Modelling periphyton in New Zealand rivers

Part 1. An analysis of current data and development of national predictions

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Contents

Tables

Figures

Executive summary

This report documents one of a series of studies aimed at providing up-to-date data, analysis and scientific information to the Ministry for the Environment (MfE) on a range of fresh water topics. The study reported here focusses on addressing a data gap identified in the most recent MfE report on the state of New Zealand's fresh water environments. The data gap was: "… the extent of our rivers affected by excessive algal growth".

Robust periphyton data are being collected by several regional councils following inclusion of periphyton standards and guidelines in regional plans and inclusion of periphyton as an attribute in the National Objectives Framework of the National Policy Statement for Freshwater Management (NPS-FM), which became operational in 2014. The purpose of this project was to use recent regional council datasets to develop updated empirical relationships and models for assessing the extent of nuisance periphyton across New Zealand's river network.

The requirement in MfE's initial request for proposals (RfP) for the work provided in this report was: "Nuisance algae: Provide a report on analysis of current periphyton data … and the further development of statistical and/or mechanistic models that can be used to predict periphyton biomass for all river segments (in the River Environment Classification [REC])."

"Nuisance algae" (periphyton) was defined based on the definition in the NPS-FM periphyton attribute of the periphyton bottom line (band D). The NPS-FM bands are defined by the 92nd percentile of chlorophyll *a* calculated from three years of monthly data. Bands are: ≤50 mg/m^2 (band A), >50 ≤120 mg/m^2 (B), >120 ≤200 mg/m^2 (C), and >200 mg/m^2 (D). We also used data on direct estimates of periphyton cover of the river bed integrated into weighted composite cover (WCC).

This study was carried out in the following steps.

In **steps 1 and 2** we acquired suitable periphyton and associated environmental data from six regional councils (Northland, Bay of Plenty, Horizons, Greater Wellington, Canterbury and Southland) and assembled a national dataset. The main requirement for the periphyton data was monthly time series, ideally spanning three years or more, with data collected using the same techniques. To extend the number of sites, shorter time series (at least 20 months) were included. The final usable dataset comprised up to 196 sites. Representation was biased toward lowland sites in pastoral catchments, but there was reasonable representation across all REC climate, source of flow, geology and land cover classes. Flow data were available at 136 sites.

In **step 3**, we identified at each site, where possible, a characteristic flow magnitude that reduces periphyton chlorophyll *a* to low levels. The flow magnitude (effective flow, EF) was expressed as multiples of the long-term median flow at each site. An EF was identified at 109 of the 136 sites with a flow record. Magnitude ranged from 1.5 to 16 x median flow. An EF was identified at 61 of 65 sites in the Greater Wellington, Canterbury and Southland regions. An EF could not be identified at 22 of the remaining 71 sites in Northland and Horizons regions. Random forest (RF) methodology was used to attempt to identify predictors of EF across the REC network but failed to define a useful model.

In **step 4**, multiple regression techniques (with cross validation) were used to develop periphyton – environment relationships. Periphyton variables were the 92nd percentiles and means of chlorophyll *a* and WCC calculated from the time series data (Chla_92, WCC_92, Chla_mean, WCC_mean). Predictor variables were those known to influence periphyton growth rates and accrual. The final generally uncorrelated set of predictor variables included mean accrual period calculated from the EF

(at sites where it was identified), along with measured DIN, DRP, conductivity, substrate composition and temperature. The dataset size varied from 94 to 194 because not all sites had all predictor variables available. Key results were:

- across all available data, chlorophyll *a* was more predictable than WCC, but the strongest relationships were relatively weak (less than 40% of variance explained);
- no national model was identified in which WCC was predictable;
- predictor variables in the strongest national models for chlorophyll *a* included DIN, DRP, conductivity and accrual period calculated from EF;
- all regional datasets except the Canterbury dataset out-performed the overall dataset in terms of model strength and predictive ability for chlorophyll *a* (but note that some datasets were very small, e.g., n < 10).

We concluded that simple regression models performed too poorly across multiple regional datasets to produce useful national predictions. However, results from regional datasets were promising, consistent with earlier studies (from a comparison in **step 5**).

The original plan for **step 6** was to use the regression models developed in step 4 to make national predictions of periphyton abundance. The plan was changed in view of weak regression models, and failure to identify a suitable model for predicting EF across the REC network. Instead, we used RF to derive predictions of periphyton chlorophyll *a* across the entire New Zealand river network, using modelled variables as predictors. The RF models for both chlorophyll *a* and WCC had "average" performance (relative to a published scale of model performance). The most important predictor variables for Chla_92 and Chla_mean were conductivity, nitrate-N, TN and rainfall variability, in that order. Inclusion of two highly correlated variables representing N supply was unexpected and was discussed. The most important predictors in the WCC models differed from those for chlorophyll *a*, and from each other.

Spatial predictions of Chla_92, WCC_92, Chla_mean and WCC_mean across the REC network (**Step 7**) produced intuitively sensible patterns. However, few reaches were predicted to fall below the bottom line (band D) in the NPS-FM. This was attributed to a feature of RF models that prevents predictions outside the range of the training data combined with few monitored sites with Chla_92 > 200 mg/m^2 (6% of sites, in a dataset biased towards rivers in pastoral catchments).

Areas of potentially high chlorophyll *a* were highlighted better when Chla_mean was mapped. Chla_mean >50 mg/m^2 was predicted for south eastern North Island and coastal north Canterbury. Lowest Chla_mean (< 7.5 mg/m^2) was predicted for the eastern mountainous areas of the North Island, and the central mountain / foothills and western coastal areas of the South Island. Predicted mean WCC differed in that all of the eastern foothills of the South Island were predicted to have higher WCC than western areas and highest WCC was concentrated along most of the east coast and northern North Island, especially western Bay of Plenty.

Discrepancies between the spatial distributions of chlorophyll *a* and WCC were attributed partly to regional discrepancies in the relationship between chlorophyll *a* and WCC. Potential reasons for the discrepancies may include differences in sample collection and analysis methods, and regional differences in periphyton community composition.

The final task in the project was to provide a review and assessment of the potential for using mechanistic (process-based) models for predicting stream periphyton chlorophyll *a* and/or biomass at a national scale. The outcome of the task (Part 2 of the project) is provided as a separate report.

The following recommendations resulted from the analysis in the present report (Part 1 of the project).

- In view of the stronger regional relationships than national, we recommend that the current effort to develop straightforward regression relationships for predicting periphyton within regions is justified and should continue, and the current effort by regional councils to accumulate robust datasets should also continue.
- Despite relatively weak statistical performance, the RF model predictions of periphyton chlorophyll *a* and WCC appeared sensible at the national scale. Therefore, we suggest that further rounds of predictive models and mapping are likely to be informative, when further robust regional data becomes available.
- We identified inconsistent relationships between WCC and chlorophyll *a* that led to differences in model predictors and spatial distributions. Potential reasons for the inconsistencies include regional discrepancies in sample collection and analyses. To eliminate or confirm sources of differences we recommend prioritising development and completion of a National Environmental Monitoring Standard (NEMS) for periphyton. The document is underway and will cover a wide range of aspects of field and laboratory methodologies related to periphyton.
- Finally, we suggest that periphyton community composition data may also be useful for understanding regional differences in periphyton – environment relationships.

1 Introduction

1.1 Background to and purpose of this report

The Ministry for the Environment (MfE) periodically reports on the state of New Zealand's fresh water environments from a national perspective as a requirement of the Environmental Reporting Act 2015. The most recent report fulfilling this requirement was released in 2017 (Ministry for the Environment & Stats NZ 2017) (hereafter the 2017 MfE report). The 2017 MfE report included summaries of the state of New Zealand's rivers in terms of water quality (dissolved nitrogen and phosphorus, and *E. coli* concentrations for indicating swimmability), water quantity, and "ecosystems, habitats and species" (including freshwater fish, invertebrates and plants, and the effects of fine sediment). The analyses in the 2017 MfE report relied on data collected by multiple agencies including regional and unitary councils and NIWA. The combined datasets were used to assess current state and trends over time and were also used to develop models of national state. Models are essential for assessing unbiased national state because collected data is likely to be biased in some way. For example, regional council data collection networks may focus more on sites with known water quality problems than on unimpacted reference sites.

The 2017 MfE report summarised data gaps, the first entry in which was: *"… the extent of our rivers affected by excessive algal growth"*. Although an account of a modelling exercise to assess the status of periphyton in rivers across New Zealand (based on Larned et al. 2015) was included in the 2017 MfE report, those models were considered to be preliminary only:

> *"The models underlying this analysis are uncertain and the thresholds were derived from periphyton and environmental data collected from a limited number of sites that are representative of large New Zealand rivers. The resulting analysis is therefore uncertain and should be considered as only indicative of periphyton issues nationally."* (Ministry for the Environment & Stats NZ 2017).

The 2017 MfE report acknowledged that several regional councils were already collecting more robust data on periphyton from a wider range of river types. Data are being collected in response to inclusion of periphyton as an ecological indicator in regional plans. In addition, increased data collection effort on periphyton by regional councils was expected following inclusion of periphyton as an attribute in the National Policy Statement for Freshwater Management (NPS-FM) (New Zealand Government 2017). The purpose of the project described in the present report was to assemble recent regional council datasets and use them to develop updated empirical relationships and models for assessing the extent of nuisance periphyton across New Zealand's river network. Further updates are expected in the future as data accumulates.

The required outcome from the analysis described in this report, as stated in the Request for Proposals, was: "Nuisance algae: provide a report on analysis of current periphyton data … and the further development of statistical and/or mechanistic models that can be used to predict periphyton biomass for all river segments (in the River Environment Classification)." The requested report is outcome 2 of a series of studies aimed at providing up-to-date data, analysis and scientific information to MfE on a range of fresh water topics.

1.2 Environmental controllers of periphyton in rivers

Periphyton abundance in rivers is primarily controlled by a combination of river flows and nutrient availability. Other factors such as light availability and temperature also affect algal growth rates and therefore biomass. Substrate composition can affect biomass by determining the area of riverbed available for colonisation by algae, and through the interaction between flow and substrate mobility, which affects potential for periphyton removal. Background water chemistry may influence biomass via effects on periphyton community composition (Chetelat et al. 1999, Rott and Schneider 2014). Finally, grazing by macroinvertebrates can be an important biological control on periphyton biomass. The effects of grazing are variable but can be substantial (Liess and Hillebrand 2004).

Comprehensive accounts of controls on periphyton are available in the literature (e.g., Biggs 2000b) and will not be repeated here. The following key points are relevant to this report.

1. The overriding controller of periphyton abundance in rivers is **flow**. Periods of low, stable flows are associated with **periphyton accrual**, while high flows (with associated increased hydraulic forces) remove biomass through sloughing processes (Biggs and Close 1989) and prevent colonisation and accrual.

2. **Nutrient availability** is a primary determinant of the maximum carrying capacity of periphyton in a river, given suitable hydrological conditions in which to accrue. Nutrient availability is usually represented by concentrations of dissolved inorganic nitrogen (DIN) and dissolved reactive phosphorus (DRP) both of which vary over time and are themselves influenced (reduced) by periphyton growth though uptake. It is important to note that water column concentrations do not always reflect availability of nutrients but are used as a convenient surrogate for nutrient availability[1]. The appropriateness of concentrations for representing nutrient availability varies from site to site, over time and with flow conditions. It is also noted that measures of total N (TN) (which include all organic and particulate N in a sample, in addition to the dissolved fraction) can be more strongly related to periphyton biomass than DIN. Issues of accounting for instream uptake and remineralisation, and difficulty in measurement of DRP, have led to the recommendation that DIN and DRP should be avoided as measures of nutrient status in favour of TN and TP (Dodds 2003). DIN and TN, in particular, are usually closely correlated. In this analysis we focused on DIN as the main N predictor because DIN (along with DRP) is specified as the variable requiring management in New Zealand waterways (NZ Government 2017). DIN was also available as a variable at all sites, whereas TN was not available in the Environment Canterbury (ECan) dataset.

1.3 Defining "nuisance algae"

The term "nuisance algae" (hereafter nuisance periphyton) can be interpreted in different ways. For example, people might perceive that periphyton above a certain threshold of abundance is a nuisance because it spoils their recreational enjoyment of a river (Suplee et al. 2009). Alternatively, periphyton could be a nuisance to other components of the river ecosystem when it changes habitat

[1] Algae typically obtain nutrients from the surrounding medium and respond to increased nutrient supply with increased growth rates (up to the point of saturation). The "surrounding medium" is usually the overlying water but can include the periphyton mat itself when nutrients are released from organic compounds during chemical (redox) processes. Furthermore, during long periods of accrual, periphyton may be taking up nutrients as fast as they are being supplied from upstream so that concentrations become decoupled from availability (and therefore accrual).

and / or water quality conditions enough to cause a shift in the species composition of (for example) macroinvertebrates or fish. Accordingly, the interim periphyton guideline developed in 2000 (Biggs 2000b) proposed limits of periphyton for the protection of aesthetics /recreational values, trout habitat and angling values, and benthic biodiversity (i.e., macroinvertebrate) values. The limits were specified in terms of both periphyton cover (i.e., percentage cover of periphyton on the stream bed) and biomass (either chlorophyll *a*[2] or ash-free dry mass[3]). A substantial body of research on periphyton was referred to in the development of the interim periphyton guideline (Biggs 2000b).

The guidelines proposed by Biggs (2000b) mainly applied to *maximum* chlorophyll *a* or cover but did not specify limits on the frequency of occurrence of breaches of the thresholds. The dynamic nature of periphyton biomass in rivers (particularly through the effects of river flow) means that limits are generally breached only periodically. An occasional breach (e.g., on less than one occasion per year, and for a short time) may have little long-term impact on river values including ecosystem "health". However, more regular, prolonged and severe breaches can have a longer-lasting effect. The damaging effect of high algal biomass on other aquatic life arises mainly from large diurnal fluctuations in dissolved oxygen (DO) as a result of high oxygen production from photosynthesis during the day followed by low DO conditions at night when oxygen is consumed through respiration. Low DO can be lethal to fish and invertebrates, with different species having different sensitivities (e.g., Landman et al. 2005). A single very severe periphyton proliferation may have immediate detrimental effects on fish and invertebrates, and longer or repeated events will have cumulative effects.

The periphyton attribute in the National Objectives Framework of the NPS-FM built on the Biggs (2000b) interim guideline, focusing on "ecosystem health" values. The four Bands in NPS-FM periphyton attribute[4] were largely based on the guidelines proposed by Biggs (2000b) (Snelder et al. 2013) with the thresholds separating different river states (termed Bands in the NPS-FM) equivalent to the Biggs (2000b) limits for protection of benthic biodiversity (maximum of 50 mg/m^2, separates Bands A and B), aesthetics / recreation (120 mg/m^2, separates Bands B and C) and trout habitat and angling (for diatoms/cyanobacteria) (200 mg/m^2, separates Bands C and D). Note that the trout habitat and angling value is effectively a value for protection of ecosystem health.

A time component is allowed for in the NPS-FM periphyton attribute by specifying a frequency of thresholds breaches considered to be unacceptable (Snelder et al. 2013). Thus, a river site falls below the bottom line (i.e., is placed in Band D) when periphyton biomass (measured as chlorophyll *a* in mg/m^2 of river bed) exceeds 200 mg/m^2 more than three times over a period of 36 months (assuming a monthly monitoring programme). In other words, the 92nd percentile of monthly chlorophyll *a* over that period should not exceed 200 mg/m^2. Exceptions are provided in the attribute for sites that are "naturally productive" and typically support relatively high periphyton biomass in the absence of anthropogenic influences on either flow or nutrients. Such sites are defined by specified combinations of underlying geology and climate in the River Environment Classification (REC) (Snelder and Biggs 2002), which lead to naturally nutrient-enriched waters (Snelder et al. 2013 and see NZ Government 2017).

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[2] Chlorophyll *a* is the photosynthetic pigment found in all types of algae; it is a widely accepted surrogate for algal biomass.
[3] Ash-free dry mass (AFDM) is a measure of the total organic content of periphyton and includes the organic parts of algae and other organisms and material such as fungi, bacteria, detritus, and meiofauna (small invertebrates).
[4] The periphyton attribute is included for protection of the ecological values of waterways and is specified in terms of chlorophyll *a* per square metre of river bed. Bands are ≤50 mg/m^2 (A), >50 ≤120 mg/m^2 (B), >120 ≤200 mg/m^2 (C), and >200 mg/m^2 (D). The metric required for assignment of a river to a band is the 92nd percentile of monthly observations of chlorophyll *a*, based on at least three years of data. Thus, for a site to fall into band D, chlorophyll a would exceed 200 mg/m^2 in at least 4 of 36 monthly surveys.

In the analysis in this report, we defined "nuisance periphyton" based on the definition in the NPS-FM periphyton attribute of the periphyton bottom line (Band D). In addition, we used the measure of mean chlorophyll *a* to enable identification of sites with extremely low periphyton biomass (refer to Section 5). We also used data on direct estimates of periphyton cover of the river bed. In the case of cover, nuisance periphyton was taken to be cover exceeding a threshold of 55% calculated as a composite of cover by mats and filaments and associated with "poor" ecological condition (Matheson et al. 2012; see Section 5.2.1).

1.4 Structure of report

Following this Introduction, Section 2 sets out a brief description of the approach we took in the analysis, along with reasons for deviations from the plan set out in the proposal and contract for this work. Section 3 summarises the data obtained from regional councils. Sections 4 to 6 cover, in turn, an analysis of periphyton in relation to flow, development of regression models linking periphyton to environmental variables, and predictions of periphyton across the New Zealand river network using a random forest approach. Discussion of the results is provided within each section. In Section 7, we provide a discussion on statistical methods used in the analysis, a summary of the main outcomes from the analyses, and recommendations arising from the work.

The final task in the proposal was to provide a review and assessment of the potential for using mechanistic (process-based) models for predicting stream periphyton chlorophyll *a* and/or biomass at a national scale. This part of the project (Part 2) is provided as a separate report (Kuczynski 2019).

2 General approach to the analysis

The analysis presented in this report was conducted in nine steps, as set out in the proposal. Some modifications to the proposed methods were necessary to accommodate the available data and in response to results of earlier steps in the analysis.

In **steps 1 and 2** (Section 3 of this report) we obtained monthly times series of periphyton and linked environmental data from regional councils and combined the data into a single dataset (step 1). Continuous flow records were also obtained from as many sites as possible. We restricted the dataset to regional council data only, where chlorophyll *a* and cover data were collected using methodology based on that set out in Kilroy et al. (2008). In step 2 (site selection), a small number of sites was dropped from the final dataset because of insufficient data. Data at each retained site were reduced to mean values (or other appropriate metrics) from the most recent 2-4 years of the time series.

Step 3 (Section 4) was an analysis of chlorophyll *a* data against flow at individual sites with the aim of determining for each site a characteristic flow magnitude (the effective flow, EF) that reduces periphyton to low levels. Flow metrics based on EF (e.g., the accrual period or mean interval between removal events) were calculated. We used the dataset of EF to develop a model for predicting EF across the New Zealand river network, using modelled data linked to the REC as predictors and random forest methodology.

In **step 4** (Section 5) we used multiple regression techniques to develop models relating periphyton abundance (as both chlorophyll *a* and periphyton cover, summarised as "weighted composite cover", WCC) to environmental explanatory variables (step 4). **Step 5** was a brief comparison with the results of previous studies.

For **step 6** (Section 6) we proposed to use the models developed in step 4 to derive predictions of periphyton chlorophyll *a* across the entire New Zealand river network. These broad spatial predictions of periphyton required substitution of modelled environmental explanatory variables for the measured explanatory variables. In view of the limited spatial extent of the dataset, the relatively weak performance of the best regression models, and limited suitable predictor variables, we instead developed a random forest model using the regional council data and modelled variables. Section 6 also includes **step 7,** which was to map spatial distribution of river reaches predicted to fall into Bands A, B, C and D of the NPS-FM periphyton attribute, and to present the results by REC class and by region.

For **step 8** we proposed to repeat the analyses in Steps 4 to 7 for periphyton cover. During the analysis, data on periphyton chlorophyll *a* and cover (WCC) were processed in tandem (Sections 5 and 6).

A general discussion in Section 7 covers **step 9** (Comparisons of model performance). We summarise the strengths and weaknesses of the modelling approaches taken, including sources of error, likely explanations for discrepancies, and prospects for improving the predictions. Recommendations for improved predictions of nuisance periphyton levels across scales are also included in Section 7 following a synthesis of the more detailed discussions provided in Sections 4, 5 and 6.

As noted in Section 1.4, a review of mechanistic modelling (**step 10**) is presented in a companion report (Kuczynski 2018).

3 Data

3.1 Data sources

The initial intention was to obtain data from a parallel project for MfE (water quality state and trends, including periphyton).[5] Data in the water quality project were sourced from regional council online repositories. However, datasets of periphyton were generally not available from those sources or were incomplete. The planned analysis of periphyton data required time-series of data on periphyton abundance collected at monthly intervals, with linked data on environmental variables and river flows. Suitable data were therefore obtained directly from the following councils: Northland, Bay of Plenty, Manawatu-Whanganui, Greater Wellington, Canterbury, Southland.

The data provided by the six councils covered 200 sites with a data series spanning up to 10 years (Table 3-1, Figure 3-1). A complete list of sites, along with details of time range and data availability is provided as Appendix A.

Table 3-1: Summary of data obtained from regional councils for this analysis. Chlorophyll *a* and water quality data were generally collected monthly. "Range of n" refers to the number of observations made at each site. Refer to Appendix A for a complete set of sites used in the analysis.

Site details and data available	Regional Council (with abbreviation)					
	Northland (NRC)	Bay of Plenty (BOP)	Horizons (HRC)	Greater Wellington (GWRC)	Canterbury (ECan)	Southland (ES)
No. of sites	39	29	62	16	24	30
Range of n	21 - 54	8 - 29	11 - 116	8 - 21	29 - 35	16 - 39
Earliest date	25-Mar-08	9-Oct-15	9-Dec-08	16-Aug-16	21-Jul-11	1-Nov-14
Latest date	24-May-18	15-Jun-18	20-Apr-17	7-Jun-18	18-Jun-14	28-Feb-18
Data available						
Chlorophyll *a*	yes	yes	yes	yes	yes	yes
% cover	yes	yes	yes	yes	yes	yes
Water quality	yes	yes	yes	yes	yes	yes
Substrate composition	yes	no	yes	no	yes	yes
Shade	yes	no	partly	no	yes	yes
Linked flow records	partly	no	partly	all but one	yes	partly

Data from an appropriate flow recording site were obtained for 136 sites from the relevant regional councils. In some cases, a simulated data set was provided. No appropriate flow data were available at the time of the analysis for any of the Bay of Plenty sites and for 31 sites in other regions. In addition to the flow data from hydrological recording sites, a modelled flow record was generated for each site using the TopNet model (Booker and Woods 2014). In the analysis in Section 4, the results using TopNet modelled flows corresponded poorly with those using measured data. Therefore, the modelled flows were not used in subsequent analyses.

[5] The complete wording in the RfP related to the Nuisance Periphyton outcome (outcome 2 of the series of studies – see Section 1.1) was: "Provide a report on analysis of current periphyton data (collected in outcome 1) and the further development of statistical and/or mechanistic models that can be used to predict periphyton biomass for all river segments (in the River Environment Classification)". Here outcome 1 referred to an update of water quality state and trends, where water quality included periphyton.

Water quality data were available for all sites, though the variables varied across datasets. Variables common to all sites included dissolved reactive phosphorus, dissolved inorganic nitrogen, electrical conductivity and water temperature. The water quality data were linked to each periphyton observation, and also averaged across missing periphyton observations. Summary statistics of the main variables available in each region are provided in Appendix B.

Figure 3-1: Locations of regional council sites from which periphyton chlorophyll *a* and periphyton cover data were available. Data at all sites comprised a time series of monthly observations, generally over a period of at least three years.

3.2 Representativeness of data relative to REC classes

All sites were linked to the appropriate reachID of the river environment classification (REC) digital network (Snelder and Biggs 2002). The original classification (REC1) categorises all reaches according to their climate, source of flow, geology, land cover, etc. (Snelder and Biggs 2002). Sites were also linked to their reach (termed nzsegment) in an updated version of the digital network (REC2, see Section 6.2 for more details). Sites (as nzsegments of REC2) in the periphyton monitoring dataset represented stream orders from 2 to 7, but most nzsegments (almost 80%) were medium-sized rivers with stream order 4, 5 or 6. About 10% each were stream order 2-3 and stream order 7.

Compared with all reaches in the REC with stream order > 1, the periphyton dataset over-represented sites in the CW/H, CW/L and WW/L classes at the second level of the REC (Table 3-2). Over-representation in these classes was driven mainly by over-representation in the climate classes CW (Cool Wet) and WW (Warm Wet) and under-represented the other classes. Of the topography classes, L (Low elevation) was over-represented, H (Hill) had approximately similar representation as over the whole network, and other classes were under-represented (Table 3-3). Geology classes were reasonably well represented in the dataset, compared to the entire network except for double representation in the VA (Volcanic acidic) class compared to the whole network (Table 3-3).

