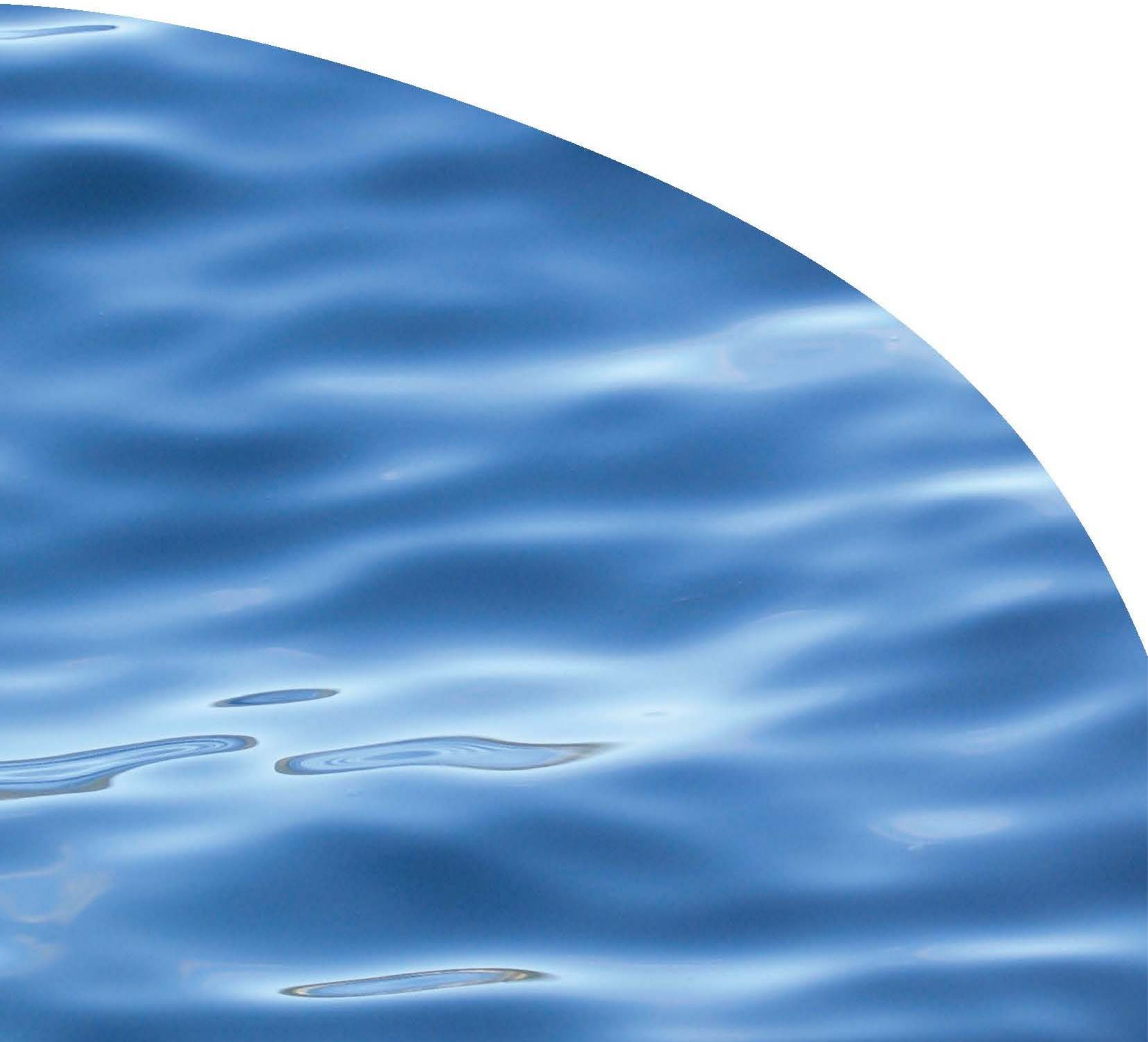
REPORT NO. 2507

RELATIONSHIPS BETWEEN MACROINVERTEBRATE COMMUNITY INDEX AND ENVIRONMENTAL DRIVERS



RELATIONSHIPS BETWEEN MACROINVERTEBRATE COMMUNITY INDEX AND ENVIRONMENTAL DRIVERS

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Prepared for Ministry for the Environment

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EXECUTIVE SUMMARY

This report details statistical analyses investigating the cause-and-effect relationship between land cover and associated land-use impacts and the Macroinvertebrate Community Index (MCI). The analyses were commissioned by the Ministry for the Environment (MfE) to inform discussion on the inclusion of MCI as an attribute in the National Objectives Framework.

The MCI measure of invertebrate community quality provides a sensitive indicator of the biological health of streams. Based on the sensitivity of macroinvertebrates to organic pollution, MCI scores have been widely applied to assess stream health. We analysed a national data set of MCI scores collected by regional council and unitary authorities predominantly from State of the Environment river monitoring sites during 2007 to 2011. We also analysed a regional data set of MCI scores collected in 2012 as part of a project in the Management of Cumulative Effects of Stressors on Aquatic Ecosystems research program (C01X1005).

Boosted regression trees, structural equation modelling and variance partitioning all identified a strong link between the MCI and catchment-scale land cover, and more proximate measures of nutrients and habitat. Sediment and nutrients were identified as the probable causal pathways for land use to impact MCI. However, results showed that multiple drivers were associated with variation in MCI and that the drivers were not independent of each other. This intercorrelation between catchment and segment scale, natural and impact variables make the relationships between MCI and specific variables hard to quantify.

Overall results suggest that site MCI scores are related to land use through a complex chain of causality, which makes isolating the role of specific variables difficult. The impact of limits placed on one effect pathway will depend on interactions with other pathways and will also be influenced by the local habitat. Catchment scale management may not result in a response in MCI scores without equal consideration of segment scale management and vice versa.

