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**Military Readiness and
Environmental Protection
Through Cost-effective Land
Conservation**

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**Military Readiness and Environmental Protection
Through Cost-effective Land Conservation**

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Abstract

Harboring a high density of threatened and endangered species on its bases leaves the U.S. Department of Defense (DoD) with a critical responsibility—establishing sound environmental policies while also continuing training and ensuring military readiness. This dual objective is the goal of the Readiness and Environmental Protection Integration program, a large conservation fund for military installations that is mandated to be cost-effective. Analyzing a unique DoD data set, we show that use of optimization models generate a 21% increase in military readiness and environmental protection or achieve the same benefits as benefit targeting at a cost saving of 37%.

Keywords: cost-effective conservation, military readiness and environmental protection, binary linear programming, goal programming

Military Readiness and Environmental Protection through Cost-effective Land Conservation

Introduction

In the United States, the federal government owns and manages approximately 28% of the country's entire land area. Military installations represent a relatively small portion of that area – 425 installations comprise approximately 25 million acres (DoD / Fish and Wildlife Service 2001) – but support an unusually large number of rare flora and fauna and the greatest densities of threatened and endangered species of any federal lands (Stein et al. 2008, Boice 2014). The military installations are managed by the Department of Defense (DoD) under the centralized direction of the secretary of defense (Gorte et al. 2012) with a duty not only to ensure and sustain the nation's military readiness, training, and testing but also to protect the natural resources within them. Under the federal Natural Resourced Conservation Program, DoD policy requires that such conservation be conducted in a cost-effective manner (DoD 2011, p. 2):

“(1) DoD shall manage its natural resources to facilitate testing and training, mission readiness, and range sustainability in a long-term, comprehensive, coordinated, and cost-effective manner ... (2) ... protecting and enhancing ... biodiversity conservation, and maintenance of ecosystem services.”

These dual military and conservation objectives are the goal of the Readiness and Environmental Protection Integration (REPI) program. REPI partners with conservation organizations and other government agencies in cost-share agreements to maintain and preserve surrounding land and has successfully protected 315,000 acres with combined funding of \$890 million through 2013 (REPI 2014).

To date, the environmental economics literature has largely ignored these important natural resources and the impacts of military operations and conservation efforts on them. This study examines the cost-effectiveness of land conservation methods available to DoD to increase both military readiness and environmental protection using a unique data set covering 44 projects to which REPI's budget of \$54 million in 2010 could have been applied. The results provide valuable information about the significant shortcomings associated with DoD's current selection methods and the consequential negative impacts affecting military readiness and environmental protection in and around military bases in the United States. Improving cost-effectiveness, not only would lead DoD to fulfill one of its mandates for the REPI program, but also shows policy makers how optimization models provide solutions to the unique opportunity of military bases to protect land for endangered species without jeopardizing military objectives.

Prior to World War II, the U.S. military established training and testing ranges on large tracts of remote rural land. As military suppliers and families moved to areas surrounding these installations, urban and suburban communities developed along their boundaries and expanded. Simultaneously, the military's land and resource requirements have grown with developments in technology and training requirements, creating conflicts between the military and bordering civilian communities. Public criticism of military operations has addressed safety issues, impacts on endangered species, light pollution, use of electromagnetic frequencies, and noise, dust, and smoke that emanate from military activities.

For example, the military installation at Fort Bragg harbors a large number of the endangered red cockaded woodpecker that thrives in the longleaf pine habitat. In the 1990s the U.S. Fish and Wildlife issues a biological opinion that military training and testing at Fort Bragg would likely jeopardize the red cockaded woodpecker and resulted in restrictions on training. The problem was a lack of land available for habitat management. Preserving land from development thus addresses the encroachment problem threatening military training and testing but also provides critically important land for habitat management for the red cockaded woodpecker. Overall, the military harbors over 320 listed species on its installations. (The Nature Conservancy 2012, U.S. Fish and Wildlife Services 2006)

As part of efforts to address this encroachment problem, DoD established the Sustainable Ranges Initiative in December 2001, and REPI is one of its key components. Under the initiative, the Office of the Secretary of Defense works with various partners, including conservation organizations, land trusts, state and local governments and agencies, nongovernmental organizations, and other federal agencies, to resolve encroachment problems. For example, expanding development around military installations can generate an excess of artificial light that is detrimental to combat training, introduce structures that are subsequently at risk of damage from combat exercises, and force wildlife out of former habitat onto training ranges (REPI 2015). REPI funding is designed to serve as a catalyst for financial investments by project partners and to provide substantial financial and technical support for joint conservation efforts (REPI 2015). The fund's projects bring together the interdependent interests of the military, environmental groups, and the community (REPI 2014, p. 1):

“Under the REPI Program, DoD works with stakeholders to find solutions to military-community-environmental encroachment issues, and enters into unique cost-sharing agreements with conservation organizations and state and local governments to maintain compatible land uses and preserve habitats around military installations.”

REPI currently selects projects via benefit targeting (BT), also known as rank-based selection, a process in which top-ranked projects in terms of environmental benefit are chosen sequentially

until the budget is exhausted. This procedure ignores the cost associated with each project and thus is not cost-effective (Babcock et al. 1997, Ferraro 2003a). Consequently, the U.S. military does not capitalize on opportunities that could not only maximize the aggregate benefit from the selected projects but also save large amounts of money. Our results are based on the analysis of a data set received from the Office of the Secretary of Defense for 44 projects considered for funding in 2010. We show that when using cost-effectiveness analysis, binary linear programming and goal programming large increases in environmental and military benefits can be achieved compared to REPI's current selection method (BT).

Goal programming, though not achieving as high a total benefit score as binary linear programming, can be especially effective when balancing multiple objectives such as military readiness and environmental preservation. Here we show that small shifts in weighting from military readiness to environmental protection (increases in λ) result in relatively minor decreases in military readiness and large additional environmental benefits.

Literature Review

The U.S. government spends millions of dollars annually on conservation programs. However, the funds of individual programs are limited. To be most effective, such programs must maximize the conservation value of projects undertaken. Many of these agencies have developed comprehensive benefit-scoring systems that allow them to prioritize potential projects according to the conservation promised. However, the cost of each project is an important factor that so far has not been widely incorporated into selection processes (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, Bryan 2010). Although models have been developed to incorporate the projects' costs and researchers have noted the importance of including costs in the selection process, few programs have adopted such techniques. Newburn et al. (2005), for example, pointed out that only 13% of papers in *Conservation Biology*, *Biological Conservation*, and *Landscape and Urban Planning* between 1999 and 2003 discussed the economic cost of conserving habitat as a component of selection. Because of the extensive funds needed for conservation and compatible land projects and the limits of its budget, the REPI must be selective in allocating funds.

