Predicting effects of contaminant load reductions on biological communities: Feasibility study

Prepared for Christchurch City Council

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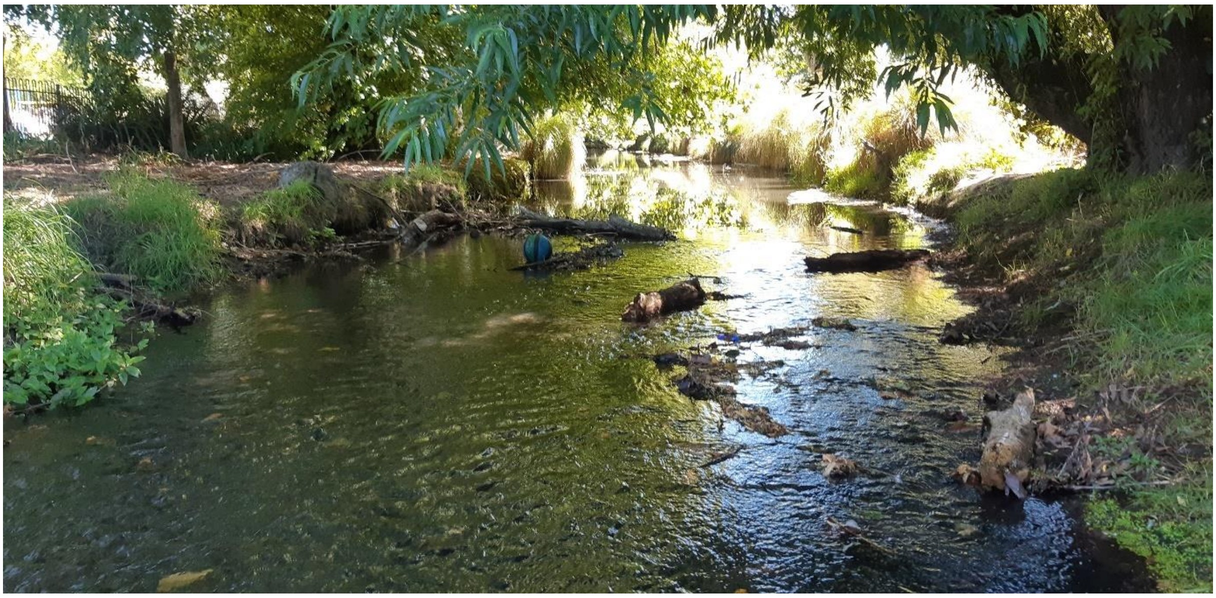

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Photo credit: Heathcote River near Lincoln Road. [Marty Flanagan, NIWA]

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Executive summary

Christchurch City Council (CCC) was granted consent by Environment Canterbury to discharge water and contaminants to land and water from the stormwater network in December 2019, under what is known as the Comprehensive Stormwater Network Discharge Consent (CSNDC; CRC2391955). The consent includes a stormwater quality investigation programme (Schedule 3) with multiple actions, one of which (Schedule 3, item d, to commence within 12 months, and be completed within 4 years of the consent commencement) is to:

"Conduct a feasibility study to establish the existing knowledge base and investigate the feasibility of robustly predicting the responses of the receiving environment to changes in network contaminant loads and resulting in-stream concentrations.

Consideration shall be given to how and when the receiving environment might respond to changes in contaminant concentrations, how much work would be involved to predict results, what sorts of models are possible, how would monitoring to obtain real world results be carried out, how long would it take the biological community to respond (i.e., lag effects)."

This document reports on that feasibility study. The objectives of the project were to:

- Assess the feasibility of:
  - Robustly predicting how and when the receiving environment might respond to changes in network contaminant loads and resulting in-stream concentrations, as well as changes in other limiting factors (e.g., habitat availability),
  - Quantifying which limiting factors (i.e., not just stormwater treatment) would have the greatest ecological benefit, the quickest ecological benefit, or limited ecological benefit, if they were to be addressed,
  - Assessing the response within the waterways with consideration of a range of variables: Cultural Health Index, Water Quality Index, Macroinvertebrate Community Index/Quantitative Macroinvertebrate Community Index, and fish diversity and abundance
  - Assessing the response within Ihutai for the following variables: Cultural Health Index, Estuary Trophic Index, and benthic invertebrate abundance and presence.
- Determine the resources required (e.g., time and money) to carry out the full assessment.

The scope of this study was constrained to the ability to predict responses within the streams and rivers of Ōtautahi, and not including streams within settlements of Banks Peninsula, as there is more monitoring data and other information for the former. The scope also includes predicting responses in coastal receiving environments – this was constrained to the Avon-Heathcote Estuary / Ihutai for the same reason. The scope was also constrained to predicting freshwater macroinvertebrate responses (based on indices) and estuarine macrofauna, as the likely influences on this trophic level are better understood than influences on fish.

Christchurch City Council aim to reduce the network contaminant loads of total suspended sediment, copper and zinc by 20-30% over 25 years, with the bulk of reductions in the first five years. The mechanisms by which sediment and metals affect freshwater and estuarine biota are relatively well-known. However, these contaminants are not the only stressors affecting freshwater and estuarine ecosystems. The ability to predict the effects of changes in these contaminants requires an understanding of the other stressors and how they may interact to either promote or curb recovery of the biological communities.

There is a considerable body of data for the Ōtautahi streams, including regular water quality monitoring at 45 sites, and habitat data throughout the majority of its stream reaches. However, macroinvertebrates and fish are surveyed only every five years. In Ihutai, macrofauna and the mud content of sediment are surveyed annually, and sediment quality every five years, though the spatial coverage of the monitoring is relatively low (4-6 sites).

There are a variety of "off-the-shelf" models for freshwater ecosystems, however few existing models include the key stressors needed for predicting responses in urban streams. The Urban Planning to Sustain Waterbodies (UPSW) Bayesian Network (BN) is one model that was developed for such a purpose, however it predicts the state of qualitative indicators of freshwater ecosystem health, rather than quantitative measures. Other existing models either do not include metals or require substantial work to parameterise relationships between stressors and invertebrate responses.

In estuaries, there are three models that have been developed in New Zealand to understand and predict the effects of changes in water quality and sediment conditions on benthic macroinvertebrates. These are the Estuarine Bayesian Network, the Benthic Health Model and the Estuarine Trophic Index. Only two of these include metals, and only one includes both metals and nutrients as stressors – the latter are known to be important drivers of ecosystem health in Ihutai.

There are also many statistical modelling methods (such as generalised linear models, generalised additive models (GAM), random forest, boosted regression trees, structural equation modelling, and risk analyses) that could be used to test which are the key stressors in Ōtautahi streams, using the available monitoring data. Each method has different strengths, such as the number of predictors and the types of relationships that can be included (e.g., linear vs more complex), and whether random terms can be included or not.

Two types of models were tested for the freshwater receiving environments: the existing UPSW BN, and a type of GAM that includes random effects, known as a generalised additive mixed model (GAMM). BNs are useful because they can incorporate expert knowledge when quantitative data are not available, while GAMMs can include random terms to account for similarities in stressors and biological communities between catchments and are recommended for developing predictive models.

Data first needed to be collated into a form suitable for use in these models – this required the calculation of summary statistics for the regular water quality monitoring, and metrics to represent hydrology. As hydrology, water quality and sediment quality are typically not measured at the same sites as the macroinvertebrate monitoring, this also required data to be matched to the closest sites, and an assumption that water quality and/or hydrology at a nearby site (either upstream or downstream) would be representative of that at the macroinvertebrate monitoring site. This exercise resulted in a final data set of 53 sites with more than 100 different metrics for potential stressors.

The freshwater BN was tested using data for seven sites in Ōtautahi where measured data spanned a range of metal concentrations, upstream impervious cover, bank lining/reinforcing, and riparian vegetation. The seven sites tested also had water quality and ecological monitoring data from the same location, or very near. The BN predictions matched the order of the monitoring data for most sites – i.e., the BN predicted highest scores for macroinvertebrate health at sites with the highest observed metrics for macroinvertebrates, and the lower predicted scores were for sites with generally lower observed metrics (although there was variation between measured metrics at these sites). The testing suggested that BNs could be appropriate for predicting macroinvertebrate community responses to key stressors and multi-stressor interactions but would need further validation in Ōtautahi streams.

The GAMM was tested using two macroinvertebrate indices: the quantitative macroinvertebrate community index for hard-bottomed streams (QMCI-hb) and the percentage of individuals in the orders Ephemeroptera, Plecoptera, and Trichoptera (EPT) excluding those in the family Hydroptilidae (as these caddisflies are generally considered to be pollution tolerant). The GAMM was developed with QMCI-hb and percentage EPT as the response variables and a random waterway term to account for the similarity of sites connected longitudinally by water flow. Due to the small size of the dataset, only four out of 100 potential predictor variables could be included in the model. We selected the following predictors: periphyton (as the weighted composite cover of filaments and mats), percent silt/sand coverage of the streambed, water velocity and median concentrations of dissolved zinc. This was an example model only; to apply this method to develop a predictive model for management decision-making would first require a detailed investigation of the best subset of predictors to include (which was out of scope of this report). The GAMM model testing highlighted the challenges of modelling large numbers of potential stressors with small datasets and difficulties attributing causality when many stressors are correlated. Furthermore, model results need to be sense-checked for over-complexity which may not be ecologically realistic.

The estuarine BN was tested for predicting responses in Ihutai. This required an assumption that the sediment quality data collected in Ihutai (i.e., metal concentrations in <2 mm fraction of surface sediment) was equivalent to that used as model inputs (i.e., metal concentrations in < 0.5 mm fraction of surface sediment). The predictions of the current state were relatively consistent with the monitoring data, suggesting this model could be useful for predicting future state with reduced sediment and metal inputs.

We recommend Bayesian Networks as the most suitable option for predicting biological responses in both freshwater and estuarine environments. BNs can incorporate multiple correlated stressors and test predictions under various future scenarios. This also makes them useful educational tools, as they demonstrate how multiple issues may need to be addressed before an improvement in macroinvertebrate communities can occur. Nonetheless, BNs are only as good as the data used to make them, and the existing freshwater and estuarine BN will need updating and/or parameterising for Ōtautahi. This could include refining the existing parameters based on local expert knowledge and adding new nodes for factors not currently included , such as distance to colonist source for freshwater macroinvertebrates. For Ihutai, a model that relates changes in sediment and metal loads to changes in estuarine benthic sediment is also needed. The updated model(s) should then be further tested for as many sites as possible in Ōtautahi. Following that, sensitivity analysis of the model should be undertaken to indicate the range of ecosystem response that might be expected with changes in contaminant loading.

We consider that it is feasible to use BN models to predict how the receiving environment might respond to changes in network contaminant loads and resulting in-stream concentrations, as well as changes in other limiting factors (e.g., habitat availability). Assessment and/or development of conditional probability tables for stressors specific to Ōtautahi waterways, and assessment of the sensitivity of model outputs to changes in these tables, would improve the robustness of predictions.

Whether a BN can predict when these changes would occur is less certain. Like other modelling methods developed from data collected across a range of stressor conditions (i.e., rather than a time-series model), BNs do not account for time required for biological communities to recover, and in reality there will be a lag between stressor reduction and any change in macroinvertebrate metric scores. The BN models are suitable for quantifying factors that have greatest ecological benefit if addressed and can be used for a range of different variables as identified by CCC, except for fish diversity and abundance, due to lack of suitable data. The resources required to develop BN models can be adapted to suit the resource available – for example, the models can use expert judgement in many places, or additional studies can be undertaken to inform relationships between nodes.

1 Introduction

1.1 Background

Christchurch City Council (CCC) was granted consent by Environment Canterbury to discharge water and contaminants to land and water from the stormwater network in December 2019, under what is known as the Comprehensive Stormwater Network Discharge Consent (CSNDC; CRC231955). The consent includes a stormwater quality investigation programme (Schedule 3) with multiple actions, one of which (Schedule 3, item d, to commence within 12 months, and be completed within 4 years of the consent commencement) is to:

"Conduct a feasibility study to establish the existing knowledge base and investigate the feasibility of robustly predicting the responses of the receiving environment to changes in network contaminant loads and resulting in-stream concentrations.

Consideration shall be given to how and when the receiving environment might respond to changes in contaminant concentrations, how much work would be involved to predict results, what sorts of models are possible, how would monitoring to obtain real world results be carried out, how long would it take the biological community to respond (i.e., lag effects)."

Under the terms and duration of the consent, CCC are installing stormwater mitigation facilities and devices to reduce the loads of total suspended sediment, copper and zinc by 20-30% over 25 years, with the bulk of reductions in the first five years (15-23%). However, it is unclear whether these reductions will result in immediate (or lagged) improvements in biological communities for two general reasons. Firstly, reductions in total metal loads may not result in the equivalent reduction in dissolved metal concentrations in streams, or within the Avon-Heathcote Estuary / Ihutai (referred to herein as Ihutai). That is, a 15% reduction in annual metal load may not result in a 15% reduction in median concentration – for example if most of load reduction is from metals delivered during storm flows, or if only particulate metals are removed with no change to dissolved metals. Further, metals contained in stream or Ihutai bed sediments are expected to take time to decline in response to a reduction of inputs, as "cleaner" sediments will mix with the existing sediments due to physical mixing and that from burrowing biota. Secondly, ecological responses are driven by multiple environmental stressors, which have both direct and indirect effects and it is possible that sediment and metal concentrations may not be the factors that are currently limiting biological communities.

Within urban streams, in particular, there are a multitude of factors that influence biological communities and lead to the "urban stream syndrome" (a term to describe the ecological degradation of streams draining urban land, (Meyer et al. 2005, Walsh et al. 2005)). For example, increased stormflow associated with the increased impervious surface area in urban areas has been recognised as the primary driver of poor stream condition in many places around the world (Konrad and Booth 2005, Walsh et al. 2005). Further complicating the matter, many mechanisms influencing urban streams are interactive – for example, changes to the hydrology effects can influence water quality, particularly sediment transport. Therefore, any assessment of the likely effect of reductions in contaminant load (and in-stream concentrations) needs to be cognisant of the other influences on water quality and biological communities.

Linking reductions in contaminant loads to ecological responses is highly complex, particularly in multi-stressor environments like urban waterways. This is an area of ongoing research internationally and one that is not easily solved. The CCC contracted NIWA with determining the feasibility of linking reductions in contaminant loads with potential ecological responses within the waterways of Ōtautahi and Ihutai, considering the current data available and complexity of multiple stressor environments.

1.2 Project goals

The objectives of this project were to:

- Assess the feasibility of:
  - Robustly predicting how and when the receiving environment might respond to changes in network contaminant loads and resulting in-stream concentrations, as well as changes in other limiting factors (e.g., habitat availability),
  - Quantifying which limiting factors (i.e., not just stormwater treatment) would have the greatest ecological benefit, the quickest ecological benefit, or limited ecological benefit, if they were to be addressed,
  - Assessing the response within the waterways with consideration of a range of variables: Cultural Health Index, Water Quality Index, Macroinvertebrate Community Index/Quantitative Macroinvertebrate Community Index, and fish diversity and abundance, consistent with those used in the Healthy Waterbodies Action Plan (Margetts 2023).
  - Assessing the response within Ihutai for the following variables: Cultural Health Index, Estuary Trophic Index, and benthic invertebrate abundance and presence.
- Determine the resources required (e.g., time and money) to carry out the full assessment.

1.3 Project scope

This project covers the response of biological communities to changes in stormwater contaminant loads. The first step in this causal chain is a change in the in-stream concentrations of suspended sediment and metals and, for Ihutai, the bed sediment concentrations. There are multiple methods to predicting changes in in-stream concentrations based on changes in contaminant loads, and a review of these is outside the scope of this project, as it is the subject of other investigations by CCC. We have included a very brief discussion of methods to predict bed sediment and metal concentrations in Ihutai as, to the best of our knowledge, this is not being addressed by other CCC investigations. Therefore, the models described in the remainder of this report are those that focus on predicted biological responses from in-stream metal concentrations and sediment (suspended and deposited) (freshwater) or bed sediment concentrations (estuary).

The scope of Schedule 3(d) includes freshwater (streams, lakes and wetlands) and estuarine receiving environments. Furthermore, the consent covers not just the city of Ōtautahi but also the smaller towns and settlements around Banks Peninsula. In this project, we have restricted the scope of works to just the streams and rivers of Ōtautahi in recognition of the following:

- There is more information (particularly routine monitoring) available regarding the water quality and ecology of Ōtautahi streams than for the many streams in the Banks Peninsula settlements.

- Contaminant loads have been predicted for the four rivers of Puharakekenui/Styx, Ōtākaro/Avon, Ōpāwaho/Heathcote and Huritini/Halswell for both current and future scenarios.
- Ōtautahi is the largest urban centre within Christchurch City Council's area, with the most commercial and industrial land, and therefore the location with the highest loads of contaminants and likely the greatest effects.
- Many of the streams in Banks Peninsula settlements also have large rural areas in the catchment and the effect of the urban land use may be lower, or confounded by rural land use effects.

Furthermore, we have restricted to the scope for coastal receiving environments to the Avon-Heathcote Estuary / Ihutai (referred to herein as Ihutai) and to the responses of the benthic invertebrate communities. This is in recognition of the following:

- There is considerable information available for Ihutai (in terms of water quality, predicted loads of contaminants, sediment quality, macroinvertebrate communities) than for estuaries or coastal areas.
- The drivers of estuarine macrofaunal community diversity and abundance are far better understood and defined than those for estuarine fish species.

1.4 Approach

We used a four-stage approach to meet the goals for this project, as outlined below.

Stage 1: Conceptual modelling of influences on freshwater and estuarine environments

We developed diagrams of conceptual models for Ōtautahi streams in a collaborative workshop with CCC staff and their expert panel of freshwater ecologists (focussing on freshwater ecosystems). A conceptual model is visual representation of the system, that describes our understanding of the system, including causes and effects[1]. We developed models for periphyton, macrophytes, macroinvertebrates, and fish, including potential connections between models (i.e., periphyton influences on macroinvertebrates). The conceptual models were used to guide the search for information (and data) that would be required to derive and use any statistical or mathematical models. During this stage, we also discussed and refined a definition of the "biological community" as referred to in the consent condition.

Stage 2: Establish the knowledge base for Ōtautahi streams and for Ihutai

This stage involved collating data and reviewing information on the biological communities and potential stressors in the freshwater receiving environments as defined above, for the four river catchments of Ōtautahi and Ihutai.

Stage 3: Review potential modelling approaches for freshwater and estuarine environments

We reviewed the modelling methods currently available to assist in understanding and predicting freshwater and estuarine ecosystem responses. We investigated models designed specifically for

[1] Note that a conceptual model is merely the first step in developing a predictive model, and does not fulfil the requirements for this project.

urban water bodies and more generic statistical approaches that could be adapted for Ōtautahi urban streams and Ihutai. We used three guiding questions:

- What 'off-the-shelf' ecological response models are available for the target biological responses? These models, which include process-based and statistical are pre-developed but may require parameters to be refined to increase specificity for Ōtautahi waterways.
- What statistical models could be used to generate predictive models using the data available?
- Do these model types meet the needs of CCC, as outlined above (in Section 1.2)?

Stage 4: Testing of models for feasibility of predicting responses in the receiving environment

The fourth stage in this project included testing selected models for freshwater and estuarine systems. The test results were then discussed in a workshop with CCC staff and their ecology expert panel to decide whether any of the models tested are suitable for the purposes specified by the consent.

1.5 Contents of this report

This report is set out in a structure that broadly follows the above steps:

- A brief review (section 2) of how the key contaminants copper, zinc and sediment influence freshwater and estuarine ecosystems, both on their own and in conjunction with other stressors.
- Section 3 focusses on knowledge specific to Ōtautahi's receiving environments and includes an overview of the data available to use or develop models, and our existing understanding of the key stressors and their effects in these locations.
- Section 4 reviews the different models that currently exist for modelling metal concentrations in receiving environments, and for predicting effects in freshwater and estuarine ecological systems. Potential statistical modelling approaches that can be used to develop bespoke models are also discussed.
- In section 5, the feasibility of modelling freshwater ecological systems is assessed. This included the preliminary development of statistical models for freshwater using GAMs; and testing of an existing 'off-the-shelf' model.
- In section 6, the feasibility of modelling estuarine ecological systems is assessed. This included testing of an existing 'off-the-shelf' model for estuarine environments.
- Section 7 discusses the limitations and uncertainties in predictive modelling, provides our conclusions from this feasibility assessment and our recommendations for next steps.

2 What is the knowledge base for predicting ecological responses?

2.1 What do we know about ecological responses to sediment and metals?

2.1.1 Sediment

The effects of sediment on freshwater biological communities were reviewed in detail in developing sediment attribute thresholds for the National Objectives Framework, including both suspended and deposited sediment (see Franklin et al. (2019) and Depree et al. (2018)). Increases in deposited fine sediment alter macroinvertebrate community composition in streams, (Burdon et al. 2013, Clapcott 2011), which is commonly attributed to decreased habitat area and volume (i.e., reductions in coarse substrate and interstitial spaces). Mayfly, stonefly and caddisfly taxa (Ephemeroptera, Plecoptera and Trichoptera; EPT) are amongst the most sensitive and show a strong nonlinear response to changes in deposited sediment (Figure 2-1), with marked declines above a threshold of 20% fine sediment cover in one study of streams in an agricultural area (Burdon et al. 2013). Suspended sediments also affect biota (see Depree et al. (2018) for a review) – reducing clarity and hence photosynthesis of in-stream plants and clogging filter feeding structures of some macroinvertebrates and fish (Boubée et al. 1997, Rowe et al. 2009).

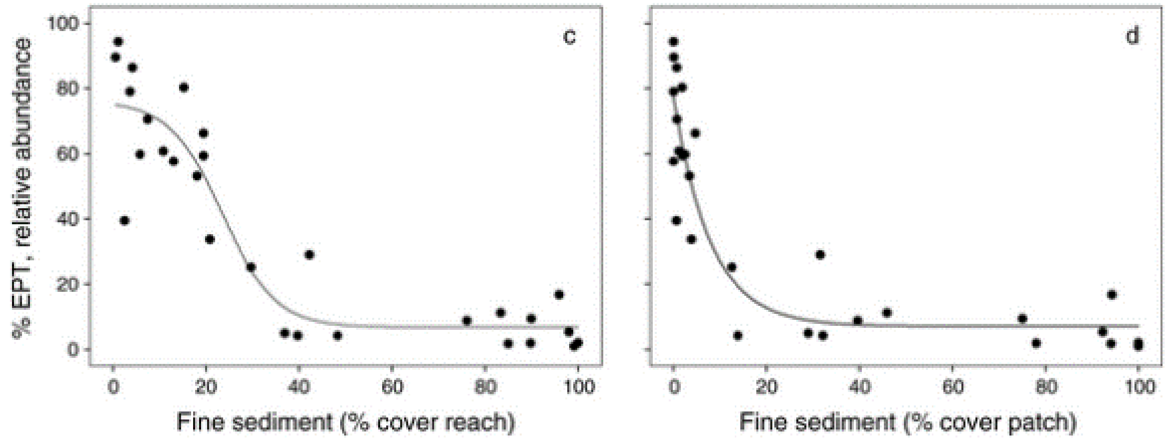

Figure 2-1: Effect of fine deposited sediment visually assessed over a reach (left plot) or a smaller patch scale (right plot) on freshwater macroinvertebrates, as shown by the EPT metric (percentage of sensitive EPT individuals). Figure from Burdon et al (2013).

Fine sediment also influences estuarine macrofaunal communities, reducing abundance and diversity as mud content increases (Thrush et al. 2008, Thrush et al. 2003c, Thrush et al. 2003d). Thrush et al. (2003c) used macroinvertebrate density data and sediment characteristics (mud to sand ratio) to develop statistical (logistic regression) models of macrofaunal presence and demonstrated that individual species vary in their habitat preference along a sand to mud gradient. These models, as illustrated in Figure 2-2 show some species are more likely to be present at higher mud content (species in box a), whilst others prefer a low mud content and are either somewhat less (box b) or much less (box c) likely to be present in sediments with higher mud content. Other species demonstrate an optimum range (d), which may be broad or narrow. Thrush et al. (2003b) stated that the models themselves may not be directly useful for predicting macrofaunal responses to changing sediment characteristics without further testing, however they do illustrate the complex relationships between sediment mud content and presence of individual species – including positive, negative and quadratic relationships. This work also illustrates some of the complications involved in the use community composition metrics (e.g., number of taxa).

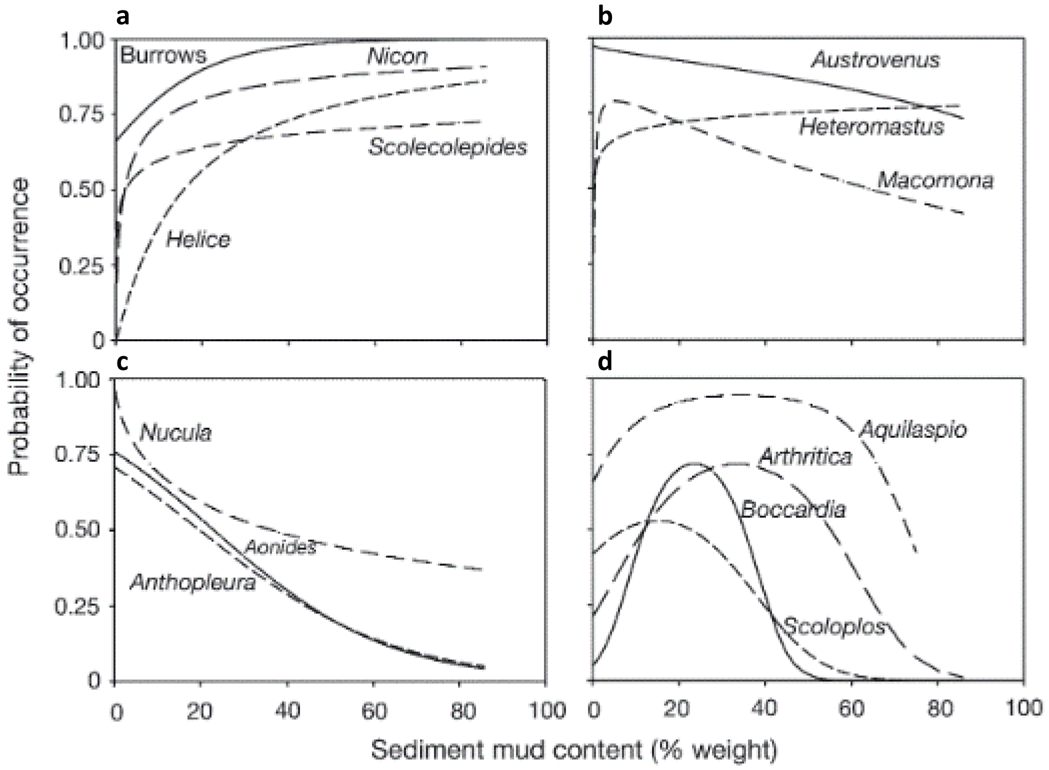

Figure 2-2: Logistic regression models for predicting probability of occurrence of macrofauna species and crab burrows relative to sediment mud content. Figure from Thrush et al (2003b).

2.1.2 Metals

There are many contaminants of concern present in stormwater, including metals (cadmium, copper, lead, nickel, zinc), hydrocarbons (including PAHs) and other organic micropollutants such as pesticides (Williamson & Mills 2009). Copper and zinc are two of the most ubiquitous (and relatively easy to monitor) and as such are frequently used as indicators of stormwater contamination. Many of the methods that would reduce the effects of these two metals would also reduce effects of other contaminants of concern.

The effects of copper and zinc on freshwater and estuarine biological communities are comparatively well-known. Although both metals are essential nutrients[2] at low concentrations and required in multiple enzymes and other proteins, they can also cause acute and chronic toxicity at higher concentrations – that is, they demonstrate hormesis (Figure 2-3). In addition to acute effects such as mortality, chronic exposure to excess metals can result in alterations of brain function, enzyme activity, blood chemistry, and metabolism which lead to adverse effects on growth, reproduction and survival of macroinvertebrates and fish, and reduced growth of algae. These effects on individuals can result in changes in population and community structure. The effects of copper and zinc are

[2] Unlike cadmium, lead and mercury, which have no biological function.

routinely evaluated in laboratory tests, most frequently to establish concentrations that are safe or lead to adverse effects, and these tests indicate that copper is more toxic than zinc (Table 2-1).

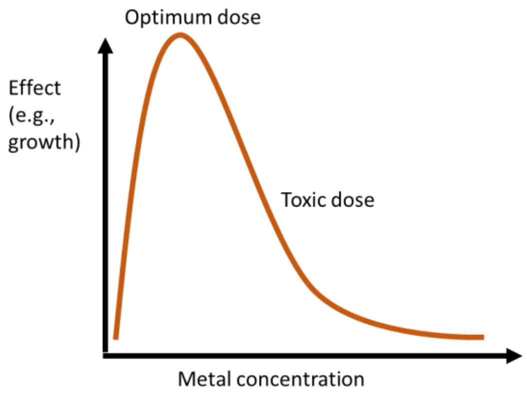

Figure 2-3: Hormesis curve for essential trace metals, demonstrating low growth at very low concentrations, stimulation at moderate concentrations and a toxic response at higher concentrations.

Table 2-1: Examples of copper and zinc toxicity data for survival of native New Zealand freshwater fish and macroinvertebrates. The data are an inexhaustive collation from published and unpublished studies (Albert et al. 2021, Clearwater et al. 2014, Hickey et al. 2000, Hickey & Vickers 1992, Thompson et al. 2021, Thompson et al. 2019).

Species	Timeframe (duration of toxicity test)	No effect concentration (NOEC), µg/L	Concentration that affects 50% organisms in test (EC50), µg/L
Copper			
Freshwater mussel (*Echyridella menziesii*)	24-hour	2.0	3.6
Pond snail (*Potamopyrgus antipodarum*)	96-hour	Not reported	17
Water flea (*Daphnia thomsoni*)	48-hour	22	31
Amphipod (*Paracalliope fluviatilis*)	96-hour	Not reported	70
Kōura (*Paranephrops planifrons*)	7-day	260	>300
Mayfly (*Deleatidium* sp.)	96-hour	Not reported	39
Common bully (*Gobiomorphus cotidianus*)	96-hour	180	520
Common bully (*Gobiomorphus cotidianus*)	10-day	Not reported	125-1000
Inanga (*Galaxias maculatus*)	96-hour	56	85
Zinc			
Freshwater mussel (*Echyridella menziesii*)	24-hour	258	368
Pond snail (*Potamopyrgus antipodarum*)	96-hour	Not reported	530
Water flea (*Daphnia thomsoni*)	48-hour	100	220
Amphipod (*Paracalliope fluviatilis*)	96-hour	Not reported	480
Koura (*Paranephrops planifrons*)	7-day	430	>430
Mayfly (*Deleatidium* sp.)	96-hour	Not reported	9,000
Common bully (*Gobiomorphus cotidianus*)	10-day	Not reported	166-382

Field studies worldwide have demonstrated the toxic effects of metals in freshwater receiving environments, particularly at sites affected by mining or historical mining (e.g., Besser & Leib 2008, Hickey & Clements 1998). Within New Zealand, copper and zinc have been demonstrated to reduce the abundance and species richness of Ephemeroptera (mayflies), and taxon richness of Plecoptera (stoneflies), and Trichoptera (caddisflies), and total taxonomic richness (Hickey & Clements 1998, Hickey & Golding 2002). Metal exposure, though not specifically copper and zinc, have also reduced the density of some fish species, including native galaxids (Gray et al. 2016). The effect of metals on freshwater organisms can be evaluated to some extent using water quality guidelines (e.g., ANZG (2018), which are derived from laboratory-based toxicological assessments of individual species and individual metals similar to those in Table 2-1.

In estuarine receiving environments, metals accumulate in sediment due to the physical and chemical processes that favour partitioning to solids, flocculation and deposition (Williamson & Wilcock 1994). They may have toxic effects on organisms residing on or within those sediments – primarily through dissolution in pore waters that are then taken up by biota, causing toxicity via the same mechanisms as water-based exposure (Burton 2010, Chapman et al. 1998). Similar to water testing, the effects of metals in sediment can be measured in laboratory tests (Burton 2010). However, due to difficulties in preparing sediments that replicate field-derived samples (in terms of metal binding and bioavailability) most laboratory tests use sediments collected from the field, which most often contain multiple metals at above background concentrations. This means that most sediment quality guidelines are derived from statistical relationships between metals in sediment and biological or ecological responses (Chapman et al. 1999). Sediment quality guideline values for copper and zinc are provided in Table 2-2 and demonstrate that copper is more toxic than zinc, with lower concentrations required to cause adverse effects.

Table 2-2: Examples of copper and zinc sediment quality guidelines used internationally and within New Zealand. Note that each of these values has used slightly different methods to develop the thresholds and the description of the guideline value is important when applying them.

Source	Guideline name	Description	Copper (mg/kg)	Zinc (mg/kg)
Sediment guidelines (Long et al. 1995)	Effects range–low (ER-L)	Low likelihood of effects below these values	34	150
	Effects range-median (ER-M)	High likelihood of effects (70-90%) above these values	270	410
Florida Department of Environmental Protection Guidelines (MacDonald et al. 1996)	Threshold effect level (TEL)	Low likelihood of effects below these values	18.7	124
	Probable effects level (PEL)	Effects frequently occur above these values	108	271
Australia New Zealand guidelines (ANZG 2018)	DGV	Low likelihood of unacceptable effects below these values	65	200
	GV-high	Toxicity-related effects expected	270	410
Auckland Regional Council guidelines (Auckland Regional Council 2004)	ERC green to amber	Low risk below this	19	124
	ERC amber to red	Biological effects probable	34	150

Increases in copper and zinc (and lead) within sediment are associated with changes in estuarine benthic communities, as demonstrated in numerous New Zealand studies (Fukunaga et al. 2011, Hewitt et al. 2009, Thrush et al. 2008). Similar to their work with sediment, Thrush et al. (2008) developed statistical models that relate the abundance of specific taxa to copper, lead, zinc, mud content and coarse sediments. These relationships suggested there are species-specific responses, and relationships between stressors were not simple. For some organisms, stressor interactions were antagonistic, potentially demonstrating that organisms become adapted to stress (Thrush et al. 2008). For other organisms, stressors showed synergistic interactions – suggesting that organisms that are stressed due to sub-optimal habitat (high mud content) have limited ability to tolerate an additional stressor such as increased copper concentrations. Most importantly, several studies in New Zealand have demonstrated changes in faunal communities at metal concentrations that are lower than most sediment quality guidelines (Hewitt et al. 2009, Hewitt & Ellis 2010).

2.2 Other stressors in urban receiving environments

2.2.1 Urban streams

Urban streams are often highly modified environments impacted by many factors, collectively called the "urban stream syndrome" (Meyer et al. 2005, Walsh et al. 2005). Historically they may have been more valued as drains creating land suitable for development rather than for their ecosystem values. This has led to many urban waterways being straightened and, in some locations, stream banks lined with wood or concrete (see Figure 2-4) to reduce bank erosion while improving drainage and flow. This alters the water velocity and reduces habitat complexity for fish and macroinvertebrates. The high levels of impervious surfaces (e.g., roads, roofs and carparks) and the piping of water causes rapid delivery of rain water to streams, resulting in increased flashiness, and increasing peak flows, peak velocity and total water volume (Roy et al. 2005). In some locations, baseflows can decrease due to the reduction in water entering the stream via slow subsurface processes (Elliott et al. 2004, Roy et al. 2005).

Figure 2-4: Lined streams in Ōtautahi City, demonstrating minimal habitat variability. Left: Timber-lined section of Curlett Stream upstream of the motorway. Photo credit M. Flanagan (NIWA). Right: concrete-lined section of Sumner Stream at Scarborough Beach, photo from Allan et al. (2012).

Compared to streams in undisturbed locations, there is often minimal riparian vegetation adjacent to urban streams. The lack of shade from tall trees elevates stream water temperature. Furthermore, this reduces the input of woody detritus, which provides both habitat and nutrients for macroinvertebrates and fish. Other aspects of water quality are affected by urbanisation. For example, dissolved oxygen concentrations can be low in streams with high temperatures, low flow velocities and low volumetric flow rates. Nutrient concentrations are also modified in urban streams, due to disruption of natural biological processes, and as nutrients influence primary production, this can have consequent effects on periphyton, macroinvertebrates and fish. Contaminants deposited on or contained in impervious surfaces are delivered to streams through the piped systems, with minimal attenuation or removal unless stormwater treatment systems are incorporated. Many metals (other than copper and zinc) and organic contaminants can cause toxic effects on stream biota, either through their presence in the water column or when they deposit and accumulate in benthic sediment.

