TOOLS FOR WATER QUALITY PREDICTION AND NPS-FM IMPLEMENTATION IN URBAN SETTINGS

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ABSTRACT

Implementation of the National Policy Statement for Freshwater Management (NPS-FM), in urban catchments is likely to require quantitative models to enable limit-setting of contaminants, including copper and zinc. Some models currently available require considerable resources in terms of the time to set-up and implement, and many have substantial data requirements for calibration (e.g., continuous flow monitoring data). More simplistic models, such as spreadsheet or GIS-based catchment load models, do not provide information on in-stream concentrations required for assessing attribute states. We are exploring new modelling methods that are suitable for catchments with minimal data (e.g., no water quality data, no continuous flow monitoring) and provide the required information for comparison to in-stream concentration-based attributes and source-based load limits. These methods can be applied as screening tools, to indicate where more resource is required (either additional monitoring or more sophisticated modelling).

Our work is focusing, firstly, on methods to incorporate uncertainty into the loads predicted by contaminant load models for suspended solids, copper and zinc. Current yield-based models traditionally provide single estimates of loads, ignoring potentially significant uncertainties introduced, for example, by the values adopted for the source yields which are often derived from limited data. We are developing a method to quantify this uncertainty using a Monte Carlo approach, implemented within a simple spreadsheet interface. The incorporation of uncertainty will improve our ability to discriminate between major contaminant sources and inform comparisons of differing scenarios.

The second part of the work is a way to convert these predicted catchment loads into in-stream concentrations. The catchment loads, calculated from a contaminant load model, are related to in-stream concentrations through an empirical relationship developed from State of the Environment monitoring data. This enables estimation of the likely median or 95th percentile in-stream concentration for a given catchment load, and uncertainty ranges around these concentration estimates. We have developed useable relationships for Auckland and undertaken initial tests on data from the Greater Wellington region and Christchurch City.

In combination, further development of these two methods aims to provide tools to undertake screening level assessments of contaminant loads and in-stream concentrations, for baseline and future scenarios, with uncertainty ranges for these estimates. This will enable more informed decision-making for catchment management under the NPS-FM.

KEYWORDS

Stormwater, urban streams, catchment modelling, contaminants, NPS-FM

PRESENTER PROFILE

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1 INTRODUCTION

Implementation of the National Policy Statement for Freshwater Management (NPS-FM) in urban catchments is likely to require quantitative models to enable limit-setting of contaminants. In urban catchments, suspended solids, copper and zinc are among the most common contaminants of concern. There are currently no nationally-adopted methods to predict metal loads derived from urban catchments or to predict concentrations within streams and hence a variety of methods have been developed and used.

One of the more widely used models is the Contaminant Load Model (CLM; Auckland Regional Council 2010a) developed by Auckland Regional Council. This, and similar models such as NIWA's Catchment Contaminant Annual Loads Model (C-CALM; Semadeni-Davies & Wadhwa 2014), calculate contaminant loads for a given catchment based on the types of land use (e.g., residential area) and land covers (e.g., roofing area). However, while these models provide an estimate of an annual contaminant load, they do not provide the information on in-stream concentrations for comparing to numerical objectives, as required by the NPS-FM. Furthermore, of the water quality models readily available that do predict in-stream concentrations (e.g., QUAL2E, Brown & Barnwell 1987), many were designed for predicting water quality downstream of point sources rather than diffuse catchment sources.

To provide both catchment load and in-stream concentrations, several Councils have chosen modelling methods that couple load models to stream hydrological models. Such hydrological models typically require considerable resources to set-up and have substantial data requirements for calibration (e.g., continuous flow monitoring data). Furthermore, the nature of these models requires specialist personnel to undertake the modelling and long model run times may restrict the number of different scenarios that can be assessed. Such models may be out of reach for smaller Councils with fewer resources and with limited flow or water quality data.

In this paper we present methods that NIWA has been exploring that will enable assessments against in-stream concentration-based attributes and the setting of source-based load limits in catchments with minimal data. These include, firstly, a method for incorporating uncertainty assessments in the estimation of catchment contaminant loads and, secondly, a method for estimating representative in-stream contaminant concentrations from catchment load estimates.

2 INCORPORATING UNCERTAINTIES INTO LOAD MODELS

2.1 INTRODUCTION

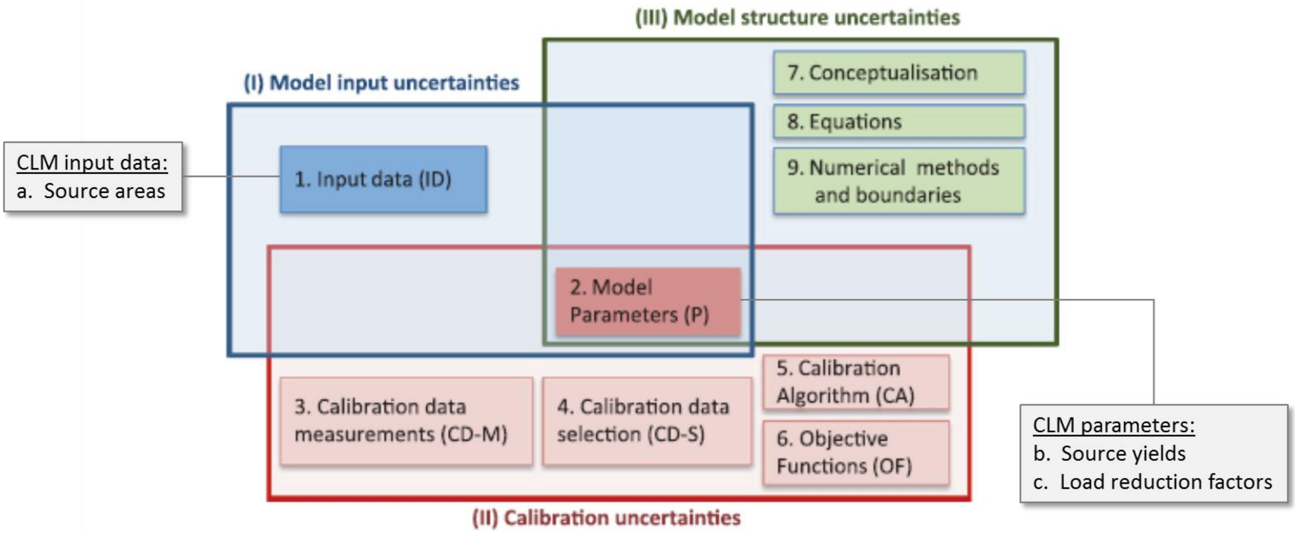
When using models to inform water quality management, or to compare against numerical objectives such as those set under the NPS-FM, incorporation of uncertainty assessment is a critical step in order to quantify the level of reliability of model results and provide a robust basis for decision making (Dotto et al. 2012). Simple, yield-based models such as the CLM typically provide single, point estimates of loads with no information on associated uncertainty. Part of NIWA's exploration into new modelling methods for NPS-FM implementation in urban settings has involved developing a means to incorporate uncertainty assessment in annual contaminant load models. In the description below, we illustrate the approach we have taken with reference to Auckland Council's CLM, being the most widely known and used annual load model in New Zealand. However, the methods described can equally apply to similar models such as C-CALM.

