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AN OBJECTIVE METHOD TO PRIORITIZE SOCIO-ENVIRONMENTAL WATER MANAGEMENT TRADEOFFS USING MULTI-CRITERIA DECISION ANALYSIS

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ABSTRACT

Rivers provide many social and environmental services that benefit humanity. A critical role of water mangers is to prioritize water allocation options that trade off socio-economic and hydro-ecological benefits in rivers. Methods for multi-criteria decision analysis (MCDA) provide a structured and systematic manner for researchers to aid in this process. In this paper, we describe a new MCDA method that prioritizes large multi-dimensional sets of tradeoffs to support well-informed water management in rivers. The method was developed based on an environmental flows planning study in the Goulburn-Broken River catchment, Victoria, Australia. A combined simulation and heuristic optimization procedure was previously integrated into a hydrological catchment network model. That process resulted in a large set of viable daily water allocation schedules that traded off long-term irrigation and hydro-ecological benefits at the catchment outlet. We provided new guidance procedures to identify priority tradeoffs that can be used in stakeholder deliberations and catchment decision-making. Our MCDA method included combined multi-dimensional ordination and cluster analysis to spread the water allocation alternatives onto a two-dimensional plane to discover alternatives with similar criteria tradeoffs. A geometric distance-based method was performed on the full set of alternatives and on the identified clusters to rank the alternatives in accordance with minimizing the distance of the alternatives to an ideal but non-feasible reference point in multi-dimensional space. This method complements the use of elicitation procedures when water manager or other stakeholder interaction is not an option or when objectivity is desired.

KEY WORDS: decision-making; environmental flows; tradeoffs; multi-criteria decision analysis

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INTRODUCTION

Across the globe, rivers are put into service to meet human needs and wants (Postel and Richter, 2003). Society depends on rivers to provide important services like water supply and good water quality for domestic consumption, agriculture, industry, transportation, recreation, and aesthetic enjoyment (Brauman *et al*., 2007). Likewise, river ecosystems transport water, sediment and nutrients, and they function to maintain adequate habitat and bio-chemical water quality to sustain instream and riparian biodiversity. Human dependence on rivers and the benefits they provide has advanced societal interests at the unanticipated cost of environmentally degrading river ecosystems (Gleick, 2003), which threatens river ecosystem function (Baron *et al*., 2002; Allan, 2004) and global freshwater biodiversity (Richter *et al*., 1998; Bunn and Arthington, 2002; Strayer and Dudgeon, 2010).

Sustainable water management in rivers requires a long-term vision to balance human and ecological freshwater needs and uncertainties in a changing environment. Applying this vision to real-world management problems exposes conflicting tradeoffs and uncertainties between the ecological needs of river ecosystems and the engineering design and operational needs of water infrastructure (Poff *et al*., 2015). To support a well-informed decision-making process, freshwater scientists are tasked with estimating the hydro-ecological needs of rivers using historical data and models (Poff *et al*., 2003), which are then integrated with socio-economic needs, constraints, and models. Clark (2002) calls the procedure an analytical audit, which includes specifying important (i.e. outcome-oriented) and measurable water management criteria and incorporating them into coupled model simplifications of individual river ecosystems in an attempt to capture their spatial and temporal complexity. Optimization techniques (Labadie, 2004; Barbour *et al*., 2016) are often applied, especially on large river networks with built infrastructure, to design water allocation alternatives that trade off benefits to societal

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criteria like economic return while minimizing impairment to environmental criteria like suitable species habitat.

Multi-criteria decision analysis (MCDA) is a science-based discipline of theory and methods that emphasizes collaborative planning and that specializes in developing systematic models to prioritize finite sets of management alternatives with conflicting criteria and tradeoffs. The MCDA problem formulation is twofold (Belton and Stewart, 2002). First, the relative importance of the goals of the problem, which are described through criteria, are parameterized as non-dimensional scaling factors or weights. Criteria weights are viewed as quantitative representations of stakeholder preferences. Second, mathematical procedures are used to aggregate and rank the management alternatives based on comparing the tradeoffs in the consequences of each alternative and by incorporating measures of uncertainty to simulate imprecision of those consequences.

The domain of MCDA has long endeavoured to provide suitable information from which to support well-informed management decisions. In the context of how preferences are integrated into weighted MCDA evaluations for water management in rivers, two schools of thought prevail. *Preference-neutral* evaluations use equal criteria weights (Shiau and Wu, 2006; Beilfuss and Brown, 2010), where the aim is to balance preferences among the management goals and criteria. By contrast, *preference-driven* evaluations incorporate estimates of criteria weights. Criteria weights can be hypothetically based on the water management context (Prato, 2003; Benini *et al*., 2010; Wu *et al*., 2016), they can be simulated (Srdjevic *et al*., 2004), or they can be estimated through expert elicitation (Joubert *et al*., 2003; Bana e Costa *et al*., 2004; Marttunen and Hämäläinen, 2008; Martin *et al*., 2015). Preference-driven evaluations purposefully skew the search towards preferred management alternatives.

