Environmental cost of using poor decision metrics to prioritize environmental projects

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Abstract

Conservation decision makers commonly use project-scoring metrics that are inconsistent with theory on optimal ranking of projects. As a result, there may often be a loss of environmental benefits. We estimated the magnitudes of these losses for various metrics that deviate from theory in ways that are common in practice. These metrics included cases where relevant variables were omitted from the benefits metric, project costs were omitted, and benefits were calculated using a faulty functional form. We estimated distributions of parameters from 129 environmental projects from Australia, New Zealand, and Italy for which detailed analyses had been completed previously. The cost of using poor prioritization metrics (in terms of lost environmental values) was often high – up to 80% in the scenarios we examined. The cost was greater when the budget was smaller. The most costly errors were omitting information about environmental values (up to 31% loss of environmental values), omitting project costs (up to 35% loss), omitting the effectiveness of management actions (up to 9% loss), and using a weighted-additive decision metric for variables that should be multiplied (up to 23% loss). The latter 3 are errors that occur commonly in real-world decision metrics, in combination often reducing potential benefits from conservation investments by 30-50%. Uncertainty about parameter values also reduced the benefits from investments in conservation projects but often not by as much as faulty prioritization metrics.

Introduction

While substantial public funds are allocated to conservation projects each year (Hajkowicz 2009; Lambert et al. 2007), funds are scarce relative to the demand from all possible projects, so prioritization is essential. Optimal prioritization involves selecting those projects that provide the greatest benefit:cost ratios until the budget is exhausted but “this simple decision rule is often not followed in practice by legislatures and agencies that manage programs with an ostensible purpose of acquiring environmental goods” (Babcock 1997: 325).

Many conservation organisations use a formula or metric to prioritize projects for funding. For example, in the Conservation Reserve Program in the United States, rankings are based on a summation of scores related to wildlife benefits, water quality, erosion, air quality, enduring benefits, and project costs (Claassen et al. 2008; Ferris & Siikamäki 2009).

Given the importance of these metrics in determining which projects get funded and, therefore, the efficiency of conservation investments, researchers have paid remarkably little attention to the performance of the metrics. Many metrics in actual use are theoretically unsound (Babcock et al. 1997; Possingham 2009; Pannell & Roberts 2010), reflecting the backgrounds of practitioners and a common neglect of decision theory and economic principles (Rogers et al. 2015). For example, Wilson et al. (2007) pointed out that some ranking systems ignore project cost (e.g., Rodriguez et al. 2004; Isaac et al. 2007). Many omit relevant variables, such as project effectiveness (Maron et al. 2013). Others add variables that should be multiplied (Ebert & Welsch 2004) or subtract costs rather than dividing by them (e.g., the Conservation Reserve Program [Hajkowicz et al. 2009]). Such differences in metric design can make major differences in the ranking of projects for funding (Johansson & Cattaneo 2006).

We investigated the quantitative improvements in environmental values that could be achieved by improving project-ranking metrics. Few studies have compared the performances of different metrics. Joseph et al. (2009) ranked investments for threatened species in New Zealand. The two weakest prioritization metrics they tested resulted in environmental benefits being reduced by 38% and 75% relative to their superior metric.

Babcock et al. (1997) compared ranking systems based on benefit:cost ratios with those based only on costs (which is rare in practice) or only on benefits (which is common). The environmental benefits of moving to a benefit:cost ratio ranking depended on the variances of benefits and costs and the correlation between benefits and costs; variance is greatest when correlation is positive. In general, one would expect the correlation to be positive (e.g., Fuller et al. 2010), or at least not negative.

We assessed 4 common sources of metric inaccuracy: use of a weighted-additive scoring metric when a multiplicative metric should be used; omission of relevant variables related to benefits; neglect of project costs; and errors in estimation of variables. Our aim was to assess how seriously these issues affect the achievement of environmental benefits.

Our study improves upon previous studies by Babcock et al. (1997) and Joseph et al. (2009). We simulated numerous ranking decisions to avoid the sample bias inherent in conducting the evaluation for a single set of projects (e.g., Joseph et al. 2009). We investigated a larger range of metrics. We explored the sensitivity of benefits to metric choice for different sizes of program budget. And, we compared the relative importance of metric choice and data accuracy.

