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Informing environmental water management decisions: using conditional probability networks to address the information needs of planning and implementation cycles

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Abstract

One important aspect of adaptive management is the clear and transparent documentation of hypotheses, together with the use of predictive models (complete with any assumptions) to test those hypotheses. Documentation of such models can improve the ability to learn from management decisions and supports dialogue between stakeholders. A key challenge is how best to represent the existing scientific knowledge to support decision-making. Such challenges are currently emerging in the field of environmental water management in Australia, where managers are required to prioritize the delivery of environmental water on an annual basis, using a transparent and evidence-based decision framework. We argue that the development of models of ecological responses to environmental water use needs to support both the planning and implementation cycles of adaptive management. Here we demonstrate an approach based on the use of Conditional Probability Networks (CPNs) to translate existing ecological knowledge into quantitative models that include temporal dynamics to support adaptive environmental flow management. It equally extends to other applications where knowledge is incomplete, but decisions must still be made.

Keywords: Environmental flow, instream flow, adaptive management, conditional probability network, ecological response, influence diagram, active management

1 Introduction

River ecosystems worldwide are complex and highly diverse, supporting a range of species and ecological processes. However, increased demand for water (e.g. for agricultural and domestic purposes) and river regulation has significantly impacted their integrity and sustainability (Bunn and Arthington, 2002). Water managers are grappling with the challenge of allocating water among environmental and consumptive uses in a sustainable manner (Richter, 2014).

Environmental water[1] is increasingly recognized within legislation and embedded within water resource planning processes (Le Quesne et al., 2010). It has historically been provided through long-term planning processes, policies and legislation, with numerous methods developed to assist in defining, for example, e.g caps on abstraction, pumping conditions on water users and/or storage operation rules (Horne et al., in press). In some rivers, water plans specify a water 'right' or allocation that must be actively managed to achieve environmental outcomes, for example, by delivering an environmental flow at a particular time of year. This ongoing and active management of environmental water presents novel challenges (O'Donnell and Garrick, in press). The creation of Environmental Water Rights in Australia provides a notable example, where managers must make ongoing within-year decisions concerning which particular environmental asset/s to target and when and how to release water from storage to achieve this (CEWO, 2013, Horne et al., 2017). Environmental water managers have responsibility to manage this water to achieve the best possible outcome for selected environmental endpoints (Horne et al., 2010). Managers make these ongoing management decisions with multiple and sometimes competing objectives and amid scientific and climatic uncertainty (Connell and Grafton, 2011).

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[1] We use the term environmental water here to encompass all water legally available to the environment through the array of possible allocation mechanisms.

Adaptive management is particularly suited to management challenges such as environmental water management where "*knowledge is incomplete, and when, despite inherent uncertainty, managers and policy makers must act*" (Allen and Garmestani, 2015). Adaptive management was first conceived for natural resource management by Holling (1978), and centers on the concept of learning through experience to improve management. There are two separate (although related) interpretations of adaptive management discussed in the natural resource management literature (Allen and Garmestani, 2015). The first highlights technical or scientific matters, such as testing scenario modeling of systems (Rivers-Moore and Jewitt, 2007, Williams, 2011) and field-scale experimentation (Pollard et al., 2011). The second works with theories and practice of participatory learning and decision making (Stringer et al., 2006), social learning (Blackmore and Ison, 2012), evaluation (Bryan et al., 2009), and governance (Ison et al., 2013a). Both interpretations are valid and useful, and in practice, adaptive management is effective when it acts as a framework within which these interpretations can be integrated. This paper focuses on the science of environmental water management and adaptive management rather than the institutional and governance aspects. However, we acknowledge that in practice, effective adaptive management must integrate both interpretations of adaptive management (Ison et al., 2013b).

Webb et al. (in press-b) suggest that the different approaches to adaptive management share three qualities: "*they are **purposeful** and **deliberate**, they are characterized by **careful documentation processes,** and they are **designed to promote learning that translates to action***". This usually requires a model that links alternative management actions to management objectives (Allan and Stankey, 2009b), which represents what we know and what we assume or predict (Allen and Garmestani, 2015, Williams and Brown, 2014). A documented model, complete with its inherent uncertainties, plays an essential role in understanding how a system behaves and in building consensus and understanding between those involved in the management process (Walters, 1986). In the case of environmental water management, the model aims to link flow delivery decisions to achieving environmental objectives that were established based on community values and ecosystem services in the river.

There are two types of models that can make a contribution to adaptive management of environmental water (Kingsford et al., 2011, Stewardson and Rutherford, 2008). The first is an explicitly defined conceptual (or mental) model of "… *how a system operates and of the effects of anthropogenic processes … to remove ambiguity*" (Kingsford et al., 2011, p1196). This type of model describes the key drivers and processes including the effects of anthropogenic influences. Such models can assist with co-learning by multiple stakeholders (Kingsford et al., 2011) by exposing different understanding of system behavior. The second type is a quantitative predictive model that is used by managers to evaluate alternate management scenarios and can be in the form of a decision support system. The relationships in this predictive model should be consistent with the conceptual model but is likely to deal with a reduced range of responses and processes. This paper is focused specifically on this second type of model, to support an adaptive management approach to active management of environmental water.

There has been considerable growth in the number of scientific publications examining the environmental effects of flow alteration (Beven and Alcock, 2012, Liebman, 1976), and increasingly, these articles refer to "management" or "decision making" (JA Webb, unpubl.) However, there are considerable challenges in developing predictive models to support environmental water management based on the best available scientific knowledge (Acreman, 2005). Many active environmental water management decisions are based on expert judgments that draw from experts' cumulative experience and understanding of current literature (Stewardson and Webb, 2010). Typically, experts either provide a preferred environmental water scenario or evaluate environmental outcomes from alternate environmental water management scenarios. The difficulties with this approach are: the expert’s reasoning is often not transparent, making it difficult to test and to consider additional scenarios without recourse to the expert; and, related to this, the assessment is not repeatable with a different set of experts. This is particularly a problem in cases where managers want to search for improved management options and also to update evaluations as time progresses. It is this key challenge that is the focal point of this paper.

The aim of this paper is to highlight the information needs for active management of environmental flows, and propose an approach for documenting this information. In this paper we introduce the concept of using Conditional Probability Networks (CPNs) as flexible and adaptive models in this context. The paper does not aim to detail the technical method, but rather, to illustrate the conceptual links between the information needs for adaptive management of environmental water, and the representation of ecological knowledge. We demonstrate the utility of this conceptual approach by applying it to a case study problem, management of Environmental Water Rights in Australia. We begin by discussing the planning and implementation cycles for environmental water management, and the types of information required to inform each process (Section 2). Importantly, this discussion recognizes that the challenges environmental water managers are addressing—and thus their information needs—differ depending on whether the allocation mechanism for environmental water is established through the long-term resource plans, or whether it requires ongoing implementation and active management. For the case of active environmental water management, we suggest that CPNs are a sound approach to predictive modeling to support implementation decisions for environmental water (Section 3). They apply available information including data-based models, and the knowledge of expert and other stakeholders. As with any model of this nature, while CPNs aim to inform the decision making process, the decision making process itself remains in the realm of managers and stakeholders.

2 Environmental water planning and implementation

We can consider environmental water management within an adaptive management framework as having two distinct, yet interconnected, cycles. These cycles correspond to the 'outer' and 'inner' loops of the adaptive management cycle (see Figure 1).

- A planning (or deliberative) cycle (5 to 10 years) centers on objective or target setting, and understanding the resource problem and decision architecture (i.e. identification of management options, predictions of management outcomes and design of evaluation) (Williams and Brown, 2014). It usually involves a wider scale institutional review and includes transformative planning in response to fundamental changes in the underlying knowledge of system behavior (Eberhard et al., 2009, Williams and Brown, 2014). This cycle corresponds to the 'outer loop' of the adaptive management cycle.
- An implementation (or iterative) cycle (normally 1 year), which centers on incremental changes to management decisions due to technical learning as a result of ongoing program implementation (Williams and Brown, 2014). This phase adopts the information from the planning phase within an ongoing learning cycle.

There will be institutional and social learning that occurs at both the planning and implementation cycles. This will include tools, systems and institutions in place to help inform and support the process for decision making (Campbell et al., 2016). The focus of this paper is on scientific or ecological learning. Importantly, the scientific information and conceptual models that inform the planning decisions must be internally consistent with the conceptual models used to inform the implementation cycle.

