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Riparian restoration offsets predicted population consequences of climate warming in a threatened headwater fish

Mischa P Turschwell*[1,2], Ben Stewart-Koster[1], Catherine Leigh[1,3], Erin E Peterson[4], Fran Sheldon[1], Stephen R Balcombe[1]

[1]Australian Rivers Institute, Griffith University, Nathan, Queensland, 4111, Australia

[2] CSIRO Data 61, Brisbane, 4001, Queensland, Australia

[3] Griffith School of Environment, Griffith University, Nathan, Queensland, 4111, Australia

[4]Australian Research Council Centre for Mathematical and Statistical Frontiers (ACEMS) and the Institute for Future Environments, Queensland University of Technology (QUT), Brisbane, Queensland, 4000, Australia

* Corresponding author: mischa.turschwell@griffithuni.edu.au

1. ABSTRACT

1. Freshwater ecosystems and their associated biota are under increasing threats from multiple stressors including climate and land use change. The conservation of these ecosystems must be based on an integration of data including species physiological tolerances, the biotic and abiotic drivers on the distribution of populations, and demographic processes, to provide the comprehensive ecological information necessary for management.
2. This study used a Bayesian belief network (BBN) to synthesise research on northern river blackfish, a threated species in the upper Condamine River, Australia, into a probabilistic framework capable of predicting the complex relationships that exist between environmental conditions and population success. This study tested how predicted air temperature scenarios for the years 2050 and 2080, and catchment restoration scenarios would be expected to affect three indices of population success: adult abundance, juvenile abundance, and juvenile recruitment.
3. Compared to current climatic conditions, climate warming scenarios reduced the probability of future population success by between 0.4 and 1.6%. These shifts were almost completely offset, and even improved when riparian zones were restored at the catchment scale, where changes ranged from an overall decrease of 0.2% to an increase of 1%. To achieve the highest probability of population success, the impacts of warming stream temperatures and the degradation of riparian zones must be mitigated. However, the model showed that there is still a possibility of complete population failure under a wide range of conditions, even when conditions appear to be suitable.
4. To maximise the future population success of river blackfish we recommend targeting the restoration of hydrologically-active catchment areas where grazing strongly

influences stream biota. The use of a BBN allowed for the combination of multiple sources of information to solve complex ecological problems, including how multiple stressors may affect threatened freshwater species.

Keywords: climate change, endangered species, fish, modelling, restoration, stream.

2. INTRODUCTION

Anthropogenic climate change is one of the primary threats freshwater ecosystems and their biota face (Dudgeon et al., 2006). Increased warming, along with increasing variability and occurrence of extreme warming and weather events, are placing unprecedented pressure on freshwater ecosystems (Ledger & Milner, 2015). Freshwater streams are likely to undergo significant warming over the next several decades compared to marine systems (Burrows et al., 2011). The responses of freshwater biota to warming streams will undoubtedly be varied, as some habitats become refugia and some species move into newly available habitats made accessible through warming (Isaak et al., 2016). In other cases, species are likely to see range restrictions due to the exceedance of thermal tolerances (Bond, Thomson, Reich, & Stein, 2011; Pörtner & Farrell, 2008) and altered biotic interactions (Lawrence et al., 2014).

Anthropogenic alterations to land use and land cover add further pressure on freshwater ecosystems and species (Allan, 2004). Increased urbanisation and the clearing of vegetation and riparian zones for agricultural purposes including grazing and cropping lead to modifications to stream hydrology, increased nutrient and sediment inputs, and losses in key ecosystem services naturally provided by riparian vegetation (Allan, 2004; Foley et al., 2005). The impacts of climate warming and land degradation on stream biota are often assessed independently (Lawrence et al., 2014; Mantyka-Pringle, Martin, Moffatt, Linke, & Rhodes, 2014; Piggott, Lange, Townsend, & Matthaei, 2012). The impact on freshwater species under future climate and land-use scenarios may be regionally specific, and the consequences for the majority of rivers and streams worldwide are unknown (Nelson et al., 2009). Thus, scientists rely on models to make inferences and predictions about why and how distributions and abundances of biotic populations will shift in the future in order to inform successful management and conservation. There has been a suite of statistical and deterministic methodologies used in such a predictive capacity; though for many, the ability to account for multiple response variables remains challenging (Leigh, Stewart-Koster, Sheldon, & Burford, 2012).

