Applying Optimization and the Analytic Hierarchy Process to Enhance Agricultural Preservation Strategies in the State of Delaware

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Using agricultural preservation priorities derived from an analytical hierarchy process by 23 conservation experts from 18 agencies in the state of Delaware, this research uses weighted benefit measures to evaluate the historical success of Delaware's agricultural protection fund, which spent nearly $100 million in its first decade. This research demonstrates how these operation research techniques can be used in concert to address relevant conservation questions. Results suggest that the state's sealed-bid-offer auction, which determines the yearly conservation selections, is superior to benefit-targeting approaches frequently employed by conservation organizations, but is inferior to the optimization technique of binary linear programming that could have provided additional benefits to the state, such as 12,000 additional acres worth an estimated $25 million.

Key Words: conservation optimization, farmland protection, analytic hierarchy process, binary linear programming

In the United States, conservation groups spend an estimated $3.2 billion annually (Lerner, Mackey, and Casey 2007). While operations research techniques are frequently used in a wide variety of areas, yielding substantial success, such techniques have rarely been applied to on-the-ground conservation efforts despite the promise of providing more conservation benefits for the same budget constraint (Prendergast, Quinn, and Lawton 1999, Rodrigues and Gaston 2002, Azzaino, Conrad, and Ferraro 2002, Messer 2006). A partial explanation for this lack of adoption is that many of the initial analyses in operations research have focused on problem setups—such as covering problems that identify the minimum number of preserves necessary to protect a set number of endangered species or the maximum number of species that could be protected with a set of protected areas (e.g., Ando et al. 1998, Balmford et al. 2001, Polasky, Camm, and Garber-Yonts 2001, Moore et al. 2004, Strange et al. 2006, Cabeza and Moilanen 2001, ReVelle, Williams, and Boland 2002)—that have little relationship to the actual priorities and problems faced by conservation organizations. Secondly, conservation objectives and goals tend to be difficult to characterize, identify, and measure, and lack a common metric for success, such as profit in business applications. Furthermore, other obstacles exist for the use of these techniques for conservation, including how to identify the true decision-space for the conservation group, which must first locate willing sellers, develop the meaning of the measures of conservation benefit, assess the relative importance of one environmental characteristic over another, and provide reliable, arm's-length estimates of the costs involved (Strager and Rosenberger 2006). In this research, we show the benefits of applying operations research techniques in a setting where these latter obstacles have already been essen-

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tially overcome given the existing program priorities of the Delaware Agricultural Lands Preservation Foundation (DALPF) and its historical data of willing sellers' offers, parcels' market appraisals, GIS information on parcels' agricultural and ecological value, and a gathering of conservation experts to help determine the relative value of different agricultural and ecological measures.

The most common approach in the economics literature for evaluating the benefits of agricultural land preservation is willingness-to-pay (WTP) surveys of the public (e.g., Bergstrom, Dillman, and Stoll 1985, Halstead 1984, Kline and Wichelns, 1996, 1998, Duke and Ilvento 2004, Ozdemir et al. 2004, Johnston and Duke 2009, Duke and Johnston 2010).[1] However, other studies have explicitly examined the public's preferences for different attribute trade-offs inevitably involved in conservation settings by employing the technique of analytic hierarchy process (AHP) (e.g., Duke and Aull-Hyde 2002, Strager and Rosenberger 2006).[2]

This research provides a template by which the techniques of AHP (Saaty 1982) and binary linear programming can be used in concert to address conservation issues.[3] Binary linear programming can be structured to achieve the results that meet or exceed the results achieved using benefit-cost ratio prioritization that has recently been advocated by Duke and Johnston (2010). To illustrate the benefits of using such an approach, we present a case study involving protection of agricultural land in Delaware—a state that, along with Connecticut and Rhode Island, has been one of the most studied agricultural preservation programs (Duke and Aull-Hyde 2002, Duke and Ilvento 2004, Duke 2004, Duke and Lynch 2007, Johnston and Duke 2009).

This research contributes to the existing literature by analyzing parcel-level benefit and cost data from actual willing sellers—in this case those who applied to sell a conservation easement to DALPF—instead of making assumptions about which parcels may be offered for enrollment to the conservation organization. This research is similar to other studies that have used multiple-objective criteria and stakeholder preferences (e.g., Ferraro 2003a, Strager and Rosenberger 2006, Messer 2006). In this case, the multiple objectives were weighted by a leadership forum of 23 conservation experts from 18 conservation agencies who participated in a group AHP exercise. This analysis directly compares the overall results obtained by the existing preservation system with what would have occurred if either benefit-targeting or binary linear programming algorithms had been employed.

The context of agricultural land protection in Delaware was selected, in part, because of the rapidly increasing threat of suburban housing development to the state's rural character and historic agricultural economy and, in part, because of the richness of the data in this area as a result of more than a decade of agricultural protection. This research contributes to the literature by outlining how the operations research techniques of AHP and binary linear programming can be used in concert to promote agricultural preservation. This research directly measures the magnitude of the benefits of this approach by comparing the results both quantitatively and spatially with those derived by Delaware's historic preservation strategy and another strategy frequently used by conservation organizations in the United States.

Background

Delaware is the second smallest state in the United States (1.25 million acres) and has a population of approximately 850,000 residents, of which more than 60 percent live in the northernmost county of New Castle, which contains the historic business center of Wilmington and the University of Delaware in Newark. Over the past decade, the population of the state has been growing at rates nearly 28 percent faster than the rest of the United States. While the population of Wilmington is projected to decrease over the next 30 years, the state's population is projected to grow by more than 230,000 people (McMahon, Mastran, and Phillips 2004). Consequently, most of the population growth will be accommodated by converting agricultural lands to residential uses. Given the scale of development occurring and slated to occur, the American Farmland Trust

[1] For a recent review of this literature see Bergstrom and Ready (2009).

[2] Duke and Aull-Hyde (2002) provide a good overview of the AHP process and how it can be applied to evaluate different conservation attributes.

