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Multiple-knapsack Optimization in Land Conservation:
Results from the first cost-effective conservation program in the US

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Abstract

The literature on optimizing conservation selection traditionally assumes that the conservation agency makes selections based on a single funding source. However, the reality is that conservation groups often piece together their selections by combining funds from multiple sources. This paper shows that, when conservation programs apply multiple-knapsack optimization (also referred to as simultaneous binary integer programming), substantial increases in social benefits, acreage, and number of parcels preserved can be achieved. In particular, we show that applying a simultaneous optimization model can generate substantially greater benefits than three other approaches: benefit targeting, cost-effectiveness analysis, and sequential optimization. By applying these four methods to data collected from 118 land easement applications in Baltimore County, Maryland, for 2007 through 2009, we show that simultaneous binary integer programming provides greater conservation benefits and preserves more acres of land. This study is the first to use data collected from an ongoing conservation program to quantify the increase in benefits of using a simultaneous optimization approach to achieve truly cost-effective conservation.

Keywords: Cost Effective Conservation, Mathematical Programming, Land Conservation, Multiple Knapsack Model

Multiple-knapsack Optimization in Land Conservation:
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Most conservation programs are not cost-effective—often, they are far from it. Although numerous studies have pointed to the benefits of cost-effective conservation(Gardner, 1977; Polasky et al., 2001; Ando et al., 1998; Kline, 2006; Kline and Wichelns, 1996; Messer, 2006; Wu et al., 2001; Duke et al., 2013; Babcock et al., 1997; Rosenberger, 1998; Malcolm et al., 2005, Naidoo and Ricketts, 2006), none so far have measured actual increases in conservation benefits achieved using cost-effective parcel selection methods with on-the-ground data. We examine transactions for 118 parcels in Baltimore County, Maryland, over a three-year period (2007–2009) and illustrate how methods that are truly cost-effective can dramatically increase conservation benefits and the number of preserved acres.

Acres of farmland in the State of Maryland dropped from 4 million to 2.2 million between 1950-2000 due to residential and commercial development (Lynch and Musser, 2001). Maryland's population, on the other hand, is projected to increase by 1.1 million between 2010 and 2040 and the number of households is expected to increase by 25% during the same period (Maryland Department of Planning, 2014a/b). Population growth coupled with declining household size and communication technologies that make it easier for people to work in widely dispersed communities will likely increase demand for land for development and drive further losses of farmland. Between 1987 and 2012, Baltimore County lost 24% of its farmland to development, and as of 2012, there were 640 farms, 15% fewer than in 2007. In 2012, Baltimore County had 70,419 acres of farmland, down from 78,419 in 2007 (Maryland Department of Planning, 2014a/b).

In terms of acres of agricultural easement acquired, Baltimore County ranked in the top twelve local programs in the nation in 2003. The county achieved recognition as the first program in the United States to adopt cost-effectiveness analysis (CEA) as its primary selection method.[1] However, the results of this study show that there is room for significant improvement. Given the large number of conservation groups and programs currently operating at state and county levels and the growth in population (70% between 2005 and 2010),[2] we use a simultaneous binary integer programing model (BIP-SIM), also referred to as multiple-knapsack optimization, to take advantage of its ability to combine multiple conservation program efforts to maximize total conservation benefits and acres preserved.

In addition to analyzing data using multiple-knapsack optimization, this study compares the performance of three popular methods used by conservation professionals: (1) benefit-targeting (BT), (2) cost-effectiveness analysis (CEA), and (3) sequential binary integer programming (BIP-SEQ). The cost-effectiveness of each method is determined by applying it to the Baltimore County dataset and comparing the derived benefits and preserved acres of each method. The method that produces the largest social benefit, *ceteris paribus*, is the most cost-effective. Given the budget constraints faced by conservation programs, the socially optimal (efficient) outcome may not be fundable. Hence, it is cost-effectiveness rather than efficiency that such programs seek.

Our analysis suggests that BIP-SIM is the superior selection method, outperforming BT, CEA, and BIP-SEQ. For example, for 2008 and 2009, BIP-SIM would have spent just 43% of what Baltimore County paid using CEA while yielding 71% of the benefit gained by the county in those two years. If Baltimore County had used simultaneous optimization instead of CEA, the same amount of funds could have protected an additional 242 acres of high-quality agricultural land valued at approximately $1.7 million. Although the data analyzed in this study were collected from Baltimore County, the results are widely applicable and serve as a prototype for how BIP-SIM can provide greater cost-effectiveness in land conservation. The results of this study offer government agencies and nonprofit conservation groups a relatable example of a method that can improve their efforts to generate the greatest possible benefit from a limited budget.

Literature Review

Ongoing losses of farmland, forestland, and open space to development and the ever-limited funding available to conservation organizations increase the importance of cost-effective conservation. By strategically targeting the most desirable agricultural conservation easements, programs can achieve a variety of objectives, including protecting the farmland that is most vulnerable to development, adjusting existing development patterns, forming large contiguous areas of protected open space to provide social and ecological benefits, and reinforcing urban growth boundaries. These conservation activities have a positive impact on the rate and probability of farmland being preserved, block development in unsuitable areas, maintain rural amenities near urban residents, and control growth (Lynch and Liu, 2007; Stoms et al., 2009).