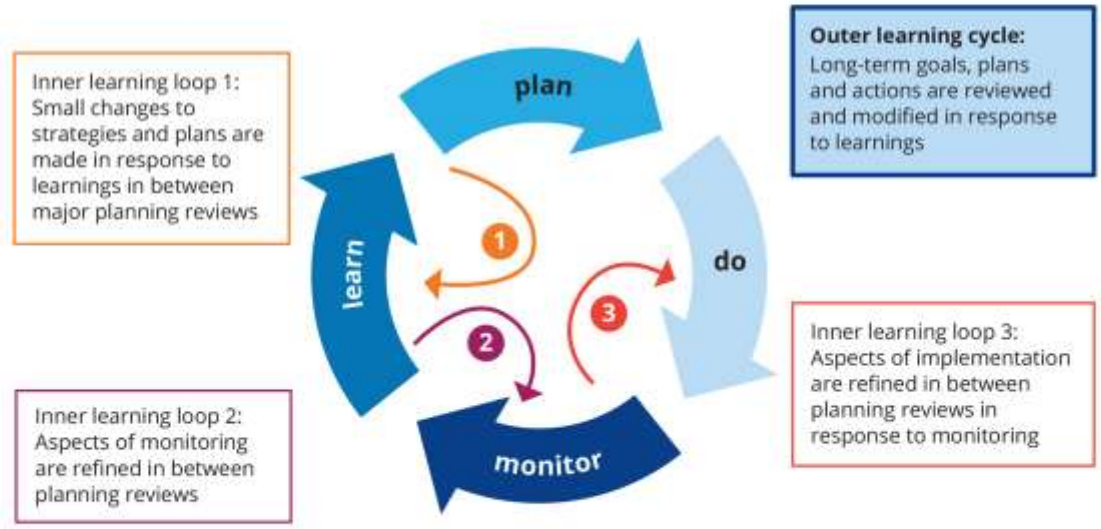


Figure 1 The adaptive management cycle showing the planning (outer loop) and implementation (inner loops) cycles (Source: Webb et al., in press-a)

The historic focus of environmental water management on the longer term planning cycle has required input from scientists to establish environmental water regimes, passing flow rules, or set caps (Tharme, 2003). Updates to flow recommendations have generally occurred on a longer time scale that more closely matches the outer loop of the adaptive management cycle.

The more recent establishment of actively managed water reserves requires environmental water managers to make ongoing and active decisions about how to release water from storage to achieve particular environmental outcomes. Decisions are often different from year to year and take advantage of the incremental changes in knowledge more generally associated with the inner loop of the adaptive management cycle. There is often within-year planning that happens at this incremental level to plan annual priorities and individual releases (Docker and Johnson, in press, Doolan et al., in press, O'Donnell and Garrick, in press).

Achieving maximum value from an allocation of environmental water requires information to inform trade-off decisions between watering at one location or time over another, or to target one ecological endpoint over another. There may also be linked flow events, such as flows to trigger both spawning and recruitment (Crook et al., 2006). Delivered in isolation from one another the benefits of such events will be greatly diminished, but in some years there may be insufficient water available to deliver both. Where environmental water is provided through a mechanism that requires active management, the manager needs to consider the merits of providing one flow event without the other, or which flow event, and to what level of fulfillment, to provide (Horne et al., 2010).

When considering the type of scientific information needed to inform the planning and implementation cycles of environmental water management, both cycles would be improved through the use of models that:

- link the decisions available (for example to release environmental water at different spatial and temporal scales) to the objectives being managed for (conceptual model); and
- provide quantitative information to the extent that it shows benefits of one option over another (quantitative model)

However, the resolution or *granularity* of information required differs between the two cycles. During planning, a recommendation will be to deliver a particular flow event (e.g. a spring ‘fresh’ or high-flow event). During implementation, the decision concerns the precise timing of when flow is required relative to releases for other users in that season (or between seasons), and also allows the flexibility to adjust the peak magnitude of an event or the duration of the event. Transparent and detailed information on the marginal return of a decision (for example, whether delivery of half the water would provide half the benefit) thus becomes important for implementation. As it will not necessarily be possible to provide the complete desired environmental flow regime in all years, making the best use of this water will require an understanding of the benefits or risks of providing one component of the flow regime without (or instead of) another, or providing one flow component but at less than the recommended volume. It requires more detailed information on the links between the decisions available and the management objectives.

Another important element of managing environmental water rights is that decisions each year will vary depending upon antecedent conditions. Longer-term planning for environmental water has tended to use average recurrence intervals for flow events or pulses (Shenton et al., 2012). The sequencing of flow events over time, coupled with the resilience and recovery trajectories of particular ecological endpoints, are particularly important for active management and the inter-annual link between flow release decisions (Anderson et al., 2006). This sort of ongoing implementation, in contrast to longer-term planning, has the advantage of being able to adjust the environmental flow regime in a dynamic way to account for feedbacks and ecological transition state (Overton et al., 2014, Shenton et al., 2012).

There is an extensive and rapidly building body of research linking flow alteration to ecological outcomes (Arthington, 2012). However, individually, these studies tend to focus on one particular aspect of the flow regime (a spawning pulse, or low flow) and its relationship to one particular ecological endpoint (e.g. King et al., 2009, Webb et al., this issue). These results may be able to be used as the type of flow-ecology relationships required by the ELOHA method (Poff et al., 2010), but they are limited by their 'bivariate' nature (one flow component vs. one simple response). Attempts to formally combine different flow-ecology response curves for more complex ecological responses (e.g. fish responses to multiple flow components) have primarily used geometric mean or the most limiting factor (Bryan et al., 2013, Marsh et al., 2007). There are also examples of decision support tools that allow combination methods based on expert judgment (Young et al., 2003). A key limitation in these approaches to date is the failure to recognize the interdependencies between individual elements of the flow regime, and interactions between species (Lester et al., 2011). For longer term planning processes, expert panels synthesize information to suggest a required flow regime (Gippel et al., 2009, Stewardson and Webb, 2010, Tharme, 2003). However, there is rarely an explicitly documented model produced through this process. While this approach to synthesizing knowledge has been effective for longer-term planning processes, we believe that the shorter temporal scales, more detailed process representations, and finer grain of ecological knowledge required to inform the implementation cycle of environmental water management (all detailed above) mean that explicitly documented conceptual and quantitative models are required.

3 Conditional Probability Networks (CPNs) to represent flow management-ecology outcomes

A CPN represents the probabilistic cause effect relationships between driver or decision variables (in this case, the environmental flow release decisions) and one or more objectives. The CPN network is represented by a series of nodes (state variables) and links (the causal relationships among those variables). For each node there is a conditional probability table with a finite set of input states and output states. These probabilities define the outcome of that node given the condition of the nodes that feed into it (Hart and Pollino, 2009). A CPN can therefore be used to represent the assumed or predicted causal link between a management decision and an environmental management objective. The node-link network represents the conceptual model relating flow management decisions to environmental outcomes, while the conditional probability tables for each node-link provide the quantitative model for how particular elements of the system will behave, and the dependency of those behaviors on other components of the system.

Bayesian Networks are probably the most familiar application of conditional probability networks (Pearl, 2000). We use the term CPN in order to recognize that this node-link structure backed by conditional probability tables has a far wider set of applications than their use within Bayesian network software programs such as Netica®. For example, such models can be directly coded into numerical optimization procedures to help identify preferred management decisions (Horne et al., 2017).

The benefits of using a CPN include that they (Henderson et al., 2008, Cain, 2001, Reckhow, 2003):

- show cause-effect relationships through a simple graphical structure;
- are easily constructed, extended and modified;
- allow the conditional probabilities between variables to be constructed using either observed data, other models, or expert knowledge (or any combination of these);
- are an accessible and intuitive modeling approach; and
- allow for temporal dynamics through inclusion of nodes representing antecedent conditions.

In developing a CPN, there will be aspects of this network that have been well studied, while other aspects will be hypotheses of how the system behaves. The conditional probability tables that define the statistical relationship between two nodes can be populated from a number of sources. Where extensive data are available, algorithms exist to populate a CPN directly. Where data are limited, expert knowledge can be used to parameterize relationships. Traditional and local knowledge can also be incorporated. There are a number of formal expert elicitation methods developed for this purpose (Speirs-Bridge et al., 2010, de Little et al., 2012). In both cases, the information will improve over time and through the adaptive management cycle. One of the recognized benefits of CPNs is the ease with which this variety of knowledge sources can be combined, and later readily updated. The source of information can be clearly documented. This provides a clear framework for updating and refining a model over time, as (for example) data-driven relationships are able to update or replace expert-driven relationships. The CPN does not overcome the need for expert judgment in situations where there is no data-driven model. However, the CPN is a permanent record of those expert judgments in a format that informs the needs of decision makers. When well implemented, adaptive management can facilitate learning through a structured dialogue between scientists and managers (Ladson, 2009). This begins with the documentation of the predictive model and discussion of the decision architecture. Developing a CPN that includes information on the sources of knowledge used to develop model structure and relationships, the relative importance and interaction between different flow components and management outcomes, and the uncertainties of model predictions, is can provide this documentation.

