

The effects of climate change on ecologically-relevant flow regime and water quality attributes

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Abstract The management of freshwater ecosystems is usually targeted through the regulation of water quantity (limiting diversions and providing environmental flows) and regulation of water quality (setting limits or targets for constituent concentrations). Climate change is likely to affect water quantity and quality in multiple ways and the future management of freshwater ecosystems requires predictions of plausible future conditions. We use a suite of ecologically-relevant hydrological indicators to determine the significance of projected climate-driven hydrological changes in the Upper Murrumbidgee River Catchment in south eastern Australia in relation to river regulation. We also determine the possible water quality changes (in relation to guidelines for aquatic ecosystem protection) associated with the climate change projections to identify the combined effects of hydrological and water quality changes. The results of this study suggest that river regulation has resulted in greater changes to ecologically-relevant streamflow characteristics than climate change

scenarios that involve a 1 and 2 °C temperature rise in the Upper Murrumbidgee River Catchment. In contrast to the projected hydrological changes, Bayesian Network modelling suggests very small changes to violations of water quality thresholds designed to protect aquatic ecosystems as a result of climate change. By identifying key components of the flow and water quality regimes that may be affected by climate change, we are able to provide managers with information that assists in developing adaptation initiatives.

Keywords Climate change · Flow regime alteration · Indices of hydrological alteration · Freshwater ecology · Water quality · Bayesian network

1 Introduction

Regulation and climate are two major drivers of significant changes in river flow and water quality regimes around the world. Regulation, to supply water for human needs, is well recognised as one of the major contributors to declining river health (Nilsson and Berggren 2000; Gehrke et al. 2006; Ward and Stanford 2006). Changes in the magnitude, duration and timing of flow in rivers caused by regulation produces modified water quality characteristics, habitat and ultimately biological communities (Poff et al. 2007; Dynesius and Nilsson 1994; Marchant and Hehir 2002). Significant changes to runoff, streamflow (Arnell 2003; Thodsen 2007; CSIRO 2008) and water quality (Delpla et al. 2009; Wilson and Weng 2011; Murdoch et al. 2000; Whitehead et al. 2009) are also widely predicted to occur as a result of a changing climate, leaving freshwater ecosystems particularly vulnerable.

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Australia is particularly exposed to changes in hydrological regimes with communities and ecosystems across the country at risk (PMSEIC Independent Working Group 2007; IPCC 2007). As a consequence, the future management of freshwater species and ecosystems, particularly those that are at or near their climate limits for survival, requires prediction of the magnitude of changes in flow and water quality likely to occur as a result of the combined effects of climate change and river regulation.

Prediction of the hydrological effects of climate change is generally based on volumetric changes (such as seasonal and mean annual flows) reflecting a need to understand water supply impacts of future climates (Heathwaite 2010). In spite of a general understanding that hydrologic regimes play a major role in structuring in-stream biological communities (Poff et al. 1997; Richter et al. 2003) the assessment of hydrological impacts on ecosystems has been at best qualitative and requires purposeful identification of flow changes beyond longer-term volumetric attributes.

Numerous statistical measures of ecologically-relevant hydrological changes have been developed to understand the human alteration of flow regimes (e.g. index of hydrological alteration, IHA, Richter et al. 1996; Dundee hydrological regime alteration method, DHRAM, Black et al. 2005; Ecosurplus and Ecodeficit, Vogel et al. 2007; Flow Stress Ranking, SKM 2005). While their main purpose has been to understand the nature of human changes on flow regimes with the focus on ecosystem health, they can be equally applied to understand the changes in flow that may be brought about by climate variation (Kim et al. 2011). Identifying which flow components are likely to be altered by regulation and/or climate conditions is essential to help focus management efforts. For instance, sensitivity to climate change may differ in natural versus managed aquatic ecosystems. Regulated rivers may experience fewer climate-driven changes than would unregulated rivers because the flow is already controlled, but there may also be increases in demand for water that amplifies existing regulation effects (Meyer et al. 1999).

In addition to predicted climate-driven hydrological changes, there is also growing concern about the consequences of climate change for water quality and its effect on freshwater ecosystem health. Analysis of historical data sets suggests that changes in precipitation, temperature and the frequency and severity of extreme events (e.g. drought) can have marked effects on water quality attributes. Such signals, however, are often masked by the effects of landuse modifications (Murdoch et al. 2000; Delpla et al. 2009; Whitehead et al. 2009). Therefore, effort is currently being directed at understanding the effects of both landuse and climate change to predict alterations in water quality attributes (Interlandi and Crockett 2003; Wilson and Weng 2011; Tong et al. 2012). For Australian conditions, a

paucity of long-term water quality data sets means that site-based, time series modelling approaches are difficult to implement and alternative approaches are required that provide predictive power when water quality datasets are at best not fully informative and contain gaps in spatiotemporal coverage.

This paper aims to determine the effects of climate change and regulation on stream flow and water quality regimes in the Upper Murrumbidgee River Catchment (UMRC), south eastern Australia. To achieve this, we applied two approaches. First, we used a suite of ecologically-relevant hydrological indicators to assess the changes in flow regimes from natural (i.e. unregulated) and regulated conditions under a set of climate scenarios. Second, we used a Bayesian Network (BN) modelling approach to calculate the probability that a set of water quality attributes may violate thresholds designed specifically for the protection of aquatic ecosystems for the same set of climate scenarios.

2 Study area

The Murrumbidgee River is the third largest river in the Murray Darling Basin (MDB), in south eastern Australia (Fig. 1). The UMRC (13,144 km²) extends from the headwaters on the Long Plain in Kosciusko National Park to the Burrinjuck Dam and encompasses the tributaries of the Bredbo, Numeralla, Goodradigbee, Cotter and Yass Rivers. The rivers of the catchment are regulated with major dams on the Murrumbidgee, Cotter and Queanbeyan Rivers (Fig. 1). This is in addition to pumped transfer systems to extract and transport water from the Murrumbidgee River to Googong and Cotter dams.

Water quality in the UMRC varies widely. For example, the quality of water flowing from the Snowy Mountains into Tantangara Dam is good, with low to moderate total phosphorous concentrations, extremely low total nitrogen concentrations, low turbidity and low concentrations of dissolved salts (Barlow et al. 2005; Snowy Scientific Committee 2010). This can be attributed to the catchment being in a National Park. As the Murrumbidgee River flows downstream there is a gradual decline in water quality as the non-point source catchment inputs of turbidity, nutrients and salts increase (Snowy Scientific Committee 2010). Generally, rivers of the UMRC display very low salinity. The Yass Catchment and the urbanised Cooma region are exceptions to this with extensive areas subject to dryland salinity (DLWC 1995; Acworth et al. 1997).

Seven regions within the UMRC were selected for use in this paper, capturing areas of differing landuse, geology and flow management practices (Table 1; Fig. 1).

Fig. 1 Map of the Upper Murrumbidgee River Catchment showing the major water courses, landuse within the catchment, water reservoirs and the seven focus regions numbered as follows: 1 Goodradigbee; 2 Gudgenby; 3 Upper Cotter; 4 Mid Molonglo; 5 Ginninderra; 6 Numeralla; 7 Yass

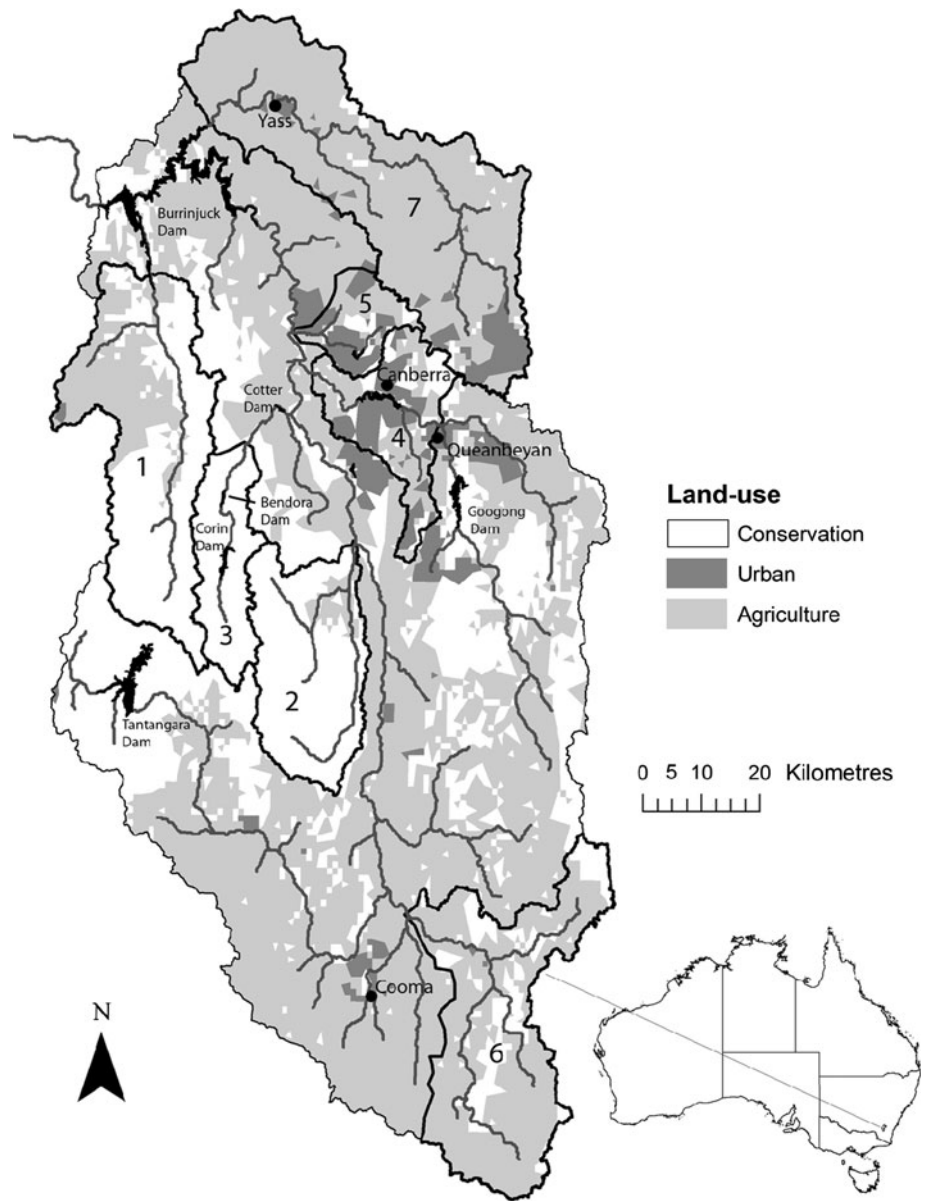


Table 1 Focus regions within the Upper Murrumbidgee River Catchment

Region	Landuse	Flow management	Flow sites (n)	Water quality sites (n)
Goodradigbee	Conservation	Unregulated	2	11
Gudgenby	Conservation	Unregulated	2	3
Upper Cotter	Conservation	Regulated	5	8
Mid Molonglo	Urban	Regulated	5	14
Ginninderra	Urban	Regulated	2	5
Numeralla	Agriculture	Unregulated	2	19
Yass	Agriculture	Unregulated	6	14

