Integrating Biodiversity Representation with Multiple Criteria in North-Central Namibia Using Non-Dominated Alternatives and a Modified Analytic Hierarchy Process

Alexander Moffett*, James S. Dyer†, and Sahotra Sarkar*[1]

* Biodiversity and Biocultural Conservation Laboratory, Section of Integrative Biology, University of Texas at Austin, 1 University Station, #C3500, Austin, TX 78712 –1180.

† Department of Management Science and Information Systems, College of Business Administration, University of Texas at Austin, 1 University Station, #B6500, Austin, TX 78712 –1180.

Abstract

A protocol is developed for the incorporation of multiple criteria, including spatial design and socio-political criteria, into the design of conservation area networks. This protocol begins with the identification of the non-dominated set of alternatives, where each alternative is a network of conservation areas that satisfies biodiversity representation targets. This set is then refined to identify a finally preferred alternative using a modification of the Analytic Hierarchy Process. This modification ensures that the results obtained are identical to those that would be obtained using standard multiattribute value theory while allowing the use of the transparent preference method of the Analytic Hierarchy Process. The final stage of the protocol consists of sensitivity analyses to test the robustness of the ranking of the alternative set. The protocol is applied to a practical data set from northern Namibia to identify a set of land units that can be targeted for biodiversity conservation beyond the existing national parks.

Keywords: Analytic Hierarchy Process; multi-criteria decision making; multi-criteria analysis; Namibia; trade-offs.

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[1] Corresponding author: address for comments: <sarkar@mail.utexas.edu>.

1. **Introduction**.

Biodiversity conservation planning typically involves the design of conservation area networks: sets of places such as national parks or reserves at which conservation plans are implemented (Margules and Pressey, 2000; Sarkar, 2003; Sarkar, 2005). Conservation area networks are selected to represent desired features of biodiversity such as species (generically called “biodiversity surrogates”) at least up to specified targets (Margules et al., 1988). Additionally, well-designed conservation area networks incorporate spatial criteria such as the size and shape of individual areas, their connectivity, and their alignment, replication, and dispersion across the landscape (Moffett and Sarkar, 2005). Moreover, conservation area network selection occurs in the context of many competing social claims on land use besides biodiversity conservation (Sarkar, 2005). These include human habitation, recreation, habitat transformation for agricultural or industrial development, and biological and industrial resource extraction. Conservation area networks are typically initially designed with economy in mind, that is, to represent biodiversity surrogates adequately in the smallest possible total area (Sarkar et al., 2004c). A central task of systematic conservation planning is to find a conservation area network that not only adequately represents surrogates but also incorporates the spatial design and socio-economic criteria as optimally as possible. A wide variety of techniques exist for the incorporation of multiple criteria. These range from heuristic methods to the well-developed multi-attribute value and utility theories (Keeney and Raiffa, 1976; Dyer et al., 1992; Dyer, 2005). Their use in conservation planning has recently been reviewed by Moffett and Sarkar (2005).

Conservation area networks are often (though not always) constructed iteratively, that is, by selecting individual land units or cells one at a time for inclusion in a potential network. Consequently, there can be two types of protocol for the incorporation of multiple criteria into conservation area network design: (i) in *iterative* stage protocols all criteria are considered as each individual cell is selected for potential inclusion (Faith and Walker, 1996; Possingham et al., 2000; Faith et al., 2001; Bojórquez-Tapia et al., 2004); and (ii) in *terminal* stage protocols, in which a set of networks is initially selected, with each network satisfying the biodiversity representation targets (Li et al., 1999; Memtsas, 2003; Sarkar et al., 2004b). The criteria other than biodiversity representation are then used to rank these networks which comprise the "feasible alternatives" or, in short, "alternatives" for these protocols. Terminal stage protocols typically privilege biodiversity representation over the other criteria because the satisfaction of the representation targets, in principle, cannot be compromised. They also typically assume that biodiversity representation can be assessed as a single parameter. Iterative stage protocols typically do not privilege biodiversity representation: they allow tradeoffs between this and other criteria. Whether an iterative stage or terminal stage protocol is appropriate depends on a partly subjective decision as to the relative importance of the biodiversity surrogates being used and the targets set for them compared to all the other criteria. The two protocols are not exclusive. Both may be used simultaneously (Moffett and Sarkar, 2005).

The main purpose of this paper is to illustrate a protocol which can be used in any situation for which a terminal stage protocol is appropriate. A sequential terminal stage protocol that consists of three stages is proposed: (i) computation of the "non-dominated" alternative set; (ii) refinement of this set based on assumptions of the relative importance of the criteria being used, resulting in an ordering of all the non-dominated alternatives; and (iii) a sensitivity analysis to test the robustness of the conclusions. This protocol was applied to a case selected by personnel from the Ministry of Lands, Resettlement and Rehabilitation of Namibia. The goal of this exercise was to identify a set of land units north of the existing Etosha National Park which, when put under a conservation plan, would together provide adequate protection for all vegetation classes of the region while simultaneously optimizing six other socio-political criteria. This example does not include design criteria but they may be treated in exactly the same way, that is, by evaluating the performance of each alternative according to each design criterion. The actual results should be regarded as only preliminary because the criteria that were modeled may require further refinement as additional stakeholders are consulted by the Ministry.

In this analysis, notional conservation area networks constituted the alternatives. The analysis began with a computation of the set of “non-dominated” alternatives. One alternative “dominates” another alternative if it performs better with respect to at least one criterion and performs at least as well with respect to all other criteria. The set of non-dominated alternatives consists of those alternatives that are not dominated by any alternative. Thus, this set consists of unequivocally superior alternatives: regardless of the particular importance attributed to the each of the individual criteria, an alternative that is dominated will never outperform a non-dominated alternative (Sarkar and Garson, 2004). Therefore, in selecting a conservation area network, the alternatives that merit further consideration should preferably be limited to this set of non-dominated alternatives. Such a use of the non-dominated alternative set in conservation planning has been explicitly advocated by Sarkar and Garson (2004) and was used even earlier by Rothley (1999) and Sarkar et al. (2000). This method is particularly important because it makes no assumption about the quantitative ranking of alternatives according to the criteria, the relative value of each criterion, or whether the criteria are valued independently without consideration of the performance levels of other criteria.

If the number of non-dominated alternatives is small, the non-dominated alternative set can be presented to political decision makers who can then select among them on the basis of considerations beyond those that have been modeled. However, typically, the cardinality (that is, the number of elements) of the non-dominated alternative set increases rapidly with the number of criteria (Sarkar and Garson, 2004). The non-dominated alternative set may be intractably large for use during the decision-making process. It then becomes imperative to refine the non-dominated alternative set, that is, to rank the non-dominated alternatives, so that some of them can be eliminated. This requires establishing preferences among the criteria and compounding this information with the rankings of the alternatives according to each criterion.

