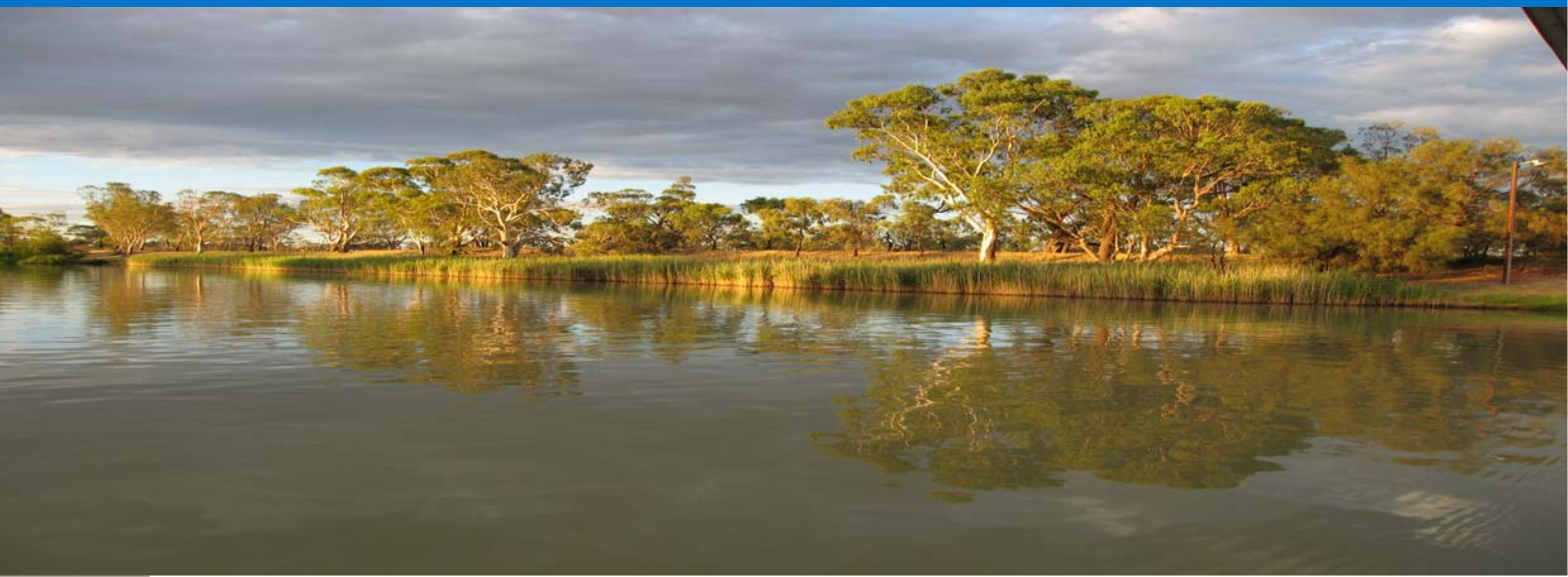
Government of South Australia
South Australian Murray-Darling Basin
Natural Resources Management Board



AUGUST 2009

Robust, cost effective investment decisions for managing natural capital and ecosystem services

Brett A. Bryan

National Research FLAGSHIPS
CSIRO

Water for a Healthy Country Flagship Report series ISSN: 1835-095X

Citation: Bryan, B. A., 2009. Robust, cost-effective investment decisions for managing natural capital and ecosystem services. CSIRO and South Australian Murray-Darling Basin Natural Resources Management Board.

Australia is founding its future on science and innovation. Its national science agency, CSIRO, is a powerhouse of ideas, technologies and skills.

CSIRO initiated the National Research Flagships to address Australia's major research challenges and opportunities. They apply large scale, long term, multidisciplinary science and aim for widespread adoption of solutions. The Flagship Collaboration Fund supports the best and brightest researchers to address these complex challenges through partnerships between CSIRO, universities, research agencies and industry.

The Water for a Healthy Country Flagship aims to achieve a tenfold increase in the economic, social and environmental benefits from water by 2025. The work contained in this report is collaboration between the South Australian Murray Darling Basin Natural Resources Management Board and CSIRO's Sustainable Regional Development theme, Sustainable Agriculture Flagship and Water for a Healthy Country Flagship.

For more information about Water for a Healthy Country Flagship, Sustainable Agriculture Flagship or the National Research Flagship Initiative visit www.csiro.au/org/HealthyCountry.html

Cover photo courtesy of the South Australian Murray-Darling Basin Natural Resources Management Board

CONTENTS

Executive Summary vi

1. Introduction 1

2. A robust portfolio selection model 3

2.1. Investment Strategies 3

2.2. Robust Portfolio Selection 4

3. Study Area 6

4. Methods 7

4.1. Regional Priorities for Managing Natural Capital and Ecosystem Services 7

4.2. Identifying Investment Alternatives and Quantifying Impacts 8

4.3. Simulating Benefits 8

4.4. Quantifying Benefits and Costs 8

4.5. Robust Portfolio Selection 9

5. Results 10

5.1. Cost-effectiveness 10

5.2. Robust Portfolio Selection under Uncertainty 10

6. Discussion 14

6.1. Supporting environmental investment decision making 14

6.2. Advantages, Limitations, and Further Research 15

7. Conclusion 16

8. Appendixes 17

References 23

LIST OF FIGURES

Figure 1 – Location and broad land use in the South Australian Murray-Darling Basin study area. 6

Figure 2 – Cost-effectiveness of targets for enhancing natural capital and ecosystem services under uncertainty. The coloured bar represents cost-effectiveness calculated under the most likely decision rule whilst the error bars represent cost-effectiveness calculated under the pessimistic (low bar) and optimistic (high bar) decision rules. Note that the letter in the target ID (top x-axis) refers to the relevant natural capital asset addressed by the target (A = Atmosphere, B = Biota, L = Land, W = Water, and P = People). 10

Figure 3 – Pareto fronts of non-dominated portfolios of targets under optimistic (green), most likely (yellow), and pessimistic (red) decision rules for each of the four investment strategies (E-max, E-max*, C-rank, and B-rank). 11

LIST OF TABLES

Table 1 – Natural capital and ecosystem services assessed in this study. 7

Table 2 – Performance of the four investment strategies under three decision rules and three budget scenarios measured in terms of benefit for natural capital and ecosystem services. 12

Table 3 – Portfolios selected under the four investment strategies, three decision rules, and three budgets. Included is the core index (%) and investment classification (core (C), borderline (B), and external (E)). 13

ACKNOWLEDGEMENTS

The author is grateful to the SAMDB NRM Board, and CSIRO's Sustainable Regional Development theme, Sustainable Agriculture Flagship, and Water for a Healthy Country Flagship for supporting and funding the research. The author is also grateful for the support of the planning team at the SAMDB NRM Board and Darran King from CSIRO, and for the participation of decision-makers and communities of the SAMDB.

EXECUTIVE SUMMARY

Identifying good investments is complex for environmental agencies as several prioritization strategies may be used and significant uncertainty often surrounds their costs, benefits, and available budgets. In this paper I developed a model for robust portfolio selection based on preference programming developed to support cost-effective environmental investment decisions under uncertainty and applied it to the South Australian Murray-Darling Basin. Benefits and costs of 46 investment alternatives (or *targets*) for managing natural capital and ecosystem services were quantified and the associated uncertainty estimated. Thirty-six non-dominated investment portfolios were selected using mathematical programming under four investment prioritisation strategies (cost-effectiveness (*E-max*), cost-effectiveness including core costs (*E-max**), cost-only (*C-rank*), and benefit-only (*B-rank*)), three decision rules (pessimistic, most likely, and optimistic), and three budget scenarios (minimum, most likely, maximum).

Compared to the optimally performing investment strategy E-max, E-max* and C-rank only slightly reduced portfolio performance and altered portfolio composition. However, the B-rank strategy reduced performance by half and radically changed composition. Uncertainty in costs, benefits, and available budgets also strongly influenced portfolio performance and composition. I conclude that in this case study the consideration of uncertainty was at least as important as investment strategy selection in effective environmental decision-making. Targets whose selection was less sensitive to investment strategy and uncertainty were identified as more robust investments. The results have informed the allocation of $69M in the study area and the techniques are readily adaptable to similar conservation and environmental investment decisions in other jurisdictions at a variety of scales.

1. INTRODUCTION

A perennial problem facing environmental agencies is how to allocate a limited budget across many worthy conservation, management, and restoration projects for enhancing natural capital and ecosystem services (Prato 2007; Wilson et al. 2007; Hajkowicz et al. 2009a). Systematically considering the costs and multiple benefits of investment options and the interactions between options makes efficient resource allocation a complex problem (Ehrgott et al. 2004; Phillips and Bana e Costa 2007). Compounding this complexity is the significant uncertainty that often surrounds estimates of the costs and benefits of environmental resource allocation (Messina and Bossetti 2003; Lesiö et al. 2007, 2008). Due in part to this complexity, environmental agencies have rarely considered both costs and benefits in setting investment priorities (Hughey et al. 2003; Ferraro 2003; Polasky 2008). Instead, investment has been directed towards projects with greatest benefit, or lowest cost, or some other *ad hoc* objective (Ferraro 2003; Newburn et al. 2005; Phillips and Bana e Costa 2007). Overall, these investment strategies usually do not result in the most effective use of environmental funds (Babcock et al. 1997; Wu et al. 2000; Bryan et al. 2008). Hence, the need for agencies to prioritise the investment of scarce resources, satisfy due diligence requirements, and maximise the effectiveness of conservation funds is widely recognised (Ferraro 2003; Polasky 2008; Hajkowicz 2009a; Wilson et al. 2009). In this paper, a model for supporting cost-effective investment decisions for managing natural capital and ecosystem services in the face of uncertainty is developed and applied in a regional context in Australia.

Similar capital budgeting investment problems are routinely faced in management economics and finance and where finite resources need to be allocated across a range of investment alternatives with the goal of maximising benefits (Steuer and Na 2003; Bana e Costa et al. 2006; Ho et al. 2007; Huang 2008). Phillips and Bana e Costa (2007) divided the investment prioritisation and selection problem into two elements – option appraisal and portfolio selection. Option appraisal involves calculating the costs and benefits, and prioritising options. Costs are typically measured in monetary terms. Whilst benefits may also be measured in monetary terms, they may also be measured in terms of multiple non-monetary criteria or *utility* (Steuer et al. 2007). Economic tools such as cost-benefit analysis, cost-effectiveness analysis, and cost-utility analysis may then be used to prioritise investment alternatives (Hughey et al. 2003; Cullen et al. 2005). Portfolio selection then involves allocating resources to those alternatives that offer the highest return on investment (Ferraro 2003; Murdoch et al. 2007; Phillips and Bana e Costa 2007). A range of operations research techniques have been used to identify efficient investment portfolios subject to budgetary and other constraints (Steuer and Na 2003).

Portfolio selection integrating both costs and benefits has been used to identify cost-effective spatial priorities for investment in biodiversity conservation (Ando et al. 1998; Balmford et al. 2000; Drechsler and Watzold 2001; Naidoo et al. 2006; Wilson et al. 2006; Bottrill et al. 2008; Polasky et al. 2008; Underwood et al. 2009; Wilson et al. 2009), restoration (Macmillan et al. 1998; Bailey et al. 2006; Crossman and Bryan 2006; Bryan and Crossman 2008), and the enhancement of natural capital and ecosystem services (Crossman and Bryan 2009; Nelson et al. 2009). Portfolio selection has also been widely used to prioritise alternative management actions in conservation (Wilson et al. 2007), water quality management (Alam et al. 2008; Hajkowicz et al. 2008; Bryan and Kandulu In Press), natural resource management (Hajkowicz 2007, 2009b; Bryan et al. 2008; Marinoni et al. 2009), and enhancing ecosystem services (Prato 2007). These studies have shown that the use of investment strategies which consider both costs and benefits may lead to substantially greater environmental benefits from limited budgets. However, few studies have considered the influence of uncertainty in decision parameters such as cost, benefit, and budget on the efficiency and composition of conservation investments or provided a means for environmental agencies to select investment portfolios robust to this uncertainty.