Budget constraints typically limit how many parcels conservation programs can acquire. To ensure that the limited quantity of funds is spent responsibly, the programs need to find selection processes that deliver the greatest benefit possible given the budget constraint or preserve a particular number of acres of land at minimal cost. Large sums of public and private money are devoted to the task. The 2008–2012 U.S. Farm Bill allocated $13 billion to land retirement programs alone (see Duke et al., 2013), and a number of studies have identified and measured the benefits of farmland preservation (Gardner, 1977; Kline and Wichelns, 1996; Rosenberger, 1998; Johnston and Duke, 2009; Geoghegan, 2002; Hajkowicz et al., 2009). Cost-effective conservation not only maximizes the benefit but adheres to the bounds of social responsibility. According to Perhans et al. (2008), cost-effective conservation (CEC) is always preferred to cost-only or benefit-only models regardless of the conservation goal.

The most common form of parcel selection by government agencies and conservation organizations is BT, which selects the parcels that offer the greatest conservation benefit but does not consider the cost of acquiring the benefit in the decision process (Messer, 2006). BT has been called “greedy” since it spends the limited funds available on prime parcels while neglecting the potential overall benefit that could be achieved. Thus, BT is not cost-effective and leaves considerable room for improvement. For example, binary linear programming models (i.e., constraint optimization) yield substantially greater social benefits and preserve more acres of land than either BT or sealed-bid-offer auctions (Kaiser and Messer, 2011).

Baltimore County started using CEA as a pilot program in 2007 to find the least costly projects by computing the ratio of the value of the estimated nonmonetary benefit to the actual monetary cost. While the CEA method can be suboptimal in some situations (Messer 2006), it does deliver greater aggregate benefits than BT because it accounts for cost. However, CEA cannot ensure truly optimal results because there may be incentives for landowners to bring previously underdeveloped land into agricultural production in response to higher commodity prices brought about by conservation efforts (Wu et al., 2001; Wu, 2004). Knapsack optimization models (BIP-SIM), borrowing from operations research and mathematical programming, deliver CEC by ensuring that decisions achieve the greatest amount of benefit possible given the budget (Hajkowicz et al., 2007).

During the past two decades, there has been a rapid increase in the development of mathematical programming models, mainly due to advances in heuristic methodologies and computing power (Higgins and Hajkowicz, 2007). Mathematical programming has applications in land allocation planning (Mallawaarachchi and Quiggin, 2001), watershed protection (Ferraro, 2003), connection of fragmented landscapes (Williams and Snyder, 2005), and soil conservation (McSweeny and Kramer, 1986), among others. Although knapsack models deliver CEC for individual conservation programs, there is potential room for improvement when considering conservation efforts by multiple groups simultaneously rather than sequentially. Specifically, sequential parcel selection may not fully take advantage of disparities in appraised parcel values and the thresholds for conservation of various programs. In addition, individual program budgets may be underutilized because of poor coordination between programs.

To address these issues, we introduce a multiple-knapsack problem involving several programs that are coordinating their efforts to establish the most cost-effective plan for purchasing easements. The multiple-knapsack model has been widely applied to various fields, including capital budgeting projects (Koc et al., 2009), municipal construction (Kozanidis et al., 2005), and the shipping industry (Ang et al., 2007). However, to the best of our knowledge, this is the first time it has been applied to land conservation. By adopting a multiple-knapsack model, we take advantage of remainders of budgets to improve cost-effectiveness and escape the sequential time constraint.

Fooks and Messer (2012) pointed out that conservation professionals face numerous political and strategic difficulties when adopting CEC. Typically, the programs receive funds from multiple sources, both private and public, and are expected to represent those interests accordingly. For example, private funders may expect particular parcels to be preserved, including parcels that might not receive consideration otherwise. Given that these difficulties arise within a single program, we expect that a simultaneous knapsack model that combines funds from multiple groups is likely to present even greater political and strategic challenges. In addition, coordination problems could arise between programs and potentially increase the cost of transactions.

Selection Models

Benefit Targeting (BT)

Consider a set of I parcels where parcel i offers conservation benefit v_i and costs c_i. Let R_i denote the rank of parcel i among the I parcels with respect to v_i. The BT selection algorithm essentially prioritizes parcels for purchase according to their rank, R_i. Parcel i is selected first for purchase when $R_i = 1$ and parcel $-i$ is selected second when $R_{-i} = 2$. The selection process ends when all allocated funds have been depleted or the funds that remain are insufficient to purchase the next parcel. Parcels with the same rank are selected according to least cost. BT is a popular method used in land conservation because of its simplicity and convenience. And given its simplicity, it is also a relatively transparent process, a characteristic that is important to landowners and conservation professionals (Hajkowicz et al., 2007; Messer et al., 2014). Since BT ignores the cost associated with purchasing each parcel, the process typically selects a few parcels that offer relatively large conservation benefits even if those parcels are relatively expensive per the amount of benefit provided and thus it is not cost-effective. Since the cost of farmland tends to be heterogeneous, especially when some is considered attractive for development, applying BT to land conservation tends to preserve fewer parcels and fewer acres of farmland. Moreover, BT is inconsistent; increases in the budget do not necessarily improve the portfolio of overall achieved conservation benefits. Therefore, with BT, money may be wasted on a few high-ranking parcels that actually generate a smaller total benefit.

Cost-Effectiveness Analysis (CEA)

Programs funded by Baltimore County currently use CEA as their selection method. CEA operates under the same procedure as BT but ranks the parcels by a ratio (R_i) of conservation benefit v_i to cost c_i rather than solely targeting benefits. CEA inherits BT's advantages—convenience, simplicity, and transparency—and outperforms BT in terms of cost-effectiveness, delivering results that approach an optimal outcome. Optimality is not guaranteed, though, since this method, unlike binary integer programming, fails to take all potential alternatives into account when selecting the portfolio. As under BT, an increase in budget does not necessarily improve the outcome under CEA.