Our study uses a unique data set consisting of 44 projects available for the \$54 million in REPI funding in 2010 provided by the Office of the Secretary of Defense as part of its effort to explore

possible improvement to its land selection methods. Using this data, we show how cost-effective selection methods can improve REPI's ability to meet its dual objective of military readiness and environmental protection. Specifically, we compare REPI's current selection method of benefit targeting to (1) cost-effectiveness analysis, (2) binary linear programming, and (3) goal programming, all of which perform substantially better than BT, resulting in smaller costs and/or greater benefits in military readiness and environmental protection for the same cost. Moreover, each of these methods offers ways to customize the selection process to fit multiple, often diverse military objectives. Goal programming in particular offers unique ways to not only improve cost-effectiveness but also combine diverse military objectives and still provide cost savings of as much as 45% more than BT.

Whenever an organization's marginal willingness to pay for benefits exceeds the price per unit that it would cost to gain the benefit, there is potential for improvement. Therefore, it is vital that programs consider not only benefits but also costs associated with targeted land in the evaluation system. Selecting projects that offer the greatest benefit-cost ratio will result in the greatest potential for improvement. Unlike BT, cost-effectiveness analysis (CEA) accounts for cost; it computes the ratio of the project's nonmonetary benefit to its actual monetary cost. Although CEA can result in suboptimal outcomes (Wu et al. 2001, Wu 2004, Messer 2006), it generally

delivers greater benefits than BT (Duke et al. 2013). In recent years, variations of CEA have been applied to account for complexity. For example, the benefit-loss cost-targeting framework by Newburn et al. (2005) accounts for a net loss of benefit prevented per unit of cost (likelihood of land-use change), and Machado et al. (2006) defined conservation value as the ratio of the aggregate social value of preserving a site to the cost of conserving it. Others have incorporated heterogeneity in factors such as land prices, project benefits, vulnerability to land-use conversion in the future, and probability of development (Ando et al. 1998, Costello and Polasky 2004, Abbitt et al. 2000).

Another strain of more complex models started growing in popularity among researchers in response to improved computational power. These models are based on mathematical programming techniques often used in operations research and aim to maximize the net benefit under a set of constraints. We refer to these models as optimization models (OMs). OMs examine all of the candidate projects and select a set that returns the greatest overall conservation benefit given the available budget and other constraints. While CEA *can* produce cost-effective outcomes, OMs do so by definition (Ando et al. 1998, Duke et al. 2013). Moreover, Messer et al. (2014a) showed that large additional benefits can be achieved by combining funds from multiple sources to maximize the aggregate benefits in a simultaneous OM relative to a sequential one in

which multiple programs conduct individual optimizations for their budgets. A disadvantage of OM is their complexity; program administrators may not have the mathematical capability to implement these advanced methods. Prendergast et al. (1999) argued that there were three primary causes for limited adoption of optimization among program administrators: Lack of awareness of the techniques, lack of resources to acquire and operate them, and the inability of OM to account for all eventualities. Optimization can be popular among program administrators who must balance maximizing conservation with the organization's responsibility to donors and efforts to be fair and transparent in the selection process (Messer et al. 2014b).

Another OM approach suggested in the literature is goal programming (GP) (Charnes et al. 1955). While typical mathematical programming models are focused on a single objective such as maximizing profit or minimizing cost, GP can incorporate secondary objectives as weighted goals in the optimization problem. It is typically formulated as minimization of the weighted sum of deviations from certain set goals (Kaiser and Messer 2011). GP can analyze the diverse interests of agencies, partners/donors, the community, and the environment simultaneously (Nijkamp 1977). For example, Fooks and Messer (2012) applied GP to the Forest Legacy Program of the U.S. Forest Service to incorporate both conservation benefits and partner in-kind cost-sharing contributions. They found that seeking to maximize a weighted function that

contained both objectives required only a 9% reduction in the maximum possible benefit to achieve a 127% increase in the amount of in-kind cost-sharing the program would receive from partner organizations.

Unlike BT and CEA, optimization can effectively handle the heterogeneous and dynamic characteristics of conservation. For example, Diaz-Balteiro and Romero (2004) applied a discrete GP model to indicators of sustainability for a set of forestry systems; Manos et al. (2010) used a multi-criteria mathematical programming model to optimize sustainable management of agricultural regions by combining multiple criteria in a utility function under a set of constraints and spatial integration of vulnerability maps of the regions. Other studies have used stochastic dynamic integer programming models to identify optimal selection processes over time in situations involving projects with heterogeneous features (Costello and Polasky 2004, Newburn et al. 2005, Strange et al. 2006).

Benefit Targeting

The BT method first assigns a score to each potential land protection project based on the overall benefit (b_i) expected from the project. Those scores are then used to rank the projects from

highest to lowest, creating a list from which the organization sequentially selects projects beginning with the highest ranked one, acquiring as many of the high-ranking projects as it can afford. Let $R_i = R(b_i, \dots, b_I)$ denote the rank operator of the i^{th} project over all conservation values. For the highest ranked project, then, $R_i = 1$. Projects are selected until the budget (W) is exhausted. Let $x_i = \{0,1\}$ where $x_i = 0$ indicates that the i^{th} project is not selected and $x_i = 1$ indicates that the i^{th} project is selected. This process is continued, working through the ranked list until either all of the available funds are exhausted or the next project is too expensive for the remaining budget. Thus, the resulting vector, $\mathbf{X} = [x_i, x_j, \dots, x_r]$, represents the portfolio of programs selected. The ranked list can be specified as follows.

RANK	PROJECT	COST	SELECTION		
1	x_i	c_i	$x_i = 1$	if	$c_i \leq W$
			$x_i = 0$	if	$c_i > W$
2	x_j	c_j	$x_j = 1$	if	$c_j \leq W - x_i c_i$
			$x_j = 0$	if	$c_j > W - x_i c_i$
3	x_k	c_k	$x_k = 1$	if	$c_k \leq W - (x_i c_i + x_j c_j)$
			$x_k = 0$	if	$c_k > W - (x_i c_i + x_j c_j)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
R	x_r	c_r	$x_r = 1$	if	$c_r \leq W - (x_i c_i + x_j c_j + x_k c_k + \dots + x_q c_q)$
			$x_r = 0$	if	$c_r > W - (x_i c_i + x_j c_j + x_k c_k + \dots + x_q c_q)$

Cost-effectiveness Analysis

Unlike BT, CEA considers the cost associated with each project and ranks projects from highest to lowest according to benefit-cost ratios (b_i / c_i) rather than only benefits. This is an important distinction because costs are heterogeneous; they largely depend on sellers' subjective valuations of their properties. Once again, projects are selected from top to bottom until the budget constraint is reached or leftover monies are insufficient to purchase another one. Thus, this selection process is identical to the one used in BT except that $R(\cdot)$ denotes benefit-cost ratios rather than the benefit scores (Babcock et al. 1996, Ferraro 2003b).