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1. INTRODUCTION

1.1. Background

A draft report has been produced outlining options for including a Macroinvertebrate Community Index (MCI) attribute in the National Objectives Framework (NOF) (Collier *et al.* 2014), but impacts of including the attribute are difficult to ascertain because of the complexity of drivers influencing MCI. The Ministry for the Environment (MfE) is now seeking advice on the links between drivers and MCI outcomes to inform work on identifying and quantifying the impacts of including an MCI attribute in the NOF, in particular the impacts of setting a national bottom line.

This report builds on the conceptual model of Collier *et al.* (2014) and the statistical models of Clapcott *et al.* (2013) to determine what catchment scale and segment scale (length of stream between two tributaries) variables are important in determining MCI values and what the strength of the relationships are. The aim of the analysis is to identify the primary causal variables (potentially available for limit setting) and the strength of the relationship with MCI.

1.2. Conceptual relationship between Macroinvertebrate Community Index and environmental drivers

The New Zealand Macroinvertebrate Community Index (MCI) uses the presence of invertebrate taxa at a site to provide a measure of ecosystem health that has been shown to respond to a range of human pressures on wadeable streams. Factors affecting MCI are discussed in detail in Collier *et al.* (2014). The main pressures influencing MCI in streams draining agricultural catchments are considered to be nutrient inputs, sediment inputs and removal of shade, whereas in urban streams the main pressures are stormwater inputs and channel modification (Figure 1).

Recent modelling of MCI using measures of environmental drivers from LCDB3 (Landcover Database version 3) and FENZ (Freshwater Ecosystems of New Zealand) databases identified a range of potential pathways through which catchment scale impacts can affect MCI (Clapcott *et al.* 2013). Predictor variables with strong explanatory power included catchment-scale measures of native vegetation and heavy pastoral cover, segment-scale measures of shade, flow, and temperature, and in-stream measures of habitat (Table 1). However, the analytical approach used did not identify causality or separate the influence of land cover from natural environmental variability in determining the values of potential driver variables.

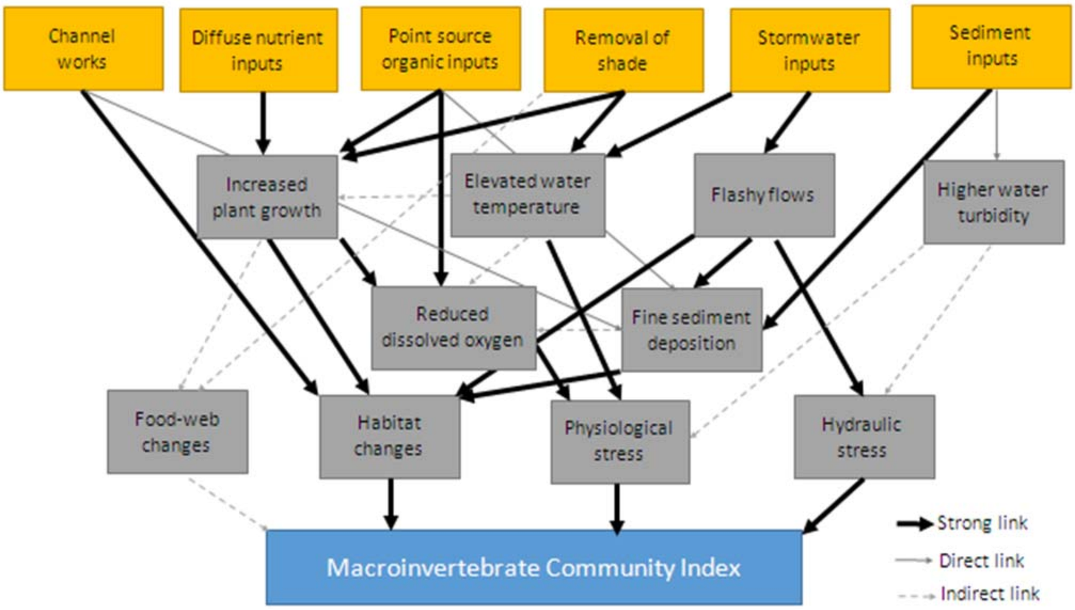

Figure 1. Conceptual causal model identifying the expected causal links between human pressures and Macroinvertebrate Community Index (MCI) from Collier *et al.* 2014.

Table 1. Predictor variable importance (% deviance explained) in a boosted regression tree (BRT) model of Macroinvertebrate Community Index (MCI) from Clapcott *et al.* (2013). Variables are grouped by the scale at which they occur and whether they are measures of human impact or natural variability.

Scale-type of variable	Predictor	Deviance explained (%)
Catchment-impact	% Native vegetation	29.52
	% Pastoral heavy	9.82
	% Urban	6.12
	Surface Water Allocation	0.89
	% Pastoral light	0.41
	% Bare ground	0.33
Catchment-natural	Catchment rain days > 25mm	5.31
	Catchment slope	3.8
	Catchment hardness	2.42
	Catchment calcium	2.23
	Catchment average temperature	2.2

Scale-type of variable	Predictor	Deviance explained (%)
	Catchment phosphorus	1.84
Segment	Segment summer temperature	8.68
	Segment flow stability	7.19
	Segment habitat	4.78
	Segment slope	3.37
	Segment shade	3.12
	Segment winter temperature normalised	3.08
	Segment particle size	2.66
	Segment low flow	2.06

1.3. Statistical approaches to exploring relationships between Macroinvertebrate Community Index and environmental drivers

1.3.1. Boosted regression trees

The BRT method combines additive regression modelling with boosting techniques, and provides an estimate of best fit from an ensemble of numerous, often thousands, of models. Results include a measure of the comparative strength of association between the response variable and predictor variables (percentage of deviance explained) and a cross-validation coefficient (CV) indicating the degree to which the model fits the holdout data (*i.e.* potential predictive performance). The model development for BRT analysis is discussed in detail in the literature (Friedman 2001; Elith *et al.* 2008; Hastie *et al.* 2009). The advantages of the BRT method are greater power for explaining and predicting ecological patterns as they are not restricted by the data assumptions of conventional, parametric approaches; an ability to accommodate different types of predictor variables and missing values; immunity to the effects of extreme outliers and the inclusion of irrelevant predictors; and automatic fitting of interactions between predictors. The BRT method has been used to identify the most important variables explaining deviance in observed measures of stream health (Clapcott *et al.* 2012; Waite *et al.* 2012) and also for predicting the spatial distribution of stream biota (Leathwick *et al.* 2008). The BRT approach does not prove causality, but does provide useful output for formulating hypotheses regarding causality.