The CLM operates by dividing a catchment into source areas based on the types of land use and land cover. Mean annual loads of suspended sediment, total copper and total zinc are calculated for the catchment as the sum of the individual source loads, which represent the source area multiplied by a respective source yield. If stormwater treatment is present, the mean annual loads are reduced by an appropriate load reduction factor. Although the CLM was developed for use in the Auckland region, it, or a similar model, has been used in other parts of the country.

The International Working Group on Data and Models, which operates under the IWA/IAHR Joint Committee on Urban Drainage, has been working on developing a common terminology and conceptual framework for assessing uncertainties in urban drainage modelling (Deletic et al. 2012). Figure 1, reproduced from Deletic et al. (2012), shows the key groups of uncertainty sources in the proposed framework and how they are interlinked. The diagram is annotated to indicate the sources of uncertainty in the CLM, which fall into two of the key groups:

1. Uncertainty in the source areas within a catchment (model input data); and
2. Uncertainty in the source yields and load reduction factors associated with stormwater treatment (fixed model parameters).

Figure 1: Uncertainty sources in the CLM placed within the key groups of uncertainty sources and associated linkages identified for urban drainage models (Deletic et al. 2012)



Uncertainty in the source areas may arise, for instance, from measurement inaccuracies or difficulties in identifying source types (e.g. classification of roofing materials). This uncertainty occurs during model implementation and can be reduced through better catchment characterization. The uncertainty in the source yields and load reduction is derived from limited data and/or a lack of knowledge on which to base the estimated values. These factors are inherent in the model and therefore for the purposes of this research we have focused on quantifying the uncertainty in this area. The focus of this paper is on methods used to define probability distributions for the source yields and load reduction factors, as an alternative to the current approach which adopts a single value for each source yield and load reduction factors.

2.2 DEFINING UNCERTAINTY IN SOURCE YIELDS

Auckland Regional Council (2010b) suggests "low", "best" and "high" values for the source yields based on uncertainties in the data from which they are derived, though there is little supporting information provided. We have used these values as a starting point, assuming samples are drawn from a uniform distribution within each range. Where possible we seek to refine this approach, exploring alternative methods to provide more information on the underlying distributions. The paragraphs below use the roof source yields as an example.

The CLM roof source yields are largely derived from the concentrations of suspended sediment, copper and zinc measured in the Kingett Mitchell Diffuse Sources (2003) study of runoff from Auckland roofs. The yield for each roof source type is calculated as the mean of the measured concentrations multiplied by a mean annual runoff of 1000 mm year^{-1}. There are several challenges in moving from this single-value approach to determining an underlying probability distribution, including:

- Very few measured concentrations are available for many of the source types;
- The extremes in runoff concentration, measured on an event-basis, do not directly inform the extremes of the source yields on an annual-basis.

Whilst there are a number of different approaches which could be used to determine probability distributions, we have chosen (where sufficient samples are available) to apply a very simple build-up wash-off model of the form given by Shaw et al. (2010). The goal of the model is not a rigorous calibration, rather for it to inform the range of annual contaminant yields that may be expected, and therefore a daily timestep was considered sufficient given the data available. Parameter values were determined from the measured concentrations for events corresponding to special cases of the model (e.g. events following a long antecedent dry period, or events not separated by an intervening dry period). We then ran the model multiple times for each source type using a 42-year timeseries of daily rainfall data, allowing the parameter values to vary around the estimated values, and fitted probability distributions to the resulting series of mean annual yields. Table 1 shows the results obtained for zinc yields for galvanised steel. In each case, the yields best fit a normal distribution with the parameter values shown.

Table 1: CLM best-estimate zinc yields for galvanised steel roofs (low and high values in brackets) compared with distributions estimated using the build-up wash-off model approach. Normal distributions provided the best fit to data in each case.

Roof source type	CLM yield (g/m^2/year)	Estimated normal distribution	
		Mean (g/m^2/year)	Std dev. (g/m^2/year)
Galvanised steel (unpainted)	2.24 (1.68, 3.19)	2.77	0.47
Galvanised steel (poorly painted)	1.14 (0.89, 1.62)	1.47	0.22
Galvanised steel (well painted)	0.15 (0.08, 0.20)	0.16	0.03

2.3 DEFINING UNCERTAINTY IN LOAD REDUCTION FACTORS

The load reduction factors (LRFs) used in the CLM were selected based on professional judgement after a review of literature. They represent the proportion by which the mean annual contaminant load is reduced due to stormwater treatment devices or source control measures such as painting of roofs. At present, the CLM uses single values for the LRFs as given in Auckland Regional Council (2010b). To assign probability distributions for the LRFs we have used the range of removal efficiencies for different devices suggested by Semadeni-Davies and Wadhwa (2014), assuming a uniform distribution within each range. The efficiencies in that report are mainly based on literature review, and on modelling for rain gardens and wet ponds. The range in possible LRFs is very broad for many of the treatment devices. For example, for constructed wetlands treating roading sources, the CLM uses an LRF for total zinc of 60%, whilst the potential reduction ranges from a 50% reduction up to 90% reduction.