Binary Linear Programming Model

The binary linear programming (BLP) model applied in this study uses a branch-and-bound algorithm to evaluate all possible combinations of projects to identify the maximum target value given the constraints. BLP is a special case of linear programming in which the decision variable is dichotomous ($x_i = 1, x_i = 0$). The model is formulated (see Nijkamp 1977) as

$$\max: E = \sum_{i=1}^n e_i x_i \quad (1)$$

subject to

$$\sum_{i=1}^n c_i x_i \leq W \quad (2)$$

$$G_i(x_1, \dots, x_n) \leq G_i \quad (3)$$

$$x_i \in \{0,1\} \quad (4)$$

Equation (1) seeks to maximize the environmental protection (E) generated from the sum of the environmental benefits (e_i) of each project (x_i). This maximization problem is subject to constraints. In the most simplistic case, the model is restricted only by the budget constraint, equation (2). However, more constraints can be included, as generalized in equation (3). The last constraint, equation (4), ensures that the optimization model is binary – either a project is selected by REPI or it is not. The preceding model is set up to maximize environmental benefits but can just as easily maximize military readiness (R_i):

$$\max: R = \sum_{i=1}^n r_i x_i \quad (5)$$

subject to

$$\sum_{i=1}^n c_i x_i \leq W \quad (6)$$

$$G_i(x_1, \dots, x_n) \leq G_i \quad (7)$$

$$x_i \in \{0,1\}. \quad (8)$$

Goal Programming Model

A limiting assumption of linear programming and other optimization models is that they are designed to focus on a single objective, such as profit maximization or cost minimization. Often, however, organizations want to optimize multiple objectives. For example, REPI must maximize both military readiness and environmental protection objectives that often are not easily aligned with each other. The GP method (Charnes et al. 1955) allows one to relax the one-objective assumption to allow for multi-objective optimization. Under GP, the organization first sets a target value for each goal and then establishes a multi-objective model to minimize deviations from the optimal level for each goal. Because GP computes deviations from set goals, the objective function is also referred to as an achievement function. Another advantage of GP is that multiple objectives can be weighted differently. For the DoD, for example, military readiness may be more important than environmental protection. In our analysis of REPI, we start with an equal distribution of weight to readiness and environmental protection and follow up with a two-way and three-way sensitivity analysis in which we vary λ . The model is formulated as (see also Nijkamp 1977)

$$\min: Z = \lambda \left(\frac{\omega_R}{R} \right) + (1 - \lambda) \left(\frac{\omega_E}{E} \right) \quad (9)$$

subject to

$$\sum_{i=1}^n r_i x_i - \omega_R^+ + \omega_R^- = \bar{R} \quad (10)$$

$$\sum_{i=1}^n e_i x_i - \omega_E^+ + \omega_E^- = \bar{E} \quad (11)$$

$$\sum_{i=1}^n c_i x_i \leq W \quad (12)$$

$$x_i \in \{0,1\}; \omega_i^+, \omega_i^- \geq 0 \quad (13)$$

where ω_i^+ and ω_i^- are positive and negative deviations of the targeted score. The objective function minimizes negative deviations from the set target values, and weights can be assigned to place more or less emphasis on each target score, military readiness (R) and environmental protection (E). The constraints are listed in equations (10) through (13) with (10) and (11) pertaining to the two objectives of the minimization problem and their respective target values. The budget constraint, depicted in equation (12), indicates that the cost (C_i) of the projects selected cannot be greater than the amount of money available. The binary character of the model is represented in the constraint in (14). This GP model addresses two objectives: military readiness and environmental protection.

We also discuss the results of a three-dimensional model, in which we add viability of agreement (V_i) to indicate the likelihood that the projects recommended for protection will actually be able

to implemented. Viability of agreement incorporates measures such as contributions of non-REPI funds and service funds and the likelihood of executing a project (Table 1) as an objective:

$$\min: Z = \lambda_R \left(\frac{\omega_R^-}{\bar{R}} \right) + \lambda_E \left(\frac{\omega_E^-}{\bar{E}} \right) + \lambda_V \left(\frac{\omega_V^-}{\bar{V}} \right) \quad (14)$$

subject to

$$\sum_{i=1}^n r_i x_i - \omega_R^+ + \omega_R^- = \bar{R} \quad (15)$$

$$\sum_{i=1}^n e_i x_i - \omega_E^+ + \omega_E^- = \bar{E} \quad (16)$$

$$\sum_{i=1}^n v_i x_i - \omega_V^+ + \omega_V^- = \bar{V} \quad (17)$$

$$\sum_{i=1}^n c_i x_i \leq W \quad (18)$$

$$x_i \in \{0,1\}; \omega_i^+, \omega_i^- \geq 0 \quad (19)$$

Data Preparation

Our data set consists of 44 projects considered for funding from REPI's 2010 budget. The data set was provided by the Office of the Secretary of Defense and consisted of 9 Air Force (AF), 23 Army (A), and 12 Navy (N) projects. Due to the sensitivity of this military data, we were asked by the Office of the Secretary of Defense to not provide project locations and actual names.

Hence, we use the following project notations to identify the projects: Air Force project i (e.g., AF-1), Army project i (e.g., A-1), and Navy project i (e.g., N-1). The data set also contains the benefit score, acquisition cost, and size in acres for each project.¹ Overall, Army projects had the highest average benefit score, followed by Air Force projects and then Navy projects. The scores were determined by experts at each service branch, other service branches, and the Office of the Secretary of Defense based on criteria set forth in REPI (Table 1) under three categories:

(1) *Encroachment threat* – The greater the encroachment threat, the more important the project is in terms of military readiness (R).

(2) *Justification used under the statute (incompatible development / habitat preservation)* – This score refers to environmental protection (E), the second objective of REPI, and that is the terminology used in the analysis.

(3) *Viability of agreement* (V) – This score includes, among other things, contributions of non-REPI funds and the likelihood of execution of the project.

We calculate average scores from the individual scores from each branch and the Office of the Secretary of Defense, and all of the scores are weighted equally. Army projects received the highest average score (80.1) followed by Air Force (71.5) and Navy (66.1) projects. We also

assigned the acquisition costs to one of four categories based on the source of funding: (1) partner contributions pledged by outside agencies; (2) amount of REPI funds requested; (3) service branch contributions; and (4) funds received from other sources. The total anticipated acquisition cost for the 44 projects (\$293,525,725) is more than twice the requested REPI cost share of \$125,986,097 and 5.4 times the total REPI budget for projects of \$54 million. The average per-project funding request was \$2.8 million and the average project size was 2,845 acres. Summary statistics on the 44 projects are presented in Table 2.

Results

We discuss outcomes of BT, CEA, BLP, and GP. Unless explicitly noted, we set the λ for GP to 0.5, giving military readiness and environmental protection equal weight. The purpose of the analysis is to identify differences, advantages, and disadvantages of each selection method in terms of the level of benefit achieved, number of acres protected, number of projects selected, and the cost incurred to guarantee the highest level of military readiness while achieving the highest possible level of environmental protection.

