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POTENTIAL SCIENCE TOOLS TO SUPPORT MAHINGA KAI DECISION-MAKING IN FRESHWATER MANAGEMENT

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By Kevin J. Collier, Russell G. Death, David P. Hamilton, John M. Quinn

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Contributing authors

Kevin Collier, University of Waikato, Hamilton

Russell Death, Massey University, Palmerston North

David Hamilton, University of Waikato, Hamilton

John Quinn, NIWA, Hamilton

Cover photo

Bed of kākahi/kaeo in a Waikato stream

Reviewed by:

Maui Hudson

University of Waikato

Approved for release by:

John Tyrrell

Research Developer

Environmental Research Institute

University of Waikato

EXECUTIVE SUMMARY

Mahinga kai is a key value for freshwater management that needs to be articulated in the National Objectives Framework (NOF) limit-setting process. To provide a basis for understanding ways to connect science with mātauranga Māori for mahinga kai management, we (i) reviewed international and local studies that have linked science and traditional ecological knowledge (TEK) in environmental management, and (ii) explored potential science tools that could link with mātauranga Māori to assist with understanding attributes, expressing these conceptually and spatially, and developing condition bands. Several examples were found in the international literature that demonstrate linkages between TEK and environmental modelling approaches. TEK provides powerful site specific information developed over long timescales whereas science tends to operate over broader spatial scales and encompasses shorter periods of time. These two worldviews therefore potentially provide complementary approaches for understanding environmental phenomena. The use of conceptual maps can be helpful for organising TEK information into a framework than can interface with science methods. Bayesian Belief Networks (BBNs) provide a tool that can combine conceptual maps with fuzzy logic in an expert system framework. BBNs have been used successfully for TEK purposes, and scored well in an evaluation of the suitability of modelling approaches for mahinga kai. Process models offer the opportunity to test a range of management scenarios and may complement other modelling approaches. Transdisciplinary modelling that combines mātauranga in a pressure-state-response framework with qualitative ecosystem modelling through BBNs and Geographic Information Systems offer potential for integrating mahinga kai into the NOF.

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1. Introduction

Mahinga kai is a key value for freshwater management that needs to be articulated in objective setting for environmental limits in the National Objectives Framework (NOF). Mahinga kai generally refers to indigenous freshwater species that have traditionally been used as food, tools or other resources. Many mahinga kai sites, both current and historical, are in lowland settings where freshwater environments are often in a degraded state and values are correspondingly compromised. With limited availability of sites in good condition within rohe to help define desired states for mahinga kai, alternative approaches are needed to establish condition bands for management. In particular, tools that assist with envisaging desired states and predicting environmental changes required to sustain those states will help communities and tangata whenua set management objectives. To achieve this effectively an approach is required that utilises mātauranga Māori and science tools.

According to Chetham et al. (2011), who undertook a national stocktake of current cultural monitoring activities, there have to date been no real effective models marrying western science and Māori approaches to monitoring. A pressure-state-response (P-S-R) model has been proposed as an appropriate framework for organising Māori environmental performance indicators for wetland condition and trend (Harmsworth 2002), and was used successfully in a study scoping actions needed to meet the Waikato River's legislated Vision and Strategy - Te Ture Whaimana (NIWA 2010). This approach was also adopted as a framework for the present project to organise information on factors affecting mahinga kai attributes and simulate attribute bands. The P-S-R framework is based on a concept of causality whereby human activities exert "pressure" on the environment and change its quality and the quantity of natural resources ("state") that, if unacceptable, would instigate societal management "responses".

As a first step in this project, a gap analysis was conducted to (i) identify existing tools and information that can be applied to the NOF process, and (ii) highlight information gaps where development of new tools or approaches might be required. This report focuses on identifying potential science tools that could link with mātauranga Māori to assist with understanding attributes, expressing these conceptually and spatially, and developing bands. Given the limited availability of benchmark sites in lowland settings, we explored in some detail the potential for tools to predict the state and response of mahinga kai attributes to environmental pressures, with a view to understanding the relevance of these tools to band setting using pre-defined criteria. Firstly, we conducted reviews of international and local studies that have linked science and traditional ecological knowledge (TEK) in environmental management. Our aim is to provide a basis for understanding how mechanisms to connect science with mātauranga Māori could assist in Māori decision-making in relation to the limit-setting process for mahinga kai, while acknowledging the concerns of Agrawal (1995) that use of objective scientific methods in isolation can decontextualise indigenous knowledge. As noted by Berkes & Berkes (2009), the challenge is to find appropriate ways of bridging scientific and indigenous knowledge without absorbing the diversity of knowledge traditions into one dominant science.

''Not everything that counts can be counted, and
not everything that can be counted, counts''
(Albert Einstein)

2. International examples of integrating TEK and science

A literature search was conducted on Web of Knowledge and Current Contents databases from 2000 to 2014 using the following search structure: Traditional ecolog* knowledge or Indigenous knowledge AND Science OR Model*. Titles and abstracts were scanned to assess whether they were likely to provide information relevant to the objective of demonstrating the integration of science and TEK approaches in resolving resource management issues. An emphasis was placed on studies in freshwater environments or for fisheries management, although other environments and resources are included where it was considered helpful. It was not the aim of this review to discuss the relative merits of science knowledge and TEK, as these have been dealt with in detail elsewhere (e.g., see Moller et al. 2004 for a review in terms of population monitoring).

Berkes & Berkes (2009) studied connections between western science and traditional knowledge in Inuit and other northern peoples, where indigenous knowledge pursues holism through the continued reading of the environment, collection of large amounts of information, and the construction of collective mental models that can adjust to new information. They concluded that this TEK serves the assessment of a large number of variables qualitatively, as opposed to focusing on a small number of variables quantitatively, and lends itself to the use of "fuzzy logic" (e.g., high, medium, low rather than yes/no or use of continuous variables). This is a mathematical approach where only approximate information on components and connections is available. It therefore breaks with the yes–no binary tradition used in most science and computer applications, although "soft computer" applications such as decision-support systems and Geographic Information Systems (GIS) utilise fuzzy logic. It is a way to deal with uncertainty and uses rules of thumb by providing tools to classify information into broad categorisations or groupings, simulating the workings of the human mind, and as such is suitable for concepts and systems that do not have sharply defined boundaries, or where the information is incomplete or uncertain.

While acknowledging that to do so takes indigenous knowledge out of its cultural context, Berkes & Berkes (2009) provide the following example of how a fuzzy logic model could operate based on Inuit seal-hunting:

> *"… the hunters observe seal fatness (variable 1) during the sampling. There is an existing mental model of the various values (different degrees of fatness/thinness) of this variable from experience and collective memory of experienced hunters and elders. Each seal is evaluated instantaneously against this model. The seals may be assessed to be generally thinner, and variable 1 is assigned a fatness/thinness value. In fuzzy models, it is assigned a certain weight between 1 and 10. Other variables such as discoloured bones (variable 2), condition of livers (variable 3), and so on, are assigned different weights, based on the existing mental model of a healthy seal that is good to eat."*

Moller et al. (2004) noted that the use of some simple "rules of thumb" coupled with fuzzy logic can help resolve complex problems and produce robust outcomes in an adaptive management framework. Mackinson (2001) and Grant & Birkes (2007) found the use of fuzzy logic in an expert system framework of IF...THEN rules to be a useful approach for combining science knowledge and local knowledge, including TEK, among contemporary fishers in the Carribean and North America. Expert systems are suited to solving problems that have irregular structure and contain incomplete, qualitative or uncertain knowledge, and where solutions must be obtained by reasoning from available evidence (Mackinson 2001). All knowledge can be incorporated into the information base with the assumption of equality in the degree of belief in a piece of information, to maximise the value of all data. Input data in the above studies were obtained from interviews of people experienced in fishing or fishery management of the target species. Most conflicts in information could be explained by observations at different scales, but where conflicts could not be resolved, individual rules were incorporated to capture each piece of knowledge.

McGregor et al. (2010) used a Bayesian Belief Network (BBN) to represent traditional knowledge of wetland health passed down through generations of traditional owners in Kakadu National Park, Australia, and to convey it to a general audience through a computer-based expert system (see Section 4.2.1 below for detailed description of BBNs). The BBN approach was considered ideal for this task since it allowed input of traditional understanding as informed opinion and non-quantifiable concepts, and provided an intuitive means of exploring system dynamics. The BBN also enabled development of a highly visual and interactive web-based expert system as an educational tool. A BBN approach was also used successfully to predict the impacts of commercialising non-timber forest products on livelihoods of communities from Bolivia to Mexico (Newton et al. 2006). The states modelled by the BBN in the latter study were "no change", "small decrease", "large decrease", "small increase" and "large increase" in capital assets.

