Applying Optimization to the Conservation Project Selection Process:

A Case Study of Readiness and Environmental Protection Initiative

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Abstract

This study presents a thorough discussion of the efficiency and effectiveness improvement from optimization models (Binary Linear Programming and Goal Programming), as applied to the Department of Defense's Readiness and Environmental Protection Initiative. The OM models can yield 21% and 19.1% higher benefit scores respectively, spending $13,013,473 and $31,463,473 less total acquisition costs. To achieve the same level of conservation benefits for the current rank based approach, the REPI would spend additional $20.1 million and approximate 50% of the budget. A counterpart of OM- the cost-effective analysis is observed to be inefficient when the problem becomes complex. In a real world of political environment of the conservation programs, we suggest a hybrid method of current rank based approach and the OM as well as the GP to address incompatible goals of interests groups.

JEL Codes: C6; Q24

Millions of dollars will be spent by the government agencies to conservation programs every year and they are trying to develop comprehensive scoring systems to make prioritization of programs, of which, the highest prioritized programs would be considered within the government budget. Although there are increasing concerns about the effectiveness and efficiency of conservation selection schemes, incorporating costs into the process have not yet been widely recognized (Naidoo et al 2006). Conservation experts develop handful of models used in conservation process, but only 13% of the plans in papers appeared in Conservation Biology, Biological Conservation, and Landscape & Urban Planning over 5 years (1999–2003) discussed economic costs of conserving habitat as a component of implementation (Newburn et al 2005). The USDA Natural Resources Conservation Service set a good example of using its 'Allocation Formulas and Methodologies' which not only incorporates weighted formula on resource base factors, resource quality factors, and performance factors, but also cost of doing business factors to allocate funding to highest scored programs (USDA 2009); however, this subjective weighted scoring system would not guarantee an optimal solution, and the costs for the government could have been largely reduced by using more scientific methods.

The process of the systematic conservation planning has been developed to integrate the social economic outcomes into the framework. As the computational technology develops, optimization theory has been extensively used in decision-making process, whether in engineering design or business strategies. This research focuses on efficiency improvement by the utilization of optimization models (OM) to conservation programs selection process. The second section is the literature review on methods used to tackle the cost-effectiveness in the conservation targeting strategies. The third section outlines the models used in the paper and the fourth section analyzes the Department of Defense's Readiness and Environmental Protection Initiative (REPI) Program for a large potential improvement. The fifth section draws the conclusion and implication from the study.

Literature Review

To take into account the social costs associated with the potential social benefits, or the efficiency of the program, the cost-benefit analysis (CBA) and the cost-effective analysis (CEA), which select the projects by ranking of cost-benefit (or cost-effectiveness) ratio, has gradually become a widely accepted concept amongst decision/policy makers. The theoretical basis in welfare economics for CBA and CEA is that if people's marginal willingness to pay (associated with the benefits) exceeds the price per unit they pay (associated with the opportunity costs), there could be a potential for improvement. Thus selecting the programs with largest benefit-cost ratios would result in the largest potential for improvement. The CEA adjusted the CBA in the way that the benefits of the programs do not need to be defined in monetary units. The CBA/CEA framework has also been adapted to the complicated, dynamic conservation environment. The benefit-loss-cost targeting framework developed by Newburn et al (2005) accounts the net loss of benefits prevented per unit cost (likelihood of land-use change); Machado et al (2006) take the conservation value as a cost-effective ratio of aggregate social value of preserving a site to the cost of conservation action of the site. Others incorporate the heterogeneity in land prices, benefits, vulnerability to future land use conversion and probability of development (Ando 1998; Costello and Polasky 2004; Abbitt et al 2000).

A more scientific method to balance the benefits and costs is the mathematical optimization model (OM), which uses mathematical programming models to maximize the aggregated benefits subject to certain constraints (usually the funding/budget). The OM would examine through all potential projects that may increase the total benefits with minimum costs, avoiding inefficient projects which exhaust the funding, and produces best results for the whole. The solution of OM is always optimal, and it can be used for other problems which do not directly related to cost – benefit relations. Like the set coverage problem (SCP), whose objective is to minimize a loss function such as the number of reserve sites subject to the constraint that all species are covered and the maximal coverage problem (MCP), whose objective is to maximize coverage subject to the constraint that the loss not exceed a specified amount (Ando 1998).