The nature of urban waterways means that many stressors of instream communities covary, as they are caused by the change from pervious to impervious surfaces and the additional infrastructure (piping, channelisation) used to accommodate that change. Furthermore, urban stressors may have synergistic, interactive effects. For example, hydrological alterations can influence water quality, particularly sediment transport, leading to a stream with both flashy flows and high deposited sediment cover, both of which reduce habitat suitability for some taxa.

Although the effects of different stressors are known in a qualitative sense (e.g., in the direction of the effect, Figure 2-5), the impacts of multiple stressors makes it complicated to disentangle individual quantitative relationships between stressors and responses, including what the form of those relationships may be (e.g., linear, exponential, with or without thresholds (Larned & Schallenberg 2019)). Any assessment of the likely effect of reductions in sediment, copper and zinc contaminant loads (and in-stream concentrations) needs to be cognisant of the other influences on water quality and biological communities. That is, a reduction in sediment, copper and/or zinc may not necessarily lead to an increase in macroinvertebrate abundance or diversity, if other stressors (e.g., habitat factors) are limiting their abundance.

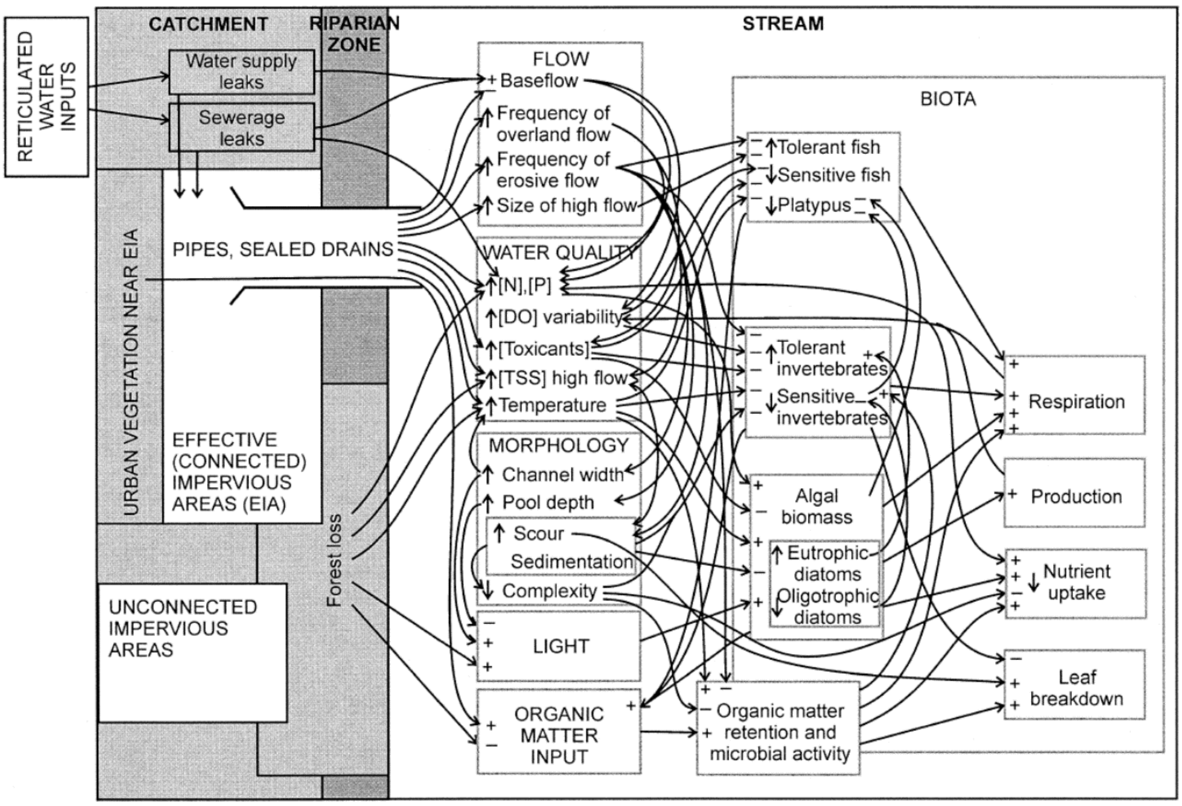

Figure 2-5: Conceptual model of how urbanisation affects stream ecosystems. From Walsh et al. (2005).

2.2.2 Urban estuaries

Urbanisation leads to changes in multiple stressors in estuarine and coastal environments. These changes include changes in infrastructure (e.g., reclamation of coastal areas, construction of artificial structures such as sea walls, ports, groynes, breakwaters and wharves) (Freeman et al. 2019, Momota & Hosokawa 2021). These changes can lead in turn to loss of intertidal area and changes in habitat through loss of salt marsh and sea grass (Freeman et al. 2019). Sediment accumulation rates are also higher in urbanised estuaries, with estuaries changing from sand- to mud-dominated systems (Swales et al. 2020).

As well as delivering sediment, copper and zinc, stormwater runoff is a significant source of other contaminants that can accumulate in coastal zones including organic contaminants and nutrients. Excess nutrients can promote macroalgal growth, and changes in algal species diversity, which may have consequent effects on macrofauna, through the food web or through smothering and changes to environmental conditions (e.g., creating low oxygen conditions). Organic contaminants may be toxic and lead to reduced growth or survival and changes in community structure (Depree & Ahrens 2007). Furthermore, urban stressors may interact in multiplicative and non-linear ways (Ellis et al. 2017; Clark et al. 2021). For example, Thrush et al. (2008) reported that heavy metals had a stronger effect on estuarine benthos at sites which also had higher mud content (i.e., mud to sand ratio). Nutrients interact with both metal loading and sediment to impact benthic macrofauna (Ellis et al. 2017). This information suggests that, as in freshwater environments, the potential effect of reducing copper, zinc and sediment loads should not be assessed in isolation from the other stressors that influence ecological communities.

3 What is the knowledge base for Ōtautahi receiving environments?

This section briefly reviews the data available for Ōtautahi freshwater and estuarine systems to either use, test or develop models to predict change in ecosystem response in relation to changes in stormwater copper, zinc and sediment loads. Further, key stressors currently influencing these ecosystems are investigated, through assessments of existing data, expert opinion and review of previous studies.

3.1 What is expected to change with stormwater management in Ōtautahi?

As described in the introduction section, CCC plan to reduce the loads of total suspended sediment, copper and zinc discharged through their stormwater network, through a mixture of improved stormwater management and source control. This is expected to reduce the concentrations of copper and zinc in the water column in the rivers, and within benthic sediments of rivers and estuaries, and to have consequent effects on the biological communities therein.

However, many of the stormwater management methods that could be used by CCC to target reductions in sediment, copper and zinc loads can also influence other stressors (Table 3-1). For example, treatment methods that involve infiltration will also decrease concentrations of other contaminants, (e.g., nutrients[3]) and affect hydrological processes in streams (e.g., peak flows). On the other hand, source control methods, such as reductions in copper in brake pads, will only affect the contaminant being controlled.

Overall, this means that whilst stormwater management methods may reduce sediment and metals (thus reducing deposited sediment and potential for aquatic toxicity), there are likely to be changes in other stressors, such as reductions in concentrations of nutrients, peak flow or water temperature. This may result in additional benefits to the biological communities. Therefore, the holistic effect of each of the management methods needs to be considered when predicting potential changes to stream and estuarine biological communities, and models to predict changes with reduced copper, zinc and sediment loads should have the capacity to include other contaminants or stressors.

Likewise, while stormwater management methods can reduce inputs, they may not decrease the contaminants already present, such as metals bound up in deposited sediment. These are likely to remain unless the contaminated sediments are removed. Alterations to hydrology due to different stormwater management methods also have the potential to alter transport of existing sediment within the waterways. For example, stormwater management may reduce peak flows within a waterway below the threshold to transport deposited fine sediment downstream, leading to an increase in deposited fine sediment in the stream. Furthermore, the benefits of these methods require that each are designed and maintained appropriately. Consequently, whilst stormwater management may be beneficial for some stressors, there may also be unintended non-beneficial effects that need to be considered.

[3] Mitigation methods may also influence *E. coli* and other faecal indicator bacteria but as their presence does not affect ecological responses, these are not included here.

Table 3-1: Stormwater mitigation methods and their potential effect on water quality and quantity. Downward arrows indicate reductions in stormwater contaminant concentrations / flows (reductions in load only are indicated with "a"), upwards arrows indicate potential increase in contaminant concentrations / flows, arrows in both directions indicates it depends on the design and location, NC indicates no change expected, o indicates minor change only, ? indicates an absence of information to assess this. Note that these mitigation methods may also affect other contaminants. Appropriate design and maintenance of each mitigation is required to achieve these effects.

		Water quality				**Water quantity**		
Mitigation methods		Cu & Zn	TSS	Nutrients	Water temp-erature	Peak flow	Total flow	Ground-water recharge
Source control	Roof replacement	↓	NC	NC	NC	NC	NC	NC
	Roof painting	↓	NC	NC	NC	NC	NC	NC
	Brake pad changes	↓	NC	NC	NC	NC	NC	NC
Non-structural	Increased catchpit clearouts	↓	↓	↓	NC	NC	NC	NC
	Increased street sweeping	↓	↓	↓	NC	NC	NC	NC
Stormwater treatment devices	Wetlands	↓	↓	↓↑	?	↓	o	o
	Proprietary filtration devices	↓	↓	↓	NC	NC	NC	NC
	Dry infiltration basins	↓ a	↓ a	↓ a	↓	↓	↓	↑
	Swales (wetland or dry)	↓	↓	?	↓	o	o	NC
	Rain gardens	↓ NC	↓	↓↑	↓	↓	o	↑
	Wet ponds	↓	↓	↑	?	↓	↓	↓↑
	Stormwater tree pit	↓	↓	↓	↓	o	o	o
	Permable pavement	o	↓	o	↓	↓	↓↑	↓↑
	Stormwater tank	NC	NC	NC	?	↓	NC	NC
	Green roofs	NC	?	?	↓	↓	↓	NC
Other mitigation methods	Waterway restoration	?	↓	?	↓	NC	NC	↓↑
	Waterway sediment removal	?	↓	?	NC	NC	NC	NC

3.2 Freshwater

3.2.1 What data do we have for Ōtautahi streams for use in models?

CCC regularly monitor a range of variables relevant for modelling the effects of stormwater contaminant loads on in-stream ecology / biological communities including water quality, sediment quality and sedimentation (see map – Figure 3-1). A key aspect is the monitoring of copper, zinc and suspended sediment concentrations – this is undertaken at 45 sites across the city, with most monitored monthly since 2007. Water level data are currently collected at 11 sites across the city with level converted to flow at three sites only (1 in each of the Puharakekenui/Styx, Ōtākaro/Avon and Ōpāwaho/Heathcote rivers). There are also water level and flow data available from short-term studies undertaken by CCC between 2016-2018.

Table 3-2: Key data available for Ōtautahi streams from monitoring by CCC (unless stated otherwise).

Type	Number of sites	Frequency	Duration
Regular monitoring			
Water level	23	Every 5-mins	Variety
Flow	8 17	Every 5-mins Every 5-mins	Ongoing Short-term studies of 1-2 years
Water quality (typically baseflow sampling); variables include DO, temperature, nutrients, sediment, metals	45	Monthly	2007-to date for many, 11 sites added in 2020
Wet weather water quality; variables include DO, temperature, nutrients, sediment, metals	28	2 events every 5 years	2019- ongoing*
Wet weather water quality; variables include nutrients, sediment, metals	Curletts Rd, Haytons Stream, Addington Brook	Event-based sampling (e.g., hourly)	Ad hoc: 2009 - ongoing
Sediment quality (PSD (mud, sand, gravel), metals, TP, PAHs, TOC)	46	Every 5 years Ad hoc	2019 – ongoing, 2003 - 2018
Fine sediment (semi-quantitative, 10 estimates of % cover using bathyscope)	17	Monthly	2020 - ongoing
In-stream habitat (range of quantitative and qualitative measures)	62 sites 4 sites	Every 5 years, catchments on rotation Annually	2019 – ongoing*

Type	Number of sites	Frequency	Duration
In-stream habitat (CREAS: bank/channel attributes, riparian vegetation)	4061	Infrequent	2004 - ongoing
Periphyton/macrophytes (as % cover/composition)	62 sites 4 sites	Every 5 years, catchments on rotation Annually	2019 – ongoing*
Macroinvertebrates (identification to species level & calculation of indices)	62 sites 4 sites	Every 5 years, catchments on rotation Annually	2019 – ongoing*
Kakahi (surveys incl. rapid surveys, presence / absence data; quantitative -> abundance, density (per m^2), length)	Ōtūkaikino, Ōpāwaho/Heathcote, Puharakekenui/Styx and Huritini/Halswell catchments; Ōtākaro/Avon and Cashmere Stream	Every 2 years in Cashmere and every 5 years at Ōtākaro Botanic gardens site; ad hoc at other locations	2009 – ongoing
Fish (EFM/nets/traps; species presence/absence + CPUE)	62 4 sites	Every 5 years, catchments on rotation, in March Annually	2019 – ongoing*
Mana whenua values General site assessment + CHI	35 sites	Every 5 years	Two studies so far*
Macroinvertebrates; periphyton and habitat assessments	9 sites	Annually	1999/2000† – ongoing; undertaken by Environment Canterbury
Spatial information			
Stormwater infrastructure (pipes, outlets, devices)	Spatial layer of city	Not applicable	Ongoing updates
Stream physical data (channel bank lining; channel invert lining, watercourse)	Spatial layer of city	Not applicable	Ongoing updates
Inanga and trout spawning sites	Spatial layer of sites	Ad hoc	Desktop review of any available data every five years
Location of springs	Spatial layer of sites	Updated during CREAS 5-yearly assessments	Ongoing updates

Note: * There is additional ad hoc/irregular monitoring prior to these dates. † Dates vary by site.

Ecological data are collected every 5 years at a total of 62 sites (Figure 3-1), with different catchments sampled each year. This includes collection of macroinvertebrates samples with various metrics calculated: the abundance of key taxa, indices such as Macroinvertebrate Community Index (MCI), its quantitative variant QMCI, taxa richness, EPT taxa richness and % EPT. In addition, Environment Canterbury monitor invertebrate ecology each summer at nine sites in these streams, with data dating back to 2004 for six of the sites.

Taxa from the EPT (Ephemeroptera, Plecoptera and Trichoptera) orders are generally considered to be more sensitive to pollution than other orders of aquatic macroinvertebrates, and EPT abundance and richness are used as indicators of water quality. The Macroinvertebrate Community Index (MCI) as defined by Stark and Maxted (2007) is a measure of stream health based on the presence of macroinvertebrate taxa and their tolerance to organic pollution. The QMCI is the quantitative variant of the MCI and is calculated including information on the abundance of taxa, and not just their presence or absence.

Fish data include species and abundance and indices such as taxa richness and total caught per net or trap (as Catch Per Unit Effort). Habitat data are also collected at the same time, including a range of quantitative and qualitative measures. Additional data are available throughout all five City catchment in the CREAS (Christchurch River Environment Assessment Survey) database, which includes bank and channel attributes, water velocity, presence and coverage of aquatic plants, and riparian vegetation (including composition). This survey assesses sites every 50 m along wadeable sections of waterways, providing a high resolution data set for the city.

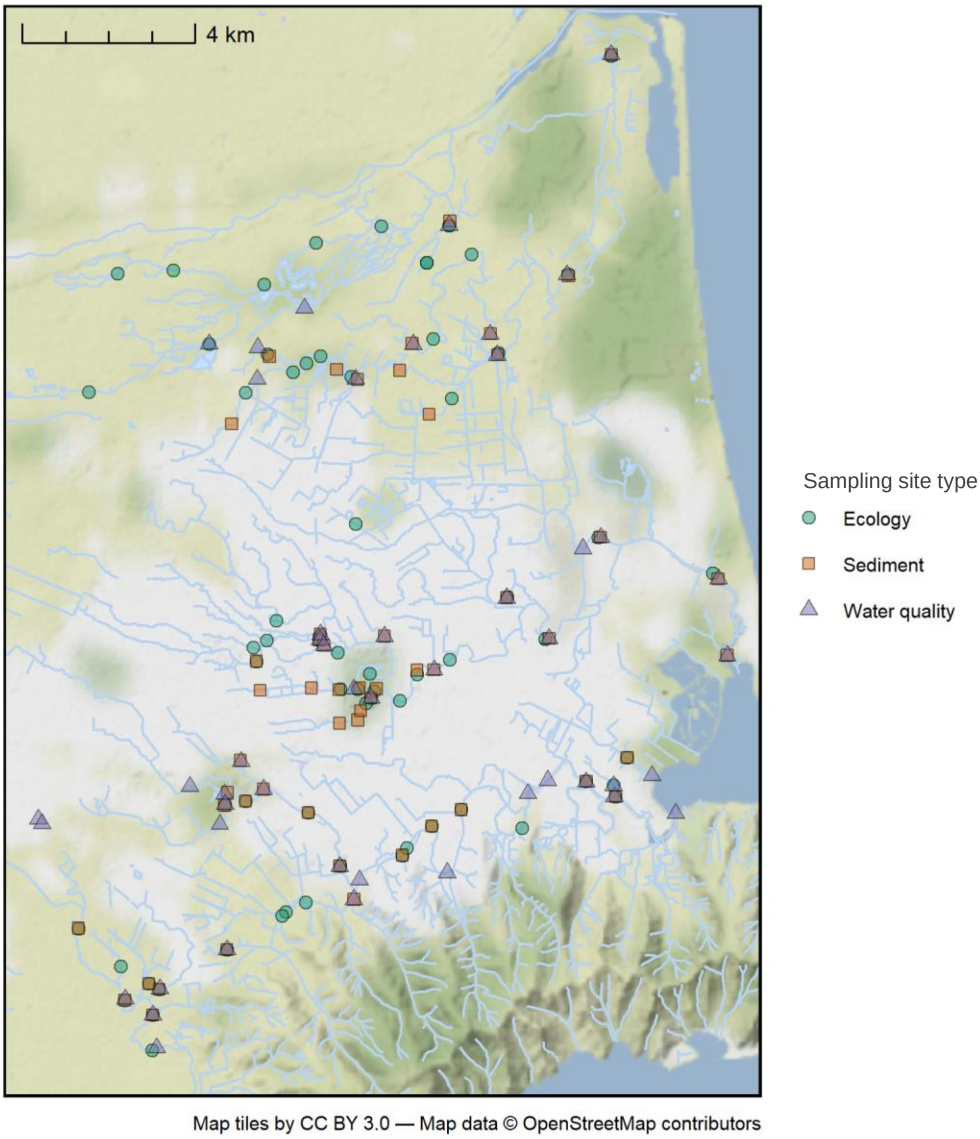

Figure 3-1: Location of sites within the Ōtautahi urban area for monitoring surface water, instream sediment and aquatic ecology/habitat. Map does not include CREAS sites surveyed every 5 years.

The spatial data available (through CCC's GIS) includes layers of impervious surfaces, stormwater catchments, pipes, outlets and location of existing stormwater treatment devices. These layers can be used to provide metrics that indicate stormwater and land use pressures such as the proportion of catchment that is impervious, the total length of pipes in the catchment or the number of stormwater outlets upstream.

In terms of cultural monitoring, there have been two "State of the Takiwā" assessments that included Ihutai; one in 2007 (Pauling et al. 2007) and a follow-up in 2012 (Lang et al. 2012). These included monitoring at 23 freshwater sites within the Ōpāwaho and Ōtākaro Rivers (24 in 2012). The scope included Takiwā site assessments which includes visual ranking assessments of site characteristics, access, pressures and suitability for harvesting mahinga kai; a Cultural Health Waterway Assessment to calculate the Cultural Health Index; and other qualitative and quantitative measurements of vegetation, macroinvertebrates, fish and birds.

Water level or flow data were available for 33 sites in Ōtautahi: 16 water level and 17 sites with flow data, Figure 3-2). Several of these sites are tidal and many were short-term monitoring sites set up for several years. A comparison of the data available between sites (Figure 3-3) indicates the different periods of monitoring – some for only a short period and several prior to 2018. This means that there are sites where the flow data does not align temporally with dates of macroinvertebrate sampling (particularly for the most recent ecological monitoring).

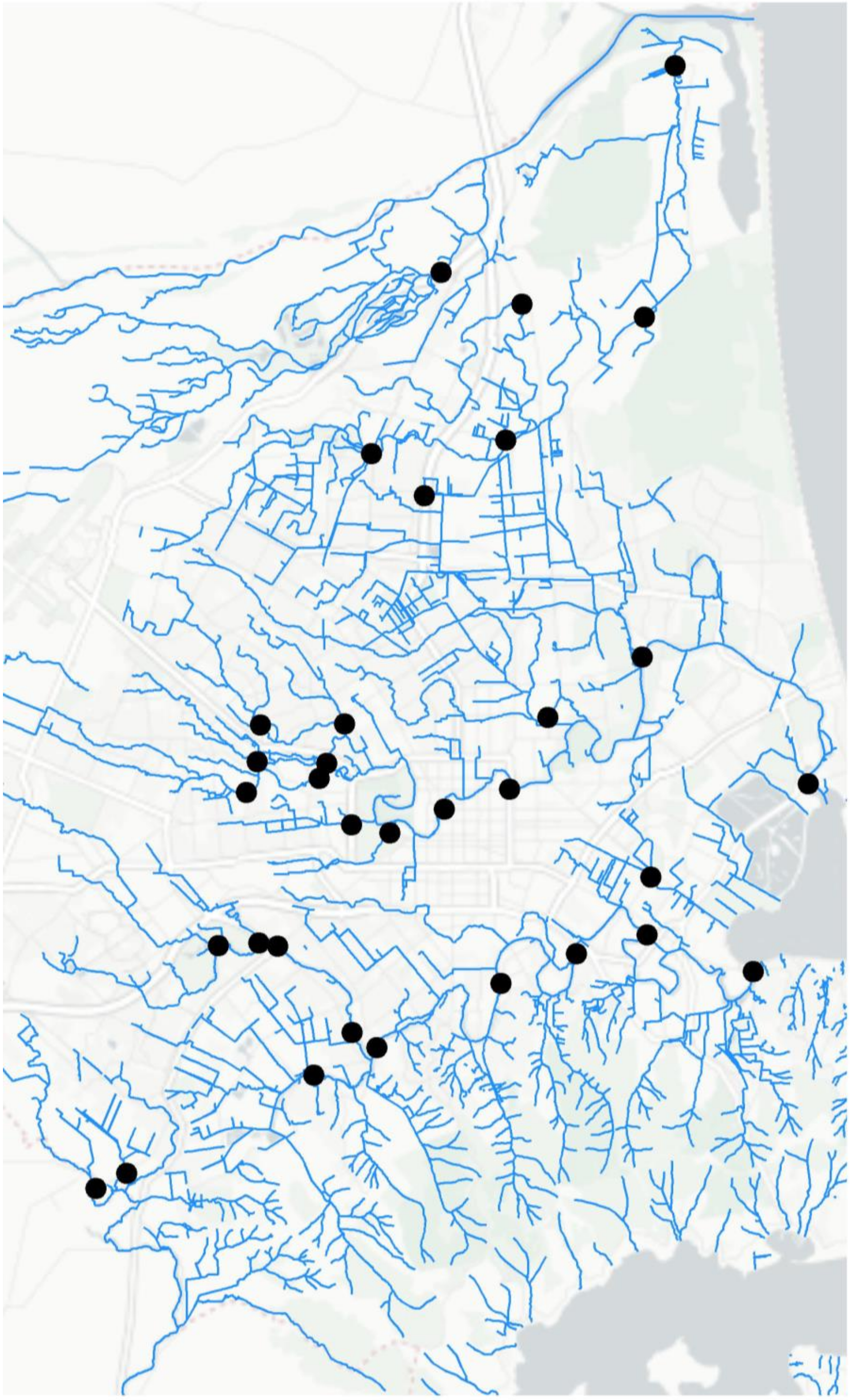

Figure 3-2: Locations of water level recorders in Ōtautahi. Recorders have been in operation over different time periods. See Figure 3-3 for record length available for each recorder from 2017.

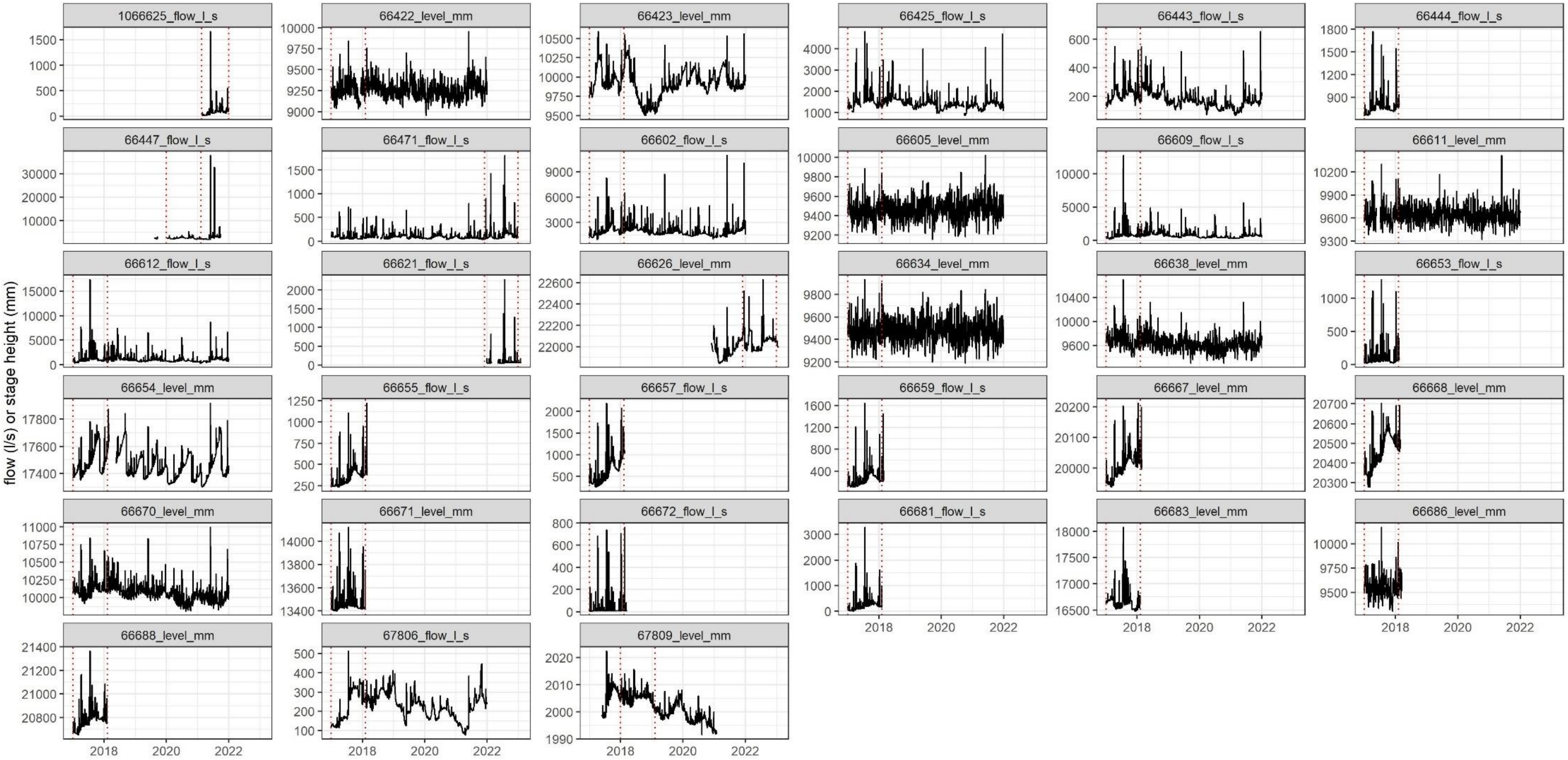

Figure 3-3: Hydrological data available for Ōtautahi streams indicating different type (water level vs flow) and different time periods. Data obtained from Christchurch City Council. Dashed lines indicate the most consistent periods of time between sites over which we could generate hydrological metrics (see Section 5 for more details).

3.2.2 Which key metrics can we use to indicate biological community state in Ōtautahi freshwater communities?

The consent condition uses the term "biological community" but does not specify what is meant by this. The definitions below were discussed and agreed on at a workshop with CCC staff, local freshwater ecologists and representatives from CCC's technical ecology panel.

In this project, we have defined the biological communities as *"populations of different species living within a specified location in space and time."* Individual taxa respond in different ways to environmental changes due to their different habitat and food preferences and tolerances to contaminants, among other factors. Univariate biological metrics are commonly used to simplify community compositional changes to one number, which makes communicating changes in community composition more efficient.

Several univariate freshwater macroinvertebrate community metrics are commonly used in New Zealand, some of which might be applicable to Ōtautahi streams and/or urban environments (Table 3-3; also see Clapcott et al. (2017) for a detailed review of the different macroinvertebrate metrics used in NZ). Key metrics for macroinvertebrates are the New Zealand macroinvertebrate community index (MCI), its quantitative variant (QMCI) and the proportion of sensitive EPT (Ephemeroptera, Plecoptera, and Trichoptera) taxa or individuals. Taxa from the EPT orders are generally considered to be more sensitive to organic pollution than other orders of aquatic invertebrates, so can give an indication of water quality. As described in section 3.2.1, MCI provides an indication of ecological condition within a waterway (Stark and Maxted 2007). Different tolerances scores are provided for taxa depending on whether the stream has a hard stoney bottom or is soft-bottomed, i.e., covered in fine sediment (Clapcott et al. 2017). Under the NPS-FM the soft-bottomed tolerance scores are required to be used in sites that are naturally soft-bottomed. The QMCI uses the same tolerance values but also includes abundance data and can be more sensitive to environmental changes than the presence-absence based MCI. QMCI, MCI and EPT metrics have been widely used during regular ecological monitoring in Ōtautahi streams and as of the NPS-FM (2020) are required to be monitored under the National Objectives Framework (MCI and QMCI as attributes; EPT as part of the average score per metric (ASPM)). The metrics generally respond to changes in organic pollution, nutrient pollution and physical habitat conditions but may also be sensitive to changes in metal concentrations.

The inclusion of individual indicator taxa, such as those with high significance to mana whenua (e.g., watercress, the abundance of large tuna (eels), and the presence of wai kōura/kēkēwai and kākahi) was discussed during the workshop. However, it was also acknowledged that the latter species are very patchy in their abundance, and because they can be very long-lived, their presence does not necessarily indicate a healthy ecosystem.

For fish, the IBI (indicator of biological integrity) metric was discussed, however there was some concern that there would be insufficient information to reliably calculate this index, given that fish are typically surveyed only once every 5 years and their presence can be patchy – related to flows and seasonal migration patterns. Furthermore, as the IBI is based only on presence/absence (not abundance) it may not be sufficiently sensitive to detect gradual improvements or declines (McDowall & Taylor 2000).

Based on the workshop, and analyses of data availability the key metrics selected for developing models for freshwater ecosystems were the univariate metrics QMCI and EPT (either taxa richness or percentage of individuals present). Statistical modelling approaches that can include multivariate (i.e., the response of multiple taxa) instead of univariate responses are discussed in Section 4.5.2, however, due to the relatively small number of sites sampled, the lack of temporal macroinvertebrate data, and common use of univariate metrics in freshwater monitoring we recommend proceeding with the selected univariate metrics.

There are some considerations when using univariate metrics to indicate biological community state. Using one number to represent community state can make communicating changes in state simple and easier to interpret, i.e., one number either declines or increases. However, using metrics can make it difficult to link changes in their values with mechanistic causes. For example, two different community responses, caused by different stressors, can result in the same metric value – that is, increased abundance of tolerant species a and decreased abundance of sensitive species c; or increased abundance of tolerant species b and decreased abundance of sensitive species d. Univariate macroinvertebrate metrics such as the MCI and QMCI have been widely used in New Zealand to assess freshwater ecosystem health. Both are commonly correlated with native land cover (Clapcott et al. 2014, Death & Collier 2010) and broad gradients in nutrient enrichment, organic pollution and sedimentation (e.g., Clapcott & Goodwin 2014). However, causative relationships linking changes in MCI (and its variants) to variation in individual stressors can be difficult to identify where multiple stressors are present (Clapcott & Goodwin 2014, Clapcott et al. 2017, Collier et al. 2014). More generally, using statistical models, which rely on correlation to infer causation, to identify the stressors causing degradation of macroinvertebrate communities based on univariate metrics is challenging, particularly where multiple correlated stressors are in effect, such as urban waterways.

Table 3-3: Key metrics considered as indicators of the freshwater biological community for this project. Metrics shaded in green are considered most likely to be useful for developing models.

Indicator	Description	Pros	Cons
Macroinvertebrate metrics			
MCI score Stark and Maxted (2007)	Assigns tolerance values to different taxa, based on presence/absence	Does not require abundance data Widely used in NZ, comparable across sites/ regions	Responds to multiple stressors, but may not respond appropriately to metals Often not to species level
QMCI score Stark and Maxted (2007)	Quantitative version of MCI, incorporates abundance of each taxa	Widely used in NZ, comparable across sites/ regions	Responds to multiple stressors, but may not respond appropriately to metals Often not to species level

Indicator	Description	Pros	Cons
EPT taxa richness or Percent EPT	Occurrence or percent abundance of sensitive: Ephemeroptera (mayflies) Plecoptera (stoneflies) Trichoptera (caddisflies)	Responds strongly to degradation	Responds to multiple stressors Often not to species level Sometimes pollution tolerant caddisflies included in score Can be naturally less abundant in some sites
UCI or QUCI Suren et al. (1998)	Urban community index, or quantitative urban community index	Developed specifically for urban streams with a focus on habitat quality	Has not been widely used or reported, scores would need to be derived from raw data
ASPM (Collier 2008)	Average score per metric Calculated from MCI, EPT richness and %EPT	Developed to discriminate between reference sites and those influenced by urbanisation or pastoral development An NPS-FM attribute and therefore may be being measured and reported on in the future	Has not yet been widely used or reported, scores would need to be derived from data
Stressor specific metrics for deposited sediment and periphyton (Wagenhoff et al. 2018)	Calculated as for MCI /QMCI using a unique set of tolerance scores developed separately for deposited sediment and periphyton	Can be more sensitive to their target stressors than the MCI / QMCI Uses same taxa identification level as the MCI	Scores only for 49 taxa so far, of which few may live in urban streams
Macroinvertebrate or fish metrics			
Species richness / taxonomic richness	Number of different taxa present	Quantitative measure Simple to calculate Represents biodiversity Calculated and reported in CCC's 5-yearly ecology monitoring reports	Species replacement can result in change in community with no change in richness Sometimes more related to sampling effort, esp with occasional rare taxa
Taxa abundance / total abundance	The total number of individuals present	Quantitative measure Simple to calculate Calculated and reported in CCC's 5-yearly ecology monitoring reports	Includes pollution tolerant taxa High abundance can be due to dominance by only a few taxa and can indicate poor conditions.

Indicator	Description	Pros	Cons
Indicator taxa or taxa of interest E.g., watercress, abundance of large tuna; kākahi & koura/kakawai	Abundance or presence/absence of particularly sensitive taxa or taxa of interest	Potential to link to specific stressors	Relies on indicator taxa being naturally present Natural variation in abundance can result in high uncertainty in the measured data. For long-lived species (e.g., kākahi) presence may not be an indicator of high quality environments.
Species distribution	Probability of occurrence of species (individual or joint) based on environmental predictors	Can be used to make predictions for non-sampled sites	Need to compare to expected distributions from comparable reference sites for context Not comparable across all sites
Multivariate composition	Presence/absence or relative abundance across all sites Can be observed/expected if reference communities are present for comparison	Can compare entire communities across sites	More complex model types required (e.g., ordination)
Fish IBI Joy and Death (2004)	Index of biotic integrity; expected and observed scores based on a combination of metrics related to native and invasive species	Relates to species sensitive to degraded habitats (which could include urban habitats)	May be insufficient sampling for reliable data Fish passage barriers may also affect presence of some fish species

3.2.3 Data availability and suitability for use in existing and when developing predictive models

In this section, the available data is assessed for its suitability for modelling. Having a broad range of data for potential stressors will help parameterise mechanistic models and/or build statistical models for Ōtautahi waterways. Further, statistical models should not be used to predict outside of the range of data that they were developed with. A range of predictor conditions is required for parameterising a model that predicts for new sites or new conditions (e.g., reduced stormwater contaminant loads). For example, when considering predicting macroinvertebrate community metrics under different levels of stormwater contaminant level in the future, the current dataset needs to include those contaminant levels.

