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# APPLYING OPTIMIZATION AND THE ANALYTIC HIERARCHY PROCESS TO ENHANCE AGRICULTURAL PRESERVATION STRATEGIES IN THE STATE OF DELAWARE

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

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**Abstract**
Using agricultural preservation priorities derived from an analytical hierarchy process by 23 experts from 18 agencies in the State of Delaware, this research uses weighted suitability attributes to evaluate the historical success of the State 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 on 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.

**Keywords:** Conservation Optimization, Farmland Protection, Analytic Hierarchy Process.

**JEL Codes: C6, Q2.**

## I. Introduction

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 (Prendergast et al. 1999; Rodrigues and Gaston 2002; Messer 2006), despite annual expenditures by conservation groups in the United Sates of an estimated $3.2 billion annually (Lerner, Mackey, and Casey 2007). A partial explanation for this lack of adoption is that many of the initial analyses in operations research have focused on problem set-ups—such as covering problems that identify the minimum numbers 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 et al. 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 conservations 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, arms-length estimates of the costs involved.

This research seeks to address these issues and provide a meaningful template by which groups can employ techniques of analytic hierarchy process (AHP) and linear programming in concert to address conservation issues (Saaty 1982).[1] To illustrate the benefits of using such an approach, we present a case study involving protection of agricultural land in Delaware. By analyzing parcel-level data from willing sellers during the first decade of operation of the Delaware Agricultural Lands Preservation Foundation (DALPF) and convening a leadership forum of 23 experts from 18 conservation agencies and having them participate in an AHP exercise, this analysis directly compares the results obtained by the existing preservation system with what would have occurred if operations research techniques 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 quantitative and spatially with those derived by the State of Delaware's historic preservation strategy and another strategy frequently used by conservation organizations in the United States.

## II. 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% live in the northern most county of New Castle, which contains the historic business center of Wilmington. Over the past decade, the population of the state has been growing at rates nearly 28% faster than the rest of the United States. While the population of Wilmington is projected to decrease over the next

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

30 years, the State's population is project to grow by more than 230,000 people (McMahon et al. 2004). Consequently, most of the population growth will be accommodated by converting agricultural lands to housing projects. Given the scale of development occurring and slated to occur, the *American Farmland Trust* 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 $837 million in 2002 and one out of seven Delawareans is employed in agriculture or a related industry (USDA Natural Resources Conservation Service 2002**)**. Delaware has 2,300 farms and is ranked 5$^{th}$ in the country in terms of percentage of area used as farmland (41.2% of the entire state). Between 2002 and 2006, Delaware lost 45,000 acres of farmland to urbanization (USDA National Agricultural Statistics Service 2006**)**. In response to this growth pressure, Governor Ruth Ann Minner in March 2001 launched the *Livable Delaware* agenda which established the goal of protecting 50% of the "remaining working agricultural land".

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). They must commit at least 200 contiguous acres that are devoted to agricultural and related uses. 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 APDs and related APD "expansions." Another 411 properties encompassing nearly 76,800 acres (57% of the total) had been permanently protected through the purchase of preservation easements at a cost of more than $90 million. As is described in detail later, DALPF chooses parcels to protect using a sealed-bid, discriminatory auction and selects easements to purchase based on the *highest percentage discount* submitted by the landowner relative the land's appraised market value. For example, if the easement is appraised at $1 million and a landowner offers a 40% discount that is accepted by DALPF, the landowner receives a payment of $600,000 for the easement. This strategy (hereto referred 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), a leading nonprofit conservation group in the United States that aims to protect "working landscapes" such as agricultural and forest lands. TCF describes itself as having:

> a balanced, nonadvocacy, nonmembership approach to conservation, one that blends environmental and economic goals and objectives. Since its founding in 1985, the Fund has helped its partners safeguard wildlife habitat, working farms and forests, community greenspace, and historic sites totaling nearly 6 million acres nationwide.

TCF was awarded funds from the U.S. National Fish and Wildlife Foundation and private foundations to develop a “green infrastructure assessment” for Kent County in Delaware that involved development of a statewide green infrastructure network design and evaluation of a full array of conservation opportunities (Allen and Phillips 2006). To assist this process, TCF convened a leadership forum in the City of Dover that consisted of 23 stakeholders representing 18 public and private conservation partners (see Table 1). TCF provided the participants 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).