This represents a first-cut approach for our uncertainty modelling given that most LRFs reported in the literature are based on individual events rather than on a mean annual basis, therefore the extremes in reported values do not necessarily (and indeed are not likely to) reflect the extremes in the mean annual value.

2.4 INCORPORATING THE UNCERTAINTY

We have developed a proof-of-concept model that propagates uncertainty in the source yields and load reduction factors through to the model output (i.e. the mean annual loads) via Monte Carlo simulation. Monte Carlo involves repeated iterations with samples of the selected model parameters drawn from underlying probability distributions (Sriwastava and Moreno 2017). The method is implemented using @RISK[1], which provides a convenient platform for carrying out Monte Carlo simulations in Microsoft Excel (the existing platform for the CLM). To date we have included the uncertainty in roofing and roading source yields and in LRFs. A complete implementation incorporating all sources of uncertainty (including paved areas) is as-yet a work-in-progress.

3 RELATING CATCHMENT LOADS TO INSTREAM CONCENTRATIONS

3.1 DEVELOPMENT OF REGRESSION RELATIONSHIPS

Whilst annual contaminant load models are useful for comparing between development scenarios and management actions, they do not provide any explicit information on in-stream water quality; a fundamental requirement for implementation of the NPS-FM. To provide this link, we are developing a simple method that relates catchment contaminant loads to instream concentrations.

We collated data for suspended solids, copper and zinc (total and dissolved forms) from Auckland Council's State of the Environment dataset, measured monthly at sites on a range of urban, semi-urban and rural streams. Monitoring data from January 2010 to December 2012 (3 full years of data) was used in the assessment to provide an assessment of the "current" water quality state for comparison to estimated catchment loads. Median and 95th percentile statistics were calculated using the robust Regression on Order statistics method to incorporate data that were below detection limits (using the NADA package in R, Lee 2017).

[1] http://www.palisade.com/risk/

For each stream site location, the upstream catchment was mapped in GIS and the land cover and land use determined, based on land use layers from around 2010/2011. The estimated annual loads of suspended solids, total copper and total zinc were then calculated using the CLM. The total contaminant load from each catchment was then 'normalised' (divided by the total catchment area to give an overall annual yield for each catchment), enabling comparisons between catchments of differing sizes.

The estimated annual yields (on a log-scale) were then plotted against the log of median or 95th percentile of the measured water quality. For the metals, this showed a linear relationship between the two, and a simple linear regression was fitted in R (R Core Team 2017) for each water quality parameter and statistic. Figure 2 shows the relationship between the measured median dissolved copper and total copper concentrations and the modelled copper yields. Figure 3 shows the relationship between measured dissolved zinc concentrations and zinc yields, using both the median and the 95th percentile statistics. For most of the fits with metals, the R-squared values were above 0.7 (Table 2).

Figure 2: Relationship between copper yields and dissolved and total copper concentrations with 95% confidence intervals around the fitted line.

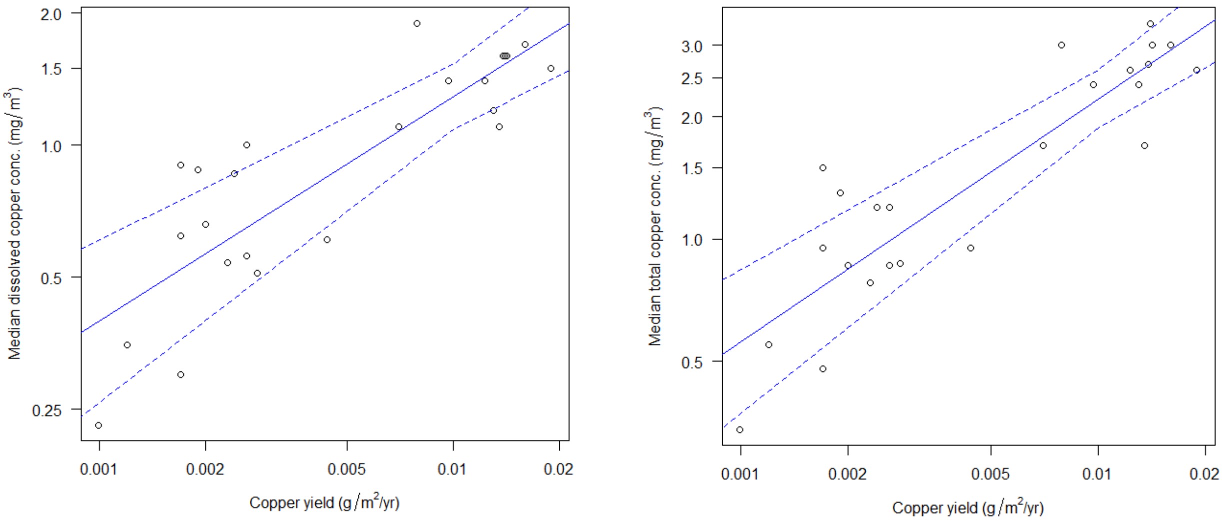


Figure 3: Relationship between total zinc yields and a) median and b) 95th percentile dissolved zinc concentrations with 95% confidence intervals around the fitted line.