REPI currently uses BT as their selection method. Hence, in terms of cost-effectiveness, we expect the overall performance of BT to be inferior to the rest of the models – as BT does not consider cost in the selection process, it is unlikely, albeit not impossible, that it scores as high as an optimization model. In total there were 44 potential projects that requested a total of \$126 million in funding from REPI’s \$54 million budget in 2010.¹ We present a summary of the outcomes of all models in Table 3.

We find that OMs outperform BT at nearly every level (see Table 4). In terms of number of projects, BT selects 19 (5 Air Force, 12 Army, and 2 Navy) while CEA, BLP, and GP each select 25 projects. Although CEA and BLP are not guaranteed to produce the same optimal result, CEA is likely to outperform BT. In this case, since CEA and BLP always produced the same outcome, we combine them in the BLP notation going forward. In terms of acres, BT protects fewer acres than BLP (66,734 vs. 71,713) but more than GP, which protects the fewest acres (50,467), which is not surprising as the number of acres was not specified as an objective that this program sought to maximize. Figure 1 presents the results for the total benefit score achieved by each method broken down by military branch. Again, the other methods outperform BT. The figure also clearly points to a primary weakness of BT – because cost is not a factor in the rankings, BT

rarely selects relatively low-cost Navy projects (169 benefit points versus 463 under BLP and 613 under GP). This is precisely the advantage of more complex methods; BT fails to consider projects that offer somewhat modest benefits but also do not cost relatively as much. Optimization models do consider the cost associated with each project and thus vastly outperform BT in terms of cost-effective selection. In fact, relative to BT, applying BLP results in a 21.0% increase in total benefit and GP results in a 19.7% increase (Figure 2). These increases are achieved for essentially the same cost to REPI – \$53,702,500 under BT, \$53,683,380 under BLP, and 53,582,130 under GP.

The advantages of OM models are even more evident when comparing the average cost per project (Figure 3). The average cost under BT is \$2.82 million; BLP spends only \$2.14 million (24% less). Interestingly, all of the OM models select the four projects considered as best by BT: A-9, A-20, A-2, and A-22 (Table 3).

As previously mentioned, benefits are assigned to one of three categories: (1) military readiness, (2) environmental protection, and (3) viability of the agreement (see Figure 4). Military readiness and environmental protection are the dual objectives of REPI. The pattern in the results for each of these categories reflects that of the overall benefit scores: BT generates the lowest values and BLP yields the highest. Under BLP, the military readiness benefit achieved is 23.8% greater, the

environmental protection benefit is 19.1% greater, and the viability of agreement is 18.2% greater. The total REPI funding requested is \$19,120 less under BLP than under BT and the total acquisition cost is \$13,013,473 less than requested under BT. This is a substantial difference. BLP achieves a greater total benefit while saving more than \$13 million.

The cost-effectiveness of OMs also can be measured by the cost-benefit ratio for each benefit score. BT pays an average of \$33,294 for each score point while BLP pays only \$27,502. In other words, each additional score point costs approximately 17.4% less under BLP than under BT. Thus, for BT to achieve the same total score achieved by BLP, the budget would have to increase by approximately 37.2% or \$20.1 million. Under GP, the cost advantage over BT per benefit point is 16.6%. Figure 5 depicts these differences in U.S. dollars.

An advantage of GP is the ability to make project-selection decisions while varying the weight assigned to each goal. In our discussion so far, military readiness and environmental protection have been weighted equally ($\lambda = 0.5$). In that case, GP selects the same number of projects as BLP (25) but chooses a different project mix. GP also identifies the projects that deviate minimally from the optimal level of both benefits. Consequently, it sacrifices the overall total benefit in favor of higher scores for both objectives. The total benefit score under GP is 22 points less than the score under BLP but GP's corresponding cost is also 0.2% less. Using slightly less

of the REPI budget (\$101,250), GP acquires a greater number of projects that have a better score concentration on military readiness and environmental protection.

Sensitivity Analysis

As previously mentioned, GP minimizes the weighted sum of deviations from the optimal levels of military readiness and environmental protection. However, the military may want to weight the importance of these goals differently. We conducted a sensitivity analysis by varying λ to study the trade-offs between the objectives (Table 5 and Figure 6). A value of zero for λ indicates that all weight is given to military readiness while a value of one represents all weight given to environmental protection. When $\lambda = 0.25$, 25% of the weight is on environmental protection and 75% is on military readiness. The greatest total benefit score (1,921) is achieved when λ ranges from 0.4 to 0.7. At small values of λ (0.00 to 0.35), indicating that military readiness is favored over environmental concerns, small shifts from military readiness to environmental protection (increases in λ) deliver large additional environmental benefits with only limited reductions in military readiness. Changes at mid-levels of λ generate more dramatic shifts from military readiness to environmental concerns. For greater values of λ (0.45 to 1.00), small shifts in favor of environmental protection have large negative effects on military readiness.

These findings suggest that relatively large increases in military readiness can be achieved with relatively small decreases in environmental protection. For instance, as λ changes from 1.0 to 0.4, military readiness increases 24 points and environmental protection declines only 1 point.

By varying λ in $[0,1]$, we can compare the benefits achieved for the two objectives. Each point on the line represents the best possible combination of scores for environmental protection and military readiness given the relative weight (λ) assigned to each objective. Herein lies the fundamental advantage of GP: it highlights favorable and less favorable trade-offs between military readiness and environmental protection. The GP analysis potentially provides a way for project administrators to improve the benefit score achieved for one objective substantially without substantially sacrificing the score achieved for other objectives. Similarly, it gives administrators the option to view multiple differently weighted options before assigning weights to the process, giving them greater control over their selections. Although GP generates a smaller total benefit score than BLP, it outperforms BLP in terms of the benefits achieved for each of REPI's primary objectives.

To see how the results for REPI's dual objectives change when viability of agreement is added into the GP problem, we conducted a three-way sensitivity analysis. While the two-criterion analysis required only one variable, λ , to designate relative weights, the three-criterion analysis

requires two: λ_1 , which favors military readiness over the other two criteria, and λ_2 , which shifts weight between viability of agreement and environmental protection. These variables are valued between 0 and 1 in 0.1 increments. For example, when $\lambda_1 = 0.6$, a total weight of $\lambda_2 = 0.4$ can be assigned to viability of agreement and environmental protection. We present the results as a series of selections at various weights of λ_1 between 0 and 1 (see Table 6). We report each individual benefit score and a corresponding percentage measuring the model's performance relative to the maximum possible score. A ranking of the possible selections is then determined by averaging the percentages for the three objectives. The analysis generates several interesting results. The three-way analysis achieves about 96% of the overall maximum possible score and an average overall score that is 21 points higher (1,931) than the average score in the two-way analysis (1,910). In addition, the three-way analysis, by including viability of agreement, which measures the likelihood that the recommended projects will be selected, provides additional insight for project administrators about likely outcomes of the selection process and therefore provides greater confidence about military readiness and environmental protection that will be achieved. While this more complex form of GP analysis lacks some of the specificity of the two-way analysis, it also can achieve demonstrably better results under the same budget. The number of occurrences in Table 6 indicates how many weighting combinations generate the same overall

level of benefit. The highest occurrence was nine for a military readiness value of 938.0, which generated total scores of 1,937 (96.8% of the total maximum).