Pesek et al. (2009) describe an approach for harnessing traditional Maya knowledge of medicinal plants from healer experts in an interactive spatial modelling framework to predict geographical distributions of medicinal plants for prioritising conservation efforts. They found that cognitive maps were a very useful way of representing the concepts of how Maya interacted with their environment. Habitat suitability models were developed using a method known as “Interactive Evolution” which enables the analyst to combine advanced mathematical geospatial and pattern recognition modelling techniques with available empirical data, conceptual knowledge representing the Maya through cognitive maps, and interactive dynamic data visualisation. As part of this work they initially used a neural network approach (adaptive resonance theory) and modified environmental descriptors of the training data to represent ranges that reflected indigenous understanding of habitat use. Multiple maps of predicted plant occurrence were produced using this method and were merged based on indigenous knowledge until an accepted representation was produced.

Espinoza-Tenorio et al. (2013) developed a transdisciplinary modelling approach to help define holistic management policies and support spatial allocations of use rights in local fisheries for a lagoon ecosystem in southern Mexico using a consensus–building process and the traditional ecological knowledge of the Huave and Zapotec ethnic groups. This transdisciplinary modelling jointly defined research questions and designs by fishermen, scientists, women, aquaculture users and local politicians, that integrated theoretical knowledge and practical problem solving based on the use of four core analytical methods: TEK, a P-S-R framework, qualitative ecosystem modelling (loop analysis), and the use of Geographic Information Systems (GIS) (see Fig. 1 below).

Loop analysis denotes the main relationships between state and pressure indicators (in this case biological and fishery variables), and uses signed digraphs to represent a simple matrix of positive interactions, negative interactions, and no interactions between model variables. Biologically, the positive effect of one variable on another translates to ecological benefits or improved conditions while the opposite is true for negative relationships; self-regulating effects are represented as links that begin and end at the same variable. PowerPlay Digraph Editor Version 2.0® and Maple Version 5.00® were used to construct the signed digraphs and generate the model predictions. TEK analysis allowed for the integration of biological and fishing variables within the context of the ecosystem, and helped to integrate the entire community by depicting the interactions between the prevailing fisheries (pressure) and the biological resources (state).

In a Solomon Islands study, Lauer & Aswani (2009) reported that maps of indigenous Roviana “ecological” categories describing climatic phenomena, habitat composition, and biotic taxonomies derived from boat-based mapping exercises and participatory image-interpretation techniques resulted in patterns that closely corresponded with scientific categories derived from dive surveys. These maps served as important tools for assessing and identifying representative areas of distinct ecology and important fish species, as well as providing data for socio-environmental change studies. Congruence between resource maps derived from TEK and science surveys or remote sensing have also been noted by other workers (see Section 4.2).

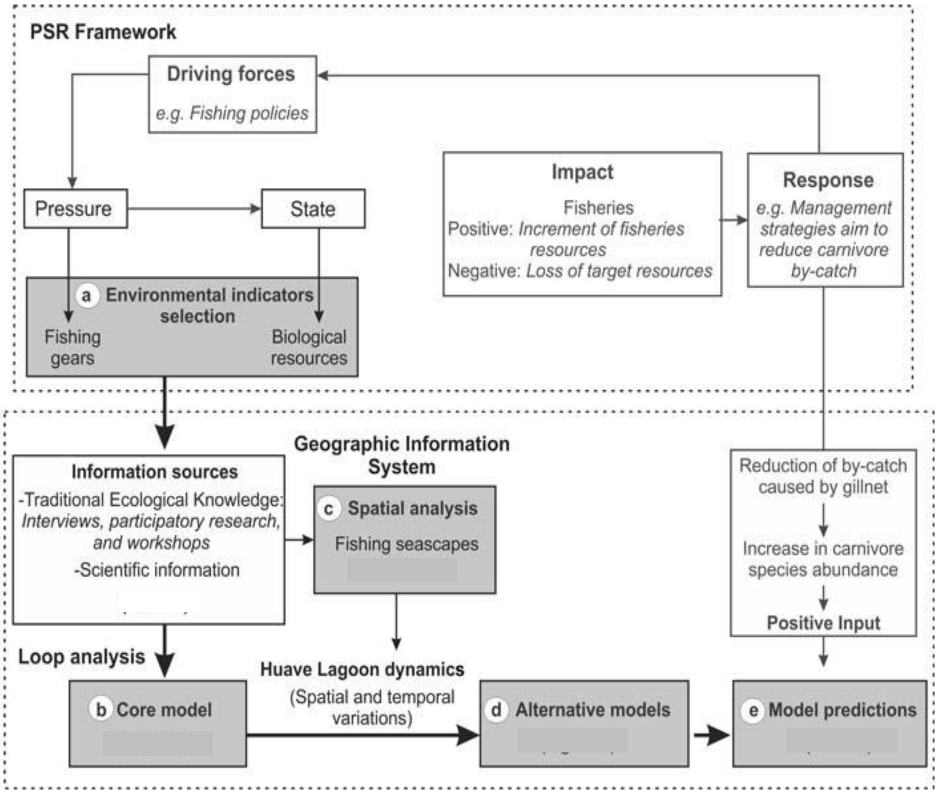


Figure 1: *Transdisciplinary modelling framework used by Espinoza-Tenorio et al. (2013) to support spatial allocations of use rights in local fisheries for a lagoon ecosystem in southern Mexico.*

3. New Zealand examples linking mātauranga and science

This section presents selected New Zealand examples of where mātauranga and science have been used alongside each other to enhance outcomes.

Moller et al. (2004) calibrated scientific and traditional methods of assessing titi abundance to provide complementary lines of evidence supporting a decline in catch per unit effort (CPUE) which was considered the most practical population-monitoring index for customary resource users. In a related study, Moller et al. (2013) reported that muttonbirders understandably focussed on areas with high chick abundance and where access was easier, with the result that understandings of population abundance based on traditional harvesting did not match those from scientific measurements based on random sampling. This finding led to the conclusion that scientific information from spatially and temporally stratified sampling will complement and assist inferences from longer term mātauranga and assist with interpreting environmental patterns. The non-random nature of species, times and places for harvesting can pose challenges in reconciling understanding of populations based on mātauranga and science which often requires random sampling to ensure representativeness. Nevertheless, there was considerable agreement between mātauranga and science in the study of Moller et al. (2013) in relation to spatial and temporal patterns, with most divergence in views related to causal mechanisms (why patterns were happening).

Tipa (2013) addressed the issue of setting appropriate management and restoration goals in the absence of undisturbed reference sites in contemporary landscapes, including for mahinga kai sites, using a combination of cultural maps, whanau manuscripts, texts from ethnographers, paintings, photographs and archaeological records. The depictions of traditional life and resources enabled the identification of specific restorative actions for mahinga kai. In the context of limit setting, the approach used by Tipa (2013) may contribute to developing bands for mahinga kai through an understanding of historical resource availability and use.

4. Potential science tools relevant to mahinga kai objective setting

4.1 Predictive tools

As noted in Section 1, the limited availability of benchmark sites in lowland settings may require tools to predict the state and response of mahinga kai attributes to environmental pressures. This section explores the suitability of various predictive tools with a view to understanding their applicability to band setting for mahinga kai based on the pre-defined criteria detailed below (see Table 1 for summary results):

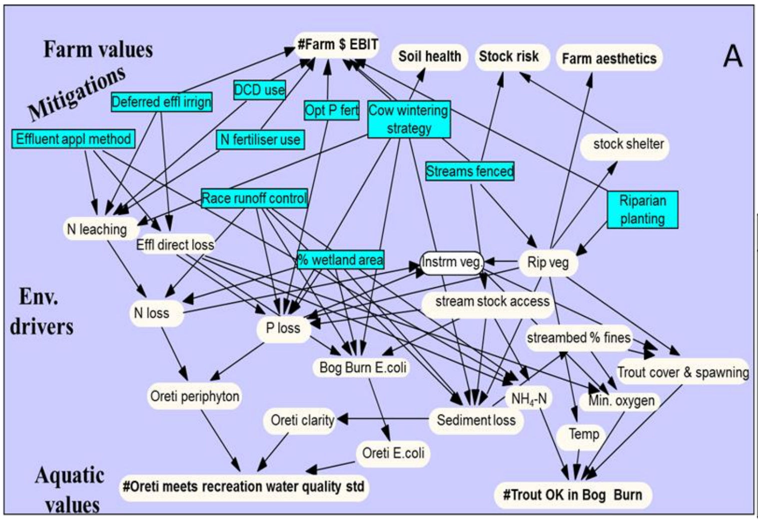
- Open source software options
- Can use qualitative data
- Can use binary data
- Can represent non-linear pathways
- Provides for feedback loops
- Enables user participation in construction
- High transparency
- Holistic
- Provides qualitative outputs
- Provides quantitative outputs

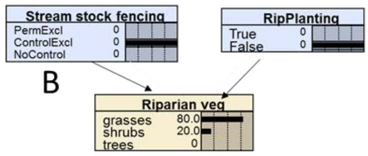
- Ability to measure accuracy

4.1.1 Bayesian Belief Networks (BBNs)

As noted in Section 2 with reference to the study by McGregor et al. (2010), BBNs are particularly useful for identifying and resolving complex environmental problems because they can incorporate the effects of multiple influences on a wide range of values (economic, social, cultural and ecological) and can include information from a variety of sources, such as empirical data, various types of models, literature and expert opinion (Reckhow 2003; Stewart-Koster et al. 2010). These qualities make them particularly useful for integrating mātauranga Māori and science information. BBN's also foster holistic approaches to environmental management, in keeping with mātauranga Māori.