Landuse refers to the dominant landuse within the region based on percentage area

3 Data sources and methods

3.1 Climate data and flow modelling

Historical climate data and future projections of rainfall, potential evapotranspiration (PET) and runoff were obtained from the South Eastern Australia Climate Initiative (SEACI). Historical daily rainfall and PET data extend from 1895 to 2008. The climate projections used are generated from 15 global climate models (GCMs) for the A1B emission scenario at both a 1 and 2 °C increase in atmospheric temperature, resulting in a total of 30 climate scenarios. SEACI uses an empirical daily scaling method to downscale climate predictions to catchment scale rainfall and PET, considering changes in future mean seasonal rainfall, PET and the distribution of daily rainfall. Runoff time series are generated as gridded daily data (at $\sim 5 \times 5$ km resolution) using the daily rainfall-runoff model SIMHYD with a Muskingum routing component. The model was calibrated using 1975–2006 daily streamflow data. For a detailed description of the climate scenarios and runoff generation, readers are referred to Chiew et al. (2009).

To estimate the inputs to flows at selected sites within each region (See Table 1), the SEACI runoff estimates were aggregated for all cells within each catchment. To convert these inputs to streamflows, the inputs were routed to the selected site. Comparison of the aggregated streamflow estimates with observed streamflows at gauged sites showed no significant correlation indicating a need for the addition of a routing model. This implies that at the scales being considered in this study, the routing of water represented in the SEACI runoff estimates (5×5 km grid cell) dominates over the routing through the Upper Murrumbidgee catchment.

Streamflow estimates were produced for all sites for “natural” conditions (assuming no dams or regulation present in the catchment). Groundwater—surface water interactions add complexity to the routing of flows through transmission losses and the addition of baseflow to the river. This can lead to an error in the volume of streamflows as well as the temporal distribution of stream flows. To estimate the uncertainty in the stream flows at ungauged locations the estimated time series of streamflow values were compared with observed flows at gauged sites to assess the accuracy of the modelled flows.

3.2 Assessing hydrological alteration

The degree of hydrologic alteration is a measure of the difference between two flow regimes: one that represents “impacted” conditions, and the other, “natural” conditions. Hydrological indicators (statistical measures) are

commonly used to measure the degree of hydrologic alteration. The risk of “flow-related” threats to ecosystems increases as the degree of alteration from natural conditions increases.

We used two complementary sets of ecologically relevant hydrological indicators to analyse and compare the effect of regulation and climate change on the degree of hydrological alteration: (1) the IHA (Richter et al. 1996) commonly used across the northern hemisphere to assess the eco-hydrological effects of alteration in flow regimes caused by regulation (e.g. dams, diversions) and climate conditions (e.g. Suen 2010); and (2) flow stress indicators (FSI, SKM 2005), a suite of variance corrected indicators developed specifically for the highly variable hydrology of Australian rivers (Finlayson and McMahon 1988). Table 2 gives an overview of the two sets of indicators.

The IHA comprises 33 indicators that characterize the differences in flow regimes, some of which are highly correlated and others that may be invariant depending on the hydrological character of the region being assessed. Several approaches have been developed and used to select a small, representative set of independent indicators that can describe the degree of hydrologic alteration, including: expert judgment, correlation coefficients (e.g. Gao et al. 2009), principle component analysis (e.g. Olden and Poff 2003), scoring methods (e.g. Black et al. 2005; Marsh 2010), and data mining techniques (e.g. Yang et al. 2008). In this study, non-parametric Kendall’s Tau correlation (Kendall 1938) was used to exclude highly correlated indicators (>0.8) while retaining those that showed the highest degree of alteration. To select the indicators that represent the highest degree of alteration, non-parametric statistics (median, 25th percentile and 75th percentile) were calculated for each indicator, then using the “natural” data set as the baseline, the absolute percentage change in these statistics were calculated. The percentage change in each statistic was then given a score using the following rule: 0 (if minor change, $<30\%$), 1 (if moderate change, $30\text{--}70\%$), and 2 (if major change, $>70\%$) and the scores summed across all four selected climate scenarios (refer to Sect. 3.3 for the selection of scenarios). The maximum score was 8 (major change across all four selected climate scenarios); and the minimum was 0 (minor change across all four selected climate scenarios). Indicators were selected that scored 50 % or more of the maximum available 24 points across all the statistics (i.e. three statistics \times eight maximum points). This resulted in the selection of six indicators: mean monthly flows in February, mean monthly flows in March, 30-day Minima, frequency of high pulses, frequency of low pulses, and duration of low pulses.

The FSI comprises ten indicators that characterize the differences in flows regimes and all indicators were retained to assist in interpreting the changes that were

Table 2 Overview of the two approaches used to assess hydrological alteration

	IHA	FSI
Use	Assess the eco-hydrological effects of regulation (widely used in the northern hemisphere)	Assess the eco-hydrological effect of regulation relative to the natural variability of the flow regimes (developed specifically for Australian conditions)
Characteristics	Measures intra- and inter-annual changes in flows, using five ecologically-relevant components of flow regimes: 1. Magnitude of monthly flow conditions 2. Magnitude and duration of annual extreme flow conditions 3. Timing of annual extreme flow conditions 4. Frequency and duration of high and low pulses 5. Rate and frequency of flow condition changes	Measures variance corrected changes in flow using four ecologically-relevant components of flow regimes: 1. Magnitude and variation of annual flow conditions 2. Magnitude and duration of annual extreme flow conditions 3. Timing of annual extreme flow conditions 4. Frequency of duration of high and low pulses
Input data	Paired time series flow data (typically pre and post impact data are used): regulated and unregulated time series; current climate and future climate time series.	Paired time series flow data (typically modelled data are used): regulated and unregulated time series; current climate and future climate time series.
Number of indicators	33 indicators with a subset of indicators selected to represent the changes	ten indicators
Indicator range	0 to >1, where 0 represent no alteration and >1 represents maximum alteration. Scores are absolute values and give no indication of the direction of change.	0–1, where 0 represent no alteration and 1 represents maximum alteration. Note that for the purposes of the current paper, the original FSI indicator scores have been modified (using 1-FSI score). Scores are absolute values and give no indication of the direction of change.
Indicator aggregation	Euclidean distance (refer Eq. 1)	Average
References	Richter et al. 1996; Black et al. 2005	SKM 2005; Slijkerman et al. 2007; Davies et al. 2010

observed. These indicators represent changes in: mean annual flow, seasonal amplitude, low flow, high flow, low flow spells, high flow spells, proportion of zero flows, flow duration, variation and seasonal period.

To facilitate comparison across regions, each set of indicators was combined to produce overall measures of hydrological alteration. For the IHA, indicators were combined using the Euclidean distance (Eq. 1), and for the FSI, indicators were combined using an average.

$$IHA.ED_j = \frac{1}{100} \sqrt{\left[\frac{1}{n} \sum_n (I_i)^2 \right]} \quad \forall j = 1 \dots m \quad (1)$$

where, IHA.ED_j is the overall measure of hydrologic alteration for region j, I_i is the absolute percentage change in a selected IHA indicator (i), n is the number of selected IHA, m is the number of region

For the overall IHA index (IHA.ED) and FSI index (FSI), values of 0 for a site under a given scenario represent conditions that are identical to that of ‘natural’ conditions. For impacted sites, IHA.ED takes a value close to 1, with highly impacted sites showing scores greater than one. FSI is confined to values between 0 and 1, with an FSI of 1 representing a complete change in the hydrological character of the stream.

3.3 Selecting plausible climate scenarios

To reduce the number of scenarios (originally 30) to a manageable set, we selected those scenarios which produced a range of changes in the flow relative to the natural flow condition. This was carried out in three steps. First, we calculated the full suite of IHA parameters for all sites and all 30 climate scenarios. Second, we calculated non-parametric inter-annual metrics (i.e. median, 25th percentile, and 75th percentile) for each data set. Using the ‘natural’ data set as a baseline, we calculated the absolute percentage change in inter-annual metrics under each climate scenario. Third, metrics are scored according to the following rules (Richter et al. 1998): 0 points if only minor change occurs (<30 %), 1 point if moderate change occurs (30–70 %), 2 points if major change occurs (>70 %). Summing up all the points for a given climate scenario gives an indication of the potential degree of flow alteration. This results in four scenarios categorised into the following classes:

- Moderate alteration: INMCM_1 and INMCM_2
- Major alteration: CSIRO_1 and CSIRO_2.

Flows derived for each of these four climate scenarios were compared against a baseline scenario (historical climate conditions) and a regulated scenario (Table 3).

