County-level pastureland area is available for 1997, 2002, 2007, and 2012 for both states from the Census of Agriculture (USDA Census of Agriculture 2012). The area data for unavailable years (i.e., 2008, 2009, 2010, and 2011) were interpolated assuming an annual average linear increase between 1997 and 2012 for the estimation of the fixed effect model and its prediction of 2001 and 2006 county-level rent per hectare of pastureland. Then, the property tax amounts were subtracted from the predicted values for 2001 and 2006 to estimate the expected annual net returns per hectare of pastureland after property tax.

A description of the steps used to estimate the expected annual return per hectare of cropland at the county level follows:

1. The ratio of livestock and poultry cash expenses to total farm production expenses was derived;
2. This ratio was multiplied by total county net cash farm income to give an estimate of net cash farm income from livestock and poultry. (Thus, net cash farm income is directly and positively correlated with farm production expenses.);

3. The estimated net cash farm income from livestock and poultry was subtracted from total net cash farm income, resulting in an estimate of net cash farm income from cropland;
4. County-level net cash farm income from cropland was divided by hectares of harvested cropland in the county; and
5. Property taxes per hectare were subtracted from net cash income from cropland per hectare for 2001 and 2006 to estimate the expected annual return per hectare of cropland after tax.

A description of the steps used to estimate the expected annual return per hectare of urban land at the county level follows:

1. Parcel-level land value ratios were obtained for counties for which parcel-level data were available by dividing assessed land value by total assessed value;
2. The parcels' land value ratios were divided by their respective plot sizes to obtain land value ratios per hectare;
3. An OLS regression was performed with the land value ratio per hectare as the dependent variable and population density in 2010 and a vector of distance variables 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 more urbanized areas that are more densely populated and closer to the city center with its associated facilities (Albouy and Ehrlich 2012) and (ii) the land value ratio does not fluctuate over time (Bourassa et al. 2011);
4. The regression coefficients and the respective census-block group data were used to estimate the average land value ratio per hectare for each census-block group;

5. The average land value ratio per hectare for each census-block group was multiplied by the respective median housing price to obtain an estimate of the median assessed land value per hectare, which was used as a proxy for the expected return per hectare of urban land for each census-block group; and

The estimates were annualized assuming 100 years and a 5% discount rate and the property tax amounts were subtracted from the annualized value to estimate the expected annual return per hectare for urban land after the tax.

S.2. Endogeneity tests for the land use and poverty alleviation models.

	Instrument Variables (IV)	Under-Identification (Kleibergen-Paap rk LM statistic)	Weak-Identification (Stock-Wright LM S statistic)	Over-Identification (P-value)	Endogenous Test (P-value)
Land use model	Natural amenity index, Urban influence index	4.065*	14.870*	-	0.04
	Instrument Variables (IV)	Under-Identification (Kleibergen-Paap rk LM statistic)	Weak-Identification (Stock-Wright LM S statistic)	Over-Identification (P-value)	Endogenous Test (P-value)
Poverty alleviation model	Slope, Elevation, Natural amenity index	6.273*	11.400*	0.252	0.06

Note: *Denotes significance at 5% level

S.3. Parameter estimates of the 1st stage land-use model

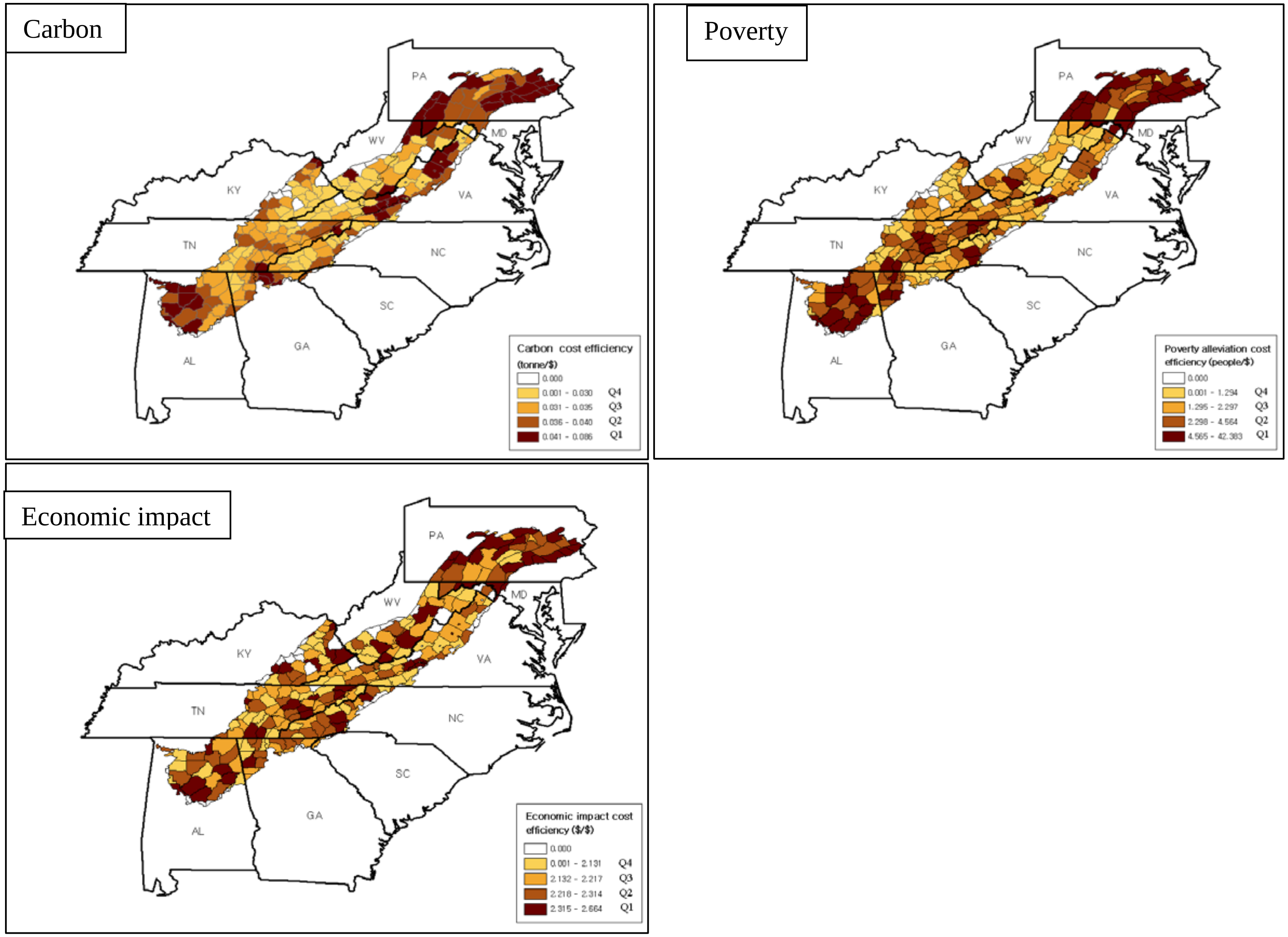
Variables	Coefficient Forest return	Coefficient Average return of Non-forested land
Geophysical variables		
Average elevation	-0.010*	0.283*
	(0.003)	(0.114)
Average slope	1.363*	-166.448*
	(0.552)	(17.868)
Appalachian forest	-6.601*	-161.723*
ecoregion	(1.761)	(56.948)
Cumberlands and southern	1.748	-445.190*
ridge and valley ecoregion	(1.790)	(57.877)
Year variable		
Year 1992 dummy variable	0.457	-11.528
	(1.185)	(38.335)
Year 2001 dummy variable	-24.019*	16.211
	(1.182)	(38.234)
Instrument variable		
Urban influence code	0.674*	-34.832*
	(0.170)	(5.500)
Natural amenity scale	-3.185*	-5.507
	(0.943)	(30.498)