A BBN is a graphical representation of the key variables in a system (termed 'nodes') in the form of a linkage diagram (e.g. left panel in Fig. 2) coupled with estimates of how changes in the state of one or more variables influence the states of other linked variables (i.e., their conditional dependencies; right hand side of Fig. 2) (Reckhow 2003; Stewart-Koster et al. 2010; Uusitalo 2007). Because BBNs are based on a relatively simple representation of cause-effect linkages, they can be built without highly technical modelling skills, and can be co-developed and understood by non-technical users and stakeholders. In the linkage diagrams the arrows connecting nodes indicate dependencies and each node has two or more 'states'. In the 'Stream stock fencing' example in Fig. 2B there are three states for stock fencing with each one potentially being true or false. The relationships between directly linked nodes are quantified by conditional probability tables (CPTs). CPTs are Bayesian in that they reflect a mixture of understanding and belief about the influence of one state upon another. They can be modified through observation, and this belief propagation enables BBNs to be used for diagnostic ('bottom–up' reasoning) or explanatory purposes ('top–down' reasoning). In Fig. 2C the probabilities are shown of the states of the node 'Riparian vegetation' in relation to the states of the nodes 'Stream stock fencing' and 'Riparian planting'; these probabilities add up to 100% across the rows.





C. CPT for Riparian Vegetation

Parent node states		Probs of riparian veg states		
Stock fence	planting	grasses	shrubs	trees
perm excl	TRUE	10	70	20
perm excl	FALSE	70	30	0
contExcl	TRUE	60	20	20
contExcl	FALSE	80	20	0
no fence	TRUE	80	0	20
no fence	FALSE	100	0	0

Figure 2: *Example of nodes in a BBN showing the relationships between on-farm and riparian mitigations with farm and aquatic values in the Bog Burn and Oreti catchments, Southland. A, the linkage diagram; B, an example of the states for 2 nodes 'Stream stock fencing' and 'Riparian Planting' and their influence the state of the node 'Riparian vegetation'; C, the conditional probability table (CPT) showing how the states of parent nodes (start of arrows) influence the probabilities of the state of the child node indicated by arrowheads (Quinn et al. 2010).*

The first phase of developing a BBN is for formulation of a conceptual linkage diagram, such as in Fig. 2A. This conceptualisation of the 'system' under consideration is a key step in developing an integrated model to support stakeholder/community deliberations and decision-making (Kragt et al. 2011; Liu et al. 2008). The use of stakeholder-derived values as endpoints in the model enhances its relevance, and development of the linkage diagram by group collaboration enhances shared understanding and group learning. In some cases, a linkage model alone may be sufficient to support decision-making. In this case, freely available graphic tools, such as yED graph Editor (www.yworks.com/en/products_yed_about.html), may be all that is needed rather than use of BBN software. In the yED tool the colour and thickness of arrows linking boxes can be used to summarise beliefs on the nature of the relationships (e.g., colouring green or red to indicate whether increases in the parent node increase or decrease the state of the child node, and arrow thickness to indicate the strength of the influence).

However, conceptual linkage diagrams lack statistical information on the relative strengths of individual and combined effects of parent nodes (from which arrows start) on child nodes (where arrows finish). This may mean they are inadequate to support some levels of decision-making in which case development of a full BBN is warranted using BBN development software. Two widely used software systems are Netica (www.norsys.com/) commercial software costing $CA285 (personal use/education) or $CA585 (Commercial use) (well-supported and user-friendly), and Bugs (MRC and Imperial College, www.mrcbsu.cam.ac.uk/bugs - free but not so user-friendly). Other BBN software platforms include Hugin Expert (Hugin,www.hugin.com), Analytica (Lumina Decision Systems,www.lumina.com), GeNIe and SMILE (University of Pittsburgh, genie.sis.pitt.edu) and BayesiaLab (Bayesia Ltd., www.bayesia.com).

After formulating the linkage model, the next step in developing a BBN is to decide on appropriate states for each node. For example, the states of 'Riparian planting' in the example above are simply 'True' or 'False' whereas the states of 'Riparian vegetation' relate to vegetation classes 'Trees', 'Shrubs' and 'Grasses' (Figs 2B, 2C). For water quality variables, classes based on known thresholds or standards are often appropriate (e.g., maximum temperature <19.5 ˚C has been used as a threshold for impacts on trout). Once the classes are decided, the relationships between the states of the parent nodes and the states of child nodes need to be assigned using conditional probability tables (CPTs). A simple example is shown in Fig. 2C that used expert knowledge to assign these probabilities. Once these are developed for all combinations of nodes, the BBN graphic model can be compiled and the predictions of the effects of altering individual and combined management decisions can be explored.

However, BBNs also have some limitations. Constraints relating to complexity can be overcome to some extent by having multiple BBNs for different scales or including different spatial scales and times (e.g., seasons) as explicit BBN variables. Another issue is the need to convert continuous variables into discrete states which is a somewhat *ad hoc* process. In this project, the NOF bands will likely define the states (i.e., data ranges for classes A to D) of key values in the BBNs. While graphically transparent, BBNs summarise a large amount of knowledge and beliefs on the nature and strengths of interactions between related variables. It is therefore important to document the basis for the BBN structure and the CPTs (e.g., in the form of a Word document) to provide transparency for the decisions made during model development and opportunities for critique and model refinement.

4.1.2 Process models

The term 'process model' refers to a subset of models that attempt to represent key processes and generate specific physical, chemical or ecological outputs for a system. These processes are most often represented in a series of mathematical equations of varying complexity. The equations are generally inter-connected through a computer language (e.g., Fortran, C++ or in an Excel spreadsheet) to form a working computer model. Modern computers have capacity to perform thousands of calculations each second and may therefore enable a level of integration of physical, chemical and biological processes that is not otherwise possible from simple empirical or statistical relationships, or observations. Complex process-based models may therefore offer opportunities for exploratory or predictive management applications that extend beyond the bounds of input data and to different times (e.g., climate change applications) or a range of systems (Robson et al. 2010).

The level of complexity of process models varies widely depending on: the size and desired degree of resolution of the system (e.g., zero- through to three-dimensional); the number and type of state variables simulated (e.g., temperature, dissolved oxygen); the degree to which the models attempt to simulate 'reality' (e.g. simulating a community, populations or individuals); and whether the model is steady state (i.e., at equilibrium) or dynamic (i.e., time-varying). Fig. 3 shows a theoretical layer (1-D model) or grid (3-D model) structure that may be used to resolve an aquatic system using a modelling approach. This choice of dimension (e.g., 1-D or 3-D) has important implications for the complexity and computer run-times of a model simulation. Highly resolved 3-D models, for example, can take many hours of computer run time on a standard PC to complete a one-year simulation of an aquatic system.

