A framework for using ant colony optimization to schedule environmental flow management alternatives for rivers, wetlands, and floodplains

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[1] Rivers, wetlands, and floodplains are in need of management as they have been altered from natural conditions and are at risk of vanishing because of river development. One method to mitigate these impacts involves the scheduling of environmental flow management alternatives (EFMA); however, this is a complex task as there are generally a large number of ecological assets (e.g., wetlands) that need to be considered, each with species with competing flow requirements. Hence, this problem evolves into an optimization problem to maximize an ecological benefit within constraints imposed by human needs and the physical layout of the system. This paper presents a novel optimization framework which uses ant colony optimization to enable optimal scheduling of EFMAs, given constraints on the environmental water that is available. This optimization algorithm is selected because, unlike other currently popular algorithms, it is able to account for all aspects of the problem. The approach is validated by comparing it to a heuristic approach, and its utility is demonstrated using a case study based on the Murray River in South Australia to investigate (1) the trade-off between plant recruitment (i.e., promoting germination) and maintenance (i.e., maintaining habitat) flow requirements, (2) the trade-off between flora and fauna flow requirements, and (3) a hydrograph inversion case. The results demonstrate the usefulness and flexibility of the proposed framework as it is able to determine EFMA schedules that provide optimal or near-optimal trade-offs between the competing needs of species under a range of operating conditions and valuable insight for managers.

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1. Introduction

[2] Rivers and their associated wetlands and floodplains provide vital ecosystem services that people depend upon, such as water purification, habitat for wildlife and climate mitigation [*Millennium Ecosystem Assessment (MEA)*, 2005]. Many of these systems have been severely altered, or have even vanished, due to the development of infrastructure, such as channelization and dams, land conversion, and the over allocation of water for human needs [*Brookes*, 1988; *Kingsford*, 2000; *MEA*, 2005; *Nel et al.*, 2009]. This has altered the hydrological regime, reducing the level of connectivity and flooding between rivers and associated floodplains and wetlands, thereby changing their ecology and causing the death or poor health of their biota [*Kingsford*, 2000; *Kingsford and Auld*, 2005]. According to *National Research Council* [1992], the rate at which freshwater ecosystems are being altered or destroyed is much greater now than at any other time in human history. To mitigate the impacts of these alterations, there is an urgent need to improve the connectivity between rivers and their adjacent wetlands and floodplains, so that they can be maintained and protected for future generations.

[3] In order to address the problem outlined above, the provision of water for environmental flows has been suggested [*Arthington et al.*, 1998; *Kingsford*, 2000]. In the past, this consisted of releasing a minimum flow, which has now been deemed to be inadequate [*Arthington et al.*, 2006]. Instead, it has been suggested that managed flow regimes should follow the 'natural flow paradigm' developed by *Poff et al.* [1997] in order to reintroduce the flow variability that has been lost as a result of human induced flow alteration [*Poff*, 2009]. Five flow components were presented by *Poff et al.* [1997] as the key to ensuring the ecological integrity of river systems, including the timing, duration, magnitude, frequency and rate of rise/fall of flow. These components are also important when flooding adjacent wetlands and floodplains, as it is these factors that govern the structure and function, and in turn, the health of wetlands and floodplains [*Junk et al.*, 1989]. For example, the timing of inundation can affect the recruitment and regeneration of plants [e.g., *Cordes et al.*, 1997], flood duration can influence plant

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cover and diversity [e.g., *Busch and Smith*, 1995], while a combination of the timing, duration and rate of change of flooding can impact the life cycles of fish species [*Junk et al.*, 1989]. River, wetland and floodplain biota are dependent on these flow components and a significant amount of research has been undertaken to quantify these ecological responses [*Poff and Zimmerman*, 2010].

[4] The pursuit of environmental integrity criteria, such as those developed by *Poff et al.* [1997] constitute the primary objective of any management program. A number of management alternatives are available for achieving the corresponding environmental flow requirements for rivers, wetlands and floodplains, including environmental flow releases from upstream storages and the operation of flow control infrastructure, such as regulators and pumps. Decisions have to be made in relation to the timing, magnitude and duration of potential flow releases and infrastructure operation. In other words, at discrete points in time (e.g., day, week, month), decisions have to be made whether an environmental flow release should be made and/or whether a change should be made to the setting of flow control infrastructure. These decisions must be made in pursuit of an objective that seeks to maximize some measure of ecological health. If the decision is made to release environmental flows and/or make a change to the setting of flow control infrastructure, a choice has to be made in relation to what fraction of the available environmental flow allocation to release at this time and/or which of the available infrastructure change options should be implemented, and how long this management action should persist. Given that these decisions generally have to be made at discrete time steps over a given planning horizon (e.g., several years) and at numerous locations (e.g., locations of reservoirs, regulators and pumps), the search space of potential management alternatives in this scheduling problem is generally extremely large, particularly when dealing with extended spatial and temporal scales.

[5] The scheduling of environmental flow management alternatives (EFMAs) is further complicated by the fact that (i) there are often different processes that must be accounted for in managing a single species, such as (a) promoting the maintenance of adult species and the recruitment of juveniles (e.g., germination of plant species and breeding of wildlife), resulting in varying flow requirements [*Rogers*, 2011a], or (b) ensuring the succession and retrogression of floodplain vegetation, which introduces an additional shear stress factor [*Benjankar et al.*, 2011], (ii) flow requirements are generally different for each species of flora and fauna, and may be in competition with each other, which is a problem that is often exacerbated when considering extended spatial scales, as the number of species that need to be considered is generally larger, and (iii) schedules generally need to be developed over multiple years, since there are species, such as the Black Box woodland (*Eucalyptus largiflorens*), that require a maintenance flood frequency of 1 in 2–5 years [*Rogers*, 2011a], thereby introducing temporal dependencies into the scheduling process (i.e., decisions made at each time step are not independent of each other).

[6] Given the extremely large search space of management options, the large number of generally competing environmental flow requirements, and the temporal dependencies between management alternatives, the problem of scheduling EFMAs so as to maximize ecological outcomes is extremely difficult. However, such a goal is very important, particularly given that limited amounts of water are generally available for environmental purposes, as there is competition for water resources between various uses, such as irrigation, domestic and industrial water supply, power generation, recreation, and the restoration, rehabilitation and maintenance of ecological services. Given this complexity, there is potential benefit in using formal optimization approaches for addressing the environmental flow management problem. However, previous optimization studies in this field have primarily focused on the higher-level problem of the development of optimal reservoir/weir operating rule parameters or monthly reservoir releases, while trying to maintain an adequate balance between the needs of the environment and other water users (e.g., irrigation), rather than the specific problem of how to allocate a given environmental water allocation so as to maximize ecological outcomes. As a result, ecological objectives have been treated in a rather simplistic manner in past optimization studies. For example, in some studies, there was no consideration of the important flow components [*Chang et al.*, 2010; *Chaves et al.*, 2003], while in others, the importance of competing ecological objectives was neglected [*Cardwell et al.*, 1996; *Tilmant et al.*, 2010; *Yang*, 2011; *Yang and Cai*, 2011]. In almost all of the studies, there was no consideration of both river and downstream wetlands and floodplains, or the temporal dependencies between management options [*Homa et al.*, 2005; *Shiau and Wu*, 2004; 2007; *Suen and Eheart*, 2006; *Tilmant et al.*, 2010; *Yang*, 2011; *Yin et al.*, 2010]. Only *Higgins et al.* [2011] considered the river, wetlands and floodplains on a landscape scale and used optimization to determine the best locations and operating regimes for wetland regulators and weirs by mimicking the natural flood timing, dry period and flood duration. However, there is no existing optimization framework that can be used to (i) develop schedules that maximize the ecological response of rivers and their wetlands and floodplains for a given environmental water allocation, (ii) incorporate not only flood timing, dry period, and duration but also depth (which affects seed germination [*Rogers*, 2011a]), and (iii) develop schedules that favor certain ecological process or species. Consequently, there is a need to develop and test a generic framework for determining the optimal schedule of EFMAs for rivers and their wetlands and floodplains for a given environmental water allocation that takes into account (i) rivers and adjacent wetlands and floodplains, (ii) a large number of potential management alternatives, (iii) multiple and potentially competing environmental objectives associated with important flow components, process and species, and (iv) temporal dependencies associated with the important flow components.

[7] In order to meet this need, the specific objectives of this paper are (i) to develop an optimization framework for maximizing the ecological response of rivers and their wetlands and floodplains (e.g., by using the Murray Flow Assessment Tool (MFAT) developed by *Young et al.* [2003], as is done in the case study presented in this paper) for a given environmental flow allocation, by determining the optimal scheduling of predetermined EFMAs, such as flow releases and regulator settings, which is able to take account of (a) a large number of possible management alternatives, (b) a range of environmental objectives (e.g., ecological responses of flora and fauna species and associated

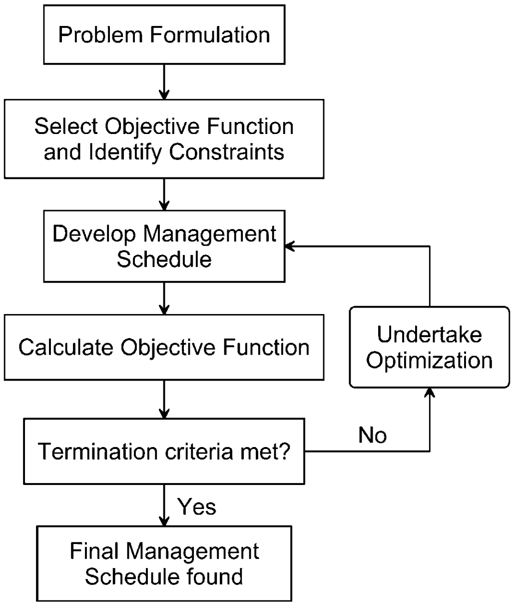

Figure 1. Representation of the optimal scheduling of environmental flow management alternatives.

processes), (c) constraints associated with environmental water allocations, and (d) the temporal dependencies associated with the management alternatives; (ii) to develop an approach that is capable of solving the optimization problem formulated in objective i, and (iii) to apply the optimization framework and solution methodology developed in objectives i and ii to a case study in order (a) to demonstrate how they are applied in practice, (b) to validate their performance, (c) to illustrate how they can be used to account for competing requirements of individual species, (d) to illustrate how they can be used to account for competing requirements of flora and fauna, and (e) to illustrate how they can be used to deal with environmental water allocations of different magnitude and timing (e.g., hydrograph inversion).

[8] The remainder of this paper is organized as follows. The novel optimization framework is introduced in section 2, followed by the optimization approach for solving it in section 3. The case study used to illustrate the utility and validate the proposed formulation and solution approach is introduced in section 4, while details of the numerical experiments conducted are provided in section 5. Results and discussion are presented in section 6, followed by a summary and conclusions in section 7.

2. Framework for the Optimal Scheduling of Environmental Flow Management Alternatives

[9] In this section, the framework for the optimal scheduling of EFMAs aimed at restoring, protecting and maintaining rivers and their wetlands and floodplains is introduced (objective i), which has been adapted from the systems approach proposed by *Biswas* [1976] and is shown in Figure 1.

[10] The first step in the optimization framework is problem formulation, which includes identification of the wetlands, floodplains and river reaches to be managed, identification and selection of appropriate ecological indicators (e.g., flora/fauna species, flow components or shear stress), the planning horizon over which the schedule for the EFMAs is to be developed (e.g., number of years), the time interval (e.g., monthly or yearly time steps) at which alternatives are to be scheduled, and finally, specification of the EFMAs that are available for achieving the desired ecological response (e.g., flow release options, regulator settings, pumping schedule), as well as the suboptions associated with each of these alternatives (e.g., magnitude, duration). Next, the objective function (e.g., maximization of ecological response) and any constraints (e.g., maximum available environmental water allocation) need to be defined, after which a schedule for the EFMAs can be developed. The objective function (e.g., overall ecological response of the system under consideration) is then calculated to assess the utility of the selected schedule. The process of selecting different schedules and evaluating their utility is generally repeated many times and guided by the selected optimization method in order to find optimal or near-optimal solutions (e.g., schedules of EFMAs). Each of these steps is discussed in more detail in sections 2.1–2.4.

