Metals in Urban Streams Tool (MUST)

Overview

MUST works through two steps to estimate concentrations of dissolved copper and zinc in an urban stream.

In **STEP 1**, MUST estimates the catchment yields of copper and zinc based on catchment land use and stormwater management characteristics.

In **STEP 2**, MUST estimates the median and 95th percentile instream concentrations of dissolved copper and zinc based on predetermined relationships derived from water quality observations and corresponding catchment yield estimates.

These two steps are repeated 100 times, with certain input parameters varying based on their random selection from predetermined datasets. Consequently, MUST generates a distribution of concentration estimates rather than a single value. By comparing this distribution of estimates against a threshold value, MUST then reports the probability that the threshold will be exceeded.

The following description provides a summary of the methods and data sources involved in each of these two steps.

Further background on the concepts involved in the development of MUST are given in Gadd *et al.* (2018).

Step 1 – Catchment Yields

Catchment yields of copper and zinc (referred to collectively as 'metals' below) are calculated by estimating the respective metal load and dividing by the catchment area.

Catchment metal loads are estimated as the sum of loads calculated for each land use class. These land use metal load estimates are the product of:

- the area of the given land use class;
- a metal yield for the land use class, modified to reflect source control if selected;
- a load reduction factor (LRF), if stormwater treatment is selected; and
- the proportion of the area of the given land use type receiving stormwater treatment.

The area of the given land use class and proportion receiving stormwater treatment are held constant, based on input entries made by the user.

In contrast, each of MUST's 100 iterations draws a metal yield and LRF at random from datasets that reflect the expected variation in these parameters in the real world. These datasets have been assembled as follows.

Metal yields

The datasets of metal yields for each **urban** land use class are made up of 100 values that reflect:

- Variability in the proportion of the given land use class occupied by different land covers (roofs, roads etc.); and
- Uncertainty in estimates of metal yields derived from sampling and modelling of stormwater runoff from each type of land cover.

Each dataset of 100 yields was derived by considering 10 sample areas of the given land use. Analysis of land use shape files was conducted to disaggregate each sample area into constituent land covers (a range of roofs, roads, paved surfaces and pervious cover types). A metal yield was assigned at random to each land cover type from one of three estimates ('best', 'low' or 'high') according to probabilities of 0.5 (best) and 0.25 (low and high). A weighted yield for each of the 10 samples was estimated based on the proportion of the sample area occupied by each land cover type. This exercise was repeated 10 times for each of the 10 sample areas, giving 100 yield estimates for the given land use class.

The best, low and high yields were drawn from those used in sensitivity testing reported in ARC (2011), with the following exceptions:

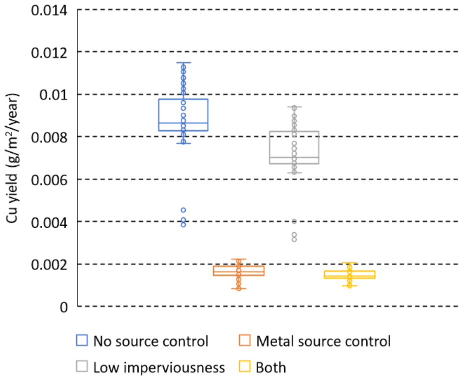
- Rather than adopting the ARC (2011) value of zero, the zinc yields for commercial paved surfaces were estimated by multiplying the equivalent copper yields by 5.5. This approach, taken previously by Moores et al. (2017), is based on Zn:Cu ratios in the yields for industrial and residential paved surfaces.
- For copper source control, the yields applying to roads and paved surfaces were reduced by 90%, reflecting California's target improvement in the mean content of copper in vehicle brake pads (CSQA, 2019).
- For zinc source control, roof replacement was represented by substituting the yields applying to unpainted and poorly painted galvanized steel roofing with yields of the lowest-Zn generating roofing materials.