As compared to OM, although CBA/CEA consistently deliver the near-optimal results in some cases (Allen and Messer 2009), it may fail to provide optimal results under certain circumstances and it does not allow additional constraints to the problem (Fooks and Messer 2010). In other words, it is very limited to be extended as the model grows with complexity. The OM cannot only incorporate more constraints (whether economic, social or political constraints), but also deal with the multi-dimensional components of the projects. Traditionally, policy makers have concentrated on maximizing the present value of net benefits generated by the program; however, other components of the welfare (e.g. interests of partners) have been ignored. The multi-objective OM, referred as the goal programming (GP), can combine the diverse interests of agencies, partners/donors and the community/environment while keeping the advantages of scientific base of OM. (Messer 2011, Nijkamp 1977). For instance, Fooks and Messer (2010) apply the GP to the U.S. Forest Service's Forest Legacy Program (FLP) to incorporate both the conservation benefits and the partner in-kind cost share contributions, which achieved a 127% gain in in-kind cost share at the only 9% cost of benefit. In addition to that, the OM handles very well with the heterogeneous and dynamic characteristic of the conservation per se. An instance is the application of stochastic dynamic integer programming, which has been used to address optimal selection process over time, with heterogeneous features of programs (Costello and Polasky 2004; Newburn et al 2005; Strangea et al 2006).

Model

The OM applied in the conservation selection process uses the branch-and-bound algorithm to evaluate all possible combinations of selections that generates the maximum target value within the constraint. This is a process of Binary Linear Programming (BLP). The BLP is a special case of OM in that the decision variables are binary variables. The model is formulated as follows (Nijkamp 1977):

$$\max \omega(x_1, \ldots, x_n) = \sum_{i=1}^{n} b_i x_i \tag{1}$$

$$s.t. \quad g_1(x_1, \ldots, x_n) \le \bar{g}_1 \tag{2}$$

$$\vdots$$

$$g_K(x_1, \ldots, x_n) \le \bar{g}_K$$

where

$$x_i = \begin{cases} 1 & \textit{if project i is selected for funding} \\ 0 & \textit{otherwise} \end{cases}$$

For i = 1, 2,.., n. Usually, b_i is the benefit of project i, and g_i is the constraints for selecting the projects. In the simplest case, only the budget constraint would be applied. And the cost for each project is implicitly included into the g_i. However, the model can be extended by adding more constraints, whether it is economic, social or political.

When the traditional OM is optimized, the components which contribute to the maximum objective value is ambiguous. Thus the multi-objective models are attempted to deal with multiple criteria optimization problems. The goal programming model is one of the most widely used among them. The first step of the GP model is to solve OM problems for individual goals separately and then establish a multi-objective model to minimize the deviations from the optimum levels of each goal. The model can be formulated as (Nijkamp 1977):

$$\min Z = \sum_{j=1}^{J} \lambda_j \, (\omega_j^+ + \omega_j^-) \tag{3}$$

$$s.t. \quad g_k(x_1, \ldots, x_n) \le \bar{g}_k, \quad k = 1, \ldots, K \tag{4}$$

$$\omega_j - \omega_j^+ + \omega_j^- = \omega_j^*, \quad j = 1, \ldots, J \tag{5}$$

Where ω_j^+ and ω_j^- are positive and negative deviations of ω_j from the optimum ω_j^*. The constraints of the deviations show that the sum of positive and negative deviations from the optimal value should be equal to zero. And the weights λ_j for competing goals are added through coefficients of the deviations, which reflect the trade-off between diverse interest components.

Case Study – the REPI Program, the Department of Defense

In the lead up to World War II, the military established many training and testing ranges on large tracts of remote rural land. As military suppliers and families moved to the areas surrounding these installations, urban and suburban communities developed and continue to grow along the installation boundaries. Simultaneously, the military's land and resource requirements are growing with the evolution of technology and training activities, creating conflicts with the civilian population. Military operations have been challenged with safety concerns, endangered species restrictions, light pollution, and electromagnetic frequency spectrum usage, while the civilian communities are affected by the noise, dust, and smoke emanating from military training activities.

