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Optimization tools for environmental water decisions: A review of strengths, weaknesses, and opportunities to improve adoption

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ABSTRACT

Public investment in river restoration through environmental watering has increased substantially in recent years. To sustain public support for such investment, management of environmental water must achieve the best possible outcomes in a transparent and defensible manner. The current management of environmental water relies on the ability of managers to estimate the impacts of their decisions under complex scenarios, often with multiple interdependent decisions that span over different spatial and temporal scales. Optimization modeling has been widely used in other forms of conservation management and an increasing body of literature documents the development of optimization models that could be used to improve environmental water decisions. This paper reviews this disparate research, showing that there are a range of different questions addressed using this modeling approach and that the representation of environmental outcomes varies. Future work must focus on improved adoption through engagement with end users and stakeholders during model development.

Contents

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1. Introduction

The growing human demand for water is placing increasing pressures on the worlds' water resources and ecosystems (Vorosmarty et al. (2010), with projected growth in food demand and irrigation likely to further stress water resources in many regions. There is wide recognition and growing political will to balance requirements for human water use with conservation of instream environments (Richter, 2014; Pegram et al., 2013; Hart, 2015), resulting in increased public investment in providing environmental flows (PC, 2010). To justify and protect this public investment, it is important that environmental flows are managed to achieve the best possible outcomes in a transparent and defensible manner.

Many methods have been developed to determine 'environmental flow' requirements (Tharme, 2003; Arthington, 2012). However, translating ecological principles and knowledge into operational decisions for environmental flow delivery remains a formidable challenge (Harman and Stewardson, 2005). Environmental water managers all over the world are being asked to achieve the best outcome with limited resources, and so methods that can trade off and balance competing environmental watering objectives are urgently needed (Acreman et al., 2014; Richter, 2014; Poff et al., 2015). The most common decision-making approach for environmental water delivery is based upon the accumulated experience of managers – so-called 'experience-based practice' (Cook et al., 2010). Decisions rely on the ability of managers to analyze complex scenarios, often with decisions nested within spatial and temporal dimensions (Turak and Linke, 2011). If considering even a single storage release, then an allocation may be delivered as one of an infinite number of potential sequential releases, all of which influence flow event magnitude, duration, seasonality, inter-annual variation and rates of change of flow at multiple downstream locations. The decisions are further complicated by the presence of: multiple points at which flows might be manipulated by dams, weirs or diversions; interactions with releases for consumptive users; and uncertain tributary inflows. Assessing the ecological consequences of these complex environmental flow decisions should ideally recognize that river "macrosystems" are hierarchical dynamic networks, influenced by strong directional connectivity that integrates processes across multiple scales and broad distances through space and time (McCluney et al., 2014). The complex interactions of these dynamic river macrosystems make environmental water decisions particularly difficult to undertake with informal, experience-based, approaches to decision-making. The increase in the number of countries that hold environmental water rights or reserves that require active ongoing management of water has highlighted these challenges (Le Quesne et al., 2010; O'Donnell, 2013). For example, in Australia, there are environmental water managers with a legal responsibility to manage environmental water rights in a transparent and accountable way (Commonwealth of Australia, 2007). They are looking to decision frameworks and support tools to improve the **consistency** and **transparency** of their decisions. The complexity of the decision space lends itself to the use of decision support tools. Such tools build on available data and expert opinion to model the link between the available management decisions and the environmental objectives. In this review, we examine existing optimization based decision support tools that focus on environmental water release decisions, using a range of optimization techniques. There are a number of other modeling tools that are used to assist in water planning decisions (for example, Multi Criteria Decision Analysis used in Ryu et al., 2009) however this paper focuses on the increasing use of optimization to address environmental watering decision making.

The use of analytical capabilities, data and tools to help tackle complex environmental problems has greatly increased (Gomes, 2009). One method is optimization modeling, which has been widely used to share water resources across multiple and competing consumptive users (Labadie, 2004) and in conservation management (Sarkar et al., 2006). Optimization modeling has the potential to support and inform the more informal decision making approaches, improving both the efficiency and transparency of decisions (Liebman, 1976; Maier et al., 2014). Even though the complexity of environmental systems is sometimes raised as limiting the usefulness of decision support tools (Rizzoli and Young, 1997), many of the challenges involved in representing environmental systems (e.g. dynamics, spatial coverage, complexity of interactions, randomness, periodicity, heterogeneity, scale and paucity of information; Guariso and Werthner, 1989) also exist in other fields where optimization has been readily adopted. There is a growing body of literature examining optimization as a tool for improving environmental water management. This paper (Section 2–5) synthesizes this existing effort, identifying common approaches, strengths, weaknesses and gaps. Importantly, this review focuses attention on literature that has viewed environmental water releases as a decision, not as a constraint. Chief among our conclusions (Section 6) is that almost none of this research has yet been used to inform actual environmental flow management decisions. This research therefore remains at the proof-of-concept phase and awaits the transition to uptake by water management practitioners. A future focus on adoption is vital if such research is to make this shift and have practical impacts on the way environmental water is managed.

2. Review of existing optimization models - literature search

We used a combination of search terms "environmental flow" or "environmental water" with "optimization" or "optimisation" in Thomson ISI web of science, Science Direct, JSTOR and Google scholar. Additional papers were located by searching bibliographies of papers found during the search – a 'snowball search', and through the professional knowledge and peer networks of the authors (Greenhalgh and Peacock, 2005). We only considered studies with an active decision variable concerning the volume of water released from storage for environmental purposes. This excludes studies that include legislated environmental water requirements modelled as constraints rather than decision variables. For example, in a review of storage models for hydropower generation, Jager and Smith (2008) found that nearly half of the models included environmental flows as a constraint on minimum flow releases. Where environmental flows are included as a fuzzy constraint, (i.e., there is still a decision around the quantity of release, albeit not through a decision variable), the study was included in this review. We excluded a number of studies that consider other aspects of managing environmental water, such as management of infrastructure associated with environmental watering (e.g. Higgins et al., 2011), or the least cost approach to acquiring environmental water (e.g. Hollinshead and Lund, 2006). Overall, 42 studies fulfilled the inclusion criteria, with more than half published since 2012 (Fig. 1).

3. What questions and timescales do the studies address?

With the broad challenge of "improving environmental water delivery", there is a suite of questions that an optimization model could answer. Broadly, models have targeted the following questions (not necessarily in isolation).

