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Non-monetary valuation using Multi-Criteria Decision Analysis: Using a strength-of-evidence approach to inform choices among alternatives

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ABSTRACT

This article demonstrates an approach to Multi-Criteria Decision Analysis that compares non-monetary ecosystem service (ES) outcomes for environmental decision making. ES outcomes are often inadequately defined and characterized by imprecision and uncertainty. Outranking methods enrich our understanding of the imperfect knowledge of ES outcomes by allowing decision makers to closely examine and apply preference measures to relationships among the outcomes. We explain the methodological assumptions related to the PROMETHEE methods (Preference Ranking Organization METHod for Enrichment Evaluation), and apply them to a wetland restoration planning study in Rhode Island, USA. In the study, we partnered with a watershed management organization to evaluate four wetland restoration alternatives for their abilities to supply five ES: flood water regulation, scenic landscapes, learning opportunities, recreation, and birds. Twenty-two benefit indicators were identified for the ES as well as one indicator for social equity and one indicator for reliability of ES provision. We developed preference functions to characterize the strength of evidence across estimated indicator values between pairs of alternatives. We ranked the alternatives based on these preferences and weights on ES relevant to different planning contexts. We discuss successes and challenges of implementing PROMETHEE, including feedback from our partners who utilized the methods.

1. Introduction

Interest in the non-monetary valuation of ecosystem services (ES) is growing, especially in the context of evaluating environmental management alternatives for decision-making purposes (Bagstad et al., 2013; Chan et al., 2012). A significant research challenge concerns how to effectively capture and evaluate the different ways people benefit from natural ecosystems using non-monetary or non-dollar estimates (Wainger and Mazzotta, 2011). An additional challenge is how to cope with uncertainty in non-monetary ES outcomes and measures (Hamel and Bryant, 2017).

There are many sources of uncertainty in modeling and measuring ES (e.g., measurement error, sampling error, systematic error, natural ecosystem variation, model assumptions, subjective judgments; Regan et al., 2002). While statistical or Bayesian techniques are typically applied to address these sources of uncertainty, uncertainty must also be acknowledged and addressed when choosing alternative courses of action. In approaches to environmental decision making, it is customary to integrate multiple monetary and non-monetary metrics to assess tradeoffs in ES outcomes in terms of the potential costs or benefits gained or lost by choosing one management alternative over another (Nelson et al., 2009; for a recent review, see Grêt-Regamey et al., 2017). Evaluating tradeoffs can be easier if alternatives are compared using a common metric; however, this requires ES analysts to transform ES data into commensurable measures.

In this article, we examine approaches to making choices among management alternatives using Multi-Criteria Decision Analysis (MCDA). In the context of ES assessments, these approaches transform ES measures into a common metric and apply preference measures to ES, so that alternatives can be more effectively evaluated for decision-making purposes. Linear and non-linear value functions (e.g., multi-attribute value functions; Keeney and von Winterfeldt, 2007) and qualitative value functions (e.g., analytic hierarchy process; Saaty, 1990) are popular methods to develop common metrics that can be aggregated and easily compared, especially for ES assessments (Langemeyer et al., 2016). Value functions produce numerical representations of preference (i.e., scores) for each measured outcome. Additive value functions are commonly used to aggregate scores and rank alternatives, which informs us of the potential "value" or "worth" of each alternative relative to others.

ES outcomes are, to a large extent, imperfectly known, meaning that they can be ambiguous, difficult to define, imprecise, and uncertain

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(Roy et al., 2014). MCDA approaches aim to cope with the imperfect nature of measures of ES outcomes in various ways. While a preferred approach may be to seek more complete information about the outcomes themselves, this may not be possible or feasible. Some approaches assign prediction probabilities to scores to reflect uncertainties that arise from measurements (e.g., decision trees with multi-attribute utility functions; Keeney and Raiffa, 1976; for a relevant application, see Maguire and Boiney, 1994). Other approaches account for imprecision by allowing for fuzziness in the way decision makers score outcomes (e.g., distance-based functions based on the concept of a best compromise for each outcome; Benayoun et al., 1971; Zeleny, 1973; for a relevant application, see Martin et al., 2016). These approaches fit within the family of additive aggregation functions, which are the most common methods for MCDA and especially useful when decision makers want a single cumulative score for each management alternative.

The usefulness of additive aggregation functions relies on the assumption that a single score adequately takes decision maker preferences over imperfectly-known ES into account (Roy, 1971). There are limitations to these types of approaches, especially when decision makers do not have strong preferences when comparing some or all of the ES outcomes. Once the scores are aggregated, any inherent ambiguity, imprecision, or uncertainty in the outcomes has been masked, and the degree to which the magnitude of changes in outcomes across management alternatives influences their ranking may be masked as well (Roy, 1989). Additive aggregation functions treat a larger aggregated score as unambiguously better than a smaller aggregated score; yet, it may not make sense to say that one alternative is strictly better than another based on its overall score alone (Roy, 1990). For example, decision maker preferences may not be well-defined for choosing an alternative that saves 100 species over an alternative that saves 99 species. Although sensitivity analysis can address some of these challenges, results are sensitive to the choice of scoring and aggregation technique (Martin and Mazzotta, 2018), and it is not always clear whether decision makers are aware of the implications of the mathematical assumptions that underlie scoring and aggregation. In this paper, we present the use of outranking methods for MCDA as an alternative approach to addressing imperfect knowledge in ES outcomes when making choices among alternatives.