Conceptual framework

Assume a conservation organisation must allocate a fixed budget among a set of potential projects. Each project has a known cost and known levels of variables related to benefits. The total cost of all projects exceeds the budget, so prioritization 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 maximizes total environmental values.

Pannell (2015) described the theoretical principles and practical considerations for selection of a decision metric for solving this knapsack problem. The problem can be closely approximated by ranking projects according to their benefit:cost ratios (Hajkowicz et al. 2007). For a set of projects with a single type of environmental benefit (or multiple types that have been converted to monetary values and summed), one version of Pannell's (2015) recommended formula for the benefit:cost ratio is

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

where V is the total value of the environmental assets affected by the project, at a reference condition, which may depend on the scale of the asset and its importance to the community (In the numerical example provided below, V was measured in dollars, but a non-monetary measure of total value could be used so long as it captured the relative importance of different assets.); W , effectiveness, is the proportional increase in environmental value (relative to V) as a result of the project ($V \times W$ represents the potential benefits of the project if it is fully successful and there is no time lag for benefits); A is the adoption of required new behaviors as a proportion of the level that would deliver the project's objectives (simplifying

assumption: benefits are linearly related to level of adoption); R is the probability of project failure depending on technical, socio-political, and financial risks (simplifying assumption: success of a project is a binary variable); L is the time lag until benefits occur (simplifying assumption: all benefits of a project commence at the same time and continue indefinitely); r is the discount rate; and C is the present value of project costs, including maintenance costs, compliance costs, and short-term project costs.

Equation 1 expands on metrics used by Metrick and Weitzman (1998) and Stoneham et al. (2003), whose numerator consisted of $V \times W$, and Joseph et al. (2009), whose numerator was $V \times W \times (1 - R)$. These authors confirm that the general structure of Eq. 1 is theoretically correct.

A feature of Eq. 1 compared with some equations in use is that the elements are multiplied. The proportional increase in environmental value (W) and the adoption of the required new behaviours (A) enter the formula multiplicatively because they are proportional to expected benefits. Multiplying by $(1 - R)$, the probability of project success yields 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.

In practice, a more commonly used metric for prioritizing conservation projects takes the following form:

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

where w_i s are weights, chosen subjectively to reflect the relative importance of different variables. For example, metrics like Eq. 2 have been used in the U.S. Conservation Reserve Program (Feng et al. 2006; Ferris & Siikamäki 2009) and Australia's Caring for Our Country program.

Some have been critical of the arbitrary way weights are chosen for this equation. They can be based on hidden assumptions (e.g., Turner 2007); sometimes arbitrary default weights of 1 have been used. However, Eq. 2 provides erroneous rankings of projects whichever weights are chosen. For example, if one uses Eq. 2, a project that should be of low priority because it fails on an essential criterion (e.g., there is zero adoption of required changes, so $A=0$) could erroneously be given a high priority because it scored well on other variables.

A second common error in prioritization metrics is to omit benefit-related variables. For example, the ranking system of Australia's Caring for our Country program in 2009 failed to consider the technical effectiveness of projects and the likely adoption of proposed management changes. As noted earlier, although they used well-structured metrics, Metrick and Weitzman (1998), Stoneham et al. (2003), and Joseph et al. (2009) omitted some of the variables in Eq. 1. If effectiveness (W) were omitted, for example, Eq. 1 would become

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

or, if, additionally, a weighted-additive system were used,

$$\alpha_1 = w_1 \times V + w_3 \times A + w_4 \times R + w_5 \times L + w_6 \times C, \quad (4)$$

where α_1 and β_1 are indices of project merit.

Projects are sometimes ranked according to benefits, ignoring costs (Hajkowicz et al. 2007; Joseph et al. 2009; Laycock et al. 2009). For example,

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

or

$$\alpha_2 = w_1 \times V + w_2 \times W + w_3 \times A + w_4 \times R + w_5 \times L. \quad (6)$$

We also examined combinations of omissions. For example, in one scenario both effectiveness (W) and cost (C) were omitted:

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

or

$$\alpha_2 = w_1 \times V + w_3 \times A + w_4 \times R + w_5 \times L. \quad (8)$$

There are situations where omission of adoption (A) would be reasonable. For example, a conservation agency may itself implement all on-ground actions in the projects, without requiring cooperation from other people. Similarly, in a conservation tender program (a reverse auction in which bidders offer to undertake certain conservation actions in return for a payment that they specify) (e.g., Stoneham et al. 2003), all successful bidders are contracted, so adoption is reasonably assured. In certain cases, value (V) might be judged to be the same for each project (e.g., the projects may focus on individual species, each of which is assigned the same value). In such cases, the omission of value would be reasonable.

