# Testing metrics to prioritise environmental projects

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## *Abstract*

Decision makers responsible for the allocation of funds to environmental projects commonly use project scoring metrics that are not consistent with basic economic theory. As a result, there is often a loss of environmental benefits due to poor prioritisation of projects. The magnitudes of these losses are estimated for various metrics that deviate from theory. We examine cases where relevant variables are omitted from the benefits metric, project costs are omitted, and where parameters are weighted and added when they should be multiplied. Distributions of parameters are estimated from 129 environmental projects from Australia, New Zealand and Italy for which Benefit: Cost Analyses had previously been completed. The cost of using poor prioritisation metrics (in terms of lost environmental values) is often high – up to 80 per cent in the scenarios examined. The cost is greater where the budget is smaller. The most costly errors were found to be omitting information about environmental values, project costs or the effectiveness of management actions, and using a weighted additive decision metric for variables that should be multiplied. The latter three of these are errors that occur commonly in real-world decision metrics, often reducing potential environmental benefits by 30 to 50 per cent.

**Key words:** Cost Analysis; Prioritisation; Environmental program; Knapsack problem

**JEL classifications:** Q50

## *1. Introduction*

Around the world, billions of dollars' worth of public funds are allocated to environmental projects each year (Hajkowicz, 2009; Lambert et al., 2007). These funds are scarce relative to the amount needed to support all possible environmental projects, so prioritisation is essential. In environmental agencies and organisations, a common approach to the prioritization process is to define a set of variables believed to be correlated with projects' benefits and costs, and combine them into a formula or metric (e.g. Feng et al., 2006). Numerical values or scores are assigned to each potential project and the metric is used to rank the projects. For example, in the Conservation Reserve Program, rankings are based on a summation of scores reflecting benefits to wildlife, water quality, erosion, and air quality, a factor for enduring benefits and a factor for project costs (Ferris and Siikamäki, 2009).

Given the importance of these metrics in determining which projects get funded and, therefore, the efficiency of environmental investments, economists have paid remarkably little attention to the design and performance of the metrics used. Many project-ranking metrics in actual use are inconsistent with basic economic theory (Pannell and Roberts, 2010; Possingham, 2009), reflecting a general neglect of economic principles in the design of many programs (Rogers et al. 2013). For example, Wilson et al. (2007) point out that some systems fail to consider project cost when ranking projects (e.g., Isaac et al. 2007; Rodriguez et al., 2004).

In this study, we investigate the extent to which improvements in the provision of environmental values could be achieved by amendments to project ranking metrics. To our knowledge, there has been only a single study in which the performance of a reasonably sound project ranking metric has been quantitatively compared with that of weaker metrics. Joseph et al. (2009) (a team of non-economists) did this in a study to rank investments for threatened species in New Zealand. The two weakest prioritization metrics they tested resulted in environmental benefits being reduced by 38 and 75 per cent relative to their superior metric.

There is scope for improvement on the Joseph et al. (2009) study. Although their relatively superior metric has subsequently been applied (e.g. Szabo et al., 2009), it has limitations. While it is well structured (dividing benefits by costs, for example), it omits relevant variables, including the environmental effectiveness of proposed management actions, the predicted level of uptake of those actions by managers, and the time lag until benefits will occur. Secondly, their evaluation is conducted for a single set of projects. We show below that metric performance can be highly susceptible to sample bias, so that metric performance should be evaluated as an average for many sets of projects. Thirdly, they did not explore the influence of the size of the program budget on the sensitivity of environmental benefits to metric choice. We show below that this influence is high.

Neglect of the issue of metric design could be very costly to the environment. It appears that there may be an unmet opportunity for economists to contribute substantially to achievement of more valuable environmental outcomes through provision of advice on metric design.

In this study, four potential sources of metric inaccuracy are assessed (reflecting common problems in real programs): the use of a weighted additive scoring metric when a multiplicative metric should be used; the omission of relevant variables from the benefits metric; the failure to adequately consider project costs; and errors in the estimation of variables. The purpose of the study is to assess how serious the different issues are likely to be. It may be that some of these problems make little difference to the delivery of environmental benefits, while others make a large difference and warrant efforts to ensure that appropriate methods are used.

## *2. Indices for prioritisation*

Assume that an investor must allocate a fixed budget among a set of projects. Each project has a known cost and known levels of variables related to benefits. The total cost of all projects would exceed the budget, so prioritisation is required. The benefits and costs of each project do not depend on which other projects are selected. The problem is to choose the set of projects that would maximise total environmental values. This is known as a "knapsack" problem (Kellerer et al. 2004).

Pannell (2013) describes the theoretical and practical principles for selection of a decision metric for solving this problem. Hajkowicz et al. (2007) demonstrated that the problem can be closely approximated by ranking projects according to their Benefit: Cost Ratios (BCRs). Pannell's (2013) recommended formula for the BCR, including a number of carefully considered simplifications, is as follows:

$$BCR = \frac{V \times W \times A \times (1-R)/(1+r)^L}{C} \quad (1)$$

where

$V$ = the total value of the environmental assets affected by the project, at a reference condition;
$W$ = the proportional increase in environmental value as a result of the project, relative to $V$;
$A$ = the adoption of the required new behaviours or practices, as a proportion of the level of adoption that would fully deliver the objectives of the project (simplifying assumption: benefits are linearly related to the level of adoption);
$R$ = the risk of project failure – a probability – depending on technical, social, political and financial risks (simplifying assumption: success of a project is a binary variable – complete success to the extent determined by other variables or complete failure);
$L$ = the time lag until benefits occur (simplifying assumption: all benefits of a project commence at the same time and continue indefinitely thereafter);
$r$ = the discount rate; and
$C$ = the present value of project costs, including maintenance costs and compliance costs as well as short-term project costs.

Equation (1) is an expansion of the metrics derived by Metrick and Weitzman (1998), whose numerator consisted of $V \times W$, and by Joseph et al. (2009), whose numerator was $V \times (1 - R)$. Both confirmed that the structure of Equation (1) is theoretically correct, but omitted some of the variables included here.

A feature of Equation (1) compared to some equations in use is that the elements are multiplied. $W$ and $A$ enter the formula multiplicatively because they are proportional to expected benefits. Multiplying the rest of the numerator by $(1 – R)$, the probability of project success, gives us the expected value of benefits. The time lag until benefits ($L$) is accounted for using standard discounting methods – a discount factor is multiplied by the benefits. Benefits are divided by costs because we assume that there is a fixed budget, and in that situation ranking by BCR provides the greatest overall benefits (Pannell, 2013).