There are problems inherent in both schools of thought, which is why estimating the relative importance of management criteria has been regarded as a primary argument against using methods for MCDA (Gershon, 1982). Arguments against preference-neutral evaluations often emphasize that results can yield unrealistic priorities if they do not incorporate actual stakeholder values. Preference-driven evaluations can yield unrealistic results if decision makers or their preferences change. We know that decision makers are naturally biassed, and there are difficulties in eliciting preferences (Mareschal, 1988; Lahdelma and Salminen, 2001), including: (i) elicitation methods are time consuming; (ii) questions of relative importance and methods to index criteria weights are inconsistent; (iii) decision makers are sometimes unreliable and/or have trouble providing straightforward answers and their answers may change over time; and (iv) decision makers can be disinterested in providing such information.

In this paper, we describe a preference-neutral MCDA method to prioritize large multi-dimensional sets of socio-environmental water management tradeoffs in rivers. Our method combines ordination with cluster analysis and uses geometric distances to provide alternative viewpoints for decision-making in a systematic and transparent manner, without using stakeholder-defined criteria weights. We applied this method to a multi-objective optimization planning study in the Goulburn-Broken River catchment, Victoria, Australia.

METHODS

A combined ordination and clustering MCDA method moves through several distinct steps (Figure 1). However, depending on problem characteristics like small numbers of criteria or alternatives, some of the steps may not be necessary (discussed further in Conclusions).

Multi-dimensional tradeoff table

Suppose a finite set of management alternatives $a_i (i = 1, \ldots, n)$ each have a finite set of measurable water management criteria $c_j (j = 1, \ldots, m)$. Each criterion is a proxy for river ecosystem function or socio-economic value, and the criterion performance value of a management alternative is x_{ij}. The $n \times m$ tradeoff table forms the basis for the MCDA method development (Figure 1a).

Ordination

Principal component analysis (PCA) ordination is used to characterize the major variance explained in the dataset by reducing the dimensionality of the problem to one or two principal components (Z_m) that explain the most variation in the set (Figure 1b; Appendix A). PCA is common in the ecological sciences. However, the procedure is rarely applied in MCDA evaluations of large numbers of water management alternatives like non-dominated or Pareto optimal sets that result from multi-objective optimization solvers (Reed *et al*., 2013; Maier *et al*., 2014). These datasets are unique in that moving from one alternative to the next improves at least one criterion performance value but not all.

Large numbers of tradeoffs are difficult for decision makers to consider simultaneously. The PCA reduces the dimensionality of the problem so that the tradeoff evaluation can concentrate on alternatives that provide the greatest differences in outcomes for correlated criteria (see below). For this reason, it is important that the PCA ordination provides maximum separation of the alternatives. Stewart (1981) suggests that the dominant component (Z_1) explain at least 90% of the variation in the alternatives so that the spread of

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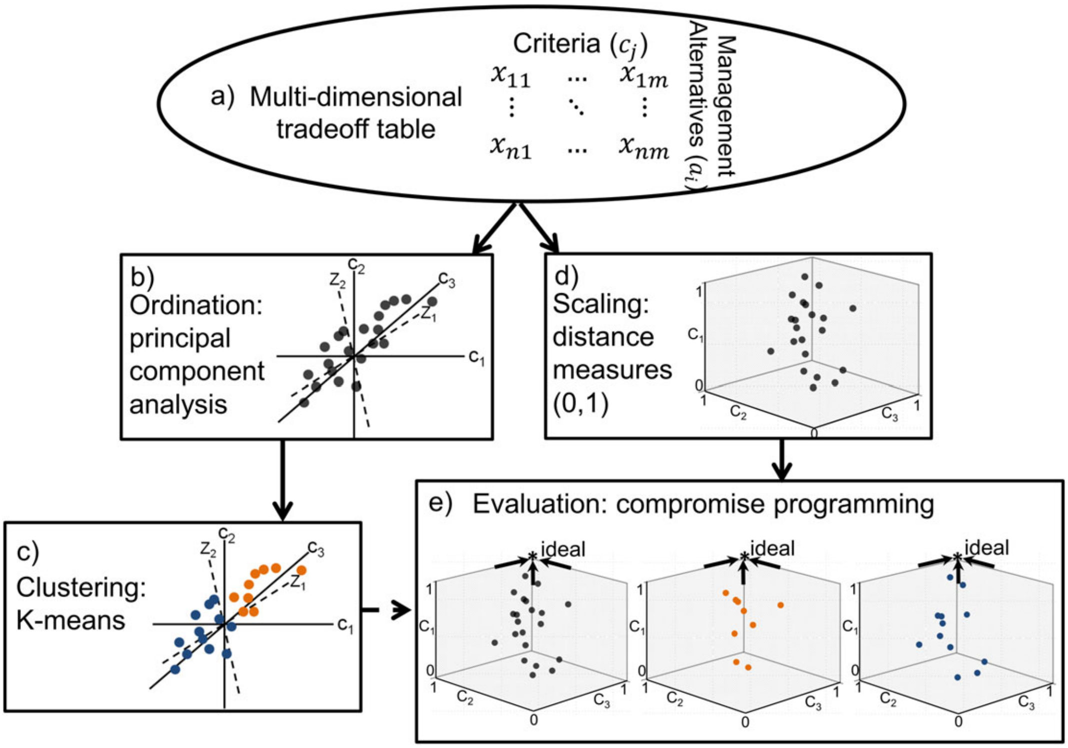