Bayesian belief networks (BBNs) are graphical, probabilistic models that can be used to represent causal relationships among multiple population indices and variables (Aguilera, Fernández, Fernández, Rumí, & Salmerón, 2011; Death, Death, Stubbington, Joy, & Belt, 2015; McCann, Marcot, & Ellis, 2006; Neapolitan, 2004), as well as explore likely outcomes for a range of scenarios. The use of BBNs in ecological and environmental literature has expanded greatly since the early 2000s (Aguilera et al., 2011), with broad applications including species-environment relationships (Death et al., 2015; Leigh et al., 2012), population viability analyses (Lee & Rieman, 1997; Marcot, Holthausen, Raphael, Rowland, & Wisdom, 2001), and environmental decision making (Gawne et al. 2012; Stewart-Koster et al., 2010; Vilizzi et al. 2013). BBNs provide a flexible modelling framework that can incorporate both empirical data and expert knowledge, represented by multiple drivers, and propagate uncertainty through to model outputs.

The aim of this study was to investigate the combined influence of climate change induced warming and land-use impacts on the protected northern river blackfish (*Gadopsis marmoratus*, Richardson 1848) (hereinafter blackfish) (Department of Agriculture and Fisheries, 2016) within the headwaters of the Condamine River, Australia. More specifically, this study tests whether the restoration of riparian vegetation throughout the catchment could buffer instream thermal conditions to improve three population indices for blackfish, namely adult abundance (AA), juvenile abundance (JA), and juvenile recruitment (JR). A data-driven BBN was developed based on the findings of previous studies, combined with field and geographic information system (GIS) data and used it to 1) predict the three population indices under projected climate warming; 2) test how riparian restoration scenarios may mitigate the effects of climate warming on stream temperature and subsequent blackfish survival; and 3) understand the environmental conditions required to maximise the probability of high blackfish recruitment and abundance, and the conditions under which local extinction is possible.

3. METHODS

3.1 STUDY REGION AND TARGET SPECIES

Within the headwaters of the northern Murray-Darling Basin (MDB), Australia, the upper Condamine River (Fig. 1) is classed as a biodiversity hotspot, home to a diverse array of birds, amphibians, insects, and fish (Department of National Parks, Sport and Racing, 2016). The region has undergone heavy deforestation and is primarily used for grazing and cropping due to the highly fertile soils (Carberry, 1995).

Blackfish are benthic-dwelling fish of the Percichthydae family (Lintermans, 2007). They are generalist carnivores, and are strongly associated with instream habitat structure including large woody debris and undercut banks (Jackson, 1978; Khan, Khan, & Wilson, 2004). Blackfish abundance is highly variable throughout the study region and populations in the upper Condamine River are at the most northerly extent of their habitat range. Blackfish demonstrate low fecundity (Lintermans, 2007) and little dispersal from their natal origin throughout their life cycle (home ranges of <50m; Koster & Crook, 2008), making these fish especially vulnerable to local disturbances (Huey, Balcombe, Real, Sternberg, & Hughes, 2017; Khan et al., 2004; Lintermans, 2007). They also have a low effective population size, making them of conservation concern (Balcombe, Huey, & Masci, 2011; Huey et al., 2017). Globally, fishes with fragmented or restricted habitat ranges and low population growth rates have demonstrated an increased risk to local extirpation (Harding, Norton, & McIntosh, 2007; Olden, Poff, & Bestgen, 2008).

3.2 DATA

Blackfish were sampled at 59 sites throughout the region in March 2014 (Fig. 1). The occurrence and abundance of both adults (>70 mm) and juvenile (<70mm) was noted in each site. Of the initial 59 survey sites used by Turschwell, Balcombe, Steel, Sheldon, & Peterson (2017), 38 sites containing a minimum of two adult blackfish (>115mm) were used to investigate JR patterns throughout the catchment (Turschwell, Stewart-Koster, Balcombe, Sheldon, & Peterson., Unpublished data). The proportion of young-of-year (YOY) fishes (<70mm) relative to YOY plus breeding females adults was used as an index to represent recruitment success.

