Ecological Economics 127 (2016) 146–155

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Analysis

A proposed framework to systematically design and objectively evaluate non-dominated restoration tradeoffs for watershed planning and management

David M. Martin [a,b,*], Virgilio Hermoso [c,d], Francis Pantus [d], Jon Olley [d], Simon Linke [d], N. LeRoy Poff [a]

[a] Department of Biology and Graduate Degree Program in Ecology, Colorado State University, Fort Collins, CO 80523, USA
[b] U.S. Environmental Protection Agency, Office of Research and Development, Atlantic Ecology Division, RI 02882, USA
[c] CTFC Forest Sciences Centre of Catalonia, Solsona, 25280, Lleida, Spain
[d] Australian Rivers Institute, Griffith University, Nathan Campus, Kessels Road, 4111, Queensland, Australia

ARTICLE INFO

Article history:
Received 30 October 2015
Received in revised form 28 March 2016
Accepted 6 April 2016
Available online 26 April 2016

Keywords:
River restoration
Systems analysis
Decision making
Pareto efficiency
Multi-criteria decision analysis

ABSTRACT

Human-driven alterations to freshwater ecosystems are leading to a global decline of river function and biodiversity. In our experience, managers want to be given many possible options to restore freshwater ecosystems that are workable within spatial, temporal, operational, and budgetary constraints of the system. Correspondingly, a new field for systematic river restoration planning has emerged through the use of well-established systems design concepts like multi-objective optimization and tradeoff analysis. In this article, we propose a decision framework for systematic river restoration planning where economic-environment systems design and tradeoff analyses are employed as a concurrent planning procedure before restoration interventions are implemented. Heuristic optimization and multi-criteria decision analysis methods are proposed to systematically design and objectively evaluate non-dominated economic-environment tradeoffs associated with restoration strategies within a watershed, and to provide a short-list of viable restoration alternatives to decision makers for negotiation and implementation. The proposed framework has the capacity to make science-based information and sophisticated decision support methods available for stakeholder deliberation. To illustrate the phases of the framework, we use a published case study of systematic restoration planning in South East Queensland, Australia.

1. Introduction

The worldwide degradation of river ecosystem function and freshwater biodiversity (Strayer and Dudgeon, 2010) has led to the development of restoration strategies, which aim to rehabilitate the physical structure and ecological function of river ecosystems. The field of ecological river restoration has been comprehensively reviewed (USNRC, 1992; Palmer et al., 2014) and awarded substantial government funding (Bernhardt et al., 2005; Brooks and Lake, 2007). Yet criticisms of the practice of ecological river restoration are extensive. Scientific concerns include the scale of restoration projects, many of which are very local and restricted to river reaches with easy land access (Wohl et al., 2005; Beechie et al., 2010). Additional concerns are the failure to select functionally important ecological processes that contribute to successful restoration (Lake et al., 2007; Palmer et al., 2010) and a lack of post-restoration monitoring to evaluate success (Palmer et al., 2005; Roni et al., 2008). More general critiques include claims that integrated methods for planning restoration projects are under-utilized (Hermoso et al., 2012) and that philosophical approaches to restoration fail to consider key interactions (e.g., socio-economic, -environmental, -biological) to more comprehensively inform decision makers on how to evaluate restoration options (Hermoso et al., 2015).

Historically, decisions to implement river restoration were performed using ad hoc planning approaches where many different sources of information were gathered to develop actionable strategies with independently predicted outcomes (Hermoso et al., 2012). To account for this and other criticisms referenced above, planning for river restoration is becoming increasingly structured and systematic. Systems thinking approaches have emerged to better facilitate decisions to “wicked” (Rittel and Webber, 1973) resource management problems, which are characterized by competing stakeholder values, conflicting data requirements and metrics, spatio-temporal factors, and disagreement or incomplete knowledge on methodological assumptions. A compendium of frameworks are described for conceptualizing economic-environment interactions using systems thinking (Binder et al., 2013), and for including economic-environment interactions in resource management scenario planning (Munda et al., 1994). Others approach environmental systems analysis by developing generic but reproducible decision-making frameworks (Failing et al., 2013). Box 1 gives a general outline for planning approaches that address complex

* Corresponding author at: 27 Tarzwell Drive, Narragansett, RI 02882, USA.
E-mail address: Martin.Davidm@epa.gov (D.M. Martin).

http://dx.doi.org/10.1016/j.ecolecon.2016.04.007
0921-8009/Published by Elsevier B.V.

Box 1

Step	Description
Problem definition	Focus group discussions to develop a common understanding of a complex watershed management problem
Conceptualization	Comprehensive understanding of the interactions of social and ecological system components (e.g., causal network diagram)
Restoration objectives	Agreement on outcome-oriented restoration objectives that are manageable, measurable, non-redundant, and socially and ecologically desirable for watershed planning (e.g., water supply, ecological habitat)
Design alternatives	Cause and effect models and expert opinion are used to develop restoration alternatives, where each alternative addresses the restoration problem with a unique set of interventions that trade off performance effects in the restoration objectives
Consequences	For each alternative, the restoration consequences are returned through predictive model responses or via expert opinion feedback
Value orientation	Individual or group stakeholder values may be incorporated into the tradeoff analysis
Prioritization	Formal tradeoff analysis of the restoration alternatives using decision making models and appropriate measures of uncertainty
Negotiation	Discussions aimed at reaching agreement on which restoration alternative(s) is preferred to implement
Adaptive management	Feedback process of implementation, monitoring, and re-evaluation

General steps in environmental systems analysis to support resource management decision making using river restoration as an example

environmental systems situations, which requires stakeholder involvement, understanding the dynamics and dependencies of social and ecological factors, development of cause and effect models to evaluate systems, and cyclical group learning.

Two complementary concepts in environmental systems analysis are seldom specified in a general decision support process but are noteworthy advances to progress the field of ecological river restoration. First, the principle of Pareto efficiency claims that decisions to enact change cannot make one party better off without making others worse off. This classical economics concept was used by Koopmans (1951) to mathematically analyze multi-objective choice problems. This was an important milestone to grow the field of multi-objective optimization, and it enabled the expansion of integrated methods to perform concurrent mathematical operations on many disparate cause and effect models. Modern approaches to artificial intelligence have aided growth in this field. Today, computer systems can use algorithms or heuristics to efficiently search through the space of feasible management consequences (i.e., geometric hyperplane where multiple management objectives are mutually satisfied) to find a set of so-called Pareto-optimal or non-dominated management consequences.

Dominance is bound by the logic that alternatives can be compared to one another using analytical methods such that less desirable alternatives can be eliminated from the decision situation and, as a result, preferred options are identified. The term non-dominated is used to refer informally to the fact that there exists a set of alternative consequences that trade off the desired performance effects of the management objectives, in other words, there is no solution from which the heuristic optimization solver can move toward which performs better for all objectives. Fig. 1 gives a simple example of how the Pareto efficiency principle may be applied to river restoration for multi-objective watershed management via restoration.

An important purpose of Koopmans' translation of the Pareto efficiency principle was to influence the design of resource management alternatives mathematically based on problem dimensions (i.e., continuous space between the upper and lower bounds of the objectives and constraints) without requiring social value orientations from decision makers (Goicoechea et al., 1982). In this sense, decision makers are encouraged to be involved in developing analytical models for the management objectives, but they don't pre-constrain the problem to a degree that only a limited set of management alternatives are feasible. This is an important approach to difficult watershed management problems because in our experience decision makers want to be presented with many feasible tradeoffs that are workable within spatial, temporal, operational, and budgetary constraints of a system, and they may not know what those options are without the support of systematic analytical models and advanced computer programs.