[3] This research effort is similar in spirit to the paper by Wilson, Reely, and Cox (1997) that sought to address the problems faced by real-world water resource management systems.

has designated the Mid-Atlantic coastal plain, including all of Delaware, to be "endangered" (American Farmland Trust 1997).

Agriculture is Delaware's top industry, with a production value of $995 million in 2007, and approximately one out of seven Delawareans is employed in agriculture or a related industry (USDA 2009). Delaware is ranked fifth in the country in terms of percentage of area used as farmland (41.2 percent of the entire state). Between 1997 and 2007, Delaware lost 600 farms and 70,000 acres of farmland, in large part due to pressures from urbanization.

DALPF was formed in July 1991. Funding comes primarily from the state but also includes local and federal matching dollars. Landowner participation in the program is voluntary and involves two components. First, landowners join the program by enrolling in an agricultural preservation district (APD). To be eligible, they must commit at least 200 contiguous acres that are devoted to agricultural and related uses or have their land within three miles of an existing APD. As noted in Duke (2004), given the wide geographic dispersion of the APDs throughout the small state, these rules mean that essentially all landowners in Delaware are eligible to become part of an APD, and thus participate in the DALPF program. Landowners who place land parcels into an APD agree to not develop the land for at least 10 years, devoting the land only to agriculture and related uses. In return, owners receive tax benefits, right-to-farm protection, and an opportunity to sell a preservation easement to the state that permanently prohibits nonagricultural development. As of 2004, there were 134,747 acres in 564 APD-designated areas. Another 411 properties encompassing nearly 76,800 acres (57 percent of the total) had been permanently protected through the purchase of preservation easements at a total expense of more than $90 million.

As is described in detail later, DALPF chooses parcels to protect using an auction mechanism and selects easements to purchase based on the *highest percentage discount* submitted by the landowner relative to the parcel's appraised market value. For example, if the easement is appraised at $1 million and a landowner offers a 40 percent discount that is accepted via the auction mechanism, DALPF pays the landowner $600,000 for the easement. This strategy (hereafter referred to as the DALPF algorithm) thereby selects parcels that cost the least relative to their appraised values. However, DALPF's algorithm does not maximize aggregate conservation benefits relative to the cost, a task that could be accomplished with optimization techniques such as binary linear programming (hereafter referred to as the OPT algorithm).

To test this hypothesis and measure the efficiency gains that might be achieved, this research built on recent work by The Conservation Fund (TCF) to develop a "green infrastructure assessment" for Kent County, Delaware (Allen et al. 2006). This effort involved development of a statewide green infrastructure network design and evaluation of a full array of conservation opportunities (Weber 2007). To assist this process, a leadership forum was convened in the city of Dover that consisted of 23 stakeholders representing 18 private conservation partners and local, state, and federal government agencies.[4] Participants were provided with overviews of various agricultural and ecological geographic information system (GIS) data sources, and forum participants provided feedback on the quality and accuracy of this information (also referred to as layers).

Forum participants were then led through an analytical hierarchy process (AHP) to establish priorities and how those priorities should be weighted in guiding agricultural conservation in Delaware (Saaty 1982). The AHP process is a quantitative method for ranking decision alternatives by developing a numerical score to rank each decision alternative based on how well each alternative meets the decision maker's criteria. AHP relies on pairwise comparisons, which is a process where stakeholders compare the value of each individual criterion with every factor in their decision making criteria, resulting in a matrix that reflects weights for all factors. When used in a conservation planning process, the stakeholders compare the relative value of GIS layers for determining the weights used in a particular benefit model.

To develop this assessment, the stakeholders were asked to evaluate Delaware's land evaluation (LE) and site assessment (SA) layers for agricultural lands and the value of the "core green

[4] For a detailed description of the leadership forum see Allen et al. (2006), pp. 9–10.

infrastructure" (Core GI) layers (Figure 1).[5] The LESA system is a widely used GIS-based decision making tool for evaluation and prioritization of agricultural lands suitable for preservation. LESA scores are traditionally assigned to an entire parcel, and thus represent the agricultural suitability of an average acre of land for a particular parcel. LESA is comprised of two parts. The LE factor measures agricultural and/or forest productivity based primarily on soils and land cover. The SA factor measures multiple impacts on long-term productivity and other environmental, economic, and social factors, including development potential, proximity to existing farming operations, utilization of farm programs, whether the farm is owner-occupied, and the biodiversity value of the parcel.

In an effort to identify and prioritize the areas of greatest ecological importance within the state's natural ecosystems, Delaware's Core GI was designated from a series of statewide GIS layers. The Core GI is defined as an interconnected network of natural areas, green spaces, and working landscapes that protect natural ecological processes and support wildlife (Allen et al. 2006). Designation of the Core GI is based on the principles of landscape ecology and conservation biology, providing a scientifically defensible framework for green infrastructure protection statewide (Benedict and McMahon 2006). Specifically, core forests, wetlands, and aquatic systems were delineated based on natural ecosystems in the state that generally were contiguous, undisturbed natural features meeting certain size and quality thresholds (Weber 2007).

For the leadership forum, a manual approach was used by creating a written questionnaire that included pairwise comparisons for each factor involved in five benefit measures: LE, SA, Core Forests, Core Wetlands, and Core Aquatic Systems.[6] The results from the questionnaires were tabulated after the meeting and entered into Expert Choice™ software, which calculated the final benefit weights. These benefit weights were added to GIS layers in ESRI ArcGIS™ software for each benefit measure, creating a raster GIS surface representing relative benefit values. The spatial analysis used a technique called "zonal statistics," which is an ESRI ArcToolbox function that calculates the mean for all raster surface values that fall within a parcel's boundaries. The benefit values were applied to individual parcels, resulting in a benefit value representing the average value for each benefit measure for each parcel. The AHP process with the leadership forum defined agricultural benefits using the scores of three factors—Core GI, LE, and SA. The results of this process were that the SA benefit measurement being weighted the most, 56 percent, with the Core GI and LE measurements being weighted 32 percent and 12 percent, respectively.