In practice, a far more commonly used metric for prioritisation of environmental project takes the form shown in equation (2):

$$\alpha = w_1 \times V + w_2 \times W + w_3 \times A + w_4 \times R + w_5 \times L + w_6 \times C \qquad (2)$$

where the $w_i$s are weights, chosen subjectively to reflect the relative importance of the different variables. For example, decision metrics of exactly this form have been used to rank projects in the US Conservation Reserve Program (Ferris and Siikamäki, 2009; Feng et al., 2006), and Australia's Caring for Our Country program. Marsh et al. (2007) used a similar additive metric to prioritise the allocation of resources amongst threatened species of frogs and mammals in Queensland, Australia.

Equation (2) clearly provides erroneous estimates of the relative priorities of projects. For example, if Equation (2) is used, a project that should be given a low priority because it completely fails on an essential criterion (such as adoption, $A$, or the effectiveness of works, $W$) can erroneously be given a high priority because it scores well on other variables[1].

[1] A perhaps more defensible weighted additive approach is to calculate $V$ by summing different types of benefits that a project may generate. For example, a project might protect or enhance several environmental assets of different types, in which case adding these benefits may be justified. Johansson and Cattaneo (2006) compared the consequences of adding versus multiplying variables to estimate $V$ from various contributors to value. They

Subsequent sections explore the potential seriousness of this error, in terms of total benefits foregone.

A second common error in formulating project prioritisation metrics is to omit variables from the calculation of benefits. For example, in prioritising investments under Australia's natural resource management programs (e.g. the Natural Heritage Trust), it was common to fail to consider both the technical feasibility of the project and the likely adoption by land managers of proposed management changes. As noted earlier, although they used well-structured metrics, Metrick and Weitzman (1998) and Joseph et al. (2009) omitted some of the variables in Equation (1). If the variable $W$ was omitted, for example, Equation (1) would be modified to:

$$\beta_1 = \frac{V \times A \times (1-R)/(1+r)^L}{C} \tag{3}$$

or, if, in addition to omitting $W$, a weighted additive system was used,

$$\alpha_1 = w_1 \times V + w_3 \times A + w_4 \times R + w_5 \times L + w_6 \times C \tag{4}$$

where $\alpha_1$ and $\beta_1$ are indices of project merit. Next, projects are sometimes ranked according to benefits, without consideration of costs. While this seems remarkable to an economist, it is not uncommon in environmental management, as noted by Hajkowicz et al. (2007), Joseph et al. (2009) and Laycock et al. (2009). This implies ranking projects according to one of the following two equations:

$$\beta_2 = V \times W \times A \times (1-R)/(1+r)^L \tag{5}$$

or

$$\alpha_2 = w_1 \times V + w_2 \times W + w_3 \times A + w_4 \times R + w_5 \times L \tag{6}$$

The analysis also examines combinations of omissions. For example, we will simulate a scenario where both $W$ and $C$ are omitted, resulting in projects being prioritised using Equations (7) or (8).

$$\beta_2 = V \times A \times (1-R)/(1+r)^L \tag{7}$$

or

$$\alpha_2 = w_1 \times V + w_3 \times A + w_4 \times R + w_5 \times L \tag{8}$$

Finally, there is likely to be uncertainty about the parameter values for each project, resulting in errors, to some extent, in the estimation of the parameter values to be used to calculate

showed that the choice of functional forms makes a substantial difference to prioritization of results, although it is not clear whether or when multiplication would be preferred to addition for calculation of $V$.

benefits. Variables can be estimated more accurately, but usually at greater cost. The analysis here estimates the likely cost of inaccuracy through introducing random errors from defined distributions into the values of the variables.

## 3. Methods

### 3.1 Data

Values for project parameters (*V*, *W*, *A*, *R*, *L* and *C*) were obtained from the database of projects that have been evaluated using the Investment Framework for Environmental Resources (INFFER) (Pannell et al. 2012). In total, 129 projects were identified as having complete sets of parameters and were used to estimate the probability distributions for each parameter and to test for correlations between parameters. These projects addressed a diverse range of environmental issues, including biodiversity conservation, threatened species conservation, native vegetation protection, wetland conservation, stream protection, water quality in streams and soil conservation. They were predominantly from Australia, but included six projects from New Zealand and Italy. Based on this data set, approximate distributions for each parameter were estimated (Table 1). Comparisons of the distributions from the raw data and the distributions assumed for this analysis are available at http://dpannell.fnas.uwa.edu.au/archive/project-errors-distributions.xlsx

Table 1. Assumed distributions for each parameter, based on data from 129 actual environmental projects.

| Parameter | Unit of measure | Distribution |
|---|---|---|
| *V* | $ millions | $ln(V/20) \times 11$ ~N(20, 10); negatively skewed in *V*. Mean(*V*) = $278 million, Standard deviation(*V*) = $262 million. |
| *W* | Proportion | *W* ~N(0.3, 0.15), winsorised at 0 |
| *A* | Proportion | *A* ~N(0.8, 0.2) , winsorised at 0 and 1 |
| *R* | Probability | *R* ~N(0.5, 0.18) , winsorised at 0 and 1 |
| *L* | Years | *L* ~N(10, 4) , winsorised at 0 |
| *C* | $ millions (present value) | $ln(C) \times 2$ ~N(2, 2); negatively skewed in *C*. Mean(*C*) = $6.7 million, Standard deviation(*C*) = $7.8 million. |

There were no significant correlations between any of the benefits-related variables (*V*, *W*, *A*, *R* and *L*), with the largest $R^2$ being 0.05. There was also no correlation between benefits and costs ($R^2$ = 0.001). The absence of covariances between variables simplified the simulations. In all simulations, a discount rate of 5 per cent is assumed.

## 3.2 Procedure

Scenarios examined in the analysis are as follows:

(a) The benefit: cost ratio (Equation 1), which is assumed to provide accurate prioritisation and is used as the benchmark;
(b) Weighted additive metric (Equation 2);
(c) Partial exclusion of benefits-related variables – 1, 2 or 3 variables excluded (similar to Equation 3, with various variables omitted);
(d) Partial exclusion of variables – 1, 2 or 3 variables excluded – and weighted additive metric (similar to Equation 4, with various variables omitted);
(e) Ranking projects considering project benefits but not costs (Equation 5);
(f) Ranking projects considering project benefits but not costs in a weighted additive metric (Equation 6);
(g) Errors in measurement: normally distributed errors in all benefits-related variables, with coefficients of variation of 15 or 30 per cent in each case; and
(h) Random project selection, with each project equally likely to be selected.