Conclusions

Development in the vicinity of military installations threatens military readiness by restricting the ability of those installations to test and train personnel and encroaches on important habitat for threatened and endangered flora and fauna that are concentrated in and around the installations. Consequently, the military has a unique, dual military and environmental interest in preserving open space adjacent to its bases, and DoD policies require that such preservation be managed cost-effectively. Through its Sustainable Ranges Program, DoD introduced REPI (Readiness and Environmental Protection Integration), a fund to address these military-community-environmental encroachment issues. REPI partners with conservation organizations and other government agencies in cost-share agreements to maintain and preserve surrounding land and has successfully protected 315,000 acres with combined funding of \$890 million through 2013 (REPI 2014). Currently, REPI selects preservation projects using BT, which does not take costs into account and therefore does not accord with DoD policy.

To our knowledge, no other study has analyzed and compared cost-effectiveness with respect to dual objectives of military readiness and environmental protection – a particularly important policy issue given the negative impacts of development on effective military training and testing and the unusually large number of endangered and threatened species in and around military installations. In this research, we apply four alternative selection methods to a data set received from the Office of the Secretary of Defense for 44 projects considered for funding in 2010. Our results show that any of the proposed methods would have produced large gains in benefits relative to BT, allowing REPI to operate cost effectively and according to DoD policy. BT consistently delivered smaller military and environmental benefits than CEA, BLP, and GP. CEA and BLP also increased the cost-effectiveness of REPI's allocations by achieving a 21% greater total benefit score from the same amount of funds expended under BT. Put differently, REPI would have had to spend an additional \$20.1 million (37.2% of its preservation budget to achieve those benefit scores using BT as its selection method.)

In practice, decisions about conservation projects often are constrained by multiple and at times conflicting factors that ideally would be considered simultaneously in the project selection process. BLP is the most cost-effective of the methods analyzed, but it may not be attractive to project administrators because it does not necessarily select highly ranked projects and can fail to

select any of the top-ranked options. For political reasons, or because of concerns that the benefit rating do not fully measure the true values of the projects, program administrators sometimes prefer to protect a few top-rated projects first before considering using an optimization algorithm to select the remainder of the projects. We demonstrate that GP can be especially useful when the selection process involves balancing multiple objectives such as military readiness and environmental preservation. Moreover, GP allows administrators to vary the weights assigned to military readiness and environmental protection. Under a two-way sensitivity analysis, the largest overall benefit is achieved when λ ranges from 0.4 to 0.7. For lower values of λ , small shifts in weighting from military readiness to environmental protection (increases in λ) result in relatively minor decreases in military readiness and large additional environmental benefits. When we add viability of agreement to the objective function (to enhance the chances of projects being funded), the average overall benefit score is 21 points higher (1,931 vs. 1,910 in the two-way analysis).

Note that the results of this study rely on REPI's existing benefit scoring system with scores assigned by military administrators. The benefit scores may thus reflect some military preferences. For example, the maximum score assigned to environmental protection in the data set is significantly lower than the maximum score assigned to military readiness. In addition, the

results are constrained by the limited data set available (44 projects). Future analyses could focus on the spatial distribution of potential projects and incorporate the benefits and costs associated with both military operations and the local community. Other issues for future study include complementary or substitution relationships between the military branches and how to incorporate such relationships into an integrated programming model.

References

- Abbitt, R., J. Scott, D. Wilcove. 2000. The geography of vulnerability: incorporating species geography and human development patterns into conservation planning. *Biol. Cons.* 96(2), 169–175.
- Ando, A., J. Camm, S. Polasky, A. Solow. 1998. Species distributions, land values, and efficient conservation. *Science* 279 (5359), 2126–2128.
- Babcock, B. A., P. G. Lakshminarayan, J. Wu, D. Zilberman. 1996. The economics of a public fund for environmental amenities: a study of CRP contracts. *American journal of agricultural economics*, 78(4), 961-971.
- Babcock, B.A., P.G. Lakshminarayan, J. Wu, D. Zilberman. 1997. Targeting tools for the purchase of environmental amenities, *Land Economics* 73, 325–339.
- Boice, L.P., 2014. “Threatened and Endangered Species on DoD Lands.” Accessed February 23, 2015. www.dodnaturalresources.net/TES_fact_sheet_12-17-14.pdf
- Bryan, Brett A. "Development and application of a model for robust, cost-effective investment in natural capital and ecosystem services." *Biological Conservation* 143, 7 (2010): 1737-1750.
- Charnes, A., W. W. Cooper, R. O. Ferguson. 1955. Optimal estimation of executive compensation by linear programming. *Management Science*, 1(2), 138-151.
- Costello, C., S. Polasky. 2004. Dynamic reserve site selection. *Resource and Energy Economics* 26 (2), 157–174.
- Department of Defense and Fish and Wildlife Service, 2001. “The Military and the Endangered Species Act.” Accessed February 23, 2015. www.fws.gov/endangered/esa-library/pdf/military_esa_factsheet.pdf
- Department of Defense, 2001. Department of Defense Instructions. Subject: Natural Resources Conservation Program. Number 4715.03. Accessed February 23, 2015. <http://www.dtic.mil/whs/directives/corres/pdf/471503p.pdf>

- Diaz-Balteiro, L., C. Romero. 2004. Sustainability of forest management plans: a discrete goal programming approach, *Journal of Environmental Management* 71(4), 351-359.
- Duke, J.M., S.J. Dundas, K.D. Messer. 2013. Cost-effective Conservation Planning: Lessons from Economics, *Journal of Environmental Management* 125, 126-133.
- Ferraro, P.J., 2003a. Assigning priority to environmental policy interventions in a heterogeneous world, *Journal of Policy Analysis and Management* 22, 27–43.
- Ferraro, P.J. 2003b. Conservation Contracting in Heterogeneous Landscapes: An Application to Watershed Protection with Threshold Constraints. *Agricultural and Resource Economics Review* 32.
- Fooks, J.R., and K.D. Messer. 2012. Maximizing Conservation and In-kind Cost Share: Applying Goal Programming to Forest Protection, *Forest Economics* 18(3), 207-217.
- Gardner, B.D. 1977. The Economics of Agricultural Land Preservation, *American Journal of Agricultural Economics*, 59(5): 1027–1036
- Gorte, R. W., C. H. Vincent, L. A. Hanson, M. R. Rosenblum. 2012. Federal land ownership: overview and data, *Congressional Research Service*, 42346.
- Kaiser, H.M., K.D. Messer. 2011. Mathematical Programming for Agricultural, Environmental, and Resource Economics. Hoboken, NJ: Wiley.
- Kline, J., and D. Wichelns. 1996. Public Preferences regarding the Goals of Farmland Preservation Programs, *Land Economics* 72(4): 538–549.
- Kline, J.D. 2006. Public Demand for Preserving Local Open Space. *Society and Natural Resources* 19(7): 645–659.
- Machado, E.A., D.M. Stoms, F.W. Davis. 2006. Prioritizing farmland preservation cost-effectively for multiple objectives, *Journal of Soil and Water Conservation* 61 (5), 250–258.
- Malcolm, S.A., J.M. Duke, J. Mackenzie. 2005. Valuing Rights of First Refusal for Farmland Preservation Policy, *Applied Economics Letters* 12(5), 285-288.

