Nitrogen, phosphorus, sediment and *Escherichia coli* in New Zealand's aquatic receiving environments

Comparison of current state to national bottom lines

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Executive Summary

This study evaluated the current state of four contaminants (nitrogen, phosphorus, *Escherichia coli* (*E. coli*) and sediment) in rivers, lakes and estuaries across New Zealand and assessed the reduction in the contaminant loads that would be required to achieve a set of minimum acceptable states. The minimum acceptable states were generally defined by the national bottom lines for attributes defined by Appendix 2A[1] of the National Policy Statement for Freshwater Management 2020 (NPS-FM) that can be modelled in a consistent and comprehensive manner across New Zealand. This includes the nitrate toxicity, periphyton, *E. coli* and suspended sediment attributes for rivers, and the total nitrogen and total phosphorus attributes for lakes. The NPS-FM does not have attributes for estuaries. We therefore nominated minimum acceptable trophic states for estuaries (defined by maximum levels of plant biomass) that are equivalent to NPS-FM's national bottom lines. This set of the minimum acceptable states does not include all the attributes listed in the NPS-FM. The attributes included in this analysis are those defined by Appendix 2A for which there are currently data and models that can be used to estimate current state in rivers, lakes and estuaries across New Zealand.

The study area includes all of New Zealand. Rivers and their catchment areas were represented by a digital drainage network that comprises 650,000 segments and their associated sub-catchments. A total of 961 individual lakes and 419 estuaries that can be linked to the digital drainage network were represented by the analyses.

The analysis utilised several models that describe concentrations and loads of nitrogen, phosphorus, *E. coli* and sediment in rivers. These models were all informed by environmental data collected at state of environment (SOE) monitoring sites on rivers, lakes and estuaries across New Zealand.

Loads of nitrogen and phosphorus discharged to lakes and estuaries were obtained by summing estimated riverine input load to each individual receiving environment. The study used criteria for nitrogen, phosphorus, *E. coli* and sediment in rivers to assess compliance with the minimum acceptable states in every river network segment, lake and estuary. The predicted current state was compared to the criteria for every receiving environment (i.e., river, lake or estuary). Where the current concentration exceeded the criteria, the receiving environment was deemed to be non-compliant. The 'load reduction required' for a non-compliant receiving environment was evaluated as the reduction that would allow the current concentration to equal the criteria.

The compliance and load reduction required can be reported for individual receiving environments and at a variety of other spatial scales. Load reductions required are reported in this study for regions and New Zealand as a whole. The study also provides maps of the catchment areas requiring load reductions and the magnitudes of these reductions for each of the four contaminants. The load reductions required are expressed in both absolute terms (mass per unit catchment area per year) and in relative terms (as a proportion of current contaminant load per year). Expressing load reductions required in relative terms allows for comparison across the four contaminants.

The assessment results for all four contaminants for regions and New Zealand are shown in Table A below. The study indicates that substantial reductions in current loads of all contaminants are required to achieve the nominated minimum acceptable states at national and regional levels. The best estimates of the load reductions required for the four

[1] Appendix 2A lists attributes requiring limits on resource use.

contaminants and for the whole of New Zealand varied between 6% to 73% of the current loads. There was large variation in the load reductions required between the different combinations of regions and contaminants (Table A). This variation reflects differences in the inherent susceptibility to contaminant loss, for example some regions are more prone to erosion than others and, therefore, have larger sediment load reductions required. Regions with large sediment loads tend to have larger phosphorus load reductions required because of the contribution of geologically derived phosphorus (e.g., Manawatu and Otago). The variation also reflects differences in the intensity of current land use, which tends to be a function of inherent land suitability, particularly for agriculture. For example, significantly greater proportions of the Canterbury and Southland regions are suitable for intensive agriculture than many other regions. This explains why the Canterbury and Southland regions have larger load reductions required for nitrogen than most other regions (Table A). There is also considerable variation in in load reductions required within regions, which is not apparent in Table A but which can be seen in maps presented in this report. For example, although the overall regional TN load reduction required in the Greater Wellington region is 12% of current load (Table A), there are catchments within the region that require considerably larger TN load reductions than this.

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 uncertainty of the individual models used in the analyses were combined using a Monte Carlo analysis. The Monte Carlo analysis was used to estimate the uncertainty of the assessments of compliance and the contaminant load reductions required. The uncertainties increase as the spatial scale over which the load reductions required are evaluated is reduced. The broad scale patterns provide a reliable indication of where load reductions are required and the relative differences in compliance and load reductions required between locations. However, there is considerable uncertainty associated with the absolute values of the load reductions required and this uncertainty increases as the spatial scale of the load reduction assessment is reduced.

The uncertainties of the load reductions required for the regions and New Zealand are quantified by 90% confidence intervals in Table A. The lower confidence intervals for most of the combinations of contaminant and regions and for New Zealand as a whole, are larger than zero. An interpretation of cases where the lower confidence interval is larger than zero is that we can be at least 95% confident that reductions are required.

The uncertainties are least for the analyses of nitrogen. This is because nitrogen concentrations and loads in catchments can be modelled more accurately than the other three contaminants. This is partly because nitrogen loss in catchments more strongly reflects the signal of land use and is less influenced by other factors, such as natural processes, than the other contaminants. This means the models used to predict loads and concentrations of nitrogen were less confounded by other factors and performed better (i.e., had lower uncertainties) than many of the models associated with the other contaminants.

The Monte Carlo analysis could not account for all sources of uncertainty, or the impact of the various assumptions made by the analyses. In general, it is reasonable to assume that sources of uncertainty that were not explicitly represented by the Monte Carlo analysis would lead to uncertainties being larger than those quantified by this study. The absence of these uncertainties means that the overall uncertainty estimates should be regarded as 'optimistic', i.e., the uncertainty would be higher if these additional model uncertainties were included in the analysis.

From a practical perspective the uncertainties are irreducible 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. Reducing the uncertainties associated with this study would probably require long term sampling at considerably more SOE sites. In addition, significantly reducing uncertainties will probably require increasing understanding of the processes involved in contaminant loss, transport, and transformation in catchments.

The NPS-FM requires regional councils to set limits on resource use to achieve environmental outcomes (e.g., TASs). This report helps inform Regional Council processes for setting limits by assessing the approximate magnitude of the contaminant load reductions needed to achieve the national bottom lines for several TASs with a quantified level of uncertainty. However, this report does not consider what kinds of limits on resource use 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.

Table A. The load reductions for the four contaminants required for individual regions and the whole of New Zealand to achieve the national bottom lines for the target attribute states that were assessed by this study. 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. Load reductions required that are greater than 100% are because contaminant loads can decrease in the downstream direction due to attenuation and retention (for example in lakes and behind dams).

Region	TN	TP	*E. coli*	Sediment
Northland	3 (1 - 5)	2 (1 - 7)	80 (70 - 91)	15 (4 - 30)
Auckland	6 (4 - 8)	3 (2 - 5)	73 (67 - 78)	7 (4 - 11)
Waikato	6 (2 - 15)	6 (2 - 20)	91 (70 - 126)	47 (29 - 66)
Bay of Plenty	7 (1 - 18)	1 (0 - 7)	61 (48 - 79)	17 (3 - 39)
Gisborne	3 (0 - 6)	6 (0 - 31)	85 (56 - 112)	41 (9 - 60)
Taranaki	17 (6 - 30)	3 (1 - 9)	72 (64 - 82)	23 (4 - 53)
Manawatū-Wanganui	15 (8 - 25)	12 (3 - 38)	90 (58 - 125)	58 (42 - 75)
Hawke’s Bay	22 (7 - 40)	6 (2 - 15)	55 (41 - 73)	20 (4 - 36)
Greater Wellington	12 (5 - 23)	9 (5 - 16)	61 (46 - 83)	18 (9 - 29)
Tasman	2 (1 - 4)	3 (1 - 10)	40 (29 - 52)	3 (1 - 10)
Marlborough	6 (2 - 13)	2 (0 - 4)	29 (19 - 50)	28 (8 - 55)
West Coast	0 (0 - 1)	1 (0 - 2)	19 (12 - 36)	18 (8 - 29)
Canterbury	44 (38 - 50)	6 (3 - 9)	45 (34 - 58)	49 (22 - 76)
Otago	33 (19 - 46)	13 (4 - 24)	60 (40 - 77)	338 (5 - 1089)
Southland	41 (28 - 55)	12 (4 - 23)	75 (60 - 88)	24 (7 - 52)
Total	19 (15 - 22)	6 (4 - 12)	73 (60 - 84)	33 (21 - 44)

1 Introduction

This study evaluated the current state of four contaminants (nitrogen, phosphorus, *Escherichia coli* (*E. coli*) and sediment) in rivers, lakes and estuaries across New Zealand and assessed the reduction in the contaminant loads that would be required to achieve a set of minimum acceptable states. The minimum acceptable states were generally defined by the national bottom lines for attributes defined by Appendix 2A of the National Policy Statement for Freshwater Management 2020 (NPS-FM; NZ Government, 2023) that can be modelled in a consistent and comprehensive manner across New Zealand. The current state of river, lake and estuary receiving environments were compared to relevant criteria and where current concentrations exceeded those criteria, the receiving environments were deemed to be non-compliant. The 'load reduction required' for a non-compliant receiving environment was evaluated as the reduction that would allow the current concentration to equal the criteria. This study did not consider how the contaminant load reductions could be achieved.

Excessive concentrations of nutrients, sediment and microbes cause adverse effects for values associated with aquatic ecosystems. Excessive nitrogen and phosphorus have at least two types of impacts. First, nitrogen concentrations in the form of nitrate can reach toxic levels that impair aquatic animal survival, growth and reproduction (Camargo and Alonso, 2006). Second, when not limited by light or other nutrients, primary production in lakes, rivers and estuaries can be stimulated by nitrogen and/or phosphorus enrichment, causing excessive plant biomass and ecological degradation associated with shifts from low productivity or oligotrophic states to eutrophic or hypertrophic states (Abell *et al.*, 2020; Biggs, 2000; Plew *et al.*, 2020). Consequently, managing the anthropogenic component of nitrogen and phosphorus loads to achieve toxicity and trophic state target attribute states in lakes, rivers and estuaries is a requirement of the NPS-FM.

The microbe *Escherichia coli (E. coli*) is an indicator of faecal contamination and associated pathogens. Excessive concentrations of *E. coli* indicates unacceptable health risks to humans coming into contact with water (MFE and MoH, 2003). Consequently, management to ensure risks to human health are within an acceptable range is a requirement of the NPS-FM.

Sediment is a contaminant that affects ecosystem health through several modes of impact. Fine suspended sediments change the optical characteristics of water (visual clarity and light penetration), which impacts on the 'visual habitat' of animals and the aesthetic and recreational value of water bodies. Reduced light penetration can inhibit growth of aquatic plants and algae leading to ecosystem impacts including significant changes to ecosystem structure. Sediments suspended in the water column can also have physical effects on animals such as gill clogging and abrasion, effects on some migratory fish species and effects on food quality and quantity. Deposition of fine sediment on the beds of rivers, lakes and estuaries degrades benthic habitat and can result in burial and suffocation of benthic ecosystems. Deposited sediment also degrades the aesthetic and recreational value of waterbodies.

In this study, the nominated minimum acceptable states for rivers and lakes were set as the national bottom lines for selected attributes defined by the Appendix 2A[2] of NPS-FM. This includes the nitrate toxicity, periphyton, *E. coli* and suspended sediment attributes for rivers, and the total nitrogen and total phosphorus attributes for lakes. The NPS-FM does not have attributes for estuaries. We therefore nominated minimum acceptable states for plant biomass

[2] Appendix 2A lists attributes requiring limits on resource use.

in estuaries based on levels that Plew *et al.* (2020) considered are equivalent to the NPS-FM's national bottom lines. We note that this set of the minimum acceptable states does not include all the attributes listed in the NPS-FM. The attributes that were included in this analysis are those for which there are currently data and models that can be used to estimate current state in all rivers, lakes and estuaries that were represented by this study.

The results of the study are reported as required reductions in current loads of the four contaminants nitrogen, phosphorus, *E. coli* and sediment. These load reductions were evaluated for all individual river segment, lake and estuary receiving environments and this fine scale data is available as supplementary material. In this report, the individual receiving environment results were aggregated to report on the 15 individual jurisdictional regions and the whole of New Zealand. The load reductions required are also summarised at the level of 'critical point catchments' (see 2.2 for details). In addition, for each critical point catchment, the 'limiting environment' is also identified (i.e., whether it is an estuary, lake or river that determines the load reduction required in the critical point catchment).

The study estimated the uncertainties associated with all assessments of the load reductions required for all four contaminants. Uncertainty is unavoidable because the analyses are based on models that are simplifications of reality and because the models are informed by limited data. The uncertainties associated with two key components of the analyses: the estimated current concentrations and loads, were quantified and were combined in Monte Carlo analyses. The Monte Carlo analyses simulated 100 'realisations' of the load reduction calculations, which were used to define the probability distributions of all estimates. The probability distribution describes the range over which the true values of the load reductions are expected to lie. The best estimate of the load reduction is the mean value of the distribution, and the extreme lower and upper values were represented by the 5^{th} and 95^{th} percentiles of the distribution (i.e., these are the limits of the 90% confidence interval).

The analysis methodology is based on two previous national-scale studies of nitrogen load reduction requirements (MFE, 2019; Snelder *et al.*, 2020). The MFE (2019) study concerned evaluating the impact of the periphyton attribute of the National Policy Statement – Freshwater (NPS-FM; NZ Government, 2023) and the proposed addition of a dissolved inorganic nitrogen (DIN) attribute. The national-scale study evaluated the total nitrogen (TN) load reductions required across New Zealand to allow rivers to achieve the NPS-FM bottom-lines associated with the periphyton attribute and the additional proposed DIN requirement. The Snelder *et al.* (2020) study evaluated the total nitrogen (TN) load reductions required across New Zealand to allow rivers, lakes and estuaries to achieve the NPS-FM bottom lines for rivers and lakes, and nominated equivalent target attribute states for estuaries. This methodology has also been applied in individual regions such as Southland to the estimation of nutrient load reductions (Snelder, 2021) and *E. coli* load reductions (Snelder and Fraser, 2021a). There has been ongoing effort to improve the methods and update the datasets used to conduct the studies over time and this has resulted in some differences in the load reductions estimated through time, which we comment on in the discussion section below.

2 Methods

2.1 Attributes, contaminants, and national bottom lines

The National Objectives Framework (NOF) of the National Policy Statement for Freshwater Management (NPS-FM; NZ Government, 2023) establishes a number of attributes and associated criteria that represent a graduated range of potential target attribute states for freshwater receiving environments in New Zealand. Each table of Appendix 2 of the NPS-FM represents an attribute that must be used to define a target attribute state that provides for a particular environmental value. For example, Appendix 2A, Table 6 defines the nitrate toxicity attribute, which is defined by nitrate-nitrogen concentrations that will ensure an acceptable level of toxicity to support the "Ecosystem health (Water quality)" value. Target attribute states are defined by one or more numeric attribute states associated with each attribute. For example, for the nitrate-nitrogen toxicity attribute there are two numeric attribute states defined by the annual median and the 95th percentile concentrations. Nitrate concentrations also need to be managed to achieve target attribute states defined for the trophic state aspect of the Ecosystem health value, such as the periphyton attribute for rivers and the total nitrogen, total phosphorus and chlorophyll a attributes for lakes. Furthermore, the NPS-FM also requires that nutrients be managed to achieve environmental outcomes sought for any nutrient-sensitive downstream environments such as estuaries. Importantly, the NPS-FM requires nutrient concentrations or loads to be set that achieve all the attributes affected by nutrients in the different parts of catchments where they are relevant (e.g., in rivers, lakes and estuaries).

For each attribute, the NOF defines categorical numeric attribute states as four (or five) attribute bands, which are designated A to D (or A to E, in the case of the *E. coli* attribute). The attribute bands represent a graduated range of support for environmental values from high (A band) to low (D or E band). The attribute bands are intended to be simple shorthand for communities and decision makers to discuss options and aspirations for acceptable water quality and to define objectives. Attribute bands avoid the need to discuss target attribute states in terms of technically complicated numeric attribute states and associated numeric ranges. Each band is associated with a narrative description of the outcomes for values that can be expected if that attribute band is chosen as the target attribute state.

For most attributes, the D band represents a condition that has been identified by the NPS-FM as universally unacceptable in any waterbody nationally. The threshold between the C and the D band (i.e., the C/D threshold) is referred to as the "bottom line". Regional councils must have a plan to improve water quality at locations that are below the bottom line to a C-band state or better. In the case of the Nitrate (toxicity) and Ammonia (toxicity) attributes in the 2020 NPS-FM, the C band is unacceptable, and the bottom line is therefore the B/C threshold.

The primary aim of setting target attribute states is to support freshwater values (Table 1) and to help subsequent specification and justification of resource use limits. Resource uses that result in the discharge of contaminants (i.e., land use and point source discharges) can be quantitatively linked to several of the NOF attributes shown in Table 1. Setting target attribute states based on these attributes allows maximum contaminant concentration and load to be specified and this can then be used to justify policies that limit resource use. Where current attribute states shown in Table 1 are below the bottom line, the minimum contaminant concentration and load reduction requirements are those that will achieve the bottom line (i.e., generally the C/D threshold).

Table 1. Values, attributes and associated contaminants. The attribute names are as defined in Appendix 2A of the NOF.

Value	Attribute and receiving environment			Relevant contaminant
	River	Lake	Estuary	
Ecosystem health	Periphyton and nitrate toxicity	Phytoplankton	Macro-algae & phytoplankton	Nutrients (Nitrogen and Phosphorus)
Human contact	*E. coli*			*E. coli*
Ecosystem health	Suspended fine sediment			Sediment

Determining whether current contaminant concentrations and loads need to be reduced in a catchment generally requires setting target attribute states. Target attribute states are chosen by decision makers from amongst the available options in political processes and therefore determining load reduction requirements is not an entirely technical problem. However, where current attribute states are below the bottom line, reductions are necessary because the political decision has already been made that the national bottom line is the minimum acceptable state. In this study, we assessed the size of the load reductions necessary to achieve at least the national bottom lines for the attributes and receiving environments shown in Table 1 for all rivers, lakes and estuaries of New Zealand. Options to achieve target attribute states that are better than the national bottom lines will require larger load reductions and quantifying these is beyond the scope of this study.

2.2 General approach

The analyses undertaken by this study used available river water quality and hydrological data and several extant models (Figure 1). The modelling is based on a spatial framework that represents New Zealand's drainage network (i.e., streams and rivers) and the associated catchments as well as the connected lake and coastal (estuary) water bodies. The drainage network was represented by the GIS-based digital drainage network (version 2.4; hereafter DN2.4), which underlies the River Environment Classification (REC; Snelder and Biggs, 2002). The digital network was derived from 1:50,000 scale contour maps and represents New Zealand's drainage network as 593,000 segments bounded by upstream and downstream confluences, each of which is associated with a sub-catchment. The terminal segments of the river network (i.e., the most downstream points in each drainage network that discharge to the ocean) were identified.

Lakes were represented in the spatial framework by the lakes layer of the Freshwater Environments of New Zealand GIS database (FENZ; Leathwick *et al.*, 2010). These lakes were represented in the spatial framework as polygons that were derived from FENZ. The 771 FENZ lake polygons that could be reliably intersected with DN2.4 were included in the study. Estuaries were represented in the spatial framework by the coastal hydrosystems database (Hume *et al.*, 2016). A total of 416 Estuaries were represented in the spatial framework as polygons that could be reliably intersected with DN2.4. All river segments, lakes and estuaries were assigned to one of 15 jurisdictional regions corresponding to regional council boundaries (or unitary authorities in the case of Marlborough and Tasman). The Nelson district was included in the Tasman region in this study.

Conceptually, contaminant (nitrogen, phosphorus, sediment and *E. coli*) loads derive from the upstream catchments and are transported to the receiving environments by the drainage network (Figure 1). Models were used to predict the current concentrations[3] of contaminants at each segment of the drainage network, each of which also represents a river receiving environment. Loads of nutrients (nitrogen, phosphorus) and *E. coli* were derived from spatial models that were based on long term river state of environment monitoring sites located across New Zealand. The nutrient loads (i.e., nitrogen and phosphorus) predicted for the drainage network were used to estimate the nutrient loads delivered to lake and estuary receiving environments. In the present report, loads of suspended sediment were obtained from modelling completed by NIWA for the Ministry for the Environment (MfE) in support of the 2020 update to the NPS-FM (Hicks, Semadeni-Davies, *et al.*, 2019).

The criteria to achieve target attribute states in river, lake and estuary receiving environments are primarily defined in terms of contaminant concentrations. The analysis converts the concentration criteria into an equivalent annual load that is called the maximum allowable load (MAL, i.e., the load that will allow the target attribute states to be achieved). The compliance of rivers, lakes and estuaries with the concentration criteria is assessed by comparison to current concentrations or the associated loads. Receiving environments with concentrations or loads that are less than or greater than the criteria or MAL are compliant or non-compliant, respectively. The current annual contaminant loads are compared to the MAL and where the current load is higher, the difference is the local excess load (i.e., the amount by which the current contaminant load at a receiving environment would need to be reduced to achieve the target attribute state).

The load reduction required at any receiving environment (including any point in the drainage network) is the minimum load reduction that ensures the current load at that and all upstream receiving environments do not exceed the MAL. The load reduction required differs from the local excess load in that it considers the excess load of all upstream receiving environments. Thus, a receiving environment 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 reflects a reconciliation of those upstream local excess loads. Load reductions required are tabulated for the 15 jurisdictional regions and for all New Zealand for each contaminant as both absolute and relative quantities. The absolute load reduction required is expressed for nitrogen, phosphorus as tonnes per year (t yr^{-1}) and as a yield per year (kg ha^{-1} yr^{-1}), for sediment as a mega tonnes per year (Mt yr^{-1}) and as a yield per year (t km^{-2} yr^{-1}), and for *E. coli* as a total number of organisms per year (*E. coli* yr^{-1}) and as a yield of organisms per year (*E. coli* ha^{-1} yr^{-1}). The relative load reduction required is calculated as the load reduction required (current load – MAL) divided by the current load and expressed as a percentage. The benefit of expressing the load reduction required in relative terms is that it is a comparable quantity across contaminants.

The final step identifies critical points, their catchments (critical catchments), the critical catchment excess load, and the limiting environment type. This begins by identifying critical points in each sea-draining catchment. A critical point is defined as a receiving environment for which the ratio of the current contaminant load to MAL is not exceeded by any upstream receiving environment (McDowell *et al.*, 2018). The catchment upstream of the critical point is the critical point catchment. The critical catchment excess load indicates the load reduction required at the critical point to allow all receiving environments upstream of the critical point (i.e., in the critical catchment) to achieve their target attribute states. The critical catchment excess load is the local excess load at the critical point. If this excess load is greater than zero,

[3] Note that the criteria for suspended fine sediment attribute (Table 1) are defined in terms of visual clarity, which is an optical property of the water column and not a concentration. Visual clarity is used as the measurement but is strongly related to the concentration of suspended fine sediment.

there is an unacceptable level of contaminant loss in the upstream catchment, which McDowell *et al.* (2018) referred to as 'pressure'. The critical catchment excess load can be expressed as an absolute (excess) yield (the excess load divided by the total area of the upstream catchment; mass ha^{-1} yr^{-1}). The critical catchment excess load can also be expressed as a proportion of the current load (i.e., excess load/current load; %). As for the load reduction required, expressing the critical catchment excess load in relative terms allows comparison across contaminants. The limiting environment of a critical point indicates whether the load reduction requirement at that point is determined by an estuary, river or lake. 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.

The process of identifying the critical points is as follows. The terminal segment of every sea-draining catchment (the river mouth or estuary) is defined as a critical point, the current load to MAL ratio is noted, and the local excess load is assigned as the critical catchment excess load. From the terminal segment, the current load to MAL ratio at successive upstream receiving environment are obtained. Note that successive receiving environments may be river segments or lakes. At each receiving environment, the current load to MAL ratio is compared with the same ratio for the downstream critical point. If the current load to MAL ratio at the receiving environment is greater than that of the downstream critical point, the receiving environment is defined as a critical point and local excess load for the receiving environment is assigned as the excess load. If the current load to MAL ratio at the receiving environment is less than that of the downstream critical point, the critical point and critical catchment excess load are unchanged. The process continues upstream to the catchment headwaters. More details of the process of defining critical points are provided by Snelder *et al.* (2020).

The results of the critical points analysis are visualised by mapping critical catchments coloured by their excess loads. The differences in the load reductions required, across the four contaminants, are compared by plotting the cumulative area of critical catchments against their excess load (expressed in relative terms).

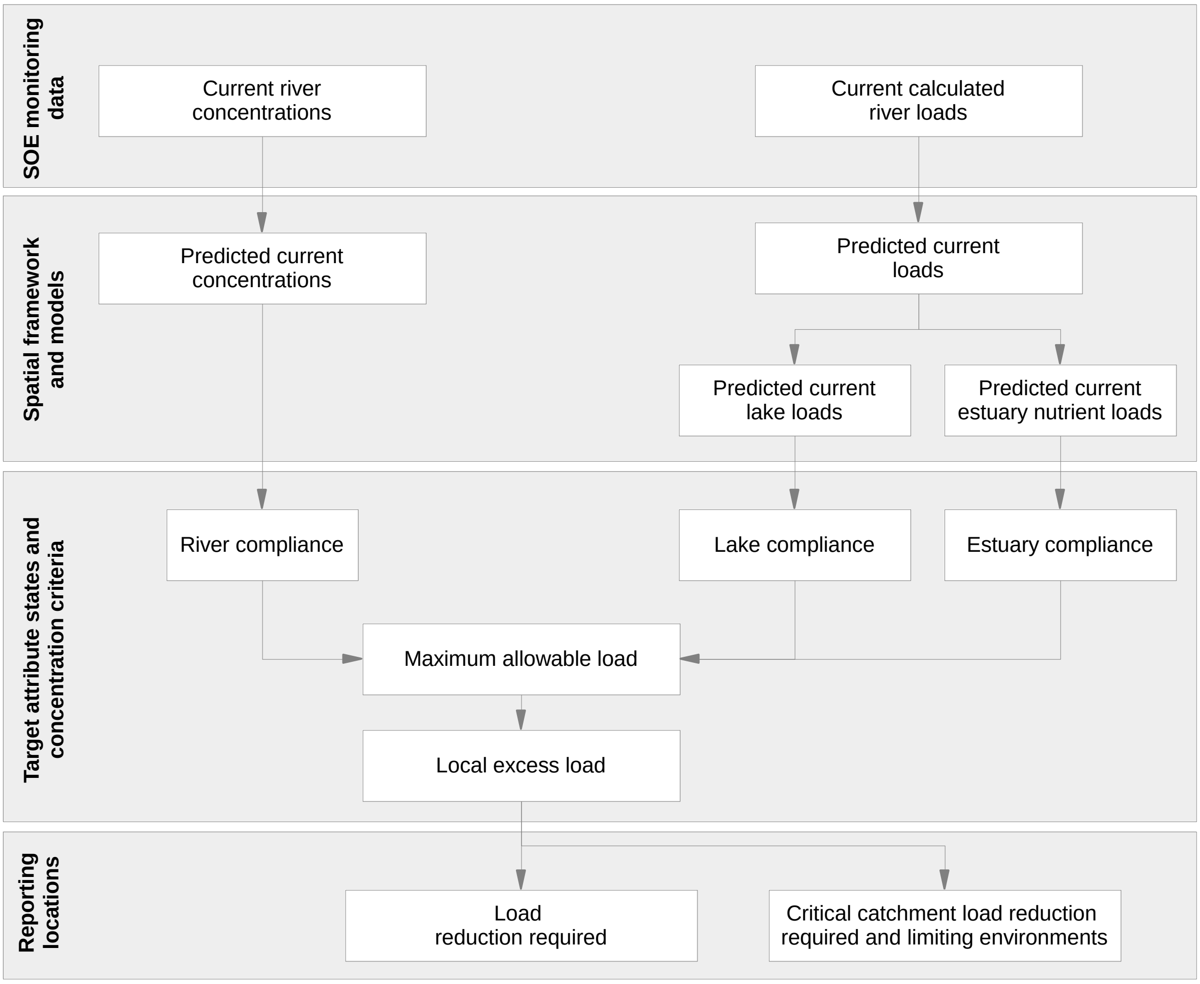

Figure 1. Schematic diagram of the general approach to assessment of contaminant load reductions required to achieve freshwater objectives. The details vary for each of the four contaminants.

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

2.3 Estimated current state

2.3.1 Nitrogen and Phosphorus

Estimates of the current median concentrations of the nutrients: total nitrogen (TN), nitrate-nitrogen (NO3N), and total phosphorus (TP), were made for all segments of the drainage network using river water quality monitoring data and statistical regression modelling. In addition, estimates of the median soluble proportion of TN (NO3N:TN) were made for all segments of the drainage network. Because the site median values of NO3N:TN represent proportions, they ranged between zero and one.

The statistical models were fitted to site median values of TN, TP, NO3N, and NO3N:TN obtained from the national state of environment (SOE) study of Whitehead *et al.* (2021). Median values pertained to a total of 850 river water quality monitoring sites that were distributed across New Zealand (Figure 2). All values were derived from monthly or quarterly observations of concentrations for the five year period 2016 to 2020 (inclusive). The values of median NO3N:TN for each site were derived by first evaluating the ratio of the soluble component to total for each observation occasion, and then taking the median of these values across all dates. We applied the same requirement as Whitehead *et al.* (2021), which restricted the site × variable combinations to those for which there were observations for at least 90% of the sampling intervals in that period (at least 56 of 60 months or 18 of 20 quarters). This resulted in slightly differing numbers of sites between variables with 848 for TN, TP, NO3N and 833 sites for NO3N:TN.

The statistical regression modelling was based on the same approach as MFE (2019), Snelder *et al.* (2020) and Whitehead, Fraser, and Snelder (2021). For each water quality variable, a type of regression model called a random forest (RF) was fitted to the observed monitoring site median values.

The regression model predictor variables were the same as those used by the national study of Whitehead, Fraser, and Snelder (2021) and describe various aspects of each site's catchment including the climate, geology and land cover. In addition, the predictor variables included five measures of 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 studies that have only had access to descriptions of the proportion of catchment occupied by different land cover categories (e.g., Whitehead, 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 (Snelder *et al.*, 2021). 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}).

Prior to fitting the models, the site median values were transformed to increase the normality of their distributions. Note that although RF models make no assumptions about data distributions, normalising the response variable improves model performance (Snelder *et al.,* 2018). The distributions of the site median concentration values for TN, TP and NO3N were $\log_{10}$ transformed. A logit transformation was applied to the values of NO3N:TN to increase the normality of the distributions. A logit transformation is defined as:

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

where x are the site NO3N:TN values. The logit transformed values range between $-\infty$ and $+\infty$.

The fitted RF models were combined with a database of predictor variables for every network segment in the region and used to predict current median concentrations of TN, TP, NO3N, and the values of NO3N:TN for all segments. Because the modelled variables were $\log_{10}$ or logit transformed prior to model fitting, the raw model predictions were in the $\log_{10}$ or logit space. The raw model predictions for TN, TP and NO3N were back transformed to the original units (i.e., mg m^{-3}) by raising them to the power of 10 and correcting for re-transformation bias as described by Whitehead (2018). The raw predictions for NO3N:TN values were back transformed to proportions (i.e., values in the 0 to 1 range) using the inverse logit transformation:

$$Proportion = \frac{e^x}{1+e^x} \qquad \text{Equation 2}$$

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

The performance of the RF models was evaluated using three measures: regression R^2, Nash-Sutcliffe efficiency (NSE), and 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. A NSE of 1 corresponds to a perfect match between predictions and the observations. A 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). PBIAS is computed as the sum of the differences between the observations and predictions divided by the sum of the observations (Moriasi *et al.*, 2007). The normalization associated with R^2, NSE and PBIAS allows the performance of TN, NO3N, TP and NO3N:TN models to be directly compared and evaluated against the three performance measures following the criteria proposed by Moriasi et al. (2015), outlined in Table 2.

The uncertainty of the RF models 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 the measures of model performance used in this study. The performance ratings are from Moriasi et al. (2015).

Performance Rating	**R^2**	**NSE**	**PBIAS**
Very good	$R^2 \geq 0.70$	NSE > 0.65	|PBIAS| <15
Good	$0.60 < R^2 \leq 0.70$	0.50 < NSE ≤ 0.65	15 ≤ |PBIAS| < 20
Satisfactory	$0.30 < R^2 \leq 0.60$	0.35 < NSE ≤ 0.50	20 ≤ |PBIAS| < 30
Unsatisfactory	$R^2 < 0.30$	NSE ≤ 0.35	|PBIAS| ≥ 30

Figure 2. Locations of the river SOE monitoring stations used to fit the nutrient concentration models.

2.3.2 E. coli

The definition of target attribute states for protection for human health in rivers across New Zealand are expressed using four *E. coli* statistics: median *E. coli* 100ml^{-1} (Q50); 95th percentile *E. coli* 100ml^{-1} (Q95); proportion of exceedances over 260 *E. coli* 100ml^{-1} (G260); and proportion of exceedances over 540 *E. coli* 100ml^{-1} (G540). The analysis was based on predicted values of these four *E. coli* statistics for all segments of the drainage network from spatial statistical regression models fitted with the same predictor variables as for the nutrient variables.

The statistical modelling commenced by calculating each of the four *E. coli* statistics for 842 SOE monitoring sites across New Zealand (Figure 3). *E. coli* had been measured at each site on a monthly basis for the five-year period ending 2020 (Whitehead, Fraser, and Snelder, 2021). For each *E.coli* statistic (i.e., Q50, Q95 G260, G540), a RF model was fitted to the observed monitoring site values using the same predictor variables as for the nutrient models.

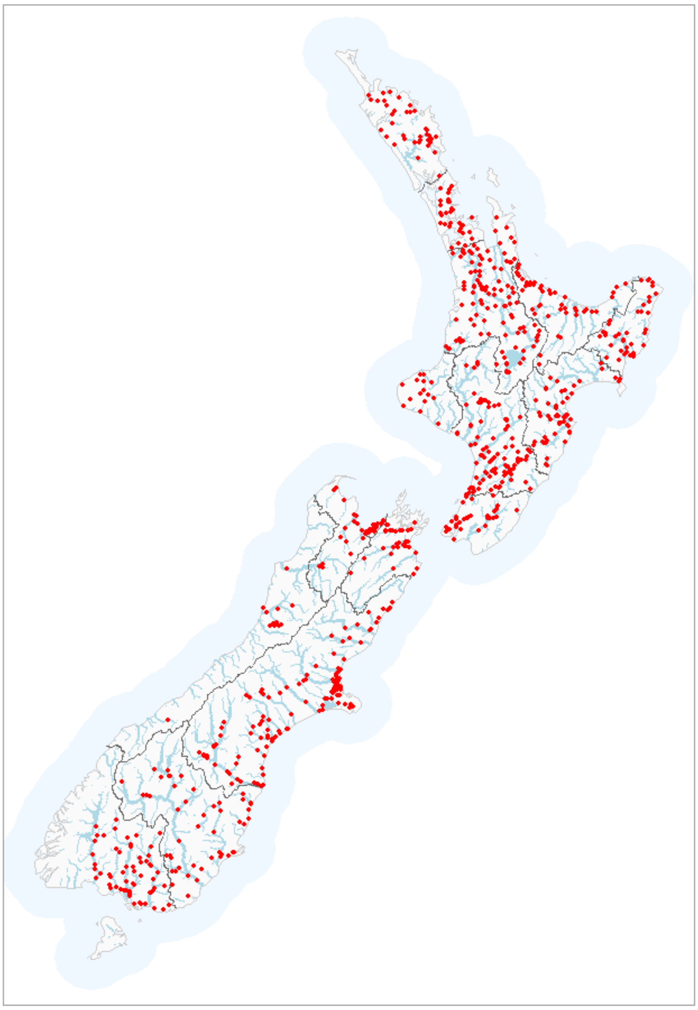

Figure 3. Locations of the river SOE monitoring stations used to fit the E. coli statistics models.

The site Q50 and Q95 values were $\log_{10}$ transformed to improve model performance. A logit transformation (Equation 1) was applied before fitting the model for G260 and G540 values. 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 performance of the RF models was evaluated using three measures: regression R^2, Nash-Sutcliffe efficiency (NSE), and bias and the uncertainty of the predictions was quantified using RMSD.

2.3.3 Sediment

Visual clarity is the measurement unit for suspended fine sediment attribute for rivers defined by the NPS-FM (2020). Estimates of current state of visual clarity in rivers are based on statistical model predictions of median visual clarity for each segment of DN2.4.

The statistical modelling commenced by calculating the median of monthly visual clarity observations at SOE monitoring sites across New Zealand for the five-year period ending 2020 (Whitehead, Fraser, and Snelder, 2021). Predicted values of river visual clarity for all segments of the drainage network were produced from the SOE site median values using spatial statistical regression (RF) modelling that used the same predictor variables as for the nutrient variables. A total of 728 river SOE monitoring sites were used to fit the river visual clarity model (Figure 3). The performance of this RF model was evaluated using three measures: regression R^2, Nash-Sutcliffe efficiency (NSE), and bias and the uncertainty of the predictions was quantified using RMSD.

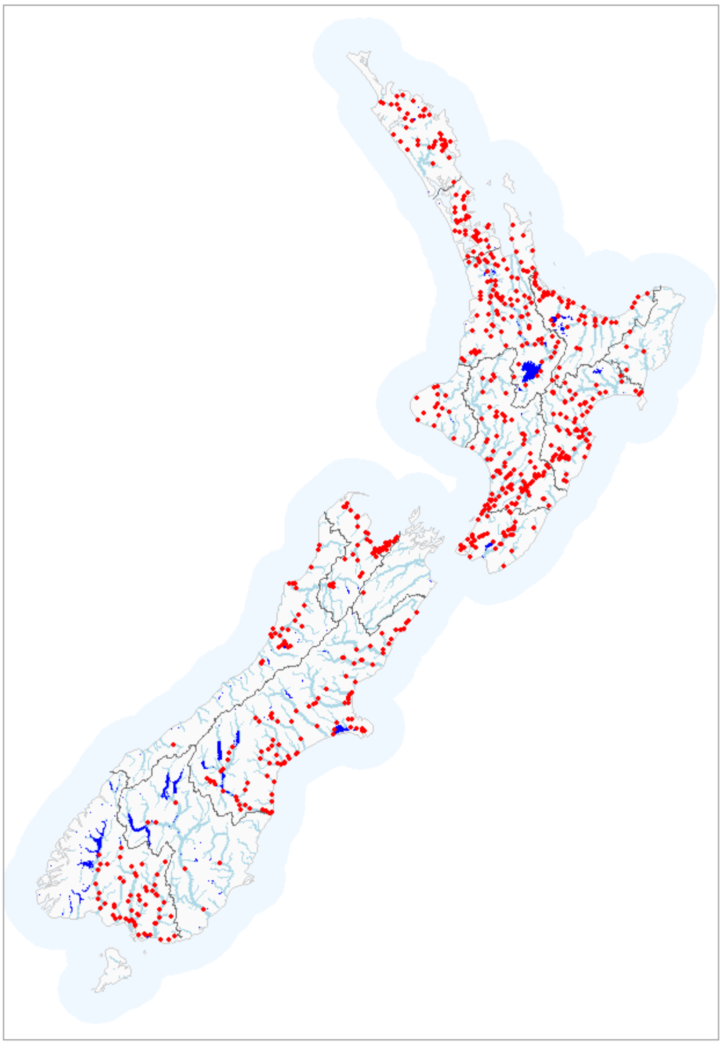

Figure 4. Locations of the river SOE monitoring stations used to fit the visual clarity models.