Table 3 Climate scenarios used for analysis

Scenario	Description	Temperature increase
Baseline	Pre-regulation using historical climate	None
Regulation	Regulated using historical climate	None
INMCM_1	INMCM GCM developed by Institute of Numerical Mathematics, Russia	1 °C
INMCM_2	INMCM GCM developed by Institute of Numerical Mathematics, Russia	2 °C
CSIRO_1	CSIRO-MK3.0 GCM developed by CSIRO, Australia	1 °C
CSIRO_2	CSIRO-MK3.0 GCM developed by CSIRO, Australia	2 °C

3.4 Water quality predictions

To address the second objective of this study, a probabilistic approach to water quality predictions was adopted using BNs to calculate the probability that a water quality attribute/parameter violates thresholds set for the protection of aquatic ecosystems. BNs (Pearl 1988) are directed acyclic graphical models comprising a series of nodes (variables) connected by arrows representing causal dependence or association. The causal dependence is described probabilistically and can be defined on the basis of statistical correlations, expert judgement, process knowledge or a combination of input depending on the information available. BNs are being increasingly used to model ecological systems (Borsuk et al. 2003; McCann et al. 2006; Ticehurst et al. 2007; Allan et al. 2012) as well as being used to assist decision making within water resource management (Castelletti and Soncini-Sessa 2007; Molina et al. 2010; Aguilera et al. 2011).

It has been proposed that BNs can be used for surface water quality assessment and prediction (Reckhow 1999) and there are some emerging applications for groundwater quality studies (Aguilera et al. 2013). Most applications are directed at eutrophication processes and biological water quality (e.g. Borsuk et al. 2003; Arhonditsis and Brett 2005; Stow et al. 2003). Here, we use BNs to assess the probability that water quality parameters violate thresholds designed to protect aquatic ecosystems given changes in climate. This approach is conceptually similar to that illustrated by Zhang and Arhonditsis (2008) and Pike (2004) to assess water quality standard violations.

3.4.1 BN model structure

Good practise in BN modelling (Chen and Pollino 2012) was followed in the development of the BN for this research. Given that we are interested in understanding water quality responses to changes in climate, and in

particular to changes in flow regimes, the approach adopted was to start with a simple model reflecting the key drivers of ecologically-relevant water quality attributes in the catchment. The water quality attributes important for aquatic ecosystems in the UMRC were identified as being temperature, dissolved oxygen, pH, salts, nutrients (total phosphorus, TP, and total nitrogen, TN) and fine sediment (Dyer et al. 2011). Each water quality attribute was linked to flow and landscape features thought to influence concentrations, thereby producing the conceptual model shown in Fig. 2.

A significant challenge in using BNs for water quality modelling was noted when the initial conceptual model (Fig. 2) was converted to a BN (Fig. 3). BNs do not appear to be well suited to the integration of spatial information (such as landuse and geology) related to a data point; either multiple nodes are required to represent each spatial category (e.g. landuse) leading to possible implausible cases or a large number of categories are required to allow meaningful prediction. This was overcome by defining regions of similar landuse, geology and landscape position and using the region as a surrogate for spatial information. This reduces the capacity of the model to be used to predict the consequences of landuse changes that may result from climate change, shifting our focus to isolating the flow-driven water quality changes. The final model structure developed for this research is shown in Fig. 3.

3.4.2 Defining the BN nodes

Trigger values set by local agencies to maintain or improve the ecological condition of water bodies (Table 4) were used to define the categories within the water quality nodes of the network. For New South Wales (NSW) sites, these were selected from the ANZECC/ARMCANZ (2000) guidelines (specified at <http://www.environment.nsw.gov.au/ieo/Murrumbidgee/maptext-03.htm#wq01>) for aquatic ecosystem protection in upland and lowland rivers in south

Fig. 2 Simplified conceptual model of climate, flow and landscape attribute relationships with water quality in the Upper Murrumbidgee River Catchment. *Dotted lines* represent indirect relationships

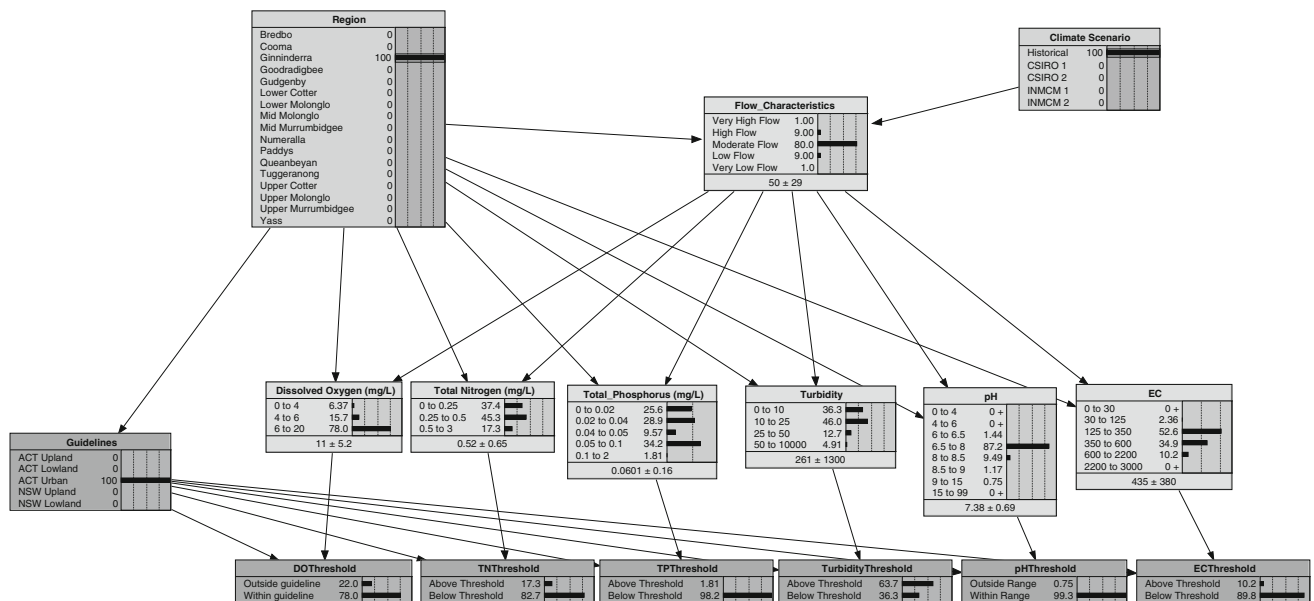
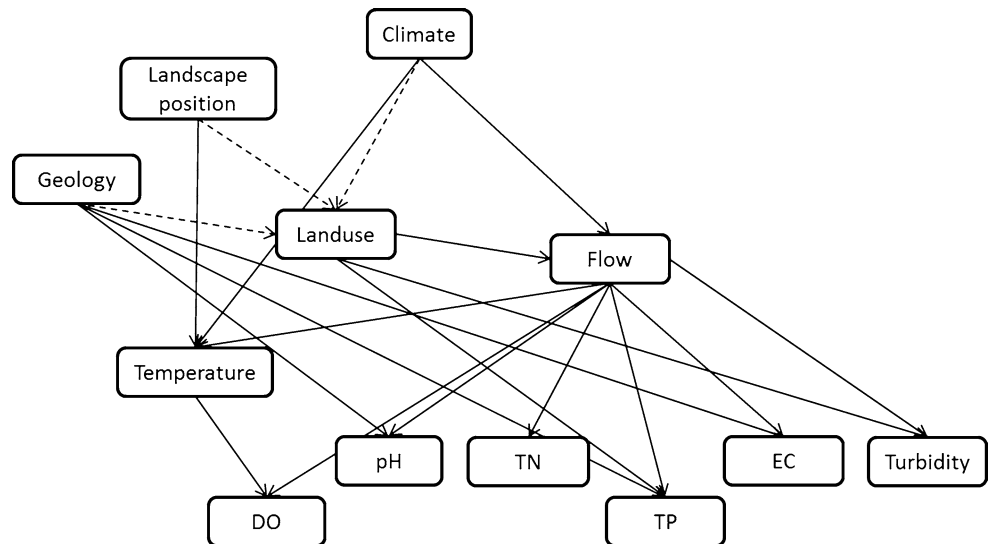


Fig. 3 Compiled Bayesian Network water quality model. Model results are shown from the Ginninderra region with historical climate conditions

eastern Australia. The exception to this was dissolved oxygen, where the ANZECC (1992) guideline value (in units of mg/L) was used rather than % saturation, as most of the data available is in mg/L. For Australian Capital Territory (ACT) sites, values specified in the Environment Protection Regulations SL2005-38 (Environment Protection Regulation 2005) were used with the addition of the ANZECC/ARMCANZ (2000) guideline for nitrogen concentrations. In all cases, where ranges are specified, the upper value was used. Given that thresholds are not set for temperature, this analysis did not consider temperature.

3.4.3 Defining the conditional probability tables in the BN model

Observed historical data (flow and water quality) were sourced from the ACT and NSW government databases, ACTEW Corporation databases and the research team. These data were used to generate frequency distributions of the measured quantities using the “automated expectation maximization learning algorithm” in Netica (www.norsys.com) and to define the conditional probability tables used within the network. The learning algorithm resulted in frequency distributions that were linked to statistics of flow

Table 4 Water quality guideline threshold values for aquatic ecosystem protection used for the water quality modelling (ANZECC/ARMCANZ 2000; ANZECC 1992; Environment Protection Regulations SL2005-38)

Water quality attribute	Indicator Numerical criteria (trigger values)
NSW sites	
Total phosphorus	Upland rivers: 20 µg/L
	Lowland rivers: 50 µg/L
Total nitrogen	Upland rivers: 250 µg/L
	Lowland rivers: 500 µg/L
Turbidity	Upland rivers: 2–25 NTU
	Lowland rivers: 6–50 NTU
Salinity (EC)	Upland rivers: 30–350 µS/cm
	Lowland rivers: 125–2,200 µS/cm
Dissolved oxygen	Upland rivers: 6 mg/L
	Lowland rivers: 4 mg/L
pH	Upland rivers: 6.5–8.0
	Lowland rivers: 6.5–8.5
ACT Sites	
Total Phosphorus	Mountain streams: ≤40 µg/L
	Lowland & urban streams: ≤100 µg/L
Turbidity	All streams: <10 NTU
Dissolved oxygen	Mountain and urban streams: ≥6 mg/L
	Lowland streams: ≥4 mg/L
pH	Mountain and lowland streams: 6.5–9.0
	Urban streams: 6.0–9.0

(where categories of flow are based on flow percentiles derived from historical data), climate and landscape attributes (through the use of regions).

