Assessment of *Escherichia coli* Load Reductions to Achieve Freshwater Objectives in the Rivers of Otago

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Prepared By:

Ton Snelder

Caroline Fraser

For any information regarding this report please contact:

Ton Snelder

Phone: 027 575 8888

Email: ton@lwp.nz

LWP Ltd

PO Box 70

Lyttelton 8092

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Executive Summary

This report describes *Escherichia coli* (*E. coli*) load reductions predicted to be needed to achieve options for freshwater objectives for human contact (FWOs) in rivers in the Otago region. The analysis does not consider how the *E. coli* load reductions would be achieved. The analysis aims to inform the Otago Regional Council (ORC) about the magnitude of the load reductions needed for each option and how these vary across the region.

The study area includes all of Otago. The underlying analysis utilised several models that describe concentrations and loads of *E. coli* in the rivers across the study area. These models were built from ORC's monthly river state of environment monitoring data at up to 103 sites across the region. The concentrations and loads were combined with criteria associated with FWOs. Calculations were made of the amounts by which current loads would need to be reduced to allow the FWOs to be achieved (i.e., the load reductions required).

The FWOs were based on *E. coli* numeric attribute states (bands A, B or C) that are defined by the National Objective Framework (NOF) (NPSFM 2020). Four sets of potential options for FWOs were included in the assessment. The first three sets of FWOs simply assigned the A, B and C NOF band, uniformly to all parts of the river network. The fourth set of FWOs were spatially variable with the NOF bands varying a proposed classification of the region's rivers into management classes defined as Mountain, Hill. Lowland, Lake Upper and Lake Lower.

Like all assessments of this type, the predicted load reductions required are subject to considerable uncertainty. The uncertainty of the assessments was quantified using a Monte Carlo analysis. The uncertainty analysis made 100 'realisations' of the calculations, with each realisation being perturbed by a random error that reflected the statistical error (i.e., uncertainty) associated with the modelled concentrations and loads. The study presents the results as best estimates (of the load reduction required) and the 90% confidence interval for these estimates. The broad scale patterns in the estimated *E. coli* load reductions provide a reliable indication of the relative differences between locations. However, there is considerable uncertainty associated with the absolute values of the *E. coli* load reductions and these become larger as the spatial scale over which the reductions are evaluated is reduced. It is unlikely that these uncertainties can be significantly reduced in the short to medium term (i.e., in less than 5 to 10 years) because, among other factors, the modelling is dependent on the collection of long-term water quality monitoring data.

The assessed load reductions required for the nine FMUs and the whole region are shown in Table A below as proportions of current *E. coli* load. The best estimate for the load reductions was always less for the C band settings compared to the B band and for the B band compared to the A band. However, the 90% confidence intervals for the four sets of FWOs overlap in all cases. This indicates that from a practical perspective the amount of effort (i.e., the reduction in *E. coli* loads required) to achieve the four sets of FWOs are not significantly different. This is because the models have considerable uncertainty and the concentrations and corresponding loads that separate the four sets of FWOs are similar, relative to this uncertainty.

Table A. the load reductions required for individual FMUs and the whole region for the four sets of FWOs. The load reductions are shown as proportion of current load (%). The first value in each column is the best estimate, which is the mean value over the 100 Monte Carlo realisations. The values in parentheses are the lower and upper bounds of the 90% confidence interval.

FMU	C band	B band	A band	Spatially variable
Catlins FMU	45 (15 - 70)	54 (21 - 78)	67 (44 - 86)	48 (19 - 73)
Dunedin Coast FMU	61 (47 - 76)	70 (54 - 83)	77 (64 - 87)	63 (47 - 78)
Dunstan Rohe	13 (0 - 61)	16 (0 - 64)	27 (0 - 73)	23 (0 - 62)
Lower Clutha Rohe	33 (0 - 83)	33 (0 - 78)	46 (3 - 89)	33 (0 - 83)
Manuherekia Rohe	13 (0 - 61)	16 (0 - 65)	27 (0 - 74)	22 (0 - 63)
North Otago FMU	50 (28 - 73)	57 (35 - 74)	68 (48 - 85)	54 (31 - 77)
Roxburgh Rohe	15 (0 - 65)	16 (0 - 61)	27 (0 - 76)	23 (0 - 66)
Taieri FMU	29 (1 - 74)	31 (1 - 79)	51 (1 - 91)	40 (1 - 88)
Upper Lakes Rohe	14 (0 - 66)	18 (0 - 72)	31 (0 - 77)	33 (0 - 78)
Total	24 (6 - 74)	31 (7 - 70)	45 (13 - 83)	31 (9 - 74)

The NPS-FM requires regional councils to set limits on resource use to achieve environmental outcomes (e.g., FWOs). This report helps inform Otago Regional Council's process of setting limits by assessing the approximate magnitude of the *E. coli* load reductions needed to achieve several options for FWOs, with a quantified level of uncertainty associated with each option. However, this report does not consider what kinds of limits on resource might be used to achieve any load reductions, how such limits might be implemented, over what timeframes and with what implications for other values. The NPS-FM requires regional councils to have regard to these and other things when making decisions on setting limits. This report shows that these decisions will ultimately need to be made in the face of uncertainty about the magnitude of load reductions needed.

1 Introduction

This report describes an assessment of *Escherichia coli* (*E. coli*) load reductions required to achieve options for numeric objectives in the rivers of Otago. The purpose is to inform the Otago Regional Council (ORC) about where potential objectives are currently being achieved and not achieved. Where objectives are not being achieved, the report describes the size of the gap between current *E. coli* loads and loads that would allow the objectives to be achieved.

The analysis described in this report does not consider how the *E. coli* load reductions would be achieved. The current report therefore only aims to inform the ORC about the magnitude of the required load reductions, how these vary across the region. and to establish a framework for future scenario testing of methods that might be employed to reduce loads. The various objectives presented in this report are options. It is assumed that objectives will remain options until the testing of methods to achieve the reductions has been completed.

The analysis methodology is based on similar studies that assessed national-scale nitrogen load reduction requirements (MFE, 2019; Snelder *et al.*, 2020) and regional scale nutrient reductions (nitrogen and phosphorus) in the Southland region (Snelder, 2020). However, the current analysis involved some modifications to methods used by these earlier studies to represent the Otago region in greater detail, and to assess load reductions for *E. coli* rather than nutrients. To keep the current report simple, the methods are described only in broad terms and the reader is referred to MFE (2019) and Snelder *et al.* (2020) for the details of the methodology. The exceptions to this are descriptions of details of the method where these pertain to modifications made for the current study.

2 Methods

2.1 Overview

Conceptually, this study represents *E. coli* loads being generated in catchments and transported to downstream river and stream receiving environments by the drainage network (Figure 1). The loads of *E. coli* (i.e., *E. coli* organisms per year) arriving at each receiving environment determine the distribution of *E. coli* concentrations through time and therefore the risk to human health (MFE and MoH, 2003). Acceptable risks to human health are defined by levels of four statistics (i.e., criteria) that describe the distribution of *E. coli* values at a site. These statistics are the annual median and 95th percentile concentrations (Median, Q95), and the proportion of samples for which concentration thresholds of 260 and 540 *E. coli* 100mL^{-1} are exceeded (G260, G540). These statistics are used because they are the basis for the *E. coli* attribute states in the National Objectives Framework (NOF) appended to the National Policy Statement – Freshwater NPS-FM; NZ Government (2017, 2020). Where one or more of the values of the four statistics exceed a defined criterion, there is a requirement to reduce the current load of *E. coli*. The four statistics are also the basis for national targets to increase the proportions of large rivers that are suitable for primary contact (i.e., that are C band state or better), as set out in Appendix 3 of the NPS-FM (NZ Government, 2017, 2020).

This study's calculations were based on a spatial framework that represents the drainage network (i.e., streams and rivers) and associated catchments. Calculations were performed for every segment of the network, which represent river receiving environments.

The calculation of load reductions required were based on statistical models fitted to *E. coli* data obtained from river state of environment (SOE) monitoring in the Otago region. The analyses are shown schematically in Figure 1. Initially, observations made at each SOE monitoring site were analysed to calculate the current values of four *E. coli* statistics and to calculate current annual loads of *E. coli* (i.e., number of organisms) per year. In addition, linear regression models were used to relate the observed values of the *E. coli* statistics at each SOE monitoring site with the associated *E. coli* loads (expressed as yields by dividing by the catchment area of each SOE monitoring site).

The four statistics and the loads (expressed as yields) were used as training data in spatial models. The spatial models were used to predict the current value for the four statistics and the current *E. coli* loads for every segment of the river network (i.e., every stream and river receiving environment) within the study area.

The criteria to achieve four sets of options for FWOs in river receiving environments are defined in terms of four statistics representing *E. coli* concentrations. Compliance with FWOs was assessed for each segment of the river network by comparing these criteria with the associated predicted value. In addition, the linear models relating *E. coli* statistics and loads were used to calculate the maximum allowable load (MAL), which is the load that will ensure the four *E. coli* statistics do not exceed their associated criteria at each segment. The local excess load for each segment of the river network was then calculated as the current load minus the MAL. The local excess load is the amount by which the current load at each segment would need to be reduced to achieve the FWO.

The load reduction required at every point in the of the river network was calculated as the maximum of the local load reduction at that and all upstream receiving environments. The load reduction required differs from the local excess load in that it considers the excess load of all upstream receiving environments. Thus, a point in the network may have a local excess load of zero but, if it is situated downstream of receiving environments that have local excess loads, it will have a load reduction required that is the maximum of the upstream local excess loads. The load reduction required can be expressed in absolute terms as a load of organisms per year (*E. coli* yr^{-1}), as a yield (organisms per catchment area per year; *E. coli* ha^{-1} yr^{-1}) and as a proportion of the current load of *E. coli* (%).

Critical points and catchments were identified by first identifying critical points in each sea-draining catchment in the study area. For every point in the drainage network there is a critical point, which is the downstream segment that has the highest ratio of current load to MAL. The catchment upstream of the critical point is a critical point catchment and has a load reduction required, which is the local excess load at the critical point. The critical catchment load reduction required is expressed as a yield (i.e., number of *E. coli* organisms per catchment area; *E. coli* ha^{-1} yr^{-1}) or as a percentage of current *E. coli* load (%). The critical catchment load reduction required indicates the spatially averaged reduction rate that would be required over the entire area of the critical point catchment to reduce the load sufficiently to allow FWO to be achieved across the entire catchment. Sea-draining catchments can have one critical point (the most downstream receiving environment) or multiple critical points, which include the most downstream receiving environment and other sub-catchments. Critical catchments can have a catchment load reduction required of zero when the current load is less than the MAL or have positive values when the current load exceeds the MAL.

It should be kept in mind that a critical catchment load reduction required represents a load reduction for the whole critical catchment. If the catchment includes areas of non-productive land, and the methods for load reduction are restricted to mitigation actions associated with pastoral land use, the required load reduction from productive land would need to be higher than the reported value.

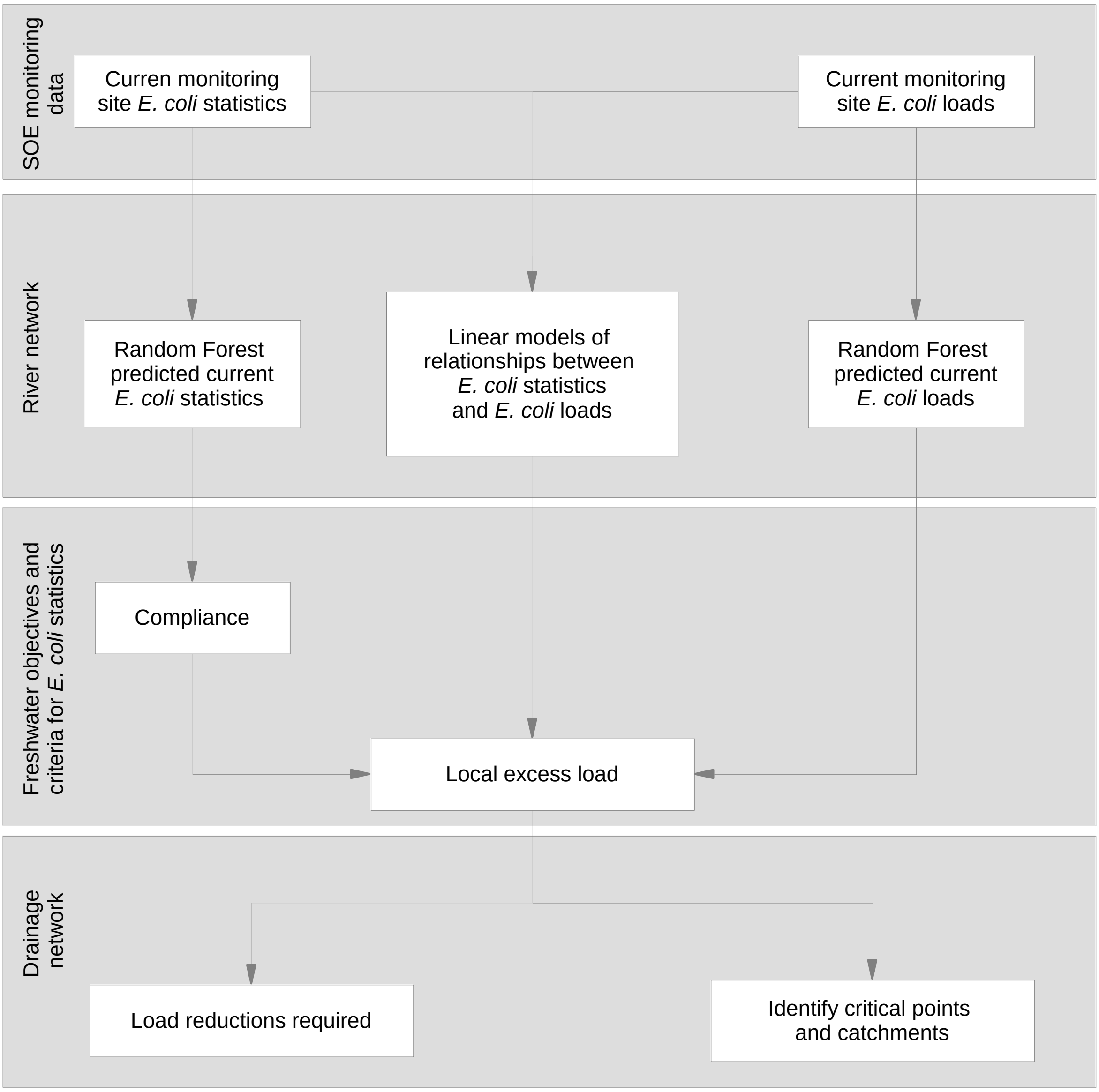

Figure 1. Schematic diagram of the assessment of E. coli load reductions required to achieve freshwater objectives.

The following sections describe the various components of the analysis shown in Figure 1 in more detail.

2.2 Spatial framework

The study area comprised the Otago region (Figure 2). The drainage network and river receiving environments were represented by the GIS-based digital drainage network, which underlies the River Environment Classification (REC version 2.4; Snelder and Biggs, 2002). This is the same drainage network that was the spatial framework used by Snelder (2020). The digital network was derived from 1:50,000 scale contour maps and represented the rivers within the study area as 70,600 segments bounded by upstream and downstream confluences, each of which is associated with a sub-catchment (Figure 2). The terminal segments of the river network (i.e., the most downstream points in each drainage network that discharges to the ocean) were identified.

Each segment in the network has been allocated to a reporting catchment that is an individual sea-draining catchment (Figure 3). The results of the load reductions required analyses can be reported at any spatial scale from individual receiving environments (i.e., river segments, Figure 2), to freshwater management units (FMUs; Figure 3) and the whole study area.

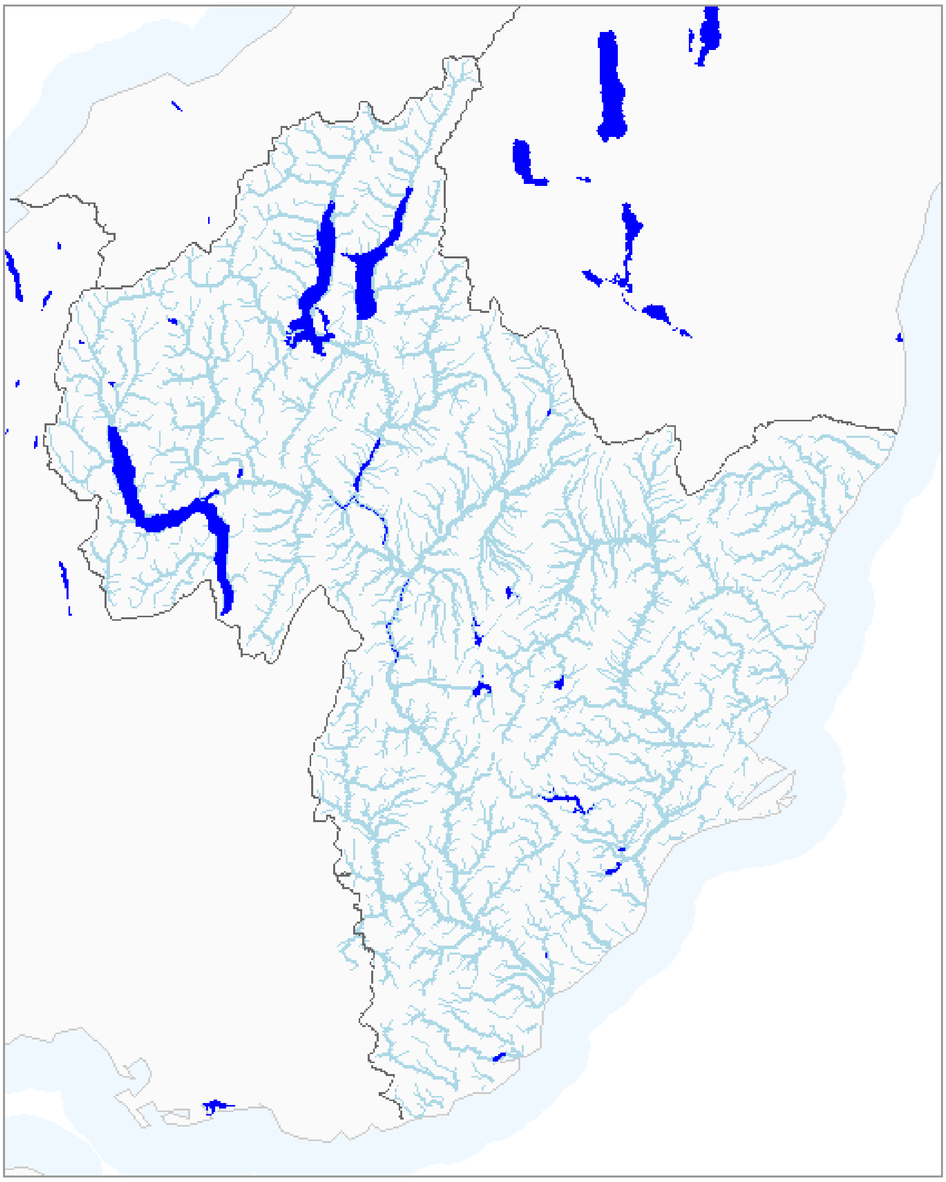

Figure 2. The digital network within the study area that provided the spatial framework for the analysis.

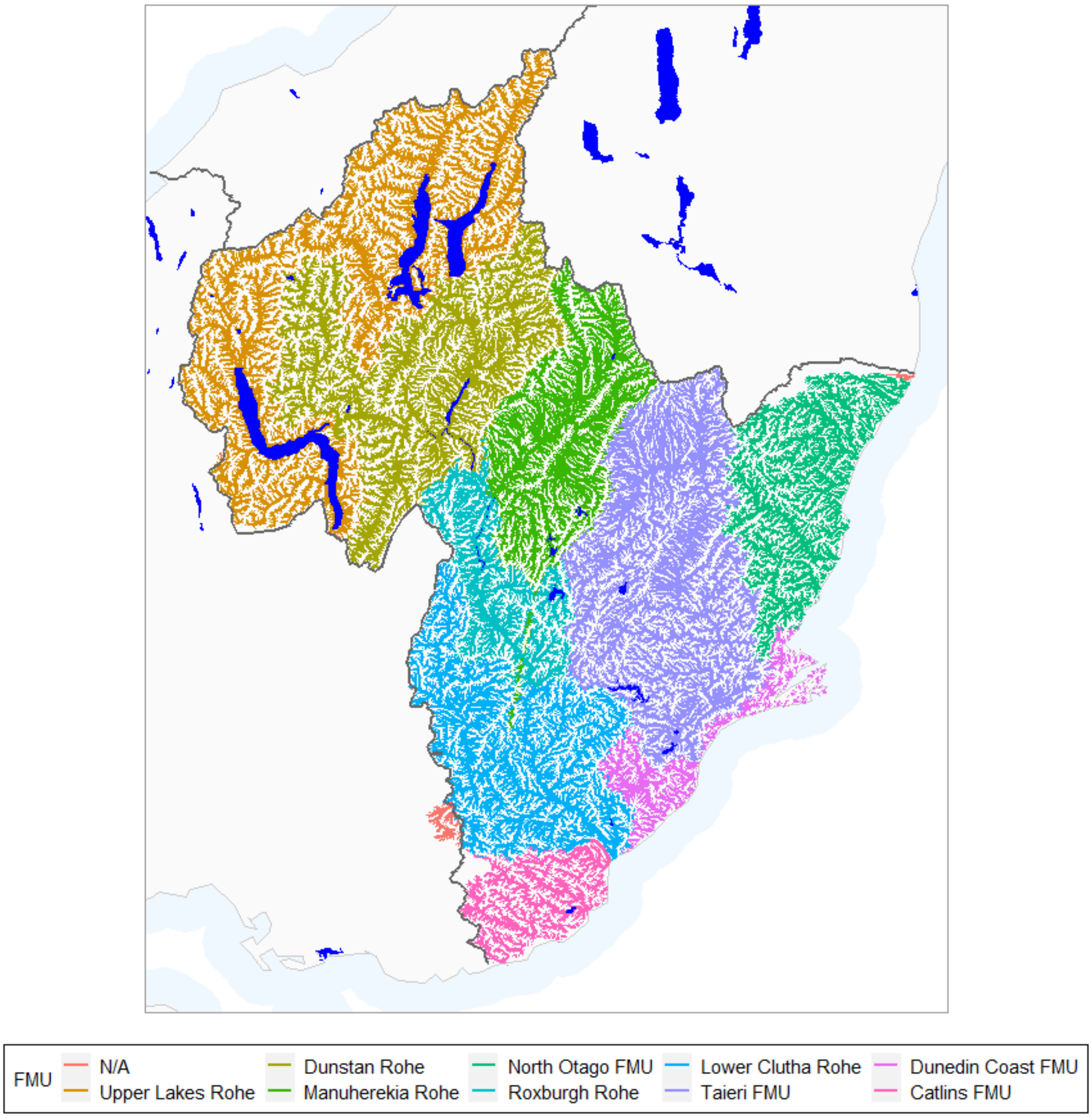

Figure 3. Freshwater management units (FMUs) used for summarising the results of the analysis.

2.3 *E. coli* criteria and predicted current *E. coli* statistics

The NOF defines five levels of environmental quality (termed "attribute states" in the NPS-FM) denoted A, B, C, D and E. The five attribute states are linked to threshold criteria for the four *E. coli* statistics shown in Table 1. The attribute states are associated with low (A) to high (E) concentrations of *E. coli*, which are linked to low to high risk of infection by microbiological pathogens for humans contacting the water. Each of the four criteria defined by Table 1 must be satisfied (i.e., the value of each statistic representing the state of a river receiving environment must be lower than the criteria) for that receiving environment to be in that attribute state. Thus, if one or more criteria cannot be satisfied in an attribute state, a lower attribute state applies.

The national targets to increase the proportions of large rivers that are suitable for primary contact are linked to NOF attribute states. The NPS-FM defines rivers as suitable for primary contact if they are in NOF attributes states A, B or C and large rivers are defined by network segments of a stream order of ≥4 as defined by the REC. In Otago, river segments of stream order of ≥4 have a minimum catchment area of 5.5 km^2 and approximately 75% of them have mean flows >1 $m^3 s^{-1}$.

Table 1. Criteria used to define the E. coli freshwater attribute states.

Criteria	Attribute state				
	A	B	C	D	E
Median *E. coli*/ 100ml^{-1} (Q50)	<130	130	130	260	>260
95th Percentile *E. coli* 100ml^{-1} (Q95)	<540	1000	1200	1200	>1200
Proportion of exceedances over 260 *E. coli* 100ml^{-1} (G260)	<0.2	0.3	0.34	0.5	>0.5
Proportion of exceedances over 540 *E. coli* 100ml^{-1} (G540)	<0.05	0.1	0.2	0.3	>0.3

The analysis described below was based on values of four NOF *E. coli* statistics (Table 1) that were predicted for all segments of the drainage network using spatial statistical regression modelling. The statistical modelling to predict the values of the four *E. coli* statistics for every network segment commenced by calculating each of the four statistics shown in Table 1 for 101 SOE monitoring sites located in the Otago region. *E. coli* had been measured at each site on a monthly basis for the five-year period ending 30 June 2020 (Figure 4). The statistic values were calculated from the monitoring data for each site and are reported in Ozanne (2021). The site values of each statistic were used as response variables in four regression models (one for each statistic) that were based on several similar national and regional studies (e.g., Whitehead, 2018) and the studies on which the current analysis was based (MFE, 2019; Snelder *et al.*, 2020).