Landcover representation was biased towards the P (pastoral) class, although most other classes were represented to some extent (Table 3-3).

Table 3-2: Comparison of percentages of sites in the periphyton dataset in climate and source of flow classes of the REC with those in the whole network. Refer to Table 3-3 for explanations of REC classes. Comparisons are shown for all network sites of stream order >1 and >3 (in REC1). Over-representation in the periphyton dataset is shown by percentages (bold black) and under-representation is shown by negative percentages (red). For key to classes, refer to Snelder and Biggs (2002).

REC class (level2)	Periphyton dataset		Compared with REC, order>1		Compared with REC, order>3	
	N	%	% in network	% difference in representation	% in network	% difference in representation
CD/H	9	4.6	9.0	-49	8.5	-46
CD/L	23	11.7	10.5	**12**	7.6	**55**
CW/H	54	27.6	17.4	**58**	19.1	**44**
CW/L	39	19.9	8.6	**132**	8.6	**131**
CW/Lk	1	0.5	1.4	-64	4.6	-89
CW/M	6	3.1	9.2	-67	9.3	-67
CX/GM	2	1.0	4.2	-76	6.5	-84
CX/H	8	4.1	9.8	-58	10.1	-60
CX/L	1	0.5	2.6	-80	1.4	-63
CX/Lk	1	0.5	1.4	-64	3.9	-87
CX/M	3	1.5	8.4	-82	6.1	-75
WW/L	43	21.9	16.3	**34**	12.9	**70**
WW/Lk	1	0.5	0.2	**156**	0.4	**24**
WX/H	1	0.5	0.2	**107**	0.3	**78**
WX/L	4	2.0	0.7	**180**	0.7	**184**

Table 3-3: Percentages of sites in the dataset in REC climate, topography, geology and landcover classess compared with entire network. all_REC refers to all reaches in the network, including stream order 1.

Level	REC class	Explanation	Percentage in: Dataset	all_REC	REC_order>1
Climate	CD	Cool dry	16.3	21.1	19.7
	CW	Cool wet	51.0	32.5	34.6
	CX	Cool extremely wet	7.7	23	24.4
	WD	Warm dry		5.4	4.5
	WW	Warm wet	22.4	17	15.9
	WX	Warm extremely wet	2.6	0.9	0.9
Topography	GM	Glacial mountain	1.0	2.3	3.7
	H	Hill	36.7	34.1	34.7
	L	Low elevation	56.1	44.6	40.9
	Lk	Lake	1.5	2.3	3.2
	M	Mountain	4.6	16.7	17.6
Geology	Al	Alluvium	11.7	11.2	9.5
	HS	Hard sedimentary	36.7	39.2	41.5
	M	Mixed	5.1	5	4
	Pl	Plutonic	0.5	6.5	6.4
	SS	Soft Sedimentary	16.8	20.8	21.1
	VA	Volcanic acidic	29.1	15.9	16.1
	VB	Volcanic basic		1.5	1.3
Land cover	B	Bare	1.0	5.7	6.9
	EF	Exotic forest	2.0	5	4.4
	IF	Indigenous forest	23.0	24.3	25
	M	Miscellaneous		0.6	0.1
	P	Pastoral	63.8	42	42
	S	Scrub	2.0	5.4	4.2
	T	Tussock	6.6	16.1	16.8
	U	Urban	1.5	0.7	0.6
	W	Water		0.1	0.1

3.3 Data screening and preparation

The raw regional council datasets with data by date were merged into a single file for the analysis. Two datasets were prepared.

Dataset A included all individual chlorophyll *a* observations at each site, along with the available water quality variables from samples collected or measurements made contemporaneously. In total, 9438 chlorophyll *a* observations were included. For 73% of these data points, environmental observations were collected on the same day and for a further 21% within a week. All observations in Dataset A were also linked to hydrological data, and the dataset was used to derive empirical estimates of the flow magnitude required to remove periphyton at each site (see Section 4).

Dataset B was derived from dataset A by calculating metrics from the time series of periphyton, environmental and flow data to obtain a single line of data representing each site. The periphyton data were collected by each council over different time periods and in some cases the time periods were non- overlapping. For example, the data from ECan spanned July 2011 to June 2014, while monthly data collection at some Northland sites did not commence until November 2014. On the other hand, time series at some sites in the Horizons region began in 2008 and are ongoing. We used all of the data, where the monthly time series were up to 4 years long. We used time series for sites in the Horizons dataset from August 2013, when many new sites were added to the programme. Ideally, we required at least 36 months because 3 years is the specified time over which a site can be graded against the NPS-FM periphyton attribute. However, to maximise the number of sites, data series covering a shorter time-span of at least 20 months were allowed. Five sites were omitted from the analysis because of insufficient data.

Environmental variables included in dataset B and available in all six datasets were: water temperature (spot temperatures taken at the time of periphyton or water sample collection), dissolved organic nitrogen (DIN, the sum of nitrate-nitrogen, nitrite-nitrogen and ammoniacal nitrogen), DRP, conductivity. For further details on variables refer to Sections 5 and 6.

3.3.1 Treatment of missing periphyton data for Dataset B

The wording in the periphyton attribute of the NPS-FM related to the period over which the grading is made is: "*Based on a monthly monitoring regime. The minimum record length for grading a site based on periphyton (chl-a) is 3 years.*" This seems reasonably unambiguous and implies that the minimum data used for an assessment against the periphyton attribute must be <u>36 samples collected over three years (i.e., in every consecutive month)</u>. The interpretation of the wording is important because the time series at all sites had sampling occasions on which no periphyton data were collected, hereafter termed "missing data". Inclusion or exclusion of the missing data points can affect a grading, depending on how it is calculated.

In practice, a small proportion of missing periphyton data should make little difference to the analysis because the metric of interest is close to the maximum value (a high percentile). However, at sites with high proportions of missing monthly datapoints (e.g., more than 20% missing), using the raw data without compensating for the missing data could lead to upward bias in chlorophyll *a* when assessments against the NPS-FM are made by calculating the 92nd percentile of chlorophyll *a* over the monitoring period. The alternative method of grading a site, by counting numbers of exceedances over periods of 36 months, is not affected by missing data.

The data were screened for missing data and the percentage missing was calculated for each site from the number of months in the monitoring period for which there was no data (see Appendix A).

A reasonable assumption was that missing data coincided with periods of high flow when sample collection was not possible, and periphyton abundance was likely to be low. We tested the assumption using data from a random subset of sites. Chlorophyll *a* data were over-plotted on the time series of daily mean flows for that site and the approximate times when the missing data should have been collected were added to the plots. Plots from four sites covering a range of proportions of missing data (10% to 40%) are shown in Figure 3-2. The plots confirmed that most of the months with missing data coincided with periods of high flow. The analysis in Section 4 reconfirmed the assumption that high flows lead to low periphyton abundance at most sites.

To compensate for missing data, we completed the time series at each site by inserting into each month with a value calculated as the 5^{th} percentile of the observed values at that site. The 5^{th} percentile of chlorophyll *a* across all measured values was <1 mg/m^2, which represents algae comprising films, or no algae (Kilroy et al. 2013). This resulted in a downward adjustment by mean chlorophyll *a* by 17% on average (median 12%), and of the 92^{nd} percentile of chlorophyll *a* by 11% on average (median 4%).

The Aparima River record in Figure 3-2 (third plot down) illustrates why compensating for missing data can be important:

- In 36 months of monitoring, chlorophyll *a* exceeded 200 mg/m^2 on three occasions, 120 mg/m^2 on four occasions, and 50 mg/m^3 on nine occasions.
- The exceedances placed the site in **Band C** of the periphyton attribute. Note that four exceedances of 200 mg/m^2 were required to place the site in Band D.
- The 92^{nd} percentile of all the chlorophyll *a* observations (n = 27) was 207 mg/m^2, which would have placed the site in **Band D**.
- Compensating for missing values by setting missing data at the 5^{th} percentile (i.e., n = 36) returned a 92^{nd} percentile of 131 mg/m^2, placing the site in **Band C**, consistent with the number of exceedances.

3.4 Other periphyton data

Periphyton data as percentage cover on the stream bed have been collected from approximately 70 sites in the National Water Quality Monitoring Network (NRWQN) since 1990. The data comprise monthly visual estimates of the proportion of the bed covered by periphyton mats and periphyton filaments. The original purpose of the surveys was to provide data to investigate the extent of nuisance periphyton in rivers across New Zealand, and changes over time. Most of the NRWQN sites are relatively large rivers and the dataset is characterised by high proportions of missing data at some sites. The dataset was used by Snelder et al. (2014) to assess the frequency distributions of periphyton cover in New Zealand rivers, and again by Larned et al. (2015) to predict WCC. The models for WCC were unable to predict periphyton WCC at sites in the Horizons region and Snelder et al. (2015) suggested that the NRWQN data may be biased towards low values. Whatever the explanation for the poor predictions, we considered that combining the NRWQN and regional council datasets may not be appropriate at this time. In this report we therefore focussed on the combined regional council dataset only.

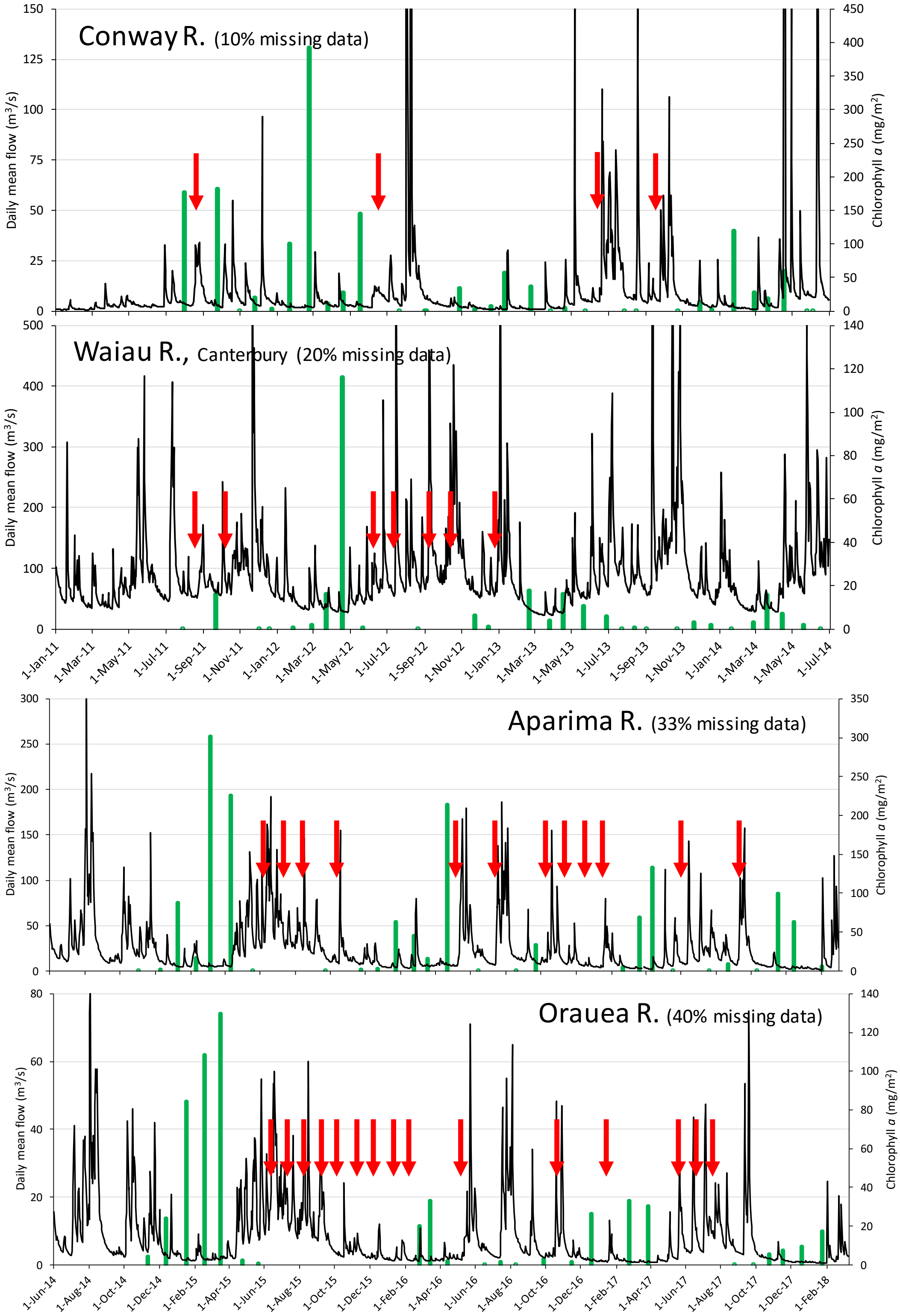

Figure 3-2: Chlorophyll *a* over-plotted on the record of daily mean flows at four sites with increasing proportions of missing data. Chlorophyll *a* data are shown as green bars. Red arrows indicate approximate times (in a month) when no data were collected. The main messages from the plots are: 1. At these sites, observed chlorophyll *a* was typically low during or immediately following high flow peaks (i.e., less than 1% of the maximum value); 2. missing data almost always coincided with a high flow events.

4 Relationships between periphyton and river flows

The aim of this part of the analysis was to identify, where possible, the flow magnitude (in multiples of the median flow) at each site that typically results in low levels of chlorophyll *a* (individual measurements). Here a "low level" refers to chlorophyll *a* equivalent to cover by thin algal films only (e.g., ~9 mg/m^2 on average, Kilroy et al. 2013), although the value is expected to vary across sites. The flow magnitude is subsequently referred to as the "effective flow" (hereafter EF). Once the EF is identified it is possible to generate flow variables related to that flow magnitude for use in between-site analyses (Section 5). For example, useful variables for explaining differences in periphyton accrual and removal among sites are the mean annual frequency of flow events greater than the EF, and the mean time available for periphyton accrual between EFs.

A flow magnitude of 3 x median flow has been commonly adopted to represent the flow magnitude that typically removes periphyton. The widespread use of FRE3 for this purpose was based on the finding by Clausen and Biggs (1997) that FRE3 (the mean annual frequency of events exceeding 3 x median flow, Booker 2013) was the hydrological variable most highly correlated with a range of biological indices and measures at a range of river sites. The original analysis by Clausen and Biggs (1997) did not explicitly explore periphyton accrual and removal, but FRE3 and its derivatives do appear to be appropriate for defining accrual periods in some cases. For example, Biggs (2000a) used 3 x median flow to calculate accrual period in rivers across New Zealand, and developed strong relationships between maximum chlorophyll *a* and dissolved N and P. However, recent analysis has confirmed the reasonable assumption that the flow magnitude required to removed periphyton to low levels differs between rivers (Hoyle et al. 2017). The objective of the present analysis was to identify such a flow threshold for as many rivers as possible, using empirical data.

Previous analyses have shown that thresholds cannot be identified for some sites (at least using the method below) (Kilroy et al. 2018). In other words, no single flow threshold is identifiable as the most effective at removing periphyton. In classifications of sites based on the effective flow, these sites can be combined into a single category.

Assuming (a) success in identifying EFs at sufficient sites, and (b) demonstration that flow variables based on EF improve predictability of periphyton in regression models, a further objective was to develop a model for predicting EF across the entire river network. As noted in Section 3, our approach was to fit a random forest model using EF as the dependent variable and a suite of relevant modelled predictor variables available from the REC as predictors.

4.1 Identification of an effective flow at each site

4.1.1 Methods

We identified effective flow thresholds (as chlorophyll *a*) in the following steps:

1. Calculate the median flow at each site using a 10-year flow record (from 2008 to the present), or as long a record as was available.

2. Extract from the flow record at each site time series of daily mean flows and daily maximum flows.

3. Using the daily time series extract for each periphyton observation (from dataset A in Section 3.3) the number of days since flows that equalled or exceeded a range of multiples of median flow, N_m, based on the median flow calculated in step 1.

4. The range of N_m used in this analysis was 1.5, 2, 3, 4 …. up to 20 x median flow.

5. Using dataset A (see Section 3.3) (with variables added for the days since the event of each magnitude, both as daily means and daily maxima), fit a series of linear regressions at each site between chlorophyll *a* and time since each defined high flow. Use log_{10}-transformed data.

6. The N_m associated with the linear regression that explained the highest proportion of variance in periphyton chlorophyll *a* was taken as the potential EF.

7. Reconfirm or adjust the automated selection of flow magnitude by examining (a) all the relationships (as scatter plots) and (b) plots of R^2 against flow magnitude.

8. Sites at which the strongest relationship explained less than 20% of the variance in chlorophyll *a* were judged as having no identifiable EF. At these sites, R^2 generally varied little across the range of multiples of median flow.

The number of days since a high flow event is potentially the accrual time available for periphyton development, assuming that smaller flow perturbations during that time have only a minor effect on biomass. Relationships in which accrual time explains a high proportion of the variability in chlorophyll *a* indicate that the flow threshold defining the accrual time approximates the threshold that removes periphyton to low levels. This method isolates the EF because if N_m is too low, high chlorophyll *a* could occur after short accrual times because some high flows would fail to remove biomass, leading to low explanatory power; if the selected flow size is too high, then low chlorophyll *a* could occur after long accrual periods after being removed by smaller flows, again leading to low explanatory power. Only at flow sizes close to the threshold for removal do we expect a strong correlation between chlorophyll *a* and days since the high flow, with the slope of the relationship approximating the rate of accrual at that site.

A caveat to the method is that care needs to be taken in interpreting relationships when accrual times are very long, because spontaneous sloughing after long periods of growth can lead to unexpectedly low biomass (Biggs and Close 1989). It is also acknowledged that the condition of the periphyton can influence the effect of a particular high-flow event (Katz et al. 2018). In that case, using quantile regression might be more appropriate. Quantile regression considers the relationship between specified quantiles (e.g., 80^{th}, 95^{th}) of the dependent variable (chlorophyll *a*) and the explanatory variable (time since a high flow), rather than the mean.

In this analysis our approach was to make the final selection of an EF after examining for each site the plots log_{10} chlorophyll *a* vs. log_{10} time since high flows and the relationship between R^2 and multiples of median flow.

4.1.2 Results

We identified the magnitude of the EF at 109 of 136 sites with a flow record. Using daily mean flows produced slightly better explanatory power overall than using daily maximum flows (mean R^2 of 0.465 vs. 0.443, respectively) with a significant difference in R^2 between the groups (paired T-test, $P < 0.01$). All results referred to hereafter are those generated using daily mean flows.

Across the 109 sites, time since a high flow explained up to 80% of the variance in chlorophyll *a* at a site, and the magnitude of the EF ranged from 1.5 to 16 x median flow. In most cases, examining the plots confirmed that the highest R^2 defined the EF. Exceptions included the following situations:

- close to maximum R^2 occurred across a range of multiples of median flow, in which case the lowest flow was selected even if a higher flow had a slightly higher R^2 (e.g., Dipton Stream);
- high R^2 at very high multiples of median flow was caused by exclusion of data at that level (e.g., Ruamahanga River at Waihenga).

Examples of the plots used to identify the thresholds are shown in Figure 4-1. The EF identified for all sites with a flow record is listed in Appendix A.

The pattern of EFs varied across regions:

- Of the 23 **Northland** sites with a flow record, no EF was identifiable at 11 sites (mean R^2=0.09) and at the remaining 12 sites, the mean R^2 was low (mean R^2 = 0.31, range 0.14 – 0.51).
- In the **Horizons dataset**, we were unable to identify an EF at 11 of the 48 sites with flow records (23% of sites). Mean R^2 at the sites with an EF was 0.45, range 0.23 – 0.64.
- An EF was identified at 12 of the 13 sites with flow records retained in the **Greater Wellington dataset** (mean R^2 = 0.49, range 0.15 – 0.69).
- An EF was identified for all 24 sites in **ECan dataset** and the mean percentage of variance in chlorophyll *a* explained by the EF (i.e., R^2) was highest of all the regions (mean R^2 = 0.55, range 0.25 – 0.80).
- The **ES dataset** similarly had strong chlorophyll *a* vs. accrual period relationships at most sites with an EF identified at 25 of the 28 sites with a flow record, and a mean R^2 of 0.51, range 0.28 – 0.71.

4.2 Model for predicting effective flow across the REC network

4.2.1 Dependent variable

Using the results from Section 4.1, five EF classes were defined based on the magnitude of the EF and applied to the 136 sites that had a flow record (Table 4-1). Modelled data linked to the REC network were then used to define a model for predicting an effective flow class across the whole network.

Table 4-1: Groupings of effective flows used in building a model for predicting EFF across the REC network. Numbers of sites in each category, by region, are shown.

			Numbers of sites in each Regional Council dataset				
Category	Abbreviation	N sites	NRC	HRC	GWRC	ECan	ES
No identifiable effective flow	none	27	12	11	1	0	3
Low threshold, up to 3 x median flow	low_ut3	35	4	9	3	10	9
Medium threshold,4 x or 5 x median flow	med_4_5	22	1	12	5	1	3
High threshold, 6 x to 9 x median flow	high_6_9	30	4	4	4	10	8
Very high threshold, ≥10 x median flow	vhigh_gt10	22	2	12	0	3	5

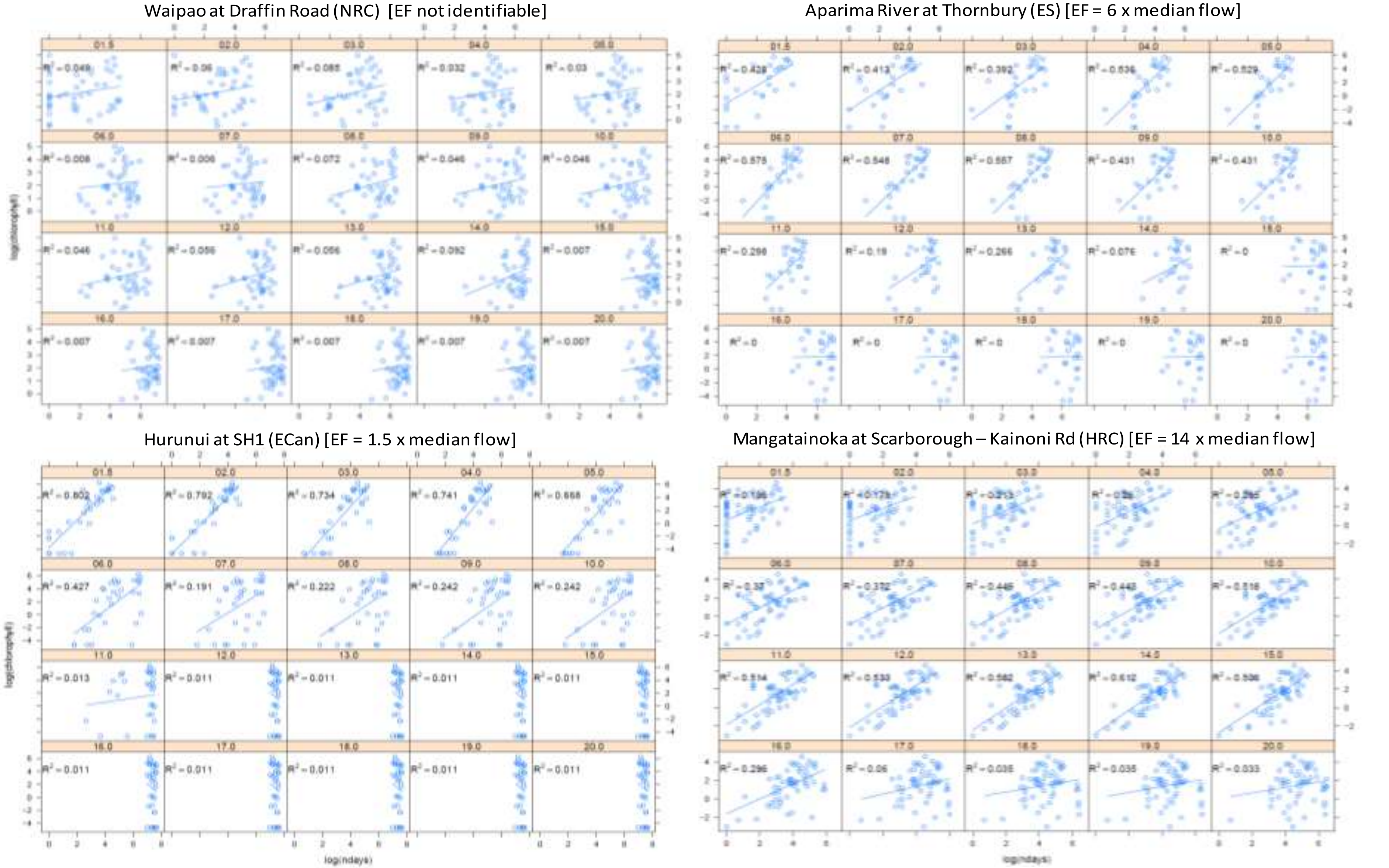

Figure 4-1: Examples of scatter plots of log$_{10}$chlorophyll a vs. log$_{10}$ time since high flows from which effective flow was identified. log$_{10}$(ndays) on the x-axis refers to the number of days at each data point since a high flow of n x median flow, where n is the number in the orange bar at the top of each plot. All plots based on daily mean flows.