1.3.2. Structural equation modelling

Structural equation modelling is a statistical technique for testing and estimating causal relationships. Hypotheses as to the nature of the relationships between predictor variables and response variables are specified *a priori* based on existing knowledge of the system. The model is fitted by analysing multiple linear equations to find a solution that minimises the difference between the model-implied and observed covariance. Results provide estimates of direct, indirect and total effects that causally link the variables in the model (Bollen 1989). Structural equation modelling (SEM) has been used to identify the pathways through which the biological integrity of streams may be impacted by land use (Riseng *et al.* 2011).

Structural equation modelling development involves three key steps: firstly, the development of a conceptual causal model (*e.g.* Figure 1); secondly, a generalised structural model (Figure 2) which identifies the specific causal hypotheses and is constrained by parameter/data availability; and thirdly, the fitted structural model or output.

1.3.3. Variance partitioning

Variance partitioning subdivides the variation of a response (MCI scores) with respect to two, three, or four explanatory tables that are referred to as factors. Each factor comprises a set of predictor variables that are grouped on some basis, such as their characteristic scale of variability or whether they represent natural or modified conditions. The explained variance of the response is partitioned into components that include the individual, shared and unique contributions of each of the factors. The individual contribution is the variance explained by a factor on its own, the shared contribution is the explained variance that is common to two or more factors and the unique contribution is the variance explained by a single factor when the contribution of all other factors have been partialled out (*i.e*. removed; Legendre & Legendre 1998). The technique examines the relative contribution of different factors in explaining variation in a response variable. We used the Bocard (1992) approach that uses a sequence of linear regressions to partition variance as described by Booker *et al.* (2014).

2. DATA ANALYSIS

2.1. Source data

We investigated the relationship between MCI and environmental drivers using two data sets:

1. A national data set consisting of MCI values from regional state of the environmental networks and modelled predictor variables.
2. A regional data set consisting of MCI values from the Manawatu region and modelled and measured predictor variables[1].

2.2. Case study 1: national data set

The national data set was described in Clapcott *et al.* (2013) and consists of MCI data collected by regional council and unitary authorities predominantly from State of the Environment river monitoring sites during 2007 to 2011. 'Site' was defined by stream segment (NZReach), being a section of river between tributary confluences. All data for any given site was combined to calculate median values, except when there were two obvious upstream and downstream locations in a segment, potentially indicating monitoring above and below a point source input, in which case only values from the upstream location were used. The working MCI dataset included 1,033 sites from all regions.

Environmental drivers included measures of land cover and other environmental descriptors. Land cover descriptors from LCDB3 were merged into six predictor variables that represented broad land cover categories including native vegetation, exotic vegetation, pastoral heavy, pastoral light, urban, bare ground, and wetland. Other environmental descriptors accessed from the FENZ database were variables with informative relationships with the distribution of freshwater invertebrates (Leathwick *et al.* 2011) and included measures of geography and topography, slope, flow and flow influencing factors, and geology. A measure of surface water allocation pressure as described by Clapcott and Goodwin (2010) was also included.

Additional environmental descriptors included in our national analyses were predicted measures of nitrate-nitrogen (NO_3N), dissolved reactive phosphorus (DRP), and percent increase in fine sediment as identified in Figure 1 as possible pathway variables. These values were predicted for all stream reaches in the country using the same spatial data to predict MCI (reported in Clapcott *et al.* 2013), using comparable modelling techniques: random forests for NO_3N and DRP (Unwin *et al.* 2010) and

[1] The Manawatu dataset was collected as part of the Management of Cumulative Effects of Stressors on Aquatic Ecosystems research program (C01X1005).

boosted regression trees for fine sediment (appendices in Clapcott *et al.* 2011). The total predictor data set contained 21 variables (Table 2).

Table 2. Description of the national data set including the mean and range of values of land-use pressure gradients and environmental variables used in this study. N = 1033.

Variable	Description	Mean (range)
% native vegetation	Native vegetation cover in the catchment (%)	34.4 (0, 100)
% pastoral heavy	Pastoral heavy cover in the catchment (%)	42.3 (0, 100)
% urban	Urban impervious cover in the catchment (%)	3.2 (0, 99)
Surface Water Allocation	Mean annual low flow remaining after the upstream daily surface water allocation is deducted (proportion)	0.9 (0, 1)
Catchment rain days	Days/year with rainfall in the catchment greater than 25 mm	14.2 (1.9, 71.4)
Catchment temperature	Average air temperature (°C) in the catchment, normalised with respect to SEGJANAIRT	-0.5 (-6.0, 1.6)
Catchment slope	Average slope in the catchment (°)	12.9 (0.0, 32.0)
Catchment hardness	Average hardness of rocks in the catchment, 1 = very low to 5 = very high	2.9 (1, 5.0)
Catchment calcium	Average calcium concentration of rocks in the catchment, 1 = very low to 4 = very high	1.6 (1.0, 4.0)
Catchment phosphorus	Average phosphorus concentration of rocks in the catchment, 1 = very low to 5 = very high	2.4 (1.0, 5)
Segment flow stability	Annual low flow/annual mean flow (ratio)	0.2 (0, 0.5)
Segment low flow	Mean annual 7-day low flow (m^3/s), fourth-root transformed	1.1 (1, 4.1)
Segment summer temperature	Segment summer air temperature (°C)	17 (12.6, 19.6)
Segment winter temperature normalised	Segment winter air temperature (°C), normalised with respect to SEGJANAIRT	0.5 (-4.2, 3.5)
Segment shade	Segment riparian shade (proportional)	0.3 (0, 0.8)
Segment slope	Segment slope (°), square-root transformed	1.3 (1, 3.9)
Segment habitat	Weighted average of proportional cover of local habitat using categories of: 1 = still; 2 = backwater; 3 = pool; 4 = run; 5 = riffle; 6 = rapid; 7 = cascade	4.0 (2.3, 4.8)
Segment substrate	Weighted average of proportional cover of bed sediment using categories of: 1 = mud; 2 = sand; 3 = fine gravel; 4 = coarse gravel; 5 = cobble; 6 = boulder; 7 = bedrock	3.6 (1, 5.9)
Fines	Increase in fine sediment cover: contemporary cover minus reference cover, logit transformed (%)	-0.2 (-3.7, 3.4)