2.1. Problem Formulation

[11] The first step in formulating the optimal scheduling problem, shown in Figure 2, involves the identification of the q wetlands, floodplains and river reaches that require protection, restoration or maintenance, where the wetlands, floodplains and river reaches are defined as H_i, and i ranges from 1 to q.

[12] Next, appropriate ecological indicators $E_{i,r}$, are specified for each wetland, floodplain and river reach, H_i, in

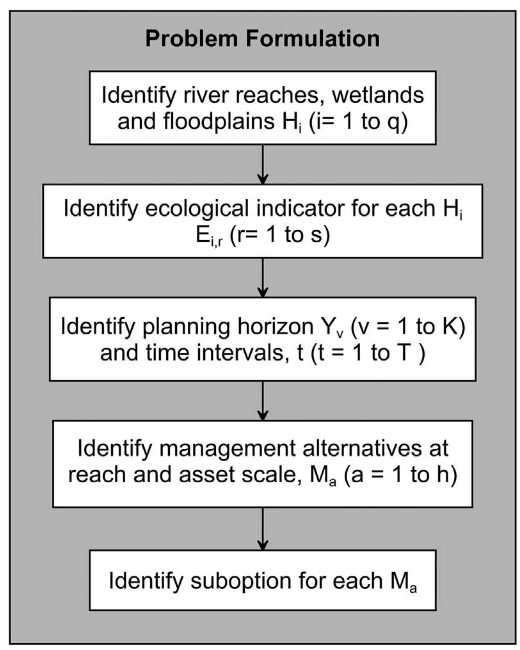

Figure 2. Steps in formulation of environmental flow management schedule optimization problem. The river reaches, wetlands, and floodplains are defined as H_i, and i ranges from 1 to q. The ecological indicators, $E_{i,r}$, where r ranges from 1 to s, are specified for each H_i. The planning horizon is defined as Y_v, where v ranges from 1 to v years, while the time interval, t, ranges from 1 to the final time interval, T. The number of management alternatives, M_a, ranges from 1 to h.

order to assess the performance of each potential management schedule in terms of ecological response. For example, the r ecological indicator/s (ranging from 1 to s) can be used to assess the ability to simulate the natural flow regime [*Richter et al.*, 1996], assess processes that govern the life cycle of different types of flora and fauna species [*Young et al.*, 2003], or measure the succession and retrogression of vegetation [*Benjankar et al.*, 2011]. The choice of the number and types of indicators is case study dependent. It should be noted that there are other ecological responses that can be taken into account, such as the fact that lower peak flows can increase ecological response through terrestrialization of riparian areas or the encroachment of the river channel by riparian communities [*Poff and Zimmerman*, 2010]. However, such ecological responses can only be incorporated if they can be represented in the form of an ecological indicator, which is a limitation of the proposed optimization framework.

[13] Once the wetlands, floodplains, river reaches and ecological indicators have been identified, the planning horizon over which the schedules need to be developed, Y_v, where v ranges from 1 to K years, and the time intervals between potential management actions during the period, t, which ranges from 1 to T time intervals, should be selected. Selection of appropriate values for these variables is also problem dependent.

[14] The next step in the problem formulation procedure is the specification of the management alternatives, which can be divided into two groups. The first category includes reach-scale management alternatives, which affect the hydrological regime of the entire river system. These include reservoir releases or weir operations that govern the flow within the entire river reach and affect wetland and floodplain inundation. The second type includes management alternatives that manipulate hydrological regimes for individual wetlands and floodplains. An example is the manipulation of water levels using individual gates and/or pumps at the entrances or exits of wetlands, which could prevent, allow, or force water from entering or leaving. The combination of reach, wetland, and floodplain scale management options constitutes the final set of management alternatives, M_a, where a ranges from 1 to h.

[15] The final stage of the problem formulation step involves the specification of the suboptions for each management alternative, that is, the magnitude, duration and timing of the proposed management interventions described in section 1. All of the available suboptions need to be specified for each of the management alternatives in order to define the decision space in its entirety.

2.2. Selection of Objective Function and Constraints

[16] The second stage of the proposed optimization framework involves definition of the objectives and constraints. It is important to select an appropriate objective function, as this characterizes how well different management schedules perform. The constraints, on the other hand, ensure that infeasible schedules are not considered.

[17] The objective function used to assess the performance of the proposed management schedules should consider all of the wetlands, floodplains and river reaches, as well as the selected ecological indicator(s). Since there are generally multiple, and at times competing, indicators, the values of individual indicators need to be summed over all ecological assets (e.g., river reaches, wetlands, floodplains) in order to obtain an estimate of the ecological response of the entire system under investigation for a given management schedule. In order to account for differences in the relative importance of various ecological assets, indicators, and time periods, user defined weights are included. Consequently, the proposed objective function takes the following form:

$$F = \sum_{i=1}^{q} w_{1i} \sum_{r=1}^{s} w_{2r} \sum_{v=1}^{K} \frac{w_{3v} E_{i,r,v}}{Y_K} \tag{1}$$

where $E_{i,r,v}$ is the indicator value for asset i, for indicator type r in the vth yearly time interval. In equation (1), the overall objective function value is obtained by summing (1) values of each ecological indicator over the q wetlands, floodplains and river reaches considered, (2) values of the s indicators used for each wetland, floodplain, and river reach, and (3) ecological indicator values over the number of years (Y_K) over which the schedule of EFMAs has been developed (i.e., the planning horizon). Weights, w_{1i}, w_{2r} and w_{3v} place emphasis on the qth wetlands, floodplains or river reaches, rth ecological indicator and Y_Kth year, respectively. Consequently, the proposed objective function is sufficiently flexible to cater to particular aspects of the problem (e.g., favoring an endangered species), while also ensuring that an overall ecological score is obtained for the river system.

[18] Once the objective function has been defined, the constraints need to be specified to ensure infeasible schedules of EFMAs are not developed. Since the aim of the research is to develop EFMA schedules that optimize the environmental benefit associated with a given amount of environmental water, constraints have to be placed on the total amount of water that is available for environmental purposes, which is likely to vary over the planning horizon (e.g., on a seasonal basis), as given by

$$\sum_{t=i\_ni(pd)}^{f\_ni(pd)} A_t \leq A_{\max\_ni(pd)} \tag{2}$$

where pd is the number of periods of constrained environmental water allocations, ranging from 1 to np, while the number of increments in each period, $ni(p)$ ranges from 1 to Vp, and $i\_ni(pd)$ and $f\_ni(pd)$ are the corresponding initial and final time steps for pd, over which a particular water allocation is released. The duration of each increment is defined as $d_{ni(p)}$, and the summation of all duration increments for each period must equal the total duration interval, T_d. Being able to have different allocation constraints for different time periods during the planning horizon provides the ability to account for situations such as hydrograph inversion, or physical constraints on water release infrastructure.

[19] Constraints also have to be placed on the magnitude and duration of the suboptions for a particular management alternative, M_a, as given in

$$M_{a,m\_\min} \leq M_{a,m} < M_{a,m\_\max}, \quad m = 1 \text{ to } n \tag{3}$$

$$M_{a,d\_\min} \leq M_{a,d} < M_{a,d\_\max}, \quad d = 1 \text{ to } p \tag{4}$$

where the magnitude suboptions for wetlands, floodplains, and river reaches are $M_{a,m}$, which are constrained by minimum and maximum values of $M_{a,m\_\min}$ and $M_{a,m\_\max}$,

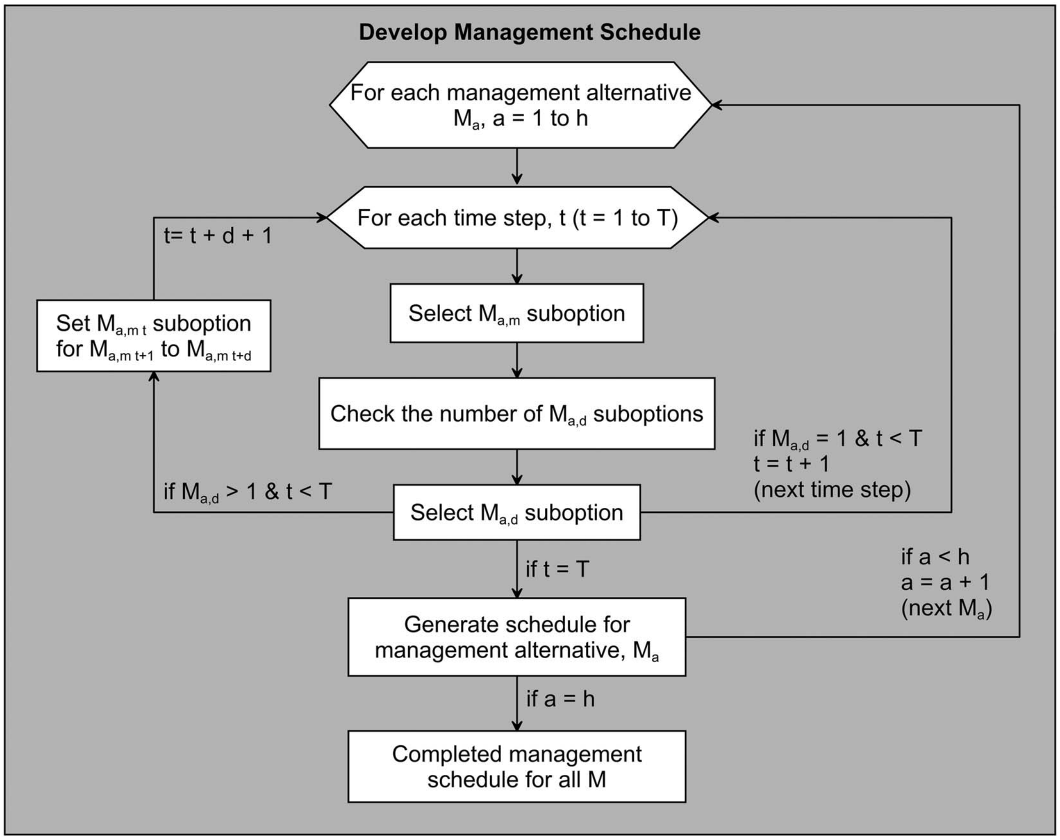

Figure 3. Environmental flow management schedule development, where the number of management alternative, M_a, ranges from 1 to h. The time step, t, ranges from 1 to T months, while $M_{a,m}$ and $M_{a,d}$ are the magnitude and duration suboptions for each M_a and d corresponds to the duration of $M_{a,d}$.

respectively, and the duration suboptions are $M_{a,d}$, which are constrained by minimum and maximum values of $M_{a,d\_\min}$ and $M_{a,d\_\max}$, respectively, for each management alternative. The m possible magnitude suboptions, $M_{a,m}$, range from 1 to n and $M_{a,d}$ is the number of duration suboptions available, where d is between 1 and p. Each management alternative must therefore be assessed individually in order to determine appropriate values for the above constraints. These ranges may depend on the characteristics of the wetlands and floodplains, or the chosen ecological indicator.

[20] If a yearly time step is chosen, then an additional timing constraint is required to determine during which month a particular management alternative should be implemented. However, such a constraint is not required if a monthly time step is adopted. Other constraints that must be taken into account are mass balance constraints, for instance the overall water entering the system must equal the water leaving system (through either water allocated to the wetlands and floodplains or evaporation).

2.3. Environmental Flow Management Schedules Development

[21] Once the problem has been formulated, management schedules can be constructed by first selecting a management alternative, as shown in Figure 3. Next, a schedule needs to be constructed for all T time intervals. In order to do this, the magnitude suboptions for M_a should be selected, followed by an assessment of the number of available duration suboptions, $M_{a,d}$. The second step is necessary, as the number of duration suboptions can change during the generation of a schedule. For example, if a monthly time step were used, there would be a maximum of twelve duration options at the beginning of a year, which would reduce to six halfway through the year. Consequently, the conditional dependencies associated with the selection of $M_{a,d}$ need to be taken into account during the schedule generation process, as shown by the loops in Figure 3. Once all suboptions have been selected at each time step for a particular management alternative, this process has to be repeated for all of the remaining management alternatives until a complete EFMA schedule has been developed.