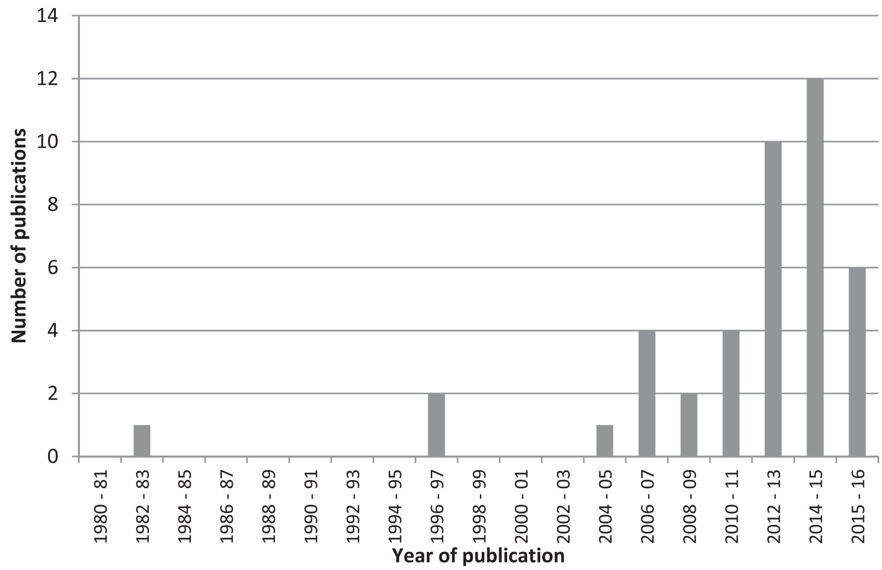

Fig. 1. Year of publication of papers using optimization for environmental watering decisions.

1. Given existing consumptive (or human) water demands, how can releases be managed to improve downstream ecological outcomes? This question has been addressed in two ways:
   a) the decisions can allow conjunctive outcomes, with changes to the way consumptive demands are met (so long as they remain met), or
   b) the decisions can allow management of the remaining water after meeting consumptive demands (or water specifically allocated to the environment) and assume that consumptive water decisions are exogenous (i.e. they cannot be altered through management decisions).
2. What is the optimal allocation between consumptive water uses and the environment?
3. How can infrastructure be used in combination with releases to improve environmental outcomes?

Fig. 2 categorizes all studies according to which question they address, by color. Environmental water management issues must consider a range of spatial and temporal scales. Operational decisions tend to focus on sub-daily or daily timeframes and single locations, whereas long-term planning employs a wider spatial scale (usually a basin-wide scale) and uses coarser time-steps, which may extend to multiple years (Fig. 2). Many of the studies are primarily focused on hydropower dams, and investigate operational decisions concerning storage releases, where sub-daily or daily time-steps are important due to the nature of hydropower operation in response to variations in power demand. These studies have tended to ask how environmental releases can be managed to improve downstream outcomes given existing consumptive outcomes (question 1a). A number of the studies that address seasonal planning are located in Australia where significant volumes of environmental water rights are held and managed by an organizations established for that task. These studies address the decisions available to an environmental water manager, assuming that the environmental water manager must not impact other water users' decisions (question 1b).

3.1. Different temporal scales of decisions - linking operational and long term planning decisions

Environmental water management decisions can be considered at a variety of temporal and spatial scales. A key remaining challenge exists in the delineation of these temporal and spatial scales of decisions. Existing studies broadly investigated either short-term operational decisions (e.g. Cioffi and Gallerano, 2012), or longer-term planning decisions (e.g. Grafton et al., 2011; Szemis et al., 2013). However in practice, there is a link between the two. The operational decision to release at one time-step depends on the longer term planning objectives and ability to meet other flow requirements (potentially of more importance) later in the year. For example, consider an environmental water manager making a decision to release a flow pulse (or fresh) in autumn to trigger a fish spawning event. This is a short term decision and an optimization model could assist in determining the best release pattern from storage to make use of any downstream flow that might occur due to rainfall events in the system. However, the decision to provide this event is also linked to seasonal planning decisions. The benefit of a spawning fresh may be significantly limited if there is no subsequent spring pulse available for fish to promote upstream migration to the river from the estuary (Shenton et al., 2014). An environmental water manager is therefore making short term decisions with a mind to the likely flow events later in the seasonal planning process. The link between these planning horizons in environmental water delivery has received little discussion in the literature, but has implications for the structure and implementation of decision support tools. A clear modeling challenge will be the need to incorporate different temporal and spatial scales within the one optimization model. Indeed, many other optimization problems rely on an appropriate linking between decisions in different temporal scales, including situations where operational, tactical and strategic decisions are closely linked (for example logistics networks, Schmidt and Wilhelm, 2000). There are a number of strategies to deal with this matter, including the use of nested models, stochastic programing (see Section 5) or the use of optimization-simulation approaches (Figueira and Almada-Lobo, 2014). In the context of broader reservoir operations, Georgakakos et al. (2012), for example, refer to the use of a hierarchy of simulation and decision models that relate to multiple temporal resolutions. The longer term decisions thus relate to the monthly release decisions, and in turn sub daily flood control objectives. There is potential to explore these types of approaches to better link the operational and planning decision processes of environmental water management.

