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Decision Support

A comparison of multiple criteria analysis techniques for water resource management

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Abstract

Multiple criteria analysis (MCA) is a framework for evaluating decision options against multiple criteria. Numerous techniques for solving an MCA problem are available. This paper applies MCA to six water management decision problems. The MCA methods tested include weighted summation, range of value, PROMTHEE II, Evamix and compromise programming. We show that different MCA methods were in strong agreement with high correlations amongst rankings. In the few cases where strong disagreement between MCA methods did occur it was due to presence of mixed ordinal-cardinal data in the evaluation matrix. The results suggest that whilst selection of the MCA technique is important more emphasis is needed on the initial structuring of the decision problem, which involves choosing criteria and decision options.

Keywords: Multiple criteria analysis; Decision making; Water resource management

1. Introduction

Water resource management decisions are typically guided by multiple objectives measured in a range of financial and non-financial units (Gough and Ward, 1996). Often the outcomes are highly intangible and may include items such as biodiversity, recreation, scenery and human health. These characteristics of water planning decisions make multiple criteria analysis (MCA) an attractive approach. MCA can be defined as a grouping of techniques for evaluating decision options against multiple criteria measured in different units (RAC, 1992; Voogd, 1983). A decision option is an action, or project, which contributes to the decision maker's objectives. In discrete choice MCA there are a finite set of decision options being appraised. Weights can be assigned to criteria to represent their relative importance. Many researchers have found that MCA provides an effective tool for water management by adding structure, auditability, transparency and rigour to decisions (Dunning et al., 2000; Joubert et al., 2003; Flug et al., 2000; Nayak and Panda, 2001).

The variety of techniques for 'solving' an MCA problem has grown rapidly over recent decades. Weistroffer et al. (2005) review 79 MCA software packages which implement a variety of MCA methods. Recent review papers identify hundreds of MCA techniques for ranking or scoring options,

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weighting criteria and transforming criteria into commensurate units (Figueira et al., 2005; Pohekar and Ramachandran, 2004; Hayashi, 2000). The opportunities for constructing new methods by combining or modifying existing ones are practically limitless. This can create uncertainty in the results of MCA, as noted some time ago by Gershon (1984, p. 247):

> "…if different techniques [for MCA] can yield conflicting results for the same problem, then the appropriateness of any of the techniques is placed into question."

Analysts considering the use of MCA in water resource planning decisions are faced with the formidable challenge of deciding which methods, or combinations of methods, are best suited to their problem. Whilst in operation, Australia's Resource Assessment Commission reviewed MCA and observed that (RAC, 1992, p. 23):

> "…a large amount of effort has been expended in developing [MCA] evaluation methods but relatively little effort has been devoted to evaluating the performance of those methods or determining which method should be used in what circumstance."

This quandary persists in contemporary MCA application and has intensified due to the rapid increase in MCA methods over recent decades. Guidelines have been proposed to help choose the most appropriate MCA technique by Guitouni and Martel (1998).

In this study six recent water resource management decision problems are selected from the literature and used to assess the impact of using one MCA method over another. An MCA evaluation matrix (EM) is obtained for each decision problem. An EM contains a set of criteria, a set of decision options, a set of criteria weights and performance measures. A performance measure is the raw score for a decision option against a criterion. Five MCA methods are applied to each of the six EMs to attain a ranking of the decision options. The similarity of rank output resulting from different MCA methods is assessed using rank correlation coefficients.

The question of how different MCA methods create different results has been examined in previous studies. Some examples come from Gershon and Duckstein (1983); Howard (1991); Ozelkan and Duckstein (1996); Eder et al. (1997) and Raju et al. (2000). One study by Tecle (1992) uses MCA itself to evaluate 15 MCA methods.

This paper provides new evidence by applying MCA to multiple EMs as opposed to a single EM for water management. The results in this paper are not problem specific and apply to numerous real water management problems published in the past decade from several countries. We show that MCA results do differ, though typically only slightly, under different ranking techniques. This has implications on deciding where to focus effort when applying MCA. Often it is far more important to focus effort on structuring the decision problem (involving identifying decision options, criteria and criteria weights) than trying to decide which MCA technique to apply.