Figure 1. Conceptual diagram showing the five steps of our MCDA method, showing (a) tradeoff table, (b) ordination, (c) clustering, (d) re-scaling of the raw criteria performance values, and (e) evaluation using compromise programming. See text for further details. [Colour figure can be viewed at wileyonlinelibrary.com]

alternatives provides a semi-rational distinction of how the alternatives deviate from one another regarding tradeoffs in the criteria performance values.

Clustering

Following the PCA, we aim to find a structure with the spread of management alternatives. This helps to discover potential tradeoffs among different groupings of the management alternatives. We use a clustering analysis of the principal component scores from the PCA (Figure 1c). We recommend the K-means algorithm (MacQueen, 1967) because its quantitative foundation is simple, it is very common, and it can be calculated efficiently using a variety of common computer programs. K-means generates clusters such that the squared difference (i.e. Euclidean distance) between the empirical mean of each cluster and the points inside the cluster are minimized.

After clustering, the raw criteria performance values of the alternatives in each cluster are partitioned into separate datasets. In effect, there exist similarities in criteria performance in each cluster. Brans and Mareschal (2005) presumed that criteria expressing similar performance values would be oriented along the PCA axes. This latent point demonstrates why PCA is an important part of the method, especially for large multi-dimensional sets of alternatives (e.g. non-dominated or Pareto optimal datasets); bypassing the PCA ordination and using clustering techniques from the tradeoff table may fail to provide clusters with similar criteria performance values unless the dataset is naturally correlated.

Scaling and evaluation

The next steps in this method perform a formal tradeoff evaluation. First, we contend that variation in criteria performance values may be large. A common currency is desired to control for that variation. We use normalized (0–1) distance measures to scale the values of the datasets so that each datum is a proportion of the highest achievable criterion value in the set (Figure 1d). Second, compromise programming (Zeleny, 1973) is performed on the full set of alternatives and on each cluster using equal criteria weights to achieve an objective ranking of the alternatives (Figure 1e). The compromise programming method organizes large datasets with conflicting criteria tradeoffs to a priority list of alternatives that are as close as possible (e.g. Euclidean distance) to an 'ideal' but non-feasible reference point in geometric space (coordinate 1,1,1 in Figure 1e; Appendix B).

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This system of methods results in several sets of ranked management alternatives, where the highest ordered alternatives and their distinct tradeoffs may be further assessed for stakeholder deliberation and decision-making. The rankings represent a set of preference-neutral viewpoints, and the rankings from each cluster represent implied preference information but without the use of stakeholder-defined criteria weights. The results can be assessed together for a more complete tradeoff analysis.

ILLUSTRATION: GOULBURN-BROKEN CATCHMENT, VICTORIA, AUSTRALIA

The Goulburn-Broken River catchment lies within the Murray–Darling Basin (Figure 2a). The region supports dryland and irrigated agriculture, food processing, forestry and tourism industries. Although it only makes up 2% of the Murray–Darling Basin's land area, the catchment generates 11% of water resources for the basin. Mean annual discharge for the catchment is approximately 3200 gigalitres (CSIRO, 2008), and approximately 50% of the discharge is diverted to meet agricultural, stock, and domestic demands.

