Multi-Criteria Decision Assessment Methods to Identify Total Water Cycle Management Strategies

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The Urban Water Security Research Alliance (UWSRA) is a $50 million partnership over five years between the Queensland Government, CSIRO's Water for a Healthy Country Flagship, Griffith University and The University of Queensland. The Alliance has been formed to address South East Queensland's emerging urban water issues with a focus on water security and recycling. The program will bring new research capacity to South East Queensland tailored to tackling existing and anticipated future issues to inform the implementation of the Water Strategy.

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FOREWORD

Water is fundamental to our quality of life, to economic growth and to the environment. With its booming economy and growing population, Australia's South East Queensland (SEQ) region faces increasing pressure on its water resources. These pressures are compounded by the impact of climate variability and accelerating climate change.

The Urban Water Security Research Alliance, through targeted, multidisciplinary research initiatives, has been formed to address the region's emerging urban water issues.

As the largest regionally focused urban water research program in Australia, the Alliance is focused on water security and recycling, but will align research where appropriate with other water research programs such as those of other SEQ water agencies, CSIRO's Water for a Healthy Country National Research Flagship, Water Quality Research Australia, eWater CRC and the Water Services Association of Australia (WSAA).

The Alliance is a partnership between the Queensland Government, CSIRO's Water for a Healthy Country National Research Flagship, The University of Queensland and Griffith University. It brings new research capacity to SEQ, tailored to tackling existing and anticipated future risks, assumptions and uncertainties facing water supply strategy. It is a $50 million partnership over five years.

Alliance research is examining fundamental issues necessary to deliver the region's water needs, including:

- ensuring the reliability and safety of recycled water systems.
- advising on infrastructure and technology for the recycling of wastewater and stormwater.
- building scientific knowledge into the management of health and safety risks in the water supply system.
- increasing community confidence in the future of water supply.

This report is part of a series summarising the output from the Urban Water Security Research Alliance. All reports and additional information about the Alliance can be found at http://www.urbanwateralliance.org.au/about.html.

C. Davis

Chris Davis
Chair, Urban Water Security Research Alliance

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EXECUTIVE SUMMARY

Total Water Cycle Management (TWCM) is an approach to water management that considers the full water cycle, as well as holistically considering social, economic and environmental impacts. It has been receiving increasing interest across Australia, as evidenced by recent literature. In fact, the South East Queensland Regional Plan 2009-2031 requires water management planning in South East Queensland (SEQ) to comply with the principles of TWCM.

Decision making is what underpins TWCM and, whilst many factors contribute to good decision making, data and models are key contributors in this process. This report explores approaches used, or that could potentially be used, in order to support TWCM. To be more specific, this report has described three approaches for assessing strategies in the context of TWCM in SEQ. As such, it is possible to compare and contrast the approaches that have been applied.

The three approaches described are: 1) traditional Multi-Criteria Assessment (MCA); 2) application of Multi-Objective Optimisation (MOO); and 3) the use of Subjective Logic (SL) for MCA.

As part of this study, it has been found that a real concern is the availability and quality of data. We have explored reliability of the modelling tools that are available. eWater CRC's Source IMS model has been extensively used both to evaluate alternate water service options as well as to undertake sensitivity analysis. At the time, it was deemed necessary to undertake some significant additional work in order to allow the type of sensitivity analysis that was necessary to support our methods.

The results from a traditional MCA and the use of Subjective Logic (SL) for MCA were consistent with each other, but the use of SL provided additional information on uncertainty and assessment reliability.

In terms of the practicalities of applying the three approaches, MCA is currently the easiest option to use. This is partly because, at the time we completed this research, the Source IMS system was not readily set up for undertaking sensitivity analysis, which supports both MOO as well as the SL approach.

Estimating uncertainties adds another level of analysis that can be time and resource consuming. Estimating information reliability also adds a further level of difficulty because a consistent method needs to be used to assign information reliability to all underlying data sources. The use of expert judgments is a good alternative for assigning information reliability, as long as efforts are made to ensure judgments are consistent with each other, and that experts only make judgments within their own domains.

Consideration of uncertainty and reliability in the assessments ought to be considered only when there are real concerns about such issues. The level of concern depends on the attitude of planners towards risk. Risk averse planners ought to consider uncertainty and information reliability; whilst those less risk averse probably don't have the need to consider this.

So far, the capability to undertake MCA is widely available amongst consultants and researchers, but capability to undertake MOO and, in particular, to undertake SL is rather scarce. CSIRO has the capacity, but training would be required in many cases to allow water planners or consultants to undertake this type of analysis.

1. INTRODUCTION

The South East Queensland Regional Plan 2009-2031 requires water management in South East Queensland (SEQ) to comply with the principles of Total Water Cycle Management (TWCM).

TWCM is described as a management philosophy based on systems thinking that recognises that all elements of the water cycle are interdependent (Water by Design, 2010; Maheepala *et al.*, 2010), and has been applied to decrease water demand, reduce stormwater run-off and improve pollutant wash-off from urban catchments by adopting sustainable water management practices (Chanan and Woods, 2006; van der Sterren *et al.*, 2009). The approach has been incorporated into water planning and management practices in a number of Australian contexts (Arbon and Ireland, 2003; Chanan and Woods, 2006; Najia and Lustig, 2006; van der Sterren *et al.*, 2009). It is a value-driven philosophy, with holistic aspirations of managing the total water cycle to achieve desirable environmental outcomes. As such, it is similar in aspirations and values to other concepts such as Water Sensitive Urban Design (Wong, 2006), Sustainable Urban Water Management (Larsen and Gujer, 1997), and Integrated Urban Water Management (Maheepala *et al.*, 2010). Activities that are typically associated with TWCM are greywater recycling, sewer mining, rainwater harvesting, stormwater harvesting or Water Sensitive Urban Design (Arbon and Ireland, 2003; Chanan and Woods, 2006; Najia and Lustig, 2006; van der Sterren *et al.*, 2009).

In SEQ, TWCM is to be achieved through the development of sub-regional and local government scale TWCM plans. Both sub-regional and local government TWCM plans are to consider the capture and use of local water sources, the contribution of local sources to securing the supply at the regional scale and environmental implications of the use of local sources. Sub-regional TWCM plans give a greater emphasis to water supply values at the regional scale whereas local government TWCM plans place a greater emphasis on values relating to protecting the health of the environment.

The common challenge at all scales of TWCM planning is to rigorously and robustly evaluate alternative urban water servicing options in order to defend decisions as being “prudent” in terms of not only direct cost of supply but also in terms of costs and benefits to the environment, which may or may not be directly translatable to monetary values. There is also a need for a high level of certainty in outcomes to ensure that important community values are not endangered.

There is a need for each impact to be presented in an explicit and comparable form so that it is clear to decision-makers what the relative impacts are and what trade-offs can be made. However, at present, there is no guidance available on the methods to be used for both quantifying the impacts and identifying the trade-offs. For example, in the recently published “Total Water Cycle Management Planning Guideline for South East Queensland” (Water by Design, 2010), it is envisaged that “information on modelling platforms”, which can be used particularly in assessing urban water options, “will be made available via www.waterbydesign.com.au/twcm” (pg 44, Water be Design, 2010) as further information and knowledge becomes available with increasing implementation of TWCM Plans and the emerging research in the area of integrated urban water management.

A project was initiated in July 2010 as part of Urban Water Security Research Alliance (UWSRA) to address this knowledge gap. The aim of the project was: to improve and provide guidance on the use of selected systems analysis methods for the quantitative assessment of water supply and the environmental implications of alternative urban water supply options; and to provide a sound scientific basis for evaluating and comparing urban water servicing options as part of the development of TWCM plans at both local government and sub-regional scales.

The analytical methods considered by the project focussed on improving the quantification of: (1) potable water savings at the regional scale; (2) energy consumption and greenhouse gas emissions; and (3) environmental costs and benefits of alternative water servicing options and improving the integrated assessment of these impacts to identify trade- offs and inform decisions on the most sustainable urban water servicing option.

This report focuses on a couple of chosen methods for integrated assessment. Firstly, we describe the widely used and emerging methods for integrated assessment of urban water servicing options in TWCM planning context. These include Multi-Criteria Assessment (MCA) and Multi-Objective Optimisation (MOO) respectively. Secondly, we describe an alternative method to MCA and demonstrate how it can be applied to the Moreton Bay case study to inform the identification of preferred urban water servicing options. The alternative method is based on Subjective Logic (SL) methodology (Moglia *et al.*, 2012b) and it has been specifically designed to capture both uncertainty and information reliability of the impact assessment of alternative urban water servicing options.

Finally, we compare results of the method based on Subjective Logic with MCA, and discuss the importance of incorporating both uncertainty and reliability of impact assessment for the decisions on urban water servicing strategies, in the TWCM context.

2. INTEGRATED ASSESSMENT MODELLING

Integrated Assessment Modelling is a class of modelling activities which is common in environmental science. It is an activity that is inter-disciplinary due to the nature of the analysed problems which typically span across multiple academic disciplines. The aim of the modelling activity is to support decision making and policy analysis. It does this by considering the environment and interactions in an holistic way, and usually leverages modern technology to explore interactions between sub-systems. In other words, it explores larger systems from understanding its pieces and then infers system properties/responses from its parts. Integrated modelling can be very challenging in terms of validation, and therefore it is important to consider data as key components in the modelling activity (Voinov and Shugart, 2013). Without validation and good data, these software are hardly more useful than computer games, rather than models that can be useful to support decisions and evaluating policy. Integrated modelling is sometimes based on using existing and mature models; either allowing these to "talk directly" to each other, or by using their outputs in an integration framework.

2.1. Decision Making Context

TWCM is described as a management philosophy based on systems thinking that recognises that all elements of the water cycle are interdependent (Water by Design, 2010), and has been applied to decrease water demand, reduce stormwater run-off and improve pollutant wash-off from urban catchments by adopting sustainable water management practices (Chanan and Woods, 2006; van der Sterren *et al.*, 2009). Integrated assessment modelling is required because TWCM is concerned with exploring systems responses based on an understanding of system components in interaction.

The steps in applying the TWCM concepts to identify a strategy are to: a) define a number of possible strategies; b) evaluate which strategy will best achieve goals according to defined criteria that are in line with TWCM principles; and c) choose and implement the strategy that appears to be the most appropriate.