2.4 Estimated current river loads

2.4.1 TN and TP

Loads of TN and TP were calculated for those river SOE monitoring sites where TN and TP were measured and where a record of measured daily mean flows could be obtained 2020 (Figure 5) using the methods described by Snelder *et al.* (2023). We required each site had at least 60 observations of concentration in at least 8 years in the 10 years observations up to the end of 2020. 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 2020[4]. The loads were expressed as yields by dividing by the catchment area (kg ha^{-1} yr^{-1}).

We used the same statistical regression modelling approach as for concentrations to fit RF models to calculated monitoring site loads for TN and TP. The site yield values were $\log_{10}$ transformed to improve model performance (Snelder *et al.,* 2018).

The fitted RF models were combined with a database of predictor variables for every segment in DN2.4 and used to predict current yields of TN and TP for all segments. Model predictions were back-transformed and corrected for re-transformation bias as described by Snelder *et al.* (2018). The load model performance was evaluated following the same criteria used for the concentration models (Table 2).

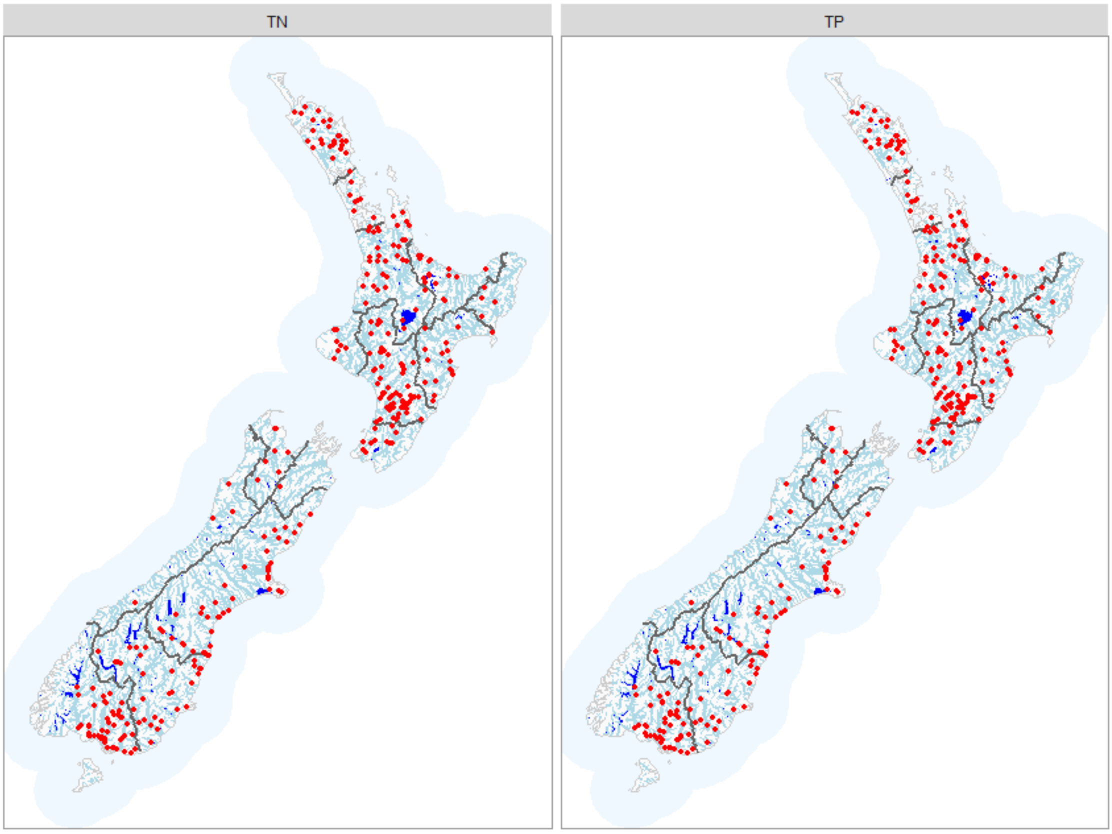

Figure 5. Locations of the river water quality monitoring stations used to fit the TN and TP load models.

[4] Note that this report refers to 'current loads and concentrations' because the loads and concentrations estimated for 2020 are unlikely to be appreciably or statistically significantly different to loads at the time this study was conducted (2023).

2.4.2 E. coli

Estimates of current loads of *E. coli* (number of *E. coli* organisms per year) were calculated for 334 river SOE monitoring sites where *E. coli* was measured monthly and where a record of measured daily mean flows could be obtained (Figure 6). Loads were calculated using the methods described by Snelder *et al.* (2018, see Appendix C for details). We required each site had at least 60 observations of concentration in at least 8 years in the 10 years observations up to the end of 2020. 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 2020[5]. The loads were expressed as yields by dividing by the catchment area (*E. coli* ha^{-1} yr^{-1}).

Estimates of current loads of *E. coli* for all segments of the drainage network were made using the same statistical regression modelling approach as for the *E. coli* state statistics to fit RF models to calculated monitoring site loads. The site yield values were $\log_{10}$ transformed to improve model performance (Snelder *et al.,* 2018).

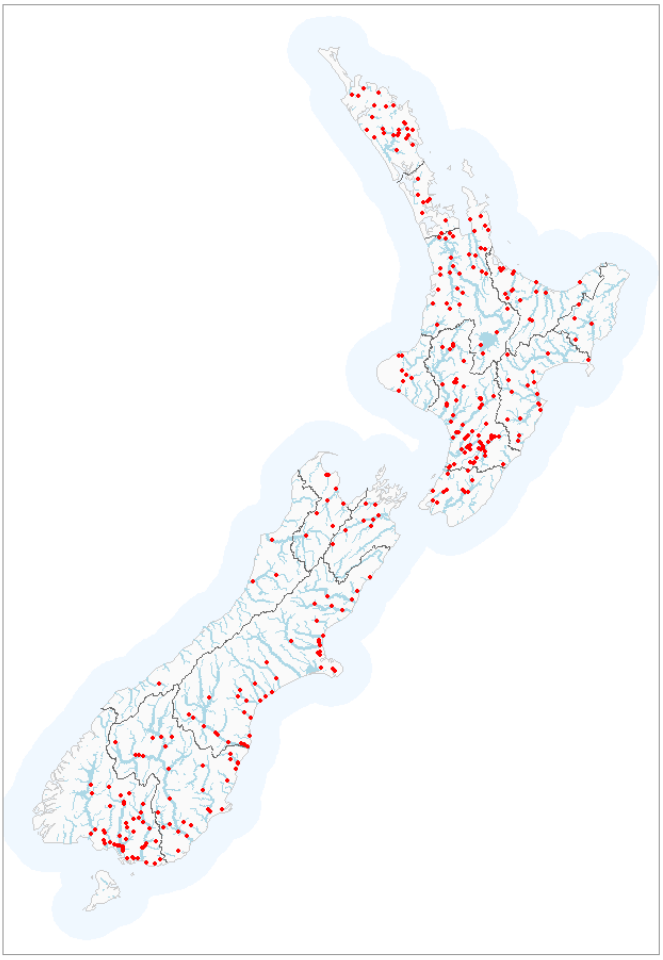

Figure 6. Locations of the 334 river water quality monitoring stations used to calculate E. coli loads.

The fitted RF 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* for all segments. Model predictions were back-transformed and corrected for re-transformation bias as described by

[5] Note that this report refers to 'current loads and concentrations' because the loads and concentrations estimated for 2020 are unlikely to be appreciably or statistically significantly different to loads at the time this study was conducted (2022).

Snelder *et al.* (2018). The load model predictions were evaluated following the same criteria used for the concentration predictions (Table 2).

2.4.3 Sediment

Estimates of current suspended sediment loads were obtained from the updated version of The Sediment Load Estimator after the regional adjustments explained by Hicks, Haddadchi, *et al.* (2019). The Sediment Load Estimator was chosen to predict sediment loads because it provides national coverage and was used to inform the 2020 update to the NPS-FM. The Sediment Load Estimator is an empirical model that provides predictions of mean annual river suspended sediment load for every segment of DN2.4[6]. The river sediment load modelling approach was based on grid-cells with an area of 1 hectare that are described by their average slope, mean annual rainfall, land cover, and erosion terrain[7]. The sediment loads for each segment were determined by summing the sediment loads from all raster units upstream and routing these loads down the stream network taking into account entrapment in lakes and reservoirs. It is noted that for the assessment of sediment, the predictions from the Sediment Load Estimator are equivalent to the RF model predictions of TN, TP, and *E. coli* yields.

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

For the 334 river SOE 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 pertaining to these sites. These models were used in subsequent steps to estimate the load reduction required (see section 2.8.2). These 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 for the Median and Q95 statistics. For the models for the G260 and G540 statistics, we log (base 10) transformed the yield values and logit transformed (Equation 1) the statistics.

The model performance and uncertainties of these models were evaluated using leave-one-out cross validation to obtain a set of independent predictions of the yields at each site. The model performance statistics shown in Table 2 were used to describe the performance of the four separate models based on the independent predictions. The characteristic uncertainty of each model was quantified by the RMSD. 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 Estimated current lake TN and TP concentrations

Actual water quality measures are available for only a small number of monitored lakes across New Zealand. However, estimates of in-lake nutrient concentrations were made by coupling estimated input loads from the drainage network with empirical lake nutrient loading models ('box models') of Abell *et al.* (2019, 2020).

The primary input to the models of Abell *et al.* (2019, 2020) is the mean flow weighted concentrations of TN and TP (hereafter TN_{in} and TP_{in}), which were obtained by dividing the estimated loads of TN and TP to each lake by the mean annual inflow volume. Annual inflow

[6] These data were accessed via MfE's Data Service (https://data.mfe.govt.nz/layer/103686-updated-suspended-sediment-yield-estimator-and-estuarine-trap-efficiency-model-results-2019/)

[7] An erosion classification developed by Manaaki Whenua / Landcare, with erosion terrain classes distinguished by slope, rock-type, soils, and dominant erosion processes.

volumes were obtained from estimates of mean flow made for every segment of the drainage network by Booker and Woods (2014).

For each lake, the concentration of TN and TP were predicted using the following models:

$$log_{10}(TP_{lake}) = \frac{log_{10}(TP_{in})}{1+(k_1+\Delta k_1 d)\tau_w{}^{k_2}} \qquad \textit{Equation 3}$$

$$log_{10}(TN_{lake}) = \beta_0 + \beta_1 log_{10}(TN_{in}) + \beta_2 log_{10}(Z_{max}) \qquad \textit{Equation 4}$$

where TP_{lake} and TN_{lake} are median concentrations of TN and TP (mg m^{-3}), k_1, Δk_1, k_2, and all β are fitted parameters provided by Abell *et al.* (2019, 2020), τ_w is water residence time (years) derived from the WONI database, and Z_{max} is the maximum depth of the lake derived from the WONI database. The variable d is a dummy variable that indicates whether a lake is shallow (d = 0) or deep (d = 1). We used the same threshold as Abell *et al.* (2019, 2020) of >7.5 m to define deep lakes.

2.7 Estimated current estuary TN and TP concentrations

Estimates of in-estuary nutrient concentrations were made by coupling estimated input loads from the drainage network (see Section 2.4.1) with simple estuary dilution models (Plew *et al.*, 2018, 2020). The dilution model predicts the TN and TP concentrations in the estuary based on annual catchment TN and TP loads, mean flow, ocean nitrogen and phosphorus concentrations, and dilution in the estuary. Each estuary included in the study was represented by a separate model, which are fully described by Plew *et al.* (2020).

2.8 Concentration criteria, compliance, maximum allowable loads, and local excess load

2.8.1 Nitrogen and phosphorus

Nitrogen and phosphorus concentration criteria for rivers, lakes and estuaries generally vary spatially to account for variation in the sensitivity of receiving environments to the effects of nutrients (Abell *et al.*, 2019; Plew *et al.*, 2018, 2020; Snelder *et al.*, 2019). For example, for an objective defined as a specific level of biomass, nutrient concentration criteria tend to be lower in rivers that have less variable flow regimes and lakes and estuaries that have longer residence times. Concentration criteria also vary with the level of biomass that is nominated by the objective; lower concentrations are required to restrict biomass to low levels compared to higher levels. The exception to this is the NO3N concentration criteria associated with the nitrate toxicity attribute.

2.8.1.1 Rivers

The first type of concentration criteria that is relevant to rivers is the NOF nitrate toxicity attribute. Bands for the nitrate toxicity attribute are shown in Table 3. In this study, predicted current nitrate concentrations in all segments of the DN2.4 network were compared to the B/C band threshold shown in Table 3 and where current concentrations exceeded the threshold, the segment was deemed to be non-compliant.

Table 3. Nitrate toxicity concentration criteria as mg NO_3-N m^{-3}.

Target attribute state	Nitrate concentration criteria
A	≤1,000
B	>1,000 and ≤ 2,400
C	>2,400 ≤ 6,900
D	>6.9

The second type of concentration criteria that is relevant to rivers is associated with the periphyton attribute. Periphyton is attached algae growing on the beds of rivers (slime). Some periphyton is a natural feature of rivers and is an essential component of the riverine food web. However, over-abundant periphyton degrades rivers from ecological, recreational and cultural perspectives. The periphyton attribute stipulates the levels of periphyton biomass in terms of a concentration of chlorophyll-*a* (the green pigment in plants) on the bed of rivers for NOF bands (Table 4).

Table 4. Periphyton biomass thresholds as mg chlorophyll-a m^{-2}. The NOF requires that this biomass threshold be not exceeded in 92% of monthly samples (i.e., not more than once per year on average for monthly sampling).

Target attribute state	Periphyton biomass thresholds
A	≤50
B	>50 and ≤120
C	>120 and ≤200
D	>200

In this study, the nutrient criteria to achieve the periphyton biomass attribute states were based on revisions to Snelder *et al.* (2022) that are described by Snelder and Kilroy (2023). The criteria are specified in terms of median concentrations of total nitrogen (TN) and total phosphorus (TP) and vary across 21 river classes defined by the second (Source-of-flow) level of the River Environment Classification (REC; Snelder and Biggs, 2002). The criteria were based on nutrient-biomass relationships that were subject to considerable uncertainty. There is therefore a risk that a proportion of locations will exceed a nominated biomass threshold even when they are compliant with the associated TN and TP criteria. Snelder, Kilroy, *et al.* (2023) provided for differing levels of this risk by incorporating an under-protection risk (UPR) criterion for the TN and TP concentration criteria. The UPR is an estimate of the proportion of locations that will exceed a nominated biomass threshold when all locations are compliant with the nutrient criteria. The UPR indicates the risk that a randomly drawn location will exceed the periphyton biomass specified for the nominated band. The level of acceptable risk is a management, rather than a scientific, decision. In this study the analyses were based on a UPR of 20%. The 20% UPR is always a lower concentration than that which would pertain to a higher level of risk (e.g., a 30% UPR) and a higher concentration than that which would pertain to a lower level of risk (e.g., a 10% UPR). The TN and TP concentration criteria to achieve the periphyton attribute states in this study are provided in Appendix A, Table 21.

It was assumed that river segments that have fine bed substrates (i.e., soft-bottomed streams and rivers) do not support conspicuous periphyton (i.e., will not allow high periphyton biomass to develop due to substrate instability). We discriminated soft-bottomed streams and rivers segments from those with coarse substrates by using substrate size index values of <3 and ≥3 respectively. Substrate size index values were based on modelled estimates that are available in the Freshwater Environments of New Zealand database (FENZ; Leathwick *et al.*, 2010) as described by Ministry for the Environment (2019).

Compliance for each river segment for nitrate toxicity and periphyton biomass (TN and TP) was derived by comparing its predicted current concentration with the relevant criteria. Where the current concentration was less than the concentration criteria, the segment was assessed as compliant and vice versa.

The nitrate toxicity concentration criteria were converted to equivalent TN concentration values at every network segment to make them consistent with the nitrogen criteria for river periphyton and for lakes and estuaries. The NO3N criteria were converted to TN equivalents by dividing by the predicted median soluble proportion of TN (NO3N:TN) for each segment (see Section 2.3). Implicit in this conversion is the assumption that that the ratio of NO3N to TN will remain the same if the loads of TN are changed.

At each segment, the governing TN criteria was whichever was the greater of the periphyton TN criterion or nitrate toxicity criterion, after conversion to its TN equivalent. This means that the nitrate toxicity criterion was always the governing TN criterion segments that were classified as soft-bottomed. The periphyton TN criterion was greater than the nitrate toxicity criterion for some REC Source-of-flow classes (Table 21), and in these cases the nitrate toxicity criterion was also always the governing TN criterion.

The MAL for TN and TP for river receiving environments was obtained by converting the concentration criteria into equivalent TN and TP loads. The conversion was based on the assumption that, because load is the integral of concentration discharge, the median concentration increases in proportion to the load, i.e., the following relationship applies:

$$\frac{Concentration_1}{Load_1} = \frac{Concentration_2}{Load_2} \qquad \text{Equation 5}$$

Therefore, the MAL for each segment of the river network was derived as:

$$MAL = Concentration_{Criterion} \times \frac{Current\ \ load}{Current\ concentration} \qquad \textit{Equation 6}$$

where $current\ load$ is the estimated current TN or TP load (kg yr^{-1}) for the network segment, $current\ concentration$ is the estimated current median concentration of TN or TP and $Concentration_{Criterion}$ is the criterion for TN or TP. Implicit in this conversion is the assumption that that the change in median concentration of the nutrients with change in load is in proportion to change in the loads of TN and TP. The local excess loads were calculated as the current TN and TP loads minus the respective MALs.

2.8.1.2 Lakes

The NOF specifies levels of phytoplankton (algae suspended in the water column) biomass in lakes to protect these ecosystems from eutrophication. In addition, the NOF specifies nutrient concentration criteria for TN and TP that are commensurate with the algae biomass levels (Table 5). In this study, only the TN and TP criteria were used, and it was assumed that compliance with these nutrient criteria would achieve the associated phytoplankton biomass criteria. The reason for this is that the available lake nutrient – phytoplankton biomass models represent biomass as a combined outcome of both TN and TP concentrations (Abell *et al.*

2019, 2020). These models are therefore not amenable to the analyses performed in this study because biomass cannot be specified by a unique concentration of TN or TP.

Table 5. Algae biomass thresholds for lakes as mg chlorophyll-a m^{-3} (annual median) and corresponding TN and TP criteria as mg m^{-3} (annual median).

Target attribute state	Chlorophyll-*a* thresholds	TN thresholds		TP thresholds
		Stratified	Polymictic	
A	≤2	≤160	≤300	≤10
B	>2 and ≤5	>160 and ≤350	>300 and ≤500	>10 and ≤20
C	>5 and ≤12	>350 and ≤750	>500 and ≤800	>20 and ≤50
D	>12	>750	>800	>50

In this study, the C/D threshold (i.e., the 'national bottom line') was adopted as the objective for lakes. The attribute band threshold specifies the TN and TP concentration criteria (Table 5) by lake type (stratified or polymictic). Lakes were assigned to the stratified type if their depth was > 7.5m for consistency with Abell *et al.* (2019, 2020), otherwise were assigned to the polymictic type.

Compliance was assessed by comparing the current estimated in-lake concentration with the concentration criteria. Where the current concentration was less than the concentration criteria, the lake was assessed to be compliant and vice versa.

The MAL for each lake was derived from the TN and TP concentration thresholds (Table 5). The TN and TP concentrations were converted into equivalent TN and TP loads (the MALs) by inverting Equation 3 and 4. Local excess loads were calculated for each lake as the current TN and TP loads minus the respective MALs.

2.8.1.3 Estuaries

Estuaries are susceptible to eutrophication when enriched with nutrients (particularly nitrogen) from the upstream catchment. Symptoms of eutrophication in estuaries include proliferations of algae, particularly benthic macro- and micro-algae and phytoplankton. These, in turn, drive organic enrichment of sediments, reduction of sediment oxygenation and water column dissolved oxygen levels, changes in benthic communities, reduced water clarity, and sometimes sulphide production due to organic matter breakdown. Many estuaries in New Zealand are shallow and have extensive intertidal areas. Symptoms of eutrophication in shallow intertidal estuaries are largely dominated by benthic impacts resulting from excessive macroalgae growth. Other estuaries are deeper and predominantly subtidal. Depending on the flushing time of deep estuaries, the expression of excessive nutrient loading and eutrophic conditions in these estuaries is high phytoplankton biomass.

Environmental objectives for estuaries are mandated by the New Zealand Coastal Policy Statement (NZCPS; DOC, 2010). However, the NZCPS does not have the structured approach to defining attribute states that the NOF does. While the NPS-FM does not define any compulsory attributes for estuaries, it does require regional councils to consider whether other attributes are needed[8] and specifically requires outcomes for downstream receiving environments such as estuaries to be considered when setting nutrient concentrations or loads[9]. This latter requirement implies the need to consider relevant attributes or criteria for assessing trophic state in estuaries. We therefore defined criteria that limit plant biomass to levels that Plew *et al.* (2020) proposed are equivalent to C/D attribute band thresholds (i.e., the national bottom line). The attribute states for estuaries are based on two types of primary production: macroalgae and phytoplankton. For macroalgae, the attributes are defined in terms of levels of Ecological Quality Rating (EQR), which is a combined metric of macroalgae cover and biomass. Plew *et al.* (2020) derived TN criteria that are based on 'potential concentrations' to achieve EQR bands that are similar to the NOF band system for rivers and lakes. In this report, we adopt higher TN concentration criteria than originally proposed by Plew *et al.* (2020), based on a recent analysis of a larger dataset of observed EQR values by Roberts *et al.* (2022) (Table 6). Potential concentrations were defined as the concentration that would occur in the absence of uptake by algae, or losses or gains due to non-conservative processes such as denitrification and nitrogen fixation. Note that the potential TN concentration criteria shown in Table 6 were calculated from different load estimates for each estuary to those estimated by this study. Macroalgae growth is not considered to be limited by phosphorus because macroalgae are very efficient at extracting phosphorus from the water column, even at low concentrations, and have a low phosphorus requirement in relation to nitrogen, compared to phytoplankton. Estuaries generally also have a sufficient supply of phosphorus due to the constant exchange of water with the ocean. There are therefore no phosphorus criteria associated with the macroalgae objective.

Table 6. EQR thresholds for estuaries and corresponding potential TN concentration criteria as mg m^{-3}.

Target attribute state	EQR thresholds	TN thresholds
A	1.0 > and ≥ 0.8	≥ 220
B	0.8 > and ≥ 0.6	220 < and ≤ 420
C	0.6 > and ≥ 0.4	420 < and ≤ 620

Plew *et al.* (2020) also suggested phytoplankton attributes states that are similar to the NOF band system for rivers and lakes. Band thresholds for estuary phytoplankton are based on annual 90th percentile biomass (as mg Chl-a m^{-3}). The phytoplankton bands differ for highly saline and less saline estuaries, and for low salinity estuaries and brackish lakes/lagoons respectively (Table 7). While the phytoplankton bands differ by salinity, in this study we used estuary type as a surrogate for salinity because the salinity of each estuary was not generally known. Thresholds for saline (euhaline) estuaries are applied to systems classified as Deep Subtidally Dominated Estuaries (DSDE) in the New Zealand Estuary Trophic Index (NZETI) classification system (Robertson *et al.*, 2016), or as a Deep drowned valley, Fjord or Coastal embayment in the New Zealand Coastal Hydrosystems (NZCHS) typology (Hume *et al.*, 2016). Thresholds for low salinity estuaries and brackish lakes/lagoons (oligohaline) are applied to NZETI Coastal Lakes, or NZCHS damp sand plain lakes, Waituna-type lagoons, or other predominantly freshwater systems. The intermediate thresholds (meso/polyhaline) are applied to NZETI Shallow Short Residence-time Tidal River Estuaries (SSRTRE) and Shallow

[8] NPS-FM clause 3.10
[9] NPS-FM clause 3.13

Intertidally Dominated Estuaries (SIDE), which are generally classified as freshwater river mouths, tidal river mouths, tidal lagoons and shallow drowned valleys in the NZCHS typology.

The TN and TP concentration criteria to achieve the phytoplankton bands differ for individual estuaries, primarily due to differences in estuary residence time. This study used the approach of Plew *et al.* (2020) to derive the MAL for TN and TP for each individual estuary based on combining a phytoplankton model with a simple dilution model that accounted for nitrogen inflows from both rivers and the ocean and for estuary hydrodynamics. Compliance for TN and TP was assessed based on 'potential concentrations' to achieve the phytoplankton bands. MAL for TN and TP were calculated separately by setting the other nutrient to a high value to avoid limitation of that nutrient. The MAL for TP apply when the equivalent MAL for TN are exceeded, and vice versa. If the MAL for TN is met, further increases in TP above its MAL will have minimal effect on the eutrophication response of the estuary.

Table 7. Phytoplankton biomass thresholds for estuaries and brackish lakes/lagoons as mg chlorophyll-a m^{-3}.

Target attribute state	**Thresholds for saline estuaries (euhaline; >30ppt salinity)**	**Thresholds for less saline estuaries (meso/polyhaline; 5-30ppt salinity)**	**Thresholds for low salinity estuaries and brackish lakes/lagoons (oligohaline; <5ppt salinity)**
A	≤4	≤8	≤10
B	>4 and ≤8	>8 and ≤12	>10 and ≤25
C	>8 and ≤12	>12 and ≤16	>25 and ≤60
D	>12	>16	>60

Compliance for TN and TP for each estuary was derived from the two relevant criteria: macroalgae and phytoplankton (Table 6 and Table 7) for the C/D attribute threshold. The TN and TP loads that are consistent with the respective criteria were derived for each estuary using the simple dilution models of Plew *et al.* (2020). These loads are detailed in Appendix B for each estuary. The lower of the two TN loads (i.e., to achieve the macroalgae or phytoplankton FWO) was used to define the MAL for TN for each estuary. The TP loads to achieve the phytoplankton FWO were used to define the MAL for TP. Compliance was assessed by comparing the current estimated TN and TP loads with their respective MAL. Where the current load was less than the MAL, the estuary was assessed to be compliant and vice versa. Local excess loads were calculated for each estuary as the current TN and TP loads minus the respective MALs.

Thresholds for TN and TP could not be derived for every estuary and objective (i.e., for both macroalgae and phytoplankton). Some estuaries are unlikely to support macroalgae due to low salinity and therefore do not have a MAL assessed for TN for the macroalgae attribute (see Appendix D). Some estuaries have low flushing times and are therefore unlikely to support high phytoplankton biomass and therefore do not have a MAL assessed for TN or TP for the phytoplankton FWO (see Appendix D). There are also estuaries that naturally exceed one or more band thresholds for TN and/or TP associated with the phytoplankton objectives due to nutrient input from the ocean. The relevant MALs for these estuaries are therefore zero, indicating that the FWO would not be achieved even if the current TN and TP loads were zero (see Appendix B).

2.8.2 E. coli

The NOF defines five target attribute states for human health denoted A, B, C, D and E. The five target attribute states are linked to criteria for the four *E. coli* statistics shown in Table 8. 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 8 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 achieve the target attribute state.

Table 8. Criteria used to define the E. coli target attribute states. The statistics are: Proportion of exceedances over 540 E. coli 100ml^{-1} (G540), Proportion of exceedances over 260 E. coli 100ml^{-1} (G260), Median E. coli/ 100ml^{-1} (Q50) and 95th Percentile E. coli 100ml^{-1} (Q95).

Target attribute state	***E. coli*** **statistic**			
	G540	**G260**	**Q50**	**Q95**
A	<5%	<20%	≤130	≤540
B	5-10%	20-30%	≤130	≤1000
C	10-20%	20-34%	≤130	≤1200
D	20-30%	>34%	>130	>1200
E	>30%	>50%	>260	>1200

The definition of target attribute states for protection for human health in rivers across NZ are expressed using the A to E grading system shown in Table 8 for each *E. coli* statistic. In this study, the C band was adopted as the target attribute state (i.e., the C/D band threshold was adopted as the 'national bottom line'). To assess compliance for each segment of the river network, the predicted current values of the four *E. coli* statistics were compared to the criteria for each *E. coli* statistic pertaining to the C/D band threshold. If all four *E. coli* statistics were less than their corresponding criteria, the segment was compliant, otherwise it was considered noncompliant.

The local excess load for *E. coli* was calculated in three steps. First, 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). Second, 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 RF model). Third, the local excess load was then evaluated as the current load minus the MAL.

For example, for the C band target attribute state, the Q50 criteria would be 130 *E. coli* 100ml^{-1} (Table 8). The *E. coli* yield corresponding to a Q50 of 130 *E. coli* 100ml^{-1} would be estimated using the linear model to be 69 giga *E. coli* ha^{-1} yr^{-1} (see Figure 9; Section 3.1.3 noting the $\log_{10}$ of 130 is 2.11). 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 250 *E. coli* 100ml^{-1}, the corresponding *E. coli* yield would be estimated from the linear model as 117 giga *E. coli* ha^{-1} yr^{-1} (see Figure 9; Section 2.8.2). 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., 41% ([117-69]/117). If the predicted current *E. coli* load were 190 giga *E. coli* yr^{-1} the MAL would be evaluated as 112 giga *E. coli* yr^{-1} (i.e., [100 – 41%] x 190). The local excess load would be evaluated as 190-112 = 78 giga *E. coli* yr^{-1}.

2.8.3 Sediment

The NOF defines four target attribute states for suspended fine sediment in rivers denoted A, B, C and D. The four target attribute states are linked to criteria that are defined in terms of visual clarity that apply to four Suspended Sediment Classes shown in Table 9. The attribute states are associated with low (A) to high (D) concentrations of suspended fine sediment, which are linked to low to high ecosystem health (Stoffels *et al.*, 2021).

Table 9. Criteria used to define the suspended fine sediment target attribute states. The criteria are defined in terms of visual clarity.

Target attribute state	Suspended Sediment Class			
	1	2	3	4
A	≥1.78	≥0.93	≥2.95	≥1.38
B	<1.78 and ≥1.55	<0.93 and ≥0.76	<2.95 and ≥2.57	<1.38 and ≥1.17
C	<1.55 and >1.34	<0.76 and >0.61	<2.57 and >2.22	<1.17 and >0.98
D	<1.34	<0.61	<2.22	<0.98

In this study, the C band was adopted as the target attribute state for suspended fine sediment (i.e., the visual clarity C/D band thresholds shown in Table 9 were adopted as the 'national bottom line'). Compliance for each segment of the river network was assessed in two steps. First, the suspended sediment class for each segment was identified based on that segment's REC class and that class's assignment to a Suspended Sediment Class defined in Appendix 2C of the NPS-FM. Second, the predicted current values of visual clarity for each segment were compared to the relevant criteria pertaining to the C/D band threshold. If current visual clarity was less than the criteria, the segment was compliant, otherwise it was considered noncompliant.

The local excess load for sediment was calculated in three steps. First, for all noncompliant segments the factor by which the current sediment load must be reduced to achieve the target visual clarity was calculated using the Sediment Load Reduction Factor model developed by Hicks, Haddadchi, *et al.* (2019). The Sediment Load Reduction Factor model is expressed as:

$$R = 1 - (V_t/V_c)^{1/d} \qquad \text{Equation 7}$$

where R is the sediment load reduction factor, V_t is the target attribute state (defined by the visual clarity C/D band thresholds shown in Table 9), V_c is the predicted current median visual clarity (m). In this study, the exponent d was assigned the national mean at-site value of -0.76 derived by Hicks, Haddadchi, *et al.* (2019). Hicks, Haddadchi, *et al.* (2019) reported the standard deviation of the at-site values as 0.13, which this study used as the characteristic measure of uncertainty for d and therefore has the same meaning as the RMSD values for the other models. Second, the local excess load for every segment was calculated as:

$$Local\ excess\ sediment\ load = \ R \times Predicted\ currrent\ sediment\ load \qquad \textit{Equation 8}$$

where the predicted current sediment load was obtained from the Updated Sediment Load Estimator for New Zealand (Hicks, Semadeni-Davies, *et al.,* 2019; Section 2.4.3). Finally, for every segment, the maximum allowable load (MAL) was evaluated as:

$$MAL = \ Predicted\ currrent\ sediment\ load - \ Local\ excess\ sediment\ load \qquad \textit{Equation 9}$$

2.9 Estimation of uncertainties

The analyses described above were based on statistical models that were all associated with uncertainties quantified as RMSD values. For each contaminant (i.e., nitrogen, phosphorus, *E. coli* and sediment) the uncertainties associated with each model propagate to all the assessments produced in this study including the assessment of compliance and the assessment of the load reduction required.

For each of the models defined by this study (i.e., all RF models and the linear models *E. coli* yield as function of attribute statistics) there was no apparent geographic pattern in the residual errors. Because these models were derived from data pertaining to a generally common set of sites it was expected that the errors of each model would be correlated to a degree with the errors of the other models. For these models therefore, we derived correlation matrices from the model errors associated with the common sites. It was assumed that this correlation structure represents the correlation in the uncertainties when the models were combined in the assessment process and, where available, we used this information in Monte Carlo analyses.

We estimate uncertainties for all four sets of assessments (i.e., TN, TP, *E. coli* and sediment) using the simple Monte Carlo analysis procedure of Snelder *et al.* (2020). The Monte Carlo analyses were based on making 100 'realisations' of the entire series calculations in four steps. First, for a realisation (r), predictions made by 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. Where the correlation structure of the model errors was quantified (i.e., for nitrogen, phosphorus, and *E. coli*), the 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.

The second step stored the assessments of compliance and load reduction requirements for the realisation. At the third step, the procedure described above was repeated for each realisation using the perturbed values. At the fourth step, the distribution of values of the concentrations, current loads, local excess loads, and load reductions required obtained from the 100 realisations were used to provide a best estimate and the uncertainty of the assessments. The uncertainty of the assessments of compliance were quantified by estimating the probability that each segment was compliant across the 100 realisations. Segment compliance was therefore assessed as a value between one (100% confident the segment was compliant) to zero (100% confident the segment is non-compliant). For the current state, local excess loads, and load reduction required assessments, the best estimate was represented by the mean value from the distribution of values. The uncertainties of these assessments were quantified by their 90% confidence intervals. For the load reduction required assessment, the best estimates and the uncertainties were estimated from the 100 realisations for each jurisdictional region and for all of New Zealand.

Because of differences in the models and approaches used across the four contaminants, there was some variation in the details of these Monte Carlo analyses. These details are explained below.

2.9.1 Nitrogen and Phosphorus

The analyses of Nitrogen and Phosphorus were based on four and two RF models, respectively that were used to predict current river concentrations and loads, the lake TN and TP concentration models (Equations 3 and 4, Section 2.6) and the estuary TN and TP concentration models (Section 2.7).

Because the response variables in the RF models pertaining to river TN and TP concentrations and loads were $\log_{10}$ transformed, the perturbed predictions for a realisation were derived as follows.

$$Nutrient_r = CF \times 10^{[log_{10}(x) + (\varepsilon_r \times RMSD_N)]} \qquad \textit{Equation 10}$$

where $Nutrient_r$ is the predicted concentration or load of TN or TP for realisation *r*, *x* is the prediction returned by the RF models, $RMSD_N$ is the characteristic error of the RF nutrient models (see Section 3.1.1), and CF is a factor to correct for retransformation bias (Duan, 1983).

Because the response variable in the RF models pertaining to river median soluble proportion of TN (NO3N:TN) was logit transformed, the perturbed predictions for a realisation were derived as follows:

$$NO3N\!:\!TN_r = \frac{e^{x + \varepsilon_r \times RMSD_{NO3N:TN}}}{(1+e^{x + \varepsilon_r \times RMSD_{NO3N:TN}})} \qquad \textit{Equation 11}$$

where $NO3N\!:\!TN_r$ is the predicted median soluble proportion of TN for realisation *r*, *x* is the prediction returned by the RF model, $RMSD_{NO3N:TN}$ is the characteristic error of the RF model of median soluble proportion of TN (see Section 3.1.1).

The uncertainties associated with the lake and estuary models were not included in the Monte Carlo analyses. The uncertainties associated with these receiving environments therefore only reflects the uncertainties in the estimated loads of TN and TP. The uncertainties of these models are quantified and could be included in future studies. The absence of these uncertainties means that the overall uncertainty estimates should be regarded as ‘optimistic’, i.e., the uncertainty would be higher if these additional model uncertainties were included in the analysis.

2.9.2 E. coli

The analysis of *E. coli* was based on nine statistical models (i.e., RF models to predict current values of the four *E. coli* statistics, an RF model 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 that were quantified by RMSD values. Because the response variables in the RF models pertaining to river *E. coli* concentrations and loads were either $\log_{10}$ or logit transformed, the perturbed predictions for a realisation were derived using appropriate modifications to Equation 10 or 11. The response variables in the four linear regression models (*E. coli* yield) were $\log_{10}$ transformed. Therefore, the perturbed predictions for a realisation were derived using Equation 10.

2.9.3 Sediment

The analysis of sediment was based on three models: the RF model predicting current visual clarity (Section 2.3.3), The Sediment Load Estimator (Section 2.4.3), and the Sediment Load Reduction Factor model (Equation 7, Section 2.8.3). The uncertainties of all three models were quantified by RMSD values but the correlation of model errors between these models was not quantified. Therefore, the random normal deviates representing errors for each model (ε_r) were drawn from independent distributions (i.e., the errors were assumed to be uncorrelated). It is noted that correlation of the errors associated with the three models will tend to increase overall uncertainty of the analyses. Therefore, the estimated uncertainties for our sediment analysis should be regarded as 'optimistic' (i.e., the uncertainty would be higher if these error corelations were included in the analysis).

Because the RF model pertaining to river visual clarity was $\log_{10}$ transformed, the perturbed predictions for a realisation were derived as follows:

$$VC_r = CF \times 10^{[log_{10}(x) + (\varepsilon_r \times RMSD_{VC})]} \qquad \textit{Equation 12}$$

where VC_r is the predicted visual clarity for realisation *r*, *x* is the prediction returned by the RF visual clarity model, $RMSD_{VC}$ .is the characteristic error of the RF visual clarity model (see Section 3.1.4), and CF is a factor to correct for retransformation bias (Duan, 1983).

Because the characteristic uncertainty of the predictions of the Sediment Load Estimator were quantified in log (i.e., natural log) space, the perturbed predictions for sediment load were derived as follows:

$$SY_r = e^{[log(x)+(\varepsilon_r \times RMSD_{SLE})]} \qquad \textit{Equation 13}$$

where VC_r is the predicted sediment yield for realisation *r* and *x* is the prediction returned by the Sediment Load Estimator and $RMSD_{SLE}$ .is the characteristic error of the Sediment Load Estimator model, which Hicks, Semadeni-Davies, *et al.* (2019) reported as 0.64.

The uncertainty of the load reduction factor was derived as follows:

$$R_r = 1 - (V_t/VC_r)^{1/[d+(\varepsilon_r \times RMSD_{SLRF})]} \qquad \text{Equation 14}$$

where R_r is the predicted sediment load reduction factor for realisation *r* and $RMSD_{SLRF}$ is the characteristic measure of uncertainty of the sediment load reduction factor model. In this study, $RMSD_{SLRF}$ was taken to be the standard deviation of the at-site values of d, which Hicks, Haddadchi, *et al.* (2019) reported as 0.13 and that has the same meaning as the RMSD values for the other models.

2.10 Specific modifications

In the analyses that follow, some modifications were made to the general approach to account for specific details in several locations including: lakes associated with the main stem of the Waikato River; lakes in the Otago Region; and the Waiau River in Southland. The modifications were as follows.