Variable	Description	Mean (range)
DRP	Dissolved reactive phosphorus (mg/L)	0.013 (0.01, 0.15)
NO_3N	Nitrate-nitrogen (mg/L)	0.396 (0.01, 5.61)

2.2.1. Boosted regression trees

Method

In previous modelling we used both catchment and segment scale predictors to explain the deviance in MCI data (Clapcott *et al.* 2013). This time, we used a selection of variables based on their identified relative importance in previous modelling and their suitability as proximate measures of the causal links identified in Figure 1. We fitted a model including catchment-scale land cover and surface water allocation variables and then repeated the model fitting procedure excluding catchment-scale variables. Model output was compared and the relative change in variable importance examined, to determine whether proximate variables are appropriate predictors of MCI when catchment-scale land cover variables are excluded. We also fitted a two-step model to investigate deviance partitioning between land cover and other variables. Output from Step A (a model fitted using land cover variables only) was used as a fixed offset in Step B (a model fitted using all other variables) and the increase in deviance explained was examined.

Results

The all-inclusive BRT model explained 63.7% of the deviance in the MCI data and had an internal cross validation of 0.80 which indicates excellent potential predictive performance. Similarly, the no land cover BRT model explained 61.5% of the deviance in the MCI data and had an internal cross validation of 0.79. The most important predictors in the all-in model included native vegetation, heavy pasture, and predicted fine sediment and nitrate. The latter were the top two predictors in the no land cover model suggesting they provide proximate measures of the effects of land cover. Segment scale descriptors of temperature and flow were also important predictors in both models.

For the two-step model, land cover variables alone (Step A) explained 50.5% of the deviance in the MCI data and the inclusion of additional variables (Step B) increased the percentage deviance explained to 66.7%. Most of the additional deviance explained was attributable to descriptors of natural environmental variability at catchment and segment scales (Table 3).

Table 3. Predictor variable importance (percent deviance explained) in predictive models of Macroinvertebrate Community Index (MCI) using boosted regression tree (BRT) model approaches.

Scale-type of variable	Predictor	All-in	No land cover	Two-step A	Two-step B
Catchment-impact	% native vegetation	20.19	-	48.6	
	% pastoral heavy	7.43	-	30.6	
	% urban	3.96	-	19.9	
	Surface water allocation	0.54	-	0.9	
Catchment-natural	Catchment rain days	5.11	9.78		9.9
	Catchment slope	3.03	4.40		3.1
	Catchment calcium	2.34	3.31		3.8
	Catchment hardness	1.48	2.28		2.4
	Catchment phosphorus	1.34	1.92		4.1
	Catchment temperature	1.19	1.22		3.6
Segment-impact	FinesOE	15.76	25.26		2.9
	NO_3N	7.07	17.27		6.9
	DRP	1.91	2.06		6.7
Segment-natural	Segment summer temperature	7.02	5.53		18.8
	Segment flow stability	6.28	6.29		10.7
	Segment slope	3.91	5.11		7.9
	Segment habitat	3.54	4.79		3.3
	Segment shade	2.68	5.00		4.5
	Segment winter temperature	2.31	2.40		6.6
	Segment low flow	1.73	1.69		3.3
	Segment substrate	1.15	1.66		1.2

2.2.2. Structural equation modelling

Method

We developed a general structural model based on available data (Table 2). The general structural model included three exogenous driving variables (percentage land cover), four unmeasured concept (latent) variables and their associated measurement models, and nine endogenous variables (measured variables that are influenced by the exogenous variables) (Figure 2). The measurement models provide an estimate of each latent variable. Some variables were transformed to meet the assumptions of normality for this linear methodology, including NO_3N and DRP (log N+1), FineOE (logit), Segment shade (logit), and Segment low flow (log N+1).