Manos, B., J. Papathanasiou, Th. Bournaris, K. Voudouris. 2010. A multicriteria model for planning agricultural regions within a context of groundwater rational management, *Journal of Environmental Management* 91, 1593-1600.

Messer, K.D. 2006. The Conservation Benefit of Cost-effective Land Acquisition: A Case Study in Maryland, *Journal of Environmental Management* 79, 305–315.

Messer, K.D., M. Kecinski, X. Tang, and R. Hirsch. 2014a. Multiple-Knapsack Optimization in Land Conservation: Results from the first cost-effective program in the US, *Forthcoming, Land Economics*.

Messer, K.D., W. Allen, M. Kecinski, Y. Chen. 2014b. Conservation Professionals Attitudes about Cost Effectiveness of Land Preservation: A Case Study in Maryland. APEC Working Paper RR14-05. University of Delaware.

<http://ag.udel.edu/apec/resources/documents/APECResearchReport14-05.pdf>

The Nature Conservancy. 2012. North Carolina 2012 Year in Review. Accessed: April 20, 2015. <http://www.nature.org/ourinitiatives/regions/northamerica/unitedstates/northcarolina/publications/annual-report-2012.pdf>

Naidoo, R. and T.H. Ricketts. 2006. Mapping the Economic Costs and Benefits of Conservation, *PLoS Biology* 4(11), e360.

Newburn, D., S. Reed, P. Berck, A. Merenlender. 2005. Conservation in practice: economics and land-use change in prioritizing private land conservation, *Conservation Biology* 19 (5), 1411–1420.

Nijkamp, P. 1977. Theory and application of environmental economics, in Andersson, A., Isard, W. (Eds.), *Studies in Regional Science and Urban Economics*. New York: North-Holland Publishing Co., pp. 170–188.

Polasky, S., J.D. Camm, and B. Garber-Yonts. 2001. Selecting Biological Reserves Cost-effectively: An Application to Terrestrial Vertebrate Conservation in Oregon, *Land Economics* 77(1): 68–78.

Prendergast, J.R., R.M. Quinn, and J.H. Lawton. 1999. The Gaps between Theory and Practice in Selecting Nature Reserves, *Conservation Biology* 13(3): 484–492.

REPI, 2014. “8th Annual Report to Congress.” Accessed February 23, 2015. www.repi.mil/Portals/44/Documents/Reports_to_Congress/2014REPI%20RTC_030414_Final.pdf

REPI, 2015. Readiness and Environmental Protection Integration. “What is REPI?” Accessed February 23, 2015. www.repi.mil/AboutREPI.aspx

Rosenberger, R. S. 1998. Public Preferences regarding the Goals of Farmland Preservation Programs: Comment, *Land Economics* 74(4), 557-565.

Stein, B. A., C. Scott, N. Benton. 2008. Federal lands and endangered species: the role of military and other federal lands in sustaining biodiversity. *BioScience* 58(4), 339-347.

Strange, N., B.J. Thorsen, J. Bladt. 2006. Optimal reserve selection in a dynamic world, *Biological Conservation* 131 (1), 33–41.

U.S. Fish and Wild Life Service. 2006. Endangered Species Bulletin 2006 Highlights. Accessed April 20, 2015. http://www.fws.gov/endangered/news/pdf/2006_highlights.pdf

Wu, J. 2004. Using Sciences to Improve the Economic Efficiency of Conservation Policies, *Agricultural and Resource Economics Review* 33, 18-23.

Wu, J., D. Zilberman, B.A. Babcock. 2001. Environmental and Distributional Impacts of Conservation Targeting Strategies, *Journal of Environmental Economics and Management* 41(3), 333-350.

Table 1. Maximal benefit scores by category as determined by the U.S. Department of Defense.

Specification		Maximum Available Points
Military Readiness	Encroachment Threat	
	1. Significance of at-risk mission	20
	2. Military benefits	20
	3. Severity of threat	12
	4. Coordinated planning to address threat	6
Subtotal:		58
Environmental Protection	Justification used under the statute	
	a. Incompatible Development	
	5a. Status/ use of project land and neighboring land	10
	6a. Zoning and land use planning	4
	7a. Secondary benefits	9
	Subtotal:	23
	b. Habitat Preservation	
	5b. Threatened and endangered species and species at risk	10
	6b. Ecological benefits	4
	7b. Secondary benefits	9
Subtotal:		23
Viability of Agreement	Viability of Agreement	
	8. Contributions of non-REPI funds	20
	9. Contributions of service funds	12
	10. Expenditure of funds	6
	11. Likelihood of execution	6
Subtotal:		44
TOTAL		148

Table 2. Summary of 44 projects by service branch and total

	Air Force	Army	Navy	Total
Number of Projects	9	23	12	44
Military Readiness Score	363	859.5	439	1662
Environmental Protection Score	117.25	346.5	149.75	614
Viability of Agreement Score	163	636	204	1003
Total Score	643.25	1842	792.75	3278
Average Total Score	71.47	80.09	66.06	74.5
Average Score Standard Deviation	9.2	11.09	12.76	12.6
REPI Funding Request	\$19,857,000	\$78,264,217	\$27,864,880	\$125,986,097
Average REPI Funding Request	\$2,206,333	\$3,402,792	\$2,322,073	\$2,863,320
REPI Funding Request Standard Deviation	\$1,219,306	\$2,313,497	\$969,060	\$1,915,153
Total Anticipated Acquisition Cost	\$31,187,250	\$211,692,048	\$50,646,427	\$293,525,725
REPI Share of Cost	63.67%	36.97%	55.02%	42.92%
Estimated Size (acres)	21,920.01	90,478.00	12,761.09	125,159.10
Estimated Average Size	2,435.56	3,933.83	1,063.42	2,844.53
Size Standard Deviation	3,468.67	5,052.78	1,007.65	4,137.07
Average Rank	26	17	30	