The advantage of this approach is that data from multiple sites within each region were combined to generate the frequency distributions linked to flow statistics rather than absolute flows, thus maximising the use of data that are discontinuous and distributed across a region. The water quality data used extend from 1967 to present, capturing a wide range of climate conditions including the prolonged drought experienced in south eastern Australia at the turn of the 21st century. While site data are discontinuous, they reflect the range of flow conditions experienced in the rivers, particularly for dissolved oxygen, pH, electrical conductivity (EC) and turbidity. Most frequency distributions were generated using in excess of several hundred data points (up to 3,500 for EC in the Goodradigbee region). The exceptions were for nutrients (TN and TP) where <100 data points were used to generate frequency distributions for each region and projections for nutrients should be interpreted with caution.

To investigate the effect that a climate scenario has on the probability of violating water quality thresholds, a climate scenario and region were selected in the BN model

and the changes in probability of violating the water quality thresholds were observed.

4 Results

4.1 Flow modelling

The high correlations between observed and modelled flows (e.g. Fig. 4) indicate that, for most catchments, the SEACI data reproduce the temporal pattern of flow. However, the data should be compensated for routing from the SEACI grid scale (25 km²) to the catchment scale. In the case of gauge 410033, deconvolution (Fig. 5) shows that a lag-route routing method was able to capture the difference between the observed and aggregated SEACI flow values, using a time constant of 0.7 days, though there was considerable uncertainty in this value. The time constant obtained for gauge 410050 (about 20 km downstream), however, was significantly higher at 1.2 days. The high residuals at negative lags indicate the presence of timing errors in the SEACI modelled flows, most likely a result of errors in the input rainfall data.

There is a significant error in the magnitude of the flow, with a mean over-estimation by a factor of 2 (median multiplicative factor = 1.43), and a standard deviation of 1.87 (error in mean = 0.62). This was not surprising as the SEACI modelled flows are regionally calibrated, and not specifically calibrated to the gauges assessed. There was an implication that flows tend to be over-estimated across these gauged sites (with respect to the observed flows, which will also have associated uncertainty). However, generalising these results to the entire region studied is problematic. The indication is that the expected uncertainty (1σ) in the magnitude of flows will be a factor of 2 (actual flow was expected to be between half and double the SEACI modelled values). While there may be a bias in any individual estimate of flow, this is considerably reduced when considering the relative impact of climate change.

4.2 Hydrological changes

The four climate scenarios tested resulted in altered flow regimes for unregulated (Fig. 6) and regulated rivers (Fig. 7). The 2 degree CSIRO climate scenario (CSIRO_2) produced the largest change in streamflow and the greatest range of scores indicating considerable variation across sites within each region. Scenarios INMCM_2 and CSIRO_1 showed moderate hydrological alteration and INMCM_1 showed minor to moderate change. Both the IHA-ED and FSI scores indicated similar patterns of change between climate scenarios (Figs. 6 and 7), but the FSI scores displayed a smaller range of values for a given

Fig. 4 Cross correlation analysis for gauge 410033

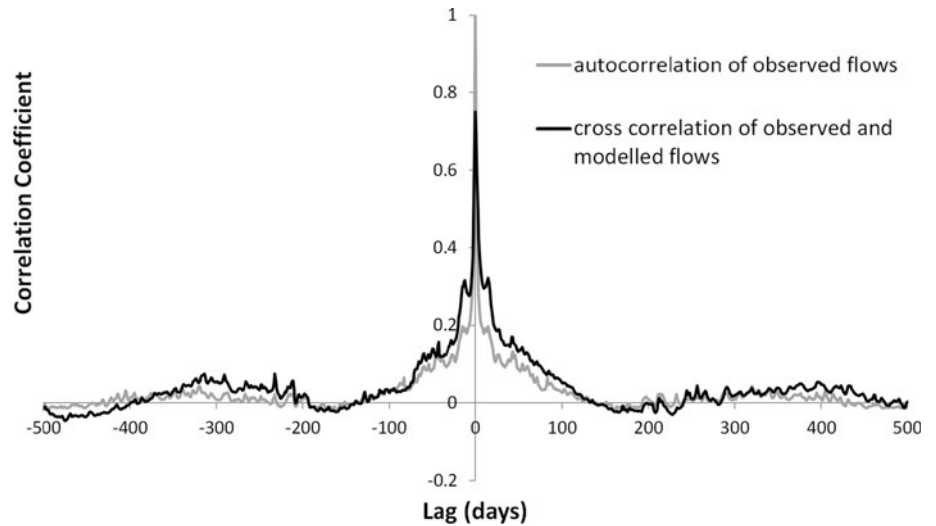


Fig. 5 Estimate of routing impulse response function for gauge 410033. The estimated value was obtained using Fourier deconvolution (i.e. estimated from the data). The fitted values were obtained using a transfer function approach (i.e. exponential decay with a time constant that was estimated based on the difference between the values for lag 0 and lag 1)

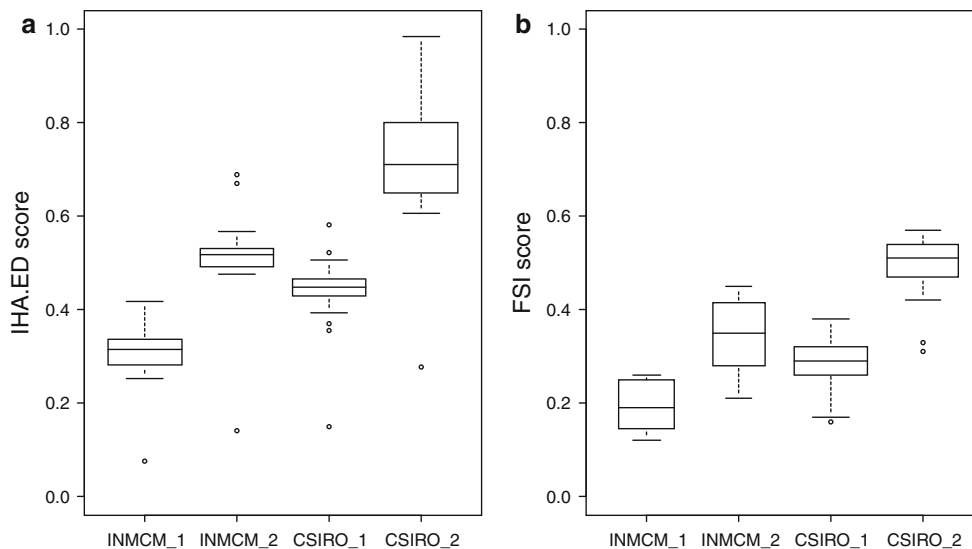
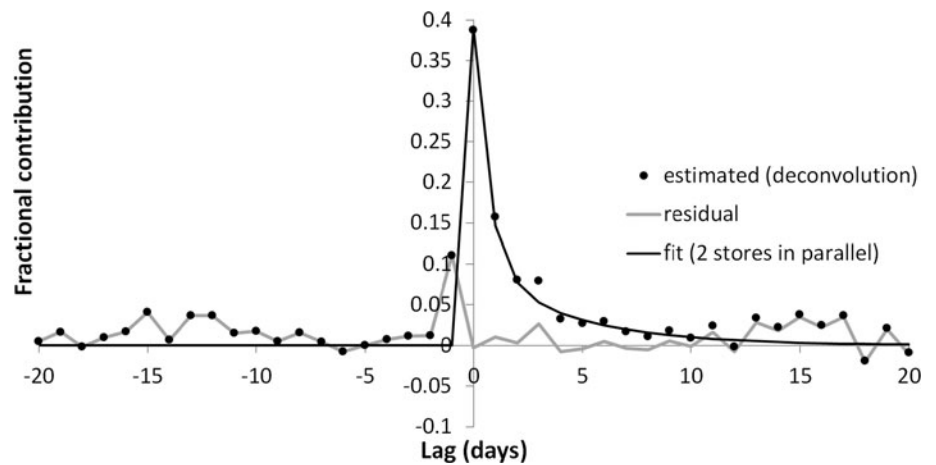


Fig. 6 The IHA.ED (a) and FSI (b) scores for unregulated sites within the Upper Murrumbidgee River Catchment for the four climate scenarios. In the plot: the median values (horizontal central line),

25th and 75th percentile values (box), the 90th percentile (upper whisker), 10th percentile (lower whisker) and outliers (circles) are shown