The second advancement that complements the Pareto efficiency principle is tradeoff analysis, which aims to investigate the tradeoffs among management consequences to find preferred or better options for stakeholder negotiation and implementation. The well-established domain of methods for multi-criteria decision analysis (MCDA) is specialized to perform systematic tradeoff analyses based on comparing discrete non-dominated options. Belton and Stewart (2002) distinguish three broad categories of methods for MCDA that vary by how they perform tradeoff evaluations: valuation, interactive, and outranking. A distinct characteristic of methods for MCDA is they all allow measures of relative importance (i.e., weights) of management objectives to motivate the tradeoff analysis, which is largely based on stakeholder preference orientations and/or expert opinions.

Valuation methods like the simple multiattribute rating technique (Edwards, 1977) and the analytic hierarchy process (Saaty, 1990) develop a comparable measure of value for each viable alternative. Weighted average models are used to estimate a utility or value function for each alternative, and a dominance relationship is established where alternatives are either more valuable than others (i.e., utility function scores are different among the set) or are indifferent to others (i.e., utility function scores are the same among alternatives). In contrast to valuation methods, interactive or “satisficing” (Simon, 1956) methods like compromise programming (Zeleny, 1973) use heuristic procedures to rank options in order of their desirability. Instead of establishing a value function, it is believed that a dominance relationship can be established that satisfies the constraints of the problem or are good enough for decision making. A way to elucidate this information is by incorporating aspiration levels, defined as specific performance effect values associated with desired or acceptable levels of the management objectives, into the tradeoff analysis. These models enrich our understanding of the dominance relationships among management tradeoffs without transforming the meaning of each alternative into a value. Outranking methods are especially useful when the underlying complexities of the problem are poorly understood. Traditional outranking methods like ELECTRE (Figueira et al., 2013) compare alternatives in pairs with emphasis on strength of evidence that one alternative is preferred over another.

In this article, we propose to incorporate the Pareto efficiency and tradeoff analysis concepts into a decision framework for systematic river restoration planning. The proposed framework combines modern planning tools like heuristic optimization and MCDA to inform a decision making process that is employed prior to implementing restoration interventions. We review the progress of ecological restoration in the literature relative to the framework, and we elucidate its potential value to inform decision making with an illustration that draws on

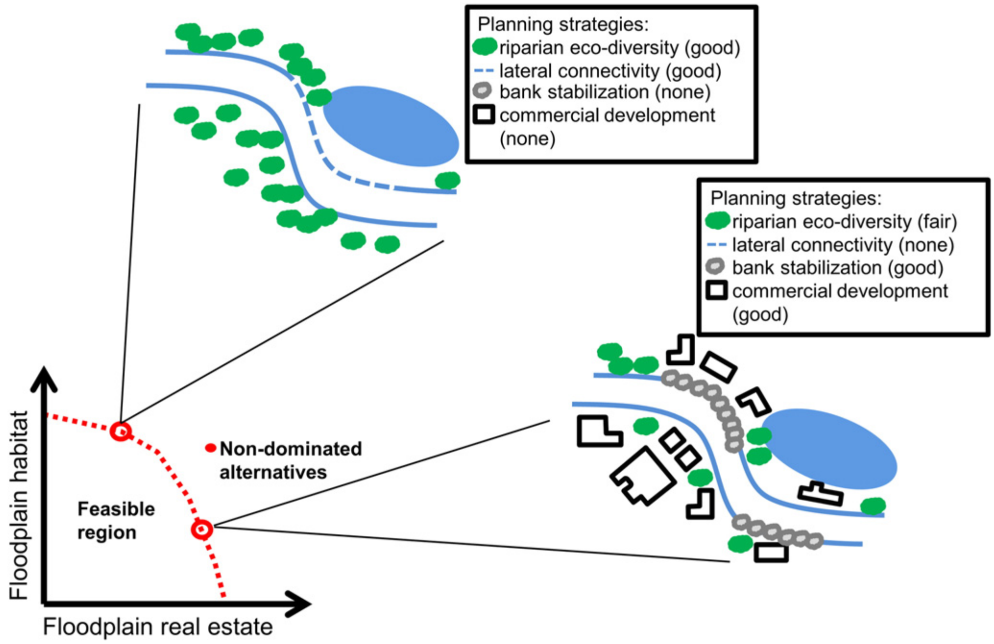

Fig. 1. Simple example of a Pareto efficiency graph. Restoration alternatives are points in the graph that trade off habitat and real estate performance values in river floodplains. The non-dominated alternatives are differentiated from the feasible set because they dominate others but not each other. Seeking a different non-dominated restoration alternative will yield a different set of strategies to improve one or more management objectives at a cost of decreasing the performance effects of others. Example configurations of two non-dominated restoration alternatives are shown in the diagrams. For other graphical examples in the field of watershed planning and management, see Null and Lund (2011); Herman et al. (2014), and Rheinheimer et al. (2015).

published work for spatial restoration planning in South East Queensland (SEQ), Australia (Hermoso et al., 2015).

2. Methodological Framework

A proposed decision framework for systematic river restoration planning is described as a process occurring in a social-scientific context with elements of hierarchical planning phases along with feedback loops (Fig. 2). In the agenda setting phase, stakeholders, facilitators, and environmental systems analysts convene to share ideas, perform a structured conceptual analysis of a local restoration decision situation, and to agree on planning goals. The group identifies important and measurable performance objectives that are linked to the area of interest. Possible land use types and parcel locations where restoration interventions may be implemented are identified to bound the planning context. This early phase is undoubtedly the most challenging because many

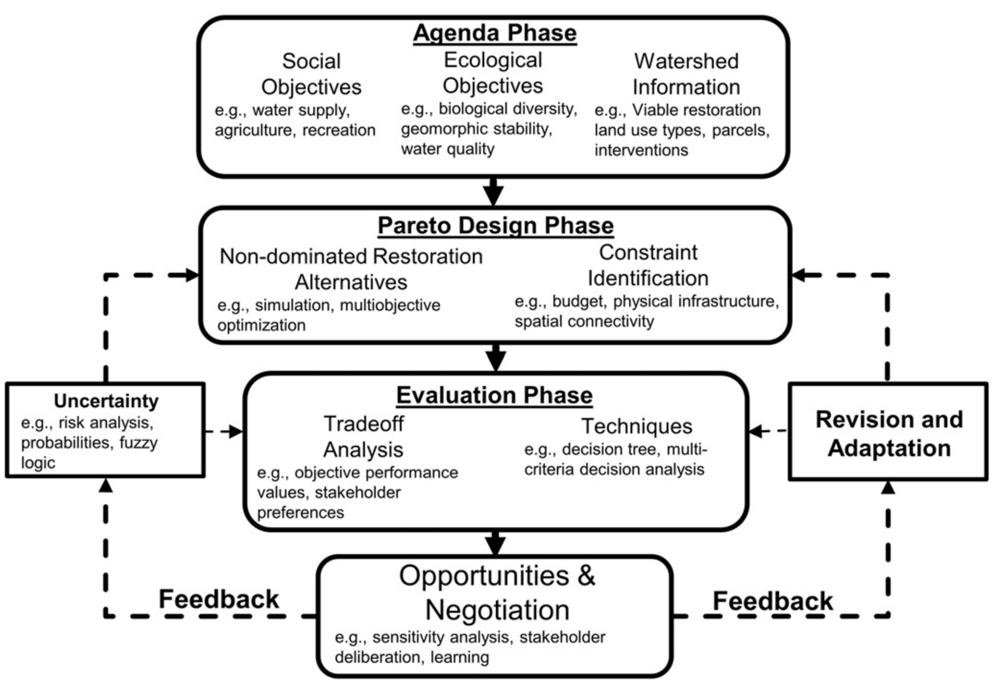

Fig. 2. Proposed conceptual decision support framework for systematic river restoration planning.

pre-planning decisions and focus group meetings are required to guide the development of scientific information, data, and models that may be used in later phases of the framework. Problem structuring techniques like DPSIR (Yee et al., 2015) help to guide this process.