The incorporation of flow–ecology relationships into operational decision-making for ecological water allocations (i.e. environmental flows) is a priority area of river management (Davies *et al*., 2014). The Goulburn-Broken River has received considerable state and federal investment in environmental flows to support improved ecological condition (e.g. Webb *et al*., 2015a). A proof of concept approach was previously developed that used ecological response models to assist with allocating environmental flows in the catchment (Powell, Nichols, Webb, Adams, de Little and Dyack, 2013). The prototype hydro-ecological predictive model used a validated quantitative response function linking the streamflow regime to the encroachment of terrestrial vegetation into the river channel (Webb *et al*., 2015b). This model was coded for integration into a simplified link-node water management model (Figure 2b) provided by the Source Integrated Water Resource Modelling framework, hereafter called Source (Welsh *et al*., 2012). The Source model used daily discharge, rainfall, and evaporation data for the period 1901 to 2012 to calibrate inflows for the

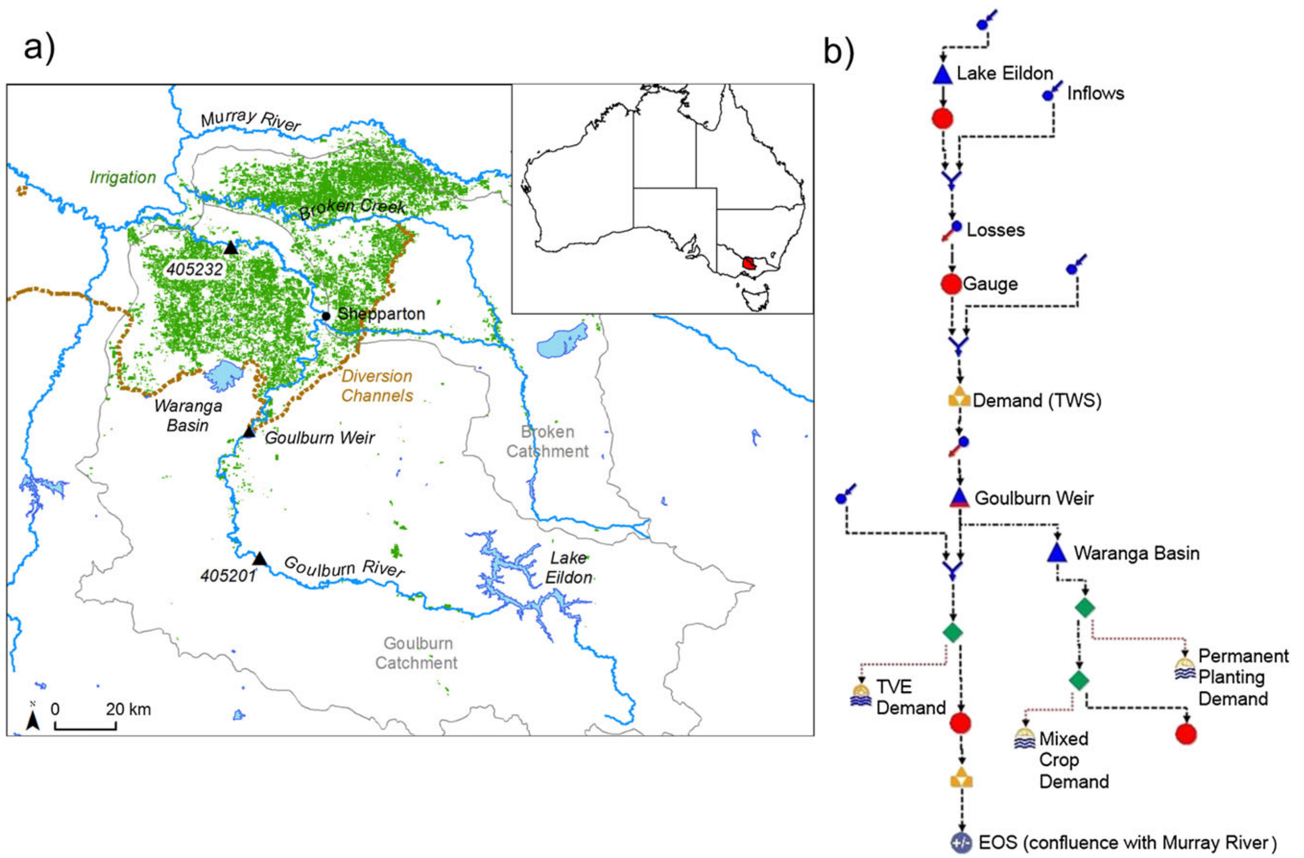

Figure 2. (a) Goulburn-Broken catchment map. (b) Simplified hydrologic network model for the catchment. [Colour figure can be viewed at wileyonlinelibrary.com]

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link-node network, and it was used to simulate ecological responses to changing environmental flow scenarios throughout the catchment.

