Predicting Effects of Water Quality Improvements on Biological Communities

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EXECUTIVE SUMMARY

Christchurch City Council (CCC) holds a Comprehensive Stormwater Network Discharge Consent. The discharge consent requires that contaminant loads are reduced over time. In addition, the consent requires that CCC uses modelling or monitoring to predict ecological responses to changed contaminant loads and instream concentrations, if feasible. Following positive results from a feasibility study, this report describes results of a modelling study to evaluate ecological responses to key stormwater contaminants, with an emphasis on total suspended solids (TSS), copper, and zinc.

We used Generalised Additive Modelling (GAM) to evaluate relationships between water quality, habitat, and invertebrate metrics across the district. No strong relationships were found between copper or zinc and any invertebrate metrics. In contrast, TSS partially predicted invertebrate health – particularly QMCI and ASPM – although predictive strength varied between metrics and was sometimes weaker than physical habitat predictors. Overall, prediction of ecological responses required both water quality and habitat information.

Physical habitat and TSS concentration were typically the best predictors of invertebrate responses. Reductions in TSS concentrations, along with habitat improvements such as wider riparian zones and reduced deposited sediment cover, are predicted to increase ASPM and QMCI scores. The quantitative influence of each predictor was captured by partial plot equations. These relationships provide a basis for predicting how invertebrate communities respond to environmental management such as sediment reduction or habitat restoration. MCI predictions were not robust due to sensitivity to outliers. Thus, ASPM and QMCI were recommended for providing the most reliable guidance for ecological assessment and management planning.

Wider riparian zones, low bed cover with deposited fine sediment, and greater hydraulic heterogeneity support structurally complex and oxygenated substrates, promoting sensitive invertebrate taxa. Among water quality variables, TSS emerged as the primary stressor, with many sites exceeding the 25 mg/L consent attribute target level, reducing clarity, increasing sediment deposition, and degrading habitat. Dissolved copper and zinc concentrations were typically near or below guideline values, with occasional local exceedances (notably in the Heathcote River), highlighting the need for continued monitoring and targeted water quality improvements.

To support ecological restoration and management, recommended actions include protecting and restoring riparian buffers, reducing suspended and deposited sediments via erosion and stormwater controls, and enhancing instream hydraulic diversity in strategic reaches. Monitoring of TSS, copper, zinc, and nutrients should be maintained, and restoration efforts should prioritise sites with distinctly low invertebrate, habitat, and/or water quality conditions (example locations are provided in text). Restoration should be coordinated within catchments to address upstream stressors and maintain ecological connectivity with key source populations, maximising ecological benefits. Sediment management and habitat restoration should offer the most immediate positive responses in ecosystem health, while metals and nutrients remain relevant in localised areas. An integrated approach addressing both habitat and water quality improvements provides the best opportunity to restore ecological health across streams in the Christchurch district.

1. INTRODUCTION

Christchurch City Council (CCC) was granted consent by Environment Canterbury (ECan) in December 2019 to discharge water and contaminants from the stormwater network to land and water. This Comprehensive Stormwater Network Discharge Consent (CSNDC; CRC231955) includes a stormwater quality investigation programme (Schedule 3), which sets out several actions. One of these (Schedule 3, item d) requires CCC 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."

That study was completed by NIWA (Gadd *et al.* 2023), which concluded that such prediction is feasible. This triggered Schedule 3(e), which states:

"If the Consent Holder considers that the feasibility study under (d) shows sufficient merit, and the Council considers it warranted, instigate a programme of research, monitoring and/or modelling to quantify expected responses in the receiving environment. For example: Undertake selected monitoring of discharges at "end of pipe", into the receiving environment to assist model development and calibration."

Accordingly, this report presents results of modelling of CCC's existing monitoring data and quantifies predicted responses in freshwater receiving environments. Of particular focus is the influence of total suspended sediment, copper, and zinc, which are contaminants targeted under CCC's consent conditions. The focus is on freshwater environments, because there is a larger and therefore more robust monitoring dataset to inform a model than there is for coastal environments.

2. METHODS

2.1. Background

Condition 19 of the CSNDC requires a 20–30% reduction in loads of zinc, copper, and total suspended solids (TSS) over the 25-year duration of the consent. This is to be achieved through the installation of stormwater mitigation facilities and devices. It remains uncertain, however, whether such contaminant load reductions will lead to immediate or delayed improvements in biological communities. Two main issues contribute to this uncertainty. The first issue is that reductions in total loads do not necessarily translate into equivalent decreases in concentrations. For instance, a 15% reduction in the annual zinc load may have little effect on median concentrations if most of the reduction occurs during storm events or primarily affects particulate forms of zinc. Legacy contamination further complicates this relationship, as metals bound within streambed sediments may only diminish gradually, with recovery mediated by mixing and resuspension. The second issue is that ecological responses are shaped by multiple, interacting stressors. This means that even marked reductions in metals or sediments may not result in clear biological gains if other factors – such as habitat simplification, nutrient enrichment, or altered hydrology – remain limiting.

The consent requirement to consider "responses in the receiving environment" refers to effects on living things in drains, streams, rivers, estuaries, and the coast. In freshwater systems, the living things we monitor for ecosystem responses tend to focus on aquatic invertebrates, like snails and the larvae of flying insects such as caddisflies and mayflies. That is because invertebrates have life cycles in the order of a year, they do not move about as much as fish, and they are important fish food. Invertebrates and fish in urban environments are affected by altered catchment hydrology, habitat, water quality, and connectivity between habitats (Figure 1). Replacement of native vegetation and soil with hard surfaces from roads and roofs results in rapid rainfall runoff and greater flood disturbance. Simplified drainage networks, in the form of channel straightening, removal of riparian vegetation, and lining of banks with timber, concrete and rock, greatly reduces the habitat available for fish and invertebrates to live in. Lack of streamside vegetation in the form of trees and shrubs further reduces habitat, while also letting more light to the stream, which contributes to nuisance growths of algae and aquatic plants (macrophytes). Heavy metals from roofs, industry, and roads, and excessive nutrients from gardens and industry also affect aquatic life. Physical barriers such as tide gates, pump stations, and culverts limit movement of fish between areas of potentially good quality habitat, while culverts, roads, and lack of forest provide similar barriers to the adult flying stages of aquatic insects to colonise quality habitats. Collectively, these urban effects result in an “urban stream syndrome” of degraded ecosystem health ((Walsh *et al.* 2005). That means that improving ecosystem health can only be achieved by addressing all the causes of degradation: altered hydrology, water quality, habitat, and connectivity.

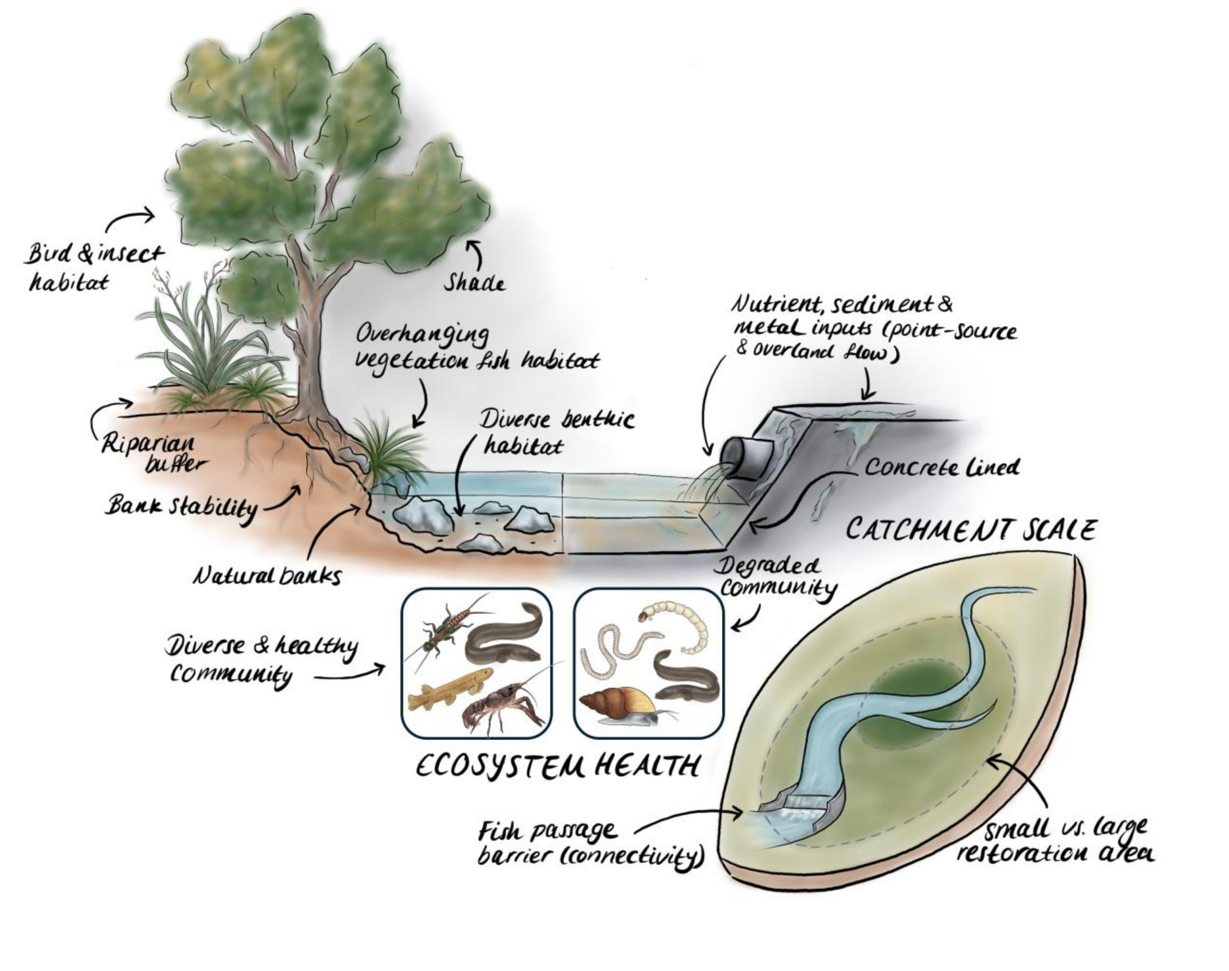

Figure 1: Diagram illustrating different aspects of habitat, water quality, hydrology, and connectivity that affect ecosystem health in natural (left) and highly modified urban environments (right). The lower right insert illustrates how catchment-scale factors also influence ecosystem health at the local scale.

The feasibility study of Gadd et al. (2023) assessed modelling options for predicting ecological responses in Christchurch's freshwater and estuarine environments, focusing on Bayesian Networks (BNs) and Generalised Additive Mixed Models (GAMMs). The BN, adapted from the Urban Planning to Sustain Waterbodies framework, performed reasonably well in ranking macroinvertebrate health across sites and was recommended as the most suitable option overall, since it can integrate multiple correlated stressors and incorporate expert knowledge where data are sparse. However, BNs rely heavily on expert opinion and assumptions rather than empirical data, and they cannot predict recovery timeframes. GAMMs were also trialled, using invertebrate community metrics as response variables, but they were constrained by the small dataset used, which limited the number of predictors and made it difficult to disentangle correlated stressors.

The expert panel convened as part of the feasibility study supported BNs as useful communication and decision-support tools but also highlighted the importance of empirical approaches to identify key stressors (Figure 2). They identified suspended sediment concentration, deposited fine sediment, movement barriers, and the presence of source populations as the most important factors directly influencing macroinvertebrate communities in Christchurch waterways. Nutrient concentrations were judged to strongly influence algae and periphyton, but their impact on macroinvertebrates was considered less significant. Flow-related stressors were not deemed highly important in Christchurch streams, due to the predominantly spring-fed baseflow of city waterways, whereas copper and zinc – while a focus of stormwater contaminant reductions – were not considered key stressors. The panel also noted that GAMM-type models could be strengthened by combining predictors into composite indices, expanding datasets with information from other urban areas, and aligning monitoring with model needs, while targeted experiments could clarify causative mechanisms. In this context, our use of Generalised Additive Models (GAMs – essentially GAMMs without random effects; see Section 2.3) provides a valuable empirical complement to BN development. By directly quantifying stressor-response relationships from monitoring data, GAMs help identify the drivers most strongly linked to ecological condition in Christchurch streams, addressing some of the key gaps identified by both NIWA and the expert panel.