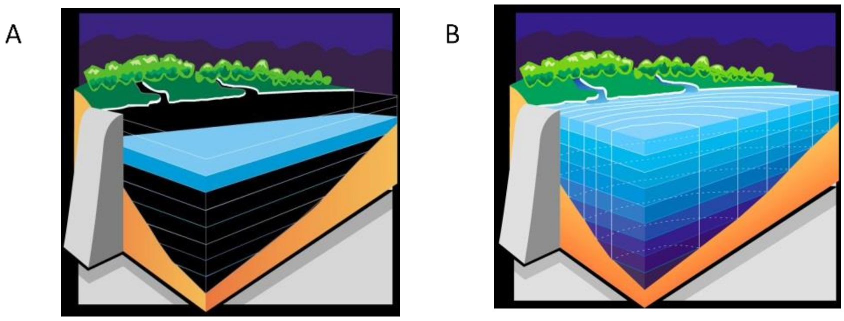


Figure 3: *Representative examples of the way in which a waterbody may be delineated in a process model. A. One-dimensional (vertically-resolved) model. B. Three-dimensional model. A system may be represented from zero-dimensional to three-dimensional.*

To non-modellers, the number of different models, variables and levels of complexity can be quite overwhelming (Trolle et al. 2011). Critics of these types of process models indicate that they are either too simple (to properly represent the enormous complexity of natural ecosystems) or too complex (and therefore cannot be calibrated sufficiently well to be insightful). The well-known quote credited to statistician George E. P. Box that "*essentially, all models are wrong, but some are useful*" (Box & Draper 1987) may at least partly be attributed to misalignment of available model input data, model complexity and questions that are asked of a model. For example, 3-D models may not contribute substantial information on inter-annual variations in an ecosystem because the duration of the simulation period is restricted by lengthy computer run times and high grid resolution. On the other hand the same model may reveal important information on spatial variability over short time scales. One such example is given in Fig. 4 which shows simulated intrusion of marine water into Waituna Lagoon (Southland) following opening of the bar separating the lagoon from the ocean. This 3-D model simulation with the Estuary, Lake and Coastal Ocean Model (ELCOM; Hodges et al. 2000) has potential to offer considerable insight into the progressive intrusion of marine water into the lagoon over several tidal cycles. It can help to provide information for design of sampling programmes to indicate when and whereabouts samples should be collected. It may also be used to test different scenarios of freshwater input and tidal forcing that might affect salinity-sensitive organisms. On the other hand the model is not going to be appropriate for simulations over several years because of the lengthy computer run times required with standard computing resources.

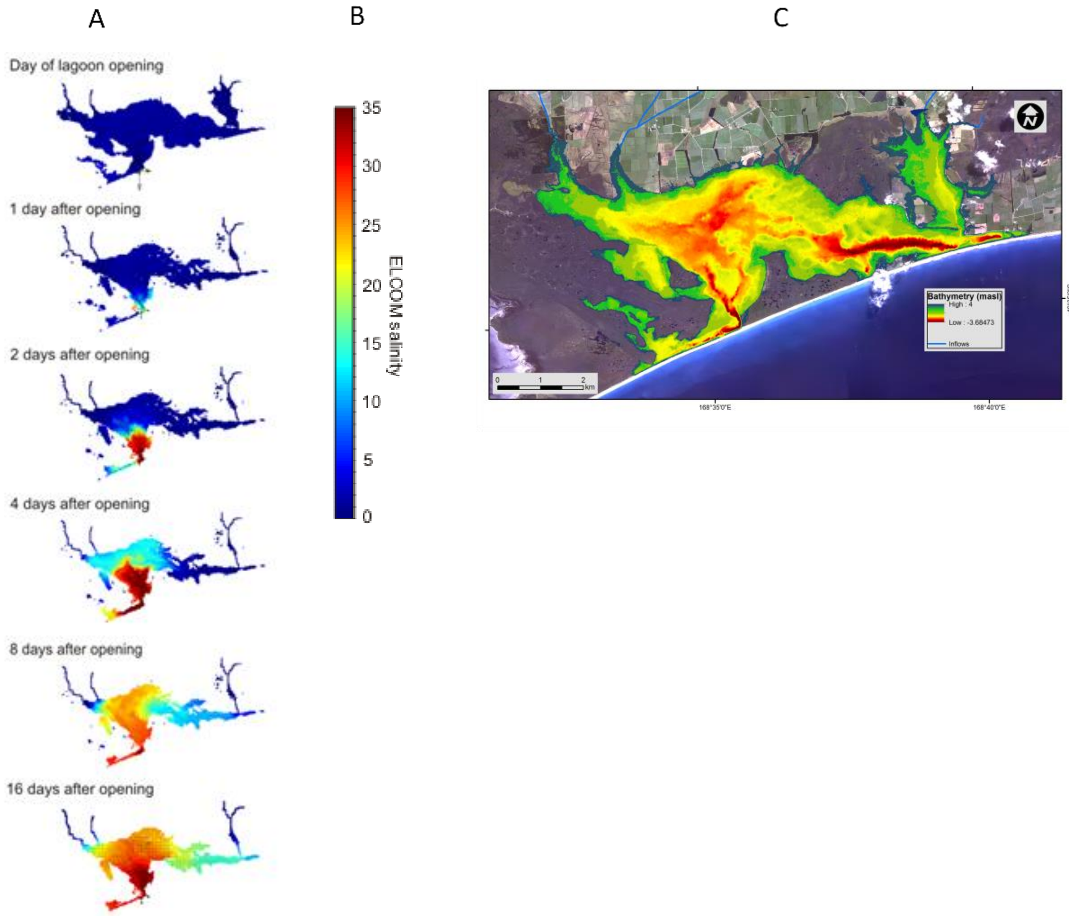


Figure 4: *Model (ELCOM) application to Waituna Lagoon, Southland. A. Simulated surface salinity in the lagoon following opening of the bar separating the lagoon and the ocean. B. Salinity scale bar. C. Map of the lagoon to complement model simulations in A, showing latitude and longitude, distance scale and direction (North). Taken from Hamilton et al. (2012).*

Another important consideration in a model application relates to the intensity and quality of input data. Models with increasing complexity and process representation tend to be 'data hungry' and may require extensive work to synthesise missing data (e.g., generation of catchment nutrient loads for a lake or estuary model). A primary drawback to the use of process models for water quality can be the extensive data requirements including, for example, bathymetric, meteorological, hydrological, tidal, and biogeochemical water quality data to simulate a lake, river or estuary. Cases where data are either inadequate or poorly synthesised have also given rise to the acronym 'garbage in, garbage out' (GIGO) because in these circumstances model simulations are unlikely to be trustworthy. A more extreme interpretation of GIGO has been 'garbage in, gospel out' because complex models can tend to generate excessive 'trust' in simulation output by users or observers. Despite these caveats there can be considerable value to running models with moderate to high levels of complexity, even when input data are sparse (Edwards et al. 2000). Such simulations can help generate information about sensitivity of model output to different input data (e.g., climatic, hydrological) and can therefore assist with refining measurement programmes that will eventually feed back to improve the quality and predictive capability of model simulations.

A further example of where a process model may be useful despite limited availability of input data is provided by 3-D simulations with Delft3D of water levels and temperature in Lake Whangape (Fig. 5). Despite limited hydrological information on inflows and outflows for this lake, it is possible to provide preliminary information on potential water inundation extent and duration. This simulation may therefore provide a basis for discussions of habitat relating to fisheries management (e.g., species of cultural and commercial value such as inanga or pest species such as koi carp (*Cyprinus carpio*)).

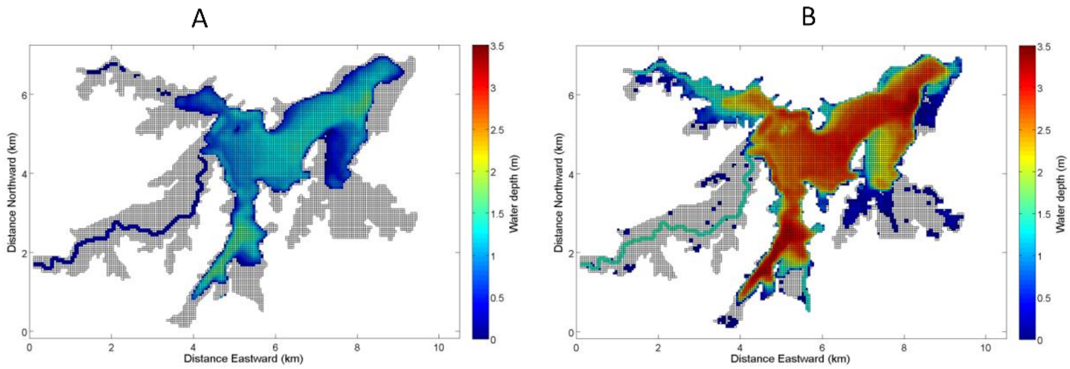


Figure 5: *Lake Whangape water depth simulated with the Delft3D model at A) low water levels (8 March 2012, water level 5 m a.s.l.) and B) high water levels (26 July 2012, 6.70 m a.s.l.). Note inundation of floodplain/wetlands surrounding the lake, particularly to the northwest, in (B). Data from Jones et al. (2014).*

The value of using the model to test system theories or hypotheses should also not be underestimated as users may be able to enhance their understanding of the dynamics of a system by repeatedly running simulations, understanding sensitivity of simulation output to input data, and examining 'directional changes' with adjustments to the input data (e.g., to simulate possible changes in management or climate). More specifically, aquatic ecological models can be used both as 'virtual environmental laboratories' to develop ecological theory, and as decision support tools to facilitate management of aquatic systems (van Nes & Scheffer 2005).