Daily maximum stream temperatures across the austral summer period (80 days in December, January and February of 2013-2014) were collected at 60 sites within the upper Condamine River (Fig. 1) and predicted at 50m intervals across the network using spatial stream-network models (Turschwell, Peterson, Balcombe, & Sheldon, 2016).

3.3 CONCEPTUAL MODEL

To build the BBN, a conceptual model (Fig. 2) was first developed to represent key relationships between environmental processes and three blackfish population indices (Marcot, Steventon, Sutherland, & McCann, 2006). Prior research on blackfish in the Condamine focused on quantifying relationships between three biological responses crucial to future population success (AA, JA, JR), thermal conditions, and land use. Turschwell et al.

(2017) used a suite of thermal metrics derived from spatial stream-network model predictions as covariates in a hurdle model to identify the ecological drivers of blackfish distribution. The presence of blackfish throughout the study region has been shown to be thermally dependent (Turschwell et al., 2017). Previous research also found that AA was negatively associated with increased fine sediment at a site, while JA was negatively affected by increased grazing pressure at a stream site (for further details see Turschwell et al., 2017). The BBN was designed to reflect the hurdle model of Turschwell et al. (2017), where abundance was modelled conditional on presence at a site, a common approach for zero-inflated data (Martin et al. 2005).

Successful JR is the likely most crucial life-history stage in this population of blackfish due to their restricted habitat range and limited dispersal capabilities (Huey et al., 2017; Koster & Crook, 2008; Turschwell et al., 2017). Successful juvenile blackfish recruitment appears to depend primarily on the riverine thermal regime and presence of adequate riparian cover. Turschwell et al. (Unpublished data) found that it was negatively affected by increasing broad-scale thermal conditions (Maximum Weekly Maximum Temperature – MWMT). In cooler stream segments, site-scale riparian foliage cover (RFC) was positively correlated with recruitment success; though as stream temperature increased, the relationship between RFC and recruitment shifted and appeared to shift and smooth, becoming neutral at intermediate temperatures (Turschwell et al., Unpublished data).

3.4 BBN CONSTRUCTION

BBNs use unidirectional links between “parent” and “child” nodes to represent causal relationships between variables within a network based on the conceptual understanding of the system (Korb & Nicholson, 2010). Nodes within the network can be filled via conditional probability tables (CPTs) which incorporate data from multiple sources. Using discrete states within these nodes (e.g. low, medium, high), BBNs use CPTs and inference algorithms to estimate posterior probabilities of event outcomes while incorporating uncertainty via Bayesian belief updating (McCann et al., 2006; Reckhow, 1994). The strength of the relationships between variables is determined by the CPTs, but the CPT of each node is only dependent on its direct parent node, described as the Markov property (Korb & Nicholson, 2010). Based on the conceptual understanding of the species and system described above, the conceptual model (Fig. 2) was converted into a probabilistic BBN (Fig. 3) using the program Netica 5.24 (Norsys Software Corporation, 2008). Nodes were categorised into discrete levels based on a combination of quantiles, natural breaks in histograms, and ecological literature (Table 1). The study then explored how different climate scenarios affected the probability of each state of the population indices. Finally it was assessed whether complete riparian restoration across the catchment could offset the effects of predicted increases in air and water temperature.

3.5 SCENARIOS

The Australian government Climate Futures Tool (Whetton, Hennessy, Clarke, McInnes, & Kent, 2012) was used to provide downscaled climate projections for the study region for two future time periods (2050 and 2080). These projections were based on RCP scenario 8.5 which represents ‘business as usual’, where there is no stabilisation in emissions, leading to a rising radiative forcing pathway of 8.5 W/m^2 (~1370 ppm CO^2 eq) by 2100 (Van Vuuren et al., 2011). Climate data derived from this tool are based on projections from up to 24 global climate models, where the highest model consensus is based on the relative likelihood of the scenario based on all model predictions (Clarke, Whetton, & Hennessy, 2011). This allows the tool to provide simple regional climate projections while accounting for variability in climate models. The highest consensus models predicted increases in daily maximum temperature over the austral summer period (DJF) of 2.44°C for 2050; and 3.40°C for 2080. These increases were incorporated into the parent node “Climate Scenario” as Scenario 1 and

Scenario 2 respectively. The “Current” scenario represents the current day conditions used to build the stream temperature model.