The Pareto design phase is performed to systematically model non-dominated restoration alternatives. Predictive cause and effect modeling platforms for the restoration objectives are used to quantify potential hydro-ecological or other metric-related restoration responses (Reichert et al., 2007) based on implementing a restoration activity.

Traditionally, the development of non-dominated alternatives was performed with ad hoc methods. A popular method was to manually vary the problem parameters between upper and lower feasible objective performance effect values to unravel a non-dominated set of alternatives (David and Duckstein, 1976). A second popular method was to manually vary the vector of relative importance weights assigned to each objective (for an example using a combination of the two methods, see Goicoechea et al., 1976).

Quantitative derivation of non-dominated alternatives has become easier with modern computing. Metaheuristic optimization models (e.g., genetic algorithms, neural networks, simulated annealing) among other combinatorial simulation and optimization methods allow for many different linear or non-linear predictive models to be integrated as decision levers in iterative searches over numerous feasible objective performance combinations that each satisfies the problem constraints. By using these tools, a set of non-dominated alternatives may be converged for systematic watershed management (for reviews, see Labadie, 2004; Nicklow et al., 2010; Reed et al., 2013). Results are typically communicated in graphs that show the tradeoffs in economic-environment condition linked to each alternative that is kept from performing the iterative search procedure (Fig. 1).

The aim of the evaluation phase is to identify a sub-set of priority restoration alternatives that is transparent and meaningful for stakeholder deliberation. Here, MCDA and related procedures are performed on the measured outcomes from the Pareto design phase that filters the set of non-dominated restoration alternatives to a smaller, condensed short list of the most preferred alternatives that decision makers may deliberate among to make informed restoration decisions. The process may be performed as a preference-driven tradeoff analysis using stakeholder-derived or simulated relative importance weights inside a MCDA model, which skews the search for preferred alternatives. Alternatively, MCDA models may be used in a preference-neutral analysis with equal or no relative importance weights, which seeks preferred alternatives that effectively balance the management objectives. Without direct stakeholder interaction, performing a preference-neutral tradeoff analysis solely with the measured outcomes of the Pareto design phase (i.e., performance effect tradeoffs for each non-dominated alternative) is a more objective manner for prioritization. Many case studies have used these techniques for prioritizing sets of restoration options (see Table A.1; for a review of case studies in water resources management, see Hajkowicz and Collins, 2007) including the illustration presented in this article.

Understanding the opportunities for decision making and negotiating restoration implementation is a final step of our framework. This is loosely defined as an exercise of disseminating relevant results of the Pareto design and evaluation phases directly to stakeholders. New knowledge (i.e., sensitivity analysis, uncertainties, feedback) is incorporated via direct decision maker interaction so that the planning assessment can be improved in an adaptive learning cycle prior to on-the-ground restoration implementation. Many current river restoration case studies suffer from insufficient monitoring and lack of foresight for changing environmental indicators and adaptation planning (Bernhardt and Palmer, 2011), and it is beneficial to require sensitivity analyses that incorporate, for example, alternative measures of climate change uncertainty or financial risk (Herman et al., 2014) for predictive model development. The proposed framework aims to address foreseeable complications in the planning process by incorporating sensitivity information and allowing social preferences to be included prior to implementing restoration strategies.

3. Illustration of the Framework

We reviewed the progress of structured decision-making methods for ecological river restoration using the primary literature (Appendix A) and found that case studies incorporating Pareto design of restoration alternatives into objective MCDA and sensitivity tradeoff evaluations are rarely used in the field of restoration planning. Based on this, an illustration combining these steps of the framework was desired. To show the value of moving a restoration planning problem through the steps, agenda setting and Pareto design methods and results from a recently published article (Hermoso et al., 2015) were complemented with objective MCDA tradeoff evaluation and sensitivity analysis phases in the article herein. In this section, we describe this process and provide insights on how tradeoff information associated with many possible restoration alternatives may be used for stakeholder deliberation and policy implementation.

3.1. Study Area and Agenda Phase

The Hermoso et al. (2015) case study was performed in the upper Bremer River catchment, which is a tributary of the Brisbane River in SEQ, Australia (Fig. 3). Restoration is especially needed in this area given that SEQ is experiencing rapid population growth and subsequent modifications and impacts to freshwater ecosystems. Approximately two thirds of the native vegetation has been cleared since European

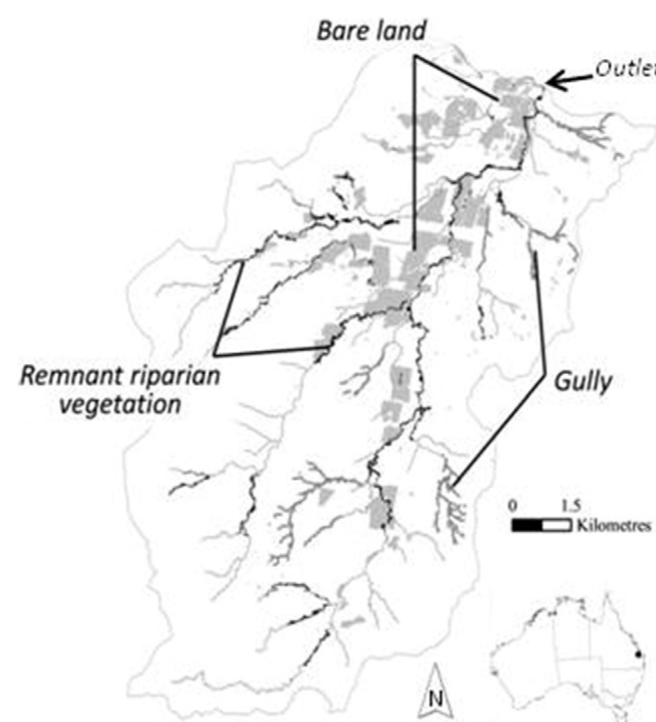

Fig. 3. Map of the upper Bremer River catchment. Many parcels of three land use types (bare land, gullies, remnant riparian) were identified for possible restoration strategies. (*Source:* Reprinted from Hermoso et al. (2015), with permission from Elsevier.).

settlement, and grazing currently occupies more than 35% of the region. Non-urban sediment loads, mainly from gully and channel bank erosion, have been identified as a cause of poor water quality and aquatic ecosystem health in freshwater and estuarine/marine systems of the region (Olley et al., 2014).

In the agenda phase of the planning project, three main objectives were determined for the catchment from a collaborative needs assessment with SEQ Healthy Waterways Partnership, a local not-for-profit organization which aims to improve the condition of regional waterways, and SEQ catchments, an entity that conducts rehabilitation work in the catchments and works closely with the local communities. The objectives pursued by the project are important for long-term socio-environmental system health and include: i) maximizing the reduction of sediment loads throughout the catchment, ii) maximizing ecological health of important catchment waterways, and iii) minimizing the socio-economic impact (i.e., commercial development) from locating restoration interventions on viable land use parcels (Fig.3) throughout the catchment. Details on how the restoration objectives and predictive models were developed are provided in Hermoso et al. (2015).