Coupled physical-biogeochemical-ecological models have been used to unravel how key biogeochemical pathways are superimposed on a dynamic physical environment (e.g., Robson et al. 2008). These models extend the simulation results presented above, which relate to application of a hydrodynamic model, and explicitly include chemical and ecological variables as part of the simulation within a single model framework. An example is provided in Fig. 6 to show the multiple variables required, and their interactions, for a model that was targeted towards simulating clams in an Italian lagoon (Spillman et al. 2008). Each of the boxes shown in Fig. 6 represents a variable that either directly or indirectly affects clam production and each is therefore explicitly represented as a variable in the model output. This approach is different from inferring habitat availability solely from modelled physical variables (e.g., water temperature, depth). Fully coupled physical-biogeochemical models can therefore be used to capture and integrate a wide range of variables (not just physics), that may impact upon the abundance and distribution of organisms, as well as providing numerical values of the primary species of interest (e.g., biomass of an organism at a specific location).

The caveats mentioned above for models that simulate the physics (quality and quantity of input data as well as ability to validate simulation output with measurements) become even more important for coupled physical-biogeochemical models. These models require additional data on biogeochemical inputs and for validation purposes, so that parameters can be reliably calibrated and model output closely matches observations of chemical and ecological variables. A transparent and reproducible process is required to show how biogeochemical input data are synthesised to fill gaps in input data to physical-biogeochemical models. Good species-based models can also test the limits of knowledge in terms of construction of reliable process-based representations (e.g., for rates of growth, mortality, respiration etc) and this consideration may be particularly important for some mahinga kai species for which this type of information has not been reported in detail.

From the above review of process models it is evident that careful decision-making is required to adopt a model framework to meet the expectations of various environmental stakeholders including scientists, iwi and managers. Careful choice of a process model at the outset of a modelling project, based on conceptualisation of the key variables and processes, matching output variables with availability of input data, capability of the modelling team (including familiarity with the models used) and ability to validate the model with measured data, are fundamental attributes of a successful model application. Importantly, good model applications can be used for testing of future possible management scenarios. This 'game-playing' approach has great potential to engage stakeholders and help with better understanding the possibilities and constraints to improve environmental management for particular objectives (e.g., mahinga kai species).

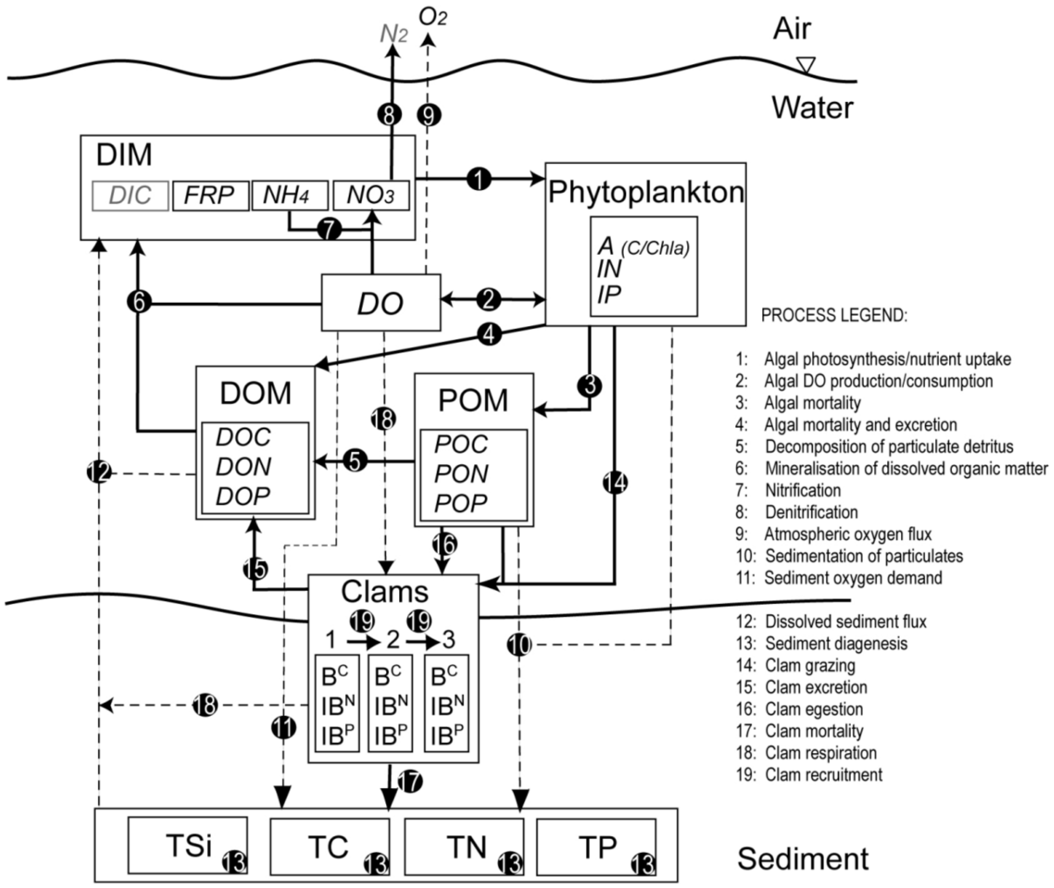


Figure 6: *Conceptual diagram of the CAEDYM ecological model set up to include explicit representation of clams for Barbamarco Lagoon, Italy. Adapted from Spillman et al. (2008)*.

With reference to use of process models as a science tool to support decision-making regarding mahinga kai values, immediate considerations could be:

- Dynamic (time-varying) or static (equilibrium) model?
- Degree of spatial representation – ranging from 0-D (box model) to 3-D (explicit spatial elements in horizontal and vertical dimensions)?
- Inferring mahinga kai habitat quality indirectly based on outputs from a physical (hydrodynamic) model or directly by explicitly representing abundance and distributions for key species?
- Creation of an inventory of input and validation data for the model (i.e., a database).
- Accuracy with which good mathematical formulations can be constructed for mahinga kai species' attributes (e.g., growth rates, loss rates etc.).

A final word is that simple process models (e.g., of target mahinga kai species) may be usefully complemented by complex process models that include multiple other variables, as well as by other modelling techniques mentioned in this document (e.g., statistical, BBNs, SEMs etc) (i.e., a hierarchical approach; Edwards et al. 2000). A priori planning for time invested in different models can be extremely valuable and rewarding, particularly because complex models generally require substantial time investments to be worthwhile to the point where they enable serious engagement with stakeholders about management options and future scenarios.

4.1.3 Other modelling approaches

There is a huge array of modelling tools that have and could be used for mahinga kai decision-making within the NOF, ranging from simple regression equations (e.g., FAT Freshwater Animal Targets (Environment 2013) and rules of thumb (e.g., Montana method for minimum flow setting (Tharme 2003)) through to extremely detailed equation based models such as TRIM (Tukituki River Model) (Rutherford 2013). There are a number of reviews of modelling approaches and techniques for managing freshwater resources and species populations (Olden et al. 2008; Elith & Leathwick 2009; Jopp et al. 2011; Vigerstol & Aukema 2011). Even within New Zealand there is a wide range of modelling approaches that have been specifically developed for local conditions (Rutledge et al. 2010; Van den Belt et al. 2010) (tools.envirolink.govt.nz/search-results/?ManagementDomains=10). Furthermore where the key aim is sustainable harvest, which may well be the case with mahinga kai, there is an even more exhaustive range of potential population models and approaches (Welcomme 1999; Gaichas & Francis 2008; Mesnil et al. 2009; Prellezo et al. 2012). This section deals only with "other" models that offer the most potential for use in mahinga kai management. All of the techniques are data dependent (some more so than others) and therefore require some degree of quantification of traditional knowledge.

Linear and nonlinear univariate and multivariate regression

Regression is a standard statistical technique that has been used in environmental management and ecological decision-making since ecological studies began. In its simplest form the approach is straight forward and often involves relating a single driving environmental variable to recorded measures of a population. It can thus be very easy to understand, and similarly the predictive power of the model can be readily and straightforwardly analysed. There is a wide range of regression analyses possible beyond the conventional linear least squares parametric regression, including logisitic regression, quantile regression, robust regression and nonlinear regression. The choice of regression method will depend on the data form and the question being addressed, but all can be freely analysed using the freely available in R software libraries (www.r-project.org/). Although these alternate approaches can allow for nonlinear pathways, multiple variables, and/or qualitative data when compared to other artificial intelligence, their efficacy is potentially more limited. Many of the alternative regression approaches require a considerably higher level of expertise to use and interpret.