A combination of both the upstream riparian buffer and GIS derived riparian cover (Table 1) was chosen as proxies for riparian restoration at a catchment scale. The upstream riparian buffer provides a measure of the intact riparian zone within a 10m wide riparian buffer extending 1km upstream from each sample site. Given both these variables have been found to significantly influence predicted stream temperature within the region (Turschwell et al., 2016), both were chosen to represent catchment scale restoration. In fact, within their observed range of values, Turschwell et al. (2016) found that for every 10% increase in riparian cover, stream temperature decreased by 0.18°C. Hence, it was then tested how restoration could negate the effects of climate warming on stream temperatures and blackfish population indices by manipulating the amount of upstream buffering and riparian cover a site received.

3.7 MAXIMISING POPULATION INDICES

The primary interest of the study was understanding and quantifying the environmental conditions needed to maximise the probability of high JR, and both high AA and JA (i.e. best case scenarios for each population index). Rather than altering the states of the parent nodes, this study used a bottom-up approach and set the three child nodes (e.g. AA, JA, JR) to the best possible ecological scenarios (high) to identify the range of environmental conditions needed to achieve those scenarios modelled by the BBN. The three population index nodes were then set to worst case scenarios, where JR failed, and both adults and juveniles were absent to test the conditions in which population failure could occur.

3.8 ANALYSIS OF THE BBN

Sensitivity analysis for BBNs with discrete nodes is often based on entropy reduction (also known as Mutual Information), which is used to assess the network and identify which nodes have the most influence on the blackfish population index (Marcot et al., 2006). Nodes with higher entropy reduction values have a greater influence on the response node (population index) than those with lower values (Marcot et al., 2006). The network's sensitivity to findings was tested for the population indices JR, AA, and JA, as well as 'Adult Occurrence' and 'Juvenile Occurrence' because the adult and juvenile abundances were conditional on fish presence as presented by the "occurrence" nodes in the BBN.

10-fold cross-validation was used to assess BBN performance. The data were randomly split and assigned to either 'training' (90%) or 'holdout' (10%) sets, which were used to train and subsequently test the network 10 times. The spherical payoff and error (misclassification) rate was used to assess model performance. Spherical payoff ranges from 0 to 1, with values of 1 indicating the best model fit (Marcot et al., 2006). The error rate is defined as the percentage of model misclassification between predicted and actual values for each node state.

4. RESULTS

The network contained the parent node "Climate Scenario" which represented current and two potential future climatic conditions (discussed below); two nodes "Upstream Riparian Buffer" and "GIS Derived Riparian Cover", which included current conditions and were used as proxies to estimate the responses to scenarios of catchment restoration. There were 10 nodes depicting relationships between environmental variables and adult and blackfish occurrence, as well as three child nodes JR, AA, and JA, which represented critical life-stages of river blackfish (Fig. 3).

Sensitivity analysis identified nodes that were most influential to the states of the three child nodes, AA, JA, and JR. As expected, parent nodes directly connected to the child nodes had the greatest influence on their states. For instance, Adult Blackfish abundance was most strongly influenced by levels of Fine Sediment and the thermal metric Event Days, which represents the successive number of days where stream temperature exceeded 28°C (Table 2), while JA was most sensitive to Grazing and also Event Days (Table 2). Juveniles were more than two times more sensitive to Event Days than adults in terms of abundance. The sensitivity of adult and juvenile occurrence (Table 2) was primarily driven by two environmental predictors; Event Days, and Daily Maximum Stream Temperature. Similar to the nodes representing blackfish abundance, the influence of Event Days on occurrence was almost twice as strong for juveniles as for adults. JR was equally sensitive to site-scale riparian cover and MWMT (Table 2). Daily maximum stream temperature was the only common node identified in sensitivity analyses for all 5 child nodes of interest (Table 2).