The cost of errors in assessment for project prioritisation will depend on the degree of selectivity involved – i.e. the budget available relative to the budget required to fund all projects. In a funding program where the available budget is sufficient to fund only a small proportion of the proposed projects, the relative cost of errors will be greater than for a program where most projects can be funded. To investigate the impact of project selectivity on the cost of assessment errors, various budget sizes are simulated: 2.5, 5, 10, 20 and 40 per cent of the budget that would be required to fund all projects. In environmental programs, selectivity can be high. For example, in the 2009 round of competitive funding under the Caring for our Country program in Australia, around 5 per cent of proposed projects were funded, in 2002 the European LIFE Environment Program funded 23 per cent of proposed projects (EC 2002) and in 2003 the US Environmental Quality Incentives Program (EQIP) funded 17 per cent of projects (USDA 2003).

To estimate the cost of poor metrics, it is assumed that 100 projects have been proposed for funding. The number of projects that is actually funded depends on the assumed budget, ranging from 2.5 to 40 per cent of the total amount required for all 100 projects (see above). For each of the 100 projects, values for $V$, $W$, $A$, $R$, $L$ and $C$ are generated randomly from the distributions given in Table 1. For cases where weighted additive benefit scoring is used, the weights used are the inverse of the means for each of the variables (negative weights for $R$, $L$ and $C$), meaning that each of the variables has a similar influence on project scores. Other than for $L$, this approach maximises the correlation between the BCR and the weighted additive metric. For other weights, the cost of using the weighted additive metric would be larger than is estimated below.

The procedure for the analysis is as follows.

1. For 100 simulated projects, generate random values from estimated distributions (Table 1) for all parameters.
2. Calculate the Benefit: Cost Ratio for each project using Equation (1).
3. Select those projects with the highest Benefit: Cost Ratios that fit within the program project.
4. For the marginal project, assume that it is funded to the extent that the budget allows, and that its benefits are proportional to the funding it receives. All other projects receive either full funding or no funding.

5. Record the total benefits for funded projects.
6. Repeat steps 2 to 4 using an alternative prioritisation metric. Also repeat step 5, but use the correct measure of benefits from step 2, not from the alternative metric, to calculate total benefits from the projects selected using the alternative metric.
7. Comparing the total benefits from the two instances of step 5, calculate the loss of environmental benefits resulting from use of the alternative prioritisation metric, as a percentage of the benefits generated using the BCR.
8. Repeat steps 1 to 7 1000 times to generate a distribution of results from which the mean percentage losses are calculated.
9. Repeat steps 1 to 8 for scenarios (b) to (h) (and combinations) and for five levels of the program budget.

Altogether, the analysis involved over 27 million simulated projects being considered in over 270,000 simulated decisions. The spreadsheet used to undertake calculations and rankings is available at http://dpannell.fnas.uwa.edu.au/archive/project-errors.xlsm

To illustrate and clarify the procedure, Figure 1 shows a single randomly generated case, comparing BCRs for a set of 100 projects calculated using Equation (1) with scores for the same projects calculated using Equation (7) (i.e., with $W$ and $C$ omitted). Overall, there is only a modest correlation between the two metrics ($R^2 = 0.40$), so the incorrect metric will result in potential environmental benefits being foregone due to poor project selection. The purpose of this analysis is to estimate those environmental losses quantitatively for realistic scenarios.

Note that each simulation of a set of 100 projects generates a somewhat different graph and a different correlation. That is why the procedure involves repeated random sampling for each scenario (as noted above) – estimates from any single simulation are likely to be biased.

Figure 2 shows the project rankings corresponding to the scores in Figure 1. Lower rankings correspond to superior projects (higher BCRs). The correlation between the two ranking systems is low: $R = 0.33$. The two dashed lines in Figure 2 show the threshold ranking for project funding, assuming that the program has sufficient funds to support approximately 10 per cent of projects[2].

The dashed lines divide the area of the graph into four sections. The upper right section contains those projects that are ranked poorly by both metrics – these projects would not be funded using either approach. The bottom left section contains projects that are ranked favourably by both metrics.

The upper left section has projects that are ranked favourably by the correct BCR and unfavourably by the equation that omits $W$ and $C$. Selection of these projects using Equation (7) results in lower expected environmental values than selecting projects using Equation (1).

[2] *Approximately* 10 per cent because cost itself is a random variable that is generated for each project. Therefore the budget required to fund all projects is itself a random variable. For the simulations in Figures 2 and 4, the program budget is set at 10 per cent of the mean of that distribution.

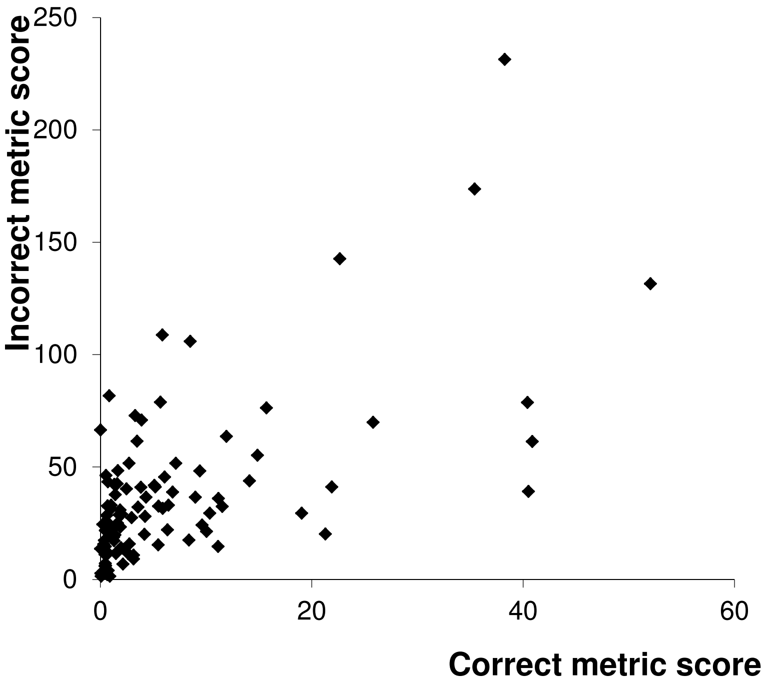


Figure 1. Scattergram illustrating correlation between benefit: cost ratios calculated correctly (Equation 1) and metric that ignores two variables: *W* and *C*. For this randomly generated case, $R^2 = 0.40$.