A modification of the Analytic Hierarchy Process (Saaty, 1980) was used to develop “weights” of all the criteria and use them to rank the non-dominated alternatives. The original Analytic Hierarchy Process has often been used in the context of conservation area network design and selection, though without first excluding dominated alternatives (Anselin et al., 1989; Kangas, 1993; Li et al., 1999; Mendoza and Prabhu, 2000; Schmoldt et al., 2001; Clevenger et al., 2002; Villa et al., 2002; Ananda and Herath, 2003). However, the original Analytic Hierarchy Process has the counter-intuitive property of allowing a rank reversal among existing alternatives when new alternatives are introduced (Belton and Gear, 1983; Dyer, 1990). Even the introduction of dominated alternatives may lead to rank reversal. A modified Analytic Hierarchy Process which avoids this problem was used. This modification also adjusts the Analytic Hierarchy Process results so that they are rank equivalent to those obtained with multiattribute value theory (Kamenetzky, 1982; Belton, 1986; Dyer, 1990; Salo and Hämäläinen, 1997) which is an added virtue of this approach. This modification has previously been used in conservation planning by Pereira and Duckstein (1993) and Phua and Minowa (2005) though not in conjunction with the initial identification of the non-dominated alternative set.

Rank reversal amounts to a violation of the axiom of the independence of irrelevant alternatives (Arrow and Raynaud, 1986) which says that such alternatives should not change the evaluation of the original alternative set. This is a serious problem in the context of conservation planning because, typically, not every possible alternative can plausibly be taken account.

Finally two types of sensitivity analyses were carried out in order to evaluate the robustness of these results to variations in the degree of importance attributed to each of the criteria. First, for each criterion, the effect of altering its importance was examined by altering its weight while holding constant the weights of all other criteria. The new rankings were then compared with the original one. Second, a large number of sets of random weights were generated and each set was assigned to the criteria in a way that preserved the rank order of the assessed weights. The rank order of the alternatives under each set of random weights was then compared to the original one. The second method is preferable to the first insofar as it allows weights of more than one criterion to be varied simultaneously. It also incorporates the possibility that there may be much more confidence in the order, or relative importance, of the criteria than in the numerical weights assigned to them. Sensitivity analyses have typically not been performed in attempts to incorporate multiple criteria into conservation planning. Even when they have been carried out, for instance, by Faith and Walker (1996), Rothley (1999) and Faith et al. (2001), only the first of these methods has been used. It is important to emphasize performing sensitivity analyses to establish the robustness of results because systematic conservation planning typically occurs in situations of considerable uncertainty regarding the relative importance of the criteria that are used.

2. **Methods**.

2.1. **Northern Namibia Data Set**.

A map of land units (or "cells") provided by the Ministry of Lands, Resettlement and Rehabilitation of Namibia was used for this analysis. The region consisted of Etosha National Park and the land between it and the border with Angola. Besides the Etosha National Park there were 119 different cells. These cells varied in size from 0.02 sq. km. to 1225.89 sq. km., with an average area of 517.95 sq. km. All 35 different vegetation classes from this region were used as biodiversity surrogates and quantitative expectations of presence were calculated for each of the surrogates in each of these 120 different cells, with the expectation value for a given vegetation class in a cell being equal to the area in the cell containing the vegetation class. All distributional data were obtained from a website of the Namibian government (http://www.dea.met.gov.na/).

Besides biodiversity representation, six other criteria were considered in this analysis: (1) area; (2) human population; (3) number of summer cattle; (4) number of winter cattle; (5) farming; and (6) number of wildlife. An optimal solution would minimize the values of criteria (1) through (5) while maximizing the value of criterion (6). These are all socio-political criteria. The number of wildlife is the total population of large non-domesticated mammals in a cell. Because there were fewer than ten species, these cannot be used as biodiversity surrogates. But, because this number provides a measure for the potential for tourism in an area, the number of wildlife is a potentially important social criterion to incorporate into an analysis Each alternative was assigned a quantitative value for each of the six criteria using data from the website mentioned above. This set of criteria was provided by the Ministry of Lands, Resettlement and Rehabilitation of Namibia and consisted of those that local Namibian experts deemed to be the most relevant.

2.2. **Place Prioritization for Biodiversity Representation**.

Place prioritization was carried out using a complementarity-based heuristic algorithm (Margules et al., 1988). A modification of the ResNet software package (Garson et al., 2002) was used for this process. A representation level of 10 % was used as the target for each biodiversity surrogate (that is, each vegetation class) and 100 randomly re-ordered input files were produced. These produced different alternatives because of the algorithm that was used (see Sarkar et al., [2002] for detail). It initially selected celly by complementarity. Ties were broken by lexical order, that is, effectively by a random selection of a cell. Each run of the algorithm was initialized with the inclusion of the cell representing Etosha National Park. This is appropriate because

Etosha is an established protected area that will remain an important component of any future conservation plan. In addition, 8 cells containing towns were masked from consideration; none of these cells were considered for inclusion during any of the runs. The rationale for this decision was that (i) biodiversity around the towns has a high likelihood of being degraded due to high human population densities; (ii) selecting these areas for protection would likely have unacceptably high economic and social costs; and (iii) managing such densely populated areas for biodiversity conservation ia also likely to be inordinately difficult. Each of the 100 solutions, from the 100 different input files, constitutes a conservation area network, or feasible alternative, in which 10 % of the habitat of each vegetation class is represented. However, some of these alternatives may be dominated by others (see below).

2.3. **Non-Dominated Solutions**.

An alternative, α_j, dominates another alternative, α_i, if α_j is better than α_i by at least one criterion, and no worse than α_i by any of the criteria. An alternative is "non-dominated" if no alternative dominates it. A set of non-dominated alternatives corresponds to a Pareto optimal set of traditional economic analysis (Keeney and Raiffa, 1976). The evaluation of a set of alternatives through the identification of such a non-dominated set has the following three advantages. First, it requires only that each criterion induce a weak linear ordering on the alternatives. The fact that no stronger assumption is required has three advantages. (i) It does not require either the assignment of quantitative values to the alternatives. (ii) It does not require an evaluation of the relative importance of the criteria. (iii) It does not require an independence assumption which postulates that preferences for values on one criterion are not influenced by values on the other criteria. Second, it introduces no subjective information into the decision making process other than that required to produce the weak orderings of the alternatives. Third, its results are compatible with those of any other rational decision procedure.

In this analysis, the MultCSync software package was used to calculate non-dominated solutions using an iterative scoring algorithm that tracks whether an alternative is preferred over another by some criterion (Moffett et al., 2005). Sarkar and Garson (2004) provide a detailed analysis of the algorithm.

If the number of non-dominated alternatives is small, the non-dominated alternative set can be presented to political decision makers who can then select among these alternatives on the basis of considerations beyond those that have been modeled (Sarkar and Garson, 2004). However, in many decision scenarios, the cardinality (or size) of this set will be too high. In such scenarios, the identification of the preferred alternative from this set will require a more refined evaluation of the alternatives than that afforded by just identifying the non-dominated alternative set.

2.4. **The Modified Analytic Hierarchy Process**.