The eight riverine lakes associated with the main stem of the Waikato River[10] are not well represented by the empirical lake nutrient loading models of Abell *et al.* (2019, 2020). These lakes have short residence times during some parts of the year, which are not well quantified by the lakes that were included in the fitting dataset used by Abell *et al.* (2019, 2020). In addition, they are shallow and internal loading from wind-driven resuspension complicates the relationship between external loading and in-lake concentration (Deniz Ozkundakci, *pers com*) These eight lakes were therefore excluded from the analysis, and this may mean that the estimated required load reductions for the main stem of the Waikato River are under-estimated by this study.

In a regional study of required load reductions, Snelder and Fraser (2021b) found that measured in-lake median concentrations of TP for eight monitored lakes across Otago were poorly represented by the models of Abell *et al.* (2019, 2020) but measured concentrations of TN were satisfactorily represented. Snelder and Fraser (2021b) fitted an alternative model to that of Abell *et al.* (2019, 2020) and used this to predict in-lake TP concentrations for all Otago lakes. This alternative model was used by this study to predict the in-lake TP concentrations for all lakes in the Otago Region.

The flow regime of the Waiau River in Southland is strongly modified by the diversion of most of the flow to Doubtful/Patea Sound by the Manapōuri Power Scheme. The natural mean flow at the Mararoa Weir control structure is estimated to be 455 $m^3\ s^{-1}$ (Booker and Woods, 2014), whereas the measured mean flow at this location is 67 $m^3\ s^{-1}$ (i.e., 15% of the natural flow). This flow modification is not represented by the digital drainage network (i.e., the network represents the natural drainage network of the Waiau River). This means that the load predictions made for the Waiau River main stem, downstream of the Mararoa Weir control structure, were not representative of actual loads due to the flow diversion. The RF model predictions of loads of TN and TP for the main stem of the Waiau River downstream of the Mararoa Weir were discarded and replaced with alternative estimates as described by (Snelder, 2021).

[10] Lakes Karapiro, Arapuni, Waipapa, Maraetai, Whakamaru, Atiamuri, Ohakuri and Aratiatia.

3 Results

3.1 Derived input models

The following sections report on the models that were derived specifically for this study including the models used to predict river nutrient concentrations, river *E. coli* statistics, and river visual clarity, the linear models of *E. coli* yield as function of attribute statistics and models used to predict river nutrient and *E. coli* loads.

3.1.1 River nutrient concentrations

The RF models of current median concentrations of TN, TP, NO3N, and NO3N:TN had at least satisfactory performance (Table 10), as indicated by the criteria of Moriasi et al. (2015; Table 2). The mapped predictions of the concentrations of the nutrient species had similar coarse-scale spatial patterns, with relatively high values in low-elevation, coastal areas of New Zealand and values decreasing with increasing elevation and distance inland (Figure 9). These patterns are consistent with expectations and reflect the increasing enrichment of rivers and streams in association with increasing proportions of catchment area occupied by agricultural and other land uses. The soluble proportion of TN had a pattern that was similar to the concentration of TN and NO3N indicating that the contribution of NO3N to TN increases with increasing enrichment of rivers and streams.

The correlations between the errors of the RF models of current median concentrations of TN, TP, NO3N, and NO3N:TN, and the models describing the river TN and TP loads are provided in Appendix B.

Table 10. Performance of the RF models of median concentrations of TN, TP, NO3N and NO3N:TN. N indicates the number of sites used to fit the model. The rating indicates the performance ratings based on R^2, NSE and PBIAS shown in Table 2.

Variable	N	R^2	NSE	PBIAS	RMSD	Rating	Transformation
TN	848	0.79	0.79	1.33	0.22	Very good	log10
TP	848	0.70	0.69	0.08	0.25	Good	log10
NO3N	848	0.67	0.66	-0.36	0.42	Good	log10
NO3N:TN	833	0.57	0.55	-2.35	0.92	Satisfactory	logit

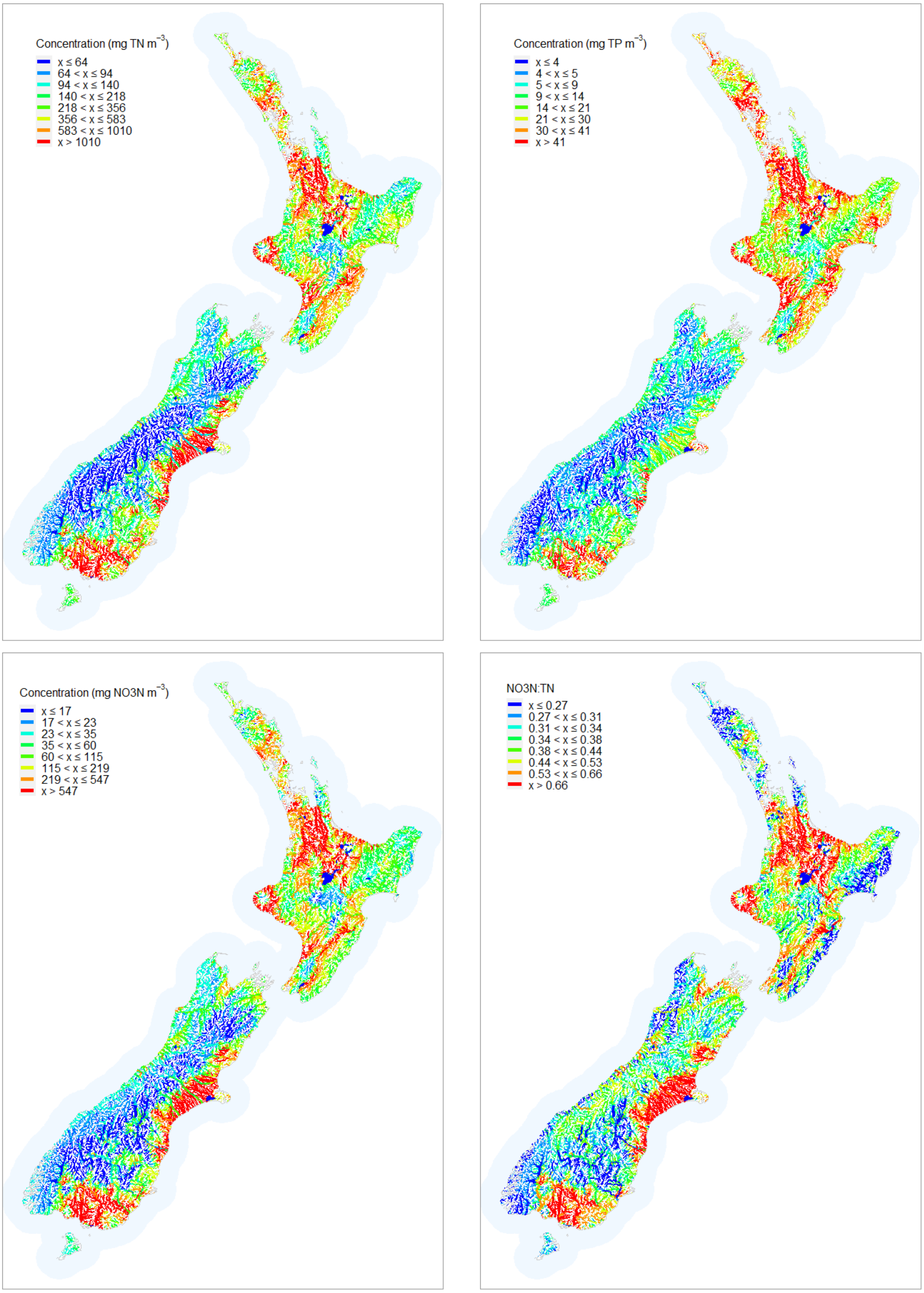

Figure 7. Predicted patterns of the current median concentrations of TN, TP, NO3N and the soluble proportions of TN (NO3N:TN), respectively. Note that the breakpoints shown in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.1.2 River *E. coli* statistics

The RF models of current median (Q50) and 95th percentile (Q95) concentrations of *E. coli* and the proportions of *E. coli* observations greater that 260 *E. coli* 100 ml^{-1} (G260) and greater that 540 *E. coli* 100 ml^{-1} (G540), had at least good performance (Table 11), as indicated by the criteria of Moriasi *et al*. (2015; Table 2). The mapped predictions of the of *E. coli* statistics species had similar coarse-scale spatial patterns, with relatively high values in low-elevation, coastal areas of New Zealand and decreasing values with increasing elevation and distance inland (Figure 8). These patterns are consistent with expectations and reflect the increasing enrichment of rivers and streams in association with increasing proportions of catchment area occupied by agricultural and other land uses.

The correlations between the errors of the RF models of current E. coli statistics, the linear models of *E. coli* yield as function of attribute statistics, and the models describing the river *E. coli* yield are provided in Appendix B.

Table 11. Performance of the RF models of the current E. coli statistics. The four statistics include median (Q50), 95th percentile (Q95) concentrations of E. coli, and the proportions of E. coli observations greater that 260 E. coli 100 ml^{-1} (G260) and greater that 540 E. coli 100 ml^{-1} (G540). N indicates the number of sites used to fit the model. The rating indicates the performance ratings based on R^2, NSE and PBIAS shown in Table 2.

Variable	N	R^2	NSE	PBIAS	RMSD	Rating	Transformation
Q50	840	0.71	0.71	-0.14	0.32	Very good	log10
Q95	840	0.65	0.65	-0.13	0.38	Good	log10
G260	840	0.68	0.67	2.03	0.85	Good	logit
G540	840	0.64	0.64	0.56	0.73	Good	logit

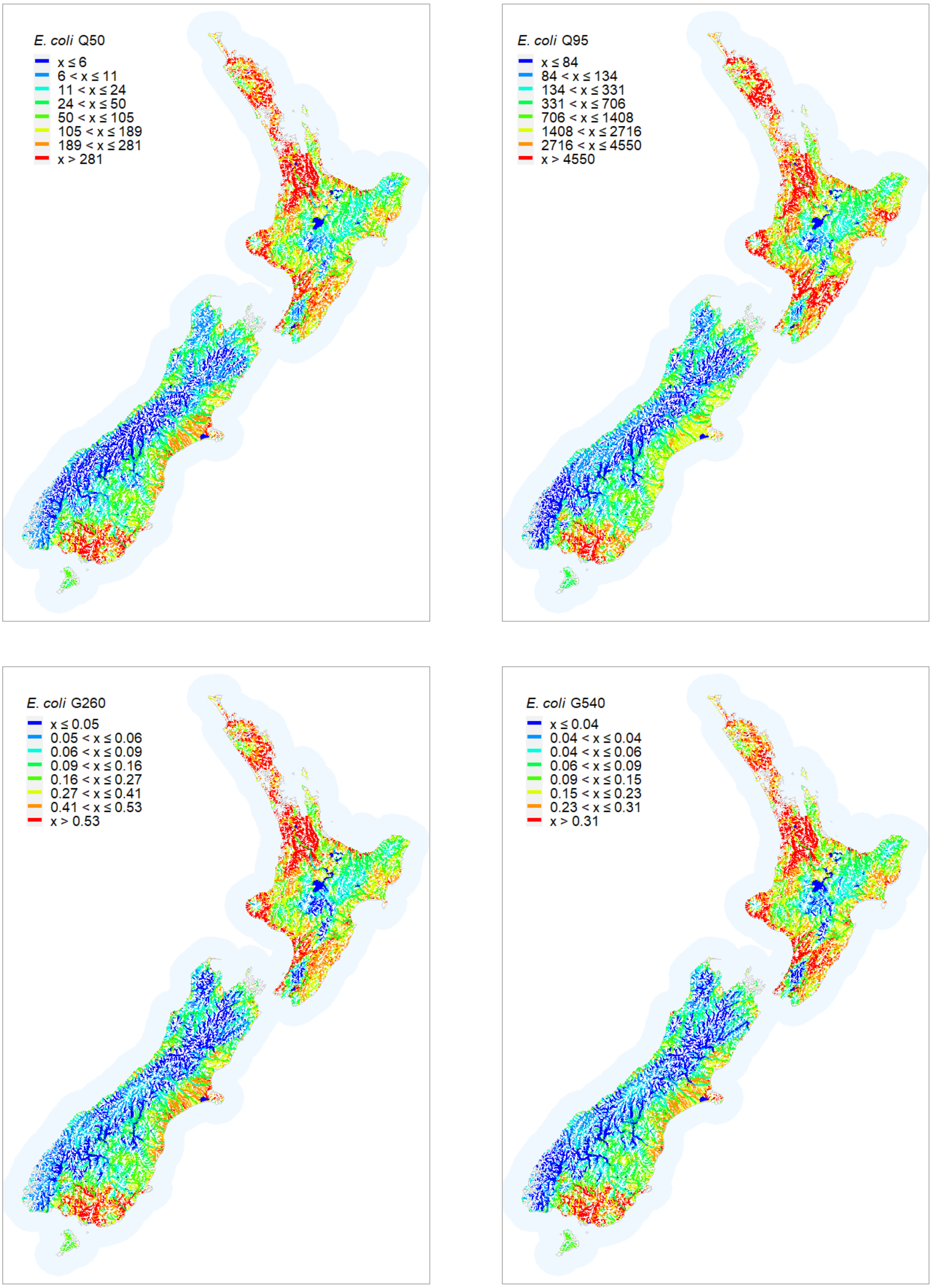

Figure 8. Predicted patterns of the current E. coli statistics. The maps show median (Q50) and 95^{th} percentile (Q95) concentrations of E. coli and the proportions of E. coli observations greater that 260 E. coli 100 ml^{-1} (G260) and greater that 540 E. coli 100 ml^{-1} (G540), respectively. Note that the breakpoints shown in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.1.3 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 at least satisfactory performance as indicated by the criteria of Moriasi *et al.* (2015; Table 2) and low bias (Table 12). The correlations between the errors of the linear models and the errors of the models describing the *E. coli* river statistics and models of *E. coli* yield are provided in Appendix B.

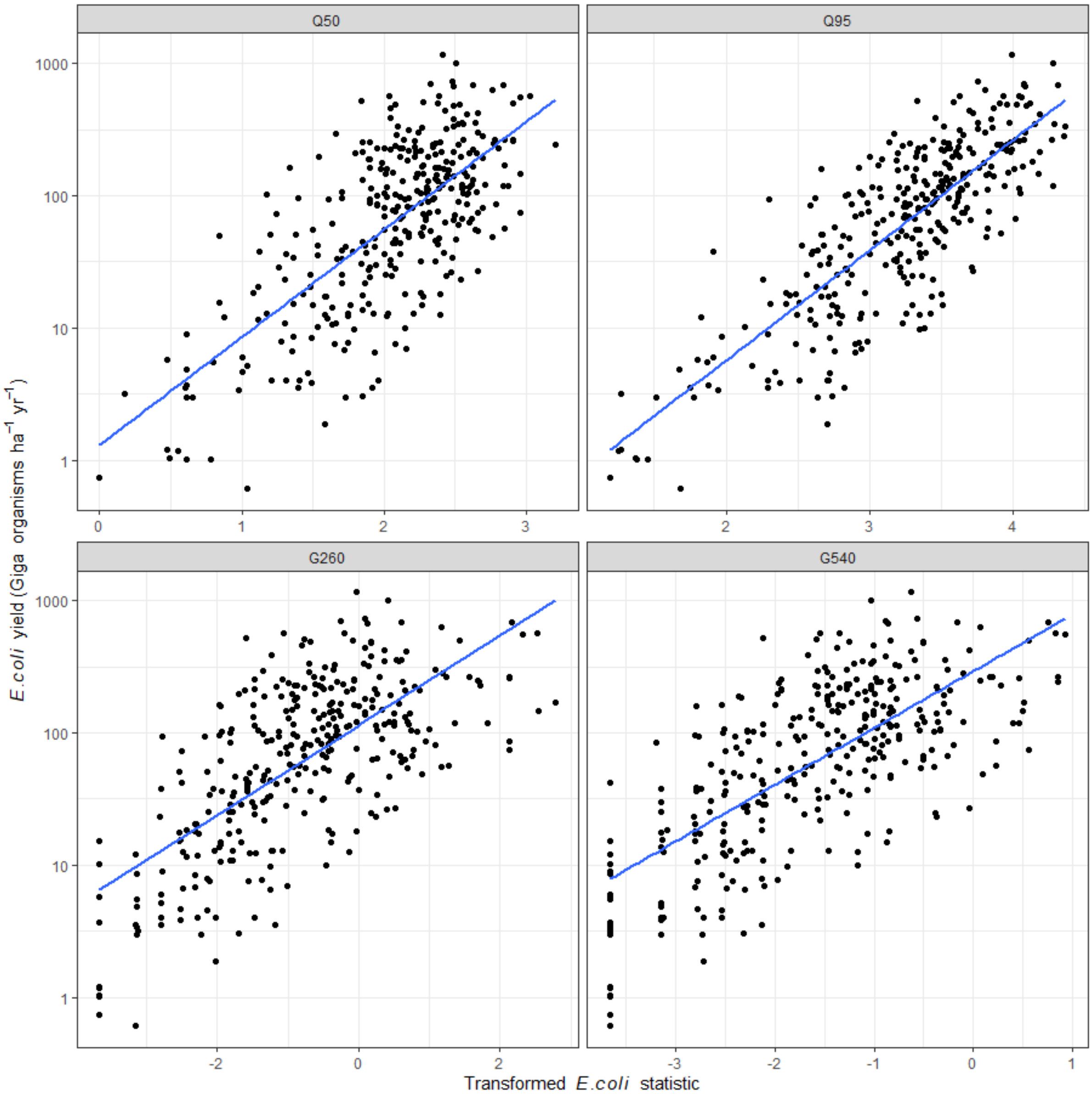

Figure 9. Linear relationships between E. coli yield and the four E. coli statistics. The black points represent the yield and E. coli statistic for the 334 sites and the blue line indicates the fitted linear regression. Note that on these plots and the fitted models, yield was log (base 10) transformed, the median and Q95 values were log (base 10) transformed and the G260 and G540 values were logit transformed.

Table 12. 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 transformation indicated was applied to the statistic. In all cases the model response (i.e., E. coli yield) was log_{10} transformed. The overall performance rating is based on the criteria of Moriasi et al. (2015) shown in Table 2.

Variable	N	R^2	NSE	PBIAS	RMSD	Rating	Transformation
Q50	334	0.50	0.50	0.00	0.45	Satisfactory	Log10
Q95	334	0.66	0.66	0.00	0.37	Good	Log10
G260	334	0.47	0.47	0.00	0.47	Satisfactory	Logit
G540	334	0.50	0.50	0.00	0.45	Satisfactory	Logit

3.1.4 River visual clarity

The RF model of current river visual clarity had satisfactory performance (Table 11), as indicated by the criteria of Moriasi *et al*. (2015; Table 2).The mapped predictions of the visual clarity indicated relatively low values in low-elevation, coastal areas of New Zealand and values increasing with increasing elevation and distance inland (Figure 10). These patterns are consistent with expectations and reflect the association between suspended sediment and increasing proportions of catchment area occupied by agricultural and other land uses.

Table 13. Performance of the RF model of the current river visual clarity. The rating indicates the performance ratings based on R^2, NSE and PBIAS shown in Table 2.

Variable	N	R^2	NSE	PBIAS	RMSD	Rating	Transformation
Clarity	728	0.58	0.57	1.24	0.2	Satisfactory	log10

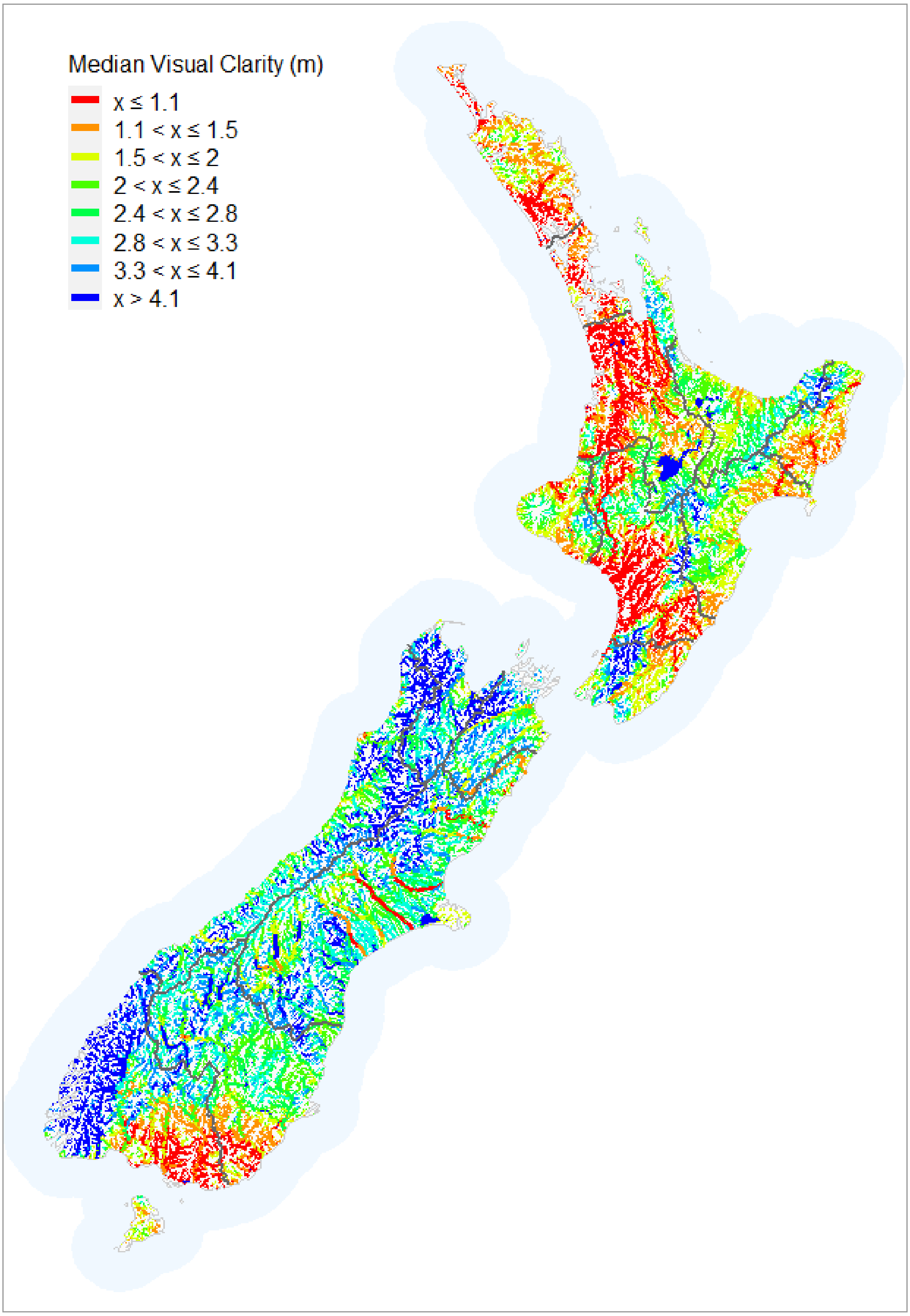

Figure 10. Predicted patterns of the current river visual clarity. Note that the breakpoints shown in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.1.5 River nutrient and *E. coli* loads

Based on the criteria of Moriasi et al. (2015; Table 2), the RF models of TN, TP and *E. coli* yield had at least satisfactory performance (Table 11). The mapped predictions of the yields of TN and *E. coli* had similar coarse-scale spatial patterns, with relatively high values in low-elevation, coastal areas of New Zealand and values decreasing with increasing elevation and distance inland (Figure 11, Figure 12). These patterns are consistent with expectations and reflect the increasing levels of TN and *E. coli* in rivers and streams in association with increasing proportions of catchment area occupied by agriculture.

The mapped predictions of the yields of TP indicated loads are greater for rivers and streams draining high-elevation and high rainfall areas of New Zealand, such as the West Coast of the South Island and mountainous catchments on both islands (Figure 11). Yields of TP were particularly low in the dry low relief parts of the Otago, Canterbury and Marlborough regions.

The correlations between the errors of these RF models of current TN, TP and *E.coli* loads and the errors of the other relevant models are provided in Appendix B.

Table 14. Performance of the RF models of median concentrations of. N indicates the number of sites used to fit the model. The rating indicates the performance ratings based on R^2, NSE and PBIAS shown in Table 2.

Variable	N	R^2	NSE	PBIAS	RMSD	Rating	Transformation
TN	335	0.74	0.73	-0.54	0.20	Very good	log10
TP	335	0.57	0.55	1.97	0.29	Satisfactory	log10
E. coli	334	0.65	0.64	-0.61	0.39	Good	log10

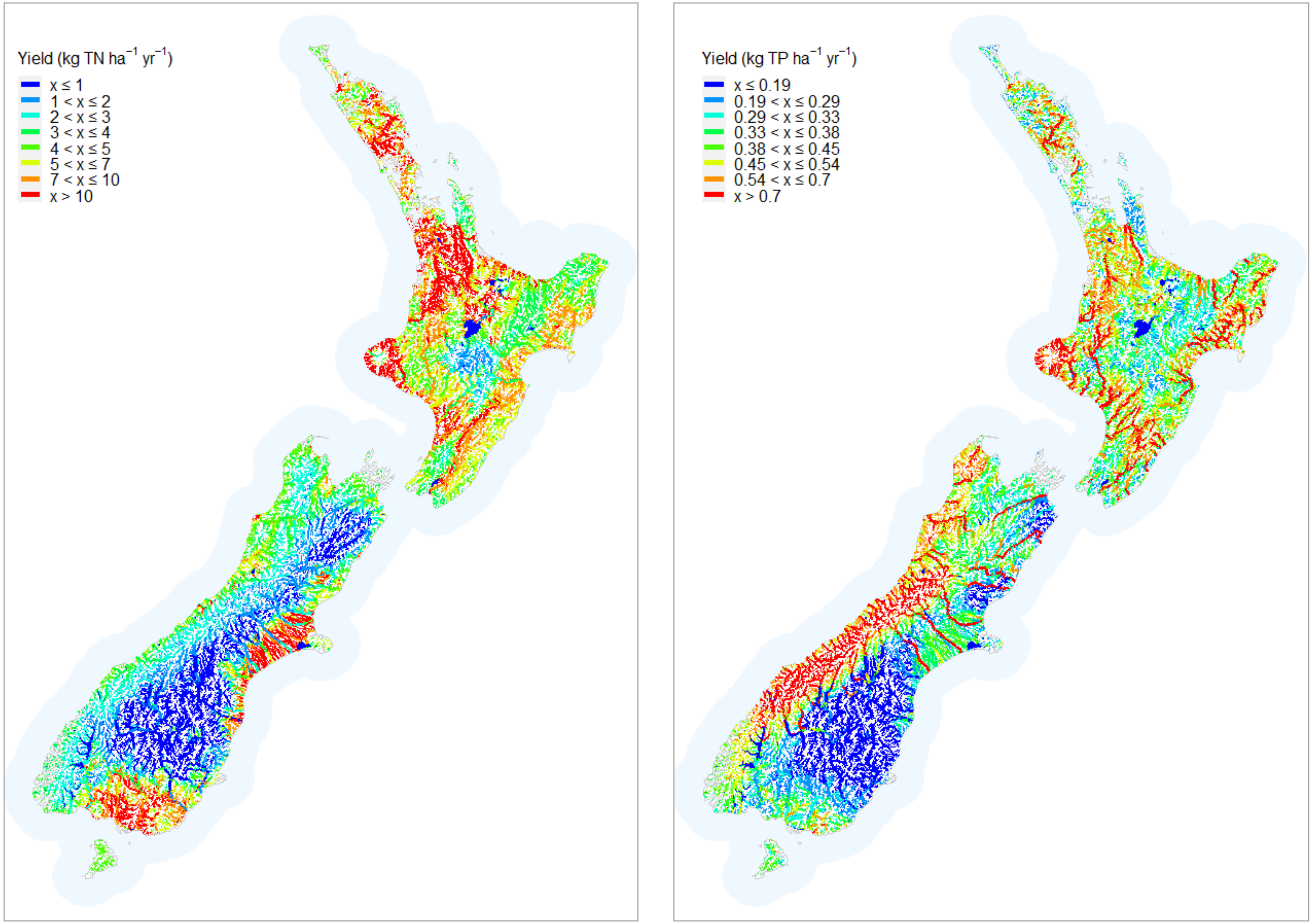

Figure 11. Predicted patterns of the current TN and TP loads (as yields kg ha^{-1} yr^{-1}) Note that the breakpoints shown in the map legend are nominal and have no special significance (i.e., are not guidelines or standards)

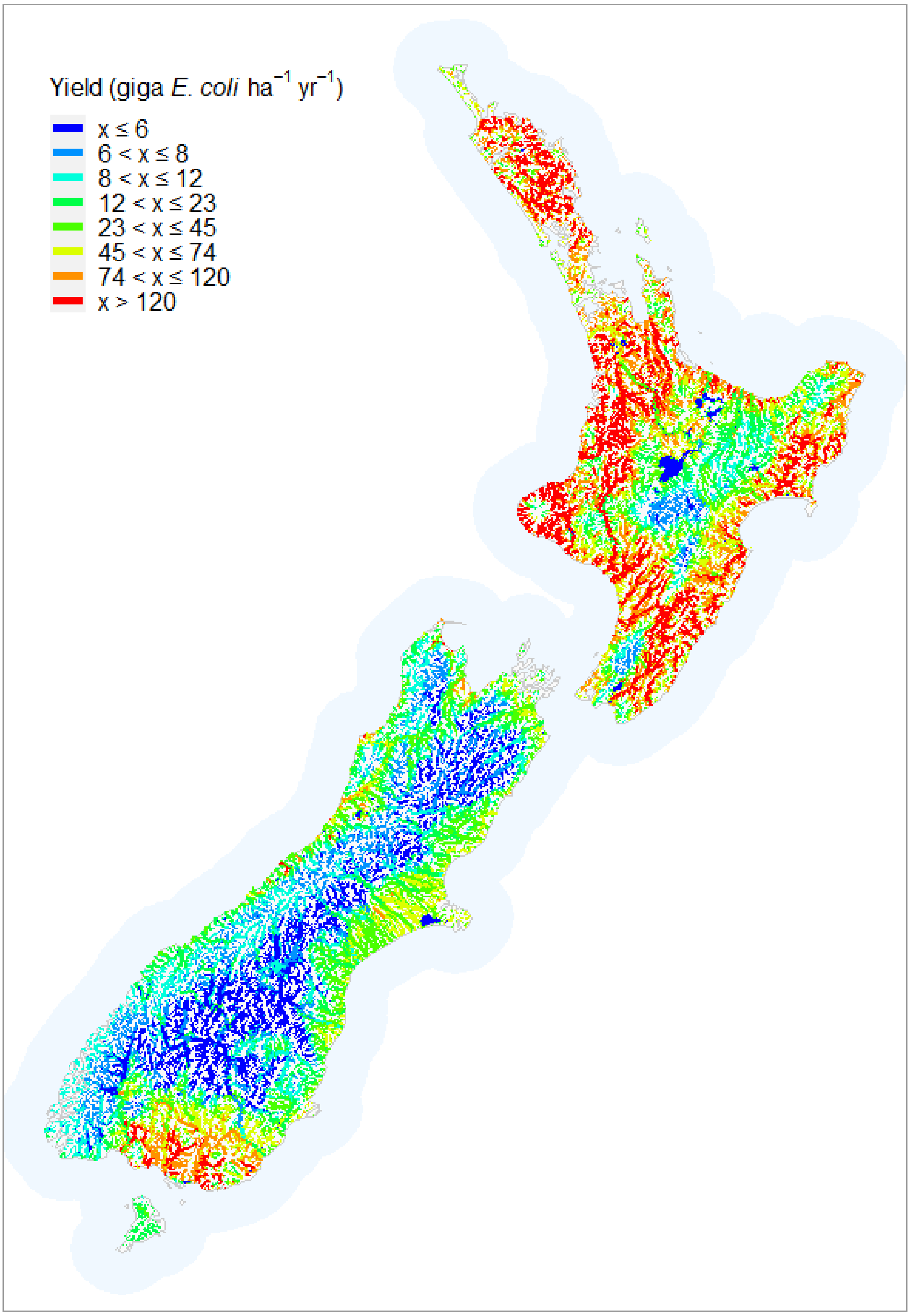

Figure 12. Predicted pattern of the current E. coli loads (as yields giga E. coli ha^{-1} yr^{-1}) Note that the breakpoints shown in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.2 Nitrogen

3.2.1 Compliance

The estimated probability that river concentrations of TN were compliant with the criteria for the periphyton attribute national bottom line and 20% UPR was greater than 0.6 for 68% of segments nationally (Figure 13). The estimated probability that river concentrations of NO3N were compliant with the nitrate toxicity criteria was greater than 0.6 for 98% of segments nationally. However, the probability that nitrate toxicity criteria is more limiting than the TN criteria for periphyton exceeded 0.6 at only 0.3% of river segments (Figure 13).

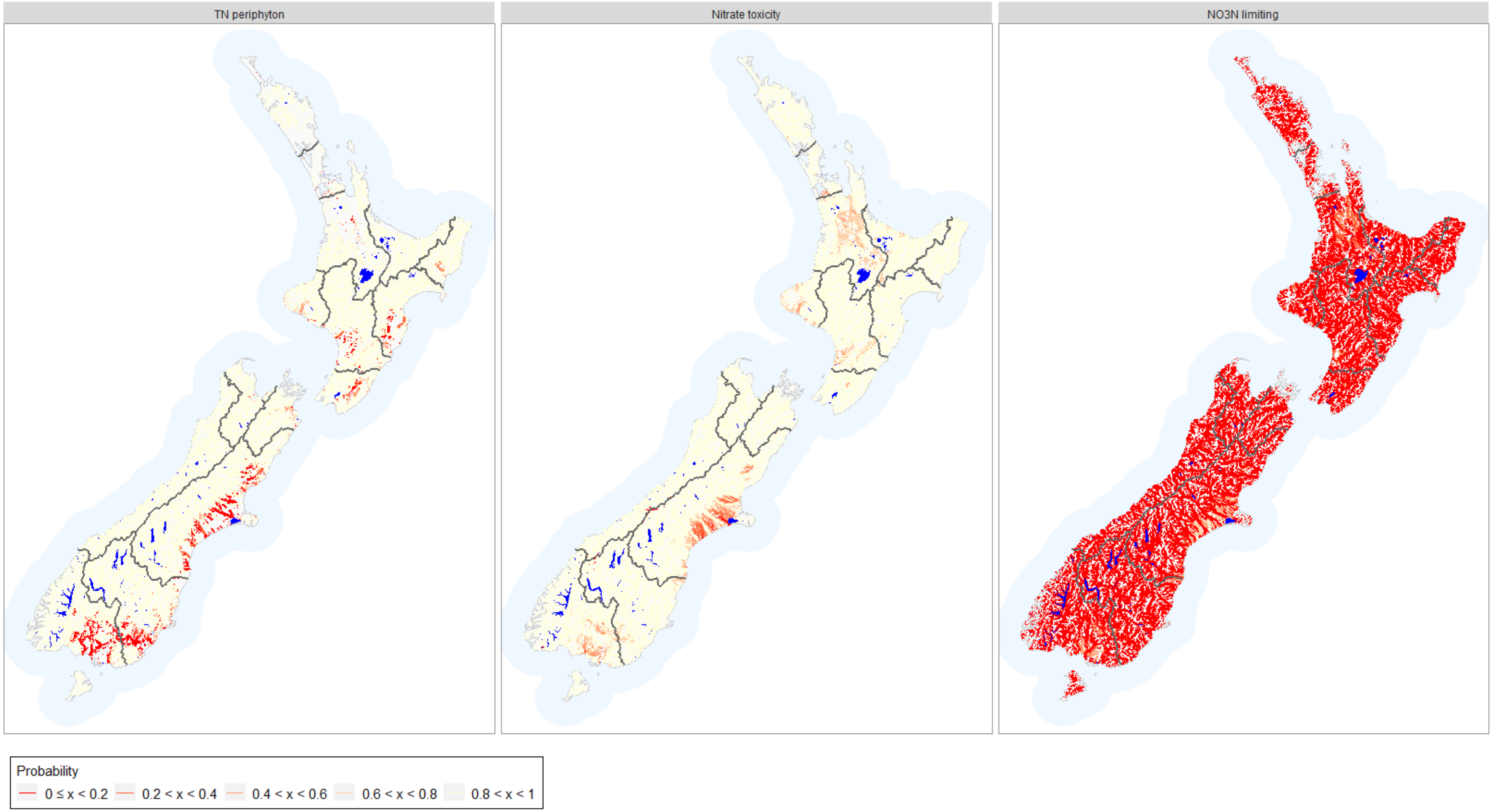

Figure 13. Probability that segments comply with river TN concentration criteria associated with the national bottom lines for periphyton (top left) and nitrate toxicity (centre and right) for the 20% UPR settings. The right-hand panel shows the probability that NO3N toxicity is the more limiting attribute than periphyton (in this analysis this was true for 0.3% of segments).

The estimated probability that lake concentrations of TN were compliant with the national bottom line was greater than 0.6 for 656 of the 771 lakes included in the analysis (i.e., 85%; of lakes nationally; Figure 14). Lakes that had low probability of being compliant (i.e., likely non-compliant) were generally at low altitude and coastal areas.

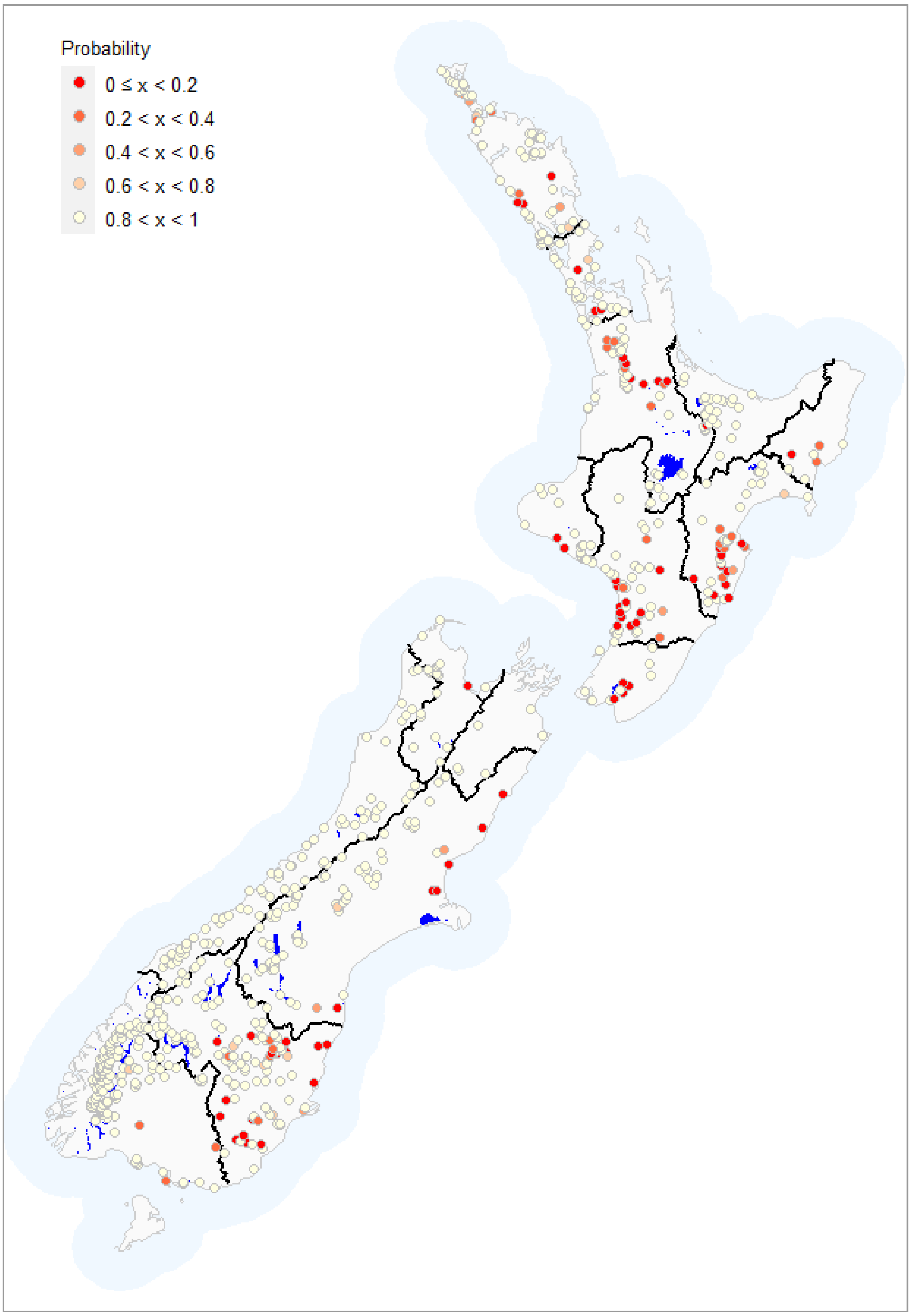

Figure 14. Probability that lakes comply with TN concentration criteria associated with the national bottom lines.