To address this encroachment problem, the Department of Defense established the Sustainable Ranges Initiative (SRI) in December 2001. One of the key components of SRI is the Readiness and Environmental Protection Initiative (REPI) Program, which is administered by the Office of the Secretary of Defense (OSD). The OSD is working with various partners: conservation organizations, land trusts, state and local governments and agencies, non-governmental organizations (NGOs), and federal departments to come up with solutions to the encroachment problem it is faced. And the REPI funding would serve as the catalyst for financial investments by project partners, and provide substantial financial and technical support for joint conservation efforts (REPI 2010). The common interests in guarding the benefits of both the military and the environment/community have brought together diverse partners to work on REPI projects.

Unfortunately, the procedure that the REPI currently uses is the rank-based approach (RBA), which selects the top-ranked projects (projects are first ranked according to their benefits) until the budget is exhausted. The procedure ignores the cost associated with the benefits and it fails to yield optimal results for covering problems, e.g. the minimum number of preserves needed to protect as many species as possible (Messer 2006). Thus the procedure fails to take other opportunities that could not only maximize aggregate benefits but also save a great deal of money (Allen and Messer 2009).

The research involves selection from forty-four installations/projects, which would be funded by the REPI to benefit both military and the environment at maximum. The installations are categorized by Services for military branches at particular locations (Air Force, Army, Navy and Marines). Data provided are project benefit scores, acquisition costs, and sizes of projects in terms of acreage affected. The benefit scores are evaluated by Services as well as OSD based on criteria required by REPI: Encroachment Threat, Incompatible Development/Habitat Preservation, and Viability of Agreement. Each criterion is broken into specific sub-criteria. For instance, the Encroachment Threat includes four sub-criteria focusing on the threat to the installation’s current and future mission, the significance of the at-risk mission to the military, the scope and physical proximity of the threat to military training, testing, and operations, as well as other coordinated planning undertaken to avoid future encroachment (REPI 2010). Each branch

(Air Force, Army and Navy) scores the projects submitted by the other services. The average score of these four is then used as the final project score in the selection process; this is the score referred to in the remainder of the paper.

The acquisition costs are also divided into four categories based on the source of funding. The Partner Contribution is the amount of money pledged by outside agencies and the other categories are Service Contribution, REPI Funding Request, and Other. The REPI Funding Request is the actual amount of money that the Project hopes to be granted by the REPI Program. It represents a potential benefit to the project in terms of fulfilled funding requirements, but it is a potential cost for the REPI program in terms of funding allocated. Also included in the data is the size of the project in terms of the amount of land, measured in acres, that would be affected by the project[1].

Table 1 summarizes the data for the selection process. The total budget for the REPI is of $54 million in the year 2010. The REPI uses a three-tiered funding allocation system, but to make the points straight, i.e. how much difference GP could make over the current system, our model assumes a non-tiered funding allocation system. Obviously, the relaxation of the assumption would not cause any changes to our conclusion.

Results

Cost Effectiveness of CEA and BLP over RBA

[1] The acreage for three projects, AF-7, N-11, and N-12, is unknown and by using power regression, they were estimated to be approximately 1,044, 1,669, and 348 acres respectively.

As previously discussed, the RBA that REPI program currently uses is the most inefficient method, while CEA and BLP could be cost-effective. In this case, the CEA and BLP generate exactly the same result, which shows that CEA could be taken as a good substitution of BLP in some cases; and BLP is as cost-effective as CEA. A hybrid of RBA and BLP is also considered. The "Hybrid-5" will select the top five ranked projects, and then use the BLP to select the remaining projects. As a result, the RBA selects the fewest projects, 19 (66,734 acres), the CEA and BLP method selects the most projects, 25 (71,713 acres), and the Hybrid-5 method selects 24 (69,958 acres) projects, slightly below the CEA/BLP. The distributions of the scores and project sizes are displayed in Figure 1- 1 to Figure 1- 3. Figure 1- 1 shows total scores distributed among three branches. Apparently, CEA and BLP obtain the highest total benefit score of 1,952, the RBA obtains the lowest total benefit score of 1,613, and the Hybrid-5 method falls in between with respective total benefit scores of 1,909. The CEA/BLP do not select the fifth ranked projects, which accounts for the differences of the hybrid models. Considering the total score in the RBA to be the baseline, a 21% increase in the CEA/BLP and an 18.4% increase in the Hybrid-5 are observed. As is shown in Figure 1-2, the Air Force consistently has 24% acreage of projects selected, as the same projects are picked by all three methods, and the Army has additional 3% size of projects selected by the BLP and 1% selected by Hybrid-5 method over the 66% size selected by the RBA. Similar to Figure 1- 1, the majority of variability is seen in the Navy: only 17% size of Navy projects are selected by the RBA; while 32% size of Navy projects are selected by the CEA/BLP, and 29% size of Navy projects are selected by the Hybrid5 method. The