The Analytic Hierarchy Process is a decision procedure used to rank order a set of alternatives on the basis of multiple criteria (Saaty, 1980). However, to use the Analytic Hierarchy Process, a quantitative value must be assigned to each alternative relative to each criterion, and the importance of each criterion must be quantitatively assessed. In order for the results of the Analytic Hierarchy Process to be meaningful, the criteria themselves must exhibit mutual difference independence (Dyer, 2005). This means that the preference difference between two alternatives differing with respect to some subset of criteria does not depend on the shared values of the other criteria (that is, values for the criteria on which the alternatives are identical) and justifies the use of the additive model of preference.

An example may be useful to clarify the notion of difference independence, since it is likely to be unfamiliar to most biologists. Suppose there is an alternative that is described by the following vector of criterion values: (28,100 sq. km. area, 177,145 population, 38,225 summer cattle, 35,219.5 winter cattle, 1,047 farms, 40.48 wildlife). Now, the decision maker should carry out a thought experiment by letting any one of these values change, and make a judgment about the difference between the subjective preferences for the original and the revised alternatives. For example, suppose that the number of summer cattle decreases from 38,225 to 28,225, a difference of 10,000 summer cattle, but all of the other criteria do not change. The decision maker should think about the subjective value for this decrease in summer cattle when all of the other criteria are held constant at common values, which is called the decision maker’s preference difference between the original and the revised alternative.

Next, the decision maker should consider another alternative, perhaps a hypothetical one, with different values for all of the criteria except for summer cattle. An example would be the vector (29,600 sq. km. area, 215,417 population, 38,225 summer cattle, 48,148 winter cattle, 1,937 farms, 42.55 wildlife) where all of the values are changed except for 38,225 summer cattle. Once again, the decision maker should consider changing the number of summer cattle by 10,000 to 28,225, and assess the preference difference between this original alternative and its corresponding revised alternative.

If the decision maker concludes that the preference difference between the first original and revised alternatives is approximately equal to the preference difference between the second original and revised alternatives, then the number of summer cattle is difference independent of the other five criteria. Intuitively, this corresponds to a judgment that the preference value of changing the number of summer cattle from 38,225 to 28,225 (or any other change in this criterion) is independent of common values of the other criteria.

Similar thought experiments would be necessary to compare changes in the other criteria. Based on an understanding of these six criteria and their significance for this choice, it was judged that this condition would be satisfied in this case over the ranges of the criterion values associated with the alternatives. This justified the use of an additive model of preference in this analysis. This is a condition that is implicitly assumed when any additive model of preference is used along with an assessment procedure that focuses on each criterion independently. (For further discussion, see Kirkwood [1996].)

Once it has been determined that the criteria are difference independent, the importance of each criterion is compared with the importance of every other criterion on a ratio scale and the results of these pairwise comparisons are used to assign a quantitative value, ω_i, to each criterion κ_i. These comparisons of the importance of each criterion should be based on the following question: how much better would it be to improve the performance on one criterion from its worst to its best value (as defined by the ranges of the criterion values among the alternatives under consideration) versus improving the performance of another criterion from its worst to its best value? Note that the notion of the importance of a criterion has no meaning without reference to the range over which it varies (Keeney, 2002).

Let ν_{ij} be the value of alternative α_j relative to criterion κ_i. Each ν_{ij} also may be obtained from pairwise comparisons of the performance of each alternative on each criterion. Each ν_{ij} is normalized yielding ν'_{ij}. The value of each alternative, π_j, is then calculated as follows:

$$\pi_j = \sum_{i=1}^{n} \omega_i \nu'_{ij} . \tag{2.4.1}$$

As a result of the procedure used to normalize the ν_{ij}, it is possible to reverse the rank order produced by the Analytic Hierarchy Process through the addition of a new alternative to the set of alternatives (Belton and Gear, 1983). Appendix 1 provides a mathematical analysis of this problem. The explicit formulae delimiting the scope of rank reversal appear to be new; this is a reason for including them. They extend the results of Dyer and Wendell (1985).

One way to prevent a rank reversal is to normalize the values of the alternatives according to each criterion in a way that does not depend on the number of alternatives under consideration. A normalization proposed by Dyer (1990) was used; it is similar to a procedure proposed by Kamenetzky (1982). Each ν_{ij} is modified to

$$\nu_{ij}{}' = \frac{\nu_{ij} - \mathbf{min}[\nu_{ij}]}{\mathbf{max}[\nu_{ij}] - \mathbf{min}[\nu_{ij}]} \tag{2.4.2}$$

where "$\mathbf{min}[\nu_{ij}]$" and "$\mathbf{max}[\nu_{ij}]$" are the minimum and maximum possible values of ν_{ij} for criterion κ_i. This method of eliciting criteria weights is transparent and easy for the decision maker to use but has the disadvantage of being cumbersome if the number of criteria becomes very large. (For n criteria, $\frac{n^2+n}{2}$ comparisons are necessary.)

The ν_{ij} were calculated for each of the non-dominated alternatives relative to each of the 6 criteria. A comparison of each pair of criteria was solicited from Mr. Hamukwaya, refined to achieve maximal internal consistency as measured by the consistency ratio statistic of the Analytic Hierarchy Process (see Saaty [1980], p. 21), and then used to assign a quantitative value to each criterion. The ν_{ij} were normalized using Equation (2.4.2) and values were assigned to each non-dominated alternative using Equation (2.4.1). On the basis of the assigned values, a rank order of the non-dominated alternatives was produced. All computations were performed using the MultCSync software package (Sarkar et al., 2004b; Moffett et al., 2005).

2.5. **Sensitivity Analysis of the Rankings**.

Two methods of sensitivity analysis were used (Butler et al., 1997) The first consisted of a single-dimensional analysis: the effect of altering the weight assigned to a single criterion was evaluated by increasing, for each criterion, the ω_i assigned to the criterion from 0 to 1.0 while holding constant the relative weights assigned to all other criteria. The modified Analytic Hierarchy Process was performed using MultCSync for each value of ω_i in the interval, and each rank ordering thus produced was compared with the original rankings using the Logical Decisions software package (Logical Decisions, 2003). The effects associated with altering the two most important criteria were graphed. A similar analysis, though restricted to two criteria was performed by Faith et al. (2001) using the Target software package.

The second method consisted of a multi-dimensional simulation-based rank order analysis: the effect of altering the weights assigned to multiple criteria was evaluated by generating 10 000 sets of random weights and assigning the weights in each set to the criteria in a way that preserved the rank ordering of the assessed weights. Thus, in each set of random weights, the greatest weight in the set was assigned to the criterion with the greatest assessed weight, while the smallest weight in the set was assigned to the criterion with the smallest assessed weight. The 10 000 rank orderings produced in this way were then compared with the original rankings. For a discussion of the use of simulation to test the robustness of a ranking based on multiple criteria and other multi-dimensional methods, see Butler et al. (1997).

3. **Results**.

3.1. **Place Prioritization and Non-Dominated Solutions**.

100 conservation area networks were produced, numbered 1 through 100 of which 94 were unique. In what follows, the 94 unique solutions constitute the feasible alternatives (or, for short, alternatives). MultCSync was first used to determine the set of non-dominated alternatives from the initial set of 94 unique feasible alternatives. Out of set of 94 unique alternatives, 49 alternatives were non-dominated. Figure 1 shows two typical non-dominated solutions.