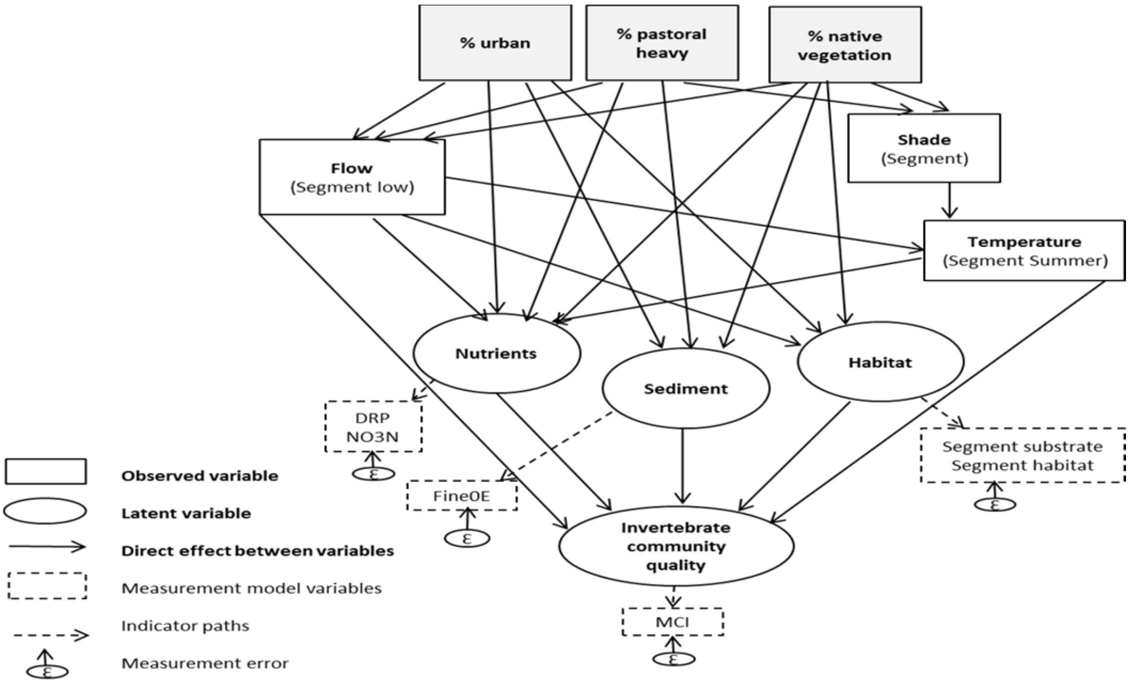

Figure 2. Generalised structural model identifying the expected causal links between human pressures and Macroinvertebrate Community Index (MCI). Exogenous or external drivers are in grey boxes and endogenous or proximate variables are in white boxes.

We fitted the general model to the national data set by iteratively refining the base model linkages to identify the best fitting causal structure consistent with known physical and biological relationships, i.e. only fitting sensible relationships. We also developed a simplified model to illustrate direct comparisons between pathways suitable for management interventions, whereby variables indicative of natural environmental variation were excluded. Model fit was evaluated using the following descriptive statistics:

- Chi-square (χ^2) statistic — a test of the null hypothesis that the model fits the data. Low χ^2 values indicate best model fit with p > 0.05 and ideally close to 1, *i.e.* p <

0.05 would indicate that the null hypothesis (that the model fits the data) should be rejected. However with large sample sizes, the Chi-square test may have large $\chi2$ values and $p < 0.05$ even when the fit is good.

- Root mean square error (RMSE) approximation — another test of how well the data fit to the causal hypothesis, where RMSE close to zero and $p < 0.05$ are considered to indicate good fit.
- Comparative Fit Index (CFI) — provides an assessment of model fit insensitive to sample size. A CFI value of 0.90 or higher is desirable.

Results

The fitted structural model illustrated the pathways between catchment-scale land cover, proximate segment-scale descriptor variables and MCI. There was a strong link between heavy pastoral cover and nutrients (predicted concentrations of DRP and NO_3N). However, the link between nutrients and MCI was not as strong as that observed for habitat and MCI and predicted increase in fine sediment and MCI. The SEM suggests that an increase in pastoral cover is likely to result in an increase in nutrient values but this may not result in a significant decrease in MCI. However, a change in stream habitat reflected by substrate composition, hydraulic diversity and fine sediment is likely to result in a direct change in observed MCI. The SEM illustrates the complexity of impact and potential recovery pathways for MCI as has been shown in previous survey studies (for review see Collier *et al.* 2014).

The inferences from this SEM are limited by the fact that descriptive statistics suggest poor model fit: CFI = 0.756; χ^2 = 1861.81, degrees of freedom = 36, $p < 0.001$; RMSE = 0.222 (95^{th} CI 0.213, 0.230), $p < 0.05$. Non-independent endogenous variables can contribute to poor model fit.

We fitted a second simplified SEM excluding variables likely to be driven by natural variability rather than catchment-scale land cover (*e.g*. habitat descriptors of hydraulic diversity and substrate size) and focussing on the impact pathways of nutrients and sediment (Figure 4). The model descriptive statistics were much improved but still suggested a poor model fit: CFI = 0.939; χ^2 =213.63, degrees of freedom = 7, $p < 0.001$; RMSE = 0.169 (95^{th} CI 0.150, 0.189), $P < 0.05$. The pathways in the model illustrate an almost equal contribution of sediment and nutrients influencing MCI, and again a dominant relationship between heavy pasture and nutrients (Figure 4).

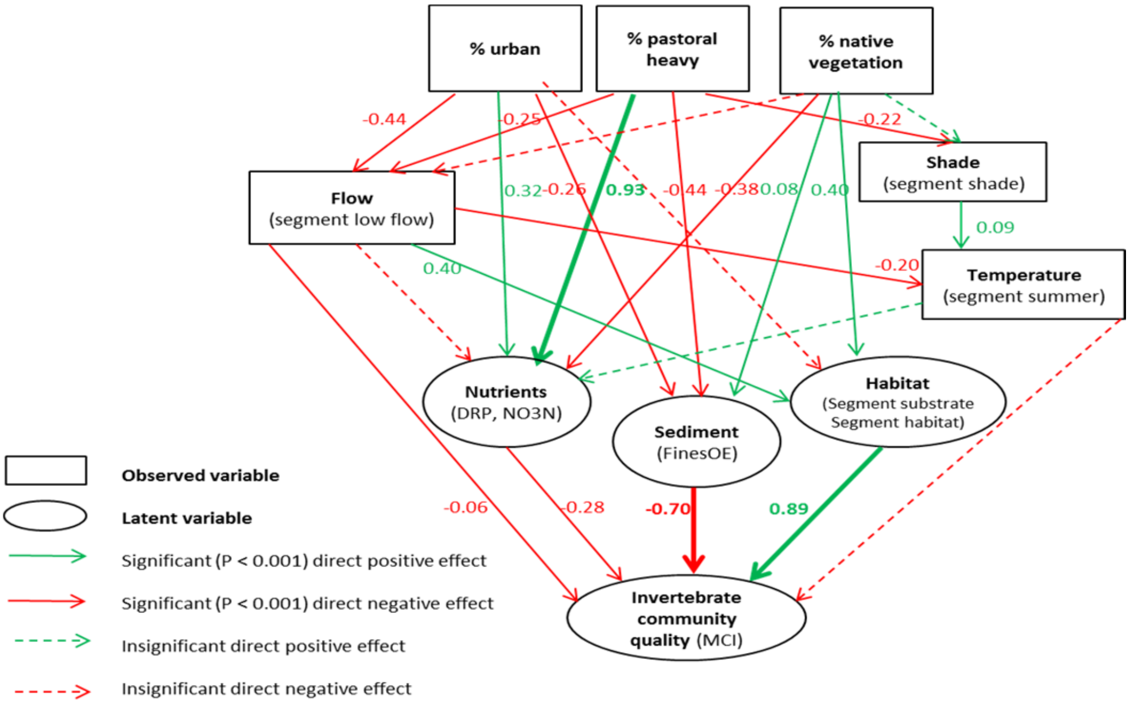

Figure 3. Parameterised structural equation model showing the relative importance (standardized path coefficients) of direct pathways between human pressures and Macroinvertebrate Community Index (MCI). Standardised effect sizes for non-significant effects and correlations were removed for clarity. The strongest effect paths are indicated by thick lines.