Preservation Strategies and Algorithms

To determine appropriate measures of benefits and costs, we compared the results of three primary tools: the selection algorithm used by DALPF, optimization using binary linear programming (OPT), and benefit targeting (BT)—the latter being the most common algorithm used by conservation groups. In this research, the OPT and BT algorithms use the benefit measurements derived from the AHP pairwise comparisons, while the DALPF algorithm utilizes a non-AHP method, percent discount from appraisal value. Each algorithm recommends a different selection of agricultural parcels for preservation by conservation easement. A commonality among them is the method by which the benefits and costs of a particular parcel are measured.

First, consider an A_{ij} matrix where $i = 1, 2, \ldots, I$ denotes an index for parcels of land, and $j = 1, 2, \ldots, J$ denotes the index of benefits. The conservation value of the ith parcel for the jth attribute is thus denoted by $A_{ij} \geq 0$. Each of the J attributes is assigned a subjective weight that is denoted W_j. This weight reflects the relative importance a conservation organization gives to that attribute. Consequently, the conservation value (V_i) of the ith parcel is given by

$$(1) \qquad V_i = \sum_{j=1}^{J} W_j A_{ij} \ .$$

[5] Forum participants also considered data layers related to forestry that had been developed by the state and other GIS layers developed by TCF related to the quality of other natural resources, water quality, and housing development. However, forum participants decided that these other data sets were not relevant to agricultural land protection in Delaware so they are excluded from this analysis.

[6] See Weber (2007, p. 30, Figure 3) for an illustration of the pairwise comparisons used in the project.

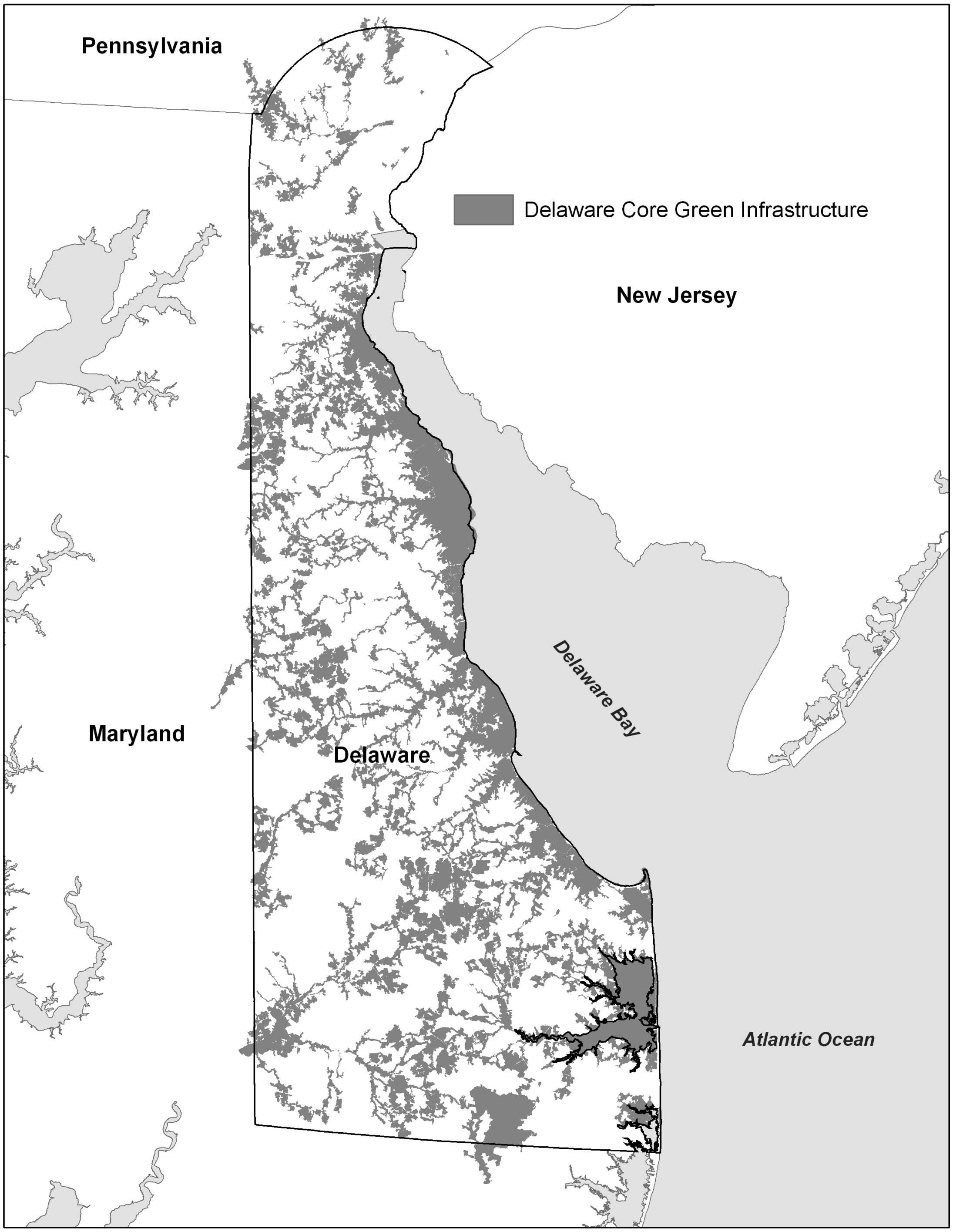

Figure 1. Map of Core Green Infrastructure Areas in the State of Delaware

Thus, the three algorithms analyze identical benefit measurements, benefit-weighting priorities determined by AHP, and the cost information for each parcel. As a result, differences between the algorithm selections come not from using different data but from how the measurements and weights are used to select parcels for preservation.

The program costs for each parcel, C_i, are calculated by multiplying the appraised market value for the parcel, M_i, multiplied by the discount, D_i, that the landowner submits in the sealed-bid auction:[7]

$$C_i = D_i * M_i . \quad (2)$$

Benefit Targeting (BT) Algorithm

The BT, also referred to as a rank-based algorithm, is the selection algorithm commonly used by conservation organizations (Azzaino, Conrad, and Ferraro 2002, Ferraro 2003b, Naidoo et al. 2006, Messer 2006, Wilson et al. 2006). In this approach, the organization ranks potential parcels for conservation from highest to lowest based on the parcels' total benefits. BT can be viewed as a type of "greedy agent" algorithm: once all parcels have been ranked, the agency seeks to purchase easements on parcels with the highest conservation values that it can afford from the set of top-ranked unprotected parcels. Through an iterative process, easements are acquired until the agency's budget, B, is exhausted.