The error rates were different across the three child nodes. The BBN's mean error rate for the JA node was only 11.7% with a spherical payoff of 0.93, indicating very good model fit. For the AA node, the BBN's mean error rate was 36.7% with a spherical payoff of 0.71 (Table 3). The JR node performed similarly to the AA node with almost identical error rates and spherical payoff (Table 3). Confusion matrices generated during cross-validation indicated the majority of error was due to minor misclassifications only (Table 3), i.e. misclassification by one category of the correct state (e.g. low vs medium, or medium vs high; but not low vs high).

The impact of climate change appeared to be smaller on the child nodes-of-interest than local-scale riparian conditions. Compared to the current climatic conditions, setting the climate scenario node to either 2050 or 2080 had a minimal effect on population indices, reducing the probability of high abundance and high recruitment by up to 0.4% and 1.6%

respectively. The incorporation of variability through the network resulted in only a small change (-0.25% to -1.6%) in probability for each level of the population indices. However, by setting both the upstream riparian buffer and GIS derived riparian cover node states to high, the effects of climate warming were reduced compared to current conditions or actually slightly improved (Fig. 3 vs. Fig. 4). For example, the probability of high JR reduced by 1.6% under climate scenario 2, but then improved by 1% under scenario 2, with full riparian restoration (see Appendix for full table of changes in probability).

Under current conditions, the probability of high JR was 27%. Within sites where high recruitment was observed, 47.1% had high site-scale riparian cover and 37.1% had low cover, indicating that high recruitment is more likely when riparian cover is high, though appears to be able to occur under all riparian conditions (Fig. 5a). High recruitment was almost impossible (0.71%) when daily maximum stream temperatures were high, and not likely under high MWMTs (12.7%). Adult abundance was also strongly influenced by thermal conditions. The current probability of high AA was only 20.3%, and was only achieved when Event Days were low, and was not possible under high levels of fine sediment. However, high AA was almost equally possible under both low and medium fine sediment loads. High JA was less likely than high AA (9.26%), though exhibited similar drivers and responses to adults. High abundance was only possible when both Event Days and Grazing had a 100% probability of being low (Fig. 5a).

Setting the three nodes to worst case scenario (i.e. recruitment failure and no adult or juvenile abundance) suggested that population failures could occur under a much wider range of conditions compared to those required to maximise the population indices (Fig. 5b). The probability within several nodes had a more even distribution among categories (Fig. 5b, “Grazing”, “Event Days”, and “Fine Sediment” nodes), signifying that there are many more potential scenarios at which blackfish populations are severely at risk than the range of conditions that maximise future survival.

5. DISCUSSION

This study successfully integrated data from multiple sources into a probabilistic framework and used this to test and explore the impacts of climate change and restoration activities on a thermally restricted headwater fish, based on empirical information and previous knowledge of the study species and system. The BBN represented, and was able to predict, the complex multi-stressor relationships previously identified between environmental conditions and a range of blackfish population indices. The models' predictive performance is comparable to other BBNs exploring species-environmental relationships including Chan et al. (2012), who explored relationships between environmental flows and fishes, Leigh et al. (2012) who investigated macroinvertebrate responses to hydrological alteration, and Vilizzi et al. (2013) who used expert elicitation to assess how environmental watering strategies could benefit native wetland fish.

Climate warming may not be as detrimental as previously thought for blackfish in this system based on the current BBN. The changes in probability for the child nodes indicate that the initial effect of climate warming scenarios were minor, and even under the predicted increases in air temperature in 2080, the probability of blackfish survival did not considerably alter. These results differ from the findings of Balcombe, Sheldon, et al. (2011), who suggested that climate change would lead to significant range reductions for blackfish across their entire distribution. Similarly, Bond et al. (2011) also predicted an almost complete loss of blackfish in some northern regions of Victoria (Southern MDB) under warming climate scenarios. Within the context of the MDB, these regions are climatically similar to the upper Condamine River, however Bond et al. (2011) incorporated hydrological information into their species distribution models, which was not available for the upper Condamine River catchment. The results from the present study may indicate that the contemporary issues facing aquatic organisms throughout both the MDB and globally including altered hydrological regimes, dispersal barriers, and increased sedimentation, are negatively affecting stream biota more than climate change (Arthington, Dulvey, Gladstone, & Winfield, 2016; Balcombe, Sheldon, et al., 2011).