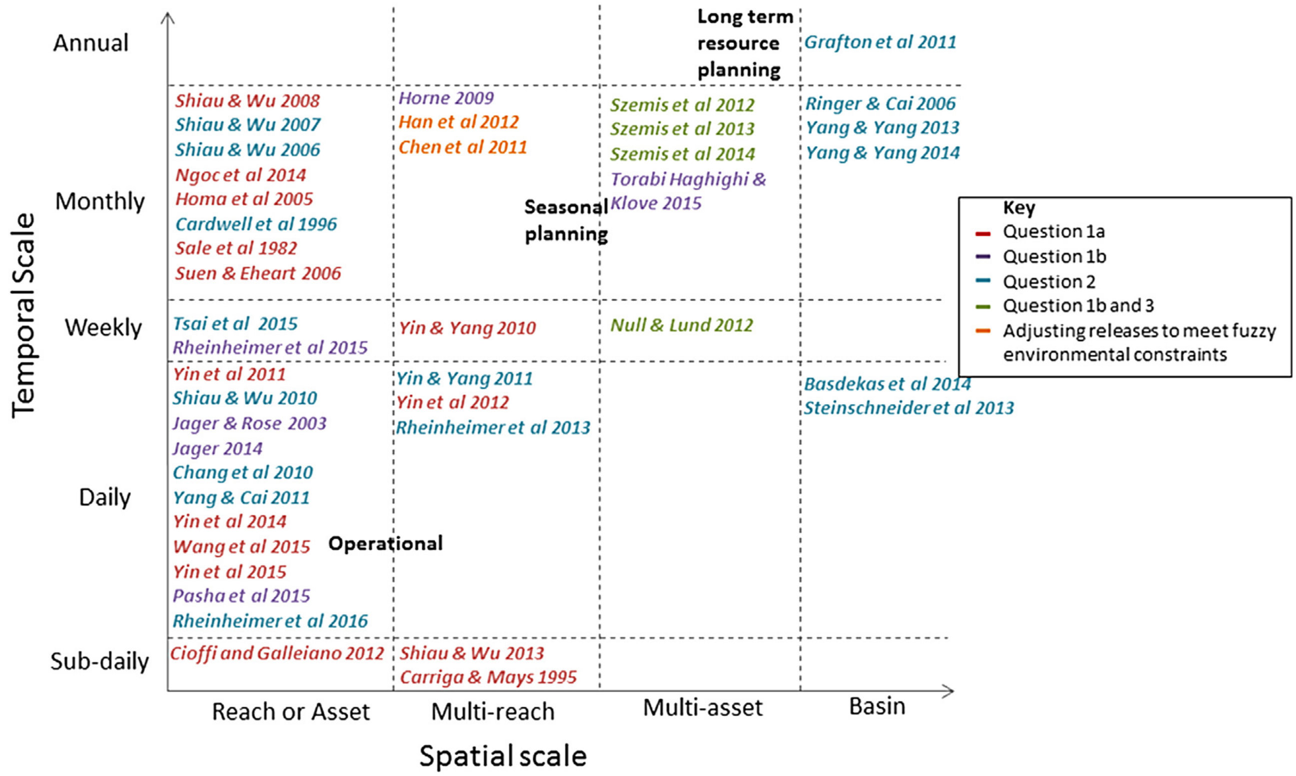

Fig. 2. Temporal and spatial scale addressed by existing optimization models. Many of the operational models were developed for optimizing environmental releases from hydropower dams.

4. How are environmental outcomes represented?

The concept of optimization hinges on understanding the relative benefit of providing water to the environment at one time-step or location over another, or between environment and other water users (Horne et al., 2010). This requires that environmental outcomes be represented in a manner that quantifies the benefit of different flow regimes. Environmental flow studies provide flow recommendations predicted to provide the ecological needs of target species of ecosystem processes (Horne et al., 2010). The majority of studies in this review rely heavily on existing environmental flows studies and related data, and the approach to representing environmental outcomes is therefore often dictated by the information available for the study catchment. Out of the 42 studies reviewed, 27 used hydrological indices to represent environmental outcome, 13 used habitat based methods (4 of these using complex relationships to link different habitat requirements) and 2 used population based methods.[1]

There are also clear geographical differences in how environmental water requirements are represented (Fig. 3). The majority of studies are based in Asia, and have adopted hydrological indices as a surrogate measure of environmental outcome (e.g. Chang et al., 2010; Han et al., 2012; Ringler and Cai, 2006; Shiau and Wu, 2013). These studies often measure alteration in a component of the flow regime from the natural or pre-regulation state. The advantage of hydrological methods is that they do not require detailed understanding of the ecological processes in the river, and are less data intensive than habitat or population methods (Han et al., 2012). The difficulty with this approach is that the relationship between flow and environmental outcome does not relate directly to environmental objectives, which may therefore limit the models' relevance to actual environmental outcomes. It also assumes a linear relationship between discharge and ecological outcome (e.g. half the water provides half the benefit). In addition to this, the natural flow paradigm, upon which these indices of hydrological alteration are based, may not be the optimal target downstream of a storage where the entire flow regime has been significantly altered for an extended period (Jager, 2014).

Stream biota and ecosystem functions respond to patch-scale hydraulic variables and the effect of flow metrics is indirect, via the influence of flow on stream hydraulics. Indeed, hydrological indices may not always be well-correlated with physical habitat responses to altered flow regimes (Turner and Stewardson, 2014). Recognizing this, a number of studies in the review used habitat based methods to evaluate environmental outcomes (e.g. Chen, 2011; Cioffi and Gallerano, 2012; Horne, 2009). Physical habitat response is more proximate to the targeted ecosystems responses than hydrological indices. These models can vary in complexity and can include a conceptual model that links habitat curves together to predict species outcomes (Szemis et al., 2014). Habitat based methods can explicitly represent non-linearity and thresholds in the response of habitat to discharge resulting from the interaction of flow with channel geometry. Examples include diminishing marginal gains in wetted channel area with increasing discharge (Gippel and Stewardson, 1998) and the range of low flows within which increases in discharge increase availability of slackwater (Vietz et al., 2013). Habitat based methods generally require some site-specific river surveys and hydraulic model development.

The most direct approach to representing environmental outcomes are population based methods for selected taxa (fish, trees etc.). These use models that try to predict the actual ecological response from the flow regime (e.g. Jager, 2014; Jager and Rose,

[1] Tharme (2003) provides a good overview of hydrological alteration, habitat (including water quality) or population based approaches.

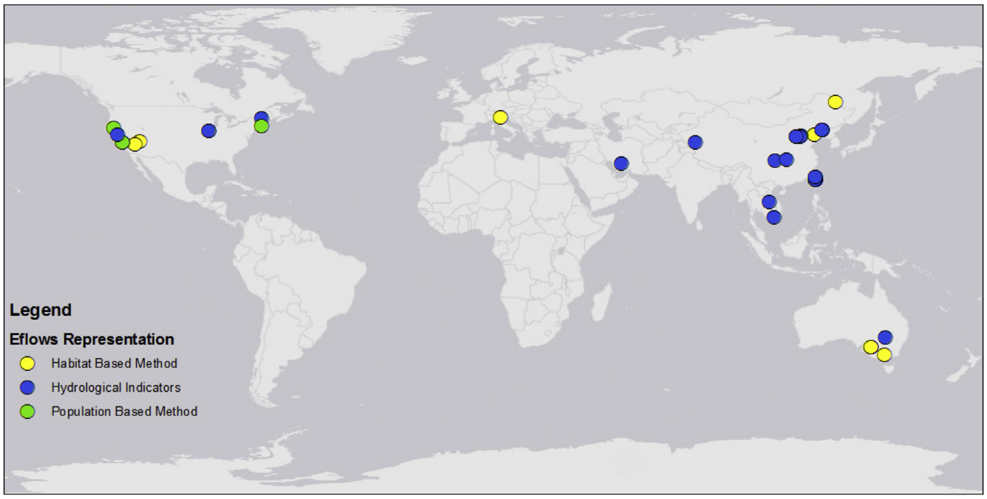

Fig. 3. Map of location of identified studies and the way that environmental water requirements have been represented.

2003). Population models are readily applicable in North America due to the focus of environmental flows on fish species protected by the Endangered Species Act (1973). A population model focusing on the relevant fish species is likely to align with the objectives of an environmental water manager. A clear advantage of population models is the ability to evaluate the interactions and sequencing between individual flow releases and their ultimate environmental effect. However, these models are more complex than hydrological or habitat methods, which has implications for successful solution of optimization model. Moreover, it has been shown that more complex approaches to representing environmental outcomes do not necessarily improve predictions (Lester et al., 2011).