2. Water resource planning and management decisions

Water resource planning and management is a sub-field of natural resource management in which decisions are particularly amenable to MCA (Romero and Rehman, 1987). Decisions in water management are characterised by multiple objectives and multiple stakeholder groups. Outcome measures are in multiple financial and non-financial units. Decision makers are increasingly looking beyond conventional benefit cost analysis towards techniques of MCA that can handle a multi-objective decision environment (Prato, 1999; Joubert et al., 1997; Bana e Costa et al., 2004). There is a need for transparent, robust and auditable analyses.

Some of common types of water management decisions being supported with MCA techniques include:

1. Selection of alternative water supply and storage infrastructure options. Eder et al. (1997) use MCA to select locations and design options for hydro-electric power plants on the Danube River in Austria.
2. Selection of water restoration or enhancement projects in light of constrained budgets. Al-Rashdan et al. (1999) prioritise projects designed to improve the environmental quality of the Jordan River using MCA.
3. Allocating a fixed water resource amongst competing uses. Flug et al. (2000) use MCA to select water flow options for Glen Canyon Dam in Colorado providing for recreation, biodiversity, fishing and cultural uses.

4. Selecting water management policies for an entire city or region. Joubert et al. (2003) use MCA to help choose water supply augmentation and demand management policies for the city of Cape Town in South Africa.

The multi-objective nature of water management decisions makes it an application-area suitable for comparative study of MCA techniques. However, the results of this paper are likely to have relevance to other fields of natural resource management and decision making.

3. Generic definition of a multiple criteria analysis model

An MCA model aims to rank or score a finite number of decision options based on a set of evaluation criteria. The MCA model can be represented by a matrix X of n decision options and m criteria (Hipel, 1992).

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{n,1} \\ \vdots & \ddots & \vdots \\ x_{1,m} & \cdots & x_{n,m} \end{bmatrix}. \tag{1}$$

In this study we refer to this as an evaluation matrix (EM). The EM may contain a mix of ordinal and cardinal data. The raw performance score for decision option i with respect to criterion j is denoted by $x_{i,j}$. For a multi-criteria evaluation task to be warranted we require at least two criteria and two decision options ($n \geqslant 2$ and $m \geqslant 2$). The importance of each criterion is given in a one dimensional weights vector W containing m weights, where w_j denotes the weight assigned to the jth criterion:

$$W = w_1 \ldots w_m. \tag{2}$$

Both X and W may contain either ordinal or cardinal level data, or a mix of both. Different MCA techniques are available to handle different levels of qualitative and quantitative measurement. The MCA algorithms aim to:

(a) Define the function $r_i = f_1(X, W)$, $R = \{r_1 \ldots r_n\}$ and provide a rank order[1] of the decision options and/or;

(b) Define the function $u_i = f_2(X, W), U = \{u_1 \ldots u_n\}$ and provide a utility score for each decision option.

Values for r_i and u_i can be used by the decision maker to: (a) select a single decision option; (b) select a subset of options; (c) determine the performance ordering of all options; and/or (d) determine the relative magnitude of performance for options. In this study the utility score (u_i) is used to rank the decision options. The utility score is a measure of the overall benefit or worth of a decision option relative to other options in the selection set.

Under some conditions options and criteria should always be excluded from an MCA model. These conditions are strict dominance and non-discriminating criteria. Strict dominance exists when one decision option is outperformed by another against all criteria (Yakowitz et al., 1993). Most MCA methods require each criterion to be transformed into a unitless value score, so they may be combined to produce the utility score (u_i). In this study we define $v_{i,j}$ as the value to the decision maker of the raw performance score $x_{i,j}$. There are many ways of computing $v_{i,j}$ and in this study we use linear transformations:

$$v_{i,j} = \frac{x_{i,j} - \min_{i=1}^{n}(x_{i,j})}{\max_{i=1}^{n}(x_{i,j}) - \min_{i=1}^{n}(x_{i,j})} \tag{3}$$