The estimated probability that estuary TN concentrations were compliant with the criteria associated with the national bottom line was greater than 0.6 for 382 of the 418 estuaries included in the analysis (i.e., 91%; Figure 15). Non-compliant estuaries were widely distributed across the North Island and the southern and eastern coasts of the South Island.

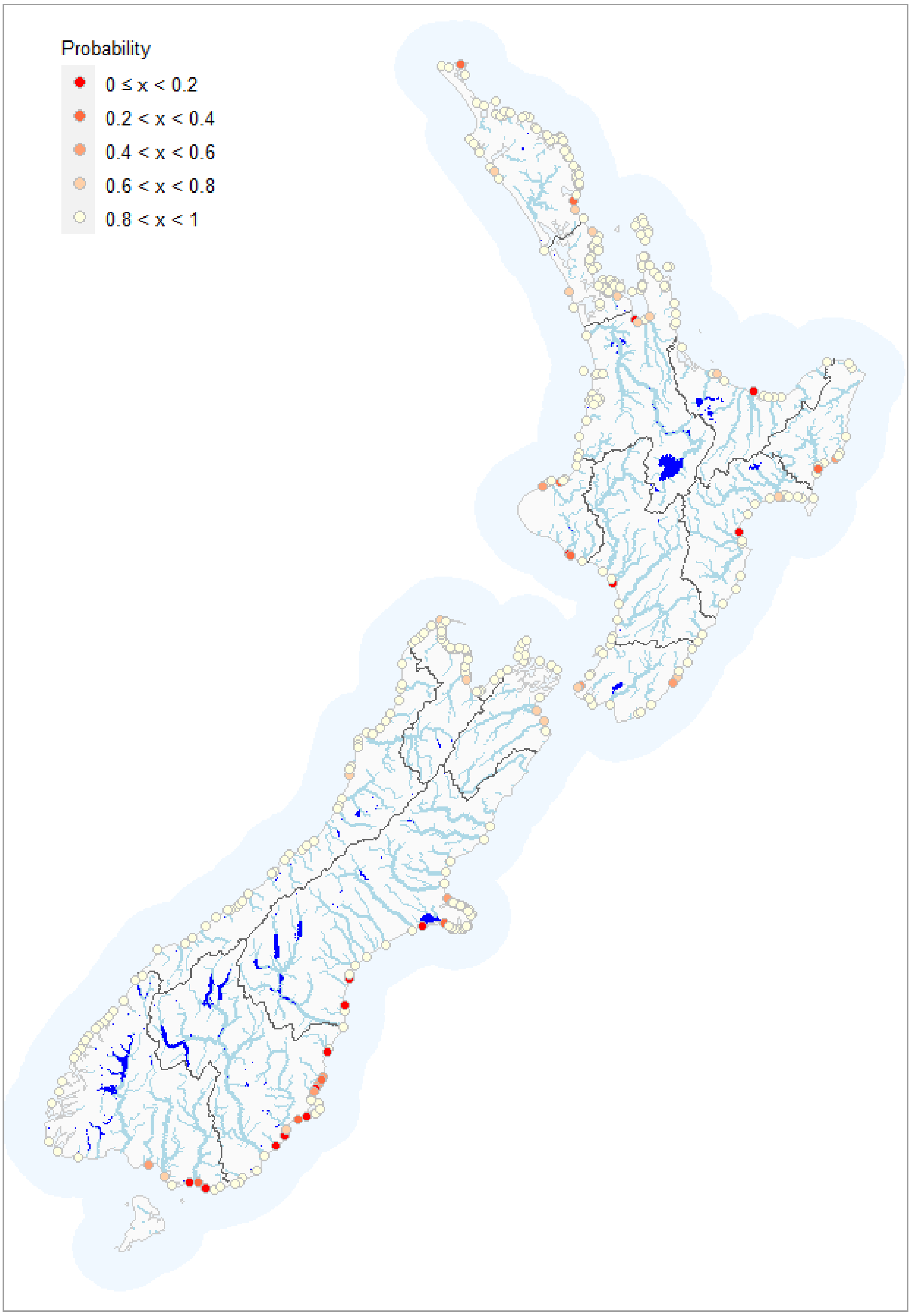

Figure 15. Probability that estuaries comply with TN concentration criteria associated with the national bottom lines.

3.2.2 Local excess loads

The local excess load is the amount by which the current TN load at a receiving environment (i.e., river segment, lake or estuary) would need to be reduced to achieve the national bottom line. The best estimate of the local excess TN yield for rivers exceeded 2 kg ha^{-1} yr^{-1} for 3% of river segments and exceeded 5 kg ha^{-1} yr^{-1} for 1% of river segments (Figure 33). Note that the 2 and 5 kg ha^{-1} yr^{-1} are nominal breakpoints that correspond to two of the legend thresholds on Figure 33. These values have no special significance (i.e., are not guidelines or standards). The local excess TN loads were zero for 95% of river segments.

The best estimate of the local excess TN yield for lakes exceeded 2 kg ha^{-1} yr^{-1} for 12% of lakes and exceeded 5 kg ha^{-1} yr^{-1} for 6% (Figure 17). Note that the 2 and 5 kg ha^{-1} yr^{-1} are nominal breakpoints that correspond to two of the legend thresholds on Figure 17. These values have no special significance (i.e., are not guidelines or standards). The local excess TN loads were zero for 85% of lakes.

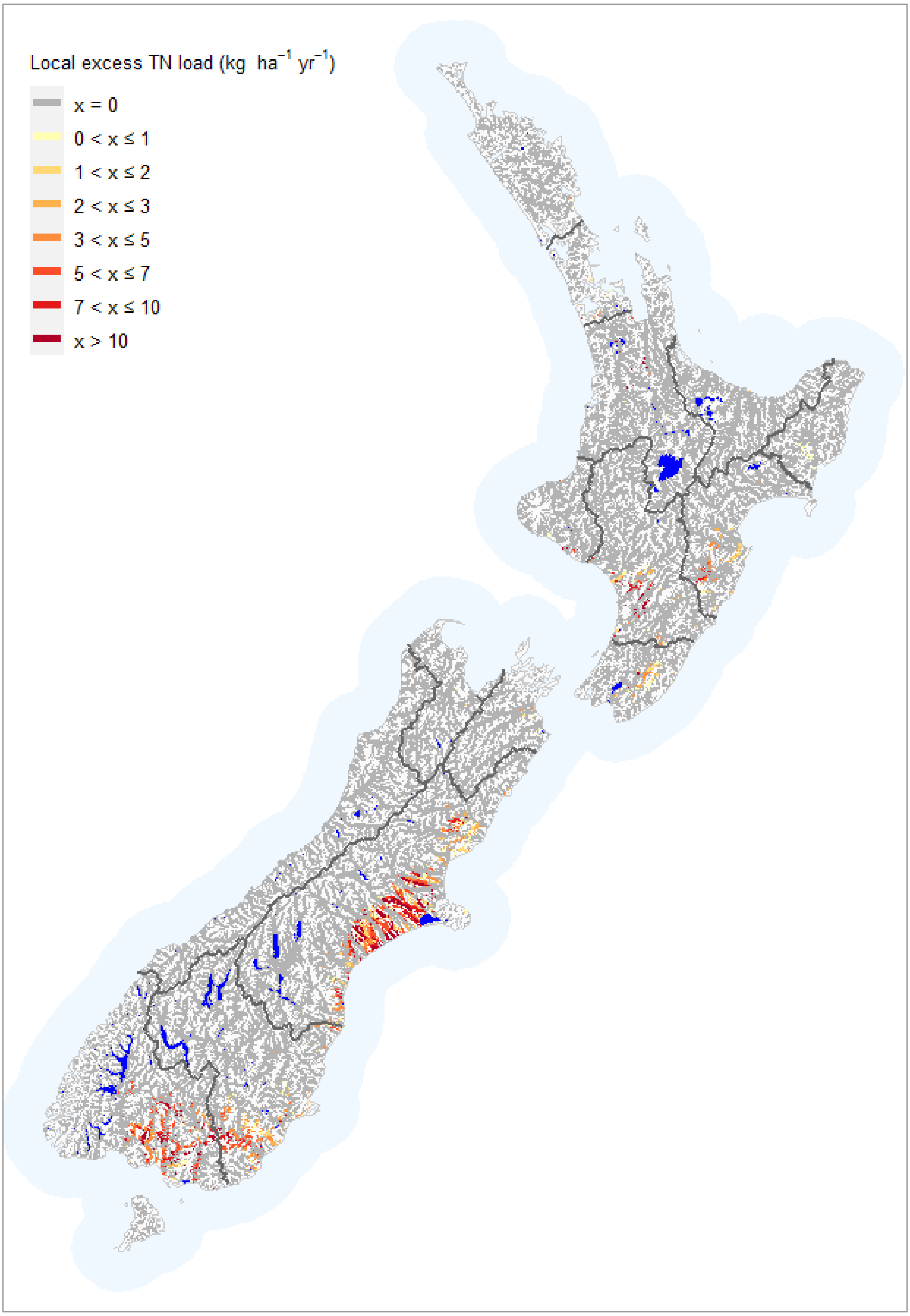

Figure 16. Local excess TN loads associated with national bottom lines for rivers. Note that the breakpoints for the local excess yield in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

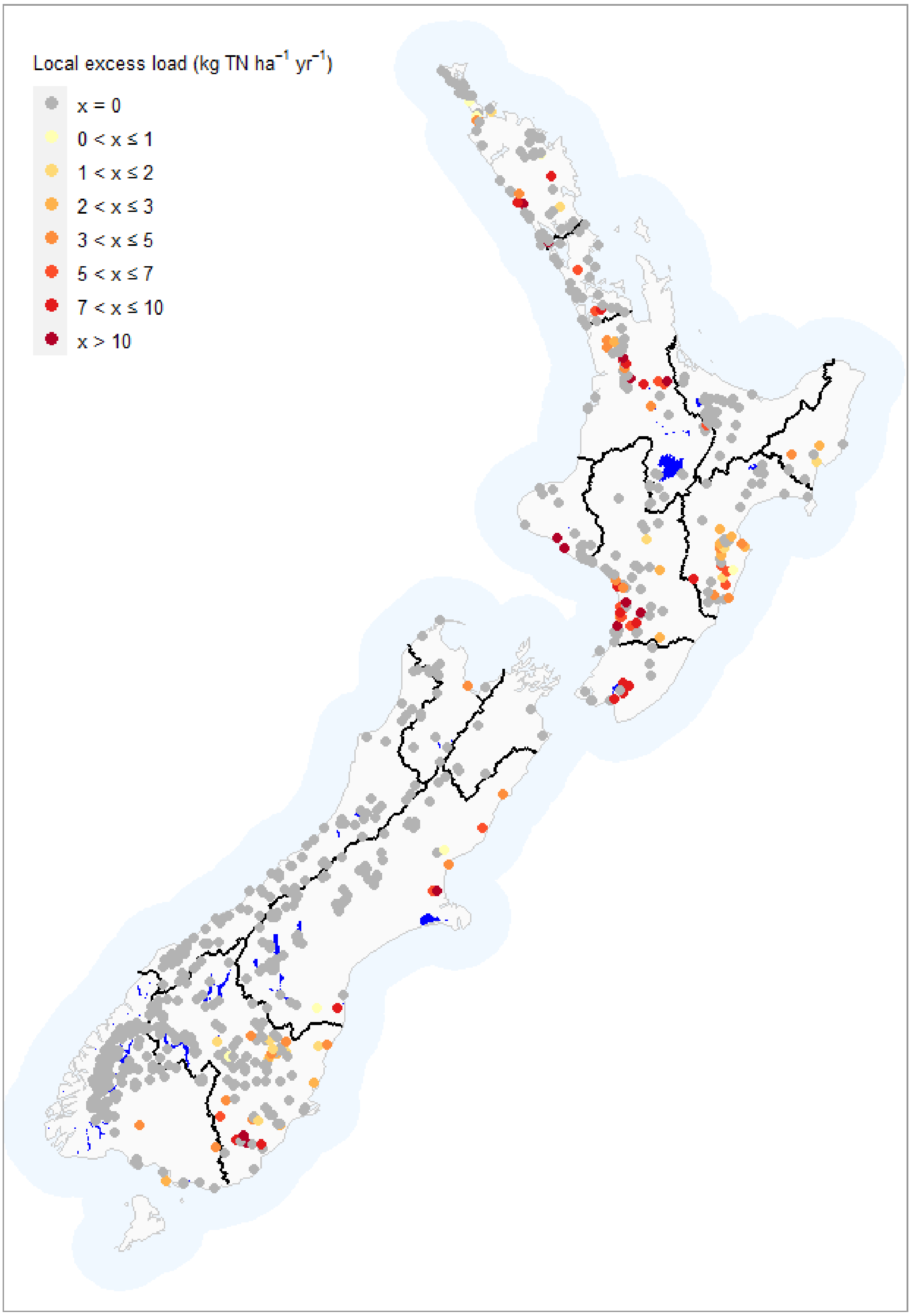

Figure 17. Local excess TN loads associated with national bottom lines for lakes. Note that the breakpoints for the local excess yield in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

The best estimate of the local excess TN yield for estuaries exceeded 2 kg ha^{-1} yr^{-1} for 6% of estuaries and exceeded 5 kg ha^{-1} yr^{-1} for 3% (Figure 18). The local excess TN loads were zero for 91% of estuaries.

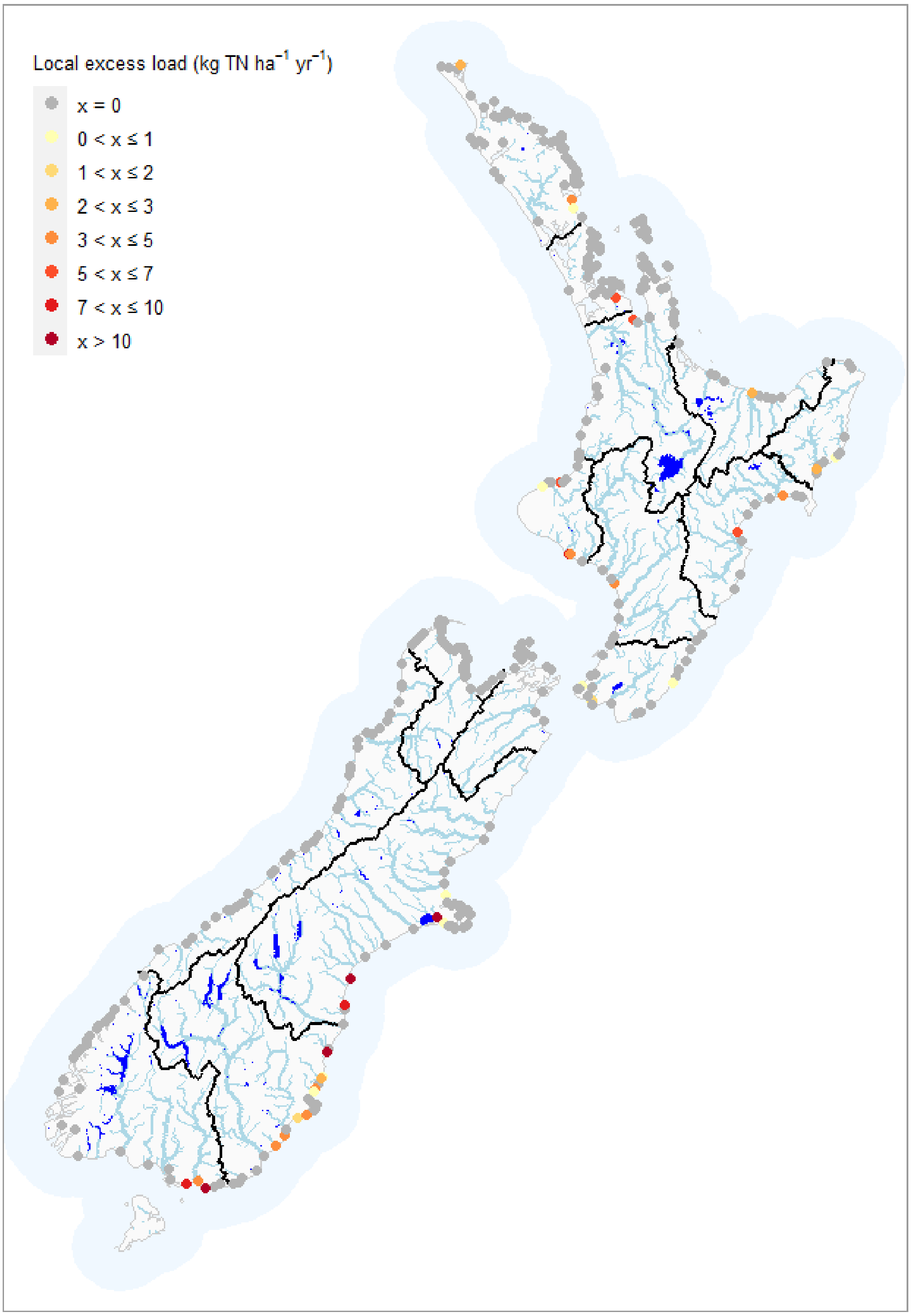

Figure 18. Local excess TN loads associated with national bottom lines for estuaries. Note that the breakpoints for the local excess yield in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.2.3 Regional and national load reduction required

The TN load reductions required to achieve the national bottom line for each region and for New Zealand in total are shown in Table 15. For the whole of New Zealand, the best estimate of TN load reduction required was 32,624 t yr^{-1}, which represents 19% of the current load. The TN load reductions required were highest (>10%) in the Taranaki, Manawatu, Hawke's Bay, Wellington, Canterbury, Otago and Southland regions. The TN load reductions required were lowest (<5%) in the Northland, Gisborne, Tasman, Marlborough and West Coast regions. It is noted that overall mean reduction rates in regions with large areas of conservation estate and unproductive land, such as Southland and West Coast, may have considerably higher load reduction requirements in agriculturally dominated catchments[11].

Table 15. Current load and load reduction required for TN by region and nationally for the national bottom line including the uncertainties at the 90% level of confidence. Note that loads are expressed in absolute terms in units of tonnes per year (t 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.

Region	Total load (t yr^{-1})	Load reduction required (t yr^{-1})	Load reduction required (%)
Northland	11,231 (8,789 - 15,107)	312 (113 - 689)	3 (1 - 5)
Auckland	3,982 (3,666 - 4,474)	236 (163 - 341)	6 (4 - 8)
Waikato	27,030 (15,591 - 41,073)	1,739 (326 - 4,263)	6 (2 - 15)
Bay of Plenty	8,596 (6,744 - 11,223)	628 (93 - 1,670)	7 (1 - 18)
Gisborne	4,188 (3,183 - 5,798)	110 (18 - 277)	3 (0 - 6)
Taranaki	9,474 (7,503 - 11,497)	1,644 (485 - 3,267)	17 (6 - 30)
Manawatū	19,270 (12,723 - 27,031)	2,852 (1,433 - 5,828)	15 (8 - 25)
Hawkes Bay	10,640 (7,584 - 14,315)	2,506 (542 - 5,297)	22 (7 - 40)
Wellington	5,211 (3,713 - 7,782)	639 (191 - 1,769)	12 (5 - 23)
Tasman	3,161 (2,277 - 4,023)	71 (17 - 197)	2 (1 - 4)
Marlborough	3,113 (2,299 - 4,052)	197 (49 - 378)	6 (2 - 13)
West Coast	13,632 (10,477 - 17,623)	42 (0 - 96)	0 (0 - 1)
Canterbury	23,283 (19,798 - 27,025)	10,169 (8,370 - 12,920)	44 (38 - 50)
Otago	9,873 (7,102 - 13,814)	3,381 (1,318 - 5,743)	33 (19 - 46)
Southland	19,317 (14,968 - 24,951)	8,099 (4,364 - 13,725)	41 (28 - 55)
National	172,000 (157,499 - 190,411)	32,624 (26,851 - 40,093)	19 (15 - 22)

3.2.4 Critical catchments for nitrogen

The critical catchment excess load is the amount by which the current contaminant load would need to be reduced to ensure loads in all receiving environments in the catchment do not

[11] Note that a regional load reductions required study for Southland by Snelder (2021) excluded large parts of the region for which catchments were entirely occupied by non-productive land including Fiordland and Stewart Island. The load reduction required to achieve national bottom lines reported by that study are consequently considerably greater than reported here.

exceed the MAL (and therefore all receiving environments achieve their target attribute states). The critical catchment excess loads for nitrogen are shown as yields on Figure 19. Reductions in TN loads are required for catchments comprising 20% of the land area of New Zealand. Critical point catchments with excess TN loads greater than 6 kg ha^{-1} yr^{-1} and 2 kg ha^{-1} yr^{-1} comprised 7% and 16% of the land area of New Zealand, respectively.

When TN load reductions required were expressed as a proportion of current loads, critical catchments that require reductions of greater than 30% occupied 14% of the land area of New Zealand (Figure 20). The comparison of load reductions expressed as yields (kg ha^{-1} yr^{-1}) with those expressed as proportion of current load (%) indicates that reduction requirements in areas with low yield reductions (e.g., coastal areas in North Otago) can be large in relative terms.

For nitrogen, the limiting environment types for critical catchment areas were 74%, 0.4%, and 25% for rivers, lakes and estuaries, respectively (Figure 21).

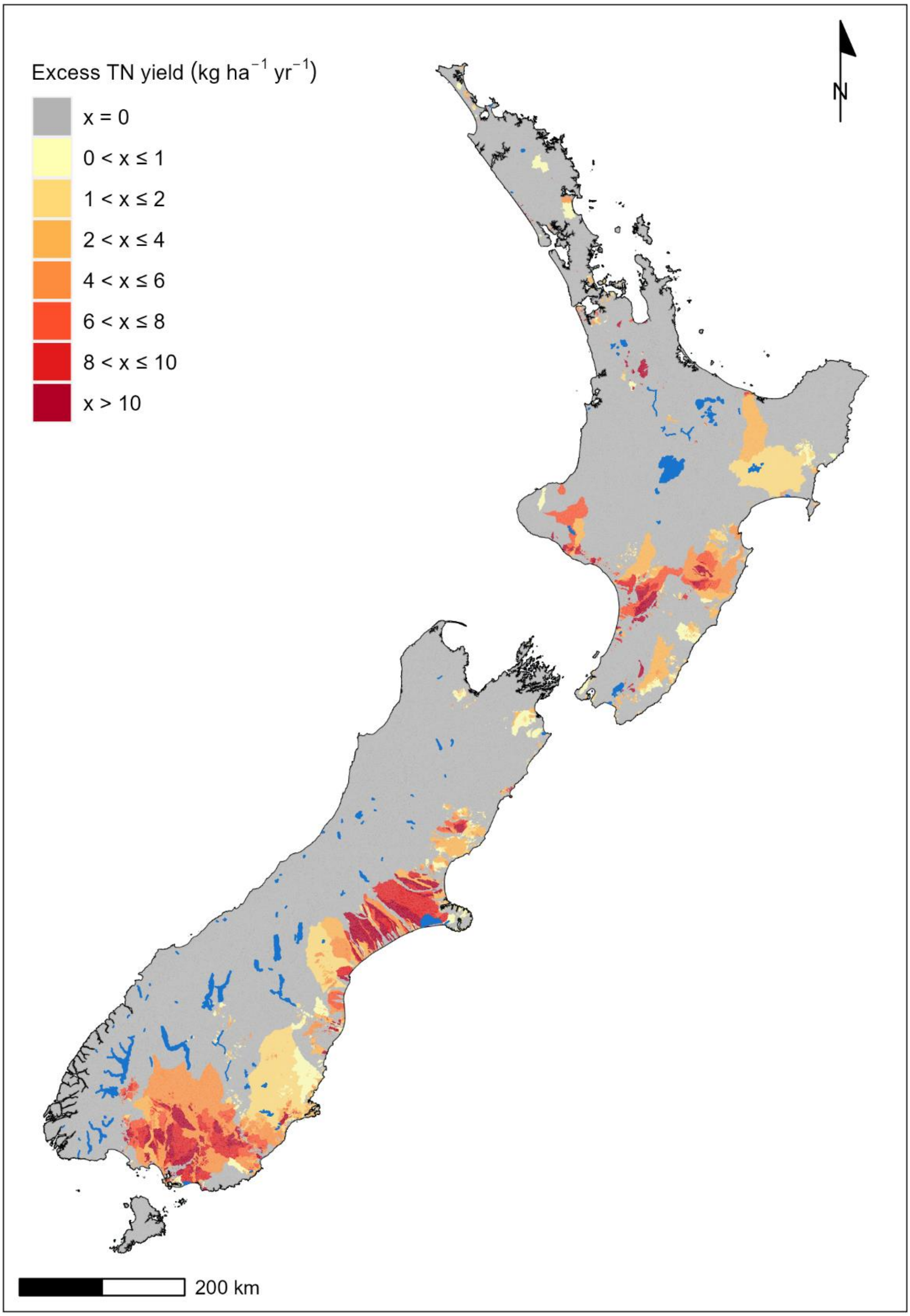

Figure 19. Critical catchment excess loads for nitrogen expressed as a yield (kg ha^{-1} yr^{-1}).

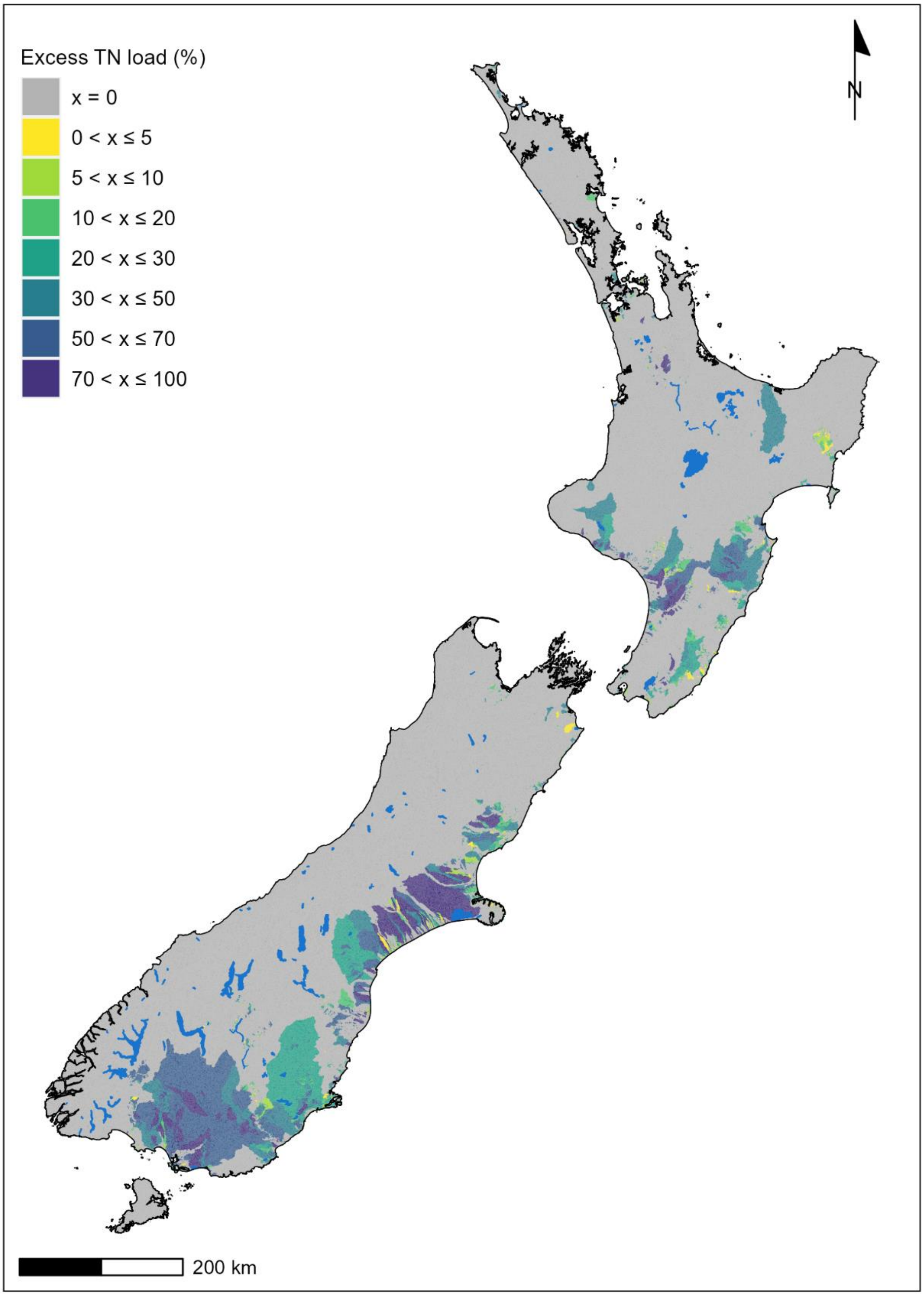

Figure 20. Critical catchment excess loads for nitrogen expressed as a proportion of current loads (%).

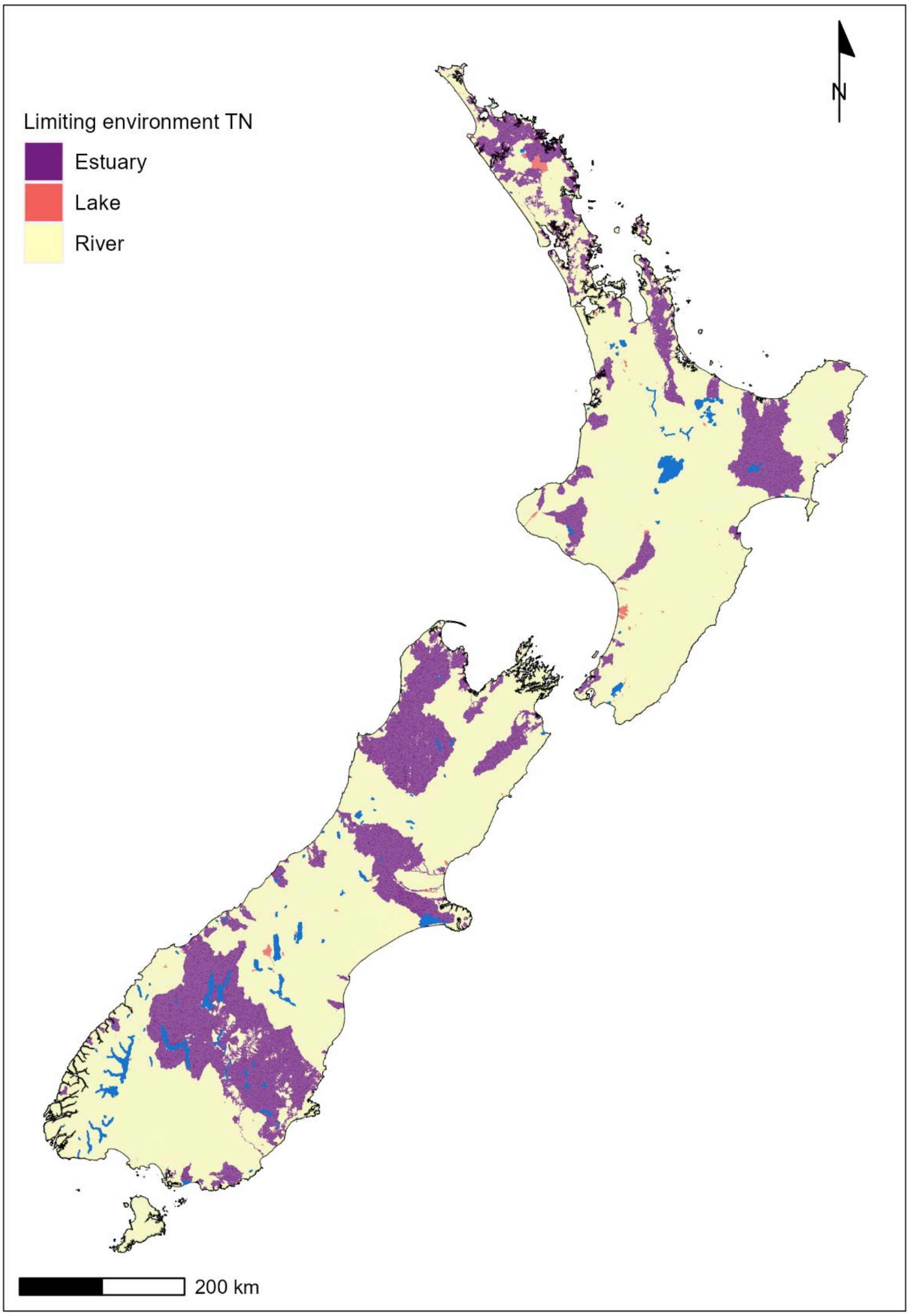

Figure 21. Critical catchment limiting environment type for nitrogen. Note that this map indicates the most restrictive environment type, but this does not mean that a load reduction is required.

3.3 Phosphorus

3.3.1 Compliance

The estimated probability that river concentrations of TP were compliant with the periphyton attribute national bottom line and 20% UPR was greater than 0.6 for 68% of segments nationally (Figure 22).

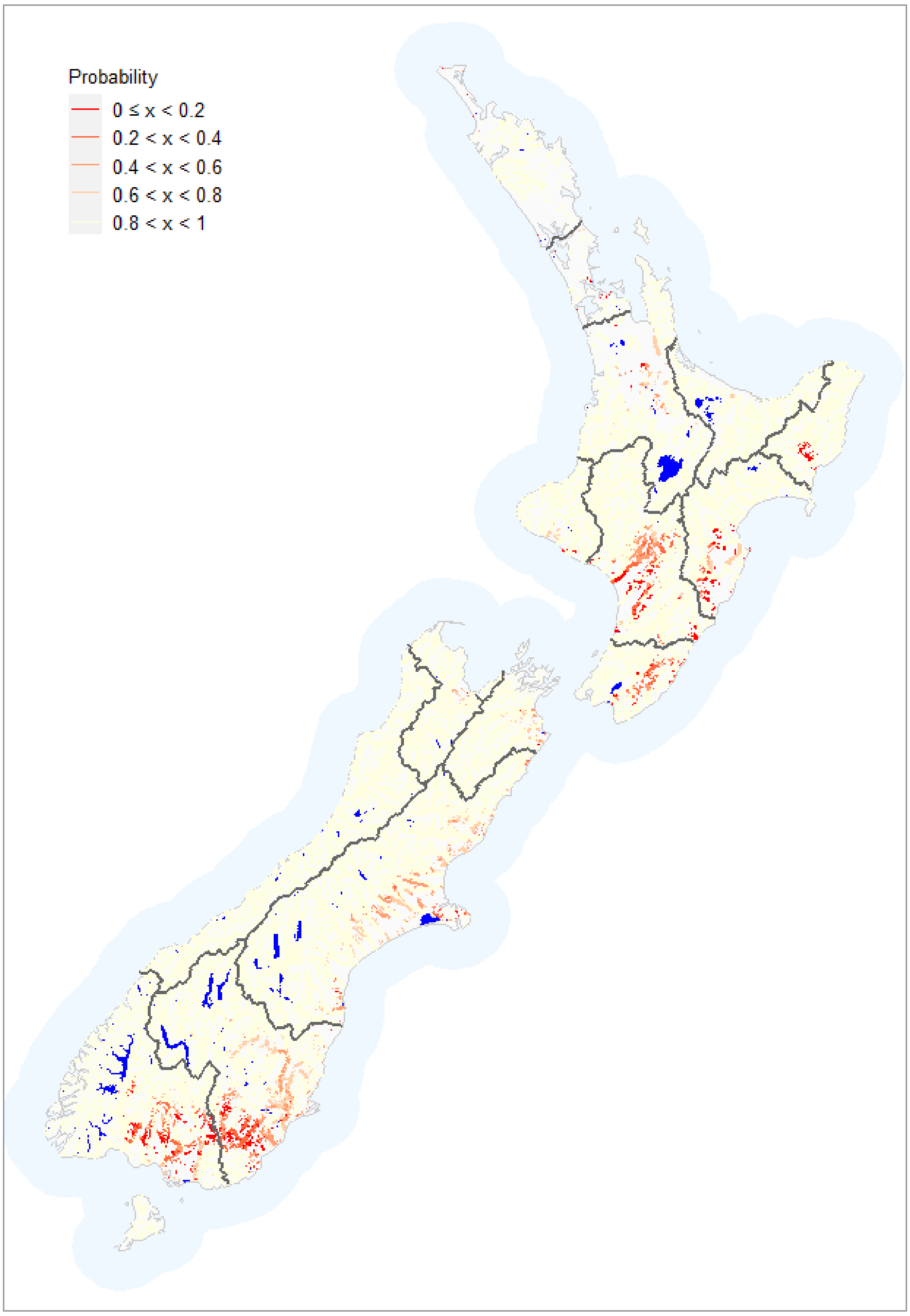

Figure 22. Probability that segments comply with river TP concentration criteria associated with the national bottom lines for periphyton for the 20% spatial exceedance criteria settings. White areas are associated with network the soft-bottomed streams and rivers river segments that are assumed not to support conspicuous periphyton.

The estimated probability that lake concentrations of TP were compliant with the national bottom line was greater than 0.6 for 661 of the 771 lakes included in the analysis (i.e., 86%; of lakes nationally; Figure 23). Lakes that had low probability of being compliant (i.e., likely non-compliant) were generally at low altitude and coastal areas.