3.2 **Criteria Weights**.

The pairwise comparisons for the criterion weights were derived by personnel from the Ministry of Lands, Resettlement and Rehabilitation of Namibia who were familiar with the ranges over which the criteria varied among the conservation area networks. MultCSync was used to assign weights to each of the criteria as shown in Table 1. Criterion (6), the number of wildlife found within a conservation area network, received a weight more than twice as large as any other criterion and more than 9 times as large as the one assigned to criterion (1), the area of a conservation area network, which was found to have the smallest weight. The relative unimportance of area is reasonable because all solutions had virtually the same area. The consistency ratio associated with the comparisons was 0.092588, which is less than the suggested upper bound of 0.10 (Saaty, 1980), indicating that these comparisons were made with an acceptable degree of consistency.

3.2. **Final Rankings**.

MultCSync was used to assign a value to each of the 49 non-dominated alternatives on the basis of the weights shown in Table 1 and the alternative values obtained from the use of Equation (2.4.2), which produced the final ranking of the alternatives shown in Table 2. As can be seen, alternative 7 was the highest ranked alternative. A map of the cells associated with this conservation area network is shown in Figure 1a. Relatively little separated the set of cells associated with this alternative from the sets associated with the other top alternatives. Of the five highest ranked alternatives, only one differed from alternative 7 by more than one cell. Alternative 93, which was ranked fourth and differed from alternative 7 by two cells, is shown in Figure 1b.

3.3. **Robustness and Sensitivity**.

The two criteria with the largest weights were criterion (6), wildlife, and criterion (2), human population, and the results obtained by the single-dimensional sensitivity analysis of varying the weights assigned to them are shown in Figure 2. As was expected, given the similar composition of the alternatives, the rank orderings produced under such alterations differed little from the final ranking.

A summary of the results obtained from the multi-dimensional rank order analysis based on the 10 000 rank orderings is provided in Table 3. Relatively little difference was found between these rankings and the final ranking. Overall, within these 10 000 rankings, alternative 7 was again identified as the preferred choice, based upon its mean and mode rankings. In the 10 000 rankings it was only ranked as low as second. The only other alternative to be ranked first was alternative 30, which was ranked second in the final ranking.

4. **Discussion**.

Biodiversity conservation is as much a socio-political enterprise as a scientific one. Consequently, socio-political criteria, which are often difficult to compare, are central to such planning. Given the socio-political context in which conservation decisions occur, the evaluation of a potential conservation area network must include consideration of these criteria, which can be incorporated into the process of conservation area network design in a number of different ways (Sarkar, 2005). Besides socio-political criteria, these methods can also be used to incorporate spatial design and other relevant criteria.

For the Namibian data, alternative 7 is clearly the preferred alternative. The robustness of this conclusion under the single-dimensional sensitivity analysis (that is, the invariance of the ranking) can be partly attributed to the fact that all the top alternatives were similar to each other, that is, consisted of very similar sets of cells. Its robustness under the multi-dimensional rank order analysis shows that the precise numerical weights assigned to the criteria do not matter so long as the order or relative rankings of the criteria remain invariant. This is important because, typically, there is more confidence in this order than in the weights themselves. These conclusions will presumably not be valid in situations where the top alternatives differ significantly from each other. This is why explicit sensitivity analyses should form part of any planning protocol.

Recall that the criteria can be incorporated into the decision process either iteratively, at the time of individual cell selection, or terminally, in the evaluation of a set of complete conservation area networks. In this analysis, a terminal stage protocol was used. Consequently, biodiversity representation was treated as a hard constraint because, regardless of the importance attributed to other criteria, a feasible conservation area network must meet the representation target designed for each surrogate. Had an iterative process instead been used, the importance attributed to socio-political criteria might have resulted in the selection of a “best found” conservation area network incapable of meeting the designated representation targets. This qualitative separation of biodiversity representation from all other criteria is a strong reason to implement a terminal stage protocol instead of its iterative counterpart. Ultimately, however, the choice of a particular protocol will ultimately prove subjective, dependent upon the perceived importance of biodiversity targets being used relative to that of the other criteria. Terminal stage protocols also have the limitation that they assume that biodiversity representation can be measured by a single parameter. If this assumption is undesirable, iterative stage protocols will generally be preferable.

Regardless of the particular protocol used, consideration of multiple criteria in the development of a conservation area network will at some point require the evaluation of multiple alternatives on the basis of multiple criteria. A precise evaluation of this type can be produced by constructing a linear additive value function using quantitative evaluations of both the criteria and the alternatives, which is the approach taken by the Analytic Hierarchy Process and other techniques based upon multiattribute value theory (Belton, 1986). Methods of this type assign a quantitative value to each alternative, and therefore provide a rank order of the alternatives. Such methods pay for this increased precision with an accompanying increase in subjectivity, coupled with the employment of a more complicated methodology. Instead of just requiring a set of weak orderings, such methods require that each criterion be assigned a quantitative weight representing the relative importance of improving its performance from its worst to best level. In addition, values must be assigned to the performance levels for each criterion. Moreover, the criteria must satisfy mutual preference difference, as discussed above.

To mitigate the effects of subjectivity and other sources of uncertainty in such assignments, the use of these methods should always be accompanied by a sensitivity analysis as was performed here. Since no single method of sensitivity analysis addresses all possible sources of uncertainty, a variety of such methods should be used whenever possible (Butler et al., 1997). Two methods were demonstrated here; the development and use of yet others deserves encouragement in the context of systematic conservation planning.

In conservation biology, as in many other disciplines, the original Analytic

Hierarchy Process has been a very popular technique for assessing these weights and for the calculation of these criterion values (Anselin et al., 1989; Kangas, 1993; Li et al., 1999; Mendoza and Prabhu, 2000; Schmoldt et al., 2001; Clevenger et al., 2002; Villa et al., 2002; Ananda and Herath, 2003). However, as shown in Appendix 1, due to its susceptibility to rank reversal, the Analytic Hierarchy Process is flawed. The fact that the addition of a new alternative to the set of those under consideration can alter their ranking makes the Analytic Hierarchy Process an arbitrary method of decision making. While this fact has been known within the decision theory community for some time, no application of the Analytic Hierarchy Process within conservation biology seems to have explicitly discussed this problem so as to avoid rank reversal (though Pereira and Duckstein [1993] and Phua and Minowa [2005] also use the modified Analytic Hierarchy Process without mentioning their reasons for doing so).

The fact that the Analytic Hierarchy Process is used with such regularity is at least somewhat surprising given the existence of comparable methods that provide the ease of use associated with the Analytic Hierarchy Process while nonetheless avoiding the possibility of rank reversal. One such technique, used in this analysis, is the modified Analytic Hierarchy Process, which also produces results that are consistent with multiattribute value theory and multiattribute utility theory methods that are well accepted by the economics and decision analysis communities (Smith and von Winterfeldt, 2004). So long as the number of criteria remains small and the elicitation of pairwise comparisons does not become cumbersome, this method provides a straightforward technique for the incorporation of multiple criteria in conservation planning.