The BT selection algorithm can be written formally as follows. Let $R(\cdot)$ denote the rank operator over all conservation values, V_i, and let $R_i = R(V_1, \ldots, V_I)$ be the rank of the ith parcel. The parcel(s) with the highest V_i receive a rank of 1. Let $X_i = \{0,1\}$, where $X_i = 0$ indicates that the ith parcel is not recommended for acquisition, and where $X_i = 1$ indicates that the ith parcel is recommended for acquisition. The resulting vector, $X = [X_1, X_2, \ldots, X_I]$, represents the portfolio of the conservation organization, and initially X is a vector of zeros. If the conservation organization uses its financial resources to acquire parcel $i = 7$, X_7 changes from $X_7 = 0$ to $X_7 = 1$.

After all of the parcels have been ranked, they are arrayed in the following format:

RANK	PARCELS	COST
1	X_i, X_k	C_i, C_k
2	X_l	C_l
3	X_m	C_m
.	.	.
R	X_r	C_r

If parcels have equal rankings, the conservation organization seeks to acquire an easement for the parcel that costs the least. For instance, if parcels i and k are ranked the highest and have the same conservation value and $C_i < C_k$, then

$$\begin{array}{lll} X_i = 1 & \text{if} & C_i \le B \\ X_i = 0 & \text{if} & C_i > B \\ X_k = 1 & \text{if} & C_k \le B - X_iC_i \\ X_k = 0 & \text{if} & C_k > B - X_iC_i. \end{array}$$

The conservation organization would then continue working through the list of ranked parcels until all available money was exhausted.

Despite its widespread use in the conservation community, BT can lead to inefficient results from both an economic and conservation perspective (Underhill 1994, Rodrigues, Cerdeir, and Gaston 2000, Rodrigues and Gaston 2002, Messer 2006). The source of the problem is that a parcel's price is explicitly factored into the decision process only to determine whether there is enough money still available or in the uncommon cases where there is a tie in the benefit ranking.

DALPF Algorithm

DALPF historically has defined a parcel's benefits purely by the price of the easement offered by the landowner within a sealed-bid, discriminatory auction mechanism. For each annual funding cycle, DALPF pays for an appraisal of the parcel's easement value to any landowner participating in an APD who expresses an interest in selling his or her development rights. After receiving the appraisal, the landowner can choose to continue the process by offering a percentage discount on the value of the easement by way of a sealed bid. Upon receiving the landowners' offers, DALPF ranks the offers by the percentage of the appraised value offered as a discount and purchases easements from owners who make the best of-

[7] In this analysis, parcel costs refer only to the DALPF program expenditures associated with purchasing the easement and do not take into account the government or society costs which would need to include other factors, such as the reduction of taxes due to the parcel's preserved status.

fers—those with the *largest* discounts—until the budget for that particular cycle is exhausted. This auction system can be characterized as a "receive what you offer" auction (also referred to as a discriminative auction) since it pays each landowner a different amount based on the discount offered. Finally, the selected parcels are professionally surveyed and the landowner receives payment based on the percent discount offered and the survey results.

An advantage of the DALPF selection algorithm is that, by making cost the sole determinant of the selection algorithm, by definition DALPF secures land with the greatest easement value given its budget constraint. This goal of maximizing total easement value is different than the objective of most agricultural protection programs, which tend to seek to maximize the number of acres protected (Lynch and Musser 2001). However, the DALPF system does not guarantee that parcels with the greatest agricultural or other ancillary ecosystem values are the ones that are protected. That occurs only if, by chance, the owners of those lands offer the largest discounts.[8] Of particular concern is whether owners of agricultural land of marginal value may offer DALPF a high discount in part because there are few other buyers given the land's low quality. Similarly, the appraised value of an easement for farms near growing urban areas may be high due to development potential, and DALPF would therefore be acquiring parcels that, even when discounted the most, are more expensive than parcels of similar quality that do not face such development pressure.

Formally, the DALPF algorithm can be expressed as a variant of the BT algorithm since it ranks the percent discounts from highest to lowest, and then, like a benefit-oriented, "greedy" agent, dictates purchases of easements for parcels with the highest ranking discounts until the budget, B, is exhausted. In this case, under BT, let $P(\cdot)$ denote the rank operator over all percentage discounts, D_i, and let $P_i = R(D_1, \ldots, D_I)$ be the rank of the ith parcel, such that the parcel with the greatest value for D_i receives a rank of 1. Again, let $X_i = \{0,1\}$. After ranking all of the parcels, DALPF proceeds down the ranked list, purchasing easements until the available money is exhausted. Consider three parcels: i, k, and l.

RANK	PARCELS	PERCENTAGE DISCOUNT
1	X_i	D_i
2	X_k	D_k
3	X_l	D_l

DALPF would select acquisitions in a similar manner but would select the parcel with the greatest benefit, V_i, if two parcels received the same rank. Thus,

$$X_i = 1 \quad \text{if} \quad D_i \le B$$
$$X_i = 0 \quad \text{if} \quad D_i > B$$

$$X_k = 1 \quad \text{if} \quad D_k \le B - X_i D_i$$
$$X_k = 0 \quad \text{if} \quad D_k > B - X_i D_i$$

$$X_l = 1 \quad \text{if} \quad D_l \le B - (X_i D_i + X_k D_k)$$
$$X_l = 0 \quad \text{if} \quad D_l > B - (X_i D_i + X_k D_k),$$

and so on.

