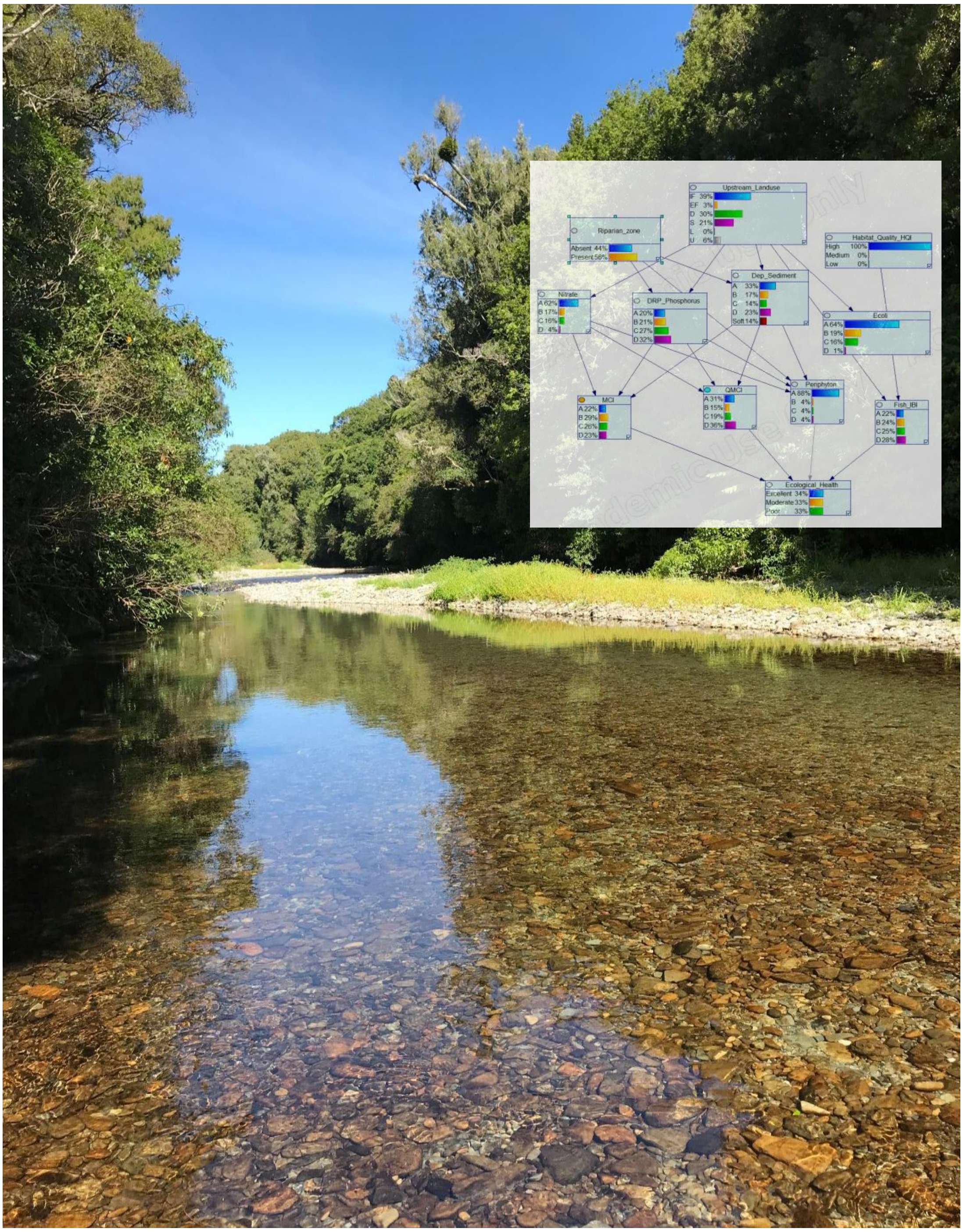
A Bayesian model to assist Te Whaitua o Kāpiti in developing freshwater ecosystem guidelines for streams and rivers in Kāpiti.