3.2. Pareto Design Phase

An iterative Pareto selection method called multi-objective simulated annealing (MOSA) was used to iterate multiple combinations of restoration interventions on catchment parcels. Each feasible restoration alternative tested during the MOSA procedure computed a unique combination of interventions (type and level) and their spatial allocation on pre-determined land use parcels throughout the catchment, measured the predicted restoration response of an objective at the parcel, and routed the cumulative (i.e., additive) responses from each parcel through the linked catchment network to the outlet where a single downstream response for each objective was estimated. The process filtered out non-dominated restoration candidates within given constraints (e.g., budget, landholder willingness), where the cumulative restoration response values or tradeoffs of objectives associated with one alternative are compared to alternatives developed at previous iterations to check that they are not better or worse than others. For demonstration purposes, all potential restoration alternatives were constrained to a maximum budget of AUD $1 Million to maintain a realistic budget.

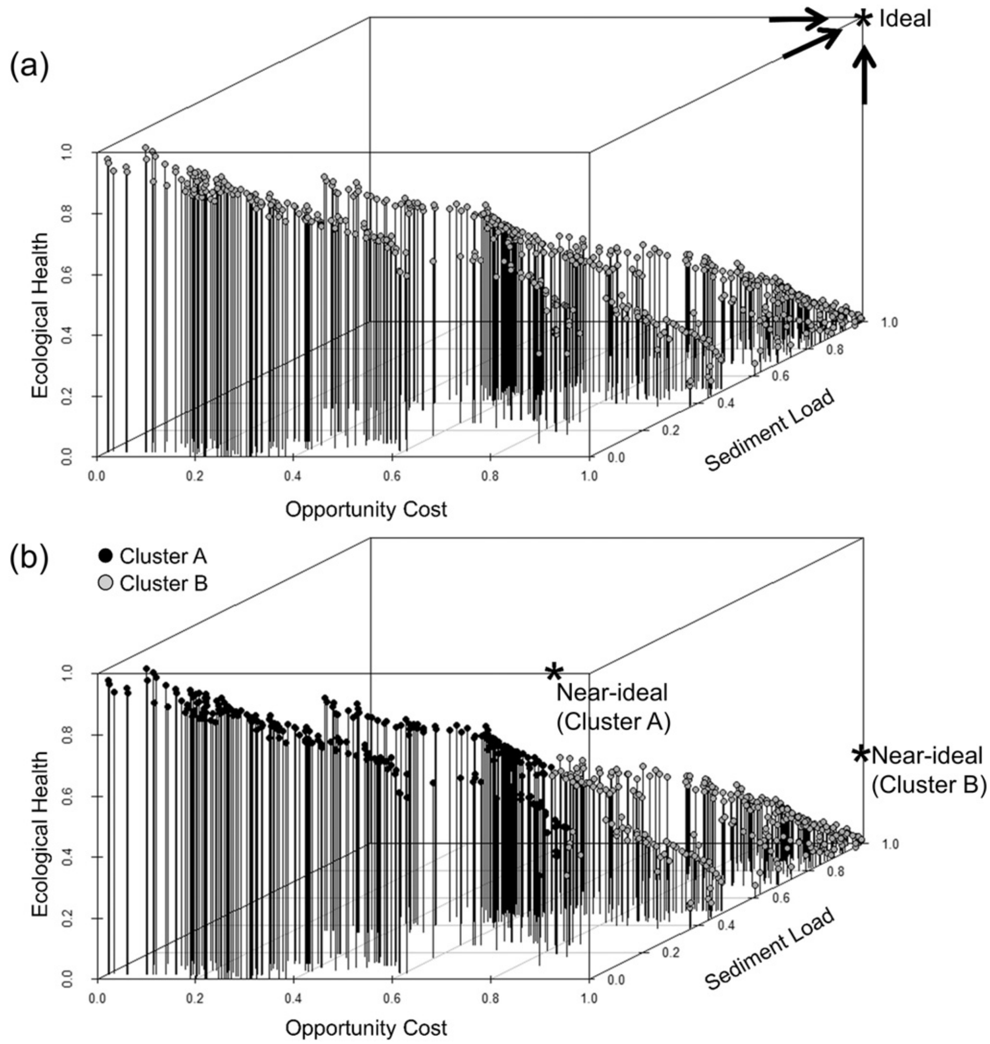

Fig. 4. Non-dominated restoration alternatives for the upper Bremer River catchment as optimized by Hermoso et al. (2015). Each point corresponds to a unique set of spatially-distributed restoration interventions throughout the catchment. The cumulative objective performance effects have been scaled to 0–1 based on a fuzzy distance metric (linearly scaled data shown; see Fig. 5a). Fuzzy compromise programming was performed on the complete set of alternatives based on the closeness of a point to an ideal but non-feasible reference point in multi-dimensional coordinate space (a) (Section 3.3). Two clusters were developed to establish complementary sub-sets of restoration alternatives that traded off cumulative benefits in the objectives, and a similar fuzzy compromise programming approach was performed on the clusters through specification of near-ideal reference points (b) (Section 3.4).

The MOSA process resulted in evaluating tens of thousands of feasible scenarios. For each scenario, a convergence graph was generated based on the proximity of the solutions within the feasible set. The annealing process tended to converge as the number of iterations increased, and indicated that a set of 566 non-dominated restoration alternatives were found (Fig. 4; scaled data shown) (Hermoso et al., 2015). Each alternative that was kept recorded a different spatially-distributed set of restoration interventions at relevant land use parcels throughout the catchment. The spatial location of interventions for each alternative was logged for future stakeholder deliberation (i.e., spatial analysis). The cumulative response of the alternatives in the catchment traded off sediment load values with ecological health values. Restoration interventions to improve ecological health throughout the catchment resulted in a higher socio-economic impact on the productivity of un-restored land use.

The conflicting tradeoff between sediment load and ecological health (Fig. 4) was a result of pre-determining suitable implementation strategies for the objectives in the catchment (Hermoso et al., 2015). It is unclear whether long-term data and future MOSA iterations would change these inverse relationships, but the ecological sciences inform that sediment loads may have a more positive relationship with instream ecological health indices over the long-term (Wohl et al., 2015).

3.3. Evaluation Phase

The set of non-dominated restoration alternatives is too large for a meaningful tradeoff evaluation using the outranking methods for MCDA. Likewise, stakeholder values were not directly involved in this case study illustration, and we refrained from establishing utility or value functions for the alternatives. Therefore, we determined that an interactive MCDA method for fuzzy compromise programming (FCP) (Bender and Simonovic, 2000) was the most appropriate tradeoff evaluation tool. We used FCP in conjunction with an objective cluster analysis to rank the set of non-dominated tradeoffs from the MOSA results. The original compromise programming method (Zeleny, 1973) was based on visualizing non-dominated alternatives as a multi-dimensional dataset and finding points with objective performance values as close as possible to an ideal but non-feasible reference point. The ideal point is generally considered to be the best achievable value for each management objective in the non-dominated set. In the case study, this is equivalent to seeking to maximize ecological health, minimize sediment loads, and minimize opportunity cost.