2.2. Data Collation

Data for statistical analysis was compiled from a combination of annual ecology monitoring data collected by CCC and ECan, and monthly water quality data collected by CCC. The annual ecology monitoring data was from 52 sites sampled over the summer of 2024-25, including 37 CCC sites sampled from 12 February to 3 March 2025 and 15 ECan sites sampled from 21 November to 3 December 2024 (Figure 2). This was the first round of a new annual ecology monitoring programme for CCC (Instream Consulting 2025)[1], whereas there is up to 25 years of annual monitoring data for the ECan ecology monitoring programme. Data analysed from the combined CCC and ECan monitoring sites included invertebrates and habitat variables (including periphyton and macrophyte cover) and Rapid Habitat Assessment (RHA) data. The RHA is a reach-scale appraisal of ten habitat components, each scored from 1 (poor) to 10 (ideal) (Clapcott 2015). Components include deposited fine sediment, hydraulic

[1] Previously, annual ecology monitoring only occurred at four CCC sites, with five-yearly monitoring occurring at a greater number of sites. The monitoring programme was changed to from five-yearly to annual, to better detect trends over time.

heterogeneity, invertebrate habitat diversity and abundance, fish cover diversity and abundance, bank erosion and vegetation, and riparian width and shade.

Monthly water quality data was available for 19 of the 52 ecology monitoring sites, meaning that 33 ecology sites only had invertebrate and habitat data. We included water quality data from January 2024 to March 2025 for comparison against invertebrate data. The full suite of water quality parameters considered included dissolved copper and zinc, TSS, dissolved oxygen, dissolved reactive phosphorus, total nitrogen, nitrate-nitrogen, total ammonia, and *Escherichia coli* (*E. coli,* Figure 3). We chose these water quality parameters because they include a range of water quality stressors that might affect ecosystem health directly and indirectly.

Following compilation, the dataset was checked for consistency, and laboratory detection limits were standardised, whereby values reported as below detection (“<”) were replaced with half the detection limit while values reported as above detection (“>”) were retained as given (as per Ballantine 2012; Perrie 2017).

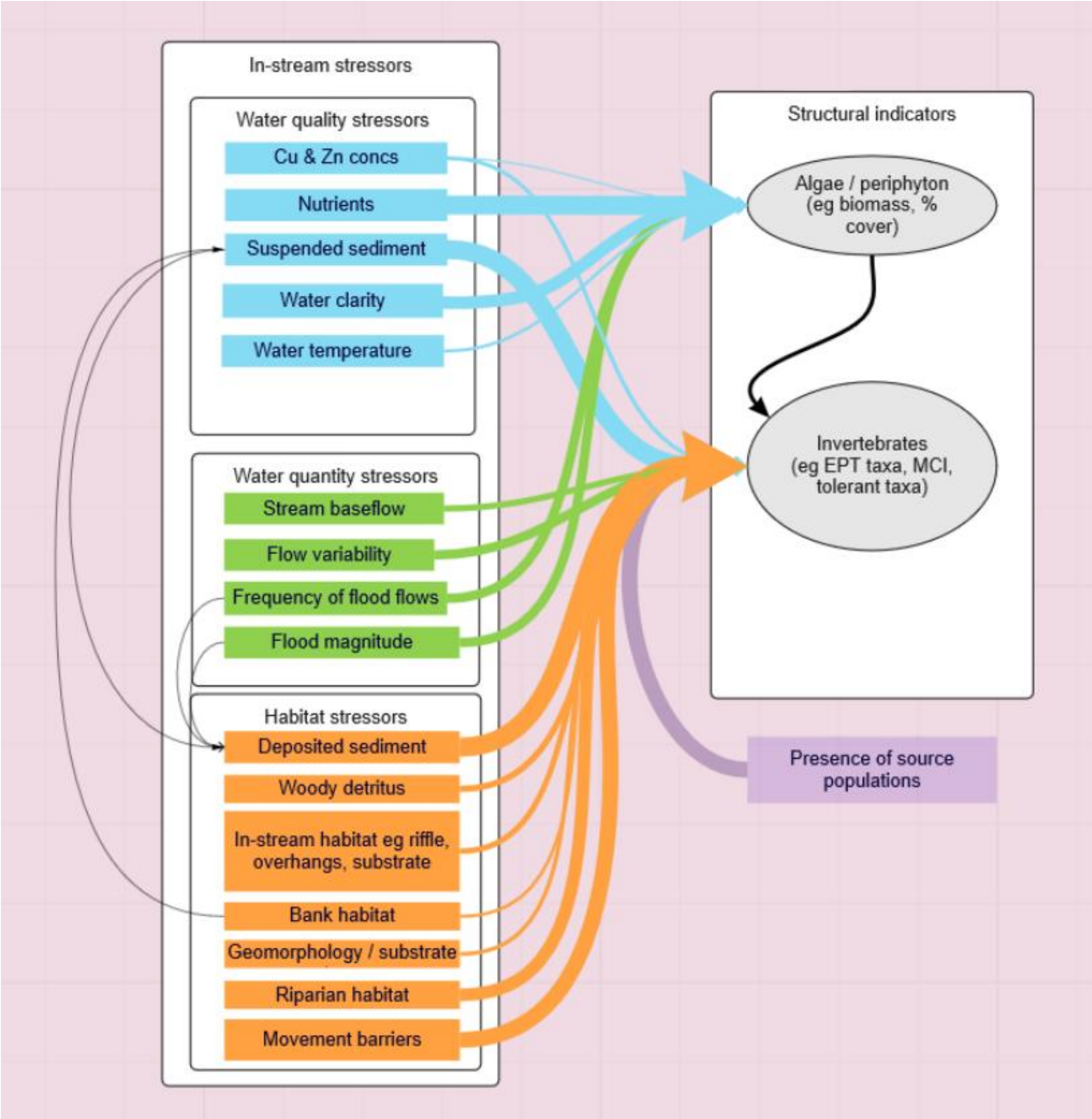

Figure 2. Conceptual model of how urbanisation affects Christchurch stream invertebrates, using information from a panel of local experts. Arrow thickness indicates the likely importance of the effect; arrow colour relates to stressor group; thin black arrows demonstrate interactions between stressors. Figure taken from Gadd et al. (2023).

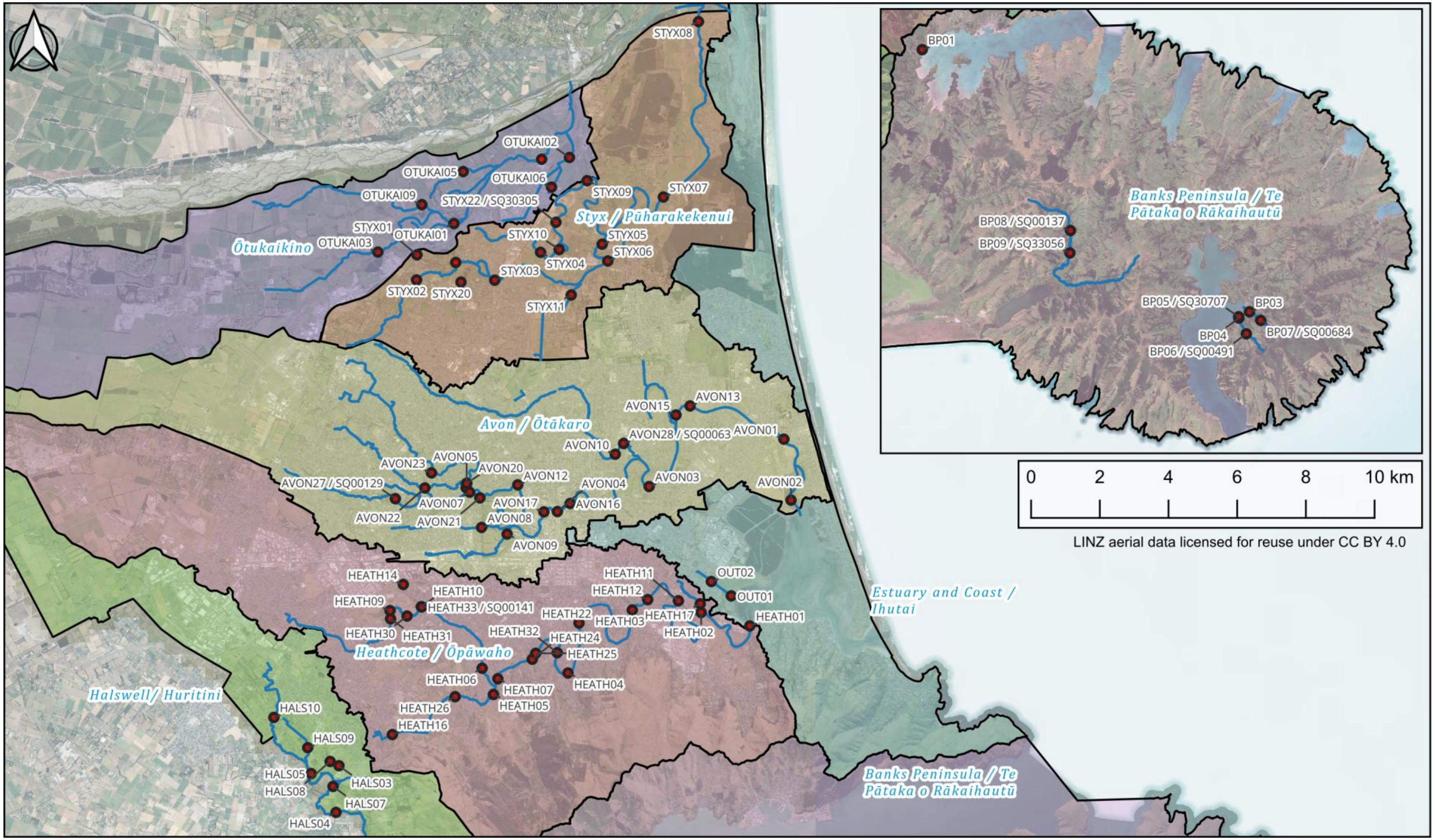

Figure 3. Christchurch district long-term CCC and ECan ecology monitoring sites across the seven major stormwater management plan catchments.

2.3. Data Analysis

We selected three widely-used macroinvertebrate indices as ecosystem response variables: the Macroinvertebrate Community Index (MCI), the Quantitative MCI (QMCI; Stark 1985), and the Average Score Per Metric (ASPM; Collier 2008). The MCI is based on presence-absence data, while the QMCI incorporates abundance by weighting taxa scores. ASPM integrates three metrics, including the abundance of pollution-sensitive Ephemeroptera, Plecoptera, and Trichoptera (EPT) taxa, EPT taxa richness, and MCI. Thus, when compared to the MCI or QMCI, the ASPM provides a broader measure of responses to stressors such as flow, sedimentation, nutrients, and temperature (Wagenhoff *et al.* 2017). As EPT taxa are generally pollution-sensitive, MCI and QMCI effectively indicate stream health based on community tolerance (Stark and Maxted 2007).

For comparison with annual invertebrate data, we calculated the average of each monthly water quality parameter, except for dissolved zinc and copper where a median was used. Despite initially using average zinc and copper measurements for consistency, the averages were unsuitable for modelling due to strong skew that could not be corrected through transformations, and we wanted to retain the full dataset without removing outliers. While medians resolved the skewing issue, we do not expect this adjustment to alter the observed ecological impacts of actual contaminant concentrations. Median values still capture the central tendency of zinc and copper across the year, reflecting the typical exposure experienced by invertebrates. Extreme high or low values may be less emphasised in the median, but because ecological responses are generally driven by sustained or recurring contaminant levels rather than single extreme events, the use of medians provides a reliable representation of the conditions that influence biological communities (Jones *et al.* 2023).