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Executive Summary

1. Rivers are complex ecosystems closely linked to the adjoining land, upstream catchment, and downstream reaches. As a consequence, managing them to ensure they remain healthy while balancing other potential uses for river water is extremely challenging.
2. To assist Te Whaitua o Kāpiti with developing the Whaitua Implementation Programme (WIP), a Bayesian Belief Network model was developed from data and expert opinion from the Western science and Mātauranga Māori perspectives.
3. Measures of model fit to the data indicated the BBN was adequate but better at predicting A and D states than B and C states for MCI, QMCI and Fish IBI.
4. This allowed the committee to explore quantitatively what attribute thresholds (e.g., National Policy Statement for Freshwater Management attribute states) were most likely to produce the ecological and cultural health outcomes desired for those waterways as determined by the Whaitua Kāpiti committee. This was done for each of the FMUs in turn.

Introduction

The Greater Wellington Regional Council's Whaitua process involves developing a management document for freshwater in each Whaitua after considerable discussion with a committee representing the views of the general public, tangata whenua, subject area experts, and regional council staff. The Whaitua Kāpiti Implementation Programme (WIP) (Greater Wellington, 2024) documents the collective recommendations of Te Whaitua o Kāpiti Committee (Committee) and seeks to focus the attention of decision-makers on Te Mana o te Wai so “the balance between the water, the wider environment and the community are restored and preserved.”

> *As the lifeblood of our ancestor Papatūānuku, we need to ensure our awa are well. Why would we allow our ancestor to remain in the hospital, only to make her partially well again? We want her to be well and functioning.*

The Treaty House framework was used for developing the Kāpiti WIP. The Te Tiriti House model is a framework for enacting Te Tiriti o Waitangi / Treaty of Waitangi (Te Tiriti). Many view the agreements within Te Tiriti as a partnership between Rangatiratanga and Kāwanatanga. In Te Whaitua o Kāpiti process, the Rangatiratanga were represented by six tangata whenua from regional hapū and iwi. The Kāwanatanga were represented by six members of the local community.

Although it is laudable that the National Policy Statement for Freshwater Management seeks to develop specific localised community aspirations for their waterways within the constraints of the ecological health framework set out in the document, it is extremely challenging for the general public to effectively understand the data and science of complex freshwater ecosystems to make informed decisions about rules on waterway health. For example, how can a citizen understand how differing instream nitrate levels are affected by different types of land use and/or how those concentrations impact ecological health? These questions are challenging enough for scientists who have spent a lifetime researching them (Canning & Death, 2023). Furthermore, stressors on freshwater ecosystems seldom act in isolation but can interact in unexpected ways to impact ecological health (Ormerod *et al.*, 2010; Davis *et al.*, 2018).

To assist the committee in understanding the impacts of differing levels of individual stressors on measures of waterway ecological health and how the stressors may potentially interact to affect the ecological health of streams and rivers, a Bayesian Belief Network (BBN) was developed for streams and rivers in Whaitua Kāpiti. This report describes the development of the BBN model that was used to assist the committee in its decision-making process.

Bayesian Belief Networks (BBNs) are a graphical, rule-based probabilistic modelling technique that is a widely used research and management tool (e.g., (McCann, Marcot & Ellis, 2006; Uusitalo, 2007; Pourret, Naim & Marcot, 2008; Death *et al.*, 2015b). In environmental management, BBNs can provide a useful visual depiction of the causal linkages between multiple environmental drivers and the state of ecological health (Aguilera *et al.*, 2011; Allan *et al.*, 2012). They also allow managers to model changes in those drivers to explore the effects on the condition of that ecological state (McCann, Marcot & Ellis, 2006). For example, a BBN can be used to investigate how changes in land use may directly and/or indirectly alter a measure of invertebrate ecological health such as the MCI (Death *et al.*, 2015b). BBNs have several advantages: 1) their graphical structure allows easy interpretation by non-modellers (McCann, Marcot & Ellis, 2006); 2) they can be used with incomplete data sets (Uusitalo, 2007); 3) they can incorporate expert knowledge (Pollino *et al.*, 2007; Uusitalo, 2007); 4) they can combine categorical and continuous variables (Marcot *et al.*, 2001); 5) there is an explicitly documented level of uncertainty (Uusitalo, 2007); 6) they can predict in both directions (e.g., water quality can be predicted from the biota present and can also predict what biota will be present with different conditions; (Paisley *et al.*, 2011); and 7) relatively inexpensive, user-friendly software allows BBNs to be constructed. One major drawback of available software for BBNs in environmental science is arguably the requirement to discretise continuous variables, as most environmental data is continuous rather than discrete; however, the NPSFM (2000) that forms the basis for the direction of the management of freshwater resources in New Zealand has inbuilt discrete categories in the form of A, B, C, and D class waterways (Government, 2020b).