Others studies have tested the influence of future climate and land-use scenarios using a top down approach and demonstrated significant changes to probable states in their nodes of interest (see Leigh et al., 2012); however this is most likely due to a stronger mechanistic relationship between parent nodes and child end-nodes in their study system compared to the current system. The current model suggests that complete riparian restoration within the catchment (as per Davies, 2010) may provide suitable blackfish habitats into the next century, given that riparian restoration completely negated the effects of warming air temperatures on stream temperature, as well as predicted blackfish abundances and recruitment. Nevertheless, the present study did not account for the influence of hydrology; thus, reduced flows may ultimately compound the effects of climate warming, as smaller streams are unable to buffer against extreme thermal events (Caissie, 2006), placing further stress on ectothermic species.

Maximising the population indices provided information about the range of suitable environmental conditions required to ensure the greatest probability of future population success for river blackfish. The required environmental changes needed to achieve such outcomes are quite extreme, and are highly unlikely. For example, high adult and JA was only achievable under conditions of low numbers of Event Days. Even under current conditions, low Event Days have often been exceeded, indicating that the probability of achieving high abundance in all locations in the study region is improbable. However, understanding the conditions required to maximise population success provides an ideal target for management given sufficient funding and resources are available for restoration. Setting the population indices to worst case scenarios provided even greater insight into the likelihood of future blackfish population survival. Complete population failures could potentially occur under a much greater range of scenarios, and even under environmental conditions deemed highly suitable to blackfish such as low grazing and low Event Days (Turschwell et al., 2017). This suggests that blackfish are highly vulnerable because there are a broader array of conditions under which local extinction might occur compared to conditions required for high abundance and recruitment.

The present BBN predicted and classified population indices reasonably well. However, the degree of misclassification suggests that there are likely other variables that impact the maintenance of blackfish populations that remain unresolved. Maximum stream temperature represents a central theme linking blackfish population indices, but it only represents one aspect of climate warming. While temperature metrics that capture the magnitude and duration of heating events were used, the altered frequency and variability of extreme climate events is highly likely under climate change (IPCC, 2012; Leigh et al., 2015) and was not comprehensively accounted for in this model. Furthermore, uncertainty in the causal relationships between the population indices and environmental variables may have arisen due to the relatively small sample size for two datasets (abundance and recruitment), or even through the process of converting continuous variables into categories (Kuhnert & Hayes, 2009).

The graphical nature of BBNs allows for the clear communication of results and can aid in directing management practices. For northern river blackfish, mitigation strategies to reduce the impact of increasingly extreme thermal events such as the extended duration of warming, and increased frequency of hotter days must be prioritised, given that of the variables tested, both adult and juvenile occurrence (and subsequently adult and JA) were the most sensitive to the Event Days node. In addition to being strongly influenced by stream temperatures, adult and JA were highly sensitive to increased levels of fine sediments and grazing. The BBN results suggest that both these variables must be significantly reduced to increase blackfish population success; indicating an urgent need to address their negative impacts on blackfish. This is most likely to be achieved with the complete restoration of the riparian zone and exclusion of ungulate grazers, which may not only improve thermal regulation of in-stream habitat but also reduce erosion and sediment input (Marsh, Rutherford, & Bunn, 2005; McKergow, Weaver, Prosser, Grayson, & Reed, 2003). The social and-economic costs associated with both active riparian restoration and fencing to exclude grazers provide considerable challenges for such a mitigation strategy (Hermoso et al., 2012). Conversations with local landholders have revealed a historical unwillingness to undertake such measures largely because rehabilitation programs offered to them have thus far not included full cost recovery for the landholder. Furthermore, the influence and extent of groundwater may also need to be quantified before any form of restoration takes place, given its importance on riparian ecosystems (Naiman & Décamps, 1997). Despite these challenges, we suggest that identifying and targeting restoration in hydrologically-active catchment areas, where greater overland flow increases the influence of grazing on streams (Peterson, Sheldon, Darnell, Bunn, & Harch, 2011), will help prioritise and deliver spatially explicit management recommendations for grazer exclusion and riparian restoration.