The derivation of urban land use yields for the 'low imperviousness' source control option involved altering the proportion of impervious and pervious land cover classes in the 10 sample areas, rather than changing the land cover yields. The areas of roofs, minor roads and paved areas in each sample were assumed to be reduced by 20%, with a consequential increase in the area of urban grassland and trees.

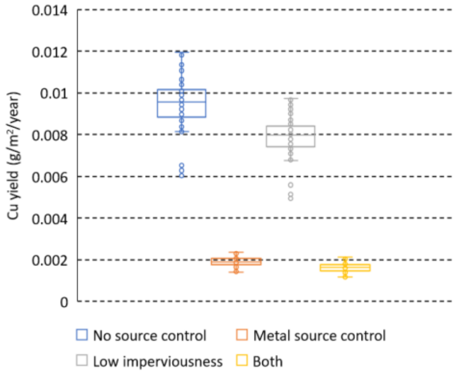
The following plots show the distribution of yields in each of the urban land use class datasets.

Copper yields

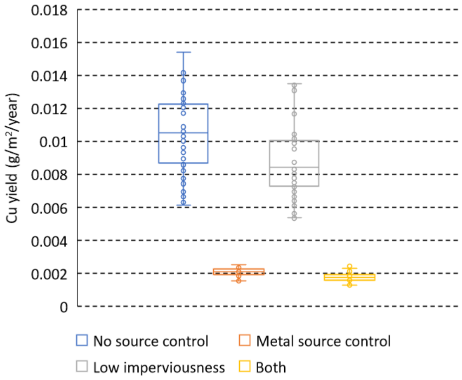
Low density residential



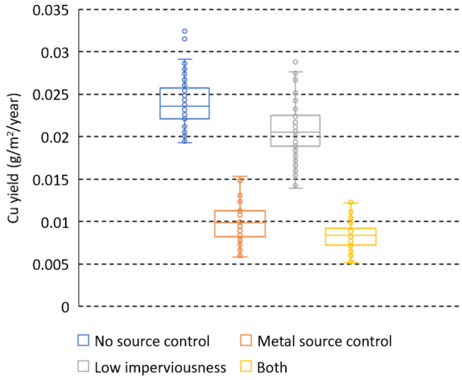
Medium density residential



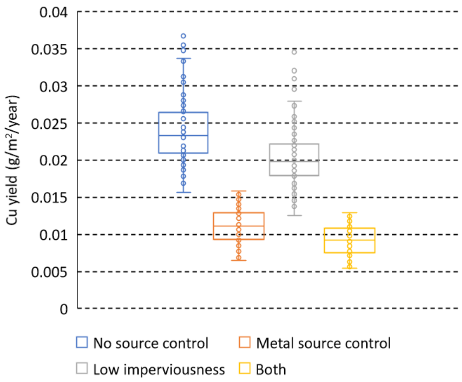
High density residential



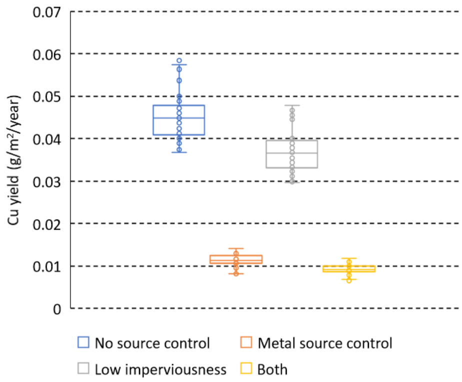
Commercial suburban



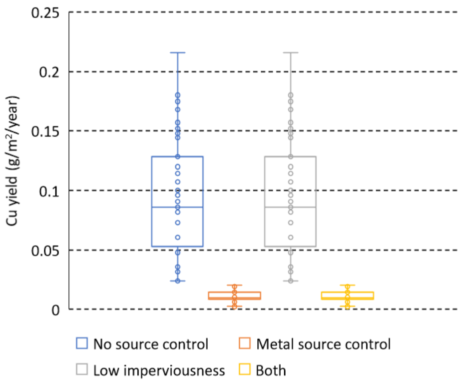
Commercial CBD



Industrial

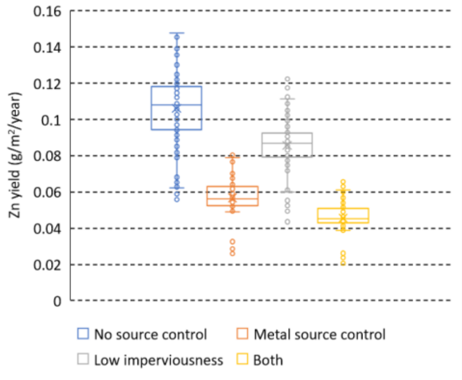


Highways

