Predicting water quality responses to a changing climate: building an integrated modelling framework

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Abstract The future management of freshwater resources for human and environmental needs requires an integrated set of tools for predicting the relationship between climate change, water quality and ecological responses. In this paper, we present the early phases of a project for building a Bayesian network (BN) based framework to link ecological and water quality responses to features of the flow regime in the Molonglo and Yass rivers in southeastern Australia. At this stage, the objective is to conceptualize the modelling components and define causal links. Expert elicitation was used to identify important drivers and interactions which influence water quality attributes and related ecological responses.

Key words Bayesian network models; water quality; prediction; climate change; integrated modelling

INTRODUCTION

The potential impact of climate changes on water supply volumes has received much attention both locally (CSIRO, 2008) and internationally (e.g. Cloke *et al.*, 2010; Huang *et al.*, 2010), yet the concomitant changes in water quality (Kundzewicz *et al.*, 2007; Whitehead *et al.*, 2009) are poorly understood. As argued by Postel *et al.* (1996), the socioeconomic and ecological costs of poor water quality are enormous. But we lack the integrated modelling tools for predicting the relationship between climate change, water quality and ecological responses. This limits our capacity to determine the extent and implications of water quality changes from a planning and management perspective.

Integrated modelling combines our understanding of multi-disciplinary processes and drivers as well as the interactions between different parts of a system. Integrated modelling tools are becoming increasingly necessary for managers who have to consider multiple end points (such as social, economic and environmental consequences) in their decision making (Jakeman & Letcher, 2003). The challenge of integrating hydrology, water quality and ecology modelling is the sheer complexity of the systems one is attempting to model, as well as constraints associated with input data (or lack thereof), process knowledge gaps, spatial and temporal complexity of responses and feedback loops (Rode *et al.*, 2010; Clark *et al.*, 2001) which ultimately lead to large uncertainties. In this paper we propose the use of a Bayesian (meta-) Modelling (BN) framework to combine hydrological, water quality and ecological response models to balance model complexity with process understanding and data availability.

BAYESIAN NETWORKS

Bayesian Networks (Pearl, 1988) are acyclic graphical models comprising a series of variables (depicted as nodes) that are linked with arrows representing causal dependence or association. The relationships between nodes can be defined on the basis of process knowledge, statistical correlations or known associations (Varis, 1995). BNs have some significant advantages that makes them useful for ecological modelling and environmental management (Uusitalo, 2007). The ability to clearly and graphically represent cause and effect as well as the capacity to combine different sources and types of knowledge and the explicit consideration of uncertainty are powerful for modelling complex systems.

BNs are being increasingly used to conduct ecological modelling and to assist in environmental management (e.g. Varis, 1995; Marcot *et al.*, 2001; Prato, 2005). They offer considerable advantages in participatory modelling and decision making, but are considered to be limited by the need to discretize continuous variables and their inability to handle time series responses or feedback loops (Uusitalo, 2007). Using BNs as an integrated modelling tool also has the disadvantage of not being able to incorporate the power of existing well-tested models of parts of the system. These disadvantages are starting to be overcome by using BNs as a modelling framework (e.g. Borsuk *et al.*, 2004; Varis & Kuikka, 1997) or by coupling BNs with other types of models (cf. Liedloff & Smith, 2010).

CASE STUDY AREA

This pilot study focuses on the Upper Murrumbidgee River and two of its tributaries: the Molonglo and Yass rivers (Fig. 1). According to the Molonglo River Rescue Action Plan document, the river's biodiversity is endangered by existing and future threats including climate change effects on inflows regimes and water quality, increasing salinity, and urban development.

The Yass River is the next major downstream tributary of the Murrumbidgee River from the Molonglo River and has a long history of water quantity and quality problems (DLWC, 1999). High salinity is a major issue within the Yass Catchment, as a result of broad-scale clearing of native vegetation for agricultural production. The Yass River provides an important point of comparison for the lower sections of the Molonglo River, allowing an assessment of the ecological responses that might be expected as a consequence of elevated concentrations of salts.

MODELLING PROCESS

BN modelling proceeds through six major phases: (1) review, (2) scoping, (3) network conceptualization, (4) data population, (5) model validation and verification, and (6) using the model for scenario analysis (Ticehurst *et al.*, 2007). In this paper, we describe the process and outputs of the first three phases.