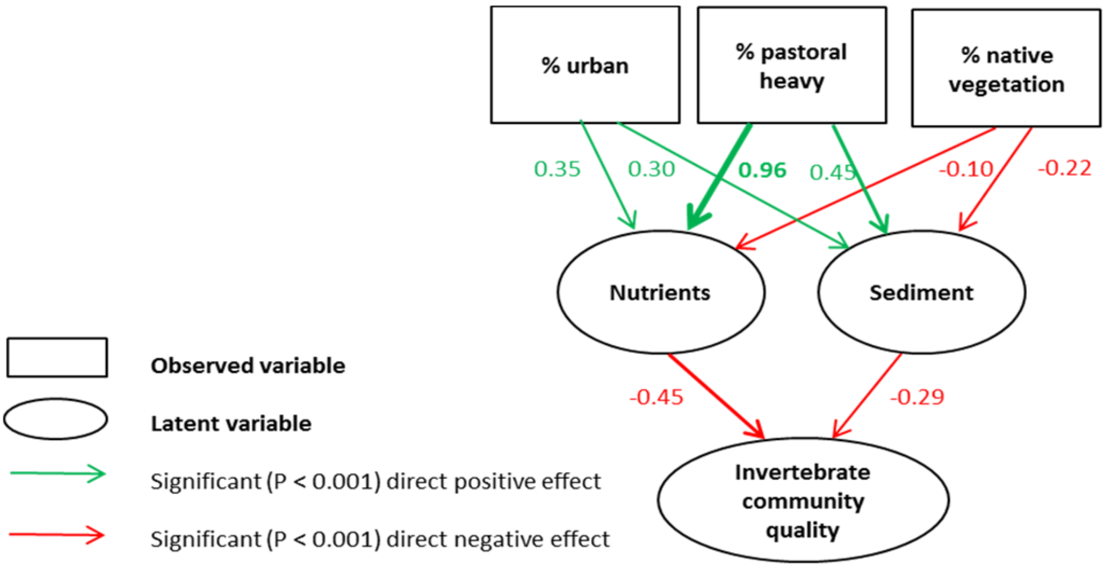

Figure 4. Simplified fitted structural equation model showing relative importance (standardized path coefficients) of direct paths between human pressures and Macroinvertebrate Community Index (MCI).

2.2.3. Variance partitioning

Method

We used variance partitioning to examine how much of the total explained variation of MCI could be attributed to explanatory variables grouped into four factors: catchment-impact, segment-impact, catchment-natural and segment natural. Explanatory variables were grouped into these factors as shown in Table 3. The output provides a measure of how much variation is attributable to individual factors, and how much is uniquely attributable to each factor.

Results

When used in combination, all four factors explained 61% of the variance in MCI. Individually, factors explained similar amounts of variation (40-50%) with ‘catchment-impact’ factor explaining the largest amount (Table 4). However, the unique variation explained by all four factors was very low (1-5%) and indicated that no individual factor is likely to explain variation in MCI not accounted for by other factors. All model components were highly significant ($p < 0.001$).

Table 4. Examination of the total variance explained in a national model of Macroinvertebrate Community Index (MCI) using linear variance partitioning. N = 1033.

Factor	Individual	Unique
Catchment-impact	49.8	3.5
Catchment-natural	40.1	2.2
Segment-impact	39.7	1.1
Segment-natural	39.5	5.1

2.3. Case study 2: regional data set

The regional data set consists of pressure and response variables measured at 58 sites in the Manawatu and Rangitikei catchments (Table 5). Land cover, flow and slope variables were spatial measures as described in Table 2. Water chemistry variables (total nitrogen [TN] and total phosphorus [TP]) were measured monthly by Horizons Regional Council. Remaining data was collected during field sampling in February to April 2012 where fine sediment cover (Fines) was measured using an in-stream visual protocol (Clapcott *et al*. 2011), periphyton cover was measured using a visual assessment method (Biggs & Kilroy 2000), riparian shade was estimated for the study reach, and average daily temperature was measured using a Hobo© temperature logger.

Table 5. Description of the regional data set including the mean and range of values of land-use pressure gradients and measured environmental variables. N = 58.

Variable	Description	Mean (range)
% native vegetation	Native vegetation cover in the catchment (%)	0.329 (0.02, 0.98)
% pastoral heavy	Pastoral heavy cover in the catchment (%)	0.569 (0.0, 0.92)
Segment low flow	Mean annual 7-day low flow (m^3/s), fourth-root transformed	1.30 (1.01, 2.03)
Segment slope	Segment slope (°), square-root transformed	1.15 (1.0, 1.62)
Fines	Site fine sediment cover (%)	27.6 (0.25, 79.9)
TN	Total phosphorus 3-yr median (mg/L)	0.69 (0.07, 1.8)
TP	Total nitrogen 3-yr median (mg/L)	0.037 (0.01, 0.19)
Shade	Site riparian shade (%)	33.98 (3.0, 94.0)
Periphyton	Site total filamentous periphyton cover (%)	10.3 (0, 65.9)
Temperature	Water temperature 7-day average (°C)	16.9 (8.0, 21.9)

2.3.1. Boosted regression trees

Method

Firstly, a BRT model including 10 predictors was developed. The number of predictors was restricted to 10 to minimise over-fitting based on a sample size of 58.Then we refitted the model excluding catchment-scale land cover variables and compared the relative importance of predictors from the two models. As in the national analysis, a two-step model was used to examine the partitioning of deviance in MCI between land cover and other explanatory variables.