Prior to modelling, QMCI and MCI responses were log transformed, while ASPM was logit transformed to meet assumptions of normality. Dissolved reactive phosphorus, *E. coli*, dissolved zinc, and dissolved copper predictors were also log transformed to resolve data skews. All predictors were first screened for collinearity using Pearson correlation coefficients (Figure 4), which highlight strong relationships between pairs of variables, and then confirmed more rigorously with variance inflation factors (VIFs), which test whether any variable is too closely related to a combination of others. Only variables with VIF < 5 (Gareth *et al.* 2017) were retained for modelling, with the final set of predictor variables included in modelling being:

- Total suspended solids
- Dissolved zinc
- Nitrate
- Dissolved reactive phosphorus
- Deposited sediment (RHA)
- Riparian width (RHA)
- Invertebrate habitat abundance (RHA)
- Invertebrate habitat diversity (RHA)
- Hydraulic heterogeneity (RHA)

Dissolved copper was excluded from the modelling, despite it being a common stormwater contaminant, for two reasons. The principal reason was due to the strong correlation between copper and zinc concentrations, meaning that it would be difficult to differentiate effects between the two parameters. The secondary reason was that zinc concentrations were overall greater than copper concentrations, meaning that zinc likely has a greater potential effect on invertebrate communities. Hence, it was logical to keep zinc and drop copper from the modelling exercise.

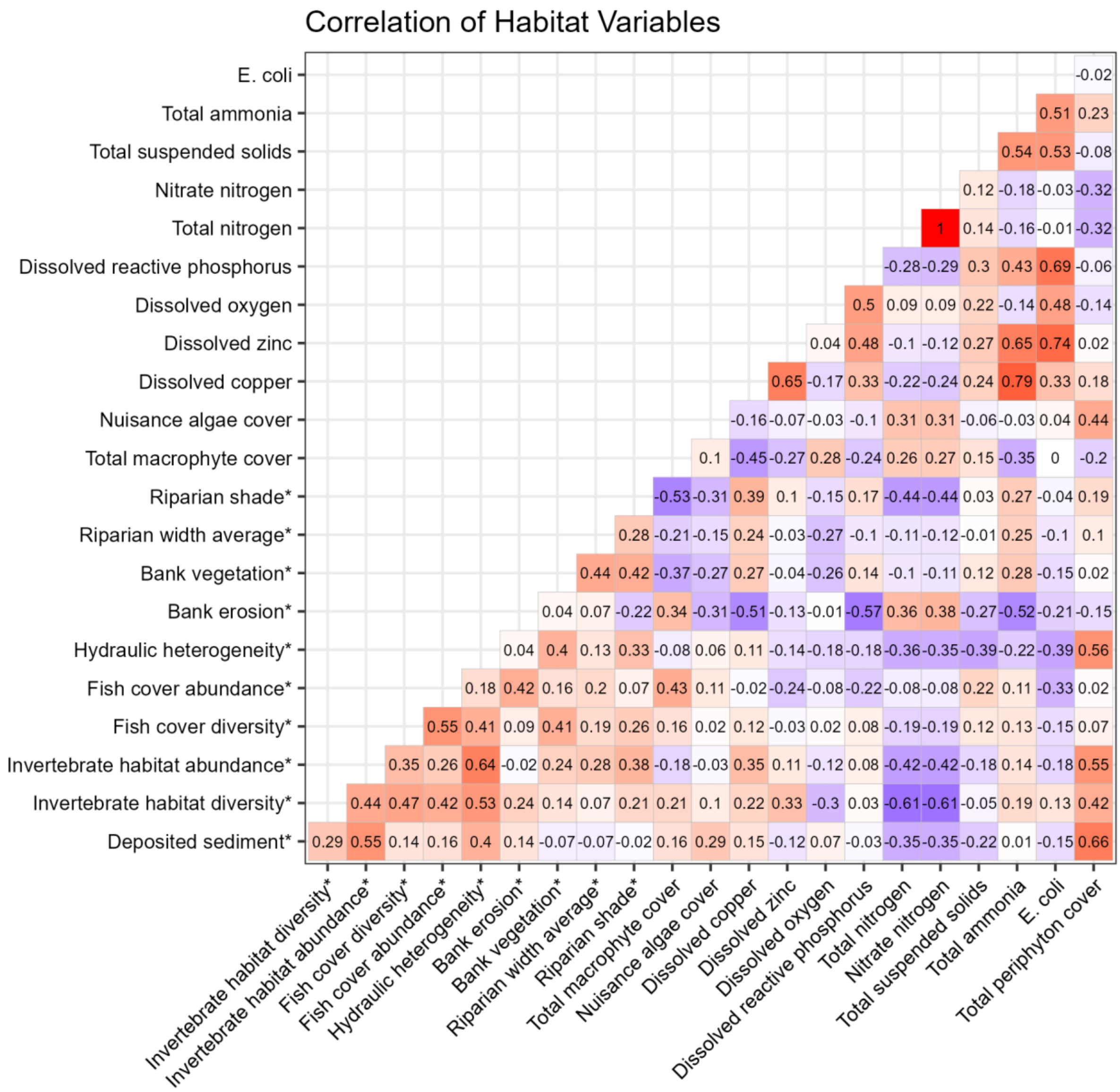

Figure 4. Correlation coefficients (Pearson's r) are shown for all habitat and water quality variables. Strong correlations are considered those with |r| above 0.5. '*' denotes RHA components.

To examine the influence of habitat on invertebrate communities, we fitted a suite of *a priori* GAMs. Each model included up to three predictors, with a minimum of 15 replicates per combination. GAMs were chosen for their ability to capture nonlinear stressor-response relationships (Gareth *et al.* 2017) and to incorporate smooth terms with restricted complexity (set at k = 4) to avoid overfitting while allowing biologically realistic responses to emerge.

Initially, interaction terms between predictors and catchment-level random effects were tested, but both were excluded; the former due to poor data spread, the latter due to convergence issues from limited replication. However, we expect the included environmental predictors to capture most of the relevant catchment-scale variation.

An information theoretic approach, using Akaike's information criterion corrected for small sample size (AICc), was used to determine which candidate models explained variation in MCI, QMCI, and ASPM most parsimoniously (Burnham and Anderson 2002). Assessing model performance using AIC is asymptotically equivalent to using leave-one-cluster-out cross-validation (Fang 2022). Each model's AICc was subtracted from the lowest AICc to determine its ΔAICc (Burnham and Anderson 2002). Parsimonious models had ΔAICc values < 2 (Burnham and Anderson 2002). For each GAM, model fit was assessed using the proportion of deviance explained (pseudo-R^2; henceforth R^2), which indicates the amount of variation in the response accounted for by the predictors. The Akaike weight (*w*), interpreted as the probability that a particular model is the most parsimonious model among the candidate models, and R^2 of parsimonious models were assessed to select the most suitable model for explaining each invertebrate community parameter.

Individual predictor importance was assessed using the sum of Akaike weights (Giam and Olden 2016), interpreted as the probability that a predictor is a component of the most parsimonious model. Partial dependence plots were also used to visualise relative importance of each environmental variable in the most suitable models. Partial dependence plots show the independent effect of a single variable on the response by accounting for the average effects of all other variables in a model (Elith *et al.* 2008).

For each top-ranked GAM, we derived equations that approximate the modelled partial effect of each predictor on the response, holding all other predictors constant at their mean values. Linear predictors were expressed directly using the fitted slope coefficients, while non-linear predictors were approximated with polynomial equations fitted to the smooth term outputs. These equations allow predictions of the expected change in invertebrate community parameters associated with each relevant predictor variable, providing an interpretable summary of how habitat and water quality factors influence invertebrate community responses.

Information-theoretic model selection is ideally performed on suites of models with equivalent sample sizes, as smaller datasets are generally penalised. We addressed the impact of smaller datasets by employing AICc, which adjusts the AIC penalty for limited replicates and provides more robust inference (Burnham and Anderson 2002). When the top-supported model was based on the "full dataset" (n = 52, including sites with missing water quality data), we compared its performance with the equivalent reduced model using the "balanced dataset" (n = 19), which contained complete habitat and water quality information. In contrast, if a balanced dataset model was selected first, we did not conduct this comparison, since the additional explanatory power of water quality variables was interpreted as overriding the small-sample penalty and, therefore, representing the most robust model.

All analyses were conducted in R v4.4.2 (R Core Team 2024).

3. RESULTS AND DISCUSSION

3.1. Key Environmental Predictors

Both water quality and habitat variables contributed meaningfully to explaining invertebrate community responses (Table 1). Models for ASPM and QMCI had the most explanatory power, whereas MCI models were comparatively weak. Thus, the top model for ASPM had an AIC_c of 7.58 and an R^2 of 0.64, while the top model for QMCI had an AIC_c of -8.91 and an R^2 of 0.62. By comparison the top models for MCI had AIC_c values of -30.1 to -32.0 and R^2 values of 0.14 to 0.39. We therefore consider that ASPM and QMCI models have greater use for predicting responses in the receiving environment than models using MCI. The following paragraphs describe modelling results for ASPM and QMCI in more detail, while results for MCI are provided in Appendix 1 for reference.

ASPM was most parsimoniously explained by a model that included deposited sediment, riparian width, and TSS (Table 1). This model provided higher explanatory power (*w* and R^2) and produced more ecologically coherent relationships than the alternative ‘next best’ model that included deposited sediment, riparian width, and dissolved zinc (Table 1). All three predictors in the top model had moderately high relative importance values (≥0.5; Figure 5). Partial plots indicated that ASPM was highest at sites with lower deposited sediment cover, greater riparian widths, and lower TSS concentrations (Figure 6). The influence of each predictor on ASPM is expressed as a simple equation on the partial plot scale (Table 2), showing its effect while other predictors are held constant.

QMCI was explained parsimoniously by a sole water quality-only model containing dissolved reactive phosphorus (DRP) and TSS (Table 1). Both predictors showed high relative importance (>70; Figure 5). Specifically, QMCI was negatively associated with TSS while the response to DRP was non-linear, with an initial peak in QMCI score around ~0.01-0.02 mg/L of DRP before decreasing (Figure 7). Like ASPM, each predictor’s influence on QMCI is captured by partial plot equations (Table 2), which approximate the GAM outputs and allow prediction of QMCI responses.

Overall, habitat and water quality variables both played influential roles in determining invertebrate community parameters, but the specific predictors and the form of their relationships differed by predictor. Water quality and sediment dynamics were prominent predictors in ASPM and QMCI models, whereas MCI was more sensitive to outlying observations and had low predictive ability. Consequently, conclusions and management recommendations focus on ASPM and QMCI and highlight the importance of sediment dynamics (including deposited and suspended sediments) and riparian condition as drivers of invertebrate community health. Moreover, the provided quantitative equations allow assessment of how invertebrate responses are likely to shift under management actions, including stormwater management (e.g., new stormwater treatment facilities) and habitat restoration.

Table 1. Top Generalised Additive Models ($\Delta AIC_c < 2$) that explain variation in ASPM, QMCI, and MCI based on Akaike's information criterion (AIC).

Model	AIC_c	n	ΔAIC_c	w_i	R^2
ASPM (full dataset)					
Deposited sediment* + Riparian width* + Total suspended solids	7.58	19	0.00	0.28	0.64
Deposited sediment* + Riparian width* + Dissolved zinc	9.15	19	1.57	0.13	0.58
QMCI (full dataset)					
Dissolved reactive phosphorus + Total suspended solids	-8.91	19	0.00	0.42	0.62

Note: AIC_c represents AIC values corrected for small sample size; delta AIC_c (ΔAIC_c) is the difference in AIC_c score between the highest ranked model and the candidate model; Akaike weight (w_i) is the probability that a particular model is the most parsimonious model among the candidate models. '*' denotes RHA components.