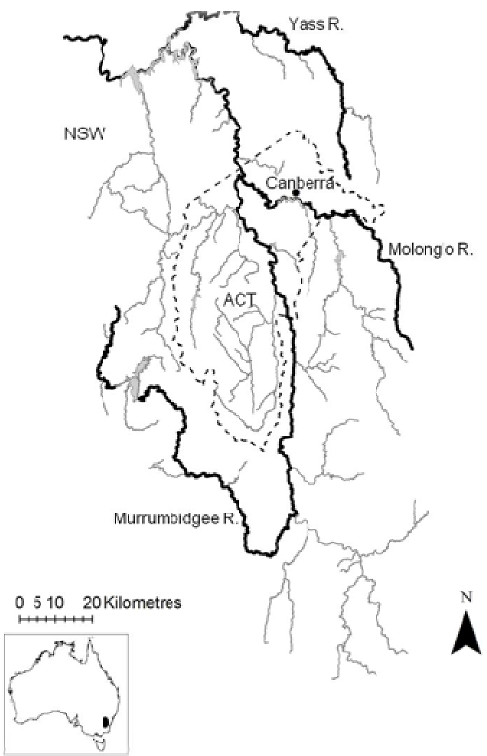

Fig. 1 Location of the Upper Murrumbidgee Catchment in southeastern Australia.

Review phase

The initial step in the model development process was a review of relevant documents, reports and scientific literature to build an understanding of the issues and appropriate modelling techniques. As a part of this phase, a high-level framework model was developed to represent the modelling components and their inter-links.

Scoping phase

This phase started with a small-scale expert elicitation workshop which included researchers in hydrology, river ecology and local government, and agency stakeholders. The workshop had three objectives: (1) to identify a preliminary list of ecological responses and related water quality attributes that modelling may target, (2) to identify data requirements and sources, and (3) identify stakeholders and experts who could participate in the construction of the BN.

The research team used the outcomes of this workshop to build a series of preliminary influence diagrams that describe the important drivers and interactions which influence water quality attributes and related ecological responses. These pilot-BNs were used as a basis for more focused discussions among experts and stakeholders in the next phase.

Network conceptualization phase

The objective was to identify relevant variables and relationships. Here the challenge is to tune the model complexity and resolution to the modelling purpose and available data (Rode *et al.*, 2010). For this, we take an outcome-driven approach where the BN structure is determined by key ecological responses defined by stakeholders.

A group of 14 experts and decision makers were involved in a half-day workshop to define the important variables, links and states of variables. Preliminary diagrams were circulated prior to the workshop. At the beginning of the workshop, participants were introduced to the pilot-BNs and were invited to review the networks and give their feedback on the following: (i) missing elements and links; (ii) variables that can be used to quantify elements; (iii) the magnitude of change in system states in relation to ecological outcomes (i.e. thresholds); and (iv) the key synergistic effects of changes in water quality attributes and inflows regime on ecological responses.

We found that starting with a preliminary conceptualization was useful for focused dialogue, especially among experts/stakeholders from different backgrounds. As a result, output from the workshop was used to construct more detailed BN components and define the input–output links between the modelling components.

INTEGRATED BN-BASED MODELLING FRAMEWORK

The proposed framework comprises three interlinked modelling components: process-based hydrological models, BN-based water quality and ecological responses models (Fig. 2). These components represent the cause-and-effect assumptions linking drivers (i.e. management policies and uncontrollable conditions) to flows regimes, water quality attributes and related ecological outcomes. Table 1 gives an overview of the key features of the modelling components.

Hydrological component

The IHACRES rainfall–runoff model (Croke & Jakeman, 2004) is being used to simulate the hydrological response of the catchment. The model of the upper Murrumbidgee is a broad-scale (i.e. low spatial resolution) daily time-series model comprising a network of approximately 13 catchment-scale models (~1000 km^2), with flows routed to the outlet. Output from the model provides input to the water quality models, as well as direct input to the ecological response models (Fig. 2).