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Software Availability

The initial prioritization of sites was carried out using the ResNet 1.2 software package (Garson et al., 2002). Multiple criterion synchronization used the MultCSync 1.0 software package (Moffett et al., 2005; Sarkar et al., 2004a). Both software packages can be freely downloaded from http://uts.cc.utexas.edu/~consbio/Cons/ResNet.html.

Appendix 1

Rank Reversal in the Analytic Hierarchy Process

Consider two structures, a set of feasible alternatives, $\mathrm{A} = \{\alpha_j : j = 1, 2, \ldots, m\}$ and a set of criteria, $\mathrm{K} = \{\kappa_i : i = 1, 2, \ldots, n\}$. It is assumed that: (i) each α_j can be assigned a definite quantitative value representing its performance relative to each of the κ_i; (ii) a quantitative value can be assigned to each pair of κ_i measuring the extent to which improving the value of one criterion from its worst to its best level is more important than a similar improvement in the other; and (iii) the κ_i exhibit mutual difference independence which justifies the use of an additive model.

For each $\alpha_j \in \mathrm{A}$ and $\kappa_i \in \mathrm{K}$ let ν_{ij} be the value representing the performance of

α_j relative to κ_i. In the original Analytic Hierarchy Process (Saaty, 1980), the ν_{ij} are normalized by calculating

$$\nu'_{ij} = \frac{\nu_{ij}}{\sum_{j=1}^{m} \nu_{ij}}; \tag{A.1.1}$$

therefore, $\sum_{j=1}^{m} \nu'_{ij} = 1$ for all κ_i. To determine the overall priority, π_j, of each α_j, each κ_i is assigned a weight, ω_i, with $\sum_{i=1}^{n} \omega_i = 1$. The ω_i are calculated using an (*m* x *m*)-matrix, $\Gamma = (\gamma_{ij})$, of pairwise comparisons of the criteria with γ_{ij} equal to the ratio of the importance of changing κ_i from its worst to its best performance relative to a similar change in the performance of κ_j, with this comparison quantified using a scale of 1 to 9 (Saaty, 1980). The normalized eigenvector, $\vec{\rho}$, corresponding to the highest eigenvalue, $\lambda_{\max}$, of Γ is then calculated. The π_j are determined using

$$\pi_j = \sum_{i=1}^{n} \vec{\rho}_i \nu'_{ij}. \tag{A.1.2}$$

The preferred α_j is the alternative with the maximal π_j.

Thus, the values of the ν'_{ij} calculated by the Analytic Hierarchy Process are dependent upon the cardinality of A. If $\nu_{i(m+1)} > 0$, the addition of α_{m+1} to A will result in a change in the value of each ν_{ij} from $\frac{\nu_{ij}}{\sum_{j=1}^{m} \nu_{ij}}$ to $\frac{\nu_{ij}}{\sum_{j=1}^{m+1} \nu_{ij}}$, where

$\frac{\nu_{ij}}{\sum_{j=1}^{m}\nu_{ij}} > \frac{\nu_{ij}}{\sum_{j=1}^{m+1}\nu_{ij}}$. As a result, the inclusion of α_{m+1} will alter the π_j. This difference can be great enough such that the highest ranked alternative α_j in $\{\alpha_j : j = 1,2,...,m\}$ is no longer the highest ranked alternative in $\{\alpha_j : j = 1,2,...,m+1\}$, even when α_{m+1} is a low-ranked alternative. This alteration of the rank ordering of the α_j caused by the inclusion of α_{m+1} in A is referred to as "rank reversal." It occurs under the following conditions. Let δ_j equal the decrease in π_j caused by the inclusion of $\alpha_{m+1} \in \mathrm{A}$. For some α_o, such that $\alpha_o \in \mathrm{A}$ and $\pi_o \geq \pi_i$ for all α_i in A, rank reversal will occur if and only if there exists some α_p in A such that, following the inclusion of α_{m+1} in A,

$$\delta_o - \delta_p > \pi_o - \pi_p . \tag{A.1.3}$$

In the Analytic Hierarchy Process

$$\delta_j = \sum_{i=1}^{n}\frac{\omega_i\nu_{ij}}{\sum_{j=1}^{m}\nu_{ij}} - \sum_{i=1}^{n}\frac{\omega_i\nu_{ij}}{\sum_{j=1}^{m+1}\nu_{ij}} . \tag{A.1.4}$$

Inequality (A.1.4) can therefore be rewritten as

$$\sum_{i=1}^{n}\frac{\omega_i\nu_{io}\nu_{i(m+1)}}{(\sum_{j=1}^{m}\nu_{ij})^2 + (\sum_{j=1}^{m}\nu_{ij})(\nu_{i(m+1)})} - \sum_{i=1}^{n}\frac{\omega_i\nu_{ip}\nu_{i(m+1)}}{(\sum_{j=1}^{m}\nu_{ij})^2 + (\sum_{j=1}^{m}\nu_{ij})(\nu_{i(m+1)})} > \pi_o - \pi_p . \tag{A.1.5}$$

Rank reversal will thus occur in the Analytic Hierarchy Process if and only if this inequality is satisfied for some suitably defined α_o and α_p.

The susceptibility of the Analytic Hierarchy Process to rank reversal has been widely discussed (Kamenetzky, 1982; Belton and Gear, 1983; Dyer and Wendell, 1985; Saaty, 1987; Dyer, 1990) and is universally acknowledged. What remain at least partly contentious, however, are the consequences of this susceptibility. While some have argued that rank reversal is a desirable feature of the Analytic Hierarchy Process (Saaty and Vargas, 1984), others have pointed out that such susceptibility provides reason to regard the results produced by the Analytic Hierarchy Process as arbitrary (Dyer and Wendell, 1985).

Arguments in favor of rank reversal have claimed that, in evaluating each α_j, it is rational to consider the other elements of A as well. As a result, alterations to A, as caused by the inclusion of α_{m+1}, should be expected to result in alterations to the π_j, in that these alterations represent rational reevaluations of the α_j in light of the knowledge gained by the consideration of α_{m+1}. Preferences are dependent upon the set of available alternatives and this dependency is modeled by the Analytic Hierarchy Process, as shown by its susceptibility to rank reversal. This ability of the Analytic Hierarchy Process to model this response is construed as an asset.

Arguments to the contrary have typically questioned whether the information gained by the discovery of α_{m+1} is at all relevant to the possibility of rank reversal. It is difficult to see why the inclusion of α_{m+1} should necessarily affect the values assigned to the π_i. There do exist scenarios in which new information based on the inclusion of α_{m+1} in A would warrant the alteration of previous preferences. For example, if one of the κ_i represents uniqueness, then changes in A could reasonably affect the performance of the α_i with respect to this criterion (Dyer, 1990). However, inequality (A.1.5) shows that rank reversal can occur regardless of the particular attributes measured by the κ_i. As a result, the claim that rank reversal is rational in certain situations (Saaty, 1990) is insufficient justification for the fact that it is possible in many situations. In order to justify the possibility of rank reversal, it must be the case that that rank reversal is justified in all decision scenarios in which inequality (A.1.5) is satisfied, regardless of the particular criteria in question. This is clearly not the case.