CCC's water quality and ecological monitoring data (as described in section 3.2.1, and provided to NIWA by CCC) are used in this section to assess the range of stressors and responses. Plots of the key stressors copper, zinc and total suspended sediment (TSS, Figure 3-4) indicate a relatively broad range in zinc concentrations from those well below water quality guidelines to site median concentrations that could be expected to have adverse effects on more than 20% of species present (i.e., exceeding the guideline for protection of 80% of species). Dissolved zinc concentrations ranged from ~1 µg/L at headwater sites to >20 µg/L at several urban sites (Figure 3-4). By contrast, median dissolved copper concentrations ranged from <0.5 µg/L at headwater sites to 5.5 µg/L at an urban site, with few sites exceeding the guideline value for protection of 99% of species (Figure 3-4). Median TSS concentrations were between 1 and 3 mg/L at many sites, with few sites exceeding the 25 mg/L guideline value. There was also considerable temporal variation within sites, particularly for zinc and TSS.

Other sediment-related stressors (measured only once, during macroinvertebrate sampling) have been measured across the entire range of 0 to 100% for fine sediment cover and stream substrate embeddedness (Figure 3-5). Shading, macrophyte and periphyton cover also demonstrated a broad range (Figure 3-6).

The biological data (Figure 3-7) indicated some range in the MCI values between sites, however when comparing to the categories used in the NPS-FM NOF, the majority of sites were ranked below the national bottom line, Band D (or indicative of severe enrichment, Stark and Maxted (2007)), with only a few sites categorised as having moderate enrichment and none with mild to no enrichment. Similarly, for QMCI, most sites (70%) were ranked below the national bottom line (Band D), with 26% sites ranked in the C band (moderate enrichment) and <1% sites in the B band (mild enrichment). The percentage of the community that are sensitive EPT individuals was low at less than 10% for all sites. This is relatively common in urban waterways (Collier et al. 2009, Suren 2000).

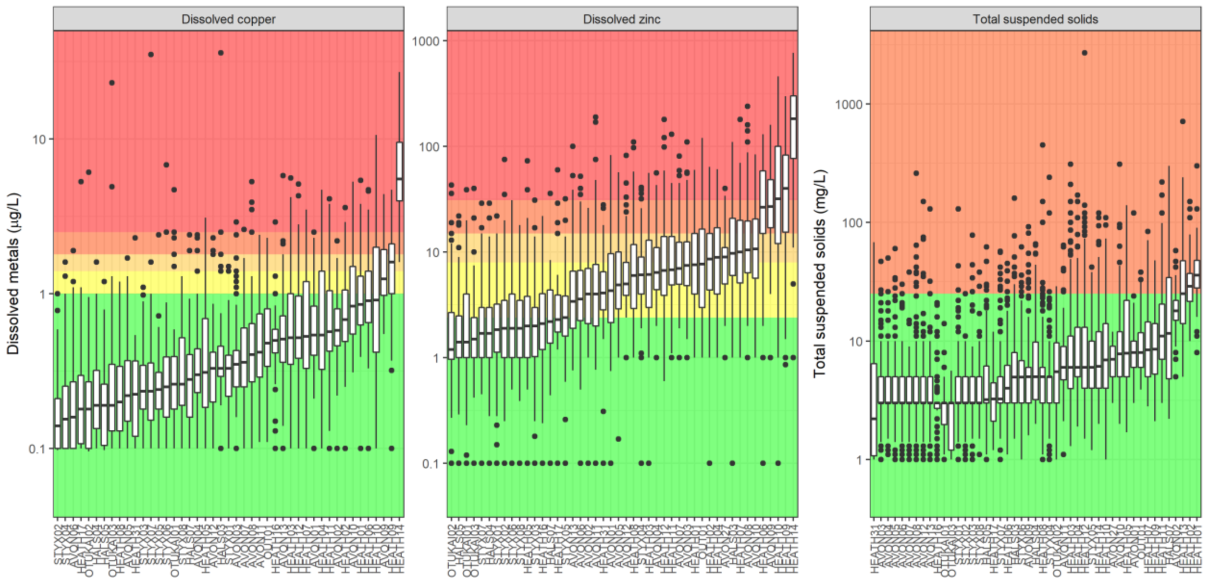

Figure 3-4: Copper, zinc and suspended solids concentrations at individual sites in Ōtautahi streams ordered by median concentration. Site labels on x-axis are site codes used by CCC. Data from monthly monitoring from January 2007 up to December 2021. This plot excludes all copper data prior to October 2016 when laboratory detection limits were 1 µg/L and most samples were below detection. Data that are below

detection are plotted here at the detection limit (0.1 µg/L for dissolved copper, 0.1 and 1 µg/L for dissolved zinc, 3 and 5 mg/L for total suspended solids. Central marker indicates median value for each site. Boxes represent the range from 25th to 75th percentiles, whiskers from 1.5x inter-quartile range and small points indicate data outside 1.5 x IQR. Note log scale on y-axes for all three variables. Background shading for copper and zinc indicates comparison to ANZG (2018) guideline values (<99% protection shown in green, <95% in yellow, <90% in light orange, <80% in dark orange and >80% in red), not adjusted for hardness. Suspended solids compared to guideline value of 25 mg/L (Hayward et al. 2009).

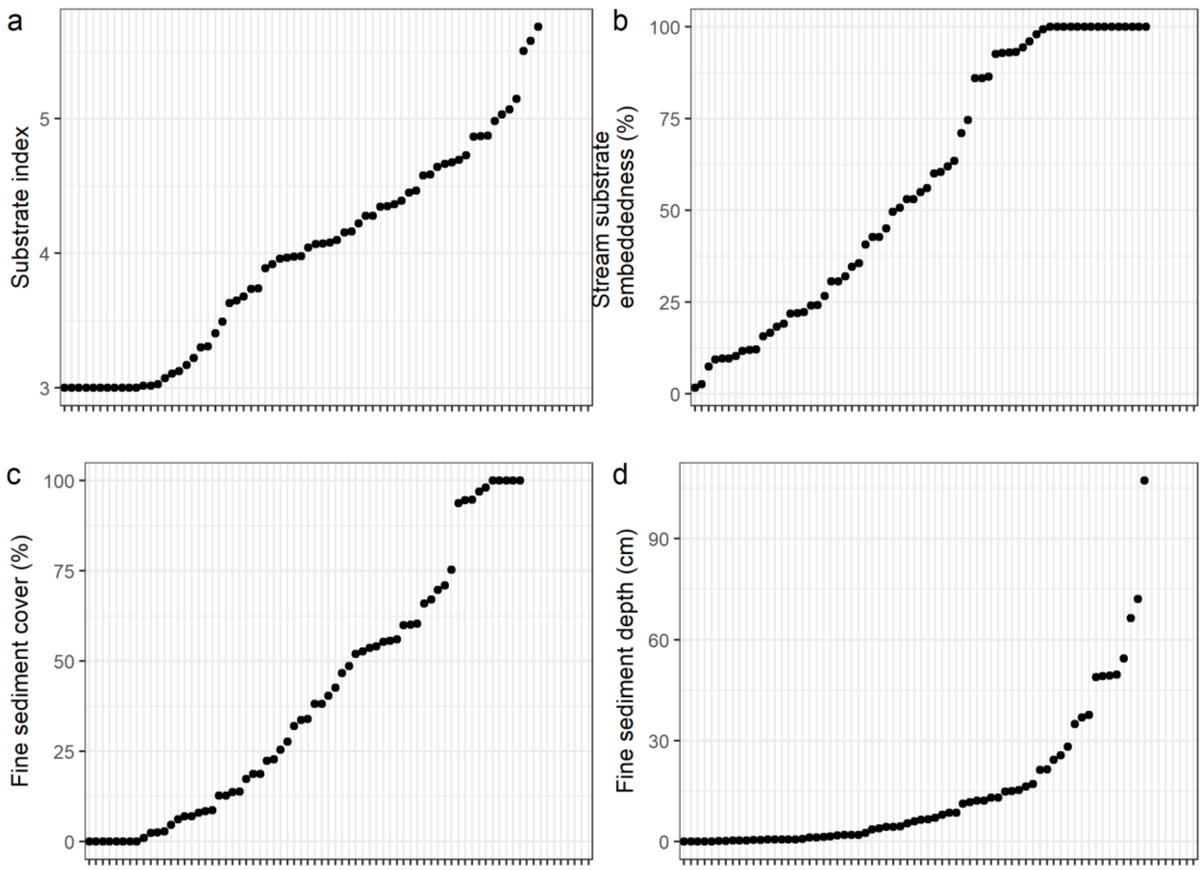

Figure 3-5: Sediment related stressor indices in Ōtautahi streams ordered by mean values for each site sampled for macroinvertebrate ecology. Each dot represents a single site in the monitoring network. All data from latest of five-yearly monitoring (i.e., from 2018 to 2022, depending on catchment).

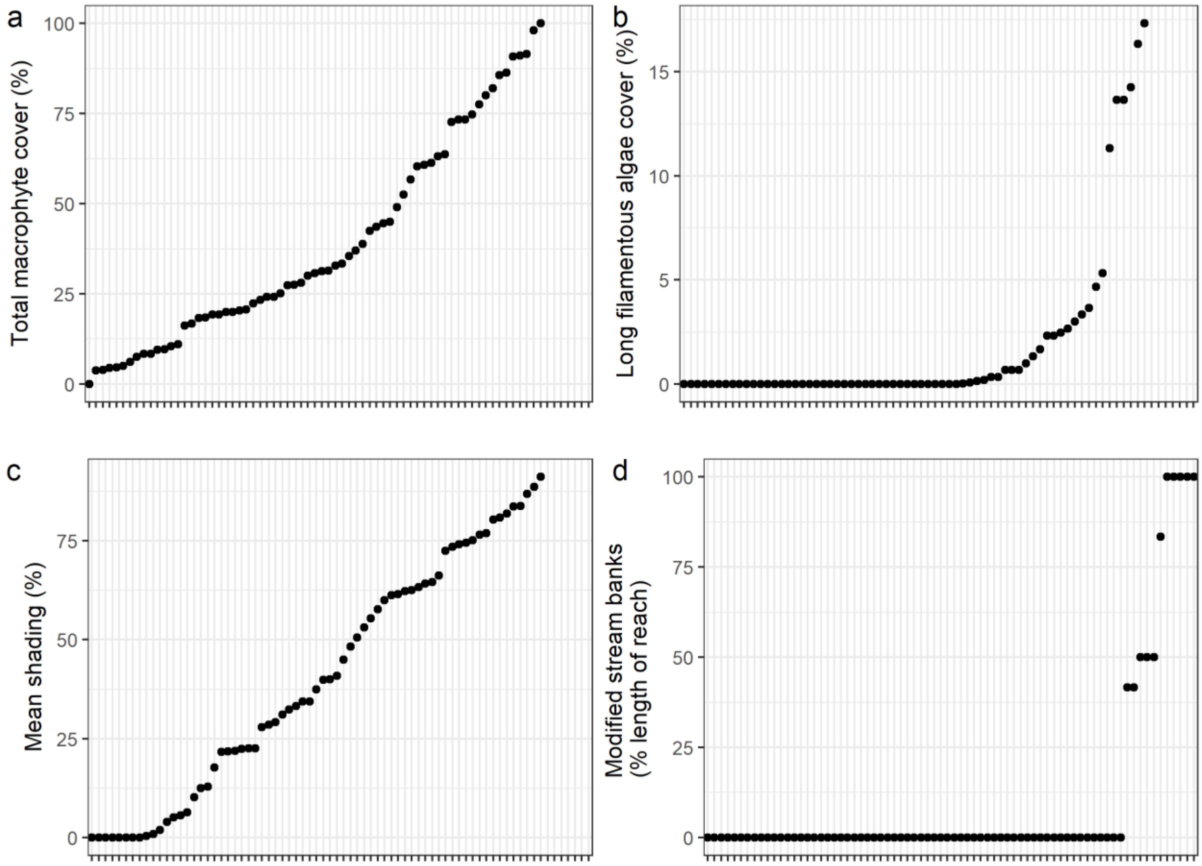

Figure 3-6: Macrophyte, periphyton, stream shading and bank modification in Ōtautahi streams ordered by mean values for each site sampled for macroinvertebrate ecology. Each dot represents a single site in the monitoring network. All data from latest of five-yearly monitoring (i.e., from 2018 to 2022, depending on catchment).

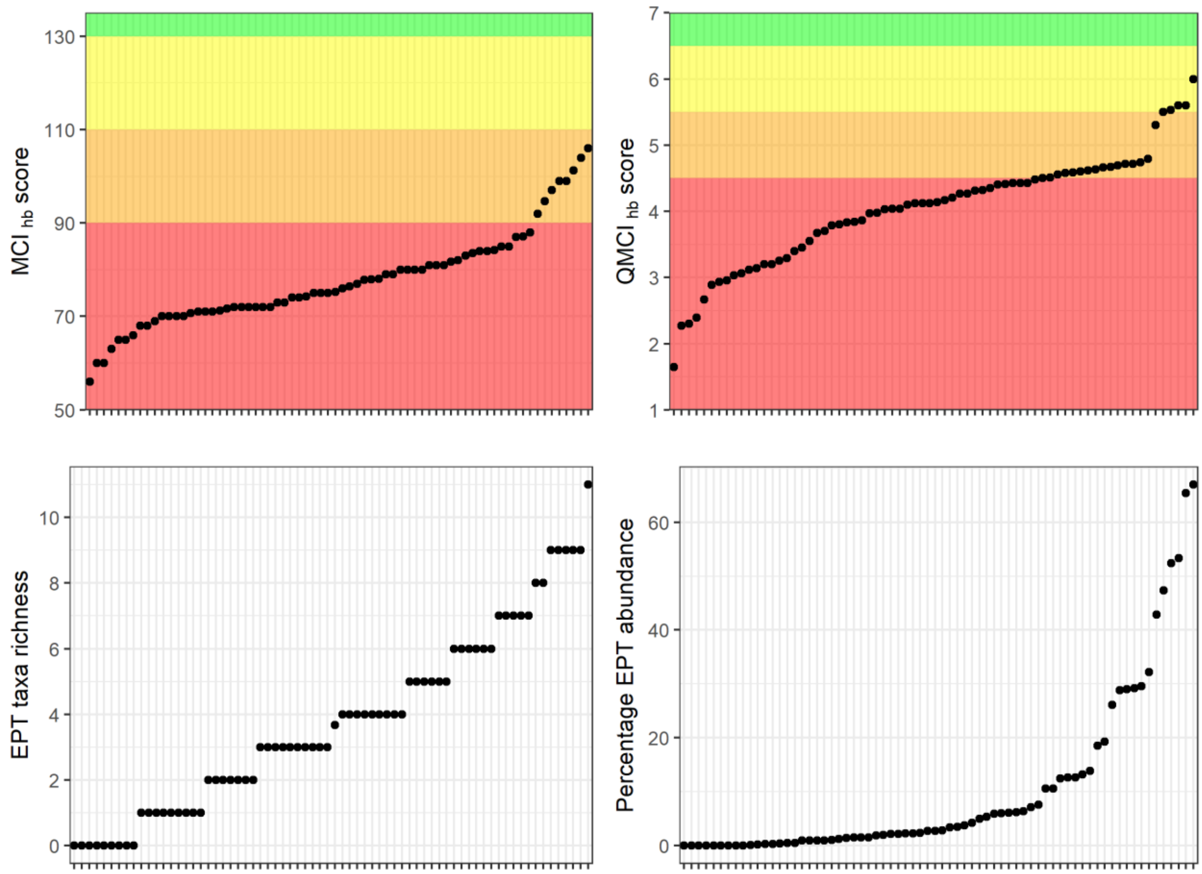

Figure 3-7: MCI and EPT scores for Ōtautahi streams. Each dot represents a single site in the monitoring network. Colour background for MCI and QMCI scores based on the NPS-FM numeric attributes (red indicates below the national bottom line, orange Band C, yellow Band B and green Band A). EPT scores calculated excluding pollution-tolerant caddisflies in the order Hydroptilidae. All scores from latest of five-yearly monitoring (i.e., from 2018 to 2022, depending on catchment).

In terms of the number of sites that could be used to develop a model, there was a maximum of 71 sites with macroinvertebrate sampling. However not all the important stressor variables have been measured at each site. For example, the regular water quality monitoring sites are not all co-located with ecological monitoring sites, and the water level / flow data are also infrequently co-located (see Figure 3-1 and Figure 3-2 for locations of each). Therefore, data sets are either reduced to the co-located sites (which would drastically reduce the number of sites) or assumptions must be made - for example that the water quality at an upstream site is broadly representative of the water quality at a downstream ecological monitoring site.

Furthermore, data have been collected at different temporal resolutions – macroinvertebrate and sediment quality sampling and habitat measurements are undertaken every 5 years (except for annual sampling at 5 sites only), water quality is sampled monthly and water levels are recorded at 15-minute intervals. Most modelling methods will need the water quality and water level data to be summarised to specific indices – for example, median or 95th percentile dissolved zinc concentrations.

If required and beneficial, the Ōtautahi data could be supplemented with data from other locations to build and test models. For example, macroinvertebrates are regularly sampled in wadeable streams all over New Zealand (currently 995 sites across NZ[4]), including in other urban centres such as Auckland (9 sites), Wellington (6 sites), Tauranga, Hamilton and Nelson (each 3 sites) and others. Although methods used to sample, process and identify macroinvertebrates has varied between councils (Whitehead et al. 2022b), the MCI and percent EPT (if calculated) are comparable, although the related quantitative (QMCI, EPT abundance) or semi-quantitative metrics (SQMCI) may be less comparable due to the different collection and processing methods. Water quality data are also regularly collected throughout New Zealand (e.g., 510-845 sites depending on variable), including metals at 46 additional sites. However, it is not clear how many of these are co-located with macroinvertebrate sampling sites. Furthermore, although flow monitoring is undertaken at many locations, the sites are generally different to macroinvertebrate monitoring sites. Although this limitation can be alleviated by substituting modelled flows, the existing national scale hydrological models (e.g., NZWaM (Kees et al. 2022)) are unlikely to accurately represent flows within urban streams.

3.2.4 What are the key stressors influencing Ōtautahi freshwater biological communities currently?

Expert knowledge, such as used to identify the likely key stressors for Ōtautahi waterways (see below), is crucial to developing models that include those stressors, and their likely mechanisms of impact on biological communities. Comparing values for stressors against published thresholds (such as National Objectives Framework (NOF) attribute bands in the National Policy Statement for Freshwater Management, NPS-FM (New Zealand Government 2020), or known toxicity thresholds) can also assist in identifying parameters that are likely acting as stressors on the biological community.

From expert opinion

Conceptual models of the key stressors affecting the biological communities within Ōtautahi streams were developed during a workshop (Appendix A). These models were based on the conceptual model of Walsh et al. (2005) and refined based on the experience of ecologists working in Ōtautahi streams. The model for macroinvertebrate communities shows the stressors considered to be of highest importance to these streams, as depicted by the thickness of the arrows in Figure 3-8. Suspended sediment concentration, deposited sediment, movement barriers and the presence of source populations were identified as the most important stressors directly influencing macroinvertebrate communities. Nutrient concentrations were judged to be very important to algae and periphyton, though the importance of these on macroinvertebrates was considered to be less significant than the stressors listed above. Flow-related stressors were not considered to be of high importance in Ōtautahi streams (compared to other locations), due to the spring-fed nature of these streams which provides a constant baseflow. Despite copper and zinc concentrations being two of the three contaminants that are the focus of stormwater contaminant load reductions by CCC, they were not considered by the ecological panel to be key stressors in Ōtautahi streams. This may be because there is currently limited evidence available from field studies for the adverse effects of copper and zinc in urban streams and comparatively more evidence nationwide for the effects of sediment and nutrients on ecological communities.

[4] Lawa.org.nz

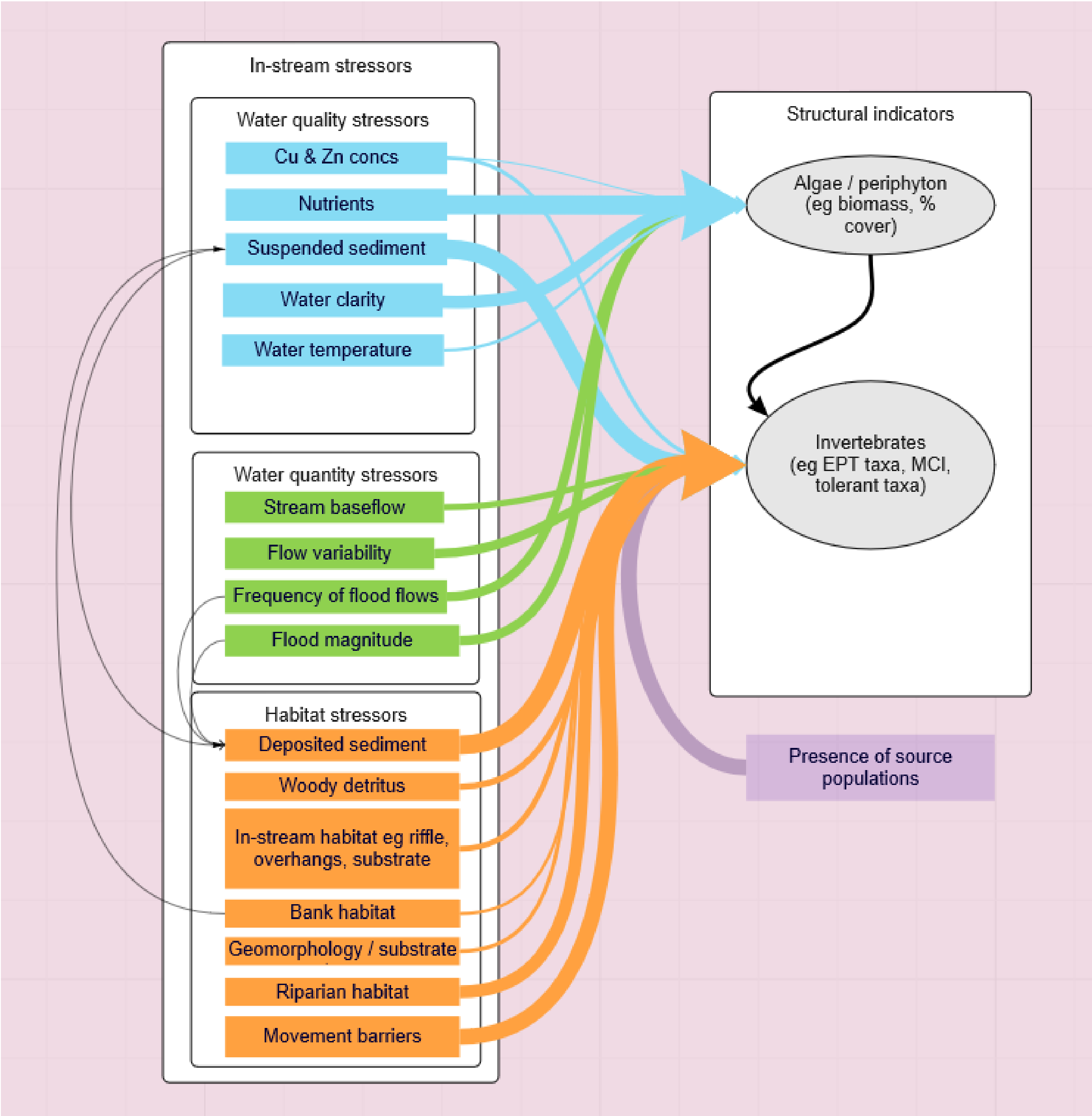

Figure 3-8: Conceptual model of how urbanisation affects Ōtautahi stream macroinvertebrates. Adapted from Walsh et al. (2005) by expert panel. Thickness of arrow indicates the perceived importance of relationship; arrow colour relates to stressor group; thin black arrows demonstrate interactions between stressors.

From monitoring data

A comparison of several different indicators measured in Ōtautahi streams to thresholds (see Appendix B for details of the thresholds used) provides some indication of possible key stressors (Figure 3-9). This suggests that lack of shade, poor substrate, fine sediment cover and high metal concentrations could be key stressors, along with nutrient concentrations that favour excess periphyton growth. Note that there are contrasts between this assessment and that of the ecological panel in the workshop – most obviously in the inclusion of dissolved zinc as a potential stressor.

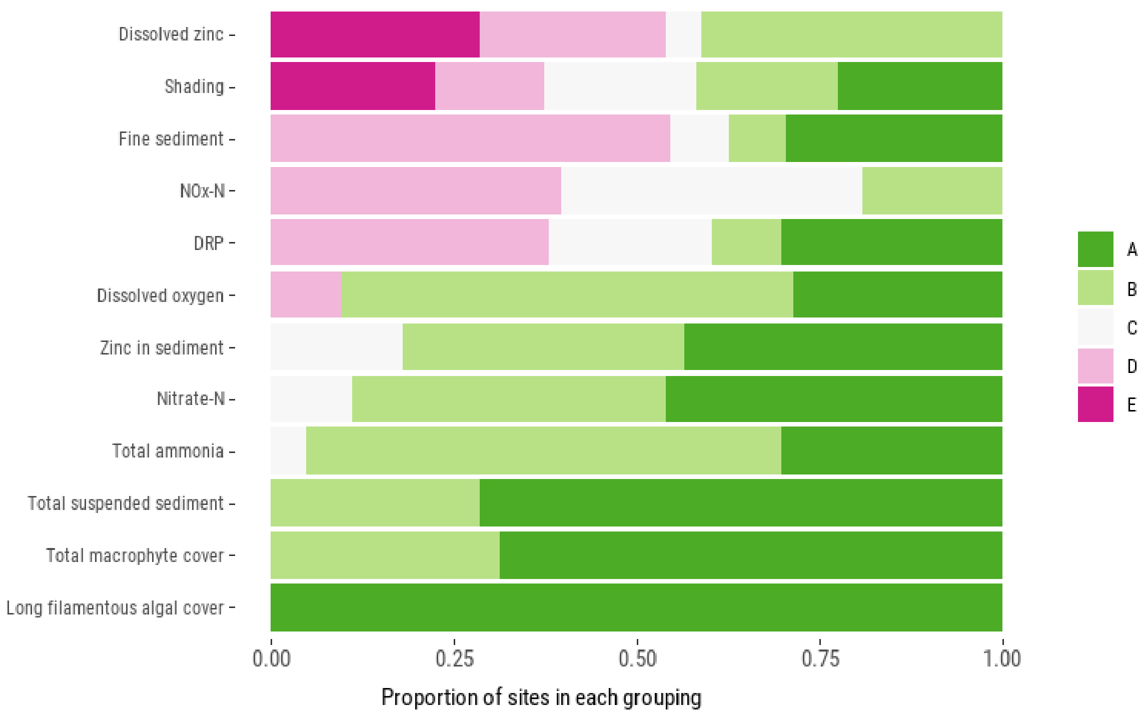

Figure 3-9: Comparison of various stressors (based on CCC monitoring data) to thresholds. Proportion of stream sites within different stressors bands based on a variety of thresholds related to ecological health (including toxicity and periphyton growth); class A indicates "high quality" - low contaminant concentrations, low levels of stressors whereas class E indicates "poor quality" – high contaminant concentrations and high levels of stressors. See Appendix B for details of the thresholds used and the statistics used for comparison.

Analysis of hydrological data indicates that some streams do demonstrate more "flashy" hydrographs than others – likely a response to the amount of imperviousness in the catchment and the size of the stream (Figure 3-10). This indicates that hydrology may be an important stressor in some streams (those with flashy hydrographs) but not others, and therefore ideal modelling methods would be able to account for site-specific differences in potential stressors, including hydrology.

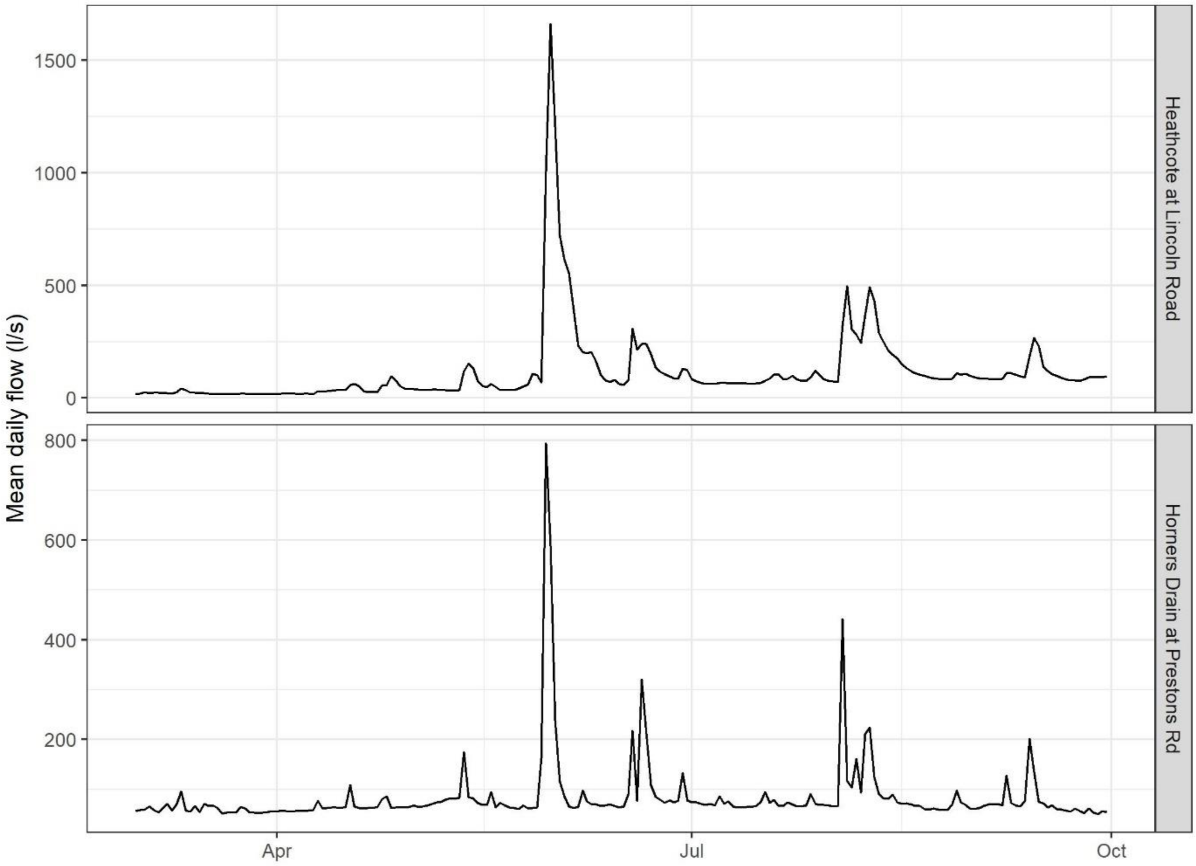

Figure 3-10: Hydrographs for Ōpāwaho/Heathcote River and Horners Drain, demonstrating increased "flashiness" at Horners Drain, associated with the higher proportion of impervious surface in the upstream catchment. Flow data from March to October 2021, mean daily flows plotted. Data obtained from Christchurch City Council.

Simple univariate relationships between the key stressors of suspended solids, dissolved copper and zinc, and deposited fine sediment, and three biological metrics (EPT taxa richness, QMCI and MCI) suggest that these stressors could indeed be influencing biological communities in Ōtautahi streams (Figure 3-11). Higher suspended solids and metals are associated with lower EPT taxa richness and lower MCI scores; and lower concentrations are associated with higher scores. This pattern is less pronounced for QMCI scores. Similarly, highest scores for all biological metrics were associated with low median dissolved zinc concentrations, and lower scores were associated with higher zinc (and copper) concentrations. On the other hand, there does not appear to be an association between deposited fine sediment and either EPT taxa, QMCI or MCI. Similar patterns are present when comparing the 95th percentile statistics for suspended solids, copper and zinc (not shown).

There are however some sites with low suspended solids and/or metal concentrations that have low EPT and/or MCI. This suggests other stressors influence the biological communities in these streams (see Figure 3-12). In such locations, reductions in contaminant loads and concentrations may have little effect. Furthermore, what is not clear from these univariate figures is whether there are other stressors that co-occur at the same locations which are in fact causing the observable reduction in biological diversity. Figure 3-13 demonstrates that some stressors are correlated, particularly for the water quality variables – sites where metals are high (compared to other sites) also tend to have higher ammonia and DRP concentrations and higher turbidity.

In addition, consistent differences in both biological metric and predictor values between catchments may reduce the chance of detecting statistically significant or meaningful relationships between stressors and metrics at larger scales. For example, the Puharakekenui/Styx and Otukaikino catchments, which are less impacted by urbanisation than other catchments, generally show the highest macroinvertebrate metrics scores, but are also associated with consistently lower concentrations of metals and suspended sediment than other catchments (Figure 3-11). The hydrological connection between sites with a catchment means sites within a catchment are likely to be more similar to each other than to sites in another catchment. To meet the assumption of independence between sampling sites that is required for many statistical models, a random term for catchment, that explains some of this variation, will be required. However, because several of the predictor variables (e.g., metals and suspended sediment) show little variation within some catchments (i.e., all sites in the Puharakekenui/Styx and Otukaikino catchments have low values) much of the relationship between stressors and metrics is likely to be explained by differences between catchments (the random term), potentially resulting in minimal remaining variation in response metrics explained by these stressors (i.e., lower ability to detect a significant fixed effect of the stressor on the metrics).

Statistical modelling techniques such as generalised linear models, GAMS or random forests (see section 4.5) could be used to create models that identify the predictor variables (potential stressors) with the highest 'importance' or strongest correlation with the biological response variables for Ōtautahi waterways. Such methods could identify whether any of the variables mitigated by stormwater management are 'highly important' predictors of any of the biological responses. These methods can also output graphs of the relationship between individual predictor variables and the response when all other predictors are held at a constant. These relationships can be linear, or non-linear with various levels of complexity. Correlations between potential stressors and appropriate random effects to meet model assumptions would need to be considered when interpreting the output of these models.

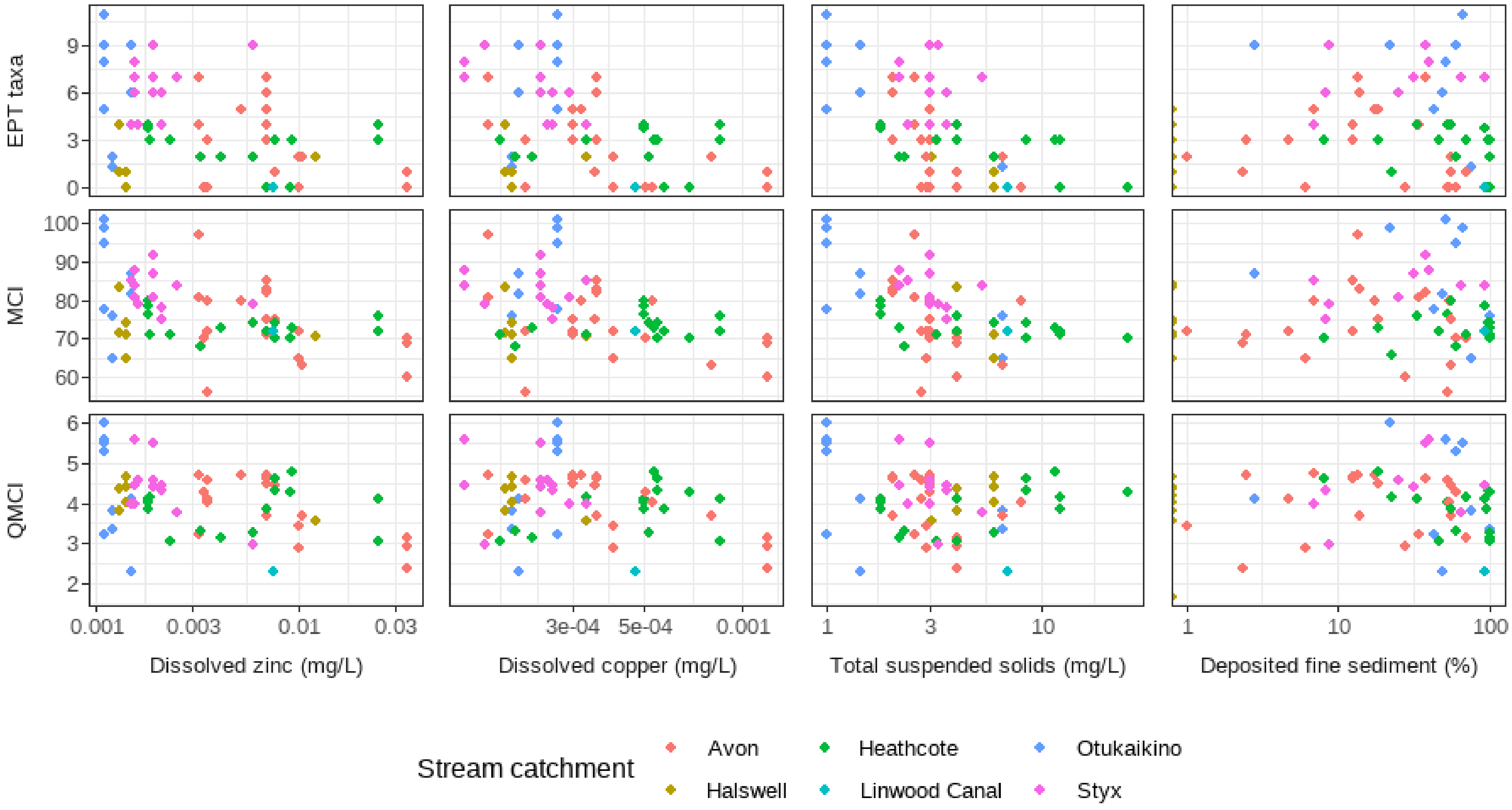

Figure 3-11: Relationship between median suspended solids, copper and zinc concentrations and biological metrics in Ōtautahi streams. Median concentrations from water quality data collected from 2017 to 2021. Deposited fine sediment and biological metric scores are from latest year of monitoring, which depends on the stream catchment.