if a higher value for $x_{i,j}$represents better performance

$$v_{i,j} = \frac{\max_{i=1}^{n}(x_{i,j}) - x_{i,j}}{\max_{i=1}^{n}(x_{i,j}) - \min_{i=1}^{n}(x_{i,j})} \tag{4}$$

if a lower value for $x_{i,j}$ represents better performance

$$\max_{i=1}^{n}(x_{i,j}) = \text{the maximum value of } x_{i,j}$$
$$\text{for } i = 1, \ldots n;$$

and

$$\min_{i=1}^{n}(x_{i,j}) = \text{the minimum value of } x_{i,j}$$
$$\text{for } i = 1, \ldots n.$$

Decision option i can be considered strictly dominated by i' if

$$v_{i',j} \geqslant v_{i,j} \quad \forall j = 1, \ldots, m \quad \text{and}$$
$$v_{i',j} > v_{i,j} \quad \text{for at least one } j = 1, \ldots, m. \tag{5}$$

[1] In this paper a value of 1 is assigned to the best performing option and n to the worst performing option.

An MCA model requires at least two non dominated decision options. In discrete choice problems, where the aim is to select one preferred option, all dominated options should be excluded from the selection set.

Non-discriminating criteria do not provide performance differentiation for at least two decision options. They are redundant and should be removed from the MCA model. Criterion j is non-discriminating if

$$v_{i',j} = v_{i,j} \quad \forall i = 1, \ldots, n; \;\; i' = 1, \ldots, n. \tag{6}$$

There are numerous descriptions of the MCA decision making process (e.g. RAC, 1992; Howard, 1991) and preference modelling (Öztürk et al., 2005). Applications of MCA generally include:

1. Choose decision options.
2. Choose evaluation criteria.
3. Obtain performance measures ($x_{i,j}$) and fill in the EM.
4. Transform into commensurate units (this depends on the type of MCA technique being applied). This may require decision maker preference inputs.
5. Weight the criteria. This is heavily dependent on decision maker preferences.
6. Rank or score the options.
7. Perform sensitivity analysis (weights, performance measures, techniques).
8. Make a decision.

4. Case study water resource evaluation matrices

Six water resource management EMs were selected to compare MCA techniques (Table 1). Each EM evaluates a set of water management options against multiple criteria in different units. Three of the EMs contain a mix of qualitative and quantitative data, the others contain only quantitative data. The studies are drawn from across the globe coming from Austria, Iran, Lebanon, India, Thailand and Brazil. Some are at a broad strategic level (e.g. at the national scale by Karnib, 2004) and others deal with specific and localised options (e.g. Raju and Kumar's, 1999; evaluation of irrigation systems for agriculture within a district of India).

Prior to the application of MCA techniques the EMs were screened for the presence of dominated options, as defined by (5) above. Strict dominance was found in two of the six EMs. In Abrishamchi et al. (2005) one of eight options was dominated. In Tiwari et al. (1999) four of ten options were dominated. The dominated options were left in the EMs for the analysis. All of the criteria in the EMs satisfied the requirement of being 'discriminating' as defined in (6) above.

4.1. Criteria weights

All of the case studies specified criteria weights. These weights were used in the analysis for this paper. In Abrishamchi et al. (2005) and Tiwari et al. (1999) four alternative weight sets were available. In both cases a single non-equal weight set was chosen from the four available sets. The weights and evaluation matrix were identical for all MCA methods, so the only parameter being changed was the MCA method itself.

5. Multiple criteria analysis techniques

The number of MCA techniques have increased rapidly over the past several decades (for a recent review see Figueira et al., 2005). They provide practically limitless options for combining weights information with the evaluation matrix to attain a result. In this study five MCA techniques are applied which treat the problem in markedly different ways.

