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# Non-monetary valuation using Multi-Criteria Decision Analysis: Sensitivity of additive aggregation methods to scaling and compensation assumptions

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ABSTRACT

Analytical methods for Multi-Criteria Decision Analysis (MCDA) support the non-monetary valuation of ecosystem services for environmental decision making. Many published case studies transform ecosystem service outcomes into a common metric and aggregate the outcomes to set land use planning and environmental management priorities. Analysts and their stakeholder constituents should be cautioned that results may be sensitive to the methods that are chosen to perform the analysis. In this article, we investigate four common additive aggregation methods: global and local multi-attribute scaling, the analytic hierarchy process, and compromise programming. Using a hypothetical example, we explain scaling and compensation assumptions that distinguish the methods. We perform a case study application of the four methods to re-analyze a data set that was recently published in *Ecosystem Services* and demonstrate how results are sensitive to the methods.


## 1. Introduction

The incorporation of ecosystem services (ES) into environmental decision making is an important topic and motivator of current research. Much of the research on ES focuses on ecological understanding of how ecosystems provide useful goods and services, economic understanding of how those goods and services are valued, and connections between the provision of ES and social benefits. Frameworks for integrating ES into environmental decision making facilitate the screening of management alternatives where the provision of ES is a valued outcome (NRC, 2004; USEPA, 2009; Wainger and Mazzotta, 2011; Olander et al., 2017). Many of these frameworks emphasize the need to quantify and evaluate trade-offs in the value of ES outcomes, which may rely on monetary or non-monetary valuation methods.

Monetary valuation methods result in estimates of marginal changes to ES in monetary units (e.g., dollars), while non-monetary valuation methods result in estimates of ES or their benefits, both quantitative (e.g., species saved, number of people or homes affected) and qualitative (e.g., "poor," "good," "excellent"). Non-monetary valuation is a way for research analysts to address the range of ES values to decision makers or other stakeholders, without excluding those that are difficult to monetize (Chan et al., 2012). Aggregating non-monetary values is less common than aggregating monetary values because it is difficult to aggregate such data, which often are not measured in common units. Yet, it is often useful to be able to aggregate a set of non-monetary measures into a single value or score that can be used to compare management alternatives for decision making purposes.

One approach to the problem of aggregation is to use mathematical concepts that have been made popular within the field of Multi-Criteria Decision Analysis (MCDA; Langemeyer et al., 2016; Saarikoski et al., 2016). Since the 1960s, over 100 methods for MCDA have been developed to support the evaluation of environmental problems with multiple competing goals, objectives, and performance measures. Regarding ES assessment, these methods can aggregate multiple potential ES measures for pre-determined management alternatives at different geographic scales, including single or multiple sites, watersheds, and planning districts, so that a clear ranking of management alternatives at those locations is achievable. Perhaps the most attractive features of these methods are their abilities to transform incommensurable data (i.e., monetary and non-monetary values) into non-monetary, dimensionless values, and to mathematically incorporate people's preferences into the aggregation.

A new collection of MCDA research articles are using additive functions (e.g., weighted linear combination) to aggregate monetary and non-monetary ES outcomes for environmental decision

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making (e.g., Liu et al., 2013; Favretto et al., 2016; Wam et al., 2016). Many studies are applying what is referred to as "spatial MCDA," where Geographic Information System mapping of ES is combined with an additive function to aggregate ES outcomes at a spatial unit (e.g., Kremer et al., 2016; Grêt-Regamey et al., 2016; Vogdrup-Schmidt et al., 2017; Tobón et al., 2017).

It is important for research analysts to recognize that different approaches to aggregating ES reflect different underlying rationales and mathematical assumptions. Results will be sensitive to those assumptions, and analysts should be transparent with decision makers about their choices and be prepared to re-evaluate their MCDA models based on input from decision makers.

In this article, we explore two important classes of assumptions, those related to scaling and compensation, and demonstrate how choice of method and its underlying assumptions can affect the ranking of management alternatives. Scaling refers to how non-monetary ES outcomes are transformed into a common metric for meaningful aggregation, whereas compensation refers to the extent to which an undesirable ES outcome will be compensated by desirable outcomes on other ES. To explain these assumptions and demonstrate their implications for decision making, we use a hypothetical example that illustrates four common additive aggregation methods: multi-attribute scaling, both global and local (Belton and Stewart, 2002; UK, 2009), the analytic hierarchy process (Saaty, 1980), and compromise programming (Zeleny, 1973). We present a case study application of the methods using a recently published data set in *Ecosystem Services* (Favretto et al., 2016) to demonstrate how results can differ among methods.