Sequential Binary Integer Programming (BIP-SEQ)

A BIP-SEQ model is also known as a knapsack model. It is an optimization algorithm that identifies optimal portfolios of conservation sites. Consider a set of $N = \{1, . . . , n\}$ items and a set of $M = \{1, . . . , m\}$ knapsacks (portfolios of items). Every item, $i \in N$, has a weight of $w_i > 0$ and a benefit of $u_i > 0$. Every knapsack, $j \in M$, has a capacity of $e_j > 0$. Some items cannot be assigned to some knapsacks; thus, assignment of item i is limited to the set of $A_i \subseteq M$. The following assumption is imposed: $w_i < e_j$. That is, every knapsack has enough capacity for any item i. The objective is to fill the knapsack with a collection of items that will yield the maximal benefit. BIP-SEQ takes one knapsack at a time, fills it with items to obtain the greatest possible benefit, and then moves on to the next knapsack. This mechanism ensures that each knapsack is optimized given the choice of items available for it. The aggregate benefit of all of the knapsacks is calculated as the sum of the optimized benefits from each knapsack.

In the case of land preservation, each conservation program is a knapsack with a budget limit, B_j, that represents the program's capacity, e_j. The selection processes aims to fill the conservation programs' knapsacks with land parcels to achieve the greatest possible conservation benefit.

Suppose there are I parcels and J conservation programs. The decision variables of the model take the form of $x_{i,j} = (0,1)$ where 0 denotes that parcel i is not recommended for purchase by program j and 1 denotes that parcel i is recommended for purchase by program j. The objective function seeks to maximize the conservation benefit for program j. In the following model specification, the constraint in equation 2 ensures that only one program can purchase an easement but an easement need not be purchased. The constraint in equation 3 ensures that any purchase made is constrained by the program's budget.

$$\max \ v_j = \sum_i^I x_{i,j} v_i \tag{1}$$

such that

$$\sum_{j=1}^{J} x_{i,j} \leq 1 \tag{2}$$

and

$$\sum_{i=1}^{I} c_{i,j} x_{i,j} \leq B_j \tag{3}$$

In Baltimore County's case, MALPF takes index *j* = 1 and the county programs take indices *j* = 2, 3, 4. Thus, if $x_{i,j} = 1$, $x_{i,j+1} \ldots, x_{i,J} = 0$, and a parcel that has been sold cannot be included in future program selections. In the model, v_i denotes the conservation benefit for parcel *i*, B_j denotes the budget for program *j*, and $c_{i,j}$ denotes the cost of parcel *i* in program *j*. After the selections are made for all programs *J*, we calculate the aggregate conservation benefit. BIP-SEQ is solved using Risk Solver Platform V9.5 in Microsoft Excel.

*Simultaneous **Binary Integer Programming** (BIP-SIM)*

Unlike BIP-SEQ, BIP-SIM fills all of the knapsacks/programs simultaneously, ensuring that every knapsack is optimized for the entire set of items available. Again, suppose there are *I* parcels and *J* conservation programs. The decision variables of the model take the form of $x_{i,j} = \{0,1\}$ where 0 denotes that parcel *i* is not recommended for purchase by program *j* and 1 denotes that parcel *i* is recommended for purchase by program *j*. The objective function seeks to maximize the aggregate conservation value for *J* programs subject to the same constraints as under BIP-SEQ.

$$\max \ v_j = \sum_i^I \sum_j^J x_{i,j} v_i \quad (4)$$

such that

$$\sum_{j=1}^{J} x_{i,j} \leq 1 \quad (5)$$

$$\sum_{i=1}^{I} c_{i,j} x_{i,j} \leq B_j \quad (6)$$

Again, Microsoft Excel's Risk Solver Platform V9.5 is used to run the optimization model.

Case Study: Selection of Farmland Preservation in Baltimore County

Historically, the process of acquiring easements in Baltimore County began with a voluntary formal application for participation by owners of parcels that met the entry threshold requirements of the program. Once the applications were submitted, the conservation benefits of the parcels were appraised and ranked quantitatively.

To evaluate the potential benefits of the parcels, conservation programs in Baltimore County have relied on a land evaluation process that is based on a national ranking system, the Land Evaluation and Site Assessment (LESA) program. Developed in the 1980s by the USDA Soil Conservation Service, LESA is composed of two parts: land evaluation (LE) and site assessment (SA) (Sokolow, 2006). The land evaluation score is focused primarily on the productivity of the soils where the parcel's soil quality is assigned a relative value between 0 and 100 with 0 being the worst and 100 the best. The site assessment score evaluates the property on a number of factors—such as its location in terms of development pressure, the distance to towns and cities, the quality of roads adjacent to the sites, availability of sewer and water, and the agricultural support services.[3]

Baltimore County sets its willingness to pay (WTP) for an easement using a formula in which the maximum amount increases with parcels' soil quality and size and with the number of development rights conveyed. Due to the variety of funding sources that support the county's conservation programs, selection of parcels by each program traditionally has been done in a sequential manner with one program selecting parcels at a time as shown in Figure 1.[4]

This study's dataset consists of information on 118 parcels that were submitted to conservation programs in Baltimore County, Maryland from 2007 to 2009. Table 1 provides descriptive statistics of the candidate parcels in the dataset, including the program funds available, the cost of acquiring all of the qualified easements, and the percent variance between the budget and the total acquisition cost, which reflects the sufficiency of the budget. MALPF's appraisal of the value of the candidate parcels in 2007 averaged $399,902 per parcel, 31% greater than the county appraisal of $304,306. In 2008, only thirteen parcels satisfied the state program's threshold. MALPF's average appraisal value per parcel was $860,635, 15% greater than the county average of $748,782. In 2009, the appraisal value of MALPF's average parcel was 80% greater than the county's. Since MALPF consistently assigned higher appraisal values than the county programs, landowners preferred to sell the easements to the state program. Parcels that qualified for the state program, on average, had higher LESA scores and more acres than parcels that qualified only for county programs. Thus, the pool of candidate easements that qualified only for MALPF generated greater benefits under LESA.