Rank reversal is not a byproduct of any information gained by the discovery of α_{m+1}; instead, it is a mathematical consequence of the normalization procedure of the Analytic Hierarchy Process. Inequality (A.1.5) is relevant not because it captures some basic requirement of rational deliberation, but because it demonstrates a flaw in the mathematical foundations of the Analytic Hierarchy Process. Instead of providing a neutral framework by which to calculate a rank ordering of alternatives based solely upon a decision maker's preferences, the Analytic Hierarchy Process is instead constructed so as to force alterations to particular rank orderings independently of any concomitant change in preferences on the part of the decision maker.

To salvage the Analytic Hierarchy Process, this susceptibility to rank reversal must be eliminated. This can be done by altering the methodology to ensure that the π_j are calculated independently of the cardinality of A. Now, if the ω_i are calculated independently of A, the π_j will be independent of A, and thus not susceptible to rank reversal, if both the ω_i and the ν'_{ij} are independent of A. The ω_i are so independent.

Therefore, to prevent rank reversal, it must only be ensured that the ν'_{ij} exhibit a similar independence. This is achieved through the use of equation (2.4.2) instead of (A.1.1) to normalize the ν_{ij}. For other approaches to modifying the Analytic Hierarchy Process to avoid this problem, see Dyer (1990).

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Table 1

Calculation of Criteria Weights

The calculation of weights for each of the six criteria used to evaluate conservation area networks in North-Central Namibia is shown below. The matrix was constructed by comparing the importance of each criterion with that of every other criterion on a scale of $1/9$ to 9 by an individual familiar with the ranges over which these criteria varied. Entry (*i*, *j*) then represents the ratio by which criterion κ_i is evaluated to be more important than criterion κ_j. For example, criterion 1 (area) is evaluated to be half as important as criterion 2 (the human population) after considering these ranges; thus, the entry (1, 2) = $1/2$. The adjoining vector is the eigenvector with the highest eigenvalue of the matrix; eigenvector components are normalized such they sum to 1. The weight of the *i*-th criterion, ω_i, is set equal to the *i*-th entry of the eigenvector.

$$\begin{pmatrix} 1 & 1/5 & 1 & 1/3 & 1/4 & 1/8 \\ 5 & 1 & 1 & 1 & 4 & 1/2 \\ 1 & 1 & 1 & 1 & 1/3 & 1/7 \\ 3 & 1 & 1 & 1 & 1 & 1/3 \\ 4 & 1/4 & 3 & 1 & 1 & 1/2 \\ 8 & 2 & 7 & 3 & 2 & 1 \end{pmatrix} \Rightarrow \begin{pmatrix} 0.047927 \\ 0.196843 \\ 0.080739 \\ 0.134108 \\ 0.143483 \\ 0.396900 \end{pmatrix} \Rightarrow \begin{matrix} \omega_1 = 0.047927 \\ \omega_2 = 0.196843 \\ \omega_3 = 0.080739 \\ \omega_4 = 0.134108 \\ \omega_5 = 0.143483 \\ \omega_6 = 0.396900 \end{matrix}$$

Table 2

Rank Order of the Non-Dominated Alternatives

Column (i) contains the number of one of the 49 non-dominated alternatives while column (ii) contains the value assigned to that alternative.

Alternative	Value
7	0.810574
30	0.810413
51	0.800338
93	0.796391
96	0.794505
59	0.792458
48	0.787427
2	0.78538
6	0.782622
19	0.776633
39	0.775075
94	0.763842
69	0.763145
8	0.755511
3	0.749268
15	0.747885
13	0.741839
5	0.740679
89	0.737508
54	0.736064
84	0.735373
81	0.732364
64	0.731947
20	0.730605
82	0.723944
50	0.723345
27	0.718564
63	0.717301
23	0.707247
98	0.699458
79	0.697681
53	0.697186
38	0.697182
91	0.691863
46	0.683856
99	0.668312
70	0.657111
1	0.655784

60	0.639826
56	0.63695
83	0.635998
66	0.615887
74	0.604431
42	0.597432
18	0.58543
9	0.566648
21	0.547435
67	0.535603
36	0.486116

Table 3

Sensitivity to Changes in Multiple Weights

Results from multi-dimensional rank order sensitivity analysis performed using the modified Analytic Hierarchy Process on 10 000 randomly assigned sets of criterion weights preserving the same rank ordering as the weights shown in Table 1. Column (i) lists one of the 49 non-dominated alternatives, column (ii) shows the actual rank, columns (iii) and (iv) list the best and worst ranks of that alternative, columns (v) and (vi) provide the mean and mode ranks of the alternative. Columns (vii) –(xi) provide the scores of the alternative at different percentiles: these are the scores corresponding to that rank order of the random rankings. For instance, the 5-percentile score is the rank below which alternative 1 was scored in 500 of the 10 000 randomizations, and so on.

Alternative	**Actual Rank**	**Best Rank**	**Worst Rank**	**Mean Rank**	**Mode Rank**	**5%**	**25%**	**50%**	**75%**	**95%**
1	38	34	41	37.51	38	35	37	38	38	39
2	8	5	22	8.66	8	7	8	8	9	12
3	15	8	20	14.46	15	9	14	15	16	16
5	18	14	20	17.58	18	17	17	18	18	18
6	9	7	13	8.87	9	8	9	9	9	10
7	1	1	2	1.335	1	1	1	1	2	2
8	14	7	18	12.79	14	8	12	14	14	15
9	46	44	49	46.84	47	46	47	47	47	48
13	17	15	23	17.62	17	17	17	17	18	19
15	16	14	22	15.69	16	14	15	16	16	17
18	45	40	48	45.65	46	44	45	46	46	46
19	10	8	21	10.78	10	10	10	10	11	13
20	24	20	27	22.57	24	20	21	23	24	25
21	47	46	49	48.31	48	47	48	48	49	49
23	29	10	33	26.82	29	17	25	28	29	32
27	27	20	41	29.44	33	24	27	29	32	36
30	2	1	4	1.666	2	1	1	2	2	2
36	49	12	49	41.17	49	29	37	42	46	49
38	33	28	35	31.65	31	30	31	31	32	34
39	11	5	32	12.37	11	10	11	11	14	16
42	44	24	46	42.98	45	39	42	44	45	45
46	35	27	37	33.86	35	32	33	34	35	36