The Treaty House approach for developing the Kāpiti WIP also meant that Western Science data and measures needed to be integrated with Mātauranga Māori data and measures. I believe the discretised probabilistic nature of BBNs lends itself to the frameworks often used in Mātauranga Māori science, where observations are often more qualitative, e.g., a stream has enough suitable tuna for harvesting or it doesn't (Hikuroa, 2017). Data from research by the Māori scientists in the Whaitua Kāpiti committee was also integrated into the BBN framework. Interestingly, this also included assessments from the social science of awa hauora using the concept of Environmental Distress Score developed by Te Ātiawa ki Whakarongotai. There appeared to be no similar Western Science data of this aspect of waterway health that could be incorporated into the model.

Purpose

Whaitua Kāpiti is tasked with developing freshwater attribute limits for their awa freshwater management units. To assist with this process a machine-learning model using Bayesian probabilities was developed that represents the current state of these attributes in the catchment. The model allowed Kāpiti Whaitua committee members to investigate the effects of particular attribute states (i.e., in bands A-D) on achieving potential desired freshwater values. For example, what nitrate thresholds would be needed in a waterway to ensure an agreed-on state of ecological health? The model provides evidence-based guidance—but not decisions—on attributes and/or their preferred numerical states.

BBN model construction

An initial simplified model network adapted from a BBN constructed for the Manawatu River and using Western Science (Death *et al.*, 2015b), was presented to the committee for consideration at a hui held on October 12, 2023. The committee debated additional attributes that should be added to the Kāpiti WIP model, and where they were deemed appropriate, they were added to the network framework. One of the challenges with building models using artificial intelligence algorithms is that a reasonable representation of data is required to make accurate predictions. This includes both the quantity of data and examples of all states of concern. For example, although there was good information on waterways in most land uses, there was no data from waterways with a rural lifestyle land use; consequently, no assessments of this land use are possible. However, public concerns about waterway management often arise from individual observations of adverse events. For example, the discharge from the Waikanae sewage treatment plant is a major point of concern for tangata whenua, but there is only one such discharge, so modelling its impacts with AI learning is impossible. As Einstein explains "Models should be as simple as possible, but no simpler". So, for many of the issues of concern raised by the committee, there were not enough examples and/or data available to include them in the BBN model (see below for more detail). It was also not possible to include wetlands, lakes or groundwater in the model, again because of lack of data and/or expertise. The model framework delivered by this process is presented in Figure 1.