Table 3. Project summary and portfolio selection by method

Project	Rank	Military Readiness Score	Environmental Protection Score	Viability of Agreement Score	Total Score	Total Acquisition Cost	REPI Funding Request	Size (acres)	BT	BLP	GP
AF-1	39	37.50	14.25	11	62.75	\$3,500,250	\$3,000,000	11,414			
AF-2	36	37.00	13.75	13	63.75	\$3,350,000	\$3,000,000	2,615			
AF-3	6	47.00	21.50	20	88.50	\$2,400,000	\$1,200,000	81	1	1	1
AF-4	35	40.00	10.00	14	64.00	\$970,000	\$485,000	1,725	1	1	1
AF-5	20	45.00	14.50	16	75.50	\$6,000,000	\$3,000,000	1,611			1
AF-6	16	39.50	12.75	26	78.25	\$7,500,000	\$3,000,000	1,850	1	1	
AF-7	41	36.50	10.50	15	62.00	\$3,250,000	\$3,000,000	1,044			
AF-8	17	46.00	10.00	22	78.00	\$3,200,000	\$3,000,000	1,560	1	1	
AF-9	26	34.50	10.00	26	70.50	\$1,017,000	\$172,000	20	1	1	1
Total		363.00	117.25	163	643.25	\$31,187,250	\$19,857,000	21,920	5	5	4
Average	26.22	40.33	13.03	18.11	71.47	\$3,465,250	\$2,206,333	2,436			
A-1	14	36.50	19.25	25	80.75	\$46,000,000	\$3,000,000	16,000	1	1	1
A-2	3	43.00	17.50	38	98.50	\$19,000,000	\$3,000,000	2,745	1	1	1
A-3	24	28.50	10.00	34	72.50	\$6,500,000	\$3,000,000	3,259			
A-4	40	28.50	10.50	23	62.00	\$3,750,000	\$3,000,000	1,647			
A-5	7	36.50	19.25	32	87.75	\$11,000,000	\$3,000,000	1,348	1	1	1
A-6	30	31.00	14.50	23	68.50	\$3,750,000	\$3,000,000	1,572			
A-7	23	33.50	17.25	22	72.75	\$3,700,000	\$2,898,750	1,045			1
A-8	10	48.50	18.50	20	87.00	\$10,667,000	\$8,467,000	6,776	1		
A-9	1	46.50	18.75	34	99.25	\$5,508,500	\$2,948,500	1,110	1	1	1
A-10	19	42.00	14.00	20	76.00	\$2,500,000	\$2,000,000	702		1	1
A-11	15	40.50	14.50	24	79.00	\$12,016,000	\$12,000,000	7,175			
A-12	33	37.00	10.25	18	65.25	\$2,952,500	\$2,952,500	1,181			
A-13	32	34.00	10.75	22	66.75	\$3,000,000	\$3,000,000	1,082			
A-14	28	34.00	13.25	23	70.25	\$3,979,290	\$2,984,467	2,593			
A-15	11	44.50	18.50	23	86.00	\$1,180,000	\$630,000	1,230	1	1	1
A-16	9	35.00	14.00	38	87.00	\$6,700,000	\$3,000,000	2,700	1	1	
A-17	29	34.50	14.25	21	69.75	\$4,527,100	\$1,798,000	10,061		1	1
A-18	18	36.00	15.75	25	76.75	\$4,315,000	\$2,800,000	3,130	1	1	1
A-19	22	35.00	10.75	29	74.75	\$3,230,000	\$1,785,000	842		1	1
A-20	2	48.00	16.75	34	98.75	\$6,416,658	\$3,000,000	2,121	1	1	1
A-21	12	30.00	13.50	38	81.50	\$19,000,000	\$3,000,000	19,968	1	1	
A-22	4	45.00	17.25	30	92.25	\$7,000,000	\$3,000,000	468	1	1	1
A-23	5	31.50	17.50	40	89.00	\$25,000,000	\$4,000,000	1,723	1		
Total		859.50	346.50	636	1842.00	\$211,692,048	\$78,264,217	90,478	12	13	12
Average	17.00	37.37	15.07	27.65	80.09	\$9,204,002	\$3,402,792	3,934			
N-1	31	34.50	14.00	20	68.50	\$8,000,000	\$3,000,000	3,639			
N-2	27	43.50	14.00	13	70.50	\$4,000,000	\$3,000,000	1,100			1
N-3	21	43.50	15.00	17	75.50	\$4,250,000	\$3,000,000	1,077			1
N-4	8	48.00	15.25	24	87.25	\$8,000,000	\$3,000,000	230	1	1	1
N-5	43	28.00	10.25	13	51.25	\$4,000,000	\$3,000,000	1,225			
N-6	13	48.50	13.00	20	81.50	\$6,000,000	\$3,000,000	1,949	1	1	1
N-7	38	36.50	11.50	15	63.00	\$2,666,667	\$2,000,000	365		1	1
N-8	44	15.50	8.00	18	41.50	\$900,000	\$450,000	71		1	1
N-9	34	37.50	12.00	15	64.50	\$2,000,000	\$1,000,000	280		1	1
N-10	25	40.00	10.75	20	70.75	\$4,829,760	\$2,414,880	808		1	1
N-11	37	38.50	14.25	11	63.75	\$4,000,000	\$3,000,000	1,669			
N-12	42	25.00	11.75	18	54.75	\$2,000,000	\$1,000,000	348		1	1
Total		439.00	149.75	204.00	792.75	\$50,646,427	\$27,864,880	12,761	2	7	9
Average	30.25	36.58	12.48	17.00	66.06	\$4,220,536	\$2,322,073	1,063			
Total		1661.50	613.50	1003.00	3278.00	\$293,525,725	\$125,986,097	125,159	19	25	25
Average	22.50	37.76	13.94	22.80	74.50	\$6,671,039	\$2,863,320	2,845			

Notes:

BT – Benefit targeting; BLP – binary linear programming; GP – goal programming. For the last three columns: 1 = project was recommended for funding by REPI, otherwise the project was not recommended for REPI funding.

