Date: 17/02/2025

# Approach used to estimate the load reductions to achieve the copper, zinc and *E. coli* TASs in Proposed Change 1 to the Natural Resources Plan for the Wellington Region

This memorandum describes the approach used to:

- Develop a baseline daily water quality model for target attribute state (TAS) sites in Whaitua Te-Whanganui-a-Tara (TWT)[1]; and
- Interrogate the eWater Source model developed for the Te Awarua-o- Porirua Whaitua Implementation Programme (WIP) to develop load-concentration relationships.

The purpose of this exercise was to allow:

1. For calculation of the load reductions required to meet the copper (Cu), zinc (Zn) and *E. coli* TAS in proposed Plan Change 1 (PC1) to the Natural Resources Plan (NRP) for the Wellington Region. This will provide wastewater and stormwater network operators an indication of what the inclusion of the term ‘commensurate load reductions’ in PC1 requires of them; and
2. Allow for the modelled impacts of the provisions on copper and zinc loads to be assessed in terms of in-stream concentrations (this is yet to be conducted).

## 1 Pilot study

### 1.1 Potential method for developing a baseline water quality model for WTWT

To develop a simplified probabilistic baseline water quality model for TWT, monthly river water quality data and daily mean flow data (measured or derived) will be sourced from Greater Wellington Regional Council (GWRC). Water quality data will then be partitioned into “bins”, based on river flow and (potentially) season at time of sampling. The =GENERATEBYBIN function in the Torlesse Environmental Freshwater Package (FPack) Excel Add-in will then be used to generate a synthetic record of water quality for every day in the available flow record. This function is based on the PointSIM approach developed by Aquanet Consulting Ltd (now Traverse Environmental Ltd) which has been used extensively in consent processes in the Manawatu-Whanganui Region.

[1] Such models have already been developed for rivers in the Te Awarua-o-Porirua Whaitua through eWater Source (Easton *et al.*, 2019a)

For each day of the available flow record =GENERATEBYBIN would:

1. Apply Box-cox transformations to the measured water quality data collected within the relevant flow bin. This would transform the non-normal water quality data into as normal a distribution as possible through the following equation:

$$BoxCox = \frac{{Conc_{measured}}^{\lambda} - 1}{\lambda}$$

   Where λ is the value between -2 and 2[2] where the transformation best normalises the measured water quality data (automatically generated by FPack as part of the =GENERATEBYBIN function.
2. Generate a modelled concentration by:
   a. Randomly sampling in a normal distribution from the transformed data frequency described above within prescribed lower and upper bounds (which can be modified to calibrate the model) (i.e., sampled results are normally distributed); and
   b. Back transforming the sampled value to a concentration through the following equation

$$Conc_{modelled} = (\lambda \times BoxCox + 1)^{\frac{1}{\lambda}}$$

A modelled daily load will then be manually calculated through:

$$Load_{modelled} = Conc_{modelled} \times Flow_{daily\ mean} \times 86400$$

and relevant summary statistics and attribute states calculated from the resulting synthetic record using the various functions in FPack.

## 1.2 Model performance

To test the potential performance of the approach described above, it has been applied to water quality (from 153 samples) and flow data from the Waiwhetu Stream at White Lines East TAS site between January 2008 and October 2024 using the following flow bins[3]:

- <1/2 median flow;
- <1/2 median flow to median flow;
- Median flow to 3 × median flow; and
- >3 × median flow.

Figure 1 to Figure 3 present the measured (observed) and modelled (predicted) probability distributions of the Cu, Zn and *E. coli* concentrations in the Waiwhetu Stream at the TAS site. The dotted lines represent the observed concentrations plus or minus the standard deviation of the observed data, as a measure of tolerance in variability. These figures show that the predicted Cu (Figure 1) and Zn (Figure 2) were within the tolerance range given by the observed concentrations ± one standard deviation, indicating what Traverse Environmental Ltd define as an acceptable fit between observed and predicted concentrations. While there was also a reasonable fit between measured and modelled *E. coli*

[2] It is possible to calculate λ from a range of -5 to 5. However, this adds significant compute time compared to 2 to -2 and trial and error revealed little impact on model performance.

[3] These flow bins were originally selected simply to match the reporting outputs in Greer & Ausseil (2018)(i.e., the flow thresholds were already available). However, a review of model performance using just these four bins revealed adequate performance and the decision was made not to increase the number.

concentrations across 96% of the measured concentration range, the 94th to 98th percentile of predicted concentrations were outside the measured ± one standard deviation range (Figure 3). I have not investigated why this occurred, but it could be due to the small number of flow bins considered here, low replication of measured data in a certain flow bin, or simply the selection of sub-optimal values as the upper /lower sampling constraints described in Point 2a in Section 1 above.