Several techniques have been proposed for portfolio selection and resource allocation under uncertainty including fuzzy simulation (Huang 2008), info-gap theory (McCarthy and

Lindenmayer 2007; McDonald-Madden et al. 2008), Bayesian inference (Prato 2007), contingent portfolio programming (Gustafsson and Salo 2005), multi-criteria and other techniques (see Kleinmuntz 2007). Preference programming (Salo and Hämäläinen 1992) has also been used to enable the robust selection of portfolios despite incomplete information about costs and benefits of investments (Lesiö et al. 2007, 2008). The dominance concepts and decision rules of preference programming provide a transparent basis for making investment decisions under uncertainty (Salo and Hämäläinen 2004) that are more likely to be adopted by decision-makers (Kleinmuntz 2007). Preference programming has been used to inform investment in research and development projects (see Lesiö et al. 2008) and offers significant potential in guiding investment in enhancing natural capital and ecosystem services under alternative investment strategies and given the inherent uncertainty in decision parameters.

In this study, a model for guiding efficient and robust investment decisions for managing natural capital and ecosystem services is developed and applied in the South Australian Murray-Darling Basin (SAMDB) region. A total of 46 conservation and environmental management targets are identified as potential investment alternatives. The benefit of achieving targets for natural capital and ecosystem services is quantified using Multi-Criteria Analysis and uncertainty estimated using Monte Carlo simulation. Costs of targets were also quantified and the uncertainty estimated. Four investment strategies are considered including prioritising by cost-effectiveness (*E-max*), prioritising by cost-effectiveness including core costs (*E-max**), prioritising by cost-only (*C-rank*), and prioritising by benefit-only (*B-rank*). Preference programming techniques are then used to assess the efficiency and composition of non-dominated portfolios selected under uncertainty. Three decision rules (pessimistic, most likely, optimistic) and three budget scenarios (minimum, most likely, maximum) were used to assess the impact of uncertainty in cost and benefit of targets, and in budgets, respectively. Non-dominated portfolios are selected under 36 combinations of investment strategy, decision rule, and budget scenario. The more robust investments are those selected for investment in more non-dominated portfolios given the uncertainty in the investment problem. The use of the results to inform conservation investment by the SAMDB Natural Resource Management Board and the adaption to other jurisdictions at a variety of scales is discussed.

2. A ROBUST PORTFOLIO SELECTION MODEL

2.1. Investment Strategies

The principle of prioritising investment based on value for money is "deceptively simple, uncontroversial, yet seldom used in organisations" (Phillips and Bana e Costa 2007). Value for money or *cost-effectiveness* can be calculated using a benefit-cost ratio B_k/C_k where B_k is the benefit and C_k is the cost of investment alternative k. Efficient portfolios may be selected simply by ranking investments in descending order and resources allocated until the budget is exhausted (Sinden 2003) – an investment strategy called *E-max* (Ferraro 2003).

Often, the E-max portfolio selection strategy is formulated as a mathematical programming problem to enable the inclusion of more complex constraints on investment. A variant on the maximal covering formulation (Church and ReVelle 1974) is used in this study which considers the level of investment in each target as a continuous variable r_k. To select an efficient E-max portfolio based on both costs and benefits we:

$$\text{maximise } \sum_{k=1}^{K} \frac{r_k}{C_k} B_k \,, \tag{1}$$

subject to:

$$0 \le r_k \le C_k \text{ for } k = 1, 2, \ldots, K, \text{ and;} \tag{2}$$

$$\sum_{k=1}^{K} r_k = R_T \,, \tag{3}$$

where C_k is the cost of achieving target k and R_T is the total budget available.

Typically, there are two features of the benefit of achieving conservation and environmental management targets. Firstly, the measure of benefit B_k is commonly comprised of multiple criteria i (in this case - natural capital assets and ecosystem services). Benefits of achieving targets for natural capital assets and ecosystem services can be combined into a single measure of utility using a multi-attribute utility function (Keeney and Raiffa 1976). Thus, the overall benefit b_k of achieving target k for natural capital and ecosystem services can be calculated as the product of the impact Q_{ik} of achieving the target on asset/service i and the management priority of the asset/service, summed over all assets/services D':

$$b_k = \sum_{i=1}^{D'} Q_{ik} M_i \tag{4}$$

Secondly, targets may be partially achieved without any agency investment. For example, consider a target that involves the restoration of 1,000 ha of native habitat. Even if no funds are allocated by the agency, some of this may occur, say 200 ha, through the actions of external agents such as private landholders or other agencies. In this model, a factor T_k is introduced representing the *background level of target achievement* to effectively reduce the real benefit achieved through agency investment B_k such that:

$$B_k = (1 - T_k) b_k \,, \tag{5}$$

Prioritising investment by benefit-only (or *B-rank*) is commonly employed by environmental agencies (Wu et al. 2000; Sinden 2003). This strategy involves ranking alternatives from highest to lowest benefit and allocating resources until the budget is exhausted (Ferraro 2003; Newburn et al. 2005). To select a B-rank portfolio we:

$$\text{maximise } \sum_{k=1}^{K} r_k B_k \,, \tag{6}$$

subject to (2) and (3).

Similarly, environmental agencies also commonly prioritise investment in alternatives based on cost-only (or *C-rank*). This strategy involves ranking investments from lowest to highest cost and allocating resources until the budget is exhausted (Ferraro 2003; Sinden 2003). To select a C-rank portfolio we:

maximise $\sum_{k=1}^{K} \frac{r_k}{C_k}$, (7)

subject to (2) and (3).

In addition, the environmental investment problem is often characterised by constraints on resource allocation (Lesiö et al. 2008). In this study, we also consider the effect of statutory costs committed to achieving specific targets. Based on Equation 5, we can include these *core costs* in a constrained E-max (termed *E-max**) investment strategy using Equation 1 and replacing Equation 2 with:

$$C_k^* \le r_k \le C_k \text{ for } k = 1, 2, ..., K \ , \quad (8)$$

where C_k^* is the core cost committed to target k.

2.2. Robust Portfolio Selection

Environmental investment is plagued by uncertainty and variability (or *incomplete information* (Lesiö et al. 2007)) in key parameters including the costs C_k and benefits b_k of achieving targets, the background level of target achievement T_k, and the available budget R_T. Estimates of the feasible distribution of these parameters is termed the *information set*. Incomplete information is represented here by the most likely (denoted ^{ml}), minimum (denoted ^{min}), and maximum (denoted ^{max}) values. Using preference programming techniques (Salo and Hämäläinen 2004), incomplete information on costs, benefits, and background target achievement can be incorporated into portfolio selection using three decision rules – optimistic, most likely, and pessimistic. Decision rules enable the selection of non-dominated portfolios based on optimistic ($C_k^{\min}$, $b_k^{\max}$, and $T_k^{\min}$), most likely (C_k^{ml}, b_k^{ml}, T_k^{ml}), and pessimistic ($C_k^{\max}$, $b_k^{\min}$, and $T_k^{\max}$) parameter estimates, respectively, under the four investment strategies: E-max (Equation 1); E-max* (Equations 1, 5); C-rank (Equation 8), and; B-rank (Equation 7).

Non-dominated portfolios are those that perform as well as or better than all others. A non-dominated Pareto front of optimal portfolios may be identified under the three decision rules and four investment strategies. By setting cut-offs at the minimum ($R_T^{\min}$), most likely (R_T^{ml}), and maximum ($R_T^{\max}$) budget estimates, a set Ρ of 36 non-dominated portfolios *p* (4 investment strategies x 3 decision rules x 3 budgets) can be selected.

Robust portfolio modelling helps quantify the robustness of investment in individual targets through a core index defined as the share of non-dominated portfolios that include the target (Lesiö et al. 2007, 2008). In this study, the core index is calculated for each target as the mean level of investment allocated in non-dominated portfolios. Core index may be calculated within each investment strategy *s* for all *s* in *S*{E-max, E-max*, C-rank, B-rank}:

$$CI_{s,k} = \left(100 \sum_{p \in \mathrm{P}_s} \frac{r_{s,k}}{C_k} \right) / \left| \mathrm{P}_s \right| \quad (9)$$

where $r_{s,k}$ is the investment in target *k* identified in the $|\mathrm{P}_s|$ non-dominated portfolios selected under investment strategy *s* (note $|\mathrm{P}_s| = 9$, 3 decision rules x 3 budgets). A core index may also be calculated across all |Ρ| non-dominated portfolios (adapted from Lesiö et al. 2007):

$$CI_k = \left(100 \sum_{p \in \mathrm{P}} \frac{r_k}{C_k} \right) / \left| \mathrm{P} \right| \quad (10)$$

where $|P| = 36$.

Core, borderline, external targets can then be identified based on the core index (Lesiö et al. 2007, 2008). Core targets are those where $CI_k = 100$ and can be recommended with certainty as they are always selected for full investment on non-dominated portfolios under all combinations of cost, benefit, background target achievement, or budget across the information set. External targets are those where $CI_k = 0$ and can be rejected with certainty as they are never selected in any non-dominated portfolio. Borderline targets are those where $0 < CI_k < 100$. The higher the core index for borderline targets the more robust an investment they represent given uncertainty.

3. STUDY AREA

The South Australian Murray-Darling Basin is an area of around 56,000 km^2 (Figure 1) characterised by mostly flat topography apart from the hilly eastern Mt. Lofty Ranges and Mediterranean to semi-arid climate. High value ecological assets include the River Murray, lower lakes, Coorong estuary, and some 30,748 km^2 (55%) of remnant native woodland and shrubland habitat. Dryland and irrigated agriculture are common land uses in the region. Agricultural land management has increased soil erosion, dryland and river salinity, and caused declines in biodiversity. Reduced environmental flows over the past decade have further degraded riparian ecosystems.

The SAMDB NRM Board is the community-based regional agency responsible for public investment in environmental management in the region. Four geographically-based NRM Groups (Rangelands, Ranges to River, Mallee and Coorong, Riverlands) advise the Board. Board and group members come from diverse backgrounds including primary production, soil conservation, local government, pest animal and plant control, salinity management, indigenous issues, ecology, and water resource management (SAMDB NRM Board, 2009a).

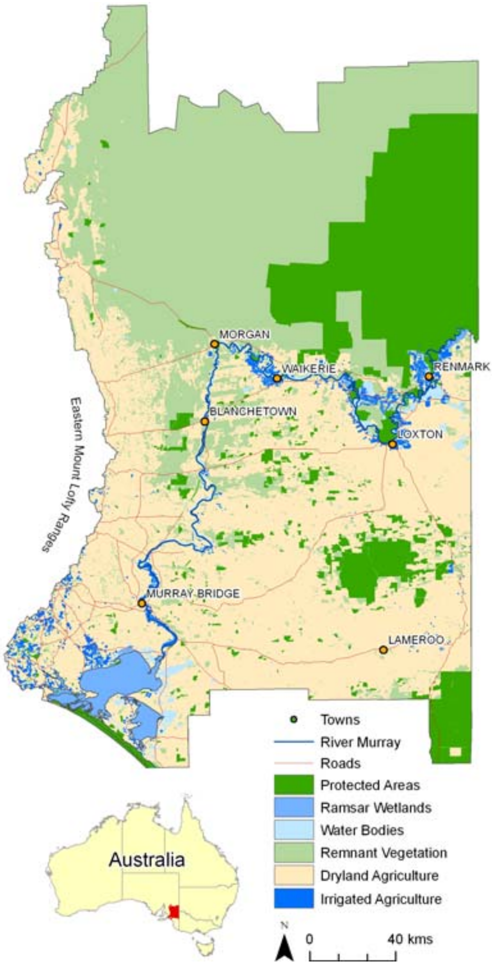


Figure 1 – Location and broad land use in the South Australian Murray-Darling Basin study area.