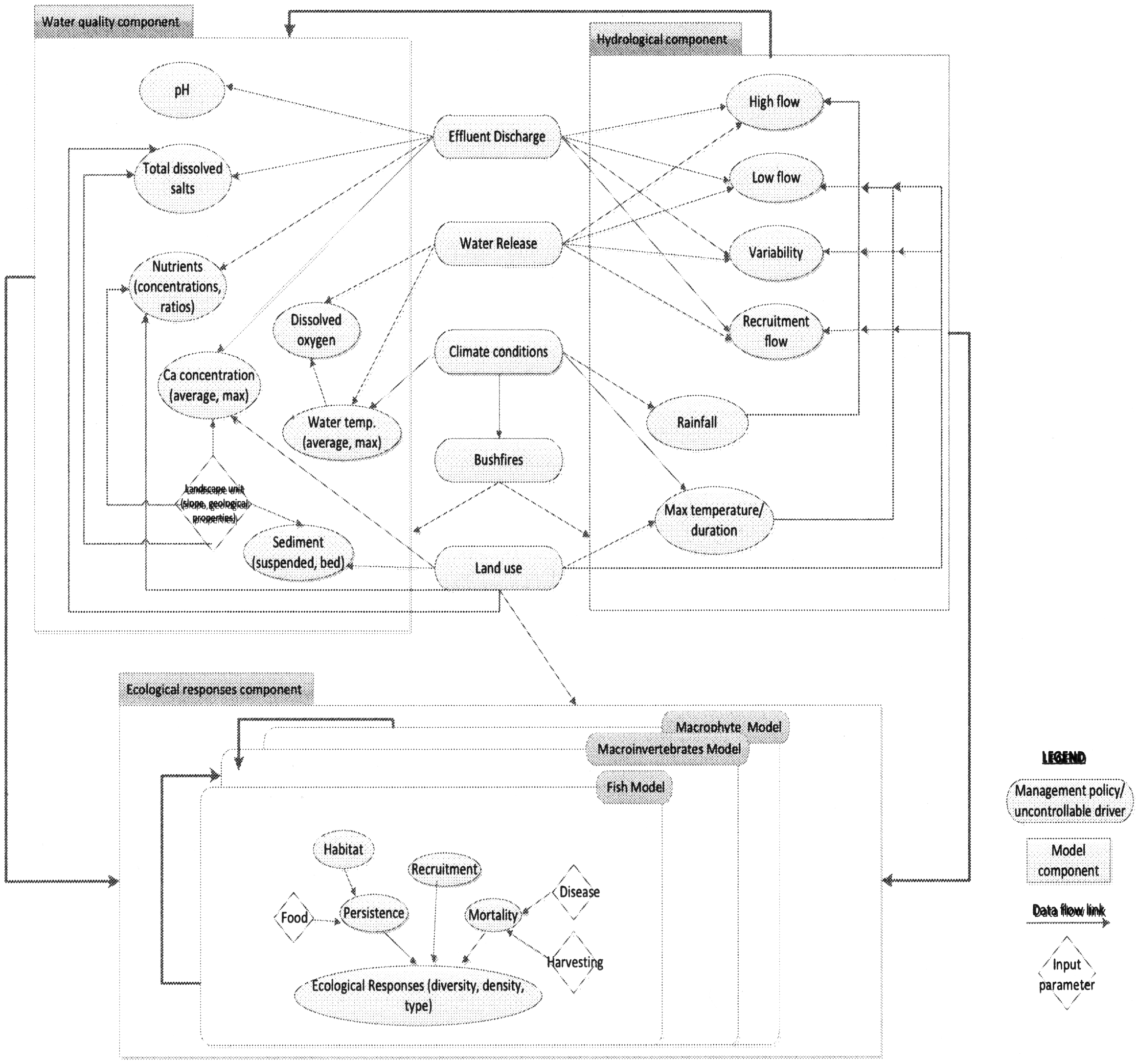

Fig. 2 Schematic diagram of the nested integrated modelling framework.

Table 1 The features of the components of the integrated modelling framework.