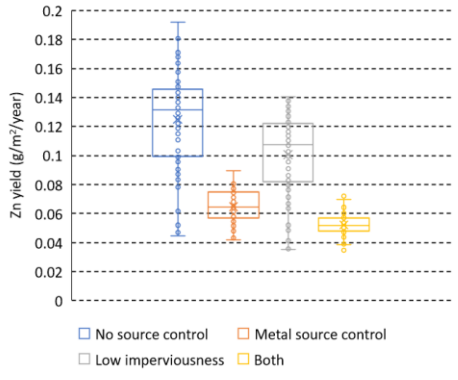


Zinc yields

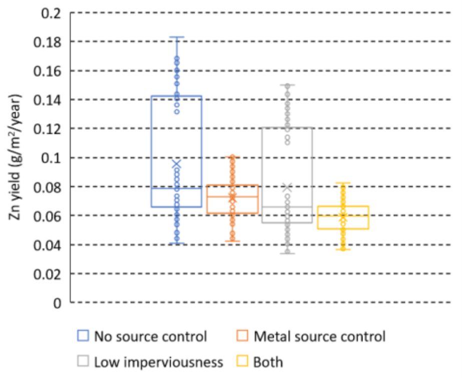
Low density residential



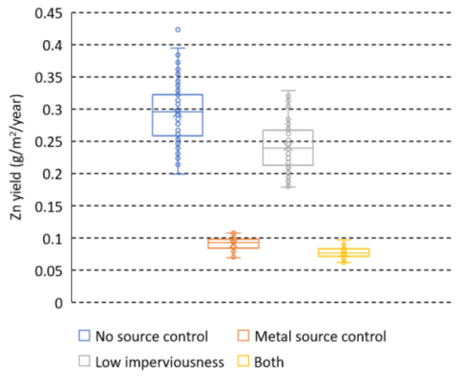
Medium density residential



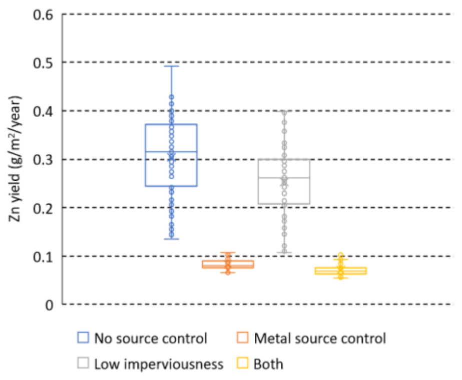
High density residential



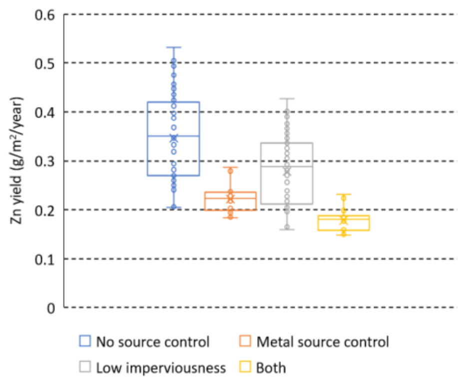
Commercial suburban



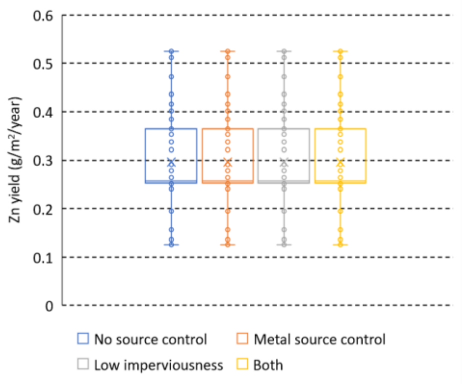
Commercial CBD



Industrial



Highways



In contrast to the urban land use classes, the **rural** land use classes were assumed to each be made up of only one land cover type. This meant that the datasets of metal yields for each rural land use class are made up of 100 values that reflect uncertainty in the yields, but not in the proportion of land cover types. The best, low and high yields for the rural land use classes were drawn from those reported in ARC (2011) for different slope classes or soil types.

Load reduction factors