4. METHODS

4.1. Regional Priorities for Managing Natural Capital and Ecosystem Services

A natural capital and ecosystem services framework was used to provide structure for quantifying regional environmental management priorities in the study area. The Board defined the suite of natural capital assets as Land, Water, Biota, Atmosphere, and People. For ecosystem services, the Millennium Ecosystem Assessment framework (MEA 2005) was used as a basis for this study. The assets and services framework was modified, including the addition of built and social capital assets, based on 56 qualitative ethnographic interviews with decision-makers described elsewhere (Cast et al. 2008, Raymond et al. 2009, Table 1).

Capital Assets
Natural Capital
(NC1) Water
(NC2) Land
(NC3) Biota
(NC4) Atmosphere
Built Capital
(BC1) Built Environs and Infrastructure
(BC2) Zoning and Planning
(BC3) Economic Viability and Employment
Social Capital
(SC1) Family
(SC2) Community
Ecosystem Services
Provisioning Services
(P1) Food and Fibre
(P2) Biochemical Resources
(P3) Fresh Water
(P4) Geological Resources
(P5) Energy
Regulating Services
(R1) Air Quality
(R2) Climate
(R3) Water Quantity
(R4) Erosion
(R5) Water Quality
(R6) Disease, Pests, and Natural Hazards
(R7) Pollination
Cultural Services
(C1) Cultural Diversity and Heritage
(C2) Spiritual, Sense of Place, and Lifestyle
(C3) Knowledge and Education
(C4) Aesthetics and Inspiration
(C5) Social Relations
(C6) Recreation and Tourism
(C7) Bequest, Intrinsic, and Existence
Supporting Services
(S1) Soil Formation
(S2) Photosynthesis and Plant Primary Production
(S3) Nutrient Cycling
(S4) Water Cycling

Table 1 – Natural capital and ecosystem services assessed in this study.

Five MCDA workshops were held with the Board and each of the four regional advisory groups to quantify the management priority of capital assets and ecosystem services based on the framework above (Table 1). The Analytical Hierarchy Process (AHP; Saaty 1980) and the SMART – the Simple Multi-Attribute Rating Technique technique (von Winterfeldt and Edwards 1986) were used to derive weights representing the management priority of capital assets and ecosystem services. A total of 43 decision-makers attended the workshops. Each participant submitted their own set of management priorities with 40 valid individual responses returned. Bryan et al. (In Review) described the distribution of management priorities for natural capital and ecosystem services in the study area.

4.2. Identifying Investment Alternatives and Quantifying Impacts

A total of 46 management action targets (or simply *targets*) have been specified (Appendix 1) within a 5 year planning horizon to 2014. Targets are grouped under five natural capital assets - Atmosphere, Biota, Land, Water and People and were developed by specialist asset-based program groups. The impact of targets on natural capital and ecosystem services were quantified in an additional five MCDA workshops with asset-based program groups attended by 49 participants. Impact scores were elicited using a variant of SMART (von Winterfeldt and Edwards 1986). At each workshop, the program group was asked to arrive at a consensus score for the relative impact of achieving each target on the nine capital assets and 23 ecosystem services (Table 1). Impact was scored on a scale of -10 to +10 where -10 represented the strongest negative impact, 0 represented no impact, and +10 was the strongest positive impact (Appendix 2). Participants were also asked about the uncertainty surrounding the impact scores.

4.3. Simulating Benefits

The benefit b_k of achieving each target k was calculated as the sum over all natural capital assets and ecosystem services D' of the product of the impact Q_{ik} of achieving the target on each asset/service i and management priority M_i of the asset/service (Equation 4). Both impact Q_{ik} and management priority M_i are random variables sampled from probability density functions (PDFs). Triangular PDFs of the impact of each action on each asset/service were specified based on results of the MCDA-derived impact scores (Section 4.2). Gaussian management priority PDFs for each asset/service were specified based on centred log transformed MCDA-derived weights. Benefit b_k was calculated as a random variable with a PDF obtained through 10,000 Monte Carlo simulations of Equation 4 with each simulation using values for the random variables of impact Q_{ik} and management priority M_i derived from the PDFs. The minimum $b_k^{\min}$, most likely b_k^{ml}, and maximum $b_k^{\max}$ benefit values were the 5$^{\mathrm{th}}$ percentile, mean, and 95$^{\mathrm{th}}$ percentile from the normally distributed benefit PDF simulated for each target k. Appendix 3 details the derivation of benefit values.

4.4. Quantifying Benefits and Costs

The SAMDB NRM Board identified a total of 248 on-ground management actions to achieve the 46 targets over the 5 year time horizon to 2014. The minimum $C_k^{\min}$, most likely C_k^{ml}, and maximum $C_k^{\max}$, and core costs R_k^* of each target k over the 5 year time horizon were estimated by the Board finance manager. In addition, minimum $T_k^{\min}$, most likely T_k^{ml}, and maximum $T_k^{\max}$ level of background target achievement were estimated by the relevant asset-based program leaders. Three budget scenarios were defined by the finance manager to reflect minimum ($R_T^{\min}$ =$37.5M), most likely ($R_T^{\mathrm{ml}}$ = $62.5M), and maximum ($R_T^{\max}$ = $87.5M) forward estimates over the 5 year time horizon.

4.5. Robust Portfolio Selection

The robust portfolio selection models developed in Section 2 were used to inform investment decisions in the study area. The cost-effectiveness of each target for enhancing natural capital and ecosystem services was calculated (Section 2.1) given uncertainty in benefits and costs. Pareto optimal frontiers of non-dominated portfolios were calculated for each decision rule under each investment strategy. A total of 36 non-dominated investment portfolios were then selected (four investment strategies x three decision rules x three budget scenarios) using linear programming and the performance and composition of each portfolio was evaluated. The robustness of targets was then assessed under each investment strategy and over all investment strategies.

5. RESULTS

5.1. Cost-effectiveness

Costs and benefits of targets are detailed in Appendix 4. Cost-effectiveness varied significantly between targets (Figure 2). The mean cost-effectiveness of targets was 1.04 ($\sigma = 1.25$) under the pessimistic decision rule, 2.45 ($\sigma = 2.98$) under the most likely, and 6.56 ($\sigma = 8.68$) under the optimistic decision rule. The cost-effectiveness of individual targets was also heavily influenced by uncertainty in parameter values as reflected by the mean difference in cost-effectiveness between the pessimistic and optimistic decision rules (5.53) being more than twice the mean cost-effectiveness of targets under the most likely decision rule (2.45).

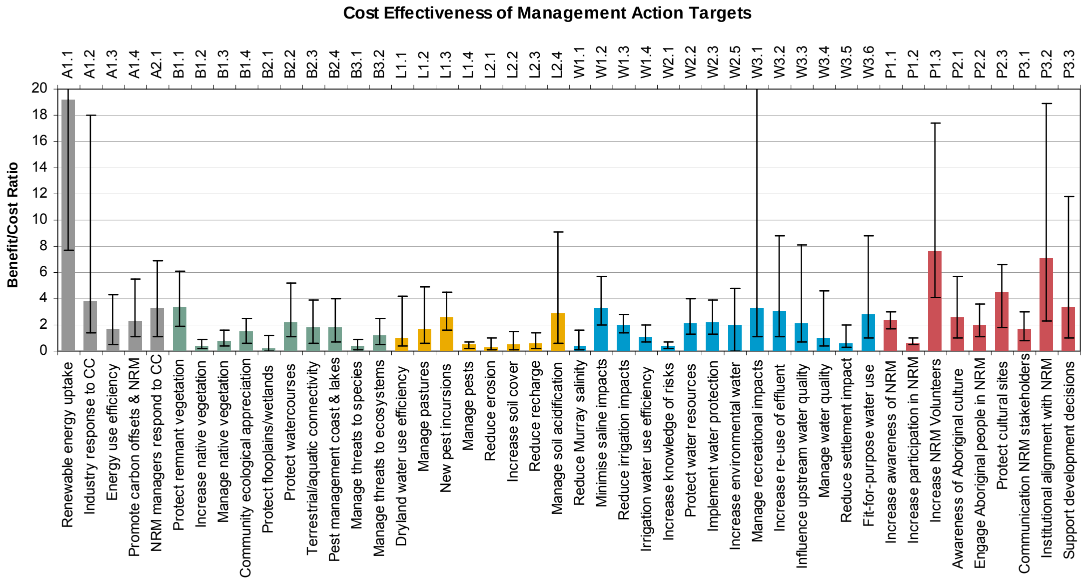


Figure 2 – Cost-effectiveness of targets for enhancing natural capital and ecosystem services under uncertainty. The coloured bar represents cost-effectiveness calculated under the most likely decision rule whilst the error bars represent cost-effectiveness calculated under the pessimistic (low bar) and optimistic (high bar) decision rules. Note that the letter in the target ID (top x-axis) refers to the relevant natural capital asset addressed by the target (A = Atmosphere, B = Biota, L = Land, W = Water, and P = People).

5.2. Robust Portfolio Selection under Uncertainty

The shape of the Pareto fronts differ under the four investment scenarios and three decision rules (Figure 3). Pareto-optimal portfolios under the E-max strategy represent the maximum total benefit for natural capital and ecosystem services (or *performance*) for a given budget. The convex shape E-max Pareto front also suggests that much of the benefit can be achieved at low cost with diminishing marginal returns from additional expenditure. Under the E-max* strategy, the inclusion of core costs causes a small dip at the beginning of the Pareto front. The C-rank strategy front also returned slightly less benefit than E-max. However, the B-rank strategy is significantly different in shape and substantially less efficient than E-max. Substantial variation also exists in the benefits achieved under the three decision rules within each investment strategy (Figure 3).