Many disciplines quantify societal benefits in terms of dollar value. Within the reviewed literature there is only one study that adopts this approach (Grafton et al., 2011), most likely due to the difficulties in placing a defensible economic value on environmental outcomes (Horne, 2009). There are other studies that use simulation rather than optimization and adopt similar economic measures for the environmental (e.g. Akter et al., 2014). Other reviewed studies instead use some measure of “environmental outcome” often scaled between zero and one (e.g. Szemis et al., 2013).

Regardless of how environmental response is represented, the difficulty is increased if environmental targets include more than one response. The consideration of multiple, often conflicting, objectives can be achieved by weighting the different goals in a single scalar measure (for example, Horne, 2009) or by explicitly searching for ‘Pareto-optimal’ solutions, in which one objective cannot be improved without degrading others (Shiau and Wu, 2008). In the first case, the difficulty remains in finding appropriate weighting functions, while the latter method usually increases the complexity of the problem to be solved and interpretation of the output.

4.1. How is the objective function designed?

Similar to many multi-objective problems arising in water resource management such as rainfall-runoff calibration and long-term groundwater monitoring (Reed et al., 2013), the problem of optimizing reservoir releases is often considered (1) with conflicting ecological objectives (Horne, 2009; Szemis et al., 2012, 2013), or (2) with ecological objectives conflicting with other objectives of meeting human demands which include domestic, agricultural and power supply demands (Chang et al., 2010; Han et al., 2012; Suen and Eheart, 2006). The conflicting nature of the objectives leads to trade-offs between them, where one objective cannot be improved without degrading one or more other objectives.

Figs. 4 and 5 categorize literature reviewed in this paper based on how the objective function represents the combined ecological objectives (or ecological and consumptive objectives where applicable). Fig. 4 refers to papers that include only ecological objectives in the objective function(s) with other non-ecological objectives (for example, agricultural or hydropower demands), where relevant, included as constraints. Fig. 5 refers to papers that include both ecological and non-ecological objectives in the objective function(s).

Most studies (32 out of 42) reviewed here consider multiple conflicting objectives. The majority of studies (16 studies) represent the multiple conflicting objectives as a single mathematical objective by taking the weighted sum of the objectives (12 studies) or the weighted distance to the ideal solution (4 studies). Different combinations of weights are then used to study the trade-offs between conflicting objectives (e.g. Szemis et al., 2012; Yin et al., 2010). Five out of the remaining 16 studies include the ecological objective as a soft or fuzzy constraint in the model with most adding penalties in the objective function if ecological requirements are not met (e.g. Chang et al., 2010; Rheinheimer et al., 2015). The remainder (11 studies) employed multi-objective optimization. When analysing trade-offs between ecological and non-ecological objectives, deviation of hydrological indices from the target values is primarily used as a measure to evaluate the ecological outcomes (Fig. 2). On the other hand, population models, perhaps due to their inherent complexity, are limited to studies where optimizing ecological outcome(s) is (are) the only objective(s) (Fig. 1).

Reservoir or dam operations are often managed using fixed reservoir operating rules. Reservoir operating rules were traditionally developed to meet the non-ecological water requirements including agricultural and human needs without considering the ecological water requirements (Shiau and Wu, 2010; Yang and Yang, 2012). Consequently, there is an increasing effort to incorporate ecological benefits into these operating rules (Suen and Eheart, 2006; Wang et al., 2015). Thus, a number of studies have designed their objectives with the aim of improving these rules through a balance between socio-economic benefits and ecological benefits. It is noted that hydrological alteration is used as a proxy to evaluate total ecological benefits in these studies.

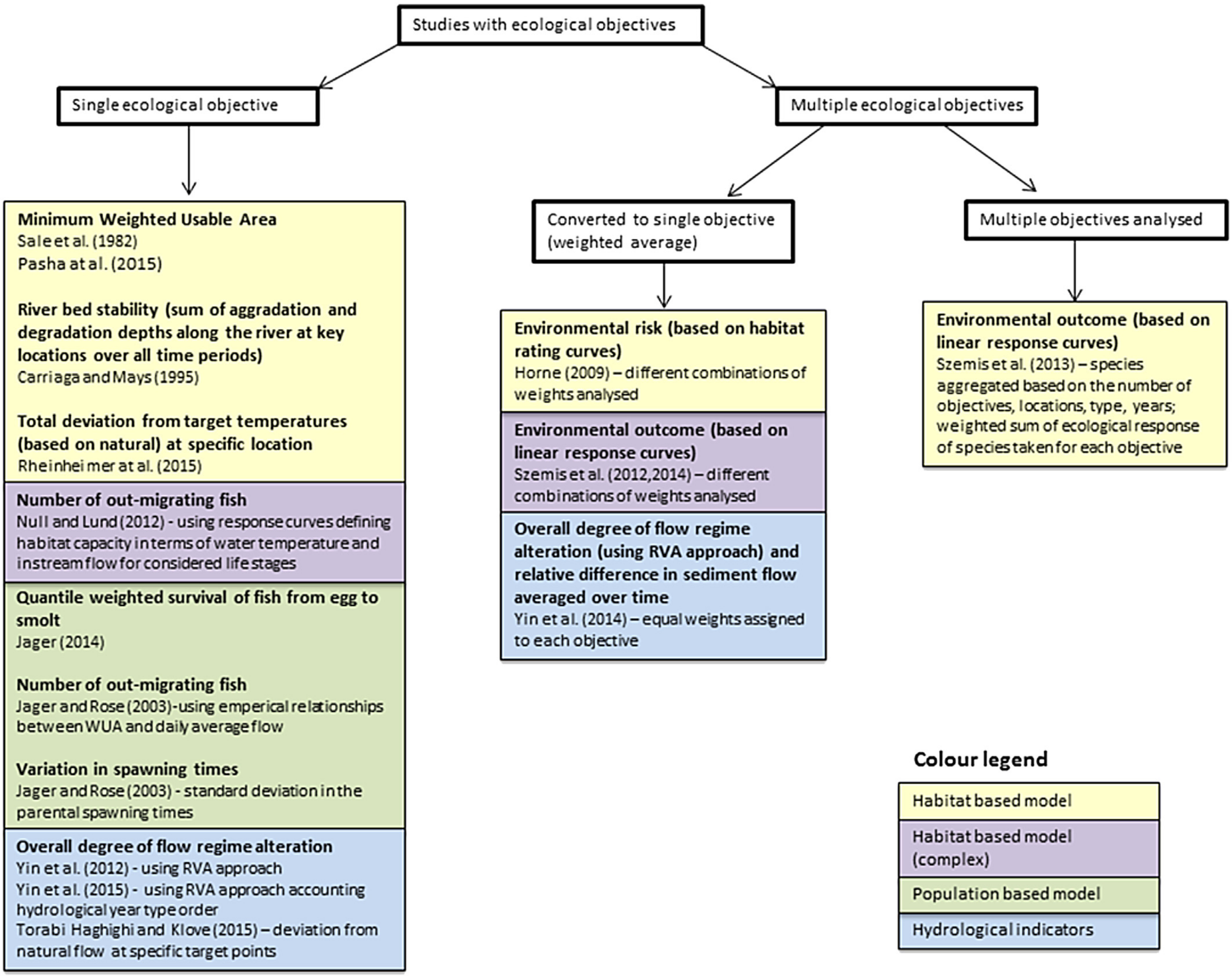

Fig. 4. Formulation of objective function for studies with environmental outcomes alone.