3.1 Demonstration CPN: Australian Grayling

The Yarra River, Victoria, Australia is a system where an environmental water entitlement is actively managed. The environmental flows study for the Yarra River establishes a number of objectives for environmental water releases. Among these, is the maintenance of a healthy Australian grayling (*Prototroctes maraena*) population. Australian grayling is an endangered fish species that inhabits coastal rivers in south-east Australia (Koster et al., 2013). Its life history is strongly tied to flow regimes, and so it is a common target of environmental flow programs (Koster, this issue, Webb et al., this issue).

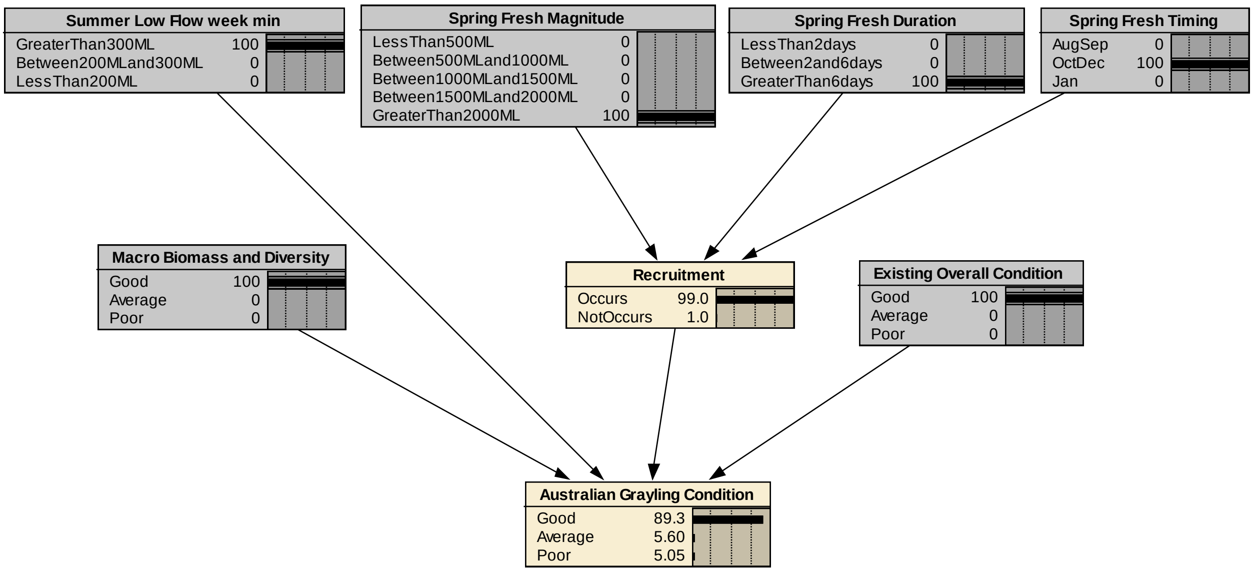
A CPN for Australian grayling populations was developed for the Yarra River, using expert elicitation. This model represents the management decisions available to the Yarra River Environmental Water Manager and how these link to the environmental flow objectives. This is not an attempt to model the complete environmental system, nor other management activities that may occur in the catchment. The aim is to capture the key factors that would improve or limit achievement of environmental flow objectives through the environmental water management options available. Should there be an exogenous catchment process (such as a point source of pollution in the river) this could be incorporated into a CPN.

However, the Yarra River Environmental Water manager did not identify any such factors as important for flow release decisions in this catchment.

The conceptual model (or influence diagram) is presented in figure 2, with full conditional probability tables provided in supplementary material. The expert panel populated these conditional probability tables based on their knowledge of the flow-ecology relationships in the river. The links and nodes extend from the management decisions (decision nodes at the top of the figure) through to the management goals (utility nodes at the bottom of the figure). There are two separate management goals for Australian grayling: firstly, to support spawning and migration; and secondly, to improve population condition within the Yarra River (described as poor, average or good condition). The management decisions are the flow components that are provided, which are represented by nodes for summer low flow, and for the magnitude, duration and timing of Spring and Autumn fresh (high flow) events (Figure 2). Each of these nodes contains a number of different possible states, allowing for example, for a fresh to be provided at a lower threshold or duration than the full environmental flow recommendation. It is the combination of the node-link network and the number of discrete possible states for each node that provide the granularity required for active management within the implementation cycle.

The CPNs show the relative importance of one flow component over another. Consider for example the provision of a spring fresh to promote juvenile migration into the system from the marine environment. Figure 3 shows that, based on current understanding, the magnitude of the event is more important than the duration (with a reduced magnitude leading to a reduction in likelihood of good condition from 89% to 58% as opposed to 77% caused by a decrease in duration). These differences have clear management implications: when where there is a shortfall in the water available to provide a complete spring fresh, current knowledge suggests that the Environmental Water Manager would do best to provide the full magnitude of the Spring Fresh event at the expense of its duration.

Within the implementation cycle, successive trialing of different watering regimes in different years can be used to generate new knowledge and adjust the CPN. An Environmental Water Manager may release a spring fresh at the recommended magnitude but with a reduced duration and find that the Australian grayling population response is less than expected. This knowledge can be incorporated into the CPN to inform subsequent release decisions. Within the implementation cycle, these adjustments would be made through adjustments to the values in the probability tables. However, it may be that due to a series of monitoring results through the implementation cycle, a new planning cycle would require a review of the node-link structure to reflect a change in our understanding of the relevant flow components. While similar learning is possible through an expert panel process alone, the documentation and structured review required by developing a CPN is likely to improve the efficiency and effectiveness of the adaptive management process.



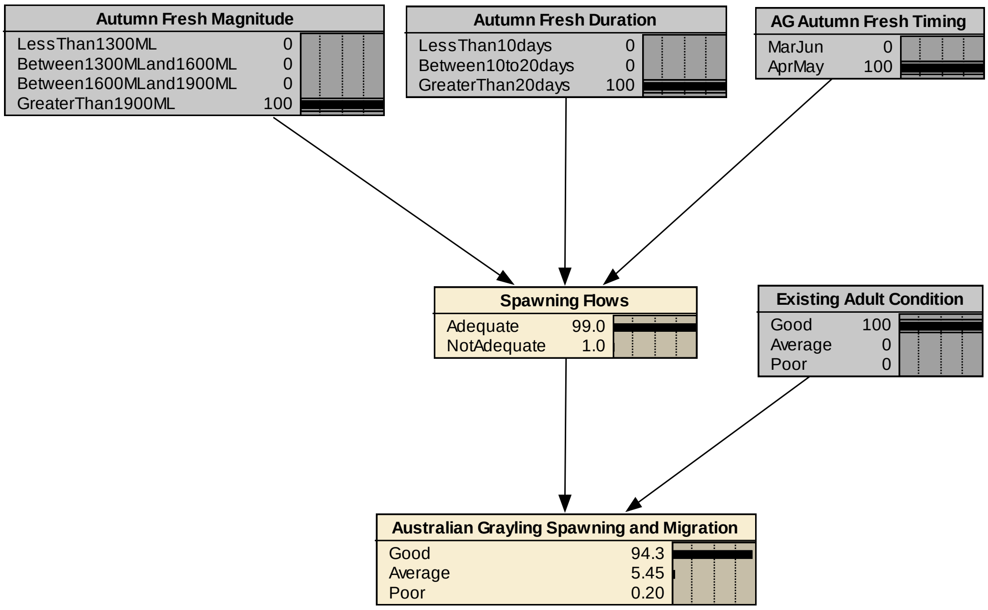
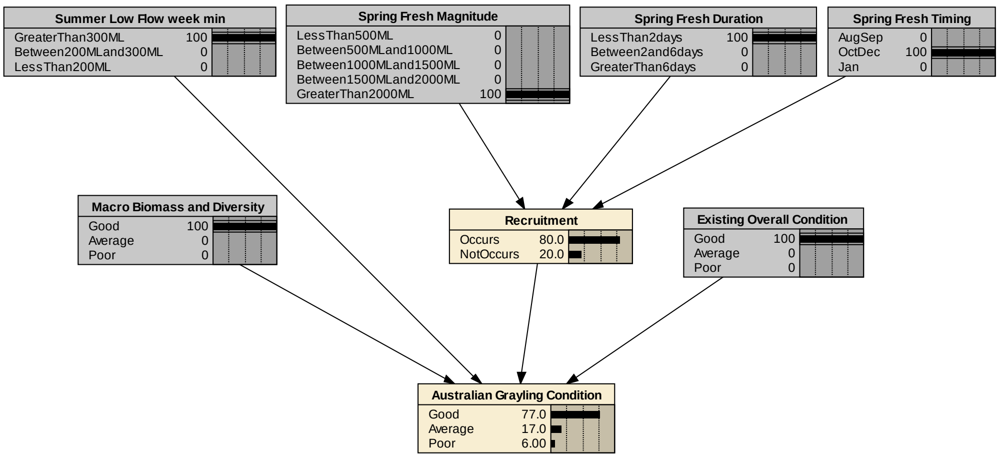