[22] This procedure demonstrates the sequential nature and dependencies of the optimal scheduling problem, where decision made at certain time steps affect the choices that are available at subsequent time steps. It is vital that such information be taken into account, as it can affect the quality of the management schedule developed, as well as the efficiency with which it is generated.

2.4. Calculation of Objective Function and Optimization

[23] Once an EFMA schedule has been developed, its utility needs to be assessed, which is done via the objective function (equation (1)). In order to calculate the objective function, a simulation model, such as a hydrological model of the river system, is generally used in order to determine the flow regime within each river reach, floodplain and wetland, as well as the resulting ecological indicator score.

Once the objective function has been calculated, its value is used during the optimization procedure in order to develop better solutions (i.e., schedules of EFMAs), as shown in Figure 1. The cycle of development, simulation and assessment of EFMA schedules using optimization continues, until the selected termination criteria are met. A discussion of the proposed optimization method for solving the optimal scheduling problem is presented in the next section.

3. Proposed Ant Colony Optimization for the Scheduling of Environmental Flow Management Alternatives

[24] There are a number of candidate optimization algorithms for solving the optimal scheduling problem formulated in section 2, including traditional forms of optimization, such as linear and dynamic programming [*Taha*, 1997] and metaheuristics, for instance, genetic algorithms (GA) [*Goldberg*, 1989] and ant colony optimization (ACO) algorithms [*Dorigo et al.*, 1996]. Linear programming only works for linear objective functions and constraints [*Taha*, 1997], resulting in the inability to solve complex nonlinear problem, such as the optimal scheduling problem presented here. Dynamic programming, on the other hand, overcomes this problem by using the principle of optimality to determine optimal solutions [*Taha*, 1997], while genetic and ACO algorithms achieve this by using the principle of survival of the fittest [*Goldberg*, 1989] and the foraging behavior of ants [*Dorigo et al.*, 1996], respectively. However, dynamic programming suffers from the 'curse of dimensionality', which means that it has difficultly solving problems with large search spaces, as the computational requirements grow exponentially with increased complexity [*Madej et al.*, 2006]. Both GAs and ACO algorithms overcome this problem to a large extent by searching for near-optimum solutions using the search principles mentioned above, thereby only exploring a small fraction of the search space. Consequently, they sacrifice "the guarantee of finding the optimal solution for obtaining good solutions in a significantly reduced time" [*Blum and Roli*, 2003]. Despite this shortcoming, in tests of problems with known theoretically optimal solutions, GAs and ACO algorithms have been found to produce globally optimal or near-optimal solutions for a range of applications [*Back et al.*, 1997; *Blum*, 2005].

[25] GAs are probably the most widely used heuristic optimization method. However, as they represent solutions as strings of genes, which are modified from one generation to the next as the algorithm attempts to find the globally optimal solution, it is difficult to account for the sequential nature and conditional dependencies of the optimal scheduling problem outlined in section 2.3. In other words, as values of all decision variables are generated simultaneously in a particular population, there is no mechanism for adjusting the value of one decision variable based on the selected value of another. This increases the size of the search space unnecessarily and introduces a larger proportion of infeasible solutions, making it more difficult to find globally optimal or near-optimal solutions. In contrast, ACO algorithms are able to account for the sequential nature and conditional dependencies of the optimal scheduling problem explicitly, as the solution space is represented by a graph structure that can be adjusted dynamically based on the choices made at previous points in the decision graph during the constructions of solutions, thereby reducing the size of the decision space and increasing the proportion of feasible solutions [*Afshar*, 2010; *Foong et al.*, 2007, 2008; *Maier et al.*, 2003]. In other words, as solutions in ACO are constructed incrementally by stepping through a decision graph, rather than generating the entire solution simultaneously, as is the case with GAs, the options that are available at subsequent steps in the decision graph can be altered during the construction of a trial solution, based on the choices that were made at previous steps. This is because in ACO, solutions are generated based on changes in the decision space, rather than by modifying solutions themselves.

[26] ACO algorithms have been applied successfully to the traveling salesman problem [*Dorigo and Gambardella*, 1997b] and found to outperform other optimization algorithms, such as genetic algorithms, in terms of computational efficiency and solution quality [*Dorigo and Gambardella*, 1997a]. Other successful ACO applications include the quadratic assignment problem [*Mainiezzo and Colorni*, 1999], shop scheduling problems [*Blum and Sampels*, 2004], water distribution systems optimization problems [*Maier et al.*, 2003; *Zecchin et al.*, 2007], reservoir operation problems [*Jalali et al.*, 2007] and power plant maintenance scheduling problems [*Foong et al.*, 2007]. The sections 3.1–3.3 discuss the problem representation and steps in the ACO algorithm, as well as the implementation of dynamic constraints to account for the conditional dependencies of the EFMA scheduling problem discussed previously.

3.1. Problem Representation

[27] Before ACO can be used to develop an optimal or near-optimal schedule as per section 2.3, each management alternative must be first mapped onto a graph, which consists of a number of discrete time steps and a set of suboptions at each of these. An example EFMA schedule graph for flow releases is shown in Figure 4. As can be seen, there are two suboptions that are considered at each time step, magnitude and duration. The magnitude suboption for this case ranges from a minimum allocation of zero to a maximum allocation of 1000 gigaliters (GL), which is independent of time, and as such remains in a closed loop. However, the next suboption, duration, branches into 12 paths after each magnitude suboption, one for each month, thereby generating multiple possible solutions. The number of possible solutions begins to expand until the final time step, T, is reached. Other suboptions, such as timing, can be also be accounted for in the graph structure. Once the graph has been defined, it can be used to develop a trial schedule using the ACO algorithm, which will be discussed in the following section.

3.2. Ant Colony Optimization Algorithm

[28] The steps involved in the ACO algorithm are given in Figure 5. The process of generating a trial EFMA schedule begins with the initialization of the ACO control parameters. Next, the optimization process takes place, where b ants construct trial schedules during each iteration (*its*). An ant achieves this by traveling to each time step and selecting magnitude and duration suboptions (Figure 4), until it reaches the final time step, T. At each time step, the suboptions are selected probabilistically based on a pheromone intensity (τ) and heuristic information (η), as well as decision policy control parameters, α and β, that determine the

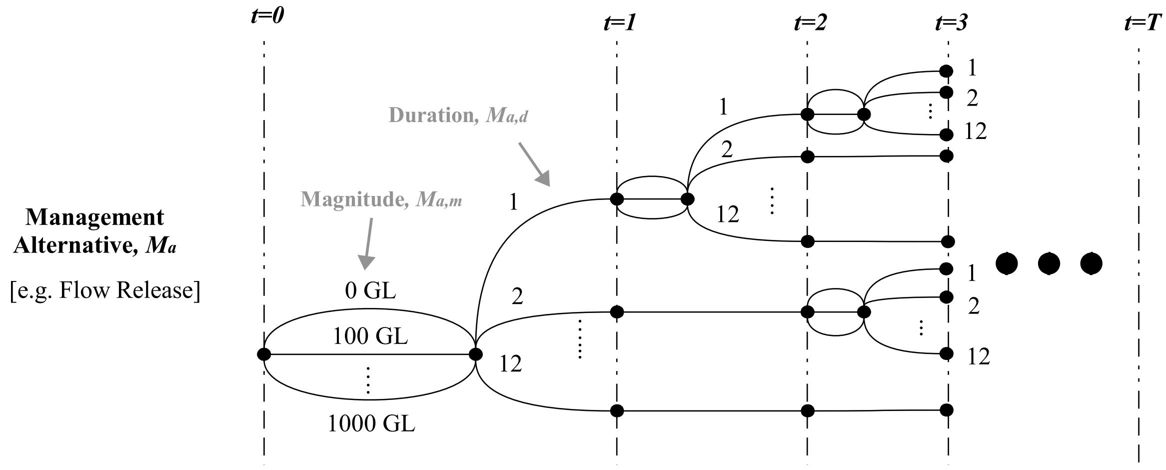

Figure 4. Example of an EFMA schedule graph for flow releases (in gigaliters (GL)).

relative importance of pheromone intensity and heuristic information, respectively [*Zecchin et al.*, 2005]. The pheromone intensity for a suboption is first initialized to a random value while for subsequent iterations, pheromone is added based on the initial pheromone (τ_o), a pheromone persistence factor (ρ) and a reward factor (Q) that is used to scale the pheromone addition [*Zecchin et al.*, 2005]. The heuristic value of a suboption, on the other hand, represents the quality of that suboption based on prior information.

[29] Once a complete trial schedule has been generated by an ant, the plan is evaluated using an objective function (see equation (1)). As discussed in section 2, a simulation model, such as a hydrological model for the river system under investigation, is used in the calculation of the objective function and any constraint violations (e.g., equation (2)). An iteration is completed once b ants have developed and evaluated a trial schedule.

[30] At the end of each iteration, the quality of the EFMA schedules generated by the ants is evaluated and pheromone values are modified accordingly (i.e., the better the solution, the higher the pheromone that is added to the "paths" that made up that solution). The pheromone intensity for a suboption thus reflects the quality of trial schedules developed in previous iterations that contained that particular suboption, which creates bias for ants in future iterations to develop solutions of high quality. Additionally, pheromone evaporation is applied to components of schedules that do not perform well, which in turn deters the ACO algorithm from choosing those paths again. In this manner, the environment is modified to guide the artificial ants to regions of the search space that contain attractive solutions. For an ACO algorithm to be effective in generating optimal or near-optimal solutions, it is important that the correct balance of exploration (i.e., exploring the search space widely) and exploitation (i.e., converging to an optimal solution as quickly as possible) is struck. A number of ACO variants that use different pheromone updating schemes have been developed to achieve this. Some of these include: Ant Systems [*Dorigo et al.*, 1996], Ranked-Based Ant System [*Bullnheimer et al.*, 1999] and MAX-MIN Ant Systems [*Stützle and Hoos*, 2000].

[31] The process of developing, assessing and updating the pheromone trails to guide the ACO algorithm to near-optimal schedules continues until the specified stopping criteria have been met. For a detailed description of the ACO algorithm and equations used, readers are referred to *Dorigo and Stützle* [2004].

3.3. Dynamic Constraint Adjustment

[32] As discussed above, ACO algorithms have the ability to cater to the sequential nature and conditional dependencies involved in the development of EFMA schedules (see section 2.3). This is achieved by dynamically adjusting the number of available suboptions as ants construct a trial schedule. An example decision tree graph that incorporates dynamic constraints for a flow release management alternative is shown in Figure 6. The example is for four time steps and considers magnitude and four duration suboptions.

[33] If the maximum duration, which is assumed to be greater than four time steps for the example in Figure 6, is

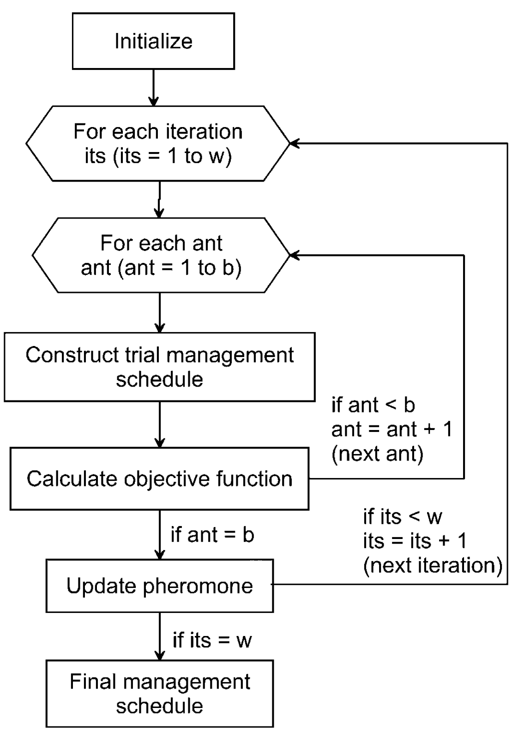

Figure 5. Steps in ant colony optimization algorithm.