48	7	3	18	7.299	7	5	7	7	7	11
50	26	20	33	26.97	26	26	26	27	28	30
51	3	3	13	3.015	3	3	3	3	3	3
53	32	28	46	34.18	35	29	32	35	35	40
54	20	2	31	21.31	20	19	20	21	23	24
56	40	35	47	41.68	41	40	41	42	43	44
59	6	6	14	6.175	6	6	6	6	6	8
60	39	34	43	40.47	40	39	40	41	41	42
63	28	24	30	27.21	28	26	27	27	28	28
64	23	20	30	22.34	20	20	21	22	24	25
66	42	36	45	42.56	43	41	42	43	43	44
67	48	39	49	48.09	49	46	48	48	49	49
69	13	6	19	13.28	13	12	12	13	14	15
70	37	34	43	37.59	38	36	37	38	38	39
74	43	41	48	44.04	44	43	43	44	45	45
79	31	12	39	29.93	30	26	29	30	32	33
81	22	20	26	22.06	22	21	21	22	23	23
82	25	22	34	26.34	25	25	25	26	27	30
83	41	14	43	38.99	39	33	39	39	41	42
84	21	3	32	22.62	21	20	21	23	24	25
89	19	16	22	19.09	19	18	19	19	19	21
91	34	11	37	31.61	34	27	30	32	34	35
93	4	3	11	4.003	4	4	4	4	4	4
94	12	7	26	11.18	12	7	10	12	13	13
96	5	4	12	5.058	5	5	5	5	5	6
98	30	23	40	32.76	34	30	31	33	34	38
99	36	35	40	36.52	36	36	36	36	37	38

Figure Captions

Figure 1: **Non-Dominated Alternatives**: The maps show north-central Namibia starting with the Etosha National Park and going north to the border with Angola. The grey cell represents Etosha National Park, the black cells represent additional sites chosen for inclusion in a conservation area network, while the white cells represent sites not chosen. (a) Alternative 7 was ranked as the optimal site using the modified Analytic Hierarchy Process in conjunction with the comparisons shown in Table 1. (b) Alternative 93 was ranked fourth and is the alternative within the top 5 that exhibited the greatest amount of variation from alternative 7. Both alternatives contain 13 cells, 11 of which are shared.

Figure 2: **Sensitivity to Changes in Individual Weights**: The effects of varying the weight associated with one criterion at a time, while holding the ratio of the relative values of all other weights constant, was analyzed. (a) demonstrates the effect on the top 10 alternatives of varying the weight associated with criterion (6), that is, the number of wildlife. (b) provides a similar analysis for criterion (2), that is, human population. Each line indicates the performance of a different alternative with their identities indicated by the legend.