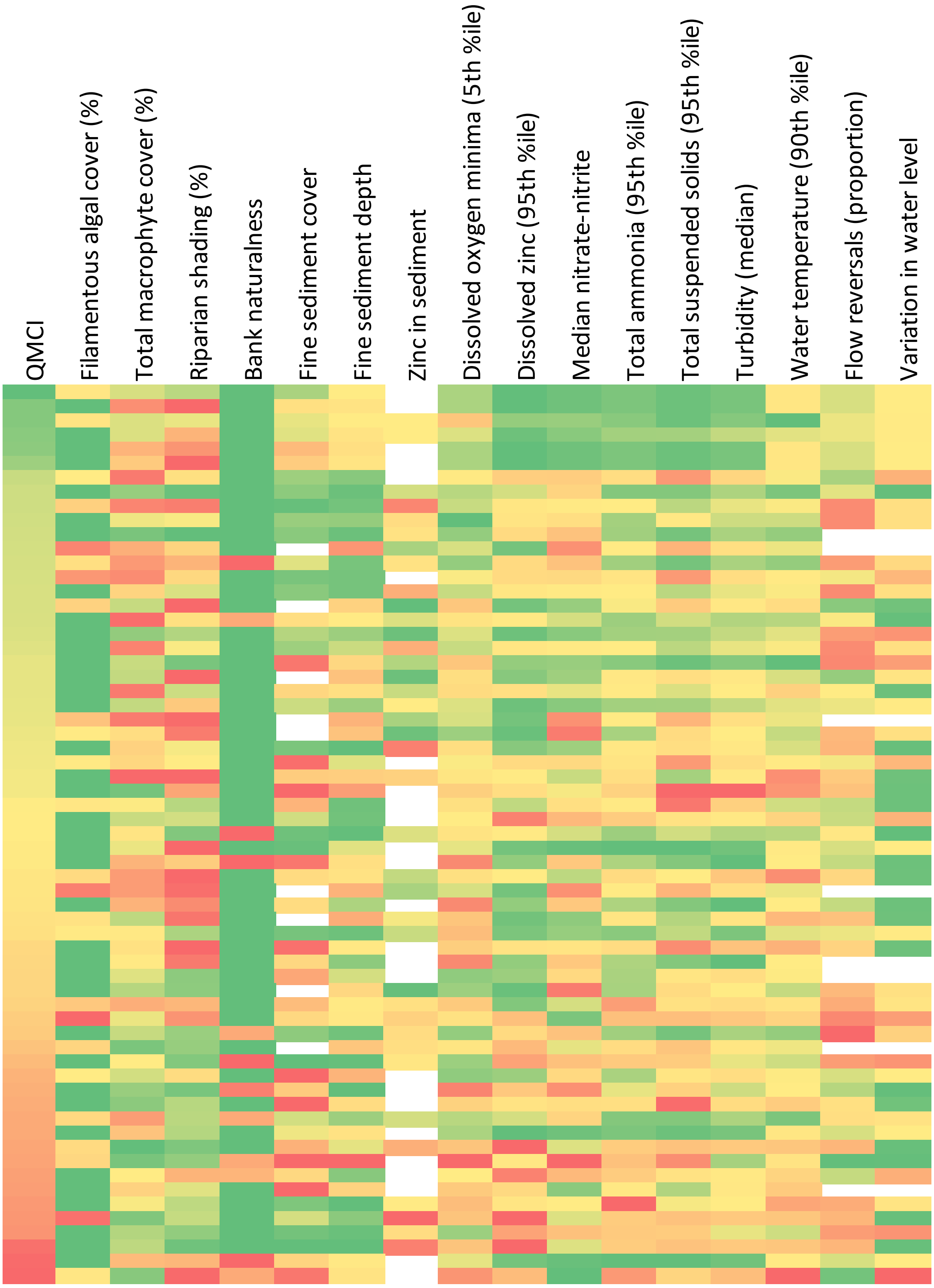

Figure 3-12: Heat map demonstrating stressor variation between sites (represented by rows) ordered by high to low QMCI (y axis). Different colours represent different percentile values for the data between sites. Dark green indicates the sites with the lowest percentile for that stressor, yellow represents the median and dark red the highest percentile for that site in the data set. Red values do not imply exceedance of thresholds for biological effects. Individual sites are rows.

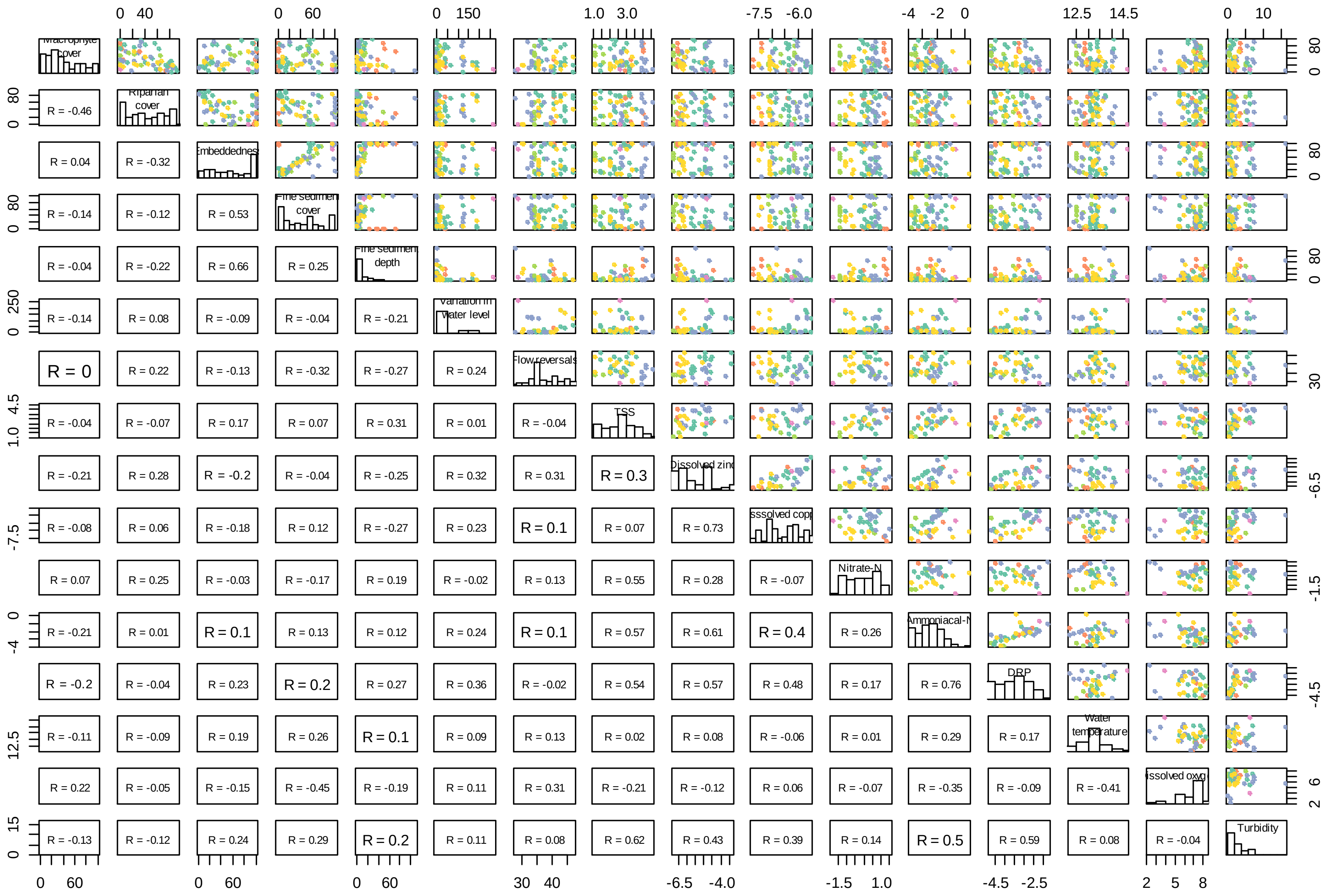

Figure 3-13: Scatterplot matrix indicating some correlations between stressors in Ōtautahi streams. Stressor variable names provided in diagonal boxes in centre, with histograms showing the spread of data. Upper right panel indicates correlations between each variable, points are coloured by stream catchment. Pearson correlation (R^2) values provided in lower left panel. Plot indicates correlations between stream embeddedness and fine sediment cover; dissolved zinc and dissolved copper; dissolved zinc and ammonical-N; ammoniacal-N and DRP. Water quality variables were log-transformed prior to inclusion.

3.3 Ihutai

3.3.1 Estuarine data

CCC and Environment Canterbury jointly monitor Ihutai under an agreement under the "Healthy Estuary & Rivers of the City" programme. This includes monitoring of water quality, sediment quality, macroalgal, macrofaunal and fish communities (Table 3-4). Sediment particle size and quality, macrofauna and macroalgae have been sampled annually (except sediment quality) at 4 to 5 estuary sites and 2 river mouth sites, though monitoring at the river sites ceased in 2021. Sediment quality was sampled at those sites approximately every 4-5 years and at 5 additional sites in at other times between 2010 and 2022.

There have also been many research studies in Ihutai, including student projects focussing on different aspects, such as microalgal communities (Malakhov 2019). A large research study focused on the effects of the wastewater diversion and the earthquakes (Barr et al. 2020, Zeldis et al. 2020), from which additional information on water/sediment quality and faunal communities is available.

The ecology of Ihutai, focussing on macroinvertebrate fauna, has been studied periodically since the 1960s, as described in several reports from the 1970s to 2000s (Knox 1992, Knox & Kilner 1973, Maclaren & Marsden 2005, Marsden 1998). There were also several studies (Deely 1991, Millhouse 1977, Robb 1988) that measured the sediment quality of the estuary, with samples collected at multiple locations around the estuary and analysed for copper, lead, zinc and other metals. These reports provide information on the macrofauna and contaminants that were present in the estuary prior to the regular monitoring that started in 2010, after the diversion of the wastewater discharge.

In terms of cultural monitoring, there have been two "State of the Takiwā" assessments that included Ihutai; one in 2007 (Pauling et al. 2007) and a follow-up in 2012 (Lang et al. 2012). This included monitoring at 5 sites around the estuary and its mouth. The scope included Takiwā site assessments which includes visual ranking assessments of site characteristics, access, pressures and suitability for harvesting mahinga kai; as well as quantitative measurements of vegetation, fish and birds.

Table 3-4: Monitoring that has been undertaken in Ihutai by CCC and Environment Canterbury (ECan).

Type	Number of sites	Frequency	Duration	Agency responsible	Comments
Water quality	10	Monthly	2007-to date	ECan	Monitoring at one site stopped in 2014
Sediment particle size (% mud)	4-6	Annually	2010- to date, plus some ad hoc prior	CCC	Some changes in sites over monitoring period
Sediment quality (copper, lead, zinc, other metals, PAHs)	6 4-6	3-5 yearly 3-5 yearly	2007-to date 2010- to date	CCC ECan	Some changes in sites over monitoring period. Sites and methods the same between surveys

Type	Number of sites	Frequency	Duration	Agency responsible	Comments
Macrofaunal communities (epifauna + infauna)	4-6	Annually	2010- to date	CCC	Some changes in sites over monitoring period
Macroalgae and seagrass cover	4-6	Annually	2010- to date	CCC	Some changes in sites over monitoring period
Broadscale mapping of macroalgae and seagrass	Whole of estuary	Approx. five-yearly	2001-ongoing	ECan	Slight changes in sites and methods post-2015
Fish surveys	12-13	Semi-annually	2005-2007, 2010-2011, 2013, 2015	CCC	Sites and methods generally the same between surveys
Cultural monitoring, including visual/cultural assessments and fish / mahinga kai surveys	5	Twice	2007, 2012	CCC	Sites and methods the same between surveys

Figure 3-14: Location of water quality, sediment quality and biota monitoring sites in Ihutai Estuary.

Figure 3-15: Maps of macroalgal cover in Ihutai. Image from Bolton-Ritchie et al. (2018).

The temporal and spatial resolution of the regular monitoring undertaken by CCC and ECan (summarised in Table 3-4) is not likely to be high enough to develop any statistical models for Ihutai. There may however, be sufficient data to use existing models (reviewed in section 4.3), depending on those model requirements. The available data include the factors that are expected to be most important in influencing macrofauna (water quality, sediment quality, macroalgae). Importantly, all variables have been collected at the same or very nearby locations, and in many cases at the same time (e.g., sediment quality data collected at the same time as macrofauna data). This should reduce uncertainty in using the data for predictions. Furthermore, the data collected between 1960s and 2000 may also be useful in evaluating the model's accuracy of predictions with different input data.

3.3.2 What are the key stressors in Ihutai?

Ihutai/Avon-Heathcote Estuary has historically been affected by the discharge from the Ōtautahi wastewater treatment plant, which delivered excess nutrients to the estuary. This resulted in blooms of nuisance macroalgal species including sea lettuce (*Ulva* sp.) and red seaweed (*Agarophyton chilense*[5]) and abundant benthic microalgal films (Zeldis et al. 2020). This growth both displaced the existing sea grass (*Zostera muelleri*) and affected the macrofaunal communities with reduced diversity at sites most affected by the discharge and eutrophication (Barr et al. 2012, Bolton-Ritchie & Main 2005, Zeldis et al. 2011).

Nutrients delivered to Ihutai have decreased substantially since the diversion of Ōtautahi's wastewater treatment plant discharge, although areas with high macroalgal growth remain (Bolton-Ritchie 2020). This is thought to be attributable to continued nutrient inputs to the estuary (potentially via the Ōtākaro/Avon and Ōpāwaho/Heathcote Rivers) and/or changes in water temperature (Bolton-Ritchie 2020, Tait et al. 2020) as higher summer temperatures increase growth, whilst higher winter temperatures decrease the seasonal die-off (Tait et al. 2020). Trophic indicators including organic carbon and nitrogen in sediment, indicate enrichment at all sites, particularly the Ōtākaro/Avon River mouth, and increasing enrichment at Plover Street and Pleasant Point. Water column chlorophyll *a*, benthic chlorophyll *a* and macroalgal growth at various sites also indicate the enriched state of the estuary (Berthelsen et al. 2022).

Metal concentrations in the sediments are low relative to other urbanised estuaries around New Zealand (Stats NZ 2019), and are consistently below sediment quality guidelines for effects on macrofauna (ANZG 2018). There is however variation around the estuary, with higher concentrations of lead and zinc typically higher close to the river mouths (Bolton-Ritchie 2015b, Robb 1988). At these sites, concentrations periodically exceed more conservative guidelines ((Hewitt et al. 2009, ARC 2004) based on changes in benthic community structure (Figure 3-16).

Most sites in Ihutai are muddy: the sediments have a high proportion of grains <63 µm in size. This is particularly true around the Ōtākaro/Avon and Ōpāwaho/Heathcote River mouths. The proportion of mud in sediment has also increased over time at the Pleasant Point Jetty and Plover Street sites (Berthelsen et al. 2022) and is now around 25% at both sites. High mud content at many sites is reflected in those infauna communities, characterised by mud tolerant species and mud BHM scores of moderate to very high impact (Berthelsen et al. 2022).

A key challenge will be to assess the ecological effects of reductions in fine sediment and metals, amongst the other key stressors of nutrients and eutrophication. The data currently available does not provide strong evidence for relationships between mud, copper or zinc content in the sediments and biological indices such as the number of taxa (Figure 3-17). There is considerable variation in the number of taxa at low metal concentrations and mud content, and there are few data for this analysis. Inclusion of data from previous years of monitoring may provide additional evidence for relationships.

[5] Previously referred to as *Gracilaria* sp.

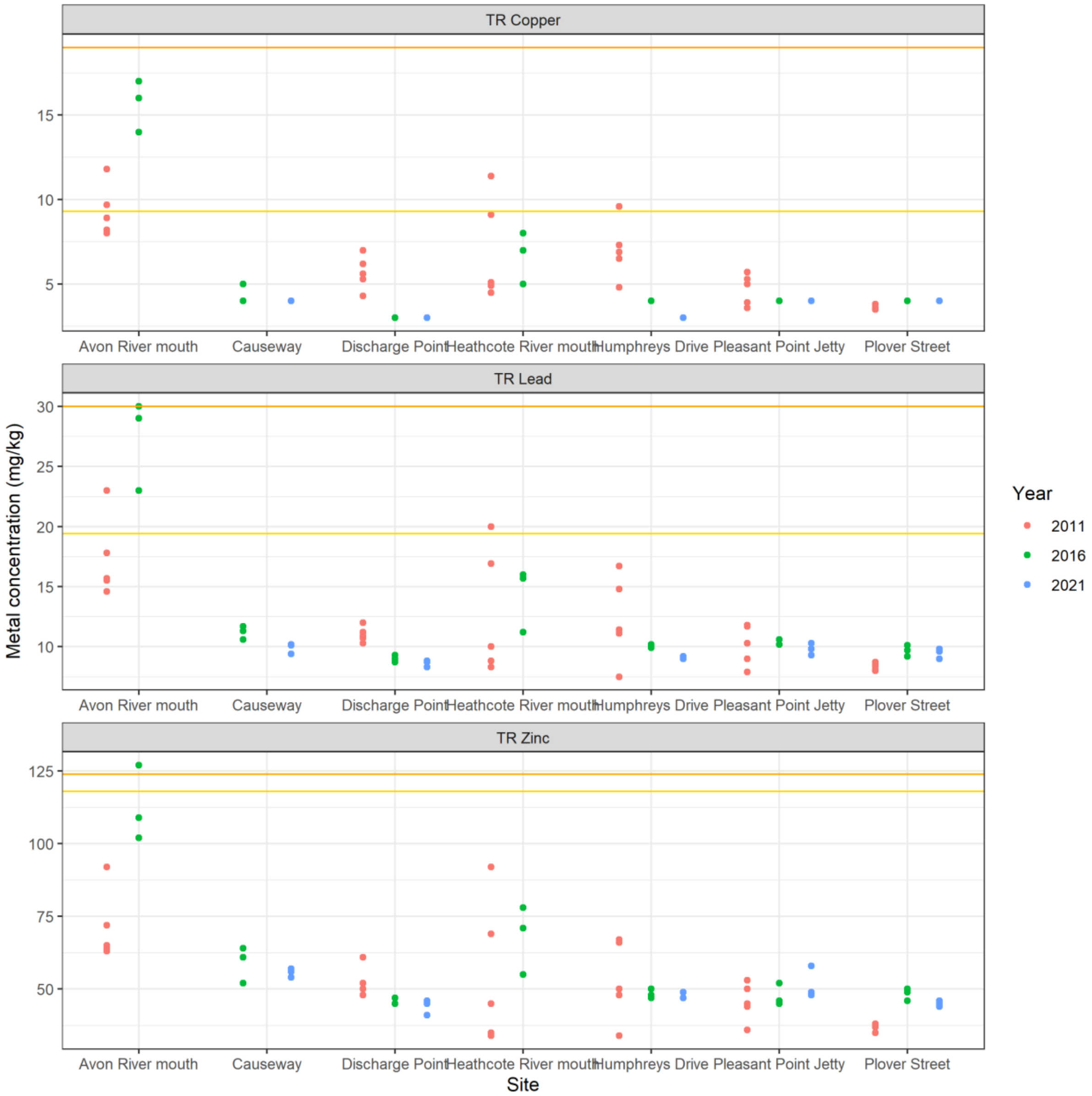

Figure 3-16: Comparison of copper, lead and zinc concentrations in sediments to thresholds derived by Hewitt et al. (2009) (fECs, shown in yellow) and ARC (2004) (ERC-green, shown in orange). Metal concentration data from ECan.

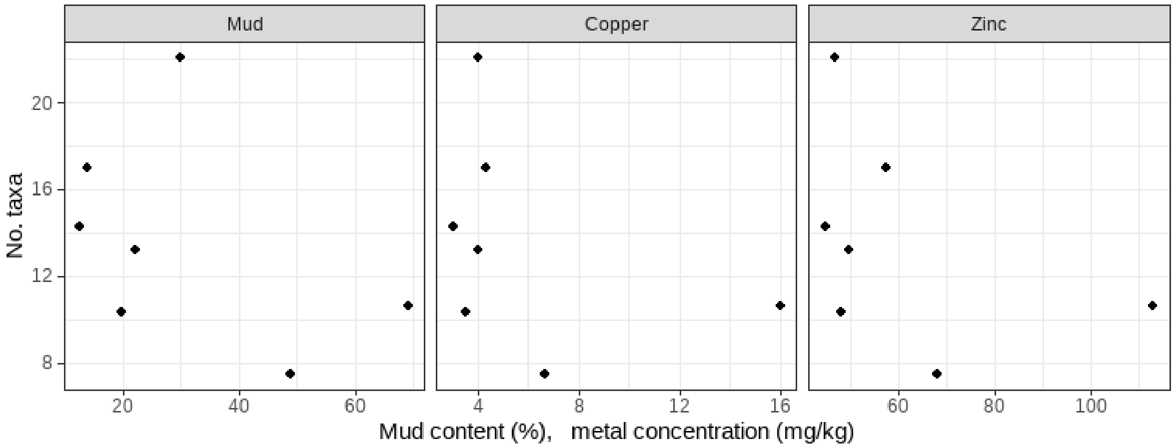

Figure 3-17: Relationship between the number of benthic macrofaunal taxa per core and mud content / metal concentrations in sediment in Ihutai. Median values are from faunal and mud data collected from 2016 to 2021; metal concentrations median data from 2016 & 2021 only. Cores are 130 mm diameter by 150 mm deep.

4 Ecological response modelling

4.1 Introduction

The term 'model' can apply to many methods that assist in understanding how changes in environmental factors (including stressors) result in, or are associated with, changes in water quality and biological communities. This includes conceptual models, statistical correlative models and mechanistic, process-based models. A conceptual model indicates the expected relationships between stressors and ecological effects. For example, Walsh et al. (2005) provides a conceptual model of the mechanisms of change in freshwater ecosystems due to urbanisation. Statistical models use data to derive correlative relationships between explanatory and response factors and can provide an understanding of the strength of those relationships. However, they are generally not capable of distinguishing between indirect and direct effects (though structured equation models, SEMs, can do this to some extent). Statistical models can only be applied with confidence within the range of data used to develop the models, while mechanistic models can be used to predict outside of the range of observations. Mechanistic models draw on ecological theory and prior knowledge of species (i.e., traits) to parameterize mathematical equations describing known ecological processes, such as growth, respiration, and mortality. They use mathematical relationships and specific parameters to describe the system and are generally capable of distinguishing amongst these effects, depending on how they are parameterised.

Table 4-1: Categories of mathematical models. Adapted from Munson (2004).

Type	Mechanistic	Mathematical descriptions based on theory
	Empirical	Based on data analysis
Time Factor	Dynamic	Describe or predict system behaviour over time
	Static or steady-state	Time-independent
Treatment of Data Uncertainty and Variability	Stochastic	Include variability/uncertainty
	Deterministic	Do not address data variability

This section outlines a variety of modelling approaches that have been used in New Zealand or internationally to model the effects of various stressors on biological communities. This includes existing models (which we term here "off-the-shelf" models) that have been specifically developed for urban water bodies, specifically developed for estuarine systems in New Zealand, or more generic methods that can be used to develop a model (or models) specifically for Ōtautahi.

For each of the models reviewed, we include a brief summary of the model, the types of data needed to run or develop that model and the sorts of processes that can be included, and relevance to Christchurch stormwater and waterway management.

4.2 Modelling receiving environment metal concentrations

Predicting the ecological responses in Ōtautahi's streams and estuary requires an understanding (or prediction) of how the receiving environment metal concentrations will change with a change in the contaminant loads (copper, zinc, sediment) delivered via stormwater.

There are a large number of models available to do this within freshwater – the review of these is outside the scope of this project and included in a different CCC project. We have however included here some brief discussion of methods to address this issue within the estuarine receiving environment.

4.2.1 Estuarine bed sediments

There are a number of hydrodynamic and sediment transport models that predict the accumulation in estuaries of sediments and metals delivered from the land. These include Delft3D, DHI-models and ROMS[6]: all of which are computationally intensive to set up and run. NIWA has already implemented a Delft3D model of Ihutai to understand salinity and nutrient mixing in the estuary (Measures & Bind 2013), however this model does not currently include sediment transport or deposition. Extending the model would take considerable effort and likely also require field studies (for example to understand wave-driven resuspension).

An alternative could be the Urban Stormwater Contaminants (USC) model which was originally devised as a spreadsheet model (Green 2008). This model takes the predicted loads of sediment and metals and calculates the rate of deposition in an estuary. The USC-3 version of this model simulates these predictions on the daily or event- basis, however the model has been upscaled to an annual model (USC-4), which runs significantly faster (Moores et al. 2012). This model would be of an appropriate scale for connecting to an ecological health model as described in section 4.4 – a more sophisticated model is unnecessary given the ecological health models are designed for understanding direction and scale of changes in ecosystems, rather than exact predictions. The inputs required for the USC-4 include the current bed sediment metal concentrations and mud content, the depth of the mixing layer, the diameter of particles sized < and > 63 µm, the area of the estuary and the proportion over which sediment deposition occurs. Some of these inputs can be obtained through measurements in the field, through previous models that have been used in Ihutai, or through expert judgement.

4.3 "Off-the-shelf" models for freshwater

4.3.1 UPSW DSS Bayesian Network

NIWA's Urban Planning to Sustain Waterbodies research programme (UPSW) developed a decision support system (DSS) to aid in understanding the potential effects of different forms of urban development (traditional / business as usual versus water sensitive urban design) and different types of mitigation (stormwater treatment, riparian planting) on stream (and estuary) health, as measured through indicators of water quality, hydrology, riparian quality, habitat quality, aquatic plants, macroinvertebrate communities and fish. In this decision support system, the model is run multiple times with changing inputs to provide a timeline of predictions, typically every 5 to 10 years.

The freshwater indicator scores are derived through a series of Bayesian Networks (also known as Bayesian Belief Networks, or Belief Networks) which provide a framework for graphically

[6] https://www.myroms.org/

representing causal relationships between variables and for quantifying the strength of these relationships using conditional probabilities. In these networks (e.g., Figure 4-1), the conditional probabilities were derived from a mixture of existing empirical relationships where available, and expert judgement where data were not available.

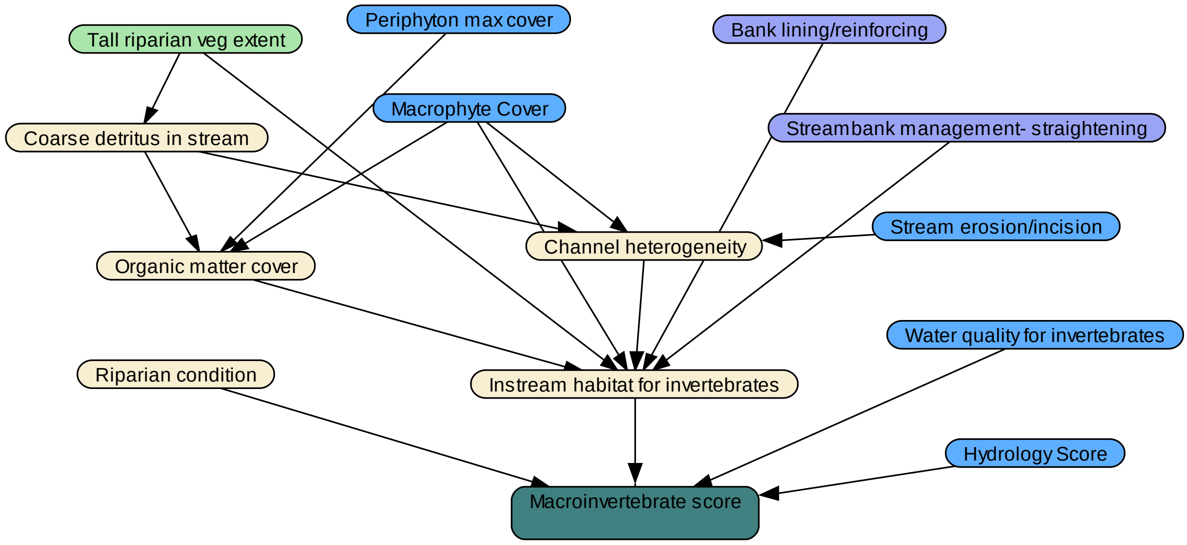

Figure 4-1: Bayesian network model for macroinvertebrates used within the UPSW DSS. Purple nodes are inputs from existing data; green nodes are defined by model users; and blue nodes are calculated within other BNs within the DSS. Figure from Gadd and Storey (2012).

The response variable is a "macroinvertebrate community score" which takes 5 discrete states (from low to high) based on the four parent nodes of riparian condition, in-stream habitat, hydrology and water quality. These parent nodes are combined according to a "limiting factor" approach – that is, a poor score in any one variable will result in a poor macroinvertebrate score. One clear limitation of this model is its minimal validation, particularly within Canterbury. The relationships between different nodes may need to be updated, based on relationships specific to Ōtautahi streams. Further as the model was developed around 10 years ago, it may need to be updated based on new information and knowledge around the effects of stressors on macroinvertebrates, given the recent work undertaken in NZ (e.g., Franklin et al. 2019, Wagenhoff et al. 2017). Although there is no obvious way to relate the "macroinvertebrate score" to an MCI or QMCI score or EPT index, it does provide both a qualitative rating (e.g., low, medium, high) and a quantitative measure that can be used to rank sites. As the model does include metals, habitat stressors and predicts macroinvertebrates, there is potential for use as is, or in an adapted form, for CCC.

4.3.2 Aquatox

AQUATOX[7] is an ecosystem model that includes aquatic plants, macroinvertebrates and fish. It is a mechanistic (process-based) model that simulates contaminant fate and transport and ecological effects in aquatic ecosystems (steams, ponds, lakes, estuaries, and experimental enclosures). As a mechanistic model, it has the potential to establish causal links between chemical water quality and biological response and aquatic life uses. Although the model includes both lethal and sublethal toxicity, this is limited to organic toxicants and ammonia – the model does not include metals. The model does enable the evaluation of multiple stressor scenarios, including nutrient and organic

[7] https://www.epa.gov/ceam/aquatox

matter loads, flow regime, herbicides, suspended sediments and light. However, it does not include habitat-related factors that may also be limiting biological communities within urban streams.

4.3.3 WHATIF

WHATIF (Watershed Health Assessment Tools Investigating Fisheries[8]) is a tool to assess the health of watersheds and streams, with an emphasis on fish communities in the Mid-Atlantic Highland region of the United States. It includes hydrologic and stream geometry calculators, fish assemblage predictors, a fish habitat suitability calculator, macroinvertebrate biodiversity calculators (including EPT taxa) and models to predict stream biomass. The model is designed to examine causes of impairment (e.g., poor fish communities) and predict ecological outcomes of habitat alteration and fisheries management actions. This suggests some suitability for the needs of CCC specifically around the prediction of habitat alteration on macroinvertebrates and fish; however again, this model does not include metals. Furthermore, having been developed for the US, the relationships between habitat variables and macroinvertebrate indices (i.e., EPT index), which are based on multiple logistic regression models, may need to be refined for New Zealand and/or Ōtautahi conditions.

4.3.4 WASP

WASP (Water Quality Analysis Simulation Program[9]) is a mechanistic water quality model developed by the US EPA for aquatic systems, including both the water column and the underlying benthos. It is a continuous simulation model, predicting water quality through time under different conditions, which means it can provide an indication of how long it would take a waterbody to respond to a change in management conditions and it can indicate duration and frequency of water quality conditions including guideline exceedance. Metals are included in the model, but this is limited to metal fate – distribution of the metals between the water column and benthic sediment. Furthermore, although this model includes predictions of effects of nutrients on periphyton, phytoplankton and macroalgae, it does not include macroinvertebrates. These issues make the model unsuitable for the CCC modelling task.

4.3.5 Streambugs

Streambugs[10] is a mechanistic food web model developed by researchers at Eawag (Swiss Federal Institute of Aquatic Science and Technology, Schuwirth and Reichert 2013). It uses differential equations to describe the growth, respiration, and mortality of macroinvertebrates based on environmental conditions and species' traits (Paillex et al. 2017). Although the model does refer to the presence of contaminants, it does not include metals explicitly. Furthermore, as it was developed overseas, and for overseas macroinvertebrate species, it would need to be tested and parameters updated with New Zealand species-specific information (when available). Based on the effort required to do the latter, and that the model scope excludes metals, we do not consider this approach useful for the CCC task.

4.3.6 Summary of existing models

Each of the models reviewed are based on mechanistic understanding of the effects of water quality on organisms (Table 4-2). However, only the UPSW BN and WASP models include metals as a water

[8] https://www.epa.gov/ceam/whatif-watershed-health-assessment-tools-investigating-fisheries
[9] https://www.epa.gov/ceam/water-quality-analysis-simulation-program-wasp
[10] https://www.eawag.ch/en/department/siam/projects/streambugs/

quality stressor. Of these, the WASP model does not simulate effects on macroinvertebrates. This suggests the only useful option for CCC’s purposes is the UPSW BN model.

Table 4-2: Summary of the existing models that could be used to model impacts of metal and sediment concentrations in Ōtautahi streams.

Factors	UPSW BBN	Aquatox	WHATIF	WASP	Streambugs
Scope (e.g., whether such methods are suited to including all the factors of importance).					
Toxicity due to metals	Yes	No	Not explicitly	Yes	No
Habitat factors	Yes	No	Yes	No	Yes
Macroinvertebrates	Yes	Yes	Yes	No	Yes
Fish	Yes	Yes	Yes	No	No
Applicable to NZ conditions	Yes	No	No, EPT taxa data would need to be refined for NZ	No	No, would need parameterising for NZ taxa
Spatial and temporal resolution					
Temporal	Predicts at a single point in time	No	No	Yes, continuous simulation, can consider lags	No
Spatial scale	Stream/sub-catchment level predictions	River segment, may be linked	Site, but currently set up only for regions of the US	Stream reach / site	Site
Information required to run					
Inputs	Requires information on habitat and water quality variables, flow metrics, riparian data. Information on stressors can be derived from monitoring datasets and/or from expert opinion.	Sediment, nutrient and organic loads, inflows, temperature, biomass estimates	Data on stream substrate, catchment area, slope, road and population density	Primarily related to nutrient concentrations	Environmental conditions including current regime, water temperature, light intensity, leaf litter, presence of pollution
Ease of use and understanding					

Factors	UPSW BBN	Aquatox	WHATIF	WASP	Streambugs
Outputs	Provides scores for indicators (not a continuous variable)	% EPT, primary production measures, trophic state indices	Quantitative measure of EPT taxa	Macroalgal density	Food webs and probabilities of taxa presence
Availability	NIWA-IP, available through research scientists	Freely available via US EPA	Freely available via US EPA	Freely available via US EPA	Freely available as an R package via CRAN

4.4 "Off-the-shelf" models for estuaries

Three modelling approaches that may be of use in the Ihutai context are reviewed in this section. These models have all been developed based on data and information from New Zealand estuaries and have been validated against multiple estuaries throughout the country. This means they have potential to be applied to Ihutai without further development. Each modelling approach has different data requirements and modelling applications/strengths which are described below and summarised in Table 4-3.