4.2. What is the appropriate level of complexity?

It is noteworthy that the most common approaches to representing environmental outcomes are the simplest to implement, but also the least realistic. It is likely the case that this is a reflection of the information available on environmental objectives and outcomes at those locations. For example, Horne et al. (2010) specifically states that the form of the environmental response curves adopted is driven by the information and approach taken in existing environmental flows studies for the region. Information on how environmental outcomes relate to changes in flow is not readily available in a format suited to optimization. While there is significant science around the impact of altered flow regimes on ecological condition (Arthington, 2012), this general understanding is often not sufficiently specific to represent marginal benefit of water at different times and locations required for optimization.

Beven and Alcock (2012) distinguish two types of uncertainty that exist in representing environmental systems (i) fundamental randomness and variation in nature (Aleatory or random errors) and (ii) lack of knowledge about how the system behaves (Epistemic errors). Aleatory errors can be addressed through statistical analysis methods or sensitivity testing (such as applied in Jager, 2014). Optimization modeling provides a means to explicitly assess the implications of uncertainty and incorporate it into the decision process (Sahinidis, 2004), allowing for the investigation into which elements of uncertainty (and which assumptions) are most crucial to a given decision. This can be done systematically through a modeling framework that tests the robustness of the solution (Kasprzyk et al., 2012). There will continue to be uncertainty around the exact nature of flow-ecology responses. Identifying those areas of uncertainty that have the greatest impact on management decisions would help environmental water managers focus effort in refining their knowledge of flow-ecology relationships. This can be used to identify specific elements of the environmental model that require field observations to either support or refine the existing hypothesis (Beven, 2002). In this way, a structured optimization model could provide a means to a transparent adaptive environmental water management approach, which would require consideration of how the tool and inputs are maintained and reviewed to support such an approach.

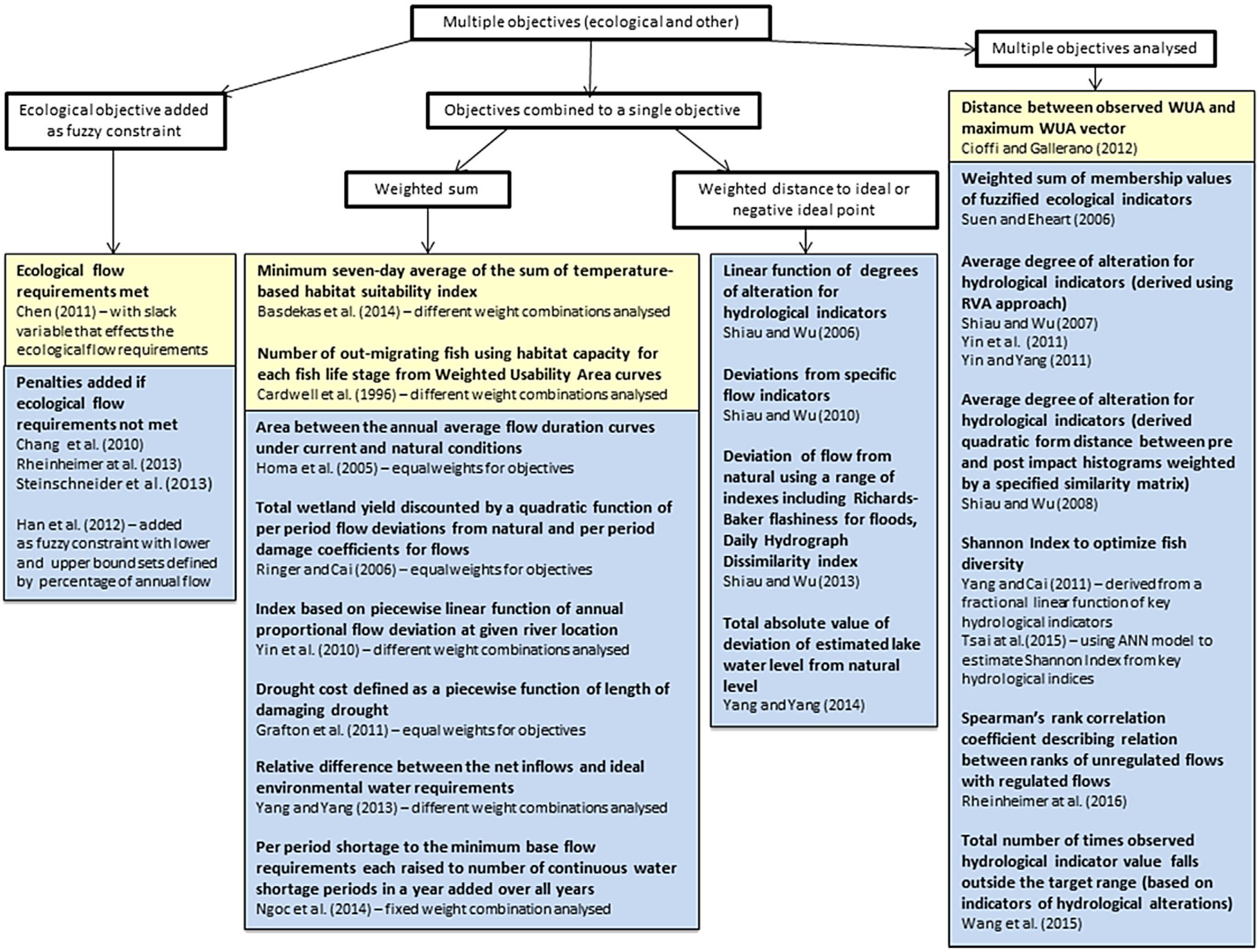

Fig. 5. Formulation of objective function for studies with environmental and other outcomes optimized.