5.1. Weighted summation

Weighted summation (WS) is arguably the most simple and widely applied technique of MCA (Howard, 1991). In weighted summation all criteria are transformed onto a commensurate scale (usually 0 to 1, where 1 represents best performance), multiplied by weights then summed to attain overall utility. The selection of options is on the basis of u_i which is determined by

$$u_i = \sum_{j=1}^{m} v_{i,j} w_j, \tag{7}$$

where

$$\sum_{j=1}^{m} w_j = 1;$$

$$0 < w_j \leqslant 1.$$

Fleming (1999) and Hyde et al. (2004) applied weighted summation to evaluate groundwater extraction options in the Northern Adelaide Plains

Table 1
Water management evaluation matrices (EMs) used to compare MCA methods

Authors	Location	Decision problem	Model structure
Abrishamchi et al. (2005)	Iran, City of Zahidan	Selecting water and wastewater management options such as new distribution networks and treatment plants	Nine criteria relating to economic, social, public health, technical and sustainability objectives Eight city water management projects Mixed ordinal and cardinal data in the evaluation matrix
Eder et al. (1997)	Danube River, Austria	Ranking water resource management projects to achieve ecological, social and economic objectives	Thirty two criteria classified under 8 sub-goals and 3 goals 12 water management projects. Mixed ordinal and cardinal data in the evaluation matrix
Karnib (2004)	Lebanon	Evaluation of water resource projects as part of a national water 'master plan'	11 criteria in technical, socio-economic, environmental and economic groups. Five water resource management projects Evaluation matrix contains both cardinal and ordinal data
Raju and Kumar (1999)	Andhra Pradesh, India	Assessing alternative policy options to improve irrigation systems	3 criteria: employment; agricultural production and; net benefits Six policy options (representing groups of more specific policies) The evaluation matrix contains cardinal performance measures
Srdjevic et al. (2004)	Paraguacu River Basin, Brasil	There is a requirement to improve the use of two multi-purpose reservoirs on the Jacuipe river	Six criteria for reliability, vulnerability, resilience, water shortages, water yield and yield risk. Twelve management scenarios for upgrading the reservoirs The evaluation matrix contains cardinal performance measures
Tiwari et al. (1999)	Northern Plains, Thailand	Selection of irrigation options to achieve improved social, environmental and economic outcomes	Seven criteria related to land suitability, energy, water use, environment and economic returns to various stakeholders Ten alternative irrigated agricultural production systems The evaluation matrix contains cardinal performance measures

of South Australia. There are many other applications of weighted summation in environmental management and water resource planning (Howard, 1991).

Whilst commonly applied weighted summation makes numerous simplifying assumptions about the decision problem, which can potentially lead to inaccurate results (Rowe and Pierce, 1982). For example, sometimes the aggregation function may be multiplicative instead of additive when the criteria are non-compensatory (i.e. good performance on one criterion does not compensate for poor performance on another). Another issue is that the criteria transformations may be non-linear; often concave or convex forms more accurately capture decision maker preferences. Sometimes weighted summation produces only very minor differences in u_i for the options, which may be insufficient to differentiate performance. It is also possible that ordinal level data, in the evaluation matrix, is incorrectly treated as cardinal data. These, and other such issues, are easy to correct but are often overlooked in the application of weighted summation.

5.2. Range of value method

The range of value method (ROVM) by Yakowitz et al. (1993) requires only ordinal specification of criteria importance from a decision maker. It has been applied to problems of watershed management by Yakowitz and Lane (1997) and Yakowitz and Hipel (1997). The ROVM approach can be useful because decision makers often find it difficult, or not meaningful, to supply quantitative weights. Studies of how decision makers interact with weighting techniques have shown they are most comfortable with ordinal rankings of criteria importance (Hajkowicz et al., 2000).

The ROVM approach calculates the best and worst utility for each decision option. This is achieved by maximising and minimising a utility function.