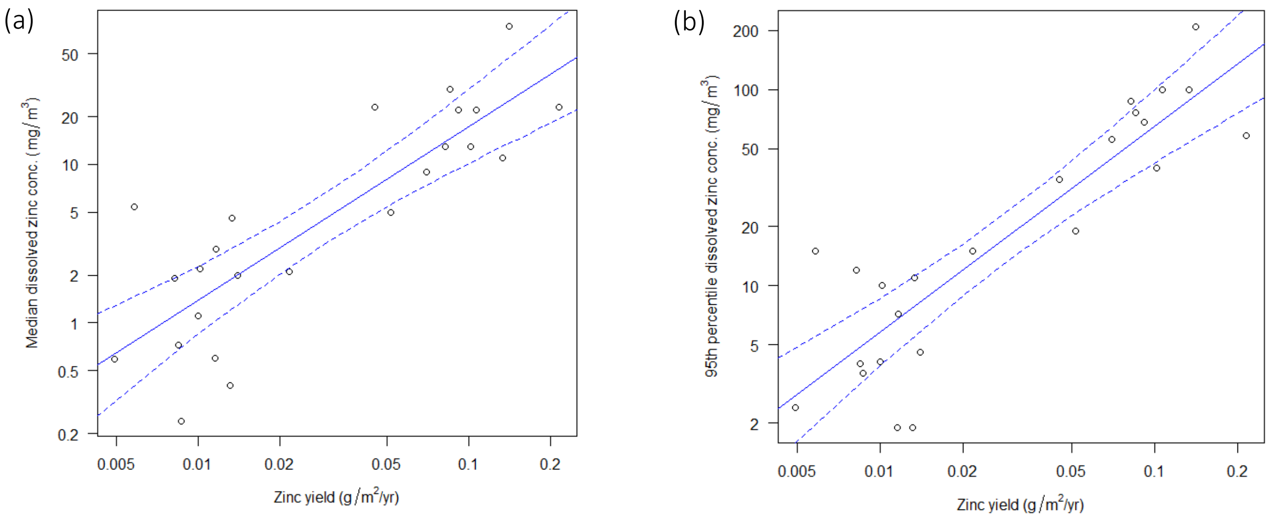


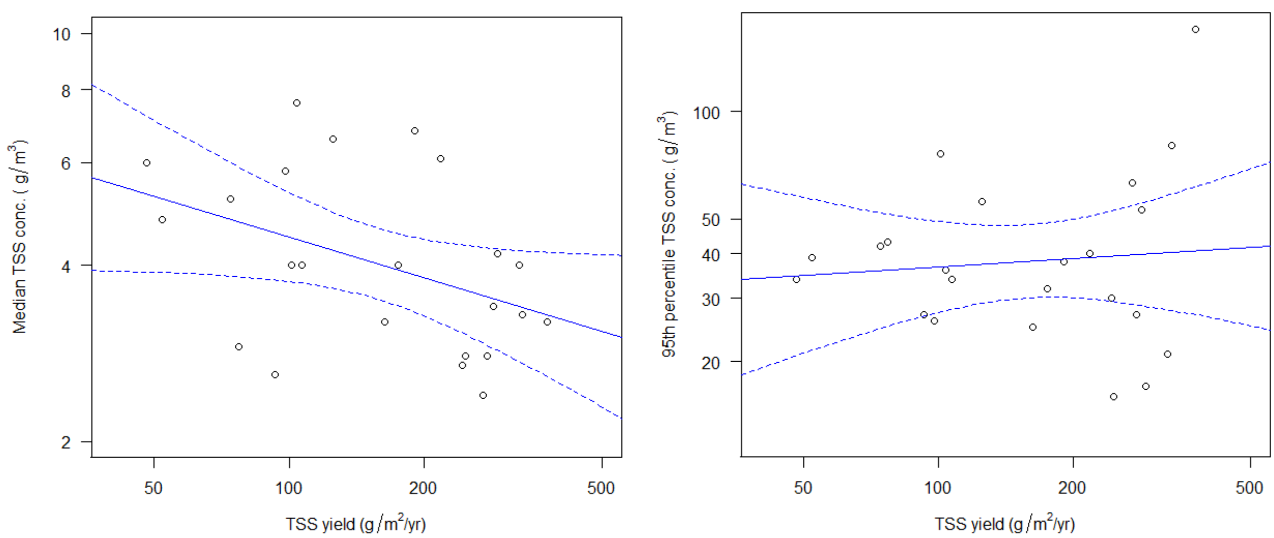
Table 2: *Linear model regression results*

	Median concentrations		95th percentile concentrations	
	R^2	Slope	R^2	Slope
Suspended solids	0.08	-0.17	0.008	0.08
Dissolved copper	0.72	0.51	0.78	0.53
Total copper	0.80	0.60	0.54	0.81
Dissolved zinc	0.71	1.1	0.78	1.0
Total zinc	0.80	1.1	0.82	0.93

For suspended solids there was only a very weak relationship between the yields of total suspended solids and the measured in-stream concentration (Figure 4). Unlike the metals, suspended solids showed an inverse relationship (albeit a very weak one) for the median concentrations: lower concentrations were found in stream catchments with the highest yields. For the 95th percentiles, there was no clear relationship between measured concentrations and suspended solids yields. This suggests that for suspended solids, reductions in catchment sediment loads would not necessarily result in reductions in in-stream TSS concentrations.

For the metals, the slope of the regression lines is not always equivalent to a 1:1 relationship between loads and concentrations. For example, a two-fold increase in total zinc yield in the catchment would be expected to increase the median total zinc concentrations in the stream by approximately double. However, for copper, a two-fold increase in the yield results in only a 1.5-fold increase in the total copper concentration in the stream. Furthermore, for total copper, the slope is not the same for the median concentration and the 95th percentile. This is an important finding as assumptions of a 1:1 increase have often been used in modelling of rural stream water quality (e.g., Green & Daigneault 2018), but this may not apply to urban catchments or all urban contaminants.

Figure 4: Relationship between suspended solids yields and measured total suspended solids concentrations (median and 95th percentiles).



3.2 POTENTIAL APPLICATIONS

This simple empirical relationship has a number of potential applications in freshwater management and modelling.