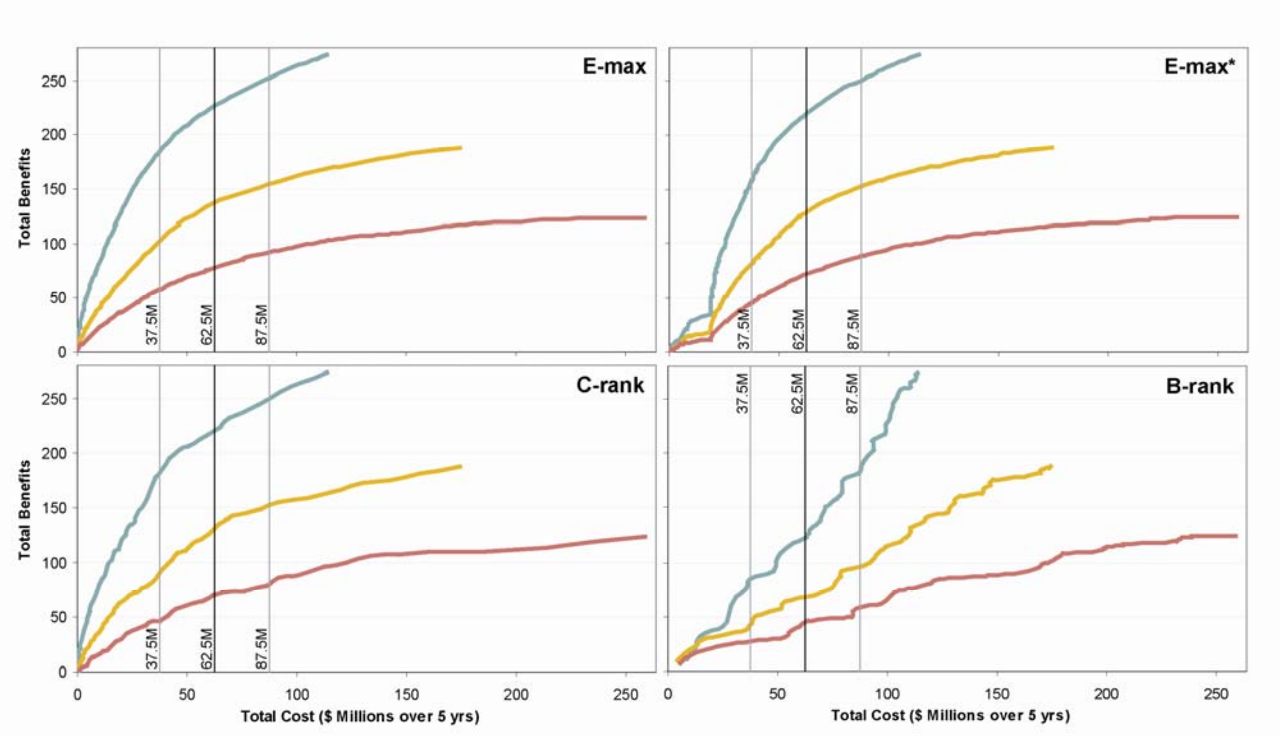


Figure 3 – Pareto fronts of non-dominated portfolios of targets under optimistic (green), most likely (yellow), and pessimistic (red) decision rules for each of the four investment strategies (E-max, E-max*, C-rank, and B-rank).

The performance of portfolios varied substantially with investment strategy, decision rule, and budget scenario (Table 2). Investment strategy, particularly B-rank, had a strong influence on portfolio performance (Table 2, Figure 3). To illustrate, under the most likely decision rule and the most likely budget, benefits achieved under both the E-max* (128.96 (94.12%)) and C-rank (131.16 (95.72%)) strategies were slightly less than the E-max strategy (137.02). However, less than half the benefits of E-max were returned under the B-rank strategy (67.71 (49.42%)) (Table 2).

Uncertainty in cost and benefit parameters had a very strong effect on the performance of portfolios (Table 2). To illustrate, under the most likely budget scenario ($62.5M), the benefit of portfolios selected under the optimistic decision rule ranges between 165.39% (E-max) and 180.96% (B-rank) of the benefit achieved under the most likely decision rule whilst under the pessimistic decision rule benefit ranges between 53.91% (C-rank) and 64.38% (B-rank) of that achieved under the most likely decision rule.

Uncertainty in available budget also had a strong influence on the performance of portfolios (Table 2). To illustrate, under the most likely decision rule, the total benefit of portfolios selected under the maximum budget scenario ranges between 112.79% (E-max) and 142.64% (B-rank) of the benefit achieved under the most likely budget scenario whilst under the minimum budget scenario, benefit ranges between 63.33% (B-rank) and 74.74% (E-max) of that achieved under the most likely budget scenario.

Budget Scenario	Decision Rule	Investment Strategy			
		E-max	E-max*	C-rank	B-rank
Minimum ($37.5M)	Optimistic	185.24	157.41	181.51	84.26
	Most Likely	102.41	81.98	89.55	42.88
	Pessimistic	57.66	45.79	46.86	27.2
Most Likely ($62.5M)	Optimistic	226.62	219.59	220.85	122.53
	Most Likely	137.02	128.96	131.16	67.71
	Pessimistic	77.78	71.86	70.71	43.59
Maximum ($87.5M)	Optimistic	252.52	250.75	250.2	183.9
	Most Likely	154.55	152.39	151.68	96.58
	Pessimistic	91.98	88.58	80.12	58.41

Table 2 – Performance of the four investment strategies under three decision rules and three budget scenarios measured in terms of benefit for natural capital and ecosystem services.

Table 3 illustrates the actual portfolios selected under each investment strategy, decision rule, and budget scenario. Increasing the budget simply has the effect of adding more targets to the portfolio. Alternative investment strategies (E-max, E-max*, and C-Rank) and decision rules have a significant impact on the composition of portfolios. However, the adoption of the B-rank investment strategy has a radical impact on the composition of portfolios (Table 3).

Over all 36 optimal portfolios, all targets were classified as borderline investments (Table 3). Targets with a high (≥80%) overall core index including L1.3 (95%), W1.2 (92%), B2.2 (88%), W2.2 (87%), B1.1 (83%), W2.3 (83%), P1.3 (83%), and W1.3 (80%) tended to have low cost and background level of target achievement, high benefit, and low levels of uncertainty in these parameters (Appendix 4). Conversely, targets with the lowest (≤20%) core index including B3.1 (8%), W2.1 (11%), L2.1 (12%), B2.1 (18%), and L2.2 (18%) tended to have high cost and background levels of target achievement, low benefit, and high levels of uncertainty in these parameters (Appendix 4). Targets with low benefit but very low cost (e.g. most Atmosphere and People targets) tended to be selected under all strategies except B-rank (Table 3; Appendix 4) whilst targets with high benefit and high cost (e.g. B1.2, P1.2) tended to be selected under B-rank only.

Target	E-max Core Index	E-max* Core Index	C-Rank Core Index	B-Rank Core Index	Overall Core Index
A1.1	100 C	100 C	100 C	0 E	75 B
A1.2	100 C	100 C	100 C	0 E	75 B
A1.3	67 B	56 B	100 C	0 E	56 B
A1.4	100 C	89 B	100 C	0 E	72 B
A2.1	100 C	89 B	100 C	0 E	72 B
B1.1	100 C	100 C	100 C	33 B	83 B
B1.2	0 E	0 E	0 E	93 B	23 B
B1.3	33 B	33 B	16 B	33 B	29 B
B1.4	60 B	63 B	80 B	0 E	50 B
B2.1	14 B	21 B	5 B	33 B	18 B
B2.2	100 C	87 B	78 B	87 B	88 B
B2.3	67 B	56 B	89 B	11 B	56 B
B2.4	78 B	77 B	100 C	0 E	64 B
B3.1	10 B	0 E	11 B	11 B	8 B
B3.2	56 B	36 B	51 B	11 B	38 B
L1.1	44 B	44 B	78 B	0 E	42 B
L1.2	67 B	65 B	89 B	11 B	58 B
L1.3	100 C	100 C	79 B	100 C	95 B
L1.4	0 E	60 B	0 E	52 B	28 B
L2.1	11 B	13 B	22 B	0 E	12 B
L2.2	22 B	13 B	17 B	20 B	18 B
L2.3	29 B	11 B	33 B	11 B	21 B
L2.4	88 B	78 B	89 B	11 B	66 B
W1.1	22 B	18 B	100 B	0 E	35 B
W1.2	100 C	100 C	100 C	67 B	92 B
W1.3	100 C	80 B	42 B	100 C	80 B
W1.4	67 B	48 B	33 B	100 C	62 B
W2.1	0 E	12 B	33 B	0 E	11 B
W2.2	100 C	93 B	100 C	54 B	87 B
W2.3	100 C	83 B	78 B	73 B	83 B
W2.5	66 B	56 B	67 B	67 B	64 B
W3.1	97 B	89 B	100 C	0 E	71 B
W3.2	89 B	90 B	100 C	0 E	70 B
W3.3	89 B	67 B	100 C	0 E	64 B
W3.4	55 B	48 B	67 B	11 B	45 B
W3.5	22 B	24 B	67 B	0 E	28 B
W3.6	89 B	89 B	100 C	0 E	70 B
P1.1	100 C	96 B	100 C	0 E	74 B
P1.2	33 B	19 B	11 B	76 B	35 B
P1.3	100 C	100 C	100 C	33 B	83 B
P2.1	89 B	89 B	100 C	0 E	69 B
P2.2	100 C	67 B	100 C	4 B	68 B
P2.3	100 C	100 C	100 C	0 E	75 B
P3.1	78 B	67 B	100 C	0 E	61 B
P3.2	100 C	100 C	100 C	0 E	75 B
P3.3	89 B	89 B	100 C	0 E	69 B

Table 3 – Portfolios selected under the four investment strategies, three decision rules, and three budgets. Included is the core index (%) and investment classification (core (C), borderline (B), and external (E)).

6. DISCUSSION

6.1. Supporting environmental investment decision making

In this study, the value for money principle is implemented by prioritising investment based on cost-effectiveness (the E-max investment strategy). Inclusion of core costs in the constrained E-max* and achieved only slightly lower performance than the maximally efficient E-max strategy as they comprised only a small proportion of the total budget. Larger reductions in portfolio performance and changes in composition may be expected when larger proportions of the budget are committed to investments not positively correlated with cost-effectiveness.

Consideration of cost-only (C-rank) caused a minor reduction in portfolio performance whilst the benefit-only (B-rank) investment strategy reduced performance by roughly half compared to E-max and the portfolio composition was radically different. These results suggest that decision makers in the study area may ignore the benefits of investment alternatives without a major impact on portfolio performance but should ignore costs at their peril. The strong influence on portfolio performance of considering benefits-only is likely a product of the greater relative uncertainty in the costs of targets compared to benefits (Babcock et al. 1997; Ferraro 2003; Appendix 4). This has been echoed by recent studies which have found that greater variation in costs rather than benefits is likely to be the rule rather than the exception in many environmental management and conservation investment problems (Bode et al. 2008). However, it is far more common for studies to focus on assembling information on the benefits of conservation and environmental management alternatives rather than the costs (e.g. Bryan et al. In Review, this study). This imbalance needs to be addressed and calls for more effort in the assembly of cost data have been made (Polasky 2008).

Uncertainty in costs and benefits was the major influence on the composition and performance of portfolios. The cost-effectiveness of individual targets in this study varied substantially due to uncertainty in parameter values. This makes the systematic consideration of costs and benefits by decision-makers extremely complex and forms a barrier to efficient environmental investment decision making. To illustrate this point, the benefits achieved by portfolios selected under the optimistic decision rule were, on average, 211% higher than achieved under the pessimistic rule. Budget uncertainty also strongly contributed to variation in portfolio performance and benefits achieved under the maximum budget scenario were 77% higher than achieved under the minimum budget. These results suggest that considering uncertainty in selecting efficient portfolios is at least as important in environmental investment decisions as is the prioritisation of investments through a cost-effective investment strategy.

Robust portfolio selection using preference programming provides a practical way of evaluating investments given the pervasive influence of uncertainty. The calculation of a core index based on the concepts of dominance provides a simple and transparent metric by which to evaluate more robust investment alternatives. The overall core index calculated over all 36 portfolios covers a diverse set of investment strategies, decision rules, and budget scenarios. To reduce complexity in making investment decisions, a more pragmatic approach for an environmental agency is to adopt a single investment strategy (ideally E-max) and to refine the selection of a robust portfolio based on this strategy. For example, under the E-max investment strategy we can identify several core targets selected for investment under any combination of decision rule and budget scenario (A1.1, A1.2, A1.4, A2.1, B1.1, B2.2, L1.3, W1.2, W1.3, W2.2, W2.3, P1.1, P1.3, P2.2, P2.3, and P3.2). We can also identify external targets that are not funded under any portfolio (B1.2, L1.4, W2.1) with all other targets being borderline investments and prioritisable on core index (Table 3).