For each *E. coli* statistic (i.e., Median, Q95 G260, G540), a random forest (RF) regression model was fitted to the observed monitoring site values using predictor variables that describe various aspects of each site's catchment including the climate, geology and land cover. In addition, this study included five predictors that quantified the density of pastoral livestock in 2017 to indicate land use intensity. These predictors were based on publicly available information describing the density of pastoral livestock (https://statisticsnz.shinyapps.io/livestock_numbers/). These predictors improve the discrimination of catchment land use intensity compared to previous studies that have only had access to descriptions of the proportion of catchment occupied by different land cover categories (e.g., (Larned *et al.*, 2018). The densities of four livestock types (dairy, beef, sheep and deer) in each catchment were standardised using 'stock unit (SU) equivalents', which is a commonly used measure of metabolic demand by New Zealand's livestock (Parker, 1998). Stock unit equivalents that were applied to dairy, beef, sheep and deer were 8, 6.9, 1.35, and 2.3, respectively. These values represent adjustments to the original equivalents of Parker (1998) to account for increasing animal size and productivity since 1998 (Ross Monaghan, AgResearch *pers comm*). These five predictors express land use intensity as the total stock units and the stock units by each of the four livestock types divided by catchment area (i.e., SU ha^{-1}).

The site Median and Q95 values were log_{10} transformed to improve model performance (Whitehead, 2018). A logit transformation was applied before fitting the model for G260 and G540 values. A logit transformation is defined as:

$$logit = log\left(\frac{x}{1-x}\right) \quad \text{Equation 1}$$

where x are the site G260 and G540 values, which are in the range 0 to 1. The logit transformed values range between −∞ and +∞. In a previous study, Snelder (2018) showed that transformation of the G260 and G540 statistics did not improve the performance of the RF models but did improve their ability to discriminate variation in small values of the statistics.

The fitted models were combined with a database of predictor variables for every network segment in the region and used to predict the current (i.e., 2017) values of the four statistics for all segments. Model predictions were back-transformed and, in the case of the log transformed statistics (Median and Q95) corrected for re-transformation bias as described by (Duan, 1983).

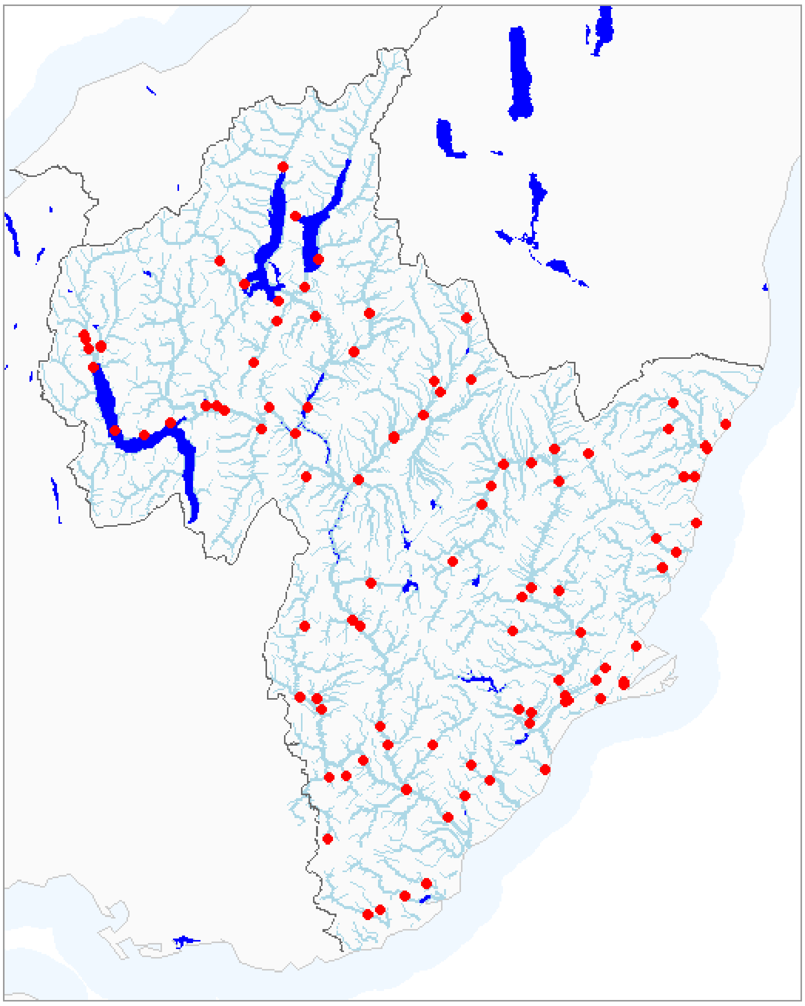

Figure 4. Locations of the 101 river SOE monitoring sites used to fit the E. coli concentration models.

The performance of the models and the uncertainty of the predictions were evaluated using three measures: regression R^2, Nash-Sutcliffe efficiency (NSE), bias. The regression R^2 value is the coefficient of determination derived from a regression of the observations against the predictions. The R^2 value indicates the proportion of the total variance explained by the model, but is not a complete description of model performance (Piñeiro *et al.*, 2008). NSE indicates how closely the observations coincide with predictions (Nash and Sutcliffe, 1970). NSE values range from $-\infty$ to 1. An NSE of 1 corresponds to a perfect match between predictions and the observations. An NSE of 0 indicates the model is only as accurate as the mean of the observed data, and values less than 0 indicate the model predictions are less accurate than using the mean of the observed data. Bias measures the average tendency of the predicted values to be larger or smaller than the observed values. Optimal bias is zero, positive values indicate underestimation bias and negative values indicate overestimation bias (Piñeiro *et al.*, 2008). The normalization associated with R^2 and NSE allows the performance of the models of the four *E. coli* statistics to be directly compared. Model predictions were evaluated against two performance measures (R^2 and NSE) following the criteria proposed by Moriasi et al. (2015), outlined in Table 2.

Model uncertainty was quantified by the root mean square deviation (RMSD). RMSD is the mean deviation of the predicted values from their corresponding observations and is therefore a measure of the characteristic model uncertainty (Piñeiro *et al.*, 2008).

Table 2: Performance ratings for statistics used in this study. The performance ratings are from Moriasi et al. *(2015).*

Performance Rating	R^2	NSE
Very good	$R^2 \geq 0.70$	NSE > 0.65
Good	$0.60 < R^2 \leq 0.70$	0.50 < NSE ≤ 0.65
Satisfactory	$0.30 < R^2 \leq 0.60$	0.35 < NSE ≤ 0.50
Unsatisfactory	$R^2 < 0.30$	NSE ≤ 0.35

For the statistics Median and Q95, model predictions require back transformation from the original $\log_{10}$ space to the original units (*E. coli* 100 mL^{-1}) using Equation 2.

$$Prediction = CF \times 10^{[log_{10}(x) - bias]} \qquad \text{Equation 2}$$

where x represents the untransformed prediction (in $\log_{10}$ space) from the model and CF is a factor to correct for retransformation bias (Duan, 1983).

For the statistics G260 and G540 the model predictions require back transformation from the original logit space to the using Equation 3.

$$Prediction = \frac{e^{x-bias}}{1+e^{x-bias}} \qquad \text{Equation 3}$$

where x represents the untransformed prediction (in logit space) from the model.

2.4 Estimated current river *E. coli* loads

Estimates of current loads of *E. coli* for all segments of the drainage network were made using river water quality monitoring data from river water quality SOE monitoring sites in the Otago region and statistical regression modelling in two steps. The first step used calculated loads of *E. coli* for 64 SOE monitoring sites that were derived for another project (Snelder *et al.*, 2021). Loads were calculated for 51 sites that had at least 96 monthly concentration observations (80% of months) over the 10 years up to the end of 2017 using the methods described in Appendix A. Load calculations were based on mean daily flows for each monitoring site that were either derived from flow recorders or, where this was not available, predicted site using the TopNet hydrological model (McMillan *et al.*, 2013). The load calculation method estimated the mean annual load but accounted for trends in the concentration data so that the final load estimates pertain to the end of 2017. The loads were expressed as yields by dividing by the catchment area (*E. coli* ha^{-1} yr^{-1}). The 51 sites had poor represented rivers draining high rainfall parts of including the Otago region (i.e., alpine headwater areas) but well represented rivers along a gradient in the proportion of the upstream catchment occupied by pastoral land use (Figure 5).

The second step used the same statistical regression modelling approach as for concentrations to fit random forest models to calculated monitoring site yields. The site yield values were $\log_{10}$ transformed to improve model performance (Snelder, 2018).

The fitted models were combined with a database of predictor variables for every network segment in the region and used to predict current yields of *E. coli*. Predictions made by the *E. coli* models were most strongly positively associated with variables representing the degree of pastoral land use in the upstream catchment and catchment rainfall. Because the sites poorly represented rivers draining high rainfall areas, predictions were not made for segments whose rainfall characteristics were greater than the 95th percentile of that represented by the fitting dataset (area categorised as outside the fitting data in Figure 5). It is noted that when the model was used to make predictions for segments with high rainfall in the upstream catchments, the predictions were unreasonably high. Model predictions were back-transformed using Equation 2, which includes correcting for re-transformation bias based on the method of Duan (1983). The load model predictions were evaluated following the same criteria used for the concentration predictions (Table 2).

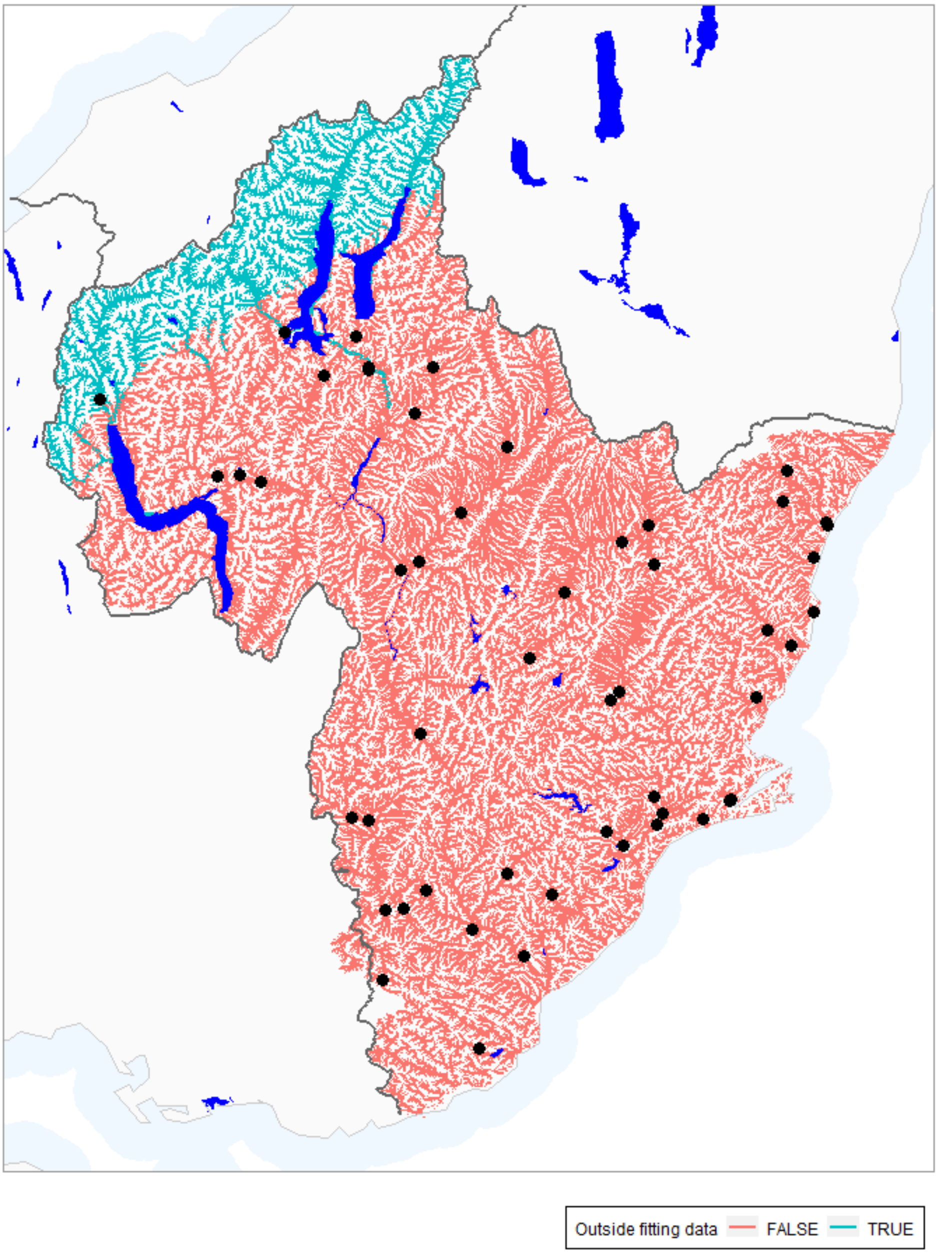

Figure 5. Locations of the 51 river SOE monitoring sites used to fit the E. coli yield models. River segments are coloured to indicate whether rainfall characteristics were greater than the 95th percentile of that represented by the fitting dataset.

2.5 Linear models describing *E. coli* yield as function of attribute statistics

For the 51 water quality monitoring sites that were used to model the *E. coli* loads, we fitted models describing the relationship between the *E. coli* yield (i.e., the load divided by the catchment area) and each of the four attribute statistics. The *E. coli* statistics for the sites were for the period ending 30 June 2020 and were obtained from Ozanne (2021). Because the loads pertained to the end of 2017, they were representative of the 5-year period ending June 2020 that the *E. coli* statistics were calculated from. The models were linear regressions with appropriate transformations applied to linearise the modelled relationships. We log (base 10) transformed both the yield and the statistic values prior to fitting the models pertaining to the median and Q95 statistics. We log (base 10) transformed just the yield values for the models pertaining to the G260 and G540 statistics.

The uncertainties of these models were evaluated using a leave-one-out cross validation process to obtain a set of independent predictions of the yields at each site. These independent predictions were then combined with the observed yields and the model statistics shown in Table 2 were used to describe the performance of the four separate models. Note that because the linear models were fitted to the $\log_{10}$ transformed values of the yield, the outputs obtained from the models were back-transformed (by raising to the power of 10) and corrected for re-transformation bias as described by (Duan, 1983).

2.6 Current state and compliance

We undertook the analyses that follow for four sets of possible objectives that were defined using the NPS-FM *E. coli* attribute states. These sets of objectives are options that could be adopted and therefore the analyses indicate the impact of choosing each option in terms of the load reductions required were that option to be adopted. Options 1, 2 and 3 assumed adoption of objectives defined by the A, B and C bands (Table 1), respectively for all rivers in the region. Option 4 allowed the objectives (defined as bands A, B or C) to vary across the Otago region according to classes that are discussed in Section 2.9. The remainder of the section describes how the predicted current values of the four *E. coli* statistics were compared with the objectives nominated under options 1, 2, 3 and 4, to assess the current attribute state and compliance (step 3 of the analysis described in Figure 1).

The current attribute state and compliance were assessed for each river segment in three steps. First, based on its nominated attribute state (i.e., band), each segment was assigned a criterion for each statistic based on the criteria in Table 1. Second, each segment was assigned a current attribute state based on the statistic that produced the lowest attribute state. For example, if the Median, Q95 and G540 were assigned to the B state but the G260 was assigned to the C state, the attribute state of the segment was assessed as C. Third, the predicted current values of each of the four *E. coli* statistics were compared to their corresponding criteria. If all four current *E. coli* statistics were less than their corresponding target values, the segment was compliant, otherwise it was considered noncompliant.

The predicted current values of the four *E. coli* statistics were also used to determine the proportion of large rivers that are currently suitable for primary contact. This assessment was performed by calculating the proportion of segments with stream order of ≥4 for which the predicted current attribute state was A, B or C. It is noted that the proportion of segments that are unsuitable is the complement of the proportion that are suitable (i.e., 1 – proportion suitable). The proportion suitable for primary contact was calculated for the region. This was done to enable comparison of the results for the whole Otago region with a previously reported estimate of the current proportion of large rivers suitable for primary contact in Otago (i.e., 78%; MFE 2018) and also to compare with the national targets laid out in the NPSFM (i.e., 80% by 2030 and 90% no later than 2040).

2.7 Load reductions required and critical catchments

The *E. coli* load reduction required to bring all segments into a compliant state was calculated in three steps (steps 3, 4 and 5; Figure 1). At step 3, for all noncompliant segments and each *E. coli* statistic, the *E. coli* yield corresponding to the criteria was estimated using the linear models describing the *E. coli* yield as a function of the four attribute statistics (section 2.5). Then, for each segment, the largest percentage reduction across all non-compliant *E. coli* statistics was found. The maximum allowable load (MAL) was evaluated as this largest percentage reduction applied to the predicted current *E. coli* load (i.e., predicted using the random forest model). The local excess load is then evaluated as the current load minus the MAL. For example, if the segment FWO was the A attribute state, the Q50 criteria would be 130 *E. coli* 100ml^{-1} (Table 1). The *E. coli* yield corresponding to a Q50 of 130 *E. coli* 100ml^{-1} would be estimated using the linear model to be 15 giga *E. coli* ha^{-1} yr^{-1} (see Figure 9). Then, the *E. coli* yield corresponding to the predicted current value of the statistic would be estimated from the linear models. If the predicted current Q50 value was 400 *E. coli* 100ml^{-1}, the corresponding *E. coli* yield would be estimated from the linear model as 26.3 giga *E. coli* ha^{-1} yr^{-1} (see Figure 9). The difference between the estimated current yield and the estimated yield to achieve the criteria can then be expressed as a percentage reduction, i.e., 43% ([26.3-15]/26.3). If the predicted current *E. coli* load were 29 giga *E. coli* ha^{-1} yr^{-1} the MAL would be evaluated as 16.5 giga *E. coli* yr^{-1} (i.e., [100 – 43%] x 29). The local excess load would be evaluated as 29-16.5 = 12.5 giga *E. coli* ha^{-1} yr^{-1}.

The load reduction required (Figure 1) was calculated by traversing the digital drainage network in the downstream direction. At all upstream-most segments, the load reduction required was defined to be the local excess load. Then, beginning at the upstream-most segments, the load reduction required was compared to the local excess load of the next segment downstream. If the local excess load at the next downstream segment was less than the load reduction required of the upstream segment, the load reduction required of the downstream segment was updated to be the load reduction required of the upstream segment. If the reverse applied, the local excess load of the downstream segment was updated to be its local load reduction required. The load reduction required therefore took a positive value (*E. coli* yr^{-1}) at any segment in the catchment for which there was a local excess load at that, or any upstream, segment. Summaries of the load reductions required as mass per year (*E. coli* yr^{-1}) were produced for FMUs (Figure 3) and the whole study area. These summaries were evaluated by summing excess loads over all terminal segments (i.e., network of segments intersecting the coastline) of the summary area.

Finally, critical points and catchments (Figure 1) were identified as follows. The terminal segment of every sea-draining catchment (the river mouth) was defined as a critical point and the ratio of the current load to MAL at that point was noted. A ratio of the current load to MAL greater than one indicates non-compliance and the larger this value is, the greater the extent to which the current load exceeds the MAL. From the terminal segment, the ratio of the current load to MAL at successive upstream river segments were obtained. At each segment, the ratio was compared with the ratio for the downstream critical point. If the ratio of the current load to MAL at the segment was greater than that of the downstream critical point, the segment was defined as a critical point and the load reduction required for the catchment upstream of this point is the local excess load of this segment. If the ratio of the current load to MAL at the segment is less than that of the downstream critical point the critical point is unchanged. The process continues upstream to the catchment headwaters. Maps indicating the load reductions required were produced for critical point catchments as yields by dividing by the upstream catchment area (*E. coli* ha^{-1} yr^{-1}) or as proportions of the current load (%). More details of the process of defining critical points and catchments are provided by Snelder *et al.* (2020)[1]. To map the critical catchment load reduction required, the quantity is expressed as a

[1] Snelder et al. (2020) based the identification of critical points on excess loads, which were expressed as the ratio of the current load to the maximum allowable load.

percentage of current *E. coli* load or as a yield (i.e., number of *E. coli* organisms per catchment area; *E. coli* ha^{-1} yr^{-1}).

2.8 Estimation of uncertainties

Our analysis was based on nine statistical models (i.e., random forest models to predict current values of the four *E. coli* statistics, random forest models to predict the current *E. coli* yield, and four linear regression models describing *E. coli* yield as function of four *E. coli* statistics). These models were all associated with uncertainties. The uncertainty of each model was quantified by its RMSD values (Table 2). These random errors propagate to all the assessments produced in this study including the assessments of current state and compliance, and the assessment of the load reduction required.

We inspected the residual errors for each of the models. There was no apparent geographic pattern in these errors and the pattern of errors was not explained by catchment characteristics. Because all models were derived from data pertaining to the same 52 sites that were common to all models, we expected that the residual errors from each model would be correlated to a degree with the errors of the other six models. We used the correlation matrix derived from the nine sets of model errors to describe the relationship between all pairs of model errors. We assumed that this correlation structure represents the correlation in the uncertainties when the models were combined in the assessment process.

We applied the same simple Monte Carlo analysis approach as Snelder *et al.* (2020) to estimate uncertainties in our assessments based on 100 'realisations' of our calculations in four steps. First, for a realisation (r), predictions made with all models were perturbed by a random error. Random errors were obtained by generating random normal deviates (ε_r) and applying these to predictions made using the models. When the response variables in the models were log (base 10) transformed the perturbed prediction for a realisation was derived as follows.

$$Prediction_r = CF \times 10^{[log_{10}(x) - bias + \varepsilon_r \times RMSD]} \qquad \text{Equation 4}$$

When the response variables in the models were logit transformed (i.e., the models of current values of G260 and G540) the perturbed prediction for a realisation was derived as follows.

$$Prediction_r = \frac{e^{x - bias + \varepsilon_r \times RMSD}}{(1 + e^{x - bias + \varepsilon_r \times RMSD})} \qquad \text{Equation 5}$$

Random normal deviates representing errors for each model (ε_r) were drawn from a multi-variate distribution with the same correlation structure as that between the observed errors. Because a concentration or load at any point in a catchment is spatially dependent on corresponding values at all other points in the catchment's drainage network, the values of the random normal deviates were held constant for each realisation within the river network representing a sea-draining catchment but differed randomly between sea-draining catchments.

At the second step, for each realisation we stored the perturbed predicted values of the four *E. coli* statistics, current load and load reduction required. At the third step, we repeated the procedure described above for each realisation. At the fourth step, we used the distribution of values of the four *E. coli* statistics, current load and load reduction required obtained from the 100 realisations to provide a best estimate and the uncertainty of the assessments. The uncertainty of the assessments of compliance and whether the segment was suitable for contact recreation were quantified by estimating the probability that each segment was compliant or suitable across the 100 realisations. Segment compliance and suitability for contact recreation was therefore assessed as a value between one (100% confident the segment is compliant or suitable) to zero (100% confident the segment is non-compliant or not suitable). For the current state and load reduction required assessments, the best estimate was represented by the mean value from the distribution of values. Where the mean value was negative, the load reduction requirement was taken to be zero. The uncertainty of these two assessments was quantified by their 90% confidence intervals.

2.9 Freshwater objectives settings

2.9.1 Management classes

To proceed with the analysis, it is necessary to nominate FWOs in terms of a band (A, B, C, D or E) for all river receiving environments (represented by network segments) in the study area. The same FWOs can be applied uniformly over all network segments or spatially variable FWOs can be defined. Some regional councils use environmental classification systems such as the River Environment Classification (REC; Snelder and Biggs, 2002) to subdivide receiving environments into groups for which differing objectives can be justified. The REC can be used, for example, to differentiate river types on the basis that they are dominated by mountain, hill, lowland and lake 'sources of flow' respectively. Spatial variation in objectives can be justified for each type of river on the basis of both what is reasonable relative to each type under natural conditions and community expectations. For example, in the Southland and Canterbury regions, objectives for a variety of river attributes (e.g., periphyton biomass, visual clarity and human health) vary according to source of flow considerations. In general, natural water quality and public expectations for water quality are highest for mountain and lake-fed source of flow types followed by hill and then lowland types. The REC has already classified all segments of the river network into these source of flow types and in this study, we nominally used these assignments to demonstrate and assess the impact of spatially variable FWOs.

We assigned all river segments to five nominal management classes (Figure 6). These classes were essentially the four REC Source of flow classes (mountain, hill, lowland and lake) however, we subdivided the lake class into upper and lower parts of the region (using a threshold of 200 m asl) to reflect the possibility of having more stringent FWOs in lake-fed rivers in the higher elevation Upper Lakes and Dunstan Rohe. The nominal classification of rivers into these fiver management classes allowed an analysis where FWOs were independently set for each river management class.