Navy has the lowest average rank of the three Services; however the corresponding costs of the projects are also relatively low. Therefore, the CEA and BLP recognizes this cost saving, which is ignored by the RBA as it only looks at projects individually and not as a group, they selects several smaller cost projects over the single large cost project.

The total benefit score is divided by three criterions which are distinguished in Figure 1- 3. Each of the three benefit score criteria follows the same pattern as the total benefit score; the RBA obtains the lowest values, and the CEA and BLP obtain the highest. The Encroachment Threat, Incompatible Development/Habitat Preservation and Viability of Agreement scores in CEA/BLP are respectively 23.77%, 19.06%, and 18.15% higher than that in RBA; while the total REPI funding needed is $19,120 less and total acquisition cost is $13,013,473 less.

The cost effectiveness of CEA/BLP over RBA can be measured by considering the cost/benefit score ratio. The RBA pays $29,293 for each score point while the CEA/BLP pay $27,509 for each score point, which means one additional score point for the CEA/BLP costs approximately 11.7% less than for the RBA. In order for RBA to achieve the same total level of score as the CEA/BLP, the budget must increase by approximately 37.2% to $20.1 million. And this increase in the cost would only bring about 3.2% increases in the score; in other words, in order to achieve 1% higher score, the costs have to increase as 12 times as previous funding.

Limitation of CEA

Although the CEA obtains the same results as the BLP in this case, it does not always guarantee the optimal solutions. As is discussed in Messer 2006, the efficiency difference between CEA and BLP becomes greater when two or more constraints are included in the problem (Messer 2006). To illustrate the point, suppose the REPI was in short of labor, or for some political reason, a constraint on the number of projects selected needs to be imposed. The inefficiency of CEA becomes apparent at this time, as is shown in Figure 2s. Figure 2- 1 presents the result when the number of projects is constrained to 20. The RBA is unaffected as it still selects the 19 highest ranked projects within the budget. However, the gains from both CEA and BLP are largely reduced due to the additional constraints. Amongst these three methods, BLP continues to search for the optimal solution and it results in a highest total score of 1688, but CEA even performs worse than RBA (61 scores lower). The reason is that CEA continues to search highest benefit-cost ratio projects regardless of additional constraints while those higher cost-effective projects would no longer satisfy the new constraints space. When the number of projects is constrained to 20, the budget constraint is also relaxed and the optimal solution is no longer identical to finding the highest benefit-cost ratio projects. Thus CEA fails to provide the optimal solution.

As the number of projects required decreases, the budget constraint could become more relaxed (the fewer the projects, the less the costs), until it is no longer a scare resource. In this case, the CEA is the worst solution to the problem as other aspects of the problem dominates the cost-effectiveness. For instance, as the number of projects is restricted to 16 (see Figure 2- 2), RBA and BLP generate the same result, while CEA obtains the lowest level of 1,219 score point. The cost is not an important issue in this case, thus selecting the projects that have the highest benefit score is the optimal solution, and consequently, RBA can generate the best solution, as well as BLP. The limitation of CEA becomes more obvious as the model expands: first, it is very hard to distinguish between constraints on which ones are active and which ones are inactive, thus it is difficult to see the appropriateness to use the CEA; second, CEA deals well with one dimensional cost-related issue, but it would become too complicated to adjust the CEA to multidimensional issues.

Extendibility of Optimization Methods - Application of GP

Using optimization methods to solve the conservation problem will always generate the optimal solution, no matter what the constraints are, and how many constraints there are. The constraints of optimization models can be extended as many as the policy maker desires and balance of interests is also possible through optimization.

The goal programming technique enables the REPI program to make project selection decisions with a view to maximizing a particular set of objectives as well as trading off between objectives: military readiness (Encroachment Threat score) and environmental protection (Incompatible Development/Habitat Preservation score) in this case. An intermediate trade-off between to targets ($\lambda = 0.5$), is used to determine the selection process (the military readiness and environmental protection goals are weighed equally).