Note: Numbers in parentheses are standard errors, and * denotes significance at the 5% level.

S.4. Goodness-of-fit and marginal effect results for the land-use and poverty alleviation models

	Land use model		Poverty alleviation model	
W matrices	Log-likelihood Ratio	Marginal Effect	Log-likelihood Ratio	Marginal Effect
K nearest neighbor (KNN)				
K = 4	-651.970	0.030(0.014)*	-616.441	-0.016(0.008)*
K = 5	-651.864	0.029(0.014)*	-616.625	-0.016(0.008)*
K = 9	-650.665	0.028(0.014)	**-616.681**	**-0.016(0.008)***
K = 27	-652.339	0.028(0.015)	-616.154	-0.015(0.008)
KNN * Inverse distance				
K = 4	-651.325	0.030(0.015)*	-607.863	-0.018(0.007)*
K = 5	-651.398	0.031(0.015)*	-611.761	-0.021(0.008)*
K = 9	-652.187	0.030(0.015)*	-613.181	-0.021(0.008)*
K = 27	-652.998	0.030(0.015)*	-613.843	-0.020(0.008)*
Inverse Distance	**-653.220**	**0.030(0.015)***	-616.273	-0.018(0.008)*

Note: Standard errors are in parentheses and * denotes significance at the 5% level



S.5. Spatial distribution of annual average carbon cost, poverty alleviation, and economic impact cost efficiencies during the 2001-2011 period

References

Albouy, D., and G. Ehrlich. 2012. "Metropolitan Land Values and Housing Productivity." National Bureau of Economic Research (NBER) Working Paper No. 18110, Massachusetts: Cambridge.

Bettinger, P., K. Boston, J.P. Siry, and D.L. Grebner. 2009. *Forest Management and Planning*. New York: Elsevier Academic Press.

Bourassa, S.C., M. Hoesli, D. Scognamiglio, and S. Zhang. 2011." Land leverage and house prices." *Regional Science and Urban Economics* 41 (2): 134-144.

Kentucky Division of Forestry (KDF). 2015. Kentucky's growing gold. Available at http://forestry.ky.gov

National Agricultural Statistics Service (NASS). 2014. Available at: http://quickstats.nass.usda.gov/

Smith, J.E., L.S. Heath, K.E. Skog, and R.A. Birdsey. 2006. *Methods for Calculating ForestEcosystem and Harvested Carbon with Standard Estimates for Forest Types of the United States*. General Technical Report 343. U.S. Department of Agriculture, Forest Service, Northeastern Research Station.

Timber Mart-South (TMS). 2015. Product and Services. Available at: http://www.timbermart-south.com./products.html

U.S. Department of Agriculture, Census of Agriculture. 2012. 2012 Census Publications. Available at: https://www.agcensus.usda.gov/Publications/2012/

U.S. Department of Agriculture Forest Service. 2015. FIA Data and Tools. Available at: https://www.fia.fs.fed.us/tools-data/index.php

Vita

Moonwon Soh is currently a Master student as well as a graduate research assistant in the Department of Agricultural and Resource Economics at the University of Tennessee, Knoxville and expected to graduate summer 2018. From fall 2018, he begins to pursue his Doctorate of Philosophy in the Department of Food and Resource Economics at University of Florida.