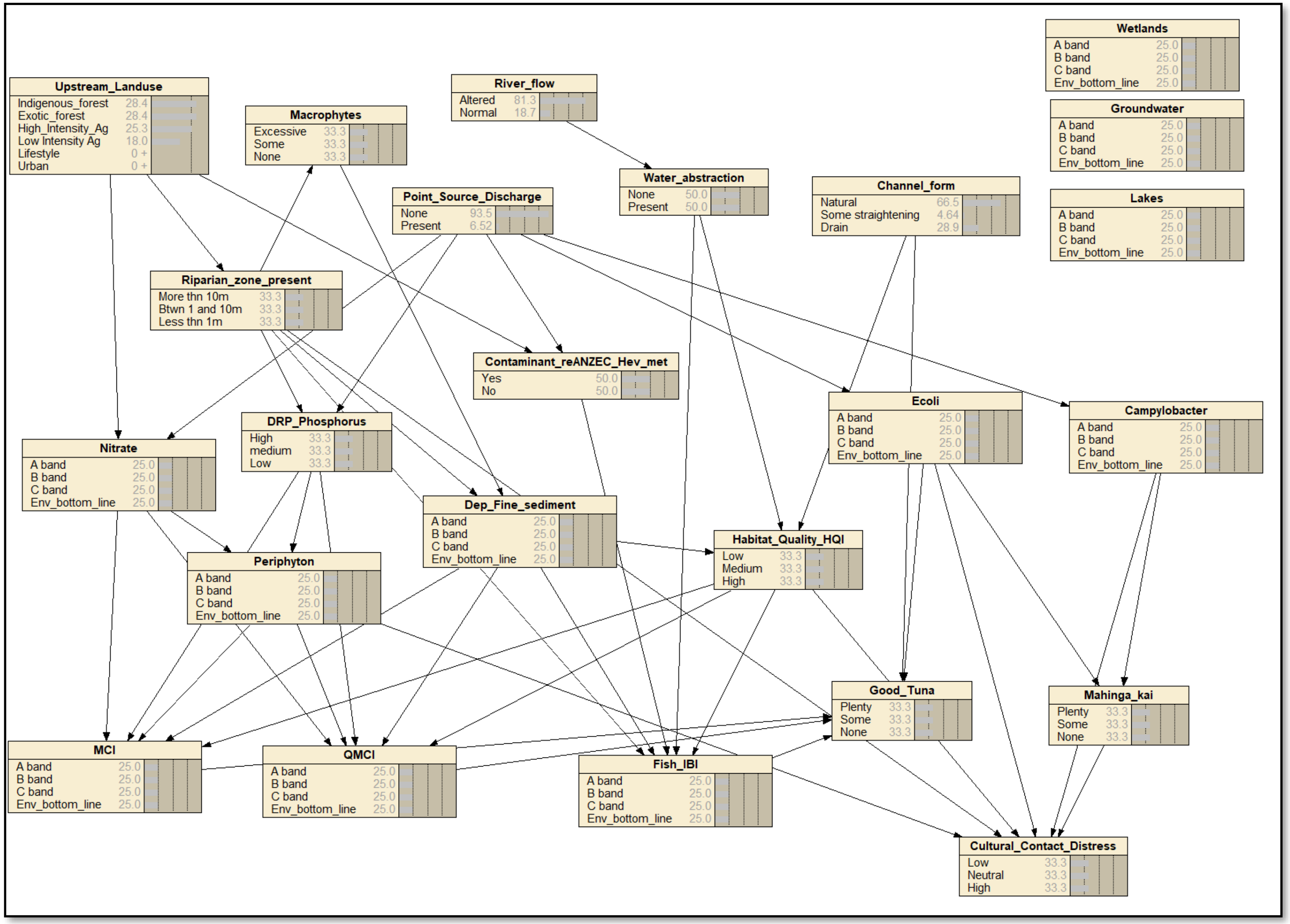

Figure 1 Original BBN model framework developed by Whaitua Kāpiti committee in October 2023.

Data and model attribute states

The compulsory attributes, and attribute states, from the National Policy Statement for Freshwater Management were used unless Whaitua Kāpiti determined otherwise (Government, 2020b). For some variables of interest surrogates with more data and/or scientific knowledge will be used as agreed by Whaitua Kāpiti, e.g., campylobacter rather than campylobacter-free watercress. Some variables of concern to Whaitua Kāpiti outside the scope of this model, e.g., wetlands, lakes, and groundwater, will be included in the model as potential influencers/environmental outcomes whose impact is unknown or unquantified. They will not be linked to the model but just represented visually as a reminder of some unknowns. In some cases, variables/outcomes of concern will be excluded (by Kāpiti Whaitua agreement) if they represent situations that are rare or uncommon, e.g., there was data on only one intermittent water abstraction so the impacts of flow alteration could not effectively be incorporated in the model. This is because the modelling of such cases is beyond the abilities of this model.

Wherever possible, data provided by Greater Wellington Regional Council will be used to build and/or evaluate the model. However, machine learning models perform better with more data, even when outside the specific region of concern. For example, the BBN model built for the Manawatu River using data from Hawkes Bay, Taranaki, Whanganui, Wellington and Waikato was a better fit to the data (and thus provided more accurate predictions) than one built from data just from the Manawatu (Death *et al.*, 2015b). Ecological processes and relationships do not change simply by moving from one catchment to another. Only the observed outcomes of those processes potentially change as stressors alter, e.g., land use change. If there are situations where models will be improved by including data from outside the region, this was achieved with other data from Greater Wellington, Ministry for the Environment and Russell Death. This was done for MCI and QMCI data.