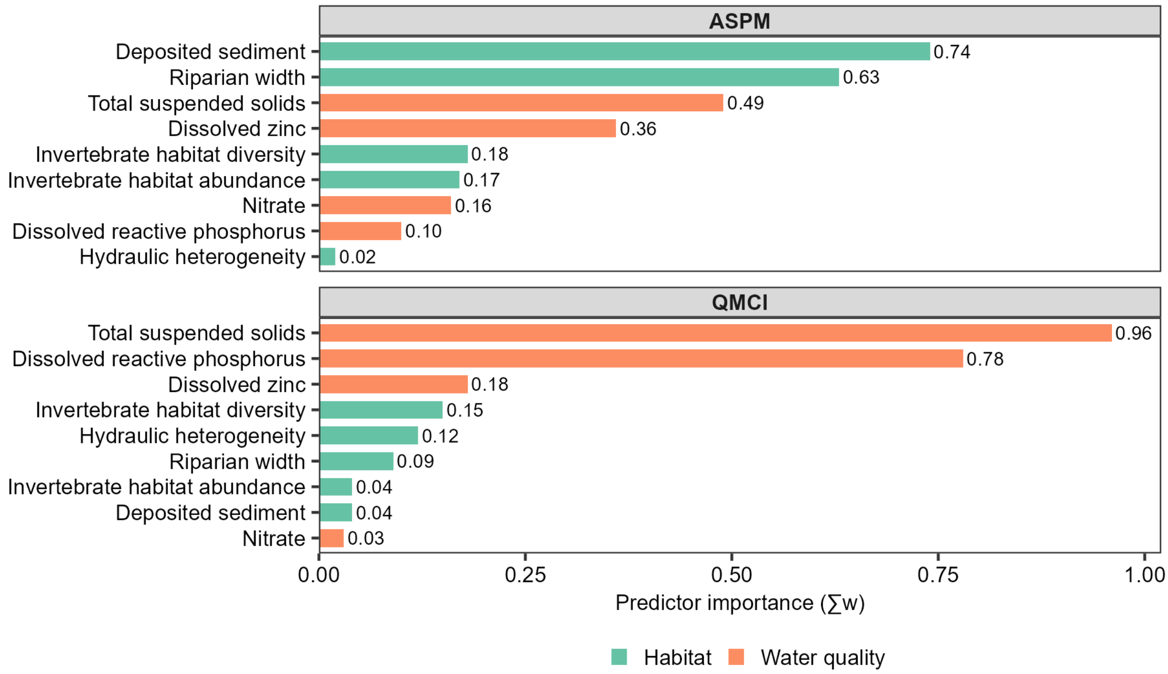

Figure 5. Relative importance of GAM modelled environmental predictors affecting macroinvertebrate responses. Relative variable importance is calculated by summing the Akaike weights (w) across the set of AICc GAM models in which the variable appears. Variables exerting a greater influence on each macroinvertebrate response are characterised by larger summed Akaike weights (∑w).

Table 2. Summary of fitted equations describing the partial relationships between invertebrate community metrics (ASPM, QMCI) and key environmental predictors derived from parsimonious GAM models.

Response	Predictor (x)	Equation
ASPM	Deposited sediment (RHA score)	y = -1.660 + $(0.053 \times x^1)$ + $(0.001 \times x^2)$ + $((8.882 \times 10^{-5}) \times x^3)$ ASPM = $\frac{\exp(y)}{1+\exp(y)}$
	Riparian width (RHA score)	y = -1.815 + $(0.064 \times x)$ + $((2.245 \times 10^{-8}) \times x^2)$ + $((1.809 \times 10^{-9}) \times x^3)$ ASPM = $\frac{\exp(y)}{1+\exp(y)}$
	Total suspended solids (g/m^3)	y = -1.225 + $(-0.029 \times x)$ + $((-3.364 \times 10^{-8}) \times x^2)$ + $((3.683 \times 10^{-10}) \times x^3)$ ASPM = $\frac{\exp(y)}{1+\exp(y)}$
QMCI	Dissolved reactive phosphorus (g/m^3)	QMCI = exp(-6.147 + $(-4.631 \times \log(x^1))$ + $(-0.926 \times \log(x^2))$ + $(-0.059 \times \log(x^3)))$
	Total suspended solids (g/m^3)	QMCI = exp(1.451 + $(-0.032 \times x)$ + $((-9.089 \times 10^{-8}) \times x^2)$ + $((-5.624 \times 10^{-10}) \times x^3))$

Note: Equations represent the non-linear (i.e., DRP) or linear components of each significant predictor, holding all other variables constant. Predictions are valid only within the observed range of the data used to fit the model (see corresponding partial plots).

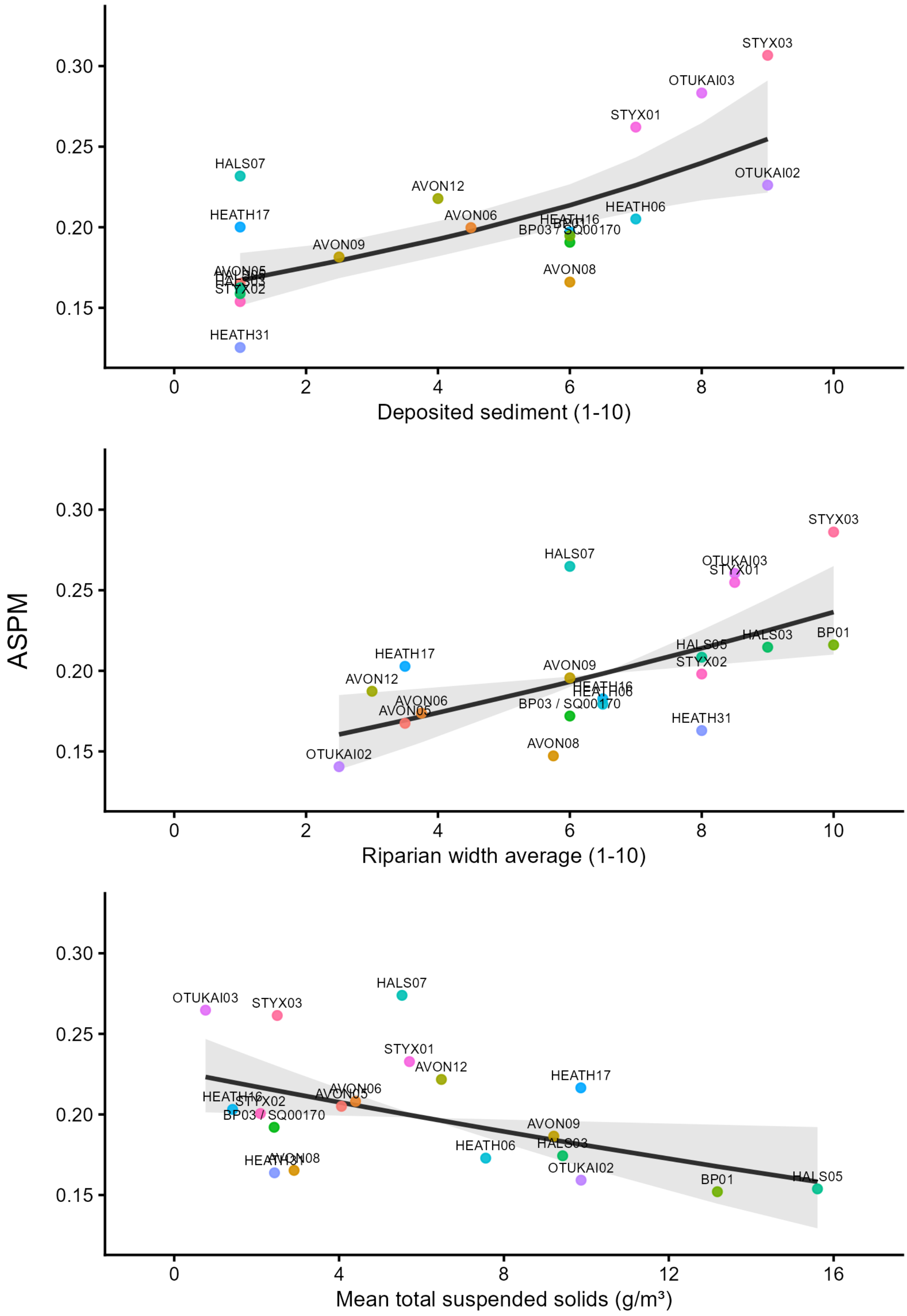

Figure 6. Partial plots of the most parsimonious ASPM model. Solid lines show modelled fits and shaded bands are 95% confidence intervals. Note that a habitat score of 10 indicates ideal conditions.

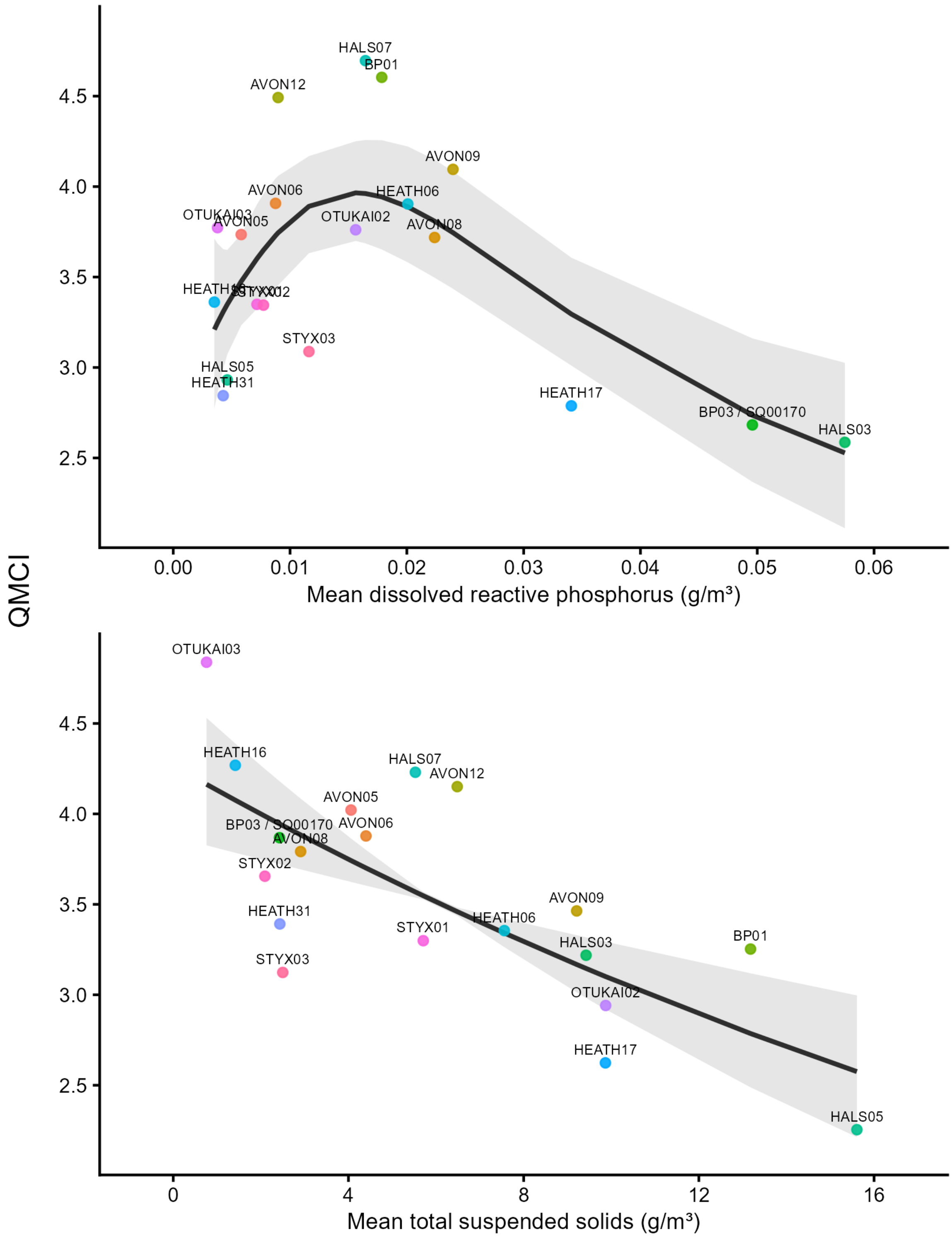

Figure 7. Partial plots of the most parsimonious QMCI model. Solid lines show modelled fits and shaded bands are 95% confidence intervals.

3.1.1. Predictor-Response Examples

The following subsections provide worked examples of how to predict invertebrate responses to changes in predictor variables, based on the equations for partial relationships provided in Table 2. We caution that the equations simplify the relationship between environmental predictors and responses. This means that changing the level of a single parameter, such as TSS concentration, will not necessarily give the resultant invertebrate response results predicted, because the actual response will depend on the influence of other variables, including other water quality parameters and habitat.