Figure 2 Example CPNs for Australian grayling where low management decisions are represented by the decision nodes (Summer low flow weekly minimum, Spring fresh magnitude, duration and timing, autumn fresh magnitude, duration and timing). Management endpoints are represented by the utility nodes(Australian Grayling Condition – panel (a) and Australian grayling spawning and migration – panel (b)), and antecedent conditions are represented by the intermediate nodes (existing condition and existing regional condition). The links (conditional probability tables) between nodes are presented in supplementary material. The graphic shown here is the calculation of outcomes (based on the conditional probability tables) for a particular combination of flow management decisions and an assumption of antecedent condition.

a)



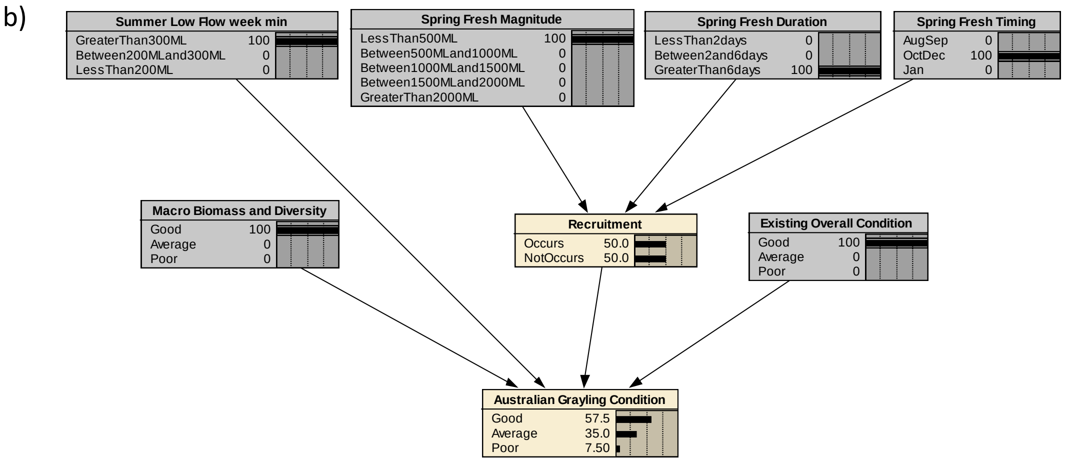


Figure 3 Changes to Australian grayling condition in the Yarra River assuming (a) the Spring Fresh is provided at a shorter duration (with the node "Spring Fresh Duration" highlighting a duration of less than 2 days) (b) the Spring Fresh is provided at a lower magnitude (with the node "Spring Fresh Magnitude" being less than 500ML).

A key requirement for the implementation cycle is the inclusion of ecological antecedent condition and response and recovery time for ecological endpoints. The CPN includes nodes that represent the existing condition of the population to represent the effect of the previous year's population on the outcome for the current year. It is expected that the outcome for the Australian grayling population to a particular flow decision will vary depending on the population's initial ecological state. The CPN developed for the Yarra River indicates that if the recommended environmental flows are released, and the existing condition is good, there is a high probability of remaining in a good state. In comparison, where the initial condition is poor, providing the same set of flow components leads to a very different outcome - a high chance (69%) that the condition will move from poor to average. This means that returning the Australian grayling population to good health will require adequate flows over multiple years. The inclusion of the "existing condition" node accounts for the varying condition of an ecological endpoint over time.

4 Discussion and conclusion

While there have been significant gains in our knowledge of flow-ecology relationships, there remains a challenge in translating and combining this knowledge to inform environmental flow management decisions. This is particularly the case for active management, where the need for ongoing decisions necessitates a finer grain of ecological knowledge and process representation compared to longer-term planning decisions.

In Australia, legislation requires that the implementation of environmental water rights occurs with the best available science (Water Act 2007). The current approach of using expert panels to synthesize existing knowledge of different parts of the ecological picture certainly has the potential to use best available knowledge, but does not guarantee it. More importantly, it could be improved from the perspective of providing transparency and rapid learning through more formal adaptive management. Clear documentation would allow knowledge to be more readily shared, provide a permanent record of why certain actions were taken, and facilitate ongoing discussion and analysis (Allan and Stankey, 2009a, Koster, this issue, Webb et al., this issue).

The CPN modeling method presented in this paper provides a promising approach to tackling these challenges, particularly in the context of making explicit (and providing a connection between) the predictive models that inform the planning and implementation cycles of environmental water management. It provides flexibility to incorporate multiple information sources, is readily updateable, and allows representation of the temporal sequencing of seasonal environmental water management decisions. It extends previous CPN approaches used to examine environmental flows (e.g. Shenton et al., 2011) by including positive population feedbacks and dynamic population behavior through time.

The case study demonstrated how a CPN can be developed to meet the requirements of both the planning and implementation cycles of environmental water management. The adaptive process of reviewing and updating the model has not yet occurred in the Yarra River. However, the process undertaken documented for the first time the interaction and relevant importance of different flow components for meeting the single objective of improved Australian grayling populations. This will inform flow release tradeoffs when there is not enough environmental water to deliver recommended flows in full. The process of developing the CPN and discussions through the expert elicitation process also clearly highlighted areas of the conceptual model and probabilistic relationships where knowledge is more limited and further research is required. A similar approach could be applied in other systems, using the environmental water manger to identify the boundaries and elements that influence their management decisions. The case study applied CPNs to a single fish species as one management objective of environmental flows in the Yarra River. The same approach and concepts could be applied to the wider suite of environmental flow management objectives. It could also be extended to incorporate other management strategies within the catchment to address environmental drivers other than flow. Importantly, the CPN approach represents existing knowledge in a format that meets the needs of resource managers at both the planning and implementation scales. The process of formally documenting the CPN helps clarify the thought process around how flow decisions are made, and ensures common understanding across those participating in the flow management process. Adaptive management theory tells us that by documenting the predictive models and the known uncertainties, and by recording the performance of predictions against observed outcomes, the models and consequent decisions can be improved over time (Webb et al., in press-a). Adaptive management requires that both the logic that leads to a management decision, and the uncertainty in the information, be documented to allow the learning cycle to improve future management decisions. It is therefore important that any predictive model is considered a "working model" and a systematic approach is in place to review and update the model as new knowledge becomes available. For CPNs, as adaptive learning proceeds with monitoring and evaluation of ecological responses, the conditional probability relationships among nodes can be updated using Bayes' rule (Pearl, 2000), thereby taking maximum advantage of both existing and new knowledge. Over time, we would expect the uncertainty in conditional probability relationships to be reduced, with a consequent improvement in the precision of decision making informed by these models. Future research could aim to at both understanding and reducing this uncertainty through a combination of models and field work. There may also be improvements in our understanding of the requisite level of complexity of such models. This corresponds to multiple cycles of the inner adaptive management loop (Figure 1). Decision support tools are becoming more prevalent in environmental management, but representing ecological endpoints within these models remains a key challenge (Horne et al., 2016). The CPN approach lends itself to inclusion in these types of tools as it employs a direct link between decision variables and endpoints and quantifies the relative importance of different causal factors, both of which can be used to inform decisions. Another potential application of CPNs is the representation of ecological outcomes for decision models attempting to compare consumptive uses (i.e. economically productive) of natural resources and environmental outcomes (for example, Grafton et al., 2011). While we have concentrated here on the use of CPNs as a conceptual and numerical modeling tool for environmental water management, the potential range of applications is much wider, and indeed extends to any adaptive management (environmental or otherwise) situation where decisions must be made, but for an endpoint for which knowledge is incomplete.