This study was undertaken in collaboration with the SAMDB NRM Board and in parallel with the development of the regional natural resource management plan (SAMDB NRM Board 2009b). The results of this study have informed the strategic investment of $69M in achieving Atmosphere, Biota, Land, Water, and People targets (Appendix 1) over 3 years to 2012 (SAMDB NRM Board 2009c). The techniques are directly transferable to other environmental investment problems where uncertainty in costs and benefits are the norm rather than the exception and transparency is important in decision support. The methods can be applied at a variety of scales including national (e.g. Caring for Our Country program in Australia, Conservation Reserve Program in US), regional (e.g. this study, Somanathan et al. 2009), and local (Hajkowicz et al. 2008; Connor et al. 2008) scales.

6.2. Advantages, Limitations, and Further Research

Although several techniques have been developed for selecting efficient portfolios under uncertainty, robust portfolio selection in this study provides a transparent picture of how investment strategies and decision parameter uncertainty affects both the performance and composition of investment portfolios. Three advantages of this approach have been found in practice. First, once costs and benefit information has been obtained the method of portfolio selection presented in this study can be implemented in a spreadsheet. Hence, robust portfolio selection can be done in-house by environmental agencies without the burdensome overhead of implementing complex algorithms (Kleinmuntz 2007). Second, transparency is important in building trust in the modelling process, acceptance of the results amongst stakeholders (Hajkowicz et al. 2009), and use of the results by decision makers (Kleinmuntz 2007). Third, embracing uncertainty and analysing its effects may also help build confidence and trust in the model amongst decision makers as they have not been forced to arrive at a single complete parameter specification when they know these values are inherently uncertain (Kleinmuntz 2007).

There are two main limitations to the robust portfolio selection techniques presented. The first limitation is associated with the combinatorial nature of the analysis. Each extra element of uncertainty (e.g. model parameters (investment strategies, decision rules, budget scenarios) and states (minimum, most likely, maximum)) included has a multiplicative effect on the resulting number of portfolios assessed. For clarity of and effectiveness of communication to decision makers the number of combinations need to be restricted to the minimum required by decision-makers to adequately cover decision uncertainty. The second limitation relates to the nature of decision making under uncertainty. Using just three decision rules restricts the assessment to these points and does not cater for the continuous scale of preferences of decision makers. Decision makers usually occur somewhere between absolute pessimism and absolute optimism. One way to address this limitation is to add an interactive stage to portfolio selection where decision makers use the Hurwicz principle to tailor the decision rule to suit their individual levels of pessimism/optimism (Lang and Merino 1993). Selecting efficient portfolios based on user-specified decision rules can further increase acceptance and use of decision model recommendations.

A number of areas can be identified for further advancement of this work. In this study, uncertainty in costs and benefits were considered for each target. In reality, there would be some correlation in these parameters between individual targets, in particular, targets that address the same asset. For example, the cost of targets involving ecological management and restoration and water quality management may all increase together following an increase in the market price of fencing materials. Similarly, the benefits of targets involving water ecosystem management may all decrease together following a sharp decrease in river inflows due to prolonged drought or climate change. Modern Portfolio Theory (Markowitz 1952) enables the selection of portfolios that maximise returns under variable risk profiles where risk also considers covariance between targets. Extending the model presented in this study to consider correlated variance in costs and benefits of targets can enhance portfolio diversification over a range of assets and mitigate risky portfolios.

7. CONCLUSION

Environmental investment decisions are plagued by a lack of a clearly articulated investment strategy, and by significant uncertainty in investment decision parameters such as the costs and benefits of investment alternatives and available budgets. This study quantified the impact of investment strategies and uncertainty on the performance and composition of portfolios of conservation and environmental management alternatives for enhancing natural capital and ecosystem services. In this study, not including the costs of investment alternatives reduced the benefit achieved by portfolios by half and radically changed the portfolio composition compared to the most cost-effective investment strategy. Uncertainty around costs, benefits, and budgets also had a very strong effect on portfolio performance and composition. Hence, it is at least as important to consider uncertainty in investment decision parameters as it is to adopt the value for money principle as an efficient investment strategy in environmental investment. Robust portfolio selection based on preference programming concepts provides a transparent means for guiding investment in those targets that are selected more often in non-dominated portfolios across the information set. These investments are good investments despite the investment strategy used and the inherent uncertainty. The techniques presented here provide a pragmatic and transparent approach to supporting conservation and environmental management decisions for enhancing natural capital and ecosystem services. As such, the resulting decision recommendations are more likely to be trusted, accepted and adopted by decision makers. The results have already informed the strategic investment of more than $69M over three years in the South Australian Murray-Darling Basin region and are directly transferable for addressing environmental investment decisions in other jurisdictions from a local to national scale.

8. APPENDIXES

Appendix 1 – Full description of the targets specified by the SAMDB NRM Board.

In the recent round of regional planning the Board set aspirational goals of sustaining Atmosphere, Biota, Land, Water and People assets in the region typically out to a time horizon of 2030. To give effect to these aspirational goals, 13 Resource Condition Targets (RCTs) were specified, also mostly to be achieved by 2030. To provide a more pragmatic basis for planning and to guide investment in environmental management, 46 Management Action Targets (MATs) were also specified as aggregate levels of achievement of on-ground actions achieved over a 5 year planning horizon to 2014. RCTs and MATs were designed using a program logic approach which attempts to identify direct causal links between the shorter term MATs and the longer term RCTs and aspirational goals. Specialist program groups were assembled within the SAMDB NRM Board charged with developing RCTs and MATs for each specific asset. The table below lists Resource Condition Targets (bold) and Management Action Targets in detail. The letter in the ID field refers to the asset addressed (A = Atmosphere, B = Biota, L = Land, W = Water, and P = People).

Target ID	Short Description	Targets
A1	**RCT: Reduce net greenhouse gas emissions in the SA MDB by 60% by 2050**	
A1.1	Renewable energy uptake	Voluntary renewable energy use at 20% and support for local generation
A1.2	Industry response to CC	Natural resource affecting industries adopting climate change sector agreements
A1.3	Energy use efficiency	Increase carbon efficiencies of vehicle fleet and buildings by 20% and 10% respectively
A1.4	Promote carbon offsets & NRM	Revegetation for future carbon (CO2-E) sequestration of 126,000 t
A2	**RCT: 100% of natural resource managers incorporating climate change adaptation into planning by 2030**	
A2.1	NRM managers respond to CC	25 % of natural resource managers incorporating climate change adaptation into planning
B1	**RCT: Native ecosystem extent increased to 60% of the region and native vegetation condition improved by 10% by 2030**	
B1.1	Protect remnant vegetation	Protect and manage an additional 10,000ha of priority remnant native ecosystems
B1.2	Increase native vegetation	The extent of native vegetation ecosystem is increased by 15,000ha
B1.3	Manage native vegetation	A 10% improvement in the condition of 25% of the native vegetation in the region
B1.4	Community ecological appreciation	Increase community appreciation of native ecosystems and species by 30%
B2	**RCT: By 2030, water dependent ecosystems in priority areas maintain ecological function, resilience and biodiversity**	
B2.1	Protect floodplains/wetlands	75% of priority floodplains and wetlands actively managed as per management plans
B2.2	Protect watercourses	Adoption of sustainable grazing practices in WDEs, erosion prevention and rehabilitation
B2.3	Terrestrial/aquatic connectivity	A 20% increase in connectivity between / within aquatic and terrestrial ecosystems
B2.4	Pest management coast & lakes	Reduce the extent of priority pest species in the coast and lower lake areas by 10%
B3	**RCT: No species moves to a higher risk category and 50% of species move to a lower category by 2030**	
B3.1	Manage threats to species	Reduce the impact of critical threats on priority threatened species
B3.2	Manage threats to ecosystems	Reduce the impact of critical threats on EPBC listed threatened ecosystems
L1	**RCT: A 10% improvement in soil and land condition from 2008/2009 levels by 2030**	
L1.1	Dryland water use efficiency	Dryland water use efficiency is maintained at 80%
L1.2	Manage pastures	90% of landholders are managing pastures sustainably
L1.3	New pest incursions	50% increase in participation in early warning system (communication network)
L1.4	Manage pests	Species specific control targets for 80% of priority species are met or 'on track' to be met
L2	**RCT: The area of land affected by land degradation processes is reduced by 2030**	
L2.1	Reduce erosion	Achieve a 6% improvement in wind erosion protection for agricultural cropping land
L2.2	Increase soil cover	A 3% increase in the area of grazing land with soil surface cover (based on 2009 levels)
L2.3	Reduce recharge	7,500 hectares of appropriate perennial vegetation established in priority areas
L2.4	Manage soil acidification	Net balance alkaline inputs are equal to acidification levels (approx 194,000 ha at risk)
W1	**RCT: Maintain or improve soil condition and water tables under irrigated land at 2007/08 levels**	
W1.1	Reduce Murray salinity	Maintain SA's position on MDBC salinity register in balance
W1.2	Minimise saline impacts	Minimise impacts of irrigation induced saline groundwater flows to water or ecosystem assets
W1.3	Reduce irrigation impacts	60% of irrigated land in at least 4 priority LWMP Districts implemented
W1.4	Irrigation water use efficiency	90% of the irrigated area achieving WUE as prescribed by the relevant WAP
W2	**RCT: All water resources managed within sustainable limits by 2030**	
W2.1	Increase knowledge of risks	100% of water resources have a risk assessment
W2.2	Protect water resources	Process for water management policy commenced for priority water resources
W2.3	Implement water protection	6 WAPs implemented
W2.5	Increase environmental water	50% of water dependant ecosystems are delivered their environmental water requirement
W3	**RCT: Improve water quality to achieve the regionally-endorsed environmental values by 2030**	
W3.1	Manage recreational impacts	All appropriate houseboat, vessel, and marina policies adopted and implemented
W3.2	Increase re-use of effluent	70% of effluent generated in region to be reused
W3.3	Influence upstream water quality	Influence investment in cross-state water quality (non-salinity) improvements
W3.4	Manage water quality	50% of land in the agricultural zone to have neutral or beneficial effects on water assets
W3.5	Reduce settlement impact	At least one major settlement (>2000 people) with neutral or beneficial effects on water assets
W3.6	Fit-for-purpose water use	70% of total water used in region shall be taken from sources that are fit-for-purpose
P1	**RCT: 80% increase in the number of people managing natural resources sustainably by 2030**	
P1.1	Increase awareness of NRM	50% of regions' community is aware of NRM
P1.2	Increase participation in NRM	25% of the NRM community have the knowledge and skills for sustainable NRM
P1.3	Increase NRM Volunteers	Increase the level of NRM volunteering in the SA MDB NRM Region above 1200 members
P2	**RCT: Increase protection and preservation of Aboriginal culture by 80% by 2030**	
P2.1	Awareness of Aboriginal culture	50% increased awareness of Aboriginal culture
P2.2	Engage Aboriginal people in NRM	50% increased participation of Aboriginal people in NRM
P2.3	Protect cultural sites	Management of cultural sites and assets improved
P3	**RCT: All landscape development and management have a neutral or beneficial impact on natural resources by 2030**	
P3.1	Communication NRM stakeholders	Effective institutional arrangements in place for all major stakeholders
P3.2	Institutional alignment with NRM	All State and Local Government, and Industry development plans align with regional plan
P3.3	Support development decisions	All Local Government development decisions are consistent with NRM goals

Appendix 2 – Impact of MATs on capital assets and ecosystem services scored during five MCA workshops with the Atmosphere, Biota, Land, Water, and People groups using the SMART technique.