TCF then administered a modified analytical hierarchy process (AHP) to forum participants 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 suitability model.

To develop this assessment, TCF asked the stakeholders to evaluate Delaware’s land evaluation and site assessment (LESA) layers for agricultural lands and the value of the “core green infrastructure” (Core GI) layers generated by TCF (Figure 1).[2] The LESA system is a widely used GIS-based decision-making tool for evaluation and prioritization of agricultural lands suitable for preservation. LESA is comprised of two parts. The land evaluation (LE) factor measures agricultural and/or forest productivity based primarily on soils and land cover. The site assessment (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, TCF designed Delaware’s Core GI 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. 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, TCF delineated core forests, wetlands, and aquatic systems based on natural ecosystems in the state that generally were contiguous, undisturbed natural features meeting certain size and quality thresholds (Allen and Phillips 2006).

For the leadership forum, TCF used a manual approach by creating a written questionnaire that included pairwise comparisons for each factor involved in five suitability algorithms: LE, SA, Core Forests, Core Wetlands, and Core Aquatic Systems**.** The results from the questionnaires were tabulated after the meeting and entered into Expert Choice™ software, which calculated the final suitability weights. These suitability weights were added to GIS layers in ESRI ArcGIS™

[2] 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.

software for each suitability algorithm, creating a raster GIS surface representing relative suitability values. Using a spatial analysis technique called zonal statistics, the suitability values were applied to individual parcels, resulting in a suitability value representing each algorithm for each parcel. The results from the AHP exercise defined agricultural suitability using the scores of two factors—LESA (78%) and Core GI (32%).

## III. 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 most common algorithm used by conservation groups. 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 $i^{th}$ parcel for the $j^{th}$ 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 $i^{th}$ parcel is given by

$$V_i = \sum_{j=1}^{J} W_j A_{ij} \,. \tag{1}$$

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.

*Benefit Targeting (BT) Algorithm*

The BT, also referred to as a rank-based algorithm, is the selection algorithm commonly used by conservation organizations (Naidoo et al. 2006**;** Ferraro 2003; 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 $R(\bullet)$ 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 $i^{th}$ parcel. The parcel(s) with the highest $V_i$ receive a rank of 1. Let $X_i = \{0,1\}$ where $X_i = 0$ indicate that the $i^{th}$ parcel is not recommended for acquisition and $X_i = 1$ indicate that the $i^{th}$ 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* have the same conservation value and $C_i < C_k$, then:

$X_i = 1$ if $C_i \leq B$

$X_i = 0$ if $C_i > B$

$X_k = 1$ if $C_k \leq B - X_iC_i$

$X_k = 0$ if $C_k > B - X_iC_i$ .

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

$X_l = 1$ if $C_l \leq B - (X_iC_i + X_kC_k)$

$X_l = 0$ if $C_l > B - (X_iC_i + X_kC_k)$

$X_m = 1$ if $C_m \leq B - (X_iC_i + X_kC_k + X_lC_l)$

$X_m = 0$ if $C_m > B - (X_iC_i + X_kC_k + X_lC_l)$

and so on.

Despite its widespread use in the conservation community, BT can lead to inefficient results from both an economic and agricultural preservation perspective (Underhill 1994**;** Rodrigues et al. 2000; Rodrigues and Gaston 2002; Messer 2006). The source of the problem is that a parcel's price is only explicitly factored into the decision process 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 project's benefits purely by the price of the easement offered by the landowner within a sealed-bid auction system designed to minimize costs. 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' sealed 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 offers—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, DALPF secures land with the greatest easement value given its budget constraint. However, the 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. This process of selecting parcels based solely on the percent discount offered can be compared to a grocery shopper who buys an item not because it is needed but because it is marked down in price more than any other item. In many cases, this approach is far from optimal. The foods on sale may be the least 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) so that they are relatively more expensive, even with the large discount, than other high-quality foods with a smaller percentage cut in price. Both scenarios can occur in the context of agricultural preservation. Owners of marginal agricultural land may view DALPF as the only entity willing to purchase it. Alternatively, 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 $P(\bullet)$ 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 $i^{th}$ 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,

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

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

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

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 Premium Solver Platform (version 6.5) by Frontline Systems.