BBNs are by no means a panacea, but they do provide a graphical framework that can be used to integrate multiple data sources and types into a probabilistic framework. Discussing the benefits and pitfalls of BBNs is beyond the scope of this article and has been previously addressed (see Kuhnert & Hayes, 2009; Uusitalo, 2007); however, in this empirical example the additional information gained from the BBN has highlighted that the thermal implications of climate change may not be as severe as previously believed for the studied species.

Nevertheless, blackfish are highly vulnerable, as local extirpation can occur under a wide range of environmental conditions. For example, a large number of flood events in 2010-2011 managed to displace blackfish and severely impact the recruitment of juveniles into the 2011 population (Balcombe, Huey, et al., 2011). Such extreme events are likely to become more frequent and intense under predicted climate change, and may significantly alter population dynamics and resilience to disturbance (IPCC, 2012; Leigh et al., 2015). BBNs have limitations, and it is unlikely that all sources of variability and uncertainty have been incorporated into this model (McCann et al., 2006). As additional empirical data become available, such as hydrological and water quality data, they can be incorporated into the current BBN to help validate and more clearly define some of the relationships between environmental variables and blackfish population indices, as the relatively small sample size for certain nodes may require supplementation. Furthermore, future climate variability must also be accounted for to increase model certainty and usability to aid in decision-making and successful management of threatened freshwater species such as the northern river blackfish.

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8. APPENDIX

Node states and changes in probability from current conditions (scenario 0) under a range of climate and restoration scenarios (scenarios 1-3). Scenario 1 represents a 2.44°C increase in maximum daily temperatures, while scenario 2 represents a 3.4°C increase. Scenario 3 represents a 3.4°C increase in conjunction with high upstream riparian buffering and high GIS derived riparian cover.

Child Node	Node States	Scenario 0: Current	Scenario 1: Climate Scenario1	Scenario 2: Climate Scenario2	Scenario 3: Climate Scenario2 + Riparian Restoration
Juvenile Recruitment	Failure	29.3	+0.8	+1	-1.4
	Low	43.7	+0.4	+0.5	+0.4
	High	27	-1.2	-1.6	+1
Adult Abundance	Absent	30	+1	+1.4	+0.6
	Low	29.2	-0.4	-0.6	-0.3
	Medium	20.4	-0.3	-0.5	-0.2
	High	20.5	-0.3	-0.4	-0.2
Juvenile Abundance	Absent	53.8	+1.3	+1.7	+0.7
	Low	28.3	-0.7	-1	-0.4
	Medium	8.46	-0.23	-0.31	-0.12
	High	9.39	-0.25	-0.34	-0.13

9. TABLES

Table 1 List of nodes used in the Bayesian belief network (BBN). Each node is described, has discrete values and methods used, as well as the data source used to gather data.

Predictor Variable Description and Unit	Low	Medium	High	Extreme	Absent	Present	Method	Data Source
Climate Scenario Projected increase in daily maximum temperature over austral summer period based on Representative Concentration Pathway 8.5 for 2050 (Scenario 1 - 2.44°C) and 2080 (Scenario 2 – 3.40°C).	-	-	-	-	-	-	-	1*.
Upstream Riparian Buffer A 10m wide riparian buffer extending 1km upstream from a sample site (%)	0 - 32	32 - 56	56 - 75	-	-	-	Quantiles	2.
Maximum Air Temperature Daily maximum air temperature (°C)	18 - 25	25 - 27.5	27.5 - 29.5	29.5 – 43	-	-	Quantiles	2.
GIS Derived Riparian Coverage Riparian coverage derived from a state-wide	0 – 33	33- 64	64 – 85	-	-	-	Quantiles	2.

foliage projective cover map (10m resolution) (%)								
Elevation Elevation derived from a 10m Digital Elevation Model (m)	500 – 600	600 – 750	750 – 900	-	-	-	Natural Histogram Breaks	2.
Maximum Stream Temperature Predicted maximum daily stream temperature (°C)	15 – 23	23 – 27	27 – 32	-	-	-	Quartiles	2.
MWMT Predicted maximum Weekly Maximum Temperature. The highest 7day moving average of daily maximum stream temperatures (°C)	19 - 23	23 – 26.5	26.5 – 30	-	-	-	Quantiles	2.
Event Days Predicted number of consecutive days stream temperature at a site exceed a threshold value of 28°C	1	2	>3	-	-	-	-	2.
Site-Scale Riparian Cover Riparian cover at a sample site derived using hand held spherical densitometer. (%)	0 – 48	48 – 86	86 – 100	-	-	-	Quantile	3.