4.4.1 Estuarine Bayesian Network (BN)

Background

The estuarine BN was developed by NIWA for the Parliamentary Commissioner to the Environment to inform multiple stressor management in Aotearoa (Bulmer et al. 2022a, Bulmer et al. 2019). The BN model illustrates how four common stressors impact estuarine health and function (Figure 4-2). The model reflects expert opinion using a probabilistic framework, which enables uncertainty and complexity to be accounted for in model outputs and management decisions. The model illustrates that the impact of one stressor is conditional on the state of other stressors; demonstrates non-linear responses of ecosystem components to stress; and illustrates how the baseline conditions of an estuary determine responses to further stress.

Bayesian Network models are useful as they can integrate a combination of empirical data and expert derived information that have been collected for multiple purposes, bridging the gap between quantitative and qualitative knowledge systems and facilitating their use in areas where underpinning data may be lacking (Gladstone-Gallagher et al. 2019). This type of expert driven probabilistic approach has significant advantages for informing management decisions in complex systems where there is incomplete knowledge or information. For example, multiple stressors have the capacity to cause sudden, unexpected non-linear shifts, or tipping points, in ecosystem function (Côté et al. 2016, Gunderson et al. 2016, Hewitt et al. 2016, Thrush et al. 2014). By applying the estuarine BN to explore these impacts, multiple potential conditional outcomes are displayed and considered. This differs from many other modelling approaches where a single likely outcome ± error is produced (such as many regression-based models). By considering relationships between stressors and ecology/function using a probabilistic framework across multiple potential outcomes, environmental managers may be better equipped to understand and conceptualise the likelihood of both ideal and less than ideal outcomes for a given management scenario of interest and to better account for the inherent variability within estuarine ecosystems (Gladstone-Gallagher et al. 2019).

Methodology

Further details of the methodology are discussed in Bulmer et al. (2022a) and Bulmer et al. (2019). In brief, model structure and parameterization was informed by expert opinion following best practice (Marcot et al. 2006). The final model consisted of 21 nodes (ecosystem components) with 51 relationships between nodes (Figure 4-3). By providing information on the four key stressor nodes (suspended sediment, mud content, nitrogen, metals) which are commonly measured in council monitoring programs, the cascading impacts on the ecology and ecosystem function can be explored. Each node (e.g., abundance of large suspension feeding bivalves) was defined and given five potential output states ranging from very low to very high, with numerical thresholds for each state. Continuous variables were discretized into states based on a literature review, expert opinion and by analysis of empirical datasets. Datasets used to inform state ranges included a dataset from a

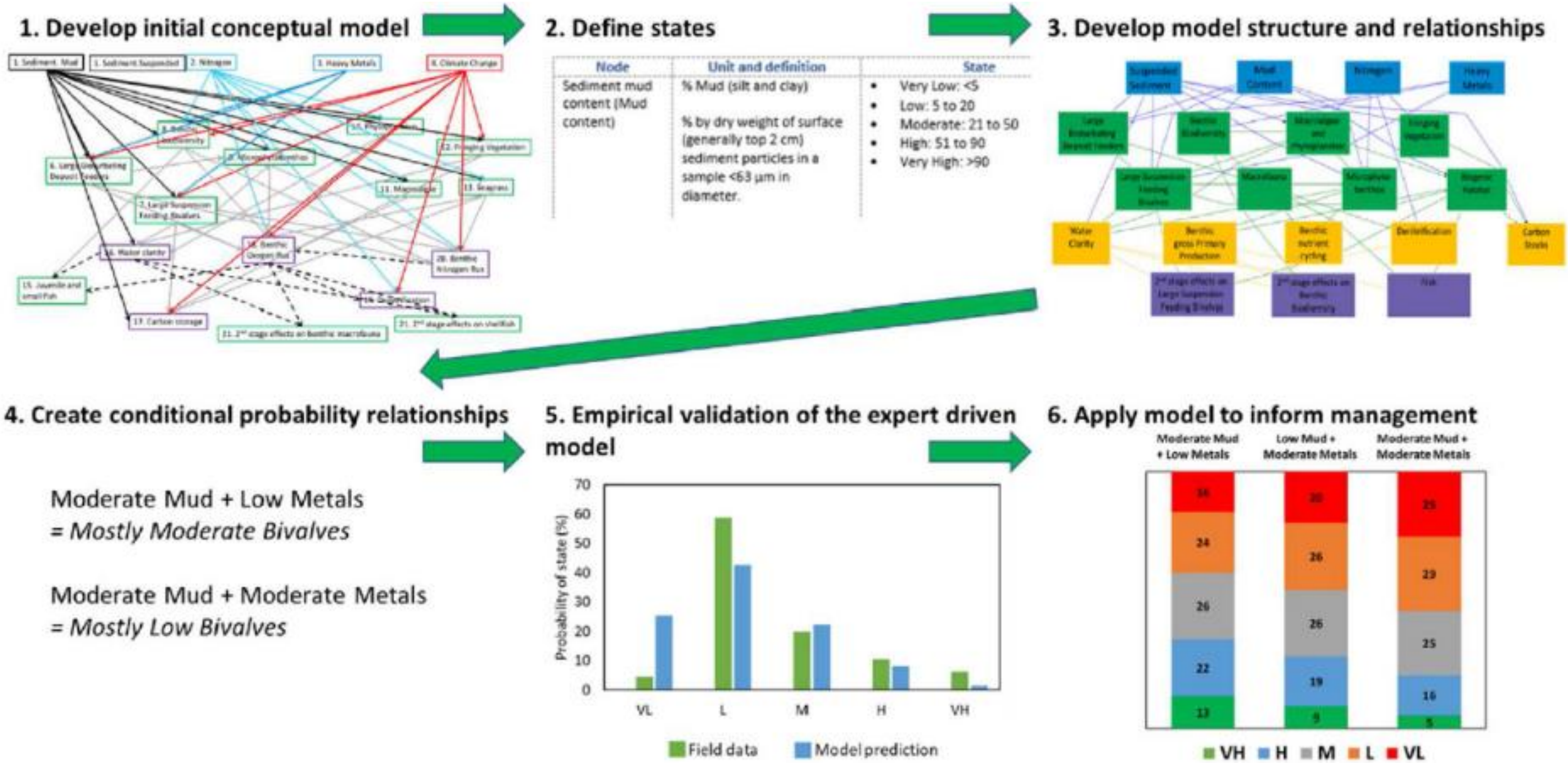

Figure 4-2: Summary figure of the key steps taken to design and apply the expert driven estuarine ecosystem Bayesian Network model to inform management. VL = Very, Low, L = Low, M = Moderate, H = High, VH = Very High. Figure from Bulmer et al. (2022a).

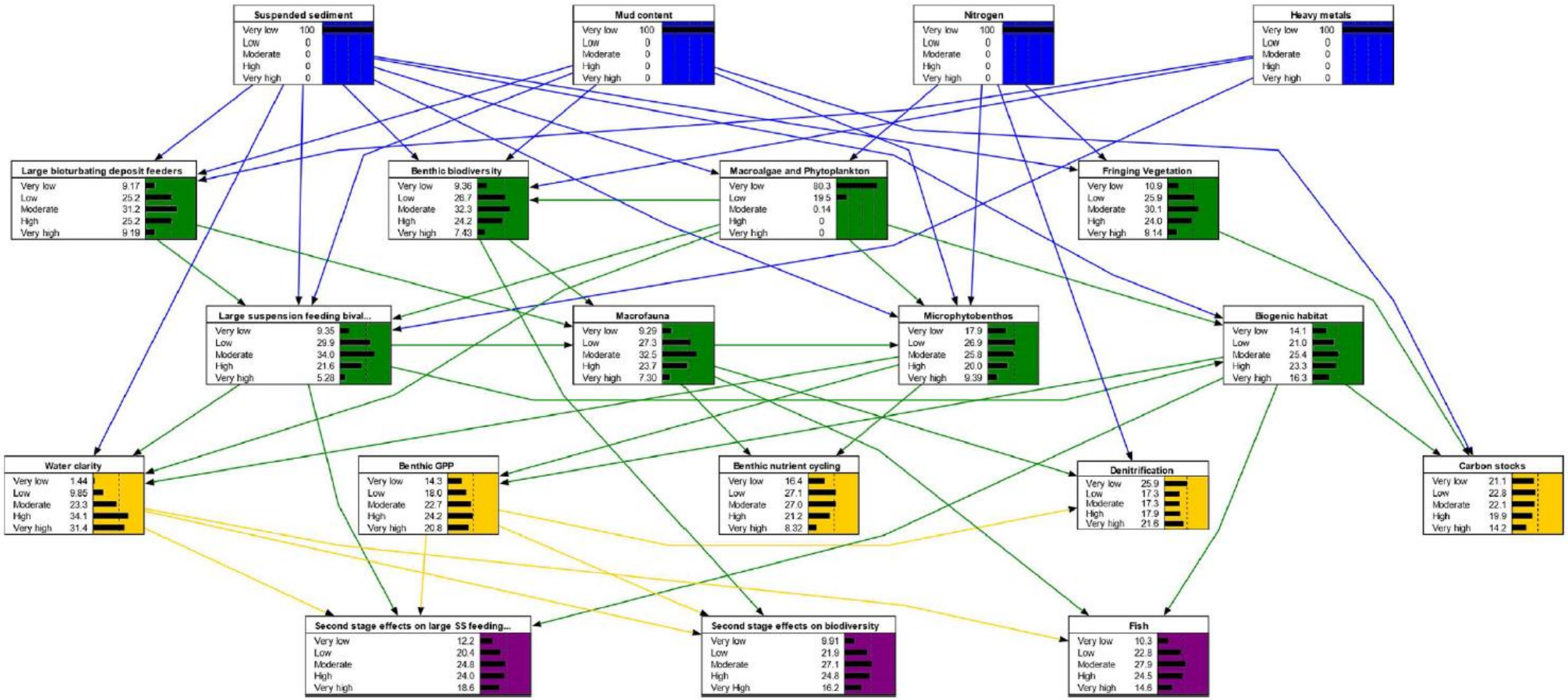

Figure 4-3: The Estuarine BN model showing conditional outcomes with Very Low stressor levels. Stressor nodes are blue, Ecological nodes green and key Ecosystem function nodes yellow. Second stage macrofaunal and fish nodes are purple and are used to examine feedback effects on these important ecosystem components. All nodes collectively can be used to infer estuarine condition. Figure from Bulmer et al. (2022a).

large national estuarine experiment on multiple stressors (Tipping Points; (Thrush et al. 2021)), and publicly available data (Berthelsen et al. 2018, Hewitt et al. 2009, Pratt et al. 2014b, Thrush et al. 2003b). If empirical data were not readily available to inform nodes, then the state ranges were based on literature review and expert opinion.

Validation

Overall trends in the model were well reflected by field observations (71 to 84% concordance), providing overall confidence in the model outputs (Bulmer et al. 2022a). Field observation data were collected as part of a national experiment (14 estuaries throughout New Zealand) (Thrush et al. 2021), and the Auckland Council east coast monitoring program (8 estuaries (Hewitt & McCartain 2017)). The 22 estuaries spanned a latitudinal gradient of 10◦ and could be broadly categorised as shallow, intertidally dominated estuaries. Experimental data were not available for every node, however this combined dataset included a total of 660 samples, with data for some or all of the following nodes (or proxies): sediment Mud, Nitrogen and Metal contents; densities of Large Bioturbating Deposit Feeders and Large Suspension Feeding Bivalves; sediment Chlorophyll a content as a representation of microphytobenthos standing stock; photosynthetically active radiation on the seafloor as a representation of Water clarity; Benthic gross primary production, Denitrification rates, Benthic nutrient cycling, Number of benthic taxa; and Carbon stocks.

Example application

The model has been used to inform management scenarios of interest for the Hawke's Bay Regional Council, including modelling a potential reduction in stressor loadings to two estuaries due to catchment management initiatives (Bulmer et al. 2022a). Results indicated that reductions in suspended sediment loading were likely to result in ecological improvements, which would be further improved by reductions in sediment mud and metal content. Notably, reductions in suspended sediment were also associated with an increased probability of high nuisance macroalgae and phytoplankton if nutrient loading was not also reduced (associated with increased water column light penetration).

4.4.2 Benthic Health Model (BHM) and Traits Based Index (TBI)

Background

A variety of benthic health models have been created which establish relationships between key environmental stressors and macrofaunal composition to aid management decisions (Berthelsen et al. 2020). Here we discuss two of these approaches, which have performed well in the New Zealand context (Clark et al. 2020, Hewitt et al. 2005, Rodil et al. 2013).

The Benthic Health Model (BHM) is a multivariate analysis of benthic macrofaunal community composition used to assess relative estuarine health, based on sediment heavy metal concentrations (BHMetal) or mud content (BHMud).

The models focus on benthic macrofaunal communities as an indicator of estuarine health. The rationale being that macrofaunal communities respond relatively rapidly to stressors, integrate the impact of multiple stressors over time, and are composed of a variety of species with different function roles, trophic levels and sensitivities (Hewitt et al. 2005).

The approach was initially developed to assist estuarine management within the Auckland Region (Hewitt et al. 2005) but has more recently been expanded and validated using a national dataset (Clark et al. 2020).

The Traits Based Index (TBI) is a functional traits based index that relates the concentration of sediment metals and mud content to the richness of macrofaunal taxa in seven different functional trait groups. Declines in TBI scores with increases in mud and heavy metals are interpreted as losses of functional redundancy. Higher TBI scores therefore infer higher functional redundancy, or resilience to stress. Unlike the BHM, the TBI provides more information on whether functional redundancy is changing and whether specific functional traits are being affected. The TBI can therefore complement the BHM scores, and vice versa (Rodil et al. 2013).

Methodology

BHM

Community data were used in separate canonical analyses of principal coordinates to create multivariate models of community responses to gradients in mud content and heavy metal contamination (Figure 4-4). Data used to inform the model relationships were obtained from regional estuarine monitoring programmes between 2002 and 2017. This dataset included 192 sites, from 34 estuaries, and spanned 12 degrees of latitude and encompassed two dominant estuary types and a range of bioregions.

TBI

The index is based on seven particular biological traits, representing broad categories relevant to ecosystem function. The index is calculated based on scores from seven functional group categories, with values near 0 indicating highly degraded sites and values near 1 indicating the opposite.

Validation

Both BHMud and BHMetal models performed well when compared to validation datasets (R^2 = 0.81, 0.71, respectively), and were unaffected by regional and estuarine typology differences (Clark et al. 2020). The dataset used to inform (and validate against) the national BHM models included monitoring data from Ihutai, however it would also be possible to validate the model against data from the Ihutai alone. This has previously been done for an earlier iteration of the BHModel, which showed variable model fits between sampling locations.

The TBI was validated against sampling data from over 100 sites in east and west coast estuaries around Auckland, with an R^2 of approximately 0.2-0.35 between observed and predicted values (Rodil et al. 2013).

Example application

BHM and TBI scores have previously been calculated for Ihutai to assess changes in macrofaunal community composition and functional resilience through time (Bolton-Ritchie 2015a). Many of the sampling sites showed increases in mud content from 2008 to 2013, associated with a decline in BHM mud scores and associated ecological health through time. TBI scores were more variable, with increases observed at some sites despite increases in mud content, suggesting that differences in scores may have been driven by factors other than changes in mud and heavy metals at these locations.

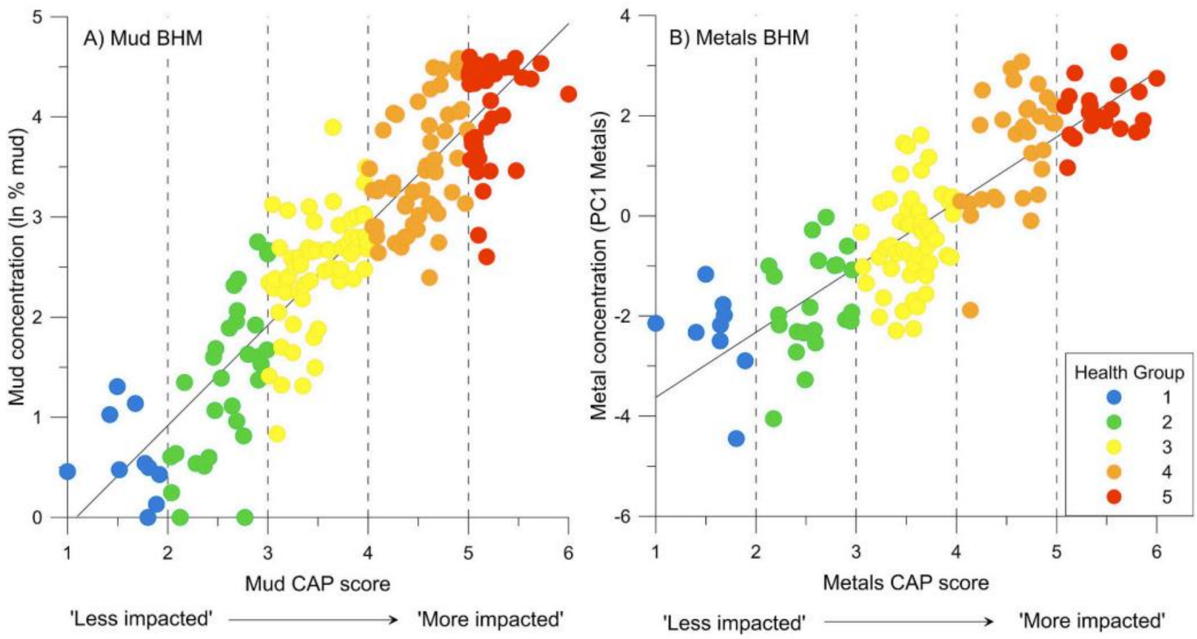

Figure 4-4: Benthic Health Models (BHMs) developed using canonical analysis of principal coordinates (CAP) constrained by either A) mud (ln % mud) or B) metals (first axis of principal component analysis based on log transformed copper, lead and zinc). Figure from Clark et al. (2020). Grey dashed lines and symbol colours demarcate the ecological health categories for each model. A linear regression has been fitted for each of the models; Mud BHM y = 1.0038x-1.0911, R^2 = 0.81, Metals BHM y = 1.3002x-49258, R^2 = 0.71.

4.4.3 Estuarine Trophic Index (ETI)

Background

The Estuarine Trophic Index toolbox includes three tools. Tool 1 is used to assess eutrophication susceptibility, whereas tools 2 and 3 are used to assess estuarine trophic state. Tools 2 and 3 are briefly discussed below, as per https://shiny.niwa.co.nz/Estuaries-Screening-Tool-2/ , https://shiny.niwa.co.nz/Estuaries-Screening-Tool-3/ , (Zeldis et al. 2022), Zeldis and Plew (2022) and Robertson et al. (2016).

ETI Tool 2 Characterises the ecological gradient of estuary trophic condition for ecological response indicators (e.g., macroalgal biomass, dissolved oxygen), and provides a means of translating these ratings into an overall estuary trophic index (ETI) score. The tool uses measurement data of primary indicators (e.g., macroalgae, phytoplankton) and secondary indicators (e.g., oxygen, redox potential depth, macrobenthos condition) to assess estuarine trophic state.

ETI Tool 3 is a Bayesian Belief Network (BBN) that calculates an Estuary Trophic Index (ETI) score ranging between 0 (no symptoms of eutrophication) to 1 (grossly eutrophic) for estuaries in Aotearoa New Zealand (NZ).
The ETI scoring is similar to that of Tool 2, but the Tool 3 BBN can operate when no or few values are known for the primary indicator nodes and secondary indicator nodes. It therefore is most useful when:

- There is little or no knowledge of the state of indicators for an estuary;
- To explore the response of estuary trophic condition to changes in loads resulting from altered land use or point sources;

- To explore the response of estuary trophic condition to nutrient/sediment load limit-setting scenarios in upstream catchments.

Methodology

The ETI 2 screens estuaries into estuary type, and then uses available monitoring data on key indicators to assess the condition of the estuary, with each indicator falling into approximately four bands ranging from no stress through to high stress. These indicators are then used to calculate an overall score for an estuary of interest (Robertson et al. 2016).

The ETI 3 BBN includes estuary physiographic characteristics (estuary type, flushing time, intertidal area, estuary closure state, water column stratification) and nutrient and sediment loads available from existing geospatial tools and databases, that drive responses of 'primary' indicators (macroalgae and phytoplankton biomass) and 'secondary' indicators (or symptoms) of estuary ecological impairment (sediment carbon, sediment apparent redox potential discontinuity depth, water column oxygen, macrobenthos and seagrass condition) (Figure 4-5). Relationships between the BBN nodes are based primarily on observational and model-based information from NZ and international studies rather than expert opinion (Zeldis & Plew 2022).

Validation

Observational data are classified into bands used to assess the health of different ecosystem indicators and ultimately the ETI 2 score. The underpinning bands are largely based on expert opinion.

The ETI 3 BBN predicted scores have been compared to the ETI 2 scores, with high agreement between scores for 11 well-studied NZ estuaries.

Example application

The ETI 3 model has been used to explore the impact of the diversion of wastewater from Ihutai via construction of an ocean outfall (Zeldis & Plew 2022). Monitoring data showed that the wastewater diversion resulted in a dissolved inorganic nitrogen load reduction of approximately 90% to the estuary, however ongoing inputs from rivers and drains was still sufficient to cause macroalgal blooms. The model was run on pre diversion and post diversion nutrient loadings and showed an improvement in ETI score, associated with improvements to predicted macroalgae blooms, sediment oxygen depth, and macrofaunal community composition.

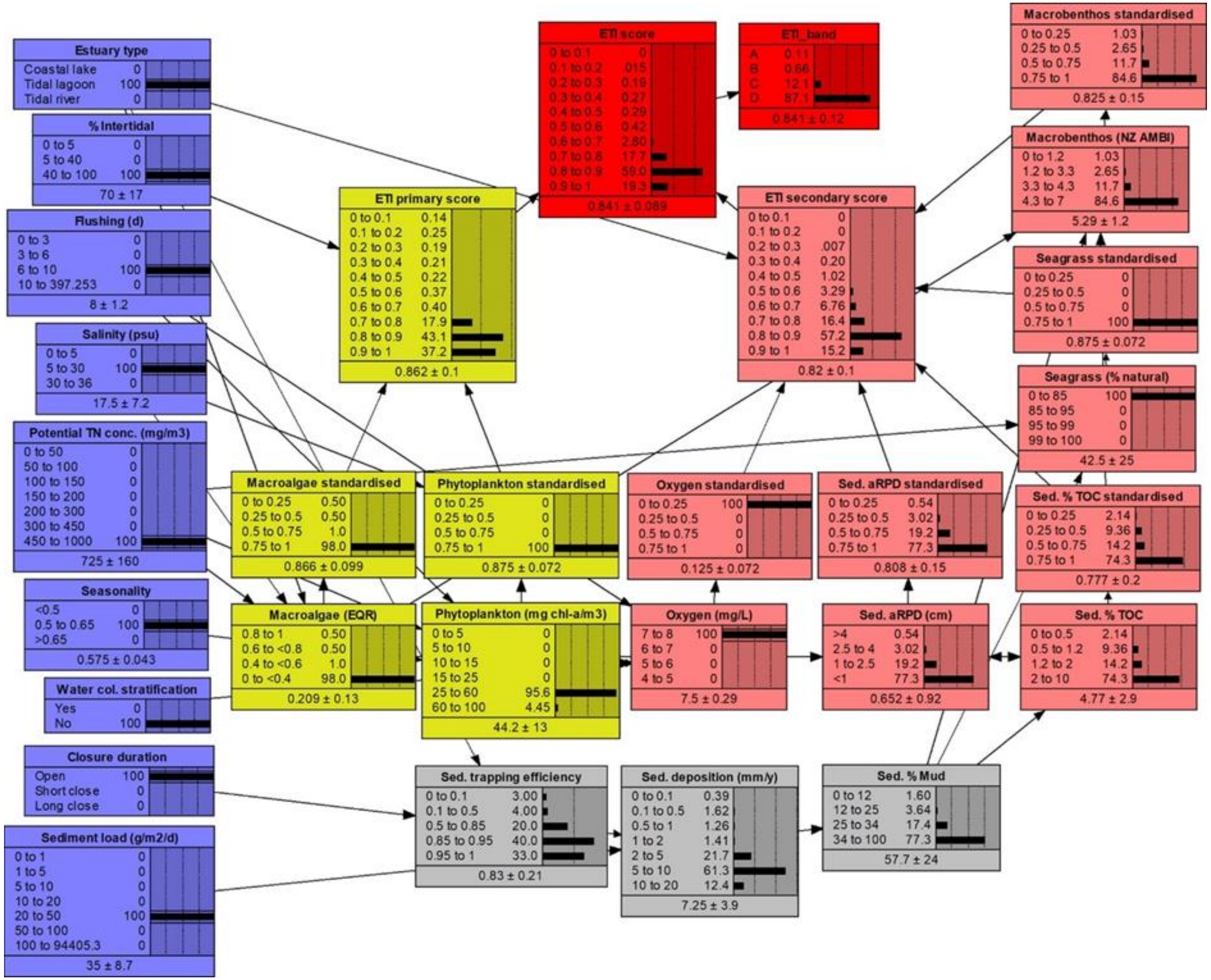

Figure 4-5: The ETI Tool 3 BBN. Blue boxes are driver nodes with values input from ETI Tool 1. Figure from ETI Tool 3, Zeldis et al. (2022). Yellow and pink nodes are primary and secondary indicator nodes and the red nodes are the final ETI score and bands. Grey nodes are intermediate calculation nodes. Indicator nodes have accompanying standardising nodes that normalise their respective scores prior to input to the primary and secondary scoring nodes. This BBN run shows results for Jacob River Estuary (Southland region, NZ) in its present state.

4.4.4 Summary

Three models developed in New Zealand for assessing estuarine health were reviewed. The ETI model does not include metals content in benthic sediments. It does include sediment load however and therefore the model could be used to assess the effect of sediment load reductions on the Estuarine Trophic Index score.

Although the BHM / TBI models do include metals and mud content, they do not include nutrients. While the CSNDC does not explicitly require a reduction in nutrient loads, existing evidence suggests that nutrients are important drivers of macrofaunal communities in Ihutai (Barr et al. 2020, Berthelsen et al. 2022, Zeldis et al. 2020).

The estuarine BN does include mud, metals and nutrients as major stressors and uses these to predict benthic macroinvertebrate abundance (of certain species) and diversity – two measures that may meet CCC's needs. On the other hand, the BN does not provide any measure of cultural health (nor does either of the other two models).

All three approaches can be applied based on existing datasets, depending on the modelling scenario of interest. For example, if the management scenario of interest is focussed on a specific area of the estuary, then ideally sampling data exists from this location to inform the model. Alternatively, it may be possible to infer this from other existing sampling sites throughout the estuary (with the assumption that conditions are representative throughout). If no sampling data exists to inform model predictions, additional sample collection may be recommended.

Table 4-3: Summary of three modelling approaches that may be of use in the Ihutai context.

Factors	Estuarine BN	Benthic Health Model (BHM) and Traits Based Index (TBI)	Estuarine Trophic Index (ETI)
Scope (e.g., whether such methods are suited to including all the factors of importance).			
Metals	Yes	Yes	No
Mud content	Yes	Yes	No
Nutrients	Yes	No	Yes
Comment	By providing information on the four key stressor nodes (suspended sediment, mud content, nitrogen, **metals**) for an estuary of interest, the cascading impacts on the ecology (macrofauna, fish, biogenic habitat, fringing vegetation etc) and ecosystem function (primary production, nutrient cycling, denitrification etc) can be explored. Can run hypothetical scenarios of interest where key stressors are increased or decreased and ecosystem outcomes explored.	Each BHM model relates to a single stressor in isolation. Applying all models in parallel would enable predictions to be made for the macrofaunal health of the site in relation to both sediment mud and metals. Other stressors such as nutrient loads and suspended sediment are not directly considered.	The health score specifically relates to the eutrophication, however the model also predicts a range of other indicators (see above). Estuary physiographic factors are considered in the model.
Data requirements			
	Four key stressors (**suspended sediment, sediment mud content, water column nitrogen, sediment metals**). Information on stressors can be derived from monitoring datasets and/or from expert opinion. Can be run with data from as little as one sampling site. **Can be applied to Ihutai without further development using existing datasets.**	BHM Metals requires **sediment metal concentrations** (zinc, copper, lead). BHM Mud requires on **sediment mud content**. Can be derived from monitoring datasets and/or from modelled concentrations. TBI requires information on **sediment mud and metal content**. Can be run with data from as little as one sampling site. **Can be applied to Ihutai without further development using existing datasets.**	ETI 2: range of indicators (such as **macroalgal biomass**, macrobenthic taxonomic composition, sediment redox potential, TOC, N, P, Sulphides, particle size) which are used to generate ETI score. Can be calculated using data from as little as one sampling site. ETI 3: estuarine scale nutrient and sediment loads which are used to infer a range of other secondary indicator values. Information can be derived from existing geospatial tools and databases. **Can be applied to Ihutai without further development using existing datasets.**

Factors	Estuarine BN	Benthic Health Model (BHM) and Traits Based Index (TBI)	Estuarine Trophic Index (ETI)
Spatial and temporal resolution			
Temporal	Predicts at a single point in time but can be used to model past, present and future (within the next ~10 years) scenarios of interest.	Predicts at a single point in time but can be used to model changes in benthic health scores through time. Typically used to look at historic changes in council monitoring datasets through time, however these models have also been used to predict future outcomes.	Predicts at a single point in time but can be used to model changes in ETI scores through time, or with changes to future nutrient and sediment loadings.
Spatial scale	Can be applied at the **estuarine or sub estuarine/site scale**.	Underpinning sediment metals and mud concentrations can be calculated from council estuarine monitoring data, but can also be calculated based on modelled/hypothetical concentrations. Calculated at the sub estuarine/site scale.	Applied at the **estuarine scale**.
Information required to run			
Inputs	Requires information on habitat and water quality variables, flow metrics, riparian data. Information on stressors can be derived from monitoring datasets and/or from expert opinion.	Sediment, nutrient and organic loads, inflows, temperature, biomass estimates	Data on stream substrate, catchment area, slope, road and population density
Ease of use and understanding			
Outputs	Model outputs and structure is visually represented however values/aspects of interest can be extracted for further analysis or simplification.	Provides an overall score to represent estuarine health with a focus on macrofaunal community composition.	Provides an overall score to represent estuarine health with a focus on eutrophication, ranging from 0 (no symptoms of eutrophication) to 1 (grossly eutrophic). As well as predictions for a range of other indicator nodes
Availability	Available through research scientists	Freely available using reported information	Freely available via online tool

4.5 Statistical modelling methods for freshwater

Statistical models can be used to test the strength of correlations between predictor (independent) and response (dependent) variables. Generally, causation can be inferred but not proven, unless predictor variables are experimentally manipulated and the effects of their values or presence or absence investigated. Statistical models can only be applied with confidence within the range of data used to develop the models.

The predictive accuracy of developed statistical models can be tested by making predictions for a new dataset or for individual points within the data set used to create the model and comparing to the observed response values.

Response metrics can be univariate (a single response) or multivariate (e.g., abundance values for multiple taxa). In this report we focus on univariate responses, as they were identified as the main variables of interest in the initial workshop. Univariate models are those in which a single response variable, e.g., the New Zealand macroinvertebrate community index (MCI), is predicted from one or more predictor variables, or covariates. The univariate modelling approaches considered include generalised linear models (GLMs), generalised additive models (GAMs), ensemble classification and regression trees (CART) methods such as random forest (RF) and boosted regression tree (BRT) models and structural equation models.

The multiple stressor environment of urban waterways means that there are likely to be synergistic, additive or compensatory interaction effects between stressors on the biological communities, that effects of contaminants may occur at threshold levels (e.g., over toxicity levels) or be influenced indirectly through other variables. Using expert opinion to pre-determine a suite of potential shapes of relationships between contaminants and predictor variables that can be tested using the data available is likely to be beneficial. For example, identifying whether metals are beneficial at low levels but toxic at high levels, equally toxic as concentrations increase or only toxic over a particular threshold, will allow hypotheses about linear or exponential declines or a threshold responses to stressors to be developed. Alternative models that include the different *a priori* defined relationships between stressors and responses can be tested to identify the relationship that fits the data best. Overly complex (i.e., "wiggly") relationships are unlikely to be biologically meaningful and may result from biases in the data set, particularly when the data set is comparatively small. The nature of the data collection also influences the choice of statistical models. When multiple sites within the same catchment have been sampled, or when sites are sampled repeatedly over time, random effects terms are likely required to address spatial or temporal autocorrelation (see Section 3.2.4). These considerations meant that the key criteria we focused on to compare the various statistical modelling methods were whether they could include:

1. Non-linear relationships that can be pre-defined between predictors and response variables.
2. Interactions between predictor variables.
3. Indirect as well as direct effects of predictor variables on the response.
4. Random effects, which can be included to help explain variation in additional factors. For example, the likelihood that sites within the same catchment are more similar to each other than to sites in a different catchment.

4.5.1 Random forests and boosted regression trees

Random forests (RF) and boosted regression trees (BRTs) are ensemble classification and regression tree (CART) methods which use machine learning to fit the models. CART models are binary decision trees in which each fork is a split on a predictor variable and each node is a predicted response value. Predictor variables are provided, and the model detects any non-linearity and interactions between variables automatically. Random forests are ensembles (forests) of many individual classification and regression trees, where each tree is built using a randomly sampled with replacement subset of the data and model predictions are made by averaging all trees. The relative importance of the different variables put into the model can be determined by permutation, and the individual effect of a given predictor by holding the values of all other predictors a constant (usually at their mean or median values) (Whitehead et al. 2022a).

Boosted regression trees are built sequentially, with each subsequent model fitted to the residuals of the previous model to explain the remaining variation in the response that is not yet explained (Elith et al. 2008). Variable selection (to determine the key predictors) can be done via stepwise model reduction procedures and comparing different models with information theoretical measures (i.e. AIC, Akaike's information criterion) (Elith et al. 2008).

RF and BRT have often been used together to investigate drivers of macroinvertebrate communities or to predict MCI at both regional and national scales, with data sets larger than that available for urban Ōtautahi waterways (Clapcott et al. 2013, Clapcott et al. 2017). Clapcott et al. (2017) also used both RF and BRT models with a combination of land cover, geology and topography, and environmental variables such as flow, temperature, and shading, to predict reference conditions at a national-scale (Clapcott et al. 2017). Both models performed similarly well, and identified similar sets of important predictor variables, namely percent native vegetation cover in the catchment, percent heavy pastoral cover in the catchment (Clapcott et al. 2017). A more recent study developed a RF model to predict MCI scores at a national scale based on a combination of climatic, geological, topographic, land cover, and hydrological variables from the River Environment Classification geodatabase (REC2.4, Whitehead et al. 2022). This model performed well, indicated by high explained variation, similarity between observed and predicted values, low bias, and low prediction uncertainty (Whitehead et al. 2022). However, the model was based solely on catchment- and segment-scale parameters and did not include finer-scale variables such as water quality. Within an urban context, boosted regression trees have been successfully used in Melbourne, Australia to investigate interactions of urban stormwater drainage, land cover and flow regime on a stream macroinvertebrate index (Walsh & Webb 2016). They found that imperviousness and forest cover, when attenuated for distance from stream (Walsh & Webb 2014), were the strongest predictors of macroinvertebrate decline. Again, this model used catchment-scale parameters and did not include finer-scale variables which may be of importance in understanding the effect of stormwater management on ecosystems.

BRT and RF methods are advantageous in that they are highly flexible and automatically include complex nonlinear responses and interactions between predictor variables. However, the shape of the relationships between predictors and responses are defined by the data, with little ability to test between different *a priori* hypotheses. When used with small datasets there is a risk that they might converge on a relationship that makes little biological sense due to biases in the data. These model types also are not able to include random terms to account for variation caused by non-independent data points.