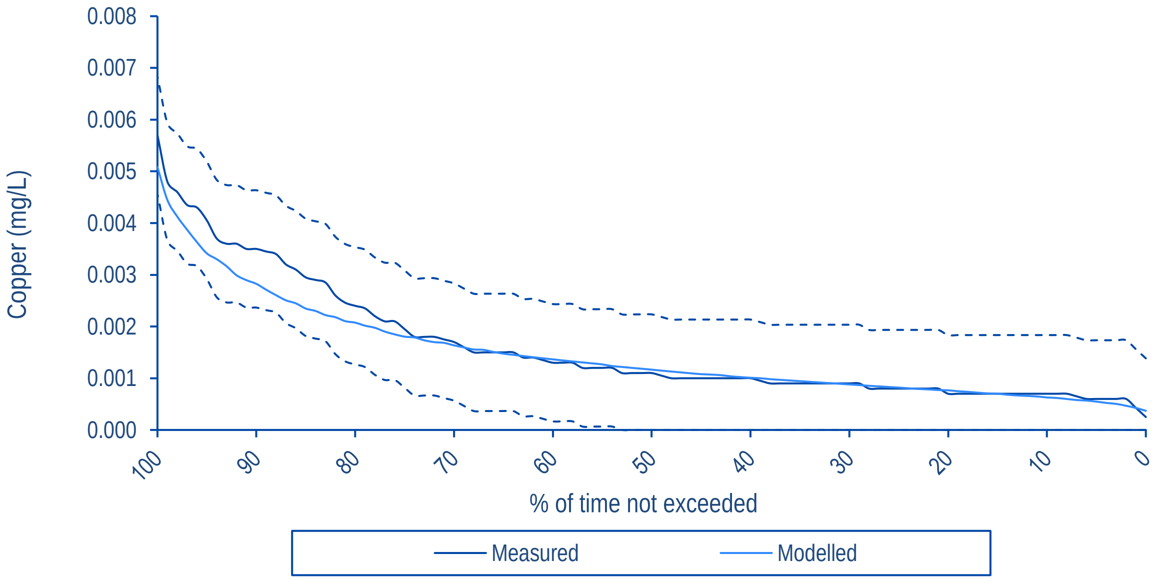


Figure 1: Probability distribution of Cu concentrations in the Waiwhetu Stream, as measured in the river (dark blue line) and predicted by the model (light blue line). The dotted black lines represent the measured concentrations plus or minus the standard deviation of the observed data, as a measure of tolerance in variability.

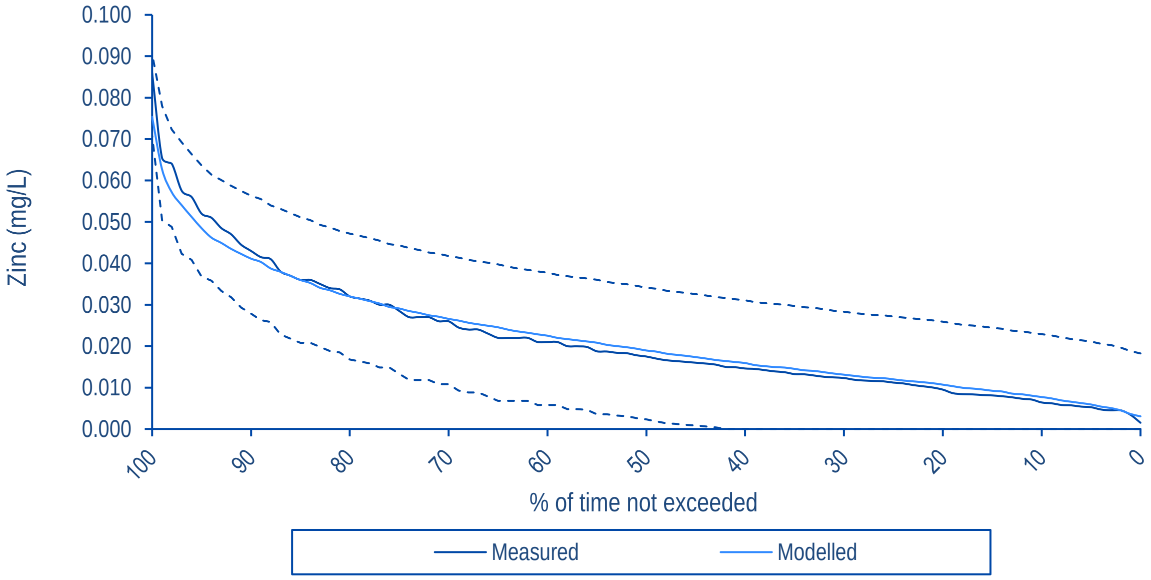


Figure 2: Probability distribution of Zn concentrations in the Waiwhetu Stream, as measured in the river (dark blue line) and predicted by the model (light blue line). The dotted black lines represent the measured concentrations plus or minus the standard deviation of the observed data, as a measure of tolerance in variability.