The resulting flow–ecology response model simulates the river segment inflows, system operations, water storages, flow management, ecological response, and consumptive demands within the Goulburn-Broken system, all linked to climate (see Powell, Nichols, Webb, Adams, de Little and Dyack, 2013). Although it was a proof of concept, the research was performed to provide ecologically defensible models, derived by considering available evidence from many sources, for integration into other socio-economic river management models to support river management and policy decisions.

Criteria development

The previously calibrated hydro-ecological response model and other custom models were used with the Source model to simulate catchment inflows, system operations, environmental flows, and irrigation demands based on crop water use at a range of spatial and temporal scales. First, we developed a set of rules (i.e. decision variables) to deliver environmental flows to suppress the encroachment of terrestrial vegetation into the river channel. These rules consider the antecedent flows, the existing terrestrial vegetation within the channel, season, and the volume of water held in storage that is available for environmental flows. Next, we developed five criteria to represent flow–ecology response (i.e. terrestrial vegetation encroachment), net irrigation benefit, and total water allocated to suppress vegetation encroachment (Table I). The irrigation criteria C_1 and C_2 were based on values extracted directly from an internal resource assessment model within Source and a calculation of annual net benefits (Appendix C) over the relevant irrigation nodes in the catchment network, respectively. The hydro-ecological criteria C_3 and C_4 were based on the previously developed flow–ecology response model and rules for the catchment. Criterion C_5 was developed to minimize the total possible water allocation for environmental flows in the river system for the purpose of reducing vegetation encroachment.

Table I. List of criteria for water allocation planning in the Goulburn-Broken River catchment (Powell *et al*., 2013)

Criterion	*Goal*	*Units*
C_1 water extracted for irrigation	Maximize	gigalitres per year (GL yr^{-1})
C_2 net benefits to irrigation	Maximize	\$AUD per hectare per year (\$ ha^{-1} yr^{-1})
C_3 average spring terrestrial vegetation encroachment into river channel	Minimize	percent (%)
C_4 maximum spring terrestrial vegetation encroachment into river channel (‘mini–max’ criterion)	Minimize	percent (%)
C_5 water allocation to suppress terrestrial vegetation encroachment	Minimize	gigalitres per year (GL yr^{-1})

Optimization and tradeoff table

A non-dominated sorting genetic algorithm NSGA-II (Deb *et al*., 2002) was integrated into the Source model as a dynamic simulation and optimization solver for water allocation in the catchment. A typical genetic algorithm is a multi-objective optimization procedure based on the development of heuristic search rules and quantitative investigations of populations of management alternatives. For the case study, the procedure included Source model scenario development for daily water allocation schedules over 24 years using historic inflows and simplified climate data. The case study period (1988–2012) was based upon the availability of good quality gauge data. It represented a sequence of dry and wet periods in the catchment and included storage levels from Lake Eildon (Figure 2) that ranged from full to effectively empty to full again. This period of all extremes of water availability indicates that the model results may have greater general validity for potential future conditions.

In the NSGA-II, an initial stochastic water allocation scenario was procured for the catchment that was intended to affect water management based on criteria goals (Table I). The initial water allocation scenario routed the responses of each criterion at relevant nodes through the catchment to a pre-defined catchment outlet, and the cumulative response was recorded for each criterion. Between each scenario run, the cumulative criteria performance values at the catchment outlet were compared and the scenario run that best met the goals was kept and recorded. The iterative process converged on 151 non-dominated tradeoff scenarios (Table II), hereafter referred to as water allocation alternatives.

The tradeoff table of water allocation alternatives is complex. Visualizing the tradeoffs in these values is a good way to summarize their complexity to decision makers. However, like many non-dominated or Pareto optimal datasets, the number of criteria and alternatives is large and difficult to interpret visually and therefore problematic to prioritize without structured decision-making methods. In response to this issue, we developed the MCDA method herein to make the decision support process more transparent for stakeholders.

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Table II. Incomplete tradeoff table of water allocation alternatives for the Goulburn-Broken catchment. Each alternative is a different 24-year daily schedule of water allocations throughout the catchment to benefit the criteria. The cumulative criteria performance values from the catchment outlet are displayed

Alternative number	C_1 (GL yr^{-1})	C_2 (\$ ha^{-1} yr^{-1})	C_3 (%)	C_4 (%)	C_5 (GL yr^{-1})
1	749	2901	11	28.5	12
2	662	2704	2.4	12.6	283
3	697	2779	4.3	12.6	130
4	749	2895	11.1	28.5	0
5	749	2901	11.2	28.5	12
…	…	…	…	…	…
151	731	2871	9.2	19.8	27

Ordination and clustering

As described above (Figure 1), we first applied PCA ordination to project the alternatives onto a two-dimensional plane (Figure 3). The resulting principal component Z_1-scores provided maximum separation (93%) of the dataset followed by Z_2-scores (7%). Upon inspection, six alternatives appeared as possible outliers (upper left alternatives in Figure 3). Although it appears that the 7% variance on the small difference in scale along the Z_2 axis may explain the distribution of the possible outliers, we took this into consideration and performed the successive steps of the MCDA evaluation with and without them to validate our results.