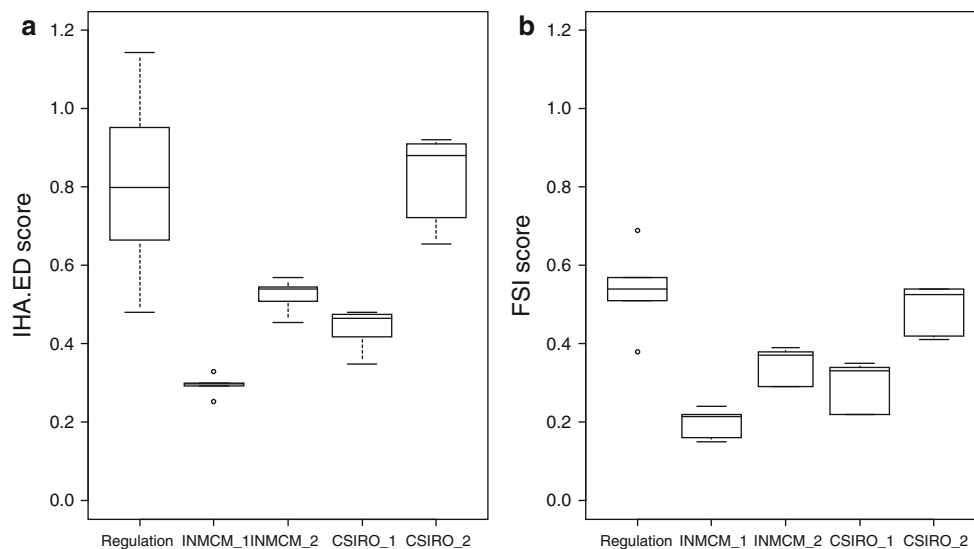
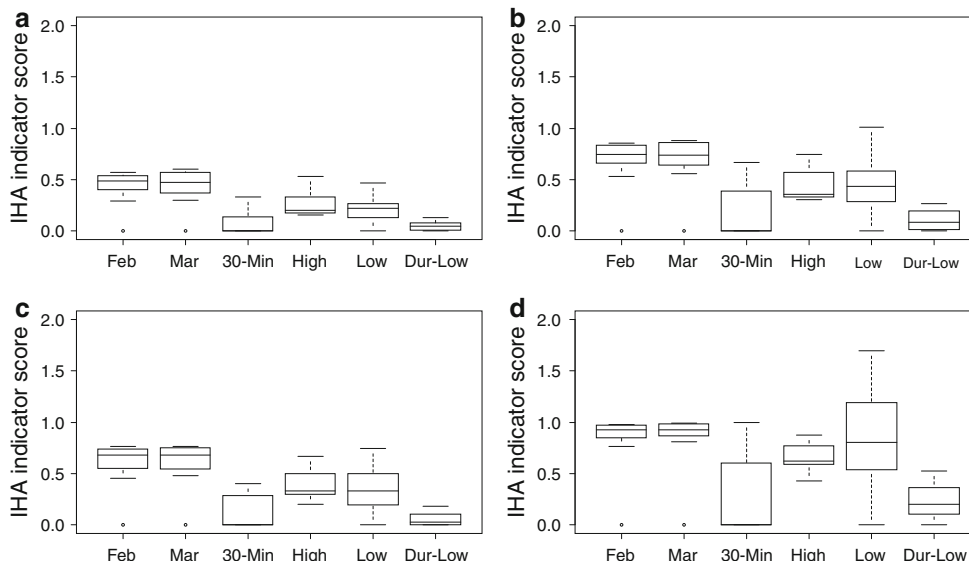


Fig. 7 The IHA.ED (a) and FSI (b) scores for regulated sites within the Upper Murrumbidgee River Catchment for the regulation scenario and the four climate scenarios. In the plot: the median values

(horizontal central line), 25th and 75th percentile values (box), the 90th percentile (upper whisker), 10th percentile (lower whisker) and outliers (circles) are shown

Fig. 8 IHA indicator scores for the four climate scenarios; a INMCM_1, b INMCM_2, c CSIRO_1 and d CSIRO_2.

IHA indicators are: mean monthly flows for February (Feb), March (Mar), annual 30-days minima (30-Min), frequency of high (High) and low pulses (Low) and the duration of low flow pulses (Dur-Low). In the plot: the median values (horizontal central line), 25th and 75th percentile values (box), the 90th percentile (upper whisker), 10th percentile (lower whisker) and outliers (circles) are shown



climate scenario reflecting the variance-corrected nature of this index.

The regulation scenario had a greater effect on flow regimes than any of the climate scenarios with only the 2 degree climate scenario, CSIRO_2, producing changes of a similar magnitude (Fig. 7). The range of IHA-ED and FSI scores for the regulation scenario were far greater than any of the climate scenarios indicating considerable variability in the site scores.

The IHA indicators generally showed similar patterns of alteration for each climate scenario (Fig. 8). For most scenarios the low flows and the 30 day minimum flows had the greatest range of values with the CSIRO_2 scenario

displaying the greatest effects (Fig. 8d). For the CSIRO_2 climate scenario, all IHA indicators (except the duration of low flows) had median interquartile ranges above 0.5 (Fig. 8d), highlighting the substantial impact of this climate scenario on a range of ecologically relevant indicators. Frequency of high and low pulses showed similar median values across the majority of climate scenarios, but high pulses generally had narrower ranges.

The FSI indicators also showed consistent patterns of alteration across each climate scenario (Fig. 9). Mean annual flows, high flows, high flow spells and the low flow spells were most strongly affected by the projected climate changes. For most scenarios, the high flow spells, low

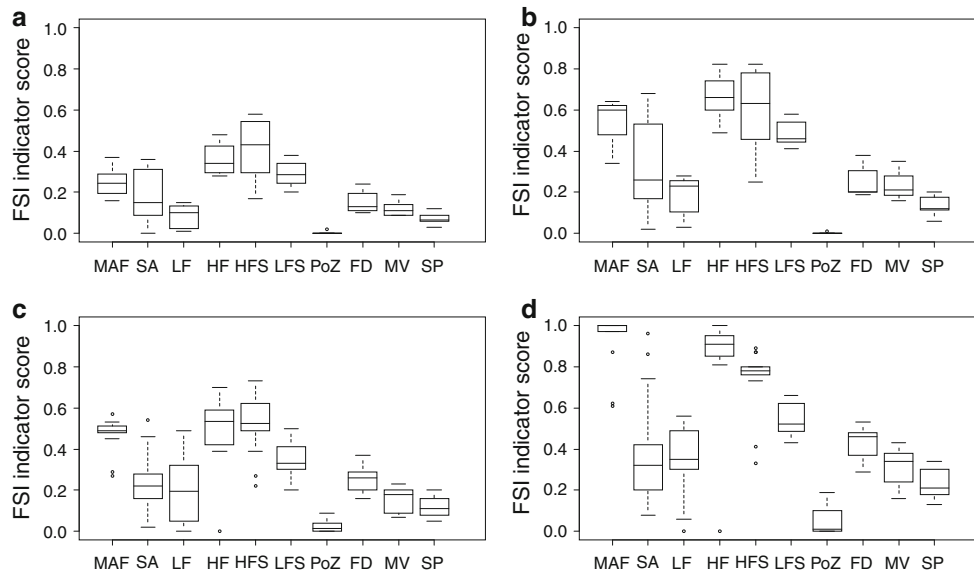


Fig. 9 FSI indicator scores for the four climate scenarios; **a** INMCM_1, **b** INMCM_2, **c** CSIRO_1 and **d** CSIRO_2. FSI indices are: mean annual flow (MAF), seasonal amplitude (SA), low flow (LF), high flow (HF), low flow spells (LFS), high flow spells (HFS), proportion of zero flows (PoZ), flow duration (FD), monthly variation

(MV) and seasonal period (SP). In the plot: the median values (horizontal central line), 25th and 75th percentile values (box), the 90th percentile (upper whisker), 10th percentile (lower whisker) and outliers (circles) are shown

flows and seasonal amplitude displayed the greatest range of values reflecting the variability across sites within the regions. While, for all scenarios there was little variation in the proportion of zero flows, monthly variation and seasonal period (Fig. 9).

The regulation scenario resulted in major changes (i.e. scores of around 1) to all IHA parameters and most FSI parameters (Fig. 10). For the IHA parameters, the frequency of low flows was the most impacted flow component, with a median change of around 1.2 reflecting the absolute impact of regulation on this parameter. All other IHA parameters (except the low flow duration) also displayed major alteration (scores of greater than 0.5). For the FSI parameters, the low flow index and proportion of zero flows indices did not display a similar change reflecting the reduced emphasis placed on these using the variance-corrected indices. Complete changes (scores of around 1) for mean annual flow, high flows and high flow spells were observed suggesting changes that are well outside the normal range of flow conditions experienced by these rivers.

The great variation in the frequency of the IHA parameter for low flow pulses may be caused by considerable spatial variation of low flows across sites, with some sites (especially in the Yass catchment) showing very low flows which are particularly sensitive to changes. The lower variation shown by the FSI parameters for low flow and proportion of zero flows suggests that the changes to low flows are considered less significant when the range of

variation in low flows at the sites is taken into account. Interestingly, the FSI parameter for low flow spells was affected quite strongly, indicating significant changes to the length of period of low flows associated with the climate scenarios.

4.3 Water quality changes

The compiled BN model for the water quality attributes is shown in Fig. 3 and the beliefs are shown for each node in the form of horizontal bars. These represent the initial frequency distributions for the water quality attributes for the Ginninderra region used to illustrate the model (a mid-catchment area, dominated by urban landuse), defined by the historical data set. The threshold nodes indicate the probability that the appropriate jurisdictional guidelines were exceeded (Table 4). In this region, historically, the probability of exceeding thresholds are very low (<5 %) for pH and total phosphorus concentrations; low (5–30 %) for dissolved oxygen, total nitrogen concentration and EC and moderate (between 30 and 70 %) for turbidity (Fig. 3).

For the four climate scenarios tested, most changes in water quality violations observed were negligible, particularly for the 1 degree scenarios (Table 5) and most changes suggest a slight reduction in the probability of violating thresholds across regions. There was some spatial variation in predicted changes between regions. The greatest projected changes in water quality occurred in the

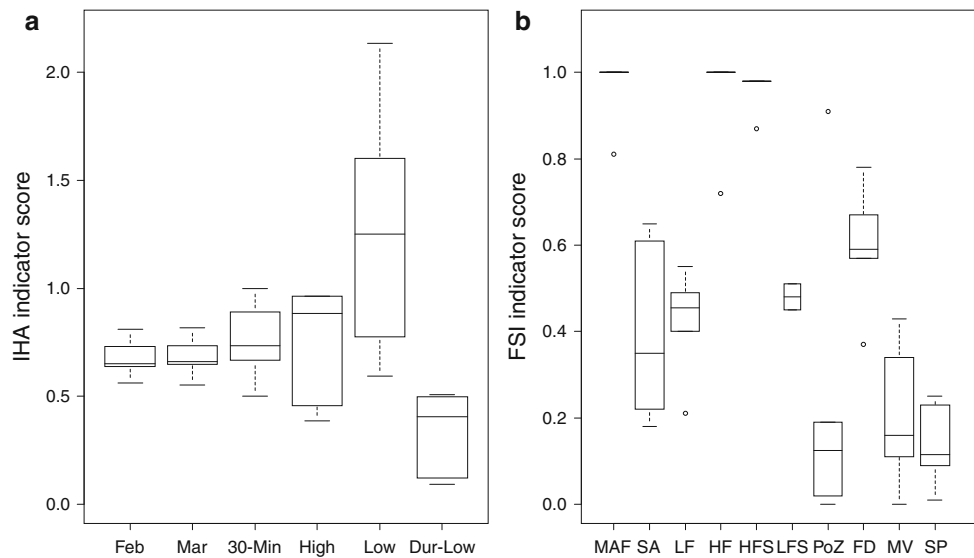


Fig. 10 IHA (a) and FSI (b) indicator scores for the regulation scenario. In the plot: the median values (*horizontal central line*), 25th and 75th percentile values (*box*), the 90th percentile (*upper whisker*),

10th percentile (*lower whisker*) and outliers (*circles*) are shown. Meanings of the abbreviations as in Figs. 8 and 9

Upper Cotter, Ginninderra, Mid Molonglo and, particularly, Gudgenby regions (Table 5). The most notable changes occur for total nitrogen concentrations with a predicted reduction in the probability of exceeding the thresholds for all climate scenarios and most regions. The largest reduction is 24 % in the probability of exceeding the total nitrogen thresholds using the 2 degree CSIRO projections (CSIRO_2) for the Gudgenby region. However, the limited number of data points used to generate the original frequency distribution means that such projections

should be treated with caution. EC, pH and dissolved oxygen concentrations showed very little response to any of the projected climate changes.