4.2.2 Predictor variables

Predictor variables were limited to those related to catchment and river geomorphology and hydrology. Geomorphology is important because previous research has indicated that the flow magnitude that removes periphyton to low levels is similar to the flow magnitude at which sand on the bed is mobilised (Hoyle et al. 2017). Variables included, with justification, are listed in Table 4-2.

Table 4-2: Variables included as predictors in a model for predicting effective flow across the NZ river network. In the model, the effective flow was a categorical variable capturing five levels of EF shown in Table 4-1.

Group	Variable abbreviation	Description and units	Units	Rationale / explanation
Rainfall	seg_rain	Mean annual rainfall in the stream segment	mm	Rainfall variables. Rainfall and its variability strongly influences flow and its variability, which in turn influence the frequency and intensity of bed moving events in a waterway. Bed moving events are generally most effective in removing periphyton (Hoyle et al. 2017).
	us_rain	Averaged mean annual rainfall in the entire upstream catchment	mm	
	us_rnvar	Mean catchment coefficient of variation of annual rainfall	mm/year	
	us_rd10	Mean number of days monthly with upstream catchment rainfall of > 10 mm	days/month	
	us_rd20	As above, 20 mm		
	us_rd25	As above 25 mm		
	us_rd100	As above 100 mm		
Flow	Q50	Estimated median flow at the reach	m^3/s	Flow variables: Flow magnitude and low flow and flood frequency are primary drivers of periphyton biomass with low flow promoting accrual and high flows driving removal
	MALF	Estimated mean annual 7-day low flow	m^3/s	
	MeanFlow	Estimated mean flow	m^3/s	
	FRE3Count	Mean annual frequency of events > 3 x median flow	Count/y	
Bed morphology	WidthQ5	Reach width at 5th percentile of flow	m	Estimated reach width at different flows. The uniformity or variation across these measures indicates channel shape, which can influence hydraulic characteristics (water depth and velocity) and periphyton removal.
	WidthMALF	Reach width at MALF	m	
	WidthMeanFlow	Reach width at mean flow	m	
	WidthQ50	Reach width at median flow	m	
	sinuosity	Waterway length divided by straight line distance between ends	ratio	Measures of reach slope, which influences water velocity and turbulence
	loc_slope	Reach slope	degrees	
Bed substrate	Bedrock	Percentage of the reach bed covered by bedrock	%	Bed substrate composition strongly influences the stability of the bed. Large stable substrate moves infrequently and favours periphyton accrual. The frequency of movement of fine material under the influence of high flows affect. Periphyton removal generally occurs
	Boulder	Ditto, by boulders (> 256 mm across)	%	
	Cobble	Ditto, by cobble (64 - 256 mm across)	%	
	CoarseGravel	Ditto, by coarse gravel (16 - 64 mm across)	%	
	FineGravel	Ditto, by fine gravel (2 - 16 mm across)	%	
	Sand	Ditto, by Sand (<2 mm, gritty)	%	
	MudVeg	Ditto, by fine sediment, including macrophyte beds	%	
Geology	usHard	Mean catchment induration (hardness) of regolith	Ordinal	Hardness influences substrate type and stability

4.2.3 Method

The relationship between EF categories and the environmental variables was explored using RF models. For further details on RF models refer to Section 6.

4.2.4 Result

The RF analysis returned a model with accuracy of 0.375 (or 37.5%, defined as the proportion of sites at which the model correctly predicted the observed group). Thus, 62.5% of predictions were incorrect. The model was significant in terms of the probability that accuracy > no information rate (P = 0.0017).

The "no information rate" is the accuracy that would be expected when there is no information about what group each site belongs to other than the number of sites in in each group. The highest no information rate depends on the size of the largest group. In the present case, the largest group was low_ut3, with 35 out of 136 sites (26%) in that class (Table 4-1). If we assigned all the sites to low_ut3, then we would be correct 26% of the time. Thus, an accuracy of 37.5% is better than no information, but not substantially better.

Table 4-3: Assignment of 136 sites to predicted EF class compared to observed EF class. Predictions were made in a cross-validation procedure in the random forest analysis. The shaded cells show numbers of sites correctly assigned.

		Observed				
		none	low_ut3	med_4_5	high_6_9	vhigh_gt10
Prediction	none	13	4	2	6	2
	low_ut3	4	13	7	9	5
	med_4_5	0	6	6	3	1
	high_6_9	6	7	4	10	5
	vhigh_gt10	4	5	3	2	9
	Total observed	27	35	22	30	22

4.3 Discussion

4.3.1 Method for empirical identification of effective flows

The magnitude of the flow that removes periphyton can be estimated empirically using a range of methods in addition to the one used above. For example, Hoyle et al. (2017) identified EF at 18 sites in the Horizons dataset by plotting chlorophyll *a* against the maximum daily flow in the 7 days prior to each chlorophyll *a* observation. The EF was taken as the flow threshold above which chlorophyll *a* was below a specified level (e.g., 10 mg/m^2) in at least 95% of cases. An alternative objective method would be to use a randomisation procedure to compare probabilities of chlorophyll *a* exceeding a designated low level within a given accrual period following a range of flow thresholds. We expect that all empirical methods would converge to a similar flow magnitude because all have the same objective of determining a flow magnitude that results in low chlorophyll *a* following the event and, usually, higher chlorophyll *a* as the flood-free period is extended.

Hoyle et al. (2017) found that using maximum daily flows produced a clearer result than using mean daily flows. Mechanistically this makes sense because observations from laboratory experiments indicate that most periphyton removal occurs as soon as the critical velocity is attained (Biggs and Thomsen 1995, Francoeur and Biggs 2006). The experimental findings thus implied that short-lived peaks that make little difference to daily mean flow may remove periphyton. On the other hand, in large floods, most periphyton could be removed long before peak flow is reached. In the present analysis we found that using daily mean flows and daily maximum flows produced similar results. We chose to use daily mean flows because the regression results were slightly stronger (on average).

We expected substantial unexplained variation in the relationship between accrual period and chlorophyll *a* because chlorophyll *a* is influenced by many variables other than flow. We did not take seasonality into account (i.e., expected higher growth rates in warm summer temperatures). We therefore considered that the overall mean R^2 of 0.46 is very good, with almost half the variance in chlorophyll *a* explained by a site-specific accrual period. Even using a fine-scale two-dimensional hydraulic modelling approach in a recent study, it was still only possible to explain 49% of the variance in chlorophyll *a* over a series of high flow events (Katz et al. 2018). An important source of variability is spontaneous sloughing of periphyton, which occurs during long periods of stable flows after periphyton develops to high levels and undergoes natural degradation. Very long accrual periods (e.g., > 90 days, Biggs and Stockseth 1996) may lead to unexpectedly low chlorophyll *a* levels following a change in periphyton structure following natural sloughing, which prevents recolonization by algae (Biggs and Close 1989).

High variability in the relationships, and the varying influences of other factors mean that, in selecting the appropriate effective flow from the regression results, it is important to manually review the plots of the relationships between chlorophyll *a* and accrual period at different flow thresholds (e.g., Figure 4-1).

4.3.2 Model for predicting EF

We considered that the model developed for predicting EF across the REC network was not sufficiently strong to be reliable. The model predictions were only slightly more accurate than random assignment. Therefore, the model was not used in subsequent analyses in this study.

Previous attempts to predict EF from site characteristics in regional datasets have had limited success. In an earlier analysis of the data from the Horizons region, sites classified into effective flow groups were compared with a range of physical variables (Kilroy et al. 2018). No single variable distinguished the groups. Using a multivariate ordination, it was possible to distinguish sites with a low to medium removal thresholds from most sites with higher thresholds and few sites at which no threshold could be identified. There was overlap between groups and the drivers of the differences were unclear except that all sites with no identifiable threshold had low flood frequencies.

Hoyle et al. (2017) provided a physical explanation for differences in removal thresholds among sites. Periphyton removal thresholds tended to approximate the threshold that mobilised the finer fractions of bed sediment at a site, and removal depended on the amount of fine sediment available and the frequency at which it was mobilised. The finding was consistent with abrasion / scouring by fine sediment as an important removal mechanism (Francouer and Biggs 2006). The empirically determined effective flow likely represents these physical processes. Since no measured site variables allow clear identification of the size of an effective flow, the simplest method may need to include one-off field measurements to determine the flow magnitude that moves fine sediment. Such a method is under development.

Following on from Hoyle et al. (2017), research is currently underway to make predictions of periphyton abundance at each segment in the New Zealand river network using a mechanistic approach. This involves estimating stream power at each segment based of reach slope, substrate and flood frequency. We consider that this approach may result in more successful predictions of EF at each reach.

In the meantime, geomorphological control of removal processes can be covered in national predictions of periphyton abundance by including a subset of the suite of variables in Table 4-2 as potential predictor variables (see Section 6).

5 Development of a national empirical regression model for predicting nuisance periphyton

5.1 Introduction

The objective of this part of the analysis was to use simple linear regression techniques to explore empirical relationships between periphyton and environmental variables, analogous to those developed by Biggs (2000a). The Biggs (2000a) study applied a linear regression approach and attributed most variability in peak chlorophyll *a* at a site to a combination of nutrient availability and accrual period. Nutrient availability was represented by mean of DIN and DRP concentrations across at least a year of monthly observations. Use of a long-term mean provided an estimate of nutrient status that averaged out: (1) strong seasonal and flow-related variability in nutrient concentrations and (2) variability in concentrations due to uptake by periphyton. The assumption was made that the long-term mean concentrations represented a characteristic nutrient availability at a site, which would be reflected in peak chlorophyll *a*. Accrual period was calculated from the frequency of flow events exceeding three times the median flow.

The Biggs (2000a) equations have been widely applied in New Zealand for predicting periphyton or for assessing nutrient concentrations that will ensure periphyton biomass remains less than a threshold (e.g., Norton and Kelly 2010). It is understood that the models have a tendency to over-predict by a considerable margin in many cases (e.g., Kilroy et al. 2017). One potential reason for overpredictions is that the range of Biggs (2000a) dataset covered a narrow range of mean DIN concentration (6 to 232 mg/m^3). The upper limit of the range is commonly exceeded in many rivers (e.g., see Table 5-3 in Kilroy et al. 2018, and see also Appendix B of this report), and in those cases the relationships cannot be validly applied for predicting at new sites.

An analysis of the representativeness of the dataset used to derive the equations concluded that:

> *"… the 2000 dataset of 30 river sites, used to develop nutrient – flow – periphyton relationships (Biggs 2000a) was a good representation of hill-fed, cobble-bed rivers in New Zealand. Other river types, notably low-order lowland streams in warm areas, were not represented. Unrepresented river types are likely to account for about 30% of all river segments. The 2000 dataset did not account for likely regional differences in periphyton – environment relationships …."* (Appendix E in Matheson et al. 2012)

Biggs (2000a) acknowledged that developing regional relationships could improve the explanatory power and predictive ability of the relationships:

> *"… Moreover, the data sets currently held by many government agencies may be useful in testing my models or constructing similar models that are more specific to an ecoregion. The result could be increased explanatory power and improved ability to manage stream eutrophication at the local scale."* (Biggs 2000a).

Over the past few years, regression techniques have been used to explore periphyton – environment relationships in datasets from the Canterbury and Horizons regions. There has been some success in identifying combinations of variables (including variables other than flow and nutrients) that explain substantial proportions of variance in regional datasets or sub-sets of those datasets (Kilroy et al. 2017, Kilroy et al. 2018). One of the differences from the Biggs (2000a) approach was to include a more site-specific approach to determining accrual period. The potential for a high flow to remove periphyton to low levels depends on the geomorphological conditions of sites (Hoyle et al. 2017) so that different sites can be affected differently (in terms of periphyton removal) by floods of the same magnitude (standardised as multiples of the median flow).

In the present analysis we conducted regression analyses using a combined dataset from several regions. We used the results of the hydrological analysis to identify EF at each site, described in Section 4, to explore the effects of this site-specific approach to defining accrual period on predictability of periphyton.

5.2 Data selection and preparation

The data used for this analysis was the complete Dataset B, as described in Section 3.3.

5.2.1 Dependent variables

The main dependent variable was the 92nd percentile of chlorophyll *a* normally calculated over a period of at least three years, or as long a period as possible, up to ~4 years, provided the period was no less than 20 months. The time series at each site was adjusted to compensate for missing values, as described in Section 3.3.1.

In addition to modelling the 92nd percentile, we modelled mean chlorophyll *a*. We expected a slightly different result for the mean because sites at which periphyton persists over time and resists removal by high flows may have higher than expected mean chlorophyll *a* and cover compared to the 92nd percentile.

All datasets included estimates of cover by periphyton. We used the data to calculate for each site a weighted composite cover (WCC) where:

$$\text{WCC} = (\%\text{ cover by thick mats})/2 + \%\text{ cover by filaments} \qquad \text{(Equation 1)}$$

WCC was proposed by Matheson et al. (2012) as a metric for representing periphyton cover. The metric was based on limits in Biggs (2000b), which included 30% cover by filaments and 60% cover by mats as thresholds for maintenance of trout habitat and angling values. Thus, cover by mats was deemed to have half the “nuisance” value of cover by filaments. Subsequent studies have shown that periphyton mats, on average, contain about half the concentration of chlorophyll *a* found in filaments (Kilroy et al. 2013). Therefore, WCC tends to be reasonably strongly correlated with chlorophyll *a* and can be a useful surrogate for measured biomass (e.g., Larned et al. 2015).

Based on analysis of matched invertebrate and periphyton cover data, Matheson et al. (2012) recommended provisional general guidelines of <20%, 20-39%, 40-55% and >55% of WCC to indicate, respectively, “excellent”, “good”, “fair” and “poor” ecological condition, respectively, at sites where other stressors are minimal.

5.2.2 Predictor variables

Candidate predictor variables were limited to those made available with the council datasets. Metrics calculated from the time-series data are summarised in Table 5-1 along with justification for inclusion of each variable. The main water quality variables DIN, DRP and conductivity were available for all six datasets, as was water temperature (monthly spot measurements). Summary statistics for each of the main environmental variables, by council, are shown in Appendix B. Correlations between variables were checked in a Spearman correlation matrix. All those listed in Table 5-1 were not strongly correlated (generally Spearman r < 0.5).

Table 5-1: Summary of dependent and predictor variables used for the regression models, with justification for inclusion of each. Under TF (transformation), sqrt = square-root.

Group	Variable name	Units	Metric	Abbreviation	TF	Explanation / notes
Dependent variables						
Periphyton	Chlorophyll *a*	mg/m^2	92nd percentile	Chla_92	log$_{10}$	Represents peak potentially "nuisance" periphyton chlorophyll *a* (see Section 1.3)
		mg/m^2	Mean	Chla_mean	log$_{10}$	Chla_mean is expected to be closely correlated with Chla_92 except that sites with persistent periphyton may have higher than expected mean values.
	Weighted composite cover	%	92nd percentile	WCC_92	sqrt	Cover is a direct estimate of periphyton abundance. WCC combines cover by mats and filaments with mats weighted by 0.5 as mats contain less chlorophyll *a* than filaments and are perceived as less of a "nuisance".
		%	Mean	WCC_mean	sqrt	
Explanatory (predictor) variables						
Temperature	Water temperature	°C	Maximum	Tmax	none	Water temperature determines growth rates in periphyton, which may be reflected in biomass given sufficiently long accrual periods. The temperature – growth rate relationship is expected to be generally positive within the range on temperature in NZ rivers. The three variables are not strongly correlated. Trange represents seasonality.
			Median	Tmed	none	
			Range	Trange	none	
Nutrients	Dissolved inorganic nitrogen	mg/m^3	Geometric mean	DIN	log$_{10}$	Major nutrients essential for periphyton growth. The long-term geometric mean down-weights the influence of occasional high spikes.
	Dissolved reactive phosphorus	mg/m^3	Geometric mean	DRP	log$_{10}$	
Water chemistry	Conductivity	µS/cm	Mean	Conductivity	sqrt	Measure of concentration of ions in water. May reflect nutrient concentrations, but also may independently influence periphyton biomass through the influence of minor nutrients (Ca, Mg).
Substrate	Percent coarse	%	Mean	Pccoarse	none	Bed substrate composition generally determines stability of the bed. Periphyton tends to accrue for longest on large stable substrates, and has short accrual times on small, mobile substrate.
	Percent fine	%		Pcfine	none	
	Percent sand	%		Sand	sqrt	
Flow	Mean flow	m^3/s		Meanflow	log$_{10}$	Flow variability controls removal of periphyton through sloughing and scouring. Periphyton in large and small rivers may respond differently to similar magnitude high flows.
	CV of flow	%		CV_flow	sqrt	
Accrual	Accrual period based on different flows	days	Mean	Da3 Da10 DaEF	log$_{10}$	Mean interval in days between successive high flows exceeding a specified threshold. Accrual represents the average time available for biomass to accumulate.

At each site where EF was identified (Section 4) we calculated a mean accrual period based on EF as:

$$DaEF = (365 – \text{mean annual no. days flow} > EF) / FRE\_EF \quad \text{(Equation 2)}$$

where FRE_EF is the mean annual frequency of events exceeding EF, with a 5-day window (i.e., events occurring 5 days or less apart were counted as a single event).

We considered that the slightly revised method of calculating accrual period (compared to Biggs, 2000a, who used 365/FRE3) was a realistic representation of the actual time available for periphyton accrual when calculated as DaEF. EF varies from 1.5 to 15 x median flow, and the proportion of time this flow threshold is exceeded could vary considerably across sites. Therefore, excluding the time under high flows from the calculation of accrual period can make a substantial difference, compared to including that time.

Accrual period at each site was also calculated based on 3 x and 10 x median flow (Da3, Da10) using the method above.

The DaEF derived for chlorophyll *a* was used in the models for WCC, because the two measures of periphyton are significantly correlated (e.g., Larned et al. 2015).

5.3 Methods

All data were first checked for normality and homoscedasticity and, if necessary, were log-transformed prior to analysis (Table 5-1). The data were screened by plotting all potential predictor variables against the dependent variables to look for obvious departures from linear relationships such that a polynomial term might need to be included. None were detected.

We used a stepwise multiple regression approach. Models were run using the GLM package in R.

The fit of each model in each dataset was assessed using **leave-one-out cross-validation**. In this procedure, the independent (predictor) variables are used to generate a series of models omitting one data point each time. Each model is used to predict the value of the dependent variable for the omitted data point. Observed values are plotted against predicted values and several statistics can be computed to allow assessment of the model fit (i.e., accuracy and precision). Useful statistics are:

- the coefficient of determination, R^2, which is a measure of the proportion of variance in the observed values explained by the predicted values;
- the root mean square deviation (RMSD), which is an absolute measure of the difference between predicted and observed values, in the same units as the dependent variable (i.e., $\log_{10}$chlorophyll *a*). The lower the value the better;
- Nash Sutcliffe Efficiency (NSE), which is commonly used to assess predictive skill in hydrological models (Nash and Sutcliffe 1970).[6] NSE ranges from $-\infty$ to 1, where the closer the number is to 1, the better model fit. NSE = 1 indicates perfect model fit, 0 indicates that model predictions are as accurate as the mean of the observed data and negative values indicate that the mean is a better predictor than the model. NSE is generally proportional to R^2 but is specifically used to quantify how well a model

[6] NSE is calculated in the same way as R^2 except that NSE uses the sum of squares of observed – independently predicted values (such as from leave-one-out cross validation), whereas R^2 uses the sum of squares of the observed value – the value estimated from the regression equation). NSE and R2 are calculated as 1 minus [(sum of squares observed – predicted/ estimated) / (sum of squares observed – mean of observed)].

simulation predicts the outcome variable. As well as testing the correlation between observed and predicted values, NSE accounts for correspondence of values (i.e., the slope and intercept in the relationship). Unlike R^2, NSE can take negative values;

- bias, a measure of the tendency to systematically over or under-predict.

In view of issues raised in the literature about the utility and validity of stepwise linear regression (see Section 7 for further discussion), we also ran, for selected models, an information-theoretic model selection (IT) procedure (Whittingham et al. 2006). The IT procedure identifies all the best subsets of models given a selection of predictor variables and ranks them on the basis of a range of model evaluators including R^2, the Akaike Information Criterion (AIC), and Mallows C_p (refer to Geyer 2003 for information on each). The ranking procedure was performed using the "best subsets" routine in SYSTAT v. 13. The models identified in the stepwise procedure were compared with those identified by best subsets to ensure that good alternative models were not ignored.

We ran thirteen sets of models (Models A to M in Table 5-2). The models successively included or omitted variables so that the effect of those variables on model performance could be evaluated. In all cases, the models were first run using all of the available data (i.e., all sites at which a complete set of predictor variables was available). For example, data from BOP, and some GWRC and HRC sites were excluded from models A and C because flow and / or substrate data were not available. The models were then re-run on a core set of sites at which all variables were available. This second set of models enabled direct comparison of the effect of including or omitting predictors. Models were also run on the individual datasets from each region when sufficient sites were available. The results of the regional models were compared with those for the overall model.

5.4 Results

In the following, detailed results are first presented for each dependent variable. We ran all 13 model sets (models A to M in Table 5-2) for Chla_92 and WCC_92, which were the main variables representing nuisance periphyton. A subset of the model sets was run for Chla_mean and WCC_mean, for comparison purposes. For each variable, results for the combined dataset are presented first, followed by a brief summary of results for each region (north to south). A comparison of the performance of all the models is made following the detailed results. We note that the strongest models (as reported below) all had low bias (less than 1% and usually 0).

5.4.1 Chlorophyll *a* – 92nd percentile

The strongest regression models for Chla_92) were those from runs A and C (Table 5-3). Runs A and C included DaEF. Substituting Da3 and Da10 for DaEF (models B and D) slightly reduced cross-validated R^2 (from 0.55 to 0.49 in models A and B respectively and from 0.54 to 0.48 in models C and D). The difference in NSE was larger (from 0.30 to 0.16 in models A and B respectively and from 0.25 to 0.06 in models C and D). These comparisons applied to regressions on the same set of sites. When all available sites were used in models B and D (i.e., including the sites that had a flow record, but where no EF was identified), their performances were weaker. Running the "best subsets" procedure on the complete set of predictors confirmed that Model A performed best in terms of both adjusted R^2, Mallow's C_p and AIC.

The strongest models included both DIN, DRP and Conductivity as predictors and the best subsets procedure confirmed that Conductivity and DIN had the strongest correlations with Chla_92 as single predictors, and the combination of Conductivity and DRP and the strongest correlation in combination (R^2 = 0.34). However, note that in all three models in Table 5-3, DRP had a negative

Table 5-2: Thirteen sets of dependent and predictor variables and datasets used in regression models. Groups of variables are those defined in Table 5-1, after omitting one variable in correlated pairs. Where accrual variables were included, they were either DaEF (Accrual (EF)), or Da3 and Da10 (Accrual (3,10)).

Dependent variables	Datasets	Model code	Available predictor variables [omitted predictors]	Regions	Max N
Chla_92 WCC_92 Chla_mean WCC_mean	All available Flow sites only Effective flow only By region	A	Temperature, Nutrients, Conductivity, Substrate, Flow, Accrual (EF)	NRC, HRC, ECan, ES	94
		B	Temperature, Nutrients, Conductivity, Substrate, Flow, Accrual (3,10)	NRC, HRC, ECan, ES	115
		C	Nutrients, Conductivity, Substrate, Flow, Accrual (EF) [no temperature]	NRC, HRC, ECan, ES	94
		D	Nutrients, Conductivity, Substrate, Flow, Accrual (3,10) [no temperature]	NRC, HRC, ECan, ES	115
		E	Temperature, Nutrients, Conductivity, Flow, Accrual (EF) [no substrate]	NRC, HRC, GWRC, ECan, ES	109
		F	Temperature, Nutrients, Conductivity, Flow, Accrual (3,10) [no substrate]	NRC, HRC, GWRC, ECan, ES	131
		G	Temperature, Nutrients, Substrate, Flow, Accrual (EF) [no conductivity]	NRC, HRC, ECan, ES	94
		H	Temperature, Nutrients, Substrate, Flow, Accrual (3,10) [no conductivity]	NRC, HRC, ECan, ES	115
		I	Temperature, Nutrients, Conductivity, Substrate, Flow [no accrual]	NRC, HRC, ECan, ES	115
		J	Temperature, Nutrients, Conductivity, Substrate [no flow, no accrual]	NRC, HRC, ECan, ES	147
		K	Temperature, Nutrients, Conductivity [no flow, no accrual, no substrate]	BOP, NRC, HRC, GWRC, ECan, ES	194
		L	Temperature, Nutrients, Conductivity, Substrate, Accrual (EF) [no flow]	NRC, HRC, ECan, ES	94
		M	Temperature, Nutrients, Conductivity, Substrate, Accrual (3,10) [no flow]	NRC, HRC, ECan, ES	115

coefficient (refer to Section 5.5.3 for further discussion). Omitting Conductivity as an available variable produced the weakest model in which a negative NSE (-0.27) indicated no predictive ability. Omitting flow and accrual variables produced a similarly low NSE (-0.26).