Finally, there is always uncertainty about parameter values, resulting in errors in their estimation. Variables can be estimated more accurately but at greater cost. We estimated the likely cost of inaccuracy by introducing random errors from defined distributions into the values of the variables.

Methods

Data

We obtained values for project parameters (V , W , A , R , L and C) from the database of projects that were evaluated using the Investment Framework for Environmental Resources (INFFER) (Pannell et al. 2012). INFFER has been used by many environmental organisations to rank projects. We included all 129 projects for which complete sets of parameters were available. We estimated the probability distribution for each parameter (Table 1) and tested for correlations between parameters. These projects addressed a diverse range of environmental issues, including conservation of ecological communities and threatened species, control of invasive species, water pollution, and soil conservation. They were predominantly from Australia but included six projects from New Zealand and Italy. The projects are typical of the types of investments made in managing these environmental problems in other developed countries, although they are more spatially discrete than those in some European and North American programs.

Parameter distributions vary in different countries depending on local conditions and institutions, but the general lessons are applicable. Raw data and the distributions we assumed are available in Supporting Information (project-errors-distributions.xlsx). There were no significant correlations between any of the benefits-related variables (V , W , A , R and

L), the largest R^2 being 0.05. There was also no correlation between benefits and costs ($R^2 = 0.001$). In all simulations, a real discount rate of 5 per cent was assumed.

Procedure

We examined the following scenarios: scenario a, benefit:cost ratio (Eq. 1) was the benchmark, assumed to provide accurate prioritization; scenario b, use of weighted-additive metric (Eq. 2); scenario c, partial exclusion of benefits-related variables – 1, 2, or 3 variables excluded (similar to Eq. 3); scenario d, partial exclusion of variables and weighted-additive metric (similar to Eq. 4); scenario e, project benefits considered but not costs (Eq. 5); scenario f, project benefits considered but not costs, in a weighted-additive metric (Eq. 6); scenario g, errors in measurement considered (normally distributed errors for each benefits-related variable, with coefficients of variation of 15-30% in each case); and scenario h, random project selection (each project equally likely to be selected).

The cost of errors in project prioritization depends on the degree of selectivity involved (i.e., the budget available relative to the budget that would be required to fund all projects). To investigate the impact of project selectivity on the cost of assessment errors, various budget sizes were simulated: 2.5%, 5%, 10%, 20%, and 40% of the amount required to fund all projects. In conservation 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% of proposed projects were funded, while in 2002 the European LIFE Environment Program funded 23% of proposed projects (EC 2002).

In estimating the cost of poor metrics, we assumed that 100 projects had been proposed. The number of projects actually funded depended on the budget, which ranged from 2.5% to 40%

of the amount required for all 100 projects. For each of the 100 projects, values for value (V), effectiveness (W), adoption (A), risk (R), lag (L), and cost (C) were generated randomly from the distributions given in Table 1. In all scenarios except (g), we assumed decision makers had perfect knowledge about the parameter values. For cases where weighted-additive benefit scoring was used, each weight equalled the inverse of the mean for its variable (negative weights for R , L , and C). Consequently, the degree of influence on project scores was similar for each of the variables. Other than for lag (L), this approach minimised the cost of using the weighted-additive metric.

Environmental losses due to parameter uncertainty, scenario (g), were simulated by adding a different normally distributed error term to each benefit-related variable. This was done in both multiplicative and additive forms of the function. We assumed no uncertainty about project costs. We prioritized projects based on perfect information and then based on uncertain information and compared the environmental values achieved (evaluated from the standpoint of perfect information). This was done using both metric types (benefit:cost ratio and additive), with and without the omission of variables. Two different levels of uncertainty were investigated: moderate (15% coefficient of variation [CV] for each variable) and high (30% CV).

Our procedure for estimating the expected value of environmental losses from use of poor metrics was based on an understanding of Bayesian decision theory, as follows. For 100 simulated projects, we generated random values from estimated distributions (Table 1) for all parameters (step 1). We calculated a benefit:cost ratio for each project with Eq. 1 (step 2). We selected projects with the highest benefit:cost ratios that fitted within the program budget (step 3). For the marginal project, we assumed benefits were proportional to the partial funding it receives (step 4). We recorded total estimated benefits for funded projects (step 5).