Results

The ‘all-in’ and ‘no land cover’ models had similar descriptive statistics suggesting fair model performance: the all-in model explained 37.1% of the deviance in the MCI data and had a cross validation correlation of 0.39; the no land cover model explained 38.2% of the deviance in the MCI data and had a cross-validation correlation of 0.56. The all-in model identified native vegetation and heavy pasture as two of the top four predictors along with segment low flow and TN. The latter were retained as top predictors along with temperature and TP in the no land cover model (Table 6).

For the two-step model, the heavy pasture and native vegetation response was directionally constrained and explained 31.8% of the deviance in the MCI data (Step A). The inclusion of additional variables (Step B) increased the percentage deviance explained to 52.9%. The majority of the additional deviance explained was attributable to segment low flow.

Table 6. Predictor variable importance (percent deviance explained) in predictive models of Macroinvertebrate Community Index (MCI) in the regional data set using boosted regression tree (BRT) model approaches.

Scale – type of variable	Predictor	All-in	No land cover	Two-step A	Two-step B
Catchment – impact	% pastoral heavy	26.47	-	62.2	-
	% native vegetation	16.99	-	37.8	-
Segment – impact	TN	16.69	32.13	-	12.9
	TP	5.24	10.25	-	6.5
	Temperature	4.77	22.09	-	4.7
	Periphyton	4.59	6.89	-	4.1
	Shade	4.00	4.46	-	11.3
	Fines	1.5	1.40	-	5.0
Segment – natural	Segment low flow	18.71	20.45	-	53.9
	Segment slope	1.03	2.31	-	1.6

2.3.2. Structural equation modelling

We developed a general structural model for the regional data (Table 5). The general structural model included two exogenous driving variables (percentage land use cover), three unmeasured concept (latent) variables and their associated measurement models, including four endogenous variables (Figure 5). The measurement models provide an estimate of each latent variable. Some variables were transformed to meet the assumptions of normality for this linear methodology, including TN and TP (log), and Fines (logit).

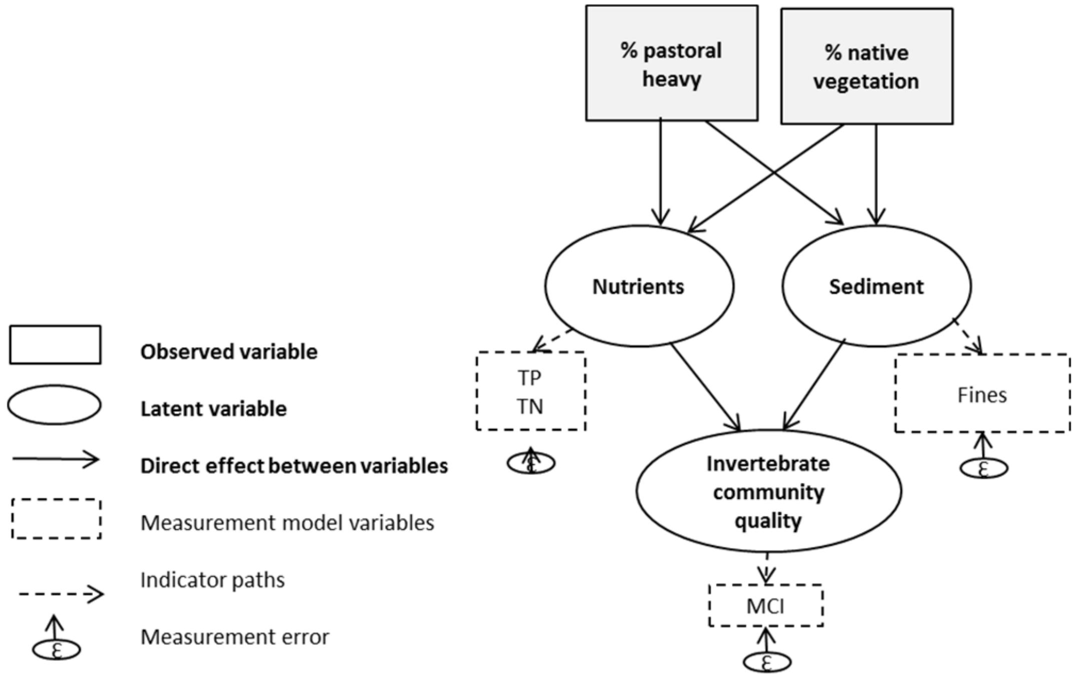

Figure 5. Generalised structural model identifying the expected causal links between human pressures and MCI in the regional data. Exogenous or external drivers are in grey boxes and endogenous or proximate variables are in white boxes.

Results

The fitted structural model illustrated the pathways between catchment-scale land cover and MCI (Figure 6). There were significant negative effects between native vegetation cover and sediment and nutrient descriptors, and a significant positive effect between heavy pasture cover and nutrients. The link from nutrients to MCI indicated a significant dominance of this pathway in driving MCI. Descriptive statistics indicated good model fit: CFI = 0.975; χ^2 = 9.01, degrees of freedom = 9, p = 0.11; RMSE = 0.120 (95th CI 0.01, 0.243), p = 0.16.