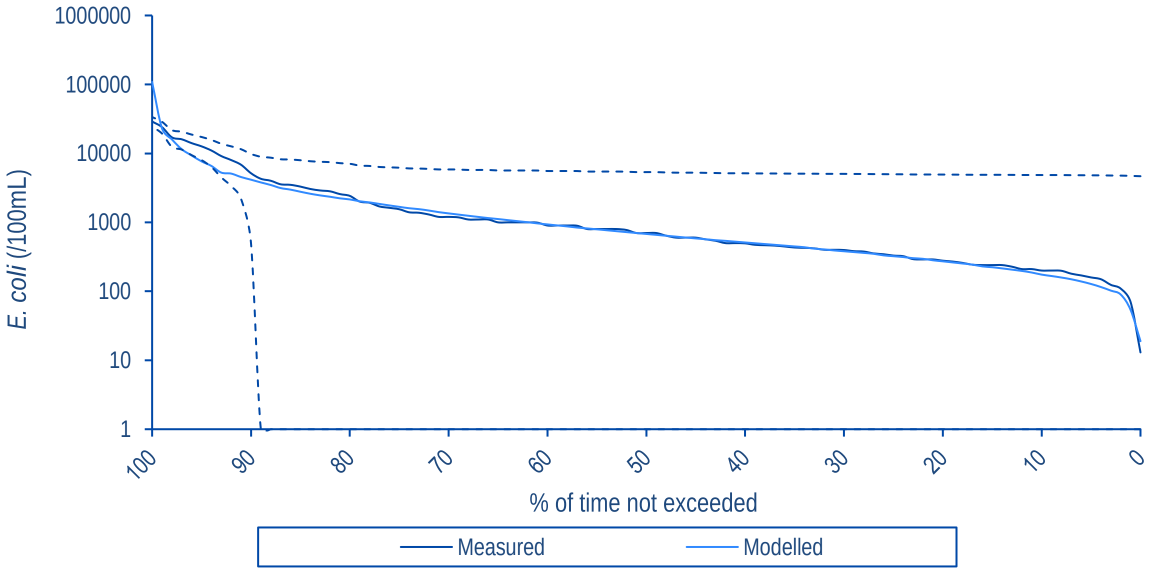


Figure 3: Probability distribution of *E. coli* concentrations in the Waiwhetu Stream, as measured in the river (dark blue line) and predicted by the model (light blue line). The dotted black lines represent the measured concentrations plus or minus the standard deviation of the observed data, as a measure of tolerance in variability.

To further assess the performance of the model, the Nash-Sutcliffe Efficiency (NSE) statistic[4] was calculated from each percentile[5] (0-100) of the modelled and measured data (shown in Figure 1 to Figure 3), and Percent bias (PBIAS) has been calculated for:

- Each percentile of the modelled and measured data (shown in Figure 1 to Figure 3);
- The average measured and modelled values for each month in the record; and
- The measured and modelled values for each day for which measured data exist.

The NSE and PBIAS is described in Easton *et al*. (2019a) as:

- NSE is a measure of goodness-of-fit, where less than 0 is poor, 0 indicates an equivalent fit to using the mean of the observed data, and 1 is a perfect fit to observed data; and
- PBIAS is the deviation of data being evaluated, expressed as a percentage. The optimal value is 0, with low-magnitude values indicating accurate model simulation.

The calculated NSE and PBIAS statistics are presented in Table 1. Based on the guidance of Moriasi *et al*. (2007) these statistics indicate the performance of the Cu and Zn models for the Waiwhetu Stream at White Lines East are 'very good', while the performance of the *E. coli* model is 'good'.

Table 1: Model performance statistics.

| Statistic | Copper | Zinc | *E. coli* |
|---|---|---|---|
| NSE – Percentiles | 0.94 (Very good) | 0.98 (Very good) | 0.87 (Very good) |
| PBIAS – Percentiles | 7.33 (Very good) | -1.6% (Very good) | 15.4% (Very good) |
| PBIAS – Monthly average concentration | 2.4% (Very good) | 0.5% (Very good) | -22.8% (Very good) |
| PBIAS – Daily measured concentration | 16.3% (Very good) | 7.4% (Very good) | 39.3% (Good) |

[4] A high NSE calculated from measured and modelled percentile data is an expected outcome of the modelling methodology employed. Generally, if it is mathematically possible to normalise the input water quality data, a randomly selected output dataset can be generated that closely fits that normal distribution. It is not an indication that the model accurately mimics the full suite of environmental factors that impact water quality which is what more complex models like eWater Source attempt to do.

[5] The GENERATEBYBIN function does not attempt to accurately calculate water quality on a specific day, rather it attempts to generate a synthetic record with percentiles that closely match the measured record (as it is percentiles that dictate attribute state) Thus, the NSE has not been calculated based directly on the measured data and the modelled data for the days on which measured data exist.

## 1.3 Method for calculating load reductions required to achieve TASs

### 1.3.1 Use of baseline model to directly determine load reductions

Future water quality under different scenarios can be estimated from the synthetic daily baseline water quality model by manipulating the daily contaminant loads or flows and calculating the resulting change in contaminant concentrations. i.e.,

$$Conc_{future} = \frac{Load_{future}}{Flow_{furture\ daily\ mean} \times 86400}$$

To demonstrate how this could be used to calculate the modelled load reductions required to achieve the Cu, Zn and *E. coli* TASs for Waiwhetu Stream, the following approaches have been tested:

- Conservative approach – Loads were reduced uniformly by the same percentage until all summary statistics achieved the relevant TASs. This involved setting a load reduction factor for an attribute equivalent to the proportion by which the most 'over-allocated' modelled assessment statistic exceeded the relevant TASs. By doing so, it requires the other assessment statistics to reduce by more than what is necessary to meet the TAS.
- Liberal approach – Loads reductions were first targeted to flow bins that had the lowest load:duration ratios. This meant that to achieve a median TAS, load reductions were not applied to the 50% of the flow duration curve where the majority of the load was discharged, except where a reduction was needed to achieve the 95$^{th}$ percentile TAS (and vice versa). This approach assumes that mitigations can be deployed in manner that targets treatment to specific flow conditions, which is unlikely.