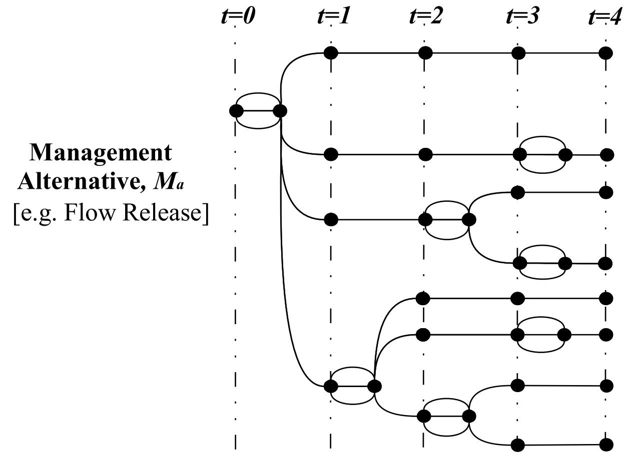

Figure 6. Example of an environmental flow management schedule decision tree graph using dynamic constraints.

selected by an ant at the first time step (decision point), then no other decision paths need to be made available at subsequent time steps (decision points), as shown by the top path in Figure 6. In this way, the decision tree is adjusted based on the choice made at the first decision point, thereby reducing the size of the search space and increasing the likelihood that globally or near globally optimal solutions will be found. On the other hand, if a duration option of one is chosen by an ant at the first time step (bottom path), then the potential duration suboptions are considered again at the following time step. However, the number of available options decreases from four to three, as there are only three more time steps remaining. If the number of available duration suboptions was not adjusted dynamically, four duration options would be considered after each magnitude suboption, which would result in a significantly larger search space. Therefore, this form of dynamically constraining the decision tree graph ensures that feasible EFMA schedules are developed, as well as ensuring that the ACO algorithm is able to find optimal solutions more efficiently.

4. Case Study

[34] In order to test and demonstrate the utility of the proposed optimization framework, it has been applied to a quasi-hypothetical case study based on the Murray-Darling river system in South Eastern Australia. The majority of this river system experiences arid or semiarid climate and incorporates a large array of connected wetlands and floodplains, which are mainly flooded during high streamflows [*Maheshwari et al.*, 1995]. However, due to the regulation of flow and over allocation of water to other users (e.g., irrigation), the flow regime has been changed, which has had significant negative impacts on the ecology of the river and adjacent wetlands and floodplains. In recent years, it has been recognized that the environment is a legitimate user of water and water allocations have been made available for environmental purposes. However, how this environmental flow allocation should be used in order to achieve the best ecological response remains a challenge.

[35] Figure 7 shows the layout of the case study used to meet the objectives outlined in the Introduction. It consists of a river reach, three wetlands and two floodplains that contain a variety of different flora and fauna species found in the River Murray. To quantify the ecological response of the species within the river reach, wetlands and floodplains, the Murray Flow Assessment Tool (MFAT) was used [*Young et al.*, 2003]. The minimum monthly river flows were based on entitlement flows used in the River Murray [*Murray-Darling Basin Authority*, 2010] and it was assumed that there were only gates (no pumps) to regulate flows into and out of the wetlands. Reservoir releases were taken as given and not considered part of the decision set. Details of how the proposed framework and solution approach, introduced in sections 2 and 3, respectively, have been applied to the case study are given in sections 4.1–4.4.

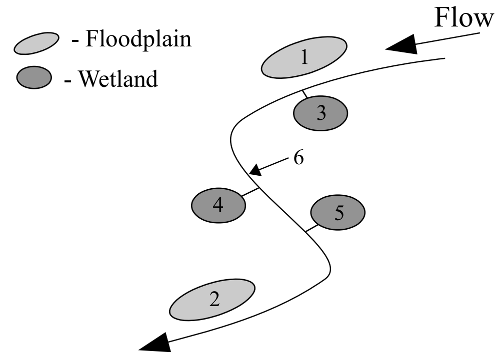

Figure 7. Layout of case study.

4.1. Problem Formulation

4.1.1. Identification of Ecological Assets and Indicators

[36] In this case study, there are two floodplains and three wetlands (Figure 7). The key flora and fauna species for each asset are given in Table 1, which were selected to represent the diversity and complexity that would occur in the River

Table 1. Wetland and Floodplain Specifications

Asset	Type	Dominant Species	Fill Value (GL/month)
1	Floodplain	Black box woodland (*Eucalyptus largiflorens*)	1200
2	Floodplain	River red gum forest (*Eucalyptus camaldulensis*)	800
		Lignum shrubland (*Muehlenbeckia florulenta*)	800
		Colonial nesting waterbird (e.g., ibis)	800
		Flood spawners (e.g., golden perch)	800
3	Wetland	Common reed (*Phragmites australis*)	300
		Cumbungi rushland (*Typha* sp.)	400
		Lignum shrubland (*Muehlenbeckia florulenta*)	500
		Waterfowl and grebes	500
4	Wetland	Ribbon weed herbland (*Vallisneria americana*)	400
		Giant rush rushland (*Juncus ingens*)	450
		Rats tail couch grassland (*Sporobolus mittchelli*)	500
5	Wetland	Spiny mudgrass grassland (*Pseudoraphis spinescens*)	300
		River red gum forest (*Eucalyptus camaldulensis*)	400
		River red gum woodland (*Eucalyptus camaldulensis*)	550
6	River	Main channel specialists (e.g., Murray cod)	450

Murray, Australia, as presented by *Rogers* [2011a]. The wetland and floodplain fill values, which relate to the minimum river flow required to inundate the assets, are also presented in Table 1. To delineate the flora and fauna species within each wetland and floodplain, a number of assumptions were made (R. Oliver, personal communication, 2009). First, it was assumed that the floodplain species lie on the same elevation plane, therefore once the river flow was above the fill value, all species were inundated at a specific depth, depending on the water level in the river. Second, wetland species were assumed to lie along a nonlinear gradient, resulting in a wetland depth range at which the species would be inundated, for instance, Cumbungi rushland would lie lower on the wetland gradient than Lignum shurbland. Therefore, if the wetland water depth (which is dependent on the river flow and regulator settings) was above the minimum species depth, then that species would be inundated.

[37] In order to obtain the required ecological flow requirements for the species of flora and fauna considered, the Murray Flow Assessment Tool (MFAT), developed by *Young et al.* [2003], was used. MFAT is a habitat simulation model that was developed specifically for the River Murray and can be used to assess the impact of different flow scenarios on vegetation and wildlife [*Young et al.*, 2003]. This is done using a set of response curves, which are based on important flow components, such as duration, timing and magnitude (which is represented in terms of depth), as well as the interdry period.

[38] The MFAT response curves for ten different species of vegetation used in this study are shown in Figure 8 for illustration purposes. As can be seen, a score between 0 and 1 is given for each flow component, where 0 corresponds to a poor and 1 to a good ecological response. It should be noted that the curves take into account different flow requirements for recruitment (i.e., promotion of seed growth) and maintenance (i.e., maintenance of adult habitat). As can be seen in Figure 8, there are curves for twelve different flow components, which can be divided into timing, frequency, duration and various inundation depth groups. It should be noted that there is an additional water depth response curve (in terms of maximum mean depth percent) for the wetland vegetation species ribbon weed herbland, which has not been presented here, as well as the flooding memory response curves for the various floodplain species. Other flow factors, such as the rate of rise and fall, have also not been presented in Figure 8. In total, there are approximately 48 curves for the vegetation species that, at times, have competing requirements, which highlights the complexity of the EFMA scheduling problem and the difficulties in developing optimal management schedules.

[39] The top four response curve graphs in Figure 8 are associated with wetlands, while the bottom six are for floodplains species. To determine the response from the wetland inundation and the floodplain flood timing and inundation depth curves, the median value of the 'best flood event' was used, where the 'best flood event' was the event that produces the highest overall ecological scores. For example, if the spiny mudgrass grassland was inundated from the beginning of March until the end of May, it would receive a wetland inundation score of 0.1, as this was the median value for that event. This region is depicted by the two bold lines in Figure 8a, where from March to May, the curve remains at a constant score of 0.1. On the other hand, inundation duration, recruitment and germination timing, and interperiod scores are based on a single value for the "best flood event." Therefore, the inundation duration for spiny mudgrass grassland is approximately 90 days, giving a score 0.5. This is represented by the bold line in Figure 8c. Additionally, it was assumed that a draw down and rewetting sequence must occur within a year, so that the interperiod could be calculated. Once all the scores have been obtained from Figure 8, they are used in equations to calculate an overall ecological response for each vegetation species in the MFAT [*Young et al.*, 2003]. It should be noted that there are weights x_1 and x_2 that emphasize, for example, the recruitment of vegetation seedlings and maintenance of adult plant species, respectively.

[40] There are an additional 12 response curves, not depicted in this paper, for assessing the health of the fauna species (i.e., fish and water birds). For waterbird responses, only the flood duration and dry period were taken into account, while for fish responses, the flood and spawning timing, inundation duration and dry period were considered. Other factors, such as thermal pollution (1.0), woody debris (1.0), the level of fish barrier (1.0), and channel straightening (0.78) were set to MFAT default values. For further details on the fauna and flora response curves and the equations used, readers are referred to *Young et al.* [2003] and the Inside MFAT Web site (http://www2.mdbc.gov.au/livingmurray/mfat/index.htm).

4.1.2. Planning Horizon and Time Interval

[41] A planning horizon of 5 years was chosen, as this (1) is the time period selected for the development of wetland management plans in the River Murray [*Schultz*, 2007; *Turner*, 2007], and (2) ensures that there is sufficient time to achieve the maximum ideal flooding frequency for the species of flora and fauna considered (see Figure 8g). A monthly time interval was selected, as this provides sufficient resolution for the hypothetical case study. This meant that the "rate of change" flow component in MFAT for flora and fauna species was not considered. Therefore, there are 60 time steps where an option has to be selected for each management alternative. This is discussed in section 5.

4.1.3. Management Alternatives and Suboptions

[42] There was one reach-scale management alternative (i.e., releases) for this case study and the associated suboptions include the magnitude and duration of the releases. An example of the resulting problem graph structure is shown in Figure 6. The number of magnitude options depends on the minimum and maximum fill values of the whole system. In this case, this could be anywhere between 100 GL/month, which was the minimum flow that needed to be added to the minimum river flows in order to inundate the wetland with the lowest fill value, and 1500 GL/month, which ensures that all of the wetlands and floodplains can be inundated simultaneously. An increment of 50 GL/month between these limits was chosen for the available suboptions to provide sufficient resolution to ensure that the ideal depth could be achieved for the different flora and fauna species considered. An additional zero allocation was defined to ensure that a "no release option" was available. Consequently, a maximum of 29 magnitude decision values are available (i.e., $n = 29$ for management alternative M_1). The number of duration options, p, available at each time step (i.e., month) varies throughout the year from 12 in January to 1 in December. The wetlands also have gates that can regulate