5 Discussion

The results of this study illustrate that the projected hydrological changes for the UMRC for 1 and 2 °C temperature rise are substantial for a range of ecologically-

Table 5 Change in percentage violations for water quality attributes, in seven regions of the Upper Murrumbidgee River Catchment under the four selected climate scenarios

INMCM_1	DO	TN	TP	Turb	pH	EC	CSIRO_1	DO	TN	TP	Turb	pH	EC
Ginninderra	0%	-1%	0%	0%	0%	0%	Ginninderra	2%	-2%	0%	1%	0%	1%
Goodradigbee	0%	-1%	0%	0%	0%	0%	Goodradigbee	0%	-1%	0%	0%	1%	0%
Gudgenby	1%	-5%	0%	-3%	0%	0%	Gudgenby	2%	-10%	0%	-5%	1%	0%
Numeralla	0%	-1%	0%	0%	1%	0%	Numeralla	0%	-2%	0%	0%	1%	0%
Yass	1%	-1%	1%	-1%	0%	0%	Yass	0%	0%	0%	-2%	0%	0%
Mid-Molonglo	0%	0%	0%	-1%	0%	0%	Mid-Molonglo	2%	0%	0%	-2%	0%	0%
Upper Cotter	0%	-3%	-2%	-2%	0%	0%	Upper Cotter	1%	-5%	-3%	-4%	0%	0%

INMCM_2	DO	TN	TP	Turb	pH	EC	CSIRO_2	DO	TN	TP	Turb	pH	EC
Ginninderra	1%	-2%	0%	1%	0%	0%	Ginninderra	5%	-5%	-1%	5%	0%	2%
Goodradigbee	0%	-1%	0%	0%	1%	0%	Goodradigbee	-1%	-1%	0%	0%	3%	0%
Gudgenby	2%	-10%	0%	-5%	1%	0%	Gudgenby	5%	-24%	-3%	-9%	1%	1%
Numeralla	0%	-2%	0%	0%	1%	0%	Numeralla	0%	-3%	0%	-1%	2%	0%
Yass	1%	-1%	1%	-2%	-1%	0%	Yass	0%	0%	0%	-4%	0%	0%
Mid-Molonglo	1%	0%	0%	-2%	0%	0%	Mid-Molonglo	6%	-1%	0%	-4%	0%	0%
Upper Cotter	1%	-6%	-4%	-4%	0%	0%	Upper Cotter	3%	-12%	-9%	-6%	0%	0%

Bars in each cell represent the magnitude and direction of the change

relevant flow attributes. However, when placed in the context of river regulation, the results suggest that regulation has resulted in far greater changes to streamflows than almost all of the changes projected to occur for the climate scenarios assessed. Two of the four climate scenarios selected for this analysis (CSIRO_1 and _2) represent major change scenarios and therefore provide an upper bound for the expected climate-driven changes. It is only the most severe of these (CSIRO_2) that produces changes of a similar magnitude to those observed from river regulation.

These findings are consistent with recent analysis that demonstrates that, worldwide, the extraction of water for human use has had a greater effect on annual catchment outflows than those projected to occur as a result of climate change (Grafton et al. 2012). The work of Grafton et al. (2012) looks simply at annual catchment outflow. We demonstrate that such findings are consistent across a range of ecologically-relevant flow regime attributes and the impacts are evident across catchments, not just at the outlet.

The range of IHA-ED and FSI scores for the regulation scenario highlight the diversity of water use from each of the regulated sites. Within the regulated study regions of the UMRC water is used to supply major urban areas with drinking water (affecting the Upper Cotter and mid-Molonglo region) and to manage ornamental lake levels (affecting the mid-Molonglo and Ginninderra regions). In addition, the mid Molonglo region receives waste water from an urban water treatment plant. These different uses will result in different degrees of flow regime modification as reflected in our indicator scores.

There are two implications of our results. Firstly, for unregulated rivers, climate change may result in changes to streamflows of a similar magnitude to that of river regulation. The features of the flow regimes most likely to be affected by the changes in climate are magnitude and duration of high flows, the duration of low flow events and total flow volumes. Specific ecological responses have not been predicted from the changes observed, however, it is possible to postulate the types of effects that might result from the predicted changes based on previous studies. Modification of mean annual flows, high flows and high flow spells would suggest changes to primary production (Robertson et al. 2001), floodplain connections (Bunn and Arthington 2002; Page et al. 2005; Frazier and Page 2006) and riparian vegetation (Poff and Zimmerman 2010). Changes to the low flow spells suggests changes to the availability of habitat (Bunn and Arthington 2002) and the ability for fish to migrate to spawn (Freeman et al. 2001). Regulation in the UMRC is observed to have severely affected total flow volumes as well as the magnitude and duration of high flows. Therefore, it is possible that climate

change may result in similar ecological effects to that of river regulation, placing many aquatic biological communities at risk. This should contribute to a discussion among stakeholders and management about where/how to focus protection and restoration efforts if the worst impacts eventuate.

Secondly, regulated rivers will be particularly vulnerable as climate change is likely to exacerbate the effects of regulation. In Australia, and in the case of the Murray-Darling system to which the UMRC belongs, the effects of river regulation for stream processes and aquatic biota are well known with considerable impairment of aquatic biological communities observed (Arthington and Pusey 2003; Walker 1985). Over the past 20 years, many programs have been implemented to provide water to rivers for the benefit of the environment. One of the challenges for the future is that the combined effects of climate change and regulation may negate the effects of environmental watering programs, with detrimental effects for aquatic ecosystems. Given that regulation for human consumption is likely to remain a major cause of stream hydrological changes, the consequences of the additional pressures provided by climate change needs careful consideration by stakeholders and management agencies to develop strategies that will protect aquatic ecosystems in the future.

There are some caveats to the hydrological analysis that need to be highlighted. First, the analysis assumes that catchment characteristics will not change over time, in particular the hydrological model parameters calibrated from historical flow data will remain valid for future projections. However, change in climate conditions may affect the catchment structurally and behaviourally, such as changes to the extent of frost hollows, movement of vegetation communities and transition from wet sclerophyll forest to dry sclerophyll forest. Given the high natural variability of the climate in south eastern Australia and the requirements of structural adjustments (Walther 2003) we expect that these changes are likely to be limited for the scenarios tested (projections for 2030 and 2070).

Second, the climate scenarios only represent changes in mean monthly climate variables, with inter-annual climate variability. They do not include, for example, changes to the distribution of inter-annual climate variability, extreme events or seasonal changes that have been widely predicted, yet remain difficult to model and forecast (Sivakumar 2011). This results in a notable lack of variation or significant change in the seasonal period and monthly variation FSI indicators. In particular, changes to seasonality were not introduced with the climate models used and, given that anecdotal evidence suggests a change in the seasonality of rainfall in recent years in parts of the UMRC, it would be desirable that future climate models consider seasonal changes.

While it is important to acknowledge limitations, we have demonstrated that the approaches adopted here can be used to test multiple scenarios and inform management of a range of possible impacts. Climate projections are uncertain and the best approach is to treat them as plausible future conditions (Chiew et al. 2011) that provide valuable information to those developing adaptation strategies. The climate projections used in this study are the best available and are currently used by agencies for planning and our analyses are useful for local water managers. As new, firmer projections become available the BN modelling undertaken here can be easily revised, as can the calculation of the indicators of hydrological change, contributing to the adaptive management process.

In contrast to the projected hydrological changes, BN modelling indicates that the projected water quality changes associated with climate change are very small in the UMRC. The change in the probability that the thresholds designed for the protection of aquatic ecosystems are violated are negligible in most cases and where changes are most notable, a decrease in threshold violations is predicted. While many studies predict large changes in water quality attributes with changes in climate (e.g. Wilby et al. 2006; Tu 2009), there are also predictions of much smaller changes. As examples, Tong et al. (2012) report changes in mean daily nitrogen concentrations changes of typically <5 % for a range of climate scenarios which is consistent with our predictions; Rehana and Mujumdar (2012) predict small changes in the probability of low dissolved oxygen conditions in accordance with our results. In addition, note that most published studies represent Northern Hemisphere examples where concentrations of nutrients are an order of magnitude greater than the system reported here. The implications of these results are that current water quality management strategies within the region are likely to remain relevant into the future.

Our results may be influenced by the scale at which the models were developed. The BN used to model changes in water quality does not account for changes that occur at a sub-daily time-step. For example, changes in storm intensities which occur at small scale are predicted to shift with climate change, resulting in changes to the frequency of peak concentrations of both sediment and nutrients. Neither the hydrological modelling available nor the historical water quality data available have sufficient resolution to allow such changes to be adequately predicted. However, before effort is directed at understanding the sub-daily water quality and hydrological behaviour, the ecological effects of very short duration, high concentrations or high flows needs to be understood to determine if the modelling effort is justified.