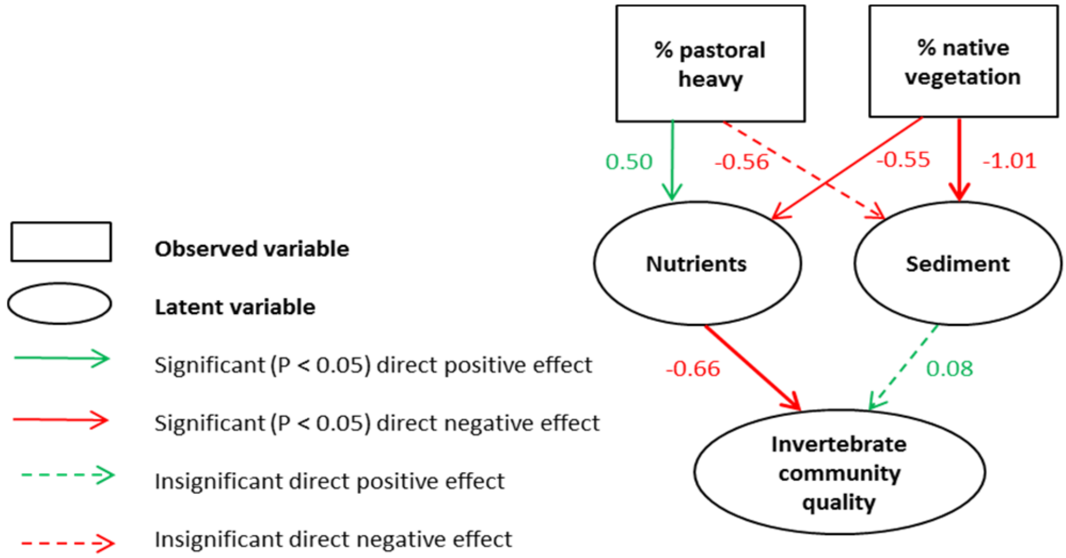

Figure 6. Fitted structural equation model showing the relative importance (standardized path coefficients) of direct paths between human pressures and Macroinvertebrate Community Index (MCI) in the regional data set.

2.3.3. Variance partitioning

Method

We used variance partitioning to examine how much of the total explained variation of MCI could be attributed to variables grouped into three factors: catchment-impact, segment-impact and segment natural. Explanatory variables were grouped into these factors as shown in Table 6.

Results

When combined, all three factors explained 43% of the variance in MCI. Individually, factors explained between 14% and 42% of variance with 'catchment-impact' factor explaining nearly twice as much variance in MCI than any other factor (Table 7). The catchment-impact factor also explained almost 10% unique variation in MCI, but unlike the individual variance components, the unique variations explained by all three factors were not statistically significant ($p > 0.1$)

Table 7. Examination of the variance explained in a regional model of Macroinvertebrate Community Index (MCI) using linear variance partitioning. N = 58.

Factor	Individual	Unique
Catchment-impact	41.9	9.4
Catchment-natural	22.8	0.2
Segment-impact	13.9	0.9

3. RELEVANCE FOR MACROINVERTEBRATE COMMUNITY INDEX AS A NATIONAL OBJECTIVES FRAMEWORK ATTRIBUTE

Both the national analyses and the regional case study identified the strong link between the MCI measure of invertebrate community quality and catchment-scale land cover, and proximate measures of nutrients and habitat. The results suggest that site MCI scores are related to land use through a complex chain of causality, which makes isolating the role of specific variables difficult.

Boosted regression tree modelling that excluded land cover variables did not significantly reduce model performance. In the national data set this may be due to the fact that habitat (FinesOE) and nutrient variables (DRP and NO_3N) are predicted in part by land cover and so these variables reflect measures of catchment land cover. However, in the regional data set, habitat (Fines) and nutrient variables (TN and TP) were measured and showed independent correlative relationships with land cover and MCI. Both national and regional BRT models illustrate that approximately two thirds of total deviance in MCI can be explained by catchment scale or segment scale measures of human impacts. Both analyses also explained approximately one third of total deviance in MCI data using additional variables that described natural environmental variation (*e.g.* segment slope, temperature and flow).

Structural equation models supported the theoretical model (Figure 1) that postulated that the causal pathways through which land use affects MCI are complex. While the national models were not robust in terms of model statistics they did highlight the relative importance of impact pathways. Results indicate that an increase in heavy pastoral cover is associated with increased nutrients and decreased MCI. Equally, high levels of fine sediment deposition (as a result of combined land cover effects) are associated with decreased MCI. Both of these impact pathways are relatively less influential than segment scale variables describing habitat, which may reflect an additional impact pathway or the influence of natural environmental variation (Figure 1). These results suggest that segment scale processes may be as important as catchment scale processes in determining MCI values. This finding is consistent with previous studies that have demonstrated a land-cover cascade (Burcher et al. 2007) linking catchment scale land cover to in-stream biotic response variables through proximate or reach-scale intermediate variables (*e.g*. Weigel *et al.* 2003; Cover *et al.* 2008). Such hierarchical models can be used to identify the most appropriate scales to manage stream health (*e.g.* Sheldon et al. 2012).

The regional structural equation model demonstrated robust correlative relationships between land cover and nutrients and sediment, and a dominant impact pathway between nutrients and MCI. Habitat descriptors were not included in this model and so the relative importance of environmental setting in influencing MCI cannot be ascertained. This model does show that nutrients (3-yr median) were a stronger driver of MCI than sediment (single measure in 2012) at the 58 sample sites.

The variance partitioning analyses demonstrated that MCI could be reasonably predicted by any given combination of catchment or segment, impact or environmental descriptor variables. This is likely to illustrate the correlation between predictor variables in the national data set, *i.e.* higher values of land use impact are associated with lower slopes and warmer temperatures. In the regional case study, the unique variance component had lower statistical certainty (possibly due to sample size), but results did illustrate that catchment scale measures of land use best informed the explanatory model of MCI. These results reiterate the observations from both SEM and BRT models that MCI values are related to land use through a complex chain of causality making it difficult to isolate specific factors.

Our results are indicative of causal pathways, but true causality can only be tested using manipulative experimentation. The results of all analyses in this study indicate that multiple drivers are associated with variation in MCI and that the drivers are not independent of each another. The impact of limits placed on one effect pathway will depend on interactions with other pathways and will also be influenced by the local habitat. Catchment scale management may not result in a response in MCI without equal consideration of segment scale management and vice versa.

Finally, as a community index the MCI integrates multiple effects and this may add to the difficulty in quantifying specific effect pathways. The strengths and weaknesses of community indices are well documented. They provide good indicators of overall ecosystem health and are not only useful indicators of current conditions, but also of cumulative effects and changes over time (Barbour et al. 2000). However, community indices can be insensitive to certain impacts and it has been argued that specific species responses provide a much more sensitive measure of impact and greater evidence of causality (Baker & King 2010). Our analyses suggest that the MCI provides a sensitive indicator of the level of human impact on stream health but the relationships between MCI and drivers are not independent and hence hard to quantify.

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