4.5.2 Generalised linear models and generalised additive models

Generalised linear models (GLMs) and generalised additive models (GAMs) are models in which the response is the sum of a linear combination of predictor variables. GLMs can include pre-specified non-linear relationships (e.g., logarithmic or quadratic) by including terms to modify the predictor variable. GAMs can use the data to identify non-linear relationships using smooth functions, or splines, where the 'wiggliness' of the smooth can be limited to user-defined levels. Both GLMs and GAMs can be used to model data where the response fits a normal, Poisson (count data), or binomial (bounded by 0 and 1) distributions. GLMs and GAMs can be moderately complex, depending on data availability, but the initial equation is user-specified. GLMs and GAMs can also include random effects to account for the non-independence of time series data collected from the same site or to quantify the variation between units in a nested study design (hierarchically-structured data). Models including random effects are known as 'mixed' models – generalised linear mixed models (GLMM) and generalised additive mixed models (GAMM).

GLMMs have been used in a wide range of freshwater studies on macroinvertebrates and fish. In New Zealand, Greenwood and Booker (2015) used GLMMs to investigate the influence of antecedent flow conditions on macroinvertebrate diversity and composition (although using alternative EPT metrics rather than MCI score) with a random site term (Greenwood and Booker 2015). They found between site differences were a significant source of variation; for nine of the fourteen potential covariates included in the models, more than half of the variation could be explained by the random site term (Greenwood and Booker 2015). Piggot et al. (2015) used GLMMs to compare macroinvertebrate responses between experimental mesocosm treatments varying in nutrients, sediment, and temperature. Crow et al. (2016) used GLMs to estimate probability of capture for freshwater fish for each year of data in the New Zealand Freshwater Fish database, while Boddy et al. (2019) applied GLMs to model relationships between water abstraction and fish communities.

GAMs have been used for hydraulic habitat modelling assessments for two common New Zealand macroinvertebrate taxa, *Deleatidium* spp. and *Aoteapsyche* spp. (Shearer et al. 2015). That analysis indicated there were both significant non-linear relationships between macroinvertebrate density and velocity, depth, and substrate, and significant interactions between some pairs of explanatory variables. GAMS have also been used to investigate habitat preferences of koura (Jowett et al. 2007a) as well as other macroinvertebrates and fish (Jowett et al. 2007b).

GAMM and GLMM methods are advantageous as the shape of the relationship between predictors and response variables can either be user-defined (GLM) or the number of limited inflection points limited (GAM). Both can include random terms can work with reasonably small datasets, although model complexity will be limited.

4.5.3 Structural Equation modelling

Structural equation modelling (SEM), sometimes called path analysis, is a way to investigate hypothesised causal pathways between variables. The main strength and point of difference of SEM from other approaches is the ability to include both direct effects and those mediated through another variable (indirect effects). Combinations of measured parameters can also be combined into individual constructs called latent variables. For example, deposited sediment depth, water velocity and water temperature may be combined into a 'habitat' construct. Traditionally path analysis was difficult to apply to ecological situations as relationships between parameters generally needed to be linear, required large datasets (e.g., 5 replicates per linkage between variables) and could not include random terms (as in GLMMs). However, recent advances mean that path analyses can be conducted using smaller data sets, including random terms, interactions and non-normal responses (e.g., piecewise SEM; Lefcheck 2016). Alternative approaches to the more traditional covariance-based path analysis, such as partial least squares path modelling (PLS-PM), have also been promoted as advantageous (Sarstedt et al. 2022).

Relevant previous uses of SEMs in New Zealand for freshwater communities have included:

- investigating the drivers of macroinvertebrate community composition in 64 agricultural streams in Canterbury (traditional SEM; Greenwood et al. 2011),
- reach and landscape-scale casual pathways to predict *Didymosphenia geminata* biomass in over 50 sites (PLS-PM; Bray et al. 2016).
- Investigating whether flood effects on fish biomass are direct or through reductions in macroinvertebrate biomass (fish food) or riverbed movement (potential mortality) in two datasets of 20 sites and 52 stream sites. (PLS-PM; Jellyman et al. 2013)
- Investigating the impacts of land cover, floods and stream size on biomass of different freshwater trophic levels in 27 streams (piecewise SEM; Fraley et al. 2021)

Path analysis is also used to test hypotheses about drivers of freshwater ecological or water quality conditions internationally. For example, to investigate the ecological status of streams using macroinvertebrate data, water quality parameters and anthropogenic pressures in Portugal (PLS-PM; Fernandes et al. 2019). Examples of use in urban waterways include a study to investigate how catchment characteristics of urban waterways are related to water quality (dissolved nutrients and conductivity) (Wu et al. 2015).

The strengths of SEM analyses are in testing alternative hypotheses of pathways of effect from potential stressors to response variables, rather than developing predictive models. Relationships between predictors and responses are limited to those that are linear or can be transformed to be linear (e.g., log transforming a predictor). Model complexity is limited by data set size.

4.5.4 Risk Analyses

Risk analyses assess biota and stressors simultaneously; biological data are used to assess ecological condition, while environmental data (physical and chemical characteristics) is used to evaluate the relative importance of stressors (Van Sickle et al. 2006). Condition classes, rather than numerical variables, are used to describe stressors and responses. The relative risk, or the likelihood that poor stressor condition and poor biotic responses co-occur (Van Sickle et al. 2006), can be determined from survey data:

$$RR = \frac{\Pr\,(poor\ biotic\ condition\ given\ poor\ stressor\ condition)}{\Pr(poor\ biotic\ condition\ given\ good\ stressor\ condition)}$$

A relative risk of 1 indicates no association between stressor and biological condition, while values >1 indicate greater relative risk. For example, a relative risk value of 2 indicates that a poor biotic condition is twice as likely when stressor condition is also poor. Confidence intervals for relative risk can be calculated by estimating the standard error using large sample approximations (Van Sickle et al. 2006) or local neighbourhood variance estimation (Pingram et al. 2019).

Relative extent is estimated as the proportion of area in geographic space which falls into a given condition class for each stressor (i.e. poor, fair, good). Relative extent can be determined from field survey data or by using GIS, depending on scale and available information. Relative extent and relative risk are combined to determine attributable risk, the percentage reduction in the extent of poor biological condition that would be expected to result from eliminating a particular stressor (Van Sickle et al. 2006, Herlihy et al. 2019, Pingram et al. 2019):

$$AR = \frac{\Pr(high\ stressor\ levels) * \ (RR - 1)}{1\ + \Pr(high\ stressor\ levels) * (RR - 1)}$$

Attributable risk calculations rely on three key assumptions: 1) causality – the stressor causes an increased probability of poor condition, 2) reversibility – if the stressor is eliminated, causal effects will also be eliminated, and 3) independence – stressors are not correlated (Herlihy et al. 2019).

If the third assumption is not met and stressors are strongly correlated, their effects will be confounded in the risk analysis. In this situation, a correlation matrix of categorical stressors converted to binary values (i.e. 1 for 'poor' and 0 for 'good') can be used to assess associations between variables (Van Sickle et al. 2006) and guide inference on the risk analysis results. For example, Van Sickle et al. (2006) noted that nitrogen and phosphorus classes were strongly correlated and therefore grouped them together into a single 'nutrient' class when interpreting risk. Alternatively, the attributable risk estimate can be adjusted for the effect of correlated stressors or non-stressor covariates, similar to a regression coefficient (Van Sickle and Paulsen 2008). However, clear guidelines for partitioning joint stressor effects are still lacking (Van Sickle and Paulsen 2008).

Risk analysis has been used in the United States to identify the relative impact of sedimentation, nutrients, and acid mine drainage on stream macroinvertebrate communities (Van Sickle et al. 2006) and to assess the risk of different stressors on wetland vegetation condition (Herlihy et al. 2019). In New Zealand, it has been applied to identify and estimate the relative importance of key environmental stressors on stream macroinvertebrates and fish in the Waikato region (Pingram et al. 2019). Pingram et al. (2019) also estimated attributable risk, or the reduction in poor biological condition (e.g. improved MCI scores) that could be achieved if stressor values were improved.

Risk analysis is well suited to evaluating the relative importance of multiple stressors (Landis and Wiegers 2007, Van Sickle et al. 2006) and clearly communicating environmental survey results to non-technical audiences (Van Sickle et al. 2006), but generally not for developing predictive models. In addition, risk estimates can have high uncertainty (Van Sickle and Paulsen 2008), which can be due to uncertainty associated with collected data and estimations of stressor extent, as well as uncertainty in assumed causal pathways (Landis and Wiegers 2007). However, confidence intervals around risk estimates can also be extremely useful for communicating uncertainty in a management context (Pingram et al. 2019).

4.5.5 Summary

Many different statistical techniques exist for developing predictive models. Generally, the choice of the best model type to use depends on the goals of the analysis and the type of data available. As previously discussed, the selection of an appropriate model depends on:

1. The amount of data available. The type or complexity of the model able to be run is limited by the amount of data available.

2. Whether to include random terms. An example is the inclusion of a random term for 'river catchment' if there are multiple sites between each catchment and sites in one catchment are likely to be more similar to each other than those on another catchment. Random terms can be included that change the intercept of the relationship between the predictors and the response between each level of the

random factor. For example, the same slope of relationships between QMCI and deposited sediment is predicted for each site, but some sites may have a higher starting QMCI than others. Statistical methods such as GLMMs, GAMs and some of the newer SEM method can include random effects

3. The nature of relationships between variables in the model, i.e., whether they are assumed to be linear or more flexible non-linear relationships. For example, SEM and GLMMs can include pre-set non-linearity while GAMs and CART models fit non-linear relationships depending on the data.

Ecological datasets are often comparatively small due to the expense and effort involved in collecting the data and this limits the complexity and type of model that can be developed. Model selection or simplification techniques are commonly used to identify which predictors to include when developing a model that fits the data best. Using expert opinion and good knowledge of the system being modelled is important during this process. One method to account for uncertainty associated with model outputs is to run several different types of statistical models and determine whether similar results are generated (White et al. 2023). In addition, statistical models based on survey data imply causation from correlations. The likelihood of relationships identified from statistical models should be assessed using expert opinion and ideally experimental manipulations, where possible.

The factors limiting the predictive accuracy and usefulness of any predictive model developed are likely to be common problems in ecological datasets - the comparatively small dataset limiting the complexity of the model that can be run, the difficulty in disentangling the impacts of correlated stressors and limitations in interpreting how a change in a univariate biological response metric (e.g., MCI) relate ecologically to changes in individual stressor values.

In general, the data available for urban Ōtautahi waterways are unlikely to be sufficient for CART models (boosted regression trees or random forests). These models also can't include random terms and, given the small data set size, have the potential to fit relationships between predictors and responses that are caused by biases in the data rather than any a biologically relevant relationship that would generate accurate predictions.

SEM models are likely to be useful for testing hypothesised relationships between potential stressors and response metrics, including indirect effects. SEM models could be useful to test the conceptual models developed during the expert workshop (Appendix A), although the small size of the dataset means that only relatively simple models will likely be able to be tested. However, SEM models are limited in their ability to predict to new data and cannot include random terms.

GLMMs or GAMMs are strong candidates for statistical models that could be used to develop predictive models for the dataset identified in this report. Both model types allow use of random effects, which could be included to account for sampling of multiple sites within catchments and can include non-linear relationships between predictors and response variables. Expected relationship shapes are pre-selected in GLMMs (e.g., logarithmic or quadratic) while GAMMs use smoothers to develop relationship shapes that best fit the data, where the degree of 'wigglyness' can be limited. These models can identify parameters that have 'high importance', i.e., are commonly correlated with the response and generate plots of individual stressor relationships with the response, when all other stressors are held constant.

5 Feasibility of modelling responses in Ōtautahi streams

5.1 Introduction

In this section we assess the feasibility of developing or utilising existing models to predict how macroinvertebrate communities will respond to reductions in concentrations of contaminants in the urban waterways of Ōtautahi. Feasibility depends on:

- The scope of the models compared to the needs of CCC, including the type of output (quantitative vs qualitative).
- The scale of the model (spatial and temporal) compared to the needs of CCC, including how the model can consider lag times.
- The data required versus the data available, including consideration of the limitations in that data.
- The monitoring required to build and/or calibrate models and, briefly how and where this should be undertaken.
- The availability (or lack of) reference sites if needed for modelling.
- The likely uncertainty in the model.
- The effort required to develop and/or run any model including some indication of the time required.

The objective for predictive models was defined as being able to:

1. Robustly predict how and when biological communities might respond to changes in network contaminant loads and resulting in-stream concentrations, as well as changes in other limiting factors (e.g., habitat availability) and
2. Quantify which limiting factors (i.e., not just stormwater treatment) would have the greatest ecological benefit, the quickest ecological benefit, or limited ecological benefit, if they were to be addressed.

The macroinvertebrate metrics QMCI and EPT were prioritised as key indicators of the biological communities (see section 3.2.2). Hard-bottomed tolerance scores were used to calculate QMCI values at all sites because naturally soft-bottomed sites were not identified, however, under the NPS-FM the soft-bottomed tolerance scores are required to be used in sites that are naturally soft-bottomed. Developing predictive models of changes in macroinvertebrate metric values in response to changes in individual stressors (e.g., contaminants) relies on:

1. quantitative or qualitative relationships between key stressors and the macroinvertebrate community metrics, and
2. an understanding of the mechanisms through which stormwater mitigations may reduce stressor impacts on macroinvertebrate communities.

5.2 Data preparation for testing models

As discussed in section 3.2.3, not all the potential stressors are measured at the same location or over the same period as the macroinvertebrate data. This means the available data needed to be collated and summarised to test models for predicting macroinvertebrate response.

Spatial matching

There were macroinvertebrate data including the indices MCI_hb, percentage EPT excluding hydroptilids and QMCI_hb available for sixty-seven sites from six catchments (Ōtākaro/Avon; 21 sites, Ōpāwaho/Heathcote; 16 sites, Puharakekenui/Styx; 12 sites, Otukaikino; 9 sites, Huritini/Halswell; 8 sites and Linwood canal; 1 site) across Ōtautahi. Other macroinvertebrate metrics (e.g., ASPM, MCI_sb, QMCI_sb) were not precalculated for all sites but could be calculated from raw macroinvertebrate data if required.

Predictor variables with data for all 67 sites included: percentage bed cover of various macrophyte and periphyton categories (e.g., emergent macrophytes, long filamentous algae), canopy and riparian ground cover percentage cover, bank heights and slopes, sediment depth, substrate index, water depth, dissolved oxygen, pH, conductivity, water temperature and velocity. These measurements were all made on site at the same time as the macroinvertebrate sampling.

Water quality monitoring sites were able to be linked to 63 of the macroinvertebrate sites with 19 sites at the same locations as macroinvertebrate monitoring sites, 27 sites downstream, 16 upstream and 1 on a different river branch. On average, locations of macroinvertebrate and water quality sampling sites were within one kilometre of each other, up to a maximum of five kilometres distance. The water quality parameters available at all 63 sites included concentrations of dissolved nutrients, turbidity, suspended solids and dissolved metals (copper and zinc).

Sediment monitoring sites were also able to be linked to 63 of the macroinvertebrate sites with 31 sites in the same location, 16 downstream and 15 upstream. The greatest distance between macroinvertebrate and sediment sites was 7 km, with a median distance of 100 m between sites.

Of the 63 sites with sediment, water quality and macroinvertebrate data, 53 sites could also be matched to nearby sites with hydrological data. Nearest flow sites were at the macroinvertebrate sampling location for 14 sites and, for the rest of sites, both upstream and downstream of matched ecological sites, and occasionally on different river branches, meaning that hydrological statistics are likely to be only broadly indicative of conditions at a matched ecological site (see Figure 5-1 below). In total eight of the 63 macroinvertebrates sites had hydrological, water quality and sediment data available for the same location. Thirty of the macroinvertebrate sites did not have any hydrological, water quality or sediment quality data collected at the same location.

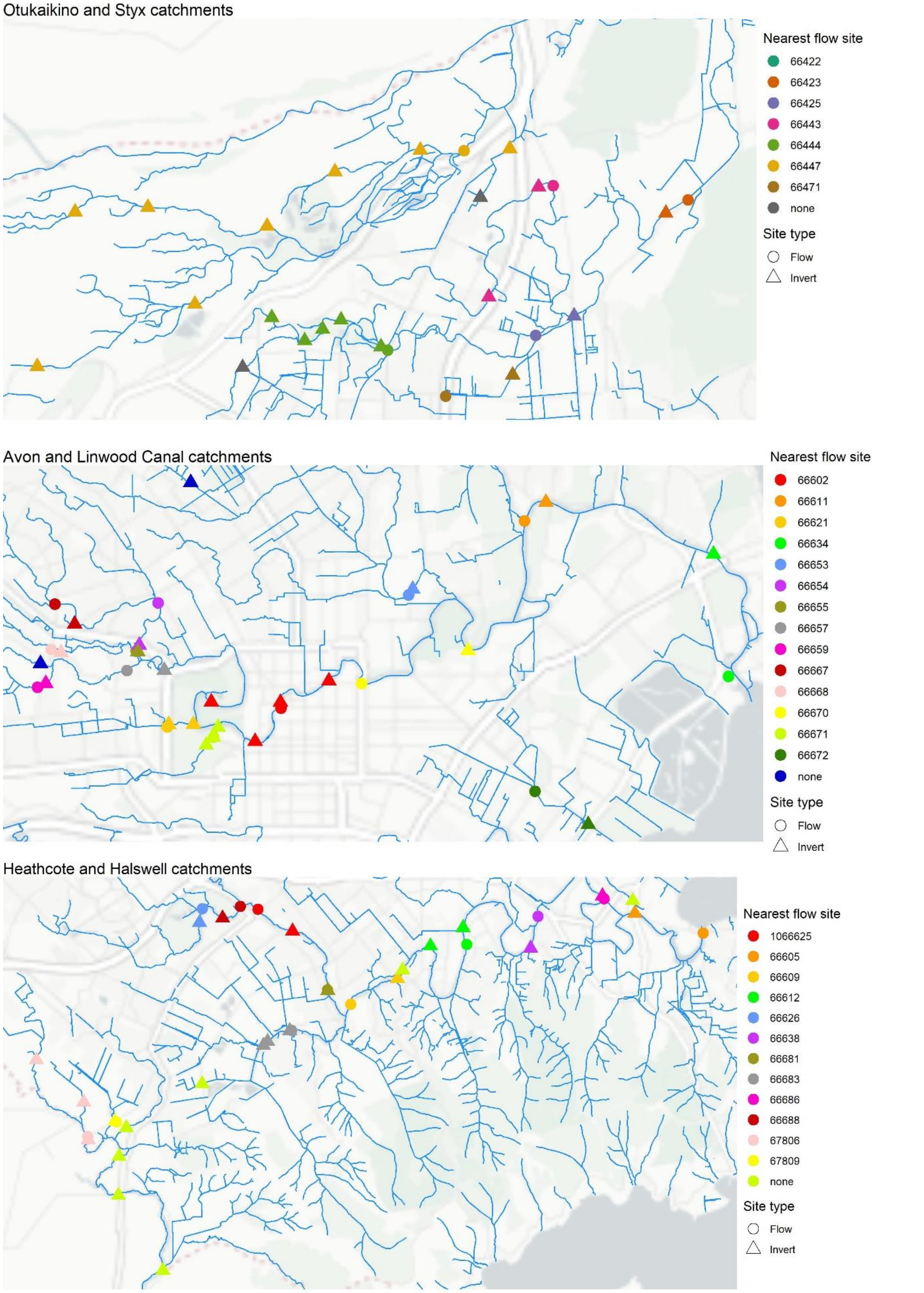

Figure 5-1: Location of ecological monitoring sites within each stream catchment and the flow sites used for indicative hydrological indices.

Calculation of metrics for predictor variables

The sampling protocol for macroinvertebrate communities within Ōtautahi where individual catchments are sampled at multiple sites once every five years provides a relatively limited temporal resolution. In cases where predictor variables have more frequent temporal sampling than the responses they needed to be summarised as long-term medians, means or other metrics.

There are many metrics that indicate changes in hydrology due to changes in land use, abstractions and/or diversions. We selected two metrics that are indicative of urban land use change and the presence of impervious surfaces: the coefficient of variation (CV), which indicates the range in flow and the number of flow reversals (Richter et al. 1996). Unlike other metrics, these can be calculated for both flow and water level and so were suitable for the mixed data set with of 16 sites with water level data and 17 sites with flow data.

The hydrological data were available for different windows of time for each hydrological site, as shown in Figure 3-3. Metrics were generated for a consistent time period for all sites where possible. Twenty-seven sites (82 %) had data for the period 1/1/2017 to 8/2/2018, across which hydrological metrics were generated. Other time periods used to generate hydrological metrics were, with one site each: 1/1/2018 to 8/2/2019, 1/1/2020 to 8/2/2021, 18/2/2021 to 31/12/2021 and for three sites between 1/12/2021 and 30/12/2022. Many of the sites had several dates missing data (all sites less than 10 days missing apart from one site each with 12, 38, 47 and 64 days missing hydrological data). The number of days with hydrological data for a site ranged from 310 to 404 days. Over the selected time window for each site we used mean daily data to calculate:

1. the CV of either flow or water level (cv = standard deviation / mean *100) and
2. the number of times the water level or flow reversed (i.e., stopped increasing and started decreasing or vice versa), as a proportion of the record length (number of days).

For water quality, we calculated percentile statistics - median, 80th, 90th and 95th percentiles[11] - based on 5 years (January 2017 to December 2021) of monthly monitoring data. For dissolved oxygen, where low concentrations (rather than high) are related to adverse effects, we also calculated the 5th percentile. For dissolved zinc the median and 95th percentile values were highly correlated (R^2 =0.90), though for other variables including copper and suspended solids the relationships were weaker.

For periphyton, Weighted Composite Cover (WCC) was calculated to summarise the percentage cover of different types of periphyton into one number for each site. WCC provides an estimate of nuisance algae using periphyton percentage cover data for filaments and mats. This index is useful at sites where both filamentous growths and mats occur and is calculated as:

WCC = (%cover by mats)/2 + % cover by filaments

Final data set

The final data set included 53 sites, with more than 100 different potential indicators for the possible stressors, including hydrological, water quality and habitat related stressors. In some cases there was more than one metric for a particular stressor – such as the median or 95th percentile zinc concentration. There was information on most of the stressors identified in the conceptual model,

[1111] Using the Hazen method, consistent with methods for assessing freshwater attributes, see New Zealand Government (2018) although there were no indicators of stream baseflow or flood magnitude or the presence of movement barriers or woody detritus.

The number of different metrics needs to be reduced to develop models. Expert knowledge, such as used to identify the likely key stressors for Ōtautahi waterways in Section 3.2.4, is crucial to refining the list of possible stressors. This requires knowledge of the likely mechanisms for stressors to impact biological communities. Comparing values for stressors against known thresholds (such as NOF attribute bands in the NPS-FM, or known toxicity thresholds) can also assist in identifying parameters that are likely acting as stressors on the biological community. Identifying and removing correlated stressors is necessary for many modelling approaches and will also help to reduce the number of possible stressors.

The fit of expert-derived conceptual diagrams such as those developed in the workshop with CCC (Section 3.2.4) to the data available for waterways in Ōtautahi could be assessed using statistical analyses such as structural equation models (SEM, see section 4.5.3). SEM models are useful tools for hypothesis testing of flow diagrams such as those developed during the workshop as they allow the inclusion of indirect effects, where one variable may moderate the impact of another on the response. For example, warmer temperatures may directly affect macroinvertebrate community composition, but could also have an indirect effect via increased periphyton growth in warmer temperatures altering food availability for macroinvertebrates. Other model types (such as Bayesian belief networks) may also be useful in identifying key stressors.

5.3 Testing the freshwater BN model

The BN model was tested using data for a subset of sites in Ōtautahi, focusing on assessing potential differences in ecological metrics associated with differences in metal concentrations. In addition, sites were selected where the measured data indicated differences in impervious cover, bank lining/reinforcing and riparian vegetation. These variables were selected as indicators of catchment-scale (impervious surface) and reach-scale stressors (bank lining/reinforcing, riparian vegetation).

This testing was only undertaken with sites where water quality and ecological monitoring occur at the same site or very near. Ōtūkaikino Creek was an exception – water quality is not monitored at the upstream of Dickeys Road site but is measured at a site 2.7 km upstream.

Input data for the BN model (Table 5-1) was acquired primarily from the CCC ecological and water quality monitoring programmes (collated as described in section 5.2). Metal, sediment and nutrient concentrations from monitoring data were used as inputs for the BN model. Note that when used within the UPSW decision support system (DSS), the BN estimates metal concentrations in the streams based on contaminant loads supplied by a contaminant load model. However, that contaminant load model was not being used in this project (the BN is run independently of the DSS) and loads were not readily available from other sources for each monitoring site. As the estimation of contaminant concentrations within the BN is indicative only (based on an annual contaminant load and an annual average river flow), we considered that using measured (rather than estimated) water quality data would reduce the uncertainty in model predictions.

Table 5-1: States of stressor inputs used to test the BN model.

Stressor input	Ōtūkaikino Creek upstream of Dickeys Road	Puharakekenui/Styx River at Claridge Road	Ōtākaro/Avon at Mona Vale	Waimairi Stream	Dudley Creek	Addington Brook	Riccarton Stream
Periphyton max cover	< 30%	< 30%	< 30%	< 30%	< 30%	< 30%	< 30%
Macrophyte cover	> 50%	< 50%	> 50%	> 50%	< 50%	< 50%	< 50%
Bank lining/ reinforcing	Not reinforced	Not reinforced	Not-partially 75:25	Partially reinforced	Not reinforced	Not reinforced	Totally reinforced
Stream straightening	Not straightened	Not reinforced	Straightened 1- 25%	Unclear, equal chance of all states used	Straightened 25-50%	Straightened 1- 25%	More than 75% straightened
Extent of tall riparian vegetation	<25%	25-50%	25-50%	25-50%	25-50%	25-50%	25-50%
Riparian condition	Exotic trees, sedge/flax/long grass	Exotic trees, shrubs, sedge/flax	Exotic trees, shrubs, sedge/flax, long grass, bare	Exotic trees, shrubs, sedge/flax, long grass, bare	Exotic trees, shrubs, sedge/flax, long grass, bare	Exotic trees, long grass	Grass, bare or artificial
Stream erosion/incision	Low	Low	Low	Low	Low	Low	Low
Impervious surface cover	<10%	17%	42%	36%	43%	57%	56%
Hydrology score	High	Medium-high	Medium	Medium	Medium	Medium	Medium
Zinc concentrations (median-95th percentile)	0.0011-0.0045	0.0019-0.012	0.007-0.038	0.0036-0.019	0.011-0.058	0.027-0.13	0.010-0.083
Copper concentrations (median-95th percentile)	0.00027-0.002	<0.002	<0.002	<0.002	<0.002-0.0031	<0.002-0.0041	0.0004-0.0036
Nitrate+nitrite-N concentrations (median-95th percentile)	0.24-0.72	0.54-1.24	2.3-3.5	1.8-2.7	0.33-0.76	1.0-1.6	2.3-3.2
TSS concentrations (median-95th percentile)	<3-4.2	3-5	<3-5.7	<3-6.7	7.8-32	5-31	3-28
Minimum DO	7.9	5.8	8.1	7.8	6.8	5.7	8.0
Maximum Temperature	17.2	15.4	15.5	15.2	19.1	19.5	16.9

The BN model calculates a hydrology score based on catchment (e.g., impervious surface) and stream characteristics, and this score is used in the prediction of the macroinvertebrate score. However, that hydrology score was not suitable for spring-fed Ōtautahi streams, with flat topography. It was not within the scope of this project to develop or recalibrate a score for Ōtautahi. Therefore, for the testing this score was simply set as "High" for the Ōtūkaikino Creek, which has little upstream impervious surface, "medium-high" for the Styx River site, and "medium" for all other sites. Similarly, the stream erosion and incision score, a qualitative assessment of the potential for erosion and stream bank incision, was set to "low" for all streams. Example BN inputs and outputs are shown in Figures 5-2 to 5-3.

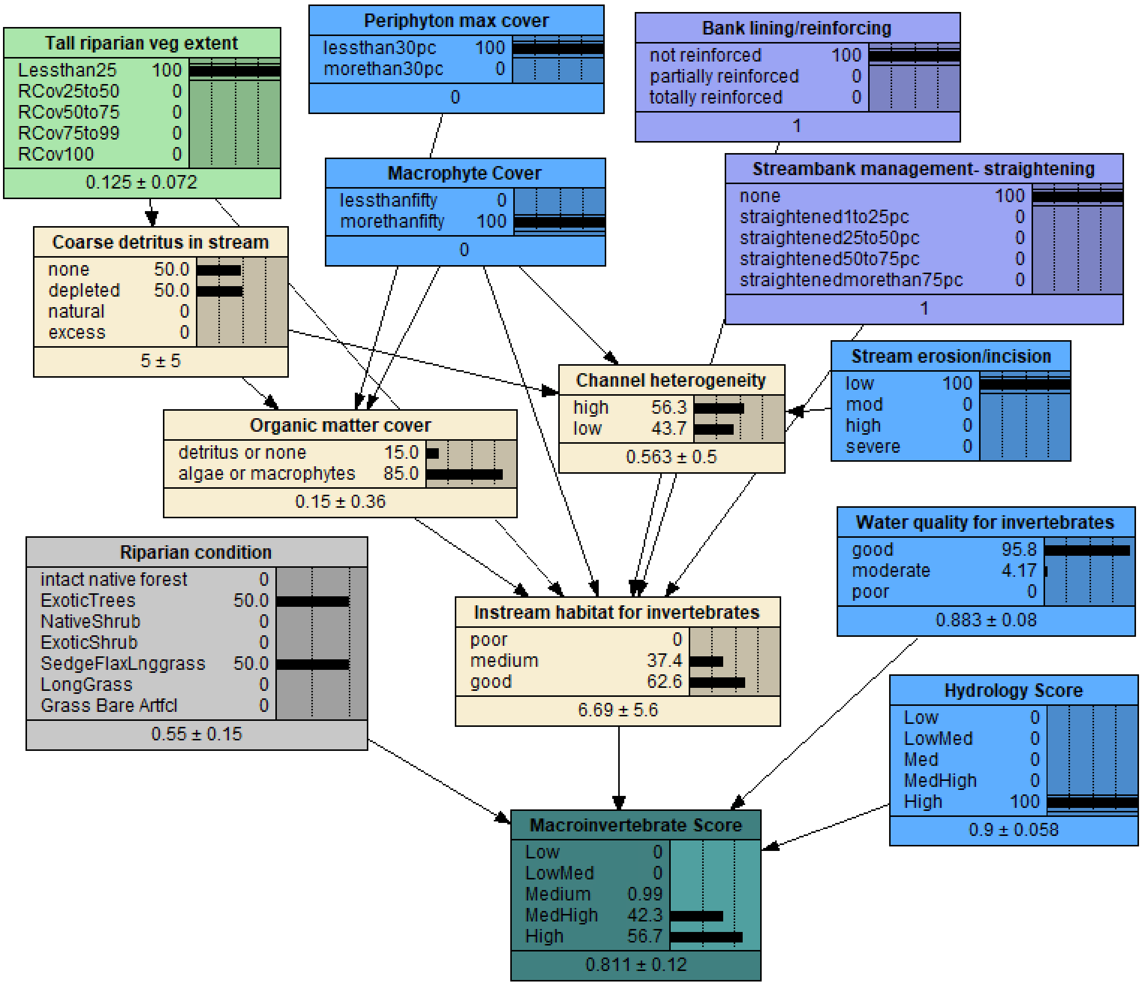

Figure 5-2: Bayesian Network model inputs and predictions for the Otukaikino Creek site upstream of Dickeys Road – current state.

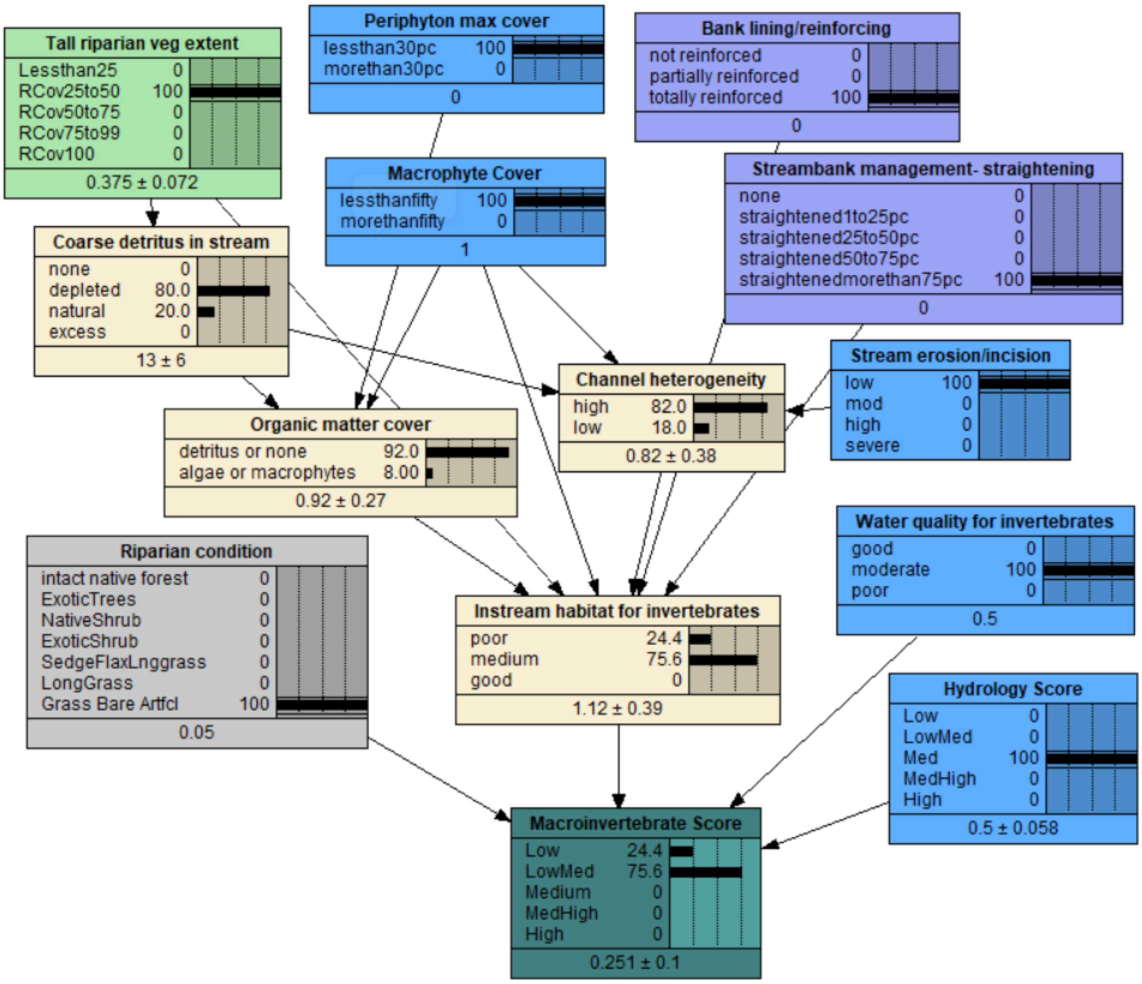

Figure 5-3: Bayesian Network model inputs and predictions for the Riccarton Stream site – current state.

The BN predicted a high score for macroinvertebrate communities at the Ōtūkaikino Creek site; a medium-high score for the Styx River site and medium scores for the Dudley Creek and Ōtākaro/Avon River at Mona Vale sites (Table 5-2). Predicted scores were low-medium for the other three sites. The order of these predictions is consistent with the monitoring data for some sites - Ōtūkaikino Creek has the highest EPT taxa richness, the highest QMCI and highest MCI of the sites included (Boffa Miskell 2022). The QMCI score at that site is in the range considered indicative of mild pollution while the MCI is in the range considered indicative of moderate pollution. The monitoring data for the Puharakekenui/Styx River (Instream Consulting 2018b) also suggests higher macroinvertebrate scores for this site compared to other sites, at least based on the EPT and QMCI scores – though these are still in the range considered indicative of severe pollution or nutrient enrichment.

Table 5-2: Predictions from BN model compared to measured stream ecological state. Green shading indicates higher scores, colour scale applied evenly across the data range.