If all of the land costs or all of the lands' benefits are identical, OPT, DALPF, and BT yield a set of parcels. However, in cases in which land costs are heterogeneous, the efficiency of OPT becomes evident. 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 2003).

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*):

$$\text{Max } V(X) = \sum_{i=1}^{I} \sum_{j=1}^{J} X_i W_j A_{i,j} \tag{2}$$

$$\text{st.} \quad \sum_{i=1}^{I} C_i X_i \leq B \, . \tag{3}$$

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

## IV. 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). Originally, DDA had only tracked information the approximately 400 parcels that were chosen for easements using the DALPF algorithm; however, staff from DDA worked to facilitate this research and provided as much information as possible on the parcels that were not selected. Agricultural and ecological benefit information was then matched to all of the data that corresponded with GIS information provided to participants in the conservation leadership forum. Of the 524 parcels acquired, 509 (97.1%) provided sufficient data for use in this research.[3]

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. 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% (donation) and the lowest was 0% (no discount offered); the average discount was 42.3%. 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% 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 annual cycles completed, DALPF purchased rights for 382 of the 509 parcels (75.0%). Unfortunately, the data provide by DDA did not distinguish between landowners who did not sell because the percent discount they offered to DALPF was too low and landowners who withdrew from the auction after receiving the free appraisal. To account for this situation, we re-estimated DALPF's acquisitions using the set of 509 parcels and a budget constraint of $93 million. Thus, the three selection algorithms were applied to a single data set representing all 509 parcels, treating them as a single simultaneous cycle so comparisons of relative efficiency could be reliably made.[4]

Data for the two agricultural suitability attributes (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 suitability attributes. Consequently, a parcel with the highest attribute score has a normalized score of 1 for that attribute. Since the agricultural suitability factors 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).

## V. Results

Table 3 and Figure 2 show the results of benefit scenarios for applications of the DALPF, BT, and OPT algorithms using the $93 million budget for all 509 parcels. The first scenario shows the aggregate results from the DALPF algorithm. As expected, DALPF's algorithm yielded the highest levels of total easement value at more than $162 million for the $93 million spent.[5] The average discount was 47.4%. DALPF protected 65,683.4 acres with an aggregate LESA score of

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[3] 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.

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

[5] 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 cost of acquiring them.

4,460,437 and aggregate Core GI score of 1,736,429.[6] Of the 386 parcels protected, 47.9% were in agriculturally rich Kent County, 12.4% were in mostly urban New Castle County, and 39.6% were in the southern county of Sussex.[7]

The BT and OPT analyses defined benefits according to the AHP results from the leadership forum, which gave a 68% weight to the LESA scores and a 32% weight to the Core GI scores. 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% higher), and distribution of the protected parcels across the state (see Table 2). The most significant difference was that BT produced those results by selecting easements on 38.6% 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 276.8 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 more than DALPF and nearly double the number protected by BT) with the same $93 million budget (Table 3). 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% more acres (13,446.1) and yielded LESA and Core GI values that were 20.6% and 19.1% higher, respectively, than DALPF. Similarly, in comparison to BT, the OPT algorithm in protected 20.6% more acres and produced aggregate LESA and Core GI values that were 19.1% and 12.9% higher.

Importantly, these gains in conservation benefit did not occur by purchasing smaller farms—in fact, the size of the average farm protected by BT was 7 acres larger than the one protected by the DALPF algorithm and the average LESA and Core GI scores for the average parcel were both slightly higher. The only variable for which DALPF's algorithm yielded higher aggregate values than OPT was for easement value as the DALPF algorithm generated aggregate scores that were 2.0% higher than the ones from the OPT analysis. However, the 2.0% gain in total easement value is unlikely to be worth more than protection of the additional 13,446 acres and nearly 20% improvement in the total LESA and Core GI scores achieved by OPT.

Another means for evaluating efficiencies 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 (Table 3). 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 3, DALPF required

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[6] Unlike number of acres, aggregate scores for LESA and Core GI are not necessarily intuitive to interpret. However, the numbers are cardinal.