Epistemic errors are more challenging to identify as they are related to the underlying knowledge gaps or systemic issues within the system representation. This is an inherent part of modeling environmental systems (Beven and Alcock, 2012). The choice between hydrological indicators, habitat based methods or population methods, and the approach to combining these in the objective function, are concerned with the representation of the system and will result in differing levels of realism and associated uncertainty. Ultimately a model of the decisions faced by an environmental water manager can only use our current best available information. This is the same information available to make decisions in the absence of an optimization model. The only difference is the way that this information is synthesized to inform the decision-making process. Importantly, the known assumptions, limitations and uncertainties should be explicitly stated and considered when making use of the model outputs.

So is a model worth having with simplified or uncertain representations of ecological outcomes? Those in favor of decision support systems for complex problems advocate that the modeling process remains beneficial in helping distil the essential elements of the problem and the links between decisions and management outcomes (McIntosh et al., 2011; van Delden et al., 2011). The model can then be seen as representing a hypothesis of how the system behaves, which is tested and refined over time, as new knowledge becomes available (Beven and Alcock, 2012).

While in theory these benefits of a formal support model exist despite the uncertainties and challenges of modeling ecological outcomes, their real potential to the application of environmental flows will only be determined through the process of application within management organizations and the testing of real on-ground environmental water release decisions.

5. What solution technique is used?

We categorized the studies in this review by their modeling and solution techniques, and found that they were dominated by the use of evolutionary algorithms, including all forms of genetic algorithms (22 out of 42 studies). Other solution approaches included (i) metaheuristic methods other than evolutionary algorithms (5 out of 42 studies), (ii) methods based on linear and mixed integer linear programming models (8 out of 42 studies), and non-linear programming models (5 out of 42 studies), dynamic programming (2 out of 42 studies), and (iii) complete enumeration of solutions (1 out of 42 studies). The boxed text provides a brief description of each of these modeling techniques.

Introduction to solution techniques

An optimization model is a mathematical representation of a decision problem. The model aims to find the decisions (defined as a set of *decision variables*), that lead collectively to an *optimal* solution. An objective function defines this solution, and a series of *constraints* define boundaries around the problem.

There is a variety of techniques available to solve these optimization problems, and researchers are constantly developing new methods (Boussaid et al., 2013; Burer and Letchford, 2012; Junger et al., 2010). Tractability of these problems strongly depend on characteristics of the constraints and objective function, and solution techniques have usually been developed so as to exploit specific characteristics. Characteristics that are particularly important include: (i) the number of variables and/or constraints and (ii) mathematical properties of the constraints and objective function, for example, whether the constraints define a convex set, or not.

Solution techniques, which are computational algorithms, may be broadly grouped into heuristic methods, that do not guarantee that the solution they find will be optimal (or even feasible, in some cases), and exact methods, which guarantee that if computation is continued for long enough, an optimal solution will be found (or within an approximate bound). We now describe some of the major categories of these techniques, focusing on problems with a finite number of decision variables and constraints, as it is these that are prevalent in conservation and environmental water management optimization modeling.

- **Metaheuristics** is a term used to describe a general class of optimization techniques that seek an optimal, or near-optimal, solution to a problem, but that cannot guarantee that the solution they find will be optimal. They can either be used to build an initial solution to the problem (construction method) or to iteratively modify an existing solution, with the goal of improving on it (improvement method). Many of these methods use greedy strategies, that is, at each modeling step they aim to get the best possible outcome for that point in time, and they do this by making "local" changes to solutions, that affect only a small part of the solution. They exploit the power of computers to explore the effects of many such changes, in sequence, and use randomization in how the solutions are built, or changed, to ensure a diversity of solutions are considered. Metaheuristics are vital for solving problems where obtaining the objective function value requires a simulation procedure (Figueira and Almada-Lobo, 2014). They can also be the most attractive procedure when the mathematical functions involved do not have "nice" properties and therefore, more tailored methods (such as linear programming, discussed below) can not be used. Metaheuristics describe high-level, guiding, principles for how optimization can occur, and can be tailored to solve a specific optimization problem, often in many possible, alternative ways. Metaheuristics can operate on a single solution, or simultaneously on a set of solutions. Well-known examples of the former include greedy randomized adaptive search (for construction), simulated annealing, tabu search and ant colony optimization. Well-known examples of the latter include genetic algorithms (discussed next), memetic algorithms and, in general, evolutionary algorithms. However there are many more metaheuristics; this is a vigorous, and active area of current optimization research.
- **Genetic algorithms (a particular form of metaheuristics)** are metaheuristics inspired by the concepts of natural evolution, based on iterative modification of a set of solutions (a *population* of solutions), in a manner analogous to how biological populations change. Solutions "evolve" from an initial population using mechanisms inspired by genetic recombination, mutation and natural selection, in which the individuals of one generation (iteration) compete to form the next one. The "fitness" of an individual in the population (so of one solution with in the population of solutions) dictates—where fitness is the feasibility and quality of the solution—determine its chances of survival through to the next iteration, Genetic algorithms are particularly useful for addressing problems in which there are multiple, conflicting objectives, and a set of solutions is sought to approximate the Pareto frontier (i.e. solutions where one objective cannot be improved without diminishing the others).
- **Linear and mixed integer linear programming algorithms** are optimization methods that can find proven optimal solutions for problems in which both objective function and constraints are explicit, linear functions of the decision variables. In the case of mixed integer linear programming, some variables may be constrained to be integer, or whole-numbered values. The use of integer variables expands the modeling range of linear programs enormously, permitting even highly nonlinear structures to be represented. This arises primarily through the use of binary variables, which are variables that must take a value of either zero or one. Both linear and mixed integer linear programming algorithms are highly effective, and can often solve problems with thousands of variables and constraints, to optimality. They can also be used heuristically to find near-optimal solutions, simply by limiting their run time, and accepting the best solution found at the end of that time. If used in this way, they provide a bound on how far the obtained solution is from optimal.
- **Nonlinear programming algorithms** are used to solve optimization problems in which either the objective function or the constraints are modelled using nonlinear functions of the decision variables, and all are given as explicit mathematical functions. The term is usually reserved for methods that seek *locally* optimal solutions. The importance of this is that, depending on the mathematical characteristics of the problem, a locally optimal solution may be a true optimum (if the constraints and objective are convex, in which case the problem is *convex*), or may be just be a good feasible solution. For nonconvex, nonlinear problems, the term *global optimization* is used to describe a method that will guarantee an optimal solution. The current state-of-the-art in nonlinear programming algorithms are quite effective, and can usually solve problems with hundreds, or possibly, thousands, of variables and constraints. However, global optimization solvers struggle with problems of this size.
- **Dynamic programming algorithms** are techniques that solve optimization problems expressed recursively, in principal solving to optimality. They do this by solving nested subproblems, finding solutions for a smaller problem and feeding this into the larger problem iteratively. The methods are particularly efficient when many of the generated subproblems are effectively the same, avoiding exponential growth in the number of subproblems to be solved.
- **Complete enumeration of solutions** solves an optimization problem by explicitly evaluating all possible solutions and choosing the best one.