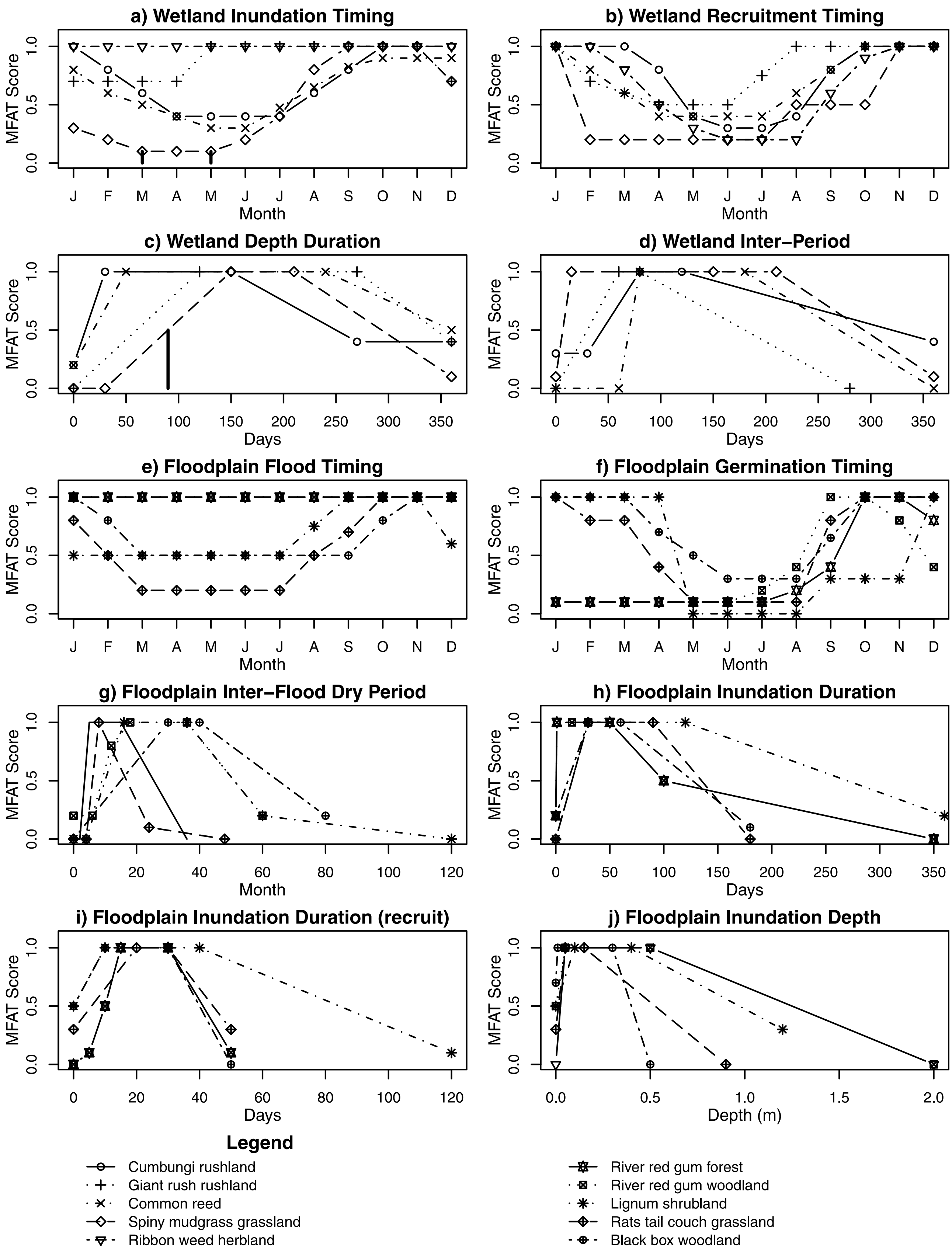

Figure 8. MFAT response curves adapted from *Young et al.* [2003] and the Inside MFAT website (http://www2.mdbc.gov.au/livingmurray/mfat/index.htm).

flow into the wetlands, while floodplains do not. This leads to three additional management alternatives, which control the flow into and out of the wetlands via gates (thus for M_2, M_3, and M_4, $n = 2$ and $p = 12$). Therefore, there are a total of four decision tree graphs similar to the one in Figure 6 that control the flow releases and flow via gates to the three wetlands. This produces a total search space size of 10^{141} discrete combinations of decision variable values, highlighting the potential benefit of using a formal optimization approach to solve this problem.

4.2. Objective Function and Constraints

[43] The ecological score for each species per asset was calculated using MFAT, which was described in section 4.1.1. The equation used to calculate an average MFAT score was based on the formulation presented in equation (1):

$$F = \sum_{i=1}^{6} \frac{w_{1i}}{6} \sum_{r=1}^{16} \frac{w_{2r}}{16} \sum_{v=1}^{5} \frac{w_{3v} E_{i,r,v}}{Y_5} \tag{5}$$

where the number of assets is 6, the number of ecological indicators is 16 for each flora and fauna species (see Table 1), and finally, the score, $E_{i,r,v}$ for each asset and indicator is calculated per year, with the total number of years equaling 5. To obtain an average score and an indication of the overall health of all the species and assets, $E_{i,r,v}$ was divided by the total number of assets and indicators. The weights (w_{1i}, w_{2r}, w_{3v}) were varied for the different investigations conducted in order to examine various trade-offs between competing objectives (see section 5 for details). In order to maximize F in equation (5), an objective function most appropriate for this case study needs to be selected, bearing in mind that the ACO algorithm minimizes the selected objective function and cannot accommodate constraints on environmental flow allocations explicitly. A number of different objective function formulations were assessed and the following form of the objective function (Y) was found to perform best and was hence used in this study:

$$Y = \frac{10}{10 + F} + Penalty \tag{6}$$

where F is the MFAT ecological score calculated using equation (5), and *Penalty* is a penalty function that was developed to ensure that the water allocation constraints for each period were adhered to and is given by

$$Penalty = \begin{cases} 0 & \text{if } \sum_{t=i\_ni(pd)}^{f\_ni(pd)} A_t \le A_{\max\_ni(pd)} \\ \left\{ \sum_{t=i\_ni(pd)}^{f\_ni(pd)} (A_t) - A_{\max\_ni(pd)} \right\} \times 100,000 & \text{if } \sum_{t=i\_ni(pd)}^{f\_ni(pd)} A_t > A_{\max\_ni(pd)} \\ 100,000 & \text{if } F = 0.0 \end{cases} \tag{7}$$

where the variables in equation (7) have been defined in equations (1) and (2).

4.3. Calculation of Objective Function

[44] In order to calculate the objective function specified in section 4.2, the wetland and floodplain hydrology must be simulated for each management schedule. The following sections discuss the equations and assumptions used to achieve this.

4.3.1. Wetland Hydrology Model

[45] To ensure that the model adequately accounts for wetland hydrology, whereby wetlands fill quickly once the river level breaches the fill value and when gates are opened but then drain slowly either when the gates are closed or when the river level drops below the fill value, equations (8) and (9) have been utilized. A simple water balance relationship is

$$I_t - O_t = S_{t+1} - S_t \tag{8}$$

where I_t refers to the wetland inflows, O_t are the wetland outflows, while S are the wetland storages at time t. The outflows O_t are the summation of the flows out of the wetland (O_w) and evaporation (E_t). To calculate the evaporation loss from the wetlands, it was assumed that the wetland is rectangular with the longer sides parallel to the river, and that the bank slope remained constant. Consequently, the surface area versus depth relationship is linear. A simple relationship of $0.7 \times$ (pan evaporation) was used to determine the evaporation from the wetland, in meters/month. The value of 0.7 was chosen as it is a common value used to determine evaporation within the Murray Darling Basin [*Gippel*, 2006].

[46] To simulate the gate operations at the wetlands, logic (If-Then) statements were used to adjust the components of the water balance equations. If the gate was closed, the inflow at that time step was zero (i.e., $I_t = 0.0$) and if there was water in the wetland, wetland storage was only affected by evaporation:

$$S_{t+1} = S_t - E_t \tag{9}$$

If there was water remaining in the wetland and the gate was opened at the next time step, water would flow out until the fill value was reached, after which water would remain in the wetland and only be affected by evaporation (i.e., equation (9)). It should be noted that the mass balance constraints associated with the problem were also satisfied within this wetland hydrology model.

[47] Assumptions made include that water seepage, the effect of rainfall and the fill and drainage rate of the wetlands were negligible. This was considered reasonable, since a monthly time step was used. Additionally the storage capacity of the wetlands was set to be very small in comparison to the streamflows, thus having negligible effect on downstream flows as a result of upstream wetlands storage.

4.3.2. Floodplain Hydrology Model

[48] The floodplain hydrology model used the same equations and assumptions as the wetland model, with the

Table 2. MAX-MIN Ant Systems Parameters

ACO Parameter	Range Investigated	Final Value
Alpha (α)	0.5,1.0,1.5.2.0	1.0
Beta (β)	0.5,1.0,1.5.2.0	1.0
Initial pheromone (τ_o)	0.5, 1.0, 2.0, 5.0, 10.0	5.0
Pheromone persistence (ρ)	0.1,0.2,0.6,0.8,0.9,1.0	0.6
Pheromone reward factor (Q)	0.5, 1.0, 2.0, 5.0, 10.0	5.0
Number of ants (ant)	50–1500	500 and 1200

exceptions of (1) being only affected by the river level (i.e., if the river level is above the fill value then the floodplain would be inundated at a depth dependent on the river level or if the river level is below the fill value then the floodplain would not be inundated) and (2) not including gates to regulate the flow, and as such the gate operational equations were not used.

4.4. ACO Algorithm

[49] As discussed in section 3.2, there are various types of ACO algorithm, which generally differ in the pheromone updating methods used [*Dorigo and Blum*, 2005]. In this study, the MMAS algorithm was used, as it has been found to outperform other ACO variants in a variety of studies [*Foong et al.*, 2007; *Zecchin et al.*, 2007]. Details relating to the procedure and equations used by the MMAS are given by *Stützle and Hoos* [2000].

[50] An extensive sensitivity analysis was undertaken to determine the optimal values of the parameters that control the searching behavior of the MMAS algorithm. The range of parameter values tried and the final parameter values chosen are shown in Table 2. It should be noted that each sensitivity run was performed with 10 different random numbers (i.e., starting positions in the decision space) to minimize the impact of the random starting position in decision variable space on the results obtained.

5. Analyses Conducted

[51] In order to meet the objectives stated in the Introduction, a number of studies were conducted, which demonstrate how the proposed framework and optimization approach are applied in practice in different settings (objective iiia). In the first study (section 5.1), the proposed optimization approach was compared with and tested against a heuristic scheduling approach by analyzing whether it performed adequately on problems of varying complexity (objective iiib). In the second and third studies (sections 5.2 and 5.3, respectively), it is demonstrated that the proposed approach can account for the competing requirements of individual species (objective iiic) and the competing requirements of species of flora and fauna (objective iiid) (section 5.3), respectively. In the final study (section 5.4), it is illustrated that the proposed framework and solution approach can deal with environmental water allocations of

Table 3. Details of Each Study and Corresponding Objective

Study	Objective	Investigations	Species	Planning Horizon
Section 5.1	iiib	1–6	Flora	5 years
Section 5.2	iiic	7–9	Flora	5 years
Section 5.3	iiid	10–11	Flora and fauna	5 years
Section 5.4	iiie	12–13	Flora and fauna	5 years

Table 4. Details of the Investigations Used in Each Study

Investigation	Allocation Constraint Period/s	Allocation Constraint/s (GL)	Weight preferences
1	5 years	5000	Equal preference
2	5 years	1750	Equal preference
3	5 years	3500	Equal preference
4	5 years	4750	Equal preference
5	5 years	10,000	Equal preference
6	5 years	10,000	Equal preference
7	5 years	500–12,000	Recruitment favored
8	5 years		Processes equally favored
9	5 years		Maintenance favored
10	5 years	10,000	Flora favored
11	5 years		Fauna favored
12	5 years and 3 months	10,000 and Table 6	Equal preference
13	5 years	10,000	Equal preference

varying magnitude and timing (objective iiie). Details of the various studies and the specific investigations conducted as part of each these are given in Tables 3 and 4, and described in detail below.

5.1. Validation of Optimization Framework

[52] In order to provide some degree of validation, and to assess the potential benefits, of the proposed optimization framework, it was compared with a heuristic EFMA scheduling approach for six investigations of varying complexity. It was recognized that the proposed ACO-based optimization approach should outperform a heuristic scheduling approach due its greater degree of sophistication. However, simply because an algorithm is highly advanced does not guarantee that it will perform well and it was therefore considered important to evaluate it against a benchmark approach that is representative of current practice in the River Murray before it was applied to more complex problems (sections 5.2 to 5.4). In addition, it highlights the complexity of the problem being addressed and the benefits of the approach introduced in this paper.

[53] The six investigations considered in this study only considered flora (Table 3), as this provided a sufficient level of complexity (i.e., 48 different MFAT response curves) to validate the optimization framework. The allocation constraint period was set to 5 years (Table 4), indicating that there were no constraints on the time periods during which the water available for environmental purposes was used over the planning horizon of 5 years (Table 3), as long as the total environmental water allocation was not exceeded. The total amount of water available for environmental flow purposes varied between investigations (Table 4) based on the outcomes of the heuristic scheduling procedure, as explained below, and equal preference was given to all components of the overall ecological score in equation (5) (i.e., species, assets and time period) (Table 4), such that w_{1i} = 0.2, w_{2r} = 0.08 and w_{3v} = 0.2 for i, r and v. Additionally, the recruitment and maintenance MFAT weights, x_1, and x_2, were both set to equal 0.5. The degree of complexity of the investigations was variable, both in terms of the number of species and the spatial extent considered (Table 5).