The FCP algorithm uses the family of distance metrics L^p to rank the multi-dimensional dataset of alternatives a_i with objective performance values z_j. The following problem formulation was used to rank the alternatives:

$$\text{minimize } L^p(i) = \sum_{j=1}^{m} w_j^p \left| \frac{z_j^* - z_j(a_i)}{z_j^* - z_j^{**}} \right|^p \tag{3.1}$$

for alternatives $i = 1,\ldots,n$; objectives $j = 1,\ldots,m$

where p is a distance norm; w_j is the relative importance weight of the objective; z_j is the objective value of *ith* alternative; z_j^* is the highest achievable objective value; and z_j^{**} is the lowest possible objective value. The Euclidean or least squares distance norm ($p = 2$) was preferred because we wanted the deviations from ideal to be weighted in proportion to their magnitudes.

3.4. Sensitivity Analysis

We performed a sensitivity analysis based on development of two decision viewpoints: i) a preference-neutral evaluation based on performing FCP ranking on two fuzzy sets of the non-dominated alternatives, and ii) an analysis based on clustering the fuzzy sets and performing FCP ranking on each cluster.

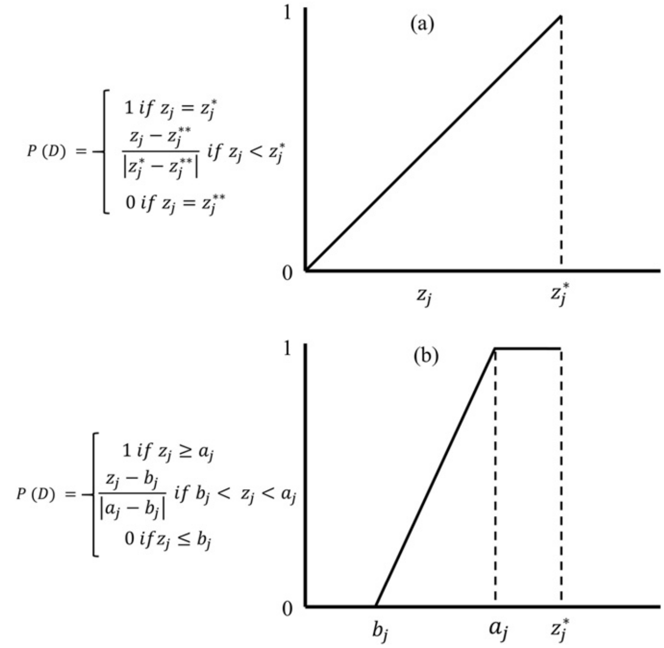

Fig. 5. Fuzzy distance metrics used in the case study illustration. A linear fuzzy set of membership function values was calculated by scaling the raw objective performance values based on normalized distance measures (a). A z-shaped fuzzy set was calculated based on simulating stakeholder aspiration levels for the objective performance values in the catchment (b), which incorporated more uncertainty into the evaluation.

3.4.1. Establishing Two Fuzzy Sets Through Aspiration Levels

The raw multi-dimensional dataset of objective performance values was scaled into two fuzzy sets of numbers for two reasons. First, the ecological health values were less differentiated than the other objectives from the MOSA results (Hermoso et al., 2015). Second, it was desirable to incorporate varying aspiration levels as they related to satisfactory watershed management. The first fuzzy set was developed using normalized distance measures that linearly scaled each raw objective performance value into a fuzzy membership function $P(D)$ between 0 and 1 (Fig. 5a). The scaled data represented the proportion of the highest achievable cumulative objective response in the catchment and maintained differentiation. With this linear fuzzy set, we presumed that decision makers want to set baseline aspirations for ranking alternatives that balance the highest ecological health value, lowest sediment load value, and lowest opportunity cost value.

The second z-shaped fuzzy set was calculated based on simulating different hypothetical stakeholder aspiration levels for the objective performance values in the catchment (Fig. 5b). Here, we presumed that stakeholders do not expect to attain the highest achievable performance outcome with the restoration strategies. Rather, they may agree on different aspiration levels for the restoration objectives based on expert knowledge of the watershed and on investigating the MOSA results. To illustrate, catchment sediment loads for the non-dominated alternatives varied between 5322 tons/yr (lowest) and 2729 tons/yr (ideal) (Hermoso et al., 2015). Two indifference thresholds were specified for sediment where a cumulative load of 3000 tons/yr or less was determined to be the aspiration level (a), loads above 4500 tons/yr were determined undesirable (b), and loads in-between were linearly normalized based on their distances from these values. Similar determinations were made to ecological health ($a = 49.26$ units, $b =$ 48.765 units) and opportunity cost ($a = AUD\ \$100,000, b =$

AUD $500,000). Setting these aspiration levels effectively incorporates more uncertainty into the evaluation.

3.4.2. Ranking the Two Fuzzy Sets

The first ranking of each fuzzy set was performed using equal importance weights, which yielded a preference-neutral decision viewpoint among the 566 non-dominated restoration alternatives. The ideal reference point to compute a preference-neutral ranking for both fuzzy sets is equivalent to coordinate 1,1,1 in Fig. 4a. To provide a different decision viewpoint, the two fuzzy sets were clustered by using the K-means clustering algorithm (MacQueen, 1967). K-means was used to organize the scaled data into clusters based on minimizing the squared difference between the empirical mean of each cluster and the alternatives inside the cluster. The dataset depicted two distinct regions of restoration tradeoffs: i) a region of alternatives with better ecological health values but less favorable sediment load and opportunity cost values, and ii) a region of alternatives with better sediment load and opportunity cost values, and less favorable ecological health values (Fig. 4b). Based on this, two clusters were specified with the aim of providing competing sets of restoration options for stakeholder deliberation.

After performing the cluster analysis, Linear Cluster A (shown in Fig. 4b) included 278 restoration alternatives and z-shaped Cluster A (results not presented) included 291 alternatives with better ecological health values but poor sediment load values throughout the catchment, and they incurred the highest opportunity costs for commercial land development on the parcels chosen for each alternative. By contrast, Linear Cluster B (shown in Fig. 4b) included 288 alternatives and z-shaped Cluster B (results not presented) included 275 alternatives that represented the lowest catchment sediment loads and low opportunity costs but poor ecological health values. FCP iterations were performed on the four clusters of scaled alternatives with characteristically similar tradeoffs in the objectives. Sensitivity iterations performed on the clusters had different z_j^* and z_j^{**} values and, as a result, different near-ideal reference points were used for ranking each cluster (Fig. 4b).

3.5. Opportunities for Decision Maker Negotiation

The highest ranked plans for each FCP iteration are considered priorities for decision maker negotiation (Tables 1–2; top 8 plans shown). Important information can be gleaned from investigating the tradeoffs among the highest ranked plans, which provides useful information to deliver to stakeholders for negotiating the choice, implementation, and monitoring of specific restoration interventions. Therefore, the following limited discussion is meant to communicate the distinctions made between the tradeoffs in the highest ranked restoration alternatives using Tables 1–2.

Upon inspection of the preference-neutral results for both fuzzy sets, we determined that the top two ranked restoration alternatives, numbered 185 and 186 in Tables 1–2, are equally important priorities to catchment restoration that decision makers should deliberate among. We make this determination for several reasons. First, they are comparable options of different spatial distributions of interventions on different land use parcels. Both alternatives reduce sediment loads throughout the catchment equally. The highest ranked alternative provides a lower opportunity cost than the second highest ranked. However, the difference in ecological health scores between these two is the cause of the FCP algorithm ranking one alternative slightly higher than the other. Since the tradeoffs were too close to determine which alternative was better, we determined that both are equally important priorities that decision makers should use in deliberation. This trend does not follow to the third ranked alternative, 226 in Table 1 and 187 in Table 2, because the tradeoffs among the restoration objectives become more distinct. Considering the tradeoffs further would infer that sediment load or opportunity cost was more important in the catchment than ecological health and would be a disservice to this preference-neutral sensitivity evaluation.