5.1. Selection of solution method

It is expected and necessary that different solution methods are used to solve models with different problem formulations. Problem formulation is dependent on the selection of decisions variables, objectives and constraints, which determines the size of the search space and characteristics of the fitness landscape (Maier et al., 2014). Ultimately, this should determine the solution method used, as well as the need for a near-optimal or optimal solution and computational efficiency of the approach. Ideally this would be discussed between the analysts and stakeholders who are involved in the development of the optimization model (Maier et al., 2014).

While the majority of studies used evolutionary algorithms as the solution method (see Section 5.1), there was wide range of adopted approaches. The literature varied widely in the level of justification provided for selecting one solution method over another. By way of example, some studies provided a detail reason to the selection (e.g. Chen, 2011; Szemis et al., 2013), others selected the solution method based on its popularity and wide use (e.g. Shiau and Wu, 2007; Suen and Eheart, 2006), while some studies provided no reason as to the method chosen (e.g. Jager, 2014; Null and Lund, 2012; Ringler and Cai, 2006). It should be noted that we are not suggesting that these studies did not select the solution method without consideration, but rather, this consideration was not documented to allow for analysis.

Of the papers that selected the optimization technique based on popularity and wide spread use, the majority used genetic algorithms. This was expected given their generality allowing them to be easily adapted to the problem in hand (Labadie, 2004). The main consideration was their ability to incorporate additional complexity into the problem, such as considering multiple objectives (e.g. Chang et al., 2010; Suen and Eheart, 2006), incorporating uncertainties (e.g. Han et al., 2012), or improving the representations of ecological outcomes (e.g. Yin et al., 2015). Alternatively, studies that gave justification, selected alternative metaheuristics that suited the problem being addressed (e.g. Jager and Rose, 2003; Szemis et al., 2012, 2013) or compared different solution methods (e.g. Cioffi and Gallerano, 2012; Shiau and Wu, 2006).

Genetic algorithms are easy to use and have the advantage of being able to determine near-optimal solutions for problems with large and complex search spaces (Sivanandam and Deepa, 2008). As a result they have the ability consider complex ecological models, such as the ecological processes represented in population dynamic models (e.g. Jager, 2014; Jager and Rose, 2003) that may be difficult to model using other mathematical programming techniques. They also have the ability to interact with existing water resource models (Maier et al., 2014). However, genetic algorithms are not guaranteed to reach the optimal solution, nor do they provide any information on how far the final solution might be from the optimum (Reeves, 1993).

In contrast, mathematical programming techniques such as mixed integer linear programming lead to a confirmed optimal solution, and, if stopped short, provide a bound on the optimal value, and hence a guarantee on the quality of the best solution found so far. Although these methods can solve such problems with high efficiency (Bixby, 2012), convergence can be an issue as the problems grow larger, which can be the case for many environmental water management problems. These methods also tend to be less flexible than metaheuristics, as they impose stronger requirements in the way the problem needs to be modelled (e.g., by imposing that the problem constraints and objective function be written with linear equations, in the case of linear programming). This may require a particular effort in the modeling stage in order to represent the necessary complexity of the environmental system. It may also mean that by simplifying or altering the representation of the problem, the solution while mathematically optimal, may be affected by the introduced deviations in the system representation.

In cases with multiple objectives, there are multi-objective versions of genetic algorithms and other methods to optimize across a number of environmental values and consumptive uses (e.g. Shiau and Wu, 2008). This is a particularly useful approach when it is difficult to use the same measure of benefit across different sub-objectives to compute a single objective function value. Such methods aim to obtain a set of non-dominated solutions, that is, those for which no single objective function can be improved without the consequent deterioration of others (Pareto curve). However, for discrete optimization problems, such as the environmental water management problem, it has been shown that the number of non-dominated solutions increase exponentially as the number of objectives increases (Benson and Sun, 2002; Lokman and Koksalan, 2013). Moreover, like the single objective case, multi-objective evolutionary search algorithms may not converge to the true Pareto-optimal set, but rather deliver a local Pareto-optimal set, i.e., a set of locally non-dominated solutions (Deb, 1999; Maier et al., 2014). Further, when many objectives are considered, the outputs may not be readily interpretable (Maier et al., 2014). Thus, while having alternate solutions may be of interest to the decision maker (as they may provide diverse options to the decision maker), the analysis and comparison of alternate solutions for multi-objective problems may be difficult in the absence of appropriate representation of the outputs.

5.2. How well does the model perform?

The studies reviewed used a range of approaches to assess model performance, including comparison to historical releases (e.g. Shiau and Wu, 2013) and comparison to current regulated environmental water releases within a catchment (e.g Yin et al., 2010). In these cases, the optimization models' recommended release patterns achieve a clear improvement in environmental outcomes compared to the historical or regulated releases. A number of studies compared different release scenarios, rather than assessing the model against current operations (Cardwell et al., 1996).

While all studies demonstrate the potential for optimization to improve environmental outcomes, there is no decisive approach for assessing model performance, in part due to the difficulty in identifying a comparable benchmark. In many fields, current practice based on expert design or an estimation of the cost of a non-optimized solution would be used as the benchmark (e.g. Ferris et al., 2015; Hu et al., 2015). It is possible to compare existing environmental water management rules to optimization model outcomes over the long term, where there are these rules in place. However, where an optimization model is considering seasonal decisions this may not be appropriate as management rules by definition are providing the best outcome on average rather than for any one season. Where decisions are made under an uncertain climate future, it becomes difficult to compare model results directly to the previous behavior of an environmental water manager as the optimization model incorporates the benefit of "perfect knowledge". In reality the decision maker would make choices as the climate conditions unfold. In all of these approaches, the assessment of model outcomes relies on a comparison of flow release decisions. The real test of how effective optimization models are in informing environment water management is to test them in practice, and review ecological performance.

Perhaps a more fundamental challenge is that the optimization model represents an understanding of the link between flow and ecology. This relationship is embedded in the model based on the chosen approach to representing ecological responses. As previously discussed (refer to Section 4), there are epistemic uncertainties in how the ecological outcomes are represented (Beven and Alcock, 2012). When investigating the outcomes from the optimization model, it may in fact be that the underlying ecological representation needs revision, rather than the construct of the decision tool itself. This reinforces the potential role of models in facilitating system understanding (Beven, 2002) and playing a role in adaptive management. A 'hypothesis of causation' that can be refined by learning from previous decisions is a central element of adaptive management (Allen and Stankey, 2009). The representation of ecological outcomes can thus be seen as a working model, rather than assuming model components remain static. Within this adaptive management process, optimization tools and their model outputs can play a role in supporting a structured dialogue between scientists and managers around how the system behaves (Ladson, 2009).