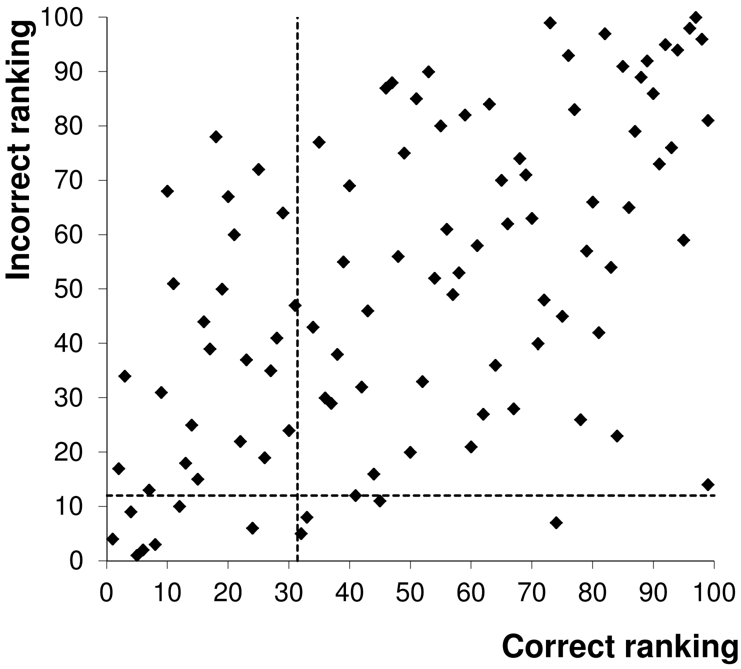


Figure 2. Project rankings for the example illustrated in Figure 1. Dotted lines show cut offs for funding under each criterion, with a program budget of 10% of the level required to fund all projects. Lower rankings are preferred. $R^2 = 0.33$, cost of poor prioritisation = 36%.

The lower right section has projects that are ranked unfavourably by the BCR and favourably by the alternative function – projects that should not be funded but would be if Equation (7) is used. In this simulation, the alternative function leads to funding of five projects with poor BCRs (ranked worse than 31 out of 100 on the 'Correct ranking' axis).

A notable feature of the figure is that the correct BCR results in funding of a larger number of projects than does the alternative metric. This is because the alternative metric ignores project costs, resulting in selection of expensive projects that lack sufficient benefits to be justified. For example, a very expensive project is ranked seventh using the incorrect metric but only 74th using the correct BCR metric. Funding this very expensive project means that many other worthwhile but smaller projects must be foregone. Overall, in this single simulation, the total benefits of projects selected for funding using Equation (7) are 36% less than the total benefits of projects prioritised using Equation (1).

Figures 3 and 4 show equivalent outputs for the additive decision metric, also omitting *W* and *C* (Equation (8)). The correlation between metric scores (Figure 3) is very low in this case – $R^2 = 0.04$. The figure shows how the distribution of BCR scores is highly skewed, with a small number of projects performing much better than the majority of projects. By contrast, scores for the additive metric are much more evenly distributed, such that outstanding projects do not stand out.

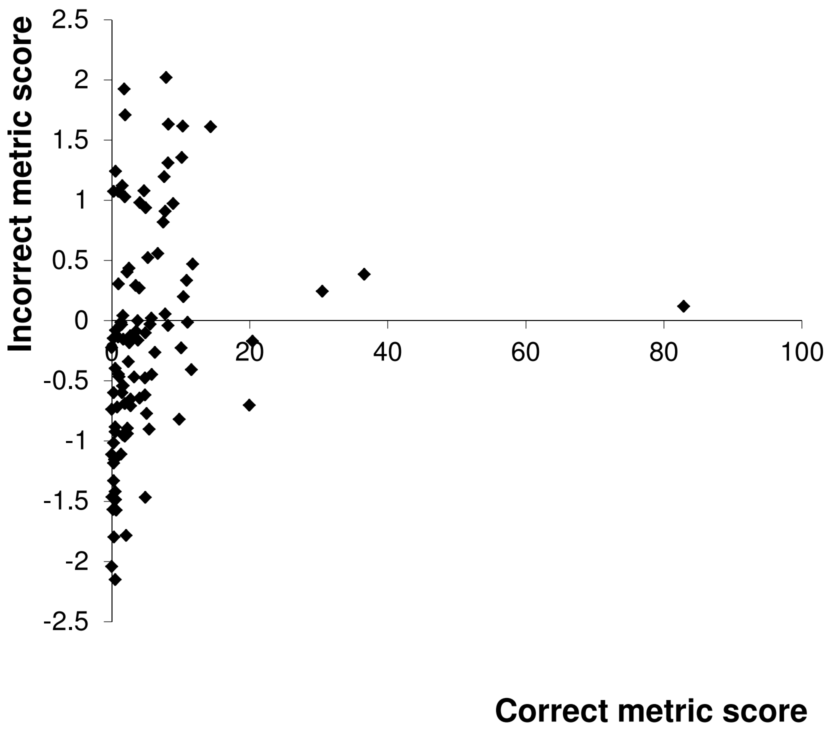


Figure 3. Scattergram illustrating correlation between Benefit: Cost Ratios calculated correctly (Equation (1)) and an additive metric with two missing variables: *W* and *C* (Equation (8)). For this randomly generated case, $R^2 = 0.04$.

The corresponding project rankings are shown in Figure 4. As in the previous example, because cost is ignored in the alternative metric, switching from the BCR to the alternative metric involves giving up a larger number of projects (top-left quadrant) than are added (bottom right quadrant). The cost of poor project selection is higher than for the previous case: 44 per cent.