The total projects selected in GP are the same as in the BLP, but different projects are selected. Table 2 shows how results are different in these two models. GP tries to find minimum deviations from both maximum military and environmental benefits, thus respective higher scores in two criteria are observed. But they are achieved by sacrificing the total benefit: the total score is 31 point lower than of the BLP and the corresponding cost is also lower than that of BLP. On top of that, the GP maintains the advantages of optimization over RBA or CEA. Using less REPI money, the purchasing fund can provide easement for more parcels with a better total score, as well as better military, environmental, and viability scoring components. A cost increase of approximately 50 percent is necessary for the RBA of land easement to match that of the GP. This further confirms the initial analysis: the use of optimization methods is a much better and flexible means of meeting the REPI program's selection objectives than the RBA.

A sensitivity analysis by varying λ is also conducted to study the trade-off between two benefit-targets as λ changes. $\lambda = 0$ presents the case favoring military operations exclusively, while $\lambda = 1$ presents the case favoring environmental protection exclusively. If $\lambda = 0.25$, then 25% of the weight will be given to environmental protection and 75% of the weight will be given to military operation. The results are displayed in Table 3. The highest total score of 1921 could be achieved when λ is in the range from 0.4 to 0.7. For small λ values ($\lambda = 0 - 0.35$), which favor military operations at the expense of environmental readiness, shifts towards the environmental and away from the military parameters have large benefits for the environment with limited repercussions for the military. The change at the mid-level λ ($\lambda = 0.4$) represents a dramatic shift away from military operations and in favor of the environmental readiness. For all greater λ values ($\lambda = 0.45 – 1$), small shifts in favor of environmental readiness have large negative repercussions for military operations. In other words, in this range, the military benefits could be improved with limited decrease in environmental benefits. For instance, when λ changes from 1 to 0.4, the military benefits would increase by 24 score point at the expenses of only 1 point score loss in environmental benefits.

The graph (figure 3) of the sensitivity analysis between environmental protection and military readiness, i.e. efficiency frontier, much like a production possibility frontier curve in economics, enables the evaluation of trade-offs between the two competing goals. All values on the line represent the best possible combinations of environmental protection and military readiness scores given a variety of weights between the two objectives. The graph is very useful for interested policy makers to balance competing targets when making decisions.

Conclusions

The results of this study strongly suggest that the REPI Program should adopt some configuration of the optimization methods for project selection. In all cases, the REPI Program's current RBA performed worse than the CEA, OM (include BLP and GP) and hybrid methods. Considering the cost-effectiveness, the CEA and BLP increases the efficiency of REPI allocations, and thus for the same cost, the CEA/BLP achieves a 21% higher benefit score than its rank-based counterpart. As another measurement of the CEA/BLP model's efficiency, an additional $20.1 million dollars must be spent for the ranking method to achieve the same score as the CEA/BLP. Using the CEA/BLP and the GP achieve 37.2%, 45.1% cost savings respectively.

In practice, selection process in the conservation programs can have multi-dimensional aspects to be considered. Extra constraints could be added into the decision process. While the optimization methods will always search for the best/optimal solution, the CEA will be too narrow to be appropriate when other components are taken into consideration. It is possible to translate additional constraints into the framework of benefit and cost, but it might be time-consuming, complicated and sometimes inappropriate. The example of additional constraints on the number of projects selected shows the inefficiency of CEA in multi-dimensional environment; while the optimization model keeps efficiency in any occasions.

While the pure BLP achieves the best results, we recognize that it may not be optimal with respect to the political environment. The BLP method, as demonstrated in this study, is not guaranteed to select any project with a given rank; although it was not observed with this data set, it is possible that the BLP will not select the highest ranked project and so forth. Such actions may invoke confusion, opposition, and anger by the concerned parties. In such a case, the authors recommend using a hybrid method, such as the Hybrid-5, to select a given number of top ranked projects and then use BLP to select the remaining projects. While this method does not achieve the best results, they still perform significantly better than the RBA, and they present a strategic benefit that may be worth the small trade-off in benefit score.