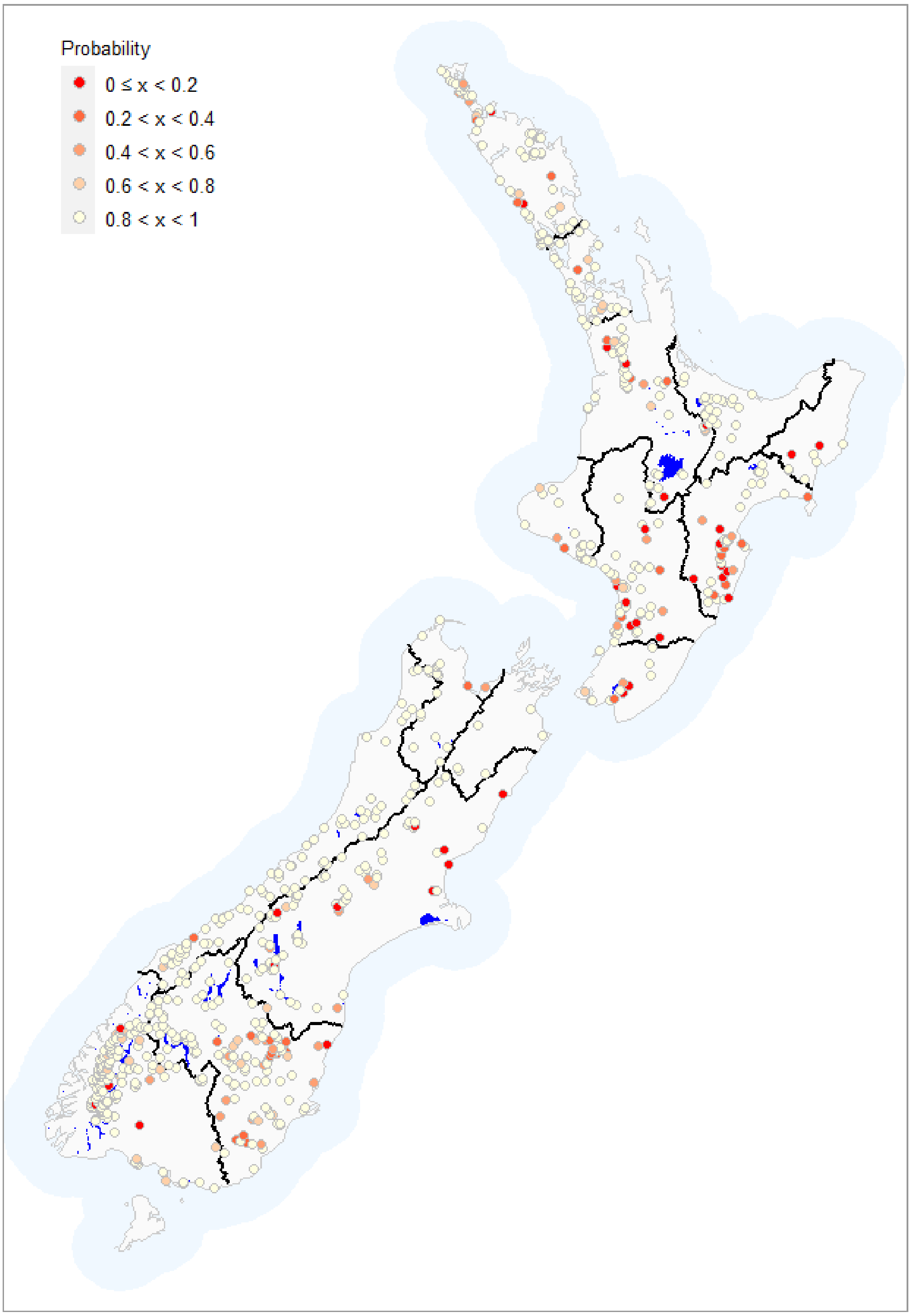

Figure 23. Probability that lakes comply with TP concentration criteria associated with the national bottom lines.

The estimated probability that estuary TP concentrations were compliant with the criteria associated with the national bottom line was greater than 0.6 for 389 of the 418 estuaries included in the analysis (i.e., 93%; Figure 24). Non-compliant estuaries were widely distributed across the North Island and the southern and eastern coasts of the South Island.

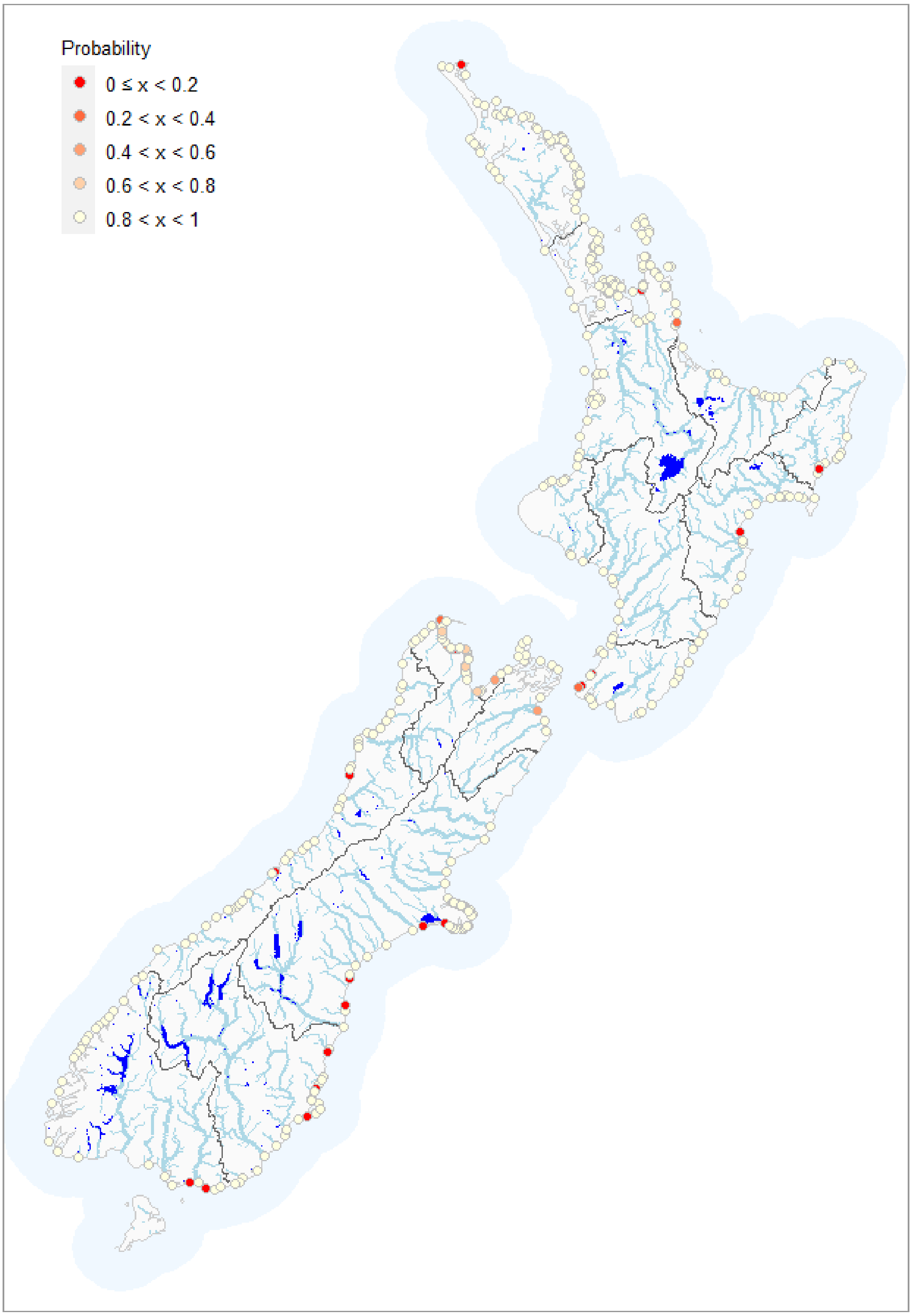

Figure 24. Probability that estuaries comply with TP concentration criteria associated with the national bottom lines.

3.3.2 Local excess loads

The local excess load is the amount by which the current TP load at a receiving environment (i.e., river segment, lake or estuary) would need to be reduced to achieve the national bottom line. The best estimate of the local excess TP yield for rivers exceeded 0.05 kg ha^{-1} yr^{-1} for 3% of river segments and exceeded 0.2 kg ha^{-1} yr^{-1} for 1% of river segments (Figure 25). Note that the 0.05 and 0.2 kg ha^{-1} yr^{-1} are nominal breakpoints that correspond to two of the legend thresholds on Figure 25. These values have no special significance (i.e., are not guidelines or standards). The local excess TP loads were zero for 68% of river segments.

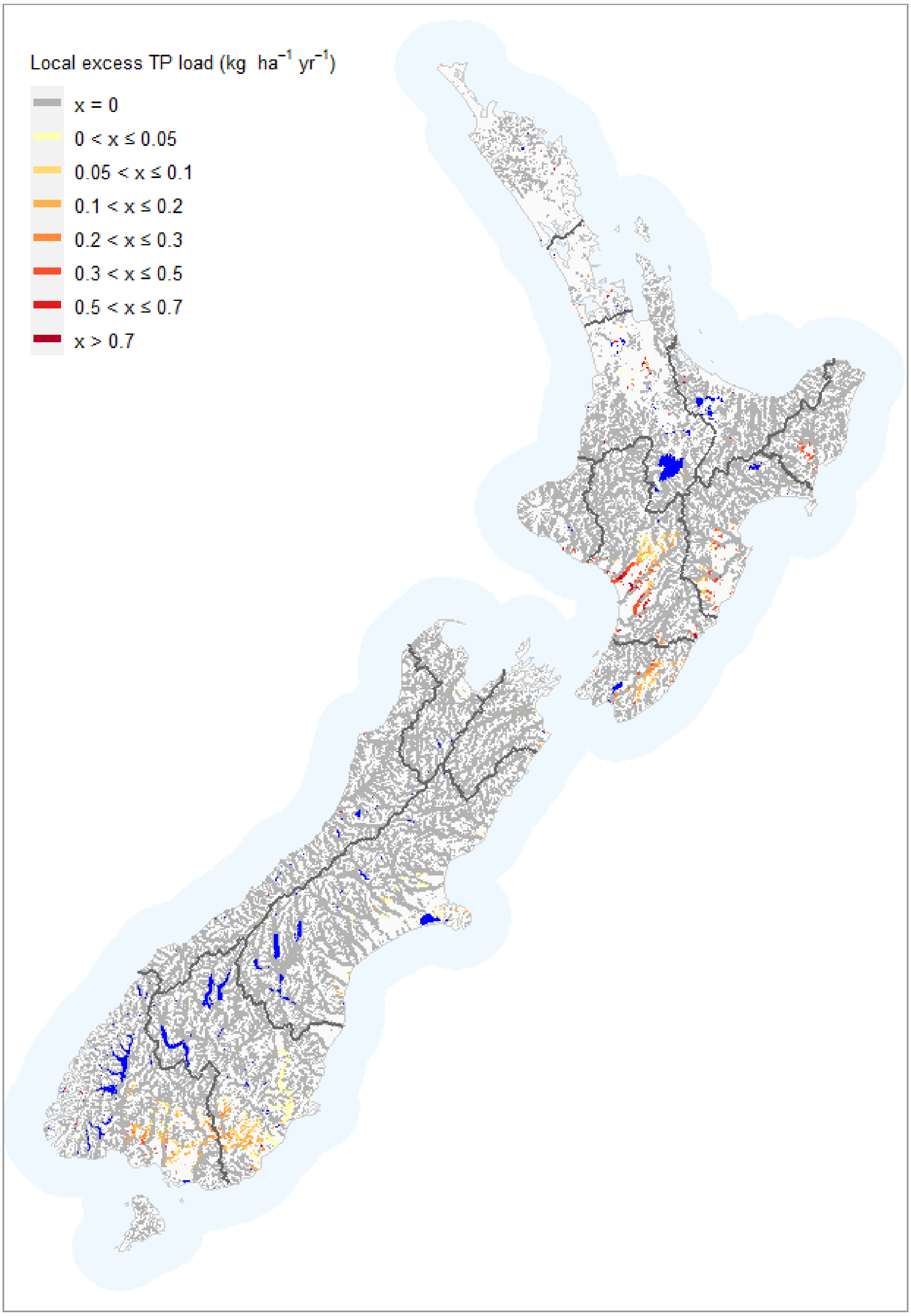

Figure 25. Local excess phosphorus loads associated with national bottom lines for rivers. Note that the breakpoints for the local excess yield in the map legend are nominal and have no special significance (i.e., are not guidelines or standards). White areas are associated with network the soft-bottomed streams and rivers river segments that are assumed not to support conspicuous periphyton.

The best estimate of the local excess TP yield for lakes exceeded 0.1 kg ha^{-1} yr^{-1} for 10% of lakes and exceeded 0.2 kg ha^{-1} yr^{-1} for 6% (Figure 26). Note that the 0.1 and 0.2 kg ha^{-1} yr^{-1} are nominal breakpoints that have no special significance (i.e., are not guidelines or standards). The local excess TP loads were zero for 84% of lakes.

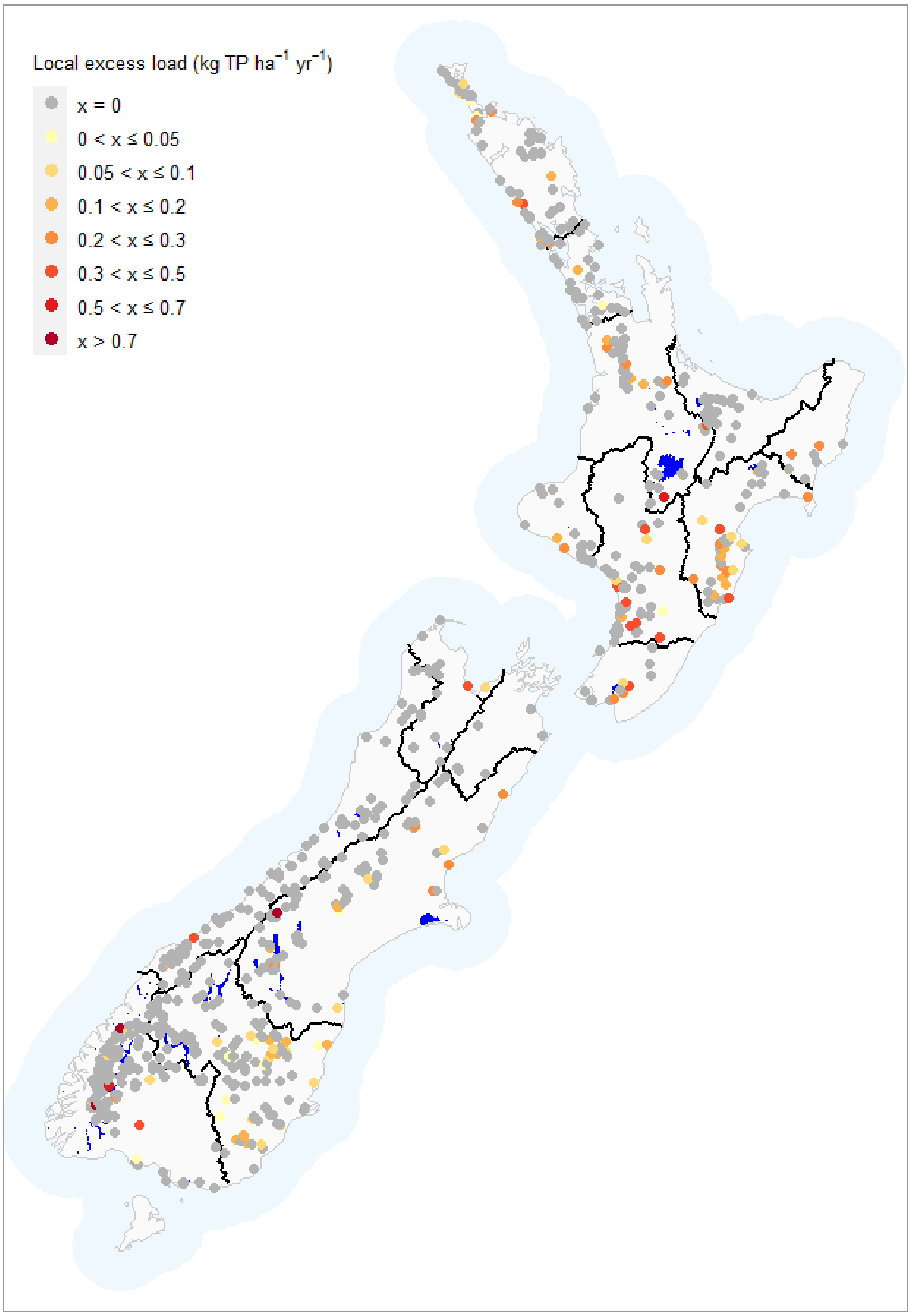

Figure 26. Local excess phosphorus loads associated with national bottom lines for lakes. Note that the breakpoints for the local excess yield in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

The best estimate of the local excess TP yield exceeded 0.1 kg ha^{-1} yr^{-1} for 6% of estuaries and exceeded 0.2 kg ha^{-1} yr^{-1} for 5% (Figure 27). The local excess TP loads were zero for 93% of estuaries.

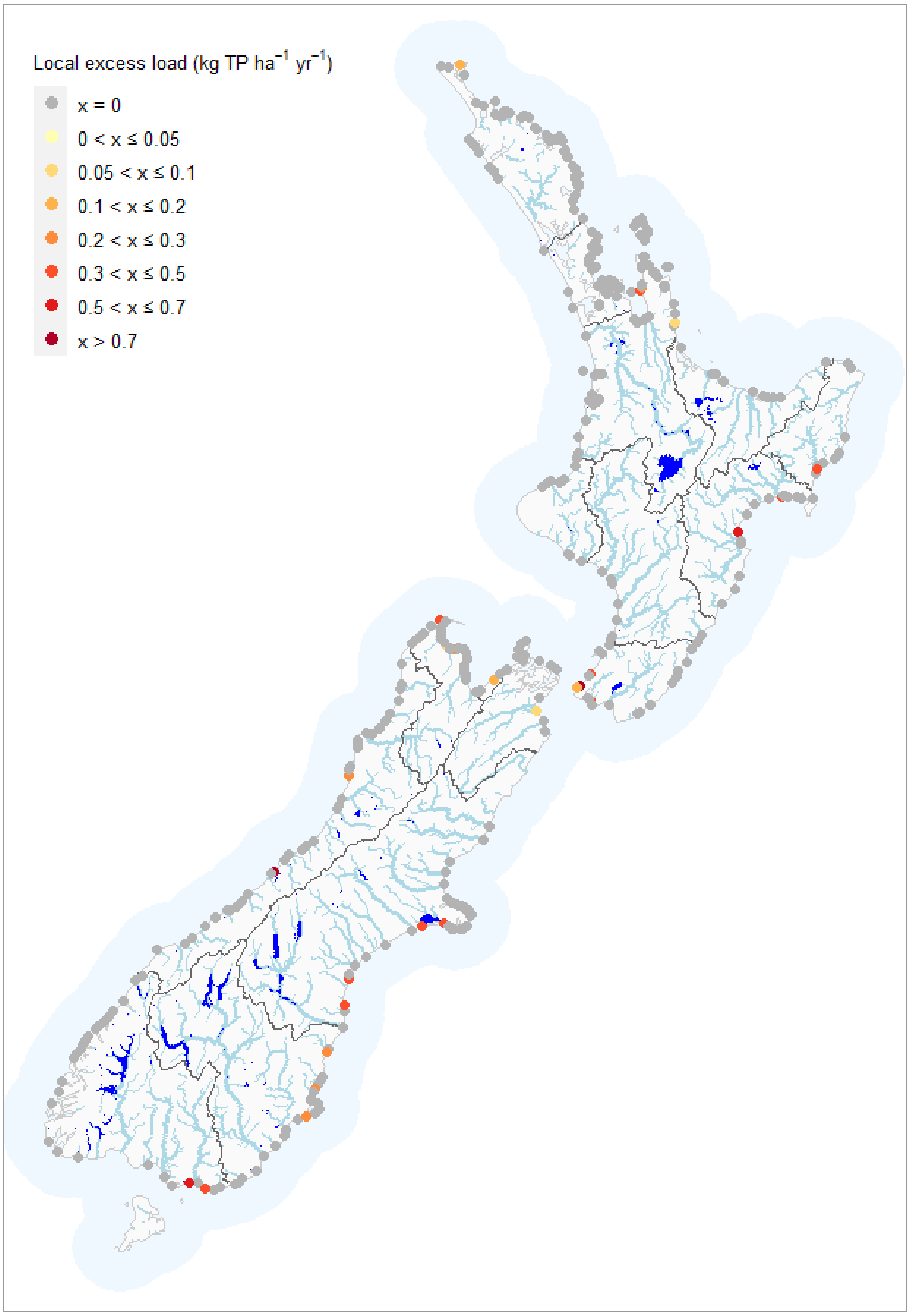

Figure 27. Local excess phosphorus loads for estuaries associated with national bottom lines.

3.3.3 Regional and national load reduction required

The TP load reduction required to achieve the national bottom line for each region and for New Zealand in total are shown in Table 16. For the whole of New Zealand, the best estimate of TP load reductions required was 1,583 t yr^{-1}, which represents 6% of the current load. The TP load reductions required were highest (>10%) in the Manawatu, Otago and Southland regions. The TP load reductions required were lowest (≤2%) in the Northland, Bay of Plenty, Marlborough and West Coast regions. It is noted overall mean reduction rates in regions with large areas of conservation estate and unproductive land, such as Southland and West Coast, may have considerably higher load reduction requirements in agriculturally dominated catchments.

Table 16. Current load and load reduction required for phosphorus by region and nationally for the national bottom line including the uncertainties at the 90% level of confidence. Note that loads are expressed in absolute terms in units of tonnes per year (t 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.

Region	Total load (t yr^{-1})	Load reduction required (t yr^{-1})	Load reduction required (%)
Northland	1,009 (691 - 1,363)	24 (6 - 72)	2 (1 - 7)
Auckland	251 (209 - 308)	8 (5 - 12)	3 (2 - 5)
Waikato	1,983 (1,186 - 3,168)	148 (25 - 662)	6 (2 - 20)
Bay of Plenty	1,267 (804 - 1,828)	21 (0 - 108)	1 (0 - 7)
Gisborne	1,426 (759 - 2,181)	113 (5 - 508)	6 (0 - 31)
Taranaki	912 (608 - 1,567)	26 (6 - 89)	3 (1 - 9)
Manawatū	3,759 (2,102 - 6,607)	528 (92 - 1,598)	12 (3 - 38)
Hawkes Bay	2,296 (1,528 - 3,603)	135 (33 - 341)	6 (2 - 15)
Wellington	730 (443 - 1,200)	68 (28 - 165)	9 (5 - 16)
Tasman	481 (296 - 816)	15 (4 - 47)	3 (1 - 10)
Marlborough	625 (267 - 1,155)	11 (2 - 27)	2 (0 - 4)
West Coast	4,158 (3,115 - 6,159)	29 (9 - 64)	1 (0 - 2)
Canterbury	2,976 (2,071 - 3,950)	163 (88 - 299)	6 (3 - 9)
Otago	707 (342 - 1,298)	100 (15 - 257)	13 (4 - 24)
Southland	1,617 (1,221 - 2,108)	196 (57 - 445)	12 (4 - 23)
National	24,195 (20,146 - 28,103)	1,583 (858 - 3,222)	6 (4 - 12)

3.3.4 Critical catchments for phosphorus

The critical catchment excess loads for phosphorus are shown as yields on Figure 28. Reductions in TP loads are required for catchments comprising 11% of the land area of New Zealand. Critical point catchments with excess TP loads greater than 0.05 kg ha^{-1} yr^{-1} and 0.2 kg ha^{-1} yr^{-1} comprised 11 and 6% of the land area of New Zealand, respectively.

When TP load reductions required were expressed as a proportion of current loads, critical catchments that require reductions of greater than 30% occupied 7% of the land area of New Zealand (Figure 29). The comparison of load reductions expressed as yields (kg ha^{-1} yr^{-1}) with those expressed as proportion of current load (%) indicates that reduction requirements in areas with low yield reductions (e.g., much of Otago and Southland) can be large in relative terms.

For phosphorus, the limiting environment types for critical catchment areas were 96%, 1%, and 3% for rivers, lakes and estuaries, respectively (Figure 30).

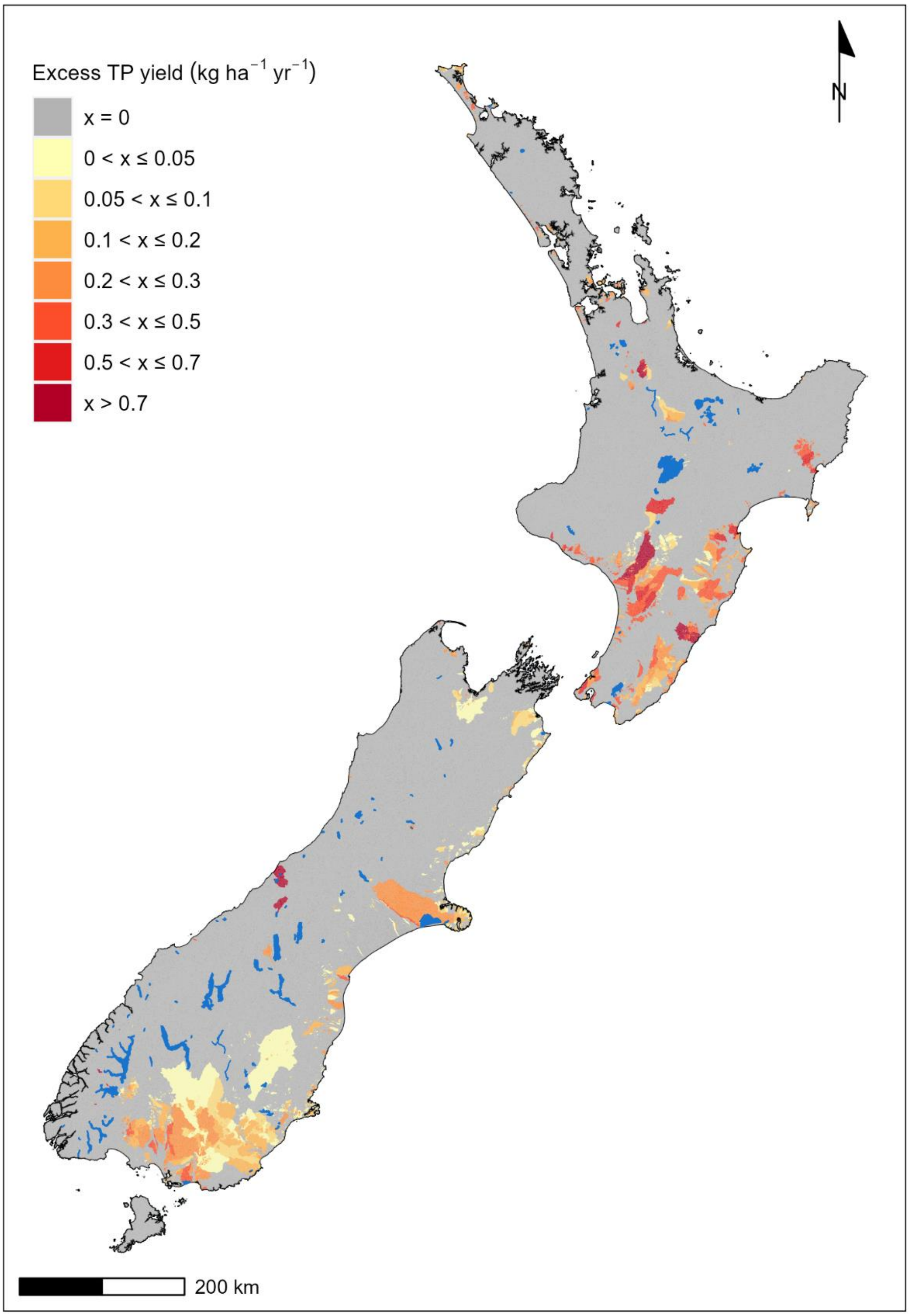

Figure 28. Critical catchment excess loads for phosphorus expressed as a yield (kg ha^{-1} yr^{-1}).

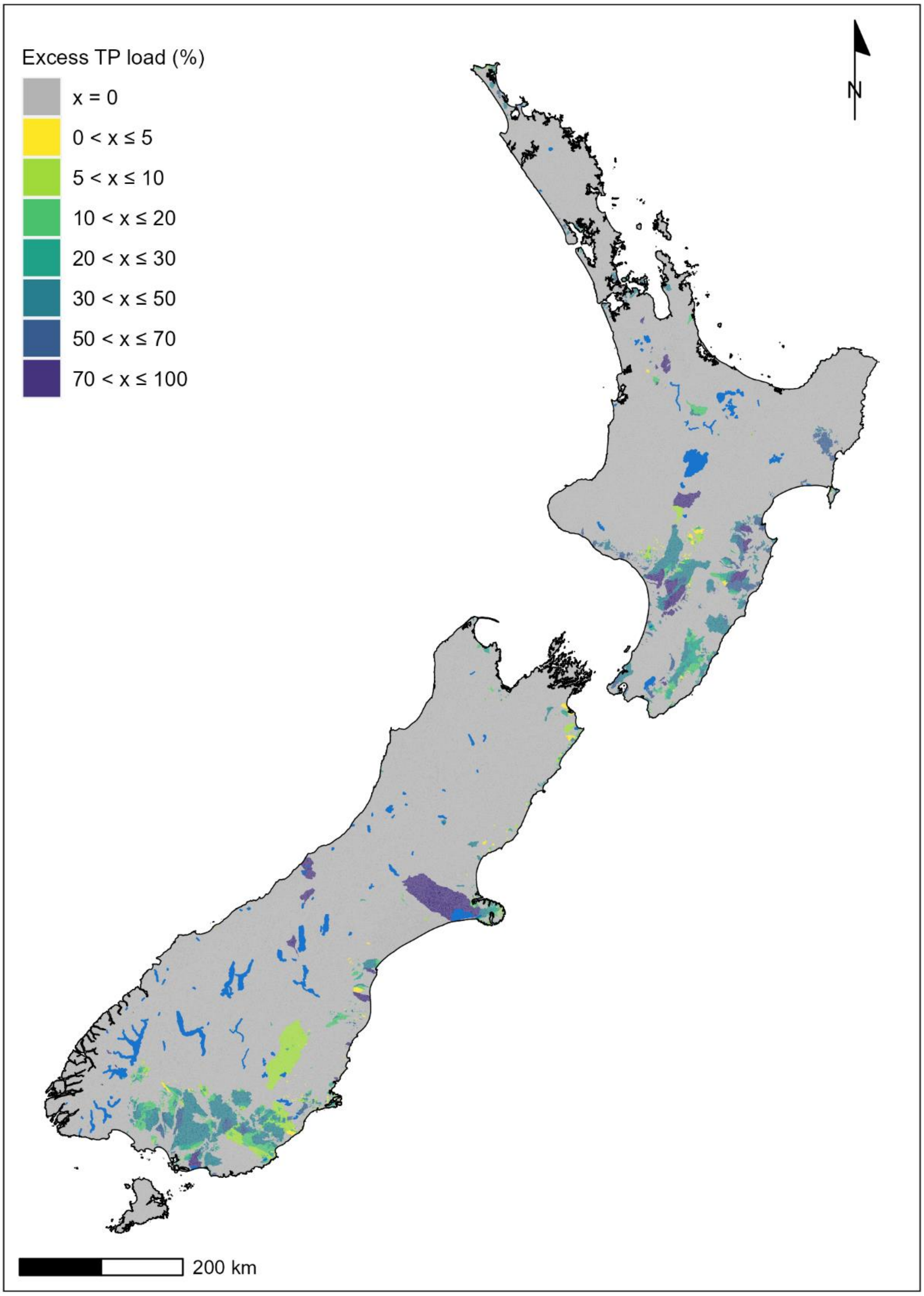

Figure 29. Critical catchment excess loads for phosphorus expressed as a proportion of current loads (%).

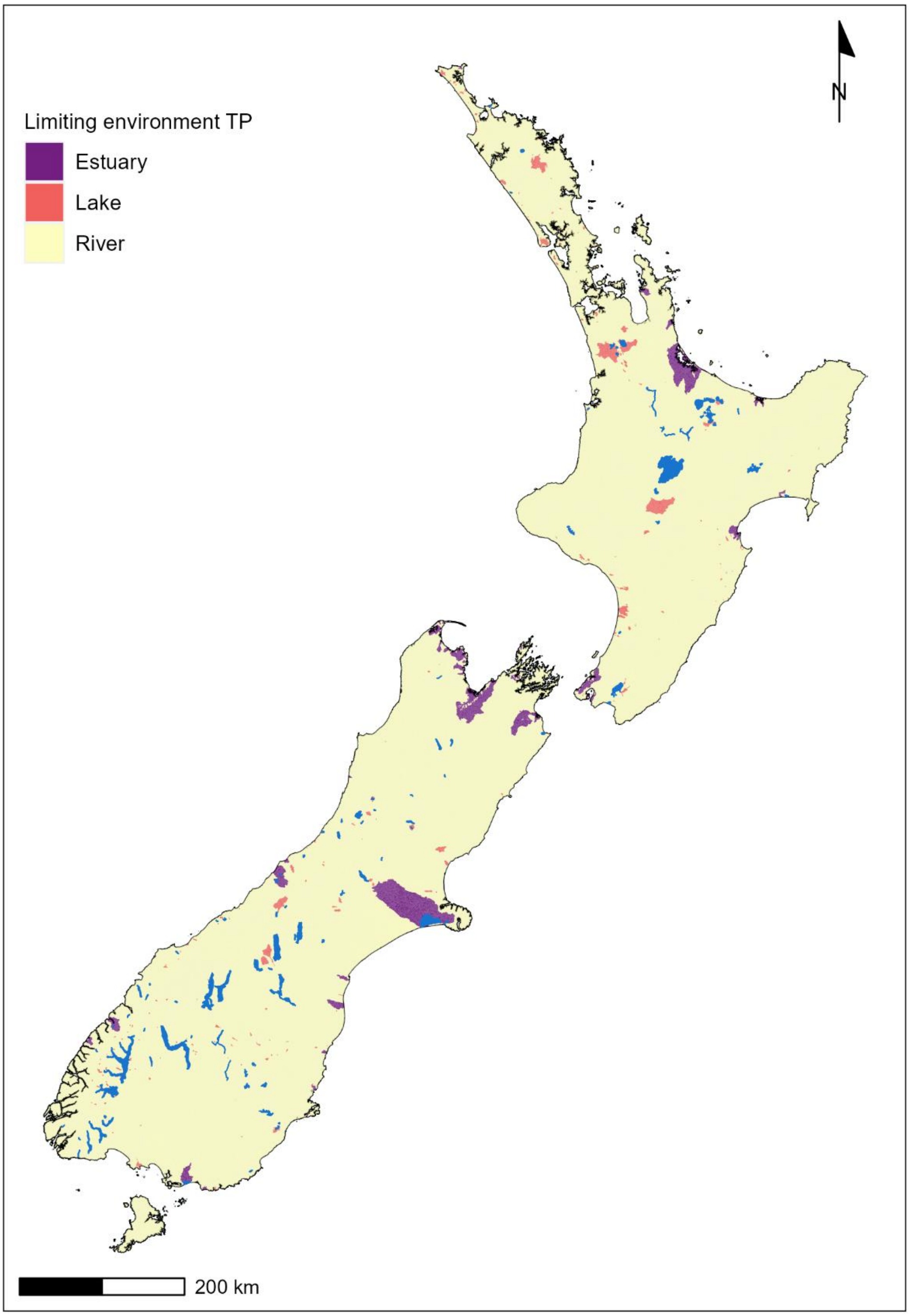

Figure 30. Critical catchment limiting environment type of phosphorus. Note that this map indicates the most restrictive environment type, but this does not mean that a load reduction is required.

3.4 *E. coli*

3.4.1 Compliance

The estimated probability that values of the four *E. coli* statistics were compliant with the criteria defined for the national bottom line was greater than 0.6 for 62%, 55%, 65% and 66% of segments for the Median, Q95, G260 and G540, respectively (Figure 31). The estimated probability that all statistics complied with the national bottom line criteria was greater than 0.6 for 52% of segments. The probability of compliance was greatest for segments in the headwater areas of the individual catchments, and particularly in the higher areas of both the North and South Islands. The probability of compliance was lowest for segments in the low elevation parts both Islands.

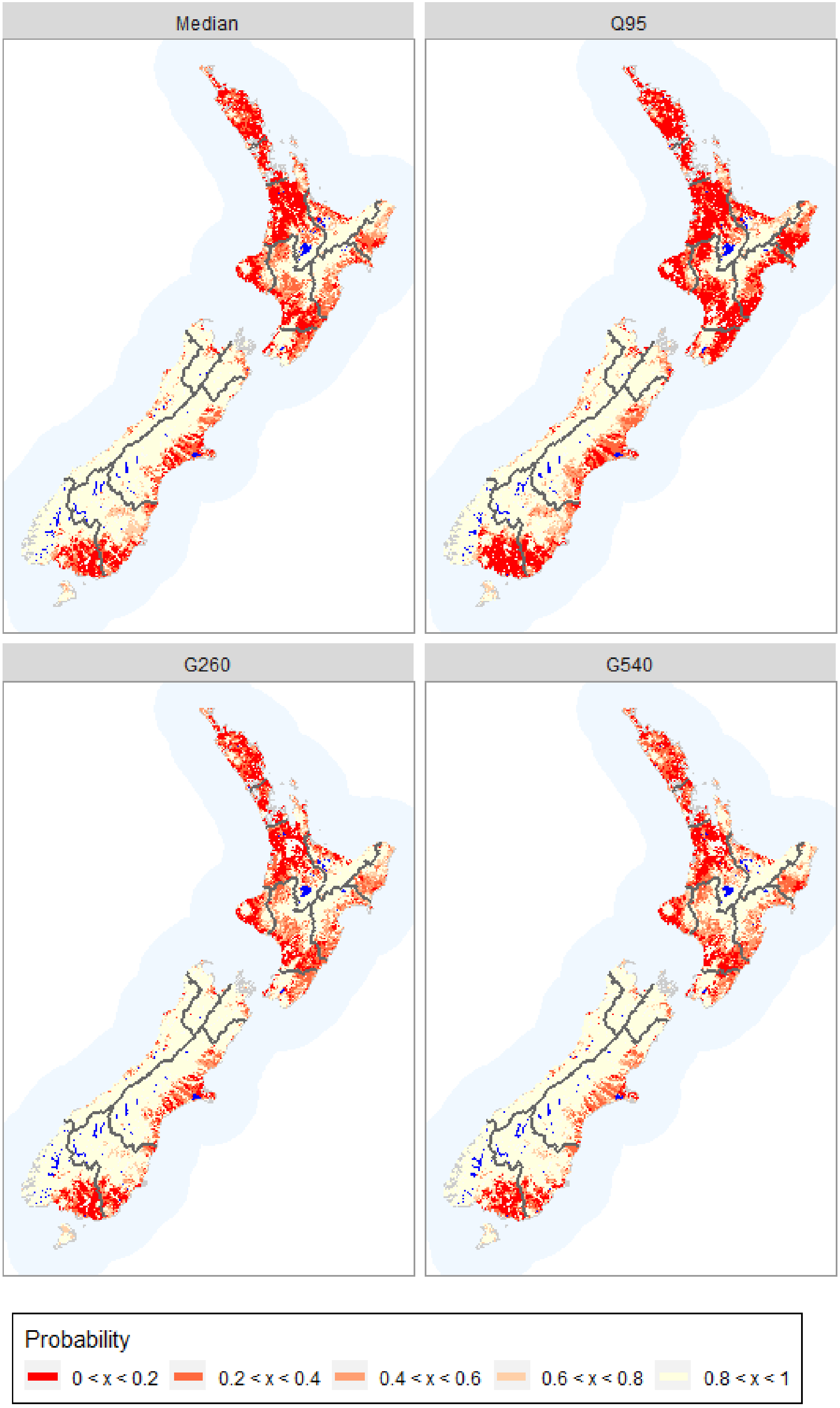

Figure 31. Probability of compliance with the criteria for each of the four E. coli statistics pertaining to the national bottom line. Each map represents the probability that segments achieve the criteria for the E. coli statistic that is associated with national bottom line.