Although often overlooked as a modelling tool, regression methods can be very useful and easy to understand with a clear assessment of the predictive ability. However, they probably rely on mahinga kai strongly affected by one or two variables (either directly or indirectly). Examples could include the effect of stock access to waterways and watercress biomass.

Structural Equation Modelling (SEM)

Structural Equation Modelling is in many ways an extension of regression that identifies the strongest direct and indirect pathways of correlation amongst a pool of potential environmental drivers for a variable of interest (Byrne 1998 2001; Grace 2006; Grace et al. 2010). Greenwood et al. (2012) have used the technique successfully to identify the important environmental effects of a range of riparian management actions in Canterbury (Fig. 7). Although this technique is proposed as a means to assess nonlinear relationships often inherent in biological systems, it still uses a stepwise linear approach and must therefore be more limited than truly nonlinear artificial intelligence approaches. The level of skill and software required to conduct the analysis is considerably higher than that for a simple regression, but it does allow the integration of a range of potentially important factors (both directly and indirectly) for the consideration of mahinga kai management.

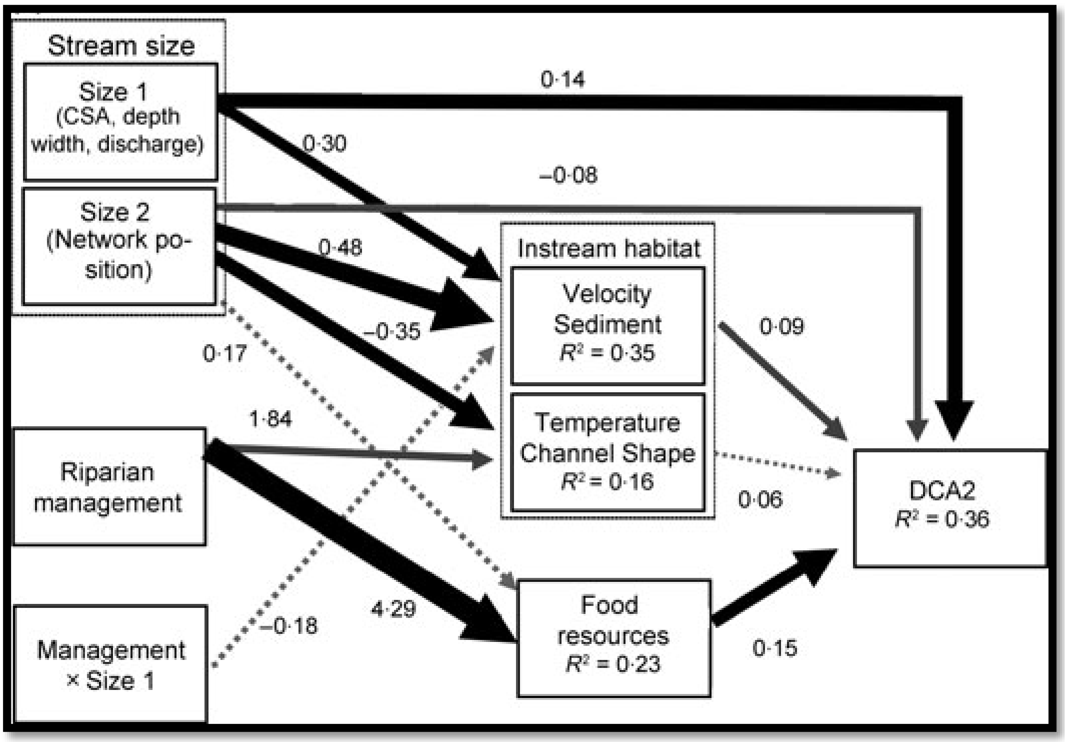


Figure 7: *Schematic of structural equation model to investigate riparian management effects in Canterbury streams. From Greenwood et al. (2012).*

Classification and Regression Trees (CART)

These techniques use a decision tree approach to create a predictive model of a binary (Classification Tree) or continuous (Regression Tree; Fig. 8) output with a tree of the decision points (De'ath & Fabricius 2000; De'Ath 2002; Elith et al. 2008; Kocev et al. 2009). Leathwick et al. (2010) used boosted regression trees to produce many of the GIS variable layers in Freshwater Ecosystems of New Zealand (FENZ). Although boosted regression trees are more challenging to create and less transparent, simple CART analysis can be easily conducted in freeware such as WEKA (www.cs.waikato.ac.nz/ml/weka/) and/or R, and is extremely transparent. The big advantage of the approach is it allows for a step decision approach where one set of management rules may apply in some circumstances and another set of rules if those circumstances do not apply (e.g., with and without harvest). This approach offers considerable merit for mahinga kai management decision support systems but does not allow for use of probability or fuzzy data or missing data points, as BBN's do.

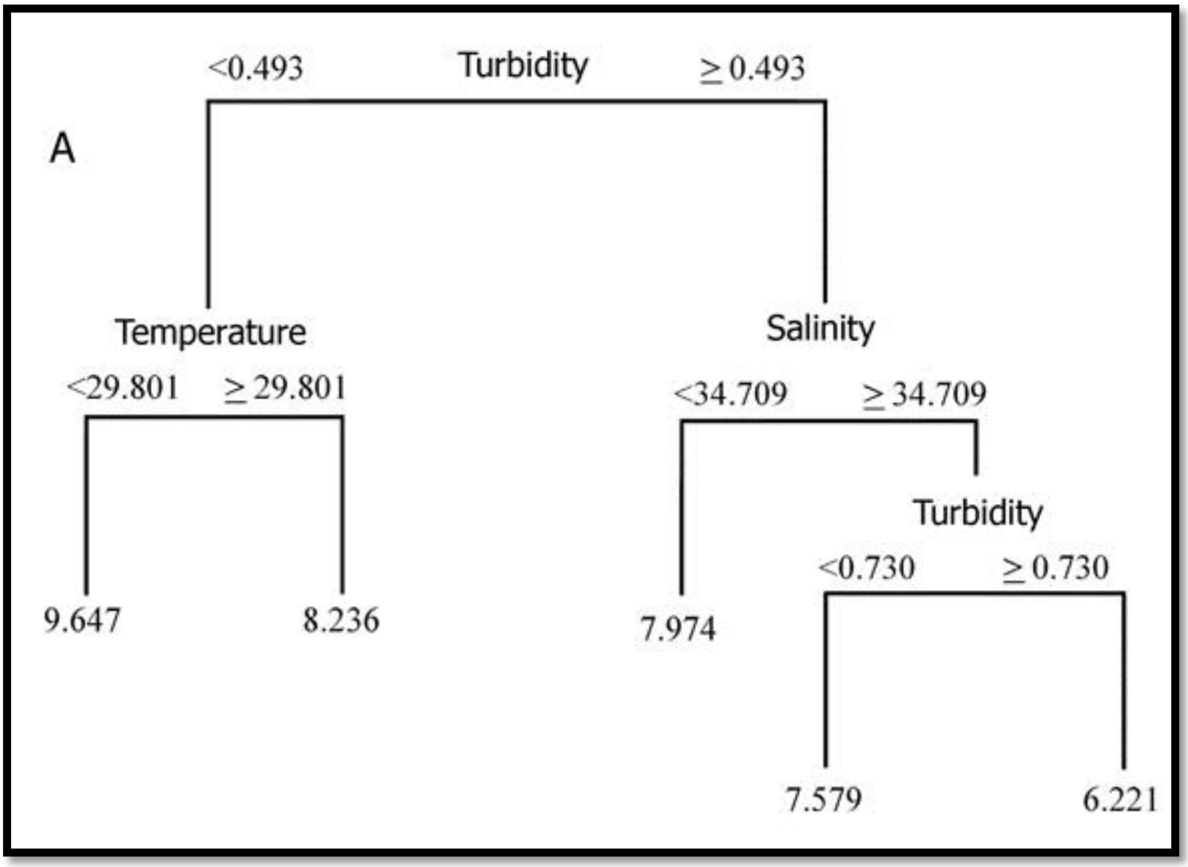


Figure 8: *Schematic of a simple regression tree on water quality.*

Artificial Neural Networks (ANN)

Artificial neural networks are a powerful technique for predictive modelling when non-linear patterns exist. A comparison of traditional (e.g., logistic regression, linear discriminant analysis) and alternative techniques (classification trees and ANNs) for predicting species presence/absence using both simulated and empirical data showed that the accuracy of ANN predictions outperformed the alternatives particularly with non-linear data (Olden & Jackson 2002). The advantages of ANNs are they are not dependent on particular functional relationships, need no assumptions regarding underlying data distributions and no a priori understanding of variable relationships (Olden et al. 2008). Their disadvantages are that they require relatively large data sets and are very difficult to understand (but see Olden et al. 2004) and thus interpret. Consequently they are unlikely to offer much benefit for use in mahinga kai modelling.