Furthermore, it is demonstrated that the goal programming methodology can be very attractive as well as efficient when the selection involves balancing benefits among different interests groups. In this case particularly, if the primary goals have to satisfy both the military and the community's needs at maximum, the goal programming could be used, and the weights on each goal is depended upon relative strengths of political powers in public sectors and priority in private sectors.

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Table 1. Descriptive Statistics for Projects Considered in REPI

	Air Force	Army	Navy	Total
Number of Projects	9	23	12	44
Encroachment Score	363.00	859.50	439.00	1662
Incompatible Development /Habitat Preservation Score	117.25	346.50	149.75	614
Viability of Agreement Score	163.00	636.00	204.00	1003
Total Score	643.25	1842.00	792.75	3278
Average Total Score	71.47	80.09	66.06	74.50
Average Score Standard Deviation	9.20	11.09	12.76	12.60
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	

Figure 1. Comparisons of results from RBA, CEA, BLP and Hybrid-5

Figure 1- 1. Distribution of Scores amongst Branches

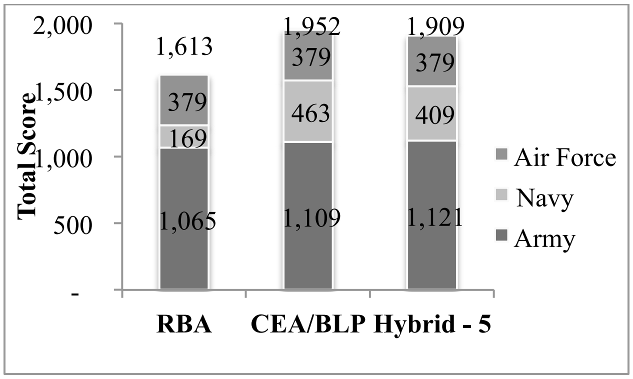

Figure 1- 2. Percentage of land protected for each branch

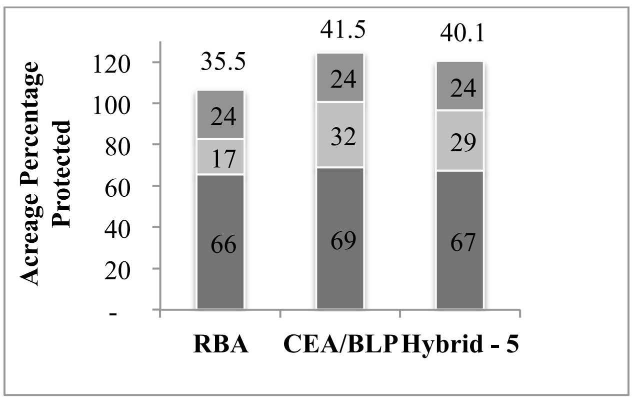

Figure 1- 3. Distribution of scores by criteria

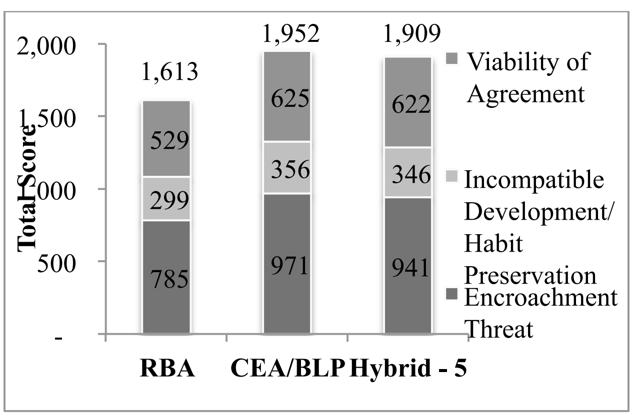

Figure 2. Distribution of scores under additional constraints

Figure 2- 1. Constraints on number of projects <= 20

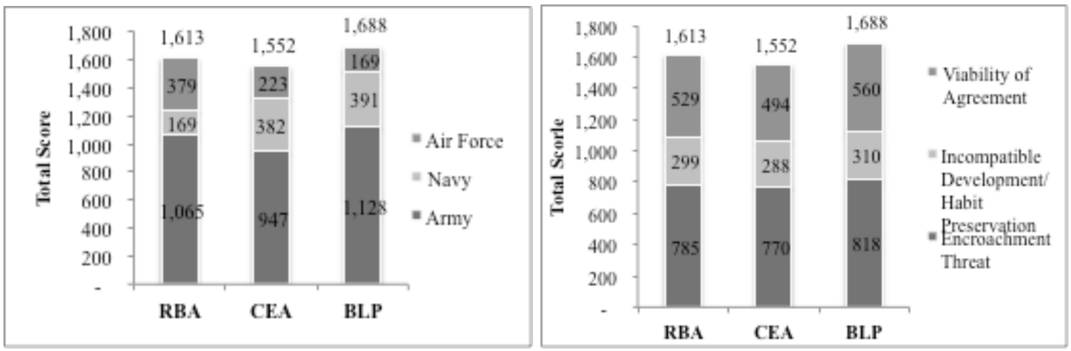

Figure 2- 2: Constraints on number of projects <= 16

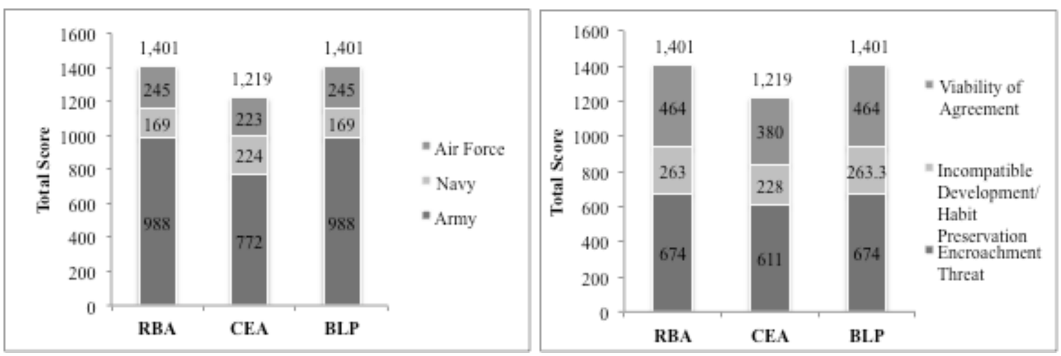