Predicted Effect of Deposited Sediment on ASPM

The effect of increasing the deposited sediment RHA score[2] from **7** to **9**:

$$logit(ASPM_{\mathbf{9}}) = -1.66 + (0.053 \times \mathbf{9}) + (0.001 \times \mathbf{9}^2) + \;((8.882\; \times\; 10^{-5})\; \times \mathbf{9}^3) \approx -1.073$$

$$ASPM_{\mathbf{9}} = \frac{\exp(-1.073)}{1 + \exp(-1.073)} \approx 0.255$$

$$logit(ASPM_{\mathbf{7}}) = -1.66 + (0.053 \times \mathbf{7}) + (0.001 \times \mathbf{7}^2) + \;((8.882\; \times\; 10^{-5})\; \times \mathbf{7}^3) \approx -1.231$$

$$ASPM_{\mathbf{7}} = \frac{\exp(-1.231)}{1 + \exp(-1.231)} \approx 0.226$$

Absolute ASPM change = $0.255 - 0.226 = \mathbf{0.029}$.

The effect of increasing the deposited sediment RHA score from **3** to **5**:

$$logit(ASPM_{\mathbf{5}}) = -1.66 + (0.053 \times \mathbf{5}) + (0.001 \times \mathbf{5}^2) + \;((8.882\; \times\; 10^{-5})\; \times \mathbf{5}^3) \approx -1.370$$

$$ASPM_{\mathbf{5}} = \frac{\exp(-1.370)}{1 + \exp(-1.370)} \approx 0.203$$

$$logit(ASPM_{\mathbf{3}}) = -1.66 + (0.053 \times \mathbf{3}) + (0.001 \times \mathbf{3}^2) + \;((8.882\; \times\; 10^{-5})\; \times \mathbf{3}^3) \approx -1.494$$

$$ASPM_{\mathbf{3}} = \frac{\exp(-1.494)}{1 + \exp(-1.494)} \approx 0.183$$

Absolute ASPM change = $0.203 - \;0.183 = \mathbf{0.020}$.

In summary, a deposited sediment score improvement from 7 to 9 increases ASPM by approximately 0.029, while the same incremental increase from 3 to 5 increases ASPM by approximately 0.020 (i.e., a smaller gain). This disproportional shift arises because the deposited sediment term has a quadratic (non-linear) component, so the effect of a given 2-point change in deposited sediment score depends on the starting value along the non-linear curve. These worked examples indicate that a moderate improvement in deposited sediment (i.e., a moderate reduction in sediment cover) will result in a very small, but positive effect on ecosystem health, as indicated by the ASPM score.

[2] Note that high deposited sediment cover will have a correspondingly low RHA score. That is because high RHA scores always equate to better ecological conditions.

Predicted Effect of TSS on QMCI

The effect of reducing TSS concentration from **9** to **7** mg/L:

$$_{\mathbf{9}} = \exp(1.451 + (-0.032 \times \mathbf{9}) + ((-9.089 \times 10^{-8}) \times \mathbf{9}^2) + ((-5.624 \times 10^{-10}) \times \mathbf{9}^3)) \approx 3.199$$

$$QMCI_{\mathbf{7}} = \exp(1.451 + (-0.032 \times \mathbf{7}) + ((-9.089 \times 10^{-8}) \times \mathbf{7}^2) + ((-5.624 \times 10^{-10}) \times \mathbf{7}^3)) \approx 3.411$$

Absolute QMCI change = $3.411 - 3.199 = \mathbf{0.212}$

The effect of reducing TSS concentration from **5** to **3** mg/L:

$$QMCI_{\mathbf{5}} = \exp(1.451 + (-0.032 \times \mathbf{5}) + ((-9.089 \times 10^{-8}) \times \mathbf{5}^2) + ((-5.624 \times 10^{-10}) \times \mathbf{5}^3)) \approx 3.636$$

$$QMCI_{\mathbf{3}} = \exp(1.451 + (-0.032 \times \mathbf{3}) + ((-9.089 \times 10^{-8}) \times \mathbf{3}^2) + ((-5.624 \times 10^{-10}) \times \mathbf{3}^3)) \approx 3.877$$

Absolute QMCI change = $3.877 - 3.636 = \mathbf{0.241}$

In summary, a reduction in TSS concentration from 9 to 7 mg/L increases QMCI score by approximately 0.212, while the same incremental TSS reduction from 5 to 3 g/m³ increases QMCI by approximately 0.241. This disproportional shift arises because the TSS term has a quadratic (non-linear) component, so the effect of a given 2 mg/L change in TSS concentration depends on the starting value along the non-linear curve. Similar to the ASPM worked example above, a moderate change in TSS concentration is predicted to have a relatively small, positive impact on ecosystem health, as indicated by QMCI scores.

3.2. Role of Habitat

Urban waterways often reflect decades of modification that prioritised drainage, flood conveyance, and land development over ecological function (Paul and Meyer 2001). Straightening, lining, and disconnection from floodplains have created channels with minimal riparian cover and reduced geomorphic diversity. These changes simplify habitat structure, reduce shading and organic inputs, and increase vulnerability to contaminant and sediment delivery from surrounding impervious surfaces. Collectively, such alterations are central to this "urban stream syndrome," where biotic communities are degraded by a combination of physical, chemical, and hydrological stressors (Walsh *et al.* 2005). Against this background, our results show that habitat features including riparian width and deposited sediment remain important features for sustaining ecosystem health, even in heavily modified catchments.

3.2.1. Riparian Width

Riparian width was a strong predictor of invertebrate condition in Christchurch urban streams, with wider vegetated margins associated with higher ASPM scores. Broad, intact riparian buffers provide multiple ecological benefits, particularly through shading, temperature regulation, and interception of sediments and contaminants. Wider vegetated strips slow overland flow, allowing sediments and sediment-bound nutrients to settle out, and supporting removal of soluble nutrients such as nitrate-nitrogen through plant uptake and denitrification in anaerobic, organic-rich soils (Parkyn 2004). In contrast, narrow or absent riparian zones typical of urban streams reduce these buffering functions, increase pollutant delivery from impervious surfaces, and exacerbate water quality stressors, reinforcing the effects of urban stream syndrome (Paul & Meyer, 2001; Walsh et al., 2005).

The effectiveness of riparian buffers depends not only on width, but also on length, continuity, composition, and catchment context, all of which influence their ability to intercept contaminants. For instance, grassed strips can remove substantial amounts of coarse sediments and particulate-bound nutrients over short distances, but finer sediments and soluble nutrients such as nitrate generally require wider, forested buffers to achieve meaningful reductions (Gharabaghi *et al.* 2002; Parkyn 2004). Steeper slopes increase runoff velocity, reducing buffer efficiency and necessitating wider or denser vegetation. Continuous buffers along a river reach further enhance contaminant interception, while gaps in coverage allow upstream pollutants to bypass local improvements. Observational evidence from urban and agricultural catchments demonstrates that wider, well-vegetated, and continuous buffers consistently outperform narrow or patchy strips in reducing sediment and nutrient loads, including nitrogen, phosphorus, and particulate matter (Parkyn *et al.* 2003; Fenemor and Samarasinghe 2020).

Riparian buffers also deliver broader ecosystem benefits, including bank stabilisation, flood-flow attenuation, and microclimate regulation, which complement their role in contaminant mitigation. Effective buffer design requires clear management objectives – such as reducing sediment, nitrate, or enhancing biodiversity – while considering local catchment characteristics, waterbody size, and surrounding land uses. When implemented alongside erosion control, sediment management, and stormwater interventions, riparian buffers can substantially reduce pollutant inputs, improve water quality, and support invertebrate communities. In contrast, narrow or fragmented buffers provide limited ecological benefits, particularly where upstream stressors dominate, emphasising the need to integrate buffer restoration with catchment-scale management and targeted habitat enhancements (Winterbourn *et al.* 2007; Death 2018; Walsh *et al.* 2023).

3.2.2. Sediment

Deposited sediment was another key habitat feature influencing invertebrate community responses. Although not colinear with water-column TSS in our dataset, both parameters reflect different aspects of sediment stress. High bed coverage with fine sediment reduces habitat quality by filling interstitial spaces, smothering benthic surfaces, and limiting oxygen exchange within substrates, all of which disadvantage sensitive taxa such as mayflies, stoneflies, and caddisflies (Burdon *et al.* 2013). Our results showed higher ASPM scores at sites with lower levels of deposited fine material, supporting the view that sediment dynamics are a central determinant of benthic community condition.

In urban streams, sediment inputs often originate from unstable banks, poorly managed construction sites, and stormwater discharges carrying road dust and eroded material (MacKenzie *et al.* 2022). Management strategies, therefore, need to address both sediment sources and in-channel accumulation. Erosion and sediment control at construction sites, stabilisation of urban streambanks, and stormwater treatment systems that capture coarse particles can all help to reduce inputs. In-channel habitat enhancement alone will be insufficient if ongoing sediment delivery overwhelms restoration efforts.

Deposited sediment also interacts with other habitat components. For example, excessive fine sediment can negate the benefits of riparian buffers and hydraulic heterogeneity by homogenising substrates and reducing niche availability. Effective sediment management thus requires a coordinated approach that integrates catchment erosion control, channel stabilisation, and habitat restoration to maintain the structural complexity necessary for diverse invertebrate communities.

3.2.3. Hydraulic Heterogeneity

In addition to riparian width and deposited sediment, hydraulic heterogeneity was one of the better predicators of MCI response. Although the strength of relationship between MCI and the predictors was weak compared to ASPM and QMCI, examination of the partial plots clearly shows that sites with the highest MCI scores also scored highly for both hydraulic heterogeneity and riparian width (Appendix 1). We observed a non-linear relationship between MCI and flow diversity, where modest gains in heterogeneity yielded limited benefits, but substantial improvements produced disproportionately large ecological responses. This suggests that modest habitat improvements (e.g., isolated riffle construction) may provide only limited gains, whereas large-scale efforts that restore continuous mosaics of pools, riffles, and runs will yield disproportionately greater improvements in invertebrate community health.

Diverse hydraulic conditions underpin ecological processes by creating a range of microhabitats for different feeding groups, life stages, and behaviours (Zerega *et al.* 2021). However, many urban channels lack this diversity due to straightening, armouring, and infilling, which homogenise flow and substrate. Restoration approaches that re-meander channels, re-establish riffle-pool sequences, and add instream structures such as wood or boulders are increasingly recognised as valuable strategies for reinstating habitat complexity (Bernhardt and Palmer 2011). However, the benefits of hydraulic enhancement depend on concurrent management of catchment-scale stressors. For example, riffle additions in highly urbanised streams may simply increase habitat for tolerant cosmopolitan species if stormwater impacts remain unchecked (Walsh *et al.* 2023).

3.3. Role of Consent Contaminants

Although dissolved metals were not retained as key predictors in our best-fit models, they remain relevant due to their status as consent-condition parameters and potential impacts on localised ecological effects. Across sites, copper and zinc concentrations generally clustered near or below the lower ANZG (2025) guideline trigger values, but exceedances were not uncommon. Median copper concentrations mostly ranged between the 95% and 99% species protection levels (1-1.4 µg/L), with occasional breaches of the 90% protection threshold (1.8 µg/L, Figure 7). Zinc concentrations were more variable, with many sites exceeding the 95% protection value (8 µg/L), with some approaching or surpassing 15-31 µg/L. Even when below guideline thresholds, episodic spikes during storm flows may stress sensitive taxa and reduce community diversity.

Experimental evidence from stream mesocosms and field surveys indicate that total macroinvertebrate richness is generally resilient at moderate zinc concentrations up until 180 µg/L, though the abundance of some sensitive species (i.e., mayflies) may decline at ~72 µg/L (Hickey and Golding 2002; Clements 2004; Iwasaki *et al.* 2012). Copper concentrations below ~2 µg/L typically have minimal effects on benthic and algal communities, with recovery observed once levels return below this threshold, but changes in algal dominance and biomass can occur at 3-18 µg/L (Chariton and Apte 2005). In a long-term lotic mesocosm experiment, Joachim et al. (2017) exposed benthic and emerging invertebrate communities to continuous copper concentrations of ~5, 25, and 75 µg/L, finding that in the

25 and 75 µg/L treatments there were significant reductions in abundance, taxonomic richness, and shifts in community structure. Taken together, these findings suggest that, although metals were not statistically dominant drivers in our models, observed copper and zinc exceedances may still impose meaningful localised ecological stress, particularly on sensitive taxa. This supports the need for ongoing monitoring and targeted mitigation alongside broader habitat and water quality management to protect stream biota.