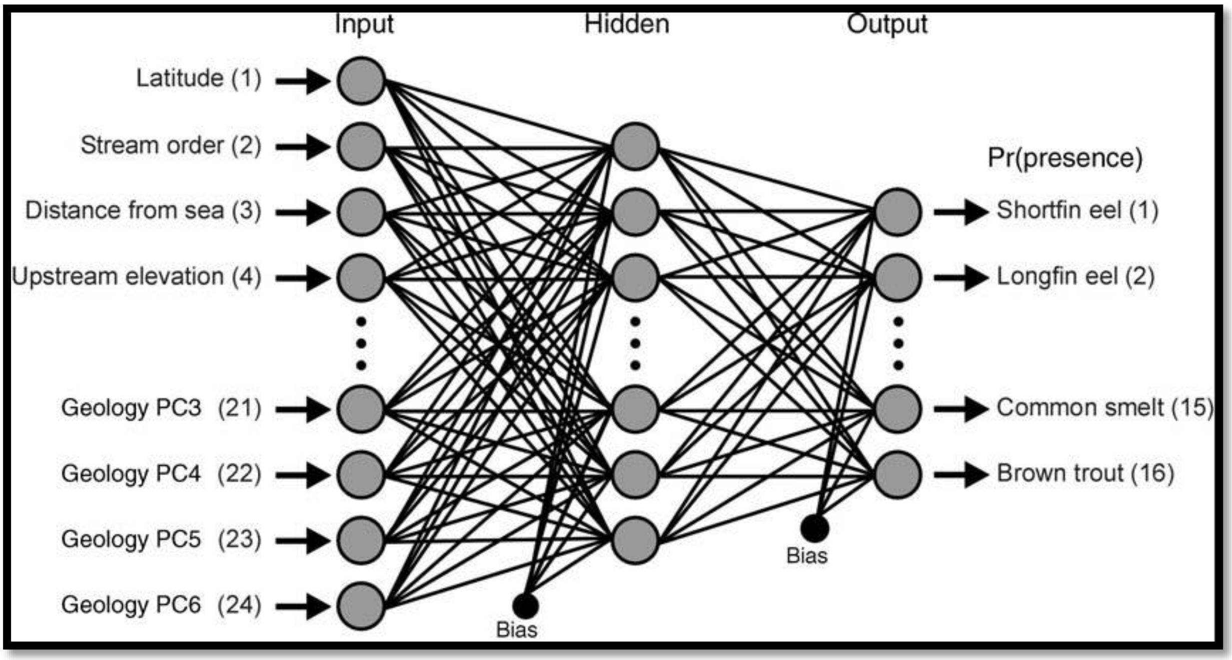


Figure 9: *Schematic of multi-response artificial neural network to model stream fish communities. Adapted from Olden et al. (2006).*

Individual- or agent- based models (IBM)

This is a class of simulation models often used for modelling populations in the context of management, particularly dealing with fisheries management (Jopp et al. 2011). They should potentially be very useful as they contain a considerable amount of detail specific to the system of interest. However, in practice the amount of detail needed demands that a number of assumptions and generalisations are applied. There are often little data against which to independently evaluate the resulting model and whether or not the assumptions are valid. In contrast to the above techniques where the data determine the structure of the model, IBM structure is determined a priori and the data fitted to that scheme. In terms of return per unit effort it seems unlikely this modelling approach would be of much benefit in mahinga kai management.

Table 1: *Summary of criteria used to evaluate predictive tools in terms of their possible suitability for measuring the state and response of mahinga kai attributes to environmental pressures for Māori decision-making.*

	Regression	SEM	CART	ANN	IBM	BBN	Process models
Open source software	Yes	Limited	Yes	Yes	No	Yes	Varies
Qualitative data	Yes	No	No	No	No	Yes	No
Binary data	Yes (logistic regression)	Yes	Yes	Yes	No	Yes	No
Non-linear pathways	Very limited (via transformation)	Limited	Yes	Yes	Yes	Yes	Yes
Feedback loops	No	No	No	Yes	Yes	No	Yes
User participation	Limited	Limited	Limited	No	No	Yes	Limited
High transparency	Yes	Yes	Moderate	No	No	Yes	No
Holistic	No	Yes	Yes	Yes	Potentially	Yes	Yes
Qualitative outputs	Limited	Limited	No	No	No	Yes	No
Quantitative outputs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ability to measure accuracy	Good	Good	Good	Good	No	Moderate	Good

4.2 Mapping and monitoring tools

This section focuses on methods to acquire and represent data over relatively large spatial scales rather than site-specific monitoring and assessment approaches.

4.2.1 Geographic Information Systems (GIS)

Robbins (2003) noted that the incorporation of indigenous knowledge in GIS analysis has become an important component of human ecology, most commonly in the form of maps that express local environmental knowledge in cartographic form. Of particular relevance in this context is the use of 'participatory GIS' (PGIS) which enables local people to implement data acquisition and analysis themselves using their own worldviews and priorities (see www.seasketch.org/ for example). Robbins (2003) also noted that GIS enables the testing of hypotheses around the accuracy of indigenous versus western science categorisations and understandings of physical processes.

Harmsworth et al. (2005) reported on the development of an iwi-led GIS initiative based on their own cultural identity and issues that blends cultural tikanga-based approaches with western approaches and technologies (see also www.landcareresearch.co.nz/science/living/indigenous-knowledge/gis for a method and framework for recording information on Māori values). This work has highlighted a number of issues that need to be considered, including the need to treat public and confidential information differently in terms of access and sharing, and the need for tikanga protocols to ensure data confidentiality. According to Harmsworth et al. (2005) desirable outputs from GIS might include polygon information of cultural sites, point information for resource consents, maps of cultural values for a given location, and spatial representation of iwi values of areas at different scales. Iwi values may include mahinga kai sites with associated information on species and quality, which could be linked with available environmental data layers. As examples, GIS was used to map customary fishing locations in the Waikato catchment at a scale that did not identify specific sites (Hicks et al. 2013), and to create regional maps of recommended meal consumption rates based on risks from contaminants accumulated in flesh of mahinga kai species (Stewart et al. 2010).

4.2.2 Remote sensing

Hernanndez-Stefanon et al. (2006) found high similarity in the categorisation of vegetation types between the Mayan classification and those obtained by statistical analysis, and noted that satellite imagery based on multispectral vegetation classification could be used to map indigenous vegetation classes over broad spatial scales. Similarly, Naidoo & Hill (2006) reported that vegetation classifications of the Ache, an indigenous hunter-gatherer tribe of the Mbaracayu Forest Reserve in Paraguay, are reflected in a supervised classification of satellite imagery of the reserve, although accuracy of classification was toward the low end of the range of published values. Comparison of the resultant map with a more traditionally elaborated vegetation map highlighted the gain in information obtained by considering TEK classifications, leading to the conclusion that integration of TEK and remote sensing provide alternative insights into the ecology of vegetation communities and land cover.

Remote sensing can also be used to assess some water quality attributes such as turbidity, temperature and the amount of algae, particularly in open waterbodies such as lakes. Hicks et al. (2013) used satellite imagery to hindcast water clarity changes in some lower Waikato River lakes, and highlighted the spatial detail that could be obtained compared to that provided by collecting water samples at one place. One issue with remote sensing is that it is reliant on satellites passing overhead on cloud-free days, and so cannot be relied on in isolation for long-term or event monitoring. However, coupling remote sensing with continuous monitoring from telemetered monitoring buoys can provide relationships that enable remotely sensed data to be extrapolated through time. If these data can be categorised into water quality classes that represent bands relevant to mahinga kai species, then this approach may have application for determining limits on environmental attributes required to sustain conditions for this value in large waterbodies such as lakes.

5. Conclusions

TEK provides powerful site-specific information developed over long timescales whereas science tends to operate over broader spatial scales and encompasses shorter periods of time (Chapman 2007). These two worldviews therefore potentially provide complementary rather than concordant approaches for understanding environmental phenomena (Huntington et al. 2004). TEK can be used as an independent line of evidence alongside environmental science to provide a weight-of-evidence approach that provides a more holistic analysis (Chapman 2007).

This review has highlighted the following conclusions regarding the use of mātauranga and science tools for integrating mahinga kai into the NOF:

- The P-S-R approach has been applied elsewhere and in New Zealand to link TEK/ mātauranga and western science for environmental management purposes.
- The use of conceptual maps (e.g., linkage diagrams) can be helpful for organising TEK information into a framework than can interface with science methods.
- There are a number of examples showing how TEK and science models have been integrated to assist with environmental management, in some instances with the use of “fuzzy logic” and expert system rules.
- Bayesian Belief Networks (BBNs) provide a tool that can combine conceptual maps with fuzzy logic in an expert system framework. BBNs have been used successfully for TEK purposes, and scored well in an evaluation of the suitability of modelling approaches for mahinga kai.
- Process models offer the opportunity to test a range of management scenarios and may complement other modelling approaches.