The 95% confidence intervals around the modelled load reductions calculated from the approaches described above were determined through the PERCENTILECI and PERECENTEXCEEDCI (*E. coli* only) FPack functions. Through bootstrapping of the observed data (100 iterations) these functions generated 95% confidence intervals around each of the baseline summary statistics used to calculate Cu, Zn and *E. coli* attribute state. The required load reductions to meet the TASs were then calculated with baseline state for each assessment static set at the upper and lower end of its calculated confidence interval (i.e., for each approach required load reductions were calculated three times for each attribute).

### 1.3.2 Use of NIWA's MUST tool to provide further estimates of required load reductions

NIWA's Metals in Urban Streams Tool (MUST) estimates concentrations of dissolved Cu and Zn in an urban stream based on its catchment land use and stormwater management characteristics (Gadd *et al.*, 2020). While this is not particularly useful for the modelling exercise being tested here, within its code (available on GITHub) MUST contains generalised national estimates of the relationship between Cu and Zn yields and instream median and 95$^{th}$ percentile concentrations. These relationships are based on modelled yields and measured water quality data for/from 56 regional council monitoring sites. Thus, they can provide an insight into how a given load reduction is likely to affect copper and zinc attribute state when applied across flows in a manner that potentially reflects real world conditions better than the approaches described in Section 1.3.1. To achieve this, the MUST yield-concentration relationships for Cu and Zn were used in two ways:

- MUST Approach 1: Cu and Zn yields for the Waiwhetu catchment were obtained from the Contaminant Load Model (CLM) developed during the TWT biophysical science process. Median and 95th percentile concentrations were then calculated from the MUST yield-concentration relationships. The resulting concentrations did not closely match modelled (see Section 1.2 above) or measured values. Thus, an alternative TAS for each summary statistic was calculated based on the proportional difference between modelled current concentrations and the TAS. Yields were then incrementally reduced until the alternative TASs for both the median and 95th percentile concentration were achieved. The difference between the final yield and the CLM yield was then recorded as the required load reduction.
- MUST Approach 2: Cu and Zn yields for the Waiwhetu catchment were calculated from the modelled median and 95th percentile concentrations and the inverse of the MUST yield-concentration relationships. The MUST yield-concentration relationships were then used to calculate the extent to which those yields must reduce to achieve the TASs for the more restrictive (i.e., harder to meet) of the median and 95th percentile concentrations.

The code behind MUST contains 100 different yield-concentrations for Cu and Zn median and 95th percentile concentrations to account for the variability and uncertainty in these relationships. Thus, the approaches described above generated 100 estimates of the required load reduction to achieve the Cu and Zn TAS. Ultimately, the required load reduction was set at the level required to achieve the TASs under at least 67 of the 100 MUST yield-concentration relationships (i.e., the TAS more likely to be achieved than not - >66% probability (Mastrandrea *et al.*, 2010)).

As in Section 1.3.1, 95% confidence intervals were also estimated for the required load reductions calculated through the MUST yield-concentration relationships:

- For MUST Approach 1 this was achieved by calculating the load reductions required to achieve the proportional concentration reductions consistent with the difference between the TASs and the upper and lower bounds of the confidence intervals around the modelled median and 95th percentile Cu and Zn concentrations (see Section 1.3.1); and
- For MUST Approach 2, this was achieved by calculating Cu and Zn yields from the upper and lower bounds of the confidence intervals around the modelled median and 95th percentile Cu and Zn concentrations (see Section 1.3.1) and then calculating the required load reductions based on those yields.

## 1.4 Results

Figure 4 shows the load reductions required to achieve the Cu, Zn and *E. coli* TASs calculated using the different approaches described in Section 1.3. For Cu the estimated required load reduction varied from 59% to 89%, with the MUST approaches generating significantly higher estimates 89% than the Liberal (59%) or Conservative (70%) Approaches. In contrast, all four approaches generated reasonably consistent required Zn load reduction estimates (69% to 78%). For *E. coli* the estimated required load reduction varied between 85% (Liberal Approach) and 97% (Conservative approach). The confidence interval round all estimated required load reduction was small (≤2.3%).

Overall, the results indicate that calculation of required load estimates can vary considerably depending on methodology, and this variability far exceeds what can be attributed to uncertainty in baseline water quality . Thus, going forward it would make sense to continue to use multiple methods (i.e., a multiple lines of evidence approach) and present results as a range rather than adopting a single approach and describing uncertainty simply in terms of confidence intervals.

## 1.5 Summary:

The results presented in this section of this memorandum indicates that developing baseline probabilistic water quality models for TAS sites in TWT is feasible and can be used to develop estimates of the load reductions required to achieve the Cu, Zn and *E. coli* TASs. However, required load estimates can vary considerably depending on calculation methodology and it is recommended that multiple methods be used for this purpose (multiple lines of evidence approach) and that results are presented as a range rather than adopting a single approach and describing uncertainty simply in terms of confidence intervals. While not explored in this memorandum, the methods described here should also be able to be used to describe future water quality under the PC1 provisions when paired with the CLM outputs being generated by Collaborations.