For a linear additive model the best utility (u_i^*) of option i and worst utility (u_i^-) of option i is found by

$$\text{Maximise}: \quad u_i^* = \sum_{j=1}^{m} v_{i,j} w_j \tag{8}$$

$$\text{Minimise}: \quad u_i^- = \sum_{j=1}^{m} v_{i,j} w_j \tag{9}$$

$$\text{Subject to}: \quad w_1 \geqslant, \ldots, \geqslant w_m; \quad \sum_{j=1}^{m} w_j = 1; \text{ and } w_m \geqslant 0.$$

If $u_i^- > u_{i'}^*$ then option i outperforms option i' regardless of the actual quantitative weights. If it is not possible differentiate the options on this basis then a scoring (enabling subsequent ranking) can be attained from the midpoint. This has been used to attain a complete ordinal ranking in the case studies. The midpoint is calculated as

$$u_i = \frac{u_i^- + u_i^*}{2}. \tag{10}$$

5.3. PROMETHEE II

This technique is an outranking MCA approach that provides a complete ordering of decision options (PROMETHEE I provides partial ordering). The PROMETHEE methods were developed by Brans et al. (1986) and is described here based on Brans and Mareschal (2005). It has been applied to water resource planning in the Middle East region (Abutaleb and Mareschal, 1995) amongst many other applications.

The starting point is to define a preference function, $P_j(i, i')$, for alternative i versus alternative i', where $i \neq i'$. There are several methods (Brans and Mareschal, 2005). Here we use

$$P_j(i, i') = \begin{cases} 0 & \text{if } v_{ij} \leqslant v_{i'j}, \\ v_{ij} - v_{i'j} & \text{if } v_{ij} > v_{i'j}. \end{cases} \tag{11}$$

An aggregated preference index incorporating the weights is defined as

$$\pi(i, i') = \sum_{j=1}^{m} P_j(i, i') w_j. \tag{12}$$

Eqs. (11) and (12) can easily be adapted to find $P_j(i', i)$ and $\pi(i', i)$. As each alternative faces $(n-1)$ other alternatives a positive and negative outranking flow is determined by

$$\phi^+(i) = \frac{1}{n-1} \sum_{i'=1}^{n} \pi(i, i'), \tag{13}$$

$$\phi^-(i) = \frac{1}{n-1} \sum_{i'=1}^{n} \pi(i', i). \tag{14}$$

It is then possible to determine an overall score for each alternative by calculating the net outranking flow, $\phi(i)$:

$$u_i = \phi(i) = \phi^+(i) - \phi^-(i). \tag{15}$$

5.4. Evamix

The Evamix approach by Voogd (1982, 1983), and described in Nijkamp et al. (1990) and Martel and Matarazzo (2005), treats data in the evaluation matrix differently depending on whether it is qualitative (ordinal) or quantitative (cardinal). This is an important contribution of Evamix to the MCA toolkit. Many MCA methods, such as weighted summation, are incorrectly applied to ordinal data by treating it as though it were at a cardinal measurement scale (Rowe and Pierce, 1982).

Published applications of Evamix are rare, however we have included it because, unlike many other MCA methods, it treats ordinal and cardinal data separately. Evamix requires cardinal information on criteria weights. Evamix commences by identifying unique pairs of options. It then determines an ordinal dominance score by

$$\alpha_{ii'} = \left[\sum_{j \in O}^{m} \{ w_j \, \mathrm{sgn}(v_{ij} - v_{i'j}) \}^c \right]^{1/c}, \quad c = 1, 3, 5 \ldots, \tag{16}$$

where $c = a$ is the parameter which controls the influences of differences arising from minor criteria (the larger c is the lesser the influences of differences on minor criteria); $O = a$ subset of criteria with an ordinal measurement scale and;

$$\mathrm{sgn}(v_{ij} - v_{i'j}) = \begin{cases} +1 & \text{if } v_{ij} > v_{i'j}, \\ 0 & \text{if } v_{ij} = v_{i'j}, \\ -1 & \text{if } v_{ij} < v_{i'j}. \end{cases} \tag{17}$$

A cardinal dominance score is calculated by

$$\gamma_{ii'} = \left[\sum_{j\in Q}^{m} \{w_j(v_{ij} - v_{i'j})\}^c\right]^{1/c}, \tag{18}$$

where Q is a subset of criteria with an cardinal measurement scale.