The average cost per acre of easement, $6,715.98, was calculated by averaging the information for the state and county appraisals for all three years ([total cost of all candidate easements / divided by the total number of qualifying easements and total acres per easement] / 6). The average cost per conservation benefit, $112.76, was calculated by dividing the sum of all of the easement costs by the sum of the easements' conservation benefits. We use these averages in the results section to calculate any savings that would have resulted from using a different parcel selection method.

Results

The results of applying each method to the 118 parcels in the dataset are presented in Tables 2, 3, and 4. Table 2 shows the results of comparing BT and CEA. Overall, CEA achieves greater conservation benefits and acquires more acres and more parcels than BT. Over the three-year study period, the conservation benefits generated by CEA are 11.2% ($2.8 million) greater than those generated by BT.[5] To convert the additional benefits achieved through CEA into a dollar value, we multiply the additional benefit achieved (25,521) by the average cost per conservation benefit ($112.76). When considering total acres preserved, CEA protected an additional 596.3 acres valued at $4 million, a 17.2% improvement over BT. To compute the monetary value for the additional acres preserved, the additional acres (596.3) were multiplied by the average cost per acre ($6,715.98). The reported cost-savings values shown in Tables 3, 4, and 5 are all calculated as average cost per conservation benefit in dollars and average cost per acre in dollars to monetize the changes. Thus, applying CEA instead of BT allowed Baltimore County to improve both the number of acres preserved and the amount of conservation benefit.[6]

Table 3 reports the comparison of CEA and BIP-SEQ. As previously noted, CEA does not consistently provide and cannot guarantee cost-effective outcomes because it cannot consider the entire range of options. Binary programming, on the other hand, can. As shown in Table 3, BIP-SEQ consistently outperforms CEA and BT in terms of acquired conservation benefits. Over the three-year observation period, the conservation benefit generated by BIP-SEQ was 8,115.2 greater than the benefit achieved by CEA, a 3.2% ($0.9 million) improvement. Since BT slightly outperformed CEA in 2008 in terms of conservation benefit, we compare BT to BIP-SEQ. Not surprisingly, BIP-SEQ outperforms BT by increasing the conservation benefit by 5,033 ($567,521). In terms of acres preserved, BIP-SEQ selects fewer acres in 2007 and 2009 because parcel size is not the target of the maximization problem. Moreover, parcel size and conservation benefit are not always perfectly associated; smaller parcels may score higher in terms of conservation benefits if they provide benefits related to biodiversity or have other especially beneficial properties. Nonetheless, over the three-year period, BIP-SEQ acquires 61 more acres (valued at $0.4 million) than CEA.

Although BIP-SEQ is superior to CEA in terms of conservation benefit, the suitability of applying mathematical programming to all conservation programs is debatable. BIP-SEQ's increase in conservation benefit (3.2%) and acres (1.5%) over CEA is not as substantial as CEA's improvements over BT (11.2% and 17.2%, respectively). Also, BIP-SEQ normally requires investments in software and training that may reduce the budget available for conservation. Binary programming is less convenient, less transparent, and more difficult for conservation professionals to use and for landowners to understand. This argument against binary programming is important when considering the rather small addition in overall benefit it provided relative to CEA. However, the argument is significantly less important when considering a simultaneous knapsack optimization problem because BIP-SIM's improvements are substantial.

Table 4 presents the comparison of BIP-SEQ to BIP-SIM. BIP-SIM preserved an additional 3 (0%) conservation benefits and 19 (1.1%) more acres than BIP-SEQ in 2007. In 2008, BIP-SIM yields a 9.6% greater conservation benefit and 7.2% more acres than BIP-SEQ. In 2009, it produces a 7.3% greater conservation benefit and 4.6% more acres. For the two years combined, BIP-SIM generates 71% of the total benefit obtained with BIP-SEQ while spending only 43% the amount spent by BIP-SEQ. Over the three-year period, compared to BIP-SEQ, BIP-SIM protects an additional 181 high-quality acres worth $1.2 million.

BIP-SIM also produces better results than CEA, which was used by the county programs during those years. Over the three-year period, BIP-SIM generates a 9.1% greater conservation benefit, an improvement valued at $2.6 million. BIP-SIM protects 6.0% more acres of land that are worth $1.6 million.

When we compare BIP-SIM to BT, the cost saving are $5.5 million in terms of conservation benefit and $5.6 million in terms of preserved acreage over three years. Figures 2 and 3 present the results of each conservation method in terms of conservation benefit and acres preserved. For all three years combined, in terms of both conservation benefit and acres, BIP-SIM outperforms the other three methods.

As with BIP-SEQ, a disadvantage of BIP-SIM is the need for software and sophisticated programming. The complexity of a simultaneous analysis increases substantially as the number of candidate parcels rises. Nonetheless, the results confirm the superiority of binary integer programming in securing the best possible portfolios for conservation programs. When we relax the constraint of sequential parcel selection, cost-effectiveness improves and conservation professionals in the various programs can coordinate their selection plans optimally.