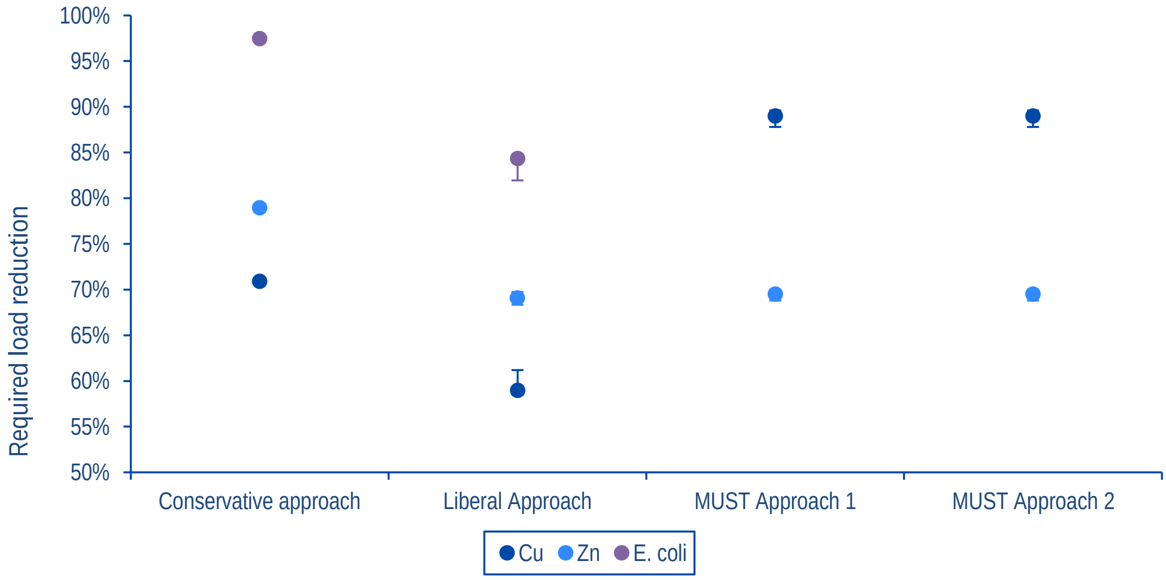


Figure 4: Required load reduction estimates (±C.I.) for the achievement in of the Cu, Zn and *E. coli* TASs for the Waiwhetu Stream calculated using four different methods.

## 2 Full implementation of pilot for use in PC1 evidence

### 2.1 Method

The methods used for the modelling conducted to inform the evidence of PC1 was the same as described above in Section 1, with the exception of the variations set out in Sections 2.1.1 to 2.1.3 below.

#### 2.1.1 Updates to TWT baseline model

The only change made to the model between the pilot described in Section 1 and full implementation was:

- The conservative approach became a new liberal approach;
- The previous liberal approach was reversed to become a new conservative approach. I.e., Load reductions were first targeted to flow bins that had the highest load:duration ratios. This approach assumes that mitigations cannot be deployed in manner that targets treatment to specific flow conditions; and
- 95% confidence intervals were not calculated around the modelled load reductions as the pilot demonstrated that bootstrapping was too compute intensive to implement at scale and yielded little additional information around uncertainty (see Section 1.4).

#### 2.1.2 Additional approach for sites in the TAoP Whaitua

To understand the load reductions required to achieve the Cu, Zn and *E. coli* TASs for rivers in the TAoP Whaitua the results of the eWater Source modelling conducted for the Porirua Whaitua were interrogated to develop log-normal relationships between contaminant loads and contaminant concentrations. I.e.:

$$Load = \alpha \times \ln(concentration) + \beta$$

For Cu and Zn log-normal relationships were established between:

- Modelled median concentrations and modelled annual loads; and
- Modelled 95$^{th}$ percentile concentrations and modelled annual loads.

For *E. coli* log-normal relationships were established between

- Modelled median concentrations and modelled annual loads;
- Modelled 95$^{th}$ percentile concentrations and modelled annual loads;
- Modelled percent exceedance of 260 CFU/100mL and modelled annual loads; and
- Modelled percent exceedance of 540 CFU/100mL and modelled annual loads.

Each of the above relationships were calculated from four datapoints; one for each scenario run through the eWater Source model (see Easton *et al*., (2019b)):

- Baseline 2004 – 2014;
- Business as usual;
- Improved; and
- Water Sensitive.