Model K included only the variables available at all sites in the regional council datasets (n = 194). The model included the following terms: DIN, Tmed, Trange. Models details were: Model adjusted R^2 = 0.32, cross validated R^2 = 0.29, NSE = -1.1 (i.e., a weak relationship leading to a model with no predictive ability).

Regional models for Chl_92 varied in strength from weak (NSE < 0) to very strong (NSE > 0.8) (Table 5-4). The two strongest models applied to very small datasets (n = 12, NRC sites at which an EF was identified; n = 9, HRC sites at which no EF was identified). A relatively high number of predictor variables included in these models (eight and five, respectively) may limit their applicability beyond the datasets.

Lack of data on both flow and substrate composition likely led to the weakest model (BOP) and this model is not referred to again. Models derived from three of the six larger regional datasets (NRC, HRC, GWRC) were stronger than the overall model (compare Table 5-3 and Table 5-4).

Variables included in the models varied across the five remaining regions. One or more of the temperature variables was included in all except the ECan model. DIN was included in the HRC and GWRC models only and DRP was included in the NRC, HRC and GWRC models using data from all sites with a flow record. Neither DIN nor DRP were included in the ECan or ES models, but conductivity was included in all except for ECan. All four regional datasets in which substrate variables were available included at least one in the best model.

DaEF featured in only two models (NRC and HRC). In both cases, including DaEF produced a better model than including Da3 and Da10 across the same set of sites. In both cases, the other available flow variables (MeanFlow and CVFlow) were also included.

Table 5-3: Variables and coefficients in the three best regression models run on all available sites with Chla_92 as the dependent variable. The best models included DaEF and also substrate variables. Therefore, sites from BOP and GWRC were not included.

	Model A		Model C		Model L	
Model statistics	**Variable**	**Coefficient**	**Variable**	**Coefficient**	**Variable**	**Coefficient**
	(Intercept)	-1.561	(Intercept)	-1.306	(Intercept)	-0.970
	Tmed	0.038				
					Tmax	0.042
	DIN	0.154	DIN	0.177	DIN	0.227
	DRP	-0.301	DRP	-0.265	DRP	-0.482
	Conductivity	0.098	Conductivity	0.105	Conductivity	0.108
	Sand	0.136	Sand	0.146	Sand	0.138
	Pcfine	-0.004	Pcfine	-0.004	Pcfine	-0.005
	Meanflow	0.202	Meanflow	0.220		
	CVflow	0.049	CVflow	0.053		
	DaEF	0.407	DaEF	0.399	DaEF	0.256
n (sites)	94		94		94	
Regression adj. R^2	0.59		0.57		0.54	
Cross-validated R^2	0.56		0.54		0.50	
NSE	0.30		0.25		0.13	
RMSD	0.32		0.33		0.34	

Table 5-4: Variables and coefficients in the best regression model(s) in each region with Chla_92 as the dependent variable. Only one model (K) was run for BOP. Results for a single model are shown for GWRC, ECan and ES. Results for two and three datasets respectively are shown for NRC and HRC. In these regions, the larger dataset included all sites with flow data and the smaller dataset included only sites at which an EF was identified. The HRC dataset with model K (n = 9) included sites at which no EF could be identified. NSE > 0.40 is highlighted in bold type.

Model variables and statistics		Dataset and model (from Table 5-2)								
		NRC	NRC	BOP	HRC	HRC	HRC	GWRC	ECan	ES
		B	C	K	A	B	K	F	B	B
Variables	(Intercept)	-4.776	-1.417	2.061	-3.356	-2.615	-2.578	-1.496	2.817	-4.830
	Tmed	0.334		0.053	-0.086	-0.118				0.107
	Tmax				0.236	0.162	0.076	-0.094		
	Trange	0.080			-0.201	-0.115	0.055			
	DIN		-0.139		0.297	0.518	0.129	0.475		
	DRP	0.782	-0.438	-0.813		0.818	0.909	-1.043		
	Conductivity	-0.026	0.078	-0.044	0.092	0.077	0.122	0.099		0.037
	Sand		0.349			0.126			-0.227	0.209
	Pcfine	-0.007	-0.008			-0.015				
	Pccoarse				0.018	0.014				
	Meanflow		0.345		0.310	0.209		0.212	0.282	
	CVflow		0.091		0.086	0.091				0.201
	Da3							3.091	1.398	1.429
	Da10								-1.350	
	DaEF		0.524		0.381					
Statistics	*n* (sites)	21	12	29	37	44	9	13	24	21
	Regression adj. R^2	0.74	0.96	0.42	0.82	0.68	1.00	0.71	0.60	0.51
	Cross-validated R^2	0.62	0.85	0.32	0.77	0.55	0.96	0.61	0.47	0.40
	NSE	**0.51**	**0.84**	-0.40	**0.73**	**0.42**	**0.92**	**0.50**	0.20	0.09
	RMSD	0.28	0.13	0.37	0.25	0.34	0.15	0.31	0.35	0.38

5.4.2 WCC – 92nd percentile

All models for WCC_92 across all sites (all regions) were weaker than those for Chla_92 and returned a negative NSE (Table 5-5). The best model for all sites was from model A, as for Chla_92, and included Da_EF as a predictor. The models therefore excluded data from BOP and GWRC, as well as data from sites in other regions where an EF was not identified.

In contrast, datasets from NRC, HRC and GWRC produced several good models, albeit from small datasets. As with the Chla_92 models, inclusion of many variables in the models suggests that the models may not be readily transferable.

Table 5-5: Variables and coefficients in the best regression model(s) in each region with WCC_92 as the dependent variable. Only one model (K) was run for BOP. Results for two datasets are shown for NRC and HRC. The larger dataset included all sites with flow data and the smaller dataset included only sites at which an EF was identified. NSE > 0.40 is highlighted in bold type.

		Dataset and model (from Table 5-2)								
Model variables and statistics		All	NRC	NRC	BOP	HRC	HRC	GWRC	ECan	ES
		A	C	B	K	A	B	F	A	A
Variables	(Intercept)	-3.91	-10.30	-29.77	9.48	-13.59	-3.25	51.98	2.13	3.22
	Tmed			1.19	0.37		-0.42	1.22		0.91
	Tmax					0.63	0.61	-2.40		0.22
	Trange			0.90		-0.62	-0.38	1.47		
	DIN		-1.42				1.21	-4.11		-3.66
	DRP	-2.50		2.90	-7.46		3.06	-4.21	-3.10	
	Conductivity	0.45	0.56	-0.17		0.37	0.34			0.46
	Sand	0.70		-0.60		0.48	0.61		-1.29	
	Pcfine					-0.08	-0.07			-0.11
	Pccoarse		0.03			0.07	0.07			-0.15
	log_meanFlow	0.57		-2.16		1.79	1.34	0.55	0.86	
	CVflow	0.12	0.58	0.48		0.46		-3.55	0.50	
	Da3			-12.12				34.37		
	Da10			8.67			-2.52	-9.68		
	DaEF	1.44	2.66			1.35				
Statistics	*n* (sites)	94	12	21	26	37	44	13	24	21
	Regression adj. R^2	0.37	0.88	0.63	0.54	0.76	0.72	0.99	0.53	0.59
	Cross-validated R^2	0.31	0.75	0.35	0.49	0.66	0.6	0.87	0.44	0.48
	NSE	-0.66	**0.74**	0.22	0.14	**0.60**	**0.53**	**0.87**	0.08	0.25
	RMSD	1.83	0.79	1.74	2.08	1.11	1.18	0.62	1.42	1.55

5.4.3 Mean chlorophyll *a*

Regressions for Chla_mean and WCC_mean were run for models A and B only (all data available), and for model K (so as to include the maximum number of sites). Across all sites, the best model for Chla_mean was relatively weak, with NSE = 0.37 (Table 5-6). Nine explanatory variables represented all five groups in Table 5-1.

The best regional models were for HRC (NSE = 0.71, n = 37) and ES (NSE = 0.50, n = 21). The All sites, HRC and ES models all included DaEF as a predictor (Table 5-6).

Table 5-6: Variables and coefficients in the best regression model(s) in each region with Chla_mean as the dependent variable. Refer to Table 5-4 for notes.

		Dataset and model (from Table 5-2)							
Model variables and statistics		**All**	**All**	**NRC**	**BOP**	**HRC**	**GWRC**	**ECan**	**ES**
		A	**K**	**B**	**K**	**A**	**K**	**A**	**A**
Variables	(Intercept)	-1.813	-0.191	-2.965	1.353	-3.572	0.504	2.408	-3.383
	Tmed	0.029		0.216		-0.068	0.143		0.134
	Tmax		0.026			0.211	-0.188		
	Trange			0.072	0.023	-0.196	0.146		
	DIN	0.172	0.194		0.245	0.270		0.209	-0.187
	DRP	-0.242	-0.162	0.594	-0.724			-0.339	
	Conductivity	0.095	0.058		-0.022	0.091	0.094		0.065
	Sand	0.136						-0.293	0.193
	Pcfine					0.023			
	Pccoarse	-0.006		-0.008					
	log_meanFlow	0.046				0.098		0.045	0.128
	CVflow	0.171				0.302		0.153	
	Da3			-0.231					
	Da10							-0.660	
	DaEF	0.407				0.281			0.485
Statistics	*n* (sites)	94	192	21	29	37	14	24	21
	Regression adj. R^2	0.62	0.32	0.72	0.47	0.81	0.58	0.62	0.73
	Cross-validated R^2	0.58	0.29	0.53	0.37	0.74	0.30	0.50	0.58
	NSE	0.37	-1.10	0.33	-0.09	**0.71**	0.16	0.33	**0.50**
	RMSD	0.29	0.39	0.29	0.32	0.25	0.46	0.32	0.30

5.4.4 Mean WCC

The combined dataset yielded weak models for explaining and predicting WCC_mean (NSE < 0) (Table 5-7). All of the regional datasets produced a stronger model with the exception of the ES dataset (NES < 0). An interesting result was that across the 29 sites in the BOP dataset, 67% of the variance in WCC_mean was explained by a combination of Tmax and DRP, with an NSE of 0.47. In that case, DRP had a negative coefficient indicating that WCC was inversely correlated with DRP. The raw data showed that sites with periodic high cover by filamentous algae tended to be those with lowest DRP in the region, although DRP concentrations across the region were relatively high in a national context (median DRP of 26.9 mg/m^2, see Appendix B; see also further discussion in Section 5.5.3).

Table 5-7: Variables and coefficients in the best regression model(s) in each region with WCC_mean as the dependent variable. Refer to Table 5-5 for notes.

		Dataset and model (from Table 5-2)						
Model variables and statistics		ALL	NRC	BOP	HRC	GWRC	ECan	ES
		A	B	K	B	K	B	A
Variables	(Intercept)	-2.439	-19.14	6.477	-4.645	5.611	1.260	-4.364
	Tmed		0.697			0.373		0.479
	Tmax			0.150	0.449	-0.744		
	Trange		0.538		-0.397	0.580		
	DIN					-1.244		-1.508
	DRP	-1.446	2.064	-4.786			-2.017	
	Conductivity	0.228	-0.104		0.198	0.282		
	Sand	0.332	-0.583				-0.892	0.381
	Pcfine				0.096			
	Pccoarse							
	log_meanFlow	0.079	0.374				0.311	
	CVflow	0.388	-1.077		0.869		0.547	
	Da3		-5.487		2.215			
	Da10		4.238		-2.154			1.211
	DaEF	1.066						
Statistics	*n* (sites)	94	21	29	37	14	24	21
	Regression adj. R^2	0.35	0.71	0.67	0.75	0.73	0.62	0.46
	Cross-validated R^2	0.30	0.48	0.62	0.65	0.57	0.50	0.32
	NSE	-0.76	0.34	**0.47**	**0.58**	**0.57**	0.22	-0.18
	RMSD	1.05	1.07	1.08	0.65	1.04	0.80	0.99

5.4.5 Comparison of performance, all models

All of the model statistics shown at the bottom of Table 5-3 to Table 5-7 are summarised together in Table 5-8. The main patterns from the summary follow.

- Across all available sites, chlorophyll *a* was more predictable than WCC, on the basis of NSE. However, the strongest models for chlorophyll *a* were weak (NSE < 0.4). The strongest models for WCC had negative NSE and consequently no predictive skill.
- Across all available sites, chlorophyll *a* was predictable only across sites at which an EF had been identified. All other datasets and models returned negative NSE (data not shown).
- The model for Chla_mean was slightly better than that for Chla_92 although the difference was small (NSE = 0.37 and 0.30, respectively).
- All of the regional datasets except the ECan dataset had at least one periphyton model that was reasonably strong (i.e., NSE ≥ 0.45), and thus apparently out-performed the overall dataset. We note that some datasets were very small (*n* < 15) and probably represented a uniform regional river type.
- In the NRC dataset, both Chla_92 and WCC_92 were strongly predictable across the small group of sites (*n* = 12) at which an EF was identified (NSE > 0.7). Predictability was poor to moderate (NSE = 0.2 – 0.5) for all four dependent variables when DaEF was omitted as a predictor (i.e., across all sites). In the latter cases, DRP was included as a predictor (positive coefficient), but not DIN.
- The BOP dataset had few available variables but a combination of DRP (negative coefficient) and median temperature yielded a reasonably strong model for WCC_mean (NSE = 0.47).
- All four dependent variables were generally strongly related to environmental variables in the HRC dataset. The best models included EF and had NSE > 0.7 (chlorophyll *a*) and >0.55 (WCC).
- In the small GWRC dataset, Chla_92 and WCC_92 produced stronger models than, respectively, Chla_mean and WCC_mean. The models for WCC were better than those for chlorophyll *a*.
- The ECan dataset generally yielded weak models (NSE < 0.35 in all cases). Poor models may have arisen because the dataset included different river types (see discussion in Section 5.5.2).
- In the ES dataset, the best model (NSE = 0.5) was for Chla_mean, and this model included DaEF and DIN, the latter with a negative coefficient. Other models were weak.
- A feature of many models was inclusion of DRP, and occasionally DIN, as predictors with negative coefficients. In other words, higher periphyton was associated with lower nutrients, which is contrary to understanding of the effects of nutrients on periphyton. This is discussed in Section 5.5.3.

Table 5-8: Summary of performance of all models tested, across all sites and within regions. Under "Model", the letters refer to the models listed in Table 5-2. Note that NSE is main metric for comparisons of model performance. Note that model bias was low in all cases (not shown).

Dataset	var	model	n (sites)	Regression adj. R^2	Cross-validated R^2	NSE	RMSD	Notes
All sites	Chla_92	A	94	0.59	0.56	0.30	0.32	Only sites with EF
	Chla_mean	A	94	0.62	0.58	0.37	0.29	Only sites with EF
	Chla_mean	K	192	0.32	0.29	-1.10	0.39	Max. no. of sites
	WCC_92	A	94	0.37	0.31	-0.66	1.83	Only sites with EF
	WCC_mean	A	94	0.35	0.30	-0.76	1.05	Only sites with EF
NRC	Chla_92	B	21	0.74	0.62	0.51	0.28	EF not included
	Chla_92	C	12	0.96	0.85	0.84	0.13	EF included
	Chla_mean	B	21	0.72	0.53	0.33	0.29	EF not included
	WCC_92	C	12	0.88	0.75	0.74	0.79	EF included
	WCC_92	B	21	0.63	0.35	0.22	1.74	EF not included
	WCC_mean	B	21	0.71	0.48	0.34	1.07	EF not included
BOP	Chla_92	K	29	0.42	0.32	-0.40	0.37	no substrate data and no flow data
	Chla_mean	K	29	0.47	0.37	-0.09	0.32	
	WCC_92	K	26	0.54	0.49	0.14	2.08	
	WCC_mean	K	29	0.67	0.62	0.47	1.08	
HRC	Chla_92	A	37	0.82	0.77	0.73	0.25	EF included
	Chla_92	B	44	0.68	0.55	0.42	0.34	EF not included
	Chla_92	K	9	1.00	0.96	0.92	0.15	EF not identified
	Chla_mean	A	37	0.81	0.74	0.71	0.25	EF included
	WCC_92	A	37	0.76	0.66	0.60	1.11	EF included
	WCC_92	B	44	0.72	0.60	0.53	1.18	EF not included
	WCC_mean	B	37	0.75	0.65	0.58	0.65	EF not included
GWRC	Chla_92	F	13	0.71	0.61	0.50	0.31	no substrate data
	Chla_mean	K	14	0.58	0.30	0.16	0.46	
	WCC_92	F	13	0.99	0.87	0.87	0.62	
	WCC_mean	K	14	0.73	0.57	0.57	1.04	
ECan	Chla_92	B	24	0.60	0.47	0.20	0.35	EF not included
	Chla_mean	B	24	0.62	0.50	0.33	0.32	EF not included
	WCC_92	A	24	0.53	0.44	0.08	1.42	EF included
	WCC_mean	A	24	0.62	0.50	0.22	0.80	EF included
ES	Chla_92	B	21	0.51	0.40	0.09	0.38	EF not included
	Chla_mean	A	21	0.73	0.58	0.50	0.30	EF included
	WCC_92	B	21	0.59	0.48	0.25	1.55	EF not included
	WCC_mean	B	21	0.46	0.32	-0.18	0.99	EF not included

5.5 Discussion

5.5.1 Model performance

Regression models (or, in fact, any models) for predicting periphyton from combinations of environmental variables are relatively scarce in the literature. Examples include those developed by Biggs (2000a) and Snelder et al. (2014). The relationships developed by Biggs (2000a) almost 20 years ago (see Section 5.1) are amongst those with the highest explanatory power (R^2 = 0.74 and 0.72 for the relationships including DIN and DRP respectively). While the Biggs (2000a) relationships were not formally tested (using, for example, cross-validation techniques), cross validation based on the data used by Biggs (2000a) indicates that these models are robust. As discussed in the introduction to this section, the limitations of the Biggs (2000a) models lie in the constrained type of river site included in the test data and in the limited range of the environmental data (especially DIN).

According to Biggs (2000a): *"All sites were in [gravel-bed] streams and rivers flowing from hill-country watersheds where snowmelt affected flow regimes for <3 mo/y, and lakes or large springs did not dominate flow regimes. None of the sites were affected by point-source pollution discharges or significant shading from riparian vegetation."*

In the present analysis, we used data from a heterogenous dataset of river sites from throughout New Zealand. The main feature all sites had in common was a cobble – gravel bed substrate suitable for periphyton growth. Other than that, the dataset included sites representing all REC source-of-flow classes (including glacier-fed and lake-fed river rivers, Table 3-3). Sites ranged from shaded to unshaded, but shading could not be included as a predictor variable because the information was not available at enough sites and, when it was available, was in different forms (continuous or categorical). Some sites in the HRC dataset were downstream of point-source discharges.

Given the heterogeneity of the dataset, a model for Chla_92 with cross-validated R^2 = 0.56 and NSE = 0.30 is reasonable. Li (2016) suggested the following scale for model performance[7]:

1. Very poor, NSE < 0.1
2. Poor, 0.1 ≤ NSE < 0.3
3. Average, 0.3 ≤ NSE < 0.5
4. Good, 0.5 ≤ NSE < 0.8
5. Excellent, NSE > 0.8.

Thus, the Chla_92 model in this study was borderline Poor / Average. Both models for WCC were very poor and could not predict WCC across multiple regions better than simply assuming the mean value (i.e., NSE ≤ 0).

Larned et al. (2015) developed two stronger regression models for the same dependent variable as used in the present report (92nd percentile of WCC, square-root-transformed) using data from 78 sites in the NRWQN (see Section 3.3.2). Predictor variables were a combination of observed data (nutrients, flow, temperature) and modelled values (substrate). One model included TN and N: P ratio; the second model included DRP but no variable for N. Even though the RMSD in both models (1.96, 2.03) was larger than that in the present model (1.83), NSE was positive in both cases (0.4 and

[7] Li (2016) used a term VEcv (variance explained by cross validation) rather than NSE. The only difference between the two terms appears to be that VEcv is expressed as a percentage rather than a proportion.

0.36 respectively, compared to -0.66, see Table 5-8). However, the Snelder et al. (2015) models performed poorly at predicting WCC at new sites in the Horizons region (negative NSE).

The following factors may have led to poor performance of the present models compared to the Snelder et al. (2015) models.

1. Heterogeneity of river types compared to those in the NRWQN. Ability to develop more robust models from the NRWQN data than from combined regional council data may reflect a more uniform dataset in terms of river type, similar to the Biggs (2000a) relationships. The NRWQN sites are almost all in relatively large rivers with large catchments, whereas the regional council dataset includes rivers of all sizes with broad representation across most categories in the REC (see discussion above).
2. Uneven spatial distribution of data. The present dataset comprised six clusters of sites, corresponding to six regions. The dataset had a good geographical spread (Northland to Southland), but large areas of the country (Auckland, Waikato, Gisborne, Taranaki, Bay of Plenty, Nelson – Marlborough, Otago and West Coast) were not represented.
3. Omission of important explanatory variables. Snelder et al. (2015) found that including the flow variable nNeg (the mean annual number of days when the flow was lower than that on the previous day) strengthened the relationship between WCC and environmental variables. nNeg is an indicator of “flashiness” in a hydrograph (i.e., rapid rates of flow increase during frequent floods) and is therefore expected to be negatively correlated with periphyton biomass (T. Snelder, pers. comm.). nNeg was not available in the predictor variable dataset. A worthwhile study would be to re-run the analyses to see whether including nNeg improves performance.

In the present regional council dataset, negative NSE or NSE substantially lower than the cross-validated R^2 indicates that the dataset includes outlying values that increase the sum of squares of Observed - Predicted values. The spread of the data relative to the 1 : 1 line (i.e., perfect fit) is best illustrated in plots of Observed vs. Predicted values. In Figure 5-1 the top two plots show data from all available sites using model A and the model statistics are shown in the top panel of Table 5-8. NSE for chl_92 is positive (0.30) but for WCC_92 is negative (-0.66) despite an R^2 of 0.30. Poor predictive efficiency for WCC_92 occurs because some predictions are far from the observed values. In contrast for chla_92, the points are clustered more closely around the 1:1 line. The bottom two plots in Figure 5-1 illustrate plots with high R^2 and NSE (i.e., strong predictive ability): points are generally clustered around the 1:1 range over the whole range of observed values.

We note that uncertainty in any predictions made using the models can be quantified in the units of the dependent variable from the RMSD value calculated as part of the cross-validation procedure (e.g., Section 5.2 in Whitehead et al. 2018).

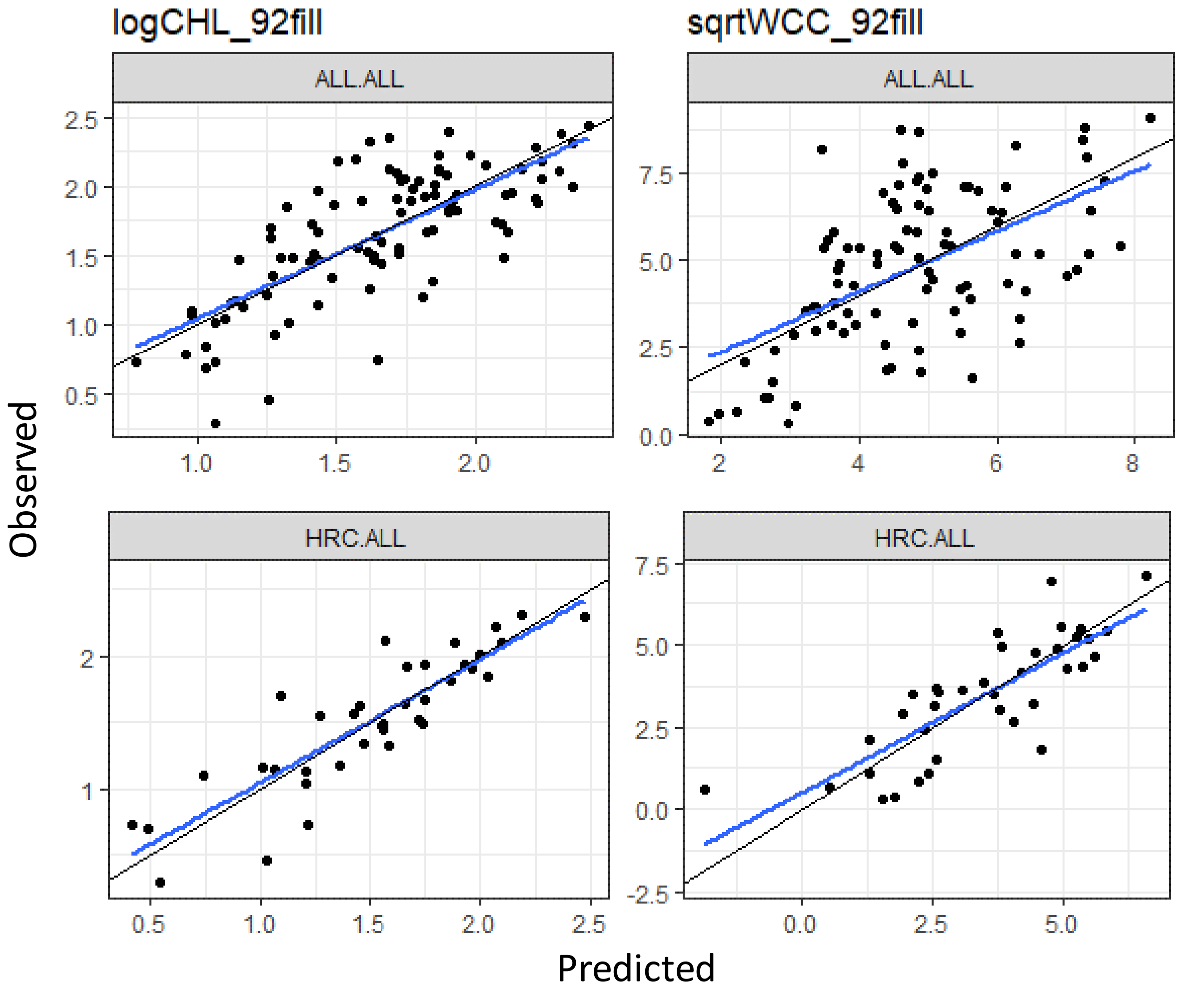

Figure 5-1: Observed chl_92 (left) and WCC_92 (right) plotted against predicted values from a leave one out cross validation. Model variables available were those in set A in Table 5-2 (i.e., including effective flows). The black line is the 1 : 1 line and the blue line is the fitted line. The top two plots show all available data; the bottom blots show data from HRC only (37 sites with an effective flow).