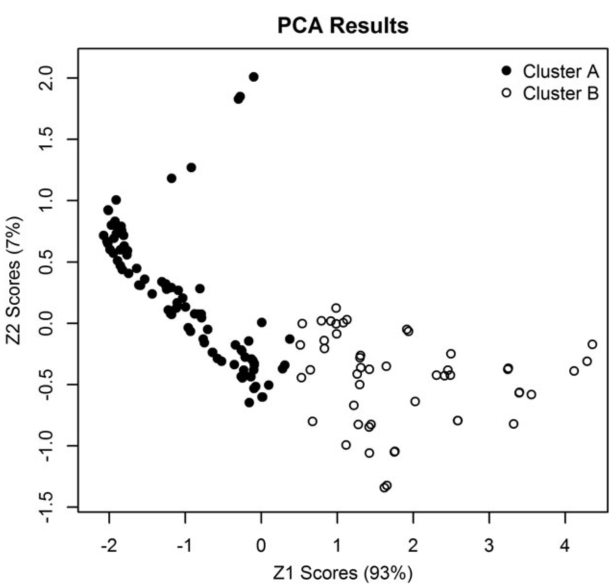

Figure 3. Principle component analysis ordination of the 151 non-dominated water allocation alternatives. Percent variance explained for each axis is in parentheses. Cluster analysis partitioned the alternatives into two groups that traded off conflicting irrigation and hydro-ecological performance

We performed a K-means cluster analysis on the Z_1- and Z_2-scores, specifying two clusters to be generated using the 'cluster' package (Maechler *et al.*, 2014) in the R programming environment. The results yielded 75 alternatives in Cluster A and 61 alternatives in Cluster B (Figure 3).

After clustering, we inspected the raw criteria values of each cluster and determined that Cluster A included alternatives with better irrigation criteria values for C_1, C_2, and C_5, whereas Cluster B included alternatives with better hydro-ecological criteria values for C_3 and C_4. The major tradeoff among the two clusters is therefore intuitive, and we determined that a preference-neutral compromise programming evaluation of each cluster would yield rankings for decision makers with an interest in better long-term irrigation outcomes (Cluster A) and, alternatively, better hydro-ecological performance (Cluster B) throughout the catchment.

Evaluation

Compromise programming was performed on the scaled cumulative criteria performance values of the full set of water allocation alternatives and each cluster individually (Table III). An additional compromise programming iteration was performed on Cluster A without the six possible outliers described above. Yet, we retained the same highest ranked results with or without those alternatives, and so this additional iteration is not considered further.

The three sets of ranked alternatives provide unique viewpoints to inform the decision-making process. These preferred alternatives come with several important caveats. First, our method yielded several rankings of alternatives in a preference-neutral manner. Second, the results from Cluster A are viewed as preferred water allocation schedules that largely benefit irrigation in the catchment, and results from Cluster B are preferred schedules that largely benefit the ecological condition of the catchment. Therefore, stakeholders who value irrigation more than ecological condition can use the highest Cluster A rankings as an appropriate set of options for water allocation in the catchment. Conversely, stakeholders who value ecological condition more than irrigation may deliberate among the alternatives from the Cluster B rankings.

Formal stakeholder deliberation of the tradeoffs is beyond the scope of this paper. Investigating the reduced set of preferred water allocation alternatives would require deliberation of the exact routing schedules of water throughout the catchment and the irrigation and ecological responses at each node in the hydrologic network model (Figure 2b). Socio-political values, water manager and other stakeholder intuition, and subjectivity play critical roles in that process. Rather, we gleaned useful information among the highest ranked alternatives in Table III and determined that

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Table III. Rankings from each preference-neutral compromise programming evaluation. The top seven ranked alternatives and their scaled criteria performance values are shown. Alternatives in bold are better options for stakeholder deliberation in each set