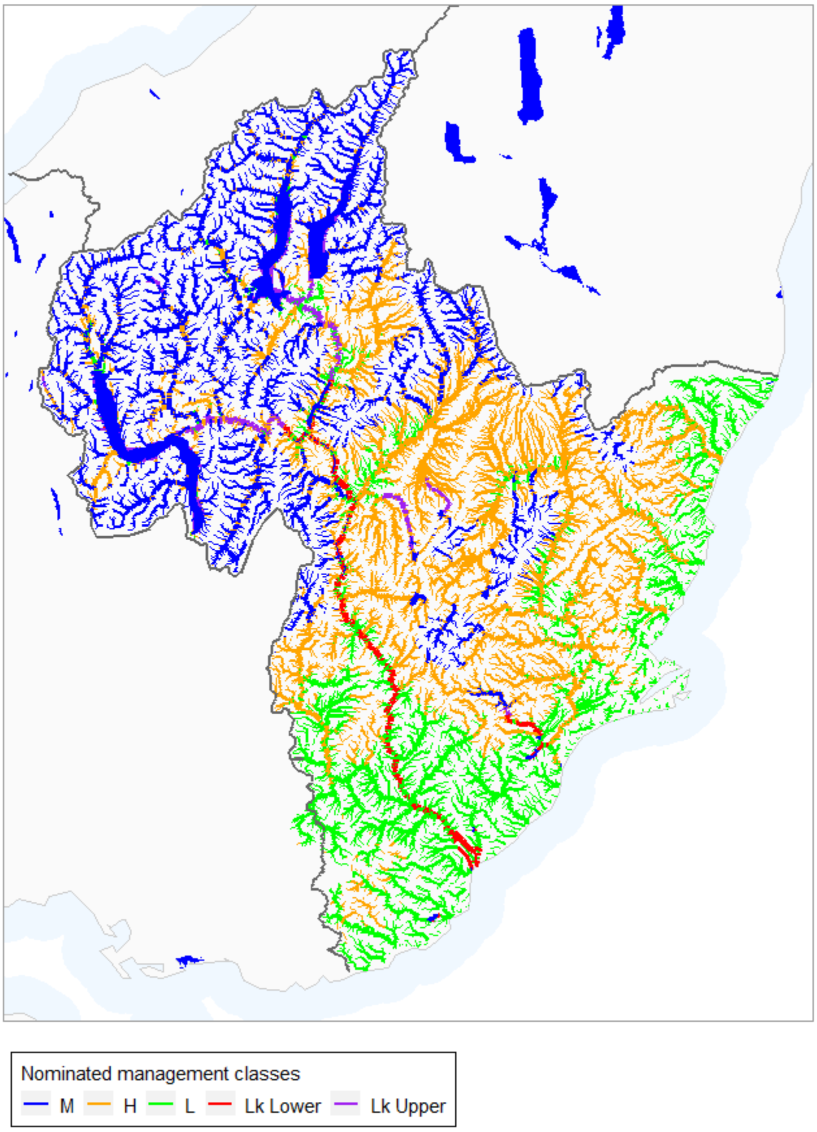

Figure 6. Map of the distribution of the nominal river management classes.

2.9.2 Objectives

Because FWOs can be applied uniformly or by management class, there were many potential spatial configurations of FWO. For this reason, and to make the analyses and presentation of results manageable, we nominated four sets of FWOs for which load reduction assessments were made. The first three sets of FWOs simply assigned the A, B and C NOF band, uniformly to all segments. Therefore, these FWOs did not vary spatially, and the objectives are consistent across all segments. The fourth set of FWOs were spatially variable with the NOF band varying by the nominated river management classes shown in Figure 6 and with NOF bands for each class as shown in Table 3.

Table 3. Nominated NOF bands of the river management classes for the spatially variable FWOs.

Management class	NOF Band
Mountain	A
Hill	B
Lake Upper	A
Lake Lower	B
Lowland	C

3 Results

3.1 Performance of random forest *E. coli* statistics models

The random forest models of the four *E. coli* statistics had at least satisfactory performance (Table 4), as indicated by the criteria of Moriasi *et al.* (2015; Table 2). The mapped predictions for all four statistics had similar coarse-scale spatial patterns, with relatively high values in low-elevation areas of Otago and low values in high elevation areas (Figure 7). These patterns were consistent with expectations and reflect the influence of increasing proportions of catchments occupied by agricultural and other intensive land uses.

Table 4. Performance of random forest models of the four E. coli statistics; Median, Q95, G260 and G540. Median and Q95E. coli ha^{-1} yr^{-1}. G260 and G540The overall performance rating is based on the criteria of Moriasi et al. (2015) shown in Table 2.

Statistic	N	R^2	NSE	BIAS	RMSD	Performance rating
Median	101	0.61	0.61	-0.60	0.38	Good
Q95	101	0.42	0.42	-0.30	0.52	Satisfactory
G260	101	0.59	0.59	1.31	0.83	Satisfactory
G540	101	0.49	0.49	0.56	0.79	Satisfactory

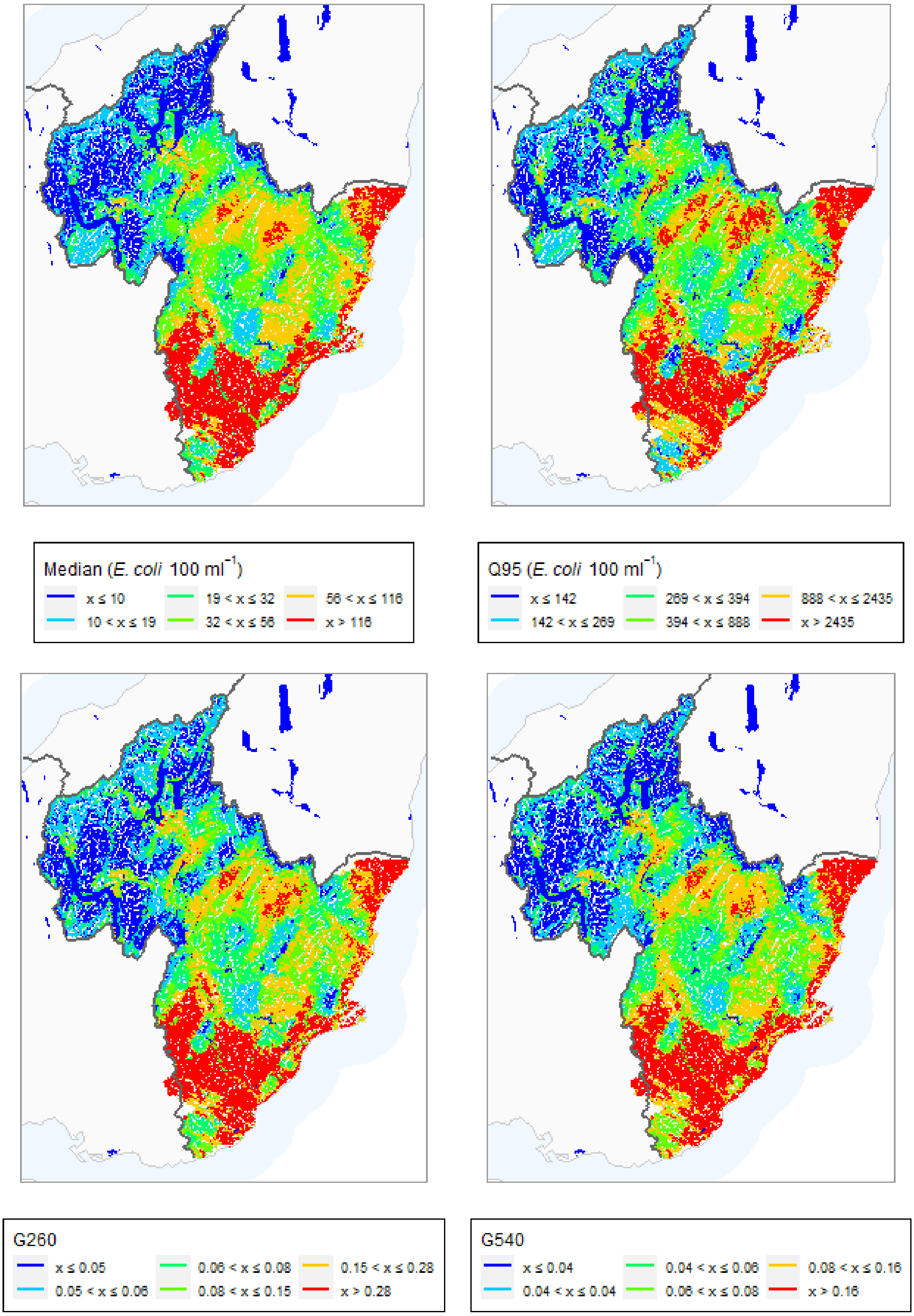

Figure 7. Predicted patterns of the current value of the four E. coli statistics. Note that the breakpoints shown in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.2 Performance of the random forest *E. coli* current yield model

The random forest models of *E. coli* annual yield had satisfactory performance (Table 5), as indicated by the criteria of (Moriasi *et al.*, 2015; Table 2). The mapped predictions of annual yield of *E. coli* had similar coarse-scale spatial patterns as the *E. coli* statistics with relatively high values in low-elevation coastal areas of Otago and generally lower values in higher elevation and inland areas (Figure 8). These patterns were consistent with expectations and reflect the increasing concentration of *E. coli* in association with increasing proportions of catchments occupied by agricultural and other intensive land uses. Model diagnostics indicated that *E. coli* annual yield was positively related to the proportion of catchment associated with pastoral land use but also to rainfall. The positive association with rainfall produced very high predicted *E. coli* yields in upland parts of Otago such as the alpine areas upstream of Lakes Wakatipu, Wanaka and Hawea.

Table 5. Performance of the random forest models of E. coli annual yield.E. coli ha^{-1} yr^{-1}. The overall performance rating is based on the criteria of Moriasi et al. (2015) shown in Table 2.

Variable	N	R^2	NSE	BIAS	RMSD	Performance rating
E. coli yield	59	0.48	0.47	-0.18	0.40	Satisfactory

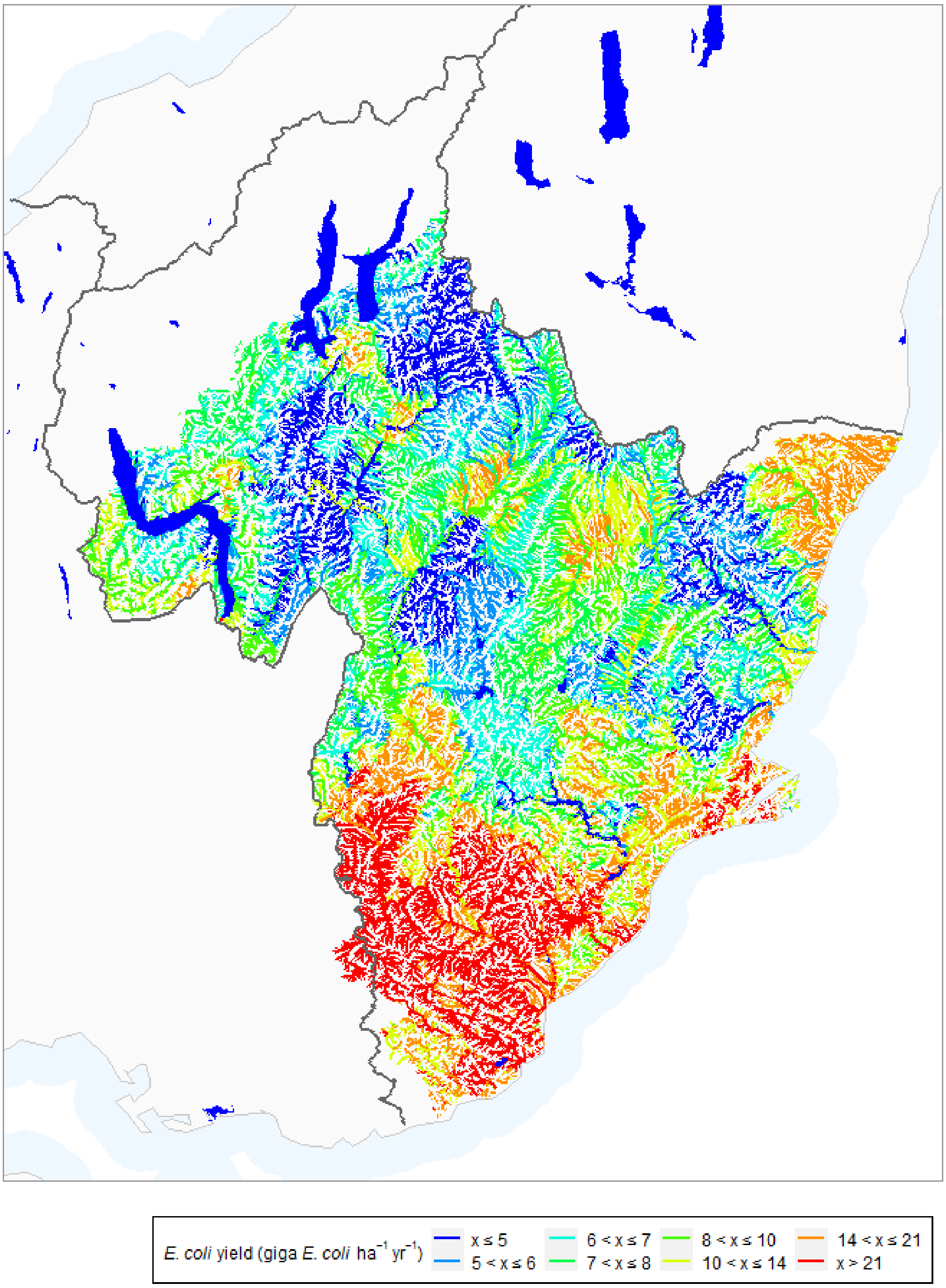

Figure 8. Predicted patterns of the current E. coli loads (as yields giga (10^9) E. coli ha^{-1} yr^{-1}). Note that the breakpoints shown in the map legend are nominal and have no special significance (i.e., are not guidelines or standards). Predictions were not made for river segments whose rainfall characteristics were greater than the 90th percentile of that represented by the fitting dataset (see Figure 5).

3.3 Performance of the linear models of *E. coli* yield as function of attribute statistics

With appropriate transformation, *E. coli* yield was linearly related to the four *E. coli* attribute statistics (Figure 9). The linear models had satisfactory performance as indicated by the criteria of Moriasi *et al.* (2015; Table 2) and low bias (Table 6).

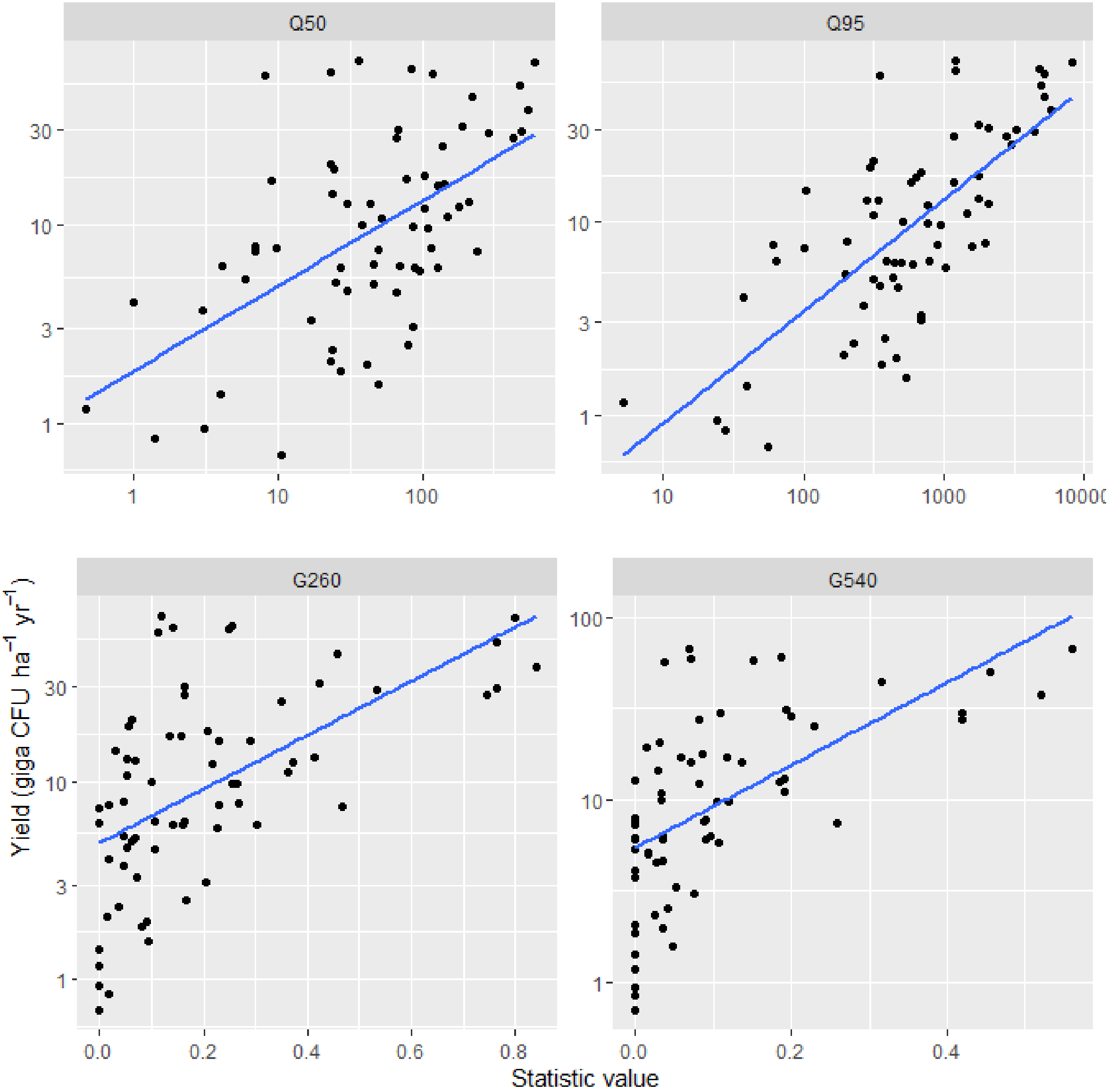

Figure 9. Linear relationships between E. coli yield and the four E. coli statistics. The black points represent the yield and E. coli statistic for the 46 sites and the blue line indicates the fitted linear regression. Note that yield was log (base 10) transformed in all models and the Median and Q95 values were log (base 10) transformed in these models, respectively.

Table 6. Performance of the linear models describing E. coli yield as function of the four E. coli attribute statistics; Q50 (i.e., median), Q95, G260 and G540. The overall performance rating is based on the criteria of Moriasi et al. (2015) shown in Table 2.

Statistic	N	R^2	NSE	BIAS	RMSD	Performance rating
Q50	64	0.39	0.38	0.17	0.43	Satisfactory
Q95	64	0.44	0.43	0.17	0.41	Satisfactory
G260	64	0.36	0.36	-0.31	0.44	Satisfactory
G540	64	0.37	0.37	-0.42	0.43	Satisfactory

3.4 Correlation of model errors

The model errors were strongly correlated (Pearson correlation coefficient (r) > 0.6) between all pairs of models that were used to predict current values of the *E. coli* statistics (Table 7). Correlations between the model errors associated with the *E. coli* statistics and the *E. coli* loads were low (r < 0.4). The model errors were strongly correlated (r > 0.6) between all pairs of the linear regression models that were used to describe the relationships between the *E. coli* statistics and loads (as yields). Correlations between the RF and linear regression models were low (r < 0.2). The correlation structure shown in Table 7 was used to generate random normal deviates (ε_r) for each model in the Monte Carlo analysis.

Table 7. Correlation of errors between all pairs of models used in the analysis. The table is a lower triangular matrix showing the correlations of model errors between all pairs of models. RF indicates random forest models and LM indicates linear regression models.

Model	RF Median	RF Q95	RF G260	RF G540	RF Load	LM Median	LM Q95	LM G260
RF Q95	0.50							
RF G260	0.71	0.58						
RF G540	0.74	0.66	0.84					
RF Load	0.29	0.22	0.33	0.37				
LM Median	0.04	0.13	0.11	0.16	0.82			
LM Q95	0.14	-0.14	0.13	0.19	0.75	0.84		
LM G260	0.10	0.11	-0.03	0.11	0.77	0.91	0.81	
LM G540	0.12	0.09	0.01	0.11	0.76	0.88	0.81	0.98

3.5 Current state

The measured current state for the 103 SOE monitoring sites is shown in Table 8 in terms of NOF swimming grades by nominated management classes. These results indicate that poor attribute grades (i.e., D and E) occur at 46 of the 103 SOE sites in the region. In addition, Table 8 indicates that the SOE sites provide some representation of rivers in all management classes.

Table 8. Measured current state as numbers of SOE monitoring sites in each NOF overall swimming grade by nominated management classes. The value in parentheses is the proportion of total sites (%).

NOF Swimming grade	Mountain	Hill	Lowland	Lake Upper	Lake Lower	Whole region
A	16 (16)	14 (14)	4 (4)	2 (2)	1 (1)	37 (36)
B	1 (1)	9 (9)	6 (6)	0 (0)	0 (0)	16 (16)
C	1 (1)	1 (1)	2 (2)	0 (0)	0 (0)	4 (4)
D	2 (2)	11 (11)	19 (18)	1 (1)	1 (1)	34 (33)
E	0 (0)	1 (1)	11 (11)	0 (0)	0 (0)	12 (12)

The best estimate of the proportions of the region's river network segments in the five NOF attribute states are shown in Table 9. The 90% confidence intervals for these estimates are very wide. For example, the best estimate of the proportion of segments that are in the A band is 32% but the 90% confidence intervals extend from 3% to 65% (Table 9). This large uncertainty reflects the, at best good, performance of the models used to predict the *E. coli* statistics (Table 4). This uncertainty is also indicated by the maps of the estimated probability of network segments belonging to the five NOF swimming grade (Figure 10). Over much of the network, the probability of segments being in a specific NOF attribute band was less than 50% indicating low certainty about the true state (Figure 10).

Table 9. Proportion of all segments (%) predicted to be in each attribute band. Note that this information by reporting catchment and management class are tabulated in Appendix B.

Attribute band	Best estimate	5% confidence limit	95% confidence limit
A	32	3	65
B	23	6	47
C	8	3	19
D	26	12	55
E	10	2	21

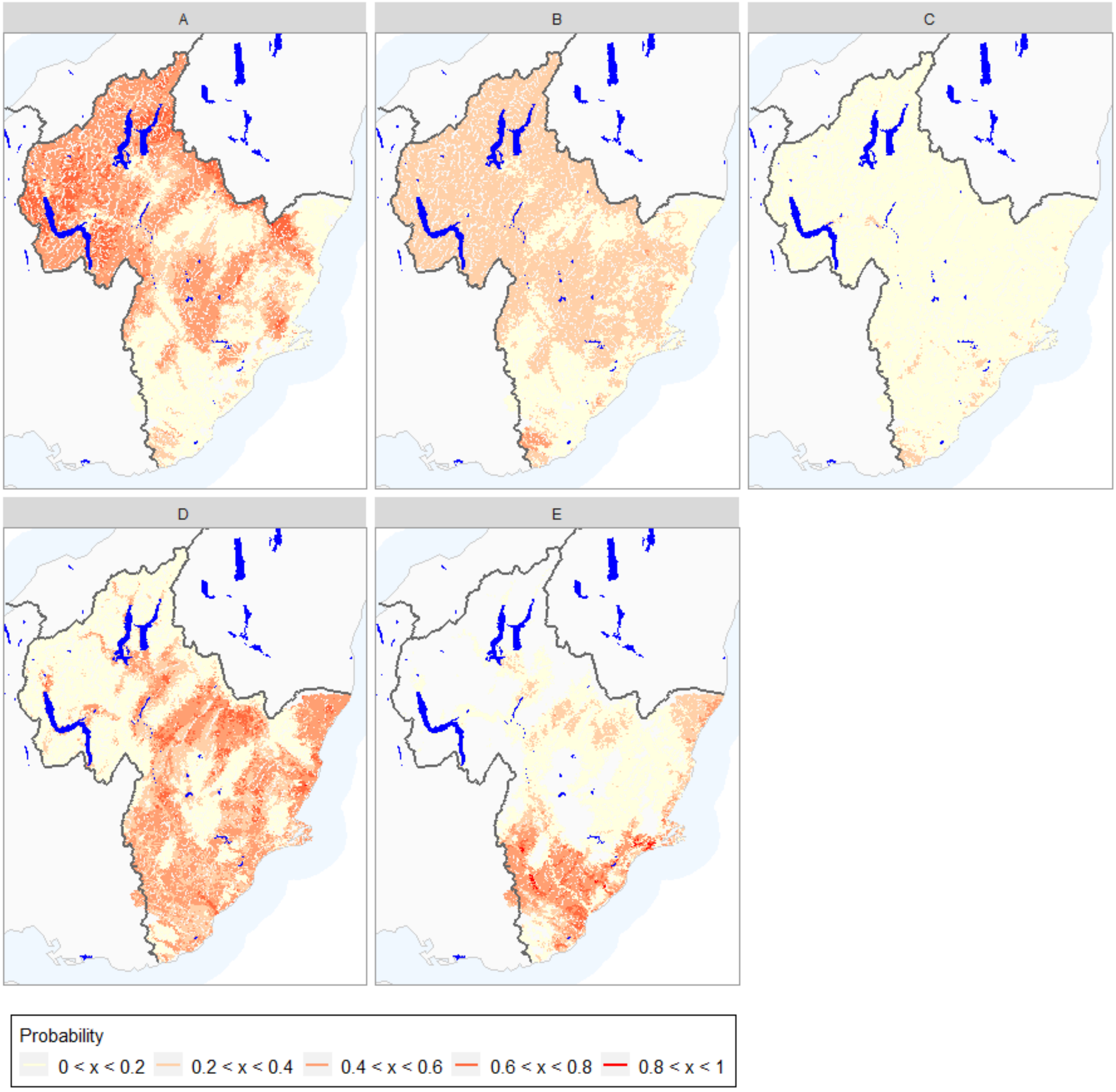

Figure 10. Estimated probability of network segments belonging to the five NOF swimming grades.

The best estimate of the proportion of river segments in the region of stream order ≥4 that are currently suitable for primary contact (i.e., NOF attributes states A, B or C) is 62%. The 90% confidence interval for this estimate is wide with the lower and upper bounds defined by 21% and 84%, respectively. This uncertainty is also indicated by a map of the estimated probability that network segments are currently suitable for primary contact (Figure 11). The map indicates that segments that have the highest probability of being suitable for primary contact are in headwater catchments. The main-stem rivers traversing lowland areas and smaller streams rising in lowland areas have low probability (i.e., <20%) of being suitable, which is equivalent to high probability (i.e., >80%) of being unsuitable.