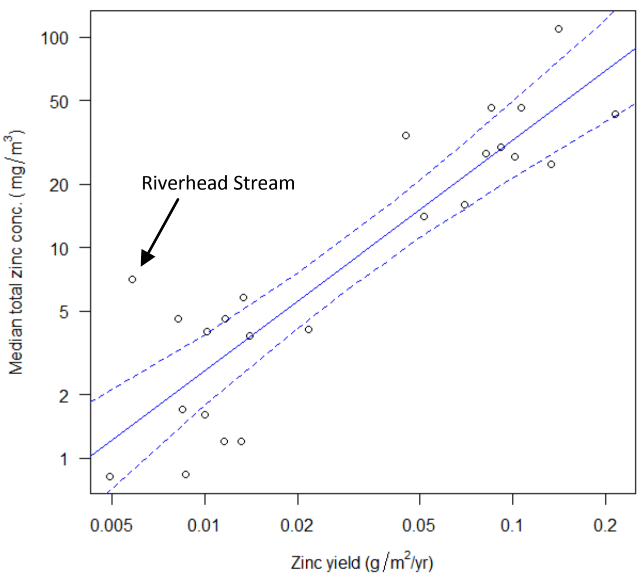
1. For streams where there is no monitoring data, current in-stream concentrations can be estimated from the calculation of the catchment annual load (converted to a yield). Use of prediction bands around the fitted regression line would provide a means to estimate the uncertainty in the predicted in-stream concentration (see Section 4.4) arising from factors such as variability in catchment hydrology.

2. For streams where there is existing monitoring data, future in-stream concentrations (and uncertainties in these predictions) can be estimated from the calculation of the catchment yield under different scenarios (see case study below, Section 4). The simplicity of this method allows for rapid testing of numerous scenarios when linked to a simple CLM.

3. Estimation of the maximum load that can be discharged from a catchment to achieve a concentration-based in-stream water quality objective. For example, for the 95th percentile stream concentration to meet the ANZECC (2000) guideline of 8 mg/m^3 of dissolved zinc, the maximum catchment yield would be around 0.014 g/m^2/year.

4. Identification of streams with contaminant sources that are additional to those included in contaminant load models, such as a point source discharge. For example, the zinc concentrations in Riverhead Stream are much higher than predicted for a site with that yield (Figure 5), suggesting there are additional zinc sources (not represented in the CLM) at that location.

Figure 5: Regression plot for dissolved zinc highlighting position of Riverhead Stream well above expected concentration.

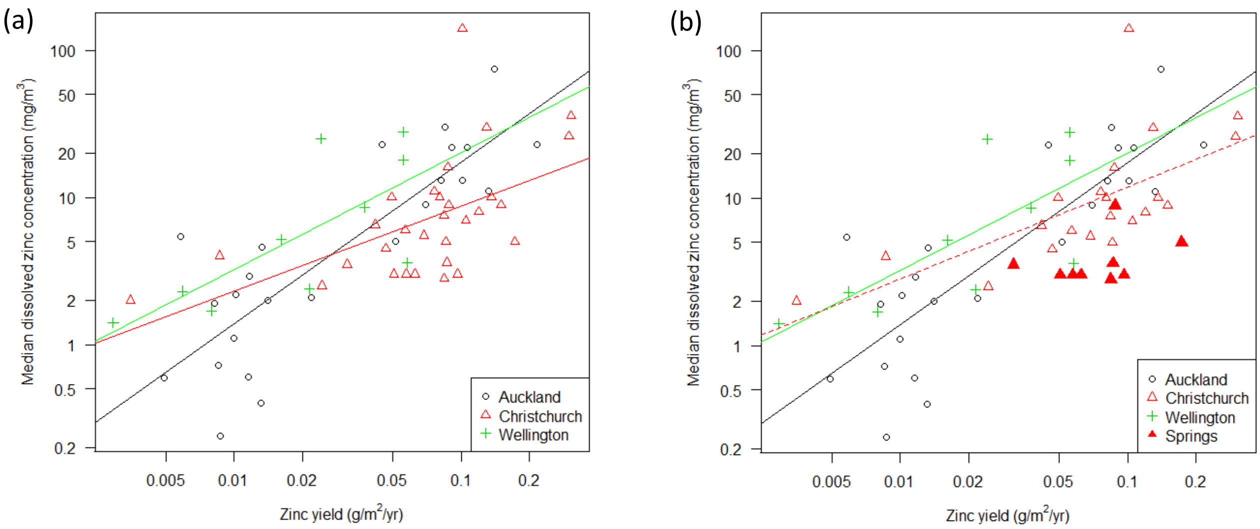


3.3 EXTENSION TO OTHER URBAN AREAS

We next investigated whether a similar relationship could be found between catchment loads and monitoring data for the Greater Wellington region and Christchurch City. The contaminant loads for these areas were estimated using Auckland's CLM, based on analysis of aerial photographs to identify land use and assuming default proportions of surface cover types for each land use. This approach to estimating loads is subject to considerable uncertainty compared to calculation of the actual source areas and would need to be refined prior to finalising regression relationships with in-stream concentrations. Furthermore, it is expected that annual loads and yields may differ between different geographic regions due to factors such as differences in topography and soil types. However, we adopted this approach as a useful starting place to investigate relationships between concentrations and yields in other urban centres. Water quality data was collated from Greater Wellington Regional Council and Christchurch City Council SOE monitoring data. While both councils monitor suspended solids, dissolved copper and dissolved zinc, we have focused our investigation on dissolved metals for these areas.

We expected that there would be differences in the relationship between instream concentration and contaminant yield for areas with different rainfall regimes, given that concentration is a function of runoff volume as well as catchment load. We found that the yield-concentration relationship for Greater Wellington was similar to that for Auckland (Figure 6), reflecting that the two regions have similar annual rainfall depths. In contrast, the relationship appeared quite different for Christchurch, which has approximately half the annual rainfall of the other two regions.