In some cases, quantitative data does not exist for particular variables of concern to the committee in a conventional Western science database, particularly with respect to mahinga kai, and social and cultural drivers/outcomes. In these cases, expert knowledge was used (Greer *et al.*, 2023). For example, nitrate thresholds in the model attribute were based on expert opinion derived from previous research (Government, 2020a; Canning & Death, 2023) However, quantitative data will be used whenever available. This process also highlighted opportunities for further data gathering relevant to Whaitua Kāpiti management.

Attribute state and source data

The information source for the states used in each of the attribute boxes in the BBN is listed below along with the source of the data that populates each of the states in the model.

Attribute	**State source**	**Data source**
Upstream Landuse	REC River Environment Classification (Snelder & Biggs, 2002)	REC. High vs low intensity relates to Dairy vs Sheep & Beef (Larned *et al.*, 2018)
Riparian zone	Presence/absence	SegRipNative in Freshwater Ecosystems of New Zealand (FENZ) (Leathwick *et al.*, 2010). Threshold SegRipNative > 0.5 or Indigenous forest.
Habitat Quality Index (HQI)	Whaitua committee	(Death *et al.*, 2015a; Fuller *et al.*, 2021)
DRP Phosphorus	NPSFM	(Larned, Snelder & Unwin, 2017)
Nitrate	Nitrate for ecological health in the Draft NPSFM. Note this is not the toxicity attribute in the current NPSFM	(Larned, Snelder & Unwin, 2017)
E. coli	NPSFM	(Larned, Snelder & Unwin, 2017)
Deposited Sediment	NPSFM	(Clapcott & Goodwin, 2017)
MCI/QMCI	NPSFM	GW data (Death *et al.*, 2015b)

Ecological health	Russell Death expert knowledge	Russell Death expert knowledge
Periphyton	NPSFM	Not included because of lack of information.
Macrophytes	Presence/absence	Not included because of lack of information.
Fish IBI	NPSFM	New Zealand freshwater fish database
Harvestable Tuna	Caleb Royal expert knowledge	Caleb Royal pers comm. Mahinga kai discussion paper 2024
Campylobacter	Presence/absence	(Phiri *et al.*, 2020)
Knowledge transfer	Mana Whenua House expert knowledge	Mahinga kai discussion paper 2024
Connection	Mana Whenua House expert knowledge	Mahinga kai discussion paper 2024
Hapū environmental distress	Mana Whenua House expert knowledge	Mahinga kai discussion paper 2024
Cultural health	Mana Whenua House expert knowledge	Mahinga kai discussion paper 2024

Final BBN model used in Kāpiti Whaitua deliberations

The model BBN that was constructed using available data and expert knowledge is presented in Figure 2. The values in each of the attribute states in the boxes represent the percentage distribution of the data used for the model construction.