Features	Hydrological	Water quality	Ecological responses
Function	Simulates streamflows along river reach.	Captures the influences of changes in the flow regimes on water quality attributes.	Captures the effect of changes in the flow regimes and water quality on ecological indicators.
Scale	Sub-catchment scale	River-reach scale	Population scale
Modelling technique	IHACRES rainfall–runoff model	BN and regression models	BN
Sub-components			Fish, macroinvertebrates, macrophytes
Input data and parameters	Climate data, GIS land-use data, and historical flow records	Historical water quality and flow records, water quality thresholds	Historical data sets, information from published studies; expert opinion
Output	Flow indicators (flows variability, low/high/ recruitment flows)	Water quality attributes (water temperature, salinity, dissolved oxygen, calcium concentration , pH, nutrient (nitrogen, phosphorus) concentrations and ratios	Population information: density, diversity, type (e.g. native/ introduced species ratio)

Water quality component

Two approaches to modelling water quality are being used: (1) spatially-lumped statistical modelling of water quality time series; and (2) using BNs to learn water quality probability distributions from historical data sets. The former is used where a considerable length of record exists (e.g. salinity data from continuous data collection) and models can be confidently calibrated. The latter is used where limited data are available (e.g. nutrient data from spot measurements) and the concentrations are linked to flow percentiles, land use and geology. Outputs from the hydrological modelling as either time series or flow percentiles are being used to predict changes in water quality under different climate scenarios.

Ecological response component

The approach adopted was to use ecologically relevant water quality attributes to define the water quality modelling needs. Variations in water quality are a form of natural disturbance that contribute to the structure of ecological communities. There are three types of disturbances to which ecosystems respond (Lake, 2000): (1) pulse disturbances are short term and often intense events (e.g. a spike in salinity); (2) press disturbances arise over a short term and result in a new constant level (e.g. discharge from a water treatment plant); and (3) ramp disturbances are a steady change over time (e.g. increasing turbidity as catchments are cleared). Thus the aspects of the water quality regime that need to be modelled are the number, duration and sequencing of threshold exceedences as well as long-term changes in average concentrations.

Stakeholders identified that the key ecological assets within the upper Murrumbidgee system were fish, macroinvertebrates and macrophytes, and within each of these water quality changes could affect the density and diversity of the population as well as community structure (e.g. influencing a change from native to non-native species). For tractability, separate models for each ecological endpoint have been developed, but it is expected that as the models are populated with probabilities, there will be considerable commonality that will allow the structures to be simplified and reduce input requirements. The preliminary model structure (Fig. 2) identified key water quality attributes as water temperature, dissolved oxygen, pH, salt (sodium (Na) and calcium (Ca)) concentrations, nutrient concentrations, turbidity and fine sediment.

DISCUSSION AND CONCLUSION

This paper presents a BN-based modelling framework that links output from hydrological modelling to water quality models based on available monitoring data, to predict the combined effect of changes in flow regimes and water quality on ecological responses (i.e. abundance and diversity of macroinvertebrates, fish and macrophytes). The complexity of relationships between hydrology and ecological responses is generally considered to make predictions difficult (Nyhus *et al.*, 2007; Overton *et al.*, 2009). By using a response-driven approach where the model boundary and structure are determined by the key ecological responses (i.e. model endpoints) it is possible to manage the complexity of the modelling task, e.g. if fish cannot live in water that has DO concentrations below a certain level, then it is only necessary to know if the concentration is above or below this level, thus simplifying the modelling required. Moreover, this approach keeps the focus on ecological indicators that represent the stakeholder's values and interests.

Using BN modelling frameworks can overcome the limitations associated with a reliance on the water quality modelling component on historical data sets. While the Molonglo and Yass catchments are data rich in comparison with many other Australian rivers, there are likely to be future climate scenarios that produce conditions outside the bounds of historical data. Targeting the modelling to thresholds and using the probabilistic capability of the BN allows maximum predictive capacity from the historical data. The ability of the BN to include multiple knowledge sources (Pollino *et al.*, 2007) means that expert opinion can be used to enhance the predictive capacity of the models and the incorporation of process based pollutant generation modelling such as CatchMODS (Newham *et al.*, 2004) may also improve the capability of the modelling effort.

The presented framework is a work in process. The next phase of the project involves using available data to construct the conditional probability tables and populate the BN structure. Validation and verification tests will be carried out to increase confidence in the output of the models before the framework is used for running and analysing scenarios.

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