Figure 6: Regression plot for dissolved zinc showing (a) differing relationships for Auckland, Wellington and Christchurch urban areas (b) New regression line for Christchurch when spring-fed streams are excluded.



There was considerable scatter in the data for Christchurch, particularly in relation to sites with moderate to high yields, where there appeared to be 2 groups. One of these groups, with lower concentrations than expected from the yields, contained sites from spring-fed streams, where the springs are from relatively deep aquifers recharged from outside the topographical catchment (Figure 6b). One explanation is that these sites do not follow the same pattern as other Christchurch streams because the spring-fed flow provides substantial dilution of the surface-sourced contaminants. However, removal of the data points relating to streams fed by groundwater from outside the catchment did not greatly alter the Christchurch regression line (Figure 6(b)), indicating that other factors need to be taken into account in explaining regional differences in yield-concentration relationships. This is an area for further investigation.

The Christchurch monitoring data also included sites on tidal reaches of streams, which were not included in the Auckland and Wellington data sets. We excluded these tidal reaches as such sites are not expected to follow the same relationship due to the additional physical and chemical processes (e.g., flocculation and deposition) that occur in these reaches and which need to be explicitly included in all stream models.

Overall, the testing showed that while a regression-based approach can be used outside the Auckland region where there are sufficient data, the regression would need to be developed for each region of application from local monitoring data and a region-specific catchment load model.

4 CASE STUDY EXAMPLE

4.1 INTRODUCTION

With further development, the two methods described above aim to enable prediction of catchment loads and in-stream concentrations for NPS-FM implementation. The assessment of uncertainty in contaminant load modelling provides a range in the estimate of annual contaminant loads, which can assist decision-makers in assessing whether there are likely to be real differences in contaminant loads between different scenarios. The range of catchment load estimates can then be used to predict the likely in-stream concentrations (median and 95th percentile), also with an estimate of the uncertainty in these concentrations. The following case study description provides an illustration of how the two methods might be applied to inform NPS-FM implementation in an urban catchment.

4.2 PUHINUI STREAM CATCHMENT

Puhinui Stream drains a predominantly urban catchment in South Auckland (Figure 7). The urban-zoned land is a mixture of residential, commercial and industrial, as well as a large area of urban parks (including the Auckland Botanic Gardens). The estimated baseline yields of zinc and copper are amongst the highest in the Auckland region, as are the measured metal concentrations at Auckland Council's stream monitoring site (Table 3).

Figure 7: Land covers in the Puhinui Stream catchment.

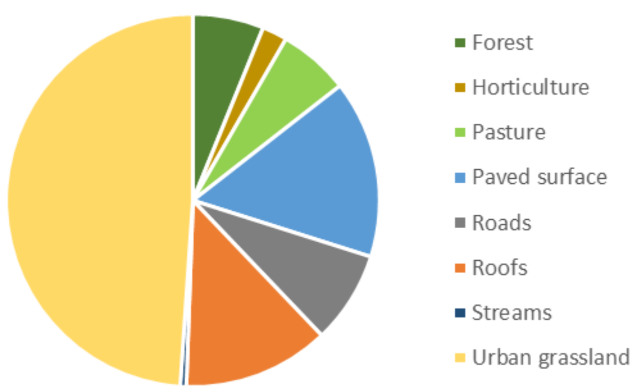


Table 3: Measured copper and zinc concentrations at Auckland Council's Puhinui Stream monitoring site

	Median metal concentration (mg/m^3)	95th percentile metal concentration (mg/m^3)
Dissolved copper	1.4	2.6
Total copper	2.0	4.4
Dissolved zinc	17	130
Total zinc	26	170

Implementation of the NPS-FM is likely to involve comparing representative measurements such as those in Table 3 against numeric objectives (or attribute states). In the absence of national objectives, we have compared the measured concentrations from Puhinui Stream to an illustrative set of numeric attribute states (Table 4) based on the ANZECC (2000) guidelines for copper and zinc[2]. These follow the example of the currently available NOF attributes that relate to toxicity, which compare a) the median measured concentrations to toxicity guideline values for varying levels of protection, with the "bottom line" based on the guideline value for protection of 80% of species; and b) the 95th percentile or maximum measured concentrations to toxicity guidelines based on acute toxicity.

Table 4: Illustrative copper and zinc objectives.

Attribute State	Numeric Attribute State (mg/m^3) for:				Narrative Attribute State
	Dissolved Copper		Dissolved Zinc		
	Annual Median	Annual 95th percentile	Annual Median	Annual 95th percentile	
A	≤1	≤1.4	≤2.4	≤8	99% species protection level: No observed effect on any species tested
B	>1 and ≤1.4	>1.4 and ≤1.8	>2.4 and ≤8	>8 and ≤15	95% species protection level: Starts impacting occasionally on the 5% most sensitive species
C	>1.4 and ≤2.5	>1.8 and ≤4.3	>8 and ≤31	>15 and ≤42	80% species protection level: Starts impacting regularly on the 20% most sensitive species (reduced survival of most sensitive species)
National Bottom Line	2.5	4.3	31	42	
D	>2.5	>4.3	>31	>42	Starts approaching acute impact level (i.e. risk of death) for sensitive species

[2] We have used the default guidelines for a hardness of 30 g/m^3 to be conservative.

Comparison of the measured copper and zinc concentrations in Puhinui Stream against the illustrative objectives in Table 4 indicates that the attribute state for dissolved copper would be band C (based on the 95th percentile), whereas for dissolved zinc the attribute state would be band D (based again on the 95th percentile). For this case study example, we have assumed that the catchment community wishes to investigate options to decrease the zinc concentrations and achieve a higher attribute state for the Puhinui Stream.