[54] Details of the heuristic approach are given in Figure 9. The first step is the identification of species groups with similar MFAT flow requirements for each management

Table 5. Details of the Six Investigations Used for Developing Heuristic and Optimization Based Management Schedules

Investigation	Total Number of Flora Species	Plant Species
1	1	River red gum forest in Asset 5
2	1	Rats tail couch grassland in Asset 4
3	1	Spiny mudgrass grassland in Asset 5
4	3	All flora species in Asset 3[a]
5	7	All flora species in Assets 1,3 and 5[a]
6	12	All flora species in Assets 1 to 5[a]

[a]Please see Table 1 for details.

alternative (M_a). These species groups are defined as $G_{a,c}$, where c ranges from 1 to nc number of species and a ranges from 1 to h (i.e., number of M_a). The groups are ordered so that the first group, $G_{1,1}$, has the largest number of species with similar MFAT requirements that is affected by M_1, $G_{1,2}$ the second largest number of species, and so on.

[55] For each management alternative, M_a, duration, timing and magnitude values are selected based on the MFAT flow requirements of the species in the largest group. $G_{a,c}$. The selection of these values may be repeated several times to ensure that the highest possible MFAT score is achieved for all species. Next, the selection process is repeated for the remaining $G_{a,c}$ species that are affected by the M_a under consideration, starting with the group with the second largest number of species. A check is then undertaken to ensure that the M_a values chosen (i.e., duration, timing and magnitude) for a particular $G_{a,c}$ do not negatively impact the MFAT scores of the species groups considered previously. This cycle continues until a complete schedule has been produced for management action M_a, after which the process is repeated for the next M_a until schedules have been developed for all M.

[56] It should be noted that this scheduling approach does not take into account any constraints on the amount of water that is available for environmental flow allocation purposes. Addressing the constrained scheduling problem would add another level of complexity, which was not considered warranted for the purposes of illustrating the complexity of this problem and validating the proposed optimization approach. Consequently, in order to provide a fair comparison between the heuristic and ACO-based approaches, the constraints in relation to the total water allocation used when developing the ACO-based schedules corresponded to the volumes found in the corresponding management schedules obtained using the heuristic approach. Additionally, for each investigation, all ACO optimization runs were repeated ten times with different random starting positions in decision variable space in order to minimize any effects of the probabilistic nature of the searching behavior of the ACO algorithm.

5.2. Determination of Optimal Trade-Offs Between Recruitment and Maintenance Scores for Different Flow Allocations

[57] As discussed in section 4.1.2, MFAT considers both recruitment (i.e., promoting and ensuring seedling growth) and maintenance (i.e., maintaining and ensuring the good

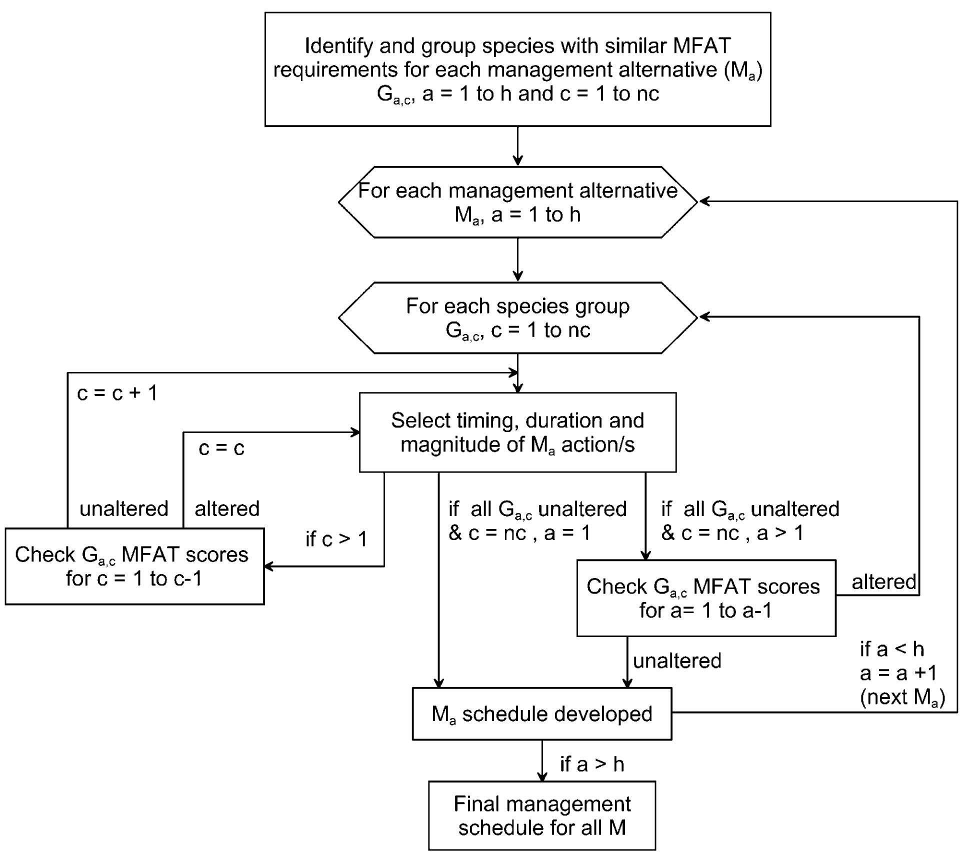

Figure 9. Environmental flow management schedule development using the heuristic approach.

Table 6. Seasonal Environmental Flow Allocation Used in Investigation 12

Season	Environmental Flow Allocation (GL)
Summer (Dec–Feb)	1500
Autumn (Mar–May)	1000
Winter (Aug–Jul)	500
Spring (Sep–Nov)	200

condition of current adult habitat) of flora species. These factors have differing and, at times, competing flow requirements and, as such, must be considered separately. In order to investigate the trade-offs between recruitment and maintenance, optimal management schedules for maintenance and recruitment of the flora species over a 5 year management period were generated (Investigations 7 to 9, Table 3). Further details of each investigation are presented in Table 4, with schedules that favor recruitment considered in Investigation 7, schedules that emphasize recruitment and maintenances equally in Investigation 8, and schedules that favor maintenance in Investigation 9. This was achieved by specifying additional weights as part of the calculation of MFAT scores that either emphasize recruitment (x_1, = 1.0 and x_2 = 0.0), maintenance (x_1, = 0.0 and x_2 = 1.0), or both (x_1, = 0.5 and x_2 = 0.5). The weights that control asset, flora type and release year (i.e., w_{1i}, w_{2r}, w_{3v}), were set to have equal preference, using the same values as in section 5.1. The planning horizon for this study was five years and seven different environmental water allocation constraints (i.e., different amounts of water available for environmental flow purposes), ranging from 500 to 12,000 GL (i.e., 500, 2000, 4000, 6000, 8000, 10,000 and 12,000 GL) were examined (Table 4), in order to investigate the impact of a number of different water policies (i.e., different amounts of water set aside for environmental flow purposes, as opposed to consumptive uses (e.g., irrigation, water supply)) on ecological response and the trade-off between maintenance and recruitment. Each optimization run for the 21 schedules developed was repeated ten times with different starting positions in the solution space in order to minimize the impact of the random starting position on the results obtained.

5.3. Determination of Optimal Trade-Off Between Flora and Fauna Ecological Response

[58] In order to investigate the trade-offs between the requirements of flora and fauna, the flow requirements of four fish and waterbird species (see section 4.1.1) were added to those of the flora species used in Investigation 6 of section 5.1 (Table 5), and optimal EFMA schedules generated using the proposed ACO-based approach. Details of this study are given in Tables 3 and 4, where a single environmental water allocation constraint of 10,000 GL was used over the adopted planning horizon of 5 years and different weightings were used to either favor fauna (Investigation 10) or flora (Investigation 11). The fauna species weights in Investigation 10 equaled 0.25 and the flora weights equaled 0.0, while in Investigation 11, the flora species weights equaled 0.08 and the fauna weights were set to 0.0. The other weights (i.e., w_{1i}, w_{3v}, x_1 and x_2) were set to provide equal preference. As was the case in section 5.1, each optimization run was repeated ten times from different starting positions in the solution space.

5.4. Determination of Optimal EFMA Schedules as a Result of Hydrograph Inversion

[59] Many regulated river systems, such as the Murray River, have reversed flow regimes with major flows now occurring in summer–autumn (i.e., December to May) to sustain human needs, instead of winter–spring (i.e., June to November). In order to assess the impact of the hydrograph inversion case, two investigations were developed, including Investigation 12, which considered an additional seasonal flow constraint, and Investigation 13, which had no such constraint. Details of these investigations are given in Tables 3 and 4. As can be seen, both flora and fauna species and a 5 year management period were considered, as well as a 10,000 GL total water allocation constraint. Additionally, equal weight values were used for all the weight groups, as was the case in the previous study (section 5.1). Table 6 presents the environmental flow allocations that were available in each season. As with the previous studies, each optimization run was repeated 10 times.

6. Results and Discussion

6.1. Validation of Optimization Framework

[60] The MFAT scores obtained using the ACO and heuristic approaches are given in Table 7. As can be seen, the ecological scores obtained using both approaches were the same for the first three investigations. This indicates that there do not appear to be any problems with the formulation and implementation of the proposed optimization framework. Additionally, the ACO-based approach was able to determine management schedules that use less water, with the exception of Investigation 2, which had identical allocations and scores. Once the number of species was increased to three in Investigation 4, the benefit of using the optimization framework was demonstrated clearly. The MFAT score of the management schedule obtained using the ACO approach was higher than that of the management schedule developed using the heuristic approach, with a significantly smaller amount of water (i.e., 600 GL less). This demonstrates the ability of the optimization approach to search effectively through the large number of potential management schedules using the ACO process described in section 3.2. This results in management schedules that use the available environmental water allocation in an efficient manner, as expected, which would be especially beneficial during times when water resources are limited and must be allocated effectively between competing stakeholders.

[61] The results for Investigations 5 and 6 (Table 7), which were significantly more complex since they considered a

Table 7. Heuristic and ACO Management Schedule Results for Investigation 1 to 6

	Heuristic		ACO	
Investigations	Allocation (GL)	MFAT Score	Allocation (GL)	MFAT Score
1	5000	1.00	4650	1.00
2	1750	0.91	1750	0.91
3	3500	1.00	3100	1.00
4	4750	0.86	4150	0.91
5	10,000	0.67	10,000	0.78
6	10,000	0.67	9850	0.83

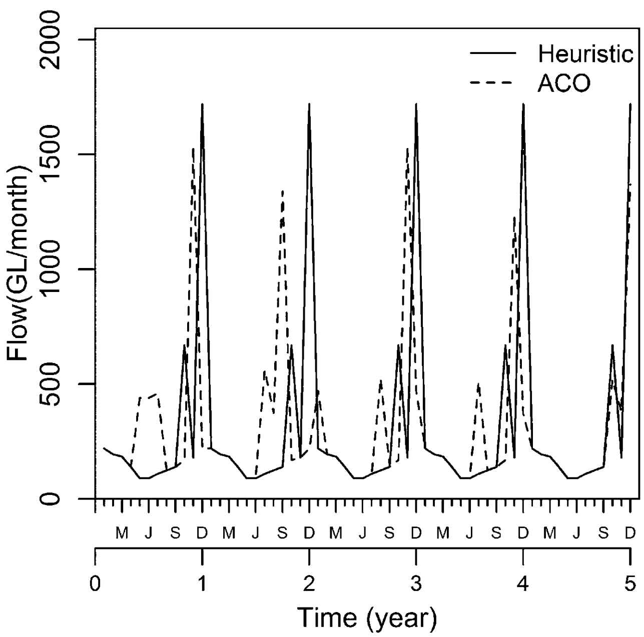

Figure 10. Monthly flow releases for heuristic and ACO management schedule for Investigation 6.

larger number of plant species (7 and 12, respectively), provided further evidence of the benefit of the proposed optimization approach. For instance, in Investigation 6, the management schedules developed using the ACO-based method resulted in an increase in MFAT scores of approximately 0.2 for all wetlands and floodplains, despite using less water. The corresponding flow releases obtained using the heuristic and ACO-based approaches are shown in Figure 10. It can be seen that there was more variability in the flows in the ACO-based management schedule, which ensured that all of the flow components in Figure 8 were accounted for. Generally, the larger flow releases obtained using both approaches occurred at similar times, except for year 2, where the flow releases obtained using the ACO-based approach occurred midyear instead of at the end of the year. These differences in flow releases contributed to a better MFAT score. In particular, there was significant improvement of approximately 0.4 in the MFAT score for assets 4 and 5, as shown in Table 8.