5.5.2 National vs. regional datasets

More often than not, regional datasets yielded stronger models than those across the whole dataset (i.e., all available sites, depending on the variables included).

Two of the regional datasets (HRC and ECan) have been analysed in previous studies (Kilroy et al. 2017, 2018). As in the present analysis, the earlier analysis of the HRC dataset showed strong relationships between chlorophyll *a* and environmental variables (Kilroy et al. 2018). There was variability across years in relationship strength and selected predictor variables. However, in all years tested, the models were "good" according to the scale of Li (2016) and the same suite of variables recurred in most models. The variables were: DIN, DRP, conductivity, a substrate variable, a temperature variable, and DaEF) (see Kilroy et al. 2018 for details).

The earlier analysis of the ECan dataset (Kilroy et al. 2017), like the present study, generated weak relationships when data from all 24 sites were analysed together (relationships very poor to average, on the scale of Li (2016)). Kilroy et al. (2017) found stronger relationships when Alpine and Hill sites were analysed separately. Peak chlorophyll *a* (as the 92nd percentile) in seven Alpine sites was strongly correlated with nutrient concentrations, regardless of the frequency of the effective flow or of other floods. Across the remaining 17 Hill sites, the best relationships were observed when sites with heavy shade were omitted, and when quadratic functions were used to describe non-linear relationships between chlorophyll *a* and DIN and DaEF, which were evident from the raw data (Kilroy et al. 2017). The relationships developed for unshaded Hill sites explained up to 83% of the variance in chlorophyll *a* and were able to predict maximum or 92nd percentile of chlorophyll *a* at independent sites with reasonable accuracy (R^2 of observed vs. predicted was 0.4, including sites where heavy invertebrate grazing was suspected to have caused lower observed chlorophyll *a* than expected).

Given demonstrated variability of relationships *within* the ECan regional dataset, our expectations for robust, simple regression relationships across all regions were low, and the result confirmed that expectation.

5.5.3 Negative coefficients for nutrient variables

All three of the best regression models for Chla_92 (Table 5-3) included both DIN and DRP as predictors, but in all three cases DRP had a negative coefficient. DRP was included as a predictor with a negative coefficient in some models in the BOP, GWRC and ECan regional datasets. DIN also had negative coefficients in the models for WCC using the GWRC and ES datasets. Such negative coefficients are counterintuitive because our general understanding of the relationships between periphyton and nutrients is that increasing nutrients enhance biomass.

In a multiple regression, unexpected negative (or positive) coefficients can be a consequence of including multiple predictor variables in the model and the phenomenon of reversed coefficients is well known (Tu et al. 2008). One form, the Simpson paradox, occurs when a positive correlation between a dependent variable and single explanatory variable reverses to negative after the addition of a second explanatory variable. Reversed coefficients (and related phenomena) confound both use of regression equations for prediction and interpretation of regression relationships in terms of potential cause and effect. Arah (2008) emphasized that to explain and avoid these effects requires background knowledge of the system being modelled, rather than reliance on statistical criteria.

In the present dataset, we investigated the cause of counterintuitive negative DRP coefficients by first comparing the directions of single variable correlation coefficients (i.e., periphyton variable vs. DRP) with those in the best multiple regression models. We found reversal of the direction of coefficients in the combined dataset (Table 5-9). Across all sites at which all relevant variables were available (see Table 5-3), the single variable correlation between DRP and all the periphyton variable was positive (although weak, range of Pearson R of 0.08 to 0.21) while the multiple regression coefficient was negative. In contrast, within regions, reversals were evident in only three of the 20 relationships (Table 5-9). Furthermore, the single variable correlations were negative in nine of the 20 relationships, including all of the relationships in the BOP dataset. Therefore, counterintuitive relationships were evident even in the simplest models.

Negative relationships between DRP and biomass associated with individual periphyton taxa are not uncommon. For example, the cyanobacterium *Phormidium* (recently re-assigned to the genus *Microcoleus*) typically only proliferates in rivers with DRP < 10 mg/m^3 (McAllister et al. 2016). *Microcoleus* has high chlorophyll *a* concentrations per unit area compared to other types of algae, including filamentous green algae) (Hart et al. 2013, Kilroy et al. 2013). Thus, widespread occurrence of summer *Microcoleus* blooms in regions where mean DRP ranges from < 5 to > 25 mg/m^3 (McAllister et al. 2016, and see Appendix B) may lead to a generally negative relationship between

DRP and chlorophyll *a*. Another example is *Didymosphenia geminata* (didymo) in South Island rivers. Didymo forms exceptionally large, chlorophyll *a* rich blooms (Kilroy et al. 2009), but appears to proliferate only in rivers where mean DRP < 2 mg/m^3 (Kilroy and Bothwell 2012).

Table 5-9: Direction of relationships between DRP and the periphyton variables in single-variable correlations and in multiple regression relationships. Reversals are highlighted in grey. NA = DRP not included in multiple regression. Note that most of the single variable correlations were weak (r < 0.2).

		Dataset						
Variable	**Relationship**	**All sites excl BOP**	**NRC**	**BOP**	**HRC**	**GWRC**	**ENC**	**ES**
Chl_92	single	Positive	Positive	Negative	Positive	Positive	Positive	Positive
	multiple	Negative	Positive	Negative	Positive	Negative	NA	NA
WCC_92	single	Positive	Positive	Negative	Negative	Negative	Negative	Positive
	multiple	Negative	Positive	Negative	Positive	Negative	Negative	NA
Chla_mean	single	Positive	Positive	Negative	Positive	Positive	Positive	Positive
	multiple	Negative	Positive	Negative	NA	NA	Negative	NA
WCC_mean	single	Positive	Positive	Negative	Negative	Positive	Negative	Positive
	multiple	Negative	Positive	Negative	NA	NA	Negative	NA

Whatever the reason for negative coefficients for DIN or DRP in periphyton – environment relationships, their effect is to render the equations unworkable for nutrient limit-setting across broad regions. When there are demonstrated negative relationships (such as the examples above), a more region-specific or even river-specific approach might need to be taken.

6 Predicting periphyton across the New Zealand river network

6.1 Introduction

The intention at the start of this project was to use the regression models developed in Section 5 to predict 92nd percentile and mean periphyton chlorophyll *a* and cover in all river segments in the REC river network. The outcome of the analyses described in Sections 4 and 5 dictated that this was not likely to yield useful predictions, for the following reasons.

- Although we obtained suitable regional council periphyton data from almost 200 sites with a wide geographical spread, not all important environmental variables were available at all sites. The strongest nationwide relationships were built from just 94 sites clustered in four regions.
- The strongest relationships all included Da_EF (accrual period derived from the effective flow at each site). Any predictions back to the entire REC network would require an equivalent variable. We attempted to model EF but considered that the result was too imprecise for further use at this stage (see Section 4.3).
- The strongest regression relationships developed in Section 5 were, in any case, relatively weak, even within the training dataset. Predicting at new sites risks introducing large errors.

Consequently, the plan for the analysis was modified and predictions of periphyton abundance across the entire New Zealand river network were made using the RF approach used for predicting water quality variables (Whitehead 2018).

6.2 Predictor variables

The spatial framework for the periphyton predictions was the digital river network used for the REC (Snelder and Biggs 2002). The digital network represents New Zealand's rivers as approximately 560,000 river segments (defined by upstream and downstream confluences). Each river segment (nzsegment) has a unique number (e.g., see Appendix A). The network defines the links between each nzsegment and its adjacent, upstream and downstream nzsegments so that an upstream catchment can be defined for all nzsegments. In this way upstream – downstream connectivity can be defined and catchment characteristics can be accumulated in a downstream direction. The original REC (Snelder and Biggs 2002) has recently been updated and improved to correct errors and enhance representation of rivers. The updated spatial geodatabase is referred to as REC2 (currently Version 2.4) and the original database and classification as REC1.

The river network that forms the basis of REC2, like that for REC1 contains spatial data layers describing the climate, topography, geology, vegetation, infrastructure and hydrology of New Zealand (https://www.niwa.co.nz/freshwater-and-estuaries/management-tools/river-environment-classification-0). These spatial data are used to link each nzsegment and its catchment to attributes that describe their environmental characteristics. Attributes include estimates of water quality and nutrient concentrations derived in parallel projects to the present project (e.g., Whitehead 2018) and from earlier projects (e.g., Unwin et al 2010; Larned et al 2016). Descriptions of catchment regolith were derived from the Land Resources Inventory (LRI) including interpretations of the LRI categories made by Leathwick et al. (2003). Additional variables for each segment have been derived from national-scale hydrological modelling (e.g., flow variables, Booker and Snelder 2012; substrate composition, Haddachi and Booker 2017).

We selected 39 network attributes from REC2 based on their potential proximal roles in influencing periphyton cover and biomass (Table 6-1). Indirect potential predictors linked to nutrient supply, such as landcover, were not included.

Table 6-1: Predictor variables used in random forest models of periphyton as chlorophyll *a* and WCC, with justification for inclusion of each one. Note that all these variables are modelled predictions for each nzsegment and are therefore strictly estimates.

Group	Variable abbreviation	Description and units	Units	Rationale / explanation
Climate	usElev	Mean elevation of the upstream catchment	m	Climate influences periphyton mainly through the direct effect of temperature on algal growth rates. Higher temperatures = faster growth rates (up to a species-specific optimum). Elevation also reflects temperature.
	usTmin	Mean temperature of the upstream catchment in June, coldest month	°C X 10	
	usTwarm	Mean temperature of the upstream catchment in January, warmest month	°C X 10	
	usTmin	Mean temperature of the upstream catchment in July, coldest month	°C X 10	
Rainfall and flow	segRain	Mean annual rainfall at the segment	mm	Rainfall affects periphyton through its control of flow volume and flow variability in rivers. High usRainVar indicates larger floods relative to median, but also longer periods of very low flows. usRainDays and FRE3 represent variability of flows
	usRain	Mean annual catchment averaged rainfall	mm	
	usRainVar	Mean catchment coefficient of variation of annual rainfall		
	usRainDays10	Mean days per month with averaged catchment rainfall > 10 mm	days/mo	
	usRainDays25	Mean days per month with averaged catchment rainfall > 25 mm	days/mo	
	usRainDays100	Mean days per month with averaged catchment rainfall > 100 mm	days/mo	
	Q50Cumecs	Estimated median flow	m^3/s	
	MALFCumecs	Mean annual 7-day low flow	m^3/s	
	MeanFlowCumecs	Mean flow	m^3/s	
	FRE3NoWindowCount	Mean annual frequency of events > 3 x median flow, no window applied between events	Events/y	
Geo-morphology	segSinuosity	Segment sinuosity (segment length divided by the straight line distance between endpoints)	No units	Reach and upstream geomorphology influence periphyton through (1) the combined roles of water velocity (determined by reach sinuosity and slope) and substrate composition on periphyton persistence and removal, (2) the role of upstream geology on sediment supply, and (3) the influence of upstream lakes on reach stability.
	segSlope	Slope of segment	degrees	
	Bedrock	Percentage of bed covered by bedrock	%	
	Boulder	Percentage of bed covered by boulders (>256 mm across)	%	
	Cobble	Percentage of bed covered by cobbles (64 – 256 mm across)	%	
	CoarseGravel	Percentage of bed covered by coarse gravel (32 – 63 mm across)	%	
	FineGravel	Percentage of bed covered by fine gravel (16 – 32 mm across)	%	
	Sand	Percentage of bed covered by sand (< 8 mm across)	%	

Group	Variable abbreviation	Description and units	Units	Rationale / explanation
	usHard	Mean catchment induration (hardness) of regolith	Ordinal	
	usParticleSize	Mean catchment particle size of regolith	Ordinal	
	usLake	Proportion of catchment under lakes	%	
Light	segRipShade	Percentage shade resulting from riparian vegetation	%	Sufficient light is a requirement for maximum growth rates in algae. In the absence of direct measures of light, surrogate variables included were estimates of shade at each nzsegment and estimates of rivers wdith at different flows, which together may indicate how incised a site is, as an indirect measure of lateral shading
	WidthQ5	Width of segment at 5th percentile of flow	m	
	WidthMALF	Width of segment at mean annual low flow	m	
	WidthMeanFlow	Width of segment at mean flow	m	
	WidthQ50	Width of segment at median of flow	m	
	CLAR_Median	Water clarity (black disk method)	m	
Water quality and nutrients	COND_Median	Conductivity (Unwin et al. 201	µS/cm	
	NH4N_Median	Median ammonium-N	mg/m^3	Nutrient availability (including micronutrients) determines the "carrying capacity" for periphyton at a site, when all other factors are not limiting. Nutrient availability is generally represented by instream concentrations of N and P, but it is important to recognise that concentrations do not necessarily represent nutrient supply because of the effect of instream uptake and organic sources.
	NO3N_Median	Median nitrate-N		
	TN_Median	Median total nitrogen		
	DRP_Median	Median dissolved reactive phosphorus		
	TP_Median	Median total phosphorus		
	NO3N_Q95	95th percentile of nitrate-N (i.e., peak nitrate)		
	usPhos	Mean catchment phosphorous content of regolith	Ordinal	
	usCalc	Mean catchment calcium content of regolith	Ordinal	

6.3 Methods

6.3.1 Random forest models

We modelled four periphyton variables (chlorophyll *a* and WCC 92nd percentiles and means, hereafter Chla_92, WCC_92, Chla_mean, WCC_mean, see Section 5.2.1) from 196 sites (see Appendix A) as functions of the predictor variables using Random Forest (RF) models (Breiman et al. 1984; Breiman 2001a; Cutler et al. 2007). Chla_92 and Chla_mean were log-transformed; a logit transformation was used for WCC_92 and WCC_mean (Warton and Hui 2011). Methodology was identical to that used by Whitehead (2018) for development of RF models for water quality variables, and the following method description largely repeats that in Whitehead (2018).

An RF model is an ensemble of individual classification and regression trees (CART). CART partitions observations (in this case the periphyton variables) into groups that minimise the sum of squares of the response variables (i.e., assembles groups that minimise differences between observations) based on a series of binary rules or splits that are constructed from the predictor variables. CART models have several desirable features including requiring no distributional assumptions and the ability to automatically fit non-linear relationships and high order interactions. However, single regression trees have the limitations of not searching for optimal tree structures, and of being sensitive to small changes in input data (Hastie et al. 2001). RF models reduce these limitations by using an ensemble of trees (a forest) and making predictions based on the average of all trees (Breiman 2001). An important feature of RF models is that each tree is grown with a bootstrap sample of the fitting data (i.e., the observation dataset). In addition, a random subset of the predictor variables is made available at each node to define the split. Introducing these random components and then averaging over the forest increases prediction accuracy while retaining the desirable features of CART.

An RF model produces a limiting value of the generalization error (i.e., the model maximises its prediction accuracy for previously unseen data; Breiman 2001). The generalization error converges asymptotically as the number of trees increases, so the model cannot be over-fitted. The number of trees needs to be set high enough to ensure an appropriate level of convergence, and this value depends on the number of variables that can be used at each split. We used default options that included making one third of the total number of predictor variables available for each split, and 500 trees per forest. Some studies report that model performance is improved by including more than ~ 50 trees per forest, but that there is little improvement associated with increasing the number of trees beyond 500 (Cutler et al. 2007).

Unlike the linear models described in Section 5, RF models cannot be expressed as equations. The relationships between predictor and response variables represented by RF models can be represented by importance measures and partial dependence plots (Breiman 2001; Cutler et al. 2007).

During the fitting process, RF model predictions are made for each tree for observations that were excluded from the bootstrap sample; these excluded observations are known as out-of-bag (OOB) observations. To assess the importance of a specific predictor variable, the values of the response variable are randomly permuted for the OOB observations, and predictions are obtained from the tree for these modified data. The importance of the predictor variable is indicated by the degree to which prediction accuracy decreases when the response variable is randomly permuted. Importance is defined in this study as the loss in model performance (i.e., the increase in the mean square error; MSE) when predictions are made based on the permuted OOB observations compared to those based on the original observations. The differences in MSE between trees fitted with the original and permuted observations are averaged over all trees and normalized by the standard deviation of the differences (Cutler et al. 2007).

A partial dependence plot is a graphical representation of the effect of a predictor variable on the response variable, when the values of all other predictor variables are held constant. Holding the other predictors constant (generally at their mean values) allows the plot to “ignore” their influence on the response variables. Partial dependence plots do not perfectly represent the effects of each predictor variable, particularly if predictor variables are highly correlated or strongly interacting, but they provide an approximation of the modelled predictor – response relationships that are useful for model interpretation (Cutler et al. 2007).

RF models can include any of the original set of predictor variables. Inclusion of marginally important and correlated predictor variables does not degrade the performance of the RF models. However, these predictor variables may be redundant (i.e., their removal does not affect model performance) and their inclusion can complicate model interpretation. We used a backward elimination procedure to remove redundant predictor variables from the initial 'saturated' models (i.e., models that included any of the original predictor variables). The procedure first assesses the MSE using a 10-fold cross validation process. The predictions made to the hold-out observations during cross validation are used to estimate the MSE and its standard error. The model's least important predictor variables are then removed in order, with the MSE and its standard error being assessed for each for each successive model. The final, 'reduced' model is defined as the model with the fewest predictor variables whose error is within one standard error of the best model (i.e., the model with the lowest cross validated MSE). This is equivalent to the "one standard error rule" used for cross validation of classification trees (Breiman et al. 1984).

An alternative approach is to choose the model with the smallest error. We used the former procedure as it retains fewer predictor variables than the latter procedure, while achieving an error rate that is not different, within sampling error, from the "best solution". Importance levels for predictor variables were not recalculated at each reduction step to avoid over-fitting (Svetnik et al. 2004).

Because fitting a RF model involves randomly selecting observations and predictor variables throughout the fitting process, successive models fitted to the same data set will exhibit subtle differences in structure and diagnostics such as total explained deviance, MSE, partial dependence plots, and the order of predictor importance. In the current study, the variability in model error between individual fits of the model for each water quality variable were within the reported model performance.

All calculations were performed in the R statistical computing environment (R Development Core Team 2009) using the *randomForest* package and other specialised packages.

6.3.2 Model performance

Model performance was assessed by comparing observations with independent predictions (i.e., sites that were not used in fitting the model), which were obtained from the out-of-bag (OOB) samples. We summarised the models using four statistics; regression R^2**,** Nash-Sutcliffe Efficiencies (NSE), bias and root mean square deviation (RMSD).

The regression R^2 value is the coefficient of determination derived from a regression of the observations against the predictions. The R^2 value shows the proportion of the total variance explained by the regression model (Piñeiro et al. 2008). However, the regression R^2 is not a complete description of model performance. The NSE (Nash and Sutcliffe 1970) provides a measure of overall model performance by indicating how closely a plot of observed versus predicted values lies to the 1:1 line (i.e., the degree to which two sets of values coincide). NSE values range from $-\infty$ to 1. An NSE of 1 corresponds to a perfect match between predictions and the observed data, an NSE of 0 indicates that the model predictions are as accurate as the mean of the observed data; and an NSE < 0 indicates that the observed mean is a better predictor than the model. Model bias measures the average tendency of the predicted values of water quality variables to be larger or smaller than the observed values. Positive values indicate underestimation bias and negative values indicate overestimation bias (Moriasi et al. 2007). The RMSD is a measure of the characteristic model uncertainty. RMSD is mean deviation of predicted values with respect to the observed values (distinct from the standard error of the regression model).

6.3.3 Representativeness of sites used in RF models

Here, representativeness refers to the degree to which the distribution of monitoring sites over the range of an environmental predictor variable matches the distribution of all network segments over the range of the same environmental variable. Poor representativeness can reduce accuracy in model predictions because certain combinations of environmental conditions are not represented in the fitting data.

A graphical comparison was used to gauge how well the periphyton monitoring sites used to fit the RF models represented environmental variation at the national scale. Histograms of the proportions of monitoring site numbers over the ranges of the 12 most important predictor variables in the RF models (i.e., the predictors with the greatest explanatory power) were visually compared with histograms of the proportions of all network segments over the same predictor variables.

6.3.4 Model predictions

Predictions are made with RF models by "running" new cases down every tree in the fitted forest and averaging the predictions made by each tree (Cutler et al. 2007). The models in this study were fitted to $\log_{10}$-transformed and logit transformed periphyton data. When these models are back-transformed, the model error term no longer has a mean of zero. Ignoring this results in retransformation bias, i.e., predictions that systematically underestimate the response (Dambolena et al. 2008). We corrected the retransformation bias using the smearing estimate (*S*) developed by Duan (1983):

$$S = \frac{1}{n}\sum_{i=1}^{n} 10^{\hat{\varepsilon}_i} \qquad \text{(Equation 3)}$$

where $\hat{\varepsilon}$ are the residuals of an RF model. The predictions were back-transformed by raising them to the power of 10, then corrected for retransformation bias by multiplying by *S. A*

The back-transformed and corrected predictions for all river segments in New Zealand were projected on a single national map for each periphyton variable. For mapping, Chla_92 was colour-coded to correspond to the four Bands in the periphyton attribute in the National Objectives Framework in the NPS-FM, and WCC_92 to correspond to the four groups defined by Matheson et al. (2012). Chla_mean and WCC_mean were subdivided into groups representing lower chlorophyll and WCC, to illustrate possible spatial patterns of periphyton at low abundances.

Predictions of Chla_92 and WCC_92 were also plotted on bar graphs as percentages of river length in all classes at level 2 of the REC (climate and source of flow), across all of New Zealand and within the 15 regions of New Zealand.

6.4 Results

6.4.1 Model performance

All four RF models for periphyton were relatively weak with R^2 and NSE between 0.3 and 0.5 (Table 6-2), which Li (2016) considered to be "average" performance. Bias was low in the chlorophyll *a* models and is shown by close correspondence of the slopes and positions of the one-to-one lines and regression lines in Figure 6-1. Bias for the WCC models was higher (Table 6-2, Figure 6-1).