Optimization (OPT) Algorithm

The OPT algorithm uses the same parcel-specific benefit information as BT and the DALPF algorithm but, in addition, it specifically accounts for the cost of each potential purchase and seeks to identify the most cost-effective solution. Thus, instead of identifying the individual parcels with the greatest benefits, OPT considers all possible combinations of parcels given the budget constraint and selects a set of acquisitions that guarantees the maximum possible total benefit. To consider the vast number of possible combinations involved, OPT is computer-driven and uses the branch-and-bound algorithm to solve the binary linear programming problem. In this study, the calculations were done using the Optimization Decision Support Tool that incorporates the Premium Solver Platform (version 6.5).

[8] The process of selecting parcels based solely on the percent discount offered can be compared to a grocery shopper who buys a food item only because it is marked down in price more than any other item. However, the item on sale may not be very desirable to the shopper. Likewise, problems can arise if the foods with the most deeply discounted prices are also the most expensive (for instance, caviar or truffles). Thus, they are relatively more expensive, even with the large discount, than other high-quality foods with a smaller percentage cut in price.

If all of the parcels' acquisition costs and all of the parcels' benefits scores are identical, OPT, DALPF, and BT would yield an identical, optimal set of parcels. However, in the vast majority of real-world cases, these costs and benefits are heterogeneous. In general, the efficiency of OPT is greatest when parcels' benefits and costs are positively correlated (Babcock et al. 1997), especially when costs are relatively more variable than benefits (Ferraro 2003b).

OPT uses binary linear programming, which limits the standard integer linear programming of a branch-and-bound algorithm to values of either 0 or 1. In this case, the binary choice is to "protect" ($X_i = 1$) or "not protect" ($X_i = 0$) a particular parcel. Unlike the BT or DALPF algorithms, the OPT algorithm takes into account both benefits and costs for each parcel at each step of the process, evaluates all of the possible purchase combinations that lie within the specified budget constraint, and selects the portfolio that yields the greatest possible aggregate conservation value, given by $V(X)$, subject to a budget constraint (B):

$$\text{(3)} \qquad \text{Max } V(X) = \sum_{i=1}^{I}\sum_{j=1}^{J} X_i W_j A_{i,j}$$

$$\text{(4)} \qquad \text{s.t. } \sum_{i=1}^{I} C_i X_i \leq B\,.$$

For this research, the tolerance in the Premium Solver Platform was set to zero and no problems with nonconvergence were encountered, as the problem was solved within a couple of seconds.

Data

This analysis evaluates the efficiency of DALPF's selection algorithm by comparing its historical results with estimations of what BT and OPT would have accomplished given the same budget and the same set of potential parcels to acquire. The analysis considers data provided by Delaware's Department of Agriculture (DDA) related to 524 parcels. All of the parcels were located in designated APDs and the landowners had received a third-party appraisal (a necessary precursor to selling the development rights to DALPF).

Traditionally, after the auction cycle is completed, DDA compiles the data for all successful sellers and uses aggregate information regarding the number of acres preserved, the average bid of the successful sellers, and the total easement value protected. This information is then released in a public announcement regarding the successes of the program. The data from unsuccessful sellers is not generally reported to the public other than being part of the calculation of the total number of bids that were received for a given cycle. For this research, DDA staff made available data for the approximately 124 parcels that were not selected due to the landowner submitting a non-winning discount offer (an offer that was lower in percentage terms than the lowest accepted discount offer). We then matched to each of the 524 parcels the agricultural and ecological benefit information derived by TCF's GIS analysis of Delaware's Green Infrastructure (Allen et al. 2006) that was presented to the conservation leadership forum. Of the 524 parcels acquired, 509 (97.1 percent) provided sufficient data for use in this research.[9]

In this set of 509 parcels, the average size was 171.7 acres, with the smallest being 4.7 acres, the largest being 1,092.1 acres, and a standard deviation of 152.2. Total acreage for all 509 parcels was 87,406.7. A parcel's overall LESA value was calculated based on the leadership forum's weightings for the LE and SA benefit measures, where the SA measure was weighted more than four times greater than the LE measure as previously described. The per-acre average LESA scores ranged from 38.3 to 90.4, with a mean of 69.2 and a standard deviation of 8.9. The range of per-acre Core GI scores was slightly larger, from 11.0 to 80.3, and had a larger standard deviation of 14.3 since the average and median values for the Core GI were considerably lower—23.2 and 16.5, respectively. The highest percentage discount offered by a landowner was 100 percent (donation) and the lowest was 0 percent (no discount offered); the average discount was 42.3 percent.[10]

[9] The other 15 land parcels presented significant data problems, such as missing appraisal values, multiple records for the same project in one cycle, or inconsistent measures of the parcel's size.

[10] This research makes the assumption that landowners would have submitted the same discounts regardless of whether the DALPF, OPT, or BT algorithms were employed by the state for agricultural protection. This clearly is a strong assumption as landowners would be expected to respond to the incentives provided by the different selection algorithms. The potential bias is likely greatest for the BT as owners of high quality agricultural lands would have little incentive to offer any discount if they knew that the state's acquisition decision would be

Given these discounts, DDA would have needed a total budget of $127.7 million to acquire all 509 parcels. The average parcel cost $250,884 after the discount was applied. The cost of the most expensive parcel exceeded $3.5 million, even after a 39 percent discount. The average appraisal value per acre for the sample was $2,476.20, providing an average price of $1,585.70 per acre after discounts were applied. In the first nine cycles completed, DALPF purchased rights for 382 of the 509 parcels (75.0 percent). The cost of the 382 parcels summed to slightly less than $93 million; therefore, a budget constraint of $93 million was set for use with all three selection algorithms. To facilitate comparisons of relative efficiency, the algorithms were applied to a single data set of all 509 parcels representing a single simultaneous cycle.[11]

Data for the two agricultural benefit measures (LESA and Core GI) were normalized to a scale from zero to one and then scaled by the size of the parcel under consideration. Normalization establishes a common metric for each of the attributes while preserving the parcel's scores for each attribute. The normalization equation is $NV_{ij} = A_{ij} \big/ A_j^{\max}$, where $A_j^{\max}$ represents the highest scores for each of the agricultural benefit measures. Consequently, a parcel with the highest attribute score has a normalized score of 1 for that attribute. Since the agricultural benefit measures represent an *average* value for the entire parcel, scaling the score by the number of acres in the parcel was necessary to ensure that the algorithms did not artificially favor small parcels (see the Appendix for an example and further explanation).