[62] It was found that this increase in MFAT score was because some species, such as giant rush rushland and spiny mudgrass grassland, were inundated for longer than one month. Ideally, giant rush rushland requires inundation for 120–270 days, while spiny mudgrass grassland requires 150–210 days of inundation. This was clearly not achieved by the management schedule developed using the heuristic approach, resulting in a much lower overall MFAT score, as the inundation requirement for maintenance was not satisfied. Another requirement that was difficult to meet in the development of the management schedule using the heuristic approach was the ideal depth for some of the floodplain species (e.g., river red gum forest, rats tail couch grassland), which corresponds to a certain depth that must be maintained to ensure the recruitment of these species. In contrast, this requirement was able to be satisfied by the management schedule developed using the ACO approach, thereby ensuring that a good recruitment score could be achieved. Overall, this study showed that once the number of wetlands and floodplains is moderately large, developing a management schedule heuristically over multiple years is extremely difficult. This is because there are too many wetlands and floodplains with different and competing water demands that must be considered. However, the optimization method can deal with these complexities with the aid of the searching process outlined in section 3.

Table 8. Difference in Annual MFAT Scores Between Management Schedules Obtained Using ACO and Heuristic Approaches for Investigation 6

Species	Difference				
	Year 1	Year 2	Year 3	Year 4	Year 5
Asset 4					
Ribbon weed herbland	0.0	0.0	0.0	0.0	0.0
Giant rush rushland	0.5	0.6	0.5	0.5	0.5
Rats tail couch grassland	0.0	0.2	0.4	0.3	0.5
Asset 5					
Spiny mudgrass grassland	0.3	0.5	0.4	0.4	0.5
River red gum forest	−0.1	0.5	0.6	0.4	0.5
River red gum woodland	0.0	0.3	0.3	0.2	0.1

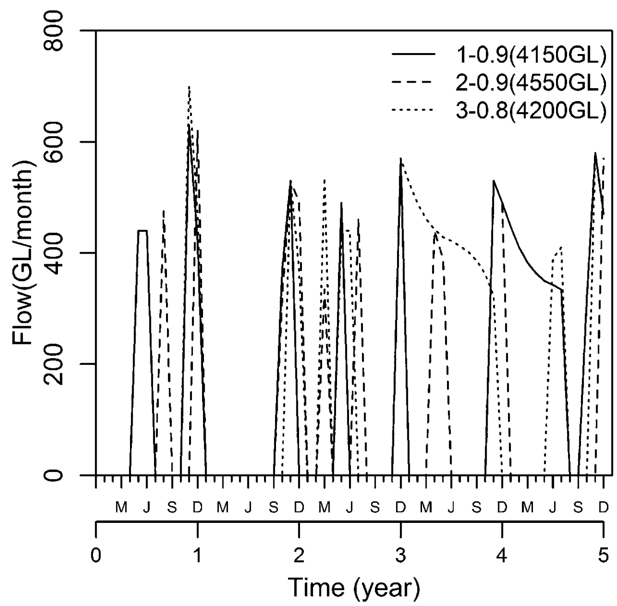

Figure 11. ACO management schedule for Investigation 3.

[63] Another benefit of the ACO approach over the heuristic approach was that it provided a number of possible optimal management schedules for each investigation. For example, the releases and corresponding MFAT scores from three different management schedules for asset 3 in Investigation 4 generated using the ACO approach are shown in Figure 11. As can be seen, water was allocated to asset 3 twice in the first year in management schedules 1 and 2, while this was not the case in schedule 3. This resulted in a lower MFAT score of 0.74 in year 1 for schedule 3, while the corresponding score for schedules 1 and 2 is 0.8. This was because the interperiod for lignum shrubland (Figure 8d) was not achieved for schedule 3. The releases for the three management schedules then followed a similar

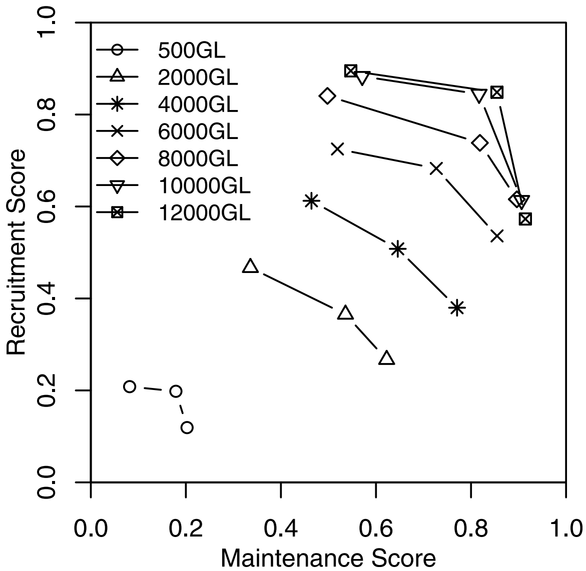

Figure 12. Optimal trade-offs between MFAT recruitment and maintenance scores for 500–12,000 GL allocations.

pattern in the second year, where, initially, there was a dry period until the end of the year, when asset 3 was inundated. In the third year, there was some variability between the management schedules, but generally flows were allocated at the end of the year in each of the schedules. Consequently, for years 2 and 3, the MFAT scores were similar for all management schedules. In the fourth year, a gate was used as part of management schedule 3, the effect of which was shown by the gradual change in flow (Figure 11). This contributed to a significantly lower maintenance score, as a longer duration of flooding negatively affected the wetland response. A gate was closed in the fourth year as part of management schedule 1; however, this did not negatively affect the final MFAT score. Finally, all three assets were inundated at the end of the fifth year, indicating that the species within this asset prefer to be flooded at the end of the year. This comparison can aid in the understanding of how sensitive the assets are to the flow regime. By knowing this sensitivity, managers have the ability to develop much more effective management schedules that efficiently use the water allocated for environmental flow management purposes, while achieving a high ecological response. Additionally, it provides wetland managers with a variety of different optimal management schedules that could be implemented, depending on prevailing social and economic factors, for example. This discussion further highlights the complexity of EFMA scheduling, as there are many different solutions that result in similar MFAT scores.

6.2. Determination of Optimal Trade-Offs Between Recruitment and Maintenance Scores for Different Flow Allocations

[64] The optimal trade-offs between recruitment and maintenance scores for total environmental water allocations ranging from 500 to 12,000 GL obtained using the ACO-based approach are shown in Figure 12. As can be seen, at an allocation of 500 GL, there was a small recruitment and maintenance response of approximately 0.2. However, this increased significantly to an average of 0.5 when the water allocation was increased to 2000 GL. The lower MFAT scores for the 500 GL allocation were due to insufficient water to inundate all of the wetlands and floodplains over the 5 year planning horizon. Only the wetlands with lower fill values were inundated. As the allocation increases from 2000 to 12,000 GL, more wetlands and floodplains were flooded and began to contribute to the overall score. Additional water was shown to have a decreasing marginal benefit and reached an asymptote of approximately 0.9, beyond which, further environmental flow allocations would not increase the overall MFAT scores.

[65] The maximum score obtained by either favoring maintenance or recruitment was approximately 0.9, which was shown by the outer two points for the 10,000 and 12,000 GL water allocations in Figure 12. The maximum value of 1.0 could not be achieved for a number of reasons. First, each wetland and floodplain had different flow requirements. Second, the maintenance and recruitment flow components for particular species were different, for instance favoring the maintenance and survival of a plant species such as, river red gum, could in turn limit its recruitment and regeneration capacity [*George et al.*, 2005; *Rogers*, 2011a], thus resulting in the inability to achieve the maximum response for all ecological processes, simultaneously. Finally, there were particular flood factors, such as the interdry flood period, which were difficult to satisfy. For example, the interflood dry period response curve was the only one that accounted for flooding over multiple years, while the remaining response curves were determined annually. Therefore, it had less impact on the objective function (and in turn the resulting management schedule), as only one graph governed the flooding over several years.

[66] Gate operations have the ability to increase significantly the efficiency of water use in the management schedule. Changes in gate settings were used extensively in the optimal schedules for the 500 and 2000 GL allocations. This was expected, since there is significant benefit in using gates to prolong inundation when a limited amount of water is available. Gate operations featured less prominently in the optimal schedules once allocations increased to 8000 GL, particularly if the aim was to favor recruitment or to balance recruitment and maintenance. As the flow allocations increased to 10,000 and 12,000 GL, gates were used to prevent inflows into wetlands, rather than prolonging inundation. It was evident from the optimal management schedules that the use of gates has the potential to improve MFAT scores, especially at times when water is limited and to prevent water flowing into the wetlands during flood events. This enables the ecological integrity of wetlands to be maintained over a wider range of flow conditions.

[67] In order to understand better the impact of the flow releases on recruitment and maintenance scores, the optimal releases obtained for the 10,000 GL allocation for Investigations 7, 8 and 9 were analyzed and are given in Figure 13. Generally, larger releases were scheduled at times that favored the timing of the processes that were emphasized by the weight preferences. For example, in Investigation 7, larger releases were scheduled between October and December (spring to summer), with the majority of the releases being allocated in November. This was a reasonable selection of releases for this investigation, as nine out of the ten MFAT plant species preferred recruitment inundation in November, with inundation in October and December being preferred

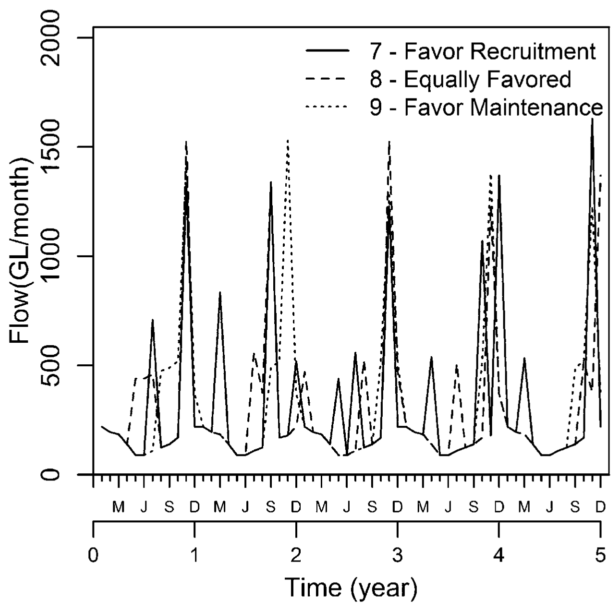

Figure 13. Monthly flow releases for the three points along the 10,000 GL allocation trade-off.

by seven and eight of the ten species, respectively. In all three investigations, most of the releases occurred in November, as the majority of the MFAT vegetation species preferred spring inundation for both recruitment and maintenance. However, the difficulty in the development of a management schedule arises in the determination of the magnitude and duration of releases, as these components vary from species to species (see Figure 8), which the optimization approach was able to account for. The maintenance and recruitment scores for each investigation and year are given in Table 9. It can be seen that, generally, when the preference is to ensure recruitment, the scores were approximately 0.95, with the exception of the first year. This was because recruitment timing for some species was based on the inundation from the previous year. When both recruitment and maintenance were favored, the scores were generally similar (see Table 9). On the whole, it seemed that the recruitment scores were higher than the maintenance scores. This was due to the difficulty associated with achieving the required interflood dry periods for maintenance, as discussed previously. The investigation favoring maintenance achieved an average score of approximately 0.9, while the recruitment score was not as high, at 0.6. This suggests that the optimization approach was able to ensure that the ideal maintenance flow components were met.