Decision-making in TWCM is, however, in some ways problematic, due to a number of important points:

1. Goal formulation: the goal of TWCM is not well-defined and there are many possible goals that one may want to achieve, and the choice of assessment metrics is a value-driven process.
2. Limited scope: strategies are not always within the control of decision–makers; they will only be able to influence a sub-set of those factors that have an impact on the desired outcomes.
3. Unlimited option space: it is virtually impossible to define an exhaustive list of conceivable strategy options, and the formulation of such a list is a process that requires creativity and analysis, in combination with some kind of filtering out of solutions that are not, for various reasons, appropriate.
4. Assessment difficulties: the nature of the TWCM problem is difficult to describe in a way that easily helps us to evaluate the effectiveness of strategies (in achieving goals). Systems are usually not very well understood, and there are serious limitations in terms of data, limiting the scope of assessments.
5. Limited planning capacity: the amount of effort spent on the task of finding and choosing strategies is more constrained by issues like the availability of money, time or understanding, rather than the sense of "being sure of having found a good solution".
6. One-off operations: every time a TWCM planning exercise is undertaken there are unique factors, such as local weather patterns, land use patterns and geography, that can't be ignored, and there are therefore limited opportunities to learn by trial-and-error. Incorporating judgments on the importance of such factors is important.
7. High stakes: every TWCM decision will have (sometimes serious) impacts on the community.

This report describes a number of approaches for evaluating strategies, and how this contributes to TWCM planning. Other approaches that have been explored by the authors in similar contexts include Agent Based Modelling (Moglia *et al.,* 2010), Index methodologies (Moglia *et al.*, 2013), and Participatory assessments (Moglia *et al.* 2007).

2.2. Multi-Criteria Assessment

Multi-Criteria Assessment (MCA), also known as Multi-Criteria Decision Analysis (MCDA), is a is a decision-aid approach, which enables the decision-maker to advance in solving a decision problem where several conflicting points of view (or criteria) must be taken into consideration (Pardalos *et al.*, 1995). Typically, no unique optimal solution exists for such problems. MCA uses decision makers' preferences to identify 'the most preferred solution'.

MCA is an effective tool to identify the most preferred solution out of a set of 'efficient' or 'non-dominated' solutions, rather than from any feasible set of solutions. The latter approach leads to choosing a non-efficient solution as the most preferred solution, whereas the former approach leads to choosing an efficient solution as the most preferred solution. An efficient or a non-dominated solution has the property that it is not possible to move away from it to any other solution without sacrificing in at least one criterion. Therefore, it makes sense for the decision-maker to choose a solution from the non-dominated set. MCA is not a tool for identifying a set of non-dominated solutions from a feasible set of solutions, instead it enables the selection of the final choice from a set of non-dominated solutions by allowing to trade-off certain criteria over others. A tool such as Multi-Objective Optimisation (described in section 2.3) is generally used to identify non-dominated solutions from a large number of feasible solutions.

There are many MCA methods, Guitouni and Martel (1998) listed about 30 MCA methods. These methods can be divided into two main categories:

- Multi-Attribute Utility Theory (MAUT) methods; and
- Outranking methods.

The MAUT method uses a utility function to represent decision-makers preferences for evaluating multiple criteria. The utility function is used when the decision is uncertain, and a value function is used when the decision is certain (in such cases MAVT – Multi-Attribute Value Theory - is used in place of MAUT). The utility or value function is expressed as either an additive or multiplicative form. For example, the form of the additive function is given below:

$$u(X) = \sum_{i=1}^{n} k_i u_i(x_i)$$

Where:

$u(X)$ is scaled from 0 to 1, attribute utility function $u_i = u_i(x_i)$ is scaled from 0 to 1, and the scaling constant or weighting factor k_i is positive and less than 1.

The first step of assessment using MAUT (and MAVT) is determining $u_i(x_i)$. That is, value for the utility function, which is expressed on an ordered metric scale. The metric scale is constructed by assigning 1 to the best possible outcome and 0 to the worst outcome. Then, $u(X)$ for each option x_i, is determined using the utility function in the above relationship. The decision-maker must supply appropriate values for k_i. Then the options are ranked according to the value $u(X)$. The MAUT and MAVT methods require only one set of information from the decision-maker to evaluate option, i.e. values for weighting used to represent relative importance of the decision criteria. This information is used to compute an index, which is then used with above preference relationships to evaluate options against criteria. Since MAUT and MAVT methods use definite preference relationships and an index for evaluation, they are also known as 'direct ranking methods' and 'index methods'.

SMART (Simple Multi-Attribute Rating Theory) is an implementation of MAUT. In SMART, the decision-maker is asked to graphically mark the relative importance of each attribute. The model then assigned values to weighting factor k_i by anchoring the best attainment at a utility of 1, the worst attainment at utility 0, and using a linear function to determine intermediate attainment (Olson *et al.*, 1999). Icke *et al.* (1999) used MAUT method for calculating an index to represent 'sustainability rate'.

The second category of MCA methods, i.e. outranking methods, compares each pair of options using preference relationships (Guitouni and Martel, 1998), which results in 'outranking' of options over another. Specifically, in outranking methods, option *a* is said to outrank *b* if *a is at least as good as b.* A key difference between the MAUT method and the outranking method is that the former does the comparisons based on trade-offs, whereas the latter does pair-wise comparisons. The outranking methods require two types of information from the decision-maker (Brans, 2002). They are: (1) information between criteria, i.e. weights of importance of each criterion; (2) information within criteria, i.e. a preference function for each criterion, say, $P_j(a,b)$ giving the preference of option *a* with regard to option *b* as a function of the difference between the evaluations of *a* and *b* on the criteria *j*.

ELECTRE was the first method implemented, based on the outranking approach (Roy, 1990). The ELECTRE method was followed by many other methods based on the outranking approach such as different ELECTRE methods and PROMETHEE (Preference Ranking METHod for Enrichment Evaluations) methods. The ELECTRE family has a number of different methods: ELECTRE I, ELECTRE IS, ELECTRE II, ELECTRE III, ELECTRE IV and ELECTRE-TRI (Guitouni and Martel, 1998). ELECTRE IS, II, III and IV can all be viewed as improved versions of ELECTRE I, with different levels of refinements provided in the algorithm. ELECTRE-TRI is an improved version of ELECTRE III with a technique in it for ordering options into categories, which is useful to reduce the number of options. The reader is referred to Rogers *et al.* (2000) for details of each method in the ELECTRE family. PROMETHEE has two methods: PROMETHEE I and PROMETHEE II, the former provides partial order of options and the latter provides total order of alternatives (Dias *et al.*, 1998). Both PROMETHEE methods are associated with a graphical module called GAIA, which provides decision-makers by providing a means to explore sensitivity of the decision graphically.

Lootsma and Schuijt (1997) compared SMART (based on MAUT), ELECTRE and AHP. The AHP (Analytical Hierarchy Process) is another MCA method, which is a variation of the MAUT (Rogers *et al.*, 2000). The Lootsma and Schuijt (1997) study revealed that AHP, SMART and ELECTRE were similar in performance. Olsen *et al.* (1999) compared a number of MCA methods including SMART, AHP and PROMETHEE, and preferred PROMETHEE over SMART and AHP. Olson (2001) compared SMART and PROMETHEE methods and concluded that PROMETHEE II with Gaussian preference function provided more accurate results than SMART. Salminen *et al.* (1998) compared ELECTRE III, PROMETHEE I and II and SMART. Their study revealed that ELECTRE III was marginally better than PROMETHEE and SMART. Thus, they concluded that it was better to apply several methods to the same problem when possible, and to use ELECTRE III when it was not possible.

Considering the fact that the outranking methods use two sets of information from the decision-maker (i.e. weighting between criteria and preferences within each criterion) as opposed to using a single set of information (i.e. only weighting between criteria) in MAUT methods, Rogers *et al.*, (2000) stated that, in general, outranking methods were preferred over MAUT methods. Srinivasa-Raju *et al.* (2000) compared ELECTRE and PROMETHEE methods and concluded that both methods produced the same result. Thus, in their opinion, both ELECTRE and PROMETHEE methods were equal in performance. By considering findings of other researchers and our observations on implementation aspects of demo software, it can be said that the outranking methods such as ELECTRE and PROMETHEE are better in performance than the methods based on MAUT such as SMART. Furthermore, both ELECTRE and PROMETHEE seem to be equal in performance.

In the TWCM context, MCA is widely used to choose the most preferred urban water servicing option from a set of alternative urban water servicing options by considering multiple assessment criteria in line with the concept of sustainability (Ashley *et al.*, 1999; Srinivasa-Raju *et al.*, 2000; Maheepala *et* *al.*, 2002; Maheepala *et al.*, 2006a; Maheepala *et al.*, 2006b; Maheepala *et al.*, 2009). The most preferred urban water servicing option is the one that is preferred by the stakeholders involved in the TWCM process. An important aspect of applying MCA to TWCM is eliciting preferences of the stakeholders for the assessment criteria being used. The most common approach is to assign preferences after consulting stakeholders, generally in a workshop setting. Maheepala *et al.* (2009) used Citizens' Jury process (Dienel and Renn 1995) to elicit stakeholder preferences. This approach is facilitated by a judge and allows stakeholders to debate and discuss preferences until consensus is reached (Proctor 2006).

2.3. Multi-Objective Optimisation

Multi-Objective Optimisation (MOO) is a decision-making tool used when evaluating the choices manually or exhaustively is not feasible due to the sheer number of possible solutions. Instead, an algorithm is used to search through the many possible decision sets and find the most optimal ones. Usually there are multiple independent objectives to measure the fitness of each solution, which may or may not be in competition with each other. Rather than producing a single score for each decision set, at the end of the MOO process decision-makers are presented with many optimal solutions, each being a different trade-off among the objectives.

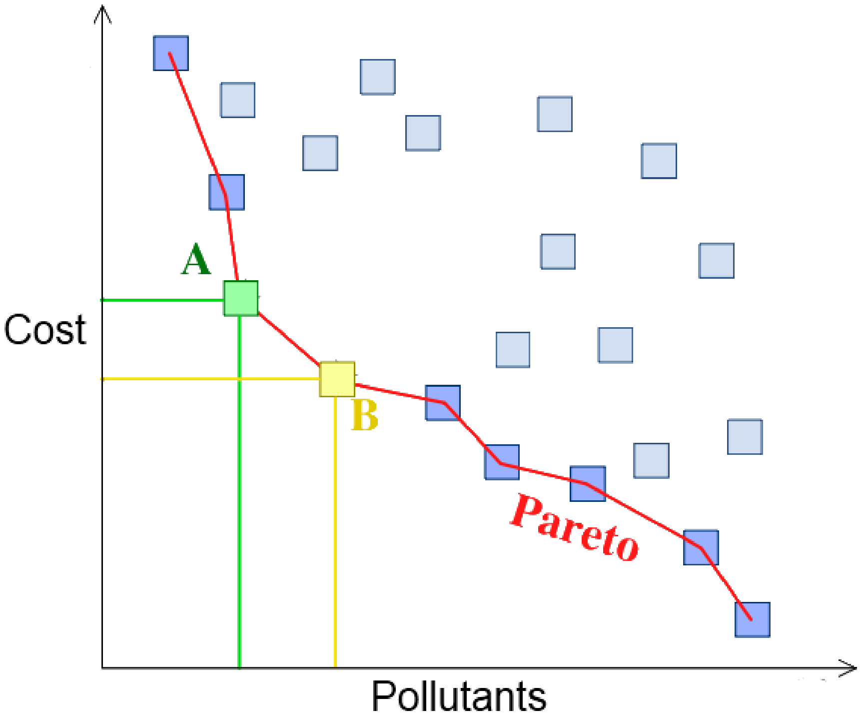

Figure 1. Example of a Pareto frontier.
Source: This figure is modified on the basis of original by Dréo 2006.