By contrast, TSS emerged as a consistently influential predictor of invertebrate community health. Both ASPM and QMCI declined as TSS increased, with a subset of sites frequently exceeding the 25 mg/L consent attribute target level. Importantly, elevated TSS is well documented to reduce clarity, increase sediment deposition, and limit the availability of clean substrates for colonisation, all of which negatively impact benthic communities (Bilotta and Brazier 2008; Davies-Colley 2013). Given the strong and consistent associations in our results, TSS represents a more immediate and pervasive risk to stream health than dissolved metals. This finding is consistent with advice from the expert panel summarised in Figure 1.

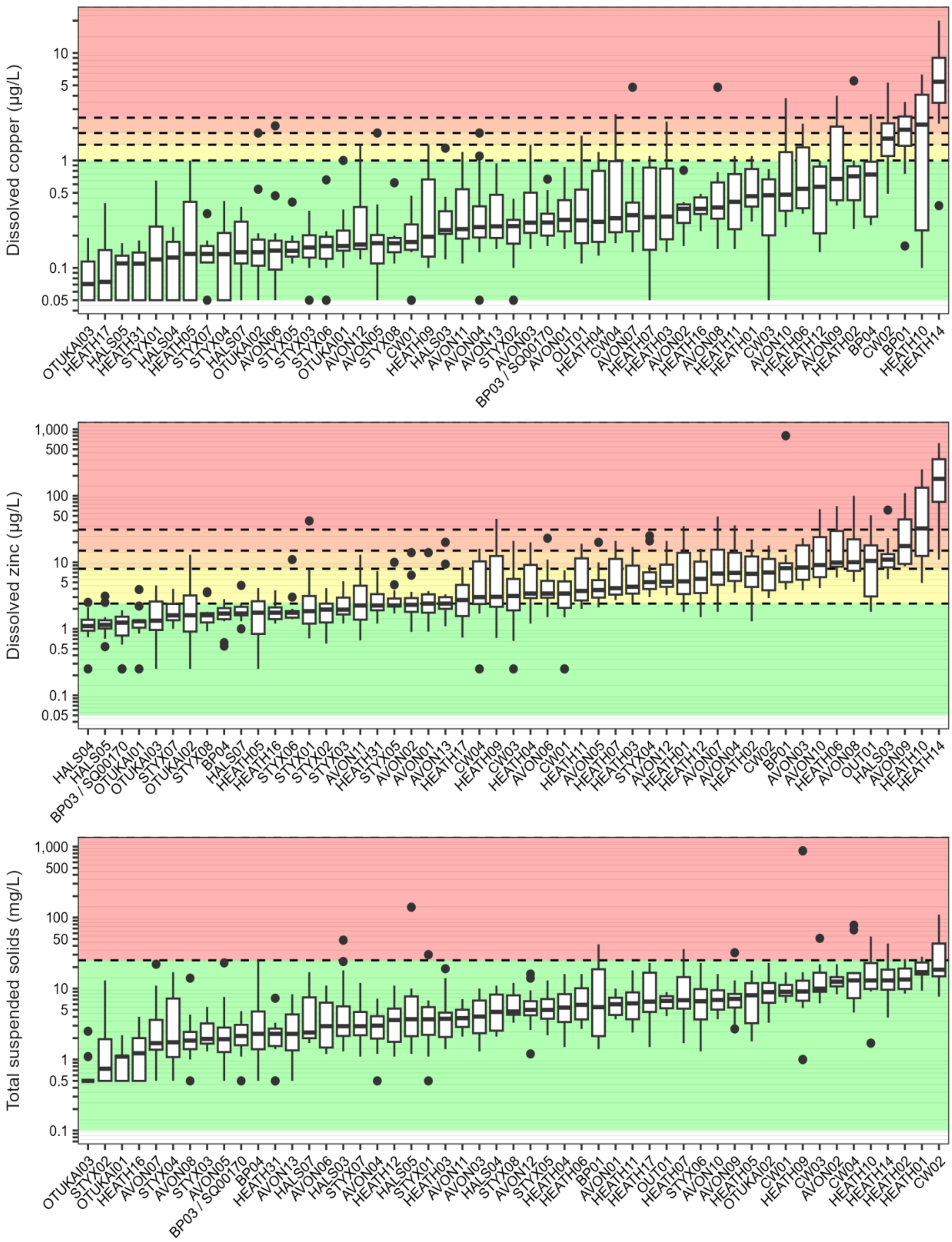

Figure 8. Copper, zinc and suspended solids concentrations across CCC monthly monitoring sites from 2024, ordered by median concentration. Central marker indicates median value for each site. Boxes represent the range from 25th to 75th percentiles, whiskers from 1.5x inter-quartile range and small points indicate data outside 1.5 x IQR. Note log scale on y-axes for all three variables. Background shading for dissolved copper (Cu) and zinc (Zn) indicates comparison to ANZG (2018) guideline values, with 99% (Cu=1 and Zn=2.4 µg/L), 95% (Cu=1.4 and Zn=8 µg/L), 90% (Cu=1.8 and Zn=15 µg/L), and 80% (Cu=2.5 and Zn=31 µg/L) levels of species detection, not adjusted for hardness. Suspended solids compared to guideline value of 25 mg/L. Figure adapted from Gadd et al., (2023).

3.4. Sites of Interest

Several monitoring sites exhibit distinctly poor invertebrate, habitat, and/or water quality conditions, making them strong candidates for targeted restoration. These locations span a range of dominant stressors – including sediment, nutrients, metals, and riparian condition – providing opportunities to evaluate the ecological benefits of specific management actions.

Multi-stressor sites
HEATH31 (Heathcote River at Warren Crescent), HEATH17 (Steamwharf Stream upstream of Dyers Road), HALS05 (Knights Stream at Sabys Road), and HALS03 (Nottingham Stream at Candys Road) all showed combinations of elevated nutrients, high suspended or deposited sediment, and low invertebrate metric scores (ASPM and/or QMCI). At these sites the focus would be integrated sediment–nutrient interventions, including riparian enhancement and widening, and measures to reduce both fine-sediment inputs and nutrient delivery.

Sediment-dominated and riparian-limited sites
AVON08 (Riccarton Main Drain) had persistently high TSS concentrations and low ASPM scores. We note that CCC is also currently investigating stormwater treatment options for Riccarton Main Drain in Hagley Park, which will target reductions in sediment and metals. OTUKAI02 (Wilsons Drain at Main North Road) displayed narrow riparian margins and elevated TSS, making it well suited for targeted riparian widening and planting to reduce sediment inputs and improve channel stability. We note that Wilsons Drain is currently undergoing naturalisation by CCC, including realignment and riparian planting.

Elevated metal contamination sites
HEATH10 (Curletts Road Stream upstream of the Heathcote River confluence) and HEATH14 (Curletts Road Stream at Southern Motorway) both have elevated zinc and copper concentrations, reflecting their industrial catchments. New stormwater treatment facilities have recently been added in both catchments, so it is unclear whether the metals issue is due to inadequate treatment and/or a legacy of contaminated sediments in the waterways and stormwater basins. AVON09 (Addington Brook) also showed high metal concentrations alongside poor sediment condition and low ASPM scores. Together, these sites provide strong opportunities to evaluate stormwater treatment and contaminant-source controls, particularly given their roles as key contributors of metals within their respective catchments. AVON09 is especially valuable for continued monitoring because recent habitat restoration enables assessment of how contaminant levels and invertebrate communities change in response to management interventions. Furthermore, stormwater treatment facilities are currently being designed for Addington Brook, which should help reduce contaminant loads and concentrations.

Collectively, these recommended sites span a range of key stressor contexts and provide a robust platform for assessing how targeted management actions could translate into measurable ecological improvements across the catchment and district.

4. CONCLUSIONS AND RECOMMENDATIONS

Our analyses indicate that both physical habitat and water quality conditions are key determinants of invertebrate community health in streams across the Christchurch district. Among habitat features, greater riparian widths and lower deposited sediment levels were consistently linked to higher invertebrate scores. Wider riparian zones provide shading, sediment and contaminant interception, and detrital inputs, while lower levels of deposited sediment help maintain structurally complex and oxygenated substrates that support sensitive taxa. As such, these habitat features likely also interact with key water quality conditions, particularly TSS, which emerged as a strong negative predictor of invertebrate metrics. Model predictions suggest that reducing TSS concentrations, together with improving riparian width and removing deposited sediment, would increase ASPM and QMCI scores. The quantitative influence of each predictor, expressed through partial-plot-derived equations, provides a basis for predicting ecological responses and estimating the scale of interventions – such as sediment reduction or habitat restoration – required to achieve target improvements in invertebrate communities. MCI predictions were not robust due to sensitivity to outlying sites and are, therefore, less reliable for guiding management decisions.

While dissolved metals (copper and zinc) were generally near or below guideline thresholds, occasional exceedances suggest potential localised ecological stress. However, these contaminants represent only a small component of the overall suite of stressors affecting urban stream ecosystems, and only a proportion of sediment and metal loads are under the direct control of stormwater discharge consents, with an even smaller fraction amenable to reduction through treatment alone. Our findings underscore that reducing sediment and enhancing habitat complexity are likely to yield more immediate and substantial benefits for aquatic communities. Importantly, habitat restoration alone is insufficient in highly urbanised catchments if water quality stressors from upstream sources persist. Local improvements in habitat or riparian condition may be limited by upstream land use, impervious surfaces, and stormwater connectivity. Riparian buffers and in-stream restoration can provide substantial benefits, but their effectiveness is maximised when paired with upstream interventions to manage runoff, nutrients, and contaminants. Furthermore, the non-linear relationships observed – particularly for DRP – indicate that modest changes may have limited ecological benefit unless implemented at sufficient scale. Consequently, achieving meaningful ecological recovery will likely require interventions that simultaneously address local habitat improvements and upstream catchment pressures, implemented at a scale sufficient to influence invertebrate responses.

The relatively small effects predicted for individual stressors are consistent with observations from highly urbanised stream systems and reflect the cumulative influence of multiple, interacting drivers of ecological degradation (Suren and McMurtrie 2005; Griffith and Mcmanus 2020). Ecological responses in urban streams are, therefore, expected to be small and incremental, given the pervasive effects of urbanisation on water quality, instream habitat, riparian characteristics, flow regimes, and connectivity. Reductions in suspended sediment and metal loads from stormwater discharges focal to the discharge consent represent an important and necessary contribution to improving ecosystem health; however, these measures alone are unlikely to produce substantial ecological change. The greatest improvements are expected where stormwater quality enhancements occur concurrently with instream habitat restoration, flow attenuation associated with stormwater detention, and improvements in longitudinal and riparian connectivity (Figure X). Empirical studies from Christchurch and elsewhere have documented modest but measurable improvements in invertebrate community structure following habitat and/or water quality enhancement, although responses are often subtle and spatially constrained due to additional unaddressed stressors at the local and catchment level (Suren and McMurtrie 2005; Collier *et al.* 2009; Sundermann *et al.* 2013). Collectively, these findings indicate that improving stormwater discharges addresses only one component of ecosystem degradation, and that coordinated, multi-stressor management is required to achieve sustained improvements in urban stream ecological condition.