[7] 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, it will not be specially addressed beyond the discussion the spatial distributions evident in Figure 3.

$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 $19.9 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 4).

It is interesting to note, as demonstrated in Figure 3, that 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% for DALPF, 51.5% for BT, and 51.9% for OPT. The next largest group of parcels came from Sussex County and the results were similar—39.6% for DALPF, 36.7% for BT, and 39.4% for OPT. This finding contradicts a common belief among residents of Delaware that, despite the state's small size, there are significant differences in the value and qualities of land in the urban areas of New Castle County, the farming areas of Kent County, and the beaches and forests in Sussex County. 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.

## VI. Conclusion

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

This historic 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 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 efficient by incorporating optimization techniques, such as binary linear programming, into its existing structure. For example, in Delaware, the use of optimization could have preserved 13,446 more acres for the same cost. An alternative way of viewing this efficiency gain is that optimization could have allowed DALPF to achieve additional agricultural preservation benefits worth an estimated $20.7 million.[8]

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. However, information from DALPF's auctions so far has not been released to the public, thereby

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

potentially mitigating these price inflation concerns. Since the average discount offered has been 42.3%, 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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Table 1. Kent County Green Infrastructure Leadership Forum – Invited Agencies.

1. City of Dover
2. Delaware Department of Agriculture
3. Delaware Department of Transportation
4. Delaware Division of Fish and Wildlife
5. Delaware Division of Parks and Recreation
6. Delaware Economic Development Office
7. Delaware Forest Service
8. Delaware Greenways
9. Delaware Office of State Planning Coordination
10. Delaware Wild Lands
11. Dover Air Force Base
12. The Nature Conservancy
13. Kent County Conservancy
14. Kent County Department of Planning Services
15. Kent County Levy Court
16. Kent County Parks Division
17. Kent County Tourism Convention & Visitors Bureau
18. U.S. Fish and Wildlife Service

Table 2. Benefit Results.

| Algorithm | Benefit Scenario | Number of Parcels | Total Cost | Total Easement Value | New Castle County Parcels | Kent County Parcels | Sussex County Parcels | Acres | LESA | Core GI |
|---|---|---|---|---|---|---|---|---|---|---|
| **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 |

Table 3. Cost Savings.

| Algorithm | Acres | LESA | Core GI | Number of Parcels | Total Cost | Difference for 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 1. Map of Core Green Infrastructure areas in the State of Delaware.