	BN predictions		Measured state †			
Site	State	Mean score (0-1) ± standard deviation	EPT	QMCI	MCI	Qualitative description based on metrics*
Ōtūkaikino Creek u/s Dickeys Rd	High	0.81 ± 0.12	11	5.5	99	Mild-moderate pollution
Puharakekenui/Styx River at Claridges Rd	Medium-high	0.64 ± 0.11	7	4.4	84	Severe pollution
Dudley Creek	Medium	0.53 ± 0.11	2	3.7	63	Severe pollution
Ōtākaro/Avon at Mona Vale	Medium	0.52 ± 0.18	7	3.2	86	Severe pollution
Waimairi Stream (d/s)	Low-medium	0.33 ± 0.22	4	3.2	81	Severe pollution
Riccarton Stream	Low-medium	0.25 ± 0.10	2	3.5	72	Severe pollution
Addington Brook	Low-medium	0.21 ± 0.20	1	3.1	70	Severe pollution

Notes: † From monitoring undertaken in 2022 for Ōtūkaikino Creek; 2018 for Styx River and 2019 for Avon catchment sites.

* Description from NPS-FM Table 14.

For the remaining five sites, the order (in terms of highest to lowest based on the measured macroinvertebrate scores) varied depending on the score used. Although there were differences in the measured QMCI and MCI scores between sites, all were below 4.5 and 90 respectively (Instream Consulting 2018a) and indicative of severe pollution or nutrient enrichment (New Zealand Government 2023). The predictions from the BN for Dudley Creek and the Ōtākaro/Avon River at Mona Vale of medium macroinvertebrate scores appear too high, when compared to the measured EPT, QMCI and MCI, which suggest severe pollution. This suggests the model may need some refinement for Ōtautahi streams. The scores for the remaining three sites have relatively large standard deviations and there is essentially no difference between the predictions for these three sites. That seems consistent with the monitoring data – particularly for Riccarton Stream and Addington Brook with minimal difference in the EPT and MCI scores.

Overall, the comparisons for the seven sites suggests the BN model may provide useful results, although the predictions may suggest distinction between some sites where the monitoring data suggests minimal difference.

The BN model can be easily used to test future scenarios by selecting different states for any of the input nodes. The effect of reducing copper, zinc and sediment was tested for Ōtākaro/Avon River at Mona Vale, Addington Brook and Riccarton Stream. Median and 95th percentile copper, zinc and sediment concentrations were reduced by 30%.

Even with this reduction, median zinc concentrations in Addington Brook would remain above water quality guidelines in at least 50% of samples. Based on that, there were no changes to the predicted macroinvertebrate score for Addington Brook (not shown).

Similarly, at the Ōtākaro/Avon River Mona Vale site, changes in copper, zinc and sediment concentrations are not expected to affect the overall water quality for invertebrates as these concentrations are already relatively low. Nitrate-N concentrations at this site are expected to remain above guideline concentrations, and thus the “water quality for invertebrates” score remains the same as does the predicted macroinvertebrate score (not shown).

In Riccarton Stream, the median zinc concentrations would be within the ANZECC (2000) guideline with a reduction of 30%. This results in a slightly improved score for the “water quality for invertebrates” which results in a slight improvement for the overall macroinvertebrate score – from 0.20 to 0.24 (Figure 5-4). A greater improvement in the macroinvertebrate score (to 0.40) is predicted by removing the bank reinforcing from the stream (Figure 5-5). The sensitivity of the predicted response to changes in zinc appears to be relatively low. If this model is used further, future steps should include a sensitivity analysis of the model. Ideally this would be include some ground-truthing of the sensitivity by comparing sites with higher and lower zinc concentration, but similar attributes in terms of riparian condition and instream habitat.

It must be noted again that parts of this model were constructed from expert judgement, the system had only limited calibration within the UPSW project and that did not include Ōtautahi streams. The model has been tested here with no further calibration. The effects on macroinvertebrate communities of reach-scale drivers, like instream habitat, including the presence of bank lining, macrophyte and periphyton cover, may need to be further assessed, either through an updated review of literature or through an expert elicitation process.

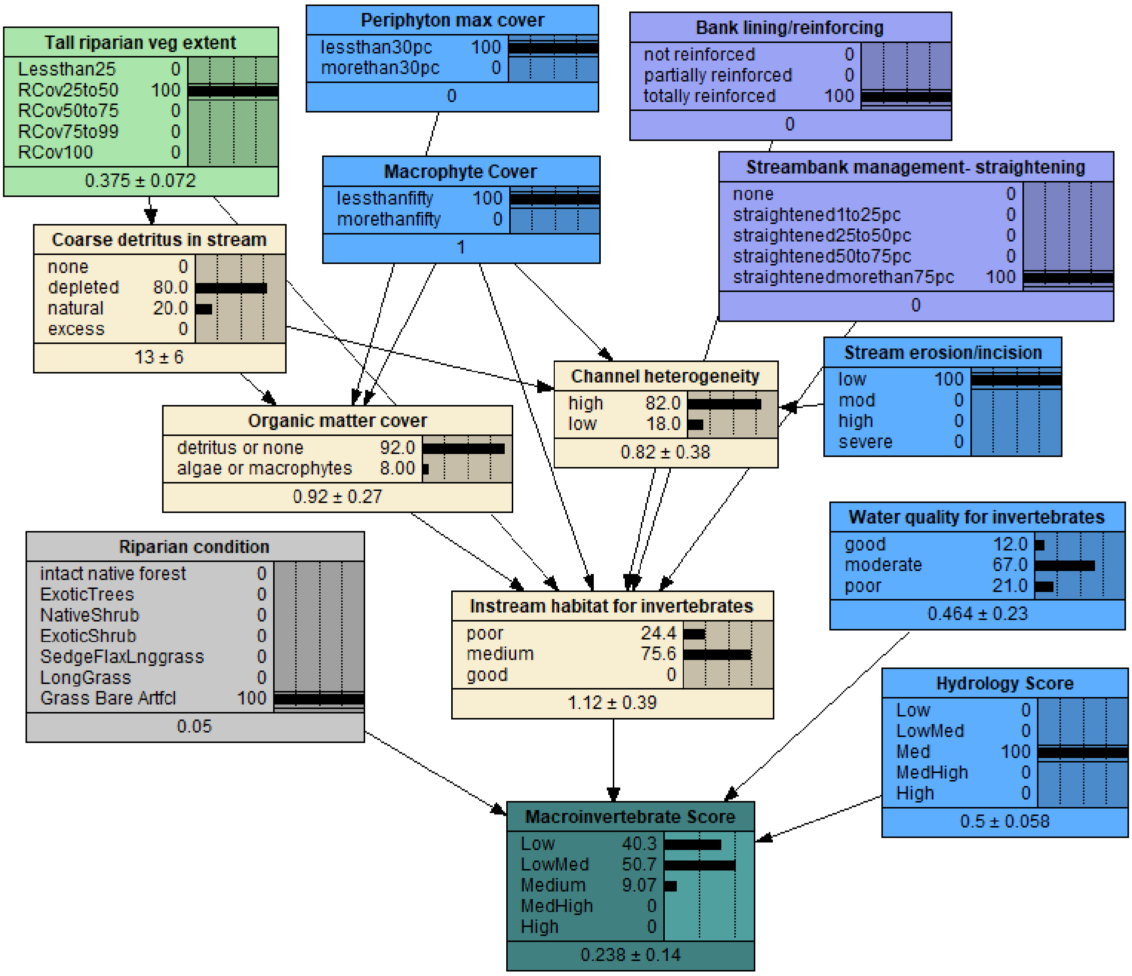

Figure 5-4: Bayesian Network model inputs and predictions for the Riccarton Stream site after improvements in water quality.

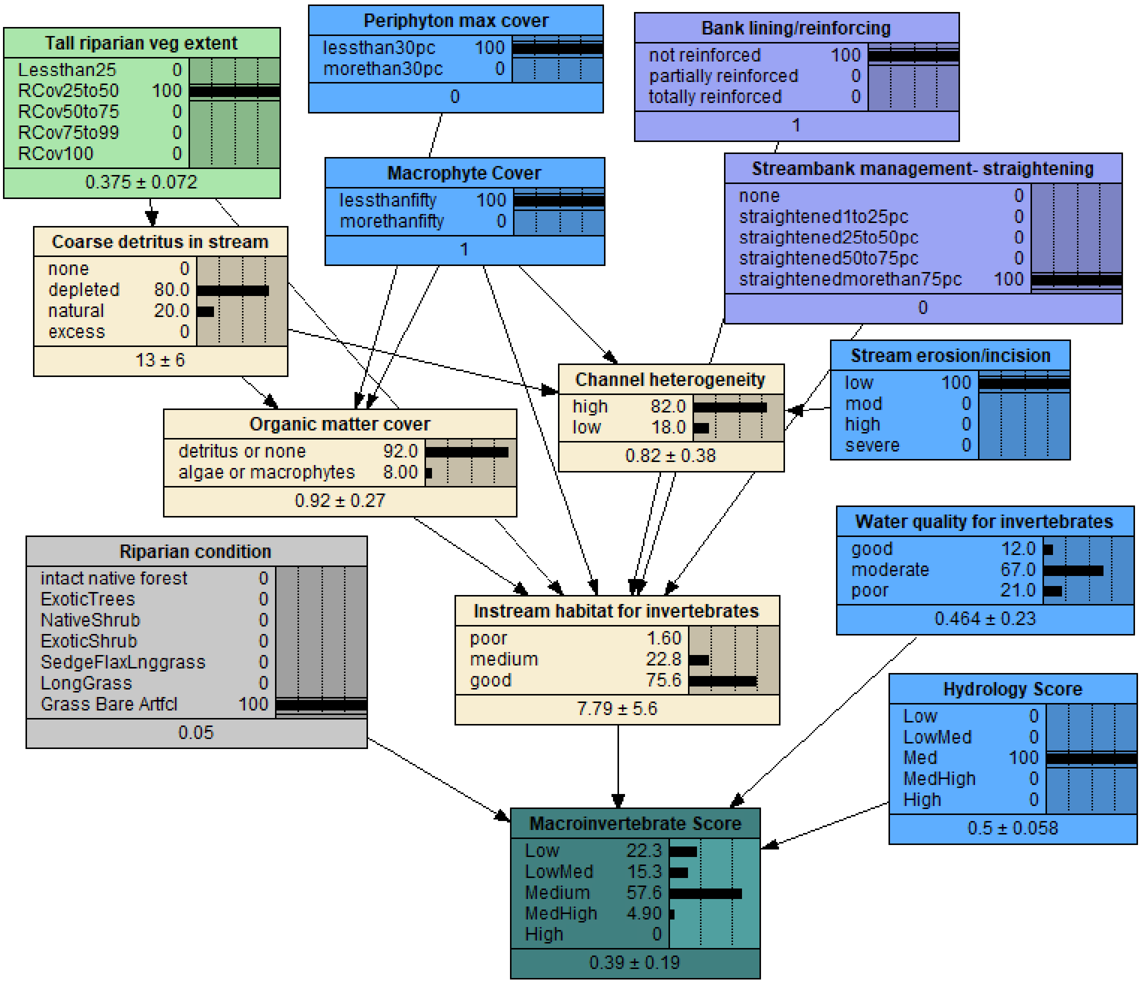

Figure 5-5: Bayesian Network model inputs and predictions for the Riccarton Stream site after improvements in water quality and removing the streambank lining.

5.4 Statistical models – GAMM example

As recommended in Section 4.5, we tested a GAMM model using the data available and report on key findings.

GAMM models were selected as the trial methodology because of their flexibility with non-linear relationships between predictors and response variables (non-linear relationships are likely in macroinvertebrate community metrics in response to some stressors, see Larned and Schallenberg (2019)) and their ability to include random terms to account for non-independence of observations within waterways. Different model types (i.e., GAMM, GLMM, RF, etc.) can give slightly different results. Combining the predictions from several different model types via ensemble modelling or model averaging can help determine the level of uncertainty in the predictions generated – however, for this feasibility stage only one model type was trialled.

We selected QMCI-hb as the response, as suggested in the workshop, and as summarised in section 3.2.2. Significant pairwise correlations with QMCI_hb and percentage EPT individuals and MCI-hb indicated that results may be similar for several of the macroinvertebrate metrics. We also included a model for %EPT (excluding hydroptilidae) for comparison with QMCI-hb models, as EPT metrics have been shown to respond to a wider range of environmental stressors, including temperature, flow alterations, and sedimentation, as well as nutrient enrichment (Wagenhoff et al. 2016). EPT taxa have also been shown to be a more reliable indicator of heavy metals in New Zealand streams (Hickey and Clements 1998).

Because many macroinvertebrates move between river reaches by drifting and crawling, sites that are connected longitudinally by water flow are likely to have more similar macroinvertebrate communities compared with non-connected sites. Therefore, a random term for each waterway was required to account for this variance and to meet the assumption of independence between sampling sites.

We identified over 100 potential predictors, including mean, median and maximum values of variables relating to dissolved metals, nutrients, clarity, deposited and suspended sediment, and hydrological metrics, among others. Many of these variables are at least moderately correlated (for example, $r = 0.44$ for DRP_median and TSS_median, $r = 0.89$ for dissolved zinc_median and dissolved copper_median), making identification of key stressors challenging. In addition, due to the relatively small dataset ($n = 53$ sites with hydrological, water quality, ecology and sediment data), only 4 predictor variables were able to be included in each model due to computational constraints. As the objective of this report was to assess the feasibility of modelling, not to develop the best possible predictive model, detailed investigations of the best subset of predictors to include were beyond the scope of this report. However, determining which predictors to include will be an important critical step when developing models for prediction, particularly in multiple stressor systems like the Ōtautahi streams where interactions between stressors are likely. In such cases, predictors can be selected using a combination of expert knowledge of stressors and likely mechanisms of impact on macroinvertebrates and statistical comparisons of different model subsets that include different predictors to identify models that have the best fit to the data.

We tested models for QMCI-hb and percentage EPT individuals (%EPT – hydroptilidae) that included the predictors below. Note that these predictors were chosen based on our expert judgement, rather than the selection procedures described above. In choosing the predictors, we excluded one of any pair of predictors which were highly correlated (e.g. retained dissolved zinc but not dissolved copper) and predictors with poor data availability across sites. We also focused on predictors which have identifiable potential mechanisms of impact on macroinvertebrates (e.g. periphyton, a key food resource, and fine sediment, which impacts habitat availability) and predictors which were important in the wider context of the study (e.g., dissolved zinc, a target of stormwater management). The predictors we chose to include were: periphyton (as weighted composite cover of filaments and mats), percent silt/sand coverage of the streambed, water velocity and median concentrations of dissolved zinc. Again, these models have not been assessed against other models including different predictors and therefore should be considered example, rather than ideal, models.

The example models explained between 43.5% and 83.5% of the variation in QMCI or %EPT, although for EPT models a high proportion of variance was explained by the random waterway term rather than potential stressors. The predictive power of the models was also limited. We briefly assessed predictive power of the models with hold-one-out cross-validations. This method involves removing the data for one site at a time from the model, generating the model using the remaining sites and then predicting the QMCI or %EPT value for the site that was left out. This is then repeated for all sites. Models that predicted accurate values for the excluded sites would show high correlation and a 1:1 relationship between predicted values for each site and the actual observed value. The predictive power of the QMCI and %EPT models were poor for omitted sites, with observed vs jack-knife predicted points being relatively uncorrelated and not following a 1:1 line (Figure 5-6). In addition, predictions for individual sites for %EPT were occasionally negative for some sites (Figure 5-6, right), although this could also be addressed by using a different model distribution more suited to percentage data (i.e., binomial rather than gaussian).

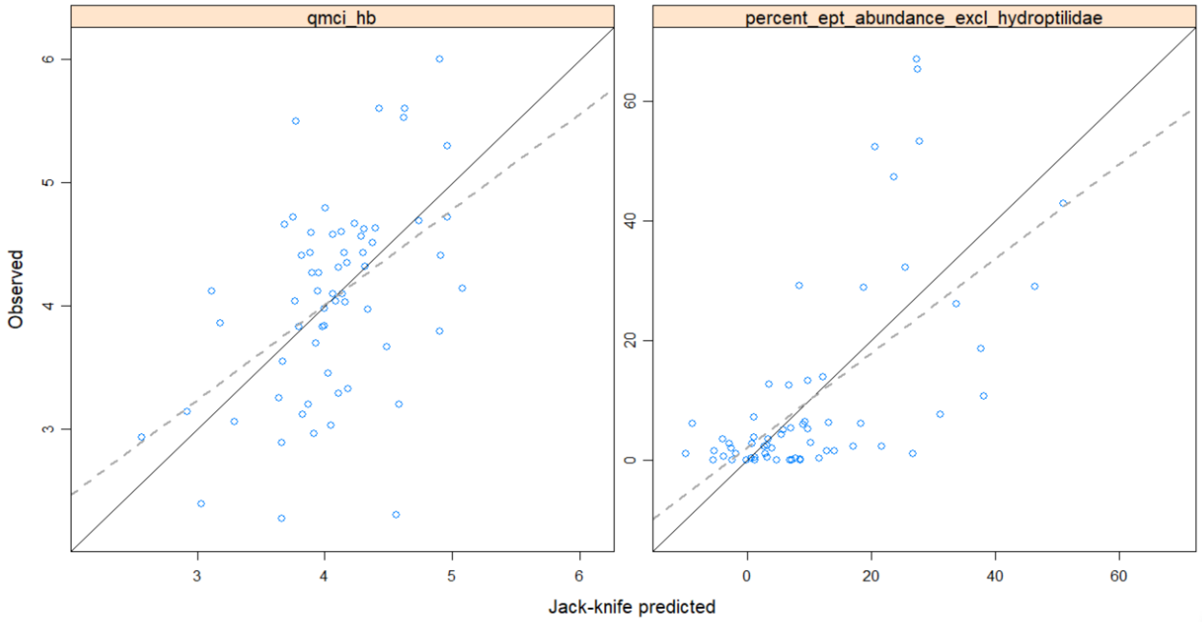

Figure 5-6: Results from hold-one-out cross-validation on GAMM models for QMCI-hb and %EPT. Observed values are on the y-axis and predicted values for each site, generated with that site excluded from the model development on the x-axis. The solid line indicates 1:1 and the dashed line the line of best fit through the data points.

Model diagnostics and partial dependence plots for each predictor, which visualise the relationship between the predictor and response when other predictors are held constant, indicated that degree of 'wiggliness' of some splines created by the models needed to be checked. For example, in Figure 5-7, the automatic settings (k = 9) led to the line being overfit to the data (left plot). The 'k' term is the number of basis functions or maximum possible degrees of freedom allowed for a smooth term in the model. A higher k makes it possible for 'wigglier' lines to be fit to the data, while reducing k limits the number of complexity of the spline that can be fit. K can be tested by comparing model fit of models with varying values of K and by examining diagnostic plots of model residuals.

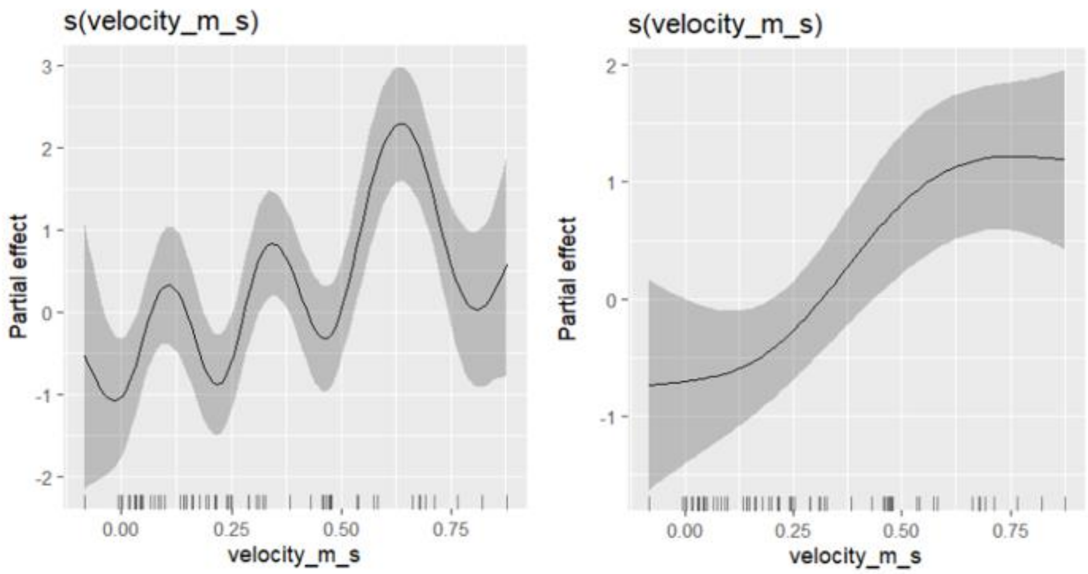

Figure 5-7: Example partial dependence plots for the relationship between water velocity and percentage ETP individuals (%EPT- hydroptilidae, yaxis) when the 'wiggliness' of the relationship is automatic (left, k =9) and limited (right, k = 4). Partial dependence plots show the relationship between the predictor and response when other predictors are held constant.

5.5 Feasibility assessment

The important factors for considering the feasibility of modelling ecological responses were outlined in section 5.1. These are summarised in Table 5-3, along with our assessment of that feasibility when using the BN or GAMM. In summary, we consider that the usefulness of GAMM models is currently constrained by the size of the dataset, which limits the number of potential predictors which can be tested at once. The BN, on the other hand, will be useful for scenario testing and making predictions for individual streams once it is parameterised for Ōtautahi.

Table 5-3: Summary of feasibility of modelling Otautahi Streams using a BN or GAMM.

Factor		BN		GAMM
Scope of model compared to CCC needs	<>	Semi-quantitative output – however the model does need further testing across Ōtautahi sites and conditional probability tables may need tweaking either for local suitability and/or to update with more recent knowledge on ecological stressors	<>	Quantitative output – however may be limited in ability to include all stressors
Scale of model – spatially	✓	Can be implemented at any site with input data. A spatial version could be developed (with considerable resource)	<>	Not site-specific, fit using data from all sites. Able to account for similarities in sites on the same waterway.
Scale of model – temporally	✗	Does not provide assessment of lag times for ecological recovery	✗	Does not provide assessment of lag times for ecological recovery
Data required	<>	The input data required is mainly available though may need additional analyses to generate the form required for model input	✗	Data is available but spatial and temporal mismatches limit the size of the dataset which in turn limits the complexity (i.e. number of predictors able to be included) of the model
Monitoring required to build or calibrate	✓	No further monitoring required but could be useful to increase spatial scope	<>	Increased collection of paired data at existing sites would be beneficial
Availability of reference sites	N/A	Not required	N/A	Not required
Uncertainty in the model	✓	BN model provides some indication of uncertainty through probabilities. Epistemic uncertainty (incomplete knowledge) cannot be assessed through model	✓	Predictive ability can be assessed through cross-validation
Effort to run model	✓	Minimal effort to run the BN, however a moderate effort would be required to validate this model for Otautahi	<>	Minimal effort to run the models once R scripts developed – however, might be necessary to run large numbers of possible models for comparison

6 Feasibility of modelling responses in Ihutai

6.1 Introduction

In this section, we consider the feasibility of using a model or models to predict future ecological state in Ihutai. As outlined for the freshwater systems, feasibility depends on:

- The scope of the models compared to the needs of CCC, including the type of output (quantitative vs qualitative).
- The scale of the model (spatial and temporal) compared to the needs of CCC, including how the model can consider lag times.
- The data required versus the data available, including consideration of the limitations in that data.
- The monitoring required to build and/or calibrate models and, briefly how and where this should be undertaken.
- The availability (or lack of) reference sites if needed for modelling.
- The likely uncertainty in the model.
- The effort required to develop and/or run any model including some indication of the time required.

The monitoring data reviewed in section 3.3.1 suggests there are insufficient data for Ihutai to develop statistical/empirical models. There are few sites and a narrow range of metal concentrations. Data for Ihutai could be combined with that for other estuaries around New Zealand for model development. However there are already exist three national-scale models for New Zealand estuaries, based on empirical data and/or expert judgement. Of these three, the estuarine BN model is the only one to include the three key variables of copper, zinc and sediment (mud) along with nitrogen. We therefore consider it to be the most suitable model for CCC in assessing the effect of changes in copper, zinc and sediment loads, in an eutrophic estuary. The model predicts benthic macroinvertebrate abundance and diversity, two responses that would be useful for CCC; though it does not include a cultural health index. The key advantage of this model over the BHM and ETI is that it incorporates multiple stressors to predict future state, rather than predictions based on single stressors alone, which do not fully account for the complexities of ecological systems and their stressor responses (Bulmer et al. 2022b). One disadvantage of this model is that it is a steady-state model and does not predict the time required for ecosystem changes to occur. However, this is also true of the BHM and ETI models.

The USC-4 model could be used first to predict the mud content and metal concentrations in the (benthic) sediment under scenarios of decreasing sediment and metal loading, and that output used for the BN inputs required. One advantage of the USC-4 model is that it can be run to provide a time-series output – that is, to predict the sediment-metal concentrations and mud content over time, with decreases in stormwater loading. This could help in understanding the time required for changes in sediment and metal loads to result in responses in the receiving environment – at least in the time it takes for changes in bed sediment concentrations.

6.2 Testing the estuarine BN model

The BN model was tested using data for two sites: Ōtākaro/Avon River mouth and Causeway. Differences in the macrofauna communities have been reported for these two sites (Berthelsen et al. 2022), with greater diversity at the Causeway site, as well as greater abundance of large bivalves (specifically the wedge shell *Macomona liliana* and the cockle/tuaki *Austrovenus stutchburyi*). These species are representatives of "large bioturbating deposit feeders" (*M. liliana*) and "large suspension feeding bivalves" (*A. stutchburyi*), two ecological indicators predicted by the BN model.

Input data were collated from the regular Ihutai monitoring data for sediment quality and water quality (Table 6-1, see Appendix C for details of states). Note that the BN requires sediment-metal concentrations in the <500 µm fraction of sediment, i.e., after coarse sand and shells have been removed. In the Ihutai monitoring, metals are analysed on the <2 mm fraction, which also excludes shells but includes coarse sand. However, these values were used for this initial BN model testing with no adjustment for the difference in grain size.

Table 6-1: States of stressor inputs used to test the BN model. States selected were based on data from CCC and Environment Canterbury monitoring. The range of concentration/values of each state are provided in this table, see Appendix C for definitions of possible states for each stressor.

Stressor input	Ōtākaro/Avon River mouth, 2016	Causeway, 2016
Mud in sediment	High (51-90%)	Low (5-20%)
Metals in sediment	High (0.23-1)	Low (-1.64—0.67)
Suspended sediment in water column	Low (5-<20 mg/L)	Low (5-<20 mg/L)
Total nitrogen in water column	High (0.33 -1.1 mg/L)	Moderate (0.2- <0.33 mg/L)

For the Causeway site, abundance of large bioturbating deposit feeders and abundance of suspension feeding bivalves had the greatest likelihood (highest percentage) of being "moderate" (Figure 6-1). The "moderate" category relates to an abundance of around 1-2 per 13 cm core for large bioturbating deposit feeders and around 10-20 per 13 cm core for suspension feeding bivalves (see Appendix C and Bulmer et al. 2022a).

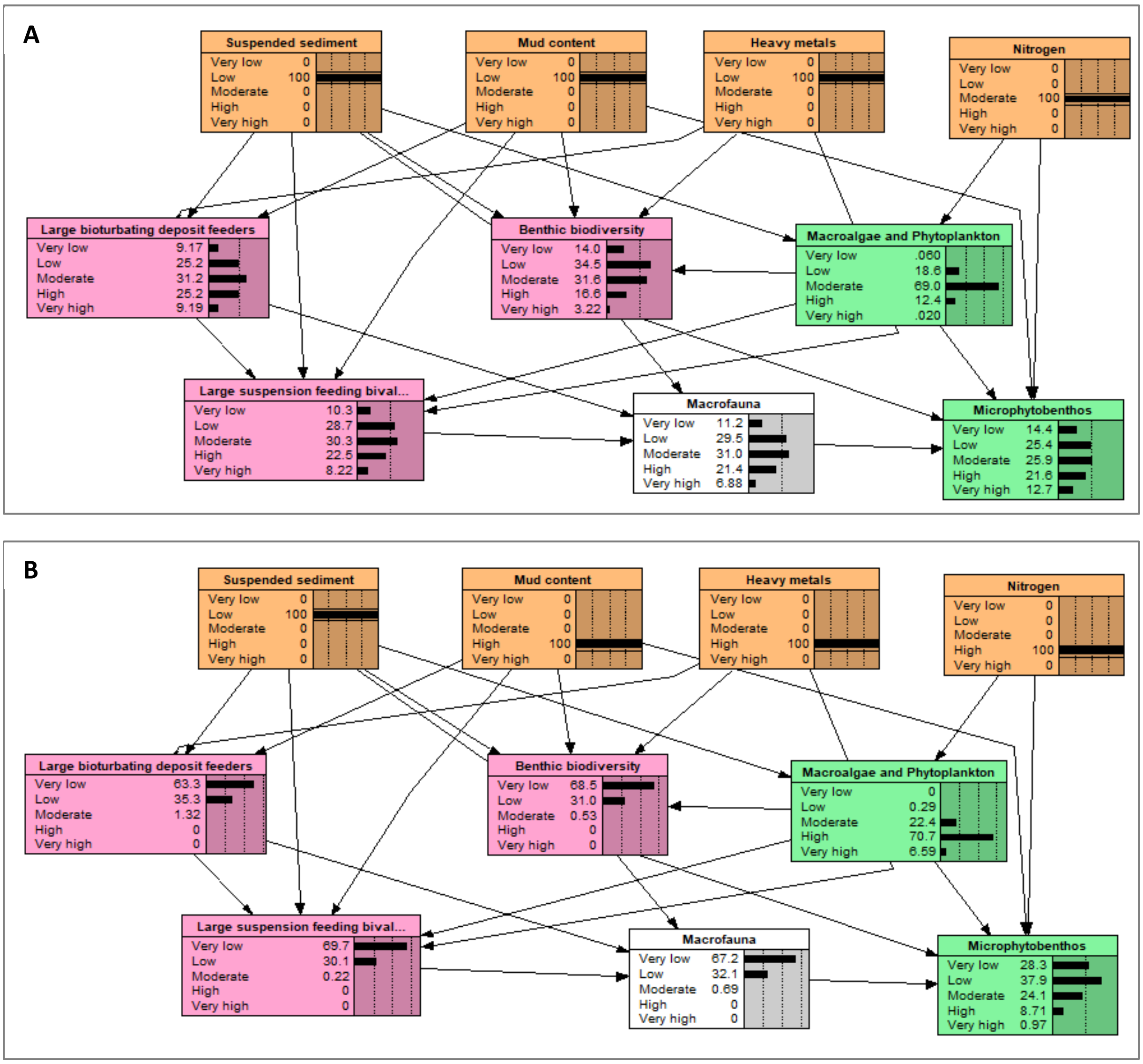

Figure 6-1: Demonstration of estuarine BN model results using input for the a) Causeway site and b) Avon River mouth under recent conditions. See Table 6-1 for input values and section 4.4 for explanation of the model.

This prediction is generally consistent with that reported by Berthelsen et al. (2022), though *M. liliana* (a large bioturbating deposit feeder) was frequently more abundant than the “moderate” state, at 2-10 per core from 2018 to 2021, which is more consistent with the high (2-3) to very high (>3) states, which were predicted with a 25% and 9% probability (Figure 6-1). Benthic biodiversity was predicted to be low to moderate (10-20 different species per core) which is consistent with the monitoring data where diversity ranges from an average of 10 to 15 infauna taxa per core (Berthelsen et al. 2022).

By contrast, the Ōtākaro/Avon River mouth site was predicted to most likely have very low abundance of large bioturbating deposit feeders (i.e., not present) and very low abundance of suspension feeding bivalves (i.e., <1 per core). This is consistent with the monitoring results demonstrating the scarcity of these two bivalves since 2012 (Berthelsen et al. 2022). Very low benthic biodiversity (<10 different species per core) was predicted for this site, consistent with monitoring data of 5-10 different species since 2008. In a future scenario, where the metal concentrations at the Ōtākaro/Avon River mouth decreased by approximately 50% to a "moderate" state (which is similar to the concentrations measured in 2011), there is a slight change in the prediction for all three macrofaunal measures. In this scenario, there is an approximately 50:50 chance of "very low" or "low" counts of bioturbating deposit feeders, and similarly the chances of other macrofauna indicators being "low" (rather than very low) increases.

6.3 Feasibility assessment

The important factors for considering the feasibility of modelling ecological responses were outlined in section 6.1. These are summarised in Table 6-2, along with our assessment of that feasibility when using the USC (or another model to predict sediment quality) combined with the estuarine BN. In summary, we consider that it is feasible to use these models to predict changes in macrofaunal communities (as an indicator of biological communities) as contaminant loads change over time.

Table 6-2: Summary of feasibility of modelling Ihutai with USC and BN.

Factor		Comment
Scope of model compared to CCC needs	✓	Quantitative output
Scale of model – spatially	✓	Can be implemented at any site with input data. A spatial version could be developed (with considerable resource)
Scale of model – temporally	✗	Does not provide assessment of lag times for ecological recovery
Data required	<>	Minimal data required. Sediment quality data available is not in the form required by the BN model but it may be possible to relate the metal concentrations measured in Ihutai sediments (within the <2mm fraction) to that required by the BN (metals in <0.5mm fraction) using data where metals have been measured in both size fractions.
Monitoring required to build or calibrate	✓	No further monitoring required but could be useful to increase spatial scope
Availability of reference sites	N/A	Not required
Uncertainty in the model	✓	BN model provides some indication of uncertainty through probabilities. Epistemic uncertainty (incomplete knowledge) cannot be assessed through model
Effort to run model	✓	Minimal effort for BN, some resource required for USC-4, moderate resource for a spatial version of BN, extensive resource required for other sediment deposition models

7 Discussion of limitations, conclusions and recommendations

7.1 Limitations of the compiled datasets for developing predictive models

The combined datasets of invertebrates, physical habitat, water quality, sediment and hydrological data for both Ihutai and the rivers were generated by compiling smaller datasets that were collected for other purposes, not with the intent of developing predictive models. This resulted in datasets, particularly for the rivers, with spatial and temporal mismatches between ecological, hydrological, sediment and water quality data. For example, 30 of the 69 freshwater macroinvertebrate sites did not have hydrological, water quality or sediment quality data for the same location, and even more sites had different types of data collected over different time periods.

The low temporal resolution of macroinvertebrate data available for this project (5-yearly monitoring for most sites) means that predictive models would need to be generated using between-site differences to generate predictions of what may happen within a site over time as mitigations are enabled. The limitations of such 'space-for-time' models are discussed in Section 7.2.

Other potential limitations of the compiled datasets include:

- The relatively small size of the estuarine (n = 6) and freshwater (n = 69 sites but n = 53 sites with hydrological, ecological, water quality and sediment data) datasets limited the complexity of statistical models that could be developed. For example, the GAMMs could only include approximately four predictor variables.
- Difficulties in separating correlation and causation between potential stressors and biological responses is a common problem in statistical models that are developed based on data collected in the field. Identifying key causative stressors is further complicated when multiple potential stressors are present. Careful selection of sites that occur along independent gradients of different stressors can make field surveys more informative regarding causative relationships. However, the multiple stressor nature of urban waterways makes it challenging, and sometimes impossible, to select appropriate sites. Experimental manipulations of different stressors can also identify causal relationships, though care must be taken to maintain relevance to real-world situations.
- In general, using macroinvertebrate metrics (such as the MCI and QMCI) is convenient for reporting efficiency (i.e., a change in one number). However, identifying the key stressors that result in changes in macroinvertebrate metrics is very challenging and currently a high priority research area within New Zealand, with no current efficient solution.

7.2 Uncertainty in predictions due to ecological constraints

A predictive model uses the data or assumptions available to predict what may happen under different scenarios. Several potential limiting factors should be considered when assessing whether the predictions of a model are likely to actually transpire.

Models developed based on data from sites with a range in stressor levels (e.g., copper, zinc and/or sediment concentrations), such as the national-scale models that are available or models that could be developed using CCC data can be considered space-for-time substitutions (Pickett 1989), for a model where contaminant concentrations decrease over time with improved stormwater management. Space-for-time substitutions indicate what the potential scope for recovery is, based on the macroinvertebrate communities that exist in sites with similar conditions to the reduction targets. However, a key limitation is that these models do not incorporate any additional constraints on ecological recovery, such as legacy effects of contaminants or limits on dispersal and recolonisation which may result in time lags between contaminant reduction and ecological improvements or smaller ecological improvements than predicted. Whilst this limitation could be overcome using a time-based model – that is, observing changes over time at a single site to develop relationships – that approach would also have limitations, including time delays and transferability of observations at one site to another.