Once established, the coefficients($\alpha$) and constants ($\beta$) of these relationships were used calculate the load at which the TASs for each assessment statistic of an attribute was met (i.e., for Cu and Zn two load reductions were generated, while for *E. coli* four were generated). i.e.,

$$Target\ load = \alpha \times \ln(target\ concentration) + \beta$$

For each attribute the minimum of the resulting loads was compared to the modelled baseline load (Easton *et al.*, 2019b) to calculate the percent reduction required to achieve the TAS. A visual representation of this approach is show below in Figure 5:

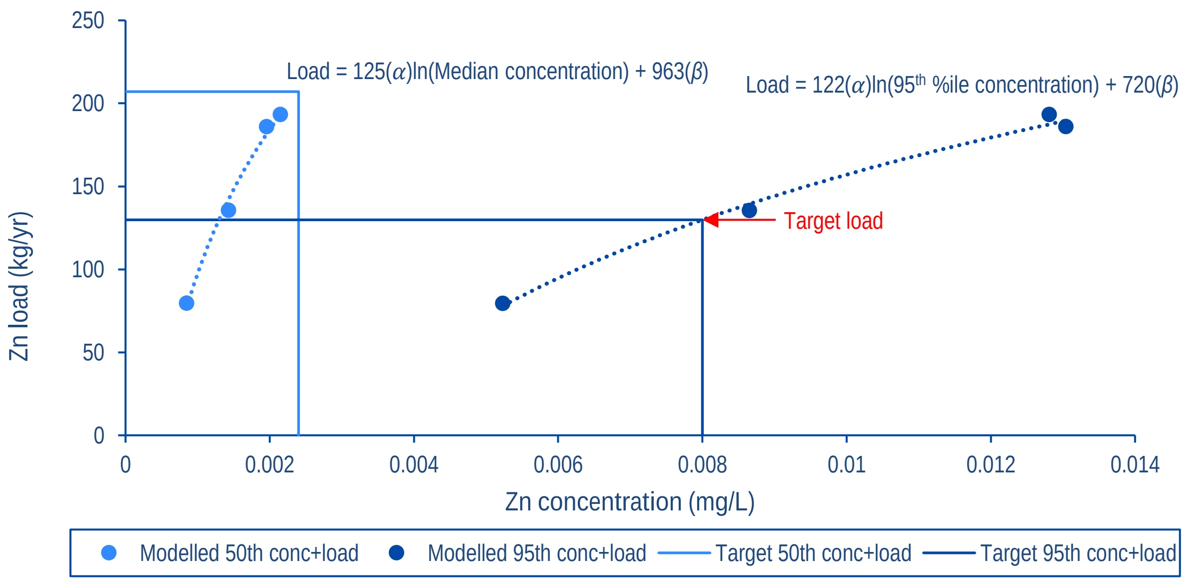


Figure 5: Visual demonstration of how load reductions have been calculated for sites in the TAoP Whaitua. The light and dark blue dots respectively depict modelled median and 95th percentile concentrations against the loads modelled under different scenarios by Easton *et al*. (2019b). The associated regression lines (and their equations) depict the calculated log-normal relationships between those modelled concentrations and loads, while the light and dark blue boxes show the target concentrations and back-calculated loads for each static. As the calculated load is lower for the 95th percentile concentration it has been selected as the target load (red arrow).

### 2.1.3 Additional target thresholds

Unlike during the pilot the required load reduction was assessed for two separate target thresholds:

- The PC1 river Cu, Zn and *E. coli* targets; and
- The minimum improvement required for Cu, Zn and *E. coli* by the NPS-FM 2020. Specifically:
    - Maintenance of baseline Cu and Zn concentrations (i.e., no load reduction); and
    - A one-attribute estate improvement in *E. coli* as required by Clause 3.11(3) of the NPS-FM 2020.

  This second lot of targets was added upon GWRC's request.

## 2.2 Model performance

The following model performance statics for each site in TWT are set out below in Table 2:

- The NSE for each percentile of the modelled and measured data;
- The PBIAS for the average measured and modelled values for each month in the record; and
- The PBIAS measured and modelled values for each day for which measured data exist.

With the exception of the NSE statistic for *E. coli* percentile at the Karori S. @ Mākara Peak site, all performance statistics were at least 'satisfactory' (Table 2). The unsatisfactory performance for *E. coli* in the Mākara Stream was the result of a single outlier value, in the absence of which model performance would be assessed as very good (Table 2). However, as this outlier only impacted the highest <1% of modelled results (>10,000 CFU/100mL – See Figure 6) the decision was made not to remove it from the training dataset for this site.

Table 2: Model performance statistics. Blue cells reflect very good performance, green cells reflect good performance, orange cells reflect satisfactory performance, and red cells reflect unsatisfactory performance (based on the guidance of Moriasi *et al.* (2007))