Table 2. Comparisons of Results from BLP and GP

	Projects Selected	Total Score	Military Readiness	Environment Protection	REPI Cost
BLP	25	1952	971	356	$53,683,380
GP	25	1921	986	367	$53,582,130

Table 3. Sensitivity Analysis of Weights between Objectives

λ	Total Score	M[2]	E[3]	V[4]	REPI Cost	Total Acquisition Cost	# of Projects	Size (Acres)
0.00	1,886	1,005	346	535	$53,883,380	$112,595,935	25	43,421
0.05	1,886	1,005	346	535	$53,883,380	$112,595,935	25	43,421
0.10	1,904	1,004	351	549	$53,883,380	$155,095,685	25	48,007
0.15	1,928	1,002	356	570	$53,883,380	$162,095,685	25	49,355
0.20	1,913	1,001	358	555	$53,883,380	$158,595,685	25	47,505
0.25	1,913	1,001	358	555	$53,883,380	$158,595,685	25	47,505
0.30	1,913	1,001	358	555	$53,883,380	$158,595,685	25	47,505
0.35	1,913	1,001	358	555	$53,883,380	$158,595,685	25	47,505
0.40	1,921	986	367	569	$53,582,130	$159,410,685	25	50,120
0.45	1,921	986	367	569	$53,582,130	$159,410,685	25	50,120
0.50	1,921	986	367	569	$53,582,130	$159,410,685	25	50,120
0.55	1,921	986	367	569	$53,582,130	$159,410,685	25	50,120
0.60	1,921	986	367	569	$53,582,130	$159,410,685	25	50,120
0.65	1,921	986	367	569	$53,582,130	$159,410,685	25	50,120
0.70	1,921	986	367	569	$53,582,130	$159,410,685	25	50,120
0.75	1,903	976	368	560	$53,582,130	$157,410,685	25	48,171
0.80	1,903	976	368	560	$53,582,130	$157,410,685	25	48,171
0.85	1,903	976	368	560	$53,582,130	$157,410,685	25	48,171
0.90	1,896	970	368	558	$53,582,130	$156,910,935	25	58,485
0.95	1,901	963	368	570	$53,582,130	$157,160,685	25	48,643
1.00	1,900	962	368	570	$53,582,130	$156,660,935	25	60,057

[2] Score for Military Readiness.

[3] Score for Environmental Protection.