5.3. Representing climatic uncertainty

One key aspect of uncertainty for environmental water managers is the likely future climate. The majority of reviewed studies, specified a set of climate conditions and environmental requirements for the model period (i.e. the model was deterministic) (e.g. Basdekas et al., 2014; Cardwell et al., 1996; Chen, 2011). This allows for a number of different scenarios to be run through the optimization model. If enough scenarios are developed, the outcomes can be summarized in a way that makes it accessible and relevant to the way an environmental manager makes decisions (e.g. information translated into release rules that help managers understand when and how to move between management scenarios based on climate triggers). There are sophisticated approaches developed in the field of reservoir operation that use weighting approaches to combine scenarios based on the probability of a scenario under future climate conditions (Brekke et al., 2009). There are also a range of approaches that look at the robustness of solutions under with changing climate (Hamarat et al., 2014; Herman et al., 2015).

However, the reality of managing environmental water for seasonal or operational decisions is that at a given point in time, the manager must make decisions faced with uncertain future climatic and streamflow conditions. In other words, the manager does not know at the start of the year whether it will be a very dry, dry, average or wet year. It is difficult to translate the outcomes of running a number of different scenarios in a deterministic optimization model into practical management outcomes faced with uncertain climate. Therefore there is scope to further develop the current optimization modeling approaches to consider how the model structure or model outputs can be adjusted to imbed this uncertainty.

One method to achieving this is employing a stochastic modeling framework and a "scenario tree" approach, where different future conditions are given a probability of occurrence, with each time-step having options that branch from the suite of conditions possible a the previous time-step (Powell, 2014). The optimal solutions from such models hedge over the range of possible future conditions, which enables environmental water managers to make a decision that places them in the best position to be able to manage outcomes whatever climate scenario unfolds. This may result in a very different release pattern to that with "complete knowledge" of climate. Given the wide range of solution methods, further research should investigate how to best incorporate this uncertainty within each technique.

6. The challenge of adoption

Our classification of existing studies focused on the technical challenges associated with developing an optimization model to manage environmental water releases. For all papers, the problem being addressed (and the basis of the objective function) is clearly identified. However, none of the papers provided any linked discussion of the interaction with potential end users neither during model development, nor of the use or application of an optimization model within the management or decision-making process. How is it envisaged that the tools will be used? We contacted the authors of the reviewed papers, and asked about the level of stakeholder involvement during model development and the uptake of the model by stakeholders. Approximately 50% of the authors responded, with the majority stating there was limited involvement from stakeholders in model development, and there were only a handful of the models that have been used by environmental water managers (despite consistent interest from environmental managers in the concept and potential of optimization models). The existing literature has progressed the technical approaches and science. The next stage will be about translating this approach to improve uptake and application of these approaches, where they can be tested in real life management scenarios. The simplistic survey of authors, provides an indication that the field of optimization for environmental watering decisions is yet to progress into this phase. It should be noted that this is consistent with conservation planning literature, where scientific literature rarely reports the complete implementation of a proposed approach. However, in conservation planning, prioritization techniques such as optimization are appearing in the non-academic literature (such as in government reports) demonstrating some translation into management (Knight et al., 2009).

There are a number of factors that can limit uptake of decisions support systems, such as optimization tools, in environmental water management (INCA Consulting, 2011; Parker and Campion, 1997; Stewart et al., 2013) including:

1. complexity of the software,
2. accessibility and accuracy of inputs,
3. cost versus benefits of using the system,
4. lack of engagement during model development, resulting in cynicism about its utility,
5. belief that expert judgment is more reliable, and
6. perception that the benefit of decision support tools is that they provide answers rather than being an input to the decision process.

Addressing these barriers to uptake hinges on the involvement of the user in the tool development process (Parker and Campion, 1997). Limited use of optimization models in environmental water management may be at least partly due to a lack of engagement with end users and stakeholders in scoping and designing a relevant tool rather than scientific limitations to potential models. Often, the ongoing use of the tool requires an individual within the relevant organization to champion the model and this process is more likely if they have been engaged in the process of defining the model needs, or have an existing strong relationship and trust with the relevant scientist or practitioner (Knight et al., 2009).

We should emphasize that optimization models will only ever be an input into the decision-making process for environmental water management, not a replacement of current decision-making processes. This has been the experience with use of optimization in conservation reserve selection (Linke et al., 2011) where optimization is now well accepted. Knight et al. (2009) highlights the importance of ensuring prioritization techniques are embedded within a broader operational model for conservation planning. This translates to environmental water management, where decision support tools such as optimization would operate within broader water management and planning structures and institutional arrangement.

Perhaps a further challenge is the difficulty of developing, maintaining and adapting a model over time. The first iteration of a tool will often by necessity be a simplification of the management space, but must be realistic enough to generate confidence among water managers that the work is worthwhile. There should be a shared understanding that model development will take time, and once further model needs are clarified they can be addressed through future iterations. There then needs to be a mechanism in place for the continued development of the model and documentation of these refinements. The systems in place for this ongoing development need to consider the ongoing role of the scientific team versus the ability of the environmental manager to take ownership and governance of the model. There must be sensitivity to the capacity constraints within the organizations that will use the model (Knight et al., 2009). Continuing through typical research funding cycles is a prerequisite for completing this journey successfully.

Part of the benefit of using an optimization model or alternative decision support tool is that it helps end users understand their own decision-making processes and the resource system (McIntosh et al., 2011; Liebman, 1976; Beven and Alcock, 2012). An optimization model provides a learning device; it is a tool in the decision process rather than an answer to the problem. The use of an optimization tool has the potential to (McIntosh et al., 2011):

- provide clarity through the process of working with end users to represent a system using a series of equations, qualitative relationships or logical rules,
- clarify the decision process and influential factors,
- generate creative planning alternatives,
- provide transparent evaluation approaches for planning alternatives, and
- provide improved governance around the decision process.

In order for these benefits to be realized, the end user must be engaged through the model development phase rather than simply being recipients of the end model. The existing research into the use of optimization models for environmental water management has demonstrated the scientific potential of this approach. Thus the next important steps in expanding this field will not only involve improved certainty of environmental outcome predictions (Section 2.2), application of efficient optimization techniques (Section 2.3) and improved model assessment approaches (Section 2.3), but more importantly, it will require engagement with end-users during the model development phase. Encouraging end-user involvement and being cognizant of institutional context will ensure these tools will assist in the adaptive management process, thereby ensuring transparent and efficient management of limited environmental water.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2016.06.028.

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