Contaminants can continue to have short- and long-term impacts on stream process and biodiversity even after inputs have ceased or decreased (Harding et al. 1998, Zhang et al. 2009, Pereda et al. 2019). The time to recovery may also vary with the magnitude (Pereda et al. 2019) and duration (Harding et al. 1998) of impact. Relatively rapid recovery has been observed following short-term disturbances, while long-term disturbances such as agricultural land use or forestry have been reported to affect stream biotic diversity up to 40 years later (Harding et al. 1998, Zhang et al. 2009). In addition, a reduction in contaminant load inputs may not affect biological communities if there are existing reservoirs in the receiving environments that are not removed from the system. For example, contaminated sediment may need to be removed from a waterway before improvements in biological communities are observed; or it may take a long time for those reservoirs to be removed through natural processes of sediment accumulation and burial.

In addition, ecological restoration studies have shown that improving in-stream conditions such as water quality and habitat heterogeneity is often insufficient to improve biodiversity of stream fauna due to dispersal and biotic constraints. Dispersal constraints relate to the capacity for recolonisation – i.e., is there a suitable source population within the distance that species can move between habitats (Sudermann et al. 2011, Tonkin et al. 2014). For example, a study on river restoration success in Germany found that restoration of stream habitat was only associated with biodiversity improvements when there was a source population of additional desired taxa within 5 km of the restored site (Sundermann et al. 2011). Physical barriers can also constrain recovery, as demonstrated in Okeover Stream (Blakely et al. 2006).

Furthermore, recolonisation takes time. Several studies have reported no significant increases in stream macroinvertebrate biodiversity for up to 20 years post-restoration (e.g., Palmer et al. 2010, Louhi et a. 2011, Leps et al. 2016). Parkyn and Smith (2011) predicted that recovery of macroinvertebrate communities in streams restored via riparian planting would likely begin 5-10 years after restoration when dispersal constraints were low (i.e., a source population within 1-2 km), but up to 20 years with moderate dispersal constraints, such as source populations > 2 km distant and separated by habitat fragmentation due to land use change.

Biotic constraints that can limit biological community recovery after contaminant reduction include trophic interactions such as competition and predation between species, as well as the sequence of colonisation and succession processes (Parkyn and Smith 2011, de Vries et al. 2020). 'Resistance to restoration' can also play a role, as in when degraded ecosystems become domination by hyper-tolerant, highly competitive species which prevent recolonization by desirable species (Barrett et al. 2021).

7.3 Conclusions of review of information and model testing

7.3.1 Freshwater

Data were available for a range of potential stressors of macroinvertebrate communities, although there were spatial and temporal mismatches in data availability for the different variables. Some potential stressors were correlated, indicating that separating effects of individual stressors may be challenging in some cases.

Given the low frequency of monitoring data for the biological communities, a ‘space-for-time’ approach is the most appropriate, where differences between sites can be used to infer potential changes within a site when conditions alter with stormwater management.

GAMM models were able to be run, incorporating a random term to account for biological similarities within waterways. However, the usefulness of these models was strongly limited by:

- the multiple stressor environment, requiring multiple predictors,

- the relatively small size of the dataset, which limits the number of predictors that can be included in each model, and

- spatial and temporal mismatches between variables in the dataset.

BN predictions broadly matched the order of the monitoring data for the seven tested sites. For two sites, the model predicted higher macroinvertebrate scores than have been measured (based on comparison to EPT, QMCI and MCI metrics). The testing suggested that BN could be suitable for predicting macroinvertebrate community responses to key stressors, including multi-stressor interactions, but that the model would need further refinement and parameterising for Ōtautahi streams.

The BN model could also be run at multiple time-steps (such as every year), using different inputs (e.g., contaminant loads) at each time step, to indicate the potential changes in ecological response over time. However, as this model is a steady-state model, each prediction is independent and does not consider what happened in the past. There is no way to assess any lags in the recovery of benthic communities at the changed sediment and water quality. The model can therefore be thought of as indicating the potential ‘best case’ for the fauna under the new sediment conditions.

7.3.2 Ihutai

The temporal and spatial resolution of the regular monitoring for Ihutai is not high enough to develop statistical models. However, it is feasible to use an existing BN model, which includes metals and nutrients, to predict the effects of those stressors on benthic invertebrate communities.

One advantage of the BN approach outlined above is the relatively low effort required to collate the data needed and to run the model. A second advantage is that the model can be used in the reverse mode – for example, a desired ecological state can be selected, and the model used to assess what sort of inputs (suspended sediment, nutrient and metal concentrations, mud content) are required to get to that state. The coarse outputs of this modelling approach may be considered a disadvantage, compared to a model that provides a definitive answer – however the probabilistic approach is more realistic, given our limited understanding of environmental systems and how they respond to multiple stressors.

The USC model (or any other sediment transport and deposition model) can be run as a time-series model to predict the metal-sediment concentrations over time with changes in sediment and metal loads delivered via stormwater. This will provide information on how long it may take for the changes in loads to result in changes in the sediment mud and metals content (i.e., lags in recovery).

As with the freshwater model, the BN model could also be run at multiple time-steps (e.g., every year) to predicted changes over time with changing loads and sediment concentrations. However, as this model is a steady-state model, it does not consider what happened in the past, and there is no way to assess lags in the recovery of benthic communities following reductions in stressor levels. Similar to freshwater streams, there may be factors that limit recovery of the benthic faunal communities, such as the need for source populations that allow organisms to recolonise sites within Ihutai. Again, the model can therefore be thought of as indicating the potential 'best case' for the fauna under the new sediment conditions.

7.3.3 Limitations of modelling

The datasets were compiled from data collected for purposes other than generating a predictive model. The following factors limit the development of predictive models using the current datasets:

1. Ecological, hydrological, sediment and water quality data are commonly not available at the same sites during the same time period, i.e., have spatial and temporal mis-matches.
2. Limited temporal data means that a 'space-for-time' approach is used, where differences in conditions between sites are used to predict what may happen within a site as contaminant concentrations decrease over time with stormwater management. This does not take into account lags in recovery times, and therefore may result in overly optimistic predictions.
3. The relatively small sizes of the datasets means that only comparatively simple statistical models can be generated using them, and it is not possible to include all identified potential stressors.
4. Separating correlation from causation is challenging using data from field surveys of environments where multiple stressors often co-vary.
5. Linking changes in values of community metrics, such as the MCI, to individual causative stressors is a challenging process for which there is no clear and simple solution currently available.

In addition, several ecological constraints may act to restrict the ability for biological communities to respond as predicted by ecological models. Historical legacies of contaminants within the waterways may be difficult to remove, and prevent establishment of new taxa. Likewise, if there are no suitable sources of sensitive taxa nearby then this lack of recolonists may limit improvement of the biological community.

7.4 Recommendations for next steps

7.4.1 Predicting future state in Ōtautahi Streams

At the workshop on 4th April, the findings of the model feasibility assessment were discussed, particularly for freshwater. Key messages discussed include:

- GAMM models are currently likely to be limited in their usefulness, given the limited number of predictors able to be included in the models.
- Summarising groups of potential stressors into combined variable scores using ordinations or similar before inclusion in a GAMM could allow more information to be included in the model, while limiting the number or predictors in the model. However, this will make it more difficult to identify particular key stressors.
- Data from other urban areas could be used to expand the datasets available for developing predictive statistical models, or for quantifying probability tables within BNs. The data would need to be assessed to make sure they are applicable to Ōtautahi.
- Bayesian Networks may be useful as a tool to demonstrate how multiple issues may need to be addressed before an improvement in macroinvertebrate communities can occur.
- Correlations between some of the stressors could be examined further to assess whether mitigations that reduce several correlated stressors could be more beneficial for biological communities than mitigations that target individual stressors.
- If/when future monitoring sites are established, consideration could be given to aligning with existing water quality, sediment, hydrology and macroinvertebrate monitoring sites.
- Locations of potential sources of sensitive taxa available to recolonise sites could be assessed to determine whether sensitive taxa are likely to disperse to restored sites.
- Targeted experimental work could help identify key stressors and the causative mechanisms through which they impact biological communities. Experiments need to be realistic to real-world field conditions to be particularly informative. Other options are to target field sites that vary independently across gradients of different stressors. Identifying such sites in the field is likely to be very challenging, if not impossible however, due to the multiple stressor environment of urban waterways.

The recommendation from this report and from the workshop is to further investigate the use of the BN model for predicting the effects of contaminants on freshwater ecosystems. The next steps required for this include:

1. Collating data in the form required for input to the BN (including impervious surface area).
2. Testing the model for all available sites across Ōtautahi and assessing the accuracy of those predictions of current state.
3. Updating the model conditional probability tables based on either data for Ōtautahi streams (learning from cases), literature information, and/or expert opinion where sufficient data are unavailable.
4. Adding new nodes for factors not currently included such as distances to colonist sources.
5. Re-testing the model predictions based on the updated model.
6. Running sensitivity analyses of the model predictions including assessing the predicted effect of reducing metals and/or sediment compared to other management actions.

7.4.2 Predicting future state in Ihutai

The combination of a sediment quality model and the estuarine Bayesian Network are recommended for predicting the future state in Ihutai under reduced copper, zinc and sediment loads. There are several steps that need to be assessed to confirm the suitability of the models recommended for Ihutai:

1. Ihutai sediment quality is most frequently measured using the <2000 µm fraction, whereas the BN model uses the <500 µm fraction. A comparison of the two would be useful to assess whether any adjustments need to be made when using existing data to calculate the BN inputs.

2. A simple sediment model is needed to calculate bed sediment metal concentrations in the estuary based on the changes in sediment and metal loads delivered to the estuary. The USC-4 (or the original USC) may be suitable for this however, this needs to be investigated further and tested. It is likely to need some expert judgement around inputs such as settling rates and mixing depth.

3. Further testing of the BN model for all sites in Ihutai across all years of available monitoring data.

7.4.3 Final conclusion

The project goals are repeated below (in plain text) with an assessment of whether these have been met (italicised text).

- Assess the feasibility of:

  - Robustly predicting how and when the receiving environment might respond to changes in network contaminant loads and resulting in-stream concentrations, as well as changes in other limiting factors (e.g., habitat availability)

    We consider that it is feasible with a BN to predict how the receiving environment might respond, including addressing possible changes due to other factors. Assessment and/or development of conditional probability tables for stressors specific to Ōtautahi waterways, and the sensitivity of model outputs to changes in these tables, would improve the robustness of predictions. A BN is not well suited to assessing when changes may occur, as discussed in sections 7.2 and 7.3.3, however we know of no other models that would be suited to this).

  - Quantifying which limiting factors (i.e., not just stormwater treatment) would have the greatest ecological benefit, the quickest ecological benefit, or limited ecological benefit, if they were to be addressed,

    It is feasible to use a BN to assess benefits of factors other than contaminant loads. We consider the BN to be very suitable for this purpose. However, it may not be feasible to robustly assess which factors have the "quickest" ecological benefit, given lag times etc.)

  - Assessing the response within the waterways with consideration of a range of variables: Cultural Health Index, Water Quality Index, Macroinvertebrate Community Index/Quantitative Macroinvertebrate Community Index, and fish diversity and abundance, consistent with those used in the Healthy Waterbodies Action Plan (Margetts 2023).

BNs are well suited to assessing a range of different variables as identified by CCC. There is insufficient data (and quantitative information for stressor-response relationships) to predicted response in fish diversity and abundance)

- Assessing the response within Ihutai for the following variables: Cultural Health Index, Estuary Trophic Index, and benthic invertebrate abundance and presence.

  The Estuarine BN is well suited to predicting benthic invertebrate abundance and presence. There is potential to extend this model to the Cultural Health Index but the Estuary Trophic Index is not considered suitable as it does not consider effects of metals)

- Determine the resources required (e.g., time and money) to carry out the full assessment.

  For reasons of commercial sensitivity, this information is provided separately to CCC.

Overall, we consider that the project goals have been achieved. The next steps were outlined in sections 7.4.1 and 7.4.2 should CCC wish to proceed.

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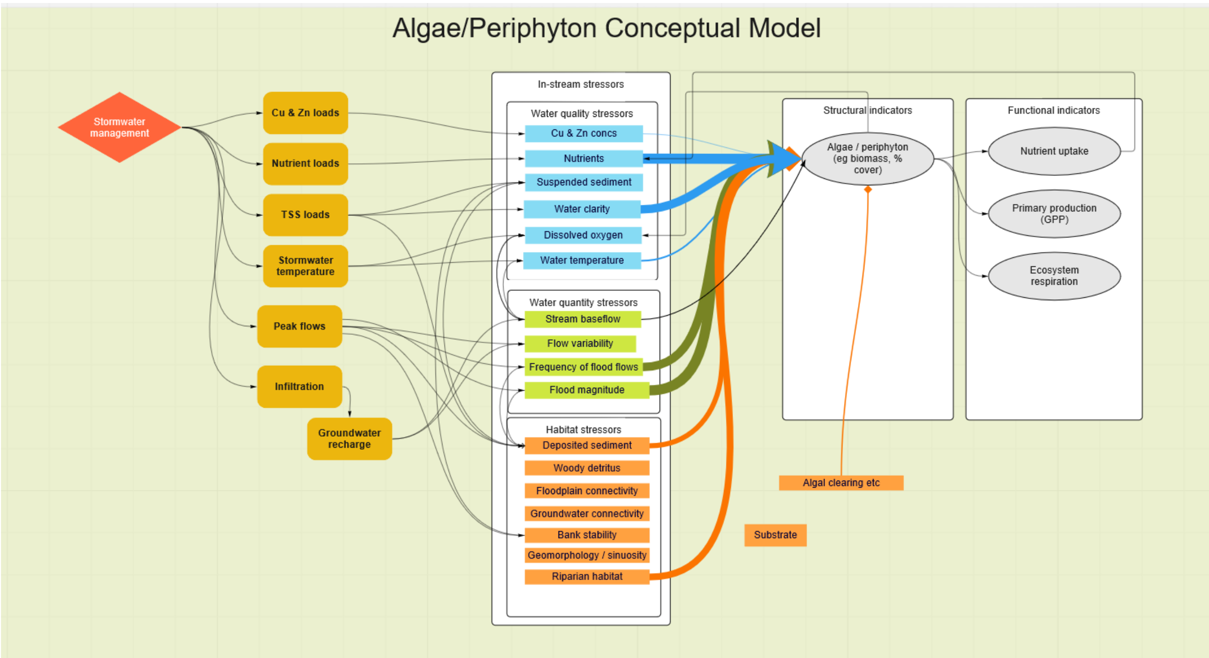
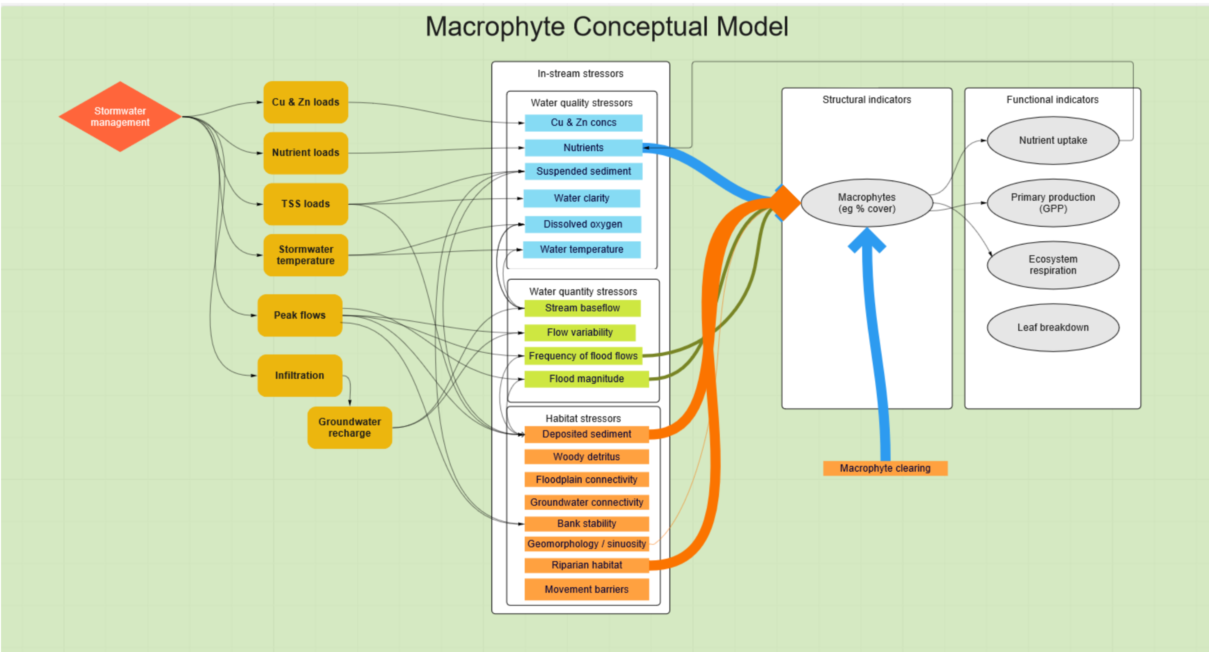
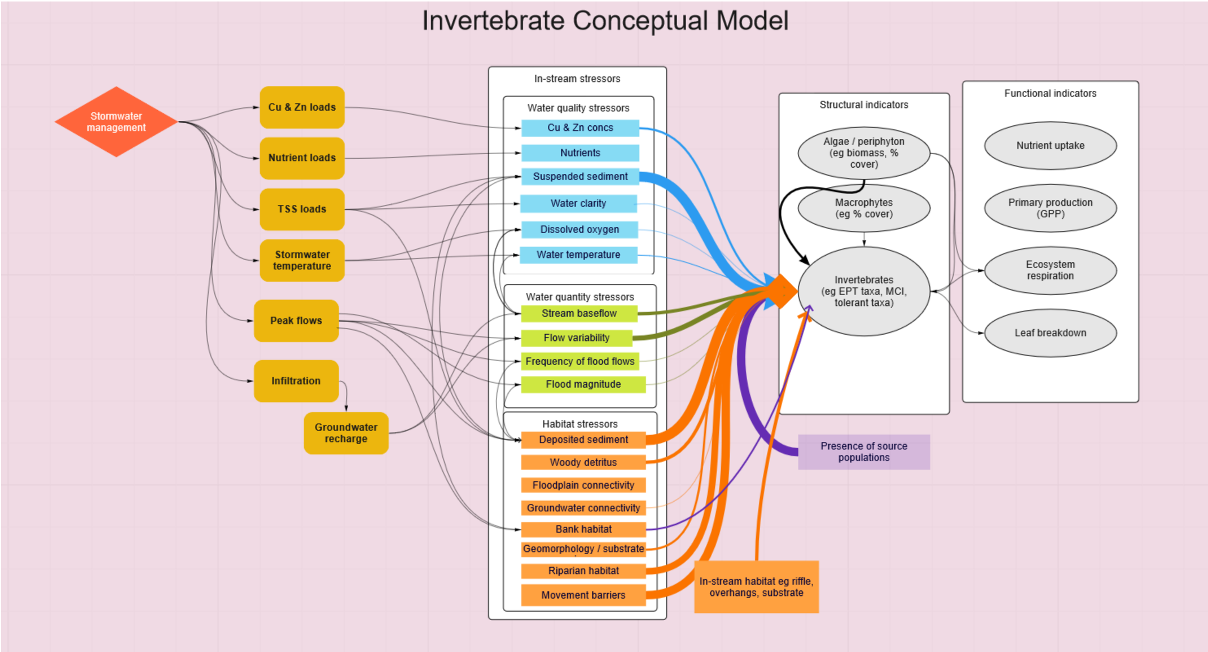
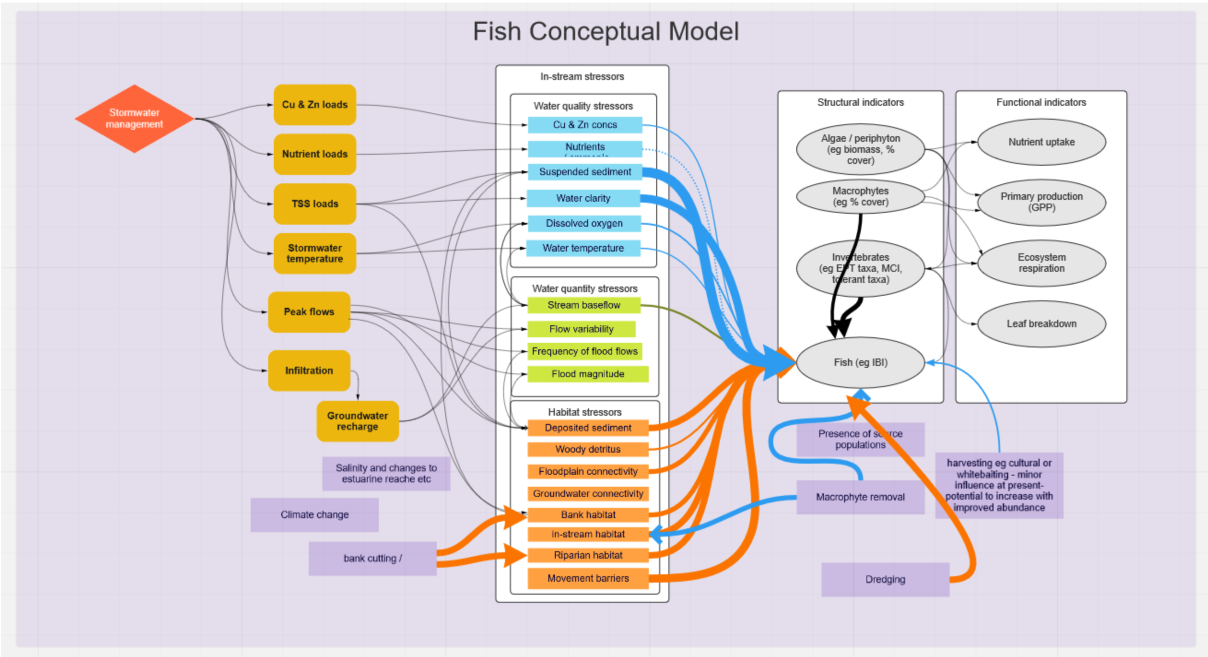
Appendix A Conceptual models derived in expert workshop

The following figures demonstrate the conceptual models as developed during the expert workshop. The thickness of arrows indicates the perceived importance of relationship. Arrow colours relate to stressor group. Thin black arrows demonstrate interactions between stormwater management and stressors or between stressors and other stressors. The relationships between stressors and biological indicators may be positive or negative and direct or indirect.






Invertebrate Conceptual Model
Stormwater management
Cu & Zn loads
Nutrient loads
TSS loads
Stormwater temperature
Peak flows
Infiltration
Groundwater recharge
In-stream stressors
Water quality stressors
Cu & Zn concs
Nutrients
Suspended sediment
Water clarity
Dissolved oxygen
Water temperature
Water quantity stressors
Stream baseflow
Flow variability
Frequency of flood flows
Flood magnitude
Habitat stressors
Deposited sediment
Woody detritus
Floodplain connectivity
Groundwater connectivity
Bank habitat
Geomorphology / substrate
Riparian habitat
Movement barriers
Structural indicators
Algae / periphyton (eg biomass, % cover)
Macrophytes (eg % cover)
Invertebrates (eg EPT taxa, MCI, tolerant taxa)
Functional indicators
Nutrient uptake
Primary production (GPP)
Ecosystem respiration
Leaf breakdown
Presence of source populations
In-stream habitat eg riffle, overhangs, substrate


Fish Conceptual Model
Stormwater management
Cu & Zn loads
Nutrient loads
TSS loads
Stormwater temperature
Peak flows
Infiltration
Groundwater recharge
Salinity and changes to estuarine reache etc
Climate change
bank cutting /
In-stream stressors
Water quality stressors
Cu & Zn concs
Nutrients
Suspended sediment
Water clarity
Dissolved oxygen
Water temperature
Water quantity stressors
Stream baseflow
Flow variability
Frequency of flood flows
Flood magnitude
Habitat stressors
Deposited sediment
Woody detritus
Floodplain connectivity
Groundwater connectivity
Bank habitat
in-stream habitat
Riparian habitat
Movement barriers
Structural indicators
Algae / periphyton (eg biomass, % cover)
Macrophytes (eg % cover)
Invertebrates (eg EPT taxa, MCI, tolerant taxa)
Fish (eg IBI)
Functional indicators
Nutrient uptake
Primary production (GPP)
Ecosystem respiration
Leaf breakdown
Presence of source populations
Macrophyte removal
harvesting eg cultural or whitebaiting - minor influence at present- potential to increase with improved abundance
Dredging

Appendix B Thresholds used for freshwater stressors

Various thresholds were collated to assess the potential key stressors (habitat, water quality and sediment quality) currently affecting biological communities in Ōtautahi streams. These thresholds are largely from regulations and guidelines used in New Zealand or Canterbury.

Table B-1: List of thresholds used to assess potential stressors in Ōtautahi streams.

Stressor (and summary statistic used for comparison)	Unit	Thresholds	Source of threshold
Habitat			
Fine sediment	% cover	9, 18, 27	NPS-FM NOF for class 3
Shading	%	10, 25, 50, 70, 90	Combination of (Davies-Colley & Quinn 1998) and (Harding et al. 2009)
Total macrophyte cover	%	50	Matheson et al. (2012)
Long filamentous algal cover	%	20, 40, 55	Matheson et al. (2012)
Periphyton Weighted Composite Cover (WCC) index	%	20, 40, 55	Matheson et al. (2012)
Water quality			
Dissolved zinc (95th percentile)	mg/L	0.0024, 0.008, 0.015, 0.031	ANZG (2018)
Total suspended solids (95th percentile)	mg/L	25	Stevenson et al. (2010)
Dissolved oxygen concentration (5th percentile)	mg/L	4, 5, 7.5	Richardson et al. (2001)
DRP (median)	mg/L	0.006, 0.01, 0.018	NPS-FM (2020)
Nitrate + nitrite-N (median)	mg/L	0.01, 0.33, 1.47	Canning et al. (2021)
Total ammoniacal-N (median)	mg/L	0.03, 0.24, 1.3	NPS-FM (2020)
Total nitrogen (median)	mg/L	0.001, 0.112, 1.833	TN (median) to achieve NOF bands A, B, C in unshaded streams, 10% risk, CD/L, (Snelder et al. 2022)
Nitrate-N (95^{th} percentile)	mg/L	1.5, 3.5, 9.8	NPS-FM (2020)
Nitrate-N (median)	mg/L	1, 2.4, 6.9	NPS-FM (2020)
Sediment			
Zinc	mg/kg	200, 410	ANZG (2018)

Appendix C States used in Estuarine BN

Table C1: Full description of stressor nodes, ecosystem component nodes, state ranges, the data used to create the states and the relationships with other nodes. (Modified based on Bulmer et al. (2019)).

Node	Unit and definition	State	Expert opinion informed by:	Relationships
Sediment mud content (Mud content)	*% Mud (silt and clay)* *% by dry weight of surface (generally top 2 cm) sediment particles in a sample <63 µm in diameter.*	• *Very Low: <5* • *Low: 5 to 20* • *Moderate: 21 to 50* • *High: 51 to 90* • *Very High: >90*	*Field data, such as the Tipping Points dataset and publicly available regional council monitoring data (Hewitt et al. 2009, Rodil et al. 2013, Thrush et al. 2012).*	*Input variable*
Suspended sediment	*Mean mg L^{-1}Total suspended solids (TSS)* *TSS is the dry-weight of all suspended particulate matter in a water sample (usually assessed by filtering the sample through a pre-weighed 0.8 or 1.2 µm pore size filter).*	• *Very Low: <5* • *Low: 5 to <20* • *Moderate: 20 to <40* • *High: 40 to 70* • *Very High: >70*	*Total suspended solid data from a nationwide summary of water quality data across New Zealand (Dudley et al. 2017) and field studies , or inferred from modelled estuarine sediment loads (retrieved from the NIWA sediment load model) (Hicks et al. 2019).*	*Input variable*
Nitrogen concentration	*Total Nitrogen mg L^{-1}* *Total Nitrogen concentration in a water sample.*	• *Very Low: <0.15* • *Low: 0.15 to <.20* • *Moderate: 0.20 to <0.33* • *High: 0.33 to <1.1* • *Very High: ≥1.1*	*Total Nitrogen data from a nationwide summary of water quality data across New Zealand (Dudley et al. 2017).*	*Input variable*
Metal concentration s (Metal)	*PC1.5* *Weighted concentrations of the metals Zinc, Copper, Lead within surface sediments (generally to 10 cm depth).*	• *Very Low: <-0.164* • *Low: -0.164 to -0.0667* • *Moderate: -0.0667 to <0.0234* • *High: 0.0234 to 0.1* • *Very High: >0.1*	*Data used to inform expert opinion obtained from principal component analysis (PCA) of publicly available monitoring datasets (Hewitt et al. 2009, Rodil et al. 2013), which include metal concentrations in surface sediments and are related to Auckland Council guidelines which are increasingly used throughout the country. Values are calculated using the equation below, where X is metal concentration in mg/kg. The PCA 1st axis explained 94% of the variability in log Copper (Cu.500), Zinc (Zn.500), and Lead (Pb.500).* *PC1.5 =* $0.615\times(X_{Cu}^{(500)})+0.528\times(X_{Zn}^{(500)})+0.586\times(X_{Pb}^{(500)})$	*Input variable*

Node	Unit and definition	State	Expert opinion informed by:	Relationships
Large bioturbating deposit feeders	Number of individuals per 13 cm diameter core (generally 15 cm depth). Large deposit feeders bioturbate the sediment, transporting organic material and changing oxygen gradients throughout the sediment column, influencing carbon and nutrient cycling processes. Examples include *Macomona liliana* (wedge shell), *Austrohelice crassa* (mud crab), *Hemiplax hirtipes* (mud crab), *Owenia petersenae* (tube worm), *Platynereis australis* (nereid polychaete worm)	• Very Low: Not present • Low: ≤1 • Moderate:1 to <2 • High:2 to 3 • Very High: >3	Field data, such as the Tipping Points dataset and publicly available regional council monitoring data (Hewitt et al. 2009, Pratt et al. 2014a, Thrush et al. 2003a).	*Suspended sediment* –Negative from Moderate to Very High (Thrush et al. 2004) *Mud content* – Positive from Very low to Low, Negative from Moderate to Very High (Ellis et al. 2017, Thrush et al. 2003b) *Metals* - Negative from Moderate to Very High (Ellis et al. 2017, Hewitt et al. 2009)
Large suspension feeding bivalves	Number of individuals per 13 cm diameter core. Act as key species in estuarine ecosystems by filtering the water column, influencing seafloor/water column carbon and nitrogen cycling, and providing an important food source for higher trophic levels, including humans. Large suspension feeding bivalves Examples *Austrovenus stutchburyi* (cockles),	• Very Low: <1 • Low: 1 to <10 • Moderate: 10 to <20 • High:20 to 40 • Very High: >40	Field data, such as the Tipping Points dataset and publicly available regional council monitoring data (Hewitt et al. 2009, Pratt et al. 2014a, Thrush et al. 2003a).	*Suspended sediment* –Negative from Moderate to Very High (Ellis et al. 2002, Lohrer et al. 2006) *Mud content* – Negative from Moderate to Very High (Ellis et al. 2017, Thrush et al. 2003b) *Metals* - Negative from Moderate to Very High (Ellis et al. 2017, Hewitt et al. 2009) *Large bioturbating deposit feeders* - Negative from Moderate to Very High (Lohrer et al. 2013) *Macroalgae and phytoplankton* – Positive from Very Low to Moderate,

Node	Unit and definition	State	Expert opinion informed by:	Relationships
	Paphies australis (pipi), *Pectinidae* (scallops), *Atrina zealandica* (horse mussel), *Perna canaliculus* (green shell mussel).			Negative from Moderate to Very High (Green et al. 2014)
Benthic biodiversity	Number of species per 13cm diameter core.	• Very Low: <10 • Low: 10 to <15 • Moderate: 15 to <20 • High: 20 to 25 • Very High: >25	Field data, such as the Tipping Points dataset and publicly available regional council monitoring data (Hewitt et al. 2009, Pratt et al. 2014a, Thrush et al. 2003a).	*Suspended sediment* – Increasingly negative from Moderate to Very High (Thrush et al. 2004) *Mud content* – Negative from Moderate to Very High (Ellis et al. 2017, Lohrer et al. 2004a, Thrush et al. 2003b) *Metals* - Increasingly negative from Moderate to Very High (Ellis et al. 2017, Hewitt et al. 2009) *Macroalgae and phytoplankton* – Negative (Green et al. 2014)
Macrofauna	Intermediate node which combines *large bioturbating deposit feeders*, *Large Suspension Feeding Bivalves*, and *Benthic Biodiversity* nodes via a simple weighted sum.	Intermediate node	Intermediate node used to reduce the number of parent nodes (and their complexity of relationships) feeding into child nodes throughout the model.	*Large bioturbating deposit feeders* – Positive *Large suspension feeding bivalves* – Positive *Benthic biodiversity* - Positive
Microphytobe nthos	Chlorophyll *a* ($\mu g\ g^{-1}$ sediment) Microphytobenthos consists of unicellular eukaryotic algae and cyanobacteria that grow within the upper several millimetres of sediments. Chlorophyll *a* is a pigment that can be measured by standard methods as a	• Very Low: <5 • Low: 5 to <12 • Moderate:12 to <20 • High: 20 to 30 • Very High: >30	Field data, such as the Tipping Points dataset and publicly available regional council monitoring data (Thrush et al. 2012).	*Suspended sediment* –Negative (Pratt et al. 2014b, Rodil et al. 2011) *Mud content* – Positive (Pratt et al. 2015) *Nitrogen* – Positive (Sandwell et al. 2009) *Macroalgae and phytoplankton* – Negative (Corzo et al. 2009, García-

Node	Unit and definition	State	Expert opinion informed by:	Relationships
	proxy for microphytobenthos abundance.			Robledo & Corzo 2011, Pratt et al. 2014b) *Macrofauna* – Positive (Lohrer et al. 2004b, Pratt et al. 2015, Rodil et al. 2011, Sandwell et al. 2009)
Macroalgae (nuisance) and phytoplankton	*Macroalgae:* Algal cover (%) and wet weight (g) per area (m^2) Nuisance Macroalgae (e.g., *Ulva* spp./sea lettuce and *Gracilaria* spp./red algae in soft-sediment areas). *Phytoplankton:* Chlorophyll *a* (mg l^{-1} water) Phytoplankton are microscopic algae within the water column. Chlorophyll *a* is a pigment that can be measured by standard methods as a proxy for phytoplankton abundance.	Due to similar model dynamics and to reduce model complexity, macroalgae and phytoplankton nodes combined. State based off the higher of the two values for nuisance macroalgae or phytoplankton. *Macroalgae:* • Very Low: Algal cover <2.5% and low biomass (<25 g/m^2 wet weight) of opportunistic macroalgal blooms. • Low: Algal cover 2.5-<5% and low biomass (25 to <50 g/m^2 wet weight) of opportunistic macroalgal blooms. • Moderate: Limited macroalgal cover (5– 20%) and low biomass (50 to <200 g/m^2 wet weight) of opportunistic macroalgal blooms. • High: Persistent, high % macroalgal cover (25–50%) and/or biomass (200 to 1000 g/m^2 wet weight), often with entrainment in sediment. • Very High: Persistent very high % macroalgal cover (>75%) and/or biomass (>1000 g/m^2 wet weight), with entrainment in sediment. *Phytoplankton:*	Nuisance macroalgae informed by outputs from a modified version of the estuary trophic index tool (Plew et al. 2019). Water column chlorophyll *a* concentrations informed from a nationwide summary of water quality data across New Zealand (Dudley et al. 2017).	*Suspended sediment* –Negative (Christine et al. 2003, Coutinho & Zingmark 1993) *Nitrogen* – Positive (Coutinho and Zingmark 1993, Anderson et al. 2002

Node	Unit and definition	State	Expert opinion informed by:	Relationships
		• Very Low:<0.001 • Low 0.001 to <0.0015 • Moderate: 0.0015 to <0.0028 • High: 0.0028 to 0.0042 • Very High: >0.0042		