| Part-FMU | TAS site | Statistic | E.coli | Cu | Zn |
|---|---|---|---|---|---|
| Kaiwharawhara Stream | Kaiwharawhara S. @ Ngaio Gorge | NSE percentiles | 0.97 | 0.91 | 0.96 |
| | | PBIAS monthly average | 13.55 | 5.59 | 2.31 |
| | | PBIAS whole record | 13.07 | 5.18 | -3.23 |
| **Waiwhetū Stream** | **Waiwhetū S. @** Whites Line E. | NSE percentiles | 0.65 | 0.95 | 0.99 |
| | | PBIAS monthly average | -12.35 | -4.96 | 7.39 |
| | | PBIAS whole record | 13.31 | -0.52 | -6.24 |
| Wellington urban | Karori S. @ **Mākara Peak** | NSE percentiles | 0.44 | 0.72 | 0.97 |
| | | PBIAS monthly average | 10.96 | 18.55 | 2.72 |
| | | PBIAS whole record | 19.46 | 21.94 | 1.97 |
| Wellington urban | Karori S. @ **Mākara Peak** (no outliers) | NSE percentiles | 0.84 | N/A | |
| | | PBIAS monthly average | -8.96 | | |
| | | PBIAS whole record | 1.20 | | |
| Te Awa Kairangi rural streams and rural mainstems | Mangaroa R. @ Te Marua | NSE percentiles | 0.68 | N/A | |
| | | PBIAS monthly average | 38.03 | | |
| | | PBIAS whole record | 37.02 | | |
| Wainuiomata rural streams | Wainuiomata R. DS of White Br. | NSE percentiles | 0.63 | | |
| | | PBIAS monthly average | 47.79 | | |
| | | PBIAS whole record | 41.21 | | |
| Wainuiomata urban streams | Black Ck @ Rowe Parade end | NSE percentiles | 0.58 | 0.93 | 0.96 |
| | | PBIAS monthly average | 18.48 | 0.88 | 4.25 |
| | | PBIAS whole record | -10.15 | 0.32 | -6.22 |
| Te Awa Kairangi lower mainstem | Hutt R. @ Boulcott | NSE percentiles | 0.78 | N/A | |
| | | PBIAS monthly average | 28.44 | | |
| | | PBIAS whole record | 7.58 | | |
| Te Awa Kairangi urban streams | Hulls Ck adj. Reynolds Bach Dr. | NSE percentiles | 0.71 | 0.99 | 0.98 |
| | | PBIAS monthly average | 36.70 | 3.76 | 8.16 |
| | | PBIAS whole record | 19.48 | -4.84 | 7.22 |

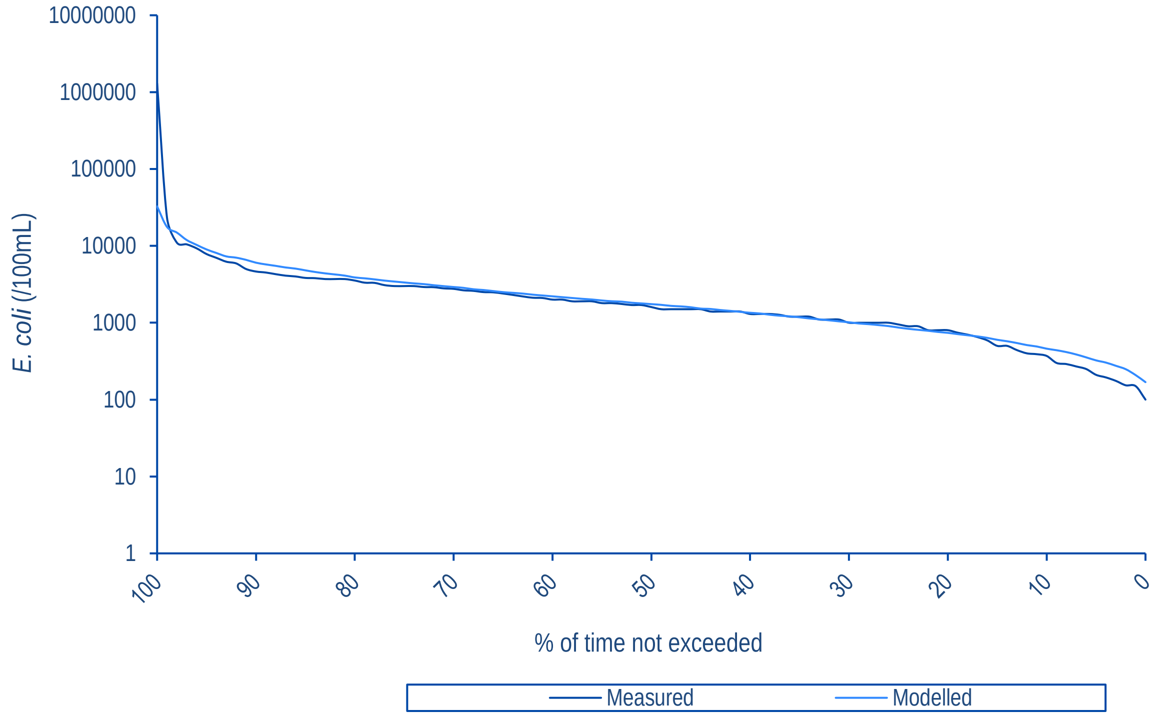


Figure 6: Probability distribution of *E. coli* concentrations in the Karori Stream, as measured in the river (dark blue line) and predicted by the model (light blue line), demonstrating a good fit for all but the top 1% of the distribution.

*Note: Baseline model performance statistics for sites in the TAoP Whaitua are presented in Easton et al. (2019b, 2019a).*

## 2.3 Results

The estimated load reductions required to achieve:

- The PC1 Cu, Zn and *E. coli* TASs; and
- The minimum improvement in Cu, Zn and *E. coli* concentrations required by the NPS-FM 2020,

are set out below in Table 3.