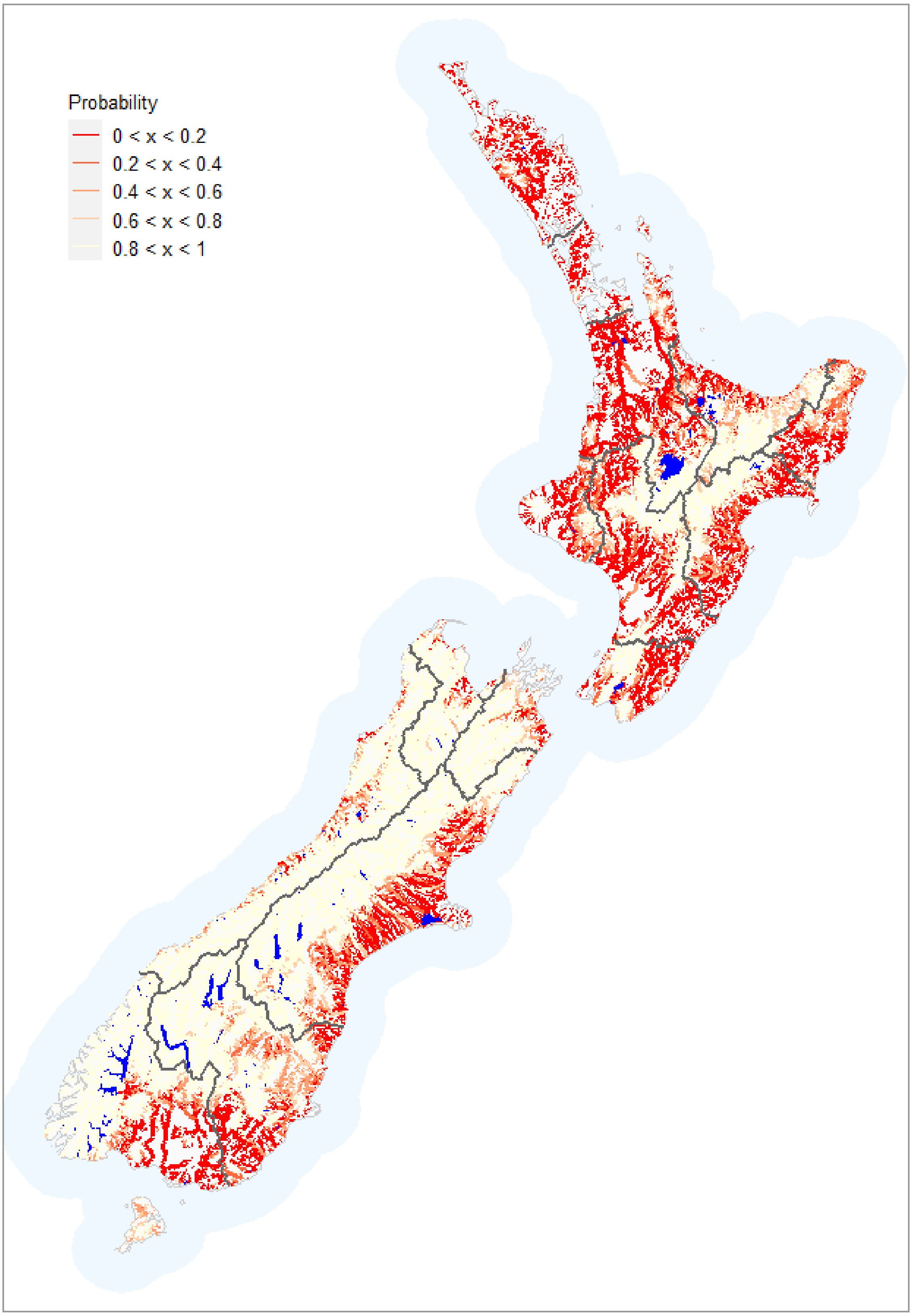

Figure 32. Probability of compliance with any of the criteria pertaining to national bottom line. This map represents the overall probability that segments achieve the national bottom line for the E. coli attribute.

3.4.2 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 national bottom line. The best estimate of the local excess *E. coli* yield for rivers exceeded 5 giga *E. coli* ha^{-1} yr^{-1} for 46% of river segments and exceeded 50 giga *E. coli* ha^{-1} yr^{-1} for 25% of river segments (Figure 33). Note that the 5 and 50 giga *E. coli* ha^{-1} yr^{-1} are nominal breakpoints that correspond to two of the legend thresholds on Figure 33. These values have no special significance (i.e., are not guidelines or standards). The local excess *E. coli* loads were zero for 50% of river segments.

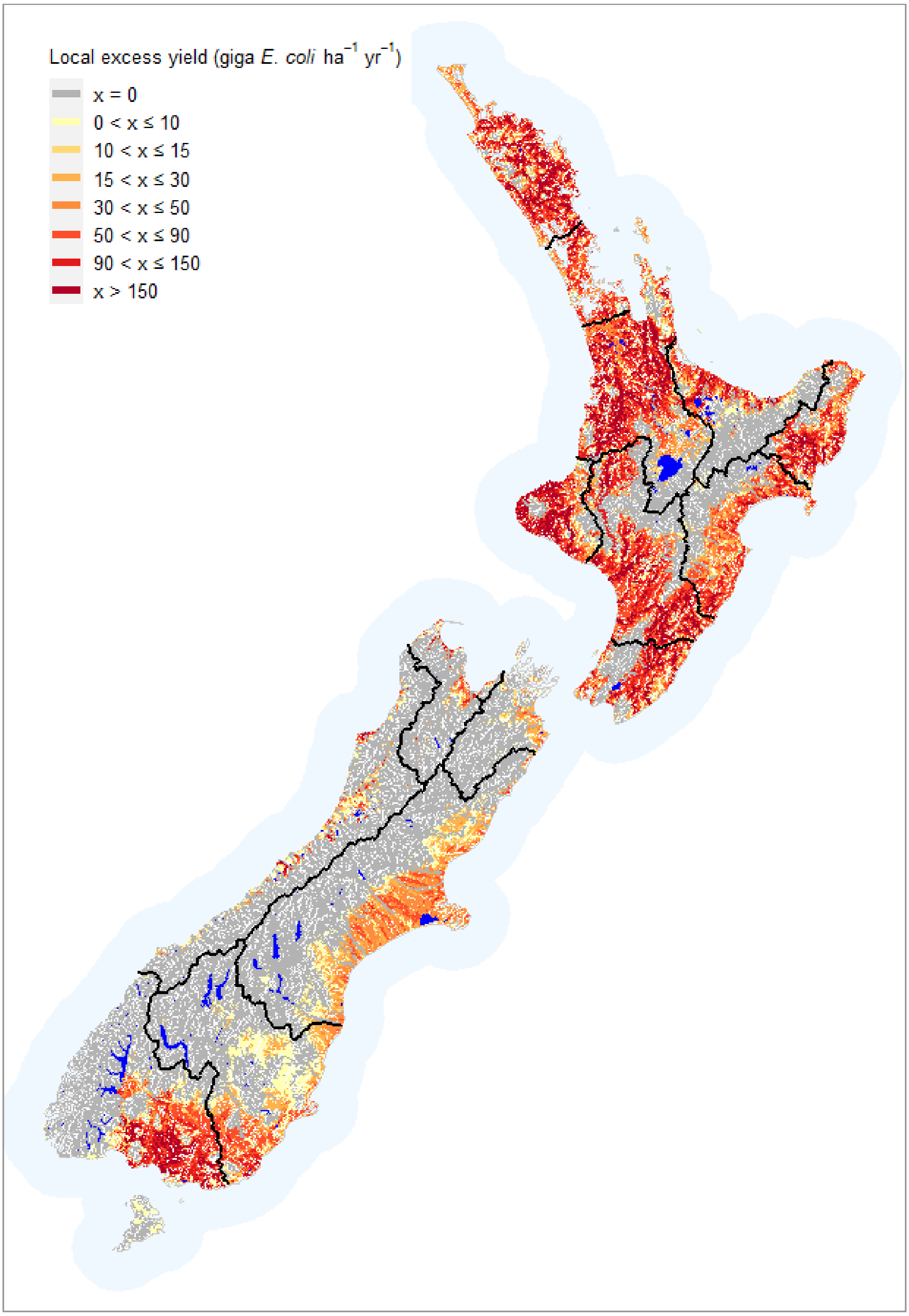

Figure 33. Local excess E. coli loads associated with national bottom lines. Note that the breakpoints for the local excess yield in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.4.3 Regional and national load reduction required

The *E. coli* load reduction required to achieve the national bottom line for each region and for New Zealand in total are shown in Table 17. For the whole of New Zealand, the best estimate of *E. coli* load reductions required was 2,237 peta *E. coli* yr^{-1}, which represents 73% of the current load. The *E. coli* load reductions required were highest (≥70%) in the Northland, Auckland, Waikato, Gisborne, Taranaki, Manawatū and Southland regions. The *E. coli* load reductions required were lowest (≤30%) in the Marlborough and West Coast regions. It is noted that regions with large areas of conservation estate and unproductive land, such as Southland and West Coast, may have low overall mean reduction rates but have high load reduction requirements in agriculturally dominated catchments.

Table 17. Current load and load reduction required for E. coli by region and nationally for the national bottom line including the uncertainties at the 90% level of confidence. Note that loads are expressed in absolute terms in units of tonnes per year (t 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.

Region	Total load (peta *E. coli* yr^{-1})	Load reduction required (peta *E. coli* yr^{-1})	Load reduction required (%)
Northland	247 (160 - 404)	202 (118 - 359)	80 (70 - 91)
Auckland	57 (43 - 76)	41 (29 - 59)	73 (67 - 78)
Waikato	335 (177 - 668)	323 (139 - 784)	91 (70 - 126)
Bay of Plenty	110 (77 - 151)	68 (40 - 117)	61 (48 - 79)
Gisborne	159 (73 - 348)	146 (43 - 371)	85 (56 - 112)
Taranaki	182 (108 - 271)	132 (71 - 205)	72 (64 - 82)
Manawatū	690 (331 - 1,148)	641 (188 - 1,119)	90 (58 - 125)
Hawkes Bay	229 (123 - 387)	129 (54 - 244)	55 (41 - 73)
Wellington	159 (74 - 381)	106 (38 - 310)	61 (46 - 83)
Tasman	38 (23 - 58)	15 (8 - 26)	40 (29 - 52)
Marlborough	39 (18 - 70)	12 (4 - 33)	29 (19 - 50)
West Coast	220 (115 - 465)	47 (17 - 166)	19 (12 - 36)
Canterbury	183 (123 - 265)	83 (46 - 129)	45 (34 - 58)
Otago	103 (45 - 216)	65 (20 - 161)	60 (40 - 77)
Southland	279 (130 - 510)	219 (82 - 453)	75 (60 - 88)
National	3,034 (2,407 - 3,765)	2,237 (1,535 - 3,076)	73 (60 - 84)

3.4.4 Critical catchments for *E. coli*

The critical catchment excess load is the amount by which the current *E. coli* load would need to be reduced to ensure loads in all river receiving environments in the catchment do not exceed the MAL (and therefore all receiving environments achieve their target attribute states). The critical catchment excess loads for *E. coli* are shown as yields on Figure 34. Reductions in *E. coli* loads are required for catchments comprising 79% of the land area of New Zealand. Critical point catchments with excess *E. coli* loads greater than 50 giga *E. coli* ha^{-1} yr^{-1} and 200 giga *E. coli* ha^{-1} yr^{-1} comprised 42% and 11% of the land area of New Zealand, respectively.

When *E. coli* load reductions required were expressed as a proportion of current loads, critical catchments that require reductions of greater than 50% and occupied 51% of the land area of New Zealand (Figure 35). The comparison of load reductions expressed as yields (giga *E. coli* ha^{-1} yr^{-1}) with those expressed as proportion of current load (%) indicates that reduction requirements in areas with low yield reductions (e.g., coastal areas in North Otago) can be large in relative terms.

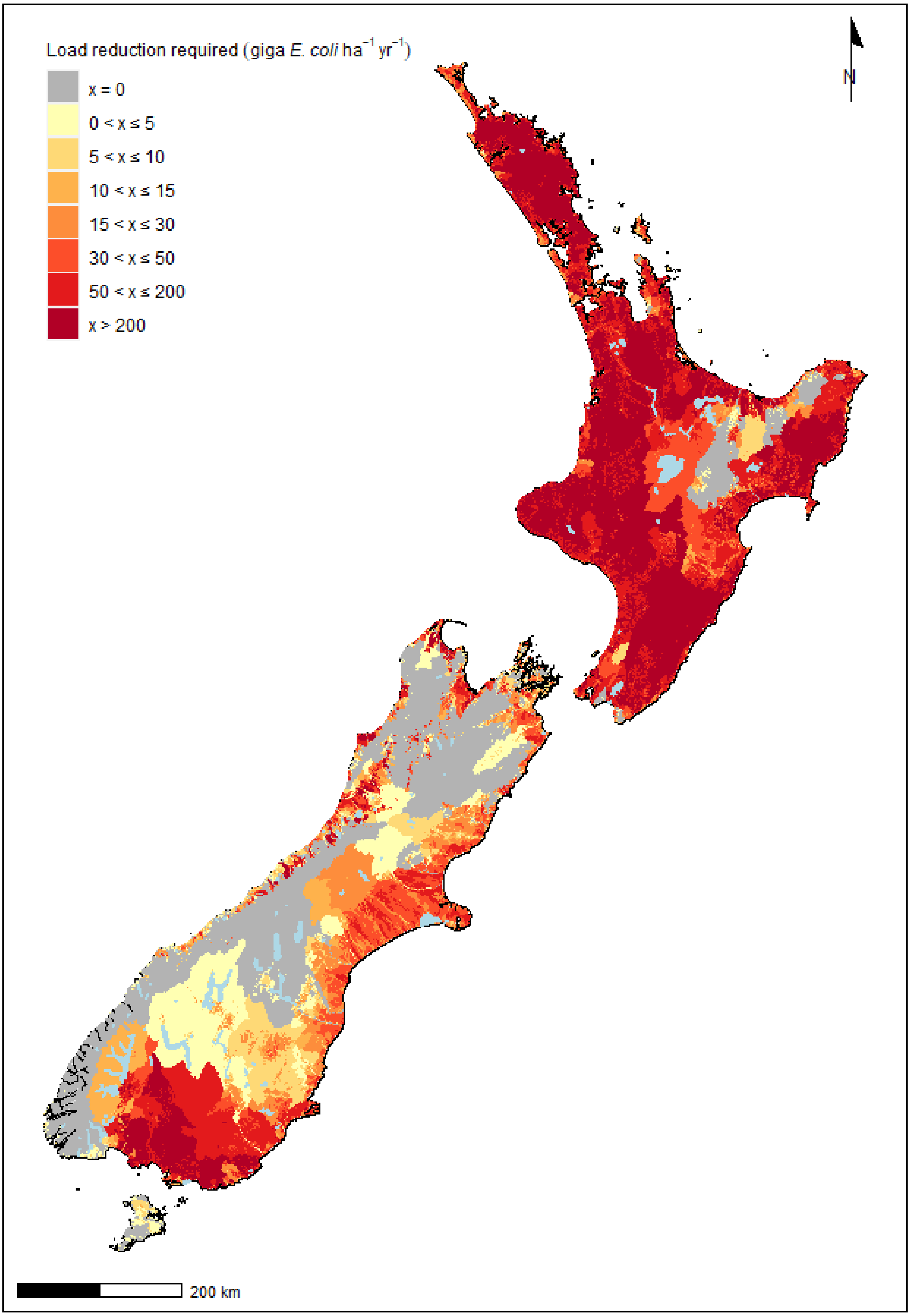

Figure 34. Critical catchment excess loads for E. coli expressed as a yield (giga E. coli ha^{-1} yr^{-1}).

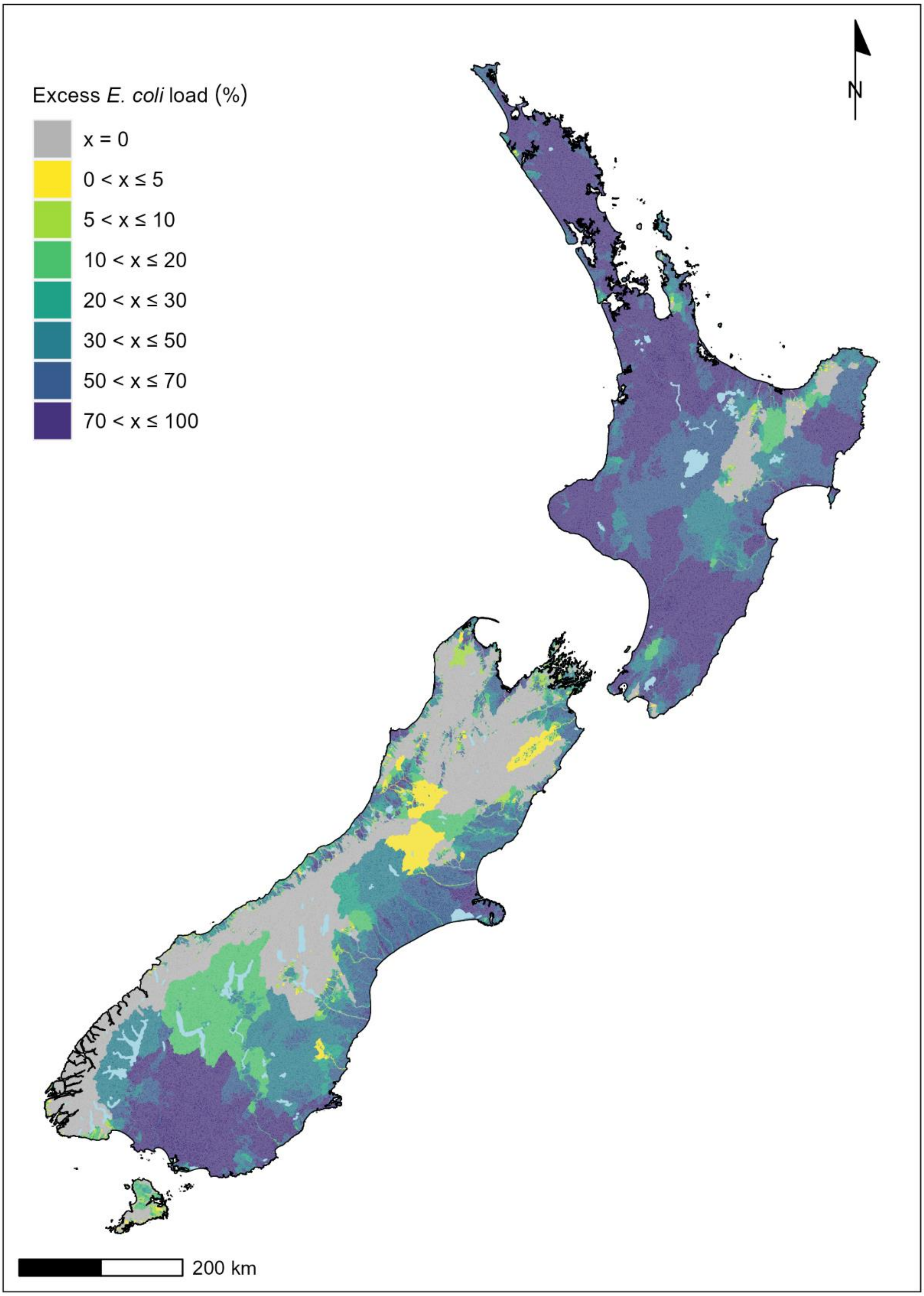

Figure 35. Critical catchment excess loads for E. coli expressed as a proportion of current loads (%).

3.5 Sediment

3.5.1 Compliance

The estimated probability that values of the suspended fine sediment attribute (river visual clarity) were compliant with the criteria defined for the national bottom line was greater than 0.6 for 76% of segments (Figure 39). Compliance was greatest for headwater areas of the individual catchments, and particularly in the higher elevation areas of both the North and South Islands. Compliance was low for segments in the low elevation parts of both islands and for the main stems of mountain-fed rivers of both Islands.

3.5.2 Local excess loads

The local excess load is the amount by which the current sediment load at a river segment would need to be reduced to achieve the national bottom line. Local excess sediment yield for rivers was zero for 86% of river segments, exceeded 2 t km^{-2} yr^{-1} for 8% of river segments, and exceeded 10 t km^{-2} yr^{-1} for 5% of river segments (Figure 37). The local excess sediment loads were zero for 90% of river segments. Note that these are nominal breakpoints that correspond to two of the legend thresholds on Figure 37) and no special significance (i.e., are not guidelines or standards).

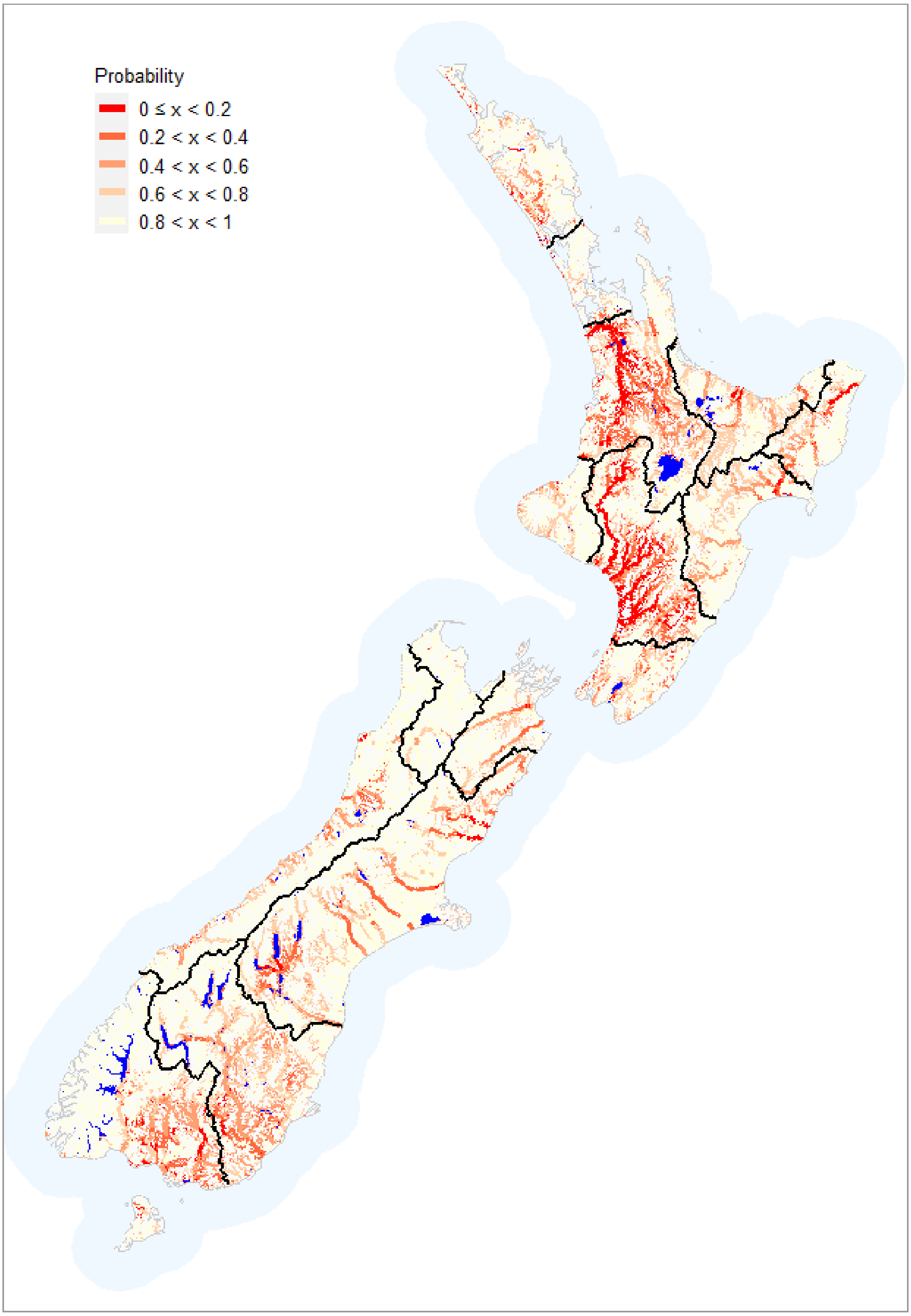

Figure 36. Probability of compliance with the criteria for the suspended fine sediment attribute (visual clarity) pertaining to the national bottom line. The map represents the probability that segments achieve the criteria that is associated with national bottom line.

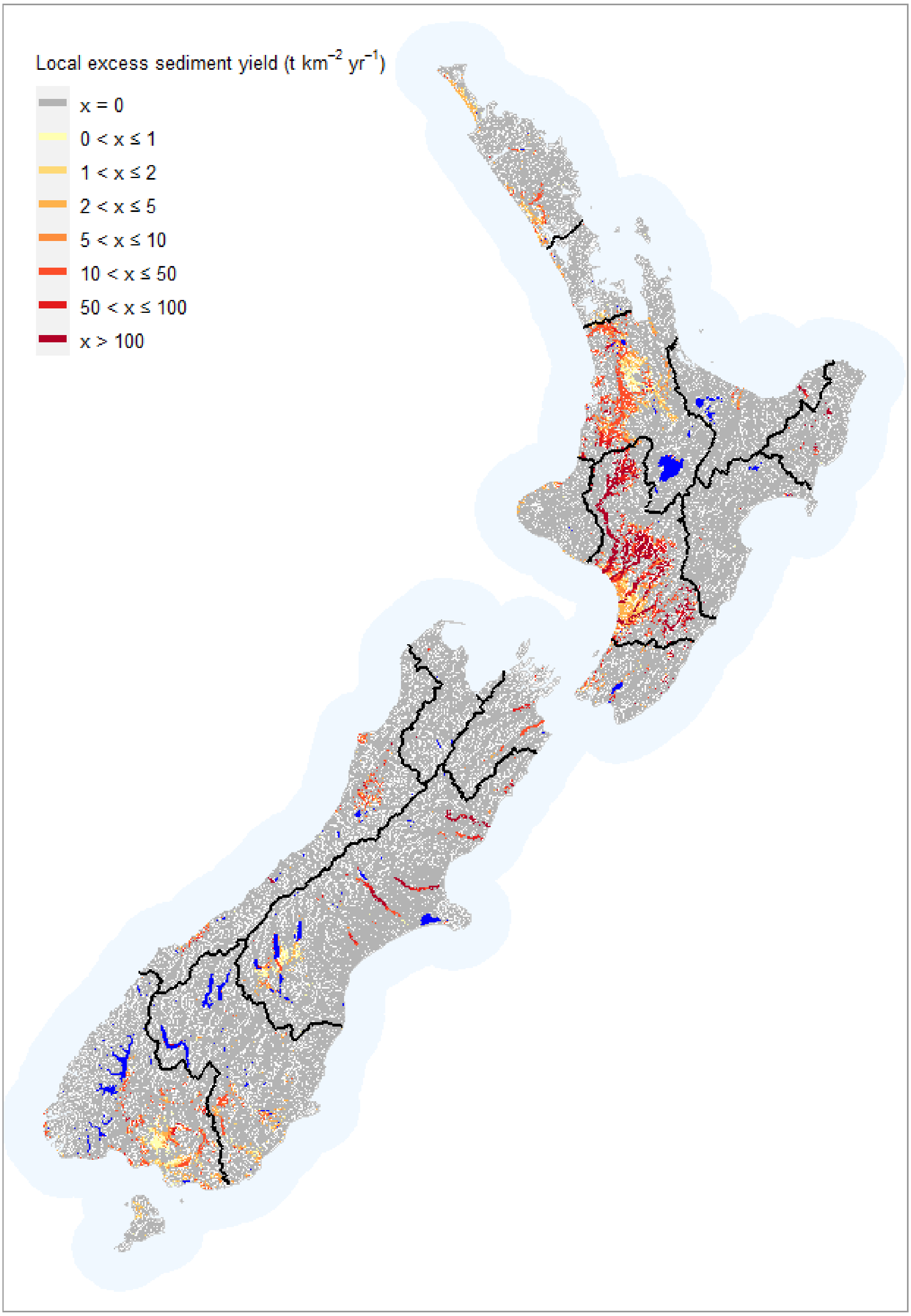

Figure 37. Local excess sediment loads associated with the suspended fine sediment (visual clarity) national bottom lines. Note that the breakpoints for the local excess yield in the map legend are nominal and have no special significance (i.e., are not guidelines or standards).

3.5.3 Regional and national load reduction required

The suspended sediment load reduction required to achieve the national bottom line for each region and for New Zealand in total are shown in Table 18. For the whole of New Zealand, the load reductions required was 33% of the current load. The sediment load reductions required were highest (>30%) in the Waikato, Gisborne, Manawatū, Canterbury, and Otago regions. The sediment load reductions required were low (<10%) in the Auckland and Tasman regions.

The load reduction required exceeded 100% for the Otago region (Table 18). This occurs because model predictions of current sediment load sometimes decreased toward the lower end of main stem rivers compared to predictions upstream. This means that the estimated upstream reductions can be larger than the predicted current load at the bottom of the catchment. This is not necessarily an error. Loads of sediment are likely to be attenuated (i.e., by being deposited in lakes or floodplains) as they are transported downstream from their source, and this would lead to reduction in loads in the downstream direction.

Table 18. Current load and load reduction required for sediment by region and nationally for the national bottom line. Note that loads are expressed in absolute terms in units of mega tonnes (10^6 tonnes) per year (Mt 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.

Region	Total load (Mt yr^{-1})	Load reduction required (Mt yr^{-1})	Load reduction required (%)
Northland	1.21 (0.89 - 1.62)	0.18 (0.06 - 0.4)	15 (4 - 30)
Auckland	0.35 (0.3 - 0.42)	0.02 (0.01 - 0.04)	7 (4 - 11)
Waikato	1.93 (1.33 - 2.8)	0.93 (0.45 - 1.8)	47 (29 - 66)
Bay of Plenty	17.32 (10.12 - 26.45)	2.99 (0.45 - 7.52)	17 (3 - 39)
Gisborne	81.7 (38.49 - 168.21)	34.89 (5.03 - 90.95)	41 (9 - 60)
Taranaki	3.26 (1.9 - 5.21)	0.81 (0.11 - 2.13)	23 (4 - 53)
Manawatū	11.99 (6.77 - 21.36)	7.12 (3.4 - 13.3)	58 (42 - 75)
Hawkes Bay	13.45 (8.93 - 18.72)	2.79 (0.57 - 5.81)	20 (4 - 36)
Wellington	9.34 (6.98 - 13.05)	1.66 (0.7 - 2.93)	18 (9 - 29)
Tasman	1.02 (0.68 - 1.57)	0.04 (0.01 - 0.12)	3 (1 - 10)
Marlborough	2.04 (1.33 - 3.16)	0.6 (0.14 - 1.41)	28 (8 - 55)
West Coast	61.04 (49.2 - 77.28)	10.71 (5.02 - 17.74)	18 (8 - 29)
Canterbury	15.67 (10.65 - 22.26)	7.42 (3.63 - 12.77)	49 (22 - 76)
Otago	1.08 (0.66 - 1.74)	3.7 (0.05 - 13.25)	338 (5 - 1089)
Southland	1.99 (1.39 - 2.89)	0.49 (0.13 - 1.48)	24 (7 - 52)
National	223 (170 - 324)	74 (42 - 128)	33 (21 - 44)

3.5.4 Critical catchments for sediment

The critical catchment excess load is the amount by which the current sediment load would need to be reduced to ensure loads in all river receiving environments in the catchment do not exceed the MAL (and therefore all receiving environments achieve their target attribute states). The critical catchment excess loads for sediment are shown as yields on Figure 38). Sediment load reductions are required for catchments comprising 49% of the land area of New Zealand. Critical catchments comprising 35% of the land area of New Zealand required sediment yield reductions of greater than 10 t km^{-2} yr^{-1}.

When sediment load reductions required were expressed as a proportion of current loads, critical catchments that require reductions of greater than 50% and occupied 17% of the land area of New Zealand (Figure 40). The load reductions expressed as a proportion of current load (%) were highest in catchments draining the central North Island including large areas of the Manawatū- Whanganui and Waikato regions.

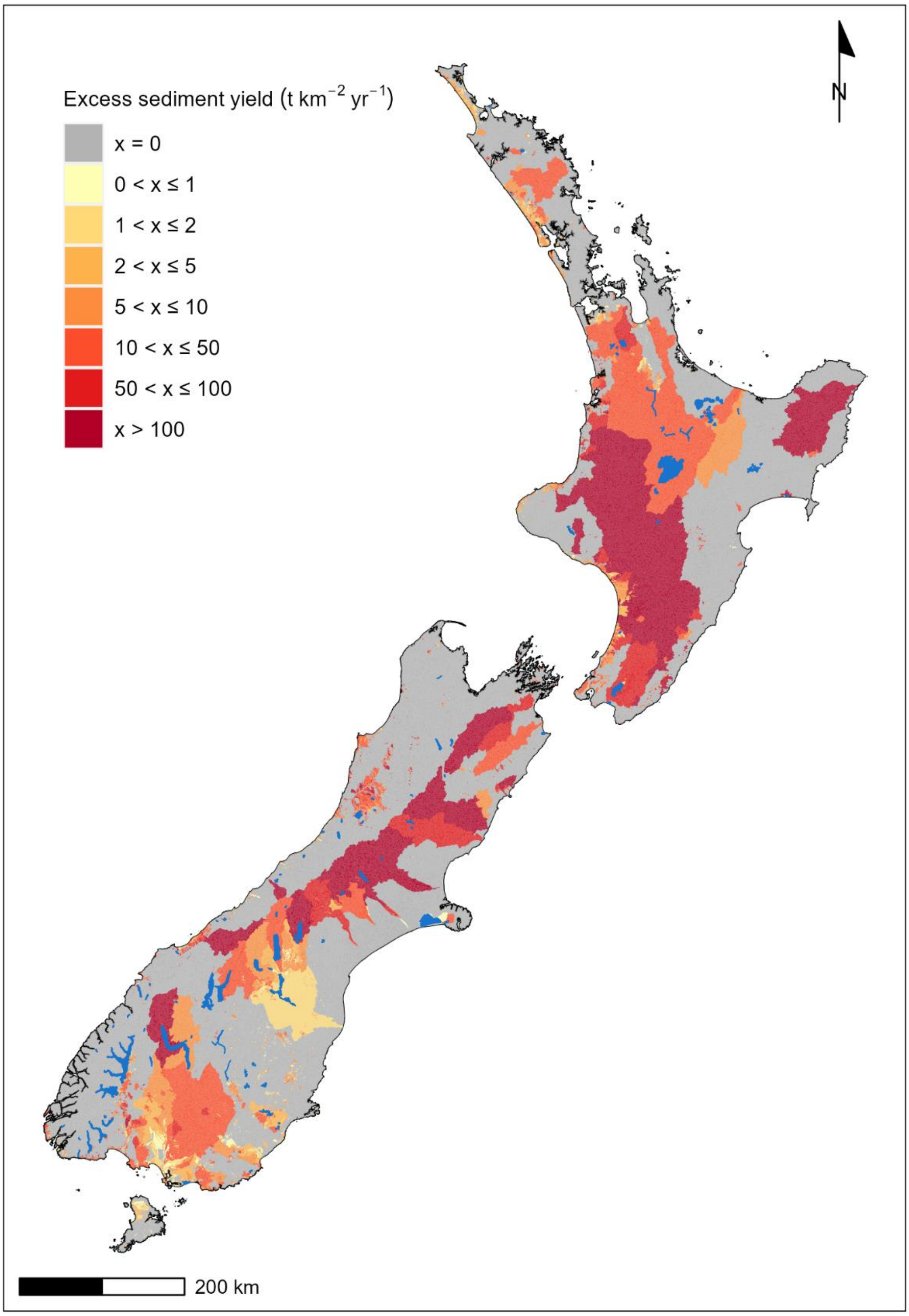

Figure 38. Critical catchment excess loads for sediment expressed as a yield (t km^{-2} yr^{-1}).

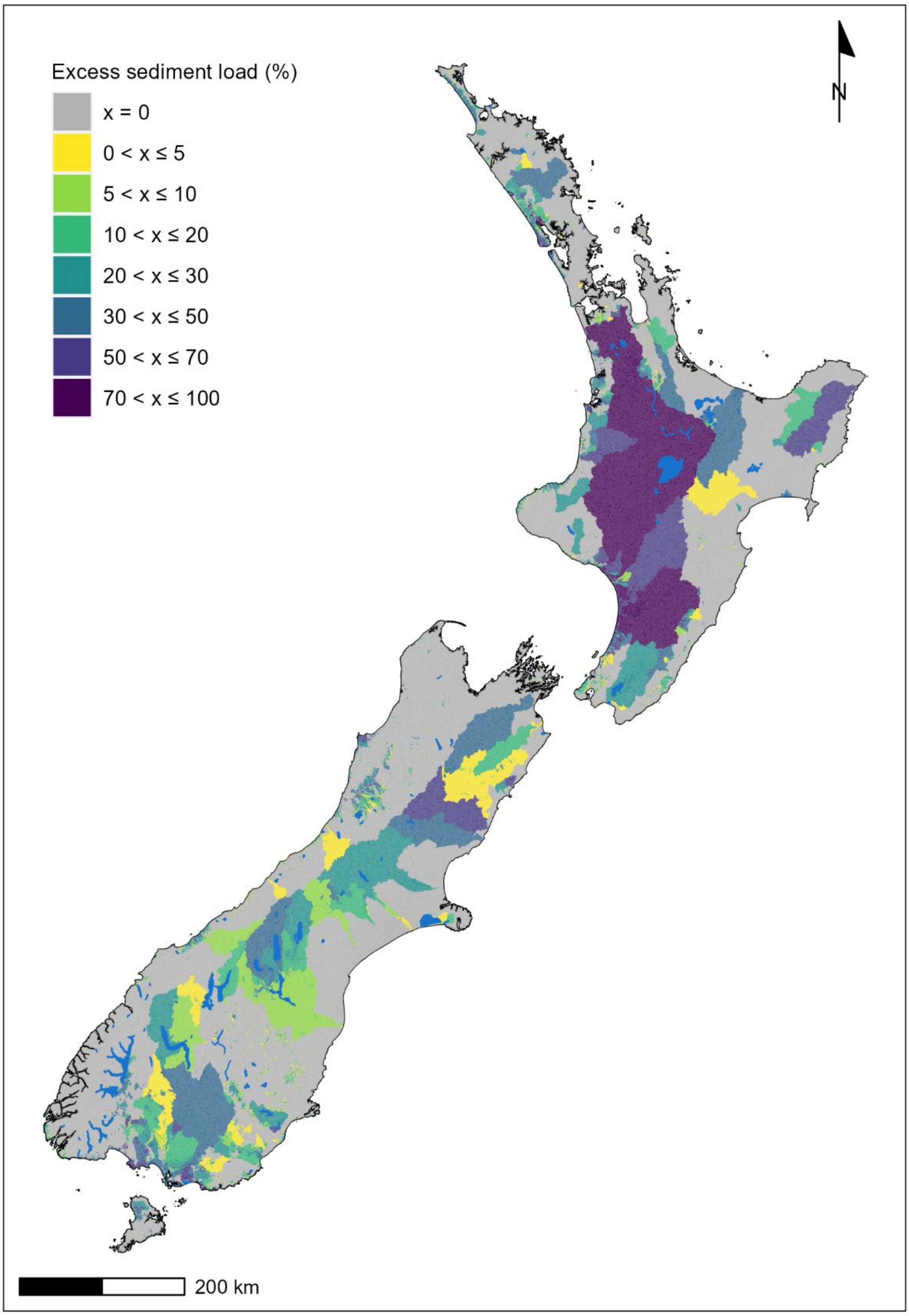

Figure 39. Critical catchment excess loads for sediment expressed as a proportion of current loads (%).