Table 6-2: Performance of the RF models for periphyton chlorophyll *a* and WCC. Performance was determined using independent predictions (i.e., sites that were not used in fitting the models) generated from the out-of-bag observations. Regression R^2 = coefficient of determination, NSE = Nash-Sutcliffe efficiency, RMSD = root mean square deviation). Units for RMSD and bias are the $\log_{10}$ transformed units of the periphyton variable.

ependent variable	Transformation	Number of sites	Regression R²	NSE	Bias	RMSD
Chla_92	$\log_{10}$	196	0.37	0.37	-0.002	0.39
Chla_Mean	$\log_{10}$	196	0.41	0.41	-0.001	0.36
WCC_92	Logit	196	0.37	0.37	0.021	1.08
WCC_Mean	Logit	196	0.36	0.35	0.037	1.06

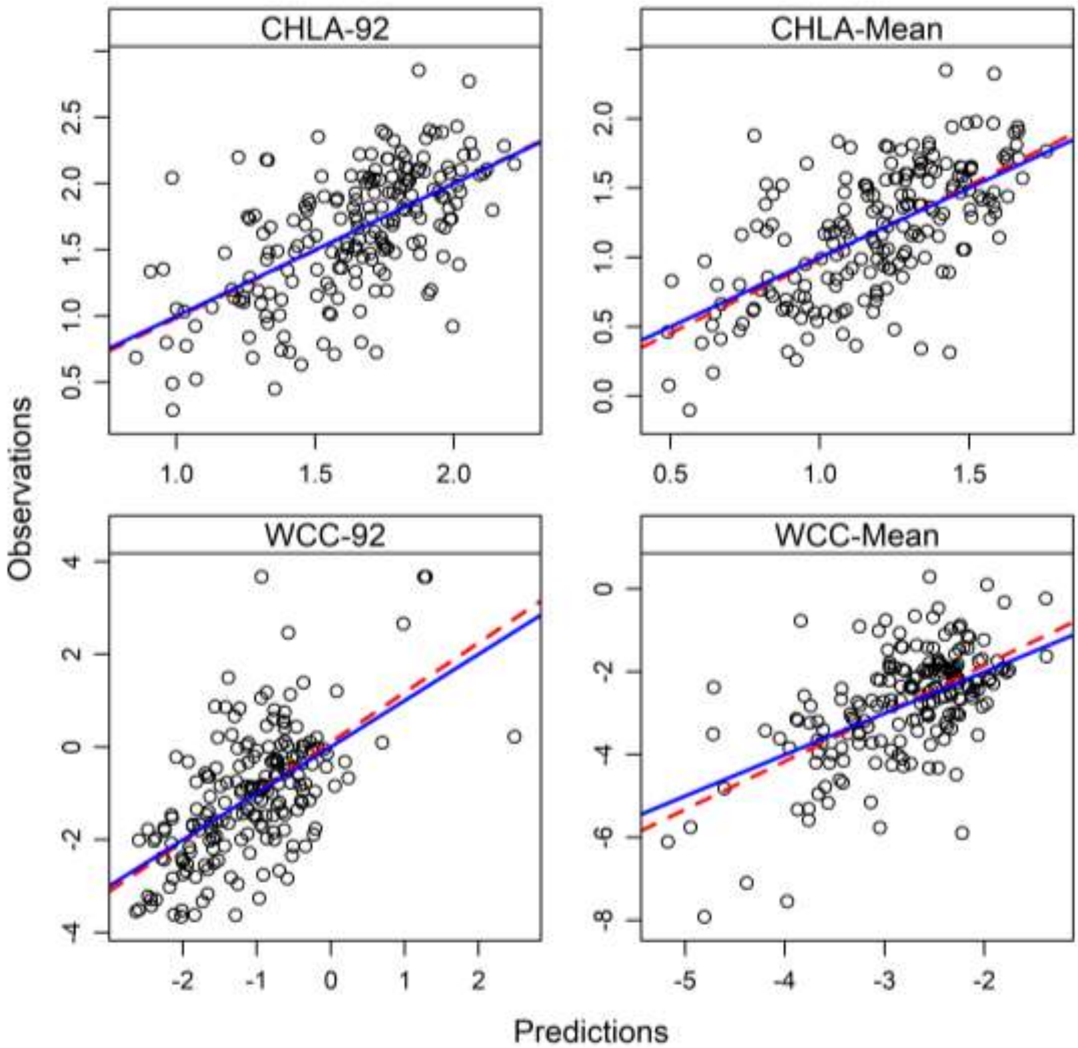

Figure 6-1: Observed periphyton (chlorophyll *a* and WCC) plotted against predictions from the RF model. Predictions were made using the OOB process described in Section 6.3.1. The red dashed line is the best fit linear regression of the observed and predicted values. The solid blue line is the one-to-one line. Units are the $\log_{10}$ transformed units.

6.4.2 Representativeness of sites with respect to predictor variables

The environmental gradients of most of the 12 most important overall predictor variables were reasonably well represented by the periphyton sites compared to the entire stream network. Discrepancies may arise from the fact that the periphyton monitoring sites were at locations with stream order 3 or more, whereas the histograms in Figure 6-2 includes all high elevation stream order 1 and 2 segments, which make up about 75% of all segments in the river network. The most marked discrepancies were:

1. a disproportionate number of periphyton sites at low elevation (Figure 6-2). In addition to differences attributable to the across the whole stream network distribution including all stream orders, the pattern may reflect a concentration of sampling at sites in areas likely to show problematic periphyton, which are generally in lowland areas, and fewer reference sites, which are often at higher elevations;

2. over-representation of sites with moderate to high peak (95^{th} percentile) and median nitrate concentration. The pattern was likely mostly driven by the same factors as the discrepancy in elevation;

3. over-representation of sites with high proportions of coarse gravel. This discrepancy highlights the fact that periphyton is typically confined to stream with hard (gravel) substrate, and sites with soft-sediment substrate are not usually considered for periphyton monitoring. Thus, periphyton sites are always biased towards hard-bottomed streams and it may be appropriate to predict only for that type of stream.

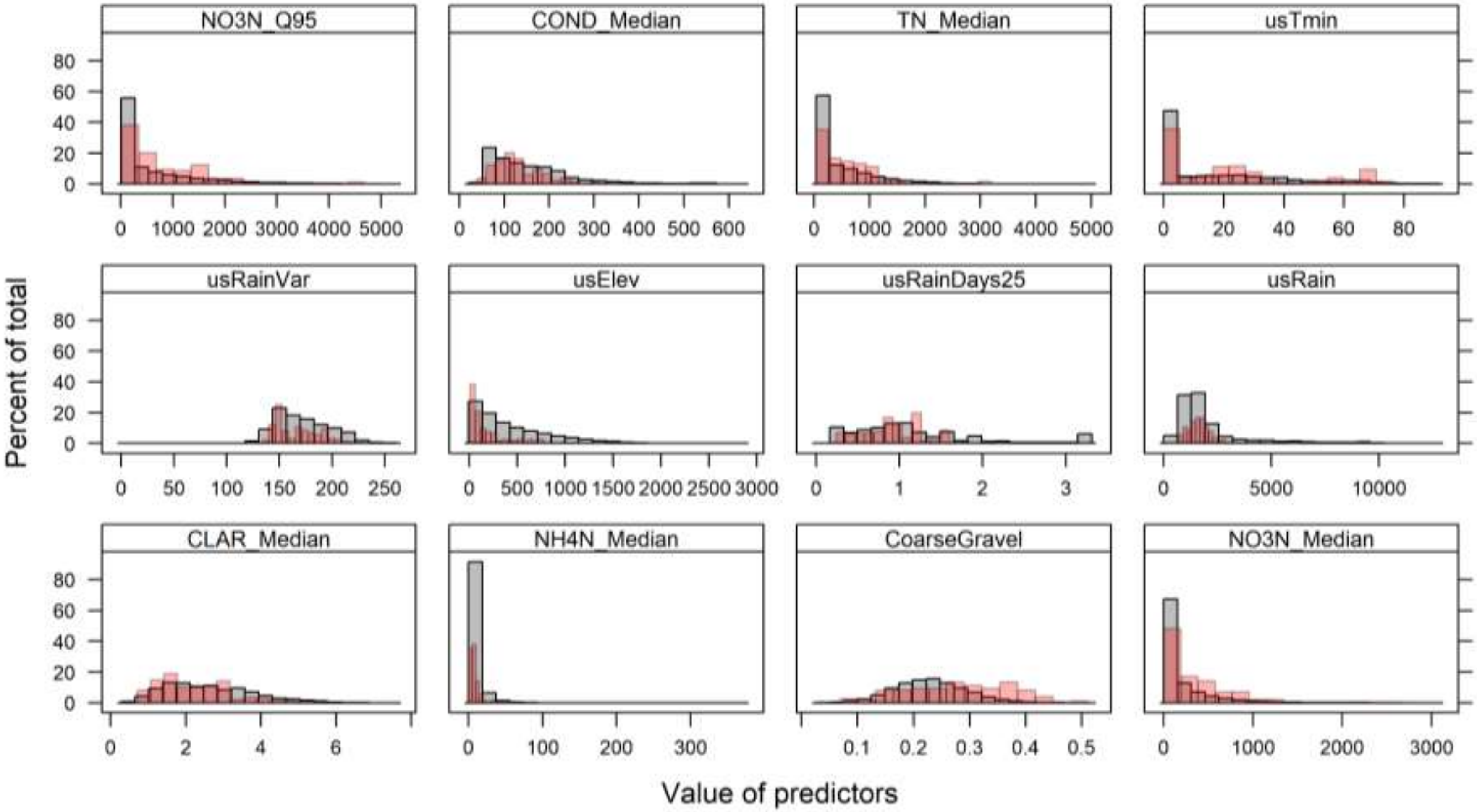

Figure 6-2: The distributions of the 12 most important predictor variables across all segments in the digital river network and at periphyton sites. Refer to table 6-3 for a complete list of variables included in each of the four models. Distributions for the network are shown in grey, overlaid by distributions for periphyton sites, shown in pink. Network distributions apply to all nzsegments (i.e., including all stream orders). An exact match between the two distributions indicates perfect representation. The twelve predictor variables shown were the most important overall predictors in the periphyton RF models.

6.4.3 Relationships between periphyton and environmental variables

Thirty-two of the 39 available variables (listed in Table 6-1) were included in at least one of the models (Table 6-3). Only four variables (COND_median, usRainVar, usRain and CoarseGravel) occurred in all four models.

There was consistency between the two models for chlorophyll *a* (Chla_92 and Chla_mean), which had the same four most important predictor variables, in the same order (COND_median, NO3N_Q95, TN_median, usRainVar). DRP was not selected as a predictor for either Chla_92 or Chla_mean but TP and usPhos were selected as predictors with low importance in both models.

NO3N_Q95 and TN_Median were strongly correlated and were both included as predictors (along with NO3N_Median) because "inclusion of correlated variables does not degrade the performance of RF models" (see Section 6.2). We expected the model to select one or the other, or at least rank one highly and the others much lower, as occurred for NO3N_Median. However, inclusion of large groups of correlated variables can reduce the importance of all the variables in the groups, despite high importance of the underlying factor (Tolosi and Lengauer 2011). In this case, inclusion of two variables representing N supply as the second and third most important predictors highlighted the overall importance of nitrogen in some form. Re-running the models including and excluding each of the variables in turn would be informative.

The most important variable for predicting chlorophyll *a*, COND_Median, was only weakly correlated with other variables. The strongest correlations were with Boulder and usElev (Spearman R = 0.7) reflecting a tendency for high altitude streams to have lower conductivity and also coarser substrate. The variable usRainVar was fourth most important, indicating the importance of flow variability in influencing periphyton abundance.

Partial plots showing the direction of influence of the predictor variables confirmed that responses by Chla_92 and Chl_Mean were generally similar (Figure 6-3). Responses of chlorophyll *a* to all four variables representing supply of N had the same shape. For example, there was a strong response to NO3N_Median across concentrations up to about 300 mg/m^2 but no response thereafter (Figure 6-3). COND_Median showed a more or less linear relationship up to about 250 µS/cm. Lower values of usRainVar were associated with lower chlorophyll *a* and there was little response at higher values. On the other hand, usRain showed a generally negative relationship with chlorophyll *a* reflecting the expected pattern of wetter catchments having less periphyton (Figure 6-3).

The most important predictors in the WCC models differed from those for chlorophyll *a*, and also differed from each other. Only one variable (usTmin) was common to the top four predictors for WCC_92 and WCC_mean. The top four predictors were, respectively, usRain, usRainDays25, usTmin, COND_median; and usPhos, usRainVar, usTmin, usElev. Neither model included any of the three N supply variables as a predictor, and phosphorus was represented only by usPhos. WCC_mean returned the most parsimonious model of all four variables, with only nine predictors retained in the final model (Table 6-3).

The pattern of correlation of the 12 most important predictors on WCC was not always consistent with that for chlorophyll *a*. For example, the positive association between COND_Median and WCC was less marked than that for chlorophyll a, while negative associations for usElev and usRain were more marked (Figure 6-3).

Table 6-3: Ranked importance of predictor variables retained in the random forest models for at least one periphyton variable. Predictor variables are listed order of the median of ranked importance across all four models. Refer to Section 6.2 for an explanation of "importance". Dashes indicate that the predictor was not included in the reduced model. The four most important predictor variables for each model are highlighted by grey shading.

Predictor variable	Chla-92	Chla-mean	WCC-92	WCC-mean
NO3N_Q95	2	2	-	-
COND_Median	1	1	4	7
TN_Median	3	3	-	-
usTmin	-	17	3	3
usRainVar	4	4	7	2
usElev	-	12	5	4
usRainDays25	15	-	2	6
usRain	7	13	1	5
CLAR_Median	6	5	-	14
NH4N_Median	5	10	-	-
CoarseGravel	9	8	8	8
NO3N_Median	8	9	-	-
Boulder	13	7	-	-
FRE3NoWindowCount	11	-	-	9
WidthQ50	10	11	-	16
usTwarm	-	26	6	11
Sand	12	6	-	12
usCalc	-	-	9	18
FineGravel	16	14	-	13
segRain	18	15	-	15
segSlope	-	16	-	-
usRainDays10	-	23	-	10
usPhos	17	22	-	1
usHard	14	20	-	-
usRainDays100	-	-	-	17
TP_Median	19	18	-	-
usParticleSize	-	19	-	-
Cobble	-	-	-	19
Q50Cumecs	-	21	-	-
usLake	-	24	-	-
MALFCumecs	-	25	-	-
Bedrock	-	27	-	-

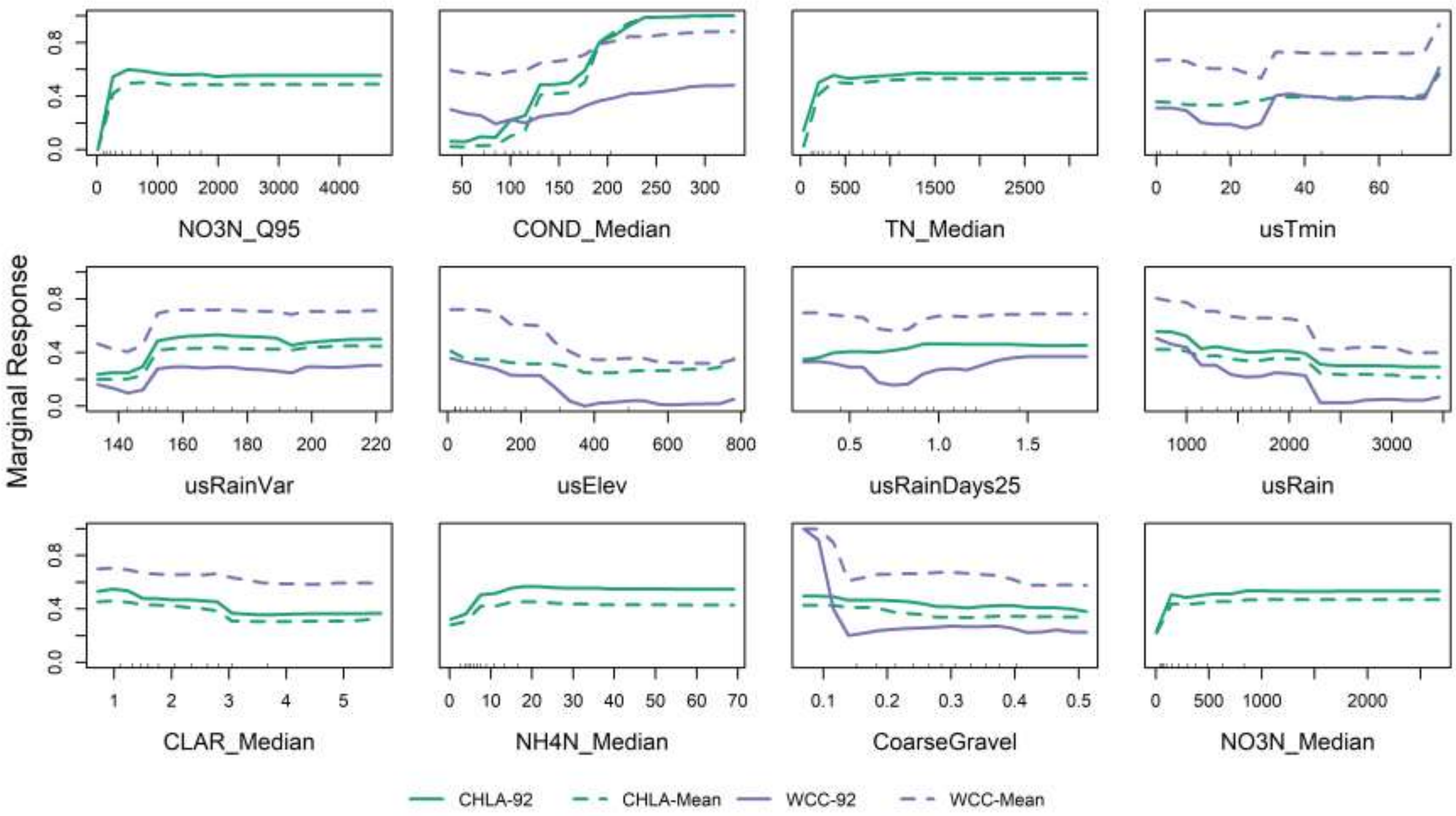

Figure 6-3: Partial plots for the twelve most important predictor variables in random forest models of periphyton. Each panel shows plot for one predictor, with predictor variables ordered by overall importance from most (top left) to least (bottom right) important (as listed in Table 6-3). Y-axis scales represent the standardised value of the marginal response for each of the four modelled response variables. In each case, the original marginal responses over all twelve predictors were standardised to have a range between zero and one. Plot amplitude (the range of the marginal response on the Y-axis) is directly related to a predictor variable's importance; amplitude is large for predictor variables with high importance.

6.4.4 Model predictions

General patterns

The minimum values predicted by the RF models were always larger than the minimum of the observed values and the maximum predicted values were always somewhat smaller than the maximum observed values (Table 6-4). This is an expected outcome of RF models, which are based on partitioning the data and predictions are derived from the means of observations that are assigned to a particular partition. Thus, the predictions for each periphyton variable were always within the range of the observations. One consequence of this feature of RF models for the overall predictions in the NPS-FM Bands was that few nzsegments were predicted to have Chla_92 in Band D (below the bottom line) (refer to Section 6.5.2 for further discussion). Mapping all nzsegments with stream order >3 showed Band D only in Northland (Figure 6-4). Predictions of nzsegments in Band B were also relatively sparse, and were concentrated in Northland, Auckland, Gisborne, Hawkes Bay, Tasman, Marlborough and Canterbury. Over the whole network, for all nzsegments with stream order ≥ 3, proportions of segments falling into Chla_92 Bands A to D were: A, 61.5%, B, 32.5%; C, 6.0%; D, 0.015%.

Table 6-4: Ranges of observed periphyton variables and predicted variables from the RF models. Predictions were made across the whole NZ river network.

		Observed		Predicted	
	Units	Minimum	Maximum	Minimum	Maximum
Chla-92	mg/m^2	1.95	717	4.14	317
WCC-92	%	0	100	4.09	92.8
Chla-Mean	mg/m^2	0.8	222.6	1.6	103.1
WCC-Mean	%	0.04	57.2	0.17	32.4

For mapping, WCC_92 was divided into the four groups defined by Matheson et al. (2012). In contrast to Chla_92, nzsegments in the highest category (WCC > 55%) made up 2.4% of all those with stream order ≥ 3 (Figure 6-5). These high cover segments were concentrated in coastal areas of Northland, Auckland, Waikato, Bay of Plenty, Gisbourne, Taranaki and Hawkes Bay with some occurrences in Canterbury and Southland (Figure 6-5). Over the whole network, for all nzsegments with stream order ≥ 3, proportions of segments falling into the four WCC_92 groups were: <20, 25.3%, 20-40, 55.8%; 40-55, 16.5%; >55, 2.4%.

Mapping predictions of Chla_mean (Figure 6-6) and WCC_mean (Figure 6-7) using colour-coding to separate periphyton abundance classes in the low range highlighted potentially more subtle patterns of periphyton abundance across New Zealand, again with contrasting patterns between chlorophyll *a* and WCC. Lowest periphyton abundance (Chla_mean of < 7.5 mg/m^2) was predicted to occur in the eastern mountainous areas of the North Island, and the central mountain / foothills and western coastal areas of the South Island. Slightly higher Chla_mean (up to 15 mg/m^2) was predicted in the Central Plateau of the North Island and in the mainstems of larger rivers in the South Island (Figure 6-6). Highest mean chlorophyll *a* (> 50 mg/m^2) was predicted for south eastern North Island and coastal north Canterbury (Figure 6-6). Predicted WCC_mean differed from Chla_mean in that all of the eastern foothills of the South Island were predicted to have higher WCC than western areas and highest WCC was concentrated along most of the east coast and northern North Island, especially western Bay of Plenty (Figure 6-7).

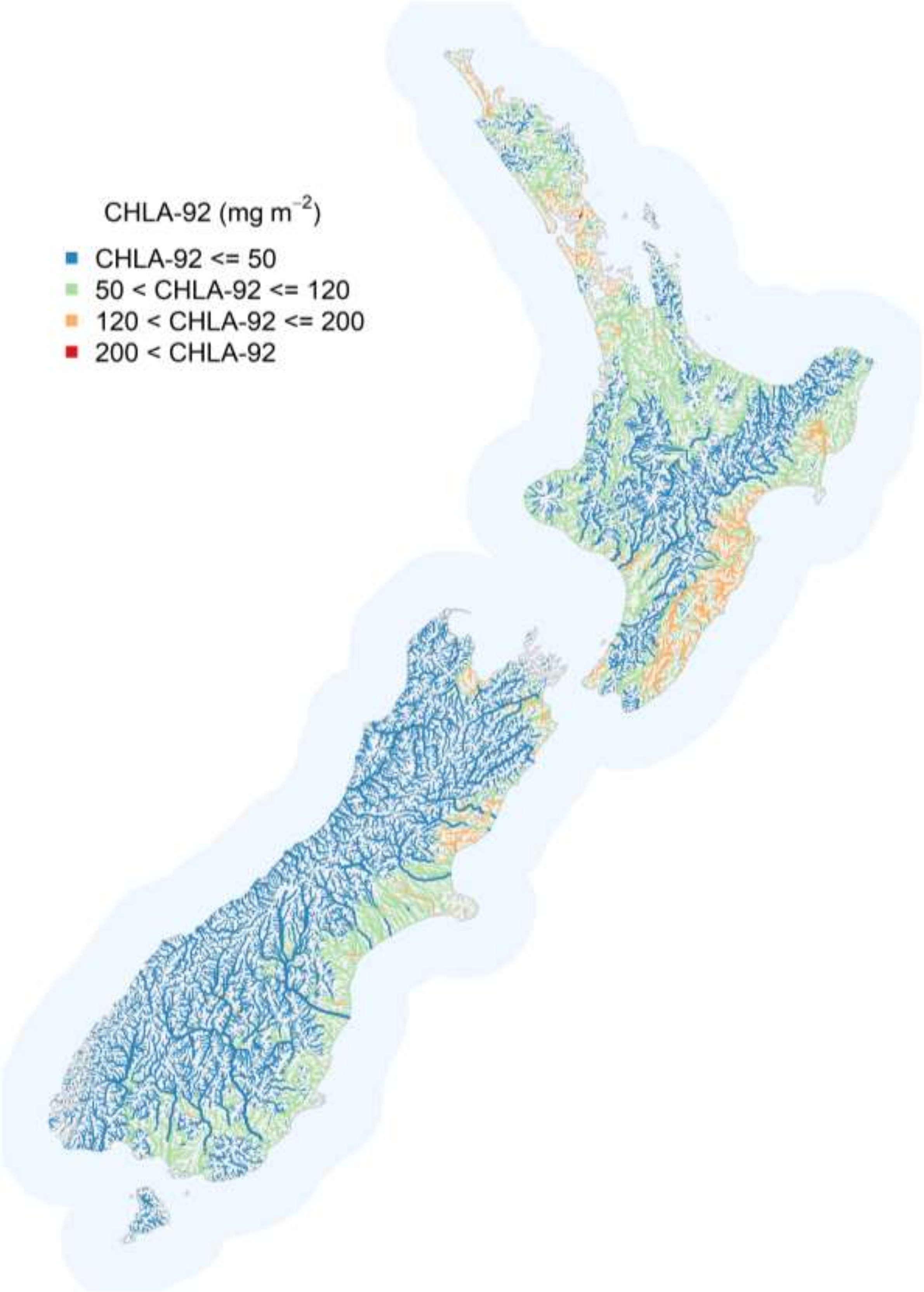

Figure 6-4: Predicted Chla_92 for all nzsegments with stream order 3 or higher. Chla_92 (the 92nd percentile of chlorophyll *a*) is colour coded to correspond to the four Bands in the periphyton attribute in the National Objectives Framework in the NPS-FM.