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7 Supplementary material

Demonstration Conditional Probability Tables for Australian Grayling in the Yarra River catchment.

7.1 Australian Grayling Condition

Table 1 Conditional Probability table for probability of recruitment of Australian Grayling

Spring Fresh Timing	Spring Fresh Duration	Spring Fresh Magnitude	Probability of recruitment	
			Occurs	Does not occur
Aug-Sept	< 500ML	< 2 days	0.10	0.90
Aug-Sept	500ML-1000ML	< 2 days	0.15	0.85
Aug-Sept	1000ML-1500ML	< 2 days	0.20	0.80
Aug-Sept	1500ML-2000ML	< 2 days	0.25	0.75
Aug-Sept	> 2000ML	< 2 days	0.30	0.70
Aug-Sept	< 500ML	2-6 days	0.20	0.80
Aug-Sept	500ML-1000ML	2-6 days	0.35	0.65
Aug-Sept	1000ML-1500ML	2-6 days	0.40	0.60
Aug-Sept	1500ML-2000ML	2-6 days	0.45	0.55
Aug-Sept	> 2000ML	2-6 days	0.70	0.30
Aug-Sept	< 500ML	> 6 days	0.30	0.70
Aug-Sept	500ML-1000ML	> 6 days	0.55	0.45
Aug-Sept	1000ML-1500ML	> 6 days	0.60	0.40
Aug-Sept	1500ML-2000ML	> 6 days	0.65	0.35
Aug-Sept	> 2000ML	> 6 days	0.80	0.20
Oct-Dec	< 500ML	< 2 days	0.30	0.70
Oct-Dec	500ML-1000ML	< 2 days	0.55	0.45
Oct-Dec	1000ML-1500ML	< 2 days	0.60	0.40
Oct-Dec	1500ML-2000ML	< 2 days	0.65	0.35
Oct-Dec	> 2000ML	< 2 days	0.80	0.20
Oct-Dec	< 500ML	2-6 days	0.40	0.60
Oct-Dec	500ML-1000ML	2-6 days	0.65	0.35
Oct-Dec	1000ML-1500ML	2-6 days	0.70	0.30
Oct-Dec	1500ML-2000ML	2-6 days	0.75	0.25
Oct-Dec	> 2000ML	2-6 days	0.90	0.10
Oct-Dec	< 500ML	> 6 days	0.50	0.50
Oct-Dec	500ML-1000ML	> 6 days	0.75	0.25
Oct-Dec	1000ML-1500ML	> 6 days	0.80	0.20
Oct-Dec	1500ML-2000ML	> 6 days	0.85	0.15
Oct-Dec	> 2000ML	> 6 days	0.99	0.01
Jan	< 500ML	< 2 days	0.10	0.90
Jan	500ML-1000ML	< 2 days	0.15	0.85
Jan	1000ML-1500ML	< 2 days	0.20	0.80
Jan	1500ML-2000ML	< 2 days	0.25	0.75
Jan	> 2000ML	< 2 days	0.30	0.70
Jan	< 500ML	2-6 days	0.20	0.80
Jan	500ML-1000ML	2-6 days	0.35	0.65
Jan	1000ML-1500ML	2-6 days	0.40	0.60
Jan	1500ML-2000ML	2-6 days	0.45	0.55
Jan	> 2000ML	2-6 days	0.70	0.30
Jan	< 500ML	> 6 days	0.30	0.70
Jan	500ML-1000ML	> 6 days	0.55	0.45
Jan	1000ML-1500ML	> 6 days	0.60	0.40
Jan	1500ML-2000ML	> 6 days	0.65	0.35

Jan	> 2000ML	> 6 days	0.80	0.20

Table 2 Conditional Probability table for condition of Australian Grayling

Recruitment	Summer Low Flow	Macroinvertebrate condition	Existing Australian Grayling condition	Probability of condition		
				Good	Average	Poor
Occurs	Good	Good	Good	0.90	0.05	0.05
Occurs	Good	Good	Average	0.80	0.15	0.05
Occurs	Good	Good	Poor	0.20	0.70	0.10
Occurs	Good	Average	Good	0.85	0.10	0.05
Occurs	Good	Average	Average	0.75	0.20	0.05
Occurs	Good	Average	Poor	0.15	0.60	0.25
Occurs	Good	Poor	Good	0.80	0.15	0.05
Occurs	Good	Poor	Average	0.65	0.25	0.10
Occurs	Good	Poor	Poor	0.10	0.50	0.40
Occurs	Average	Good	Good	0.85	0.10	0.05
Occurs	Average	Good	Average	0.75	0.20	0.05
Occurs	Average	Good	Poor	0.15	0.60	0.25
Occurs	Average	Average	Good	0.75	0.20	0.05
Occurs	Average	Average	Average	0.25	0.70	0.05
Occurs	Average	Average	Poor	0.05	0.25	0.70
Occurs	Average	Poor	Good	0.70	0.25	0.05
Occurs	Average	Poor	Average	0.55	0.35	0.10
Occurs	Average	Poor	Poor	0.01	0.19	0.80
Occurs	Poor	Good	Good	0.00	0.00	1.00
Occurs	Poor	Good	Average	0.00	0.00	1.00
Occurs	Poor	Good	Poor	0.00	0.00	1.00
Occurs	Poor	Average	Good	0.00	0.00	1.00
Occurs	Poor	Average	Average	0.00	0.00	1.00
Occurs	Poor	Average	Poor	0.00	0.00	1.00
Occurs	Poor	Poor	Good	0.00	0.00	1.00
Occurs	Poor	Poor	Average	0.00	0.00	1.00
Occurs	Poor	Poor	Poor	0.00	0.00	1.00
Does not occur	Good	Good	Good	0.25	0.65	0.10
Does not occur	Good	Good	Average	0.05	0.60	0.35
Does not occur	Good	Good	Poor	0.00	0.05	0.95
Does not occur	Good	Average	Good	0.15	0.60	0.25
Does not occur	Good	Average	Average	0.05	0.40	0.55
Does not occur	Good	Average	Poor	0.00	0.05	0.95
Does not occur	Good	Poor	Good	0.05	0.55	0.40
Does not occur	Good	Poor	Average	0.00	0.20	0.80
Does not occur	Good	Poor	Poor	0.00	0.05	0.95
Does not occur	Average	Good	Good	0.70	0.20	0.10
Does not occur	Average	Good	Average	0.05	0.85	0.10
Does not occur	Average	Good	Poor	0.00	0.05	0.95
Does not occur	Average	Average	Good	0.65	0.25	0.10
Does not occur	Average	Average	Average	0.05	0.75	0.20
Does not occur	Average	Average	Poor	0.00	0.05	0.95
Does not occur	Average	Poor	Good	0.60	0.20	0.20
Does not occur	Average	Poor	Average	0.00	0.70	0.30
Does not occur	Average	Poor	Poor	0.00	0.05	0.95
Does not occur	Poor	Good	Good	0.00	0.00	1.00
Does not occur	Poor	Good	Average	0.00	0.00	1.00
Does not occur	Poor	Good	Poor	0.00	0.00	1.00
Does not occur	Poor	Average	Good	0.00	0.00	1.00

Does not occur	Poor	Average	Average	0.00	0.00	1.00
Does not occur	Poor	Average	Poor	0.00	0.00	1.00
Does not occur	Poor	Poor	Good	0.00	0.00	1.00
Does not occur	Poor	Poor	Average	0.00	0.00	1.00
Does not occur	Poor	Poor	Poor	0.00	0.00	1.00

7.2 *Australian Grayling Spawning and Migration*

Table 3 Conditional Probability table for probability of spawning flows for Australian Grayling

Autumn Fresh Timing	Autumn Fresh Duration	Autumn Fresh Magnitude	Probability of spawning flow	
			Occurs	Does not occur
March/June	< 10 days	< 1300 ML	0.10	0.90
March/June	< 10 days	1300 - 1600 ML	0.15	0.85
March/June	< 10 days	1600 - 1900 ML	0.25	0.75
March/June	< 10 days	> 1900 ML	0.30	0.70
March/June	10-20 days	< 1300 ML	0.20	0.80
March/June	10-20 days	1300 - 1600 ML	0.35	0.65
March/June	10-20 days	1600 - 1900 ML	0.45	0.55
March/June	10-20 days	> 1900 ML	0.60	0.40
March/June	> 20 days	< 1300 ML	0.30	0.70
March/June	> 20 days	1300 - 1600 ML	0.55	0.45
March/June	> 20 days	1600 - 1900 ML	0.65	0.35
March/June	> 20 days	> 1900 ML	0.70	0.30
April/May	< 10 days	< 1300 ML	0.20	0.80
April/May	< 10 days	1300 - 1600 ML	0.45	0.55
April/May	< 10 days	1600 - 1900 ML	0.65	0.35
April/May	< 10 days	> 1900 ML	0.70	0.30
April/May	10-20 days	< 1300 ML	0.40	0.60
April/May	10-20 days	1300 - 1600 ML	0.70	0.30
April/May	10-20 days	1600 - 1900 ML	0.85	0.15
April/May	10-20 days	> 1900 ML	0.80	0.20
April/May	> 20 days	< 1300 ML	0.50	0.50
April/May	> 20 days	1300 - 1600 ML	0.80	0.20
April/May	> 20 days	1600 - 1900 ML	0.90	0.10
April/May	> 20 days	> 1900 ML	0.99	0.01