We repeated steps 2-4 using an alternative prioritization metric and repeated step 5 with the correct measure of benefits from step 2, not the measure of benefits from the alternative metric, to calculate total benefits from projects selected using the alternative metric (step 6). By comparing the total benefits from the 2 instances of step 5, we calculated the loss of environmental benefits resulting from use of the alternative metric as a percentage of the benefits generated using the benefit:cost ratio (step 7). We repeated steps 1-7, 1000 times to generate a distribution of results from which we calculated mean percent losses (step 8). We repeated steps 1-8 for scenarios b-h (and combinations) and for 5 program budget levels.

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 in Supporting Information.

Results

We start with an illustration of the procedure. For a single randomly generated case, benefit:cost ratios for a set of 100 projects were calculated using Eq. 1 (the benchmark) and compared with results using Eq. 7 (with W and C omitted) (Fig. 1a). There was a low correlation between the metrics ($R^2 = 0.11$), so use of the incorrect metric could result in environmental benefits being foregone.

Each simulation of a set of 100 projects generated a different graph and a different correlation. That is why the procedure involved repeated random sampling for each scenario – estimates from any single simulation were biased.

The correlation between the project rankings for the correct benefit:cost ratio and a benefit:cost ratio that omits W and C was not high: $R^2 = 0.33$ (Fig. 1b). (Lower project rankings corresponded to superior projects.) The thresholds for project funding, assuming that funding is sufficient to support 10% of projects (dotted lines Fig. 1b), divided the projects into four groups. Projects that were poorly ranked by both metrics (upper-right section) would not be funded using either approach. Projects ranked favorably based on both these metrics (lower-left section) would be funded in both cases. Some projects were ranked favorably by the correct benefit:cost ratio and unfavorably by the equation that omitted W and C (upper-left section). Omission of these projects, as a result of ranking based on Eq. 7, resulted in a reduction in expected environmental values. Some projects were ranked unfavorably by the correct benefit:cost ratio and favorably by the alternative function (lower-right section). These are projects that should not be funded but would be funded if Eq. 7 were used. In this simulation, the alternative function would lead to funding of 6 projects with poor benefit:cost ratios (ranked worse than 59 out of 100). Overall, in this single simulation, the total environmental benefits of projects selected for funding based on Eq. 7 were 18% less than the total benefits of projects prioritized based on Eq. 1.

The comparison of results for the correct benefit:cost ratio (Eq. 1) and the additive decision metric (Eq. 2) for a single random sample (Fig. 1c) produced a higher correlation ($R^2 = 0.37$) than the previous example ($R^2 = 0.11$) (Fig. 1a). The distribution of benefit:cost ratios was highly skewed; a few projects performed much better than most (Fig. 1c, horizontal axis). However, this result was obscured when the additive metric was used (Fig. 1c, vertical axis); the best projects did not stand out as being far superior to the others.

The correlation between project rankings for the second example (Fig. 1d) was relatively high ($R^2 = 0.75$). Nevertheless, there was still a cost of poor project selection due to use of a weighted-additive metric amounting to 12% loss of conservation benefits. However, this result was for a single simulation with a random sample of 100 potential projects. For over 1000 simulations (Fig. 2), the mean cost was 7%. This illustrates that evaluations based on a single sample of projects may be subject to sample bias. From here on, results presented are means of 1000 random samples.

When projects were selected at random with no input of information, the mean loss of potential benefits (from step 9 of the procedure) varied depending on the program budget: 55% loss for a budget that was sufficient to pay for 40% of projects, 81% loss for a 10% budget, and 89% loss for a 2.5% budget. Clearly, the environmental cost of failing to prioritize projects was high.

The expected cost of omitting variables from the benefit:cost ratio equation varied depending on which variable was omitted (Table 2, columns 2-6). Going from greatest to least cost of omission, the order was *C*, *V*, *W*, *R*, *A*, and *L*. Although adoption had a higher SD than some other variables, it had the second lowest cost of being omitted. It was the CV that determined this result, rather than the absolute SD (see Supporting Information for further details and results).