Conclusion

Traditionally, conservation programs have used BT to select parcels of land for preservation. That method, though not cost-effective, has the advantage of being simple, convenient, and transparent, making it easy to implement for conservation professionals, who may not set cost-effectiveness as the top priority. However, conservation professionals have a responsibility to conserve the greatest amount of social benefit possible from the public and private funds used for conservation. Economists have proposed multiple techniques for improving the selection process to make it more cost-effective. We chose four methods that are used in land preservation—benefit-targeting, cost-effectiveness analysis, sequential binary integer programing, and simultaneous binary integer programing—and applied them to data collected from Baltimore County, Maryland, for 2007, 2008, and 2009. Baltimore County introduced CEA as its primary parcel-selection method in 2007 as a pilot program in an effort to improve cost-effectiveness. We show that Baltimore County was able to improve the amount of conservation benefit by 11.2% and acres preserved by 17.2% using CEA instead of BT.

Our results suggest that Baltimore County's benefits and acres preserved can be further improved using more complex mathematical programming techniques. Specifically, we show that BIP-SEQ can do slightly better than CEA and BIP-SIM can do substantially better than CEA. Using BIP-SIM instead of BIP-SEQ provides an additional 5.7% in total conservation benefit on top of the 3.2% increase provided by BIP-SEQ. In terms of total acres, BIP-SIM preserves 4.4% more than BIP-SEQ, which preserves 1.5% more than CEA.

Although CEA substantially improves selection of the "best" parcels for a conservation program relative to BT, it cannot guarantee cost-effectiveness, and thus, more complex tools are needed. BIP-SIM's mathematical complexity and resource consumption (financial and technical) may present significant challenges in introducing its use. However, various programs could jointly invest in the software and training to reduce the impact on individual programs. Losses of the simplicity, convenience, and transparency that made BT an attractive method can be addressed through training for conservation staff members and educational seminars for landowners, another cost that could be shared by multiple agencies.

Studies of locally grown food, preservation of farming as a way of life, protection of water quality, and provision of agricultural and environmental buffer zones between developments (Duke and Aull-Hyde, 2002) have pointed to the benefits of land conservation and farmland preservation. Our results provide the first case of application of advanced mathematical programming to improve the cost-effectiveness of such conservation efforts in the United States. This analysis of Baltimore County can serve as an example for other state and county programs endeavoring to improve the conservation benefits obtained with the funds available.

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Table 1. Descriptive statistics of dataset of participating easements.

	2007 State	2007 County	2008 State	2008 County	2009 State	2009 County
Number of Qualified Easements	19	39	13	29	12	6
Total Budget	$4,800,000	$3,000,000	$5,800,000	$5,000,000	$2,670,000	$1,000,000
Total Cost of Easements (TCE)	$7,598,129	$10,687,214	$11,188,254	$15,081,173	$6,644,841	$645,686
Budget / TCE (%)	63%	28%	52%	33%	40%	155%
Average Appraised Value of Easement by MALPF	$399,902	—	$860,635	—	$553,737	—
Average Appraised Value **of Easement** by **County**	$304,306	$274,031	$748,782	$520,040	$304,485	$129,137
Difference of Average **Value**[a]	$95,596	—	$111,853	—	$249,252	—
% of Cost Difference[b]	31%	—	15%	—	82%	—
Coef. of Variation of Appraised Value by MALPF[c]	0.72	—	0.62	—	0.73	—
Coef. of Variation of Appraised Value by County	0.71	1.05	0.69	1.95	0.64	0.38
Maximum Acres	156	269	228	187.5	133.6	49.1
Minimum Acres	8	4	37.9	17.9	20.8	25.5
Average Acres	62	63	111.7	51.9	60.8	40.4
Average Easement Cost per Acre	$6,450	$4,350	$7,705	$10,020	$9,108	$2,117
Maximum LESA	71	76	86.4	91.8	95	67.3
Minimum LESA	35	31	61.2	41.4	64.7	62
Average LESA	55	52	71	54.5	76	62.9
Total Conservation Benefit of Easements	66,469	130,077	105,402	83,672	58,883	15,267

Total Number of Easements 2007-2009:	118
Total Conservation Benefits 2007-2009:	459,770
Total Cost of Easement 2007-2009:	$51,845,297
Average Cost per Conservation Benefit 2007-2009:	$112.76
Average Cost per Acre 2007-2009:	$6,715.98

[a] This is the difference in average cost appraised by MALPF and by the county programs.

[b] The percent of cost difference is calculated as 100% * Difference of Average Cost / Average Appraised Cost by the County.

c The coefficient of variation (CV) is calculated as the ratio of standard deviation of the sample over the average of the sample. Distributions with CV < 1 are considered low-variance while those with CV > 1 are considered high-variance.

Table 2. Comparison of results of BT and CEA methods.

	Conservati on Benefit	Acreage	Parcels Selected	Program Expenditures	Savings of CEA over BT (Benefits)	Savings of CEA over BT (Acres)
BT 2007	72,585	1,283	11	$ 7,763,496	—	—
CEA 2007	93,218	1,691	33	$ 7,697,528	$ 2,326,650	$ 2,740,119
BT 2008	117,845	1,738	15	$ 10,566,648	—	—
CEA 2008	116,578	1,770	28	$ 10,175,255	($ 142,871)	$ 214,911
BT 2009	36,512	439	5	$ 3,558,570	—	—
CEA 2009	42,667	596	13	$ 3,490,259	$ 694,060	$ 1,054,408
BT (Total)	226,942	3,460	31	$ 21,888,714	—	—
CEA (Total)	252,463	4,057	74	$ 21,363,042	$ 2,877,839	$ 4,009,440
Difference between CEA and BT (percentage)	*25,521 (11.2%)*	*596.3 (17.2%)*	*43 (138.7%)*	*- $ 525,572 (- 2.4%)*	(13.1%)[a]	(18.3%)[a]

[a] Percentage difference in savings in comparison to BT (Total).