4 Comparison across contaminants and regions

A comparison of the catchment areas requiring load reductions for each of the four contaminants across all New Zealand is shown in Figure 40. A larger proportion of catchments require reductions for *E. coli* than for the other three contaminants. For *E. coli*, 79% of land area nationally required reductions (i.e., has a load reduction greater than zero on Figure 40). This compares to 20%, 11% and 49% for nitrogen, phosphorus and sediment, respectively. The high proportion of land area that requires reductions for sediment is partly because of the non-compliance with the national bottom line criteria in large mountain dominated catchments in the South Island. It is noted that clause 3.32 of the NPS-FM recognises that natural processes can mean that current states are below the bottom line in some receiving environments. Clause 3.32 and allows for exceptions to be applied when it is demonstrated that non-compliance with the national bottom line is due to naturally occurring processes.

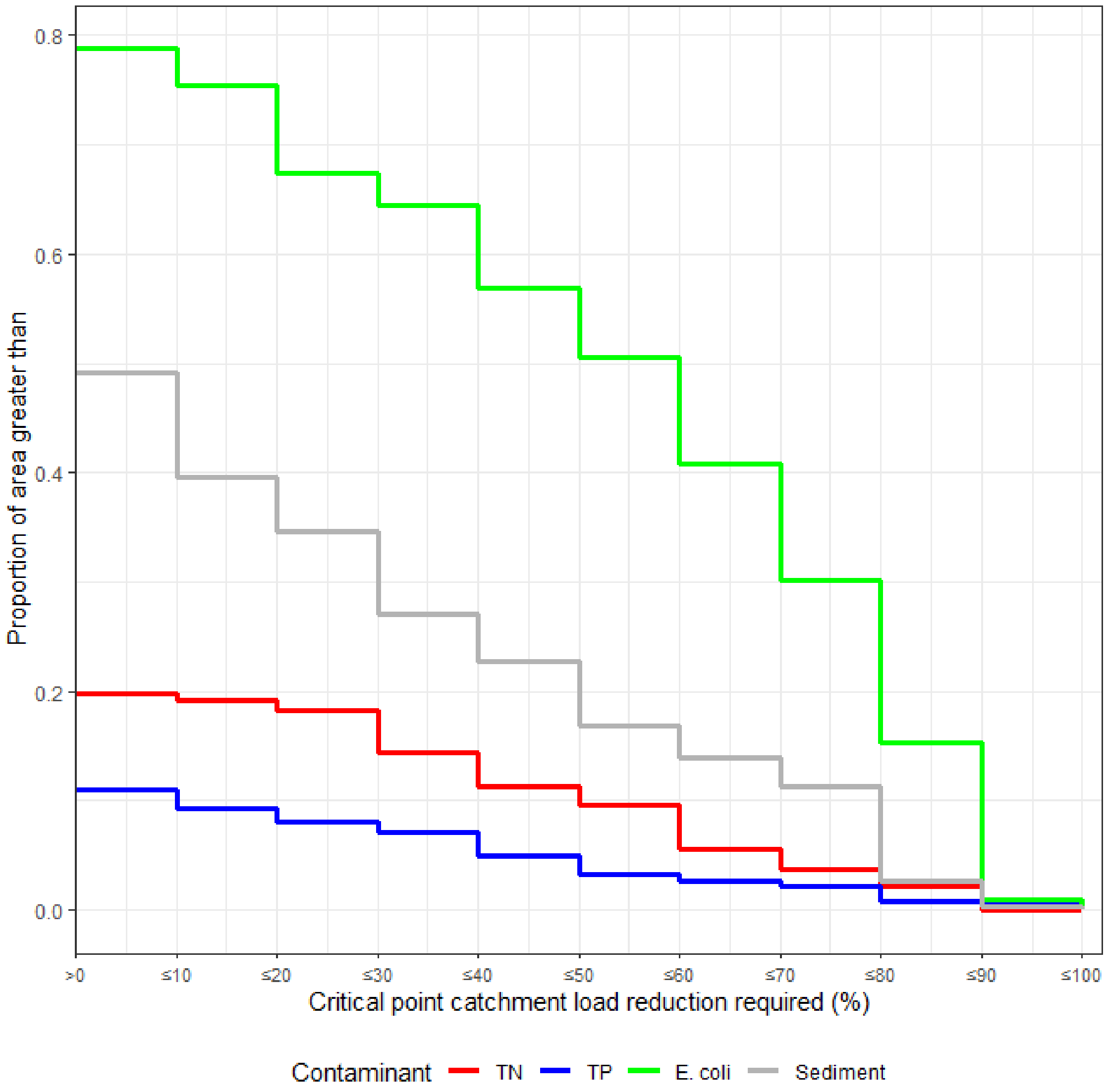

Figure 40. Cumulative frequency distribution of the total area nationally having load reduction requirements equal to or less than the reduction categories. The value of the intercept on the y-axis shows the proportion of total area requiring load reduction of any magnitude.

At the regional level, a larger proportion of land generally required reductions for *E. coli* than for the other three contaminants (Figure 41). Only the Marlborough region had larger land areas requiring reductions for sediment than that for *E. coli*. There was significant variation between regions in the areas that required load reductions across all levels of reduction requirement. For example, West Coast had low levels of load reduction required across all four contaminants. Within the West Coast region, 0%, 1%, 33% and 18% of land area required reductions for TN, TP, *E. coli* and Sediment (Figure 41). In contrast, in the Manawatū-Whanganui region, 19%, 22%, 100% and 97% of land required reductions for TN, TP, *E. coli* and Sediment, respectively (Figure 41).

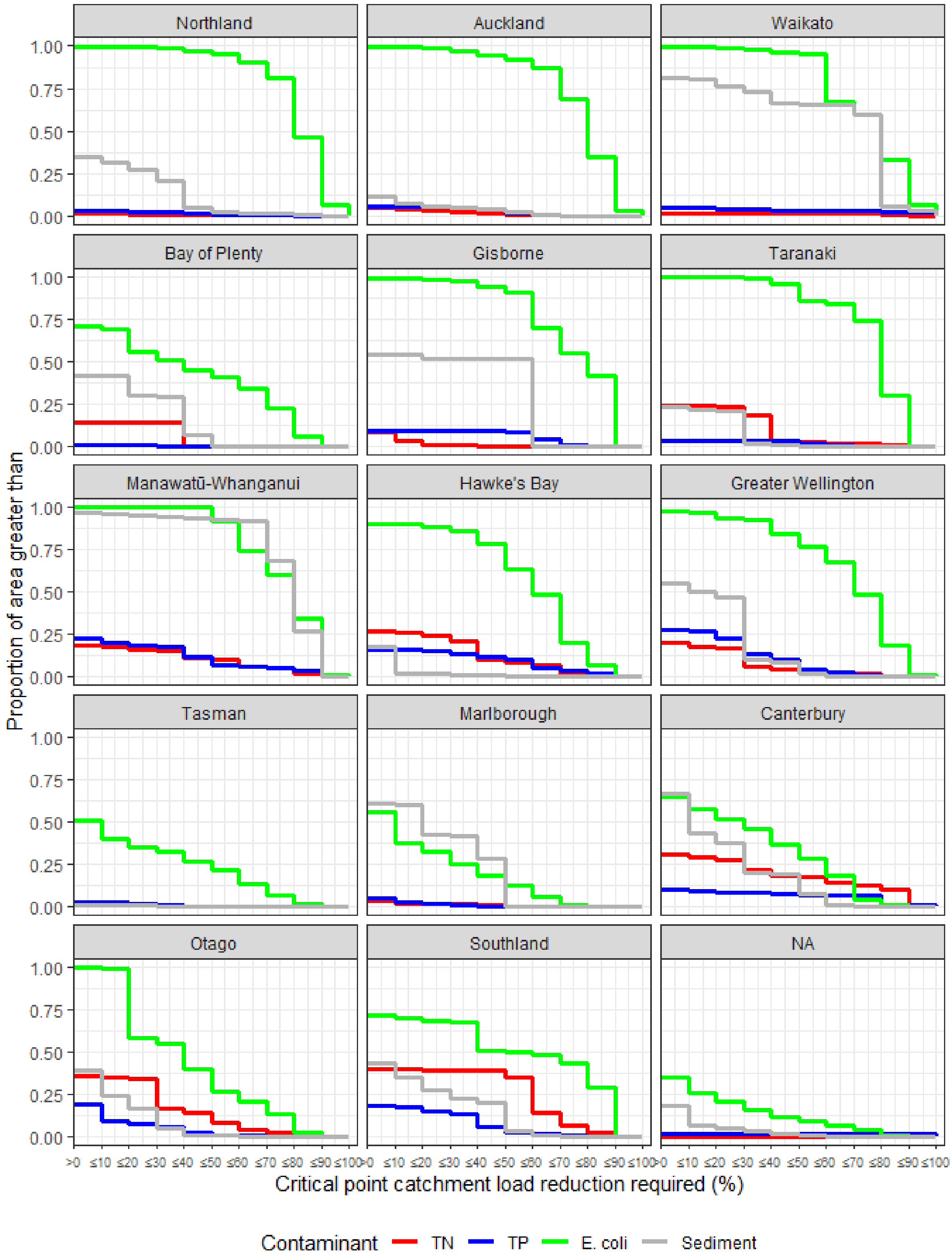

Figure 41. Cumulative frequency distribution of the proportion of total area in each region having load reduction requirements equal to or less than the reduction categories. The value of the intercept on the y-axis shows the proportion of total area requiring load reduction of any magnitude.

Achieving critical catchment load reductions of greater than 30% will likely require at least some land use change (McDowell *et al.*, 2021). The total area of critical catchments requiring load reductions of greater than 30% for one or more of the four contaminants are shown in Table 19 and are mapped in Figure 42. Table 19 and Figure 42 indicate that 70% of New Zealand is occupied by critical catchments that have at least one contaminant that requires a load reduction of greater than 30%.

Table 19. Total area of critical catchments requiring load reductions of one or more contaminants.

Number of contaminants	**Land area (percentage of total national land area)**
1	38
2	24
3	6
4	2

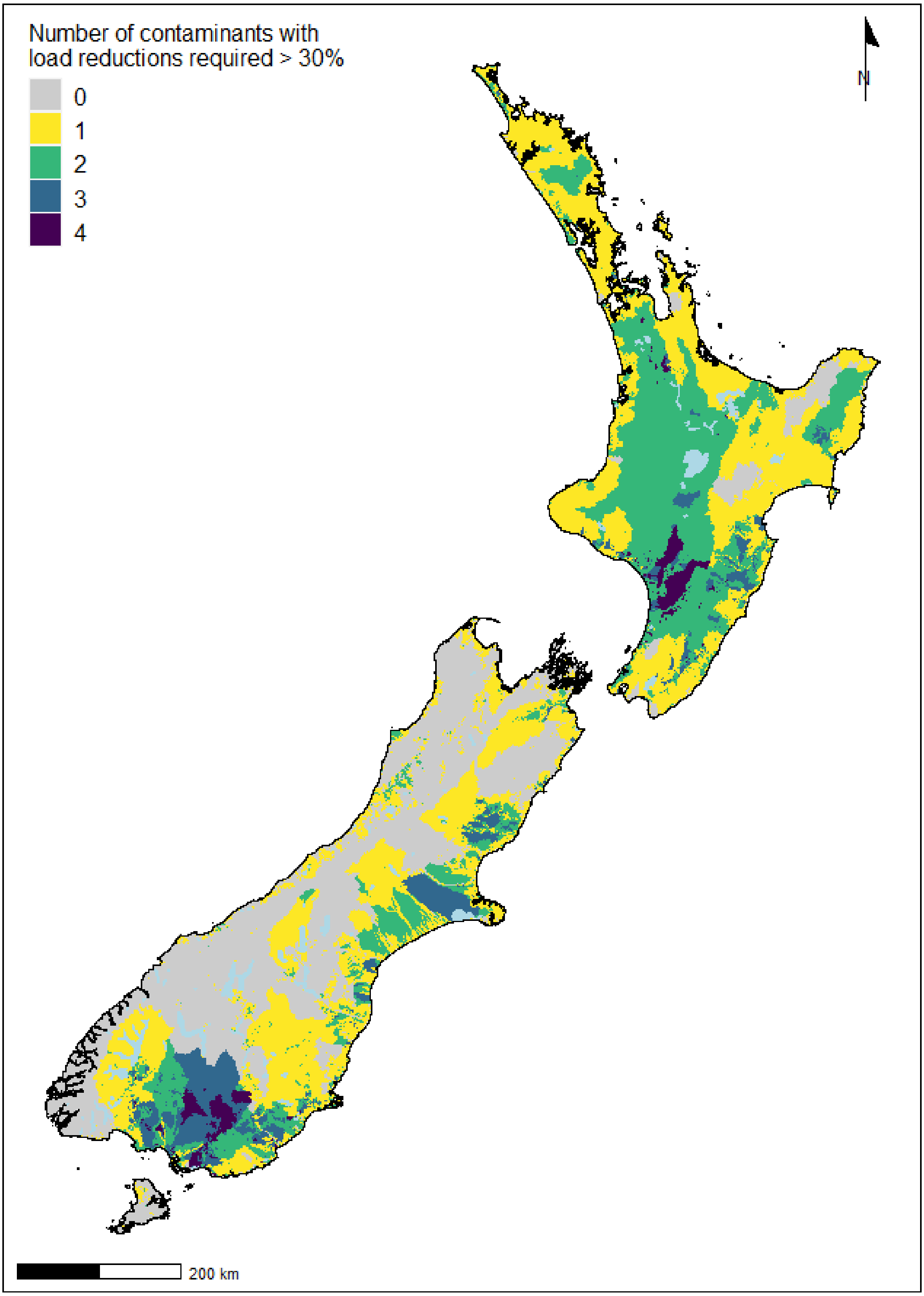

Figure 42. Critical catchments indicating how many contaminants have load reductions required of greater than 30%.

Discussion

4.1 Load reductions required

This report has assessed the reduction in the loads of four contaminants that would be required to achieve the minimum acceptable states for a selected set of target attribute states (TASs) for rivers and lakes across New Zealand. The TASs that were represented in this study include river periphyton and nitrate toxicity, river *E. coli* and river fine suspended sediment, lake total nitrogen (TN) and total phosphorus (TP). These attributes are those set out in Appendix 2A of the NPS-FM that can be modelled in a consistent and comprehensive manner across New Zealand. The minimum acceptable states for these attributes were the national bottom lines as set out in Appendix 2A of the NPS-FM. This is generally the NOF C/D band threshold except for nitrate toxicity in which case it is the B/C band threshold. For *E. coli*, the minimum acceptable state was that deemed suitable for primary contact in the national targets laid out in Appendix 3 of the NPSFM, which are also the C/D band thresholds. The study has also assessed the reduction in the loads of TN and TP that would be required to achieve trophic states (i.e., peak algal biomass) for estuaries that are nominated in this study as being equivalent to the NOF C/D threshold. It is important to note that no national policy currently prescribes any compulsory attributes or national bottom lines for estuaries.

For the whole of New Zealand, the best estimate of the load reductions required varied between 24% to 66% of the current loads (Table 20) of the four contaminants. There was large variation in the load reductions required between the different combinations of regions and contaminants (Figure 41). This variation reflects differences in the inherent susceptibility to contaminant loss, for example some regions are more prone to erosion than others and, therefore, have larger sediment load reductions required. Some regions have greater concentrations of geologically derived phosphorus and, therefore, have larger phosphorus load reductions required (e.g., Taranaki and Bay of Plenty). The variation also reflects differences in the intensity of current land use, which tends to be a function of inherent land suitability, particularly for agriculture. For example, significantly greater proportions of the Canterbury and Southland regions are suitable for intensive agriculture than many other regions. This explains why the Canterbury and Southland regions have larger load reductions required for nitrogen than most other regions (Figure 41).

Table 20. Summary of load reductions required for four contaminants to achieve the national bottom line for a selected set of TASs for rivers, lakes and rivers across New Zealand. The reductions are reported as a percentage of current loads. 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.

Contaminant	Load reduction required
Total Nitrogen (TN)	19 (15 - 22)
Total Phosphorus (TP)	6 (4 - 12)
Escherichia coli (E. coli)	73 (60 - 84)
Sediment	33 (21 - 44)

A portion of the required load reductions may be achievable by implementing a suite of mitigations on pastoral land that McDowell *et al.* (2021) projected would be feasible by 2035.

However, because large catchments are generally not entirely occupied by pastoral land use, these mitigations alone would not produce the necessary load reductions for nitrogen, phosphorus and sediment. Reductions in *E. coli* from pastoral land based on fencing have estimated effectiveness in the range 40% to 60% (Semadeni-Davies *et al.*, 2018). However, the same study also estimated that this level of fencing was largely complete on dairy farms and uptake was 40% to 65% complete on other pastoral farm types. Therefore, as for the other contaminants, because large catchments are generally not entirely occupied by pastoral land use, these mitigations alone will not produce the necessary load reductions for *E. coli*. The overarching conclusion is that achieving the load reductions required to achieve the minimum acceptable states set out in this study would be extremely challenging in many catchments in New Zealand where the dominant source of all four contaminants is land that is under pastoral use.

4.2 Comparison with previous studies and national targets

A previous study by Snelder *et al.* (2020) estimated that national scale load reductions required for TN, to achieve the same target attribute state (national bottom lines and their equivalent for estuaries) and the same level of under-protection risk for the periphyton attribute was 11% of the current load compared to 19% estimated by this study (Table 15). Reasons for the difference with this study include the use of more up-to-date input data, the change in the bottom line for the Nitrate Toxicity attribute from the C/D band threshold to the B/C band threshold and the use of updated and more stringent (i.e., lower concentrations) TN criteria associated with the periphyton attribute (Snelder and Kilroy, 2023).

A study by Elliott *et al.* (2020) estimated national scale load reductions required for TN, TP and *E. coli* of approximately 20%, 3% and 43%, respectively. There are several potential reasons for differences between the results of the present study and that of Elliott *et al.* (2020). First, Elliott *et al.* (2020) evaluated load reductions required for segments of the DN2.4 network of Strahler order three or greater. This study evaluated load reductions associated with all stream orders and this is likely to have increased the number of locations for which this study has estimated load reductions are required (McDowell *et al.*, 2017). Second, Elliott *et al.* (2020) used different criteria to this study. For example, for estimating reductions in *E. coli* loads, Elliott *et al.* (2020) used one criteria only, a 95th percentile concentration < 540 CFU 10 ml^{-1}. In addition, Elliott *et al.* (2020) used different models to estimate current loads.

We used the results of the study by Hicks, Haddadchi, *et al.* (2019) to estimate the national scale load reductions required for sediment, using the same methods and to achieve the same target attribute state (national bottom lines) that was used in this study. The best estimate of the national scale load reduction required made from Hicks, Haddadchi, *et al.'s* (2019) was 30%, which is close to this study’s estimate (33%). We note that the predictions of current state visual clarity used by this study were, on average, lower than Hicks, Haddadchi, *et al.* (2019) (the national mean value of estimated visual clarity for all DN2.4 segments made by the two studies were 2.6m and 2.3m; respectively). This difference is the reason for the difference in the national scale sediment load reductions required between the two studies.

Overall, all the studies indicate that substantial reductions in current loads are required to achieve nominated minimum acceptable states (generally national bottom lines). Differences between the studies reflect many differences in input data and assumptions that will inevitably occur in studies of this type, some of which are discussed below.

4.3 Uncertainties and assumptions

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 contaminant load reduction estimates that are associated with two key components of the analyses: the modelled current contaminant concentrations (e.g., median TN, NO3N and TP) and attribute states (e.g., river *E. coli* statistics and median visual clarity) and the modelled contaminant loads (see Section 2.4). The statistical uncertainty of these models is associated with the inability of the RF 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. The Monte Carlo analysis combined these model uncertainties to make assessments of the uncertainty of several characteristics and quantities that were evaluated by this study.

The Monte Carlo analysis indicates that the assessment's uncertainties are large. This is consistent with other studies (e.g., Hicks, Haddadchi, *et al.*, 2019; Snelder *et al.*, 2020). We present the results of the uncertainty 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 regional and national load reductions required for each of the four contaminants (Table 15, Table 16, Table 17, and Table 18). We also use the 90% confidence interval for our estimates of the uncertainty of these estimates. The lower and upper confidence limits can be interpreted as the values for which we are 95% confident the load reductions are not lower than or greater than. We also presented maps showing compliance with criteria associated with the TASs (e.g., 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 all receiving environments (i.e., river segments, lakes and estuaries) represented in the analysis. These data are not presented in this report but are available as supplementary files that are available from the Whitiwhiti Ora Land Use Opportunities website (https://landuseopportunities.nz/).

The uncertainties are least for TN. This is because nitrogen concentrations and loads in catchments are more strongly related to land use and can therefore be modelled more accurately than the other three contaminants. For example, spatial variation in phosphorus concentrations and loads is associated with three important natural processes that influence P concentrations: geogenic supply, mobilisation and transport, and microbially mediated reduction-oxidation (redox) which influences mobility, and speciation of P (Boomer and Bedford, 2008; Maynard *et al.*, 2011; Parsons *et al.*, 2017). Porder and Ramachandran (2013) found a 30-fold difference in median P concentration among rock types, ranging from 120 ppm (several ultramafic rocks) to >3,000 ppm (several alkali basalts). Mage and Porder (2013) showed that parent material explained the most variation in P availability in soils (56% of variation explained) and topographic position (ridges, slopes or valleys) explained an additional 10-15% of variation. Many of these rock types are found in New Zealand and there can be significant variation in these types even within large catchments. The variation in these natural processes was not well represented by our models and this leads to reduced accuracy and higher uncertainty compared to TN where sources of natural variation appear to be less. We note that, as for phosphorus, a cause of natural spatial variation in nitrogen loss from catchments is variation in redox processes (Boomer and Bedford, 2008; Maynard *et al.*, 2011; Parsons *et al.*, 2017). However, our understanding of redox processes and ability to discriminate its' spatial variation is limited at best (Snelder *et al.*, 2023).

Our assessments of uncertainties could not account for all sources of uncertainty, or the impact of the various assumptions made by the analyses. One of these sources of uncertainty is the imprecision of the site estimates of current contaminant concentrations and attribute states and the contaminant loads calculated for each site. These values are estimates of a population statistic (e.g., the true median visual clarity or the true TN load) that are imprecise because they are calculated from a sample (i.e., the water quality observations). The load estimates derived from the SOE sites that informed this study have high uncertainty (e.g., Appendix C) that was not explicitly represented in the Monte Carlo analysis. We note that estimated loads have large uncertainties (see Appendix C, Figure 43) that are irreducible in the short to medium term (Snelder *et al.*, 2017).

The assumptions that were made to perform the analyses in this study are sources of uncertainty that could not be included in the Monte Carlo analyses. An example of an assumption is that the load of *E. coli* at any point in the river network is attributable to contributions from all land in the upstream catchment. This is not necessarily true because 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 of 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 to obtain the excess load at every point in the drainage network (Figure 1). This analysis assumes 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 and is not represented by our analysis, and these are therefore sources of additional uncertainty associated with the estimation of load reduction required.

It is reasonable to assume that sources of uncertainty that were not explicitly represented by the Monte Carlo analysis would lead to uncertainties being larger than those quantified by this study. This means that the overall uncertainty estimates should be regarded as 'optimistic', i.e., the uncertainty would be higher if these additional model uncertainties were included in the analysis.

It is noted that the nutrient loads estimated by this study do not explicitly include point source discharges. Point source discharges are only represented to the extent that their effect on nutrient loads is implicit in the monitoring data used to estimate loads at SOE sites and to predict (i.e., model) loads for all network segments (see Section 2.4.1). In contrast, Roberts *et al.* (2022) revised the potential TN band thresholds, used here to set the MALs for estuaries, using load estimates that explicitly included significant point sources in the catchments of estuaries included in their analysis. This means the contribution of point source discharges that occur in the lower parts of catchments (i.e., below the SOE sites) or directly to estuaries, may be underestimated by this study. Consequently, for some estuaries, the assessment of estuary state that would be derived from the data used by Roberts *et al.* (2022) will differ to the assessment derived by this study. Because of the national extent of this study and limited data quantifying the point sources nationally, this study was not able to explicitly represent all point source discharges in New Zealand.

An important conclusion from the analysis of uncertainty is that we are 95% confident that load reductions for all four contaminants are required to achieve the nominated minimum acceptable states for the whole of New Zealand. This is because the lower bound of the 90%

confidence interval for load reduction required is greater than zero for all four contaminants (Table 20). Similarly, we are 95% confident that load reductions are required for most contaminants to achieve the nominated minimum acceptable states in most regions.

The uncertainties described in this study indicate that the best estimates and maps provided should be appropriately considered as indicative of the regional-scale patterns of compliance and contaminant 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 load reductions required and this uncertainty is larger as the spatial scale over which the reductions are evaluated is reduced. From a practical perspective the uncertainties are irreducible 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. Reducing the uncertainties involved would probably require long term sampling at considerably more SOE sites and improvements in the approach to modelling by increasing understanding of the processes involved in contaminant loss, transport and transformation in catchments.

4.4 National bottom line target attribute states and load reductions required

The results of this study indicate that some receiving environments whose catchments are largely occupied by natural land cover can have high probability of non-compliance with national bottom line target attribute states and therefore require load reductions. For example, catchments draining from the Southern Alps in Canterbury such as the Waimakariri River and the Rakaia River were assessed as non-compliant (Figure 39) and requiring sediment load reductions (Figure 38) and most of the Waitaki River catchment was indicated as requiring phosphorus load reductions (Figure 28). These results can occur due to model inaccuracies but also because either criteria or the TAS are set at levels that may not be achievable even under natural conditions. Clause 3.32 of the NPS-FM recognises that natural processes can mean that current states are below the bottom line in some receiving environments. Clause 3.32 and allows for exceptions to be applied when it is demonstrated that non-compliance with the national bottom line is due to naturally occurring processes. This study has not considered whether non-compliance occurs due to natural processes. Regional councils will need to resolve this at the regional level when setting TAS in their regional plans as part of implementing the NPS-FM.

Non-compliance with the national bottom line for the *E. coli* attribute is particularly widespread. For example, the estimated probability that the four *E. coli* attribute statistics complied with the national bottom line criteria was greater than 0.6 for only 52% of segments (Figure 31). We can have relatively high confidence in this assessment because it is based on RF models for each statistic, all of which performed well (Table 11). The assessment indicates that the national bottom line for *E. coli* is a very ambitious target because the ability to reduce *E. coli* loads from catchments with large areas of non-productive land is negligible (Semadeni-Davies *et al.*, 2018).

In their assessment of sediment load reductions to achieve suspended fine sediment target attributes states, Hicks, Haddadchi, *et al.* (2019) excluded catchment areas that lay within the Department of Conservation (DOC) estate even though receiving environments downstream of these catchments sometimes did not achieve the national bottom line. Hicks, Haddadchi, *et al.* (2019) excluded the DOC estate primarily because this included mountain catchments with glaciers that produce naturally turbid waters that cannot be mitigated. We did not follow the approach of excluding DOC estate or any other arbitrary land classes so as to produce consistent assessments. Natural processes could result in contaminant concentrations that are non-compliant with national bottom lines on land that is outside the DOC estate. For example, see the discussion of natural variability in phosphorus in the section above. We therefore recommend that the results of this assessment are interpreted as an assessment of current state with respect to national bottom lines but not necessarily as where water quality improvements are possible.

4.5 Informing decision-making on limits

The NPS-FM requires regional councils to set limits on resource use to achieve environmental outcomes (e.g., TASs). This report helps inform Regional Council processes for setting limits by assessing the approximate magnitude of the contaminant load reductions needed to achieve the national bottom lines for several TASs with a quantified level of uncertainty. However, this report does not consider what kinds of limits on resource use might be used to achieve any load reductions, how such limits might be implemented, over what timeframes, and what the implications for other values might be. 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 Total nitrogen and total phosphorus criteria for periphyton target attribute states used in the analysis

The criteria for periphyton target attribute states are shown for each REC Source-of-flow class that occurs in New Zealand (Table 21). The values in the table are derived from Snelder and Kilroy (2023) and are median concentrations in units of mg m^{-3}.

Table 21. The total nitrogen and total phosphorus criteria for periphyton target attribute states used in this study. The criteria are provided for each REC Source-of-flow class that occurs in New Zealand and correspond to the NOF C band (i.e., national bottom line) and the 20% UPR.

REC Source-of-flow class	Total Nitrogen	Total Phosphorus
CX/GM	4,374	270
CX/M	4,359	285
CX/H	4,196	257
CX/L	4,212	281
CX/Lk	4,326	193
CW/GM	4,359	240
CW/M	4,292	196
CW/H	3,024	149
CW/L	2,034	95
CW/Lk	4,195	136
CD/M	4,295	93
CD/H	2,001	30
CD/L	522	29
CD/Lk	3,190	48
WX/L	3,997	205
WX/H	3,954	208
WW/H	3,369	157
WW/L	2,307	97
WW/Lk	3,105	96
WD/L	473	16
WD/Lk	1,929	64

Appendix B Correlation of errors between input models used in the analysis

The correlation structures shown in Table 22 and Table 23 were used to generate random normal deviates (ε_r) for each model in the Monte Carlo analyses of nutrients and *E. coli*, respectively.

Table 22. Correlation of errors (Pearson correlation coefficient) between pairs of models used in the analysis of nutrients. The table is a lower triangular matrix showing the correlations between all pairs of model errors for the 325 sites that were common to all models. All models were random forest models. Conc indicates a concentration model and Load indicates the load models.

Model	TN Conc	TP Conc	NO3N Conc	NO3N:TN	TN Load
TP Conc	0.18				
NO3N Conc	0.77	0.22			
NO3N:TN	0.59	0.09	0.88		
TN Load	0.52	0.04	0.49	0.46	
TP Load	-0.02	0.38	0.08	0.11	0.35

Table 23. Correlation of errors (Pearson correlation coefficient) between all pairs of models used in the analysis of E. coli. The table is a lower triangular matrix showing the correlations between all pairs of model errors for the 334 sites that were common to all models. RF indicates random forest models and LM indicates linear regression models.

Model	Yield_RF	G260_RF	G540_RF	Q50_RF	Q95_RF	Q50_LM	Q95_LM	G260_LM
G260_RF	0.51							
G540_RF	0.51	0.85						
Q50_RF	0.51	0.83	0.70					
Q95_RF	0.61	0.63	0.71	0.62				
Q50_LM	0.62	0.01	0.07	-0.07	0.23			
Q95_LM	0.56	0.04	-0.02	0.06	-0.10	0.78		
G260_LM	0.62	-0.07	-0.02	0.02	0.22	0.93	0.78	
G540_LM	0.62	-0.02	-0.11	0.07	0.17	0.89	0.82	0.96

Appendix C Calculation of *E. coli* loads at monitoring sites

C1 Water quality data

We obtained *E. coli* monitoring data for 334 river SOE monitoring sites where flow was also measured or estimated. Observations of *E. coli* were generally made at SOE sites on a monthly basis. These sites had variable start and end dates and total numbers of observations. However, site numbers listed above all met the minimum data requirements that, for the 10-year period ending 2021, they had: (1) 60 or more observations; (2) observations in 8 of the 10 years; and (3) observations in 80% of the quarters.

C2 Flow Data

We obtained observed daily timeseries of flow at the monitoring sites from regional councils and NIWA (see Snelder *et al.*, 2023 for details). Start years for the flow records ranged from 1959 to 2011.

C3 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: *E. coli* concentration for each day in period of record (*E. coli* 100 ml^{-1}, 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 *E. coli* loads as annual export coefficients (i.e., for giga *E. coli* yr^{-1} ha^{-1}) by dividing the annual load (*E. coli* 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).

C3.1 Methods for defining rating curves

C3.1.1 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:

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

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):

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

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:

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

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.

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

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:

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

C3.1.2 L5 Model

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

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

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:

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

C3.1.3 Flow stratification

For sites where L5 and L7 models were unrealistic, we 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'). We used 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 *E. coli* concentrations, $\hat{C}$, for all days with flow observations. At step 2, the export coefficient is calculated following equation (1a), providing an estimate of average annual export coefficient over the observation time period.

$$L = \frac{K}{A_c N} \sum_{j=1}^{N} \hat{C}_j Q_j \quad \text{(Equation A1d)}$$

where $\hat{C}_j$ is calculated mean concentration associated with the flow quantile bin of the flow Q_j., and all other variables are as per equation A1.

C3.2 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.

C3.3 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. All sites had L5 and L7 models fitted. Where these models were considered to provide unrealistic representations of the observed data, the load estimates were either excluded, or a flow stratification model was fitted and assessed for suitability.

C4 Verification of loads

Load estimation involves subjective decisions, such as the choice of method. We sought to verify our load estimates (i.e., demonstrate they were reasonable) by calculating them using an alternative method. We undertook the validation of our *E. coli* load estimates by applying a new sophisticated load estimation method called Weighted Regressions on Time, Discharge, and Season (WRTDS; Hirsch et al., 2015, 2010). The WRTDS method is complex and is not explained here. However, it can be understood as a form of regression modelling that fits a relationship to concentration based on time and flow. WRTDS is more flexible than the methods we used to calculate the loads and allows for changes in the underlying relationships over time. WRTDS is also more resistant to bias than the load calculation methods that we used, although not entirely immune (Hirsch, 2014). WRTDS is "unsupervised" in the sense that the loads are calculated without requiring any judgements by the analyst, whereas the "rating curves" methods used by this study required expert judgement to select an appropriate model at each site.

We calculated *E. coli* loads at each site using WRTDS with the same input data described above. Calculations were performed with the Exploration and Graphics for RivEr Trends and data Retrieval: R package (EGRET; Hirsch *et al.*, 2015). The outputs of the EGRET package are numerous and complicated. We obtained from the output the flow normalised flux (*E. coli* day^{-1}) for 2020. Flow normalised flux is a representation of flux that integrates over the probability distribution of discharge in order to remove the effect of year-to-year variation in discharge. It is therefore consistent with the approach we used to calculate loads which integrated unit loads over the entire flow time series. Using the flux estimate for 2020 was consistent with our load estimates which pertain to 2020. We converted the flux to the units of *E. coli* yields used by this study (giga *E. coli* ha^{-1} yr^{-1}) by dividing by catchment area of the water quality stations and multiplying by the appropriate unit conversion factor.

It should be noted that there are many methods of load calculation that differ in how the underlying relationships are represented in subtle ways. Many studies have documented differences in loads calculated from the same data but using different methods and it is often shown these differences can be large (e.g., Cohn, 2005; Johnes, 2007; Preston et al., 1989; Quilbé et al., 2006; Snelder et al., 2017). Therefore, differences between our loads and those estimated by WRTDS are expected. Notwithstanding this, the plot shown in Figure 43 indicates strong correspondence between the two sets of loads. The majority of the 95% confidence intervals estimated by this study intersect the one-to-one line indicating that the two sets of estimates are consistent. Our conclusion is that the loads calculated and used in this study are reasonable and are the best estimates that we could produce, given the data.

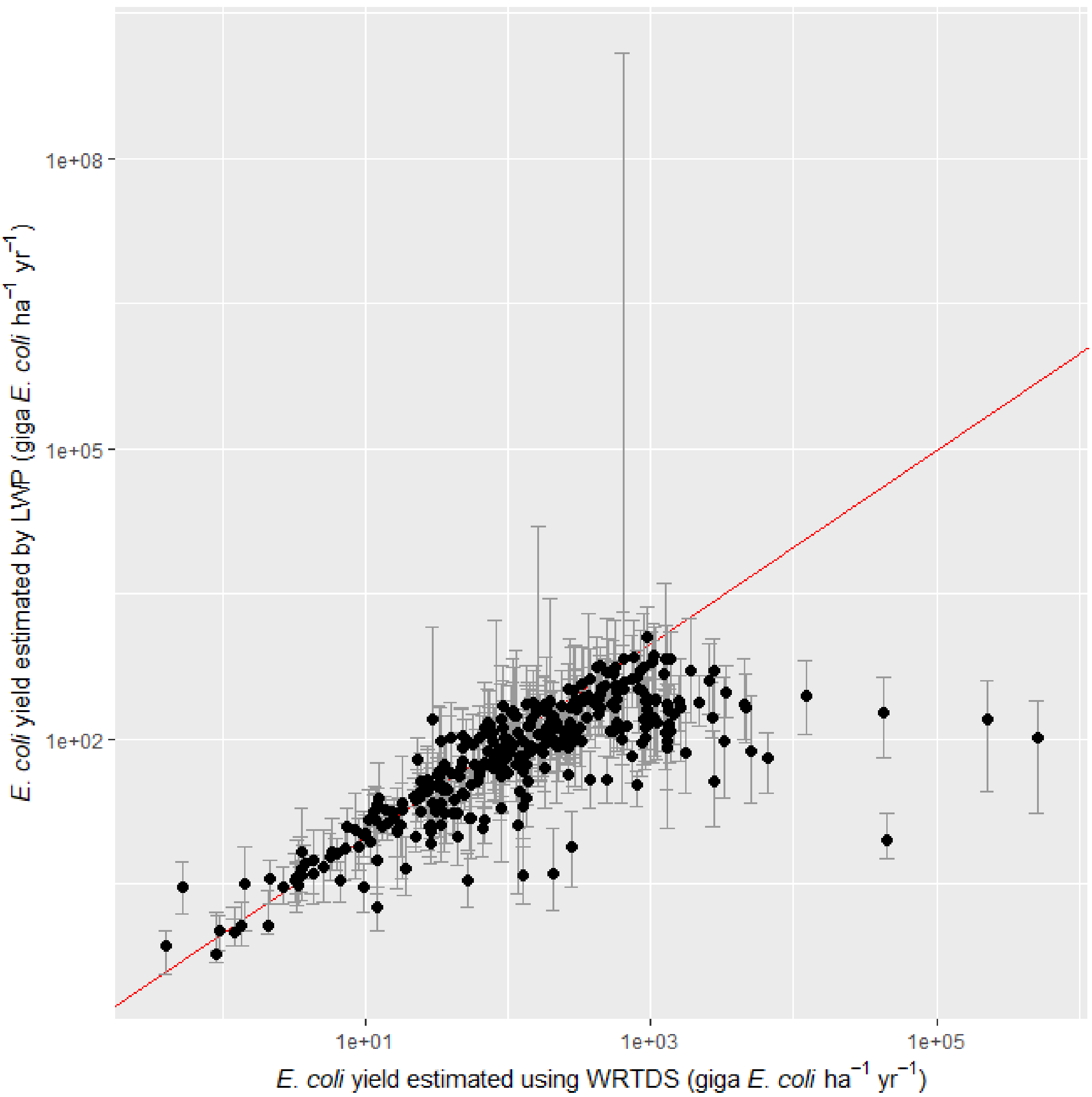

Figure 43. Comparison of E. coli loads (expressed as yields) calculated by this study (y-axis) and by WRTDS (x-axis). The error bars show the 95% confidence intervals estimated by this study. The red line indicates perfect correspondence (one-to-one).