Table 4 Conditional Probability table for condition of Australian Grayling

Spawning flow	Existing Australian Grayling condition	Probability of Australian Grayling Spawning and Migration		
		Good	Average	Poor
Adequate	Good	0.95	0.05	0.00
Adequate	Average	0.70	0.20	0.10
Adequate	Poor	0.10	0.70	0.20
Not adequate	Good	0.30	0.60	0.10
Not adequate	Average	0.05	0.15	0.80
Not adequate	Poor	0.00	0.05	0.95

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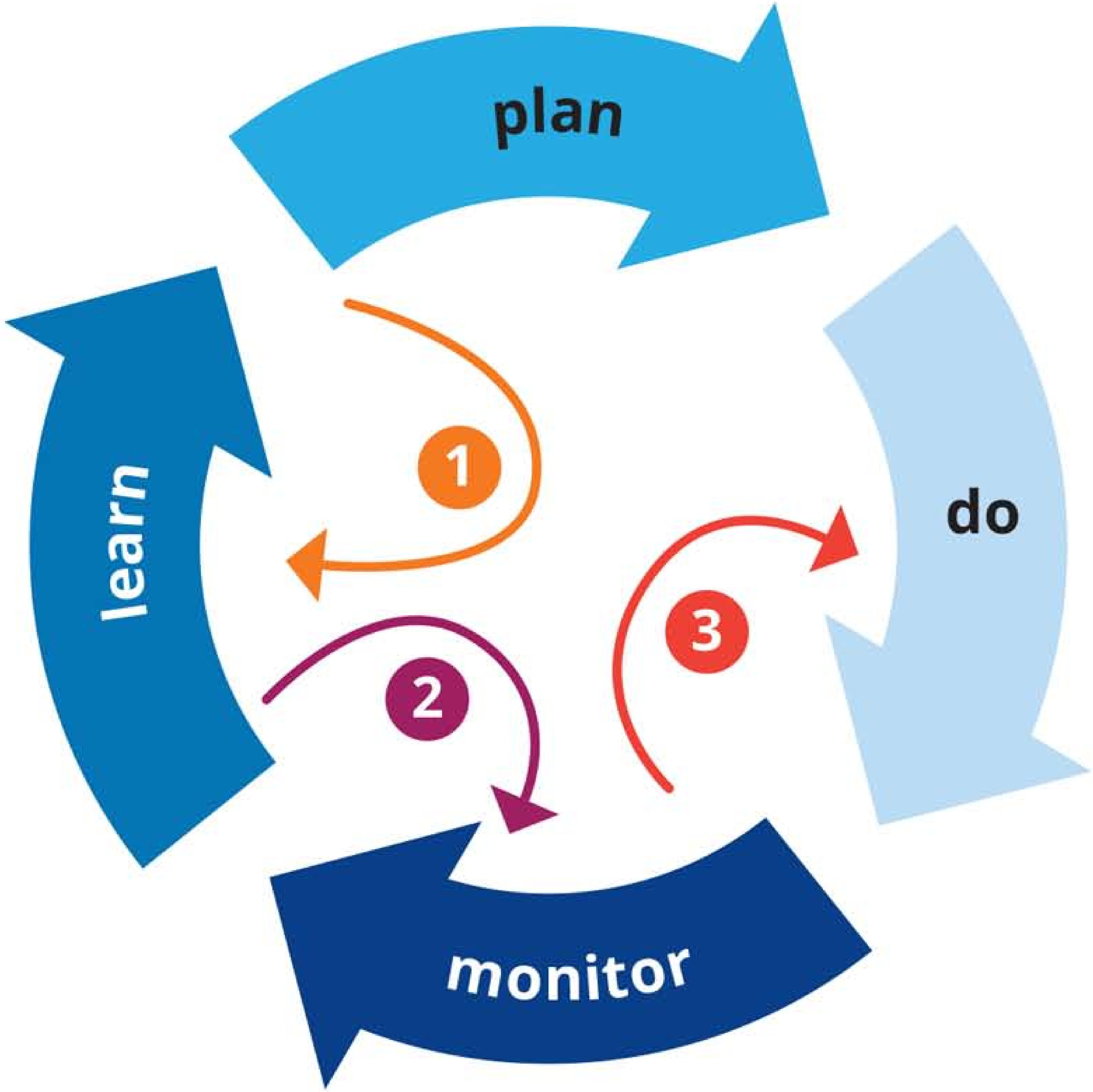
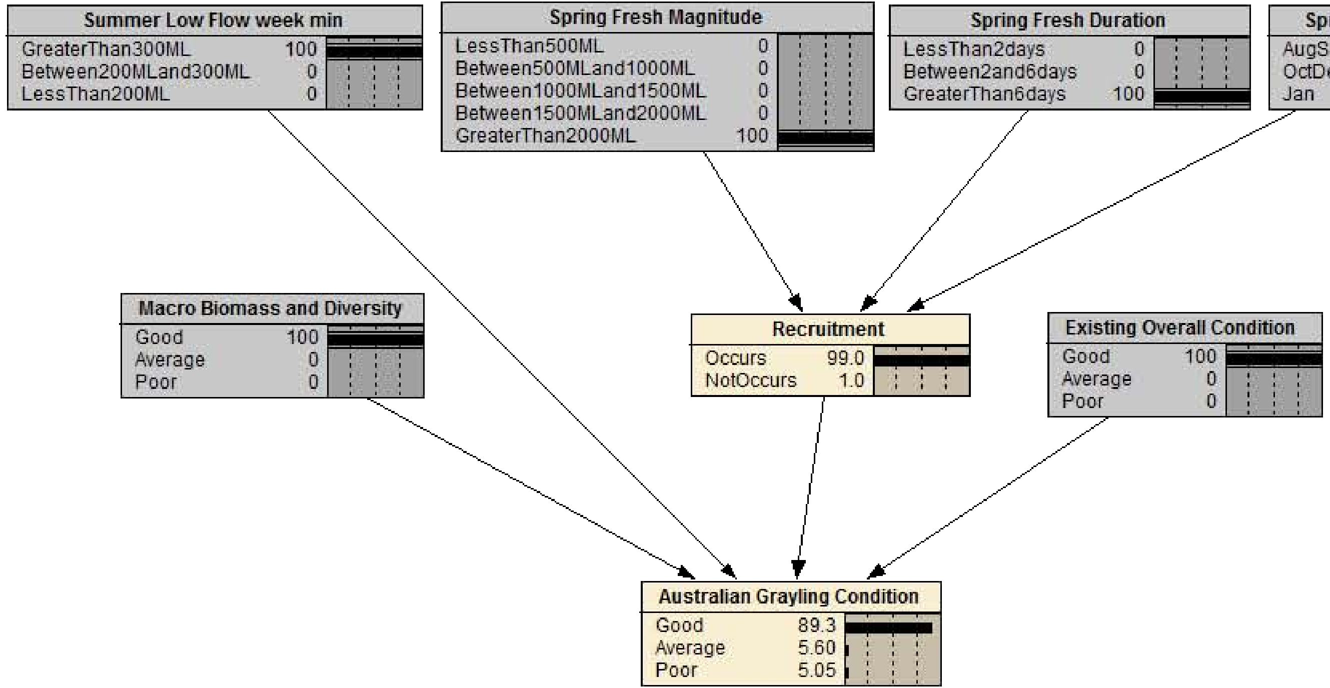


Outer learning cycle:
Long-term goals, plans and actions are reviewed and modified in response to learnings

Inner learning loop 1:
Small changes to strategies and plans are made in response to learnings in between major planning reviews

Inner learning loop 2:
Aspects of monitoring are refined in between planning reviews