The datasets of LRFs for the two stormwater treatment options are derived from data obtained from the International BMP database[1], supplemented with data from a small number of New Zealand studies.

Analysis was conducted on paired event mean concentrations (EMCs) of total copper and total zinc in samples of inflows to and outflows from stormwater treatment devices. The proportion of each metal removed by treatment was calculated for each event sampled. The median of the event metal removal rates was adopted to represent the long-term performance of each treatment device sampled. The median removal rates of all devices sampled were collated to give the following LRF datasets:

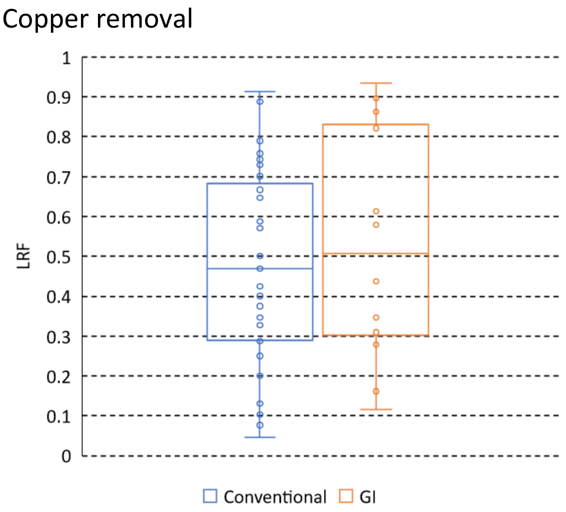
- Ponds and wetlands, to represent conventional, bottom-of-catchment, stormwater treatment; and
- Bioretention and raingardens, to represent stormwater treatment by Green Infrastructure (GI).

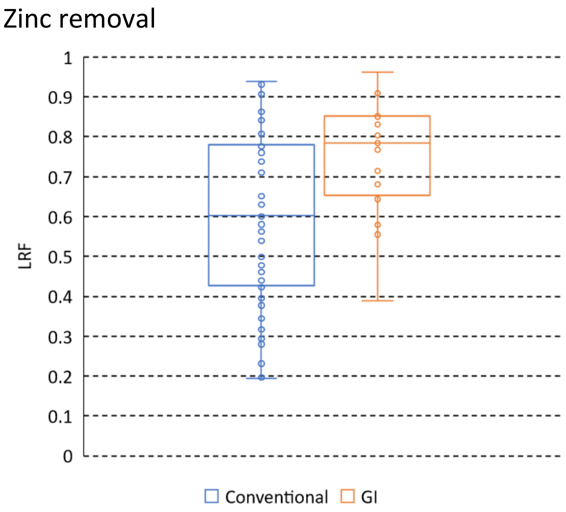
A small number of outliers (negatives, zeros and very low positives) were excluded from these datasets.