This is also the reason omission of value or cost from the metric caused such large losses. In the sample of projects used to parameterise the model, they had the highest CVs (>1 in each case), much larger than the other variables. For a program focused on projects that have

smaller relative ranges of value or cost, the costs of their omission would be smaller than estimated here.

The effect of combining omissions was approximately additive (Table 2). The greater the number of variables omitted, the greater the loss of environmental values resulting from poor project selection. In cases where the 2 most costly variables were omitted, value and cost, the loss of values (71% for a 2.5% budget) approached the losses from completely uninformed random project selection (89% for a 2.5% budget).

Metric quality was relatively more important when funds were scarcer. Typically, the percent loss of environmental values resulting from use of a poor decision metric was 3-5 times greater for a very small budget (2.5%) than for a large budget (40%).

When a weighted-additive formula was used (columns 7-11, Table 2) losses of conservation values were greater again than for the benefit:cost ratio (columns 2 to 6, Table 2). Even when all relevant variables were included (the first line of results), using a weighted-additive metric was a costly error, exceeded in the benefit:cost ratio results (columns 2 to 6, Table 2) only when we omitted cost or value (among the individual omissions).

When an additive metric was used, the marginal loss from omitting variables was lower than when the benefit:cost ratio was used (e.g., at 2.5% budget, the cost of omitting *V* was 22% [45 – 23] compared with 31% for the benefit:cost ratio). However, the combined cost of omitting variables and using an additive metric was greater than the cost of omitting variables from a benefit:cost ratio (e.g., 45% versus 31% at 2.5% budget) (Table 2).

The ranking of variables (in terms of losses due to their omission) was similar between a weighted-additive metric and the benefit:cost ratio. When 3 of the 4 most costly variables were omitted, the total losses were similar between the 2 metrics.

Finally, we estimated environmental losses due to uncertainty about parameters. Even when all variables were included and the correct benefit:cost ratio formula was used, uncertainty was much less costly (in terms of conservation values foregone) than omission of the more costly variables or combinations of variables (Table 3). The loss due to high uncertainty (12% for a 5% budget) was less than one-half the loss from omitting cost (31%) or value (26%), for example. The loss from moderate uncertainty was <5% at all budget levels simulated.

When a poor decision metric was used (additive or omitting variables), the marginal cost of uncertainty was even lower. The poorer the metric, the lower the cost of uncertainty. Even high uncertainty had a marginal loss of <10% under the poorer metrics, and the loss due to moderate uncertainty ranged from 0.5% to 4%.

Discussion

The loss of conservation benefits resulting from poor project prioritization due to use of inappropriate metrics can be very high. We found losses of up to 80% – little better than completely uninformed random selection of projects. In scenarios where program budgets were relatively small (e.g., 10% or less of the cost of all proposed projects), commonly made errors in decision metrics resulted in losses of 30-50%, even under perfect information. These errors are readily avoidable. Conservationists advocating for improvements in program

outcomes may find that seeking improvements in decision processes would generate much greater conservation benefits than equivalent efforts devoted to increasing program budgets. Decision makers should avoid using weighted-additive decision metrics inappropriately and should include all the key variables, particularly variables representing environmental values, the effectiveness of management actions, and project costs.

Our results could be used to evaluate the quality of specific decision metrics. For example, the project prioritization protocol of Joseph et al. (2009) included value, effectiveness, risk, and cost and used a benefit:cost ratio style formula, omitting adoption and time lag. If applied to the projects evaluated here, the loss of potential benefits from this metric would be approximately 1-3%, depending on the budget, and assuming perfect information (Table 2). This might be viewed as an acceptable trade-off for the benefits of simplicity from omitting two variables. However, it is not uncommon for ranking processes to employ a metric that omits risk, cost, effectiveness, adoption, and lag (e.g., Rodriguez et al. 2004; Isaac et al. 2007). The estimated expected losses from this approach were 20-50% (40-50% under small budget scenarios). Conservation programs that use such poor metrics to rank projects are missing substantial benefits that could be readily obtained.

The benefit-related variable to which results were most sensitive was value. Fortunately, ranking systems for conservation projects typically include some measure of value. The quality of the measure of value is often questionable (it is sometimes based solely on scientific criteria, ignoring community preferences), but at least it is included. Sometimes it is the only one of these six variables that is included.