Inner learning loop 3:
Aspects of implementation are refined in between planning reviews in response to monitoring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Spring Fresh Magnitude
LessThan500ML 0
Between500MLand1000ML 0
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Between1500MLand2000ML 0
GreaterThan2000ML 100
Spring Fresh Duration
LessThan2days 0
Between2and6days 0
GreaterThan6days 100
Spring Fresh Timing
AugSep 0
OctDec 100
Jan 0
Macro Biomass and Diversity
Good 100
Average 0
Poor 0
Recruitment
Occurs 99.0
NotOccurs 1.0
Existing Overall Condition
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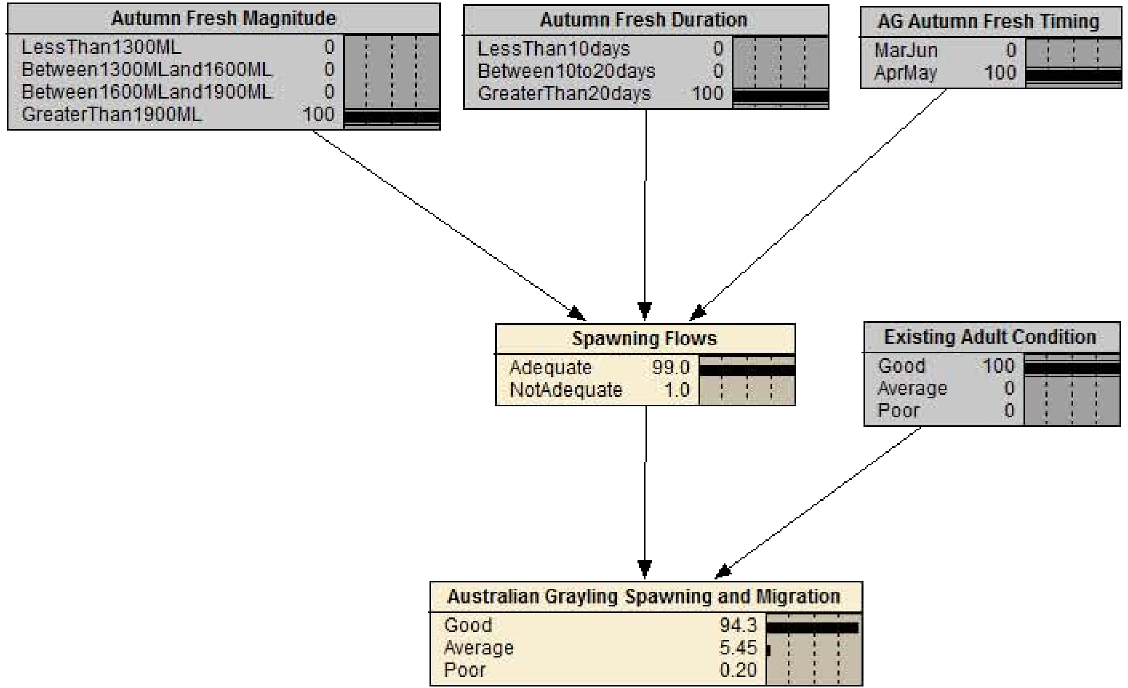
Average 0
Poor 0
Australian Grayling Condition
Good 89.3
Average 5.60
Poor 5.05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Between1600MLand1900ML 0
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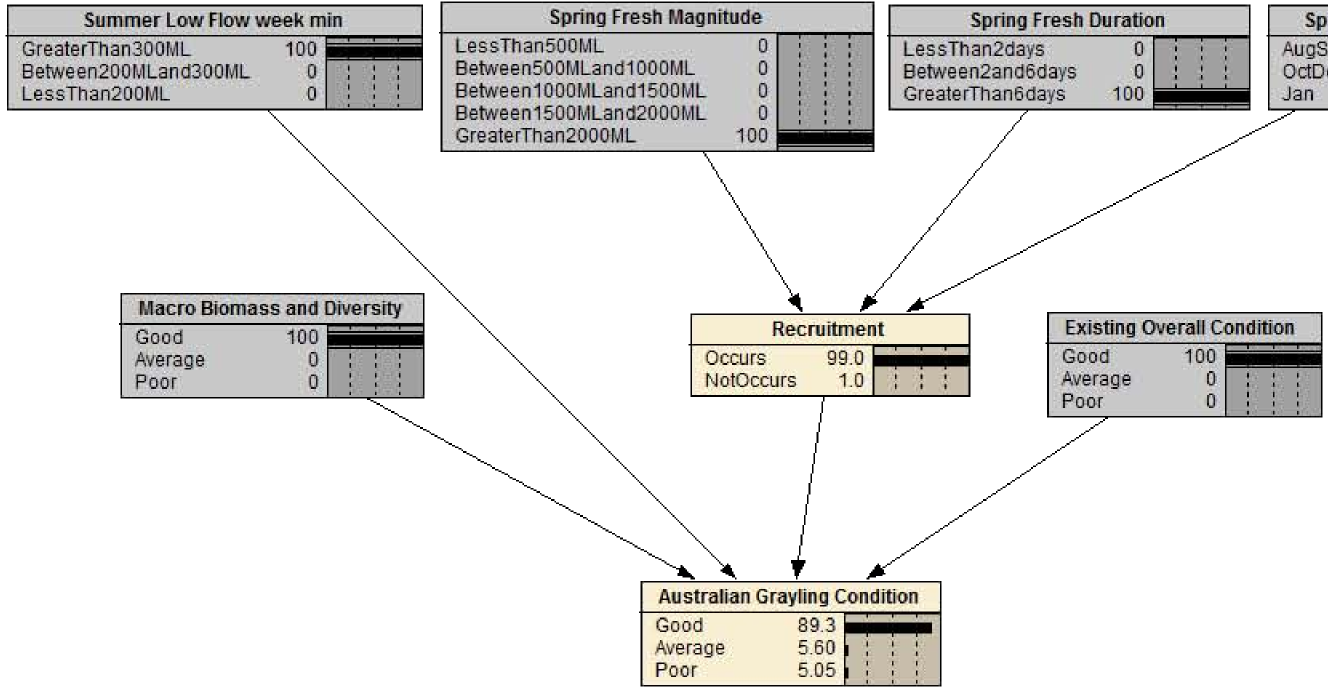
Autumn Fresh Duration
LessThan10days 0
Between10to20days 0
GreaterThan20days 100
AG Autumn Fresh Timing
MarJun 0
AprMay 100
Spawning Flows
Adequate 99.0
NotAdequate 1.0
Existing Adult Condition
Good 100
Average 0
Poor 0
Australian Grayling Spawning and Migration
Good 94.3
Average 5.45
Poor 0.20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Spring Fresh Timing
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OctDec 100
Jan 0