Figure 1 presents an example of the use of the "Pareto frontier" to identify optimal solutions. The decisions that led to the solution at *point A* cost more than those at *point B*, but are also more effective at reducing pollution. All such solutions on the "Pareto frontier" are optimal, but represent different choices in this trade-off between objectives.

MOO is useful when:

- the relationship between the decisions being made and the resulting outcomes is complex;
- there are thousands of different possible decision combinations;
- the runtime of the underlying simulation model is significant; and
- the model is considered reliable (it's uncertainty is not too large).

While there have been applications of MOO at scales on par with TWCM planning in MBRC, they typically are more concerned with water quantity analysis rather than water quality. Mortazavi *et al.* (2009) investigated the Canberra headworks water supply system using a variety of multi-objective optimisation approaches. They used a model of the system built in WATHNET and extended it to allow decision variables to alter the inputs to the model, and objective functions to be calculated for each run. The decision variables used include:

- Altering various pumping and diversion capacities;
- Water treatment plant capacity upgrades;
- Reservoir capacity upgrades;
- Water restriction levels; and
- Rainwater tank adoption.

The objectives optimised for were:

- Minimising cost (economic); and
- Minimising water restrictions.

They tested the optimisation of the model using the eMOEA genetic algorithm (Laumanns *et al.* 2002) and the MOAQ ant colony optimisation algorithm (Dongo 1996). They concluded that such optimisation was applicable to urban water supply networks.

Farmani *et al.* (2006) investigated the hypothetical AnyTown, USA. Although a smaller scale system than those in the Moreton Bay Regional Council (MBRC), it concluded that the optimisation was "able to identify the pay-off surface characteristic between total water cost, water age (a surrogate measure for water quality) and the resilience index (a surrogate measure for reliability)". Decision variables used include:

- New pipes;
- Reconditioning pipes;
- Replacing pipes;
- Location of new tanks;
- Size of new tanks; and
- Operation of existing pumps.

Farmani *et al.* (2006) also used the NSGA-II optimisation algorithm to produce their results.

To apply MOO to TWCM, we must first create a model we can trust to represent the system. Ideally, it would be calibrated and validated using real world data. Additionally, we must be able to calculate the objective functions (e.g. monetary cost, greenhouse gas emissions) in an automated fashion. The model must also interact with the multi-objective optimisation algorithm, meaning that it must be able to take the decision variables as inputs and modify its simulation accordingly. This will often require parts of the model to be independent, so they can effectively be turned on and off at will. In practice, we have found that adapting existing models for this purpose can be difficult, and it is often better to start with MOO as an intention from the beginning of model development.

The benefits of applying MOO to TWCM are being able to evaluate a large number of possible decisions automatically and limit them to the optimal choices in which the trade-offs can be shown. Often, the main limitation of MOO is that it does not consider uncertainty. The underlying model used to simulate the real system will never be a perfect representation. Some optimal solutions identified by MOO may be less certain than others. For example, consider a "business as usual" solution versus a solution relying on a large amount of investment and change. The latter will be susceptible to a much larger uncertainty, but a standard MOO analysis alone will not highlight this.

Over-optimisation is another pitfall. If the model contains some assumptions which prove to be false, choosing a solution which has been optimised relying on those assumptions can be unwise. If these limitations are considered and taken into account, MOO can give a decent indication of the trade-offs in a system and where they are likely to occur.

2.4. MCA by means of Subjective Logic and Bayesian Networks

This section describes an approach to evaluate strategies against multiple criteria by using Subjective Logic (SL) within a Bayesian Network (BN) framework. The analysis is carried out in a software system called *Intelfuze*[1].

At a glance, thresholds are chosen that define the acceptable outcome space, and within this space the statistical expectation of the monetary value of each strategy is calculated. The approach explicitly models two types of uncertainty: uncertainty in variable outcomes; and varying levels of accuracy of the underlying analysis. The mathematical formulation is achieved in the model design by using *Intelfuze* software, which supports BN analysis with SL. This section describes the theory of the approach only in general terms. Further details can be found in Moglia *et al.* (2012b).

2.4.1. Theory of Subjective Logic

This study has been applied within the *Intelfuze* software environment, which is based on Subjective Logic (SL). SL deals with the aspect of the human condition that nobody can truly tell whether a proposition about the world is true or false. It asserts that whenever the truth of a proposition is assessed, it is always done by an individual and no belief can be considered to represent a general or objective belief (Jøsang, 2001). As such, probabilities are taken as "beliefs" or "opinions" and have an assigned level of certainty. Methodologies for applications of SL to water related problems have been published in a number of articles (Moglia *et al.* 2009; Moglia *et al.* 2012a; Moglia *et al.* 2012b; Moglia *et al.* 2012c)

The formalism of SL is based on a belief model similar to that used in the Dempster-Shafer theory of evidence (Shafer, 1976), and is based on set theory applied to the state space (the set of possible outcomes of a random event). SL assumes that only one state can be true at any one time and it assigns belief to different outcomes via belief mass assignment (similar to probability mass assignment in probability theory). Any given outcome in the state space has a belief, disbelief and a level of uncertainty, which all sum up to one. Intuitively and approximately, the belief represents the probability space for which we know a particular event is occurring, the disbelief represents the probability space for which we know that the event will not occur, whilst the uncertainty represents our lack of knowledge of a situation. Another expression of an uncertain event is via the focused relative atomicity which coincides with the probability expectation value, which can be calculated based on estimates of the belief, disbelief and uncertainty.

Based on the calculus of SL, it is possible to combine evidence (i.e. beliefs). The Consensus operator takes as input two propositions which are both described with the belief, disbelief, uncertainty and the probability expectation value. This is similar to a trial where several witnesses give consistent testimony and hence amplifies the judge's opinion. However, the consensus of two uncertain opinions (i.e. two unreliable witnesses) results in a new uncertain opinion. Similarly, based on calculus of SL, it is possible to adjust the uncertainty of a proposition provided by source A (which may be a person or a report, etc), on the basis of the opinion by person B on the reliability of source A. Hence, this is a chain of evidence about two related items: 1) the proposition about event Q described with the four numbers above (belief, disbelief, uncertainty and the probability expectation value); and 2) the proposition about whether the first piece of information can be trusted. This, hence, dilutes the strength of the evidence (i.e. the certainty) provided by source A. The calculus of SL can also be applied when the evidence is contradictory, as described in a paper on Analysis of Competing Hypotheses using Subjective Logic (Pope and Jøsang, 2005). In brief terms, a range of possible hypotheses are identified and the evidence for and against each hypotheses are collated and furthermore the relative diagnosticity of each hypothesis is calculated. The advantage of the SL approach is that it can consider the uncertainty of the evidence. This enables the creation of assessments that reflect data availability, highlighting the uncertainty created by lack of relevant or reliable data.

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[1] For further information, see http://www.veriluma.com/products/intelfuze/

2.4.2. Theory of Bayesian Networks

Bayesian Networks (BN) are based on what is called plausible reasoning, which is, in turn, based on probability theory, and in particular the theory of conditional probabilities (Castelletti and Soncini-Sessa, 2007). Computationally, BN are made up of a series of nodes (representing factors) and directed arcs (representing causal links between factors) creating an acyclic graph. Causal links are represented by conditional probabilities, and the repeated application of Bayes theorem using such conditional probabilities generates a system of equations which can be solved to provide the probability distributions of all model factors. Bayesian Network in this way allows for representing causal chains, i.e. linking the likelihood of defined events occurring if one knows a number of underlying conditions.

2.4.3. Framework

This approach relies on integrating data from secondary sources; each of which needs to be assessed for its accuracy. Details of the method have been published (Moglia *et al.*, 2012a; Moglia *et al.*, 2012b) and the method has a number of steps:

1. Selection of strategies to be assessed.
2. Selection of objectives, i.e. the variables describing outcomes.
3. Discretisation of the outcome space for each model variable.
4. Categorisation of all outcome variables as either mandated or value-adding.
5. Simulating strategies to estimate impact on outcome variables.
6. Estimate the probability distribution of each outcome variable.
7. Assign monetary values to outcomes.
8. Assign accuracy/reliability to each outcome assessment.
9. Entering all data and information into software *Intelfuze* to estimate the cumulative monetarised benefits and the probability of achieving mandatory goals.

3. MORETON BAY CASE STUDY

The TWCM Plan for Moreton Bay Regional Council (MBRC) was developed to satisfy requirements of the Environmental Protection (Water) Policy (2009). The TWCM Plan was developed by BMT WBM Consultants (2010 and 2012) in two phases:

1. Phase 1 involved the identification of water servicing options to address water related issues identified for MBRC area, and
2. Phase 2 involved the development of the TWCM Plan.

MCA was applied in both phases. It was applied in Phase 1, to identify a preferred set of water servicing solutions and in Phase 2 to identify a preferred portfolio of water servicing scenarios. A scenario consisted of a number of preferred water servicing solutions.

3.1. Application of MCA

Full details of how MCA was applied to the Moreton Bay case study can be found in BMT WBM (2010, 2012). A brief summary is provided here.

Workshops were set up with the participants being comprised of Councillors, the Council's existing Strategic Coordination Advisory Group (SCAG), MBRC representatives, and Unitywater representatives. A list of criteria was developed by consensus, and given a weighting based on their importance. These weightings can be seen in Table 1.

Table 1. Criteria weightings used in MCA analysis.

Criteria	Category	Weighting (%)
Changes in water quality in inland water systems, as well as changes to biodiversity, and bed and bank integrity	Environmental	3.3
Changes in hydrology	Environmental	3.3
Changes to water quality and biodiversity in estuaries and Moreton Bay	Environmental	10
Changes in water quality and flow and biodiversity of groundwater systems	Environmental	1.7
Changes in emissions of greenhouse gases	Environmental	5
Impact on environmentally sensitive values	Environmental	10
Impacts on water supply	Social	8.3
Impacts on human health	Social	8.3
Impacts on public amenity/recreation	Social	6.7
Level of community understanding, engagement and ownership	Social	3.3
Public acceptability	Social	6.7
Financial impacts on MBRC – Outlays, capital and operating expenditure and revenue	Economic	11.7
Financial impacts including costs and cost savings on consumers (e.g. infrastructure charges) and other organisations	Economic	11.7
Impacts on local industries that rely on the environment (Fisheries, tourism)	Economic	5
Employment plus local economic sustainability	Economic	5

Note: This information has been sourced from BMT WBM (2012).

Each catchment was then looked at individually, and given scores for each criterion by the workshop attendees using a consensus method. These scores and the MCA analysis were later revised during stage 2 when quantitative analysis of some of the criteria was possible. From these scores and weightings, it was possible to rank each solution. Key stakeholders then chose the preferred solutions for each catchment based on these rankings.