- Transdisciplinary modelling that combines mātauranga in a P-S-R framework with qualitative ecosystem modelling through BBNs and Geographic Information Systems (GIS) offers potential for integrating mahinga kai into the NOF.

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Appendix 1

Example of BBN graphics for catchment management decision-making in the Bog Burn, Southland, showing the change in the probabilities of states of system nodes when the decision nodes are set at the current state (Fig. A1) and with deferred effluent irrigation in the wet (Fig. A2). This allows simultaneous exploration of the effects of interventions on several key values (in this case Farm EBIT, the Oreti Rivers suitability for recreational use and the trout in Bog Burn). The states of several decision nodes can be altered simultaneously allowing their combined effects to be evaluated (Fig. A3).

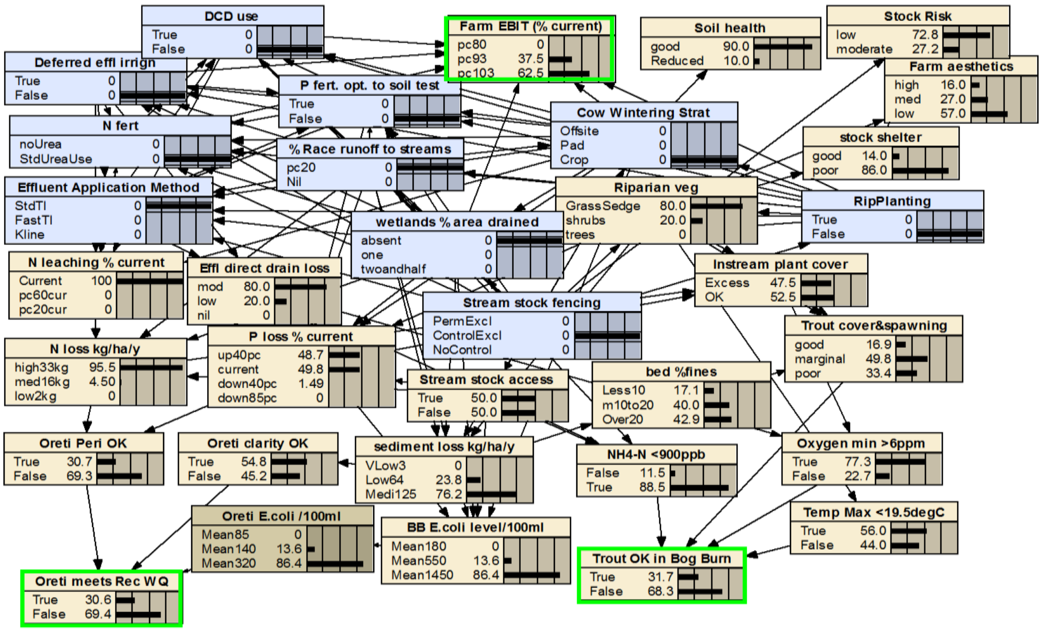

Figure A1: The Bog Burn BBN showing predictions for states of nature nodes (response variables, brown coloured boxes) when all decision nodes (blue boxes) set at the current state when the model was developed. The key stakeholder values are identified by green boundaries on their boxes.

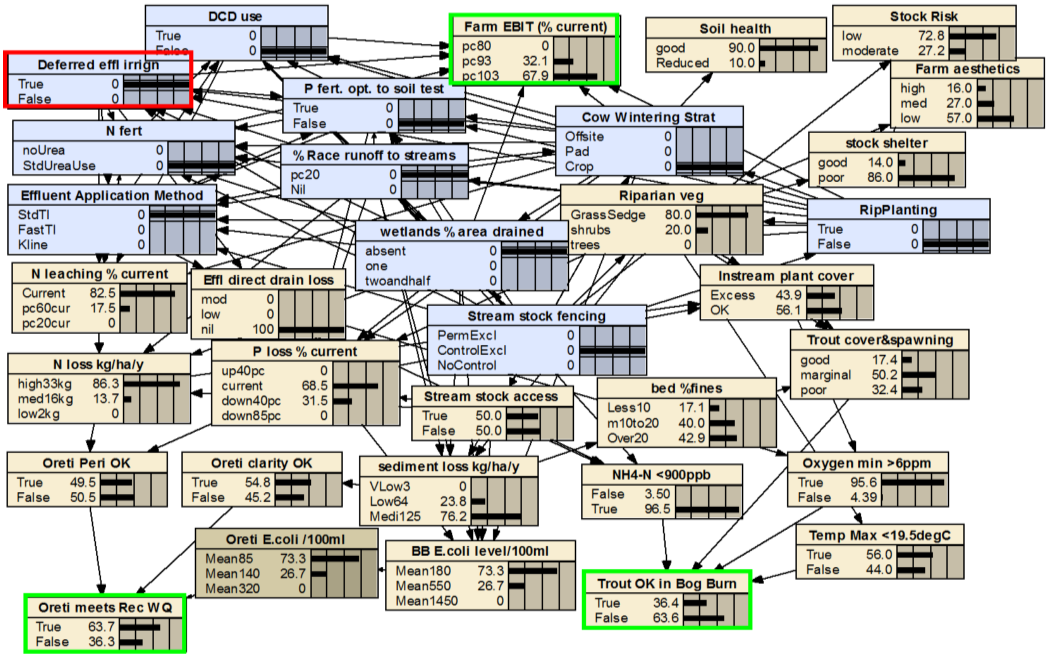

Figure A2: The Bog Burn BBN showing the predictions when all the decision nodes (blue boxes) set at the current state except that 'Differed effluent irrigation' (decision node outlined in red) is set as 'True'.

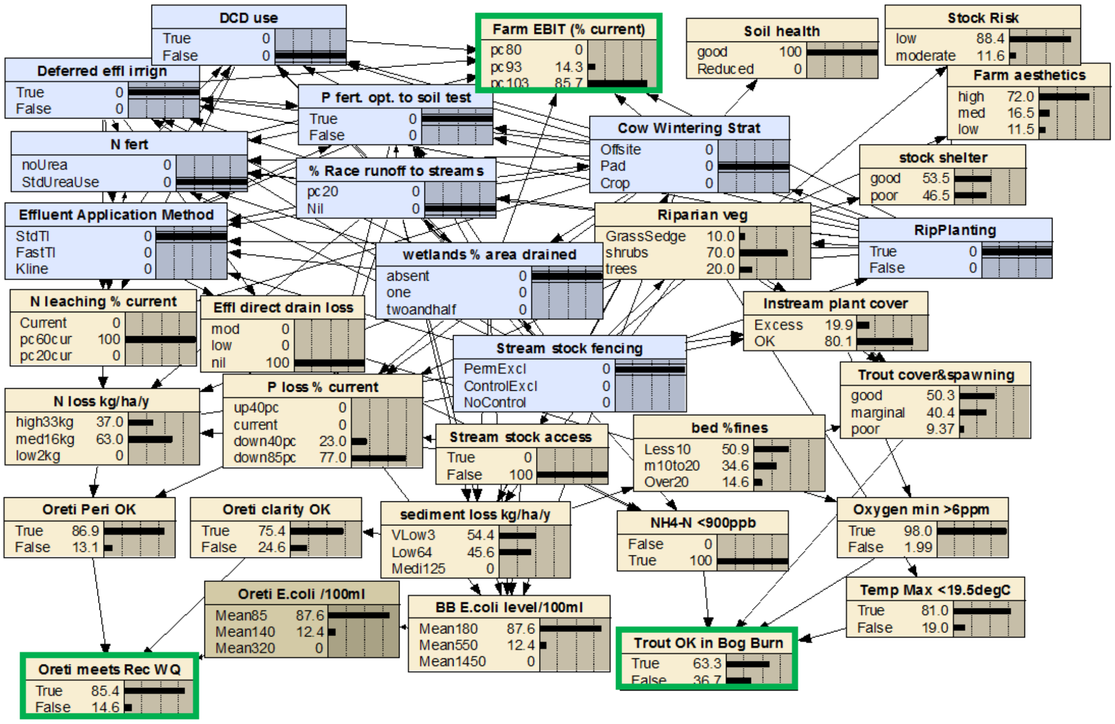

Figure A3: The Bog Burn BBN showing the predictions when all the decision nodes (blue boxes) are altered from current state to investigate the effects of the combined effects of deferred effluent irrigation, optimising P fertilising to soil test results, wintering cows on a pad, permanent exclusion of livestock from streams and riparian planting.