Our results reinforce the importance of using mathematically sound and logical indexes in conservation planning and decision making. For example, McCarthy et al. (2004) were critical of the Habitat Hectares index (which is used for measuring vegetation quality) because it relies on an additive metric. They argue that the implied substitutability between variables was unfounded and proposed a geometric-mean approach. In a different context, Rickels et al. (2014) criticised the index of Halpern et al. (2012), which was proposed to measure the state of the human-ocean system against ten societal goals. Again, the criticism was that the additive form of the index inappropriately allowed perfect substitution between objectives. These and other cases highlight that care is needed when selecting an index or metric to guide conservation decisions.

The results for parameter uncertainty have some strong, and perhaps surprising, implications. Where uncertainty is high and a poor metric for ranking projects is used, the expected benefits of improving the metric are much greater than the benefits from reducing uncertainty. Further, if a very poor metric is used, then the benefits of going from high uncertainty to perfect information are remarkably low: 3-6%. Improving information quality only generates benefits greater than 10% if a reasonably good decision metric is used and the available budget for projects is low. Finally, even if uncertainty about a variable is high, it is important to include it in the decision metric. This is consistent with the conclusion of Carwardine et al. (2010), who examined the consequences of uncertainty about the costs of conservation projects. They concluded that cost data should be included in conservation planning, even if it is highly uncertain. We found that the same conclusion applies to all relevant variables, not just cost.

Our quantitative findings are specific to the case study, which is based on a set of 129 environmental projects mainly from Australia. In other contexts, the parameters for the simulation will vary to some degree. Nevertheless, we anticipate that several key findings will be robust: losses of conservation value from use of poor metrics can be large, particularly where budgets are small; omission of costs from ranking metrics is generally a serious error; choice of functional form for combining variables into a measure of benefits requires care and rigour; and uncertainty about parameter values, although a negative influence on conservation outcomes from public programs, can be a less serious problem than use of a poor metric for ranking projects.

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Supporting Information

Source of data (Appendix S1), results illustrating the effect of CV on the cost of omitting variables (Appendix S2), distributions of parameters used in the numerical analysis (project-errors-distributions.xlsx) (Appendix S3), and the spreadsheet used for the simulations conducted in this study (project-errors.xlsm) (Appendix S4) are available online. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

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Table 1. Assumed distributions for each parameter used in the analysis of conservation project prioritization, based on data from 129 conservation projects. *

Parameter	Unit of measure	Distribution
V	\$ millions	$\ln(V/20) \times 11 \sim N(20, 10)$, negatively skewed in V ; mean(V) = \$278 million; SD(V) = \$262 million
W	proportion	$W \sim N(0.3, 0.15)$, Winsorized at 0
A	proportion	$A \sim N(0.8, 0.2)$, Winsorized at 0 and 1
R	probability	$R \sim N(0.5, 0.18)$, Winsorized at 0 and 1
L	years	$L \sim N(10, 4)$, Winsorized at 0
C	\$ millions (present value)	$\ln(C) \times 2 \sim N(2, 2)$; negatively skewed in C ; mean(C) = \$6.7 million; SD(C) = \$7.8 million

*Monetary units are in Australian dollars.

Table 2. Expected loss of environmental benefits from poor prioritization of conservation projects (as a percentage of the benefits of perfect prioritization).

Scenario*	Benefit:cost ratio					Weighted-additive metric				
	budget (percentage of cost of funding all projects)					budget (percentage of cost of funding all projects)				
	2.5%	5%	10%	20%	40%	2.5%	5%	10%	20%	40%
All data included	0.0	0.0	0.0	0.0	0.0	23	14	7.0	3.4	2.3
Omit <i>V</i>	31	26	20	14	7.0	44	36	26	17	8.5
Omit <i>W</i>	9.6	7.7	6.0	4.4	2.4	30	21	13	7.1	4.2
Omit <i>A</i>	2.0	1.6	1.2	0.8	0.4	25	16	8.2	4.1	2.6
Omit <i>R</i>	5.0	4.1	3.2	2.2	1.1	27	18	10	5.4	3.3
Omit <i>L</i>	1.4	1.2	0.8	0.5	0.2	26	15	7.1	2.9	2.2
Omit <i>C</i>	35	31	26	18	8.8	42	37	30	21	12
Omit <i>V</i> and <i>W</i>	39	34	28	20	11	53	44	33	22	11
Omit <i>V</i> and <i>R</i>	37	31	24	16	8.7	49	41	30	19	10
Omit <i>V</i> and <i>C</i>	71	65	57	43	26	70	65	57	45	27
Omit <i>W</i> and <i>R</i>	15	12	10	6.6	3.7	34	24	16	9.1	5.2
Omit <i>W</i> and <i>C</i>	45	40	33	24	13	48	43	36	26	15
Omit <i>R</i> and <i>C</i>	41	36	30	22	12	45	40	32	24	14
Omit <i>V</i> , <i>W</i> , and <i>R</i>	45	38	31	23	13	58	49	38	26	14
Omit <i>V</i> , <i>W</i> , and <i>C</i>	78	73	65	53	35	78	73	67	55	36
Omit <i>V</i> , <i>R</i> , and <i>C</i>	76	70	62	50	30	75	70	63	51	31
Omit <i>W</i> , <i>R</i> , and <i>C</i>	50	43	37	29	17	49	45	38	29	18