Our estimate of 62% of river segments of stream order ≥4 being currently suitable for primary contact (i.e., NOF attributes states A, B or C) is comparable to a previous estimate of 78% of these large rivers being suitable for primary contact in Otago reported in MFE (2018) and to the national targets laid out in the NPSFM (i.e., 80% by 2030 and 90% no later than 2040).

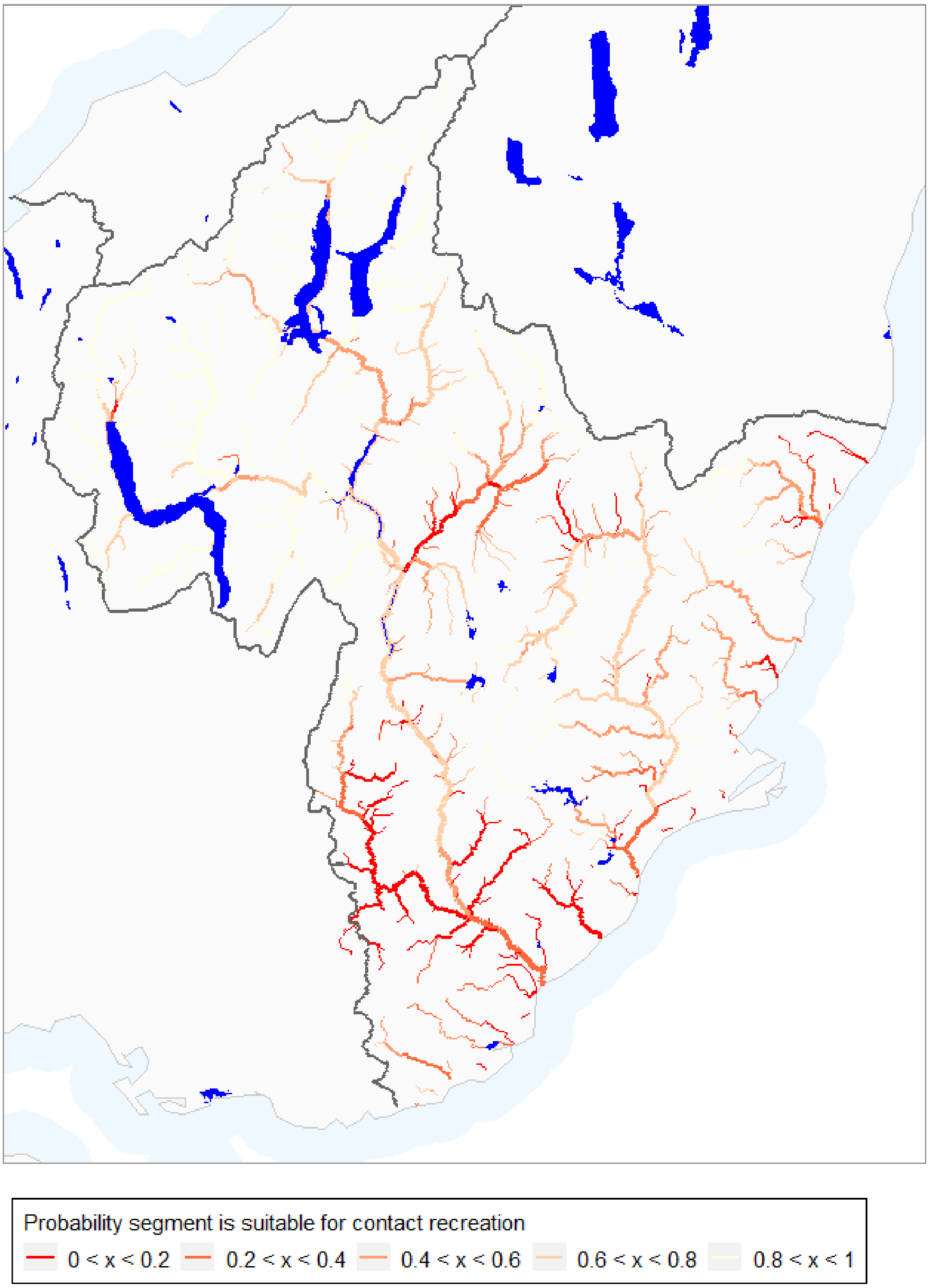

Figure 11. Estimated probability that network segments with stream order ≥ 4 are suitable for primary contact recreation.

3.6 Assessment of C band option

3.6.1 Compliance

The estimated probability that values of the four *E. coli* statistics are compliant with the C band was greater than 0.6 for 82%, 64%, 85% and 84% of segments for the Median, Q95, G260 and G540, respectively (Figure 12). The estimated probability that all statistics complied with the C band was greater than 0.6 for 63% of segments (Figure 13). The probability of compliance was greatest for segments in the headwater areas of the individual catchments, and particularly in the higher elevation parts of the region. The probability of compliance was lowest for segments in the low elevation parts of the region that have high proportions of catchment in pastoral land cover. This was consistent with the predicted pattern in the current values of all four *E. coli* statistics shown in Figure 7 and Figure 8.

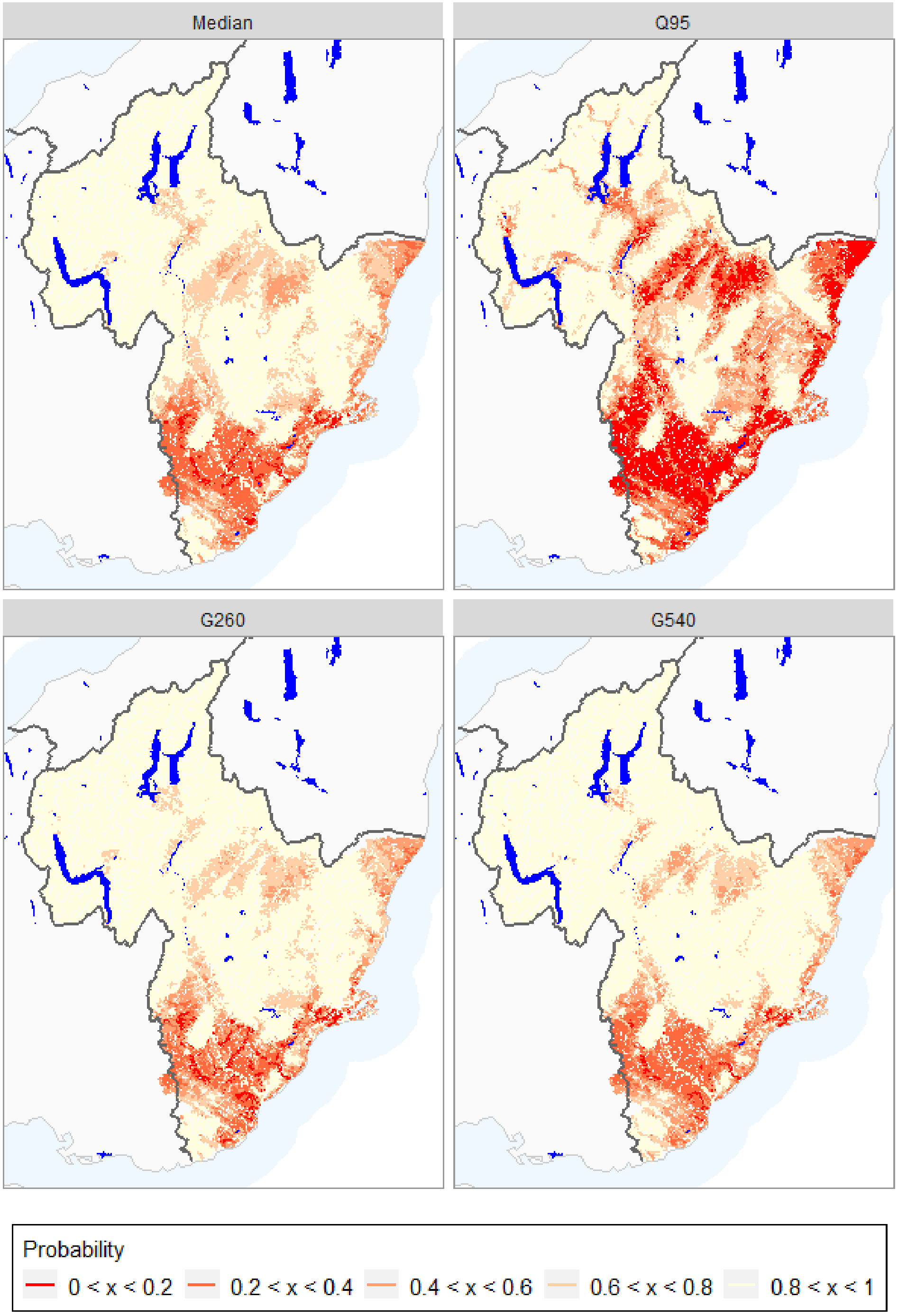

Figure 12. Probability of compliance with the criteria for each of the four E. coli statistics when the FWO is the C band. Each map represents the probability that segments achieve the criteria for the E. coli statistic that is associated with C band.

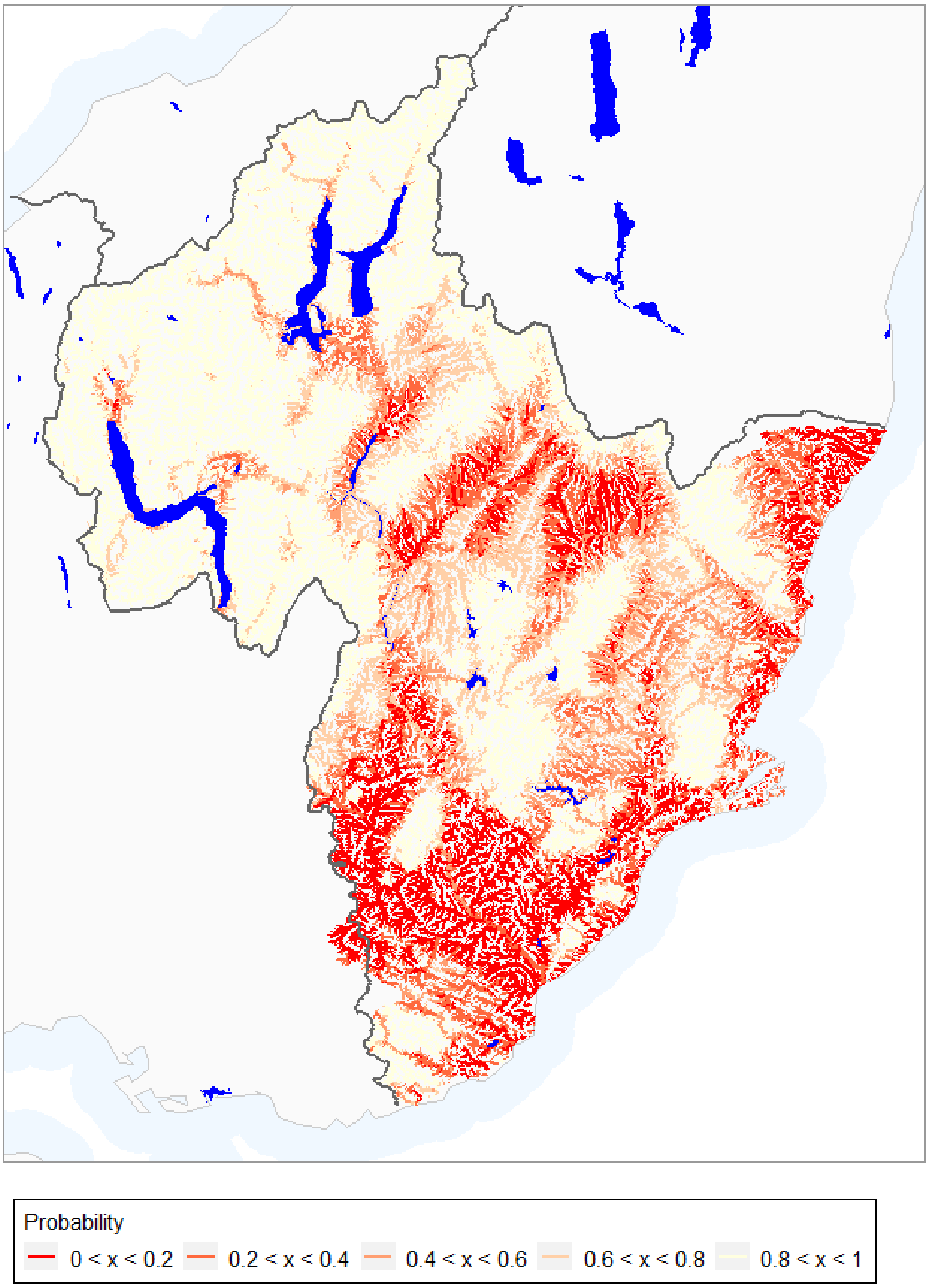

Figure 13. Probability of compliance when the FWO is the C band. This map represents the overall probability that segments achieve the C band.

3.6.2 Local excess loads

The local excess load is the amount by which the current *E. coli* load at a river segment would need to be reduced to achieve the objective for that receiving environment. For the C band, the best estimate of the local excess *E. coli* load local was zero for 65% of segments and exceeded 2 giga *E. coli* ha^{-1} yr^{-1} for 30% of river segments, and exceeded 10 giga *E. coli* ha^{-1} yr^{-1} for 9% of river segments (Figure 14). Note that the 2, and 10 giga *E. coli* ha^{-1} yr^{-1} are nominal breakpoints for communication purposes and correspond to the legend thresholds on Figure 14. These values have no special significance (i.e., are not guidelines or standards).

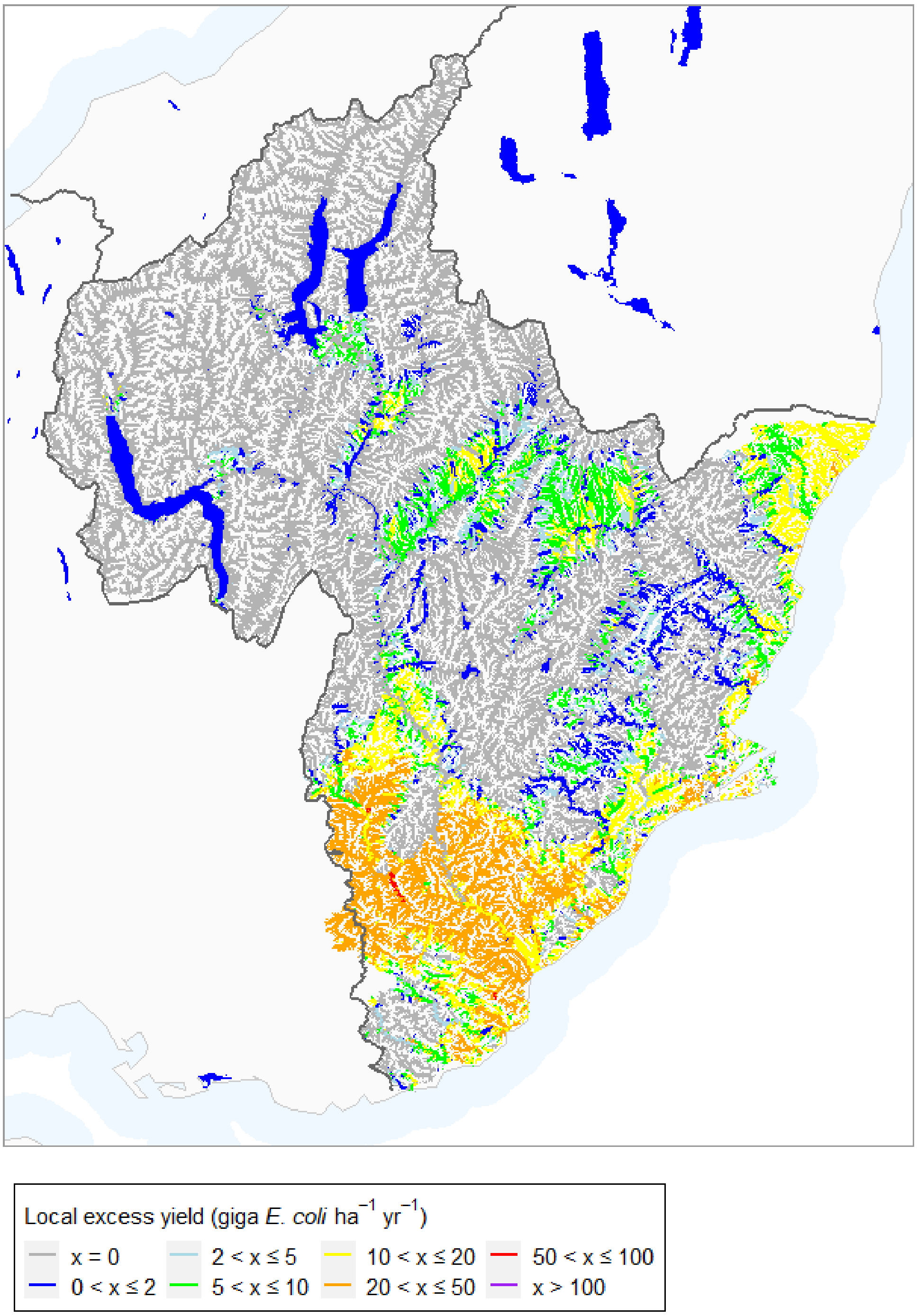

Figure 14. Local excess E. coli loads when the FWO is the C band. Note that the breakpoints for the local excess yield in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.6.3 Critical point catchment load reductions required

The load reduction required for critical point catchments is the minimum load reduction that ensures the loads for all receiving environments in the critical catchment do not exceed the MAL (and therefore all FWOs in the catchment are achieved). The load reductions required therefore differ from the local excess loads in that they consider all river segments in a critical point catchment. The load reductions required for the C band FWO are expressed below as yields (i.e., *E. coli* ha^{-1} yr^{-1}) and as a percentage of the current load.

The load reductions required by the C band FWO for critical point catchments are shown on Figure 15 and Figure 16. Critical point catchment *E. coli* load reduction requirements of greater 10 giga *E. coli* ha^{-1} yr^{-1} occupied 66% of the study area (Figure 15). Critical point catchment *E. coli* load reduction requirements of greater 20 giga *E. coli* ha^{-1} yr^{-1} occupied 16% of the study area (Figure 15). The comparison of load reductions expressed as yields (*E. coli* ha^{-1} yr^{-1}) with those expressed as proportion of current load (%) indicates that reduction requirements in catchments with low yield reductions (e.g., much of the Upper Lakes FMU and Dunstan Rohe) are nevertheless large in relative terms. Critical point catchments with *E. coli* load reductions of greater than 30% occupied 87% of the study area and critical point catchments with *E. coli* load reductions of greater than 60% occupied 16% of the study area (

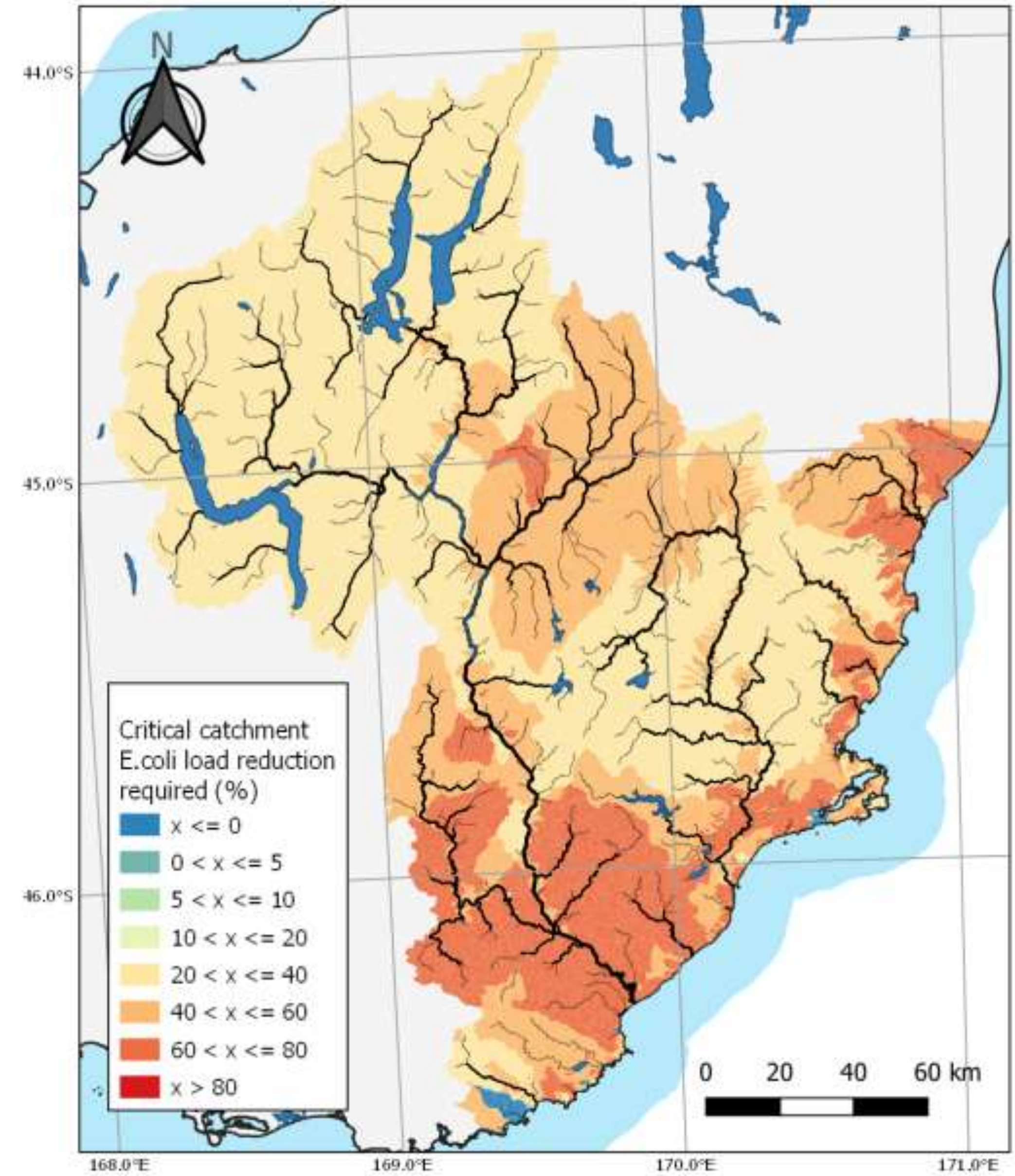

Figure 16).

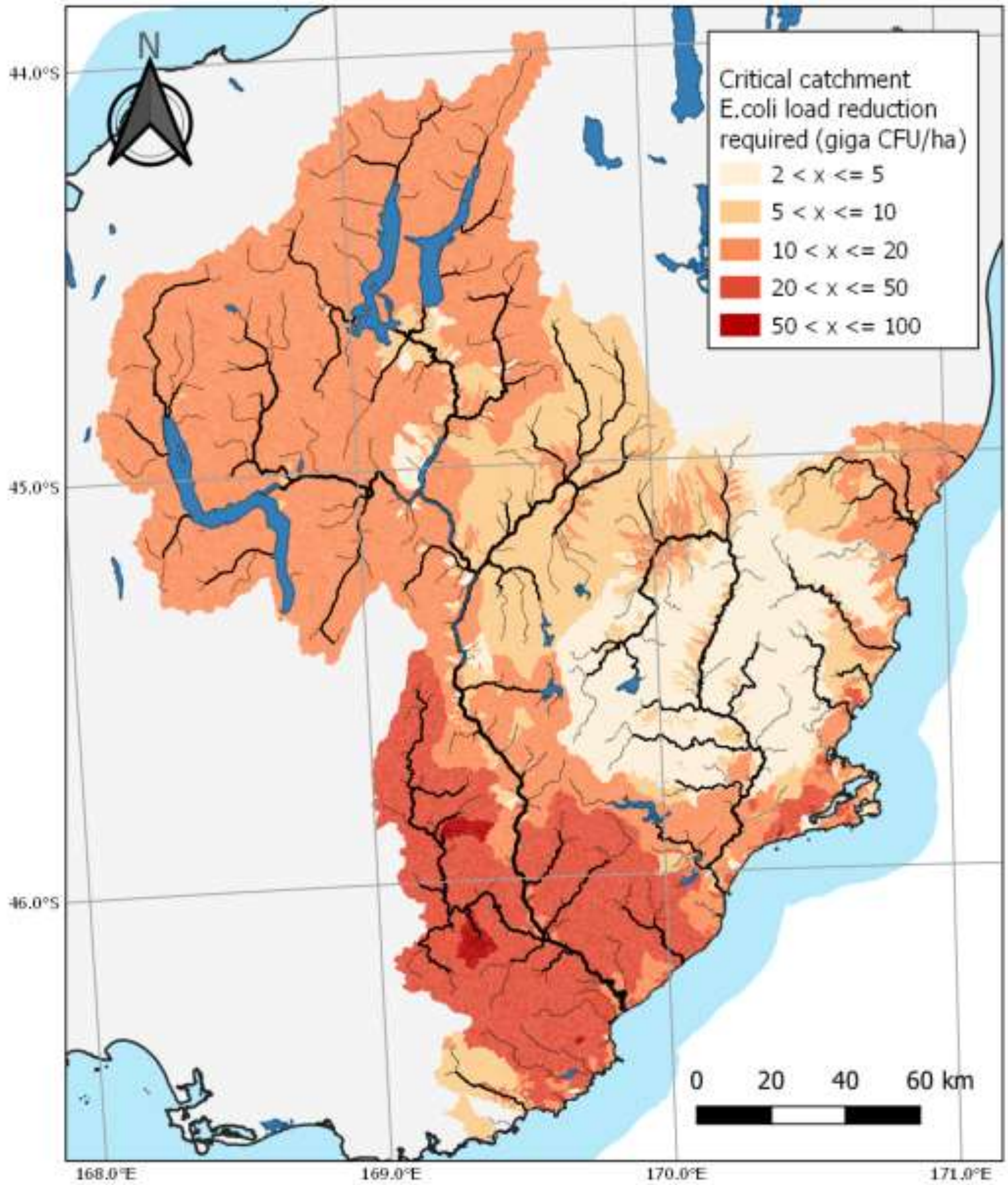

Figure 15. The E. coli load reduction required, expressed as yields, for critical point catchments when the FWO is the C band. The critical point catchment colours indicate the mean E. coli load reductions required to allow all FWOs be achieved in the critical point catchment (including the critical point at the bottom of the catchment).