Table 3. Comparison of results of CEA and BIP-SEQ methods.

	Conservation Benefit	Acres	Parcels Selected	Program Expenditures	Savings of BIP-SEQ over CEA (Benefits)	Savings of BIP-SEQ over CEA (Acres)
CEA 2007	93,218	1,691	33	$ 7,697,528	—	—
BIP-SEQ 2007	93,956	1,670	30	$ 7,783,642	$ 83,220	($ 141,036)
CEA 2008	116,578	1,770	28	$ 10,175,255	—	—
BIP-SEQ 2008	122,878	1,880	29	$ 10,725,157	$ 710,410	$ 738,758
CEA 2009	42,667	596	13	$ 3,490,259	—	—
BIP-SEQ 2009	43,744	568	10	$ 3,560,051	$ 121,446	($ 188,047)
CEA (Total)	252,463	4,057	74	$ 21,363,042	—	—
BIP-SEQ (Total)	260,578	4,118	68	$ 22,068,850	$ 915,076	$ 409,675
Difference between BIP-SEQ and CEA (percentage)	*8,115 (3.2%)*	*61 (1.5%)*	*-6 (-8.1%)*	*$705,808 (3.3%)*	*(4.3%)*[a]	*(1.9%)*[a]

[a] Percentage difference in savings in comparison to CEA (Total).

Table 4. Comparison of BIP-SEQ and BIP-SIM models.

	Conservation Benefit	Acres	Parcels selected	Program Expenditures	Savings of BIP-SIM over BIP-SEQ (Benefits)	Savings of BIP-SIM over BIP-SEQ (Acres)
BIP-SEQ (2007)	93,956	1,670	29	$ 7,783,642	----	----
BIP-SIM (2007)	93,959	1,689	29	$ 7,789,066	$ 338	$ 127,604
Difference (%)	*3 (0.0%)*	*19 (1.1%)*	*0 (0.0%)*	*$ 5,424 (0.1%)*	*(0.0%)*[a]	*(1.6%)*[a]
BIP-SEQ (2008)	122,878	1,880	29	$ 10,725,157	----	----
BIP-SIM (2008)	134,648	2,016	29	$ 10,728,994	$ 1,327,227	$ 913,373
Difference (%)	*11,770 (9.6%)*	*136 (7.2%)*	*0 (0.0%)*	*$ 3,837 (0.0)*	*(12.4%)*[a]	*(8.5%)*[a]
BIP-SEQ (2009)	43,744	568	10	$ 3,560,051	----	----
BIP-SIM (2009)	46,928	594	11	$ 3,596,608	$ 359,039	$ 174,615
Difference (%)	*3,184 (7.3%)*	*26 (4.6%)*	*1 (10.0%)*	*$36,557 (1.0%)*	*(10.1%)*[a]	*(4.9%)*[a]
BIP-SEQ (total)	260,578	4,118	68	$ 22,068,850	----	----
BIP-SIM (total)	275,535	4,299	69	$ 22,114,668	$ 1,686,604	$ 1,215,592
Difference (%)	14,957 (5.7%)	181 (4.4%)	1 (1.5%)	$45,818 (0.2%)	(7.6%)[a]	(5.5%)[a]

[a] Percentage of savings compared to BIP-SEQ.

Figure 1. Sequential Selection Method and Typical Benefit Targeting Approach.