6 Conclusions

The management of freshwater ecosystems is usually targeted through the regulation of streamflows (limiting diversions and providing environmental flows) and regulation of water quality (setting limits or targets for constituent concentrations). By identifying key components of the flow and water quality regimes that may be affected by climate change, we provide managers with information relevant to their activities. In this study we have shown that the projected hydrological changes for the UMRC for 1 and 2 temperature rise are significant for a range of ecologically relevant flow attributes, but not as significant as the effects that flow regulation already present within the catchment. In contrast, predicted changes to water quality threshold violations designed to protect aquatic ecosystems as a result of climate change were small. Although we did not predict the direct ecological effects of climate change, the indicators of hydrologic alteration (IHA and FSI) were selected for being ecologically-relevant (Richter et al. 1996; SKM 2005), and water quality thresholds considered were based on the guidelines designed to protect aquatic ecosystems. Models that link hydrological, water quality and ecological components are needed to assess direct ecological outcomes and this is the subject of ongoing research.

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References

- Acworth RI, Broughton A, Nicholl C, Jankowski J (1997) The role of debris-flow deposits in the development of dryland salinity in the Yass River catchment, New South Wales, Australia. *Hydrogeol J* 5:22–36
- Aguilera PA, Fernandez A, Fernandez R, Rumi R, Salmeron A (2011) Bayesian networks in environmental modelling. *Environ Model Softw* 26(12):1376–1388. doi:10.1016/j.envsoft.2011.06.004
- Aguilera PA, Fernandez A, Roperio RF, Molina L (2013) Groundwater quality assessment using data clustering based on hybrid

- Bayesian networks. *Stoch Env Res Risk Assess* 27(2):435–447. doi:[10.1007/s00477-012-0676-8](https://doi.org/10.1007/s00477-012-0676-8)
- Allan JD, Yuan LL, Black P, Stockton TOM, Davies PE, Magierowski RH, Read SM (2012) Investigating the relationships between environmental stressors and stream condition using Bayesian belief networks. *Freshw Biol* 57:58–73. doi:[10.1111/j.1365-2427.2011.02683.x](https://doi.org/10.1111/j.1365-2427.2011.02683.x)
- ANZECC (1992) Australian water quality guidelines for fresh and marine waters. National Water Quality Management Strategy. Australian and New Zealand Environment and Conservation Council, Canberra
- ANZECC/ARMCANZ (2000) Australian and New Zealand Guidelines for Fresh and Marine Water Quality. Australian and New Zealand Environment and Conservation Council, Agriculture and Resource Management Council of Australia and New Zealand, Canberra
- Arhonditsis GB, Brett MT (2005) Eutrophication model for Lake Washington (USA) Part II - model calibration and system dynamics analysis. *Ecol Model* 187(2–3):179–200. doi:[10.1016/j.ecolmodel.2005.01.039](https://doi.org/10.1016/j.ecolmodel.2005.01.039)
- Arnell NW (2003) Relative effects of multi-decadal climatic variability and changes in the mean and variability of climate due to global warming: future streamflows in Britain. *J Hydrol* 270(3–4):195–213. doi:[10.1016/s0022-1694\(02\)00288-3](https://doi.org/10.1016/s0022-1694(02)00288-3)
- Arthington AH, Pusey BJ (2003) Flow restoration and protection in Australian rivers. *River Res Appl* 19(5–6):377–395. doi:[10.1002/rra.745](https://doi.org/10.1002/rra.745)
- Barlow A, Norris RH, Wilkinson L, Osborne W, Lawrence I, Lowery D, Linke S, DeRose R, Wilkinson S, Olley JM (2005) Report on the existing aquatic ecology that may be affected by each of the proposed future water supply options. Draft Environmental Impact Statement. Appendix H: Aquatic Ecology Study. ACT-EW Corporation. Canberra
- Black AR, Rowan JS, Duck RW, Bragg OM, Clelland BE (2005) DHRAM: a method for classifying river flow regime alterations for the EC Water Framework Directive. *Aquatic Conserv Marine Freshw Ecosyst* 15(5):427–446. doi:[10.1002/aqc.707](https://doi.org/10.1002/aqc.707)
- Borsuk ME, Stow CA, Reckhow KH (2003) Integrated approach to total maximum daily load development for Neuse River Estuary using Bayesian probability network model (Neu-BERN). *J Water Resour Plan Manag-ASCE* 129(4):271–282. doi:[10.1061/\(asce\)0733-9496\(2003\)129:4\(271](https://doi.org/10.1061/(asce)0733-9496(2003)129:4(271)
- Bunn S, Arthington A (2002) Basic principles and ecological consequences of altered flow regimes for aquatic biodiversity. *Environ Manage* 30(4):492–507
- Castelletti A, Soncini-Sessa R (2007) Bayesian Networks and participatory modelling in water resource management. *Environ Model Softw* 22(8):1075–1088. doi:[10.1016/j.envsoft.2006.06.003](https://doi.org/10.1016/j.envsoft.2006.06.003)
- Chen SH, Pollino CA (2012) Good practice in Bayesian network modelling. *Environ Model Softw* 37:134–145. doi:[10.1016/j.envsoft.2012.03.012](https://doi.org/10.1016/j.envsoft.2012.03.012)
- Chiew FHS, Teng J, Vaze J, Post DA, Perraud J-M, Kirono DGC, Viney NR (2009) Estimating climate change impact on runoff across south-east Australia: method, results and implications of modelling method. *Water Resour Res* 45:W10414. doi:[10.1029/2008WR007338](https://doi.org/10.1029/2008WR007338)
- Chiew FHS, Young WJ, Cai W, Teng J (2011) Current drought and future hydroclimate projections in southeast Australia and implications for water resources management. *Stoch Env Res Risk Assess* 25:601–612. doi:[10.1007/s00477-010-0424-x](https://doi.org/10.1007/s00477-010-0424-x)
- CSIRO (2008) Water availability in the Murray-Darling Basin. A report to the Australian Government from the CSIRO Murray-Darling Basin Sustainable Yields Project. CSIRO
- Davies PE, Harris JH, Hillman TJ, Walker KF (2010) The sustainable rivers audit: assessing river ecosystem health in the Murray–Darling Basin, Australia. *Marine Freshw Res* 61(7):764–777. doi:[10.1071/MF09043](https://doi.org/10.1071/MF09043)
- Delpla I, Jung AV, Baures E, Clement M, Thomas O (2009) Impacts of climate change on surface water quality in relation to drinking water production. *Environ Int* 35(8):1225–1233. doi:[10.1016/j.envint.2009.07.001](https://doi.org/10.1016/j.envint.2009.07.001)
- DLWC (1995) State of the Rivers Report Murrumbidgee Catchment 1994–1995. DLWC, Leeton
- Dyer F, El Sawah S, Harrison E, Broad S, Croke B, Norris R, Jakeman A (2011) Predicting water quality responses to a changing climate: Building an integrated modelling framework. In: Peters N, Krysanova V, Lepisto A et al. (Eds) IAHS Symposium on Water Quality: Current trends and expected climate change impacts, IAHS Press, Melbourne, pp 178–183
- Dynesius M, Nilsson C (1994) Fragmentation and flow regulation of river systems in the northern third of the world. *Science* 266(5186):753–762
- Environment Protection Regulation (2005) made under the Environment Protection Act 1997. Australian Capital Territory Government
- Finlayson BL, McMahon TA (1988) Australia vs the World: a comparative analysis of streamflow characteristics. In: Warner RF (ed) *Fluvial Geomorphology of Australia*. Academic Press, Sydney, pp 17–40
- Frazier P, Page K (2006) The effect of river regulation on floodplain wetland inundation, Murrumbidgee River, Australia. *Marine Freshw Res* 57(2):133–141. doi:[10.1071/MF05089](https://doi.org/10.1071/MF05089)
- Freeman MC, Bowen ZH, Bovee KD, Irwin ER (2001). Flow and habitat effects on juvenile fish abundance in natural and altered flow regimes. *Ecological Applications* 11:179–190. doi:[10.1890/1051-0761\(2001\)011\[0179:FAHEOJ\]2.0.CO;2](https://doi.org/10.1890/1051-0761(2001)011[0179:FAHEOJ]2.0.CO;2)
- Gao Y, Vogel RM, Kroll CN, Poff NL, Olden JD (2009) Development of representative indicators of hydrologic alteration. *J Hydrol* 374(2009):136–147
- Gehrke PC, Brown P, Schiller CB, Moffatt DB, Bruce AM (2006) River regulation and fish communities in the Murray-Darling river system, Australia. *Regul Rivers Res Manag* 11(3–4):363–375. doi:[10.1002/rrr.3450110310](https://doi.org/10.1002/rrr.3450110310)
- Grafton RQ, Pittock J, Davis R, Williams J, Fu G, Warburton M, Udall B, McKenzie R, Yu X, Che N, Connell D, Jiang Q, Kompas T, Lynch A, Norris R, Possingham H, Quiggin J (2012) Global insights into water resources, climate change and governance. *Nat Clim Chang*. doi:[10.1038/nclimate1746](https://doi.org/10.1038/nclimate1746)
- Heathwaite AL (2010) Multiple stressors on water availability at global to catchment scales: understanding human impact on nutrient cycles to protect water quality and water availability in the long term. *Freshw Biol* 55:241–257
- Interlandi SJ, Crockett CS (2003) Recent water quality trends in the Schuylkill River, Pennsylvania, USA: a preliminary assessment of the relative influences of climate, river discharge and suburban development. *Water Res* 37(8):1737–1748. doi:[10.1016/s0043-1354\(02\)00574-2](https://doi.org/10.1016/s0043-1354(02)00574-2)
- IPCC (2007) Climate Change 2007: Synthesis Report. Intergovernmental Panel on Climate Change
- Kendall M (1938) A new measure of rank correlation. *Biometrika* 30:81–89
- Kim BS, Kim BK, Kwon HH (2011) Assessment of the impact of climate change on the flow regime of the Han River basin using indicators of hydrologic alteration. *Hydrol Process* 25(5):691–704. doi:[10.1002/hyp.7856](https://doi.org/10.1002/hyp.7856)
- Marchant R, Hehir G (2002) The use of AUSRIVAS predictive models to assess the response of lotic macroinvertebrates to dams in south-east Australia. *Freshw Biol* 47:1033–1050
- Marsh N (2010) Hydrological indicators of water stress, Report prepared for the Bureau of Meteorology for the National Water Commission, Canberra