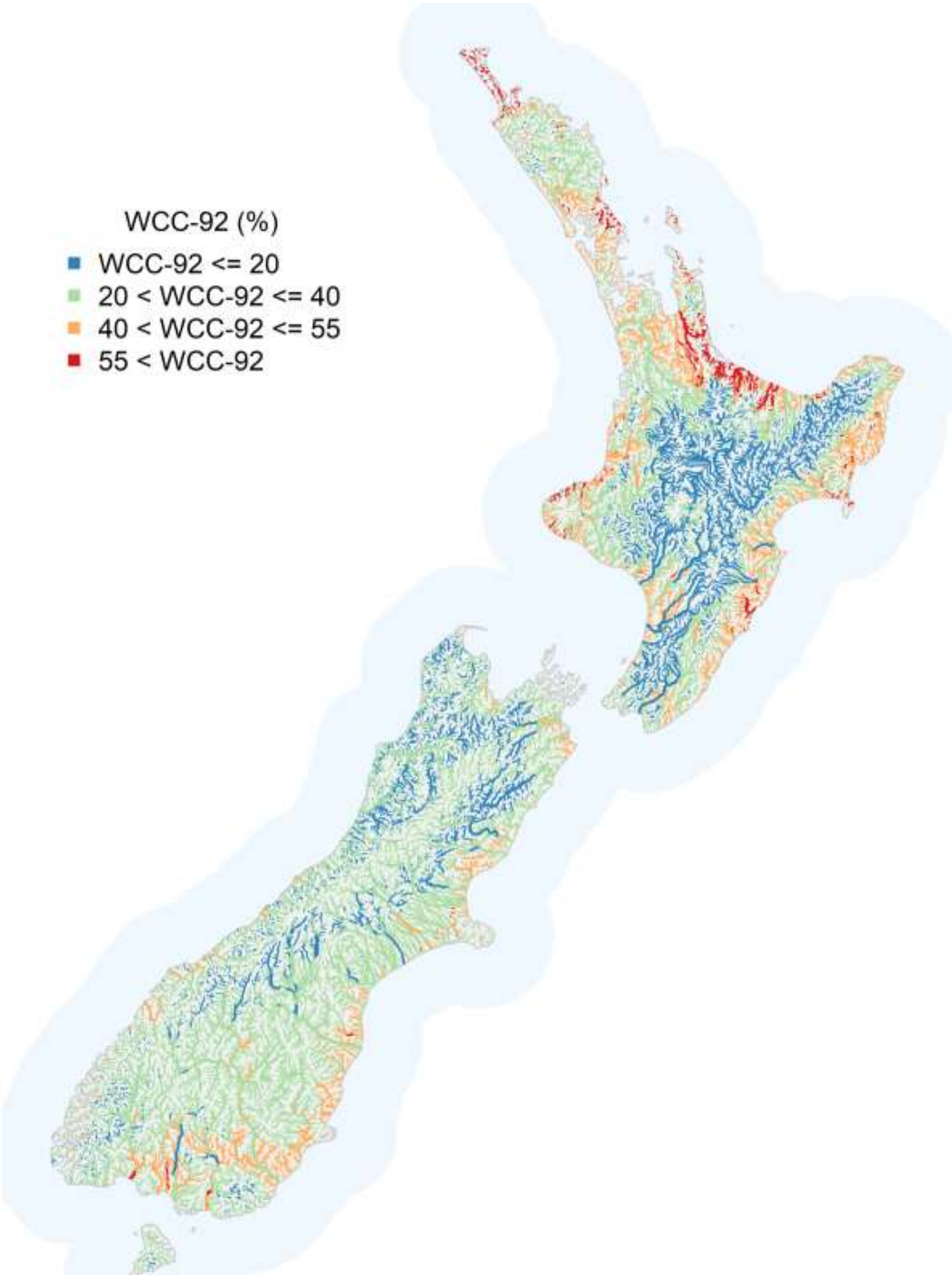

Figure 6-5: Predicted WCC_92 for all nzsegments with stream order 3 or higher. WCC_92 (the 92nd percentile of WCC) is colour coded to correspond to the four groups defined by Matheson et al. (2012) representing “excellent”, “good”, “fair” and “poor” ecological condition, respectively, at sites where other stressors are minimal.

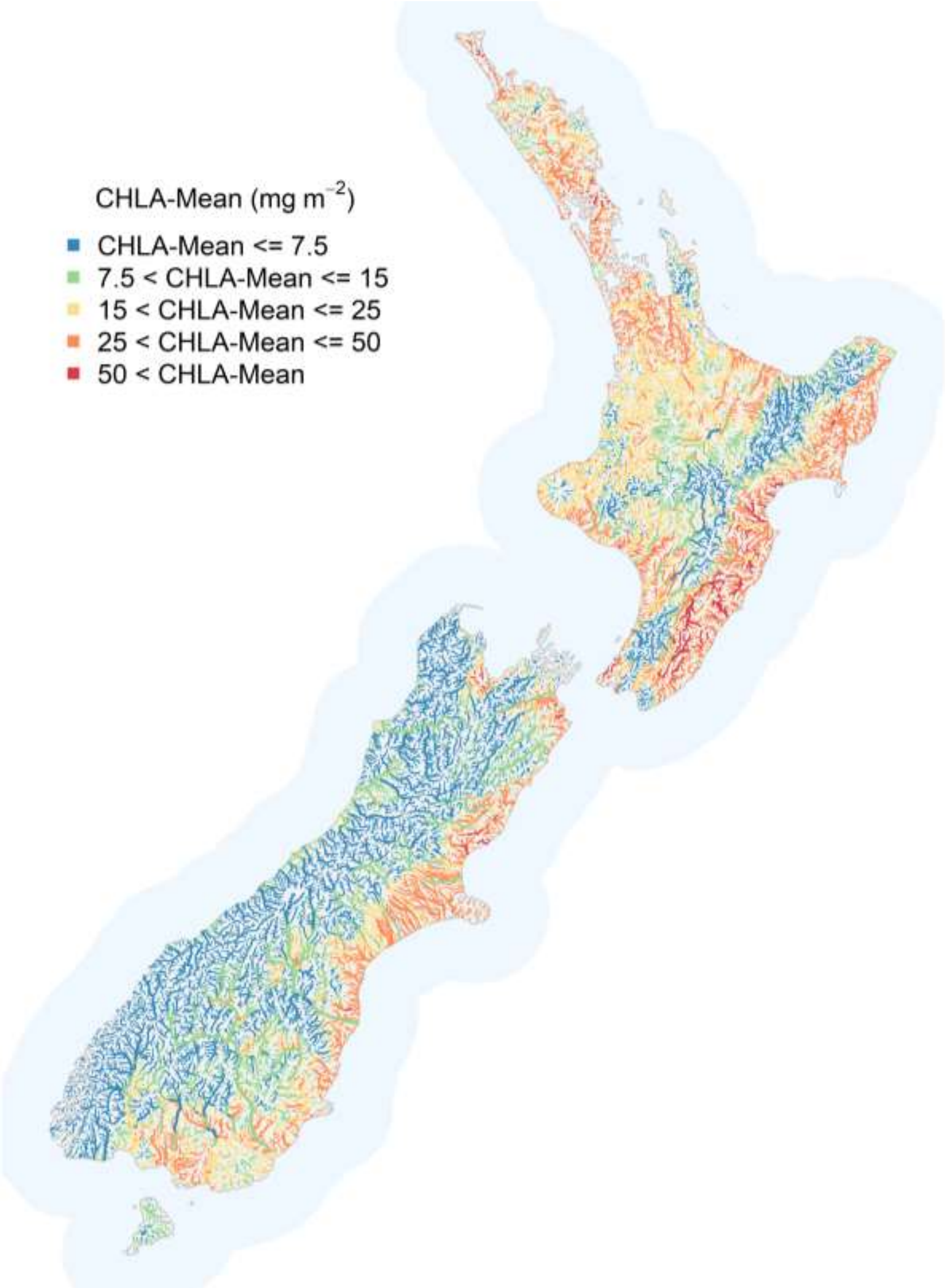

Figure 6-6: Predicted Chla_mean for all nzsegments with stream order 3 or higher. The thresholds for colour-coding are centred around the Biggs (2000a) guidelines for protection of biodiversity values (i.e., maintenance of good quality invertebrate communities), which specify a threshold for "mean monthly chlorophyll *a* of 15 mg/m^2" (i.e., annual mean chlorophyll *a* based on monthly measurements should be <15 mg/m^2). The lowest category (<7.5 mg/m^2) indicates that periphyton cover other than thin films rarely occurs.

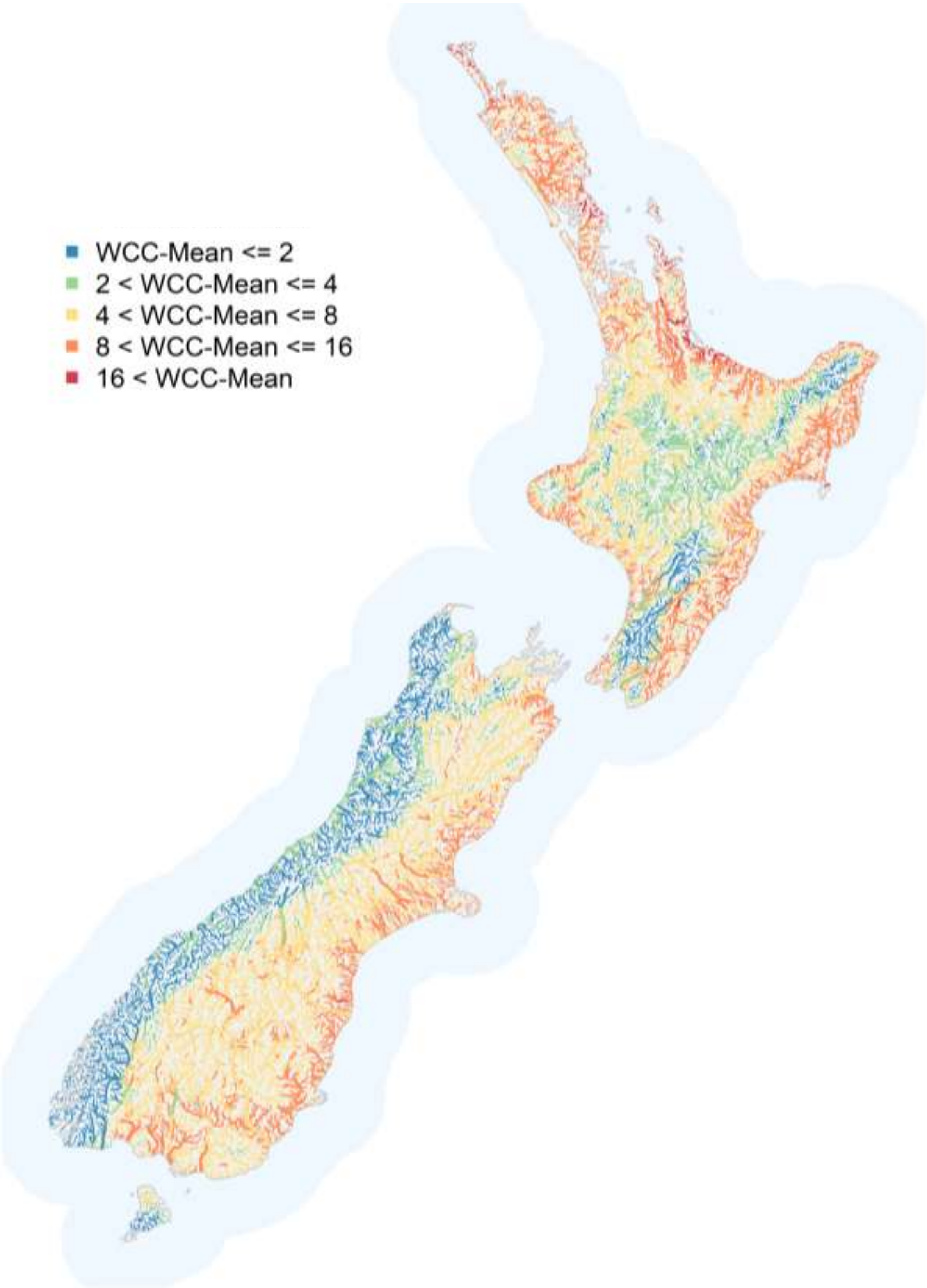

Figure 6-7: Predicted WCC_mean for all nzsegments with stream order 3 or higher. The thresholds for colour-coding are based on successive doubling of mean WCC starting at a low value (2) corresponding to rare and low cover by periphyton mats or filaments. WCC_Mean > 16 implies either noticeable cover by mats and filaments for much of the time, or periodic very high cover.

Predictions across REC classes and regions

Highest proportions of river length predicted to have Chla_92 > 120 mg/m^2 were in the WD L (Warm dry, Low elevation) and WD Lk (Warm dry, Lake fed) classes. The latter class is represented by less than 1% of the river length of the former (Figure 6-8). As reflected by the map (Figure 6-4), reaches in the CX (Cool extremely wet) climate class, and GM and M (glacial mountain and mountain) source of flow classes generally had lowest Chla_92.

Breaking down the classification by region shows that higher proportions of river length with Chla_92 > 120 mg/m^2 are predicted for Northland, Auckland, Hawke's Bay and Wellington than for Waikato, Bay of Plenty and Manawatu-Whanganui in the North Island, and most Chla_92 > 120 mg/m^2 in the South Island is predicted to occur in Canterbury.

The equivalent breakdown for WCC_92 shows highest WCC_92 (WCC_92 > 55%) occurring in mainly in the WX, WW and WD (Warm extremely wet, Warm wet and Warm dry) climate classes (Figure 6-11). These predictions of high periphyton cover were mainly in Northland and Bay of Plenty (Figure 6-12). The remaining North Island regions had predictions of intermediate WCC_92 (40 – 55%) in high proportions of reaches in the WX, WW and WD classes. In the South Island, WCC_92 > 40% was predicted to predominate in reaches in the WX, WW and WD climate classes. However, the total length of reaches in these climate classes was low (Figure 6-13).

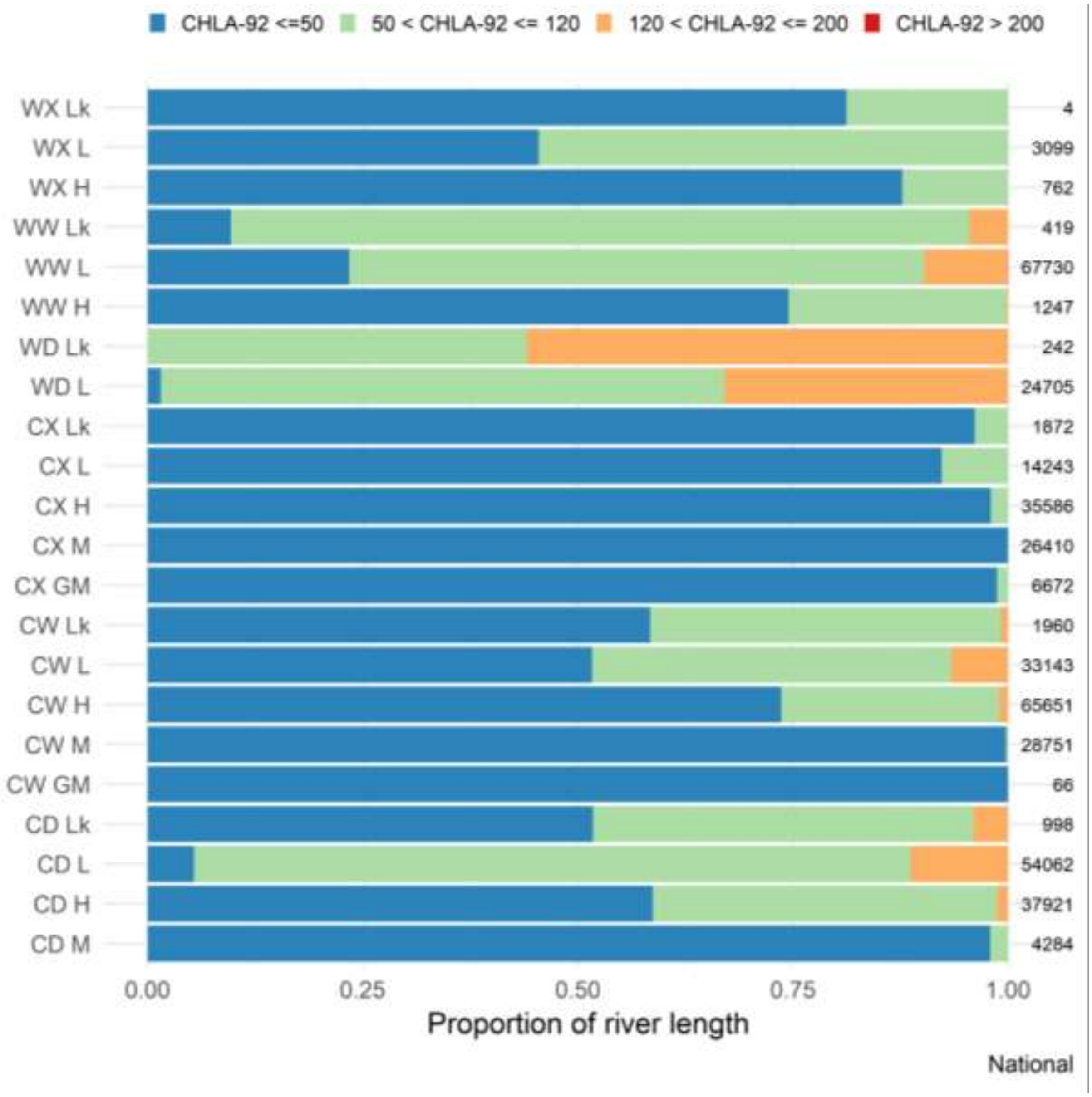

Figure 6-8: Proportions of river length predicted to fall into four classes of Chla_92 in each of 22 REC classes (level 2) across all New Zealand. River length calculated for Chla_92 classes corresponding to the four bands in the periphyton attribute in the NPS-FM. Level 2 REC classes distinguish reaches on the basis of climate and source of flow. Reach length in km is shown to the right of each horizontal bar plot. Note that some classes have very low representation. Note also that so few sites were predicted to have Chla_92 > 200 that thy are not visible on the plots.

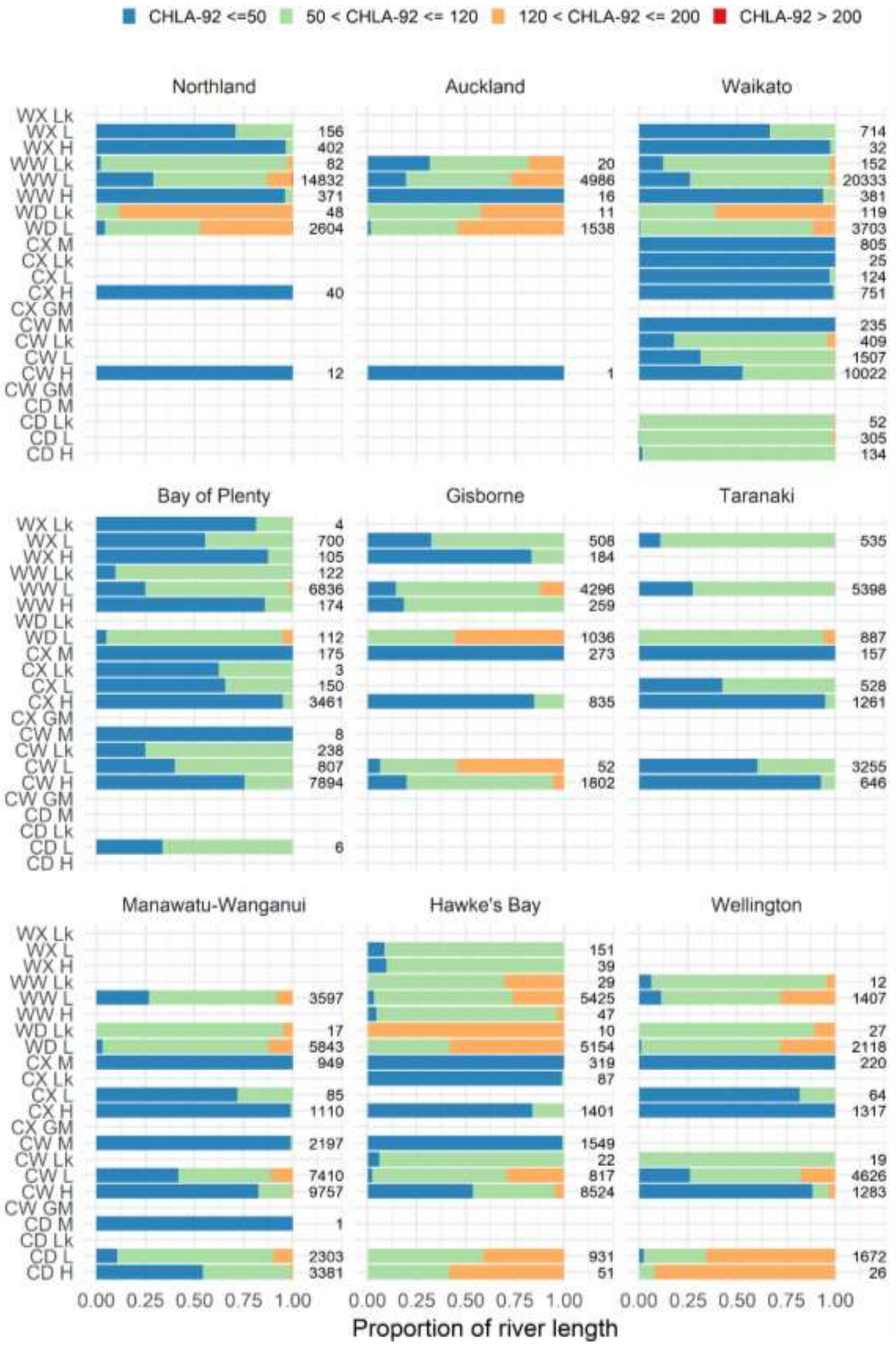

Figure 6-9: Proportions of river length predicted to fall into four classes of Chla_92 in each of 22 REC classes (level 2) by North Island region. Refer to Figure 6-8 for further legend.

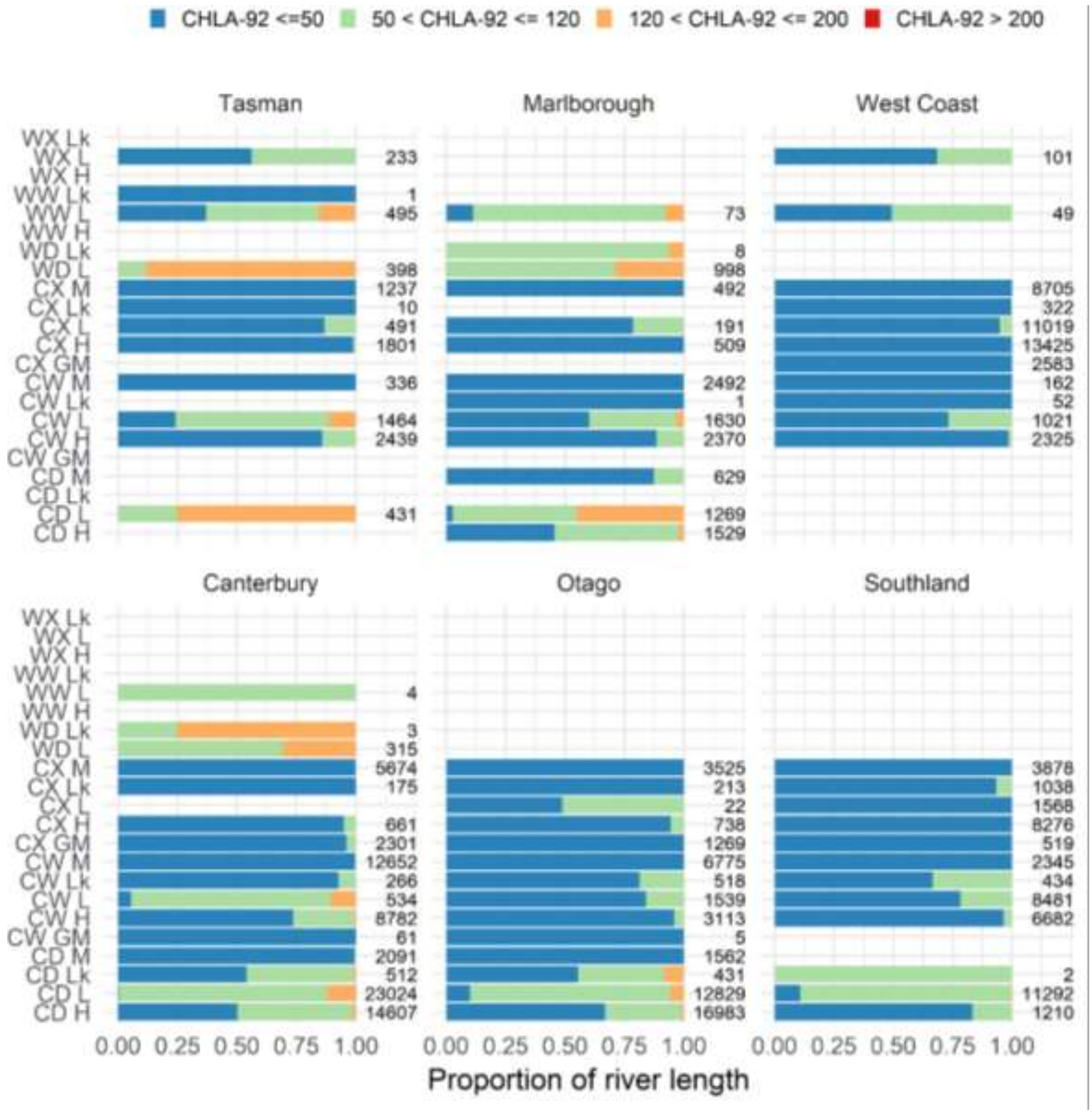

Figure 6-10: Proportions of river length predicted to fall into four classes of Chla_92 in each of 22 REC classes (level 2) by South Island region. Refer to Figure 6-8 for further legend.