Rank	Alternative number	C_1 Maximize water for irrigation	C_2 Maximize net irrigation benefit	C_3 Minimize average springe TVE	C_4 Minimize maximum spring TVE	C_5 Minimize water delivered to suppress TVE
Full dataset						
1	**146**	**0.57**	**0.58**	**0.63**	**0.88**	**0.82**
2	**121**	**0.57**	**0.58**	**0.61**	**0.88**	**0.83**
3	**81**	**0.54**	**0.58**	**0.62**	**0.88**	**0.86**
4	**92**	**0.56**	**0.55**	**0.64**	**0.88**	**0.82**
5	**143**	**0.56**	**0.55**	**0.64**	**0.88**	**0.82**
6	47	0.58	0.70	0.47	0.86	0.82
7	104	0.59	0.61	0.52	0.84	0.80
Cluster A (better alternatives for irrigation)						
1	**62**	**0.92**	**0.88**	**0.33**	**0.52**	**0.97**
2	**56**	**0.91**	**0.88**	**0.33**	**0.51**	**0.97**
3	59	0.89	0.85	0.31	0.59	0.95
4	139	0.93	0.91	0.27	0.52	0.95
5	46	0.90	0.88	0.31	0.49	0.95
6	132	0.94	0.94	0.22	0.52	0.99
7	42	0.95	0.91	0.24	0.48	0.98
Cluster B (better alternatives for ecological condition)						
1	**36**	**0.40**	**0.40**	**0.86**	**1.00**	**0.58**
2	**3**	**0.40**	**0.40**	**0.78**	**1.00**	**0.54**
3	112	0.49	0.52	0.65	1.00	0.70
4	93	0.45	0.52	0.66	0.99	0.57
5	69	0.36	0.46	0.70	1.00	0.55
6	85	0.36	0.34	0.71	1.00	0.69
7	17	0.39	0.37	0.68	0.93	0.62

Scaled values are a proportion of the highest achievable, and, therefore, values closer to unity (1) represent better water allocation schedules for the criterion.

deliberation among the top five ranked water allocation schedules from the full dataset evaluation and top two ranked schedules from the cluster evaluations are sufficient for well-informed water management in the catchment. We reached this conclusion because the differences in the tradeoffs of criteria values in the ranked alternatives become more apparent after the first several are screened. This can be seen in the difference between scaled criteria performance values in bold and non-bold alternatives in Table III. Fundamentally, we cannot say that one alternative is better than another in the sets of bold alternatives in Table III because the differences in the tradeoffs are too close.

To support this determination, notice that significant changes in the tradeoffs of criteria C_2 and C_3 occur between the fifth and sixth highest ranked alternatives from the full dataset evaluation, and the water allocation schedules thereafter create an imbalance in the catchment relative to the higher ranked alternatives. Using percentages, the catchment response values for C_2 changed from 55% of highest achievable to 70% and values for C_3 changed from 64% to 47%. The tradeoffs in criteria between alternatives remain relatively close until this break point. In Cluster B, significant losses in the catchment performance of criterion C_3 result at a cost of significantly improving the performance of criteria C_1, C_2, and C_5 between the second and third highest ranked alternatives. Consideration of the third or lower ranked alternatives in Cluster B are not useful because they begin to trade off benefits to irrigation more so than ecological condition. The tradeoffs are closer for Cluster A, but we made a similar determination.

In summary, we reduced the large number of possible alternatives to a few small sub-sets of preferred alternatives for stakeholder deliberation in a more objective manner than by incorporating stakeholder preferences. We determined that considering alternatives further down the ranked lists was unnecessary and would constitute possible bias into the analysis.

CONCLUSIONS

Our MCDA method provides objective prioritizations of socio-environmental water management tradeoffs in rivers without direct interaction with decision makers. The value of our method is demonstrated by its ability to perform seemingly subjective evaluations (i.e. prioritizing tradeoffs that favoured either irrigation or hydro-ecological condition) when preference elicitation is not an option or when objectivity is desired. The method is particularly useful with large multi-dimensional datasets such as non-dominated or Pareto

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optimal solutions to a multi-objective optimization solver. Results may be communicated to decision makers in the same way as other methods, but with our approach, an evaluation of preferred alternatives for irrigation or ecological management of the catchment may be delivered alongside a more balanced evaluation through the described procedures.

The method works well for the case study presented. The full method was tested on other published datasets (Martin, 2015) of socio-environmental tradeoffs (e.g. Duckstein and Opricovic, 1980; Mareschal and Brans, 1988; Chung and Lee, 2009; Hermoso *et al*., 2015). Success was found where the percentage of variance explained in the ordination procedure was high enough to spread the data onto the PCA axes so that the clustering pre-determined sets of alternatives with characteristically similar criteria performance values in the tradeoffs. Conversely, the full method is not useful for case studies with only two or three management criteria because the raw data tend to be spread appropriately. In these situations, ordination is not needed and clustering should be undertaken directly upon scaling the criteria performance measures (see Martin *et al*., 2016). Specifying clusters for prioritizing management alternatives is highly subjective and dependent on stakeholders having to consider mutually contradictory sets of choices (in our case: irrigation vs. hydro-ecological benefits). Our method aims to identify similar tradeoffs in the clusters to aid decision-making, and we think that more clusters will be harder to describe and will likely complicate stakeholder deliberations.