- McCann RK, Marcot BG, Ellis R (2006) Bayesian belief networks: applications in ecology and natural resource management. *Can J For Res-Revue Canadienne De Recherche Forestiere* 36(12):3053–3062. doi:[10.1139/x06-238](https://doi.org/10.1139/x06-238)
- Meyer JL, Sale MJ, Mulholland PJ, Poff NL (1999) Impacts of climate change on aquatic ecosystem functioning and health. *J Am Water Resour Assoc* 35(6):1373–1386. doi:[10.1111/j.1752-1688.1999.tb04222.x](https://doi.org/10.1111/j.1752-1688.1999.tb04222.x)
- Molina JL, Bromley J, García-Aróstegui JL, Sullivan C, Benavente J (2010) Integrated water resources management of overexploited hydrogeological systems using object-oriented Bayesian networks. *Environ Model Softw* 25(4):383–397. doi:[10.1016/j.envsoft.2009.10.007](https://doi.org/10.1016/j.envsoft.2009.10.007)
- Murdoch PS, Baron JS, Miller TL (2000) Potential effects of climate change on surface-water quality in North America. *J Am Water Resour Assoc* 36(2):347–366. doi:[10.1111/j.1752-1688.2000.tb04273.x](https://doi.org/10.1111/j.1752-1688.2000.tb04273.x)
- Nilsson C, Berggren K (2000) Alteration of riparian ecosystems caused by river regulation. *BioScience* 50(9):783–792. doi:[10.1641/0006-3568\(2000\)050\[0783:AORECB\]2.0.CO;2](https://doi.org/10.1641/0006-3568(2000)050[0783:AORECB]2.0.CO;2)
- Olden JD, Poff NL (2003) Redundancy and the choice of hydrologic indices for characterizing streamflow regimes. *River Res Appl* 19:101–121
- Page K, Read A, Frazier P, Mount N (2005) The effect of altered flow regime on the frequency and duration of bankfull discharge: Murrumbidgee River, Australia. *River Res Appl* 21(5):567–578. doi:[10.1002/rra.828](https://doi.org/10.1002/rra.828)
- Pearl (1988) *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. Morgan Kaufmann, San Mateo
- Pike WA (2004) Modeling drinking water quality violations with Bayesian networks. *J Am Water Resour Assoc* 40(6):1563–1578
- PMSEIC Independent Working Group (2007) *Climate Change in Australia: Regional Impacts and Adaptation—Managing the Risk for Australia*, Report Prepared for the Prime Minister's Science, Engineering and Innovation Council, Canberra
- Poff NL, Zimmerman JKH (2010) Ecological responses to altered flow regimes: a literature review to inform the science and management of environmental flows. *Freshw Biol* 55(1):194–205. doi:[10.1111/j.1365-2427.2009.02272.x](https://doi.org/10.1111/j.1365-2427.2009.02272.x)
- Poff NL, Allan JD, Bain MB, Karr JR, Prestegard KL, Richter BD, Sparks RE, Stromberg JC (1997) The natural flow regime. *Bioscience* 47(11):769–784. doi:[10.2307/1313099](https://doi.org/10.2307/1313099)
- Poff NL, Olden JD, Merritt DM, Pepin DM (2007) Homogenization of regional river dynamics by dams and global biodiversity implications. *PNAS* 104(14):4732–4737
- Reckhow KH (1999) Water quality prediction and probability network models. *Can J Fish Aquat Sci* 56:1150–1158
- Rehana S, Mujumdar PP (2012) Climate change induced risk in water quality control problems. *J Hydrol* 444–445:63–77. doi:[10.1016/j.jhydrol.2012.03.042](https://doi.org/10.1016/j.jhydrol.2012.03.042)
- Richter BD, Baumgartner JV, Powell J, Braun DP (1996) A method for assessing hydrologic alteration within ecosystems. *Conserv Biol* 10(4):1163–1174. doi:[10.1046/j.1523-1739.1996.10041163.x](https://doi.org/10.1046/j.1523-1739.1996.10041163.x)
- Richter BD, Baumgartner JV, Braun DP, Powell J (1998) A spatial assessment of hydrologic alteration within a river network. *Regul Rivers Res Manag* 14(4):329–340. doi:[10.1002/\(sici\)1099-1646\(199807/08\)14:4<329:aid-rrr505>3.0.co;2-e](https://doi.org/10.1002/(sici)1099-1646(199807/08)14:4<329:aid-rrr505>3.0.co;2-e)
- Richter BD, Mathews R, Harrison DL, Wigington R (2003) Ecologically sustainable water management: managing river flows for ecological integrity. *Ecol Appl* 13(1):206–224. doi:[10.1890/1051-0761\(2003\)013\[0206:ESWMMR\]2.0.CO;2](https://doi.org/10.1890/1051-0761(2003)013[0206:ESWMMR]2.0.CO;2)
- Robertson AI, Bacon P, Heagney G (2001) The responses of floodplain primary production to flood frequency and timing. *J Appl Ecol* 38(1):126–136. doi:[10.1046/j.1365-2664.2001.00568.x](https://doi.org/10.1046/j.1365-2664.2001.00568.x)
- Sivakumar B (2011) Global climate change and its impacts on water resources planning and management: assessment and challenges. *Stoch Env Res Risk Assess* 25:583–600. doi:[10.1007/s00477-010-0423-y](https://doi.org/10.1007/s00477-010-0423-y)
- SKM (2005) *Development and application of a flow stress ranking procedure*. Department of Sustainability and Environment, Melbourne
- Slijkerman J, Kaye J, Dyer F (2007) Assessing the health of Tasmanian rivers: collecting the evidence. In: Wilson AL, Dehaan RI, Watts RJ, Page KJ, Bowmer KH, Curtis A (Eds) 5th Australian Stream Management Conference. Australian rivers: making a difference, Charles Sturt University, Albury
- Snowy Scientific Committee (SSC 2010) *The adequacy of environmental flows to the upper Murrumbidgee River*. Prepared by the Snowy Scientific Committee for the Water Administration Ministerial Corporation of New South Wales, Canberra
- Stow CA, Roessler C, Borsuk ME, Bowen JD, Reckhow KH (2003) Comparison of estuarine water quality models for total maximum daily load development in Neuse River Estuary. *J Water Resour Plan Manag—ASCE* 129(4):307–314. doi:[10.1061/\(asc\)0733-9496\(2003\)129:4\(307](https://doi.org/10.1061/(asc)0733-9496(2003)129:4(307)
- Suen JP (2010) Potential impacts to freshwater ecosystems caused by flow regime alteration under changing climate conditions in Taiwan. *Hydrobiologia* 649(1):115–128. doi:[10.1007/s10750-010-0234-7](https://doi.org/10.1007/s10750-010-0234-7)
- Thodsen H (2007) The influence of climate change on stream flow in Danish rivers. *J Hydrol* 333(2–4):226–238. doi:[10.1016/j.jhydrol.2006.08.012](https://doi.org/10.1016/j.jhydrol.2006.08.012)
- Ticehurst JL, Newham LTH, Rissik D, Letcher R, Jakeman AJ (2007) A Bayesian network approach for assessing the sustainability of coastal lakes in New South Wales, Australia. *Environ Model Softw* 22:1129–1139
- Tong STY, Sun Y, Ranatunga T, He J, Yang YJ (2012) Predicting plausible impacts of sets of climate and land use change scenarios on water resources. *Appl Geogr* 32(2):477–489. doi:[10.1016/j.apgeog.2011.06.014](https://doi.org/10.1016/j.apgeog.2011.06.014)
- Tu J (2009) Combined impact of climate and land use changes on streamflow and water quality in eastern Massachusetts, USA. *J Hydrol* 379(3–4):268–283. doi:[10.1016/j.jhydrol.2009.10.009](https://doi.org/10.1016/j.jhydrol.2009.10.009)
- Vogel RM, Sieber J, Archfield SA, Smith MP, Apse CD, Huber-Lee A (2007) Relations among storage, yield, and instream flow. *Water Resour Res* 43(5):W05403. doi:[10.1029/2006wr005226](https://doi.org/10.1029/2006wr005226)
- Walker KF (1985) A review of the ecological effects of river regulation in Australia. *Hydrobiologia* 125(1):111–129. doi:[10.1007/bf00045929](https://doi.org/10.1007/bf00045929)
- Walther G-R (2003) Plants in a warmer world. *Perspect Plant Ecol Evol Syst* 6(3):169–185. doi:[10.1078/1433-8319-00076](https://doi.org/10.1078/1433-8319-00076)
- Ward JV, Stanford JA (2006) Ecological connectivity in alluvial river ecosystems and its disruption by flow regulation. *Regul Rivers Res Manag* 11(1):105–119. doi:[10.1002/rrr.3450110109](https://doi.org/10.1002/rrr.3450110109)
- Whitehead PG, Wilby RL, Batterbee RW, Kernan M, Wade AJ (2009) A review of the potential impacts of climate change on surface water quality. *Hydrol Sci* 54(1):101–123
- Wilby RL, Whitehead PG, Wade AJ, Butterfield D, Davis RJ, Watts G (2006) Integrated modelling of climate change impacts on water resources and quality in a lowland catchment: River Kennet, UK. *J Hydrol* 330(1–2):204–220. doi:[10.1016/j.jhydrol.2006.04.033](https://doi.org/10.1016/j.jhydrol.2006.04.033)
- Wilson CO, Weng Q (2011) Simulating the impacts of future land use and climate changes on surface water quality in the Des Plaines River watershed, Chicago Metropolitan Statistical Area, Illinois. *Sci Total Environ* 409(20):4387–4405. doi:[10.1016/j.scitotenv.2011.07.001](https://doi.org/10.1016/j.scitotenv.2011.07.001)
- Yang, Y.C., Cai, X., Herricks, E.E., 2008. Identification of hydrologic indicators related to fish diversity and abundance. A data mining approach for fish community analysis. *Water Resources Research* 44(4) doi:[10.1029/2006WR005764](https://doi.org/10.1029/2006WR005764)
- Zhang W, Arhonditsis (2008) Predicting the frequency of water quality standard violations using Bayesian calibration of eutrophication models. *J Great Lakes Res* 34:698–720