Results

Table 1 and Figure 2 show the results of when the DALPF, BT, and OPT algorithms are used to select acquisitions from the set of 509 parcels given a $93 million budget. The first scenario shows the aggregate results from the DALPF algorithm. The DALPF algorithm yielded the highest levels of total easement value at more than $162 million for the $93 million spent.[12] This result is not surprising, since, as discussed above, by definition the DALPF algorithm makes the discount from total easement value its sole decision criteria in its auction mechanism—and thus by definition it maximizes the total easement value given the program applicants. The average discount was 47.4 percent. DALPF protected 65,683.4 acres with an aggregate LESA score of 4,460,437 and aggregate Core GI score of 1,736,429.[13] Of the 386 parcels protected, 12.4 percent were in mostly developed New Castle County, while 47.9 percent and 39.6 percent were in the agriculturally rich counties of Kent and Sussex, respectively.[14]

The BT and OPT analyses defined benefits according to the AHP results from the leadership forum, which gave a 68 percent weight to the combined LESA scores and a 32 percent weight to the Core GI scores.[15] The aggregate results from the BT analysis were consistent with those of the DALPF algorithm in terms of the number of acres protected (just 71.5 acres fewer), the aggregate LESA score (1.3 percent higher), and

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based solely on the land's agricultural quality. Therefore, the estimates of the inefficiencies of the BT are likely a lower bound, as acquisition costs would have been expected to increase. However, economic theory offers little insight on whether landowners would submit different offers when facing the OPT versus the DALPF algorithms. While this empirical question is beyond the scope of this research, laboratory economics experiments may be able to provide some insights into this issue.

[11] By treating all of the acquisition decisions as a simultaneous choice, this analysis does not take into account uncertainty. For good examples of how to account for decision over time see Messina and Bosetti (2006) and Messina and Bosetti (2003).

[12] Total easement value measures the *undiscounted* appraisal value of the parcel and is a statistic frequently used by DALPF as an estimation of how its protection strategy yields benefits worth more than the acquisition costs.

[13] Unlike number of acres, aggregate scores for LESA and Core GI are not necessarily intuitive to interpret since they have been scaled by parcel size. However, the numbers are cardinal.

[14] In many conservation contexts, especially those dealing with habitat protection, the issue of adjacency is a top priority and is an important area of research [for instance, see Hof and Bevers (2000)]. However, in the context of agricultural preservation, adjacency is not as important, as one of the goals is to retain a healthy agricultural economy throughout the state. Therefore, issues of adjacency will not be specially addressed in this research beyond the discussion of the spatial distributions evident in Figure 3.

[15] This analysis does not examine the sensitivity of the results to the benefit weights provided through the AHP process, but instead seeks to make direct comparisons between outcomes from different algorithms given historical data from willing sellers while holding constant a set of benefit weights that were derived via an AHP process. Changes in the weighting would certainly affect which parcels were acquired by the BT and OPT algorithms and would also affect the aggregate results for the DALPF algorithm (though changes in the weighting would not change which parcels were selected by DALPF). Even with changes in the weighting of the different attributes, the research's general finding that the OPT algorithm would provide significantly higher agricultural and ecological benefits compared to the DALPF or BT algorithms would likely remain unchanged. For examples of how sensitive results can be to changes in weights for multiple objectives, see Malczewski (1999), Cattaneo et al. (2006), and Strager and Rosenberger (2007).

Table 1. Benefit Results

					Number of Parcels					
Algorithm	Benefit Scenario	No. of Parcels	Total Cost	Total Easement Value	New Castle	Kent	Sussex	Acres	LESA (scaled)	Core GI (scaled)
DALPF	Highest percentage discount	386	$92,986,682	$162,582,371	48	185	153	65,683.4	4,640,437	1,736,429
BT	LESA (68%) Core GI (32%)	237	$92,997,985	$151,706,558	29	121	87	65,611.9	4,701,728	1,831,548
OPT	LESA (68%) Core GI (32%)	447	$92,999,225	$159,410,710	41	230	176	79,129.5	5,597,928	2,067,438