Regarding viewpoints toward improved ecological health (Cluster A) and sediment load reduction (Cluster B), distinctions in the tradeoffs are apparent after the first two or three alternatives in the ranking. For example, the second ranked alternative in Linear Cluster B, numbered 217 in Table 1, is considered a priority alongside the highest ranked alternative, 216, because it reduced opportunity cost in slight proportion to the loss in ecological health in the catchment. Tradeoffs in the next ranked alternatives were more distinct, yielding significantly lower sediment loads and opportunity costs while benefiting ecological health values in the catchment. Since Cluster B alternatives are directed toward reducing sediment load and opportunity cost, these ranked alternatives are likely undesirable candidates for decision maker deliberation in this context. To summarize the results from the sensitivity analysis on the clusters, we determined that two restoration alternatives, 419 and 296, were the preferred compromises for implementing restoration interventions that may improve ecological health and, in contrast, reduce sediment loads because they ranked highly for both fuzzy sets.

This limited tradeoff evaluation is a key step in our framework and the broader systematic planning process. By reducing the large number of non-dominated alternatives to a sub-set of two or three preferred alternatives using the FCP process, advantageous information may be provided for post-hoc project-specific deliberation, raw data evaluation, and spatial analysis of the alternatives by decision makers. To caveat the illustration, this tradeoff evaluation was performed without stakeholder-assigned measures

Table 1
Top 8 ranked restoration alternatives based on linear fuzzy membership values are displayed from each sensitivity FCP iteration.

	Linear (preference-neutral)				Linear Cluster A (better options for ecological health improvement)				Linear Cluster B (better options for sediment load & opportunity cost reduction)			
Rank	Alternative	Sediment load	Ecological health	Opportunity cost	Alternative	Sediment load	Ecological health	Opportunity cost	Alternative	Sediment load	Ecological health	Opportunity cost
1	185	0.73	0.37	0.70	460	0.42	0.61	0.55	216	0.80	0.25	0.86
2	186	0.73	0.36	0.73	459	0.42	0.60	0.57	217	0.80	0.24	0.87
3	226	0.78	0.32	0.77	419	0.52	0.60	0.50	296	0.74	0.31	0.82
4	187	0.73	0.35	0.74	442	0.46	0.63	0.47	295	0.74	0.28	0.84
5	221	0.74	0.33	0.75	342	0.41	0.63	0.51	218	0.77	0.27	0.84
6	298	0.74	0.32	0.79	461	0.42	0.59	0.57	294	0.74	0.25	0.86
7	296	0.74	0.31	0.82	421	0.52	0.59	0.51	231	0.80	0.23	0.87
8	227	0.78	0.31	0.77	332	0.43	0.60	0.53	203	0.86	0.25	0.82

Scaled values are a proportion of the highest achievable in the set and, therefore, values closer to unity (1) offer better restoration benefits for the objectives.

Table 2
Top 8 ranked restoration alternatives based on z-shaped fuzzy membership values are displayed from each sensitivity FCP iteration.

Rank	z-Shaped (preference-neutral)				z-Shaped Cluster A (better options for ecological health improvement)				z-Shaped Cluster B (better options for sediment load & opportunity cost reduction)			
	Alternative	Sediment load	Ecological health	Opportunity cost	Alternative	Sediment load	Ecological health	Opportunity cost	Alternative	Sediment load	Ecological health	Opportunity cost
1	185	0.72	0.41	0.84	419	0.35	0.76	0.57	226	0.80	0.33	0.93
2	186	0.72	0.40	0.87	421	0.35	0.74	0.57	298	0.72	0.33	0.96
3	187	0.72	0.37	0.89	420	0.35	0.72	0.57	308	0.82	0.29	0.97
4	226	0.80	0.33	0.93	422	0.35	0.70	0.59	296	0.72	0.31	1
5	178	0.73	0.39	0.76	486	0.38	0.73	0.50	227	0.80	0.31	0.93
6	221	0.73	0.35	0.90	423	0.35	0.68	0.60	291	0.73	0.31	0.96
7	429	0.58	0.49	0.73	487	0.37	0.70	0.54	214	0.84	0.27	0.97
8	190	0.74	0.35	0.85	424	0.34	0.66	0.63	307	0.82	0.27	0.99

Values closer to unity (1) offer better restoration benefits for the objectives.

of relative importance, which makes our results more objective than ones that assign weights to the management objectives.

4. Future Research Directions

In this article, we developed a theoretical and methodological foundation for the systematic design and objective evaluation of non-dominated alternatives for ecological river restoration planning. Following a goal of incorporating empirical ecological and socio-economic research and models into multidisciplinary decision support methods, the proposed decision framework (Fig. 2) and illustration described in this article can be used as a template for systematic river restoration planning around the world. We expect the framework to inspire multi-objective ecological river restoration studies that aim to deliver technical but transparent planning materials to decision makers regarding the design and evaluation of economic-environment restoration tradeoffs.

The raw information on the non-dominated restoration alternatives and the spatial locations of restoration actions for each alternative could have been delivered to the stakeholders who contracted the work performed in Hermoso et al. (2015). However, this would have complicated the selection of alternatives because the design model converged on 566 different restoration options. Yet we provided a transparent and objective evaluation of the information with development of an approach for combining Pareto design with formal MCDA tradeoff evaluation using the proposed decision framework. In effect, we organized and filtered the tradeoffs so that stakeholders can deliberate among the most preferred (i.e., top two or three highest rank) options to make more balanced restoration decisions at the catchment scale. Although the opportunities and negotiation phase of the framework was performed without direct stakeholder interaction, the methods and sensitivity analysis presented herein are useful for carrying out similar decision support processes on other restoration planning problems in a systematic and objective manner, and to deliver those results for post-hoc stakeholder negotiations.

The illustration is an example of how the described framework may be used and it worked well because a related case study was previously performed in Hermoso et al. (2015) with sufficient data and published predictive models for the restoration objectives. If data availability is a limitation, appropriate measures for uncertainty should be incorporated so that all relevant objectives are included prior to the analysis (Failing et al., 2013). Predictive models that use ecological process-based inputs and parameter estimates will guide science-based restoration and accordingly inject defensible ecological understanding into the decision making process. Stakeholder preferences on the design model parameter estimates were incorporated in the case study described (Hermoso et al., 2015), but not in the tradeoffs evaluation. Changing economic-environment indicators were not simulated in the predictive models because catchment-specific information was not available. Incorporation of these measures into the described framework may be important to the emerging field of multi-objective robust decision making (Herman et al., 2014).

Including a cluster analysis in the sensitivity iterations worked well for the case study illustration because the dataset was highly correlated (Fig. 4). We aimed to provide an alternative decision viewpoint for decision maker deliberation, but cluster analysis is not a requirement to follow the proposed decision framework. A similar method has been performed on a number of published datasets of non-dominated alternatives (Martin, 2015), which concluded that additional multivariate techniques are required to sort through complex multi-dimensional datasets. Likewise, specification of clusters may be difficult for problems of high dimensionality. In decision situations, seeking clusters is dependent on stakeholders having to consider competing sets of objectives (in our case: ecological health vs. sediment load benefits). It was believed that identifying more clusters would weaken this assumption and would likely confuse stakeholder deliberations.