4 Score for Viability of Agreement.

Figure 3. Efficiency frontier for the GP model

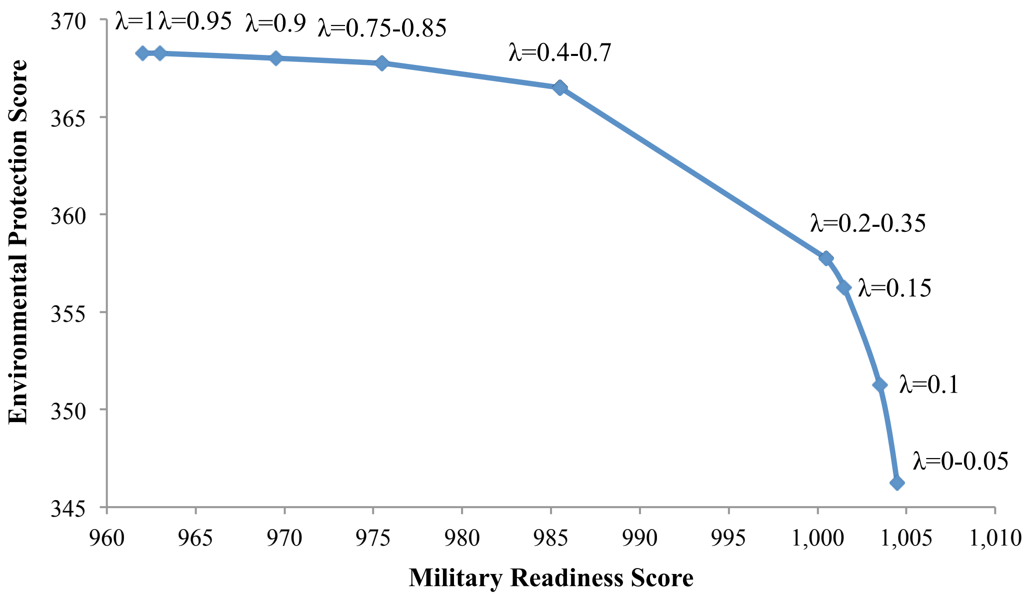

Table 4. Selection of Projects[5] Using Different Methods

	Budget Constraint					Budget + Project Constraint (Projects <=20 & <=16)					
Project	RBA	CEA	BLP	Hybrid-5	GP	RBA-20	CEA-20	BLP-20	RBA-16	CEA-16	BLP-16
A-1	1	1	1	1	1	1		1	1		1
A-2	1	1	1	1	1	1	1	1	1	1	1
A-3											
A-4											
A-5	1	1	1	1	1	1	1	1	1		1
A-6											
A-7					1						
A-8	1					1			1		1
A-9	1	1	1	1	1	1	1	1	1	1	1
A-10		1	1	1	1		1	1		1	
A-11											
A-12											
A-13											
A-14											
A-15	1	1	1	1	1	1	1	1	1	1	1
A-16	1	1	1	1		1	1	1	1		1
A-17		1	1	1	1		1			1	
A-18	1	1	1		1	1	1	1		1	
A-19		1	1	1	1		1	1		1	
A-20	1	1	1	1	1	1	1	1	1	1	1
A-21	1	1	1	1		1		1	1		1
A-22	1	1	1	1	1	1	1	1	1	1	1
A-23	1			1		1		1	1		1
AF-1											
AF-2											
AF-3	1	1	1	1	1	1	1	1	1	1	1
AF-4	1	1	1	1	1	1	1			1	
AF-5					1			1			
AF-6	1	1	1	1		1		1	1		1
AF-7											
AF-8	1	1	1	1		1		1	1		1
AF-9	1	1	1	1	1	1	1	1		1	
N-1											
N-2					1						
N-3					1						
N-4	1	1	1	1	1	1	1	1	1		1
N-5											
N-6	1	1	1	1	1	1		1	1		1
N-7		1	1	1	1		1			1	
N-8		1	1	1	1		1			1	
N-9		1	1	1	1		1			1	
N-10		1	1	1	1		1				
N-11											
N-12		1	1		1		1			1	
Total	19	25	25	24	25	19	20	20	16	16	16

[5] The actual names of the projects are not listed. The names of the Services plus the numbers indicate a specific installation. Spatial distribution of projects is not discussed in this article.