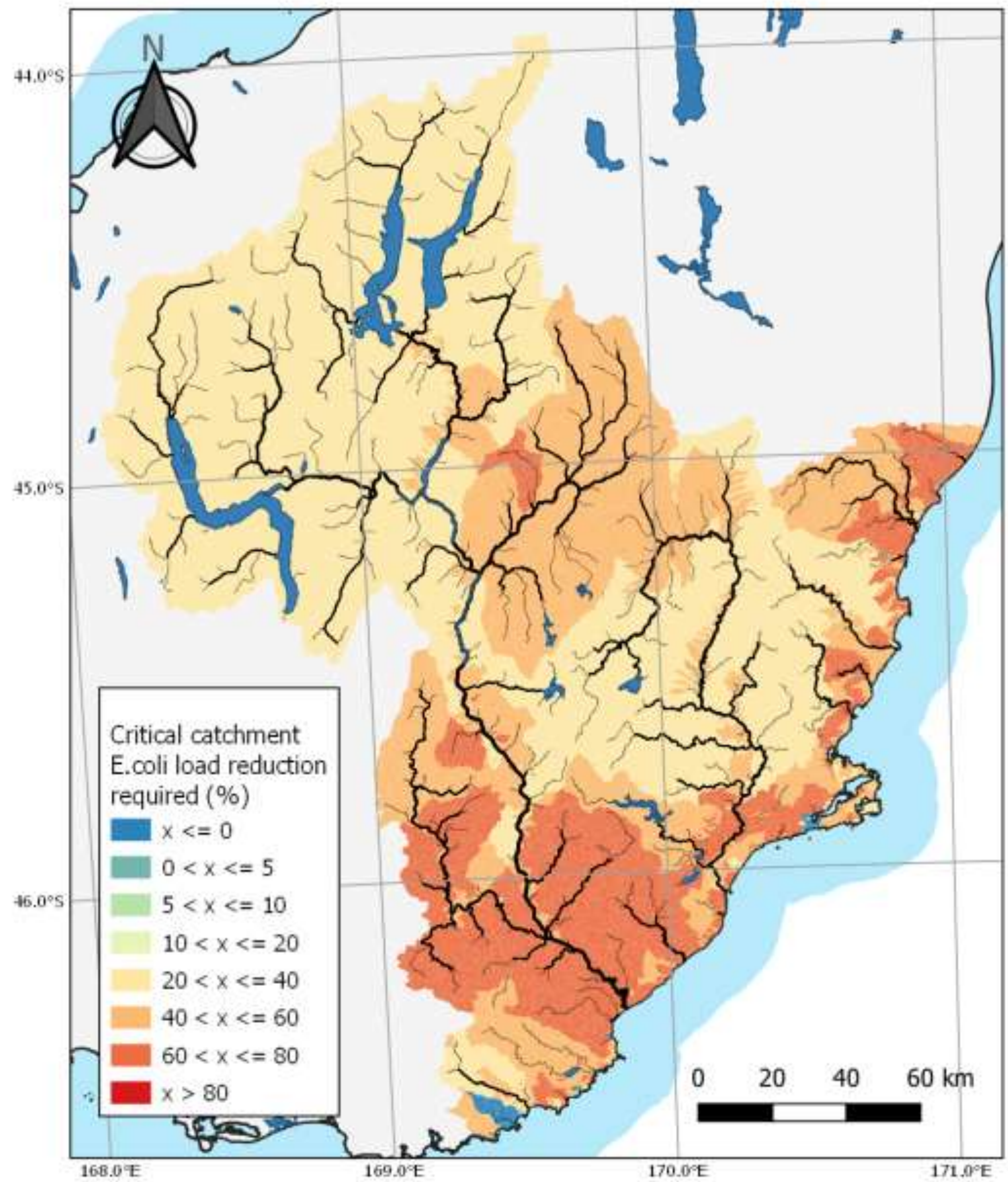

Figure 16. The E. coli load reduction required, expressed as proportion of the current load (%), for critical point catchments when the FWO is the C band. The critical point catchment colours indicate the E. coli load reductions required to allow all FWOs be achieved in the critical point catchment (including the critical point at the bottom of the catchment).

3.6.4 FMU and regional load reductions required

The load reduction required when the FWO is the C band for each FMU and for whole region are shown in

Table 10. For the whole study area, the best estimate of E. coli load reductions required was 31 peta E. coli yr^{-1}, which represents 24% of the current load. The E. coli load reductions required were highest, relative to current loads (>40%), in the Catlins FMU, Dunedin Coast

FMU and North Otago FMU. The E. coli load reductions required were lowest, relative to current loads (<15%) in the Upper Lakes Rohe, Manuherekia Rohe and Dunstan Rohe.

Table 10. Current load and load reduction required for E. coli by FUM and for the Otago region when the FWO is the C band. Note that loads are expressed in absolute terms in units of E. coli organisms per year (peta E. coli yr^{-1}) and as a proportion of current load (%). The first value in each column is the best estimate, which is the mean value over the 100 Monte Carlo realisations. The values in parentheses are the lower and upper bounds of the 90% confidence interval.

FMU	**Total load (peta *E. coli* yr^{-1})**	**Load reduction required (peta *E. coli* yr^{-1})**	**Load reduction required (%)**
Catlins FMU	3 (1 - 6)	2 (0 - 4)	45 (15 - 70)
Dunedin Coast FMU	4 (2 - 6)	2 (1 - 4)	61 (47 - 76)
Dunstan Rohe	20 (4 - 58)	4 (0 - 18)	13 (0 - 61)
Lower Clutha Rohe	116 (21 - 345)	49 (0 - 213)	33 (0 - 83)
Manuherekia Rohe	20 (4 - 61)	4 (0 - 19)	13 (0 - 61)
North Otago FMU	4 (2 - 8)	2 (1 - 5)	50 (28 - 73)
Roxburgh Rohe	28 (5 - 83)	6 (0 - 29)	15 (0 - 65)
Taieri FMU	10 (1 - 26)	4 (0 - 14)	29 (1 - 74)
Upper Lakes Rohe	7 (1 - 21)	1 (0 - 8)	14 (0 - 66)
Total	159 (58 - 598)	31 (7 - 291)	24 (6 - 74)

3.7 Assessment of B band option

3.7.1 Compliance

The estimated probability that values of the four *E. coli* statistics are compliant with the B band was greater than 0.6 for 80%, 64%, 80% and 68% of segments for the Median, Q95, G260 and G540, respectively (Figure 17). The estimated probability that all statistics complied with the B band was greater than 0.6 for 58% of segments (Figure 18). The probability of compliance was greatest for segments in the headwater areas of the individual catchments, and particularly in the higher elevation parts of the region. The probability of compliance was lowest for segments in the low elevation parts of the region that have high proportions of catchment in pastoral land cover. This was consistent with the predicted pattern in the current values of all four *E. coli* statistics shown in Figure 7 and Figure 8.

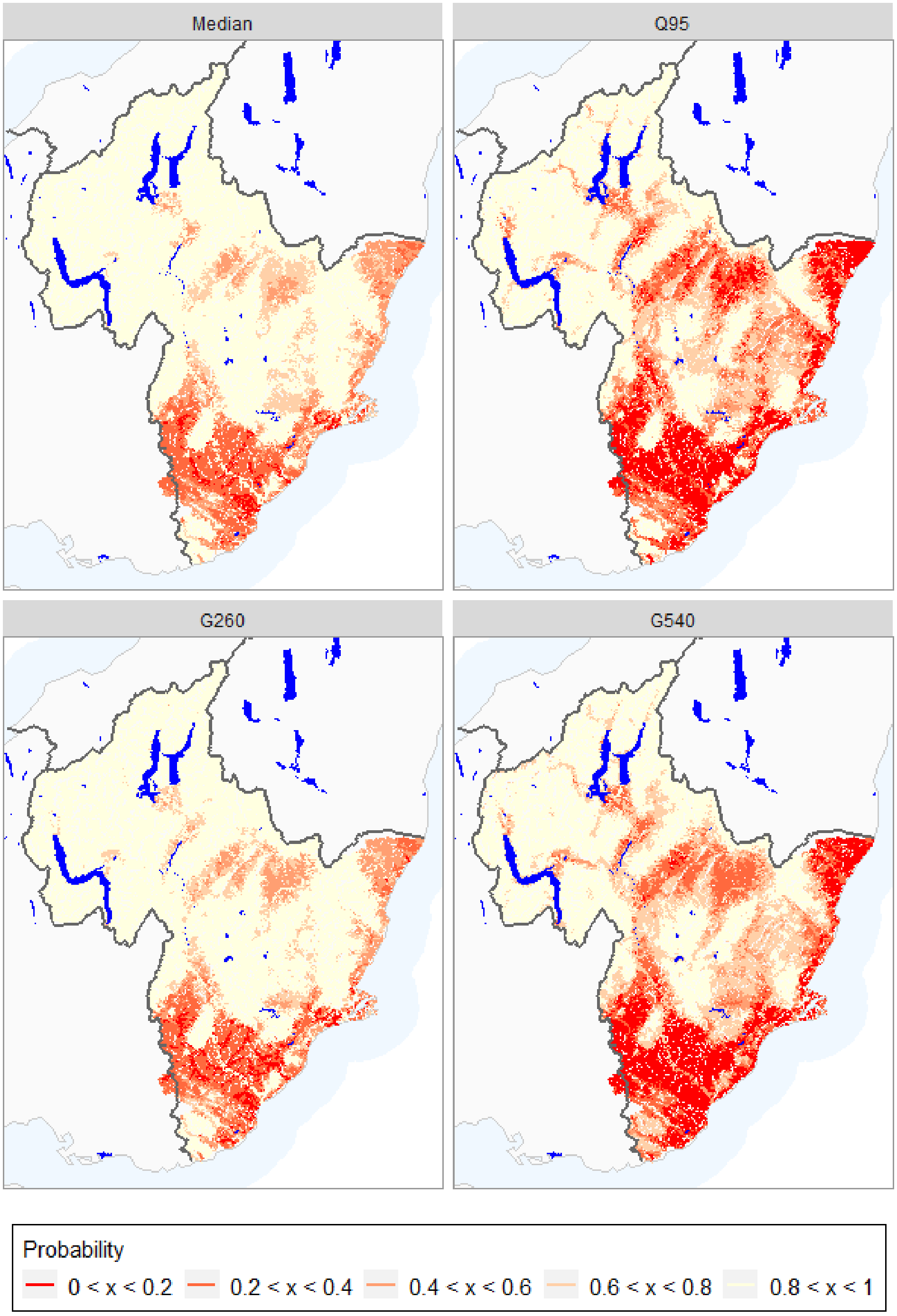

Figure 17. Probability of compliance with the criteria for each of the four E. coli statistics when the FWO is the B band. Each map represents the probability that segments achieve the criteria for the E. coli statistic that is associated with B band.

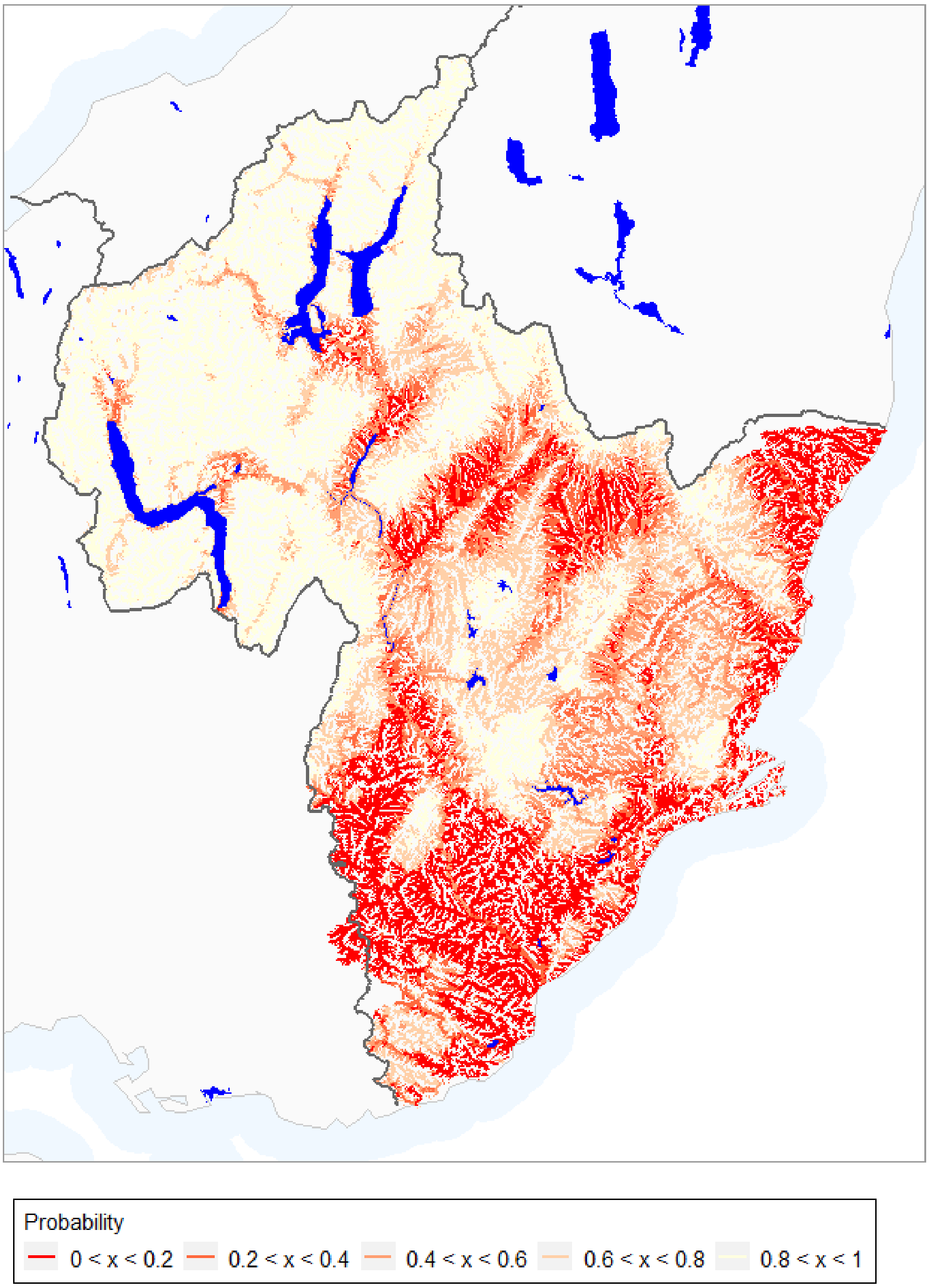

Figure 18. Probability of compliance when the FWO is the B band. This map represents the overall probability that segments achieve the B band.

3.7.2 Local excess loads

The local excess load is the amount by which the current *E. coli* load at a river segment would need to be reduced to achieve the objective for that receiving environment. For the B band, the best estimate of the local excess *E. coli* load local was zero for 52% of segments and exceeded 2 giga *E. coli* ha^{-1} yr^{-1} for 27% of river segments, and exceeded 10 giga *E. coli* ha^{-1} yr^{-1} for 11% of river segments (Figure 19). Note that the 2 and 10 giga *E. coli* ha^{-1} yr^{-1} are nominal breakpoints for communication purposes and correspond to the legend thresholds on Figure 14. These values have no special significance (i.e., are not guidelines or standards).

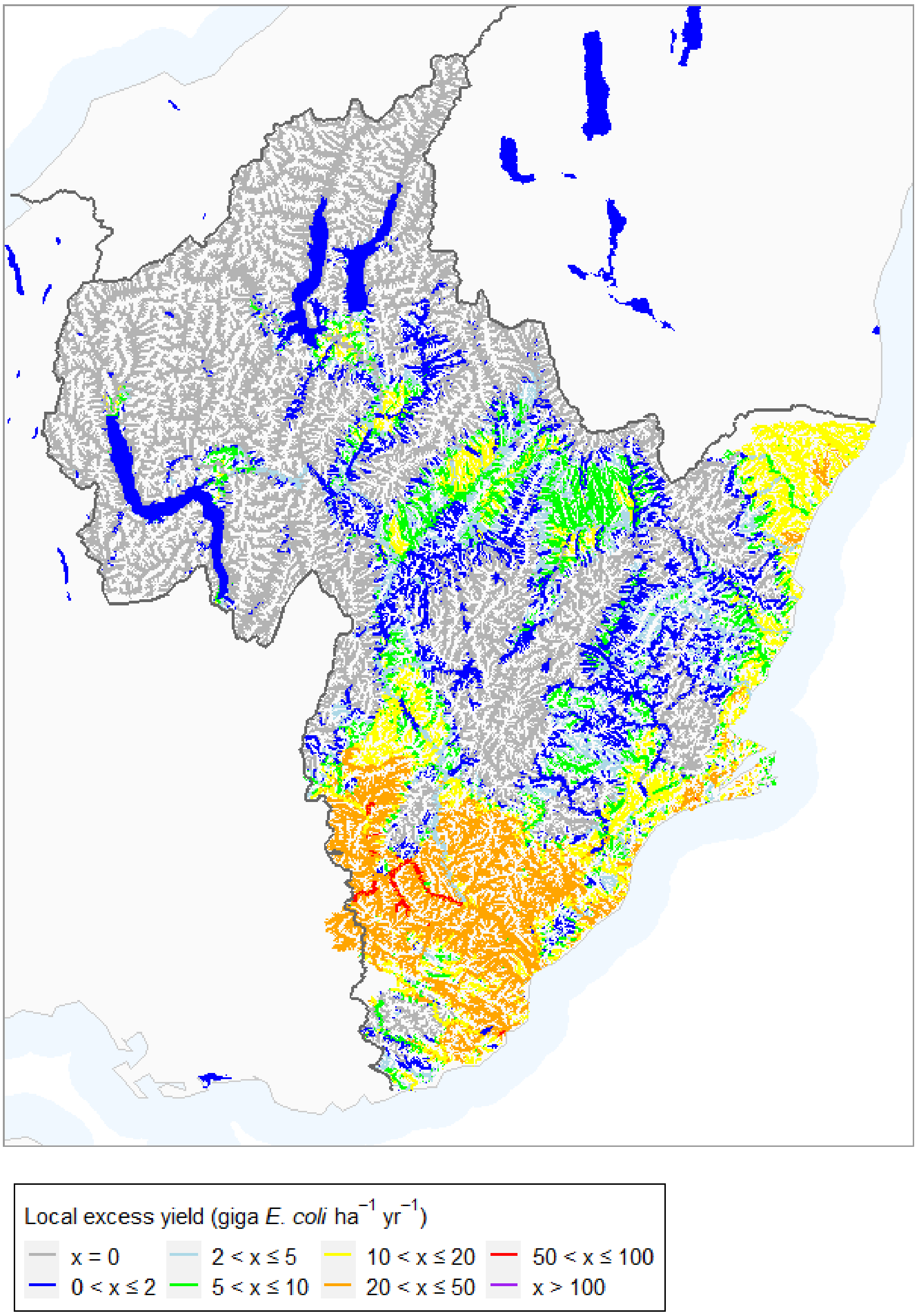

Figure 19. Local excess E. coli loads when the FWO is the B band. Note that the breakpoints for the local excess yield in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.7.3 Critical point catchment load reductions required

The load reduction required for critical point catchments is the minimum load reduction that ensures the loads for all receiving environments in the critical catchment do not exceed the MAL (and therefore all FWOs in the catchment are achieved). The load reductions required therefore differ from the local excess loads in that they consider all river segments in a critical point catchment. The load reductions required for the B band FWO are expressed below as yields (i.e., *E. coli* ha^{-1} yr^{-1}) and as a percentage of the current load.

The load reductions required by the B band FWO for critical point catchments are shown on Figure 20 and Figure 21. Critical point catchment *E. coli* load reduction requirements of greater 10 giga *E. coli* ha^{-1} yr^{-1} occupied 69% of the study area (Figure 20). Critical point catchment *E. coli* load reduction requirements of greater 20 giga *E. coli* ha^{-1} yr^{-1} occupied 57% of the study area (Figure 20). The comparison of load reductions expressed as yields (*E. coli* ha^{-1} yr^{-1}) with those expressed as proportion of current load (%) indicates that reduction requirements in catchments with low yield reductions (e.g., much of the Upper Lakes FMU and Dunstan Rohe) are nevertheless large in relative terms. Critical point catchments with *E. coli* load reductions of greater than 30% occupied 99% of the study area and critical point catchments with *E. coli* load reductions of greater than 60% occupied 23% of the study area (Figure 21).

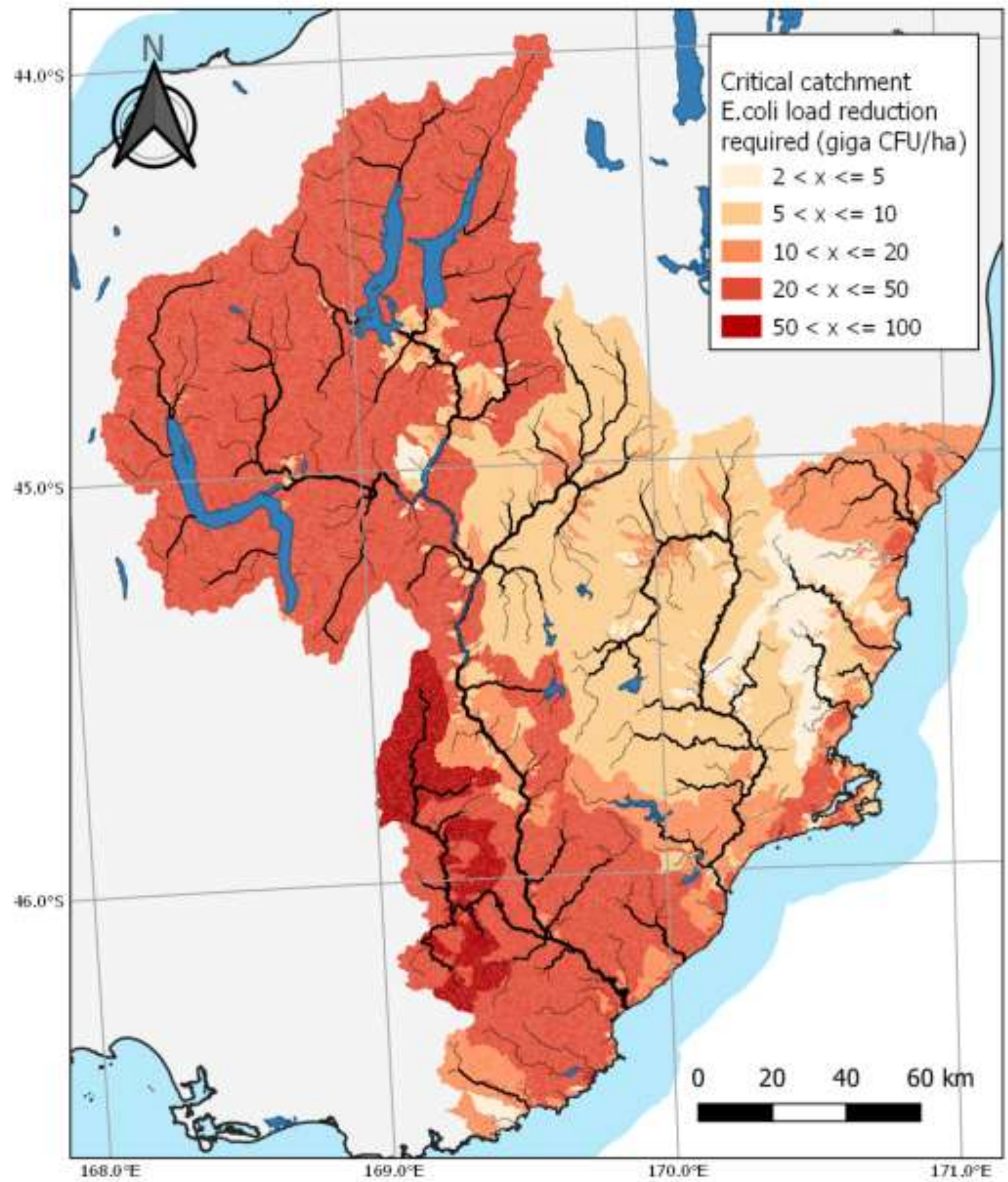

Figure 20. The E. coli load reduction required, expressed as yields, for critical point catchments when the FWO is the B band. The critical point catchment colours indicate the mean E. coli load reductions required to allow all FWOs be achieved in the critical point catchment (including the critical point at the bottom of the catchment).