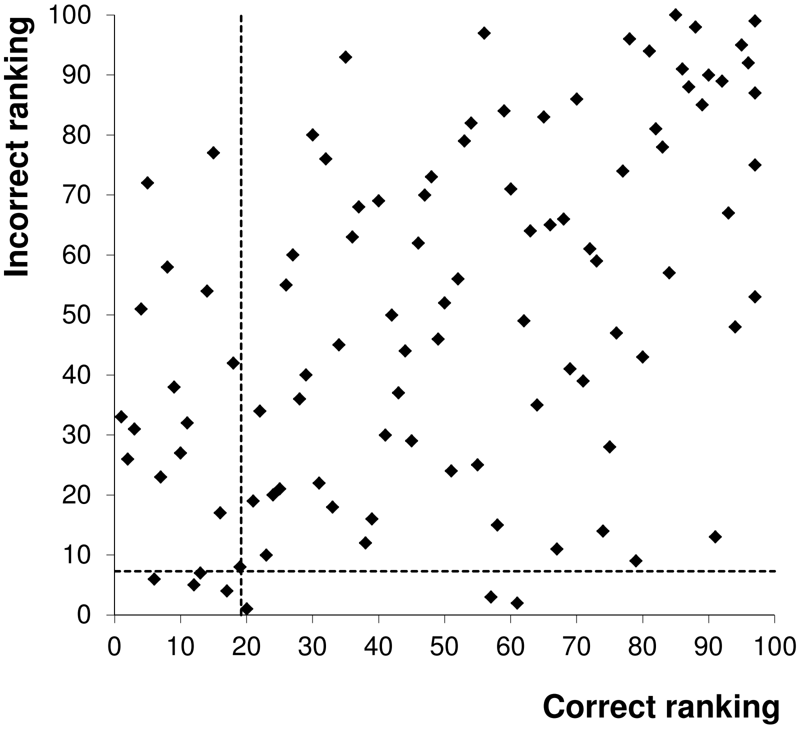


Figure 4. Project rankings for the example illustrated in Figure 3. Dotted lines show cut offs for funding under each criterion, with a program budget of 10% of the level required to fund all projects. Lower rankings are preferred. $R^2 = 0.25$, cost of poor prioritisation = 44%.

The results in Figures 1 to 4 illustrate the output from steps 1 to 7 of the procedure (see above), for two particular metrics, for a 10 per cent budget. Step 8 involves repeating the process 1000 times to generate a frequency distribution of the results. Figure 5 shows the frequency distribution of the percentage cost of using the alternative metric for the scenario illustrated in Figures 3 and 4. In the single simulation for Figures 3 and 4, the cost of poor prioritisation was 44 percent, but over 1000 simulations in Figure 5 the 95 per cent range includes costs from 15 to 69 per cent, with a mean of 36 per cent. This mean cost is used below as the summary measure of the cost of poor prioritisation. In step 9, 1000 simulations are conducted for a large number of scenarios and the mean costs in each case are recorded and compared.

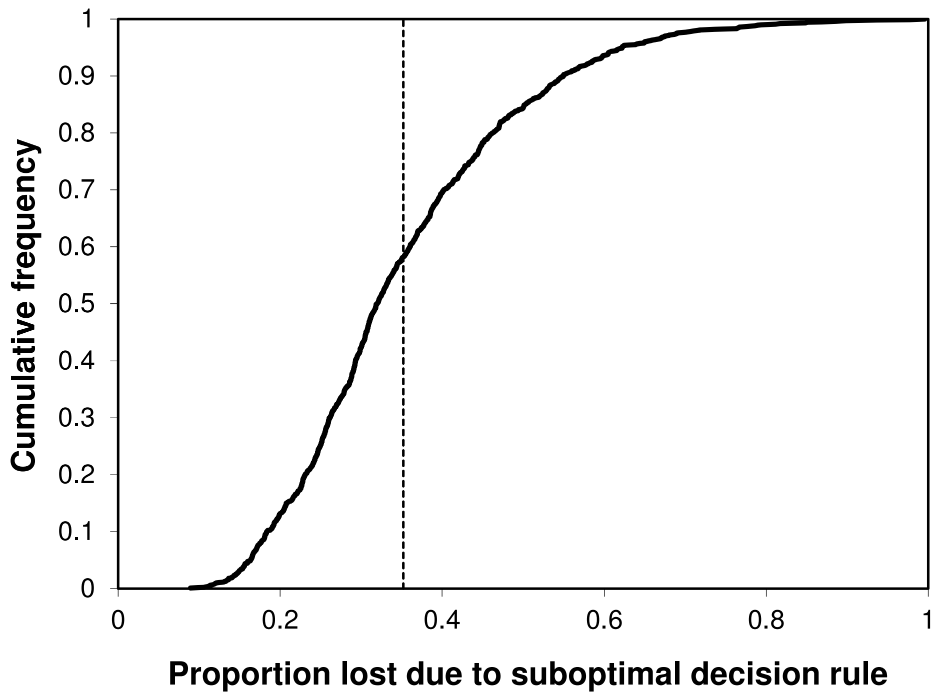


Figure 5. Frequency distribution (1000 random simulations) of cost of poor prioritisation for the scenario illustrated in Figures 3 and 4. Mean cost = 36%, standard deviation of cost = 15%, for 95% of cases cost < 62%.

Figure 5 shows that evaluating a decision metric based on a single sample of projects may be subject to considerable sample bias (depending on the number of projects in the sample). In this example, depending on the particular sample of 100 projects, we could conclude that the loss from excluding $W$ and $C$ was anything from 0.1 to 0.9. It is only by repeating the process for a large number of samples that we can identify the expected losses. The only previous study to estimate the losses from poor metrics compared to a reasonably sound metric (Joseph et al., 2009) based the analysis on a single set of projects.

## *3. Results and Discussion*

Tables 2 to 6 show results from step 9 of the procedure: mean losses for different metrics in different budget scenarios. To provide a benchmark for comparison, Table 2 shows the mean losses due to completely failing to prioritise. In these simulations, projects are selected at random with no input of information. The mean loss of potential benefits ranges from 55 to 89 per cent, depending on the program budget. Clearly, the environmental cost of failing to prioritise projects is high for these budget levels. Results for the various alternative metrics (Equations 2 to 6) will perform better than this, but not as well as Equation (1).

Table 2. Expected loss of environmental benefits from random project selection (as a percentage of the benefits of perfect prioritisation), with each project equally likely to be selected

| | Budget (relative to full funding) | | | | |
|---|---|---|---|---|---|
| | 2.5 | 5 | 10 | 20 | 40 |
| Loss | 89 | 87 | 81 | 72 | 55 |

Table 3 shows the expected loss of benefits from omitting variables from the BCR equation (Equation 1). In this table and the next three, it is assumed that decision makers have perfect knowledge about the parameters values for each project. Later we relax this assumption.