The effectiveness of implementing restoration alternatives is beyond the scope of the article. In general, we aimed to provide a short list of preferred restoration alternatives as deliberation points prior to implementing restoration interventions. Systematic procedures to review the details of preferred restoration alternatives for compliance risks (Thorne et al., 2015) may be of interest to state or federal agencies to guide on-the-ground implementation and adaptive management.

Disclaimer

The research described herein was co-developed by DMM, an employee of the U.S. Environmental Protection Agency (EPA), on his own time. It was conducted independently of EPA employment and has not been subjected to the Agency's peer and administrative review. Therefore, the conclusions and opinions drawn are solely those of the author(s) and are not necessarily the views of the Agency.

Acknowledgments

This article was supported by the National Science Foundation IGERT Grant No. DGE-0966346 (DMM), The Queensland government, the SEQ Healthy Waterways Partnership, SEQ catchments, the eWater Cooperative Research Centre, the Ramon y Cajal fellowship RYC-2013-13979 (VH) and by ARC DECRA DE130100565 (SL). We thank one anonymous referee and the editor(s) who reviewed the manuscript.

Appendix A. Literature Review Relative to the Proposed Framework

We screened many river restoration planning applications relative to the described framework. We chose to include published studies that directly evaluated discrete restoration alternatives in a decision making context that aimed to examine competing social and ecological restoration objectives and tradeoffs. This significantly reduced the amount of case studies to analyze. Table A.1 indicates that incorporating systematic Pareto design phases (i.e., no ad hoc design of restoration alternatives) into formal MCDA tradeoff evaluation phases are rarely used for the advancement of systematic river restoration planning.

Table A.1
Survey of river restoration planning framework.

Decision situation	Agenda phase	Pareto design	Tradeoff evaluation	Sensitivity analysis	Comments	Citation
Four riparian re-vegetation options are developed and prioritized from several stakeholder groups of north Queensland, Australia	X	X	X	X	- Pareto efficient restoration alternatives were designed ad hoc - Sensitivity analysis was based on incorporating three MCDA methods into a tradeoff evaluation based on independent preferences from each stakeholder group and comparing the results	Qureshi and Harrison (2001)
Prioritization of basins and sub-basins based on qualitative and quantitative features within Zuni Reservation, New Mexico (USA)		X	X	X	- Restoration alternatives appeared to be Pareto efficient (though maximizing agent for watershed objectives was not specified) - Sensitivity analysis was based on incorporating stakeholder-assigned weights into a general weighted average MCDA analysis	Gellis et al. (2001)
Five alternative water allocation options to restore fish and wildlife habitat in the Missouri River system (USA) were prioritized using valuation methods		X	X	X	- Pareto efficient restoration alternatives were designed ad hoc - Sensitivity analysis was based on incorporating hypothetical stakeholder weights into a MCDA analysis	Prato (2003)
Five river restoration options on a reach of the Thur River (Switzerland) were evaluated with value-based stakeholder decision analysis		X	X	X	- Pareto efficient restoration alternatives were designed ad hoc - Sensitivity analysis included performing structured stakeholder preference surveys	Hostmann et al. (2005)
Stakeholder negotiation process to improve water management along a river reach in the White River Watershed, Vermont (USA)	X	X	X		- Pareto efficient restoration alternatives were designed ad hoc - Tradeoff evaluation included ranking the restoration alternatives based on individual and group stakeholder preferences for the management objectives	Hermans et al. (2007)
Development of tradeoffs associated with fish recruitment economic cost applied to water allocations in the Shasta River system, California (USA)		X			- Pareto efficient restoration alternatives were designed with multi-objective optimization algorithm - No formal tradeoff evaluation	Null and Lund (2011)
Case study approach in Victoria, Australia, for applying multi-objective optimization to develop water allocation schedules for benefitting irrigation and instream ecological function		X			- Pareto efficient restoration alternatives were designed with multi-objective optimization software - No formal tradeoff evaluation	Powell et al. (2013)
Experimental decision making process for flow-based habitat restoration on Lower Bridge River,	X	X			- Superior description of stakeholder planning process - Restoration alternatives appeared to be Pareto efficient (though objective performance values were not listed for each alternative) - Pareto efficient restoration alternatives were designed ad hoc - Deliberative (i.e., non-structured) stakeholder evaluation of restoration alternatives was performed	Failing et al. (2013)
Case study approach in South East Queensland, Australia, for apply multi-objective optimization to develop socio-environmental restoration planning strategies whole catchments.	X	X			- Pareto efficient restoration alternatives were designed with multi-objective optimization algorithm - No formal tradeoff evaluation	Hermoso et al. (2015)

References

Beechie, T.J., Sear, D.A., Olden, J.D., Pess, G.R., Buffington, J.M., Moir, H., Roni, P., Pollock, M.M., 2010. Process-based principles for restoring river ecosystems. Bioscience 60, 209–222.

Belton, V., Stewart, T.J., 2002. Multiple Criteria Decision Analysis: An Integrated Approach. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Bender, M.J., Simonovic, S.P., 2000. A fuzzy compromise approach to water resource systems planning under uncertainty. Fuzzy Set. Syst. 115, 35–44.

Bernhardt, E.S., Palmer, M.A., 2011. River restoration: the fuzzy logic of repairing reaches to reverse catchment scale degradation. Ecol. Appl. 21, 1926–1931.

Bernhardt, E.S., Palmer, M.A., Allan, J.D., Alexander, G., Barnas, K., Brooks, S., Carr, J., Clayton, S., Dahm, C., Follstad-Shah, J., Galat, D., Gloss, S., Goodwin, P., Hart, D., Hassett, B., Jenkinson, R., Katz, S., Kondolf, G.M., Lake, P.S., Lave, R., Meyer, J.L., O'Donnell, T.K., Pagano, L., Powell, B., Sudduth, E., 2005. Synthesizing U. S. river restoration efforts. Science 308, 636–637.

Binder, C.R., Hinkel, J., Bots, P.W.G., Pahl-Wostl, C., 2013. Comparison of frameworks for analyzing social-ecological systems. Ecol. Soc. 18, 26.

Brooks, S.S., Lake, P.S., 2007. River restoration in Victoria, Australia: change is in the wind, and none too soon. Restor. Ecol. 15, 584–591.

David, L., Duckstein, L., 1976. Multi-criterion ranking of alternative long-range water resource systems. Water Resour. Bull. 12, 731–754.

Edwards, W., 1977. How to use multiattribute utility measurement for social decisionmaking. IEEE Trans. Syst. Man Cybern. 7, 326–340.

Failing, L., Gregory, R., Higgins, P., 2013. Science, uncertainty, and values in ecological restoration: a case study in structured decision-making and adaptive management. Restor. Ecol. 21, 422–430.

Figueira, J.R., Greco, S., Roy, B., Slowinski, R., 2013. An overview of ELECTRE methods and their recent extensions. J. Multi-Criteria Decis. Anal. 20, 61–85.

Gellis, A.C., Cheama, A., Lalio, S.M., 2001. Developing a geomorphic approach for ranking watershed for rehabilitation, Zuni Indian Reservation, New Mexico. Geomorphology 37, 105–134.