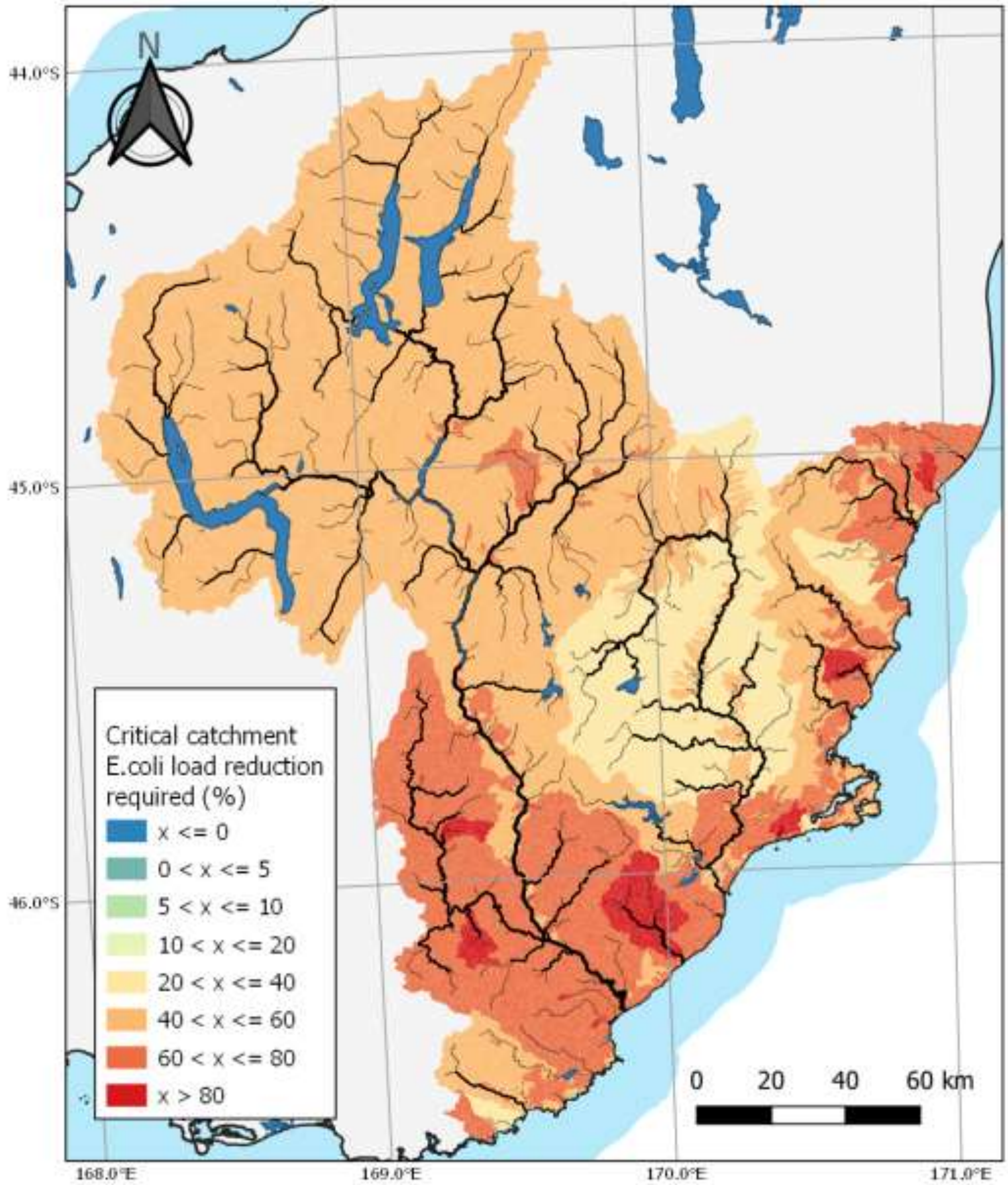

Figure 21. The E. coli load reduction required, expressed as proportion of the current load (%), for critical point catchments when the FWO is the B band. The critical point catchment colours indicate the E. coli load reductions required to allow all FWOs be achieved in the critical point catchment (including the critical point at the bottom of the catchment).

3.7.4 FMU and regional load reductions required

The load reduction required when the FWO is the B band for each FMU and for whole region are shown in Table 11. For the whole study area, the best estimate of *E. coli* load reductions required was 36 peta *E. coli* yr^{-1}, which represents 31% of the current load. The *E. coli* load reductions required were highest, relative to current loads (>50%), in the Catlins FMU, Dunedin Coast FMU and North Otago FMU. The *E. coli* load reductions required were lowest, relative to current loads (<20%) in the Dunstan Rohe, Manuherekia Rohe, Roxburgh Rohe and Upper Lakes Rohe.

Table 11. Current load and load reduction required for E. coli by FUM and for the Otago region when the FWO is the B band. Note that loads are expressed in absolute terms in units of E. coli organisms per year (peta E. coli yr^{-1}) and as a proportion of current load (%). The first value in each column is the best estimate, which is the mean value over the 100 Monte Carlo realisations. The values in parentheses are the lower and upper bounds of the 90% confidence interval.

FMU	Total load (peta *E. coli* yr^{-1})	Load reduction required (peta *E. coli* yr^{-1})	Load reduction required (%)
Catlins FMU	4 (1 - 11)	3 (1 - 8)	54 (21 - 78)
Dunedin Coast FMU	4 (2 - 7)	3 (1 - 6)	70 (54 - 83)
Dunstan Rohe	20 (2 - 52)	5 (0 - 26)	16 (0 - 64)
Lower Clutha Rohe	118 (15 - 310)	55 (0 - 185)	33 (0 - 78)
Manuherekia Rohe	21 (3 - 54)	6 (0 - 28)	16 (0 - 65)
North Otago FMU	4 (2 - 8)	2 (1 - 5)	57 (35 - 74)
Roxburgh Rohe	28 (4 - 75)	8 (0 - 39)	16 (0 - 61)
Taieri FMU	9 (2 - 23)	3 (0 - 14)	31 (1 - 79)
Upper Lakes Rohe	7 (1 - 19)	2 (0 - 10)	18 (0 - 72)
Total	154 (50 - 531)	36 (7 - 291)	31 (7 - 70)

3.8 Assessment of A band option

3.8.1 Compliance

The estimated probability that values of the four *E. coli* statistics are compliant with the A band was greater than 0.6 for 78%, 53%, 67% and 33% of segments for the Median, Q95, G260 and G540, respectively (Figure 22). The estimated probability that all statistics complied with the A band was greater than 0.6 for 30% of segments (Figure 23). The probability of compliance was greatest for segments in the headwater areas of the individual catchments, and particularly in the higher elevation parts of the region. The probability of compliance was lowest for segments in the low elevation parts of the region that have high proportions of catchment in pastoral land cover. This was consistent with the predicted pattern in the current values of all four *E. coli* statistics shown in Figure 7 and Figure 8.

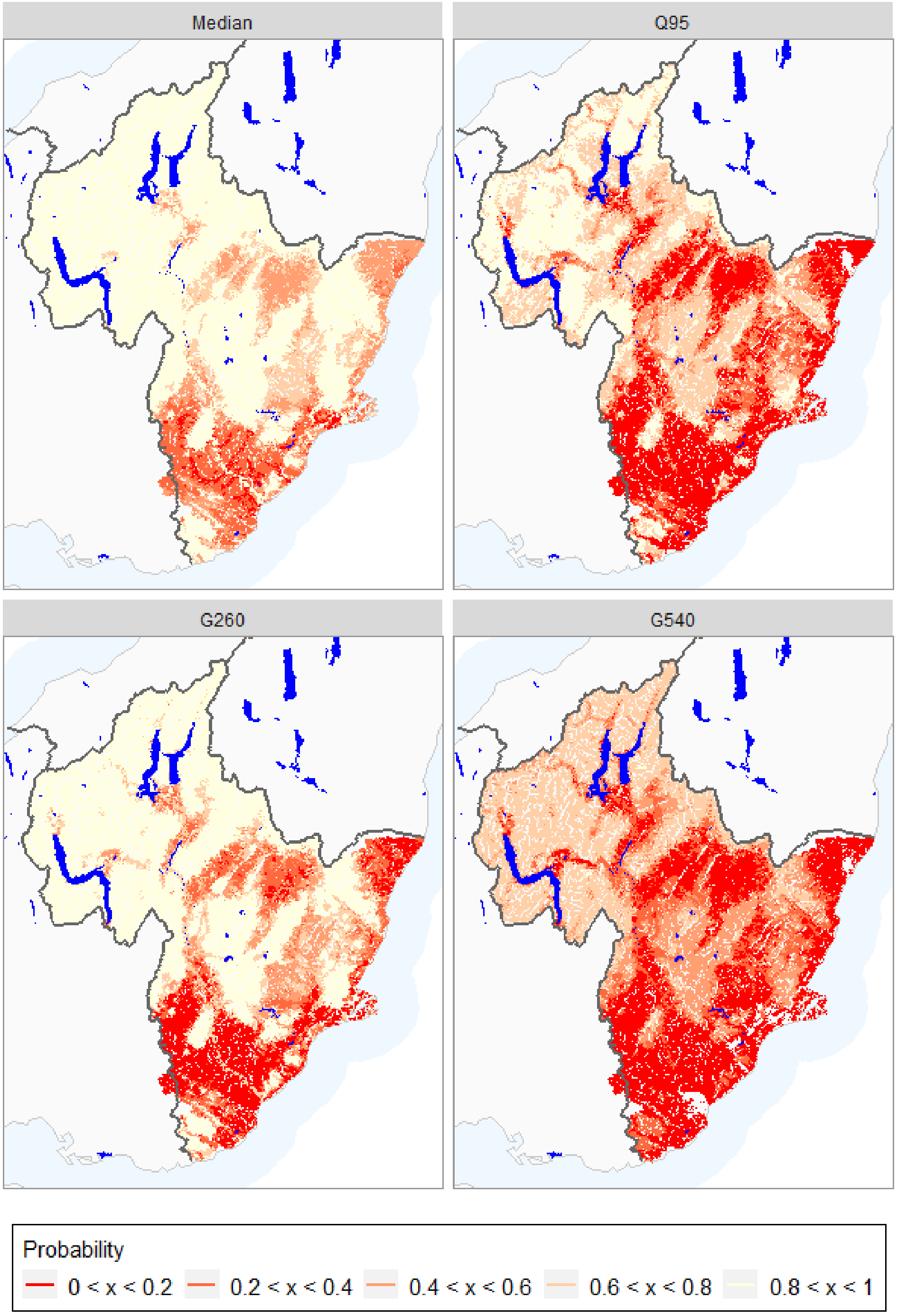

Figure 22. Probability of compliance with the criteria for each of the four E. coli statistics when the FWO is the A band. Each map represents the probability that segments achieve the criteria for the E. coli statistic that is associated with A band.

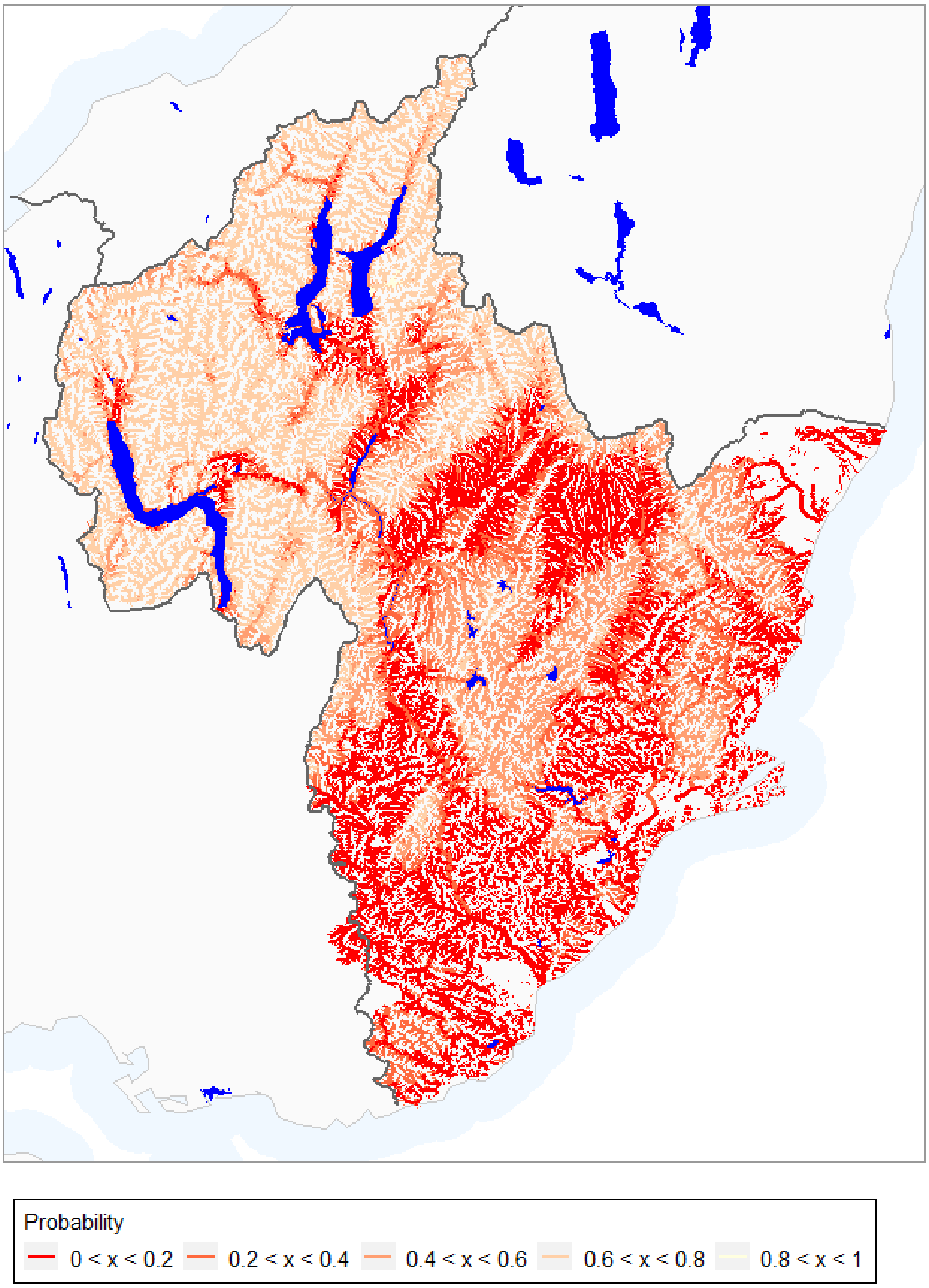

Figure 23. Probability of compliance when the FWO is the A band. This map represents the overall probability that segments achieve the A band.

3.8.2 Local excess loads

The local excess load is the amount by which the current *E. coli* load at a river segment would need to be reduced to achieve the objective for that receiving environment. For the A band, the best estimate of the local excess *E. coli* load local was zero for 15% of segments (Figure 24). Most of these segments were located in the area categorised as outside the fitting data (Figure 5). Therefore, the zero load reduction is because a load reduction could not be estimated despite the probability that segments in this area were compliant often being <0.6 (i.e., predicted statistics indicating that current state may be poorer than the A band). The load reductions exceeded 2 giga *E. coli* ha^{-1} yr^{-1} for 38% of river segments and exceeded 10 giga *E. coli* ha^{-1} yr^{-1} for 13% of river segments (Figure 24). Note that the 2 and 10 giga *E. coli* ha^{-1} yr^{-1} are nominal breakpoints for communication purposes and correspond to the legend thresholds on Figure 24. These values have no special significance (i.e., are not guidelines or standards).

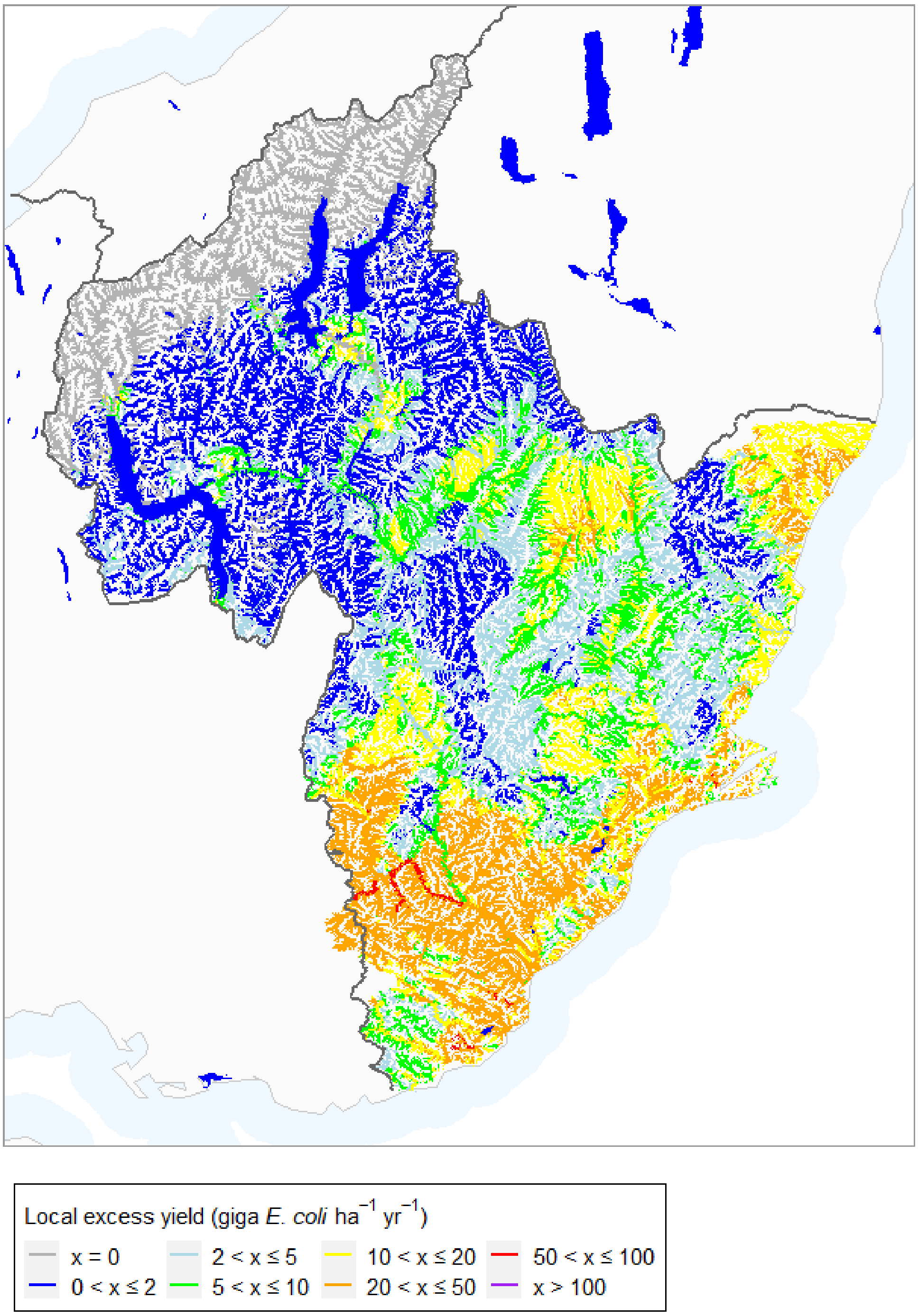

Figure 24. Local excess E. coli loads when the FWO is the A band. Note that the breakpoints for the local excess yield in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.8.3 Critical point catchment load reductions required

The load reduction required for critical point catchments is the minimum load reduction that ensures the loads for all receiving environments in the critical catchment do not exceed the MAL (and therefore all FWOs in the catchment are achieved). The load reductions required therefore differ from the local excess loads in that they consider all river segments in a critical point catchment. The load reductions required for the A band FWO are expressed below as yields (i.e., *E. coli* ha^{-1} yr^{-1}) and as a percentage of the current load.

The load reductions required by the A band FWO for critical point catchments are shown on Figure 25 and Figure 26. Critical point catchment *E. coli* load reduction requirements of greater 10 giga *E. coli* ha^{-1} yr^{-1} occupied 85% of the study area (Figure 20). Critical point catchment *E. coli* load reduction requirements of greater 20 giga *E. coli* ha^{-1} yr^{-1} occupied 62% of the study area (Figure 26). The comparison of load reductions expressed as yields (*E. coli* ha^{-1} yr^{-1}) with those expressed as proportion of current load (%) indicates that reduction requirements in catchments with low yield reductions (e.g., much of the Upper Lakes FMU and Dunstan Rohe) are nevertheless large in relative terms. Critical point catchments with *E. coli* load reductions of greater than 30% occupied 100% of the study area and critical point catchments with *E. coli* load reductions of greater than 60% occupied 56% of the study area (Figure 26).

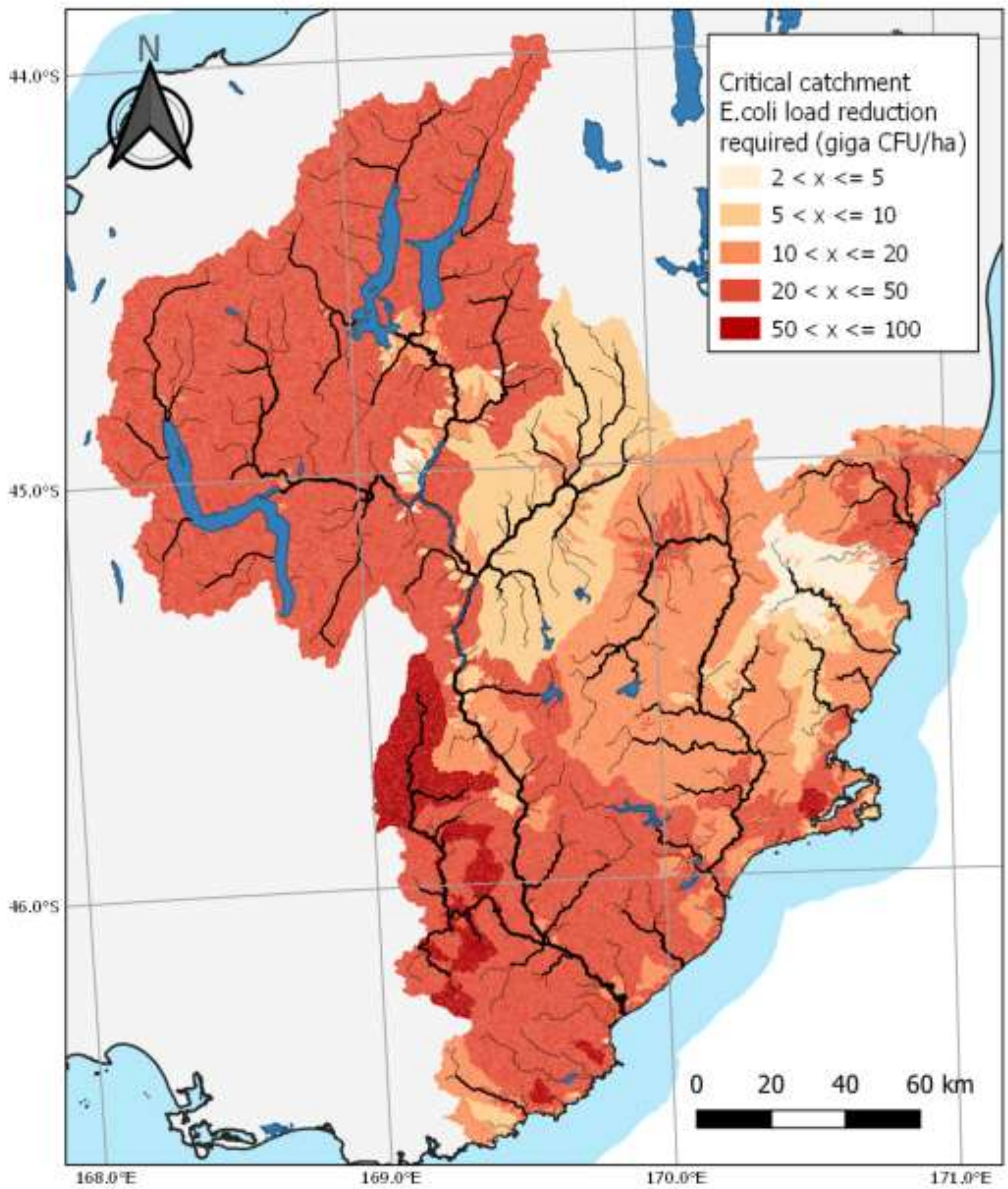

Figure 25. The E. coli load reduction required, expressed as yields, for critical point catchments when the FWO is the A band. The critical point catchment colours indicate the mean E. coli load reductions required to allow all FWOs be achieved in the critical point catchment (including the critical point at the bottom of the catchment).