As a check on these datasets, they were compared with the results of modelling conducted in the development of LRFs for New Zealand's C-CALM stormwater contaminant load model (Semadeni-Davies, 2008). That modelling involved estimating many thousands of iterations of LRFs for ponds/wetlands and raingardens, with one of several design (e.g. sizing, shape, inlet and outlet configuration) and catchment (e.g. size, slope) parameter values varied in each iteration. Because the modelling was restricted to particulate metal removal it generated distributions of LRFs that reflected generally better performance than the data in the International BMP database. However, by combining the modelled LRFs for particulate metal removal with representative LRFs for dissolved metal removal (based on literature review, also reported in Semadeni-Davies, 2008), distributions of LRFs for total metal removal were generated. These compare well with the distributions of LRFs generated from the International BMP database, giving confidence in these latter datasets for use by MUST.

The following plots show the distributions of LRFs in the two stormwater treatment datasets.

[1] http://www.bmpdatabase.org/bmpstat.html





Step 2 – Instream Concentrations

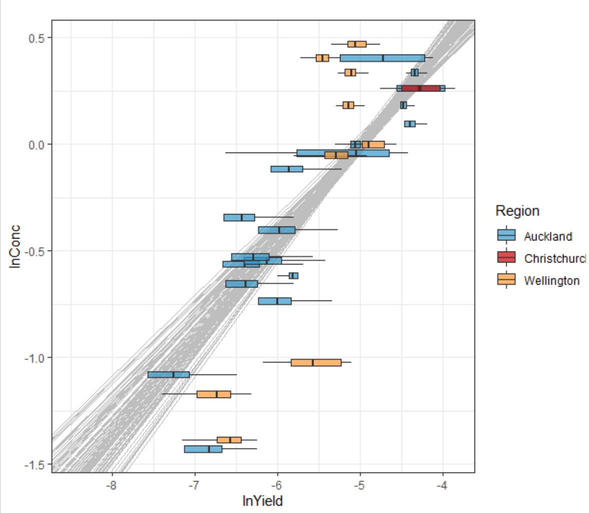
Instream dissolved metal concentrations are estimated from regression relationships between modelled catchment yields and concentrations calculated from urban stream monitoring data. The relationships incorporate uncertainty associated with both the yields and concentrations.

The concentrations are the median and 95th percentile instream dissolved metal concentrations measured in samples collected for State of the Environment (SoE) monitoring in the Auckland (23 sites), Canterbury (23 sites) and Wellington (10 sites) regions. Confidence limits were generated to reflect uncertainty associated with each median and 95th percentile concentration estimate.

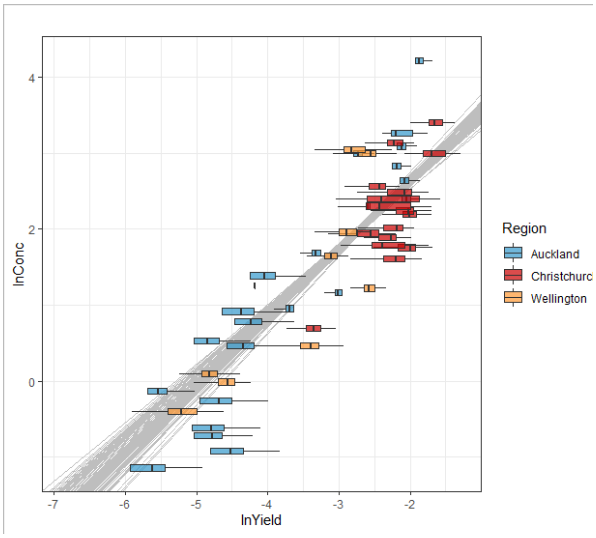
The modelled catchment yields associated with each SoE monitoring location were estimated from the land use characteristics of the corresponding catchments. With the exception of Auckland, these estimates were derived using the same approach as described above (see section on "Metal yields"), generating 100 estimates per SoE catchment. In the case of Auckland, more detailed information on catchment land cover was available, such that the 100 estimates of catchment yields reflect uncertainty in land cover yields but not land cover proportions.