Table 3: Estimated load reductions required to achieve Cu, Zn and *E. coli* targets in rivers in the TWT and TAoP Whaitua.

| Whaitua | Part-FMU | TAS site | Attribute | Baseline state | Current state | Achieve TAS | | Minimum required by national direction | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | State | Load reduction | State | Load reduction |
| TWT | Kaiwharawhara Stream | Kaiwharawhara S. @ Ngaio Gorge | Copper | C | | B | 53% (38% - 68%) | C | 0% |
| | | | Zinc | B | | A | 76% (62% - 89%) | B | |
| | | | *E. coli* | E | | C | 89% (84% - 94%) | D | 79% (64% - 93%) |
| | Wellington urban | Karori S. @ Mākara Peak | Copper | D | | C | 4% (0% - 9%) | D | 0% |
| | | | Zinc | D | C | | 8% (7% - 10%) | D | |
| | | | *E. coli* | E | | C | 96% (93% - 99%) | D | 92% (85% - 95%) |
| | Waiwhetū Stream | Waiwhetū S. @ Whites Line E. | Copper | C | | A | 80% (67% - 93%) | C | 0% |
| | | | Zinc | D | | B | 76% (71% - 80%) | D | |
| | | | *E. coli* | E | | C | 90% (82% - 98%) | D | 80% (61% - 98%) |
| | Te Awa Kairangi urban streams | Hulls Ck adj. Reynolds Bach Dr. | Copper | C | | B | 69% (53% - 84%) | C | 0% |
| | | | Zinc | | | | 40% (35% - 45%) | | |
| | | | *E. coli* | E | | C | 91% (86% - 95%) | D | 85% (73% - 98%) |
| | Wainuiomata urban streams | Black Ck @ Rowe Parade end | Copper | C | C | | 0% | C | 0% |
| | | | Zinc | D | | | | D | |
| | | | *E. coli* | E | | C | 91% (84% - 99%) | D | 80% (62% - 99%) |
| | Wainuiomata rural streams | Wainuiomata R. DS of White Br. | Copper | ? | | A | 0% | ? | 0% |
| | | | Zinc | | | | | | |
| | | | *E. coli* | B | D | | 18% (6% - 30%) | A | 18% (6% - 30%) |
| | Te Awa Kairangi rural streams and rural mainstems | Mangaroa R. @ Te Marua | Copper | ? | | | 0% | ? | 0% |
| | | | Zinc | | | | | | |
| | | | *E. coli* | D | E | B | 61% (38% - 83%) | C | 53% (38% - 67%) |
| | Te Awa Kairangi lower mainstem | Hutt R. @ Boulcott | Copper | A | | | 0% | A | 0% |
| | | | Zinc | | | | | | |
| | | | *E. coli* | D | | C | 17% (0% - 33%) | C | 17% (0% - 33%) |
| | Ōrongorongo, Te Awa Kairangi and Wainuiomata small forested and Te Awa Kairangi forested mainstems | Whakatikei R. @ Riverstone | Copper | ? | | A | 0% | ? | 0% |
| | | | Zinc | | | | | | |
| | | | *E. coli* | A | | | 0% | A | 0% |
| | Parangārehu catchment | Mākara S. @ Kennels | Copper | ? | | | 0% | ? | 0% |
| | | | Zinc | | | | | | |

| Whaitua | Part-FMU | TAS site | Attribute | Baseline state | Current state | Achieve TAS | | Minimum required by national direction | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | State | Load reduction | State | Load reduction |
| | streams and South-west coast rural streams | | *E. coli* | E | | D | N/A (No wastewater infrastructure above TAS site) | | |
| | Korokoro Stream | Korokoro S.@ Cornish St. Br. | Copper | ? | | A | 0% | ? | 0% |
| | | | Zinc | | | | | ? | 0% |
| | | | *E. coli* | | | B | N/A (Insufficient *E. coli* and flow data to determine required load reductions) | | |
| TAoP | Pouewe | Horokiri S. @ Snodgrass | Copper | A | A | | 0% | A | 0% |
| | | | Zinc | | | | | | |
| | | | *E. coli* | E | D | B | 67% | D | 48% |
| | Takapū | Pāuatahanui S. @ Elmwood Br. | Copper | | ? | A | 0% | A | 0% |
| | | | Zinc | | | | | | |
| | | | *E. coli* | E | | C | 59% | D | 15% |
| | Taupō | Taupō S. @ Plimmerton Domain | Copper | C | B | | 0% | C | 0% |
| | | | Zinc | | A | | 56% | | |
| | | | *E. coli* | E | E | B | 99% | D | 49% |
| | Te Rio o Porirua and Rangituhi | Porirua S. @ Milk Depot | Copper | C | C | | 0% | C | 0% |
| | | | Zinc | D | | | | D | |
| | | | *E. coli* | E | | C | 92% | D | 60% |
| | Wai-o-hata1 | Duck Ck @ Tradewinds Dr. Br. | Copper | C | ? | A | 99% | C | 0% |
| | | | Zinc | B | | | 32% | B | |
| | | | *E. coli* | E | | C | 83% | D | 54% |

## 3 Important note on limitations

The probabilistic modelling approach described in this memorandum is coarse and the results should be considered indicative of the scale of improvement required to achieve the TAS, rather than absolute estimates of the load reduction required. Importantly, load reductions are not targeted in a manner that reflects real world conditions, and any hydrological impacts (e.g., through land-cover change or stormwater detention) that a change in contaminant loads may generate are not considered. The results should not be considered comparable to the eWater Source modelling presented in Easton *et al*. (2019b, 2019a), but rather as an additional tool to help inform the drafting of technical evidence for PC1.

## 4 References


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