Table 3. Expected loss of environmental benefits from poor prioritisation (as a percentage of the benefits of perfect prioritisation)

| Scenario | Budget (relative to full funding) | | | | |
|---|---|---|---|---|---|
| | 2.5% | 5% | 10% | 20% | 40% |
| Omit *V* | 31 | 26 | 20 | 14 | 7 |
| Omit *W* | 9 | 8 | 6 | 4 | 2 |
| Omit *A* | 2 | 2 | 1 | 0.8 | 0.4 |
| Omit *R* | 5 | 4 | 3 | 2 | 1 |
| Omit *L* | 1 | 1 | 0.8 | 0.5 | 0.2 |
| Omit *C* | 35 | 31 | 26 | 18 | 9 |
| Omit *V* and *W* | 39 | 34 | 28 | 20 | 11 |
| Omit *V* and *R* | 37 | 31 | 24 | 16 | 9 |
| Omit *V* and *C* | 71 | 65 | 57 | 43 | 25 |
| Omit *W* and *R* | 15 | 12 | 10 | 7 | 4 |
| Omit *W* and *C* | 45 | 40 | 33 | 24 | 13 |
| Omit *R* and *C* | 41 | 36 | 29 | 22 | 12 |
| Omit *V*, *W* and *R* | 45 | 38 | 31 | 22 | 13 |
| Omit *V*, *W* and *C* | 78 | 73 | 65 | 53 | 35 |
| Omit *V*, *R* and *C* | 75 | 70 | 62 | 50 | 30 |
| Omit *W*, *R* and *C* | 50 | 43 | 37 | 29 | 16 |

Results are consistent with the expectation that the quality of the metric is relatively more important when investment funds are scarcer. Typically, the percentage loss of environmental values resulting from use of a poor decision metric is three to five times greater for a very small budget (2.5%) than for a large budget (40%).

The cost of omitting variables from the BCR equation varies depending on which variable is omitted. Going from greatest to least cost of omission, the order of the variables is *C*, *V*, *W*, *R*, *A* and *L*. (Note that the three variables for which Pannell (2013) made simplifying assumptions when formulating his BCR formula – *R*, *A* and *L* – are the three to which the cost of omission is lowest, indicating that the simplifications would have low costs.) To understand the reason for this order, consider *W*, *A* and *R*, three variables that are defined similarly (as winsorised normal distributions). Interestingly, although *A* has the highest standard deviation, it has the lowest cost of being omitted. The reason is that it has the highest mean value and, as a result, it has the lowest coefficient of variation (CV). It is the CV that determines this result, rather than the absolute standard deviation.

To illustrate, Table 4 shows results where the mean of *A* has been reduced, leaving all other parameter distributions unchanged, and leaving the standard deviation of *A* unchanged. The lower the mean (i.e. the higher the CV), the greater the expected cost of omitting *A* from the ranking formula. If the mean of *A* (pre-winsorisation) had been zero, omitting *A* would have caused the highest loss of any variable. The reason that *A* has a high mean value of 0.8 is that it is defined as adoption of changed practices with the project in place, including whatever policy mechanisms the project entails (e.g. payments, education, enforcement). In most of the projects in the database, it was judged that adoption with the project in place would be reasonably high.

Table 4. Expected loss of environmental benefits from omitting A (as a percentage of the benefits of perfect prioritisation).

| Mean of *A** | Budget (relative to full funding) | | | | |
|---|---|---|---|---|---|
| | 2.5% | 5% | 10% | 20% | 40% |
| 0.8 | 2 | 2 | 1 | 0.8 | 0.4 |
| 0.6 | 4 | 3 | 2 | 2 | 0.8 |
| 0.4 | 9 | 7 | 6 | 4 | 2 |
| 0.2 | 20 | 17 | 14 | 10 | 5 |
| 0 | 41 | 36 | 29 | 20 | 10 |

* Mean prior to winsorisation.

These results reveal the reason why omission of *V* or *C* from the metric causes such large losses. In the sample of projects used to parameterise the model, they have the highest CVs ( over 1 in each case) much larger than the other variables. For a program that focused on projects which had smaller relative ranges of *V* or *C*, the costs of their omission would be smaller than estimated here.

Returning to Table 3, the effect of combining omissions is approximately additive. Combinations are shown for the four variables to which results are most sensitive. The greater the number of variables omitted, the greater is the loss of environmental values resulting from poor project selection. In cases where the two most costly variables are omitted (*V* and *C*), the loss of environmental values approaches the losses from completely uninformed random project selection.

Fortunately, project ranking systems do typically include a measure of *V*. Sometimes it is the only one of these six variables that *is* included – it is not unusual for project decision metrics to ignore *W*, *A*, *R L* and/or *C*. Although omitting *A* and *L* is not costly, the last line of the table indicates that expected environmental losses from omitting *W*, *R* and *C* are substantial. Further, the quality of the measure of *V* is often questionable. In many cases, it is based solely on scientific criteria, without considering the social values, such as would be estimated from non-market valuation studies.

Table 5 shows a similar set of result for the case where the decision metric is formulated as a weighted additive formula (as in Equation (2)). The first line of results shows the environmental losses from using the additive formulation if all relevant variables are included. It is a costly error, exceeded in Table 3 only by omission of *C* or *V* (amongst the individual omissions).