Target ID	(NC1) Water	(NC2) Land	(NC3) Biota	(NC4) Atmosphere	(BC1) Built Environs	(BC2) Zoning & Planning	(BC3) Economic Viability & Employment	(SC1) Family	(SC2) Community	(P1) Food and Fibre	(P2) Biochemical Resources	(P3) Fresh Water	(P4) Geological Resources	(P5) Energy	(R1) Air Quality	(R2) Climate	(R3) Water Quantity	(R4) Erosion	(R5) Water Quality	(R6) Disease, Pests, and Natural Hazards	(R7) Pollination	(C1) Cultural Diversity and Heritage	(C2) Spiritual, Sense of Place, and Lifestyle	(C3) Knowledge and Education	(C4) Aesthetics and Inspiration	(C5) Social Relations	(C6) Recreation and Tourism	(C7) Bequest, Intrinsic, and Existence	(S1) Soil Formation	(S2) Photosynthesis and Plant Primary Production	(S3) Nutrient Cycling	(S4) Water Cycling
A1.1	0	0	0	7	5	1	4	1	3	0	0	1	0	10	3	7	0	1	1	0	0	-1	0	6	-2	0	0	4	0	1	0	0
A1.2	1	3	3	3	2	0	1	0	1	2	0	1	0	4	3	5	1	1	1	0	0	0	0	6	1	1	0	4	0	1	0	0
A1.3	0	0	0	3	3	0	0	0	0	0	0	0	0	5	0	5	0	0	0	0	0	0	0	8	3	0	0	2	0	0	0	0
A1.4	1	4	6	8	0	1	4	1	1	0	0	1	0	0	2	8	0	4	1	-1	1	2	1	6	2	0	3	5	1	3	3	2
A2.1	3	4	1	1	2	1	6	3	3	4	0	3	0	2	2	2	4	4	3	0	0	0	4	3	4	1	1	6	3	3	3	3
B1.1	3	3	8	1	0	1	0	3	3	-2	6	1	-3	0	2	2	4	4	3	6	7	7	7	6	10	7	4	10	3	3	4	4
B1.2	2	5	10	5	1	0	2	3	3	-2	3	5	0	0	7	8	3	9	5	0	5	2	1	5	5	5	0	5	7	7	6	6
B1.3	1	3	10	1	0	0	1	1	2	3	3	1	0	0	1	2	4	6	3	8	5	4	3	3	3	5	0	5	4	5	5	5
B1.4	2	3	5	3	2	2	0	2	2	0	1	2	0	0	2	2	2	2	2	2	2	2	2	4	2	2	4	4	2	2	2	2
B2.1	10	7	10	1	1	1	0	1	1	0	6	5	0	0	1	2	7	6	7	2	1	7	3	6	10	2	3	10	2	4	5	5
B2.2	7	5	8	1	0	0	-1	1	1	-1	1	7	0	0	2	2	7	7	7	4	1	2	4	4	8	2	6	9	3	1	5	5
B2.3	4	2	9	1	0	0	0	1	1	-1	1	4	0	0	1	1	2	8	4	4	1	7	8	5	4	2	2	8	1	1	4	4
B2.4	0	3	8	0	0	0	1	1	1	0	4	0	0	0	0	0	0	1	0	10	0	7	4	3	2	2	5	9	0	0	0	0
B3.1	0	0	10	0	0	2	0	1	1	0	8	0	0	0	0	0	0	0	0	8	1	6	4	6	9	2	8	10	0	0	0	0
B3.2	2	4	10	1	0	1	-2	1	1	0	3	2	0	0	0	1	2	2	2	1	1	3	3	5	4	3	4	10	1	1	1	1
L1.1	4	10	5	2	0	0	3	5	5	8	0	2	0	1	0	2	-1	2	1	2	2	0	0	6	3	1	1	4	4	4	7	9
L1.2	4	10	5	2	0	0	2	3	3	6	0	2	0	0	0	0	-1	5	3	6	2	0	0	6	5	1	1	4	3	4	5	5
L1.3	6	8	8	2	3	0	9	3	5	8	5	4	2	2	3	0	3	2	2	10	7	2	4	7	6	4	4	5	1	6	2	4
L1.4	6	8	8	2	3	3	8	3	5	8	2	6	2	2	-1	0	6	9	7	10	2	5	5	6	6	5	6	7	1	6	2	5
L2.1	1	10	2	2	1	0	7	5	7	7	0	2	0	2	4	1	-1	10	3	-1	0	0	0	6	2	3	0	4	8	3	8	2
L2.2	3	10	5	2	1	0	5	3	5	7	0	4	0	0	2	1	-1	10	4	1	4	0	0	6	2	3	2	4	8	5	8	4
L2.3	5	10	5	3	2	0	2	1	1	3.5	1	4	1	2	0	2	-1	3	6	2	3	0	2	6	6	2	1	4	4	5	5	4
L2.4	5	10	5	2	0	0	5	2	2	5	0	2	-2	1	0	1	-1	6	5	3	2	0	0	6	3	1	1	4	8	6	7	7
W1.1	9	5	5	3	6	3	8	7	7	8	3	10	0	-7	0	-1	0	1	8	0	1	0	6	5	3	2	3	8	2	7	5	5
W1.2	5	5	5	3	4	3	6	6	6	3	5	4	0	0	0	1	3	1	6	0	4	0	6	5	5	2	5	8	4	6	3	3
W1.3	7	8	6	3	4	5	6	8	8	6	4	5	0	0	0	1	2	3	6	0	1	0	6	7	3	5	6	6	5	7	4	3
W1.4	8	7	5	3	4	2	8	6	6	7	0	7	0	3	0	1	2	1	6	0	1	0	6	7	3	5	2	4	2	8	4	3
W2.1	5	2	4	0	3	4	0	3	3	2	0	6	0	0	0	0	3	0	2	0	0	0	2	7	0	0	0	0	0	0	0	2
W2.2	7	5	7	0	4	5	0	7	7	2	0	7	0	0	0	0	5	0	2	0	0	2	4	7	1	0	2	2	1	0	0	4
W2.3	10	6	9	1	5	6	0	8	8	2	0	8	0	0	0	0	8	2	5	0	0	2	6	7	2	3	5	6	2	0	0	4
W2.5	5	5	10	1	0	0	5	4	4	0	3	7	0	0	2	1	10	5	8	2	2	4	5	2	7	5	6	8	4	5	4	7
W3.1	9	1	7	0	2	10	0	0	0	0	0	8	0	0	3	0	0	1	10	8	0	0	-5	7	4	-5	4	5	0	0	4	0
W3.2	9	0	4	0	6	5	2	2	2	3	0	8	0	-1	-1	0	2	0	8	5	1	0	0	3	2	1	3	3	0	2	3	2
W3.3	3	0	4	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	5	1	0	0	0	1	1	2	0	2	0	0	0	2
W3.4	9	8	6	0	1	0	1	1	1	0	0	8	0	0	1	0	0	6	8	5	1	0	1	7	5	5	2	6	2	2	3	2
W3.5	5	2	1	0	5	1	4	2	2	0	0	3	0	-1	0	0	0	0	5	2	0	2	1	6	2	4	2	2	0	1	1	1
W3.6	7	2	5	0	5	4	4	2	2	4	0	8	0	-1	0	0	5	0	7	1	1	0	0	3	0	1	3	4	0	2	1	4
P1.1	2	2	2	2	1	1	1	3	9	1	1	1	0	1	1	1	1	1	1	1	1	3	4	10	4	5	7	9	2	0	0	2
P1.2	4	4	4	4	2	2	1	5	7	3	2	3	0	3	3	3	3	3	3	3	3	3	7	10	4	5	7	9	3	2	1	3
P1.3	3	2	5	1	1	2	1	5	8	0	3	3	0	0	1	1	3	1	3	4	1	2	3	4	6	7	4	9	1	1	2	2
P2.1	1	1	2	1	0	1	1	4	8	2	2	1	0	0	1	1	4	1	1	2	1	10	8	10	4	9	3	10	0	0	0	2
P2.2	2	2	3	2	0	3	4	5.5	7	2	6	1	0	0	1	1	4	3	2	5	1	6	6	6	4	6	3	6	0	0	0	1
P2.3	1	1	2	0	0	2	1	3	5	1	3	0	0	0	0	0	1	2	0	1	1	9	9	5	6	4	3	10	0	0	0	0
P3.1	2	2	2	2	1	2	1	0	1	0	1	1	0	3	1	3	2	3	5	2	0	0	4	9	4	7	3	4	1	0	0	1
P3.2	4	4	4	4	8	8	0	0	3	0	1	3	0	3	1	3	2	3	6	2	0	1	4	8	4	2	6	4	0	0	1	1
P3.3	2	2	2	2	5	1	0	0	0	0	1	1	0	1	1	1	1	1	1	1	0	1	1	1	1	2	1	2	0	0	0	0

Appendix 3 – Simulating benefit probability distributions for targets and extracting maximum, most likely, and minimum values for inclusion in robust portfolio selection.

The benefit b_k of achieving each target k was calculated as the sum over all natural capital assets and ecosystem services D' of the product of the impact Q_{ik} of achieving the target on each asset/service i and management priority M_i of the asset/service (Equation 4). Both impact Q_{ik} and management priority M_i are random variables sampled from distributions defined by probability density functions (PDFs) $f(z)$ such that $f(z) = P(Z = z)$ and $P(Z = z)$ is the probability that the random variable $Z = z$ at any given random draw. Benefit b_k was also modelled as a random variable with a PDF obtained through Monte Carlo simulation.

A triangular PDF was used to describe the uncertainty surrounding the group consensus score for the impact Q_{ik} of each target k on each asset/service i. Three parameters are required to describe the triangular distribution: mode (most likely value); minimum, and; maximum. The mode_{ik} was equal to the group consensus impact score. The minimum ($\text{min}_{ik} = \text{mode}_{ik} - 1$, $-10 \leq \text{min}_{ik} \leq 10$) and maximum ($\text{max}_{ik} = \text{mode}_{ik} + 1$, $-10 \leq \text{max}_{ik} \leq 10$) values of the distribution were specified to reasonably reflect the level of uncertainty. Thus, the triangular probability density functions for impact were defined as:

$$P(Q_{ik} = q_{ik}) = \left\{ \begin{array}{ll} \dfrac{2(q_{ik} - \min_{ik})}{(\text{mode}_{ik} - \min_{ik})(\max_{ik} - \min_{ik})} & \text{for } \min_{ik} \leq q_{ik} \leq \text{mode}_{ik} \\ \dfrac{2(\max_{ik} - q_{ik})}{(\max_{ik} - \text{mode}_{ik})(\max_{ik} - \min_{ik})} & \text{for } \text{mode}_{ik} \leq q_{ik} \leq \max_{ik} \end{array} \right\} \quad (11)$$

PDFs describing variation in management priority M_i for each asset/service i were derived from the variation in weights over the 40 decision-makers. However, simulating raw MCDA-derived weights is not straightforward. As the weights for capital assets and for ecosystem services sum to 1 (a *unit-sum* constraint) for each participant, the data is *compositional*. The sample space of compositional data is the simplex S rather than unconstrained real space $\mathbb{R}$ (Aitchison 1986). In simulation, random sampling from probability distributions fit to compositional data does not maintain the unit-sum constraint.