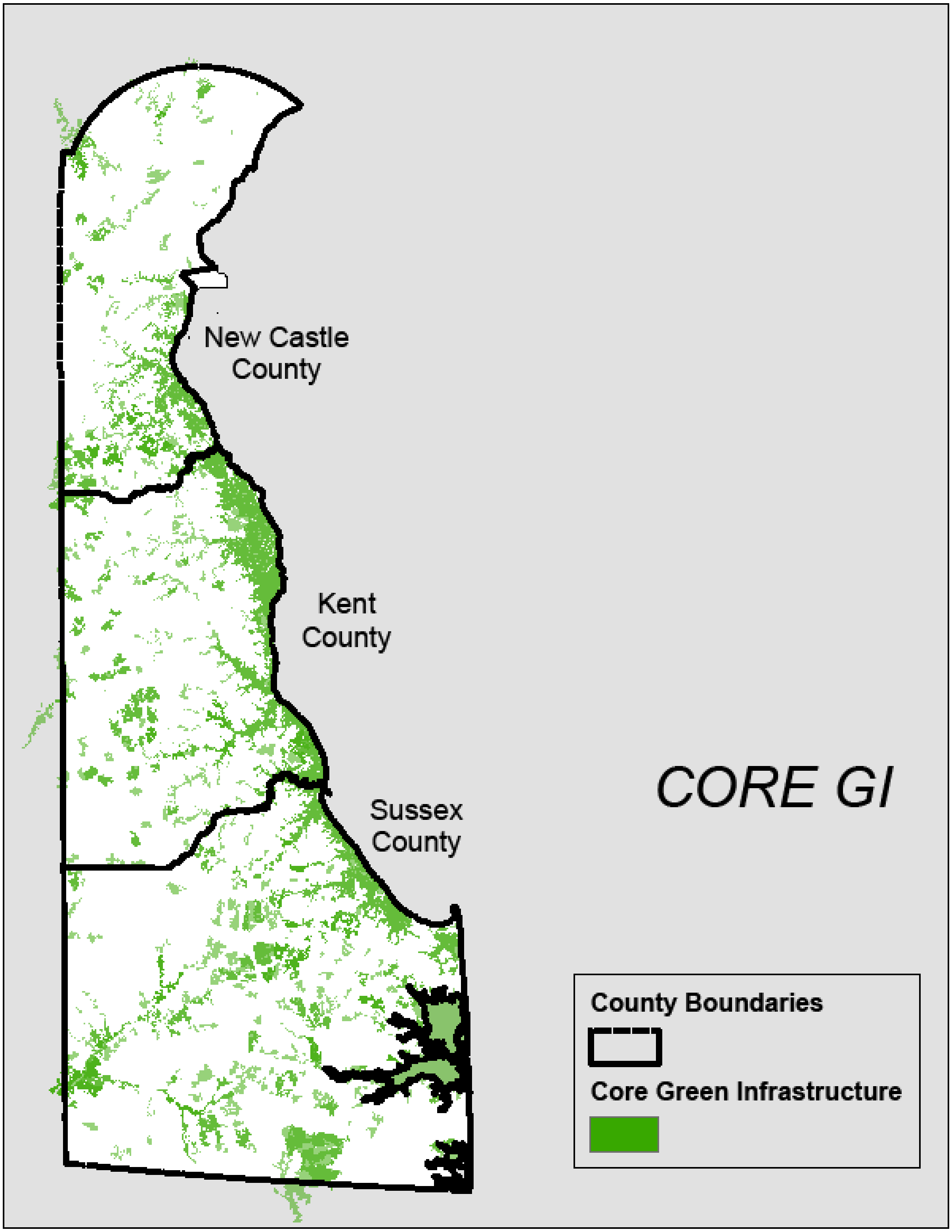
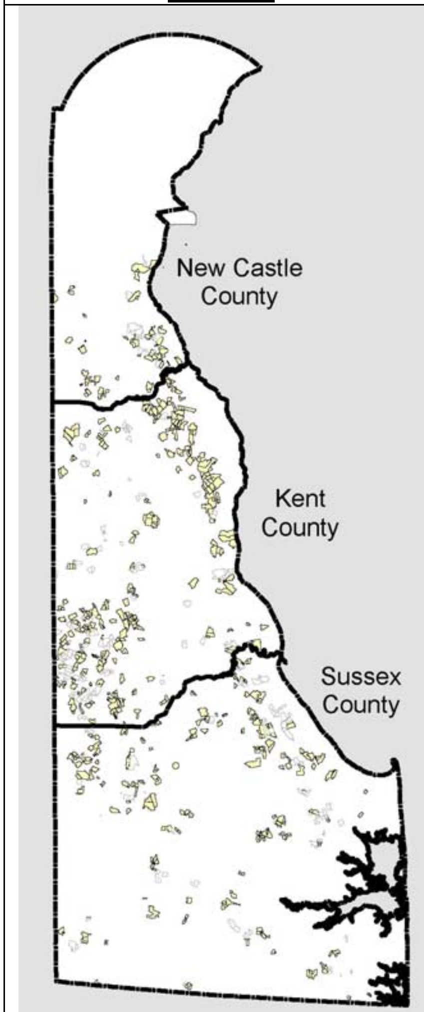
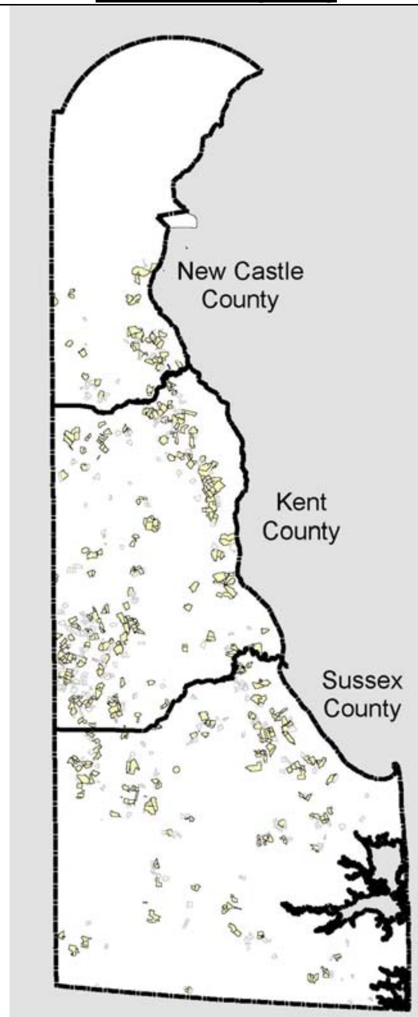
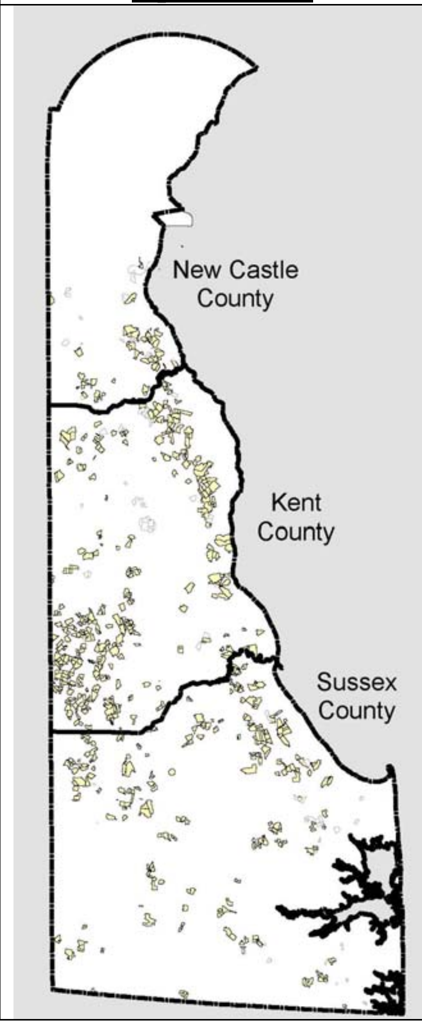