Table 5. Expected loss of environmental benefits from poor prioritisation (as a percentage of the benefits of perfect prioritisation), using a weighted additive metric

| Scenario | Budget (relative to full funding) | | | | |
|---|---|---|---|---|---|
| | 2.5% | 5% | 10% | 20% | 40% |
| All data included | 23 | 14 | 7 | 3 | 2 |
| Omit *V* | 45 | 36 | 25 | 17 | 2 |
| Omit *W* | 30 | 20 | 13 | 7 | 4 |
| Omit *A* | 25 | 16 | 8 | 4 | 3 |
| Omit *R* | 27 | 18 | 10 | 5 | 3 |
| Omit *L* | 26 | 15 | 7 | 3 | 2 |
| Omit *C* | 42 | 37 | 30 | 21 | 12 |
| Omit *V* and *W* | 53 | 44 | 33 | 22 | 11 |
| Omit *V* and *R* | 49 | 41 | 30 | 19 | 10 |
| Omit *V* and *C* | 70 | 65 | 57 | 45 | 27 |
| Omit *W* and *R* | 34 | 24 | 16 | 9 | 5 |
| Omit *W* and *C* | 48 | 43 | 36 | 26 | 15 |
| Omit *R* and *C* | 45 | 40 | 32 | 24 | 14 |
| Omit *V*, *W* and *R* | 58 | 49 | 38 | 26 | 13 |
| Omit *V*, *W* and *C* | 78 | 73 | 67 | 55 | 36 |
| Omit *V*, *R* and *C* | 75 | 70 | 63 | 51 | 31 |
| Omit *W*, *R* and *C* | 49 | 45 | 38 | 29 | 17 |

When an additive metric is used, the marginal loss from omitting variables is lower than when the BCR formula is used (e.g. at 2.5 per cent budget, the cost of omitting *V* is 22 per cent (45 – 23) compared with 31 per cent in Table 3). However, the combined cost of omitting variables and using an additive metric is greater than the cost of omitting variables in Table 3 (e.g. 45 versus 31 per cent in the above example).

The ranking of variables in terms of losses due to variable omission in Table 5 is similar to Table 3, although the differences between them are smaller. When three of the four most costly variables are omitted, the total losses are similar between the two metrics.

These results could be used to evaluate the quality of specific decision metrics. For example, the Project Prioritisation Protocol of Joseph et al. (2009) includes *V*, *R* and *C* and uses a BCR style formula, omitting *W*, *A* and *L*. We can see from Table 3 that the loss of potential environmental benefits from this metric would be approximately 3 to 12 per cent, depending on the budget, and assuming perfect information. This might be viewed as an acceptable trade-off for the benefits of simplicity. On the other hand, it is not uncommon for ranking processes to employ an additive metric that omits *R*, *C*, *W*, *A* and *L* (e.g., Isaac et al. 2007; Rodriguez et al., 2004). The expected losses from this approach are 20 to 50 per cent (40 to 50 per cent under small budget scenarios). These are clearly unnecessary environmental losses that would be readily avoidable by improvements in the decision metric.

The final set of results explores the losses due to uncertainty about parameter values. This is simulated by adding a normally distributed error term to each of the benefits-related variables. (It is assumed that there is no uncertainty about project costs.) In the simulations we prioritise projects based on perfect information and then based on uncertain information and compare the environmental values achieved (evaluated from the standpoint of perfect information). This is done using both metric types (BCR and additive), with and without the omission of variables. Two different levels of uncertainty are investigated: moderate (15 per cent CV for each variable) and high (30 per cent CV for each variable). Results are shown in Table 6.

Table 6. Expected loss of environmental benefits from uncertainty in project prioritisation (assuming equal CV for each benefit-related parameter) as a percentage of the benefits of perfect prioritisation.

| Scenario | Budget (relative to full funding) | | | | |
|---|---|---|---|---|---|
| | 2.5% | 5% | 10% | 20% | 40% |
| **Coefficient of variation 15%** | | | | | |
| All data included correctly | 4 | 3 | 2 | 2 | 1 |
| Omit *C* | 4 | 3 | 2 | 2 | 0 |
| Omit *W* and *C* | 3 | 2 | 2 | 2 | 2 |
| Omit *V*, *W* and *C* | 2 | 3 | 3 | 3 | 3 |
| Additive | 3 | 3 | 2 | 2 | 0.7 |
| Additive, Omit *C* | 3 | 0.9 | 2 | 2 | 2 |
| Additive, Omit *W* and *C* | 1 | 2 | 0.7 | 1 | 2 |
| Additive, Omit *V*, *W* and *C* | 0.5 | 1 | 1 | 2 | 2 |
| **Coefficient of variation 30%** | | | | | |
| All data included correctly | 13 | 12 | 10 | 7 | 1 |
| Omit *C* | 12 | 11 | 9 | 8 | 2 |
| Omit *W* and *C* | 8 | 8 | 9 | 9 | 6 |
| Omit *V*, *W* and *C* | 5 | 6 | 7 | 7 | 3 |
| Additive | 8 | 9 | 9 | 6 | 3 |
| Additive, Omit *C* | 7 | 7 | 6 | 7 | 6 |
| Additive, Omit *W* and *C* | 3 | 5 | 5 | 6 | 6 |
| Additive, Omit *V*, *W* and *C* | 3 | 3 | 4 | 5 | 5 |

Even if all variables are included and the correct BCR formula is used, uncertainty is much less costly (in terms of environmental values foregone) than omission of the more costly variables or combinations of variables. The loss due to high uncertainty is less than half the loss from omitting *C* or *V*, for example. The loss from moderate uncertainty is less than 5 per cent at all budget levels simulated.

Notably, if a poor decision metric is used (additive and/or omitting variable), the marginal cost of uncertainty is even lower. The poorer the metric, the lower the cost of uncertainty. Even high uncertainty has a marginal loss less than 10 per cent under the poorer metrics, and the loss from moderate uncertainty falls to very low levels.

These results have some strong, and perhaps surprising, implications. If a decision maker faces high uncertainty about project parameters and is currently using a poor decision metric for ranking projects, then the expected benefits of improving the metric are much greater than those for reducing parameter uncertainty. It is clear to which of these options effort should preferably be directed.

Further, if a very poor metric is used, then the benefits of going from high uncertainty to perfect information are remarkably low: 3 to 6 per cent. Improving information quality only generates benefits greater than 10 per cent if a reasonably good decision metric is used, and even then only if the available budget is low.

Thirdly, even if uncertainty about a variable is high, it is important to include it the decision metric. The environmental cost of omitting it is likely to be higher than the cost of uncertainty if it is included, potentially much higher.

## *4. Conclusion*

The loss of environmental benefits resulting from poor prioritisation of environmental projects due to use of inappropriate metrics can be very high, with losses of up to 80 per cent of environmental values in extreme cases – little better than completely uninformed random selection of projects. If program budgets are small relative to the cost of all proposed projects (e.g., 10 per cent or less), commonly made errors in decision metrics result in losses of 30 to 50 per cent, even under perfect information. These errors are readily avoidable. Environmentalists advocating for improvements in environmental outcomes may find that seeking improvements in environmental decision processes may generate much greater improvements in environmental values than equivalent efforts devoted to increasing environmental budgets. Decision makers should avoid using weighted additive decision metrics inappropriately, and should be sure to include all the key variables, particularly variables representing environmental values, the effectiveness of management actions, and project costs.