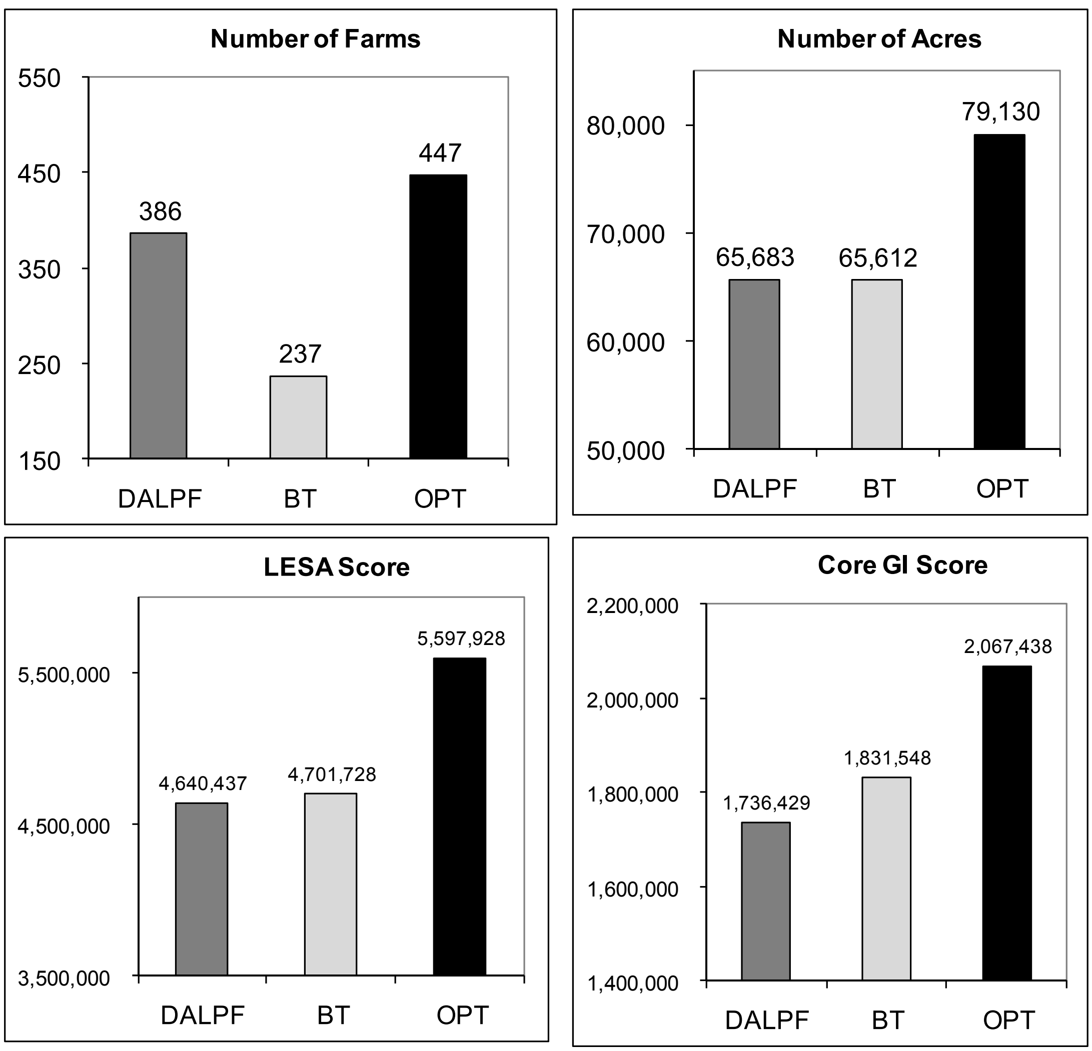

Figure 2. Results of Benefit Scenarios

distribution of the protected parcels across the state (see Table 1). The most significant difference was that BT produced those results by selecting easements on 38.6 percent fewer parcels and earning $10.9 million *less* in total easement value. Compared to DALPF's algorithm, BT selected, on average, larger parcels (an average of 277.1 acres for BT compared to 170.2 acres for DALPF) that offered higher average scores for LESA (19,839 compared to 12,022) and Core GI (7,728 compared to 4,499).

The OPT algorithm produced more conservation benefits than either the DALPF or BT algorithms, as it protected 447 parcels (15.8 percent percent more than DALPF and nearly double the number protected by BT) with the same $93 million budget (Table 1). This outcome is expected since the DALPF algorithm gives sole priority to the percent discount offered by the landowner and thus maximizes easement value. If the sole benefit used in OPT was easement value instead of the number of acres and the LESA and Core GI scores, then the results from the DALPF algorithm and OPT would have been identical.

OPT also protected 20.5 percent more acres (13,446.1) and yielded aggregate LESA and Core GI values that were 20.6 percent and 19.1 percent higher, respectively, than DALPF. Similarly, in comparison to BT, the OPT algorithm protected 20.6 percent more acres and produced aggregate LESA and Core GI values that were 19.1 percent and 12.9 percent higher. Importantly, these gains in conservation benefit did not occur by purchasing smaller farms—in fact, the size of the average farm protected by OPT was 7 acres (4.0 percent) larger than the one protected by the DALPF algorithm.

Another means for evaluating efficiencies or the relative cost effectiveness is to estimate the difference in cost between the sets of acquisitions produced by each algorithm. Using the set of 509 parcels described previously, we calculated the potential savings of using OPT. Recall that the OPT algorithm would have acquired 447 parcels at a total cost of $92,999,225 and that this portfolio of parcels would have yielded 79,129.5 acres. We allowed the DALPF algorithm to spend additional money (beyond the original budget of $93 million) until it achieved an equivalent or slightly greater number of acres than the OPT selection. As seen in Table 2, DALPF required $113,693,669 to acquire 79,175.8 acres—an additional cost of $20.7 million. A similar analysis for BT resulted in spending an additional $19.8 million to achieve an equivalent number of acres. In both cases, the additional funds provided aggregate values for the LESA and Core GI benefits that were quite similar to those achieved by OPT with the budget of $93 million (Table 2).

It is interesting to note that, as demonstrated in Figure 3, despite a wide range in the number of parcels selected—from a low of 237 by BT to a high of 447 with OPT—the geographic distribution of the parcels is fairly similar. For example, the share of parcel acquisitions located in Kent County was similar for all three applications—47.9 percent for DALPF, 51.5 percent for BT, and 51.9 percent for OPT. The next largest group of parcels came from Sussex County and the results were similar—39.6 percent for DALPF, 36.7 percent for BT, and 39.4 percent for OPT. This result would be beneficial from a political perspective, as OPT's statewide efficiency gains did not require one county being favored more than another any more than the DALPF algorithm has historically done.[16]

For the sake of making the direct comparisons presented above, this analysis assumes that landowners would have submitted the identical discounts regardless of which selection algorithms were used by the state. This clearly is a strong assumption, as landowners would be expected to respond differently to the incentives provided by the different selection algorithms. For instance, owners of high quality agricultural lands would have little incentive to offer any discount if they knew that the state's acquisition decision used the BT algorithm and would be solely based on the land's agricultural quality. Therefore, the results presented here are likely to understate the efficiency loss of using the BT algorithm. However, economic theory offers little insight on the more important question of whether landowners of different types of land would submit different discount offers when facing the OPT versus the DALPF algorithms. Ultimately, this is an empirical question beyond the scope of this research.

[16] Additional inspection of Figure 3 shows that the OPT acquires a larger number of possible parcels in the southwest section of Kent County and northwest Sussex County.