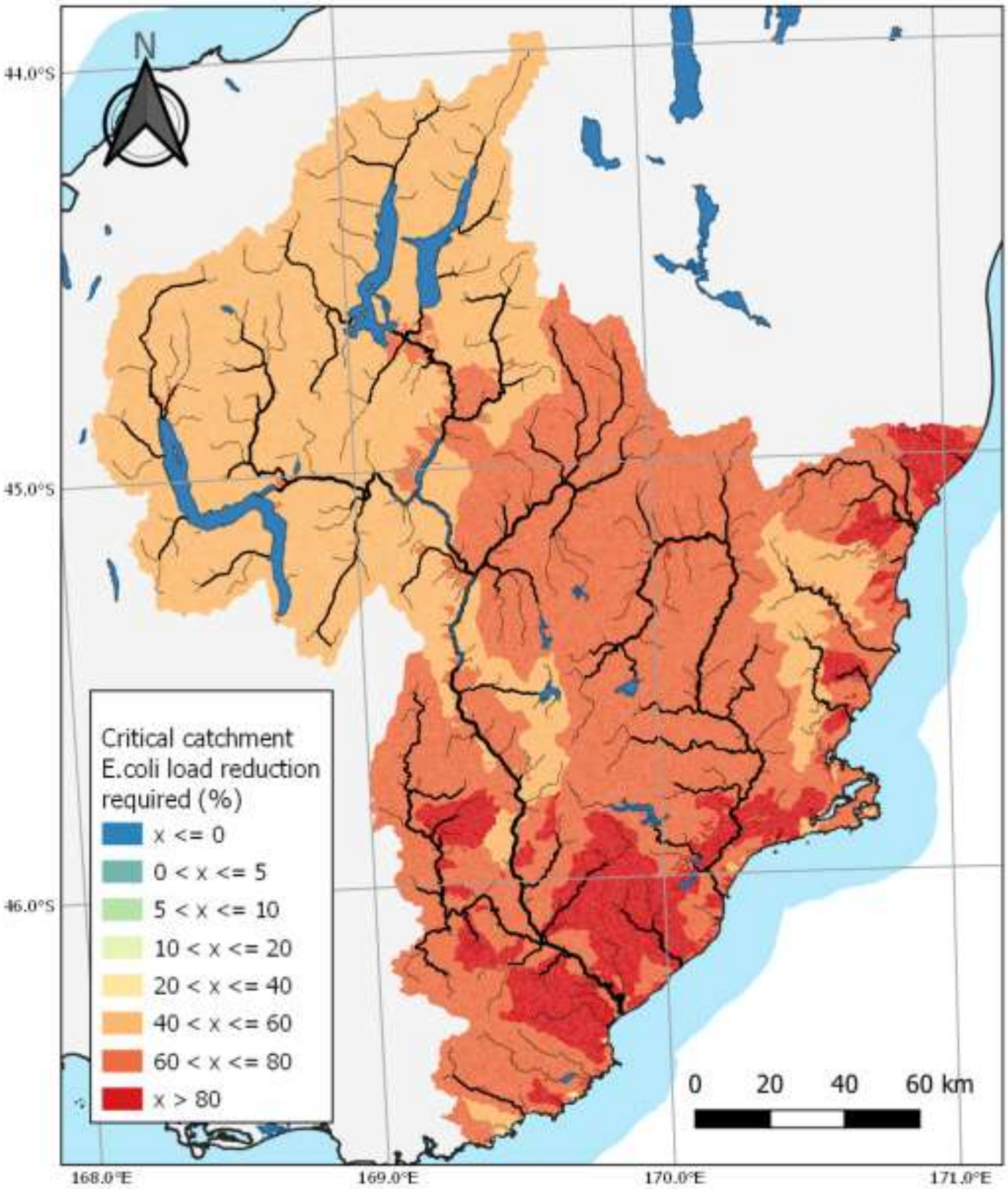

Figure 26. The E. coli load reduction required, expressed as proportion of the current load (%), for critical point catchments when the FWO is the A band. The critical point catchment colours indicate the E. coli load reductions required to allow all FWOs be achieved in the critical point catchment (including the critical point at the bottom of the catchment).

3.8.4 FMU and regional load reductions required

The load reduction required when the FWO is the A band for each FMU and for whole region are shown in Table 12. For the whole study area, the best estimate of *E. coli* load reductions required was 63 peta *E. coli* yr^{-1}, which represents 45% of the current load. The *E. coli* load reductions required were highest, relative to current loads (>50%), in the Catlins FMU, Dunedin Coast FMU, North Otago FMU and the Taieri FMU. The *E. coli* load reductions required were lowest, relative to current loads (<30%) in the Dunstan Rohe, Manuherekia Rohe and Roxburgh Rohe.

Table 12. Current load and load reduction required for E. coli by FUM and for the Otago region when the FWO is the A band. Note that loads are expressed in absolute terms in units of E. coli organisms per year (peta E. coli yr^{-1}) and as a proportion of current load (%). The first value in each column is the best estimate, which is the mean value over the 100 Monte Carlo realisations. The values in parentheses are the lower and upper bounds of the 90% confidence interval.

FMU	Total load (peta *E. coli* yr^{-1})	Load reduction required (peta *E. coli* yr^{-1})	Load reduction required (%)
Catlins FMU	4 (1 - 8)	3 (1 - 6)	67 (44 - 86)
Dunedin Coast FMU	4 (2 - 7)	3 (1 - 6)	77 (64 - 87)
Dunstan Rohe	17 (3 - 50)	7 (0 - 29)	27 (0 - 73)
Lower Clutha Rohe	103 (17 - 294)	60 (1 - 227)	46 (3 - 89)
Manuherekia Rohe	18 (3 - 52)	7 (0 - 30)	27 (0 - 74)
North Otago FMU	5 (2 - 10)	3 (1 - 8)	68 (48 - 85)
Roxburgh Rohe	25 (4 - 71)	10 (0 - 43)	27 (1 - 76)
Taieri FMU	12 (2 - 34)	8 (0 - 30)	51 (1 - 91)
Upper Lakes Rohe	6 (1 - 18)	3 (0 - 11)	31 (0 - 77)
Total	145 (53 - 506)	63 (14 - 364)	45 (13 - 83)

3.9 Assessment of spatially variable option

3.9.1 Compliance

The estimated probability that values of the four *E. coli* statistics are compliant with the spatially variable FWOs was greater than 0.6 for 81%, 65%, 82% and 63% of segments for the Median, Q95, G260 and G540, respectively (Figure 27). The estimated probability that all statistics complied with the spatially variable FWOs was greater than 0.6 for 47% of segments (Figure 28). The probability of compliance was greatest for segments in the headwater areas of the individual catchments, and particularly in the higher elevation parts of the region. The probability of compliance was lowest for segments in the low elevation parts of the region that have high proportions of catchment in pastoral land cover. This was consistent with the predicted pattern in the current values of all four *E. coli* statistics shown in Figure 7 and Figure 8.

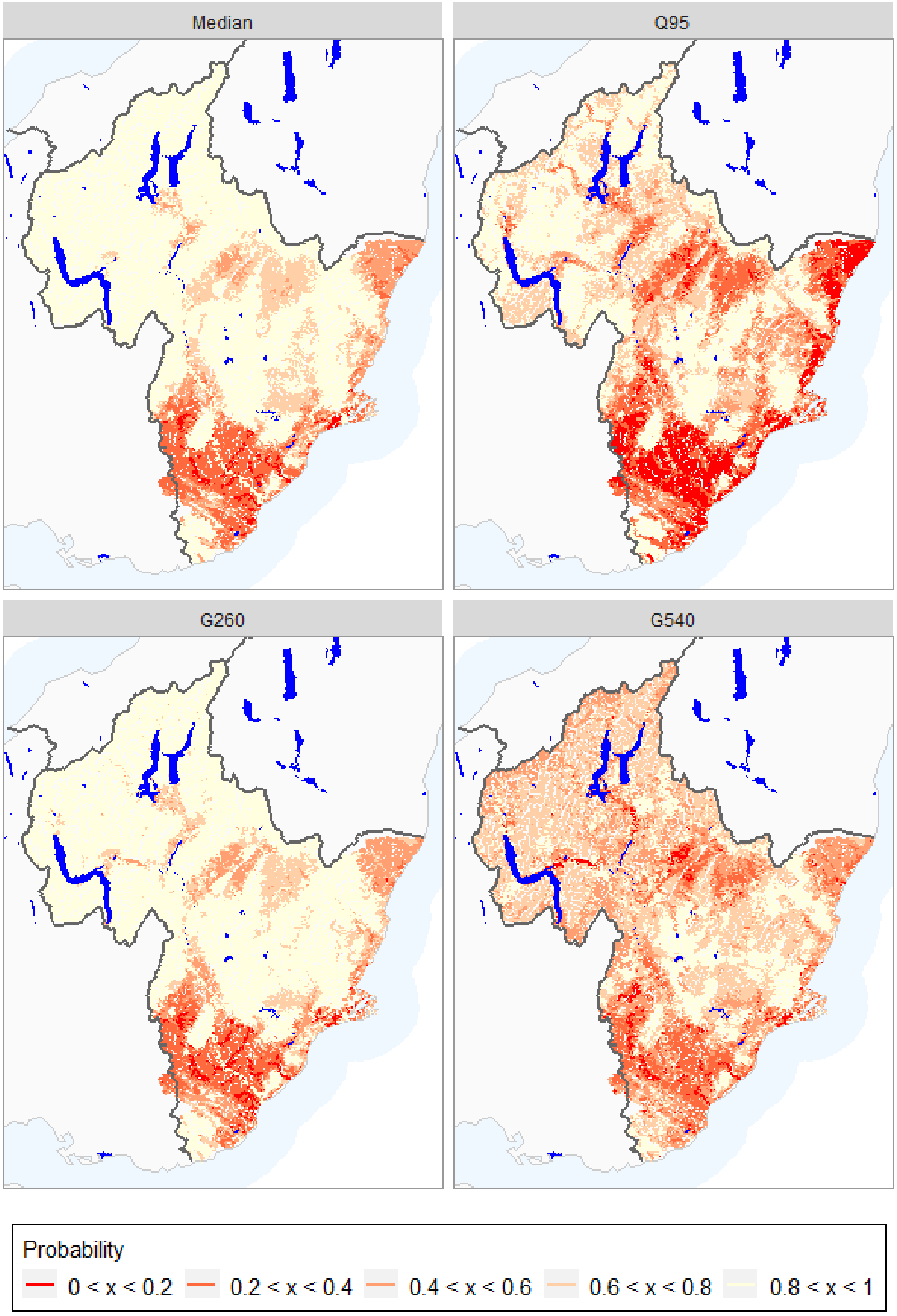

Figure 27. Probability of compliance with the criteria for each of the four E. coli statistics when the FWOs are spatially variable. Each map represents the probability that segments achieve the criteria for the E. coli statistic that is associated with the spatially variable FWOs.

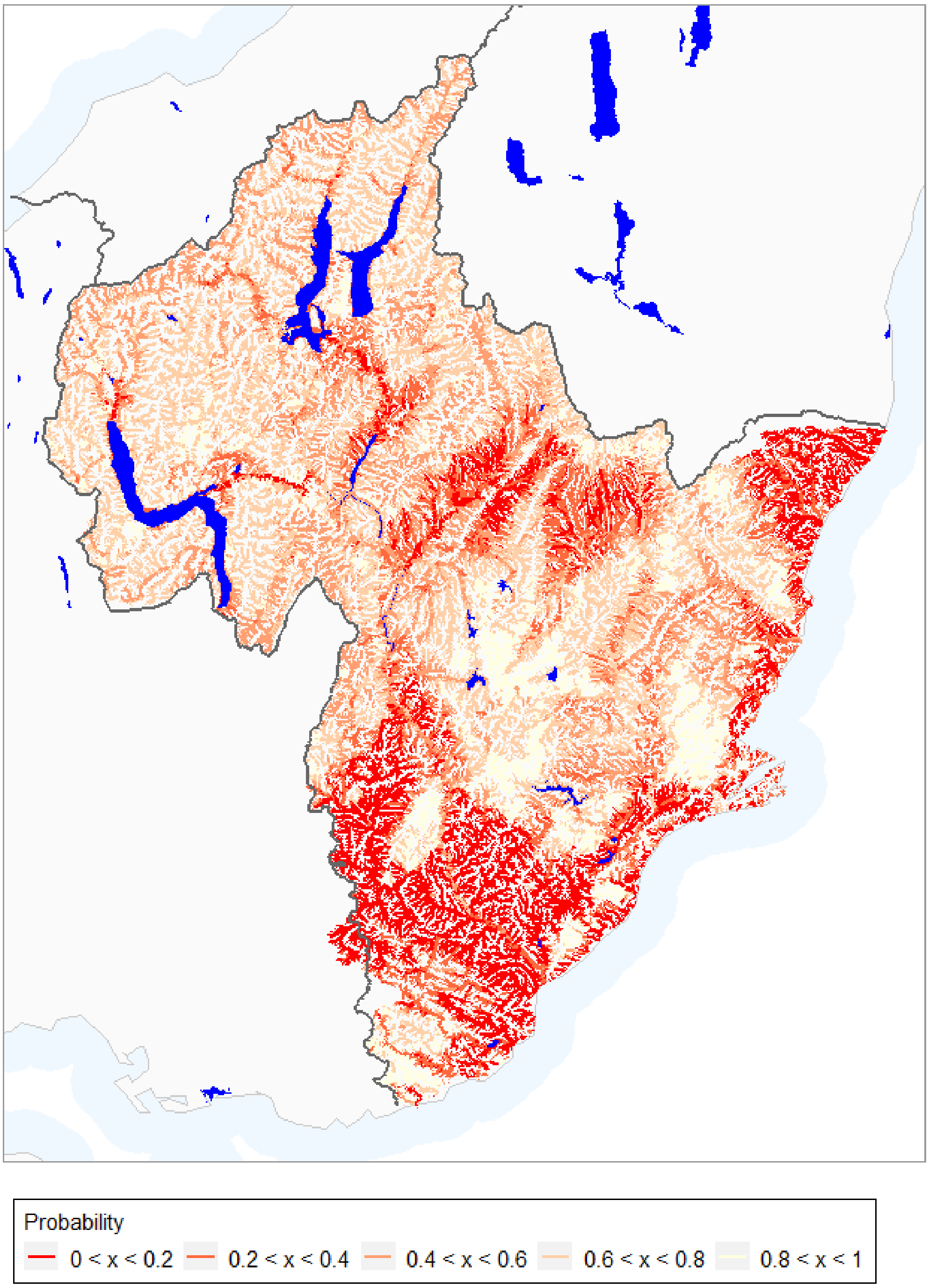

Figure 28. Probability of compliance with the spatially variable FWOs. This map represents the overall probability that segments achieve the spatially variable FWOs.

3.9.2 Local excess loads

The local excess load is the amount by which the current *E. coli* load at a river segment would need to be reduced to achieve the objective for that receiving environment. For the spatially variable FWOs, the best estimate of the local excess *E. coli* load local was zero for 33% of segments (Figure 29). Most of these segments were located in the area categorised as outside the fitting data (Figure 5). Therefore, the zero load reduction is because a load reduction could not be estimated despite the probability that segments in this area were compliant often being <0.6 (i.e., predicted statistics indicating that current state may be poorer than the A band). The load reductions exceeded 2 giga *E. coli* ha^{-1} yr^{-1} for 28% of river segments and exceeded 10 giga *E. coli* ha^{-1} yr^{-1} for 10% of river segments (Figure 29). Note that the 2 and 10 giga *E. coli* ha^{-1} yr^{-1} are nominal breakpoints for communication purposes and correspond to the legend thresholds on Figure 29. These values have no special significance (i.e., are not guidelines or standards).

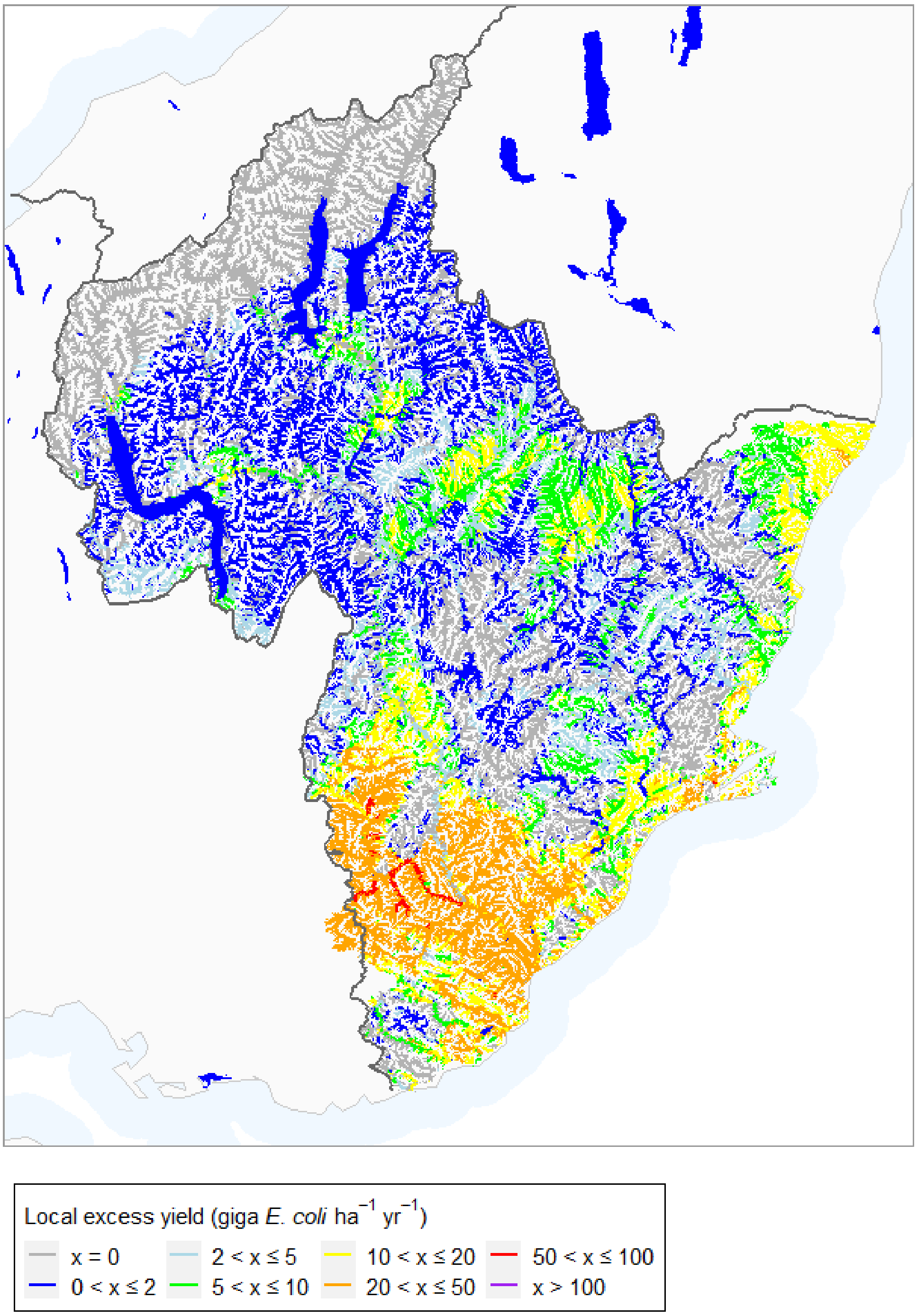

Figure 29. Local excess E. coli loads when the FWO are spatially variable. Note that the breakpoints for the local excess yield in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.9.3 Critical point catchment load reductions required

The load reduction required for critical point catchments is the minimum load reduction that ensures the loads for all receiving environments in the critical catchment do not exceed the MAL (and therefore all FWOs in the catchment are achieved). The load reductions required therefore differ from the local excess loads in that they consider all river segments in a critical point catchment. The load reductions required for the spatially variable FWOs are expressed below as yields (i.e., *E. coli* ha^{-1} yr^{-1}) and as a percentage of the current load.

The load reductions required by the spatially variable FWOs for critical point catchments are shown on Figure 30 and Figure 31. Critical point catchment *E. coli* load reduction requirements of greater 10 giga *E. coli* ha^{-1} yr^{-1} occupied 47% of the study area (Figure 30). Critical point catchment *E. coli* load reduction requirements of greater 20 giga *E. coli* ha^{-1} yr^{-1} occupied 25% of the study area (Figure 30). The comparison of load reductions expressed as yields (*E. coli* ha^{-1} yr^{-1}) with those expressed as proportion of current load (%) indicates that reduction requirements in catchments with low yield reductions (e.g., much of the Upper Lakes FMU and Dunstan Rohe) are nevertheless large in relative terms. Critical point catchments with *E. coli* load reductions of greater than 30% occupied 100% of the study area and critical point catchments with *E. coli* load reductions of greater than 60% occupied 20% of the study area (Figure 31).

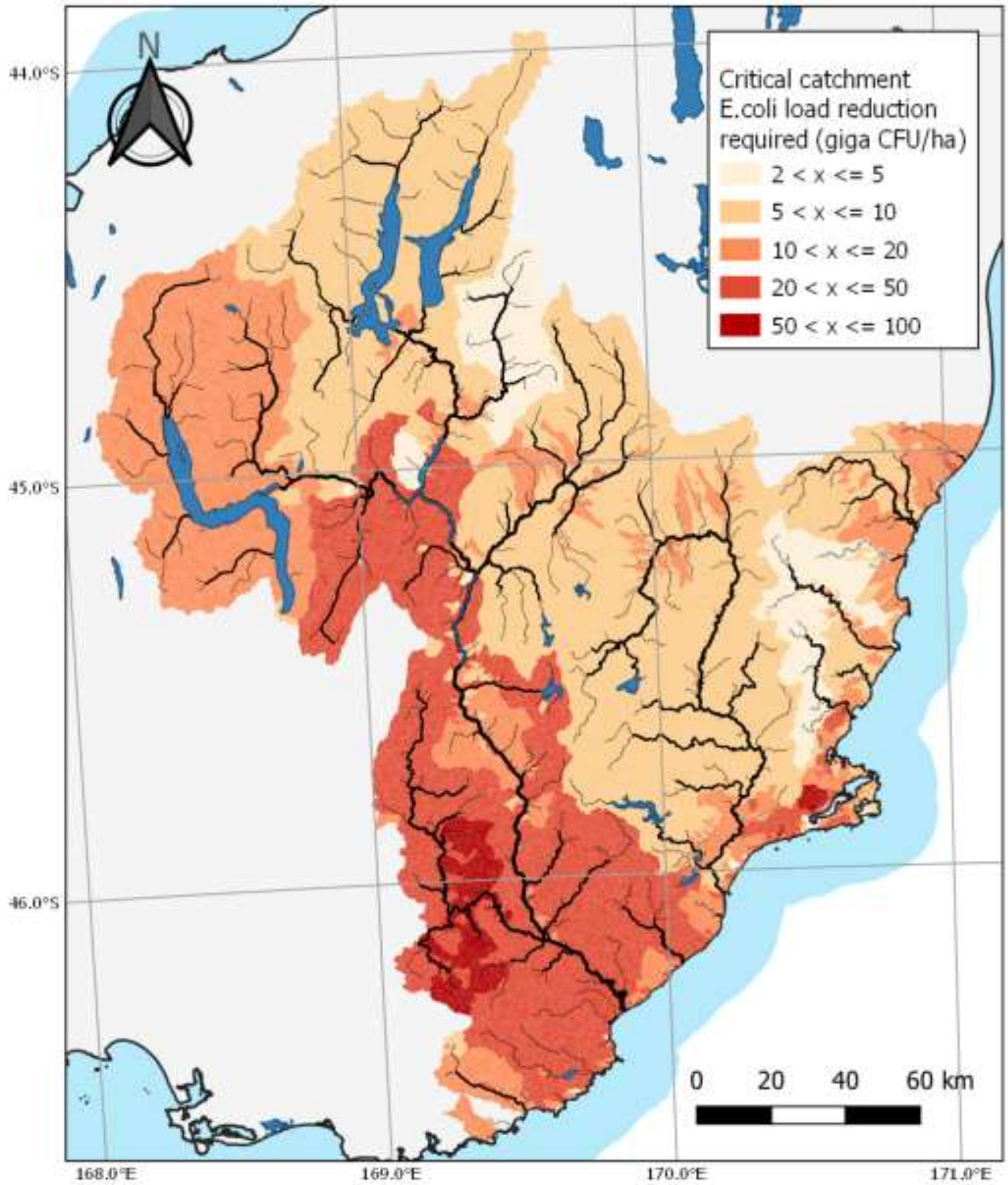

Figure 30. The E. coli load reduction required, expressed as yields, for critical point catchments when the FWOs are spatially variable. The critical point catchment colours indicate the mean E. coli load reductions required to allow all FWOs be achieved in the critical point catchment (including the critical point at the bottom of the catchment).

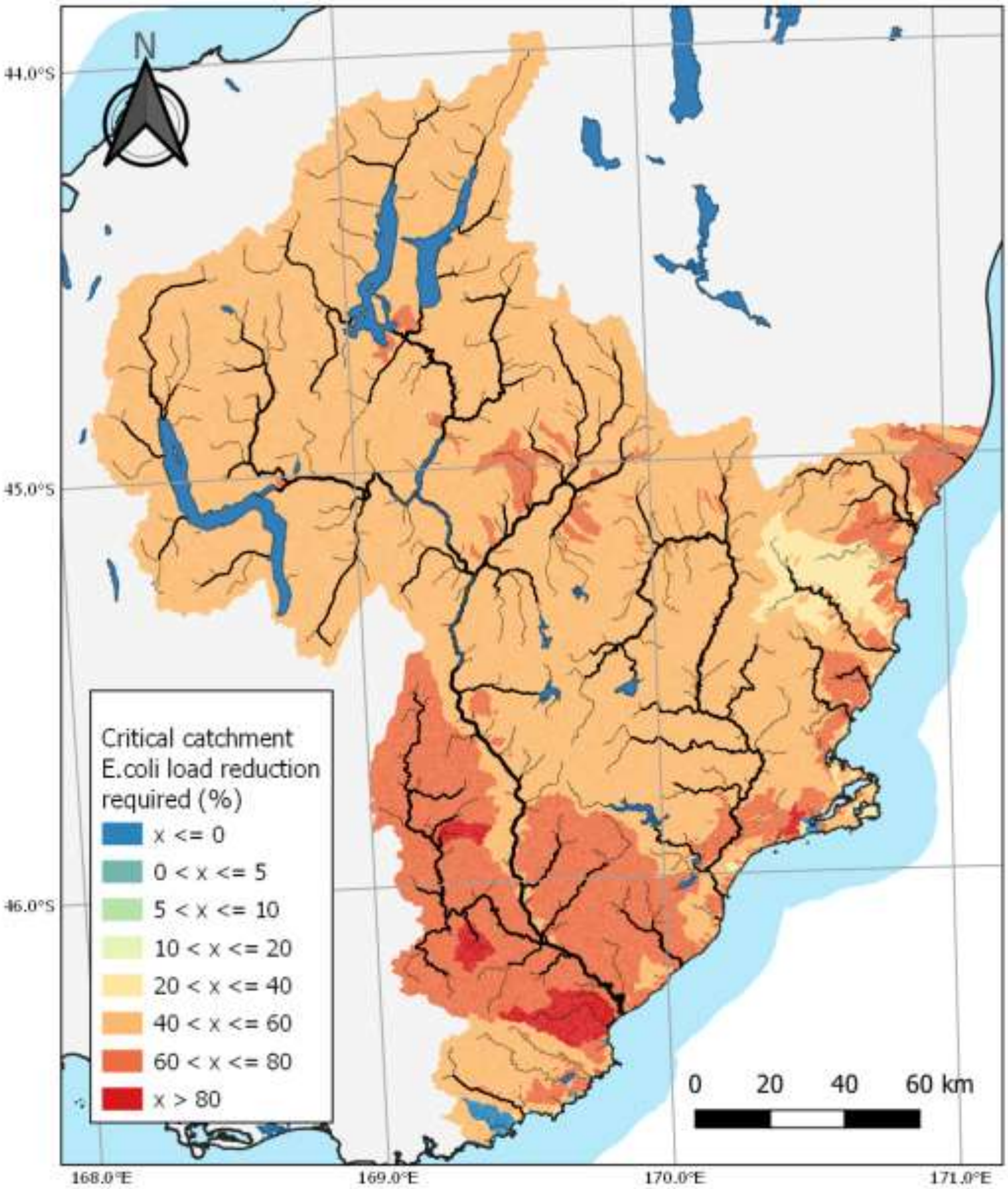

Figure 31. The E. coli load reduction required, expressed as proportion of the current load (%), for critical point catchments when the FWOs are spatially variable. The critical point catchment colours indicate the E. coli load reductions required to allow all FWOs be achieved in the critical point catchment (including the critical point at the bottom of the catchment).