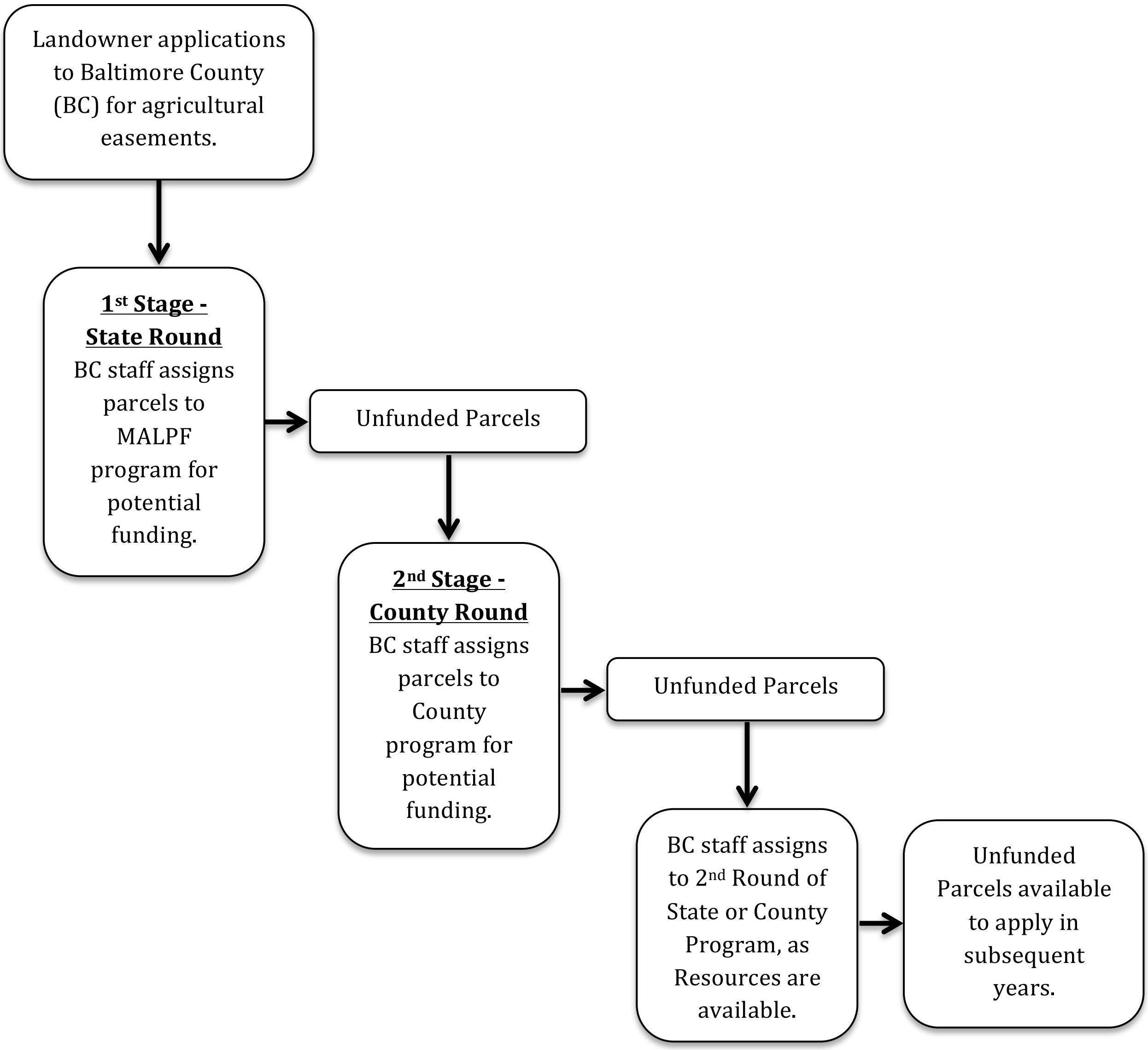


Figure 2. Conservation benefits achieved by each method for 2007–2009 and total.