3.2. Application of MOO

The Stage 1 analysis undertaken as part of Moreton Bay TWCM Plan development identified a set of solutions (or management responses) to address the issues identified in the Moreton Bay Region. It identified preferred solutions among the 35 proposed using MCA. These preferred solutions may or may not be the optimal solutions. An alternative method is to apply MOO to identify the optimal solutions. The excerpt of 35 solutions that were considered by the MCA analysis is shown in Table 2 (see BMT WBM 2010 for the full list).

Table 2. Excerpt of mitigation strategies considered in MCA analysis of Moreton Bay.

#	Solution
S1	Build new regional surface water storages and associated infrastructure
S2	Upgrade Water Treatment Plants to provide additional capacity/ improve water quality
S3	Rely on Water Supply Guarantee in the SEQ Water Strategy
S4	Upgrade and/or construct new trunk water supply infrastructure to boost capacity
S5	Recycled water supplied to urban users
S6	Recycled water supplied to agricultural users
S35	Cap at current Population without any other solutions implemented

The MCA undertaken by the Options Analysis Team analysed each solution in turn. A score was given based on how effective the solution would be for each of the criteria in each catchment. Finally weightings were applied to the criteria. This process ultimately produced a large table of scores, an extract of which is shown below.

Table 3. Excerpt of MCA scores used for mitigation strategies.

Solution	Catchment	Criteria	Score
S6	Stanley	Public acceptability	0.27
S6	Caboolture	Changes in emissions of greenhouse gases.	-0.1

The scores from each criterion were summed, providing a total score for each solution in each catchment. From these scores the following graph was produced, showing the performance of each of the solutions.

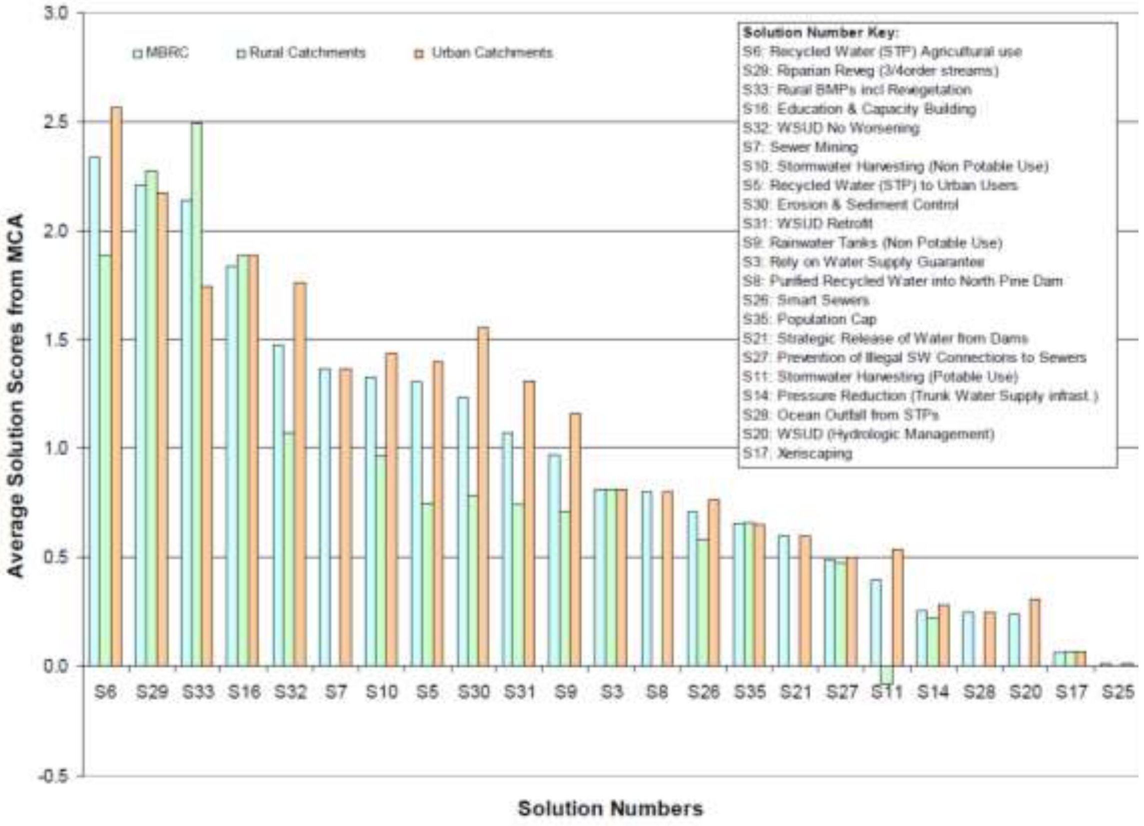

Figure 2. **MCA Solution results for whole of region (MBRC), rural and urban catchments (BMT WBM 2012).**

By weighting each of the criteria, and adding the scores together, the MCA effectively collapsed the problem to a single objective – the overall score. If we examine this for a single catchment (Caboolture), we can generate a graph of the scores (Figure 3).

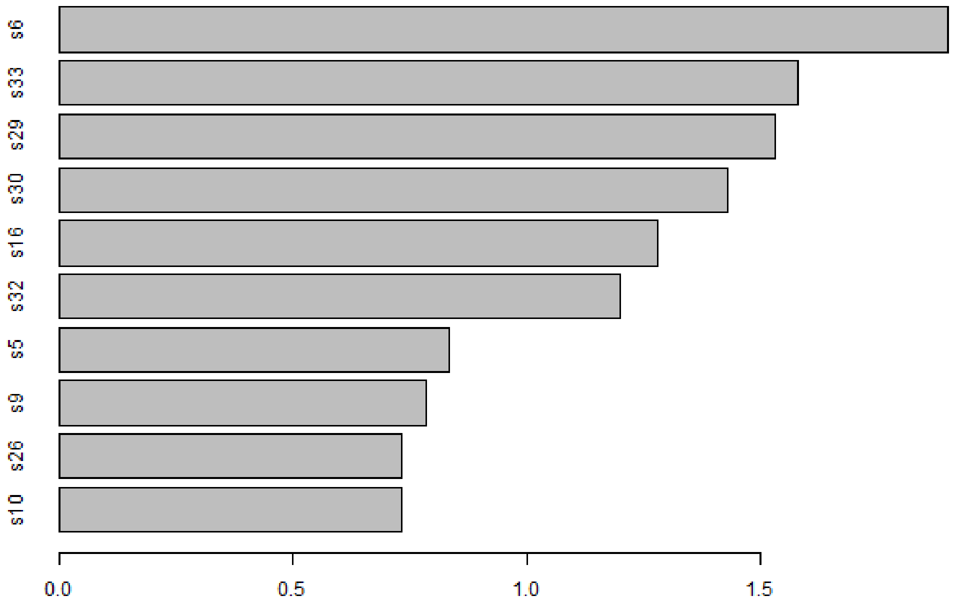

Figure 3. **Top 10 MCA unweighted scores for the Caboolture catchment.**

Although this graph can be used to recommend the best options to implement, it does not allow decision makers to explore the trade-offs between the different objectives. Why does s33 score one of the highest? Does it sacrifice one of the objectives at the expense of others? The only way to answer these questions is to avoid collapsing the problem into a single objective. While there are fifteen objectives (or criteria – Table 1) specified in the MCA, they break down into three categories: economic, social and environmental. Instead of all 15 criteria, if we collapse down to these three categories, we begin to see the trade-offs between them. Examining the raw criteria scores in detail, we find that s33 achieved a high total score because it performed strongly in all three objective categories. We can also see that s29 performed slightly better than s33 in both the economic and social objectives, with the trade-off being a worse environmental result. Solution s6 performed the best on the economic objective, with middling performance on the other two. We can also see that some of the solutions are dominated by others. Using s2 as an example, we can see that s6 performed better economically, environmentally and socially than s2. Therefore, s2 is not Pareto optimal. In this way, we can identify the Pareto optimal solutions, but if we did not collapse the objectives down to three, and instead were to explore the trade-offs between each of the original sixteen criteria, a different approach would be needed.

We took the (weighted) score data obtained during the MCA for all fifteen catchments and all sixteen criteria and subjected it to a Pareto analysis to see which solutions were optimal, and which were dominated. An excerpt of the results of this analysis is shown in Table 4.

Table 4. Pareto optimality of mitigation strategies for the Stanley catchment.

Catchment	Optimal	Dominated	No Scores Available
Stanley	2, 3, 5, 6, 10, 16, 18, 26, 27, 29, 30, 33, 35	9, 11, 12, 14, 17, 19, 20, 23, 24, 31, 32	1, 4, 7, 8, 13, 15, 21, 22, 25, 28, 34

With these results we can now compare the outcomes of the MCA to ensure that the Pareto optimal solutions were the most likely to be chosen. Again we will examine the Caboolture catchment for this purpose.

Table 5. Pareto optimality of strategies cross referenced with MCA preferences for Caboolture.

Pareto Optimal and Chosen in MCA	Pareto Optimal and Not Chosen in MCA	Sub-Optimal and Chosen in MCA	Sub Optimal and Not Chosen in MCA
6, 33, 29, 30, 16, 32, 5, 9, 10, 26, 7, 8, 27, 23	35, 28, 18, 2	31, 25	20, 21, 11, 14, 12, 17, 34, 19, 24

Almost all of the solutions chosen by the MCA were Pareto optimal, except for s31 and s25. It is possible that both s25 (Diversion of sewage to STPs with capacity) and s31 (Existing WSUD Retrofit) were chosen despite their low scores because they were mandatory for regulatory or other reasons.

Solution 31 (existing WSUD retrofit) could be an erroneous choice. It should be noted however that in traditional Pareto analysis, the options presented are mutually exclusive, but the MCA solutions are designed to be complimentary – for example choosing both s6 (recycled water) and s29 (waterway rehabilitation) is of course reasonable. The Pareto optimality of each scenario assumes that it will be the only option chosen. It could be for this reason that s31 was legitimately chosen in addition to the other solutions.

During Stage 2 of the TWCM process, a catchment model for Moreton Bay was developed by BMT WBM. With water quality being a main focus, the model was created in the “Catchments” mode of Source IMS, which models water quality by having spatial catchments and land uses that generate runoff from rainfall. We attempted to use that model as the basis for a MOO analysis.

Unfortunately, at the time of undertaking this research, Source IMS in Catchments mode does not interact with Source's inbuilt optimiser (called Insight). To be specific, Catchments mode has no features compatible with the expression editor, which is used in Source IMS as an external interface by other programs, including the command line version of Source IMS.

To work around this limitation, we used the BMT WBM model as a basis and extracted a single sub-catchment to construct a much smaller model. The sub-catchment chosen was from the Caboolture Identified Growth Area (CIGA). This model was primarily created to assist in generation of data for the Subjective Logic analysis, but it could prove useful for MOO as well.