The use of poor metrics interacts with uncertainty about project parameter values. If a poor metric is used, the benefits of improving the quality of information used to prioritise projects falls, in some situations to very low levels. Even using a perfect metric, the loss from relying on poor information is substantially less than some common errors or combinations of errors in the design of decision metrics. This suggests that, for environmental project prioritisation, it is more important to ensure that high quality decision metrics are used than to invest in improving the quality of information about projects.

## *References*

European Commission (2002). *LIFE – Environment Projects*. European Commission, Brussels.

Feng, H., Kurkalova, L.A., Kling, C.L. and Gassman, P.W. (2006). Environmental conservation in agriculture: Land retirement vs. changing practices on working land, *Journal of Environmental Economics and Management* 52, 600-614.

Ferris, J. and Siikamäki, J. (2009). Conservation reserve program and wetland reserve program: primary land retirement programs for promoting farmland conservation, Resources for the Future, Washington D.C.

Hajkowicz, S. (2009). The evolution of Australia's natural resource management programs: Towards improved targeting and evaluation of investments, *Land Use Policy* 26, 471-478.

Hajkowicz, S. and McDonald, G. (2006). The Assets, Threats and Solvability (ATS) model for setting environmental priorities, *Journal of Environmental Policy and Planning* 8(1), 87-102.

Hajkowicz, S., Higgins, A., Williams, K., Faith, D.P. and Burton, M. (2007). Optimisation and the selection of conservation contracts, *Australian Journal of Agricultural and Resource Economics* 51(1), 39-56.

Improscio, D.L. (2003). Overcoming the Neglect of Economics in Urban Regime Theory, *Journal of Urban Affairs* 25, 271-284.

Isaac, N.J.B., Turvey, S.T., Collen, B., Waterman, C., Baillie, J.E.M. (2007). Mammals on the EDGE: Conservation Priorities Based on Threat and Phylogeny. PLoS ONE 2(3), e296. doi:10.1371/journal.pone.0000296

Johansson, R.C. and Cattaneo, A. (2006). Indices for working land conservation: form affects function, *Review of Agricultural Economics* 28(4), 567-584.

Joseph, L.N., Maloney, R.F. and Possingham, H.P. (2009). Optimal allocation of resources among threatened species: a project prioritisation protocol, *Conservation Biology* 23(2), 328-338.

Kellerer, H., Pferschy, U. and Pisinger, D. (2004). *Knapsack Problems*, Springer-Verlag, Berlin.

Lambert, D.M., Sullivan, P., Claassen, R., Foreman, L. (2007). Profiles of US farm households adopting conservation-compatible practices. *Land Use Policy* 24, 72–88.

Laycock, H., Moran, D., Smart, J., Raffaelli, D. and White, P. (2009). Evaluating the cost-effectiveness of conservation: The UK Biodiversity Action Plan, *Biological Conservation* (forthcoming). doi:10.1016/j.biocon.2009.08.010

Marsh, H., Dennis, A., Hines, H., Kutt, A., McDonald, K., Weber, E., Williams, S. and Winter, J. (2007). Optimizing allocation of management resources for wildlife, *Conservation Biology* 21(2), 387-399.

Mendoza, G.A., Mcoun, P., Prabhu, R., Sukadri, D., Purnomo, H. and Hartanto, H. (1999). *Guidelines for Applying Multi-Criteria Analysis to the Assessment of Criteria and Indicators*, The Criteria & Indicators Toolbox Series 9, Center for International Forestry Research, Jakarta, http://www.cifor.cgiar.org/acm/methods/toolbox9.html [accessed 8 September 2009].

Metrick, A., and Weitzman, M.L. (1998). Conflicts and choices in biodiversity preservation. *Journal of Economic Perspectives* 12, 21–33.

Pannell, D.J. (2013). Ranking environmental projects, School of Agricultural and Resource Economics, University of Western Australia, Working Paper 1312, http://ageconsearch.umn.edu/handle/156482 (accessed 2 Jan 2014).

Pannell, D.J. and Roberts, A.M. (2010). The National Action Plan for Salinity and Water Quality: A retrospective assessment, *Australian Journal of Agricultural and Resource Economics* 54(4), 437-456.

Pannell, D.J., Roberts, A.M., Park, G., Alexander, J., Curatolo, A. and Marsh, S. (2012). Integrated assessment of public investment in land-use change to protect environmental assets in Australia, *Land Use Policy* 29(2), 377-387.

Possingham, H. (2009). Five objections to using decision theory in conservation and why they are wrong, *Decision Point* Issue 26, March 2009, pp.2-3, http://www.aeda.edu.au/docs/Newsletters/DPoint_26.pdf [accessed 8 September 2009].

Rodríguez, J.P., Rojas-Suárez, F. and Sharpe, C.J. (2004). Setting priorities for the conservation of Venezuela's threatened birds, Oryx 38(4), 373-382.

Rogers, A.A., Kragt, M.E., Gibson, F.L., Burton, M.P., Petersen, E.H. and Pannell, D.J. (2013). Non-market valuation: usage and impacts in environmental policy and management in Australia, *Australian Journal of Agricultural and Resource Economics* (forthcoming). http://onlinelibrary.wiley.com/doi/10.1111/1467-8489.12031/abstract (accessed 2 Jan 2014).

Szabo, J.K., Briggs, S.V., Lonie, R., Bell, L., Maloney, R., Joseph, L.N., Hunter, I. and Possingham, H.P. (2009). The feasibility of applying a cost-effective approach for assigning priorities for threatened species recovery with a case study from New South Wales, Australia, *Pacific Conservation Biology* 15: 238–245.

United States Department of Agriculture (2003). Financial Year EQIP Unfunded Application Information. USDA, Washington DC.

Wilson, K.A., Underwood, E.C., Morrison, S.A., Klausmeyer, K.R., Murdoch, W.W., Reyers, B., Wardell-Johnson, G., Marquet, P.A., Rundel, P.W., McBride, M.F., Pressey, R.L., Bode, M., Hoekstra, J.M., Andelman, S., Looker, M., Rondinini, C., Kareiva, P., Shaw, M.R., and Possingham, H.P., 2007. Conserving biodiversity efficiently: what to do, where, when, *PLoS Biology* 5(9), 1850-1861.