The relationships between modelled catchment yields and median and 95th percentile instream concentrations of dissolved copper and zinc are given below. The grey lines represent a sample of 100 bootstrapped regression relationships fitted to the data. These lines capture uncertainty in estimates of the yields, as described above.

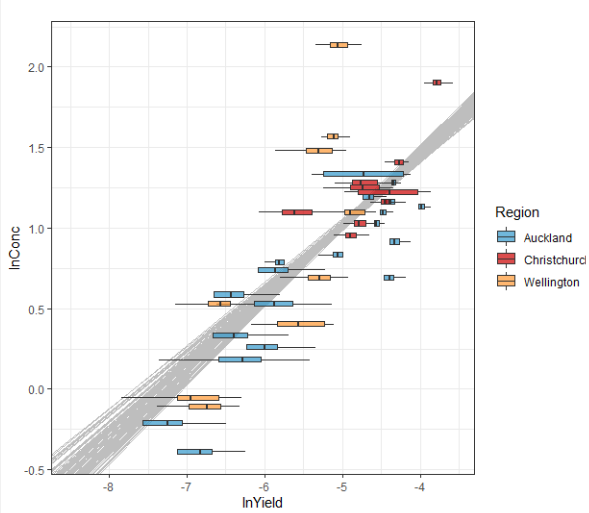
Median dissolved copper concentration



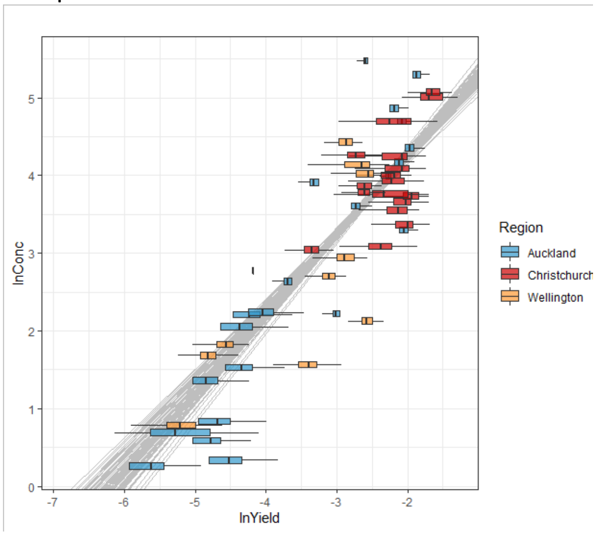
Median dissolved zinc concentration



95th percentile dissolved copper concentration



95th percentile dissolved zinc concentration



Once a user has entered input information on a catchment or project area of interest MUST calculates 100 possible estimates of the catchment yield. From each of these 100 catchment yield estimates, MUST then queries the regression relationships shown above to estimate 100 possible instream concentrations. These distributions of concentrations and their associated prediction intervals then provide the basis for estimating the probability that a given threshold concentration will be exceeded.

References

Auckland Regional Council (2010). Development of the Contaminant Load Model. Auckland Regional Council Technical Report 2010/004.

California Stormwater Quality Association (CSQA; 2019). Brake Pad Copper Reduction Status Report 2018. https://www.casqa.org/sites/default/files/downloads/brake_cu_reduction_status_report_12-20-18_final.pdf

Gadd, J., Harper, S., Moores, J. and Semadeni-Davies, A. (2018) Tools for water quality prediction and NPS-FM implementation in urban settings. Water NZ Stormwater Conference 2018, Queenstown, 23-25 May 2018.

Moores, J., Easton, S., Gadd, J. and Sands, M. (2017) Te Awarua-o-Porirua Collaborative Modelling Project: Customisation of urban contaminant load model and estimation of contaminant loads from sources excluded from the core models. NIWA client report 2017050AK prepared for Greater Wellington Regional Council.

Semadeni-Davies, A. (2008). C-CALM review of removal efficiencies for stormwater treatment options in New Zealand. NIWA Client Report AKL2008-031 prepared for Landcare Research Ltd.