Macro Biomass and Diversity
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Average 0
Poor 0
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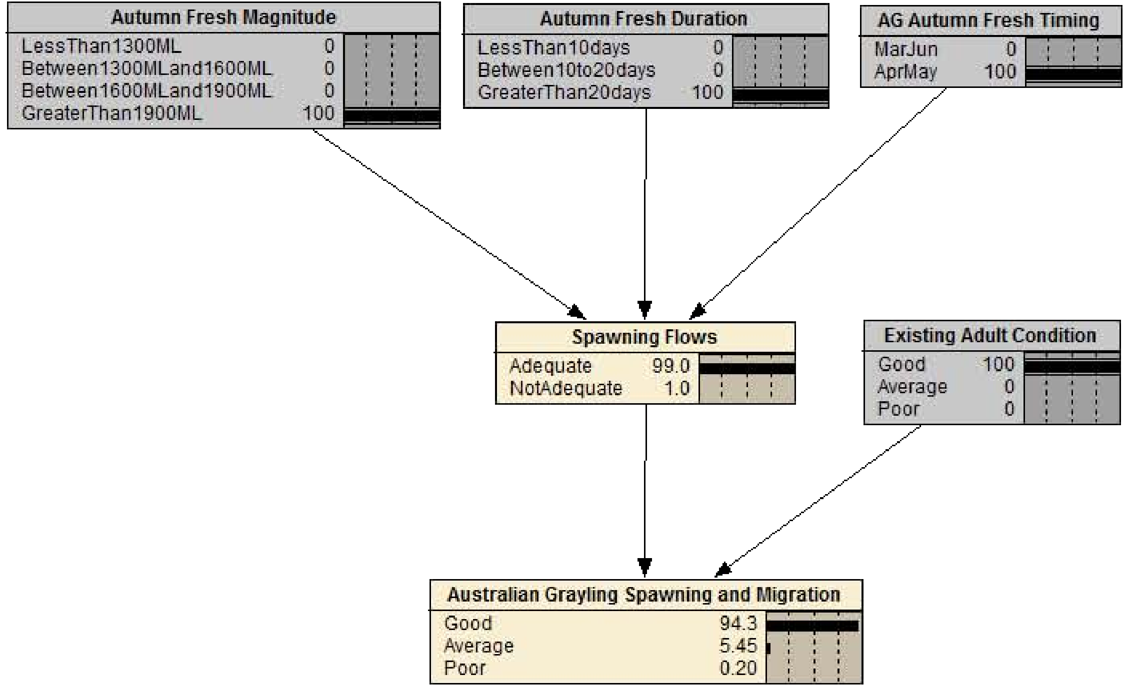
Australian Grayling Condition
Good 89.3
Average 5.60
Poor 5.05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AG Autumn Fresh Timing
MarJun 0
AprMay 100
Spawning Flows
Adequate 99.0
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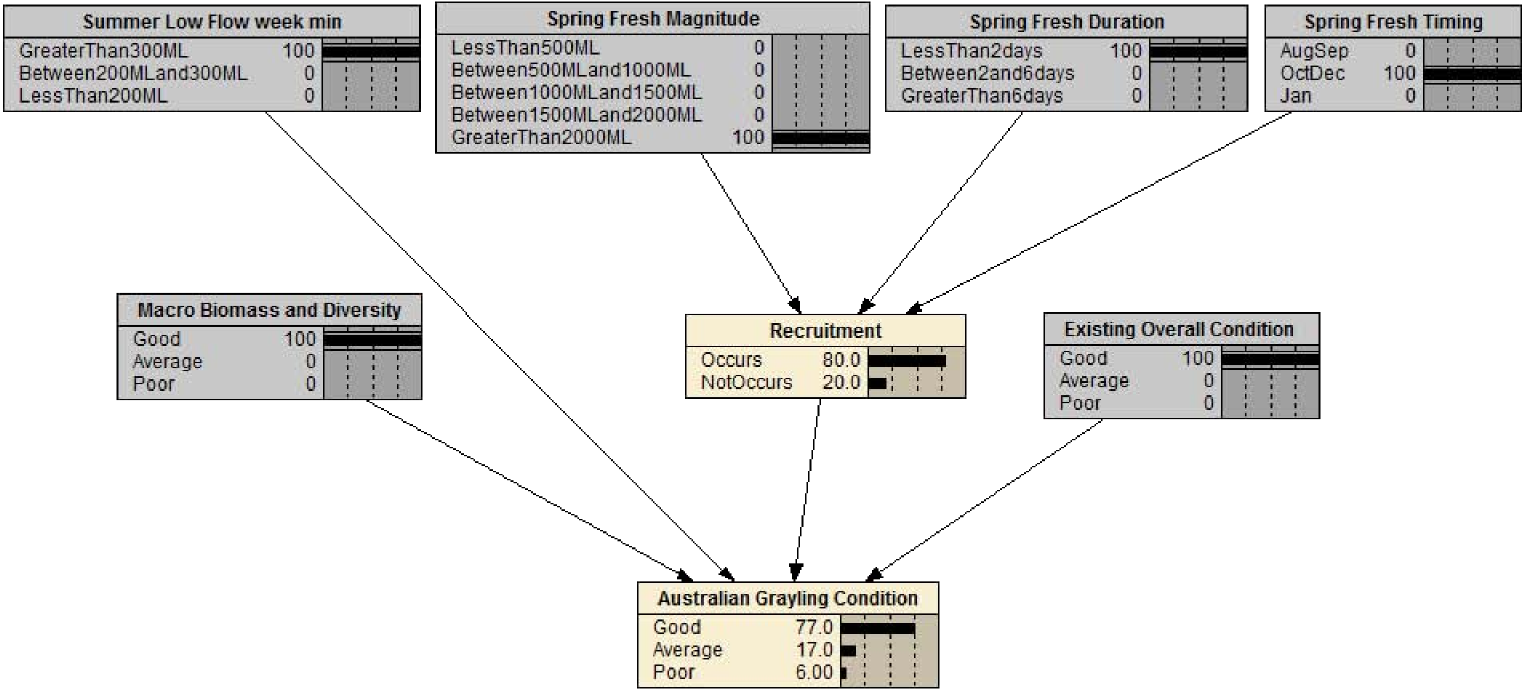
Good 100
Average 0
Poor 0
Australian Grayling Spawning and Migration
Good 94.3
Average 5.45
Poor 0.20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Between2and6days 0
GreaterThan6days 0
Spring Fresh Timing
AugSep 0
OctDec 100
Jan 0
Macro Biomass and Diversity
Good 100
Average 0
Poor 0
Recruitment
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Existing Overall Condition
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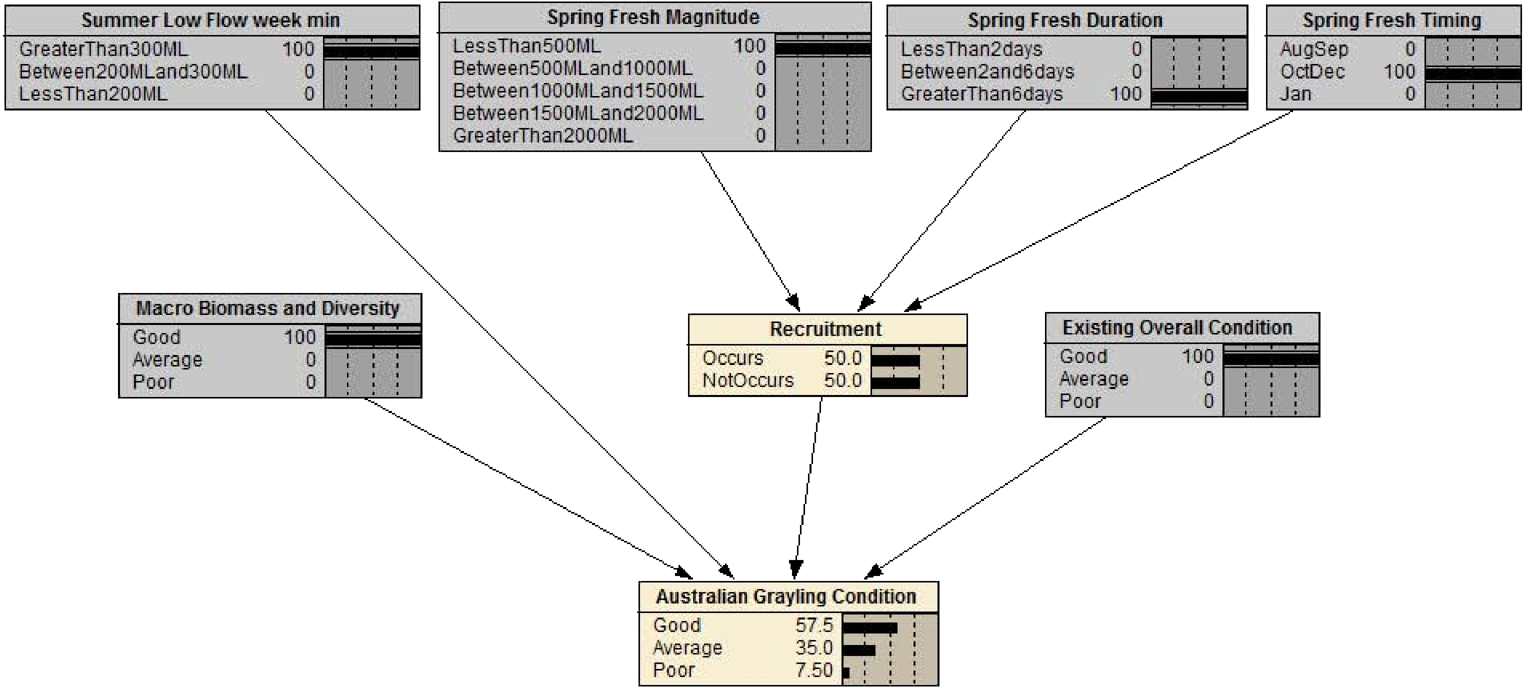
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GreaterThan2000ML 0
Spring Fresh Duration
LessThan2days 0
Between2and6days 0
GreaterThan6days 100
Spring Fresh Timing
AugSep 0
OctDec 100
Jan 0
Macro Biomass and Diversity
Good 100
Average 0
Poor 0
Recruitment
Occurs 50.0
NotOccurs 50.0
Existing Overall Condition
Good 100
Average 0
Poor 0
Australian Grayling Condition
Good 57.5
Average 35.0
Poor 7.50