Goicoechea, A., Duckstein, L., Fogel, M.M., 1976. Multi-objective programming in watershed management: a case study of the Charleston watershed. Water Resour. Res. 12, 1085–1092.
Goicoechea, A., Hansen, D.R., Duckstein, L., 1982. Multi-Objective Decision Analysis with Engineering and Business Applications. John Wiley & Sons, New York.
Hajkowicz, S., Collins, K., 2007. A review of multiple criteria analysis for water resources planning and management. Water Resour. Manag. 21, 1553–1566.
Herman, J.D., Harrison, B.A., Reed, P.M., Characklis, G.W., 2014. Beyond optimality: multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty. Water Resour. Res. http://dx.doi.org/10.1002/2014WR015338.
Hermans, C., Erickson, J., Noordewier, T., Sheldon, A., Kline, M., 2007. Collaborative environmental planning in river management: an application of multicriteria decision analysis in the white river watershed in Vermont. J. Environ. Manage. 84, 534–546.
Hermoso, V., Pantus, F., Olley, J., Linke, S., Mugodo, J., Lea, P., 2012. Systematic planning for river rehabilitation: integrating multiple ecological and economic objectives in complex decisions. Freshw. Biol. 57, 1–9.
Hermoso, V., Pantus, F., Olley, J., Linke, S., Mugodo, J., Lea, P., 2015. Prioritising catchment rehabilitation for multi objective management: an application from SE-Queensland, Australia. Ecol. Model. 316, 168–175.
Hostmann, M., Bernauer, T., Mosler, H.J., Reichert, P., Truffer, B., 2005. Multi-criteria value theory as a framework for conflict resolution in river rehabilitation. J. Multi-Criteria Decis. Anal. 13, 91–102.
Koopmans, T.C., 1951. Analysis of production as an efficient combination of activities. In: Koopmans, T.C. (Ed.), Cowles Commission for Research in EconomicsMonograph No. 13. John Wiley & Sons, Inc., New York, pp. 33–97.
Labadie, J.W., 2004. Optimal operation of multireservoir systems: state-of-the-art review. J. Water Resour. Plan. Manag. 130, 93–111.
Lake, P.S., Bond, N., Reich, P., 2007. Linking ecological theory with stream restoration. Freshw. Biol. 52, 597–615.
MacQueen, J., 1967. Some methods for classification and analysis of multivariate observations. In: Lecam, L., Neyman, J. (Eds.), Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability. University of California Press, California, pp. 281–297.
Martin, D.M., 2015. Socio-Environmental Tradeoff Analysis Using Decision Science Tools to Guide River Management (PhD dissertation) Colorado State University 146 pages. (Publication No. ProQuest 3746121).
Munda, G., Nijkamp, P., Rietveld, P., 1994. Qualitative multicriteria evaluation for environmental management. Ecol. Econ. 10, 97–112.
Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A., Karamouz, M., Minsker, B., Ostfeld, A., Singh, A., Zechman, E., 2010. State of the art for genetic algorithms and beyond in water resources planning and management. J. Water Resour. Plan. Manag. 136, 412–432.
Null, S.E., Lund, J.R., 2011. Fish habitat optimization to prioritize river restoration decisions. River Res. Appl. 28, 1378–1393.
Olley, J., Burton, J., Hermoso, V., Smolders, K., McMahon, J., Thomson, B., Watkinson, A., 2014. Remnant riparian vegetation, sediment and nutrient loads, and river rehabilitation in subtropical Australia. Hydrol. Process. 29, 2290–2300.
Palmer, M.A., Bernhardt, E.S., Allan, J.D., Lake, P.S., Alexander, G., Brooks, S., Carr, J., Clayton, S., Dahm, C.N., Follstad Shah, J., Galat, D.L., Loss, S.G., Goodwin, P., Hart, D.D., Hassett, B., Jenkinson, R., Kondolf, G.M., Lave, R., Meyer, J.L., O'Donnell, T.K., Pagano, L., Sudduth, E., 2005. Standards for ecologically successful river restoration. J. Appl. Ecol. 42, 208–217.
Palmer, M.A., Menninger, H., Bernhardt, E., 2010. River restoration, habitat heterogeneity and biodiversity: a failure of theory or practice? Freshw. Biol. 55 (Suppl. 1), 205–222.
Palmer, M.A., Hondula, K.L., Koch, B.J., 2014. Ecological restoration of streams and rivers: shifting strategies and shifting goals. Annu. Rev. Ecol. Evol. Syst. 45, 247–269.
Powell, S.J., Nichols, S.J., Webb, J.A., Adams, G., de Little, S.C., Dyack, B., 2013. Optimising flow management for ecological response and consumptive use. In: Piantadosi, J., Anderssen, R.S., Boland, J. (Eds.), MODSIM2013, 20th International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, December 13, Adelaide, Australia (http://www.mssanz.org.au/modsim2013/H12/powell.pdf, Accessed 5 June 2015).
Prato, T., 2003. Multi-criteria evaluation of ecosystem management for the Missouri River system. Ecol. Econ. 45, 297–309.
Qureshi, M.E., Harrison, S.R., 2001. A decision support process to compare riparian revegetation options in scheu creek catchment in north queensland. J. Environ. Manage. 62, 101–112.
Reed, P.M., Hadka, D., Herman, J.D., Kasprzyk, J.R., Kollat, J.B., 2013. Evolutionary multiobjective optimization in water resources: the past, present and future. Adv. Water Resour. 51, 438–456.
Reichert, P., Borsuk, M., Hostmann, M., Schweizer, S., Sporri, C., Tockner, K., Truffer, B., 2007. Concepts of decision support for river rehabilitation. Environ. Model. Software 22, 188–201.
Rheinheimer, D.E., Liu, P., Guo, S., 2015. Re-operating the Three Gorges reservoir for environmental flows: a preliminary assessment of tradeoffs. River Res. Appl. http://dx.doi.org/10.1002/rra.2866.
Rittel, H.W.J., Webber, M.M., 1973. Dilemmas in a general theory of planning. Pol. Sci. 4, 155–169.
Roni, P., Hanson, K., Beechie, T., 2008. Global review of the physical and biological effectiveness of stream habitat rehabilitation techniques. N. Am. J. Fish Manag. 28, 856–890.
Saaty, T.L., 1990. How to make a decision: the analytic hierarchy process. Eur. J. Oper. Res. 48, 9–26.
Simon, H.A., 1956. Rational choice and the structure of the environment. Psychol. Rev. 63, 129–138.
Strayer, D.L., Dudgeon, D., 2010. Freshwater biodiversity conservation: recent progress and future challenges. J. N. Am. Benthol. Soc. 29, 344–358.
Thorne, C., Castro, J., Cluer, B., Skidmore, P., Shea, C., 2015. Project risk screening matrix for river management and restoration. River Res. Appl. 31, 611–662.
US National Research Council, 1992. Restoration of Aquatic Ecosystems: Science, Technology, and Public Policy. The National Academies Press, Washington, D.C.
Wohl, E., Angermeier, P.L., Bledsoe, B., Kondolf, G.M., MacDonnell, L., Merritt, D.M., Palmer, M.A., Poff, N.L., Tarboton, D., 2005. River restoration. Water Resour. Res. http://dx.doi.org/10.1029/2005WR003985.
Wohl, E., Bledsoe, B.P., Jacobson, R.B., Poff, N.L., Rathburn, S.L., Walters, D.M., Wilcox, A.C., 2015. The natural sediment regime in rivers: broadening the foundation for ecosystem management. Bioscience 65, 358–371.
Yee, S.H., Carriger, J.F., Bradley, P., Fisher, W.S., Dyson, B., 2015. Developing scientific information to support decisions for sustainable coral reef ecosystem services. Ecol. Econ. 115, 39–50.
Zeleny, M., 1973. Compromise programming. In: Cochrane, J., Zeleny, M. (Eds.), Multiple Criteria Decision Making. University of South Carolina Press, South Carolina, pp. 262–301.