To overcome this effect, centred log ratio (clr) transformation was used to *open* and normalise the raw MCDA-derived weights for capital assets and ecosystem services. Let $\mathbf{X} = \{\mathbf{x}_j = [x_{1j}, x_{2j}, ..., x_{Dj}] \in S^D : j = 1, 2, ..., n\}$ define the two matrices of compositional raw weights (capital assets weights and ecosystem services weights) each consisting of 40 rows $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_{40}$ with one row per decision-maker (i.e. $n = 40$), and D columns $X_1, X_2, \ldots, X_D$ ($D = 9$ for capital assets and $D = 23$ for ecosystem services). Each row $\mathbf{x}_j$ represents management priority weights x_{ij} for each capital asset/ecosystem service i for $i = 1, 2, \ldots, D$ of each decision-maker j. Weights for both the capital assets and ecosystem services were subject to clr transformation calculated, for each decision-maker (row) j, as the natural log of the raw weights over the geometric mean of the raw weights $g_D(\mathbf{x}_j)$:

$$\mathbf{x}_j^* = \text{clr}(\mathbf{x}_j) = \left[\ln \frac{\mathbf{x}_j}{g_D(\mathbf{x}_j)} \right] = \left[\ln \frac{x_{1j}}{g_D(\mathbf{x}_j)}, \ln \frac{x_{2j}}{g_D(\mathbf{x}_j)}, ..., \ln \frac{x_{Dj}}{g_D(\mathbf{x}_j)} \right], \; j = 1, 2, ..., n \quad (12)$$

and:

$$g_D(\mathbf{x}_j) = \left(\prod_{i=1}^{D} x_{ij} \right)^{1/D} = \exp\left(\frac{1}{D} \sum_{i=1}^{D} \ln x_{ij} \right), \; j = 1, 2, ..., n \quad (13)$$

Kolmogorov-Smirnov tests confirmed that clr-transformed weights for each asset/service over all 40 participants did not differ significantly from a normal distribution ($P < 0.05$). A maximum likelihood estimator was then used to fit Gaussian PDFs $P(M^* = m^*)$ to the column vector of clr-transformed management priority weights X_i^* of each asset/service i such that:

$$P(M_i^* = m_i^*) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{1}{2}\left(\frac{m_i^* - \mu_i}{\sigma_i} \right)^2 \right) \quad (14)$$

where μ_i and σ_i are the mean and standard deviation of the column vector of clr-transformed weights X_i^* of each asset/service.

Each iteration in the simulation returned two vectors of simulated clr weights $\mathbf{m}^* = [M_1, M_2, ..., M_D] \in \mathbb{R}^{D-1}$ where D = 9 for capital assets and D = 23 for ecosystem services. At each iteration, an inverse clr transformation was used to return the simulated random management priority variable vector $\mathbf{m}^*$ to the raw simplex sample space for capital assets and ecosystem services:

$$\mathbf{m} = \mathrm{clr}^{-1}(\mathbf{m}^*) = \left[\frac{\exp M_1}{\sum_{i=1}^{D} \exp M_i}, \frac{\exp M_2}{\sum_{i=1}^{D} \exp M_i}, ..., \frac{\exp M_D}{\sum_{i=1}^{D} \exp M_i} \right] \quad (15)$$

Thus, for each simulation iteration $\mathbf{m} = [M_1, M_2, ..., M_D] \in S^D$ and $\sum_{i=1}^{D} M_i = 1$ for both capital assets and ecosystem services.

Benefit probability distributions were established using 10,000 Monte Carlo simulations of Equation 4 with each simulation using values for the random variables of impact Q_{ik} and management priority M_i derived from the PDFs. The minimum $b_k^{\min}$, most likely b_k^{ml}, and maximum $b_k^{\max}$ benefit values were the 5th percentile, mean, and 95th percentile from the normally distributed benefit PDF simulated for each target k.

Appendix 4 – Cost, benefit, and background target achievement of Management Action Targets.

Target ID	Min Cost to Achieve Target ($)	Most Likely Cost to Achieve Target ($)	Max Cost to Achieve Target ($)	Total Core Costs	Min Background Target Achievement (%)	Most Likely Background Target Achievement (%)	Max Background Target Achievement (%)	Min Benefit	Most Likely Benefit	Max Benefit
A1.1	83,000	126,000	180,000	0	10	20	30	1.98	3.02	4.26
A1.2	166,000	238,000	350,000	0	20	70	80	2.37	3.03	3.73
A1.3	345,000	490,000	660,000	0	30	40	50	0.70	1.35	2.11
A1.4	750,000	1,002,000	1,280,000	0	30	50	60	3.66	4.70	5.89
A2.1	605,000	780,000	995,000	0	30	50	75	4.47	5.22	5.93
B1.1	1,300,000	1,675,000	2,030,000	0	0	10	25	5.08	6.41	7.94
B1.2	10,450,000	18,140,000	24,660,000	0	0	10	15	6.23	7.69	9.41
B1.3	4,775,000	7,800,000	10,000,000	0	0	0	15	4.58	5.88	7.77
B1.4	2,045,000	2,445,000	4,470,000	469,816	0	15	25	3.69	4.33	5.08
B2.1	8,925,000	12,325,000	14,550,000	1,290,108	0	75	100	7.41	9.10	10.84
B2.2	1,750,000	3,000,000	4,500,000	0	0	10	15	5.93	7.46	9.03
B2.3	1,690,000	2,354,000	4,000,000	0	10	25	40	4.29	5.67	7.36
B2.4	1,300,000	1,935,000	3,000,000	0	0	0	0	2.25	3.51	5.23
B3.1	6,170,000	8,570,000	13,220,000	0	5	15	20	2.29	3.78	5.91
B3.2	2,500,000	3,900,000	6,500,000	0	0	0	10	3.26	4.53	6.32
L1.1	1,000,000	2,500,000	5,000,000	0	50	65	70	5.85	7.03	8.34
L1.2	1,250,000	2,500,000	4,500,000	0	20	35	50	5.40	6.52	7.68
L1.3	2,000,000	2,750,000	3,750,000	0	15	25	30	8.38	9.54	10.69
L1.4	10,900,000	13,650,000	19,650,000	8,404,985	30	40	50	9.37	10.50	11.59
L2.1	4,750,000	9,875,000	19,500,000	239,058	40	60	75	5.20	6.55	8.02
L2.2	4,750,000	9,875,000	19,500,000	239,058	20	30	60	6.34	7.55	8.80
L2.3	4,500,000	7,000,000	14,000,000	0	20	40	60	5.98	7.05	8.12
L2.4	750,000	1,500,000	3,750,000	0	20	40	60	6.04	7.28	8.55
W1.1	1,750,000	2,375,000	3,387,500	0	75	90	95	7.99	9.46	10.92
W1.2	1,372,500	1,932,500	2,581,250	388,442	10	20	30	7.21	7.95	8.69
W1.3	3,775,000	4,625,000	5,850,000	345,698	0	5	10	8.93	9.83	10.70
W1.4	4,262,500	6,075,000	7,781,250	388,442	20	25	30	8.21	9.28	10.39
W2.1	4,400,000	6,100,000	6,350,000	675,923	40	50	60	3.47	4.32	5.23
W2.2	2,050,000	2,645,000	3,150,000	1,788,741	0	20	30	5.92	7.04	8.14
W2.3	2,200,000	2,950,000	3,700,000	1,351,846	20	30	40	8.02	9.41	10.76
W2.5	2,115,000	3,420,000	4,880,000	0	0	20	100	7.29	8.68	10.24
W3.1	135,000	970,000	1,700,000	0	40	50	60	4.62	6.35	8.13
W3.2	525,000	795,000	1,370,000	196,261	40	60	70	4.87	6.23	7.73
W3.3	310,000	745,000	1,112,500	0	20	30	40	1.36	2.18	3.12
W3.4	1,557,500	3,640,000	5,325,000	327,101	20	50	60	5.82	7.34	8.88
W3.5	1,657,500	3,235,000	4,745,000	65,420	30	50	60	3.10	3.93	4.80
W3.6	510,000	1,115,000	2,145,000	65,420	40	50	60	5.18	6.29	7.45
P1.1	1,720,000	1,720,000	2,020,000	1,100,101	0	2	5	3.52	4.27	5.14
P1.2	7,540,000	10,137,500	11,115,000	1,022,489	5	10	12	6.38	7.08	7.80
P1.3	361,200	710,000	1,110,000	0	0	0	0	4.58	5.40	6.28
P2.1	745,000	1,150,000	1,950,000	0	20	30	40	3.36	4.28	5.32
P2.2	1,525,000	2,075,000	2,750,000	0	10	20	30	4.45	5.25	6.10
P2.3	600,000	650,000	1,100,000	0	5	10	20	2.46	3.27	4.20
P3.1	1,300,000	1,730,000	2,800,000	173,845	10	20	30	3.02	3.67	4.35
P3.2	260,000	520,000	930,000	0	30	40	60	5.33	6.18	7.03
P3.3	200,000	500,000	1,000,000	0	20	30	50	1.95	2.43	2.94

REFERENCES

Aitchison, J., 1986. The Statistical Analysis of Compositional Data, Monographs on Statistics and Applied Probability. Chapman & Hall Ltd, London, UK.

Alam, K., Rolfe, J., Donaghy, P., 2008. Assessing the cost-effectiveness of water quality interventions in South-East Queensland. Aust. J. Environ. Manag. 15, 30-40.

Ando, A., Camm, J., Polasky, S., Solow, A., 1998. Species distributions, land values, and efficient conservation. Sci. 279, 2126-2128.

Babcock, B.A., Lakshminarayan, P.G., Wu, J.J., Zilberman, D., 1997. Targeting tools for the purchase of environmental amenities. Land Econ. 73, 325-339.

Bailey, N., Lee, J.T., Thompson, S., 2006. Maximising the natural capital benefits of habitat creation: spatially targeting native woodland using gis. Landsc. Urban Plan. 75, 227-243.

Balmford, A., Gaston, K.J., Rodrigues, A.S.L., James, A., 2000. integrating costs of conservation into international priority setting. Conserv. Biol. 14, 597-605.

Bode, M., Wilson, K.A., Brooks, T.M., Turner, W.R., Mittermeier, R.A., McBride, M.F., Underwood, E.C., Possingham, H.P., 2008. Cost-effective global conservation spending is robust to taxonomic group. Proceedings of the National Academy of Sciences of the United States of America 105, 6498-6501.

Bottrill, M.C., Joseph, L.N., Carwardine, J., Bode, M., Cook, C., Game, E.T., Grantham, H., Kark, S., Linke, S., McDonald-Madden, E., Pressey, R.L., Walker, S., Wilson, K.A., Possingham, H.P., 2008. Is conservation triage just smart decision making? Trends in Ecology & Evolution 23, 649-654.

Bryan, B.A. and Kandulu, J.M. (In Press). Cost-effective alternatives for mitigating Cryptosporidium risk in drinking water and enhancing ecosystem services. Water Resources Research. doi: 10.1029/2008WR007606

Bryan, B.A., Crossman, N.D., 2008. Systematic regional planning for multiple objective natural resource management. Journal of Environmental Management 88, 1175-1189.

Bryan, B.A., Grandgirard, A., and Ward, J.R. (in review). Quantifying and exploring strategic regional priorities for managing natural capital and ecosystem services given multiple stakeholder perspectives. Submitted to Ecosystems, May 2009.

Carlos A. Bana e Costa, Tânia G. Fernandes, Paulo V. D. Correia, 2006. Prioritisation of public investments in social infrastructures using multicriteria value analysis and decision conferencing: a case study. International Transactions in Operational Research 13, 279-297.

Cast, A., D. Hatton MacDonald, A. Grandgirard, T. Kalivas, S. Strathearn, M. Sanderson, B.A. Bryan, and D. Frahm. 2008. South Australian Murray Darling Basin Environmental Values Report. Water for a Healthy Country National Research Flagship Report, CSIRO.

Church, R. and ReVelle, C.1974. The maximal covering location problem. Papers of the Regional Science Association 32: 101-118

Connor, J.D., Ward, J.R., Bryan, B., 2008. Exploring the cost effectiveness of land conservation auctions and payment policies. Australian Journal of Agricultural and Resource Economics 52, 303-319.

Costanza, C., R. d'Arge, R. de Groot, S. Farber, M. Grasso, B. Hannon, K. Limburg, S. Naeem, R.V. O'Neill, J. Paruelo, R.G. Raskin, P. Sutton, and M. van den Belt. 1997. The value of the world's ecosystem services and natural capital. *Nature* 387:253 – 260.