Appendix D Estimated estuary nutrient loads and maximum allowable loads

Table 24. Modelled annual estuary loads (tonnes year^{-1}) of Total Nitrogen (TN) and Total Phosphorus (TP), and maximum allowable load (MAL) estimates for all estuaries included in this study. NA indicates that no MAL could be calculated because the estuary is unlikely to experience macroalgal or phytoplankton growth. Zero values for MAL indicate there is sufficient supply of nutrient from the ocean that the estuary naturally exceeds objectives for phytoplankton, or otherwise no MAL is considered appropriate. LAT and LON indicate the latitude and longitude of the middle of each estuary. NZCHS class indicates the New Zealand Coastal Hydrosystem classification of each estuary (Hume et al.*, 2016). A summary of the NZCHS classes is provided in Table 25.*

Estuary	NZCHS class	LAT	LON	Modelled TN load (t yr^{-1})	Modelled TP load (t yr^{-1})	MAL TN (t yr^{-1})	MAL TP (t yr^{-1})
Admiralty Bay	11	-40.95	173.87	284.6	25.0	3014.5	233.9
Ahuriri Estuary	7A	-39.48	176.90	95.8	7.3	29.7	3.1
Akaroa Harbour	9	-43.89	172.96	58.9	3.5	758.2	0
Akatore Creek	7A	-46.12	170.19	33.0	1.2	12.8	0
Akitio River	6B	-40.61	176.43	354.1	68.8	NA	NA
Anatori River	3B	-40.70	172.36	41.7	5.2	147.9	NA
Anaweka River	5C	-40.75	172.28	25.4	3.7	135.8	NA
Aotea Harbour System	8	-38.02	174.78	145.2	8.4	1486.2	8.8
Aropaoanui River	4C	-39.29	177.00	117.4	11.6	NA	NA
Ashburton River (Hakatere)	3B	-44.05	171.81	868.5	72.4	NA	NA
Ashley River (Te Aka aka)	3D	-43.27	172.73	454.6	37.5	1046.9	NA
Avon-Heathcote Estuary (Ihutai)	7A	-43.56	172.76	266.5	8.5	273.0	0
Awaawaroa Bay	11	-36.85	175.10	7.9	0.5	70.5	1.0
Awahoa Bay	11	-35.75	174.56	NA	NA	17.9	NA
Awakino River	6B	-38.67	174.61	262.9	41.1	NA	NA
Awana Bay	4C	-36.21	175.49	5.8	0.6	NA	NA
Awapoko River	6B	-34.97	173.43	74.9	6.1	118.7	NA
Awaroa Inlet	7A	-40.85	173.03	2.2	0.2	187.3	6.8
Awaroa River KHS	8	-38.08	174.89	NA	NA	601.0	NA
Awarua River	3C	-44.29	168.11	26.7	3.6	NA	NA
Awatere River	3B	-41.61	174.17	387.6	48.2	444.3	NA
Awhea River	6C	-41.51	175.53	82.9	11.9	NA	NA
Bark Bay	7A	-40.92	173.06	7.0	0.6	13.5	1.2
Big River	5C	-40.76	172.26	13.5	1.5	345.2	NA
Big River (Lake Hakapoua)	9	-46.22	166.92	48.6	6.4	225.6	0
Bland Bay	11	-35.34	174.37	1.3	0.1	37.4	0
Bligh Sound	10	-44.77	167.48	60.1	9.4	8797.7	134.8
Blind Bay	11	-36.28	175.42	3.6	0.3	42.5	0
Blind/Big Bay	11	-43.61	172.89	3.1	0.1	14.9	0
Blueskin Bay	7A	-45.73	170.61	47.7	1.9	135.4	0

Estuary	NZCHS class	LAT	LON	Modelled TN load (t yr^{-1})	Modelled TP load (t yr^{-1})	MAL TN (t yr^{-1})	MAL TP (t yr^{-1})
Bluff Harbour	8	-46.61	168.36	39.5	1.9	1727.4	0
Bon Accord Harbour	11	-36.42	174.81	3.3	0.2	37.9	0.4
Breaksea/Dusky Sound	10	-45.62	166.57	359.9	47.0	58873.9	0
Buller River	6B	-41.73	171.59	36.7	3.0	6502.8	NA
Cascade River	6B	-44.03	168.35	165.9	96.8	NA	NA
Castlepoint	11	-40.92	176.23	0.1	0.0	6.2	0.3
Caswell Sound	10	-45.00	167.13	79.4	12.8	13662.0	220.3
Catherine Cove	11	-40.88	173.89	5.3	0.3	56.3	5.6
Catlins River	7A	-46.49	169.73	311.6	17.5	532.3	0
Catseye Bay	11	-44.81	167.38	13.5	1.7	235.8	0
Chalky Inlet	10	-46.03	166.49	140.4	15.1	32253.5	0
Charles Sound	10	-45.05	167.09	48.9	6.6	9869.1	103.7
Clutha River	6B	-46.33	169.84	4905.4	421.3	12701.2	NA
Coal River	11	-45.49	166.70	24.7	2.7	111.8	3.9
Colville Bay	8	-36.62	175.42	20.3	1.6	136.6	2.6
Coralie Bay	11	-36.60	175.80	0.5	0.0	10.7	NA
Coromandel Harbour	8	-36.80	175.43	29.6	2.1	523.6	19.4
Croisilles Harbour	9	-41.04	173.63	4.4	0.4	1047.9	93.4
Dagg Sound	10	-45.39	166.76	34.2	3.6	4503.3	20.9
Damons Bay (Mangarohotu)	11	-43.89	172.99	1.7	0.1	9.9	0
Decanter Bay (Te Kakaho)	11	-43.65	173.00	3.6	0.2	14.7	0
Deep Water Cove	11	-35.20	174.29	0.9	0.1	16.1	0
Delaware Estuary	7A	-41.16	173.44	39.1	3.2	226.7	6.0
Deverys Creek	4B	-42.20	171.31	5.9	0.4	7.9	0.8
Duffers Creek/Te Rahotaiepa River	6D	-42.99	170.58	34.5	3.5	NA	NA
Ferrer Creek	6C	-41.07	173.01	910.2	109.8	27.4	0.9
Firth of Thames	9	-36.89	175.30	NA	NA	39304.1	NA
Firth of Thames System	9	-36.89	175.30	NA	NA	23081.5	706.3
Flea Bay (Pohatu)	11	-43.88	173.02	4.2	0.2	13.5	0
Frenchman Bay	7A	-40.94	173.06	4.7	0.4	3.3	0.1
Gardiner Gap	11	-36.77	174.89	0.6	0.0	11.7	0.1
George Sound	10	-44.84	167.35	91.2	12.0	12135.9	147.6
Green Hills Stream	3C	-40.50	172.65	2.6	0.2	4.9	0.5
Greville Harbour	11	-40.82	173.79	4.3	0.4	271.9	24.3
Grey River	6C	-42.44	171.19	2981.1	473.2	NA	NA
Haldane Estuary	7A	-46.67	169.03	47.0	2.8	123.3	NA
Heaphy River	5A	-40.99	172.10	41.1	6.8	NA	NA
Helena Bay	11	-35.42	174.39	11.6	0.9	50.9	0
Herekino Harbour	8	-35.30	173.15	52.7	3.8	254.4	0
Hobbs Bay (Gulf Harbour)	11	-36.63	174.78	0.5	0.0	3.9	0.1
Hokianga Harbour System	8	-35.54	173.35	1125.6	95.1	6537.9	0

Estuary	NZCHS class	LAT	LON	Modelled TN load (t yr^{-1})	Modelled TP load (t yr^{-1})	MAL TN (t yr^{-1})	MAL TP (t yr^{-1})
Hollyford River	6B	-44.34	168.00	NA	NA	NA	NA
Hoopers Inlet	7A	-45.88	170.68	5.1	0.2	63.6	0
Horahora River	7A	-35.67	174.52	70.7	4.8	147.0	NA
Horseshoe Bay	11	-43.88	172.82	2.1	0.1	16.2	0
Houhora Harbour	8	-34.84	173.17	78.1	5.3	371.5	0
Huruhi Bay	11	-36.81	175.00	1.0	0.1	60.9	0.6
Huruhi Harbour	11	-36.61	175.77	0.5	0.0	20.6	NA
Hurunui River	3B	-42.91	173.29	1073.7	248.0	NA	NA
Island Bay (Whangakai)	11	-43.90	172.87	1.9	0.1	3.4	0
Islington Bay	11	-36.80	174.90	0.7	0.0	39.0	0.4
Jacobs River (Riverton) Estuary	7A	-46.36	168.03	1425.2	56.6	1490.4	NA
Jones Creek	4E	-41.68	171.77	318.1	98.2	55.4	NA
Kaikorai Stream	6C	-45.94	170.39	33.9	1.4	26.9	NA
Kaipara Harbour System	8	-36.45	174.09	5491.4	485.9	38865.3	0
Kaitawa Inlet KHS	8	-38.10	174.85	NA	NA	25.0	NA
Kaiteretere Estuary	7A	-41.04	173.02	8.6	0.5	13.1	0.4
Kaitoke Creek	4C	-36.23	175.49	10.8	1.2	31.7	NA
Kakanui River	6B	-45.19	170.90	376.2	10.2	NA	NA
Karakatuwhero River	3C	-37.62	178.35	35.8	3.7	NA	NA
Karamea River	7A	-41.26	172.09	72.1	7.0	4086.2	NA
Katherine Bay	11	-36.12	175.35	5.9	0.5	54.0	0
Kauranga River	6A	-37.15	175.54	45.2	4.1	267.2	NA
Kawhia Harbour System (KHS)	8	-38.09	174.74	363.6	25.1	3578.9	23.6
Kawhia Inlet KHS	8	-38.09	174.78	NA	NA	2201.0	NA
Kennedy Bay Estuary KBS	7A	-36.67	175.60	NA	NA	83.2	NA
Kennedy Bay System (KBS)	11	-36.68	175.58	17.3	1.6	89.9	3.4
Kerikeri/Waingaro Arm	8	-37.79	174.91	NA	NA	1122.2	NA
Kirita Bay	11	-36.87	175.41	3.1	0.2	17.2	0.4
Lake Brunton	7B	-46.66	168.89	19.9	0.7	8.0	0.8
Lake Ellesmere (Te Waihora)	2A	-43.86	172.38	2949.3	86.6	396.2	46.9
Lake Forsyth (Te Roto o Wairewa)	2B	-43.83	172.71	48.3	4.2	40.2	4.1
Lake Grassmere	2A	-41.71	174.19	NA	NA	0	0
Lake Kohangapiripiri	2B	-41.37	174.85	1.3	0.1	1.3	0.2
Lake Kohangatera	2B	-41.38	174.86	9.7	1.0	8.2	0.9
Lake Onoke/Turanganui River	2A	-41.41	175.14	2428.8	300.4	NA	NA
Lavericks Bay (Whakarari)	11	-43.72	173.11	5.7	0.3	10.4	0
Le Bons Bay	11	-43.73	173.12	14.0	1.3	47.2	0
Le Bons Bay Estuary (Katawahu)	7A	-43.74	173.10	NA	NA	17.6	NA
Ligar Bay	7A	-40.82	172.90	16.8	1.4	24.0	0.7
Little Akaloa Bay (Whakaroa)	11	-43.65	173.01	7.5	0.4	35.4	0
Little Pigeon Bay	11	-43.62	172.91	2.2	0.1	5.8	0

Estuary	NZCHS class	LAT	LON	Modelled TN load (t yr^{-1})	Modelled TP load (t yr^{-1})	MAL TN (t yr^{-1})	MAL TP (t yr^{-1})
Little Wanganui River	6B	-41.39	172.06	548.3	133.5	483.0	NA
Long Bay (Kawatri)	11	-43.89	172.86	2.0	0.1	16.3	0
Looking Glass Bay	11	-44.92	167.21	5.1	0.6	39.0	2.7
Lucas Creek WHS	8	-37.77	174.66	NA	NA	125.4	NA
Lyall Bay	11	-41.35	174.80	1.7	0.1	15.9	1.3
Lyttelton Harbour (Whakaraupo)	9	-43.60	172.82	47.3	2.0	608.3	0
Mahinepua Bay	11	-35.00	173.87	3.1	0.2	12.8	0
Mahitahi River	6B	-43.60	169.59	69.4	24.6	NA	NA
Mahurangi Harbour System	8	-36.51	174.73	76.4	4.5	1062.4	6.6
Makawhio River (Jacobs River)	6B	-43.57	169.63	58.0	18.0	906.0	NA
Maketu Estuary	7A	-37.75	176.45	NA	NA	96.5	NA
Maketu River	6A	-37.76	176.43	40.7	1.0	1416.7	NA
Manaia Harbour	8	-36.84	175.42	20.1	1.6	352.5	5.3
Manakaiaua River	6D	-43.54	169.68	28.0	3.5	NA	NA
Manawaora Bay	11	-35.25	174.18	4.8	0.3	76.2	0
Manawatu River	6B	-40.48	175.21	5135.1	649.2	NA	NA
Mangakuri River	6B	-39.95	176.93	66.0	4.8	NA	NA
Mangaora Inlet KHS	8	-38.06	174.86	NA	NA	427.3	NA
Mangawhai Harbour	7A	-36.09	174.61	61.6	2.8	178.5	0.3
Mangemangeroa Estuary WES	8	-36.91	174.96	NA	NA	38.3	NA
Mangonui Harbour	8	-34.98	173.52	172.6	14.3	578.6	NA
Manuhakapakapa Bay	11	-40.90	173.78	17.4	1.3	77.4	6.4
Manukau Harbour System (MHS)	8	-37.07	174.50	1001.7	34.2	15052.1	92.0
Maraetaha River	6A	-38.79	177.94	59.3	5.8	NA	NA
Marahau River	7A	-40.99	173.01	23.1	2.3	51.9	NA
Marakopa River	6B	-38.31	174.70	321.0	33.6	673.8	NA
Matai Bay	11	-34.82	173.42	1.3	0.1	20.6	0
Mataikona River	6B	-40.79	176.28	94.7	13.9	NA	NA
Matakana River	8	-36.40	174.74	36.7	2.3	153.5	0.9
Matapouri Bay MBS	11	-35.56	174.51	0.3	0.0	5.8	0
Matapouri Bay System (MBS)	7A	-35.56	174.52	NA	NA	48.5	NA
Matapouri Estuary MBS	7A	-35.57	174.51	8.6	0.5	33.2	NA
Matiatia Bay	11	-36.78	174.98	1.0	0.0	7.9	0.1
Maungawhio Lagoon	7A	-39.07	177.91	NA	NA	103.4	NA
Mawhitipana Bay	11	-36.78	175.04	0.6	0.0	6.6	0.1
Menzies Bay	11	-43.63	172.97	4.4	0.2	15.1	0
Mercury Bay MBS	11	-36.81	175.76	NA	NA	NA	NA
Mercury Bay System (MBS)	11	-36.81	175.76	NA	NA	1112.2	61.8
Mikonui River	6C	-42.90	170.77	57.1	13.0	791.2	NA
Milford Sound	10	-44.56	167.80	141.6	46.1	17953.1	187.7
Millon Bay	11	-36.40	174.76	5.1	0.2	39.6	0.1

Estuary	NZCHS class	LAT	LON	Modelled TN load (t yr^{-1})	Modelled TP load (t yr^{-1})	MAL TN (t yr^{-1})	MAL TP (t yr^{-1})
Mimi River	6B	-38.95	174.42	91.4	8.9	181.3	NA
Mimiwhangata Bay	11	-35.43	174.41	1.7	0.1	67.8	0
Miranda Stream	7A	-37.19	175.34	18.5	0.7	9.7	NA
Moeraki (Blue) River	4C	-43.70	169.25	42.0	8.5	NA	NA
Mohakatino River	6B	-38.74	174.60	53.3	5.4	NA	NA
Mokau River	6B	-38.71	174.60	1686.7	169.1	NA	NA
Mokihinui River	6B	-41.52	171.93	100.6	12.4	1694.9	NA
Motueka Estuary North	7A	-41.10	173.03	1.2	0.1	21.1	0.4
Motueka Estuary South	7A	-41.13	173.03	133.4	10.1	70.9	1.5
Motueka River	5B	-41.08	173.02	0.8	0.0	NA	NA
Motupipi River	7A	-40.83	172.85	2.7	0.1	106.5	2.9
Motuwaireka Stream	4C	-41.09	176.09	16.5	1.7	22.2	NA
Moutere Inlet	8	-41.16	173.04	415.3	32.4	145.5	NA
Nancy Sound	10	-45.10	167.02	25.3	2.8	6204.6	49.1
Nelson Haven	7A	-41.27	173.26	35.7	3.0	804.0	23.7
New River (Oreti) Estuary	8	-46.51	168.27	3894.6	170.2	4690.1	0
Ngakawau River	6B	-41.61	171.87	94.4	11.6	458.5	NA
Ngunguru River	7A	-35.64	174.52	53.1	4.0	263.6	0
North Cove	11	-36.41	174.82	0.5	0.0	8.4	0.1
Nuhaka River	4C	-39.07	177.75	167.0	16.6	NA	NA
Ohariu Bay	11	-41.21	174.70	42.7	4.5	42.4	1.8
Ohau Bay	11	-41.24	174.65	1.7	0.1	2.0	0.2
Ohau River	4D	-40.66	175.14	133.8	11.3	NA	NA
Ohinemaka River	6D	-43.63	169.50	32.3	3.8	NA	NA
Ohinetamatatea River (Saltwater Creek)	6E	-43.46	169.76	44.1	6.6	NA	NA
Ohiwa Harbour	9	-37.98	177.15	174.3	8.7	804.2	32.1
Ohuia Lagoon	2A	-39.07	177.47	24.1	1.6	16.5	1.7
Okains Bay (Kawatea)	11	-43.68	173.08	3.1	0.1	74.8	0
Okains Bay Estuary (Opara)	7A	-43.69	173.06	NA	NA	22.0	NA
Okari Lagoon	7A	-41.81	171.45	3038.1	597.9	318.2	NA
Okarito Lagoon	7B	-43.22	170.16	140.6	20.1	1132.1	0
Oke Bay	11	-35.22	174.27	0.3	0.0	7.7	0
Okoromai Bay	11	-36.62	174.81	0.9	0.1	21.7	0.2
Okupe Lagoon	1	-40.83	174.96	NA	NA	0	0
Okura River	7A	-36.66	174.75	9.8	0.7	33.0	NA
Okuru River	6B	-43.91	168.89	184.8	103.1	1918.6	NA
Omaha Cove	11	-36.29	174.82	2.6	0.1	5.3	0
Omakiwi Cove	11	-35.24	174.24	NA	NA	NA	NA
Onaero River	6B	-38.98	174.36	105.9	6.4	66.0	NA
Onahau River	7A	-40.80	172.77	1.3	0.1	46.1	1.6
Onekaka Inlet	7A	-40.75	172.71	13.0	2.5	40.9	NA

Estuary	NZCHS class	LAT	LON	Modelled TN load (t yr^{-1})	Modelled TP load (t yr^{-1})	MAL TN (t yr^{-1})	MAL TP (t yr^{-1})
Oneroa Bay	11	-36.77	175.02	0.3	0.0	22.1	0.3
Oparara River	7A	-41.21	172.09	129.5	23.9	661.9	NA
Oparau River KHS	8	-38.07	174.89	NA	NA	461.2	NA
Opihi River	3C	-44.28	171.36	NA	NA	NA	NA
Opotoru River RHS	8	-37.80	174.87	NA	NA	208.2	NA
Opua Inlet System	9	-35.22	174.13	691.7	61.0	1139.5	0
Orewa River	7A	-36.59	174.71	20.0	0.8	58.9	0.5
Orore Creek	4C	-45.21	170.89	18.5	0.4	1.1	0.1
Orowaiti Lagoon	7A	-41.74	171.66	11.6	1.2	248.5	NA
Otago Harbour	9	-45.77	170.72	59.2	2.3	1192.4	0
Otahu River	7A	-37.24	175.90	34.5	2.3	163.1	NA
Otaki River	6C	-40.76	175.10	150.1	20.6	NA	NA
Otanerito Bay	11	-43.85	173.07	4.4	0.4	13.2	0
Oterei River	6C	-41.49	175.58	28.7	3.3	NA	NA
Otu Bay	11	-40.76	173.84	12.5	0.9	21.3	2.1
Otuwhero Inlet	7A	-41.01	173.01	1.7	0.1	147.8	5.1
Outu Bay	11	-35.22	174.31	0.1	0.0	5.2	0
Owahanga River	6B	-40.69	176.36	210.7	74.2	NA	NA
Owhanake Bay	11	-36.77	174.99	0.7	0.0	3.9	0
Pahaoa River	6C	-41.40	175.73	345.4	48.7	NA	NA
Pahurehure Inlet MHS	8	-37.05	174.86	NA	NA	1388.0	NA
Pakarae River	6B	-38.56	178.25	180.1	25.8	NA	NA
Pakawau Inlet	7A	-40.59	172.69	1.2	0.1	36.3	1.1
Pakiri River	7A	-36.24	174.73	28.2	2.1	36.0	NA
Papanui Inlet	7A	-45.84	170.74	5.0	0.2	63.4	0
Parapara Inlet	7A	-40.71	172.69	17.9	1.3	168.6	6.2
Parekura Bay	11	-35.24	174.21	8.0	0.7	43.7	0
Parengarenga Harbour System	8	-34.53	173.02	89.2	6.7	1606.2	0
Paringa River	5C	-43.63	169.43	137.9	54.2	1602.4	NA
Paroa Bay	11	-35.24	174.15	1.6	0.1	22.2	0
Patanui Stream	6D	-41.16	176.03	19.3	1.9	19.6	NA
Pataua River	7A	-35.70	174.53	36.0	2.2	121.3	0
Patea River	6B	-39.78	174.48	1119.6	116.1	594.6	NA
Paturau River	6B	-40.64	172.43	30.3	3.0	NA	NA
Pelorous/Kenepuru Sound	9	-40.95	174.09	9.2	0.7	7427.1	656.5
Peraki Bay (Pireka)	11	-43.88	172.81	5.5	0.4	23.7	0
Piako River	6A	-37.19	175.49	NA	NA	1088.6	NA
Pigeon Bay	11	-43.62	172.92	25.8	1.4	162.3	0
Pleasant River	7A	-45.57	170.73	37.5	1.4	40.0	0
Poerua River (Hikimutu Lagoon)	6C	-43.05	170.40	123.9	19.6	NA	NA
Poison Bay	11	-44.65	167.62	22.0	3.8	NA	NA

Estuary	NZCHS class	LAT	LON	Modelled TN load (t yr^{-1})	Modelled TP load (t yr^{-1})	MAL TN (t yr^{-1})	MAL TP (t yr^{-1})
Ponganui/Paihere Creeks	8	-37.79	174.87	NA	NA	58.8	NA
Porangahau River	7A	-40.26	176.71	NA	NA	483.3	NA
Pororari River	6B	-42.10	171.33	47.9	5.6	NA	NA
Port Charles	11	-36.51	175.46	10.7	1.0	79.1	1.4
Port Fitzroy/Port Albercrombie	9	-36.17	175.30	12.3	1.1	248.0	0
Port Gore	11	-40.99	174.27	95.2	7.8	9067.1	767.4
Port Hardy	9	-40.73	173.90	2.6	0.2	517.4	48.5
Port Levy (Koukourarata)	11	-43.61	172.84	26.7	1.3	130.6	0
Port Puponga	7A	-40.53	172.74	4.3	0.4	20.4	0.7
Port Underwood	9	-41.35	174.11	10.5	0.9	222.3	18.6
Pouawa River	6B	-38.62	178.19	29.2	2.9	30.0	NA
Pourerere Stream	4C	-40.10	176.88	23.8	1.5	NA	NA
Preservation Inlet	10	-46.14	166.61	144.6	17.4	15606.0	0
Puhinui Creek MHS	8	-37.03	174.85	NA	NA	71.1	NA
Puhoi River	7A	-36.53	174.72	33.9	2.2	111.5	0
Punakaiki River	4C	-42.12	171.32	30.5	3.3	NA	NA
Purakunui Inlet	7A	-45.74	170.63	4.0	0.1	21.4	0
Purangi River	7A	-36.83	175.75	23.0	0.8	40.3	NA
Putiki Bay	11	-36.82	175.02	4.5	0.3	55.4	0.6
Queen Charlotte Sound (Totaranui)	9	-41.05	174.35	13.2	1.2	54776.2	4855.0
Raglan Harbour System (RHS)	8	-37.81	174.81	476.6	26.4	1270.9	NA
Raglan Inlet RHS	8	-37.80	174.84	NA	NA	555.1	NA
Rakaia River	3A	-43.90	172.21	788.8	201.1	NA	NA
Rakaunui Inlet KHS	8	-38.10	174.86	NA	NA	180.8	NA
Rangaunu Harbour	8	-34.88	173.27	591.7	37.6	3007.2	0
Rangitata River	3B	-44.18	171.52	716.4	172.1	NA	NA
Rangitikei River	6B	-40.30	175.21	2026.2	529.9	NA	NA
Rangiwhakaea Bay	11	-36.09	175.41	1.8	0.2	13.4	0
Rocky Bay	11	-36.83	175.05	1.8	0.1	23.8	0.3
Ruakaka River	7A	-35.90	174.47	119.1	6.8	98.9	NA
Ruataniwha Inlet	7A	-40.67	172.68	18.9	2.1	1564.0	NA
Saltwater Creek	4D	-44.43	171.26	48.5	1.4	5.3	0.6
Saltwater Creek/New River	6D	-42.53	171.15	92.2	8.9	NA	NA
Saltwater Lagoon	7B	-43.10	170.33	8.8	1.0	47.4	6.2
Sandfly Bay	7A	-40.93	173.06	0.4	0.0	32.4	NA
Scrubby Bay	11	-43.63	172.95	1.6	0.1	4.4	0
Shag River	7A	-45.48	170.82	123.6	3.4	138.1	NA
Sleepy Bay	11	-43.85	173.06	1.0	0.1	3.7	0
South Cove Harbour	11	-36.44	174.83	0.5	0.0	5.4	0
Stony Bay	11	-36.50	175.43	4.9	0.5	25.5	0.6
Stony Bay (Opatoti)	11	-43.86	173.05	2.8	0.2	7.5	0

Estuary	NZCHS class	LAT	LON	Modelled TN load (t yr^{-1})	Modelled TP load (t yr^{-1})	MAL TN (t yr^{-1})	MAL TP (t yr^{-1})
Stony Creek	4C	-45.51	170.78	5.6	0.2	4.3	0
Sutherland Sound	10	-44.73	167.55	44.1	8.6	487.4	34.5
Taemaro Bay	11	-34.93	173.58	1.5	0.1	11.0	0
Tahaenui River	4D	-39.07	177.68	45.6	4.1	NA	NA
Tahakopa River	7A	-46.56	169.48	186.3	13.7	315.5	NA
Tahoranui River	7A	-35.12	173.97	21.9	1.7	44.0	NA
Tahunanui Estuary	7A	-41.28	173.22	40.5	3.7	14.0	0.3
Taieri River	6B	-46.06	170.21	1207.5	78.8	1350.7	NA
Taiharuru Bay	11	-35.73	174.55	NA	NA	NA	NA
Taiharuru River	7A	-35.70	174.56	15.6	0.5	93.5	0
Taipa River	7A	-34.98	173.48	83.5	7.4	220.5	NA
Tairua Harbour	7A	-37.01	175.89	107.7	9.0	877.4	NA
Takaka Estuary	7A	-40.82	172.81	34.0	2.1	1259.7	NA
Takaka River	5B	-40.82	172.80	356.0	52.7	7.1	0.6
Takerau Bay	11	-34.93	173.55	0.4	0.0	3.6	0
Takou River	7A	-35.10	173.95	69.0	4.8	105.9	NA
Tamaki River	8	-36.84	174.89	46.0	2.7	300.7	2.9
Tanutanu Stream	4C	-35.23	173.08	6.7	0.6	17.8	0
Tapotupotu Bay	7B	-34.43	172.71	4.5	0.3	7.0	0
Tapuaetahi Creek	7A	-35.12	173.98	10.7	0.4	23.4	NA
Taramakau River	6C	-42.56	171.12	400.6	132.8	2898.0	NA
Tauranga Harbour System	8	-37.47	176.00	1045.9	57.7	6058.3	193.2
Tautuku River	7A	-46.60	169.43	32.4	2.4	74.7	NA
Te Awarua-o-Porirua Harbour	8	-41.08	174.83	99.4	8.0	155.4	8.3
Te Ikaamaru Bay	11	-41.24	174.66	2.3	0.2	3.2	0.3
Te Kouma Harbour	8	-36.83	175.43	3.2	0.2	124.3	2.0
Te Matuku Bay	11	-36.85	175.13	5.1	0.4	64.0	0.5
Te Muri-O-Tarariki	7A	-36.52	174.72	3.7	0.2	12.0	NA
Te Oka Bay (Pareaihe)	11	-43.86	172.77	2.4	0.2	11.7	0
Te Paeroa Lagoon	2A	-39.06	177.52	NA	NA	1.7	0.2
Te Puna /Kerikeri Inlet System	9	-35.19	174.11	236.1	13.0	560.2	0
Te Wharu Bay KHS	8	-38.06	174.83	NA	NA	64.6	NA
Thompson/Doubtful sound	10	-45.15	166.96	272.4	36.4	41660.4	15.1
Three Mile Lagoon	7B	-43.24	170.13	12.4	1.2	86.2	NA
Titahi Bay	11	-41.10	174.82	0.5	0.0	3.2	0.3
Toetoes Harbour	7A	-46.59	168.80	4956.8	225.6	3105.2	NA
Tokomairiro River	7A	-46.22	170.05	252.1	10.3	115.3	NA
Tomahawk Lagoon	4B	-45.91	170.54	2.8	0.1	1.1	0.1
Tongaporutu River	6B	-38.82	174.57	131.5	15.0	470.8	NA
Torrent Bay	7A	-40.95	173.06	11.1	1.0	39.3	3.7
Totara River	6D	-41.86	171.45	71.7	8.8	NA	NA
Totara River	6D	-41.86	171.45	57.9	5.4	207.4	NA

Estuary	NZCHS class	LAT	LON	Modelled TN load ($t\ yr^{-1}$)	Modelled TP load ($t\ yr^{-1}$)	MAL TN ($t\ yr^{-1}$)	MAL TP ($t\ yr^{-1}$)
Totaranui Stream	7A	-40.82	173.02	22.0	2.0	15.9	0.5
Tryphena Harbour	11	-36.32	175.46	5.4	0.4	104.7	0
Tukituki	6B	-39.60	176.95	NA	NA	897.5	NA
Tumbledown Bay (Te Kaio)	11	-43.86	172.77	1.5	0.1	3.4	0
Turakina River	6B	-40.09	175.14	652.3	96.3	337.9	NA
Turanga Creek WES	8	-36.91	174.96	20.7	1.1	62.9	NA
Turanganui River	6B	-38.68	178.02	220.9	27.0	NA	NA
Turimawiwi River	3B	-40.73	172.31	32.8	5.2	87.1	NA
Tutukaka Harbour	9	-35.62	174.54	1.9	0.1	13.8	0
Two Thumb Bay	11	-44.95	167.18	13.0	1.4	87.8	5.4
Uawa River (Tolaga Bay)	6B	-38.37	178.31	256.9	95.7	580.1	NA
Urenui River	6B	-38.98	174.39	83.0	7.8	NA	NA
Waiaro Estuary	7A	-36.59	175.42	4.8	0.4	NA	NA
Waiatoto River	6B	-43.97	168.79	178.6	143.8	2401.2	NA
Waiatua Stream	4C	-35.29	173.14	2.4	0.2	9.2	NA
Waiau River	3B	-42.77	173.38	1744.6	121.5	NA	NA
Waiaua River	7A	-37.98	177.39	52.5	4.2	124.0	NA
Waiau-uha / Waiau River	3B	-42.77	173.38	1083.5	359.3	NA	NA
Waihao River	4D	-44.77	171.17	215.6	5.5	NA	NA
Waiharakeke Stream	8	-38.13	174.81	NA	NA	472.8	NA
Waihi Estuary	7A	-37.75	176.48	448.0	20.2	593.5	NA
Waihou River	6A	-37.16	175.53	2675.7	153.9	3372.6	NA
Waihua River	3D	-39.10	177.30	103.8	10.9	NA	NA
Waikanae River	6B	-40.86	174.99	68.4	5.5	171.2	NA
Waikari River	6C	-39.17	177.10	278.8	30.5	NA	NA
Waikato Estuary	7A	-40.63	172.68	357.6	88.8	10.6	0.3
Waikato River	6B	-37.37	174.68	NA	NA	14958.0	NA
Waikawa Harbour	7A	-46.65	169.13	216.4	14.9	424.5	0
Waikawa Stream	4D	-40.69	175.13	58.4	4.0	80.6	NA
Waikawau Estuary	7A	-36.59	175.53	10.7	0.9	42.2	NA
Waikawau River	4C	-38.48	174.61	41.4	3.7	NA	NA
Waikopua Creek WES	8	-36.90	174.98	7.9	0.4	49.8	NA
Waikouaiti Lagoon	4B	-45.61	170.68	8.4	0.3	0.7	0.1
Waikouaiti River	7A	-45.64	170.66	103.2	3.5	105.1	0
Waimahana Bay	11	-34.94	173.63	2.5	0.2	4.5	0
Waimakariri River	6B	-43.39	172.71	1830.9	358.2	3360.8	NA
Waimaukau River	6B	-35.60	173.40	95.5	6.2	150.2	NA
Waimea Inlet	8	-41.29	173.20	1.4	0.1	2640.4	74.1
Wainono Lagoon	2A	-44.71	171.17	113.3	3.8	6.9	0.7
Wainui Inlet	7A	-40.81	172.94	3.1	0.3	134.4	3.7
Wainuiomata River	3C	-41.43	174.87	54.7	5.0	NA	NA
Waioeka River	7A	-37.98	177.30	564.1	92.1	1093.8	NA

Estuary	NZCHS class	LAT	LON	Modelled TN load (t yr^{-1})	Modelled TP load (t yr^{-1})	MAL TN (t yr^{-1})	MAL TP (t yr^{-1})
Waiomoko River	6B	-38.58	178.23	56.4	5.2	NA	NA
Waiongana Stream	6B	-38.98	174.19	310.1	14.4	NA	NA
Waiotahi River	7A	-37.99	177.21	85.3	7.1	260.5	NA
Waipaoa River	6B	-38.72	177.94	1641.2	611.7	NA	NA
Waipara River	3C	-43.16	172.80	310.2	10.7	NA	NA
Waipati Estuary	7A	-46.62	169.36	41.8	3.1	90.5	NA
Waipoua River	6B	-35.68	173.47	61.2	3.4	145.4	NA
Waipu River	7A	-35.99	174.49	243.4	16.0	264.2	NA
Wairau Lagoon	2A	-39.06	177.50	NA	NA	0.5	0.1
Wairau River	6B	-41.50	174.06	242.2	11.5	317.9	21.7
Wairoa River	8	-36.94	175.10	195.9	15.9	373.0	NA
Waita River	6D	-43.80	169.09	62.2	11.7	474.4	NA
Waitaha River	6C	-42.96	170.66	128.5	39.7	1595.1	NA
Waitahanui Stream	4	-37.83	176.60	102.7	7.0	NA	NA
Waitahora Stream	7B	-34.46	172.79	0.3	0.0	1.5	0.2
Waitakaruru River	6A	-37.22	175.39	79.5	4.1	102.7	NA
Waitakere River (Bethells Beach)	4C	-36.89	174.43	29.4	2.3	35.8	NA
Waitakere River (Nile River)	5C	-41.90	171.44	57.6	8.0	NA	NA
Waitaki River	3A	-44.94	171.15	1709.8	187.9	NA	NA
Waitangi Estuary / Ngaruroro River	6B	-39.57	176.94	1769.3	461.6	NA	NA
Waitangi Stream	4C	-34.43	172.96	4.5	0.3	3.4	0.4
Waitara River	6B	-38.98	174.23	1472.7	229.7	NA	NA
Waitemata Harbour System	8	-36.84	174.82	269.4	15.5	1887.4	20.9
Waitetuna Creek RHS	8	-37.79	174.92	NA	NA	673.7	NA
Waitotara River	6A	-39.86	174.68	594.8	103.9	NA	NA
Waituna Lagoon	2A	-46.57	168.66	238.9	9.9	36.7	4.3
Waiwakaiho River	6B	-39.03	174.10	186.7	11.6	178.0	NA
Waiwera River	7A	-36.55	174.72	22.7	1.7	73.7	0.7
Wanganui River	6C	-39.95	174.98	5646.5	1030.4	NA	NA
Washdyke Lagoon	2A	-44.37	171.26	NA	NA	NA	NA
Weiti River	6B	-36.66	174.76	20.9	1.1	106.5	0.8
Wellington Harbour	9	-41.35	174.83	302.5	49.7	35387.5	1326.2
Whakaki Lagoon	2A	-39.06	177.57	NA	NA	17.2	2.0
Whakatane River	6B	-37.94	177.01	840.1	143.5	401.9	NA
Whananaki Inlet	7A	-35.52	174.47	31.1	2.1	127.2	0.7
Whangaehu River	6B	-40.04	175.10	1273.3	263.6	NA	NA
Whangaihe Bay	11	-34.98	173.82	1.0	0.1	4.5	0
Whangamata Harbour	7A	-37.21	175.90	22.5	1.4	189.0	3.6
Whangamoa River	7A	-41.10	173.53	25.2	2.2	143.5	NA
Whangamumu Harbour	11	-35.24	174.33	0.5	0.0	33.6	0
Whanganui Inlet	8	-40.57	172.54	3.5	0.4	761.3	22.1

Estuary	NZCHS class	LAT	LON	Modelled TN load (t yr^{-1})	Modelled TP load (t yr^{-1})	MAL TN (t yr^{-1})	MAL TP (t yr^{-1})
Whangapae Harbour System	8	-35.38	173.20	180.6	12.7	835.0	0
Whangaparaoa River	6B	-37.57	177.99	74.6	9.0	NA	NA
Whangaparapara Harbour	11	-36.26	175.39	2.8	0.2	27.0	0
Whangapoua Creek	7A	-36.14	175.44	9.4	0.8	81.5	0
Whangapoua Harbour	7A	-36.72	175.64	48.2	3.3	460.2	4.5
Whangarei Harbour System	8	-35.85	174.51	239.3	12.9	3246.1	0
Whangaroa Harbour	9	-35.00	173.77	127.6	11.5	441.7	0
Whangaruru Harbour	9	-35.36	174.35	27.6	2.2	160.9	0
Whangateau Harbour	7A	-36.33	174.79	26.5	1.3	226.2	0.4
Whareama River	6A	-41.02	176.12	296.4	54.8	NA	NA
Wharekahika River	6D	-37.58	178.30	63.2	7.9	224.3	NA
Wharekawa Harbour	7A	-37.12	175.89	41.1	2.3	224.0	NA
Whenuakura River	6B	-39.79	174.51	294.0	35.7	192.7	NA
Wherowhero Lagoon	7A	-38.75	177.95	18.8	1.5	12.6	1.1
Whitford Embayment System (WES)	8	-36.89	174.97	10.7	0.5	382.4	1.5
Whitianga Harbour MBS	7A	-36.81	175.73	210.0	15.7	1174.4	NA

Table 25. New Zealand Coastal Hydrosystem types

NZCHS class	NZCHS name
1	Damp sand plain lake
2A	Waituna-type lagoon (coastal plain depression)
2B	Waituna-type lagoon (valley basin)
3A	Hāpua-type lagoon (large)
3B	Hāpua-type lagoon (medium)
3C	Hāpua-type lagoon (small)
3D	Hāpua-type lagoon (intermittent)
4	Beach Stream
4B	Beach Stream (damp sand plain stream)
4C	Beach Stream (stream with pond)
4D	Beach Stream (stream with ribbon lagoon)
4E	Beach Stream (intermittent stream with ribbon lagoon)
5A	Freshwater river mouth (unrestricted)
5B	Freshwater river mouth (deltaic)
5C	Freshwater river mouth (barrier beach enclosed)
6A	Tidal river mouth (unrestricted)
6B	Tidal river mouth (spit enclosed)
6C	Tidal river mouth (barrier beach enclosed)
6D	Tidal river mouth (intermittent with ribbon lake)
6E	Tidal river mouth (deltaic)
7A	Tidal lagoon (permanently open)
7B	Tidal lagoon (intermittently closed)
8	Shallow drowned valley
9	Deep drowned valley
10	Fjord
11	Coastal embayment