The goal for a MOO analysis of TWCM is to decide which mitigation strategies to employ. The model created by BMT WBM represented only 3 possible solutions, - a low, medium and high level of mitigation applied. MCA analysis was performed using human judgement to decide which mitigation strategies should be included in each of these three scenarios. Using MOO instead, it is possible to consider thousands of combinations of mitigation strategies, and find optimal choices that may otherwise be missed.

In order to perform such an analysis, the model must be able to simulate the interaction of the various mitigation strategies when some of them are undertaken and some are not, or indeed for any arbitrary combination. As these strategies were implemented in the original model as percentage reduction of constituents, it was not possible to differentiate them using the data we had available. For this reason we chose to focus our efforts instead on evaluating uncertainty in the model and performing a Subjective Logic analysis.

To adequately perform MOO, a new model would need to be created, linking in to an optimiser and ideally including the entire Moreton Bay catchment rather than a single urban sub-catchment. The model would also have to incorporate the calculation of objective functions. The suggested objectives for any future work are:

- Minimising monetary cost
- Minimising constituent outputs
- Maximising water savings and reliability

As mentioned before, the likely decision variables would be which mitigation strategies to implement. Through the MCA analysis, 35 solutions were identified. The decision variable will then become a set of true / false values indicating which solutions should be implemented. This leads to 2^{35} possible combinations, many more than it is feasible to simulate exhaustively, though some solutions can probably be eliminated due to either being fairly impractical, or impossible to be modelled accurately.

For choice of software to perform a MOO analysis, Source IMS / Insight could only be used to account for water quality objectives if Source IMS were to be improved to allow for the "Catchments" based modelling features to interact with the expression editor. These features include:

- Rainfall runoff models
- Functional units (land uses)
- Constituent generation models
- Constituent filtration models

This would be a significant undertaking. Alternatively a new, less general purpose model could be created, much like we have done, but incorporating more than a single sub-catchment. Determining which course is most beneficial depends on many factors, but ultimately the more long-term solution of upgrading Source IMS would be appealing as it can be used in case studies other than Moreton Bay.

3.3. Application of MCA by means of SL and BNs

The method has been applied as per the steps identified in previous section.

3.3.1. Strategies

The solutions for TWCM that were explored in this application are aligned with those that were evaluated by BMT WBM (2010) for the CIGA sub-catchment 63. These are bundled into three scenarios, as per Table 6.

Table 6. Management solutions embedded into scenarios.

Scenario	Management Solutions
1&2&3	Future development to meet 80/60/45 % load reduction for TSS/TP/TN.
1&2&3	Future development to meet Queensland Development Code for alternative water supply.
2&3	Increased implementation/enforcement of E&SC management practice.
2&3	Waterway and riparian revegetation of 3rd and 4th order streams.
2&3	Education and/or capacity building and investment in incentive schemes.
2&3	Prevention of illegal stormwater inflow connection to sewer.
3	Future greenfield development WSUD measures to achieve no-worsening.
3	Recycled water supplied to urban users.
3	Stormwater harvesting.

3.3.2. Outcome Variables and Model Structure

The chosen objectives are shown the model structure in Figure 4: Total Nitrogen (TN), Total Phosphorous (TP), Total Suspended Solids (TSS) as well as flow outcomes are evaluated using Source IMS in catchment mode. As per the previously applied methodology (Moglia *et al.*, 2012b), these have been categorised as "adding benefit" and therefore have a monetary value assigned to each outcome. The discrete states of the outcome variables, representing ranges, are shown in Table 7. Each of the 5 outcome variables are evaluated for each combination of scenario (1, 2 and 3) and climate (Neutral, El Niño and La Niña); i.e. nine different combinations.

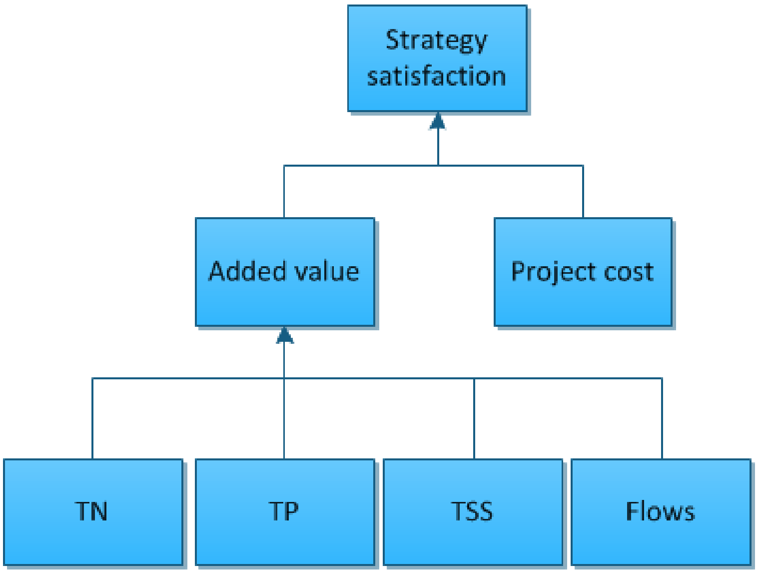

Figure 4. Model structure.

Table 7. Definition of discrete states of variables.

Range Name	Outcome Variable			
	Flow	TN	TP	TSS
Base Level	6183749	7842	980	378538
50% worse	9275624	11763	1470	567807
25% worse	7729686	9803	1225	473172
25% better	4637812	5882	735	283903
50% better	3091875	3921	490	189269
75% better	1545937	1961	245	94634
90% better	865725	1098	137	52995

Outcomes have further been defined in the *Intelfuze* software by assigning a dollar-value to each start and end value in each range, on the basis of the numbers in Table 8. These numbers have been assigned on the basis of data from project partners for the "no worsening" scenario (Hall, 2012).

Table 8. Benefits in dollars per unit for each outcome variable.

Outcome Variable	Benefit per Unit
TN	$ 273,000 per tonne
TP	$ 220,000 per tonne
TSS	$ 213 per tonne
Flow	$ 0.2 per m^3

The project cost of strategies has also been evaluated in a similar manner as done in the MCA by BMT WBM (BMT WBM, 2010); although with uncertainty considered.

Unlike in the previous applications of the SL methodology for a Melbourne case study (Moglia *et al.*, 2012b), project cost has not been classified as a "mandated outcome variable"; or in other words it is not deemed to be completely necessary to stay within a given budget threshold. Instead, a more gradual threshold is being used where the cost is balanced against the evaluated benefit. As such, each combined outcome of value and project cost has been evaluated on the basis of perceived likely acceptability, as indicated in Table 9. The ultimate output of the assessment is a "likelihood of strategy satisfaction". Colours in the table indicate the likelihood of strategy satisfaction for different combinations of outcomes of the variables relating to project cost and added value.

Table 9. Cost-benefit acceptability matrix.

Cost Range	Added Value*		
	No Added Value 0 to $1,000,000	Some Added Value $1,000,000 to $3,000,000	Significant Value $3,000,000 to $15,000,000
<$1,000,000	1	0.3	0.1
$2,500,000	3.5	1.2	0.2
$5,000,000	3.5	1.2	0.2
$7,500,000	12.5	4.2	0.7
$10,000,000	17.5	5.8	1.0
>$10,000,000	30	10.0	1.7

Note: The colours of the cells indicate the likelihood of strategy satisfaction: dark red = extremely unlikely (1%); light red = quite unlikely (25%); yellow = neither likely nor unlikely (25%); light green = quite likely (75%); dark green = highly likely (90%); blue = extremely likely (99%).

*Note: the added value variable is based on the aggregated estimated benefits of outcomes in the underlying variables. For example, a certain reduction in TN is assigned a value which is added to the value from reductions in TP, etc. The software Intelfuze estimates the probability that the added value is within any given range.

3.3.3. Simulating Strategies: Source IMS and Cost Estimations

Due to the limitations of Source IMS in catchments mode (discussed in Section 3.2), it was not used to generate results directly. Instead the parameters from a single sub-catchment (called sub-catchment 63) in the Caboolture Identified Growth Area (CIGA) were used in a model constructed specifically for the purpose, to work around the limitation of not being able to interact with the expression editor in catchments mode. This model used some of the source code from Source IMS, in particular for rainfall runoff simulation using the SymHyd model. Analysis was done to ensure the results from our custom model matched the results from the original BMT WBM model. These results consisted of flow volume as well as constituent totals for suspended solids (TSS), nitrates (TN) and phosphorus (TP) discharged.

The proposed mitigation strategies for TWCM were implemented as constituent filtration models in Source IMS, which reduced the constituent loads by set percentages. This was done separately for scenarios 1, 2 and 3, representing the increasing levels of mitigation strategies employed. This method was extended to our custom model, but in addition, the percentage reductions were randomly varied by a standard deviation of 10% in order to perform a Monte-Carlo analysis. Each scenario was run 20,000 times.

Though the simulation period was 30 years (1980-2010), we discriminated among the time series of outputs to provide results differentiated by climate, specifically the Southern Oscillation and whether it was operating in a normal, La Niña or El Niño pattern. The time series used to define these periods can be found in Appendix B. Our custom model gave us daily outputs for the whole 30-year simulation period; we simply picked out those dates which corresponded to the different Southern Oscillation modes. Taking this daily data we aggregated it into the mean of each month and used the resulting values for the next step.

3.3.4. Cost Estimations

Cost estimations for the each solution in CIGA were obtained from BMT WBM (2012) (see Table 10). Area of the sub-catchment 63 is 5% of the total area of CIGA catchment. Cost estimates for sub-catchment 63 were obtained by multiplying the cost estimates for the whole CIGA catchment by 5%, assuming that costs were proportional to the areal extent (see Table 10).

Minimum and maximum cost values corresponding to a particular solution represent the cost of implementing the solution in different major catchments in the MBRC area. Details of the catchments can be found in BMT WBM (2012).

Table 10. Mean, minimum and maximum cost estimates for each solution in CIGA catchment and sub-catchment 63 of the CIGA catchment.

		CIGA Catchment (NPV Costs in 2011 $)			Sub-Catchment 63 of CIGA Catchment (NPV Costs in 2011 $)		
Scenario	**Solution**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
1	Future development meet 80/60/45 % load reduction for TSS/TP/TN	153,764,000	100,000	154,000,000	7,700,448	5,008	7,712,267
1	Future development meet QDC alternative water supply	28,342,000	900,000	56,000,000	1,419,358	45,072	2,804,461
2	Future development meet 80/60/45 % load reduction for TSS/TP/TN	153,764,000	100,000	154,000,000	7,700,448	5,008	7,712,267
2	Future development meet QDC alternative water supply	28,342,000	900,000	56,000,000	1,419,358	45,072	2,804,461
2	Increased implementation/enforcement of E&SC management practice	12,691	20	20,000	636	1	1,002
2	waterway and riparian revegetation of 3rd and 4th order streams	3,600,000	300,000	15,000,000	180,287	15,024	751,195
2	Recycled water supplied to urban users	37,000,000	19,500,000	81,600,000	1,852,947	976,553	4,086,500
3	Future greenfield development WSUD measures to achieve no-worsening	153,764,000	200,000	154,000,000	7,700,448	10,016	7,712,267
3	Future development meet QDC alternative water supply	28,342,000	900,000	56,000,000	1,419,358	45,072	2,804,461
3	Increased implementation/enforcement of E&SC management practice	12,691	20	20,000	636	1	1,002
3	Recycled water supplied to urban users	3,600,000	300,000	15,000,000	180,287	15,024	751,195
3	stormwater harvesting	68,900,000	25,000,000	69,000,000	3,450,488	1,251,991	3,455,496

3.3.5. Probability Distributions

Based on the estimates from Source IMS as well as estimates of project costs, we were able to estimate the means and standard deviations of outcome variables in a number of different types of situations as per Table 11.