Method development of this kind is infrequently applied to water resource management in rivers. Yet, sustainable water management will require managers to deal with larger and more complex real-world problems and, hence, the dimensionality of future tradeoff designs and evaluations will grow. Describing the complex multi-disciplinary tradeoffs among performance criteria to water managers and decision makers will continue to be problematic because results can be unwieldy and difficult to interpret and they are normally not integrated with systematic prioritization procedures like MCDA. Stakeholders may be more hesitant to offer subjective preferences if the dimensionality and extraneous factors like space and time, river flow regime, climate change, and financial risks grow (Herman *et al*., 2014; Arnold *et al*., 2014). The dynamics of environmental change may reveal new stakeholder preferences and new data and may require new or revised management goals, specifications, and data into the design modelling or optimization part of the process. Although this will likely change the results of the evaluation part of the process, it does not change the method. Our method adapts to any change in input data in a tradeoff table. It is in these areas of research and water management that our method is likely to prove most useful.

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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 authors and are not necessarily the views of the Agency.

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APPENDIX A

PRINCIPAL COMPONENT ANALYSIS

Quantitative measures of spread used in the PCA ordination procedure include:

Criterion mean:

$$\overline{c_j} = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \tag{A1}$$

Distance between observed and mean criteria performance values:

$$D_{ij} = x_{ij} - \overline{c_j} \tag{A2}$$

Criteria variance:

$$var(j) = \frac{1}{n-1}\sum_{j=1}^{m} D_{ij}^2 \tag{A3}$$

Criteria standard deviation:

$$stdv(j) = \sqrt{var(j)} \tag{A4}$$

Criteria covariance:

$$cov(i,j) = \frac{1}{m-1}\sum_{j=1}^{m}\left(x_{ij} - \overline{x}\right)\left(x_{ij} - \overline{x}\right) \tag{A5}$$

A square variance–covariance matrix (A) is developed with diagonal elements equal to the sample variances of each criterion (c_j) and off-diagonal elements equal to the sample covariance of all possible pairs of criteria performance values:

$$A = \begin{bmatrix} var(1) & cov(1,2) & \dots & cov(1,m) \\ cov(2,1) & var(2) & \dots & cov(2,m) \\ \vdots & \vdots & \ddots & \vdots \\ cov(n,1) & cov(n,2) & \dots & var(m) \end{bmatrix} \tag{A6}$$

Eigenvalue analysis is used to estimate a vector $\rightarrow v$ that satisfies $A \rightarrow v = \lambda \rightarrow v$, where $\rightarrow v$ are the m eigenvectors of matrix A, and $\boldsymbol{\lambda}$ are the corresponding eigenvalues. The eigenvalues are associated with new variables called principal components Z_m. The principal components are used to characterize the variance explained in the raw dataset. The eigenvectors associated with each principal component are used as coefficients in linear combinations with the raw criteria performance values. Each scaled ordination value is called a Z_m-score. Development of the principal components and Z_m-scores reduces the dimensionality of the original dataset so that one or two components explain most of the variation.

The dominant eigenvalue λ_1 and its corresponding eigenvector $\rightarrow v_1$ explain the most variation in the set of management alternatives. The corresponding dominant components Z_1 and Z_2 represent the highest variation in the management alternatives.

APPENDIX B

COMPROMISE PROGRAMMING ALGORITHM

Closeness is based on using the family of distance metrics (p). The ideal point is equal to unity for all criteria (1), and the Euclidean distance norm is used as an appropriate distance metric ($p = 2$). The following problem formulation was used based on incorporating the scaled data into the calculations:

$$\min L^p(i) = \sum_{j=1}^{m} w_j^p \left|1 - x_{ij}\right|^p \tag{B1}$$

where w_j^p is the criterion weight for criteria j, alternatives i.

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APPENDIX C

NET IRRIGATION BENEFIT CRITERION

Criterion C_2 was developed to maximize the average annual net benefit (I) over the combined irrigation nodes (\$AUD ha^{-1} yr^{-1}). The average annual net benefit is the sum of net benefit for each crop *a* for each year *y*, where net benefit is a function of area planted *AP*, yield *Y*, the price *P*, input costs *C*, volume of water *V*, and cost of pumping *CP*.

$$I = \frac{\sum_{y=o}^{n\ years} \sum_{a=0}^{crop} \left[\left(AP_{ay} * Y_y * P_y \right) - \left(AP_{ay} * C_c \right) - \left(V_{ay} * CP \right) \right]}{n * A_{max}} \tag{C1}$$

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