1.1. Outranking methods

The main objective of outranking methods for MCDA is to deconstruct the way decision makers make choices. In the context of ES assessments, this is achieved by assigning different types of preferences to relationships between ES outcomes. This makes the role of ambiguity, imprecision, and uncertainty in how ES are measured and used for decision making more transparent (Roy, 1989). With outranking methods, decision makers assign preference measures directly to comparisons of ES outcomes, based on explicit consideration of *strength of evidence* across those outcomes (Roy, 1991).

Using traditional additive aggregation, two types of preference relationships exist for making choices between two alternatives *a, b* (Table 1): strict preference (*aPb*) and indifference (*aIb*), which may refer to comparisons of numerically different and identical aggregated scores, respectively. Outranking methods were developed to allow for two additional preference relationships (Table 1; Roy and Vincke, 1987): fuzzy preference ($a \wr P \wr b$), meaning that it is difficult to say that one alternative is strictly preferred to another because the strength of evidence is incomplete (i.e., there are thresholds where decision makers vacillate between indifference and strict preference); and incomparability (*aRb*), meaning that some comparisons cannot be clearly distinguished because of insufficient strength of evidence. These latter two relationships allow decision makers to incorporate insufficient information, allowing for choices to be more nuanced in some cases of comparing ES outcomes.

Table 1
Binary preference relationships between two alternatives *a,b* (adapted from Figueira et al., 2013).

Relationship	Notation	Description
Indifference	*aIb*	No difference in preference between alternatives *a* and *b*
Strict preference	*aPb*	Alternative *a* is strictly preferred to *b*
Fuzzy preference	$a \wr P \wr b$	The degree to which alternative *a* is preferred to *b* is distinguished by some function reflecting ambiguity in preferences over outcomes
Incomparable	*aRb*	Special situation in which a preference relationship cannot be determined without additional information

Outranking methods can provide more flexibility than scoring and aggregation; for instance, in situations where aggregated scores are too close to judge that one alternative is better than another, or where decision makers want to closely examine the actual differences in ES outcomes. Decision maker preferences for a large change in outcome (100 vs. 1 species saved) can be much stronger than for a small change (100 vs. 99 species saved). Accounting for such differences eliminates some of the undesirable effects of aggregation (Brans and Mareschal, 2005). Outranking methods force decision makers to focus their judgment on actual measurements and the degree of change, not scores, which can more fully inform choices among alternatives.

In the remainder of this article, we describe the basics of outranking methods, focusing on the PROMETHEE methods (Preference Ranking Organization METHod for Enrichment Evaluation; Brans et al., 1986). Applications of ES assessments using outranking methods are rare and require empirical testing (Langemeyer et al., 2016). We describe the PROMETHEE methods and their assumptions using a real-world ES assessment to plan for wetland restoration in Rhode Island, USA.

1.2. Study area

The Woonasquatucket River flows southeast through northern Rhode Island, into the city of Providence, the state's capital (Fig. 1). The river is threatened by development pressures and water quality degradation. We partnered with the Woonasquatucket River Watershed Council (WRWC), a non-profit watershed organization whose mission is to support and promote sustainable development in the watershed. Among its many initiatives, the WRWC is seeking to research and plan for wetland restoration in the watershed. Following guidelines set forth in The American Heritage Rivers initiative, the WRWC is considering options to restore previously damaged or destroyed wetlands for their social benefits. Implementing restoration requires the WRWC to secure funding. Because they often have opportunities to write grant proposals to perform restoration, having a set of "shovel-ready" projects identified with potential ES benefits as justification is most useful for them. Therefore, our objectives with the partnership were to develop research methods, including a rapid assessment approach (Mazzotta et al., 2016), estimate the social benefits of ecological restoration, and test how decision-focused processes could be applied to aid the WRWC in ecological restoration planning (Martin et al., 2018).

Many conversations within and outside the WRWC (Druschke and Hychka, 2015) were used to select five ES to analyze candidate wetland restoration sites (Fig. 1; Mazzotta et al., 2016): flood risk reduction (FR), scenic views (SV), environmental education (E), recreation (R), bird watching (BW). The ES are not comprehensive; they were identified based on availability of information and preferences of the WRWC and other restoration managers in Rhode Island. ES benefits and 22 associated benefit indicators were identified with conceptual modeling and measured using spatial analysis (Table 2; Martin et al., 2018). Two additional benefit indicators were developed and measured using spatial analysis to reflect social equity – referring to whether socially