Table 9. Annual Recruitment and Maintenance Scores for the Three 10,000 Water Allocation Investigations

Investigation	Score	Year 1	2	3	4	5
7, Favor recruitment	Maintenance	0.47	0.48	0.70	0.59	0.62
	Recruitment	0.58	0.97	0.96	0.95	0.95
8, Equally favored	Maintenance	0.80	0.80	0.84	0.79	0.85
	Recruitment	0.55	0.89	0.93	0.93	0.93
9, Favor maintenance	Maintenance	0.91	0.91	0.88	0.91	0.92
	Recruitment	0.53	0.66	0.63	0.63	0.62

Table 10. Maintenance and Recruitment Scores for Investigations 10 and 11

Investigation	Maintenance Score	Recruitment Score
10	0.80	0.86
11	0.68	0.57

[68] Overall, the ACO-based approach was able to be guided by the preferences of either maintenance, recruitment, or even both, quite successfully. Even though the management schedules had similar major release timings, the magnitudes for the smaller allocations were different, thus introducing the required flow variability to incorporate the ideal recruitment and maintenance flow components shown in Figure 8 into the schedule. There was however a limitation with the use of MFAT as the ecological indicator, as it was unable to account for vegetation encroachment. According to *Dolores Bejarano and Sordo-Ward* [2011] altered flow regimes as a result of dams influence tree and shrub establishment patterns along the river and as such should be taken into account. Even with this limitation, the approach was able to be used to develop near-optimal management schedules based on preferences chosen by managers. This is not only restricted to maintenance and recruitment scores, but can also incorporate emphases on different types of species or river reaches, wetlands and floodplains, as shown in the following subsections.

6.3. Determination of the Optimal Trade-Off Between Flora and Fauna Ecological Response

[69] Table 10 shows the overall maintenance and recruitment scores for Investigations 10 and 11 (i.e., favoring flora and fauna, respectively). As can be seen, the overall maintenance and recruitment scores were significantly lower for Investigation 11, where fauna was favored, as only four species were considered within the objective function and therefore used to guide the ACO algorithm. Assets 1 and 5 were particularly affected, achieving a zero recruitment score, as there were no fauna species present in these assets, and there was therefore no contribution from these assets to the objective function. However, the fauna ecological scores in Investigation 10 were high, ranging from 0.8 to 1.0, which indicated that the optimization framework could be used to successfully find a management schedule that only focused on the fauna ecological response.

[70] On the other hand, higher recruitment and maintenance scores of 0.86 and 0.8, respectively, were obtained in Investigation 10. This was because, first, there were more species governing the development of the management schedule and second, the flora response curves were more difficult to satisfy and needed to be incorporated in the objective function, so that the resulting management schedules had higher overall MFAT scores. Although the flora species were preferred in Investigation 10, the fauna species also achieved high MFAT scores. This was because some of the fauna response curves were similar to the flora curves. For example, the ideal flood and spawning timing for main channel specialist fish, such as Murray Cod, is in late spring [*Ralph et al.*, 2011], which is within the range required for the ideal timing for the maintenance and recruitment of the majority of plant species (i.e., November). This suggests

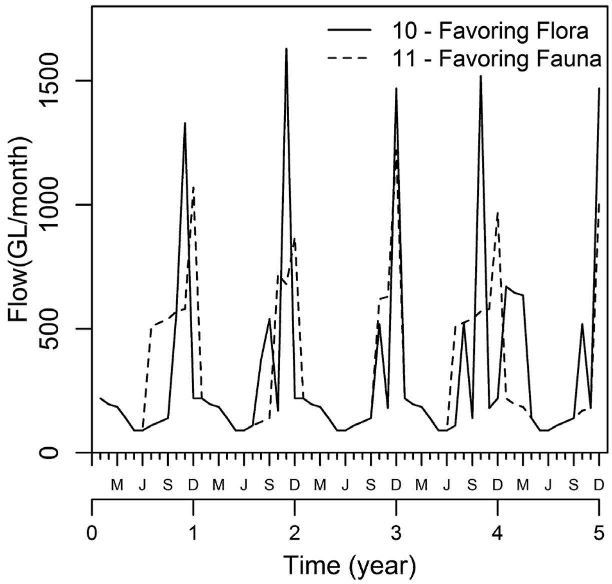

Figure 14. Flow releases for Investigations 10 and 11.

that ensuring major flows in late spring not only enhances the vegetation within the wetlands and floodplains, but also promotes the spawning and of recruitment of fish. Additionally, by flooding wetland/floodplain vegetation, habitat productivity is encouraged, resulting in an abundance of waterbird prey [*Rogers*, 2011b] and an ideal environment for waterbirds to forage and reproduce. Therefore, by ensuring flora species are of good health, the health of waterbird and fish species is also taken into account, indicating that in this particular case study, it is best to favor flora over fauna, as an overall better MFAT score can be achieved.

[71] The optimal flow releases for both investigations are presented in Figure 14, and it can be seen that the larger releases occurred between October and December in Investigation 10, which corresponded to the preferred timing (i.e., spring–early summer) for all the vegetation types in the case study. On the other hand, in Investigation 11, major releases of lower magnitude were scheduled in December, since the fish species preferred that timing and the fauna species did not require such high flow releases during that time. Additionally, longer inundation times of approximately 6 months in years 1 and 4 ensured that the waterbird species in asset 3 could achieve the ideal inundation duration. In doing so, there was not enough water to support the surrounding biota, resulting in a lower overall MFAT score, and in turn, a poorer ecological state.

[72] This study demonstrates the development of management schedules that favor specific species and the impact this might have on the remaining species. The results suggest that the proposed framework can be applied to cases when particular species (e.g., endangered species) need to be favored in the development of EFMA schedules, thereby providing wetland managers with valuable information about the trade-offs in ecological outcomes between different species for different management schedules. Finally, the study demonstrates the flexibility and versatility of the proposed optimization framework, as the additional fauna species could be incorporated into the study with ease.

6.4. Determination of Optimal EFMA Schedules as a Result of Hydrograph Inversion

[73] The average MFAT scores obtained for Investigations 12 and 13 are given in Table 11. The scores achieved when the seasonal constraints (i.e., Investigation 12) were included were lower compared with those produced when an overall constraint was applied over the entire 5 year planning horizon (i.e., 0.75 and 0.84, respectively). This was because the majority of environmental water allocation in the seasonal constraint case was available in summer and autumn (i.e., December–May), which was not ideal for the flora and fauna species in the case study. For instance, a total release of 200 GL was scheduled in spring (with the majority scheduled in summer) when a seasonal constraint was applied, while a release of 5450 GL of the 10,000 GL allocation was scheduled in the spring months (i.e., September–November) in Investigation 13, resulting in a higher MFAT score, as the majority of the biota prefer to be inundated at this time. On the other hand the hydrograph inversion case score was higher than expected, which may have been due to the assumptions made, such as setting the MFAT water temperature score to 1.0 (see section 4.1.1). In reality, river thermal regimes are altered by reservoir operations and can have a significant impact on fish species spawning [*Clarkson and Childs*, 2000] and the overall integrity of the ecosystem [*Olden and Naiman*, 2010]. Even though, the hydrograph inversion scores were relatively high, the seasonal restrictions had an impact on the overall ecological health of the river and associated wetlands and floodplains, since the required flow was not provided to the biota. However, by using the optimization approach introduced in this paper, the best possible ecological outcome, given the constraints on the water available for ecological purposes at different times of the year, can still be achieved.

[74] The individual MFAT scores for each asset are also given in Table 11. As can be seen, the scores were generally lower when the seasonal constraint was applied, with the exception of the fish species at asset 6, which had the same score. This was because, first, the ideal inundation duration of one month, as well as the ideal dry period of between 6 and 12 months, could be met, and, second, the preferred timing for spawning and flooding could both be achieved in spring and summer. This means that a high MFAT score for main channel specialists can be achieved in cases when the majority of environmental water is available in summer or spring.

[75] In comparison, there was a significant drop in MFAT scores for assets 2 and 5 of 0.14 and 0.19, respectively, when

Table 11. MFAT Scores for Each Asset and Overall MFAT Score for Investigations 12 and 13

	MFAT Scores	
Asset	Investigation 12	Investigation 13
1	0.72	0.79
2	0.76	0.90
3	0.82	0.86
4	0.71	0.78
5	0.58	0.77
6	0.95	0.95
Average score	0.75	0.84

the seasonal constraints were applied. This was mainly due to lower recruitment and maintenance scores for river red gums. Both assets contain this species of vegetation and both had lower MFAT scores. This was because the ideal flow requirements were not met, particularly the ideal timing for maintenance of current adult habitat and germination of seedlings, as both prefer inundation in spring. This indicates that for the hydrograph inversion case, there is significant impact on river red gums, which might threaten their survival. This impact would be worse if the available total environmental water allocation over the 5 year period was reduced. In the River Murray, the health and growth of river red gum areas have declined as a result of river regulation [*Bren*, 1988] and for this reason wetland management plans in this region focus on maintaining this particular species [*Tucker et al.*, 2002].

[76] Overall, the optimization framework was able to cater to the hydrograph inversion case and show that a particular plant species (i.e., river red gum) was particularly susceptible to seasonal constraints. It can therefore be used to identify species under threat and provide wetland and water resource managers with a better understanding of the management schedule that will ensure the ecological health of the entire river system, even if the river is regulated. Furthermore, the study demonstrated that the optimization framework can incorporate other constraints (e.g., seasonal, monthly or yearly), which managers may need to employ in other investigations.

7. Summary and Conclusions

[77] This paper provides a detailed formulation of the EFMA schedule optimization problem (section 2) and presents a novel and robust optimization framework for solving it (section 3). In order to be able to account for the sequential nature of the EFMA problem, it has been suggested to use ant colony optimization (ACO), as it uses a graph structure to represent the problem, which is able to be adjusted dynamically during the construction of trial solutions, thereby reducing the size of the search space and increasing the chances of finding globally optimal solutions. In order to demonstrate the utility of the proposed optimization framework, a case study based on the Murray River, Australia, was used, which consists of a river reach, three wetlands and two floodplains. In order to evaluate the effectiveness of the management schedules developed, the Murray Flow Assessment Tool, MFAT [*Young et al.*, 2003], was used.

[78] To validate the management schedules developed using the ACO-based optimization framework, the schedules obtained using the framework were initially compared with those developed using a heuristic approach. Although it is recognized that the use of a heuristic approach as a basis of comparison has its limitations, it provides some degree of validation of the proposed optimization approach, as well as illustrating its potential benefits. Six investigations of varying complexity were used as part of the validation process, with Investigations 1–3 having only one plant species, while the number of plant species ranged from 3 to 12 in the remaining three investigations. Identical MFAT scores were obtained for the first three investigations using both techniques, while for the more complex investigations, the management schedules constructed using the optimization approach were able to save water and achieve higher MFAT scores than the management schedules obtained using the heuristic approach. Based on these results, the optimization approach was considered successful in developing management schedules for both simple and complex circumstances.

[79] The optimization framework was then applied to a range of different studies that include (1) the development of optimal trade-offs between recruitment and maintenance for 12 species of flora for different 5 yearly flow allocations ranging from 500 to 12,000 GL, (2) the development of an optimal trade-off in ecological response between flora and fauna species, and (3) the development of EFMA schedules for a hydrograph inversion case. The results of the first study indicated that allocations greater than 10,000 GL did not change the final MFAT ecological scores for the wetlands and floodplains. Additionally, a maximum score of approximately 1.0 for both recruitment and maintenance could not be achieved, as there were competing flow components, where an increase in the score for a particular flow component decreased the score of another component, and vice versa. The second study indicated that favoring fauna species resulted in the surrounding biota having a lower score, while prioritizing flora achieved an overall higher score. Finally, the third study showed that the hydroinversion case could be easily incorporated within the optimization framework, as well as providing information on which species were particularly threatened. Overall, these studies were able to provide further understanding regarding when recruitment, maintenance, or a particular species are favored, the water allocation necessary to improve the ecological integrity of biota, as well as developing optimal flow management schedules in a regulated river system. This suggests that the proposed approach is a valuable tool in achieving the best possible ecological outcomes, given particular environmental flow allocations.

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