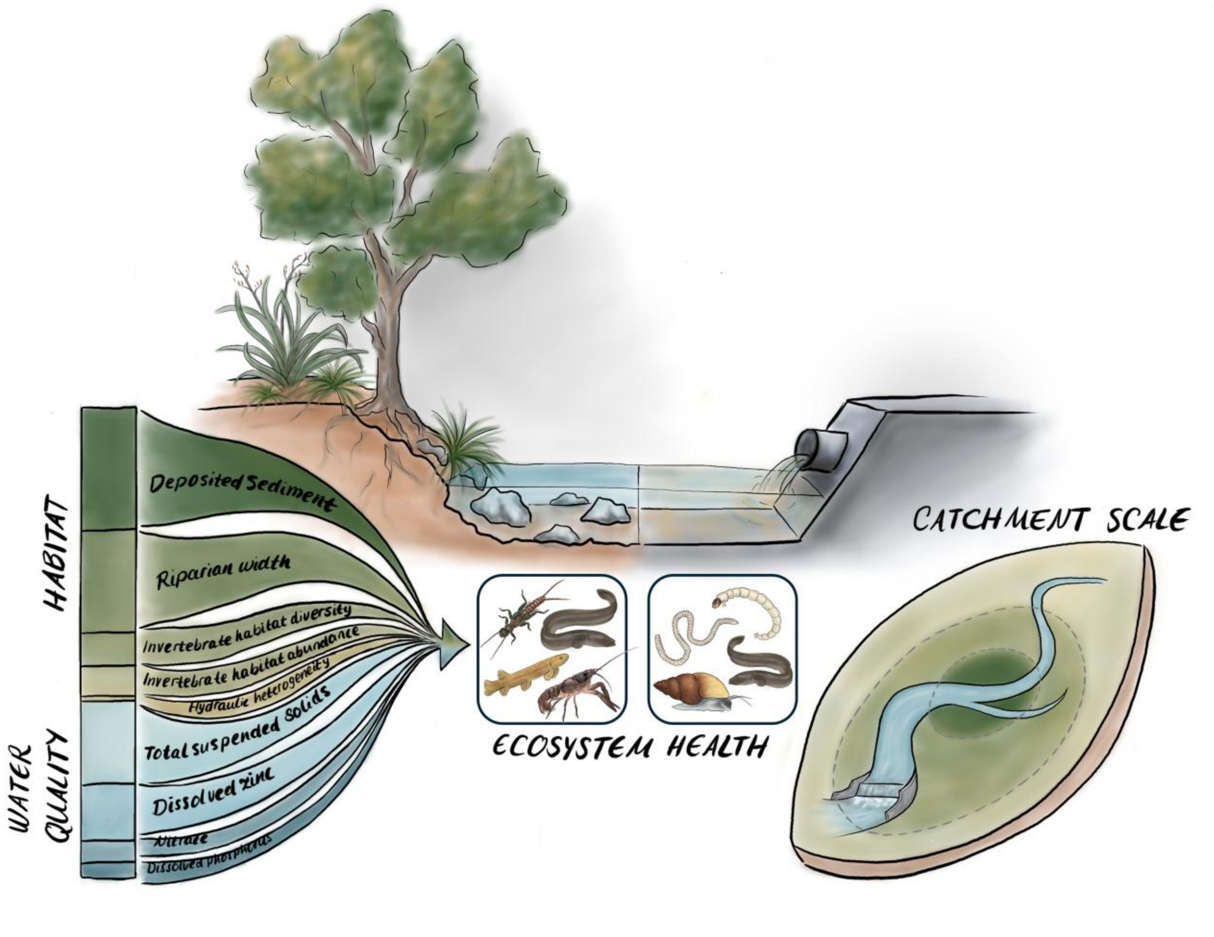

Figure 9: The relative importance of modelled environmental factors affecting ecosystem health, split into habitat and water quality components. The illustration is based on the model for the ASPM macroinvertebrate indicator results in Figure 5. The diagram shows how degraded ecosystem health is caused by multiple factors and therefore that actions to improve ecosystem health must consider more than simply improving stormwater discharge quality.

Based on these findings, we propose the following recommendations for stream management in the Christchurch district:

- **Riparian management** – Restore and protect wide riparian buffers to provide shading, intercept sediment and nutrients, and supply instream and terrestrial habitat. Design buffers with consideration of catchment hydrology, slope, soil drainage, and terrestrial-aquatic connectivity, and integrate with upstream land uses to ensure maximum ecological benefit.
- **Sediment and erosion control** – Reduce fine sediment inputs from bank erosion, construction sites, and urban stormwater, and stabilise stream beds and banks in combination with riparian planting. Ongoing monitoring of both deposited sediment and TSS is recommended to capture chronic and acute sediment stressors and guide management.
- **Hydraulic and habitat restoration** – Enhance hydraulic diversity through riffle-pool sequences, instream boulders, or woody debris to create varied microhabitats.
- **Water quality management** – Continue monitoring TSS, copper, zinc, and other consented contaminants, with particular attention to localised exceedances. Improving stormwater quality discharges should be viewed as a critical but partial contribution to ecosystem health, and water quality improvements should be integrated with habitat restoration and management of correlated stressors (e.g., nutrients, metals, *E. coli*) to achieve broader ecological gains. Stormwater detention associated with water quality treatment will also contribute to partial mitigation of altered flow regimes.
- **Targeted restoration and monitoring** – Focus on degraded sites for restoration and monitoring to evaluate ecological responses over time. Monitoring programmes should be coordinated with existing networks and consider upstream source populations to assess the potential for recolonisation by sensitive taxa. Recommended sites are those exhibiting distinctly low invertebrate, habitat, and/or water quality conditions both within and between catchments, including AVON08, AVON09, HEATH10, HEATH14, HEATH17, HEATH31, HALS03, HALS05, and OTUKAI02. Restoration efforts at these potential locations could provide valuable insights into the effectiveness of habitat and water quality interventions and support adaptive management across the catchment and district.
- **Integrated catchment approach** – Plan interventions at the catchment scale to manage upstream impacts on water quality, sediment, and flow. Identify critical source areas for remediation and prioritise restoration where it will deliver the greatest ecological and biodiversity benefits.

5. REFERENCES

ANZG (2025). Australian and New Zealand Guidelines for Fresh and Marine Water Quality. Australian and New Zealand Governments and Australian state and territory governments, Canberra, ACT, Australia. Available at: www.waterquality.gov.au/guidelines [accessed 1 July 2025]

Ballantine DJ. (2012). Water quality trend analysis for the Land and Water New Zealand website (LAWNZ) : advice on trend analysis. *Prepared by National Institute of Water & Atmospheric Research Ltd for Horizons Regional Council*, 30.

Bernhardt ES, Palmer MA (2011). River restoration: the fuzzy logic of repairing reaches to reverse catchment scale degradation. *Ecological Applications* **21**, 1926–1931.

Bilotta GS, Brazier RE (2008). Understanding the influence of suspended solids on water quality and aquatic biota. *Water Research* **42**, 2849–2861. doi:10.1016/j.watres.2008.03.018

Burdon FJ, McIntosh AR, Harding JS (2013). Habitat loss drives threshold response of benthic invertebrate communities to deposited sediment in agricultural streams. *Ecological Applications* **23**, 1036–1047.

Burnham K, Anderson D (2002). 'Model selection and multimodel inference: a practical information-theoretic approach' 2nd ed. (Springer: New York)

Chariton A, Apte S (2005). Field and experimental responses of biota to copper-enriched and acidic waters: literature review. *Prepared by Centre for Environmental Contaminants Research for Ok Tedi Mining Limited*, 17.

Clapcott J (2015). National rapid habitat assessment protocol development for streams and rivers. *Prepared by Cawthron Institute (report 2649) for Northland Regional Council*.

Clements WH (2004). Small-scale experiments support causal relationships between metal contamination and macroinvertebrate community responses. *Ecological Applications* **14**, 954–967. doi:https://doi.org/10.1890/03-5009

Collier KJ (2008). Average score per metric: an alternative metric aggregation method for assessing wadeable stream health. *New Zealand Journal of Marine and Freshwater Research* **42**, 367–378. doi:10.1080/00288330809509965

Collier KJ, Aldridge BMTA, Hicks BJ, Kelly J, Macdonald A, Smith BJ, Tonkin J (2009). Ecological values of Hamilton urban streams (North Island, New Zealand): constraints and opportunities for restoration. Available at: www.stats.govt.

Davies-Colley RJ (2013). River water quality in New Zealand: an introduction and overview. *Ecosystem services in New Zealand: conditions and trends. Manaaki Whenua Press, Lincoln*, 432–447.

Death R (2018). Buffer management-benefits and risks. *Report for Greater Wellington Regional Council*, 46.

Elith J, Leathwick JR, Hastie T (2008). A working guide to boosted regression trees. *Journal of Animal Ecology* **77**, 802–813. doi:https://doi.org/10.1111/j.1365-2656.2008.01390.x

Fang Y (2022). Asymptotic equivalence between cross-validations and Akaike information criteria in mixed-effects models. *Journal of Data Science* **9**, 15–21. doi:10.6339/JDS.201101_09(1).0002

Fenemor A, Samarasinghe O (2020). Riparian setback distances from water bodies for high-risk land uses and activities. *Report prepared by Manaaki Whenua Landcare Research for Tasman District Council, September 2020*.

Gadd J, Greenwood M, Graham E, Bulmer R (2023). Predicting effects of contaminant load reductions of biological communities: feasibility study. *Prepared by NIWA for Christchurch City Council, May 2023.*

Gareth J, Witten D, Hastie T, Tibshirani R (2017). 'An introduction to statistical learning: with applications in R'. (Springer : Springer Science+Business Media)

Gharabaghi B, Rudra RP, Whiteley HR, Dickinson WT (2002). Development of a management tool for vegetative filter strips. *Journal of Water Management Modeling*, 208–226. doi:10.14796/JWMM.R208-18

Giam X, Olden JD (2016). Quantifying variable importance in a multimodel inference framework. *Methods in Ecology and Evolution* **7**, 388–397. doi:https://doi.org/10.1111/2041-210X.12492

Griffith MB, Mcmanus MG (2020). Consideration of spatial and temporal scales in stream restorations and biotic monitoring to assess restoration outcomes: A literature review, Part 1 EPA Public Access.

Hayward SA., Meredith AS., Stevenson Michele (2009). 'Review of proposed NRRP water quality objectives and standards for rivers and lakes in the Canterbury Region'. (Environment Canterbury)

Hickey CW, Golding LA (2002). Response of macroinvertebrates to copper and zinc in a stream mesocosm. *Environmental Toxicology and Chemistry* **21**, 1854–1863. doi:https://doi.org/10.1002/etc.5620210913

Instream Consulting (2025). Christchurch annual aquatic ecology monitoring 2025. *Report prepared for Christchurch City Council by Instream Consulting, June 2025*.

Iwasaki Y, Kagaya T, Miyamoto KI, Matsuda H (2012). Responses of riverine macroinvertebrates to zinc in natural streams: implications for the Japanese water quality standard. *Water, Air, and Soil Pollution* **223**, 145–158. doi:10.1007/s11270-011-0846-1

Joachim S, Roussel H, Bonzom J-M, Thybaud E, Mebane C, Van den Brink P, Gauthier L (2017). A long-term copper exposure in a freshwater ecosystem using lotic mesocosms: invertebrate community responses. *Environmental toxicology and chemistry* **10**. doi:10.1002/etc.3822

Jones JI, Lloyd CEM, Murphy JF, Arnold A, Duerdoth CP, Hawczak A, Pretty JL, Johnes PJ, Freer JE, Stirling MW, Richmond C, Collins AL (2023). What do macroinvertebrate indices measure? Stressor-specific stream macroinvertebrate indices can be confounded by other stressors. *Freshwater Biology* **68**, 1330–1345. doi:10.1111/fwb.14106

MacKenzie KM, Singh K, Binns AD, Whiteley HR, Gharabaghi B (2022). Effects of urbanization on stream flow, sediment, and phosphorous regime. *Journal of Hydrology* **612**, 128283. doi:https://doi.org/10.1016/j.jhydrol.2022.128283

Ministry for the Environment (2024). National Policy Statement for Freshwater Management 2020 (amended October 2024).

Parkyn S (2004). Review of riparian buffer zone effectiveness. *Prepared by NIWA for Ministry of Agriculture and Forestry, September 2004.*, 37.

Parkyn SM, Davies-Colley RJ, Halliday NJ, Costley KJ, Croker GF (2003). Planted riparian buffer zones in New Zealand: do they live up to expectations? *Restoration Ecology* **11**, 436–447. doi:https://doi.org/10.1046/j.1526-100X.2003.rec0260.x

Paul MJ, Meyer JL (2001). Streams in the urban landscape. *Annual review of Ecology and Systematics* **32**, 333–365.

Perrie A (2017). Lake water quality and ecology monitoring programme: annual data report, 2016/17. Available at: www.gw.govt.nz

R Core Team (2024). R: A language and environment for statistical computing.

Stark JD (1985). A macroinvertebrate community index of water quality for stony streams. *Water and Soil Miscellaneous Publication* **87**, 53 p.