Figure 1a

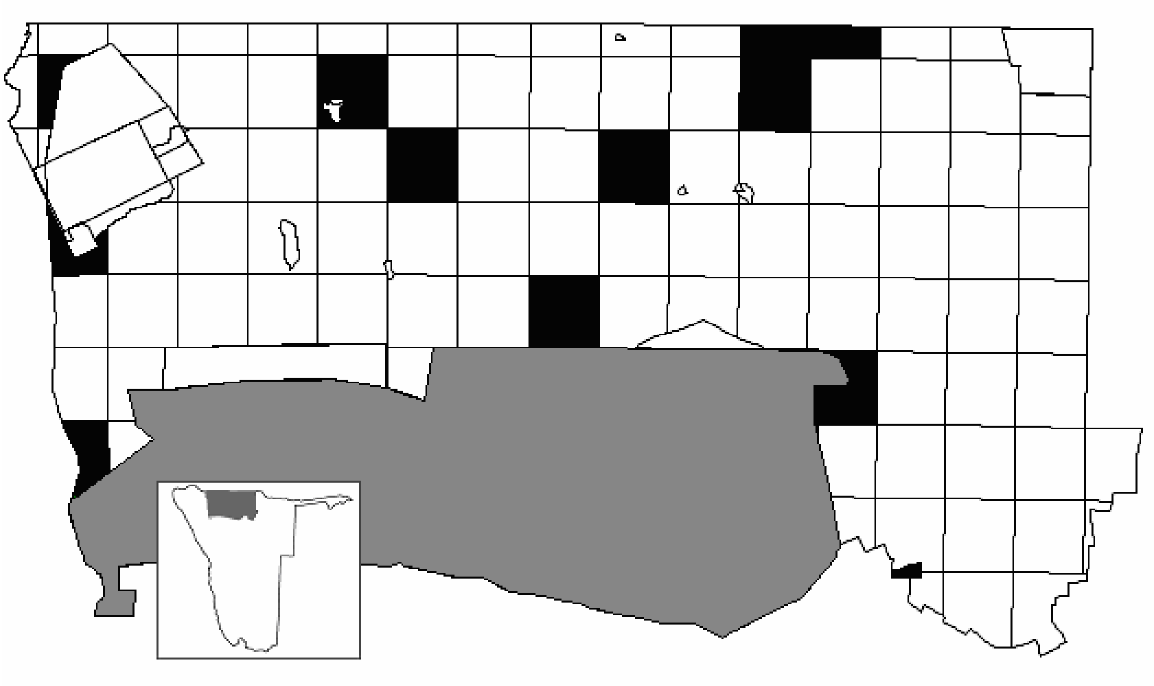


Figure 1b

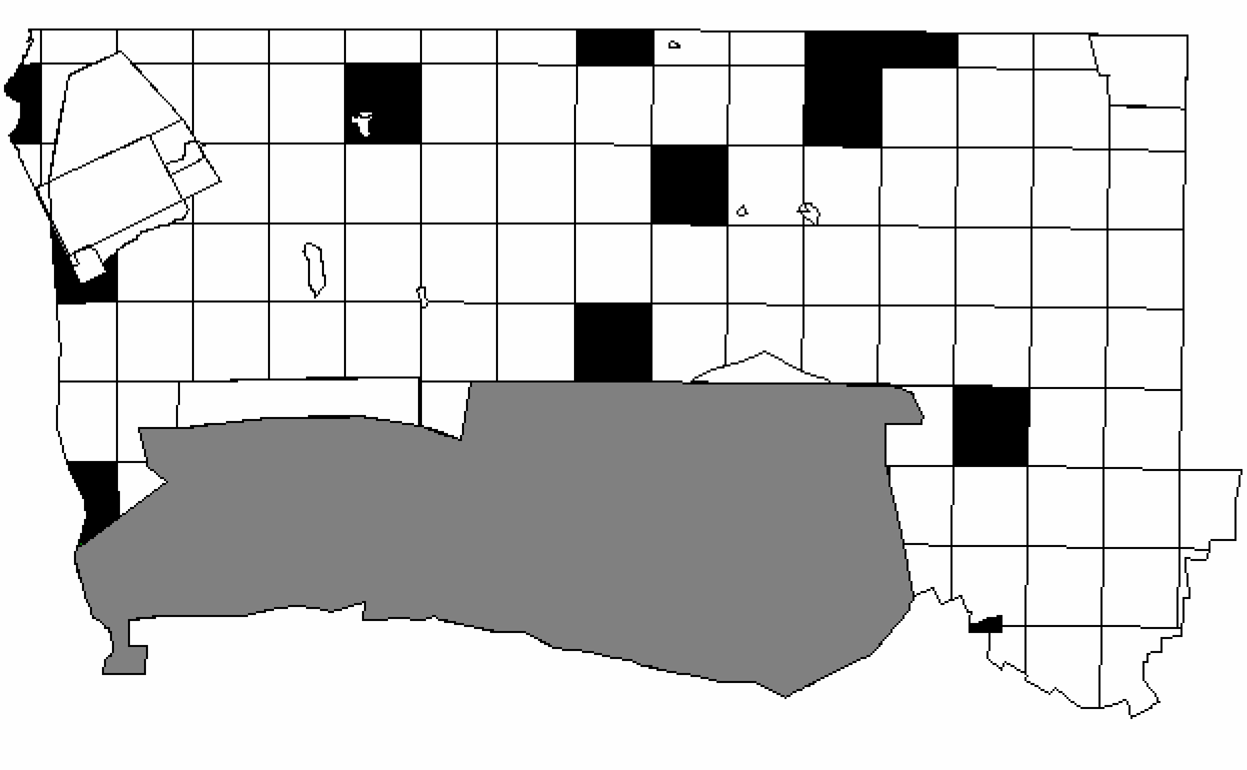


Figure 2a

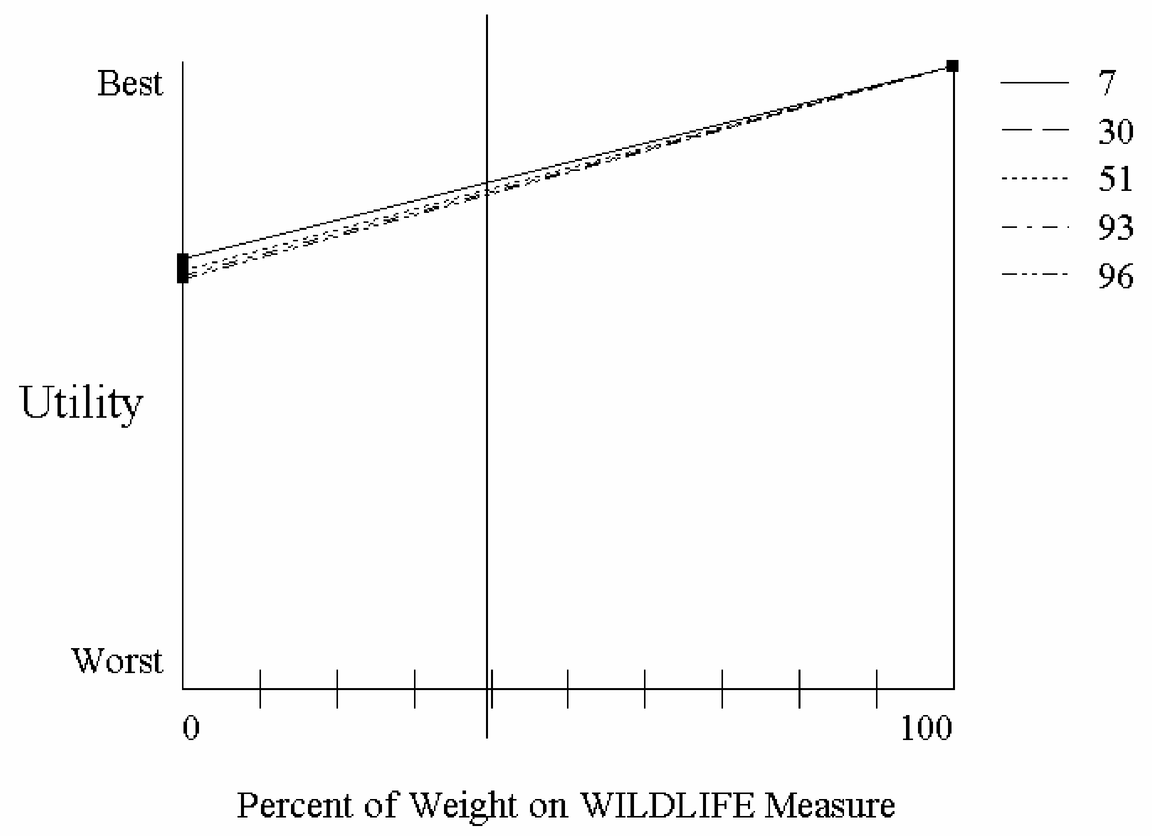
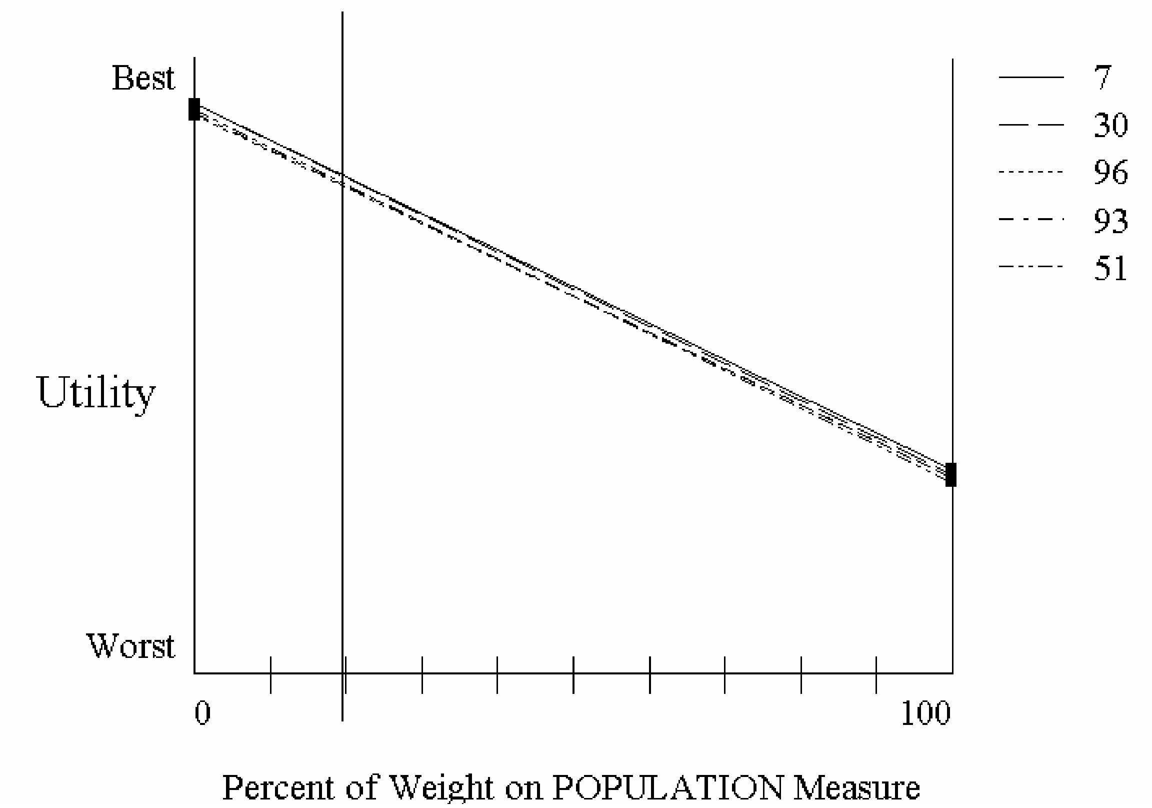

Best
Utility
Worst
0
100
Percent of Weight on WILDLIFE Measure
7
30
51
93
96

Figure 2b


Best
Utility
Worst
0
100
Percent of Weight on POPULATION Measure
7
30
96
93
51