Table 11. Mean and Standard Deviations for flow, TN, TP and TSS for various scenarios.

Inputs		Flow		TN		TP		TSS	
		Mean	Std*	Mean	Std*	Mean	Std*	Mean	Std*
Scenario 1	La Niña	15.89	1.07	9.21	1.14	7.13	1.24	13.09	1.38
Scenario 1	El Niño	12.96	1.10	6.29	1.15	4.21	1.25	10.16	1.38
Scenario 1	Normal	15.64	1.11	8.97	1.17	6.89	1.28	12.84	1.41
Scenario 2	La Niña	13.41	1.07	6.73	1.14	4.65	1.24	10.34	1.34
Scenario 2	El Niño	12.96	1.10	6.29	1.15	4.21	1.25	9.90	1.36
Scenario 2	Normal	12.96	1.10	6.29	1.15	4.21	1.25	9.90	1.36
Scenario 3	La Niña	13.41	1.07	6.68	1.13	4.56	1.23	10.18	1.33
Scenario 3	El Niño	12.96	1.10	6.24	1.14	4.12	1.24	9.74	1.36
Scenario 3	Normal	13.15	1.11	6.44	1.16	4.32	1.27	9.95	1.38

*Note: Std here refers to the standard deviation of a Log-Normal distribution.

Based on the discretisation of the outcome variables as well as the probability distributions defined in Table 11, we are able to estimate the probability distributions for outcome variables in the various situations, as per Table 12.

Table 12. Probability distribution for flow variable.

Inputs		Flow					
		50% worse	Same	25% better	50% better	75% better	90% better
Scenario 1	La Niña	44.0%	25.0%	12.0%	13.0%	4.0%	2.0%
Scenario 1	El Niño	0.2%	1.2%	2.0%	8.4%	13.8%	74.3%
Scenario 1	Normal	35.7%	24.6%	13.2%	16.0%	6.7%	3.8%
Scenario 2	La Niña	1.0%	2.8%	4.1%	13.9%	18.7%	59.8%
Scenario 2	El Niño	0.2%	1.2%	2.0%	8.4%	13.8%	74.3%
Scenario 2	Normal	0.2%	1.2%	2.0%	8.4%	13.8%	74.3%
Scenario 3	La Niña	0.7%	2.8%	4.1%	13.9%	18.7%	59.8%
Scenario 3	El Niño	0.2%	1.2%	2.0%	8.4%	13.8%	74.3%
Scenario 3	Normal	0.5%	1.9%	2.9%	10.8%	15.9%	68.0%

3.3.6. Judgments on Assessment Reliabilities

We note that this assessment is inherently subjective, and it is impossible to objectively assign these scores. Instead we use cues and rules in order to assign reliability scores. However, in this case we have taken the liberty of using the expert judgment of the modeller.

There are two sources of information feeding into this analysis: Source IMS modelling; and project cost analysis. The Source IMS modelling data has been perceived as somewhat reliable because, whilst it is an advanced and useful tool, there is sometimes limited justification for a number of parameter values (justification beyond mere calibration), consistent use of linear functions, potential for user-errors in running models, and the perception that it is a type of model that requires a fair amount of effort to to fully grasp or understand. This information source was hence given reliability score of 75%.

The lifecycle costing data analysis has been perceived as somewhat reliable because each of the components of the costing analysis is something we have some experience with. Assumptions are relatively clear and parameters in the costing are well defined and based on known values. Hence the reliability score for this analysis is 75%.

3.3.7. Simulation and Results

By entering all the information into the software system *Intelfuze*, it is possible to evaluate the three scenarios in terms of their likelihood of achieving strategy satisfaction (Table 13). Scenario 2 is the most likely to achieve a high level of satisfaction, although both other scenarios have some likelihood of also achieving strategy satisfaction. However, a concern is raised regarding the reliability of this evaluation. In the best case scenario, for scenario 2, it is deemed that the assessment is neither certain nor uncertain, whilst the two other analyses are deemed to be somewhat uncertain. There are two reasons for this conclusion: 1) the high level of inherent uncertainty in the assessment; and 2) the somewhat poor reliability of the contributing assessments.

Table 13. Results of SL/BN analysis.

Scenario	Estimated Outputs	
	Likelihood of Strategy Satisfaction	Reliability of Evaluation
1	Neither likely or unlikely (56%)	Somewhat uncertain (33%)*
2	Quite likely (75%)	Neither certain nor uncertain (49%)
3	Neither likely or unlikely (61%)	Somewhat uncertain (22%)

*Note: This is indicated in the software with a warning: derived observation has the potential for being derived from inadequate information.

We are also able to explore these results in different climate scenarios, such as El Niño and La Niña conditions. The most important insight from this is that during El Niño conditions, strategy 1 has the highest likelihood of achieving strategy satisfaction (77% likelihood with 54% certainty).

In terms of the sensitivity of the analysis to model structure, two key factors have been shown to have considerable impact on the outcome:

- The definition of the ranges of the discrete states of the outcome variables can significantly impact on the estimated likelihood of strategy satisfaction. Therefore effort should be made to make such modelling choices in a careful manner.
- The exact values cost-benefit acceptability matrix impacts strongly on the outcome of the modelling exercise, and this is where subjective values judgments are introduced. Therefore, it is critical that this matrix is not populated on the basis of modeller judgment alone, but should be based on judgments by stakeholders.

We also note that this type of modelling exercise allows for exploring possible changes in climate, as long as such changes can be described in terms of input files into the Source IMS software system. The approach could also allow for exploration of the sensitivity of results to other factors, such as those relating to model assumptions in the Source IMS software system.

Another benefit of this approach is that it allows for mixing data sources in a way which makes concerns about information reliability more transparent.

The results are also relatively sensitive to the estimated uncertainty in the cost estimations. It is relatively straightforward to estimate the uncertainty in costs if the cost estimation is broken down into a number of assumptions where each component has assigned minimum and maximum costs.

3.3.8. Limitations of Uncertainty Modelling

The uncertainty modelling performed using a customised version of Source IMS could be improved significantly. This would raise the confidence value assigned to it in the SL analysis. Many assumptions were undoubtedly part of the original model created by BMT WBM, but further to this, more limitations were imposed on it for technical reasons, for example, only a single urban sub-catchment could be investigated as part of the analysis, rather than the whole of the CIGA or the MBRC TWCM planning area.

In the Source IMS model, mitigation strategies were represented by constituent filtration models which removed certain percentage of constituents from the flow for a given land use (e.g. urban). For our analysis, we assumed a 10% uncertainty surrounding these filtration values. A greater understanding of how the filtration parameters were determined and applied may allow more precise estimation of the uncertainty surrounding them, leading to a more accurate analysis.

There was also an error in the time series used to classify certain dates of the simulation period as El Niño, La Niña, or “normal”. This error is described in Appendix B, and led to a 14% error in flow volumes for El Niño periods and a 20% error in La Niña periods, with “normal” periods unaffected. Though this error has since been rectified, we could not repeat the Subjective Logic assessment again given the time constraints.

4. CONCLUSIONS

This report has described three approaches for assessing TWCM strategies in the context of SEQ. As such, it is possible to compare and contrast the approaches that have been applied.

A key concern that has been identified in this context is that there is typically only incomplete information in order to make fully reliable judgments about strategy effectiveness. Personal judgments and assumptions are a key part of the modelling process. Also, subjective value judgments are often incorporated into the process in a way that may not fully acknowledge the level of disagreement that exists among stakeholders on key assumptions.

The MCA method applied by BMT WBM (2010) allowed for assessing a large number of strategies for a large number of locations. It is based on the best available data and relies on running the Source IMS model. This approach has successfully evaluated a number of strategies against a number of criteria and has come up with some recommendations. However, the approach did not consider uncertainty or information reliability.

The approach using Subjective Logic and Bayesian Networks for assessing strategies was consistent with the MCA approach in the sense that it recommended the same strategies as being most likely to achieve desired results. However, this approach had the added advantage of also exploring uncertainty; both inherent as well as that which depends on underlying factors such as climate. In some circumstances, other strategies have been shown to be more desirable showing its advantage of providing insights into possible future outcomes rather than providing just statistical expectation values across a range of possible futures. This approach also has the advantage that it explicitly takes into account the information reliability (i.e. quality of information) within assessments, allowing the mixing of data sources of variable quality in a transparent manner. In essence, more weight is given to information that is reliable. Finally, the cost-benefit acceptance matrix allows for incorporating subjective value judgments into the modelling process; in a different manner compared to more traditional MCA approaches. Because this matrix in itself describes uncertainty, it is possible to describe stakeholder disagreement on what entails a successful strategy.

In terms of the practicalities of applying the three approaches, MCA is currently the easiest option to use. Partially this is because the Source IMS model, at least at the time of undertaking this research, was not readily set up for undertaking the type of sensitivity analysis that was required in order to support both MOO as well as the SL approach. We expect this capability to be available soon.

Estimating uncertainties adds another level of analysis that can be time and resource consuming to undertake. Estimating information reliability also adds a further level of difficulty because a consistent method needs to be used to assign information reliability to all underlying data sources. The use of expert judgments is a good alternative for assigning information reliability, as long as efforts are made to ensure judgments are consistent with each other, and that experts only make judgments within their own domain of expertise.

Analysis of uncertainty and reliability in the assessments ought to only be considered when there are real concerns about such issues. The level of concern depends on the attitude of planners towards risk. Risk averse planners ought to consider uncertainty and information reliability; whilst those less risk averse probably do not need to consider this.

The capability to undertake MCA is widely available amongst consultants and researchers, but capability to undertake MOO, and in particular to undertake SL, is rather scarce at this point in time. CSIRO has the capacity, but training would in many cases be required in order to allow water planners or consultants to undertake this type of analysis.

APPENDIX A

This appendix contains a summary of the data generated using Source IMS model with varied inputs to its constituent filtration percentages, which are representative of the mitigation strategies implemented. These inputs were a percentage of removal (0-100%) for the each constituent (TSS, TN, TP) for each land use in the studied sub-catchment. The original percentage removal figures were used as the mean and then randomly varied by 10% to produce 20,000 samples. The graphs in this appendix show histograms of these 20,000 samples for each constituent, climate, and mitigation scenario.