Grazing The percentage of grazing at a sample site based on hydrologically-active inverse-distance-weighted metrics that account for the influence of grazing in areas prone to overland flow (%)	0 – 51	51 – 81	81 – 100	-	-	-	Quantile	2.
Sediment The percentage of instream fine sediment (<16mm diameter) measured at each sampling location (%)	6 – 19	19 – 41	41 – 100	-	-	-	Quantile	3.
Adult Occurrence Binary measure of whether adult fish were present at a site	-	-	-	-	0	1	Binary	3.
Juvenile Occurrence Binary measure of whether juvenile fish were present at a site	-	-	-	-	0	1	Binary	3.
Adult Abundance Total number of adult fish caught at each sample site	1 – 10	11 – 20	21 – 60	-	0	-	Natural Histogram Breaks	3.
Juvenile Abundance	1 – 10	11 – 20	21 – 140	-	0	-	Natural	3.

Total number of juvenile fish caught at each sample site							Histogram Breaks	
Juvenile Recruitment The proportion of Young-of-year fishes (<70mm) relative to breeding females (>115mm) in the sampling site (see Turschwell et al., *Unpublished data* for full details) (0-1)	0.01 – 0.5	-	0.51 – 1	-	0	-	Quantiles	4.

1. Whetton et al., 2012 *https://www.climatechangeinaustralia.gov.au/en/climate-projections/climate-futures-tool/projections/
2. Turschwell et al., 2016
3. Turschwell et al., 2017
4. Turschwell et al., Unpublished data

Table 2 Mean and standard deviations of error rates and spherical payoff based on 10-fold cross validation for the three child nodes of interest (Adult Abundance, Juvenile Abundance, and Juvenile Recruitment), as well as sensitivity analysis for the five nodes of interest (Adult Abundance, Juvenile Abundance, Juvenile Recruitment, Adult Occurrence, and Juvenile Occurrence). Corresponding nodes and entropy reduction values indicate the influence of each node on the five nodes of interest. Note that error rate and spherical payoff were only calculated for the three primary child notes, and not occurrence nodes (Denoted by asterisks).

Child Node	**Error Rate (SD) (%)**	**Spherical Payoff (SD) (0-1)**	**Node**	**Entropy Reduction**
Adult Abundance	36.7 (17.9)	0.71 (0.10)	Adult Occurrence	0.89836
			Fine Sediment	0.17686
			Event Days	0.10913
			Daily Maximum Stream Temperature	0.02057
Juvenile Abundance	11.7 (7.6)	0.93 (0.05)	Juvenile Occurrence	0.99221
			Grazing	0.27802
			Event Days	0.20409
			Daily Maximum Stream Temperature	0.02765
Juvenile Recruitment	37.5 (30.1)	0.72 (0.11)	Site-scale Riparian Cover	0.18595
			Maximum Weekly Maximum Temperature	0.16578
			Daily Maximum Stream Temperature	0.02376
Adult	-	-	Event Days	0.10913

Occurrence*			Daily Maximum Stream Temperature	0.02057
Juvenile Occurrence*	-	-	Event Days	0.20411
			Daily Maximum Stream Temperature	0.02765

Table 3 Adult and Juvenile Abundance, and Juvenile Recruitment showing predicted and actual abundance and recruitment values.

Model	**Predicted Values**				**Actual Values**
	Absent	Low	Medium	High	
Adult Abundance	13	0	0	0	Absent
	0	16	3	4	Low
	0	7	3	4	Medium
	0	3	1	6	High
	Absent	Low	Medium	High	
Juvenile Abundance	30	0	0	0	Absent
	0	18	0	1	Low
	0	6	0	0	Medium
	0	0	0	5	High
Juvenile Recruitment	Failure	Low	High		
	14	0	1		Failure
	9	3	0		Low
	5	0	8		High