## 2. Mathematical concepts for aggregating non-monetary ecosystem service values

The case studies performed in recent articles using additive aggregation have similar problem formulations. They are designed to estimate and evaluate the overall performance of specific land management alternatives $a_i$, each with a finite set of ES criteria $c_j$, defined loosely as measurable and manageable contributions of ecosystem structure and function to human well-being (Burkhard et al., 2012). For each management alternative, there is a set of quantitative and qualitative ES criteria performance values $z_{ij}$ based on the potential ES outcomes provided at a site or spatial unit. The criteria performance values are estimated using available market information, natural and social science models or metrics, or expert opinion-based models. We assume that measurements for each of the criteria performance values do not depend on any of the other criteria performance values.

Based on these problem formulation assumptions, a benefit function $B_i$, sometimes referred to in the literature as a value function, is used to aggregate criteria performance values into an overall non-monetary value for each alternative. Additive benefit functions are the most common; they appear as:

$$B_i = \sum_{j=1}^{k} w_j x_{ij} \tag{1}$$

for all criteria $j = 1, \ldots, k$, alternatives $i = 1, \ldots, m$.
where $B_i$ is the overall value or benefit of alternative $i$; $w_j$ are importance weights for the criteria; $x_{ij}$ are criteria performance values that have been transformed based on the methods discussed in this article. In order to aggregate, it is necessary to transform each of the original criteria performance values $z_{ij}$, which are often measured using different metrics and scales, into a commensurable value $x_{ij}$ that can be aggregated. Criteria performance values are almost always transformed as scaled numbers in the benefit function to facilitate comparisons across criteria. Importance weights generally reflect the importance of ES criteria to relevant beneficiaries or stakeholders; they are scaled to an interval (0–1) and sum to one. By combining criteria performance values into an aggregate benefit value, Eq. (1) estimates a single overall benefit score for each management alternative, which can make it easier for decision makers to compare and rank many management alternatives.

### 2.1. Four methods to transform ecosystem service values into a common metric

Additive aggregation methods for MCDA differ in terms of how quantitative and qualitative criteria performance values $z_{ij}$ are transformed into commensurable performance values $x_{ij}$ before being aggregated using Eq. (1). In this section, we briefly explain four common methods. The first two methods are used in multi-attribute value assessment – global and local multi-attribute scaling (Belton and Stewart, 2002; UK, 2009), hereafter referred to as global and local scaling. The second two are well-established additive aggregation methods for MCDA – the analytic hierarchy process (Saaty, 1980) and compromise programming (Zeleny, 1973).

#### 2.1.1. Global scaling

One of the most practical procedures is to transform criteria performance values using upper and lower numerical boundaries (Keeney and von Winterfeldt, 2007). Global scaling refers to transformations using the maximum and minimum possible values for each criterion as upper and lower boundaries. These boundaries are often assigned prior to actual criteria measurements for the alternatives. Quantitative performance values are transformed to a selected range, such as 0 to 100; linear transformation is commonly used:

$$x_{ij} = \frac{z_{ij} - z_j^{\wedge}}{|z_j^{\wedge} - z_j^{\wedge\wedge}|} * 100 \tag{2}$$

where $z_j^{\wedge}$ and $z_j^{\wedge\wedge}$ are the worst and best *possible* measurements for each criterion, respectively. Qualitative data may be assigned numbers on a constructed scale (e.g., "none" = 0, "poor" = 25, "fair" = 50, "good" = 75, "excellent" = 100) before they are transformed using Eq. (2).

With global scaling, the lowest and highest transformed performance values for most criteria will often not be 0 and 100, since the measured values will typically not encompass the worst or best possible outcomes for the criteria. Because of this, the transformed criteria performance values will span different sized ranges (e.g., one criterion may span the range of 0 to 100 while another may only span the range of 40 to 60). This difference in range makes the global scaling method subject to individual criteria having greater influence on the results because criteria with larger ranges act like a weight on the results (Otway and Edwards, 1977; Section 3.1). An advantage of the global scaling method is that it allows for later addition of alternatives to the decision problem without disrupting criteria boundaries.

#### 2.1.2. Local scaling

Local scaling uses the maximum and minimum criteria performance values that are measured to set the upper and lower boundaries of the transformation. As with global scaling, linear transformation is commonly used:

$$x_{ij} = \frac{z_{ij} - z_j^{*}}{|z_j^{*} - z_j^{**}|} * 100 \tag{3}$$

where $z_j^{*}$ and $z_j^{**}$ are the worst and best *actual* measurements for each criterion, respectively.