Figure 2. Results of Benefit Scenarios.

**Figure 3. Selected Parcels by Preservation Algorithm.**

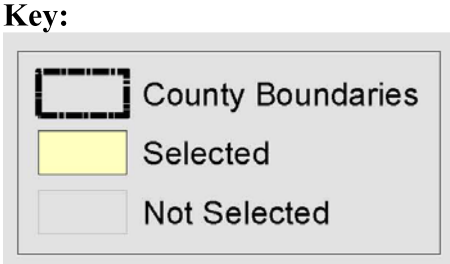
| DALPF | Benefit Targeting | Optimization |
|---|---|---|
|  |  |  |







**Key:**



## Appendix

The need for scaling can be illustrated by considering a hypothetical scenario of two sets of parcels being considered for acquisition with a budget of $30,000.

| | | LESA | Acreage | LESA* Acreage | Cost |
|---|---|---|---|---|---|
| **Set One:** | Parcel A | 50 | 25 | 1,250 | $10,000 |
| | Parcel B | 50 | 25 | 1,250 | $10,000 |
| | Parcel C | 50 | 25 | 1,250 | $10,000 |
| **Set Two:** | Parcel D | 100 | 100 | 10,000 | $30,000 |

The first set consists of three small, low-quality parcels (A, B, and C), each 25 acres in size with a LESA score of 50 (out of a possible 100) and costing $10,000 each. The second set contains a single 100-acre parcel with a LESA score of 100 and costs $30,000. If the LESA score is used as the sole source for defining benefits, OPT would select the three small parcels as optimal because they yield an aggregate LESA score of 150 and use up the entire budget. However, this result clearly is not optimal from a real-world perspective because the three unconnected, low-quality parcels provide only 75 acres. Multiplying the LESA scores by the number of acres allows for proper calculation of the LESA value for the entire set under consideration. OPT then reveals that acquiring Parcel D yields the greatest benefit from the available funds.