Cowling, R.M., B. Egoh, A.T. Knight, P.J. O'Farrell, B. Reyers, M. Rouget, D.J. Roux, A. Welz, and A. Wilhelm-Rechman. 2008. An operational model for mainstreaming ecosystem services for implementation. *Proceedings of the National Academy of Sciences of the United States of America* 105:9483-9488.

Crossman, N.D., Bryan, B.A., 2006. Systematic landscape restoration using integer programming. Biological Conservation 128, 369-383.

Crossman, N.D., Bryan, B.A., 2009. Identifying cost-effective hotspots for restoring natural capital and enhancing landscape multifunctionality. Ecological Economics 68, 654-668.

Cullen, R., Hughey, K.F.D., Fairburn, G., Moran, E., 2005. Economic analyses to aid nature conservation decision making. Oryx 39, 327-334.

Daily, G.C. 1997. What are ecosystem services? In: G.C. Daily (Ed.), Nature's Services: Societal Dependence on Natural Ecosystems. Island Press, Washington, DC, USA.

Daily, G.C., S. Polasky, J. Goldstein, P.M. Kareiva, H.A. Mooney, L. Pejchar, T.H. Ricketts, J. Salzman, and R. Shallenberger. 2009. Ecosystem services in decision making: time to deliver. *Frontiers in Ecology and the Environment* 7:21-28.

Drechsler, M., Watzold, F., 2001. The Importance of Economic Costs in the Development of Guidelines for Spatial Conservation Management. Biological Conservation 97, 51-59.

Ehrgott, M., Klamroth, K., Schwehm, C., 2004. An Mcdm Approach to Portfolio Optimization. European Journal of Operational Research 155, 752-770.

Emma C. Underwood, Kirk R. Klausmeyer, Scott A. Morrison, Michael Bode, M. Rebecca Shaw, 2009. Evaluating conservation spending for species return: A retrospective analysis in California. Conservation Letters 2, 130-137.

Ferraro, P.J., 2003. Assigning priority to environmental policy interventions in a heterogeneous world. Journal of Policy Analysis and Management 22, 27-43.

Figueira, J., S. Greco, and M. Ehrgott. (Eds.) 2005. Multiple Criteria Decision Analysis: State of the Art Surveys. Springer, New York.

Fisher, B., K. Turner, M. Zylstra, R. Brouwer, R. de Groot, S. Farber, P. Ferraro, R. Green, D. Hadley, J. Harlow, P. Jefferiss, C. Kirkby, P. Morling, S. Mowatt, R. Naidoo, J. Paavola, B. Strassburg, D. Yu, and A. Balmford. 2008. Ecosystem services and economic theory: Integration for policy-relevant research. *Ecological Applications* 18:2050-2067.

Fisher, B., R.K. Turner, and P. Morling. 2009. Defining and classifying ecosystem services for decision making. *Ecological Economics* 68:643-653.

Gustafsson, J., Salo, A., 2005. Contingent Portfolio Programming for the Management of Risky Projects. Oper. Res. 53, 946-956.

Hajkowicz, S., 2007. Allocating scarce financial resources across regions for environmental management in Queensland, Australia. Ecological Economics 61, 208-216.

Hajkowicz, S., 2009b. Cutting the cake: Supporting environmental fund allocation decisions. Journal of Environmental Management 90, 2737-2745.

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

Hajkowicz, S., Spencer, R., Higgins, A., Marinoni, O., 2008. Evaluating water quality investments using cost utility analysis. Journal of Environmental Management 88, 1601-1610.

Hajkowicz, S., Higgins, A., Miller, C., Marinoni, O., 2009. Is getting a conservation model used more important than getting it accurate? Biological Conservation 142, 699-700.

HO William (1) ; HIGSON Helen E. (2) ; DEY Prasanta K. (1) ; An integrated multiple criteria decision making approach for resource allocation in higher education. International journal of innovation and learning 2007, vol. 4, no5, pp. 471-486

Huang, X.X., 2008. Mean-variance model for fuzzy capital budgeting. Computers & Industrial Engineering 55, 34-47.

Hughey, K.F.D., Cullen, R., Moran, E., 2003. Integrating Economics Into Priority Setting and Evaluation in Conservation Management. Conservation Biology 17, 93-103.

Jack, B.K., C. Kousky, and K.R.E. Sims. 2008. Designing payments for ecosystem services: Lessons from previous experience with incentive-based mechanisms. *Proceedings of the National Academy of Sciences of the United States of America* 105: 9465–9470.

Keeney, R. L., H. Raiffa. 1976. Decisions with multiple objectives: Preferences and value tradeoffs. John Wiley & Sons, New York.

Kleinmuntz, D.N. 2007. Resource allocation decisions. In W. Edwards, R.F. Miles Jr., D. von Winterfeldt (Eds) Advances in Decision Analysis: From Foundations to Applications. Cambridge university press, NY, USA. pp. 400-418.

Lang, H.J., D.N.Merino. 1993. The Selection Process for Capital Projects. John Wiley, New York.

Liesio, J., Mild, P., Salo, A., 2007. Preference Programming for Robust Portfolio Modeling and Project Selection. European Journal of Operational Research 181, 1488-1505.

Liesio, J., Mild, P., Salo, A., 2008. Robust portfolio modeling with incomplete cost information and project interdependencies. European Journal of Operational Research 190, 679-695.

Macmillan, D.C., Harley, D., Morrison, R., 1998. Cost-effectiveness analysis of woodland ecosystem restoration. Ecological Economics 27, 313-324.

Marinoni, O., Higgins, A., Hajkowicz, S., Collins, K., 2009. The multiple criteria analysis tool (MCAT): A new software tool to support environmental investment decision making. Environmental Modelling & Software 24, 153-164.

Markowitz, H.M. 1952. Portfolio selection. Journal of Finance 7, 77–91.

McCarthy, M., Lindenmayer, D., 2007. Info-Gap Decision Theory for Assessing the Management of Catchments for Timber Production and Urban Water Supply. Environmental Management 39, 553-562.

McDonald-Madden, E., Baxter, P.W.J., Possingham, H.P., 2008. Making robust decisions for conservation with restricted money and knowledge. Journal of Applied Ecology 45, 1630-1638.

MEA. 2005. Ecosystems and Human Well-being: Synthesis. Millennium Ecosystem Assessment. Island Press, Washington DC.

Messina, V., Bosetti, V., 2003. Uncertainty and option value in land allocation problems. Annals of Operations Research 124, 165-181.

Murdoch, W., Polasky, S., Wilson, K.A., Possingham, H.P., Kareiva, P., Shaw, R., 2007. Maximizing return on investment in conservation. Biological Conservation 139, 375-388.

Naidoo, R., Balmford, A., Ferraro, P.J., Polasky, S., Ricketts, T.H., Rouget, M., 2006. Integrating Economic Costs Into Conservation Planning. Trends in Ecology & Evolution 21, 681-687.

Nelson, E., Mendoza, G., Regetz, J., Polasky, S., Tallis, H., Cameron, D.R., Chan, K.M.A., Daily, G.C., Goldstein, J., Kareiva, P.M., Lonsdorf, E., Naidoo, R., Ricketts, T.H., Shaw, M.R., 2009. Modeling multiple ecosystem services, biodiversity conservation, commodity production, and tradeoffs at landscape scales. Frontiers in Ecology and the Environment 7, 4-11.

Newburn, D., Reed, S., Berck, P., Merenlender, A., 2005. Economics and land-use change in prioritizing private land conservation. Conservation Biology 19, 1411-1420.

Phillips, L.D., Bana e Costa, C.A., 2007. Transparent prioritisation, budgeting and resource allocation with multi-criteria decision analysis and decision conferencing. Annals of Operations Research 154, 51-68.

Polasky, S., 2008. Why conservation planning needs socioeconomic data. Proceedings of the National Academy of Sciences of the United States of America 105, 6505-6506.

Polasky, S., Nelson, E., Camm, J., Csuti, B., Fackler, P., Lonsdorf, E., Montgomery, C., White, D., Arthur, J., Garber-Yonts, B., Haight, R., Kagan, J., Starfield, A., Tobalske, C., 2008. Where to put things? Spatial land management to sustain biodiversity and economic returns. Biological Conservation 141, 1505-1524.

Prato, T., 2007. Selection and Evaluation of Projects to Conserve Ecosystem Services. Ecological Modelling 203, 290-296.

Raymond, C.M., B.A. Bryan, D. Hatton MacDonald, A. Cast, S. Strathearn, A. Grandgirard, and T. Kalivas. 2009. Mapping community values and risks towards natural capital and ecosystem services for environmental management. *Ecological Economics* 68:1301-1315.

Roberts, A.M., and D.J. Pannell. 2009. Piloting a systematic framework for public investment in regional natural resource management: Dryland salinity in Australia. *Land Use Policy* 26:1001-1010.

Saaty, T. 1980. The Analytical hierarchy Process. McGraw-Hill, USA.

Salo, A.A., R.P., Hämäläinen, 1992. Preference assessment by imprecise ratio statements. Oper. Res. 40, 1053-1061.

Salo, A.A., R.P., Hämäläinen, 2004. Preference programming. Systems Analysis Laboratory, Helsinki University of Technology. http://www.sal.hut.fi/Publications/pdf-files/msal03b.pdf

SAMDB NRM Board 2009a. SAMDB Website. http://www.samdbnrm.sa.gov.au. Accessed 11/05/09.

SAMDB NRM Board 2009b. Regional NRM Plan. Volume 1: Strategic Plan 2009 – 2019.

SAMDB NRM Board 2009c. Regional NRM Plan. Volume 4: Business Plan 2009 – 2012.

Sinden, J. 2003. Decision rules, government rules, and the costs of vegetation protection in New South Wales. Journal of Forest Economics 9, 1-4.

Smith, G. 2007. Logical Decision for Windows: Users Manual. Fairfax, VA. http://www.logicaldecisions.com

Somanathan, E., R. Prabhakar, B.S. Mehta, B. Singh. 2009. Decentralization for cost-effective conservation. Proceedings of the National Academy of Sciences of the United States Of America 106:4143-4147.

Steuer, R.E., Na, P., 2003. Multiple Criteria Decision Making Combined With Finance: a Categorized Bibliographic Study. European Journal of Operational Research 150, 496-515.

Steuer, R.E., Qi, Y., Hirschberger, M., 2007. Suitable-portfolio investors, nondominated frontier sensitivity, and the effect of multiple objectives on standard portfolio selection. Annals of Operations Research 152, 297-317.

Turner, R.K., and G.C. Daily. 2008. The ecosystem services framework and natural capital conservation. *Environmental and Resource Economics* 39:25-35.

von Winterfeldt, D., and W. Edwards. 1986. Decision Analysis and Behavioral Research. Cambridge University Press.

Wilson, K.A., Carwardine, J., Possingham, H.P., 2009. Setting Conservation Priorities. Year in Ecology and Conservation Biology 2009 1162, 237-264.

Wilson, K.A., McBride, M.F., Bode, M., Possingham, H.P., 2006. Prioritizing global conservation efforts. Nature 440, 337-340.

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., Possingham, H.P., 2007. Conserving biodiversity efficiently: What to do, where, and when. Plos Biology 5, 1850-1861.

Wu, J.J., R. D. Adams, D. Zilberman, and B. A. Babcock. 2000 “Targeting Resource Conservation. Expenditures.” Choices, 2nd Quarter, 33-38.

Wu, J.J., Boggess, W.G., 1999. The optimal allocation of conservation funds. Journal of Environmental Economics and Management 38, 302-321.