*Abbreviations: *V*, value; *W*, effectiveness; *A*, adoption; *R*, risk; *L*, time lag; *C*, cost.

Table 3. Expected loss of environmental benefits from uncertainty in conservation-project prioritization, assuming equal coefficients of variation (CV) for each benefit-related parameter^a.

Scenario ^b	Budget (percentage of cost of funding all projects)				
	2.5%	5%	10%	20%	40%
CV 15%					
All data included correctly	3.8	3.3	2.5	1.7	1.0
Omit <i>C</i>	4.4	2.9	2.3	2.4	1.9
Omit <i>W</i> and <i>C</i>	2.5	2.2	2.0	1.8	1.6
Omit <i>V</i> , <i>W</i> and <i>C</i>	1.6	3.1	2.8	2.5	3.2
Additive	2.8	3.0	2.4	1.8	0.7
Additive, Omit <i>C</i>	2.9	0.9	1.9	2.5	1.6
Additive, Omit <i>W</i> and <i>C</i>	1.0	1.6	0.7	1.5	1.8
Additive, Omit <i>V</i> , <i>W</i> and <i>C</i>	0.5	1.1	1.5	1.6	1.7
CV 30%					
All data included correctly	13.0	12.0	9.7	7.2	4.3
Omit <i>C</i>	11.0	11.0	9.2	8.5	6.7
Omit <i>W</i> and <i>C</i>	8.2	8.0	8.6	8.6	6.0
Omit <i>V</i> , <i>W</i> and <i>C</i>	4.5	6.2	7.0	7.3	8.1
Additive	7.9	9.5	8.9	6.4	2.8
Additive, Omit <i>C</i>	6.5	6.6	6.2	7.0	5.6
Additive, Omit <i>W</i> and <i>C</i>	2.5	5.0	4.8	6.4	5.9

Additive, Omit <i>V</i> , <i>W</i> , and <i>C</i>	2.7	2.9	4.5	5.1	5.0
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^a Values in the body of the table are percent loss of environmental benefits due to poor prioritization as a result of uncertainty. For example, when cost (*C*) is omitted, the values shown are the additional losses due to uncertainty, not the losses due to omitting cost, which are shown in Table 2.

^b Abbreviations: *V*, value; *W*, effectiveness; *A*, adoption; *R*, risk; *L*, time lag; *C*, cost.

Figure 1.

Correlations between (a) project benefit:cost ratios calculated correctly (Eq. 1) and a benefit:cost ratio metric that omits effectiveness (W) and cost (C) ($R^2 = 0.11$), (b) project rankings for the benefit:cost ratio and a benefit:cost ratio that omits W and C (dotted lines show cut offs for funding under each criterion given a program budget of 10% of the level required to fund all projects; $R^2 = 0.33$; cost of poor prioritization 48%), (c) benefit:cost ratio and a weighted-additive metric ($R^2 = 0.33$), (d) project rankings for the benefit:cost ratio and a weighted-additive metric (dotted lines as in [b]; $R^2 = 0.75$).

Figure 2. Frequency distribution (1000 random simulations) of cost of poor prioritization of conservation projects for the weighted-additive metric used in Fig. 1c and d (mean cost 7.0% [SD 4.5%]; cost <15% for 95% of cases).

Figure 1

b)

c)

d)

Figure 2