4.3 ESTIMATING ZINC LOADS

We estimated the mean annual load of zinc from the Puhinui catchment using the CLM, incorporating assessment of uncertainty (as described in Section 2), under four different scenarios:

1. Baseline scenario – this represents the existing catchment landuse, assuming no stormwater treatment

2. Source control scenario – this represents the baseline scenario with painting of all unpainted or poorly painted galvanised steel roofs

3. Wetland treatment scenario – this represents the baseline scenario with wetland treatment of all roof, road and paved source areas

4. Source control with wetland treatment scenario – this represents the baseline scenario with both the source control and wetland treatment options in place.

Table 5 presents the mean annual loads of zinc from the catchment predicted under the four scenarios, including the existing CLM loads for comparison. The results represent illustrative values only, since a complete implementation of the model with all sources of uncertainty addressed remains a work-in-progress. Sources of uncertainty reflected in the results include the roof and road source zinc yields as well as the LRFs. The yields for paved surfaces and all remaining source areas are held equal to their existing (fixed) CLM values. It can be expected that the ranges of the predicted loads will be somewhat broader once uncertainty in the yields for paved surfaces and other sources has also been accounted for.

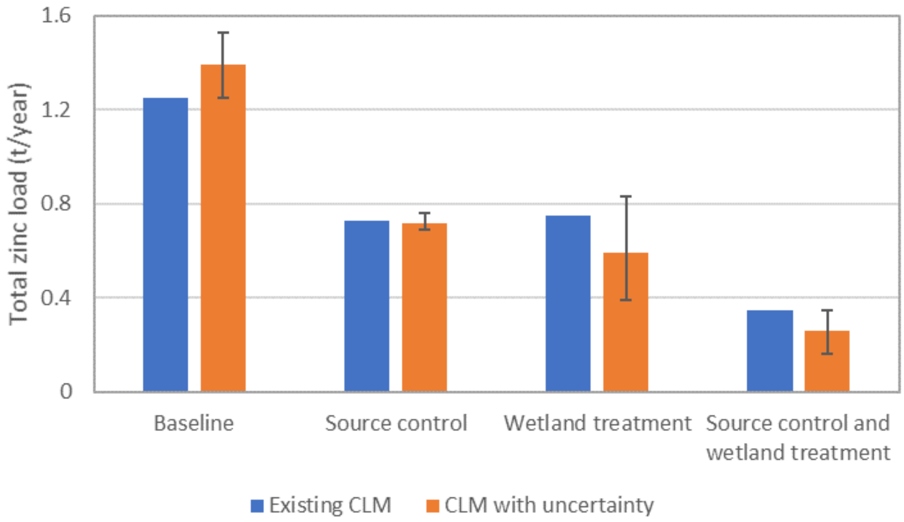
Table 5: Mean annual loads of zinc (t year^{-1}) predicted from the Puhinui catchment using both the existing CLM and the CLM with uncertainty. Values for the CLM with uncertainty reflect the mean produced by the Monte Carlo simulation with 10th and 90th percentiles in brackets

	Mean annual zinc load	
	Existing CLM	CLM with uncertainty
CLM baseline	1.25	1.39 (1.25, 1.53)
Source control (roof paint) scenario	0.73	0.72 (0.69, 0.76)
Wetland treatment scenario	0.75	0.59 (0.39, 0.83)
Source control with wetland treatment	0.35	0.26 (0.16, 0.35)

The source control scenario is influenced by uncertainty in the source yields only (since this scenario does not involve any stormwater treatment), whereas the wetland treatment scenario is influenced by uncertainty in both the source yields and LRFs. These LRFs have a wide range of possible values, as discussed in Section 2.3. As a result, there is a much greater range in the mean annual loads predicted for the wetland treatment scenario than for the source control scenario (Figure 8).

This case study illustrates some of the benefits of assessing uncertainty within the load model. Firstly, even though the annual loads are estimated as ranges, there are still clear differences between the baseline and the mitigation scenarios (the 10th and 90th percentiles do not overlap), giving confidence in the value of mitigation (although bearing in mind that not all sources of uncertainty are included in this example). Secondly, these results also show differences in the potential variation in outcomes delivered by different mitigations. For instance, whilst the source control and wetland scenarios provide similar results using the existing CLM, once uncertainty is taken into account a much wider range in loads is predicted for the wetlands scenario than for the source control scenario. In this example, the benefit of the source control scenario appears to be more certain, however the wetland scenario has the potential to achieve a much larger load reduction. When combined with information on the costs of alternative mitigation scenarios, this kind of information has the potential to be highly informative for decision-makers involved in NPS-FM implementation.

Figure 8: Comparison of scenarios for zinc management in Puhinui Stream catchment. Error bars represent 10th and 90th percentiles.



4.4 ESTIMATING IN-STREAM ZINC CONCENTRATIONS

The predicted annual zinc loads described above have been used to predict in-stream concentrations from the yields-to-concentrations regression. For this prediction, we have used the regression relationship described in Section 3.1 after removing the Riverhead Stream site, which is a clear outlier. This analysis (Figure 9, Table 6) suggests that an attribute state of "C" could be achieved by implementing either the source control (roof painting) or wetland treatment scenarios. An attribute state of "B" could be achieved by implementing both measures in combination.

Figure 9: Plot of median dissolved zinc concentrations versus zinc yields with yields for the four scenarios shown in vertical dashed lines.