Table 4. Summary of outcomes by selection method

	BT	BLP	GP
Number of selected projects			
Air Force	5	5	4
Army	12	13	12
Navy	2	7	9
Total	19	25	25
Total REPI fund allocation (cost)			
Air Force	\$7,857,000	\$7,857,000	\$4,857,000
Army	\$39,845,500	\$32,961,500	\$29,860,250
Navy	\$6,000,000	\$12,864,880	\$18,864,880
Total	\$53,702,500	\$53,683,380	\$53,582,130
Military Readiness			
Air Force	207	207	167
Army	481	513	484
Navy	97	251	341
Total	785	971	992
Environmental Protection			
Air Force	64	64	57
Army	207	210	200
Navy	28	82	112
Total	299	356	369
Viability of agreement			
Air Force	108	108	76
Army	377	387	333
Navy	44	130	160
Total	529	625	569
Acres protected			
Air Force	5,236	5,236	3,437
Army	59,319	62,425	40,802
Navy	2,179	4,052	6,228
Total	66,734	71,713	50,467
Cost per benefit score			
Air Force	\$20,730.87	\$20,730.87	\$16,190.00
Army	\$37,413.62	\$29,695.05	\$29,361.11
Navy	\$35,502.96	\$27,785.92	\$30,774.68
Total	\$33,293.55	\$27,501.73	\$27,762.76
Total benefit score	1,613	1,952	1,930
% change from BT		+21.0%	+19.7%
Average score per project	84.89	78.08	77.20
% change from BT		-8.0%	-9.1%
Average cost per project	\$2,826,447.37	\$2,147,335.20	\$2,143,285.20
% change from BT		-24.0%	-24.2%
Average cost per score point	\$33,293.55	\$27,501.73	\$27,762.76
% change from BT		-17.4%	-16.6%
Total acreage protected	66,734	71,713	50,467
% change from BT		+7.5%	-23.5%
Average acres per project	3,512	2,869	2,019

Notes:

BT – Benefit targeting; BLP – Binary linear programming; GP – Goal programming

Table 5. Sensitivity analysis (two-way) of weights between military readiness and environmental protection

λ	Total Score	R	E	V	REPI Cost	Total Acquisition Cost	No. of Projects	Size (Acres)
0	1,886	1,005	346	535	\$53,883,380	\$112,595,935	25	45,437
0.05	1,886	1,005	346	535	\$53,883,380	\$112,595,935	25	45,437
0.1	1,904	1,004	351	549	\$53,883,380	\$155,095,685	25	50,023
0.15	1,928	1,002	356	570	\$53,883,380	\$162,095,685	25	49,702
0.2	1,913	1,001	358	555	\$53,883,380	\$158,595,685	25	49,521
0.25	1,913	1,001	358	555	\$53,883,380	\$158,595,685	25	49,521
0.3	1,913	1,001	358	555	\$53,883,380	\$158,595,685	25	49,521
0.35	1,913	1,001	358	555	\$53,883,380	\$158,595,685	25	49,521
0.4	1,921	986	367	569	\$53,582,130	\$159,410,685	25	50,467
0.45	1,921	986	367	569	\$53,582,130	\$159,410,685	25	50,467
0.5	1,921	986	367	569	\$53,582,130	\$159,410,685	25	50,467
0.55	1,921	986	367	569	\$53,582,130	\$159,410,685	25	50,467
0.6	1,921	986	367	569	\$53,582,130	\$159,410,685	25	50,467
0.65	1,921	986	367	569	\$53,582,130	\$159,410,685	25	50,467
0.7	1,921	986	367	569	\$53,582,130	\$159,410,685	25	50,467
0.75	1,903	976	368	560	\$53,582,130	\$157,410,685	25	50,187
0.8	1,903	976	368	560	\$53,582,130	\$157,410,685	25	50,187
0.85	1,903	976	368	560	\$53,582,130	\$157,410,685	25	50,187
0.9	1,896	970	368	558	\$53,582,130	\$156,910,935	25	60,501
0.95	1,901	963	368	570	\$53,582,130	\$157,160,685	25	50,659
1	1,900	962	368	570	\$53,582,130	\$156,660,935	25	60,404
Maximum	1,928	1,005	368	570	53,883,380	162,095,685	25	60,501
Minimum	1,886	962	346	535	53,582,130	112,595,935	25	45,437
Average	1,910	988	362	560	\$53,696,892	\$154,076,447	25	50,670

Notes:

R – Military Readiness Score; E – Environmental Protection Score; V – Viability of Agreement Score

Table 6. Sensitivity analysis (three-way) of weights between military readiness, environmental protection and viability of agreement

	R	% of Max	E	% of Max	V	% of Max	Total Score	Overall % (*)	Number of Occurrences
	958.00	95.37	363.25	98.64	625	96.90	1946	96.97	2
	962.00	95.77	365.50	99.25	616	95.50	1944	96.84	1
	953.00	94.87	365.25	99.19	622	96.43	1940	96.83	1
	953.00	94.87	356.00	96.67	637	98.76	1946	96.77	2
	938.00	93.38	360.25	97.83	639	99.07	1937	96.76	9
	970.50	96.62	356.00	96.67	625	96.90	1952	96.73	1
	940.50	93.63	364.75	99.05	628	97.36	1933	96.68	1
	958.50	95.42	367.00	99.66	612	94.88	1938	96.65	3
	944.50	94.03	367.00	99.66	619	95.97	1931	96.55	4
	950.50	94.62	353.00	95.86	639	99.07	1943	96.52	4
	929.50	92.53	362.00	98.30	636	98.60	1928	96.48	2
	979.50	97.51	354.75	96.33	616	95.50	1950	96.45	1
	963.00	95.87	350.25	95.11	634	98.29	1947	96.43	5
	983.00	97.86	362.00	98.30	598	92.71	1938	96.29	1
	977.00	97.26	366.50	99.52	594	92.09	1943	96.29	3
	993.00	98.86	356.25	96.74	595	92.25	1944	95.95	2
	986.50	98.21	350.50	95.18	608	94.26	1945	95.88	1
	985.50	98.11	366.50	99.52	569	88.22	1921	95.28	5
	1000.00	99.55	351.00	95.32	583	90.39	1893	95.09	2
	893.00	88.90	355.50	96.54	644	99.84	1934	95.09	1
	998.00	99.35	359.25	97.56	569	88.22	1926	95.04	1
	1001.50	99.70	356.25	96.74	570	88.37	1928	94.94	2
	890.50	88.65	352.75	95.79	645	100.00	1888	94.81	1
	975.50	97.11	367.75	99.86	560	86.82	1903	94.60	1
	1000.50	99.60	357.75	97.15	555	86.05	1913	94.27	2
	1003.50	99.90	351.25	95.38	549	85.12	1904	93.47	1
Maximum	1,004	99.90	368	99.86	645	100.00	1,952	96.97	9
Minimum	891	89	350	95	555	86	1,888	94	1
Average	965	96.06	359	97.53	607	94.14	1,931	95.91	

Notes:

R – Military Readiness Score; E – Environmental Protection Score; V – Viability of Agreement Score

Figure 1. Total benefit score by military branch

Figure 2. Comparison of selection methods by benefits

Figure 3. Comparison of selection methods by average per project cost

Figure 4. Summary of achieved benefits by military branch

Figure 5. Cost per benefit point separated by military branch for each selection method

Figure 6. Sensitivity analysis between Environmental protection and military readiness

Notes:

λ shifts weight between environmental protection and military readiness, with $\lambda = 0$ indicating that all weight is given to military readiness, while $\lambda = 1$ indicates that all weight is assigned to environmental protection.

Endnotes:

¹ Acreage for three projects (AF-7, N-11, and N-12) was unknown and was estimated by a power regression based