Because the ordinal and cardinal dominance scores are in different units they must be standardised prior to being combined. One approach[2] to obtain a standardised ordinal and cardinal dominance score $(\delta_{ii'}, \sigma_{ii'})$ given in Voogd (1983), and applied in this paper, is called the subtractive summation technique where

$$\delta_{ii'} = \alpha_{ii'}\left(\sum_{i}^{n}\sum_{i'}^{n}|\alpha_{ii'}|\right)^{-1}, \tag{19}$$

$$\sigma_{ii'} = \gamma_{ii'}\left(\sum_{i}^{n}\sum_{i'}^{n}|\gamma_{ii'}|\right)^{-1}. \tag{20}$$

The combined dominance measure $(q_{ii'})$ for each pair is determined by

$$q_{ii'} = w_o\delta_{ii'} + w_Q\sigma_{ii'}, \tag{21}$$

where w_o is the sum of weights assigned to the ordinal criteria and w_Q = The sum of weights assigned to the cardinal criteria.

The decision option's final appraisal score is given by

$$u_i = \frac{1}{n}\sum_{i'=1}^{n} q_{ii'}. \tag{22}$$

5.5. Compromise programming

Compromise programming aims to rank or score decision options based on their distance to some ideal point and is based on the 'displaced ideal' concept by Zeleny (1973, 1982). It has recently been applied by Abrishamchi et al. (2005) to select urban water supply options in Iran. The disutility (u_i^-) of each option is the weighted distance from the ideal points:

$$u_i^- = \left[\sum_{j=1}^{m} w_j^c\left|\frac{f_{bj} - x_{ij}}{f_{bj} - f_{wj}}\right|^c\right]^{1/c}, \tag{23}$$

[2] Two other approaches called the "subtractive shifted interval technique" and the "additive interval technique" are described in Nijkamp et al. (1990).

where f_{bj} is the best value for all options for criterion j, ftextsubscriptwj is the worst value for all options for criterion j and $c = a$ parameter that reflects the importance of maximal deviation from the ideal solution.

In selecting decision options the aim is to minimise u_i. Where possible f_{bj} and f_{wj} can be set to ideal and anti-ideal values, such as a water quality guideline. Where no such ideal or anti-ideal exists, as in this study, they may be drawn from within the evaluation matrix. In this study f_{bj} was set to the maximum value within criterion j and f_{wj} to the minimum value (vice versa when a lower score indicated better performance). When c is set to 1, all distances from the ideal solution are weighted equally. If c is >1 (e.g. $c = 2$) larger distances from the ideal solution are penalised more than smaller distances from the ideal.

6. Results

The aim of this analysis is to test the level of agreement between the five MCA techniques for each EM. Weights and performance measures in the evaluation matrix are held constant for each MCA technique. Three tests are performed to measure the level of agreement:

1. The similarity between two sets of rankings was measured using Spearman's rank correlation coefficient (q). Values for q range from −1 to 1, where 1 represents perfect rank correlation. Because the outputs have no tied rank positions we compute q for rank output from two MCA methods, $R' = \{r'_1 \ldots r'_n$ and $R'' = \{r''_1 \ldots r''_n$, by Sheskin (2004):

$$q = \frac{\sum_{i=1}^{n}(r'_i - r''_i)^2}{n^3 - n}. \tag{24}$$

2. The similarity of ranks produced from the five MCA methods was measured using Kendall's Coefficient of Concordance (z). Values for z range from 0 to 1, where 1 represents perfect rank correlation. As the output has no tied rank positions z is computed by Sheskin (2004)

$$z = \frac{\sum_{i=1}^{n}\left(s_i - \frac{\sum_{i=1}^{n} s_i}{n}\right)^2}{\frac{1}{12}k^2(n^3 - n)}, \tag{25}$$

Table 2
Kendall's coefficient of concordance (z) for all evaluation matrices (EMs)

Evaluation matrix	z
EM1. Abrishamchi et al. (2005)	0.81
EM2. Eder et al. (1997)	0.91
EM3. Karnib (2004)	1.00
EM4. Raju and Kumar (1999)	1.00
EM5. Srdjevic et al. (2004)	0.98
EM6. Tiwari et al. (1999)	1.00

where k is the number of MCA methods, which equals 5 for this paper and s_i is the sum of ranks assigned to a decision option i across all k MCA methods.