3.9.4 FMU and regional load reductions required

The load reduction required when the FWOs are spatially variable for each FMU and for whole region are shown in Table 13. For the whole study area, the best estimate of *E. coli* load reductions required was 39 peta *E. coli* yr^{-1}, which represents 31% of the current load. The *E. coli* load reductions required were highest, relative to current loads (>50%), in the Dunedin Coast FMU and North Otago FMU. The *E. coli* load reductions required were lowest, relative to current loads (<30%) in the Dunstan Rohe, Manuherekia Rohe and Roxburgh Rohe.

Table 13. Current load and load reduction required for E. coli by FUM and for the Otago region when the FWOs are spatially variable. Note that loads are expressed in absolute terms in units of E. coli organisms per year (peta E. coli yr^{-1}) and as a proportion of current load (%). The first value in each column is the best estimate, which is the mean value over the 100 Monte Carlo realisations. The values in parentheses are the lower and upper bounds of the 90% confidence interval.

FMU	**Total load (peta *E. coli* yr^{-1})**	**Load reduction required (peta *E. coli* yr^{-1})**	**Load reduction required (%)**
Catlins FMU	4 (2 - 8)	2 (0 - 5)	48 (19 - 73)
Dunedin Coast FMU	4 (2 - 7)	2 (1 - 5)	63 (47 - 78)
Dunstan Rohe	22 (3 - 70)	7 (0 - 30)	23 (0 - 62)
Lower Clutha Rohe	129 (19 - 412)	60 (0 - 297)	33 (0 - 83)
Manuherekia Rohe	23 (3 - 72)	7 (0 - 31)	22 (0 - 63)
North Otago FMU	4 (2 - 8)	2 (1 - 5)	54 (31 - 77)
Roxburgh Rohe	31 (5 - 100)	11 (0 - 56)	23 (0 - 66)
Taieri FMU	10 (1 - 31)	6 (0 - 24)	40 (1 - 88)
Upper Lakes Rohe	8 (1 - 25)	4 (0 - 17)	33 (0 - 78)
Whole region	134 (49 - 701)	39 (9 - 468)	31 (9 - 74)

3.10 Comparison between FWO settings

A comparison of the *E. coli* load reductions required by the four sets of FWOs for the FMUs and the whole region is shown in Table 14. The best estimate for the load reductions is always less for the C band settings compared to the B band and for the B band compared to the A band. However, the 90% confidence intervals for the four sets of FWOs overlap in all cases. This indicates that from a practical perspective the amount of effort (i.e., the reduction in *E. coli* loads required) to achieve the four sets of FWOs are not significantly different. This is because the models have considerable uncertainty and the concentrations and corresponding loads that separate the four sets of FWOs are similar, relative to this uncertainty.

Table 14. Comparison of the load reductions required for individual FMUs and the whole region for the four sets of FWOs. The load reductions are shown as proportion of current load (%). The first value in each column is the best estimate, which is the mean value over the 100 Monte Carlo realisations. The values in parentheses are the lower and upper bounds of the 90% confidence interval.

FMU	C band	B band	A band	Spatially variable
Catlins FMU	45 (15 - 70)	54 (21 - 78)	67 (44 - 86)	48 (19 - 73)
Dunedin Coast FMU	61 (47 - 76)	70 (54 - 83)	77 (64 - 87)	63 (47 - 78)
Dunstan Rohe	13 (0 - 61)	16 (0 - 64)	27 (0 - 73)	23 (0 - 62)
Lower Clutha Rohe	33 (0 - 83)	33 (0 - 78)	46 (3 - 89)	33 (0 - 83)
Manuherekia Rohe	13 (0 - 61)	16 (0 - 65)	27 (0 - 74)	22 (0 - 63)
North Otago FMU	50 (28 - 73)	57 (35 - 74)	68 (48 - 85)	54 (31 - 77)
Roxburgh Rohe	15 (0 - 65)	16 (0 - 61)	27 (0 - 76)	23 (0 - 66)
Taieri FMU	29 (1 - 74)	31 (1 - 79)	51 (1 - 91)	40 (1 - 88)
Upper Lakes Rohe	14 (0 - 66)	18 (0 - 72)	31 (0 - 77)	33 (0 - 78)
Total	24 (6 - 74)	31 (7 - 70)	45 (13 - 83)	31 (9 - 74)

4 Discussion and conclusions

4.1 Load reductions required

This report has predicted *E. coli* load reductions needed to achieve options for freshwater objectives (FWO) for human health in rivers in the Otago region. The options for FWOs are defined in terms of NOF attribute bands for all river receiving environments (represented by network segments) in the region. Four sets of FWO options were nominated and are referred to as the A, B and C band options and the spatially variable option. The A, B and C band options represent uniform adoption of the A, B or C *E. coli* attribute state as defined by the NPS-FM. The spatially variable option proposes differing NOF *E. coli* attribute states by a nominal classification of Otago's rivers into Mountain, Hill, Lowland, Lake Upper and Lake Lower classes that were derived based on the REC.

The study area includes all of Otago, however the modelling was unable to produce realistic current *E. coli* loads for rivers in alpine headwater areas (Figure 5). This means that load reduction requirements from this area have been evaluated as zero under all FWO options. Although the analysis indicates that there is a not insignificant probability that current *E. coli* concentrations in some parts of the alpine headwater areas may not comply with the most stringent FWOs (i.e., A attribute state; Figure 22), load reductions from this area are unlikely to be feasible because it is almost entirely under natural land cover. The load reductions required for each option were estimated for all individual river segments outside of the alpine headwater areas and these individual results were also aggregated to report on individual FMUs and the whole study area.

For the whole study area and the C band option, which is the minimum state deemed suitable for primary contact in the national targets laid out in Appendix 3 of the NPSFM, the best estimate of the *E. coli* load reductions required were 31 peta *E. coli* yr^{-1}, which represents a best estimate of 24% of the current loads. For the whole study area and the A band option, the *E. coli* load reductions required were estimated to be 63 peta *E. coli* yr^{-1}, which represent 45% of the current loads. The difference in the percentage load reduction for both the whole study area and the FMUs were always consistent with expectations, that is, reductions were always less for the C band option than the A band option (Table 14). The large load reduction for the A band option reflects the stringency of the FWOs. However, the 90% confidence intervals for all sets of load reduction estimates were strongly overlapping. This indicates that, from a practical perspective, the reduction in *E. coli* loads required to achieve all sets of FWO options are not significantly different.

4.2 Comparison with previous studies and national targets

This study also provided an estimate that 62% of the large rivers (i.e., those with stream order ≥4) across the whole region are currently suitable for primary contact according to the NPSFM Appendix 3 criteria (i.e., in attribute state C or better). The 90% confidence interval for this estimate is wide, with the lower and upper bounds defined by 21% and 84%, respectively. The estimate by this study is therefore consistent with the previous estimate of 78% of these large rivers in Otago being suitable for primary contact as reported in MFE (2018). It is noteworthy that all sets of FWO options assessed in this study lead to 100% of rivers being suitable for primary contact (i.e., better than C band). These options represent a considerably greater increase in swimmable rivers than the 3.2% increase (to 81.5% swimmable) associated with committed work in the rural area of Otago reported by (MFE, 2018).

4.3 Uncertainties

Uncertainty is an unavoidable aspect of this study because it is based on simplifications of reality and because it has been informed by limited data. The study estimated the statistical uncertainty of the *E. coli* load reduction estimates that are associated with two key components of the analyses: the modelled regional river *E. coli* statistics and loads (see Sections 3.1 and 3.2). The statistical uncertainty of these models is associated with the imprecision of the *E. coli* statistics calculated for each site due to high sample variability and the inability of the random forest models to perfectly predict the statistics and loads observed at water quality monitoring sites; the error associated with these predictions is quantified by the model RMSD values (Table 4 and Table 5).

A Monte Carlo analysis was used to combine the above model uncertainties and to make assessments of the uncertainty of several characteristics and quantities. The Monte Carlo analysis recognises and is based on the uncertainties associated with the nine individual models that are used in the assessment. We have presented the results of the analyses differently depending on the assessed characteristics. In general, the mean of results obtained from 100 Monte Carlo realisations was used to represent the best estimate of any quantity. For example, we provide a best estimate of the proportion of network segments in each of the five NOF attribute bands (Table 9). We also use the 90% confidence interval for our estimates of these proportions to indicate the uncertainty of these estimates. The lower and upper confidence limits can be interpreted as the values for which we are 95% confident the proportions are not lower than or greater than. The estimated load reductions required for the region and the FMUs have followed this same approach with a best estimate and 90% confidence intervals (e.g., Table 10 and Table 12). We have presented maps showing compliance with criteria associated with the FWOs (e.g., Figure 12 and Figure 13). These maps show the estimated probability that segments comply with the criteria. We note that the distributions of load reductions over the 100 realisations (and mean and 90% confidence intervals) derived by the analyses can be obtained for each of the 70,600 segments represented in the analysis. These data are not presented in this report but are available as supplementary files.

An important conclusion from the analysis of uncertainty is that we are 95% confident that *E. coli* load reductions are required to achieve all sets of FWO options for the whole region. This is because the lower bound of the 90% confidence interval for load reduction required is greater than zero for all sets of FWOs (Table 14). Similarly, we are 95% confident that *E. coli* load reductions are required to achieve all sets of FWO options for the following FMUs: Catlins FMU, Dunedin Coast FMU, Lower Clutha Rohe, North Otago FMU, and Taieri FMU.

There are sources of uncertainty that this study has not accounted for. A key uncertainty is the source of *E. coli* at any point in the river network. An underlying implicit assumption in this study is that *E. coli* concentrations at any point are the outcome of load and that this load is attributable to contributions from all land in the upstream catchment. This is not necessarily true, concentrations at a location may be more strongly influenced by immediate local sources than contributions from upstream. Local sources may be from local land areas, point sources, or may be associated with transfer of *E. coli* from the river bed, particularly during high flow events (Wilkinson *et al.*, 2011). The assumption that *E. coli* loads at any point are the outcome contributions from all land in the upstream catchment is manifested in our analysis by the additive reconciliation of local load reductions in the downstream direction at step 4 of the analysis to obtain the load reduction required at every point in the drainage network. This analysis is based on an assumption that any reduction upstream of a location contributes to the load reduction necessary at that location. This assumption would be violated if local contributions were important determinants of concentrations and loads at a point. The existence of these processes is not well understood or represented by our analysis and are therefore sources of additional uncertainty associated with the estimation of load reduction required.

The uncertainties described in this study indicate that the best estimates and maps are appropriately considered as indicative of the regional-scale patterns of compliance and *E. coli* load reductions required. The broad scale patterns provide a reliable indication of the relative differences in compliance and load reductions required between locations. However, there is considerable uncertainty associated with the absolute values of the *E. coli* load reductions required and these become larger as the spatial scale over which the reductions are evaluated is reduced. It is unlikely that these uncertainties can be significantly reduced in the short to medium term (i.e., in less than 5 to 10 years) because, among other factors, the modelling is dependent on the collection of long-term water quality monitoring data.

4.4 Informing decision-making on limits

The NPS-FM requires regional councils to set limits on resource use to achieve environmental outcomes (e.g., FWOs). This report helps inform Otago Regional Council's process of setting limits by assessing the approximate magnitude of the *E. coli* load reductions needed to achieve several options for FWOs, with a quantified level of uncertainty associated with each option. However, this report does not consider what kinds of limits on resource might be used to achieve any load reductions, how such limits might be implemented, over what timeframes and with what implications for other values. The NPS-FM requires regional councils to have regard to these and other things when making decisions on setting limits. This report shows that these decisions will ultimately need to be made in the face of uncertainty about the magnitude of load reductions needed.

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Appendix A Calculation of E. coli loads at monitoring sites

A1 Water quality data

We obtained E. coli monitoring data for 59 river SOE monitoring sites from the ES database. E. coli was generally observed at the river sites on a monthly basis. These sites had variable start and end dates and total numbers of observations. Most sites had greater than 200 observations for over 15 years. Five sites were excluded from the subsequent load calculation as they had fewer than 96 observations (80% of monthly observations over a ten-year period).

A2 Flow Data

We obtained daily timeseries of flow for all 59 E. coli monitoring sites from ES. Of these 59 sites, 17 were observed timeseries and the remaining 42 sites were simulated timeseries of flow. Start years for the flow records ranged from 1955 to 2002 (one site started in 2011 but was already excluded due to short E. coli record). All but 4 sites had more than 20 years of daily flow observations, with a median of 43 years of flow data across all sites.

A3 Load calculations

Calculation of E. coli loads at monitoring sites generally comprise two steps: (1) the generation of a series of flow and concentration pairs representing 'unit loads' and (2) the summation of the unit loads over time to obtain the total load. In practice step 1 precedes step two but in the explanation that follows, we describe step 2 first.

If flow and concentration observations were available for each day, the export coefficient, (the mean annual load, standardised by the upstream catchment area) would be the summation of the daily flows multiplied by their corresponding concentrations:

$$L = \frac{K}{A_c N} \sum_{j=1}^{N} C_j Q_j \qquad \text{(Equation A1)}$$

where L: mean annual export coefficient (giga *E. coli* yr^{-1} ha^{-1}), A_c: catchment area, ha, K: units conversion factor, C_j: contaminant concentration for each day in period of record (mg m^{-3}), Q_j: daily mean flow for each day in period of record (m^3 s^{-1}), and N: number of days in period of record.

In this summation, the individual products represent unit loads. Because concentration data are generally only available for infrequent days (i.e., generally in this study, monthly observations), unit loads can only be calculated for these days. However, flow is generally observed continuously, or the distribution of flows can be estimated for locations without continuous flow data, and there are often relationships between concentration and flow, time and/or season. Rating curves exploit these relationships by deriving a relationship between the sampled nutrient concentrations (c_i) and simultaneous observations of flow (q_i). Depending on the approach, relationships between concentration and time and season may be included in the rating curve. This rating curve is then used to generate a series of flow and concentration pairs (i.e., to represent Q_j *and* C_j in Equation A1) for each day of the entire sampling period (i.e., step 1 of the calculation method; Cohn *et al.*, 1989). The estimated flow and concentration pairs are then multiplied to estimate unit loads, and these are then summed and transformed by K, N and A_c to estimate mean annual export coefficients (i.e., step 2 of the calculation method; Equation A1).

There are a variety of approaches to defining rating curves. Identifying the most appropriate approach to defining the rating curve requires careful inspection of the available data for each site and contaminant. The details of the approaches and the examination of the data are described below in Section A3.3.

For each site, we calculated the load for each contaminant using three commonly used and recommended methods that are based on different types of rating curves, which we refer to as the the flow stratification method, the seven-parameter (L7) rating method and the five-parameter (L5) rating method. We expressed all contaminant loads as annual export coefficients (i.e., for giga *E. coli* yr^{-1} ha^{-1}) by dividing the annual load (kg yr^{-1}) by the catchment area (ha). Loads were estimated for an evaluation date of 31/12/2019 (rather than a long term mean load).

A3.1 Methods for defining rating curves

A3.1.1 Flow stratification

Roygard *et al.* (2012) employed a flow stratification approach to defining rating curves. This approach is based on a non-parametric rating curve, which is defined by evaluating the average concentration within equal increments of the flow probability distribution (flow 'bins'). In their application, Roygard *et al.* (2012) employed ten equal time-based categories (flow decile bins), defined using flow distribution statistics and then calculated mean concentrations within each bin. This non-parametric rating curve can then be used to estimate nutrient concentrations, $\hat{C}$, for all days with flow observations. At step 2, the load is calculated following Equation A1a, providing an estimate of average annual load over the observation time period.

$$L = \frac{K}{A_c N} \sum_{j=1}^{N} \hat{C}_j Q_j \qquad \text{Equation A1a}$$

where $\widehat{C_j}$ is calculated mean concentration associated with the flow quantile bin of the flow Q_j., and all other variables are as per Equation A1.

A3.1.2 L7 model

Two regression model approaches to defining rating curves of Cohn *et al.* (1989, 1992) and Cohn (2005) are commonly used to calculated loads. The regression models relate the log of concentration to the sum of three explanatory variables: discharge, time, and season. The L7 model is based on seven fitted parameters given by:

$$ln(\widehat{C_i}) = \beta_1 + \beta_2\left[ln(q_i) - \overline{(ln(q))}\right] + \beta_3\left[ln(q_i) - \overline{(ln(q))}\right]^2 + \beta_4(t_i - \bar{T}) + \beta_5(t_i - \bar{T})^2 + \beta_6 sin(2\pi t_i) + \beta_7 cos(2\pi t_i) \qquad \text{Equation A2}$$

where, *i* is the index for the concentration observations, $\beta_{1,2,..7}$: regression coefficients, t_i: time in decimal years, $\bar{T}$: mean value of time in decimal years, $\overline{(ln(q))}$ mean of the natural log of discharge on the sampled days, and $\widehat{C_i}$: is the estimated *i*th concentration.

The coefficients are estimated from the sample data by linear regression, and when the resulting fitted model is significant ($p < 0.05$), it is then used to estimate the concentration on each day in the sample period, $ln(\widehat{C_j})$. The resulting estimates of $ln(\widehat{C_j})$ are back-transformed (by exponentiation) to concentration units. Because the models are fitted to the log transformed concentrations the back-transformed predictions were corrected for retransformation bias. We used the smearing estimate of Duan (1983) as a correction factor (S):

$$S = \frac{1}{n}\sum_{i=1}^{n} e^{\hat{\varepsilon}_i} \qquad \text{Equation A3}$$

where, $\hat{\varepsilon}$ are the residuals of the regression models, and n is the number of flow-concentration observations. The smearing estimate assumes that the residuals are homoscedastic and therefore the correction factor is applicable over the full range of the predictions.

The average annual load is then calculated by combining the flow and estimated concentration time series:

$$L = \frac{KS}{A_c N} \sum_{j=1}^{N} \hat{C}_j Q_j \qquad \text{Equation A1b}$$

If the fitted model is not significant, $\widehat{C}_j$ is replaced by the mean concentration and S is unity.

To provide an estimate of the load at a specific date, (i.e. t^{est} = 1/3/2004) a transformation is performed so that the year components of all dates (t_j) are shifted such that all transformed dates lie within a one-year period centred on the proposed observation date (i.e. Y=1/9/2003 to 31/8/2004). For example, flow at time t=13/6/2007 would have a new date of Y =13/6/2004, and a flow at time t=12/11/1998 would have a new date of Y=12/11/2003.

$$ln\left(\widehat{C_j^Y}\right) = \beta_1 + \beta_2\left[ln(q_j) - \overline{(ln(q))}\right] + \beta_3\left[ln(q_j) - \overline{(ln(q))}\right]^2 + \beta_4(Y_j - \overline{T}) + \beta_5(Y_j - \overline{T})^2 + \beta_6 sin(2\pi Y_j) + \beta_7 cos(2\pi Y_j) \qquad \text{Equation A2a}$$

where $\widehat{C_j^Y}$ is the estimated j^{th} concentration for the estimation year, and Y_j is the transformed date of the i^{th} observation, and all other variables are as per Equation A3. The regression coefficients ($\beta_{1,2,..7}$) are those derived from fitting Equation A2 to the observation dataset. It follows that the estimated load for the year of interest can be calculated by:

$$L^Y = \frac{KS}{A_c N} \sum_{j=1}^{N} \hat{C}_j^Y Q_j \qquad \text{Equation A1c}$$

A3.1.3 L5 Model

The L5 model is the same as L7 model except that two quadratic terms are eliminated:

$$ln(\widehat{C}_i) = \beta_1 + \beta_2(ln(q_i)) + \beta_3(t_i) + \beta_4 sin(2\pi t_i) + \beta_5 cos(2\pi t_i) \qquad \text{Equation A4}$$

The five parameters are estimated, and loads are calculated in the same manner as the L7 model. Following the approach outlined for the L7 model, the L5 model can be adjusted when used for prediction to provide estimates for a selected load estimation date:

$$ln\left(\widehat{C_j^Y}\right) = \beta_1 + \beta_2[ln(q_j)] + +\beta_4(Y_j - \overline{T}) + +\beta_6 sin(2\pi Y_j) + \beta_7 cos(2\pi Y_j) \qquad \text{Equation A4a}$$

A3.2 Precision of load estimates

The statistical precision of a sample statistic, in this study the mean annual load, is the amount by which it can be expected to fluctuate from the population parameter it is estimating due to sample error. In this study, the precision represents the repeatability of the estimated load if it was re-estimated using the same method under the same conditions. Precision is characterised by the standard deviation of the sample statistic, commonly referred to as the standard error. We evaluated the standard error of each load estimate by bootstrap resampling (Efron, 1981). For each load estimate we constructed 100 resamples of the concentration data (of equal size to the observed dataset), each of which was obtained by random sampling with replacement from the original dataset. Using each of these datasets, we recalculated the site load and estimated the 95% confidence intervals, using the boot r package.

A3.3 Identifying a best load estimate

We developed an expert judgement-based methodology to evaluate the 'best' rating curve approach for each site and used this to make a 'best' load estimate. We did this by inspecting summaries of the flow-concentration-time (Q-C-T) data and model diagnostic information and performance measures pertaining to the rating curves. Data availability and sampling distribution with season, time and flow were also considered in this assessment. An example of the diagnostic plots that we used in this process is shown in Figure 32.

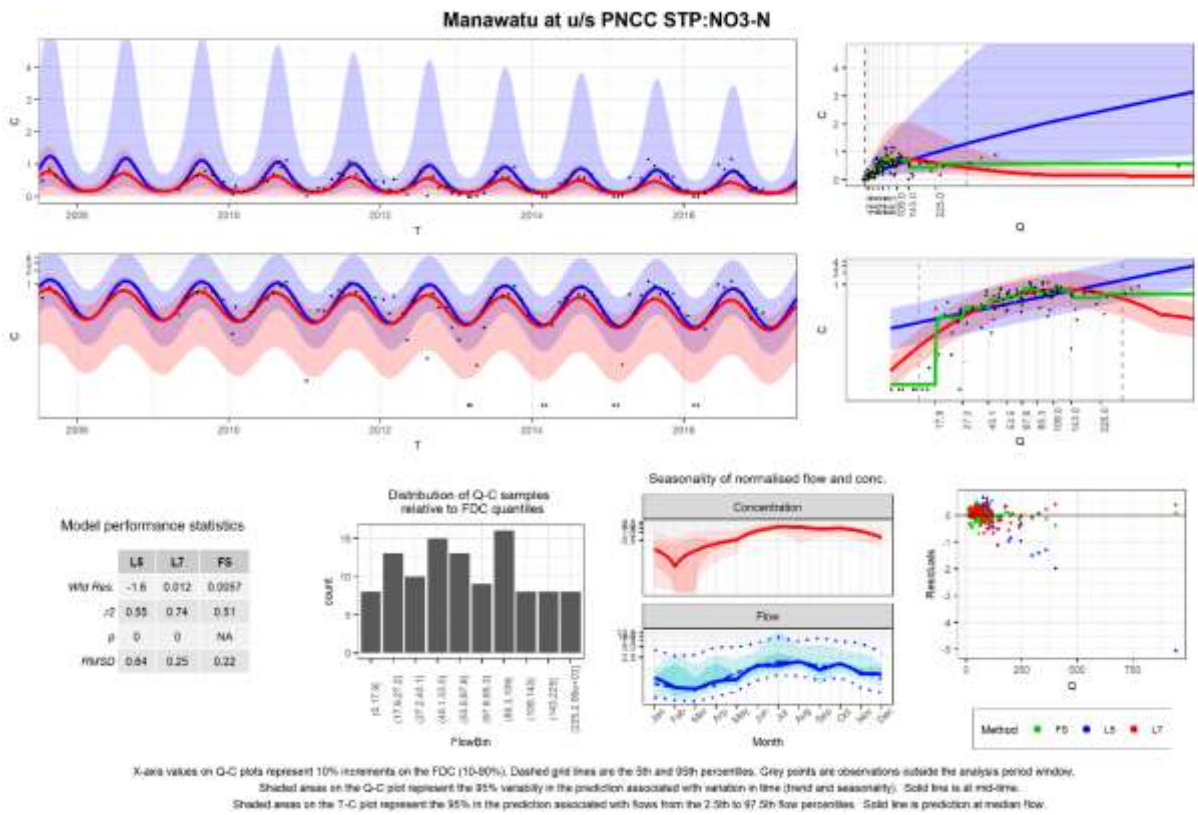

Figure 32: Example of a diagnostic information summary page that was used to examine the rating curves fitted to each site.