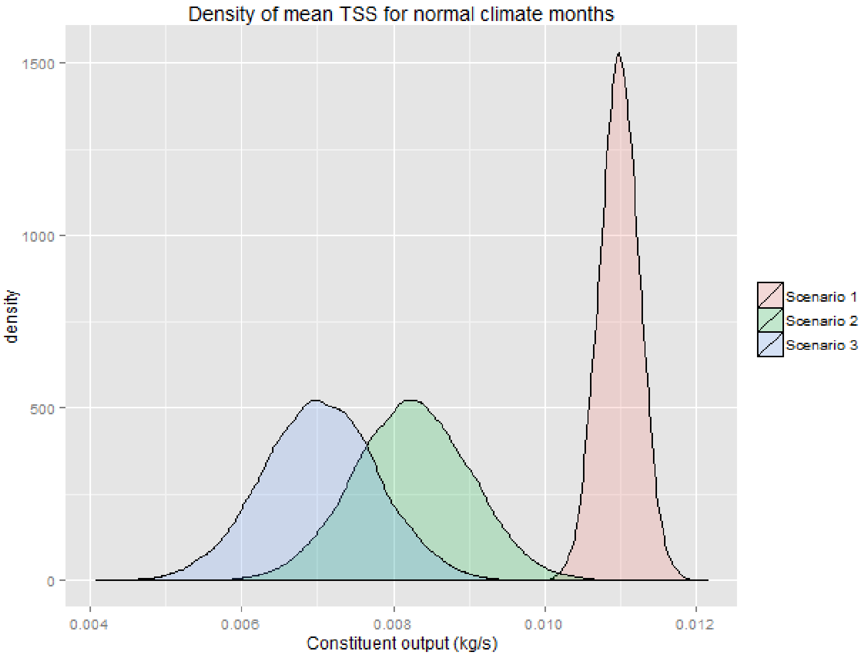

Figure 5. Distribution of mean TSS for normal climate months.

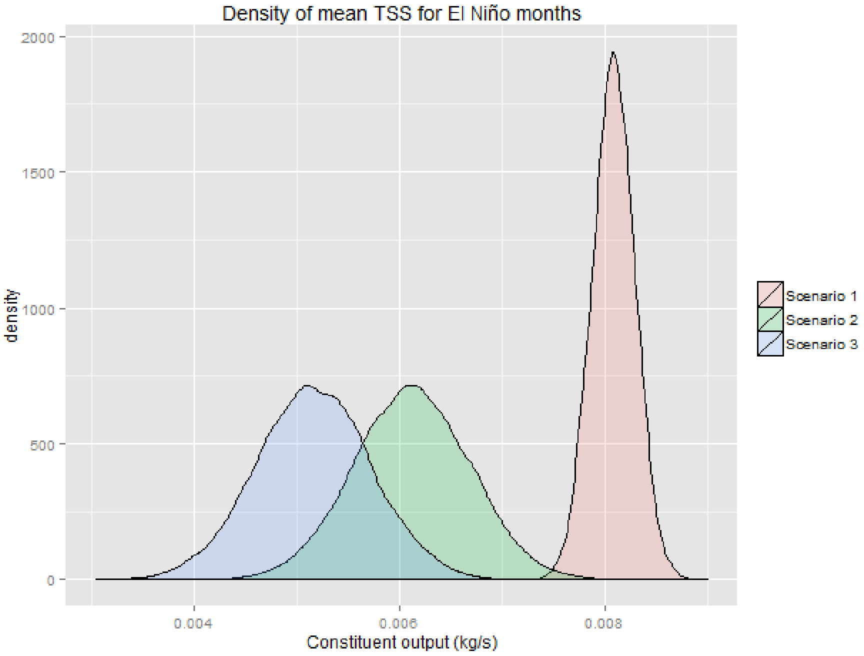

Figure 6. Distribution of mean TSS for El Niño months.