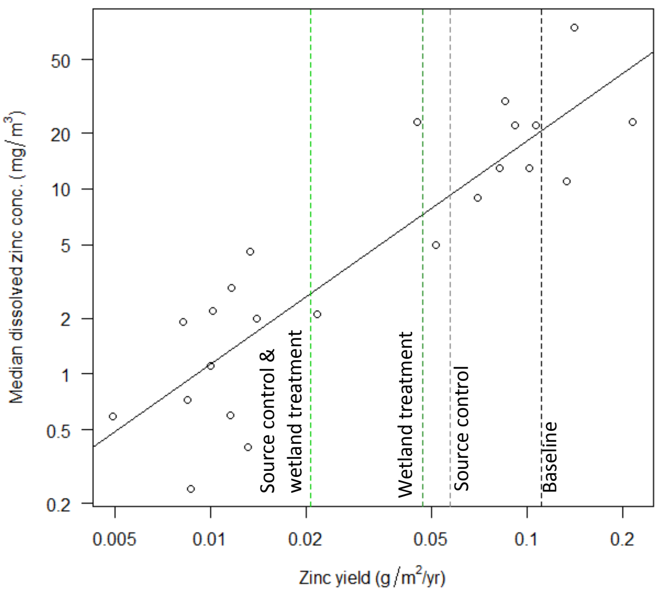
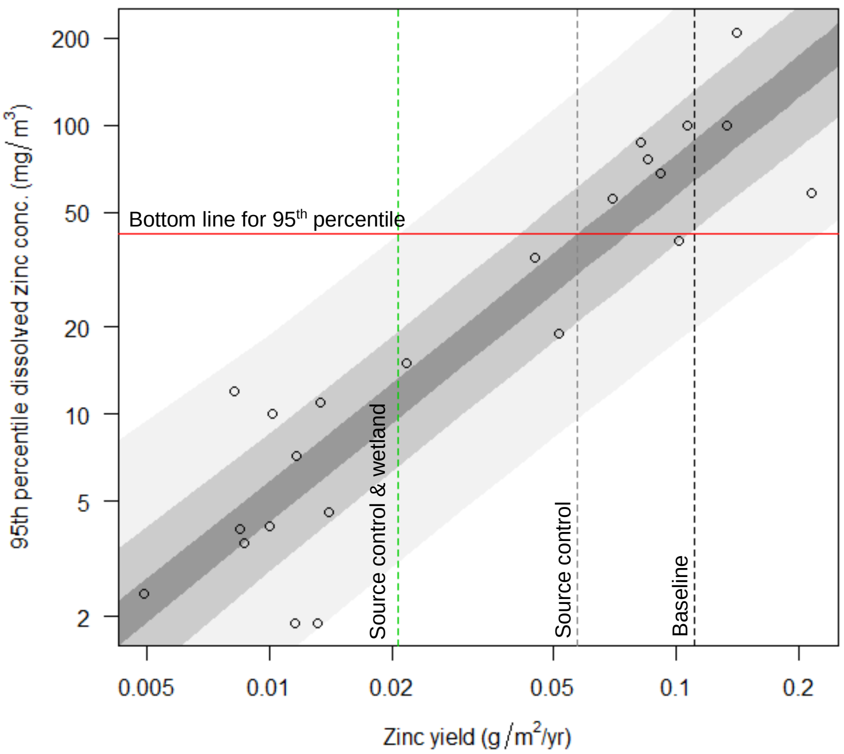


Table 6: Predicted zinc concentrations and attribute states for each scenario

	Baseline scenario	Source control scenario	Wetland treatment scenario	Source control and wetland treatment
Yield ($g/m^2/yr$)	0.11	0.057	0.047	0.021
Predicted median zinc concentration (mg/m^3)	20	9.3	7.3	2.7
Attribute state from median	C	C	B	B
Predicted 95th percentile zinc concentration (mg/m^3)	75	36	29	11
Attribute state from 95th percentile	D	C	C	B
Overall attribute state	**D**	**C**	**C**	**B**

Furthermore, because a linear regression is a statistical relationship, 'prediction intervals' for the regression can be used to assess the likelihood of reaching a particular attribute state, at a given yield. A prediction interval is an estimate of an interval in which future observations will fall, with a certain probability, based on the existing observations (the regression). For a yield of 0.11 g/m^2/year (baseline scenario), there is approximately an 80% likelihood that the 95th percentile bottom line concentration will be exceeded. For the yield of 0.057 g/m^2/year (source control), there is only a 40% chance that the 95th percentile bottom line concentration will be exceeded. For the yield of 0.021 g/m^2/year (source control and wetland treatment), there is only a 2.5% chance that the 95th percentile bottom line concentration will be exceeded.

Figure 10: Shaded prediction bands for 95th percentile concentrations vs zinc yields. The darkest shading represents the concentrations with 20% likelihood of occurring for a given yield. The mid-grey represents the concentrations with 60% likelihood and the light grey with 95% likelihood. Concentrations in the white area have a low likelihood of occurring. The bottom line for the 95th percentile concentration is shown in red and yields from three scenarios shown in vertical dashed lines.



5 CONCLUSIONS

The implementation of the NPS-FM in urban catchments is likely to be a challenging exercise. Models can help, but they need to be fit-for-purpose and capable of generating useful information for decision-makers. In this paper we have described two complementary areas of exploratory research that, with further development, aim to provide support for NPS-FM implementation.

The first recognizes that there are many sources of uncertainty in water quality modelling. Some sources are inherent in the model while others occur during model implementation. Whilst it is relatively easy to identify the sources of uncertainty, quantifying those uncertainties is less straightforward. Such uncertainties can propagate through a model, resulting in model outputs taking a broad range of values. An absence of any assessment of model uncertainty creates difficulties for decision-makers trying to consider the implications of alternative management scenarios. We have described two ways that we are attempting to quantify uncertainties in annual contaminant load models, one through modelling and the second through literature review. A case study application of the methods has demonstrated the value of incorporating uncertainty assessments in scenario modelling, for instance showing that uncertainty need not mean a lack of discrimination between scenarios.

A second problem for decision-makers involved in implementation of the NPS-FM is an absence of explicit effects-based information when considering catchment load estimates. We have shown that an empirical relationship (between measured metal concentrations and catchment yields based on contaminant load modelling) offers a simple way to predict in-stream contaminants concentrations for sites with no monitoring data. In our case study, we also showed how the method could be used to examine the probability of achieving improved attribute states under alternative future management scenarios.

In combination, further development of these two methods aims to provide tools to undertake screening level assessments of freshwater management outcomes in data-poor catchments. In further work we intend to expand and refine the coverage of uncertainty assessments in annual contaminant load models and investigate additional national and regional level relationships between contaminant loads and instream concentrations.

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