Stark JD, Maxted JR (2007). A user guide for the Macroinvertebrate Community Index. *Report prepared by Cawthron for the Ministry for the Environment, report number 1166.*

Sundermann A, Gerhardt M, Kappes H, Haase P (2013). Stressor prioritisation in riverine ecosystems: Which environmental factors shape benthic invertebrate assemblage metrics? *Ecological Indicators* **27**, 83–96. doi:10.1016/j.ecolind.2012.12.003

Suren AM, McMurtrie S (2005). Assessing the effectiveness of enhancement activities in urban streams: II. Responses of invertebrate communities. *River Research and Applications* **21**, 439–453. doi:10.1002/rra.817

Wagenhoff A, Clapcott JE, Lau KEM, Lewis GD, Young RG (2017). Identifying congruence in stream assemblage thresholds in response to nutrient and sediment gradients for limit setting. *Ecological Applications* **27**, 469–484. doi:https://doi.org/10.1002/eap.1457

Walsh CJ, Roy AH, Feminella JW, Cottingham PD, Groffman PM, Ii RPM (2005). The urban stream syndrome: current knowledge and the search for a cure. *Journal of the North American Benthological Society* **24**, 706–723.

Walsh CJ, Webb JA, Gwinn DC, Breen PF (2023). Constructed rock riffles increase habitat heterogeneity but not biodiversity in streams constrained by urban impacts. *Ecosphere* **14**. doi:10.1002/ecs2.4723

Winterbourn MJ, Harding JS, Mcintosh AR (2007). Response of the benthic fauna of an urban stream during six years of restoration. *New Zealand Natural Sciences* **32**, 1–12.

Zerega A, Simões NE, Feio MJ (2021). How to improve the biological quality of urban streams? Reviewing the effect of hydromorphological alterations and rehabilitation measures on benthic invertebrates. *Water (Switzerland)* **13**. doi:10.3390/w13152087

APPENDIX 1: INVERTEBRATE RESPONSE MODELS

Table A1 below expands on Table A1 in Section 3.1 to include MCI response results. The MCI data are provided here for completeness but were excluded from the body of the report due to the relatively weak explanatory power of the MCI models. See Section 3.1 for discussion of QMCI and ASPM model results.

MCI was the only response to initially exclusively select for habitat components with the full data set – a result that may reflect either penalisation of water quality predictors due to smaller sample sizes or comparatively weaker water quality signals. To address this uncertainty, we compared outcomes from the full and balanced datasets. The full data set yielded four habitat-exclusive parsimonious models, each of which including the extremely influential riparian width parameter (relative importance value = 0.93; Table A1 and Figure 5). No model stood out among the rest in terms of AIC weight or explanatory power (R^2), so we report the top model that included hydraulic heterogeneity and riparian width (Table A1). This top model explained a modest proportion of variance (R^2 = 0.29) but indicated a non-linear, accelerating (approximately exponential) increase in MCI with greater hydraulic heterogeneity and wider riparian zones (Figure A1).

When model selection was repeated using a balanced dataset that gave habitat and water quality predictors equal weight, two candidate models emerged – nitrate vs. riparian width – with the nitrate model marginally preferred based on AIC weight and R^2 (Table A1). The nitrate partial effect was non-linear (S-shaped, cubic), whereby MCI declined at low-to-moderate increases in nitrate, rose toward a peak near ~3 g/m³, then declined (Figure A2). We caution that this complex shape appears partly driven by one influential soft-bottom site (HALS07); nevertheless, the initial exponential decrease in MCI with rising nitrate is ecologically plausible and aligns with reported negative ecological impacts when >1 g/m³ (Ministry for the Environment 2024). However, given the weakness in explanatory power of the MCI models, predictive equations are not provided for MCI models, instead ASPM and QMCI are preferred for interpretation, as their predictors demonstrated both statistical strength and ecological relevance.

Table A1. Top Generalised Additive Models (ΔAIC_c < 2) that explain variation in ASPM, QMCI, and MCI based on Akaike's information criterion (AIC).

Model	AIC_c	n	ΔAIC_c	w_i	R^2
ASPM (full dataset)					
Deposited sediment* + Riparian width* + Total suspended solids	7.58	19	0.00	0.28	0.64
Deposited sediment* + Riparian width* + Dissolved zinc	9.15	19	1.57	0.13	0.58
QMCI (full dataset)					
Dissolved reactive phosphorus + Total suspended solids	-8.91	19	0.00	0.42	0.62
MCI (full dataset)					
Hydraulic heterogeneity* + Riparian width average*	-64.28	52	0.00	0.21	0.29
Invertebrate habitat abundance* + Riparian width*	-63.91	52	0.36	0.17	0.26
Deposited sediment* + Hydraulic heterogeneity* + Riparian width*	-63.39	52	0.89	0.13	0.30
Invertebrate habitat abundance* + Hydraulic heterogeneity* + Riparian width*	-62.71	52	1.56	0.10	0.29
MCI (balanced dataset)					
Nitrate	-32.0	19	0.00	0.19	0.39
Riparian width*	-30.1	19	1.94	0.07	0.14

Note: AIC_c represents AIC values corrected for small sample size; delta AIC_c (ΔAIC_c) is the difference in AIC_c score between the highest ranked model and the candidate model; Akaike weight (w_i) is the probability that a particular model is the most parsimonious model among the candidate models. '*' denotes RHA components. *Multiple MCI models are presented: the primary model based on the full dataset (n = 52) and a conservative model fit to a balanced subset that equalised selection opportunity for water quality and habitat predictors (n = 19).*

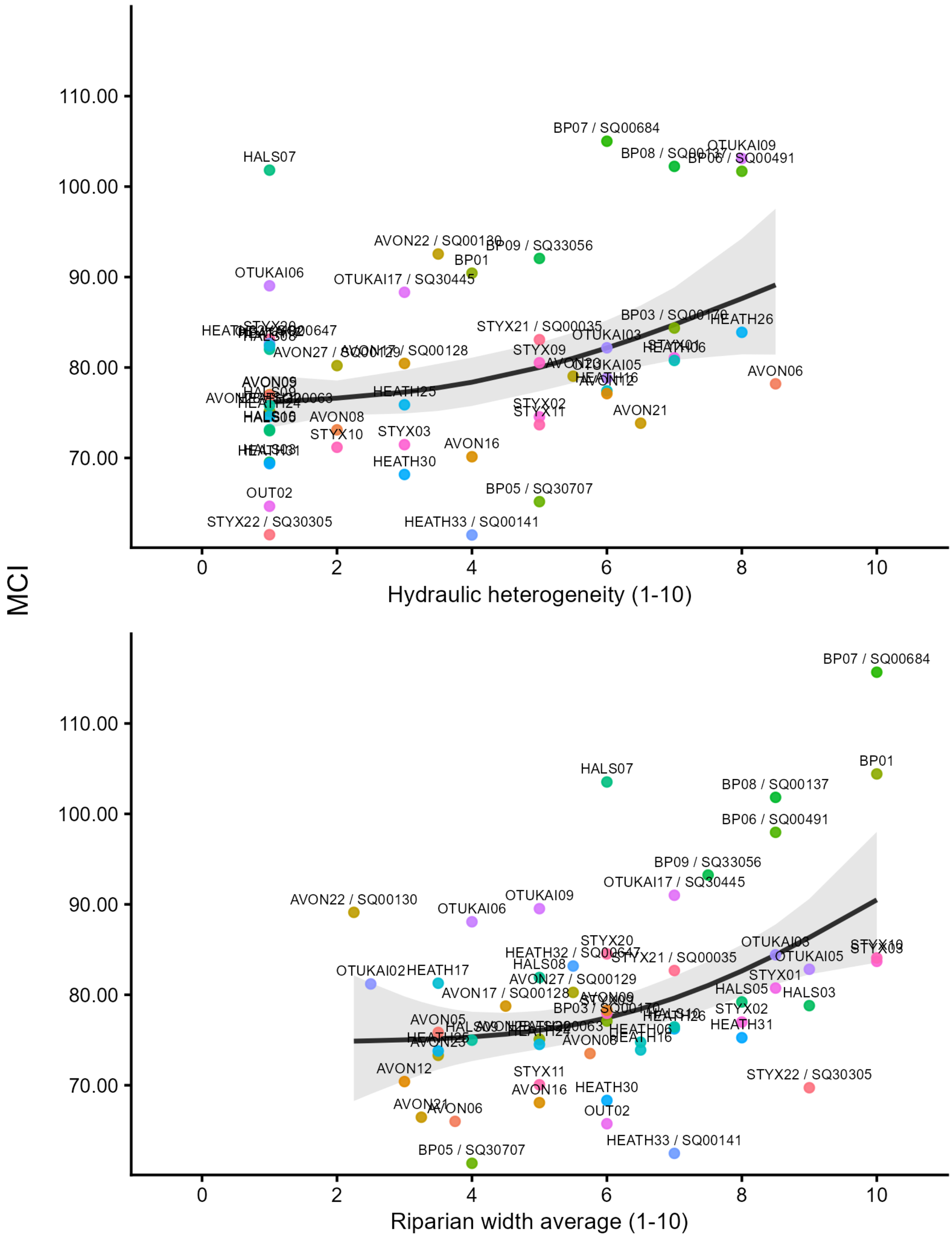

Figure A1. Partial plots of the most parsimonious MCI model fitted to the full dataset. Solid lines show modelled fits and shaded bands are 95% confidence intervals. Note that habitat score of 10 indicates ideal conditions.

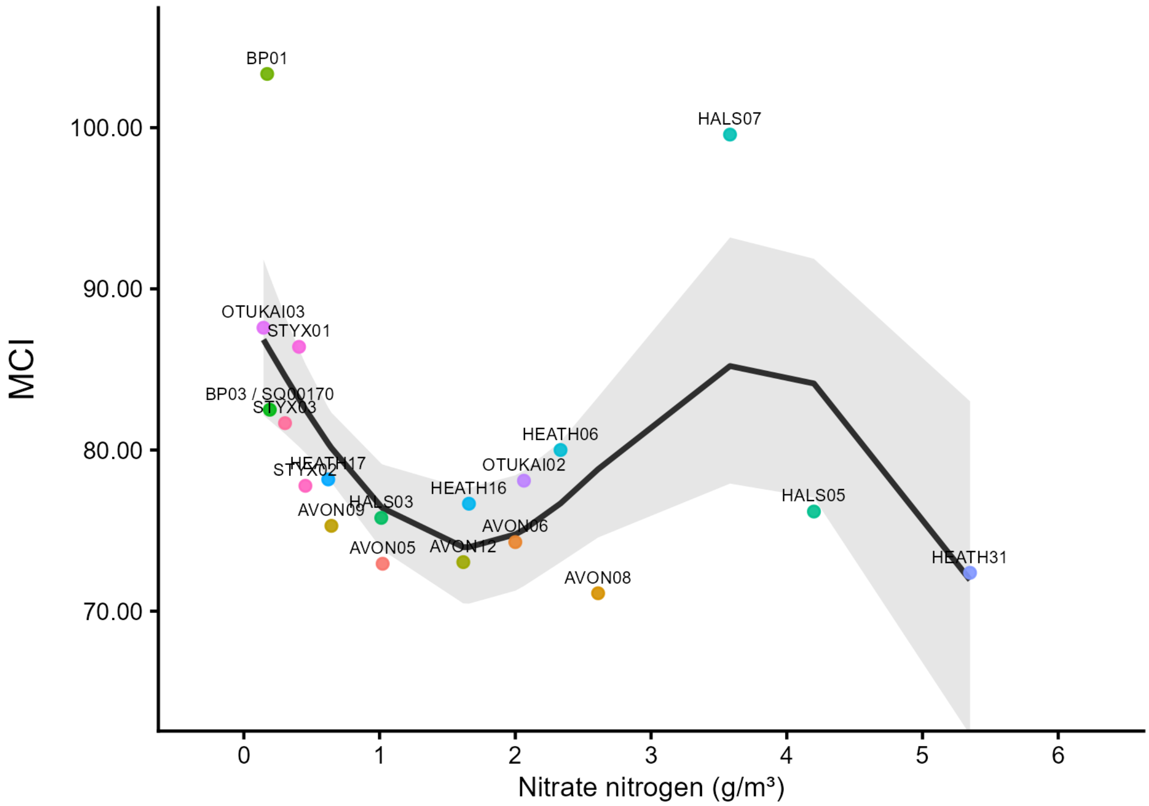

Figure A2. Partial plot of the most parsimonious MCI model fitted to the balanced dataset. Solid lines show modelled fits and shaded bands are 95% confidence intervals.