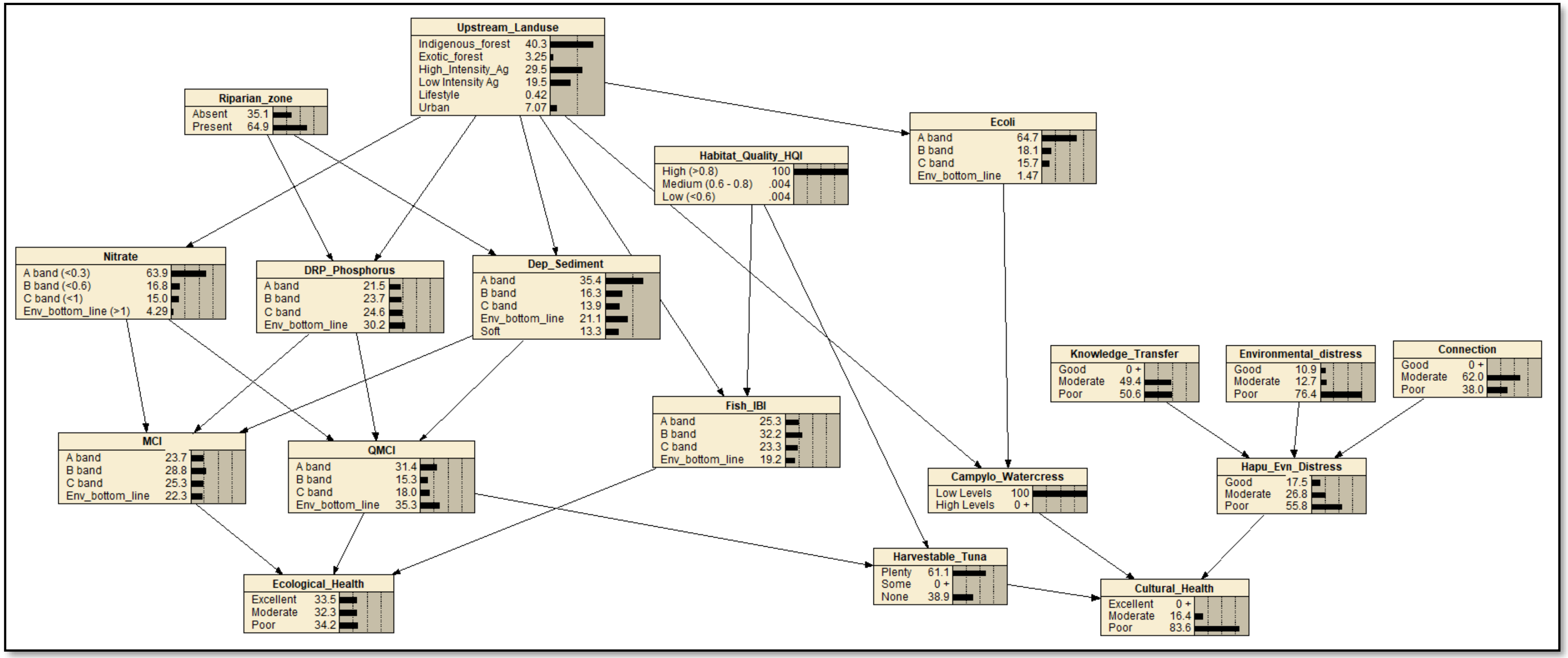

Figure 2 BBN model used for Kāpiti Whaitua committee deliberations.

Model construction and testing

The BBN was constructed using Netica™ 6.09 (Pourret, Naim & Marcot, 2008). The network of interconnected variables is represented as a series of nodes. Conditional Probability Tables (CPTs) were developed with the expectation-maximization algorithm (EM Learning) in Netica™ from the compiled data. The expectation–maximization (EM) algorithm is an iterative method for finding maximum likelihood estimates of parameters in statistical models, where the model depends on unobserved latent variables (Do & Batzoglou, 2008). CPTs calculate the probability of each state in a node occurring, given each combination of conditions in the parent (input) nodes (Pourret, Naim & Marcot, 2008).

Models were evaluated by hold-out validation with a randomly selected 10% subset of the training data. There is a wide range of metrics that can be used to evaluate model fit and performance (for a detailed review see (Witten, Frank & Hall, 2011; Marcot, 2012)). We used several commonly used metrics that assess both raw predictive ability and ability relative to occurrence. The percentage of incorrect predictions (percent error) is a simple, easily understood metric but is sensitive to the number and size of the nodes. For example, if you have a very common state in the node and predict it will always occur (P=1.0) then you have a high probability of being correct simply because it usually occurs. Area under receiver operating characteristic curves (AUC) attempt to correct for this by plotting true positives against false positives to search for a balance between sensitivity and specificity (Hand, 1997). They range from 1 to 0, with 0.5 denoting totally random models and >0.5 improvement on random (Marcot, 2012). The logarithmic loss score (Dlamini, 2010) was used to compare BBNs of alternate architecture (which boxes are linked to each other, and in what direction). The index ranges from 0 to infinity, with 0 being the best possible score.

Model performance

There was data on mahinga kai and cultural health at 18 sites. This is arguably too limited a data set to get an accurate assessment of model predictions, so model performance was assessed only with the Western Science components of the model.