3. A test was made on agreement between the top three rank positions. This was made because sometimes the purpose of MCA is to select a single option. A decision maker using MCA is likely to select from the top few options. In this test a result of $(1,2,3)$ indicates first, second and third rank positions are identical; $(1,2,\#)$ indicates first and second rank positions are identical; $(1,\#,\#)$ shows only the first is identical and; $(\#,\#,\#)$ shows none is identical.

Values for z for each evaluation matrix are given in Table 2 and range from 0.80 to 1. In three EMs, Karnib (2004), Raju and Kumar (1999) and Tiwari et al. (1999), z is equal to 1. This means there is perfect agreement[3] between the MCA techniques. Here it would not matter which approach was applied as the result would be identical. There is near perfect agreement between the MCA techniques applied to the EMs by Srdjevic et al. (2004) and Eder et al. (1997) with values for z of 0.98 and 0.91. Again it would make little difference to the overall result which technique were applied. A values for z of 0.81 was obtained for the EM by Abrishamchi et al. (2005) revealing some disagreement between MCA methods. Overall, the values for z reveal strong agreement with a change in MCA technique typically resulting in only a minor variation in results.

The strength of agreement, measured with q, for each pair of techniques is shown in Tables 3–5. We only show these results for the three EMs where there is at least some disagreement between methods. The EMs for Karnib (2004); Raju and Kumar (1999) and Tiwari et al. (1999) were in perfect agreement and produce an r of 1 for every pair of MCA methods.

Whilst all techniques typically produced high levels of agreement the strongest disagreement was recorded by the range of value versus Evamix techniques with a q of 0.29. The EMs with higher disagreement were those that contained a mix a quantitative and qualitative performance data.

This is particularly noticeable in the Abrishamchi et al. (2005) EM which has the minimum q of 0.29. The technique with strongest disagreement to the others in this EM is Evamix. This is probably because Evamix employs different algorithms to handle ordinal and cardinal appropriately. Other techniques, such as weighted summation, are sometimes misapplied by treating ordinal data in the EM as though it were cardinal. The similarity of rank orders in the top three positions is also high under different MCA techniques. If MCA were being used to select a single 'best' option then variation of technique would lead to the same choice in each EMs.

These results are supported by prior studies of a similar nature. In forestry applications of MCA Howard (1991) found that: (a) no single MCA technique had a particular mathematical advantage over the others; (b) the most important aspect is the selection of criteria and options and; (c) the bulk of the decision maker's effort should go towards specifying preferences.

Gershon and Duckstein (1983) conducted a study of four MCA techniques[4] to evaluate water management strategies in a semi-urbanised area in the United States. They found the different techniques yielded 'similar' results and all were potentially applicable for river planning. Finally a study of MCA to evaluate water management projects in the Austrian part of the Danube river by Ozelkan and Duckstein (1996) applied five MCA techniques.[5] Again it was found that changing MCA technique produced minor differences in the final ranking of options.

[3] The agreement of MCA techniques applied to the Tiwari et al. (1999) evaluation matrix is near-perfect. When rounded to three decimal places it produces a z of 0.997.

[4] The MCA techniques applied by Gershon and Duckstein (1983) included ELECTRE, compromise programming, co-operative game theory and multi-attribute utility theory.

[5] The MCA techniques applied by Ozelkan and Duckstein (1996) included PROMETHEE, Geometrical Analysis for Interactive Assistance (GAIA), multicriterion Q-analysis, compromise programming and cooperative game theory.

Table 3
Rank correlation (q) results for evaluation matrix #1 by Abrishamchi et al. (2005)[a]

	Range of value	PROMETHEE II	Evamix	Compromise programming
Weighted summation	0.90 (1,#,#)	1.00 (1,2,3)	0.52 (1,#,#)	1.00 (1,2,3)
Range of value	–	0.90 (1,#,#)	0.29 (1,#,#)	0.90 (1,#,#)
PROMETHEE II	–	–	0.52 (1,#,#)	1.00 (1,2,3)
Evamix	–	–	–	0.52 (1,#,#)

Here (1,2,3) indicates first, second and third rank positions are identical; (1,2,#) indicates first and second rank positions are identical; (1,#,#) shows only the first is identical and; (#,#,#) shows none is identical.
[a] The agreement between methods for the top three rank positions is supplied in parenthesis.