Table 2. Cost Savings

Algorithm	Acres	LESA (scaled)	Core GI (scaled)	Number of Parcels	Total Cost	Difference from OPT
OPT	79,129.5	5,597,928	2,067,438	447	$92,999,225	--
DALPF	79,175.8	5,600,126	2,082,259	460	$113,693,669	$20,694,444
BT	79,161.8	5,605,649	2,106,844	355	$112,798,298	$19,799,073

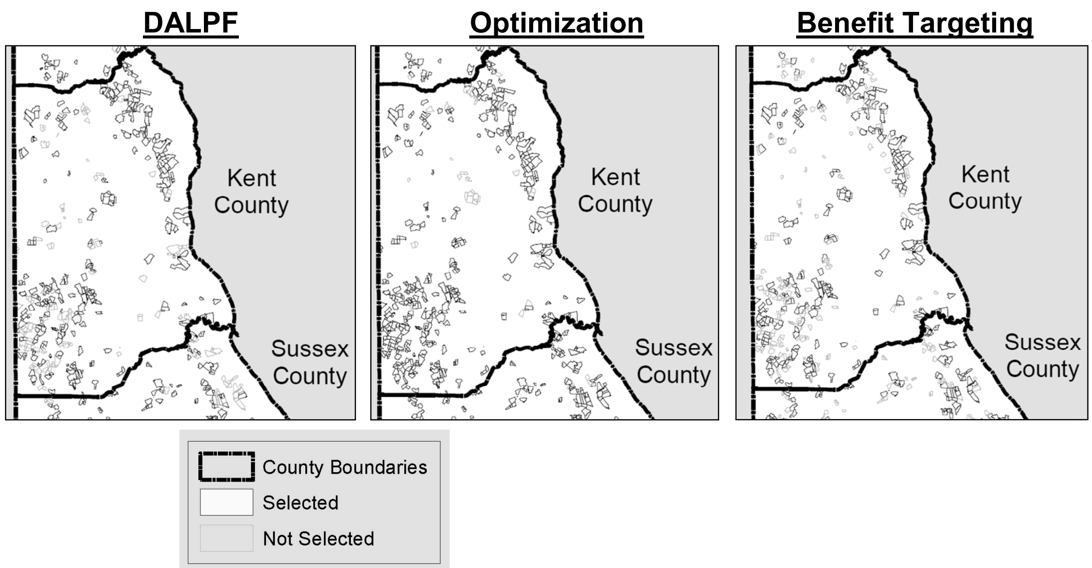

Figure 3. Selected Parcels by Preservation Algorithm: Kent County, Southern New Castle County, and Northern Sussex County, Delaware

Conclusion

This research has applied the operations research techniques of the analytical hierarchy process (AHP) and optimization through binary linear programming to the problem of agricultural preservation in the state of Delaware. This research demonstrates how these two techniques can be used in a complementary manner to develop an analysis that is meaningful for on-the-ground conservation efforts.

This analysis of the selection process used by the Delaware Agricultural Lands Preservation Foundation (DALPF) shows that the current system offers a number of positive characteristics, such as a competitive auction structure and provision of free appraisals to increase the number of potential sellers. DALPF's algorithm maximizes the total aggregate easement value and yields aggregate results that are consistent with those generated by benefits targeting (BT), an algorithm that is commonly used in conservation settings. However, DALPF's algorithm can become considerably more effective by more appropriately incorporating cost into its existing structure. For example, in Delaware, the use of binary linear programming could have preserved 13,446 more acres for the same cost. An alternative way of viewing this gain in cost effectiveness is that optimization could have allowed DALPF to preserve additional agricultural lands worth an estimated market value of $20.7 million.[17]

[17] While the emphasis of this research has been on agricultural land protection, the analysis has direct implications for Delaware's forest and coastal protection efforts as well.

An area for future research is how DALPF's auction system affects the discount rate of offers over time. As discussed earlier, DALPF currently uses a sealed-bid discriminative auction structure (the landowner receives a sales price based on the percent discount offered). While this structure has intuitive appeal, it has been known in perfect-information settings to engender price inflation in multiple rounds because a seller has an incentive to inflate the offer above his or her true willingness to sell. Furthermore, the value of the smallest percentage discount from the previous cycle tends to establish a focal point that can discourage higher percent discount offers in future rounds. In the DALPF context, the worry is that these factors would lead to smaller discount rate offers over time, which would be suboptimal from a conservation perspective. Since the average discount offered has been 42.3 percent, it appears that sellers to DALPF have been motivated by factors other than simple profit maximization. However, this trend may change over time and thus DALPF may want to explore the ability of alternative auction designs to ensure larger discounts. A cost-effective environment for testing alternative auction designs is an experimental economics laboratory.

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Appendix

The need for scaling variables that represent the parcel’s average benefit value can be illustrated by considering a hypothetical scenario of four parcels being considered for acquisition with a budget of $300,000. Recall that LESA scores are traditionally assigned to an entire parcel, and thus represent the agricultural suitability of an average acre of land for a particular parcel.

	Parcel LESA Score	Acres	Scaled LESA Score (parcel LESA score × acres)	Acquisition Cost
Parcel A	40	30	1,200	$120,000
Parcel B	50	25	1,250	$100,000
Parcel C	60	20	1,200	$80,000
TOTAL (3 parcels)	150	75	3,650	$300,000
Parcel D	100	100	10,000	$300,000
TOTAL (1 parcel)	100	100	10,000	$300,000

Parcels A, B, and C each have a relatively low parcel LESA score (40 to 60 out of a possible

100), are small in size (ranging from 20 to 30 acres), and have acquisition costs of $12,000, $10,000, and $8,000, respectively. In contrast, Parcel D is a 100-acre parcel with a parcel LESA score of 100 and an acquisition cost of $300,000. If the objective is to maximize LESA benefits, then without scaling the variable by the parcel size, the OPT would select the three small, low-quality parcels at a total cost of $300,000, because these three parcels would yield a total LESA score of 150. In contrast, the total LESA score from spending the entire budget on Parcel D is just 100. However, this result is clearly not optimal from a real-world perspective because individually the three separate parcels had benefit scores that were individually 20 percent to 30 percent as good as Parcel D, and combined they total only 75 acres.

Scaling the LESA score by the size of the parcel size (multiplying the parcel LESA score by the number of acres) solves this problem. In this case, by seeking to maximize the scaled benefit of LESA, the OPT would select Parcel D with its $300,000 budget since it yields a higher aggregate score of 10,000 instead of 3,650.