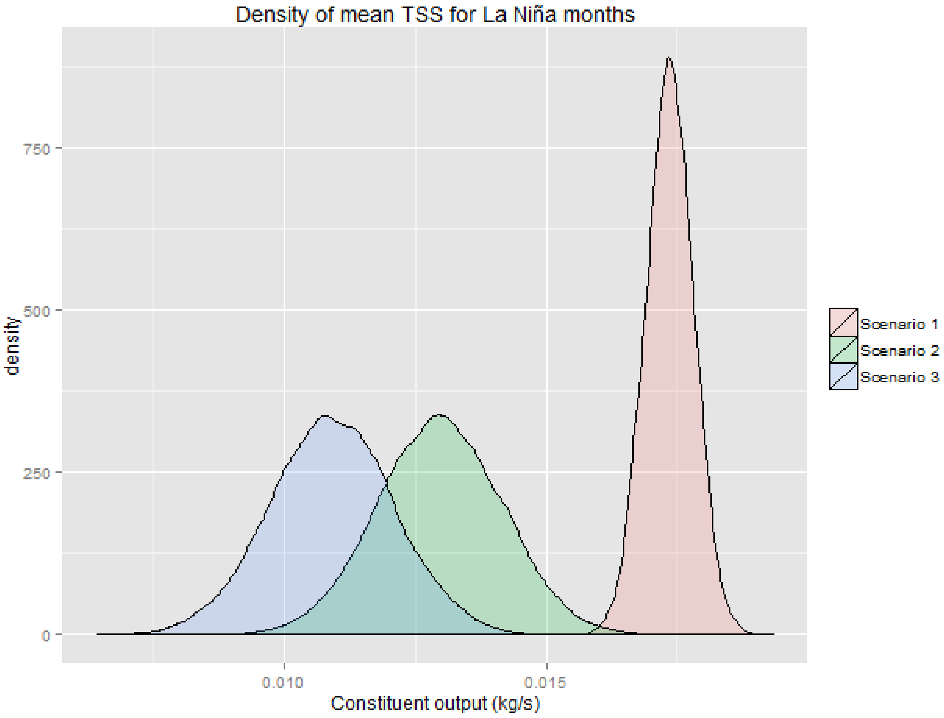

Figure 7. **Distribution of mean TSS for La Niña months.**

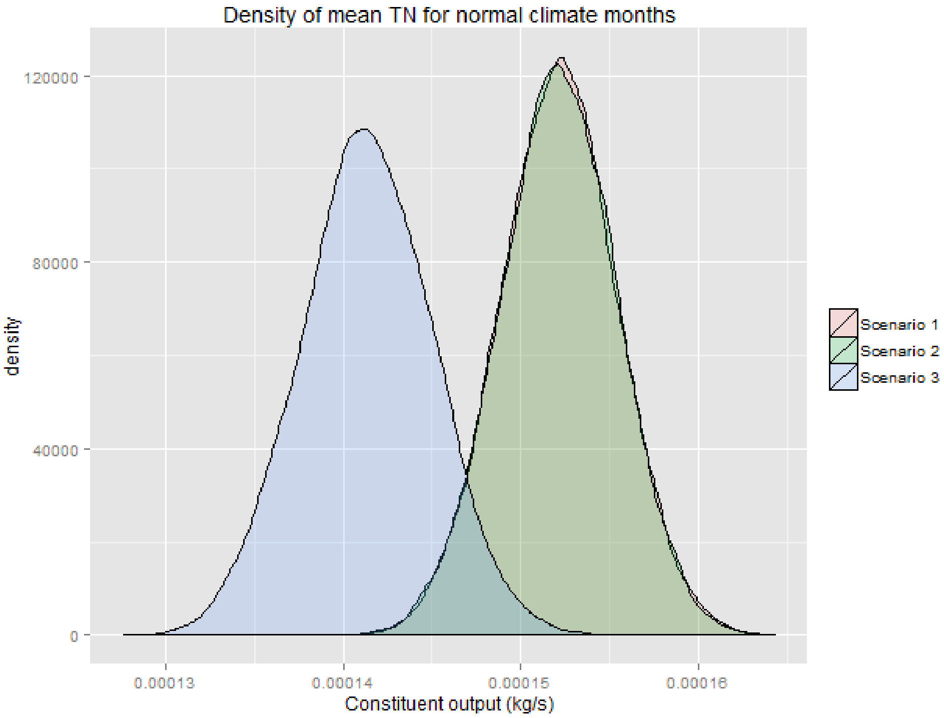

Figure 8. **Distribution of mean TN for normal months.**

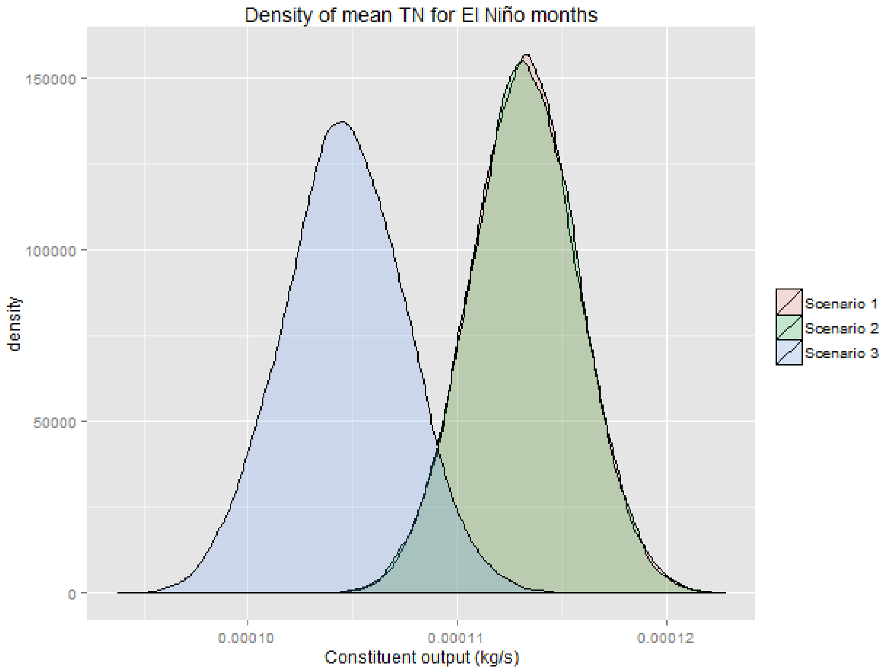

Figure 9. **Distribution of mean TN for El Niño months.**

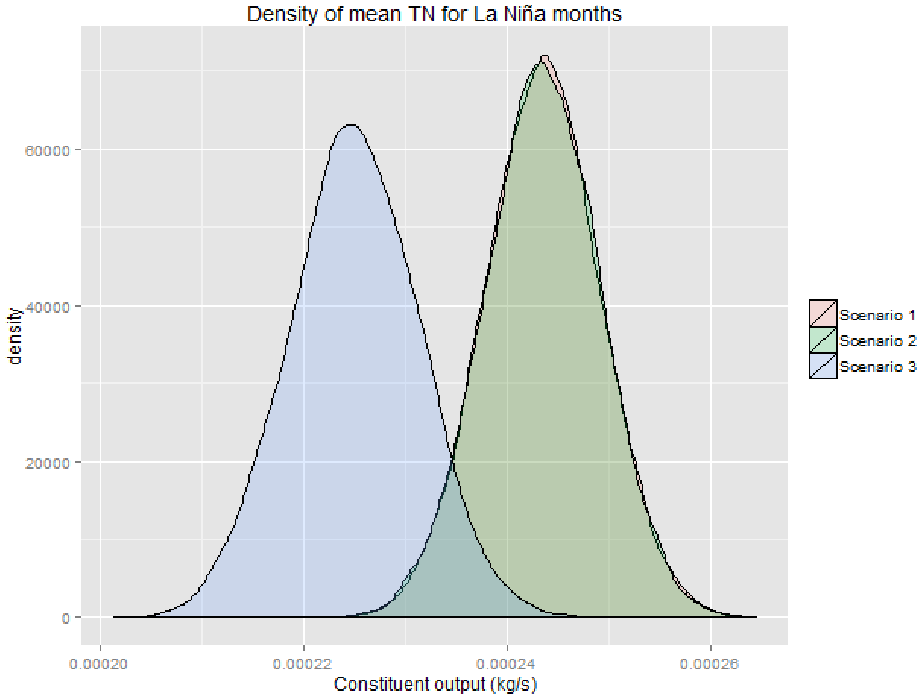

Figure 10. **Distribution of mean TN for La Niña months.**

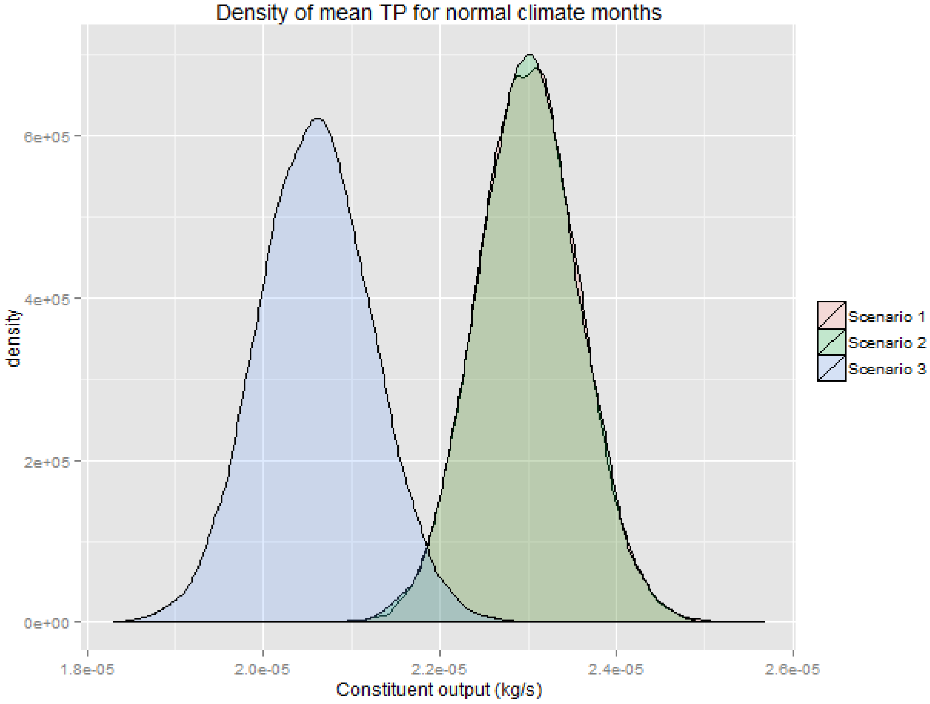

Figure 11. Distribution of mean TP for normal months.

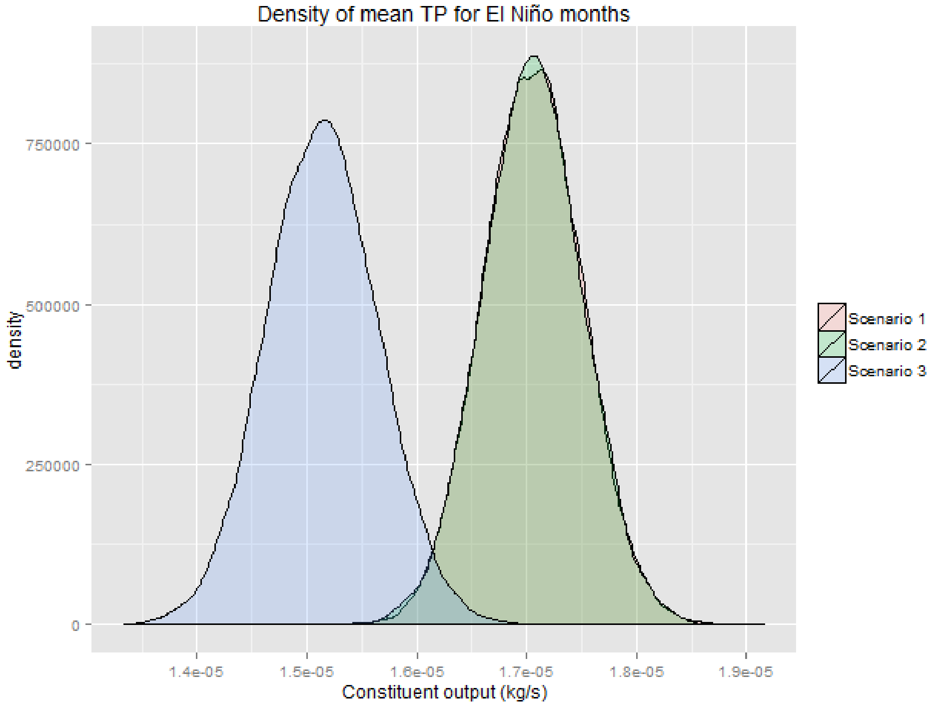

Figure 12. Distribution of mean TP for El Niño months.

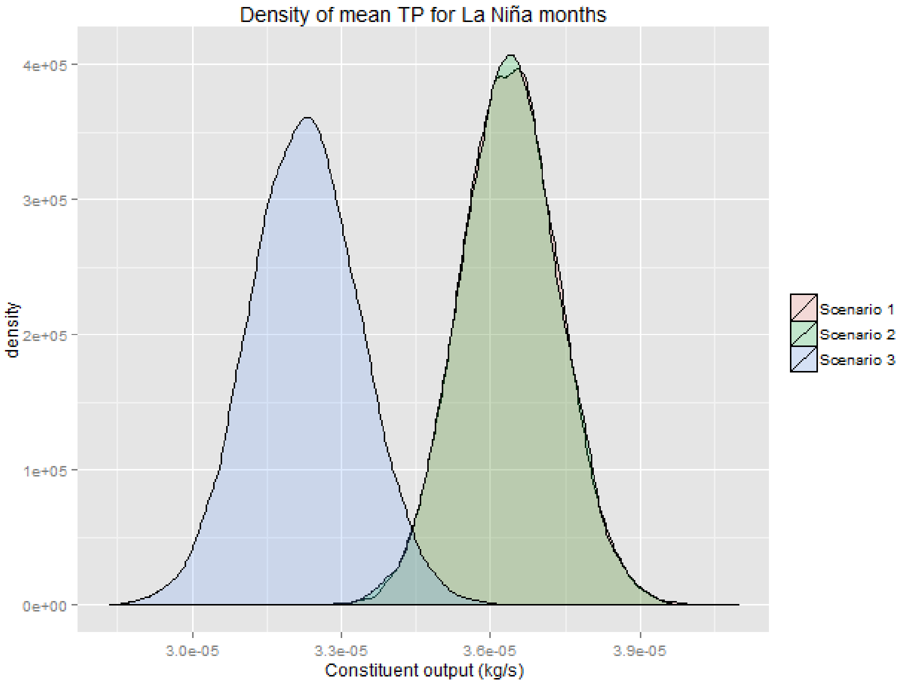

Figure 13. Distribution of mean TP for La Niña months.

APPENDIX B

This appendix lists changes in the Southern Oscillation 6 month index. This data was used to classify different months of the simulated model results as either lying in a normal climate pattern, an El Niño pattern, or a La Niña pattern. Each entry states the time at which a certain climate period began, with the period lasting until the next change in the pattern.

We can see that the simulation period of the Source IMS Model began in 1980, which was a normal climate. This lasted until May 1982 when an El Niño pattern began, and so on down Table 14. The source data for this came from the Australian Bureau of Meteorology.

Table 14. Changes in the Southern Oscillation 6 month index.

Date	Southern Oscillation
1/01/1980	normal
1/05/1982	el nino
1/05/1983	normal
1/11/1986	el nino
1/10/1987	normal
1/07/1988	la nina
1/08/1989	normal
1/03/1991	el nino
1/06/1991	normal
1/09/1991	el nino
1/05/1992	normal
1/05/1993	el nino
1/11/1993	normal
1/03/1994	el nino
1/01/1995	normal
1/03/1997	el nino
1/05/1998	normal
1/06/1998	la nina
1/06/1999	normal
1/10/1999	la nina
1/01/2000	normal
1/02/2000	la nina
1/05/2000	normal
1/09/2000	la nina
1/03/2001	normal
1/12/2007	la nina
1/04/2008	normal
1/08/2008	la nina
1/03/2009	normal
1/01/2010	el nino
1/04/2010	normal
1/07/2010	la nina

This input data had an error with the 1 year period starting in May 1982 being marked as La Niña instead of El Niño. The implications of this error are indicated for flow (Table 15) and for TSS (Table 16), TN (Table 17) and TP (Table 18) for scenario 3.

Table 15. Mean Flow (cm3/s).

Climate	Correct Value	Incorrect Value	Difference	Difference as a %
el nino	0.0774	0.0880	0.0107	13.82%
la nina	0.1663	0.1387	0.0276	19.89%
normal	0.1033	0.1033	0.0000	0.00%

Table 16. TSS (mean of monthly average) scenario 3 (kg/s).

Climate	Correct Value	Incorrect Value	Difference	Difference as a %
el nino	0.00516	0.00587	0.00071	13.68%
la nina	0.01091	0.00911	0.00180	19.72%

Table 17. TN (mean of monthly average) scenario 3 (kg/s).

Climate	Correct Value	Incorrect Value	Difference	Difference as a %
el nino	0.000105	0.000119	0.000015	13.96%
la nina	0.000225	0.000188	0.000037	19.98%

Table 18. TP (mean of monthly average) scenario 3 (kg/s).

Climate	Correct Value	Incorrect Value	Difference	Difference as a %
el nino	1.51E-005	1.73E-005	2.12082E-006	14.01%
la nina	3.23E-005	2.69E-005	5.36968E-006	19.96%

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