The BBN had a logarithmic loss score of 7.49 (this ranges from 0 to infinity, with 0 the best possible score). This is higher than the 0.72 log loss score for the Manawatu QMCI BBN (Death *et al.*, 2015b) but with the available data, this was the best architecture achievable.

The area under receiver operating characteristic curves (AUC) for three key attributes (MCI, QMCI and IBI) are presented in Table 1. All attributes performed well, although the MCI attribute was narrowly the best. Similarly, the percentage of correct predictions from a leave-one-out cross-validation process was good and best for the QMCI and A and D states. Predictions for intermediate states of B and C were, however, poor for all three attributes.

Table 1Measures of performance of BBN for MCI, QMCI and IBI

Attribute	State	AUC	Percentage correct in model	Percent correct by chance
MCI	A	0.84	89	23.7
	B	0.66	25	28.8
	C	0.74	42	25.3
	D	0.87	57	22.3
	Overall	0.78	53	
QMCI	A	0.82	86	31.4
	B	0.58	3	15.3
	C	0.67	17	18
	D	0.79	72	35.3
	Overall	0.72	58	
Fish IBI	A	0.73	78	25.3
	B	0.58	19	32.2
	C	0.55	0	23.3
	D	0.77	77	19.2
	Overall	0.66	47	

I would consider the BBN model overall to be adequate but not excellent, particularly as it was poor at predicting alternate states of an intermediate nature. The BBN model, however, is excellent at differentiating between good (A) and bad (D, below the environmental bottom line) states. Interestingly, the low predictability with the intermediate B and C states probably reflects that the distinction between B and C states is subtle with respect to how environmental drivers can impact those states. Sites incorrectly predicted as B were often C, and those predicted to be C were often B. A model with a single intermediate state would probably have been excellent, but this would not have been consistent with the NPSFM framework. That there was a subtle distinction in the B and C states for several ecological health measures was conveyed to the committee for their deliberations. For example, I explained that, in my opinion, a shift in MCI from a C to a B would require a modest change in environmental conditions, but achieving an A would require a much larger change.

Similarly, raising a site from a D to a C was likely to require a major change in the prevailing environmental state.

Model use by the Committee

Models are usually used in environmental science to inform what might happen with a particular change in the environment. Predictions from a given set of conditions inform possible outcomes; for example, a model could predict how much the ecological health of a waterway would decline if nitrate levels rose. In contrast, the committee used the model to forecast what environmental parameters would be required to yield a particular outcome. Thus, for each Freshwater Management Unit (FMU), a desired state of A, B, or C for MCI, QMCI or IBI was designated by the consensus opinion of the committee based on the existing state and input into the model. The states for nitrate, DRP, and deposited sediment for that FMU were then determined from the highest probability predictions in the model states which achieved the desired state for MCI, QMCI, or IBI. This is the advantage of BBN models: they can predict in both directions (e.g., water quality can be predicted from the biota present and can also predict what biota will be present with different conditions). Although one could potentially argue the BBN model is not as accurate as it could be for precise predictions, it is certainly better than if citizen committees are making similar decisions with only qualitative statements from experts and/or quantitative data in reports.

Conclusion

The BBN model constructed for advising the Whaitua Kāpiti committee was very accurate at predicting the A and D states of ecological health attributes, but poor at distinguishing intermediate B and C states. However, the ability of the model to back-forecast from a desired ecological health state (decided by the committee) allowed them to make data-based objective decisions about what nitrate, DRP and deposited sediment states would be required to achieve those waterway health outcomes.

Acknowledgments

I would like to acknowledge how enlightening, fair-minded, and informed the development of the Whaitua Kāpiti Implementation Programme (WIP) has been and that it is a credit to all

involved. After thirty-plus years of being involved in similar processes, this one has been an order of magnitude better than any others I have been a party to, and serves as an example to others of how such a process should be run. It is refreshing to see a committee of dedicated citizens willing to grapple with the hard reality of the state of their waterways and, furthermore, who are not afraid to hear from all perspectives and real data. The Treaty House framework seemed to work amazingly well to ensure views of both tangata whenua and the general public were carefully considered. Thanks so much to all the members of the Kāwanatanga House, Mana Whenua House, and GW staff who shared their data, wisdom and insight so willing to make this model and the WIP what it is.

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