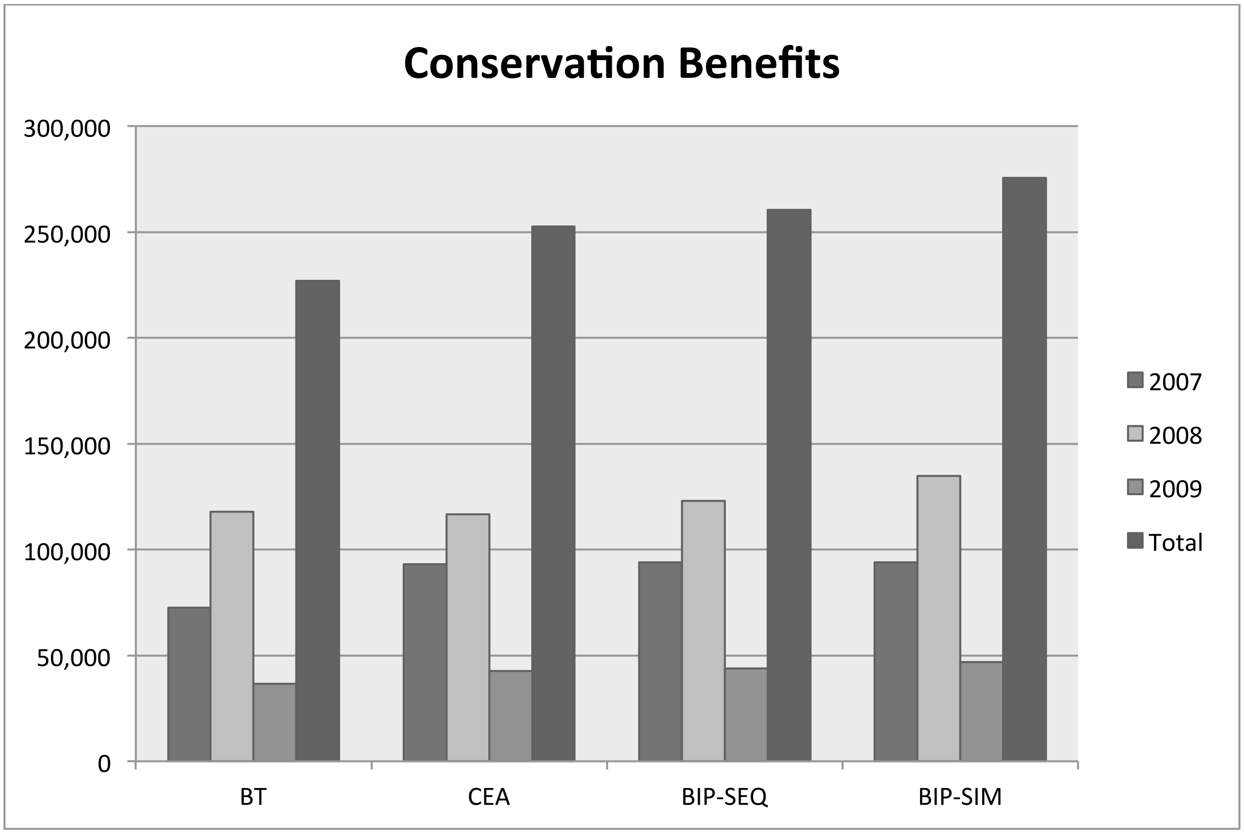
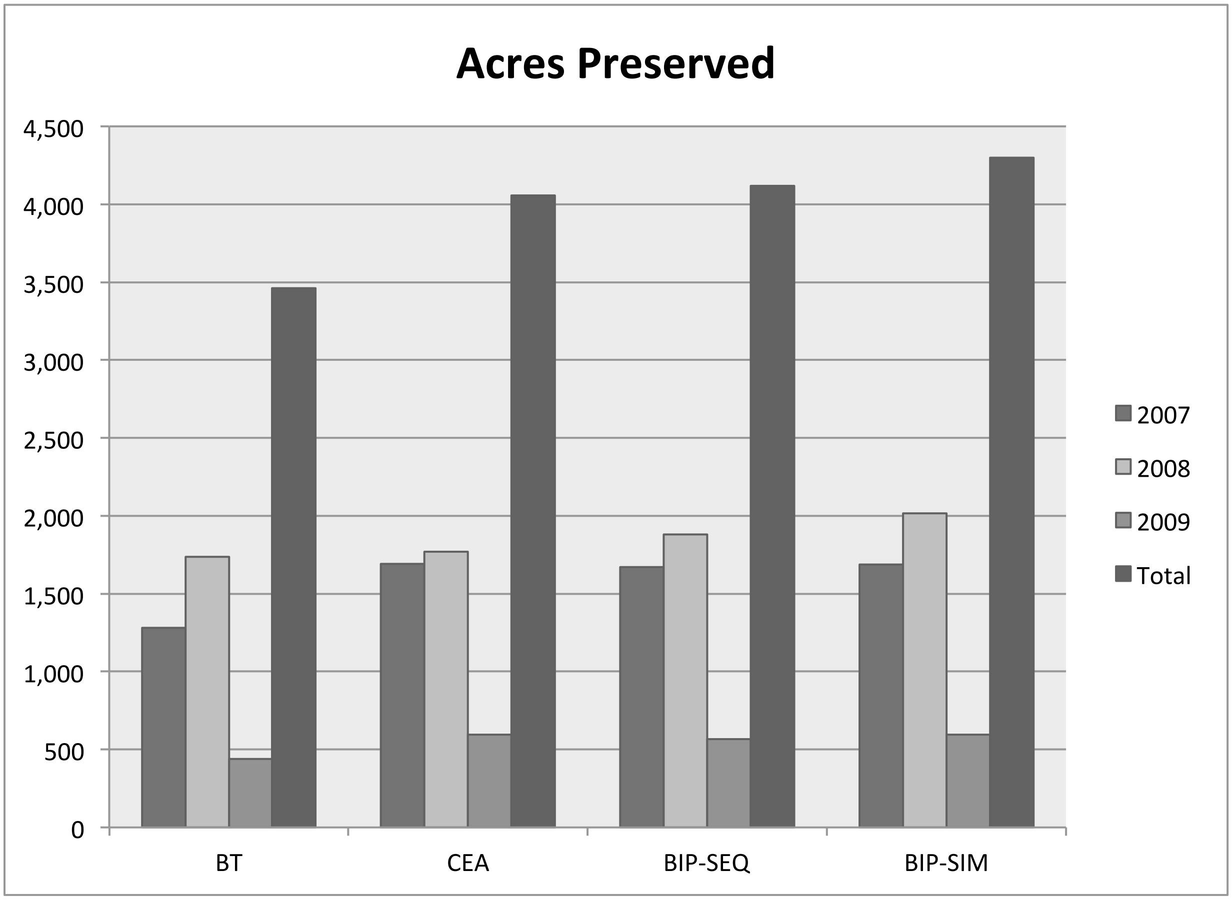


Figure 3. Acres preserved by each optimization method for 2007–2009 and total.



[1] Baltimore County first introduced CEA in 2006. Due to resulting gains in conservation benefits and acres preserved, the county has continued to use CEA with clearly identifiable and measurable success. For example, in 2012, the county was able to preserve an additional 852 acres with a 10% gain in conservation benefits compared to the previously used method, benefit-targeting (data provided by Baltimore County Department Environmental Protection and Sustainability).

[2] According to the 2010 census report by the National Land Trust, there were 1,723 land trust organizations in the United States; 1,699 were state and local groups and 24 were national land trusts, and together the groups had secured 47 million acres by the end of 2010.

[3] Since a parcels' LESA score comes from the average of its per-acre scores, problems can arise when using this value for maximization (Messer and Allen, 2010). In this analysis, the LESA values were scaled by parcel size.

[4] The selection process varied slightly during those three years. In 2008, the parcels had to have a threshold LESA score of 61 to qualify for consideration by MALPF. The threshold was set at roughly the mean of the scores of all of the parcels in the applicant pool and had the effect of removing parcels of below-average quality. The county-level programs required parcels to have development potential or to be located in an agricultural preservation or "Rural Legacy" area to qualify for the county round. In 2007 and 2009, no such requirements were placed on candidate parcels. These variations did not substantively affect the results of the analysis presented in this paper.

[5] Data made available by the Baltimore County Department of Environmental Protection and Sustainability show that the county was able to report an additional conservation benefit of $1.2 million for 2010 through 2014 by using CEA instead of to BT.

[6] For large budget remainders CEA may provide lower results compared to BT (Duke et al., 2013). This is evident in 2008 where BT produced slightly lower conservation benefits. In this particular case the budget remainder is $391,393, which was too low to purchase any of the remaining parcels.