Table 4
Rank correlation (q) results for evaluation matrix #2 by Eder et al. (1997)

	Range of value	PROMETHEE II	Evamix	Compromise programming
Weighted summation	0.75 (1,2,#)	1.00 (1,2,3)	0.97 (1,2,3)	1.00 (1,2,3)
Range of value	–	0.75 (1,2,#)	0.74 (1,2,#)	0.75 (1,2,#)
PROMETHEE II	–	–	0.97 (1,2,3)	1.00 (1,2,3)
Evamix	–	–	–	0.97 (1,2,3)

Table 5
Rank correlation (q) results for evaluation matrix #5 by Srdjevic et al. (2004)

	Range of value	PROMETHEE II	Evamix	Compromise programming
Weighted summation	0.92 (1,2,#)	1.00 (1,2,3)	1.00 (1,2,3)	1.00 (1,2,3)
Range of value	–	0.92 (1,2,#)	0.92 (1,2,#)	0.92 (1,2,#)
PROMETHEE II	–	–	1.00 (1,2,3)	1.00 (1,2,3)
Evamix	–	–	–	1.00 (1,2,3)

7. Discussion and conclusion

This study finds strong agreement between different MCA techniques used for water resource management. This finding was repeated in six EMs taken from published water management decisions. There were only a few cases where different techniques generated markedly different results. When it occurred, disagreement was more pronounced in EMs that contained both ordinal and cardinal performance data, as opposed to just cardinal data.

The Evamix method was distinct from other MCA techniques in the mixed ordinal-cardinal EMs. Unlike the other MCA methods Evamix employs separate algorithms to handle ordinal and cardinal data. Applications of Evamix are rare compared to the other MCA techniques in this paper. Evamix may warrant greater application in water resource management to better handle EMs with mixed ordinal and cardinal data.

Apart from the ordinal-cardinal issue, results of discrete choice analysis in water management were found to be relatively insensitive to variation in MCA technique. Guitouni and Martel (1998) propose a structured approach for choosing MCA techniques. However, in many applications there is no overwhelming reason to adopt one MCA technique over another and several (or dozens of) approaches are potentially valid. The results in this paper may offer some comfort to users of MCA in water management. So long as ordinal and cardinal data are handled appropriately, the ranking of decision options is unlikely to change markedly by using a different MCA technique.

Sometimes the ease of understanding an MCA technique will be a primary concern in the choice of whether (or not) it is used. Weighted summation is a relatively easy technique (Howard, 1991; Zanakis et al., 1998) that can be modelled with a simple spreadsheet. The adoption of more sophisticated, and more complicated, techniques may not be necessary if they are likely to confuse decision makers. If decision makers cannot understand the MCA technique, and how it generated a result, it is unlikely to be used. This has been highlighted by Beynon et al. (2002) as one of the biggest obstacles to adoption of decision support tools.

The selection of MCA technique will typically be of lesser importance than the initial structuring of the decision problem which includes: (a) selection of criteria, (b) selection of decision options, (c) weighting the criteria and (d) obtaining performance measures to populate the EM. This was also observed by Janssen (2001) in a case where MCA was scrutinised in a court of law in the Netherlands. Janssen (2001, p108) concludes that:

> "The main methodological challenge is not in the development of more sophisticated MCA methods. Simple methods, such as weighted summation, perform well in most cases. More important is the support of problem definition and design."

Compared to the expansive work on MCA algorithms there is little guidance available to help a decision analyst structure an MCA problem and choose criteria and options to begin with (Kasanen et al., 2000). Recent work by Mingers and Rosenhead (2004) on problem structuring methods (PSM) and a computer interface by Scheubrein and Zionts (2006) provide a useful starting point. However, further work is required on MCA problem structuring for it to reach its full potential in supporting water resource management decisions. In the coming years our research aims to address this need by developing multi-criteria decision support tools for the Australian water industry.

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