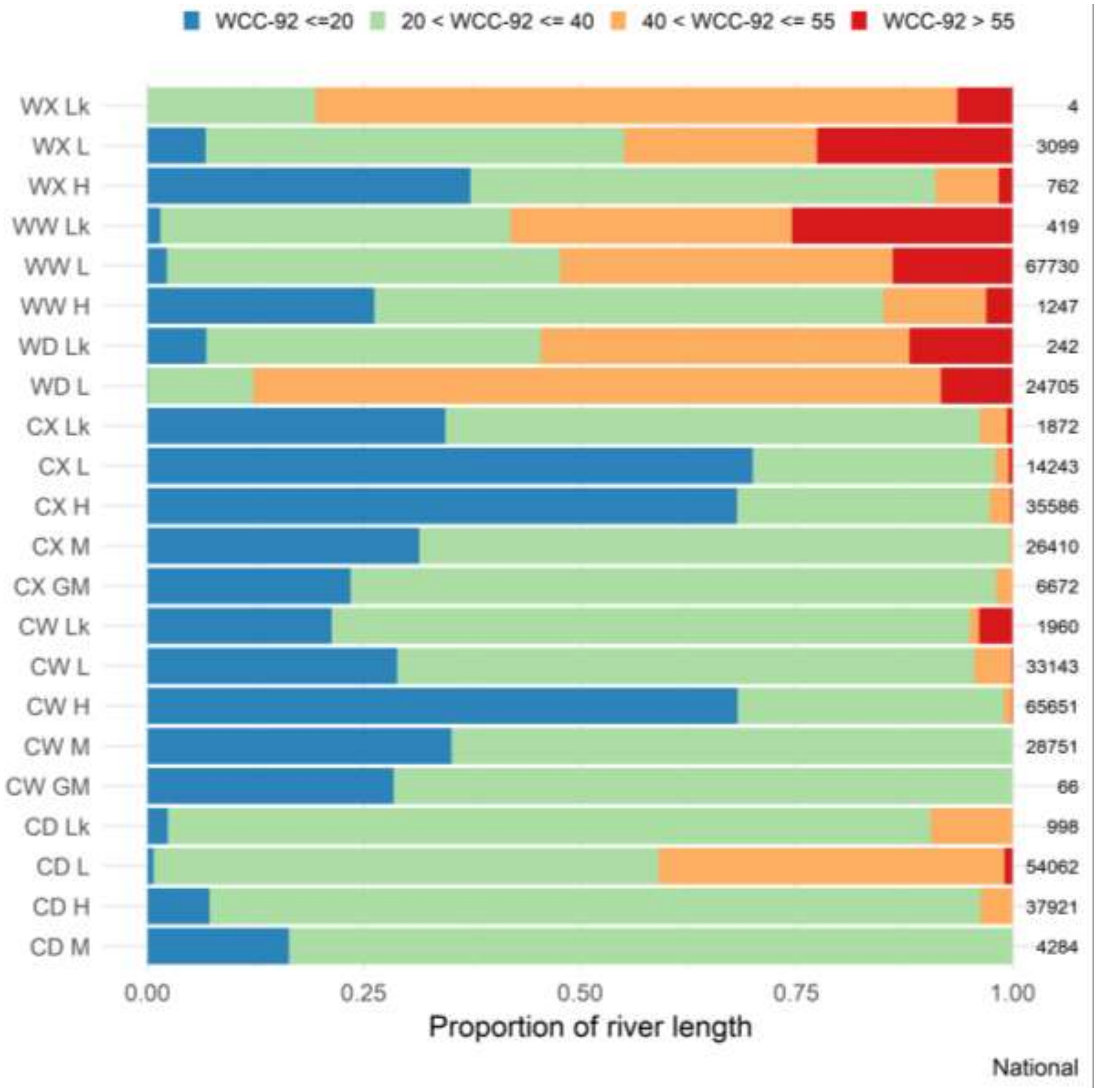

Figure 6-11: Proportions of river length predicted to fall into four classes of WCC_92 in each of 22 REC classes (level 2) across all New Zealand. River length calculated for WCC_92 classes corresponding to the four categories defined by Matheson et al. (2012). Level 2 REC classes distinguish reaches on the basis of climate and source of flow. Reach length in km is shown to the right of each horizontal bar plot. Note that some classes have very low representation.

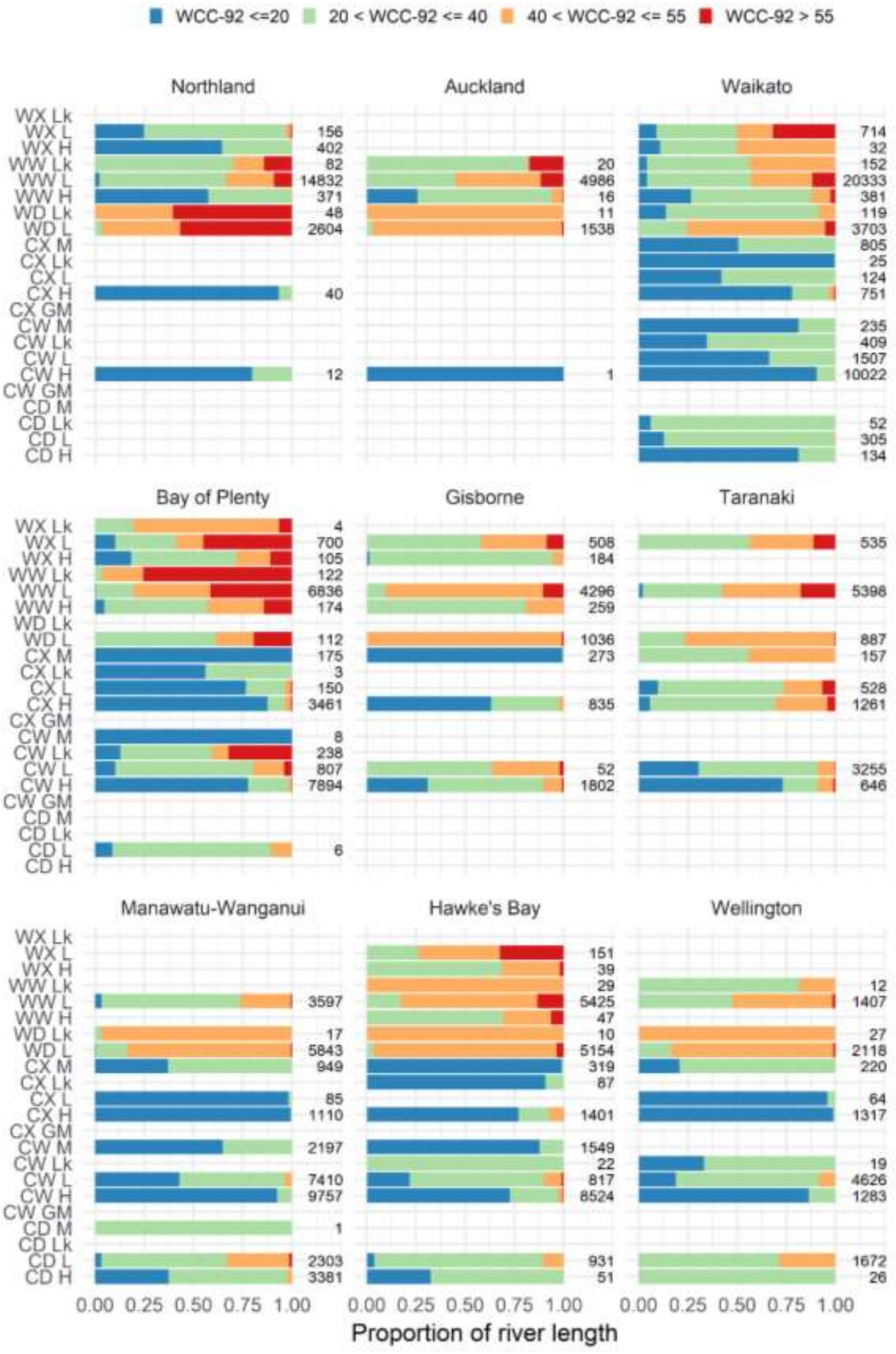

Figure 6-12: Proportions of river length predicted to fall into four classes of WCC_92 in each of 22 REC classes (level 2) by North Island region. Refer to Figure 6-11 for further legend.

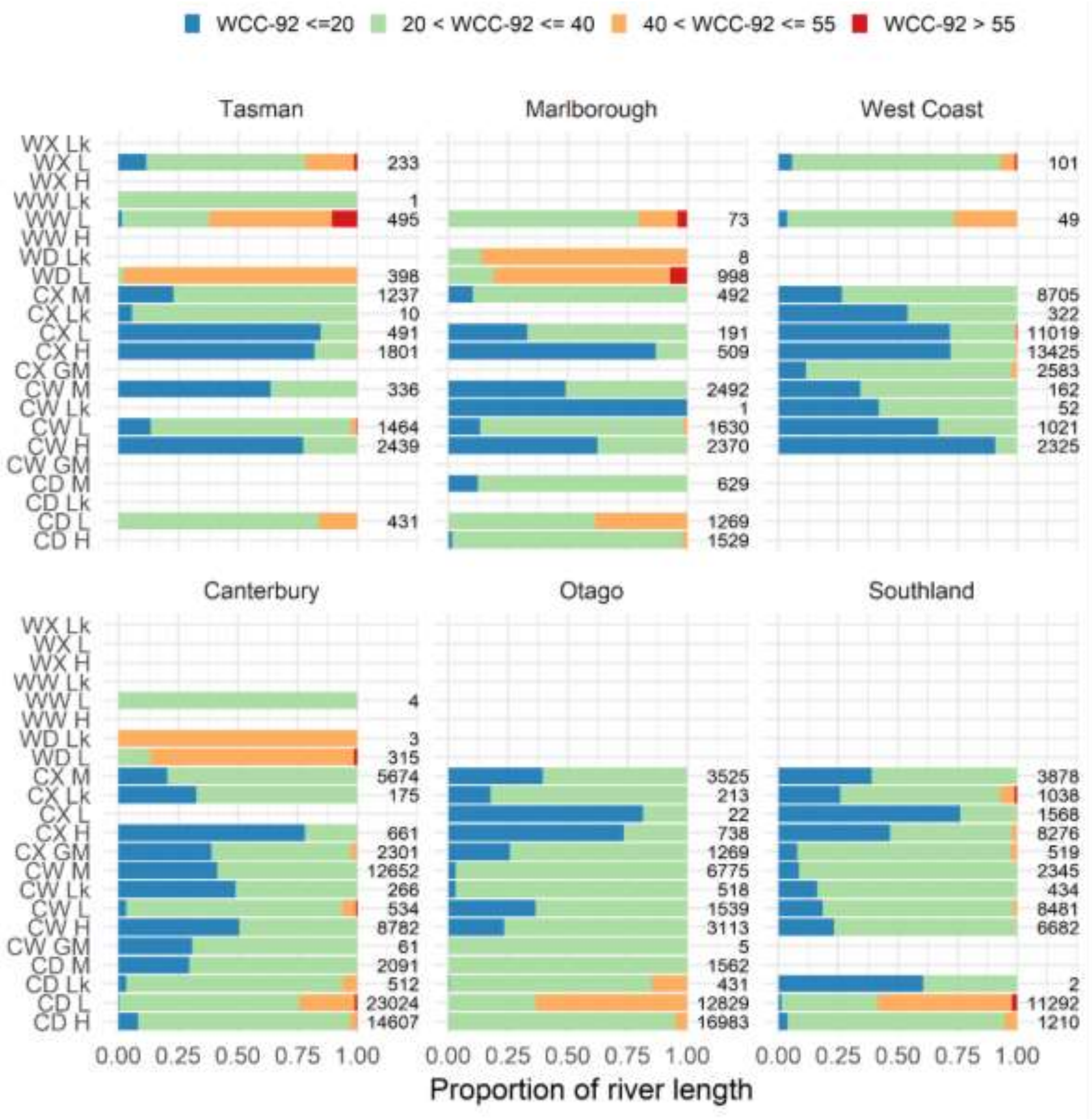

Figure 6-13: Proportions of river length predicted to fall into four classes of WCC_92 in each of 22 REC classes (level 2) by South Island region. Refer to Figure 6-11 for further legend.

6.5 Discussion

Random Forest models of periphyton developed using data from 196 sites across six regions of New Zealand had predictive performance no better than “average”, using the classification of Li (2016) (NSE range 0.37 to 0.41), but nevertheless produced intuitively sensible predictions of general patterns of periphyton abundance across New Zealand. As anticipated from a large body of research into drivers of periphyton biomass, lowest abundance was predicted to occur in high rainfall and/or mountainous areas, which also tend to have low nutrient concentrations, while highest abundance was predicted for warmer regions and coastal regions with high catchment development.

Two patterns that warrant discussion are:

- the major difference in the predictor variables driving the models for chlorophyll *a* and WCC, which led to a lack of correspondence between predictions for these periphyton variables;
- predictions of very low occurrence of river reaches that may fall below the bottom line of the chlorophyll *a* attribute in the NPS-FM (NZ Government 2017).

A further discussion topic is the degree of correspondence between modelled spatial patterns of periphyton and modelled spatial patterns of nutrients (primarily NO_3-N and DRP) presented by Whitehead (2018). Modelled nitrogen variables and DRP were predictor variables in the periphyton RF models. Nitrogen variables were important predictors, but DRP was not. In view of the results of the regression analyses (see Section 5.5.3), a comparison of periphyton and nutrient spatial patterns may be informative in relation to nutrient limit setting for the management of nuisance periphyton.

6.5.1 Chlorophyll *a* versus WCC

We expect a correlation between WCC and chlorophyll *a* because both are measures of periphyton abundance. Periphyton cover and chlorophyll *a* can be closely related in individual rivers (Kilroy et al. 2013) though the relationship does not hold in all rivers (Kilroy et al. 2018). Across all sites in the current dataset, WCC_92 and WCC_mean explained, respectively, 41% and 43% of the variance in Chla_92 and Chla_mean in the relationships:

$$\log_{10}\text{Chla\_mean} = 0.578 + 0.219\ (\text{sqrtWCC\_mean}) \qquad \text{(Equation 4)}$$

$$\log_{10}\text{Chla\_92} = 0.958 + 0.138\ (\text{sqrtWCC\_92}) \qquad \text{(Equation 5)}$$

Using these relationships, the chlorophyll *a* equivalents of the WCC thresholds specified by Matheson et al. (2012) to separate Excellent, Good, Fair and Poor stream condition were lower than the thresholds separating bands A and B, B and C and C and D in the NPS-FM periphyton attribute (Table 6-5). This discrepancy partly explains why the national WCC and chlorophyll *a* mapped predictions showed different patterns.

Table 6-5: Chlorophyll *a* corresponding to the WCC thresholds defining stream condition, estimated using relationships from the regional council dataset. Back-transformations of $\log_{10}$ chlorophyll *a* were corrected as described by Dambolena et al. (2009). Uncertainties around the estimates not shown.

	Matheson et al. (2012) WCC thresholds converted to chlorophyll *a* (mg/m²)		
Equation	**20**	**40**	**55**
Mean (Equation 4)	42	106	184
92nd percentile (Equation 5)	44	79	112
NPS thresholds (for comparison)	50	120	200

The differences in distribution patterns are also explained by the fact the WCC vs. chlorophyll *a* relationship varied across regions. The relationships were all positive and significant (Figure 6-14), but their explanatory power (R^2) ranged from 0.32 (Southland, ESD), to 0.45 (ECan, ECN), to 0.67 (HRC). In addition, the relationships differed so that the mean chlorophyll *a* equivalent of any given WCC varied across the regions. For example, the chlorophyll *a* equivalent of WCC at sites in the Bay of Plenty was, on average, lower than in any other region. Conversely, sites in the Greater Wellington and Horizons datasets had higher chlorophyll *a* relative to WCC than in other regions, on average (Figure 6-14).

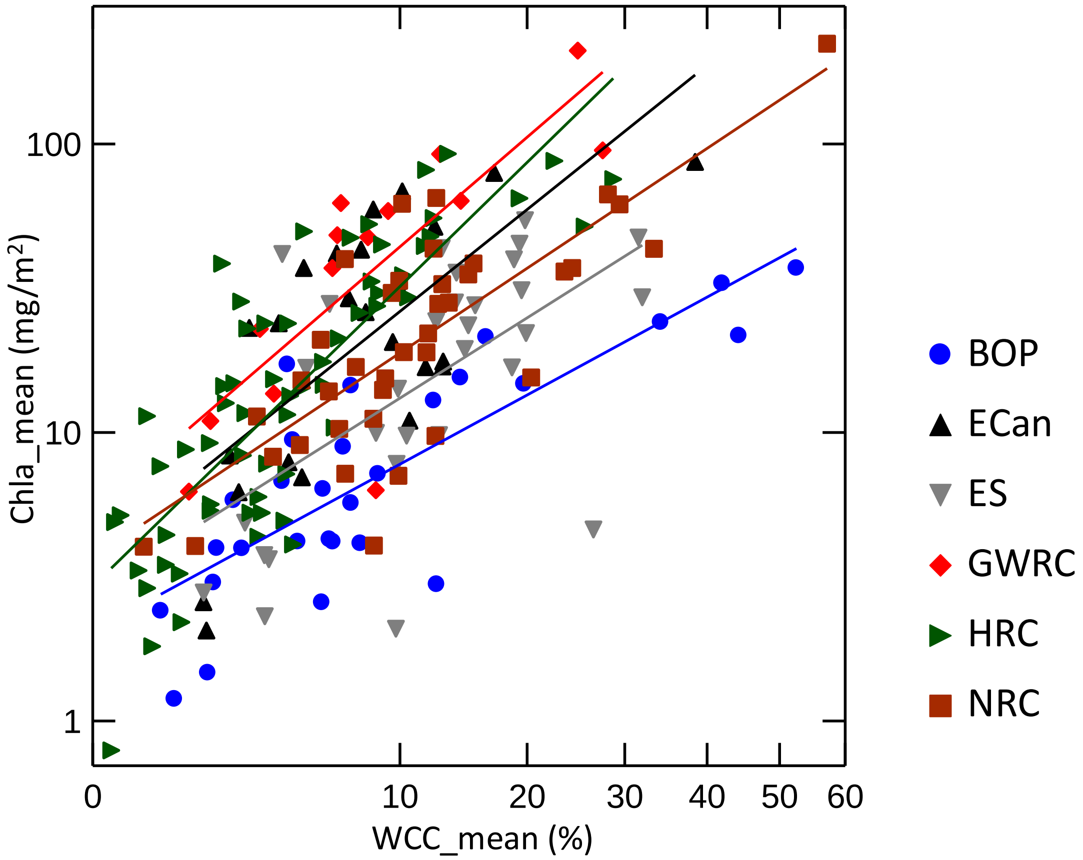

Figure 6-14: Mean chlorophyll *a* plotted against mean WCC at all 196 sites in the dataset, with sites colour-coded by region. Best fit lines are drawn through the data for each region. Regional Council abbreviations as in Table 3-1. Note that the x-axis is square-root transformed and the y-axis is log-transformed.

At least three factors may explain regional differences in WCC vs. chlorophyll *a* relationships. First, regions may have adopted different techniques for measuring both chlorophyll *a* and WCC. Several laboratories in New Zealand carry out sample analyses for chlorophyll *a* and use different methodologies. One source of variability is the extractant used. In New Zealand, the current MfE guidelines (Biggs 2000a) are based on chlorophyll *a* measured spectrophotometrically following extraction in boiling 90% ethanol (Biggs and Kilroy 2000). However, APHA guidelines specify extraction using acetone, which is used by some New Zealand laboratories. Several studies have demonstrated that the two extraction methods produce different results (e.g., Webb et al. 1992, and see discussion in Biggs and Kilroy 2000). It is beyond the scope of this report to discuss this in detail. We note that a National Environmental Monitoring Standard (NEMS) for periphyton is in preparation, and the issue of discrepancies in chlorophyll *a* as a result of collection, handling, and laboratory analysis techniques is within the scope of that document. Inter-laboratory comparisons are planned to inform the recommendations in the NEMS.

Secondly, in addition to discrepancies attributable to analysis techniques, there may be differences in the way visual assessments are carried out across regions. For example, some regions may distinguish periphyton mats of different thicknesses and include only thick mats (>3 mm thick, as estimated in the field) in the calculation of WCC. The NEMS document should also provide guidance on standardisation of visual assessments.

Thirdly, there may be genuine differences in the chlorophyll *a* – WCC relationship across regions because of regional differences in periphyton community composition. Such differences have already been noted within regions. For example, in Canterbury, sites classed as Alpine rivers were shown to have lower chlorophyll *a* per unit relative to cover than sites in Hill rivers (Kilroy et al. 2016). Furthermore, chlorophyll *a* concentrations can be directly affected by DIN concentrations, even with no change in cover or cell biovolume (Menendez et al. 2002). Therefore between-region and within-region drivers of differences in cover – chlorophyll *a* relationships could include DIN concentrations as well as other factors affecting periphyton community composition, such as temperature and water chemistry.

One clear pattern in the data was the tendency for many Bay of Plenty sites to have relatively low chlorophyll *a*, yet high WCC, with the latter driven by high cover by filamentous algae even though DIN concentrations were relatively low in the region (see Appendix B). A more detailed regional analysis would be required, with some information on community composition, to tease out potential causes of the pattern. Overall, discrepancies in relationships between WCC and chlorophyll *a* very likely lie behind the differences in predictor variables selected by the RF procedure for the two measures of periphyton.

6.5.2 Predicted low rate of breaches of the periphyton bottom line

The extremely low rate of prediction of Chla_92 exceeding the bottom line of the periphyton attribute in the NPS-FM (200 mg/m^2) was partly attributable to the feature of RF models that precludes predictions outside the range of the training data. Twelve sites in the training set of 196 sites (i.e., 6%) had Chla_92 > 200 mg/m^2 (maximum 744 mg/m^2). Given the bias in the dataset towards sites with Warm climate, Lowland source of flow and Pastoral land cover (see Section 3.2) the percentage of predicted Chla_92 > 200 mg/m^2 would be expected to be much lower than 6%. In fact, only 23 nzsegments of almost 150,000 (<0.015%) with stream order ≥3 were predicted to have Chla_92 > 200 mg/m^2. Thus, the RF predictions appeared to under-represent high Chla_92 and this may be a disadvantage of the RF method. Alternatively, it may indicate that Chla_92 > 200 mg/m^2 is a high threshold to cross at any site.

The spatial distribution map of Chla_mean (Figure 6-6) highlighted high values in parts of Northland, south-east North Island and north Canterbury (i.e., a similar distribution to Chal_92 > 120 mg/m^2 in Figure 6-4). Mean chlorophyll *a* > 50 mg/m^2 is approximately equivalent to a 92nd percentile of 126 mg/m^2, based on the assumption that periphyton abundance in rivers generally follows an exponential distribution (Snelder et al. 2014).[8] Therefore, mean chlorophyll *a* > 50 mg/m^2 roughly corresponds to NPS-FM periphyton bands C or D. However only ~1.8% of reaches had predicted Chla_mean > 50 mg/m^2, compared to ~6% with predicted Chal_92 > 120 mg/m^2 (bands C and D combined, see Section 6.4.4). Thus apparent under-prediction was even more evident for Chla_mean than for Chla_92. In the original dataset, 13% of sites had Chla_mean > 50 mg/m^2.

Another possible source of under-estimation of Chla_92 is that, in order to maximise the number of sites, we included sites with time series shorter than the three years required to place a site in a band of the NPS-FM periphyton attribute. Estimates of the 92nd percentile from such short records are likely imprecise. This cannot be remedied without further data from regional councils.

[8] The exponential distribution is defined only by its mean value. The chlorophyll *a* corresponding to any given quantile (i.e., proportion of samples) is defined using the function: $-\ln(Pr) * \lambda$, where Pr ($0 < Pr < 1$) is the probability that mean chl a (λ) is exceeded. Therefore the 92nd percentile of mean chlorophyll *a* of 50 mg/m^2 is estimated from the mean value as $-\ln(0.08)*50 = 2.526 * 50 = 126.3$ mg/m^2.

6.5.3 Spatial patterns of periphyton compared with spatial patterns of NO_3-N and DRP

A third topic that warrants brief discussion is the potential for a comparison of the predictions of periphyton with those for NO_3-N and DRP made by Whitehead (2018). The comparison should be of interest in view of the following directive to regional councils included in a "Note" following the periphyton attribute of the NPS-FM (NZ Government 2017):

> "To achieve a freshwater objective for periphyton within a freshwater management unit, regional councils must at least set appropriate instream concentrations and exceedance criteria for dissolved inorganic nitrogen (DIN) and dissolved reactive phosphorus (DRP)."

Predicted NO_3-N (as the variable NO3N_median) and DRP concentrations were used as predictor variables in the periphyton models. To be relevant to the "Note" in the periphyton attribute of the NPS-FM, strictly we should be using DIN rather than NO_3-N. DIN was not modelled by Whitehead (2018), but NO_3-N is a close substitute as most DIN comprises NO_3-N with only a small proportion of NH_4-N. For example, mapped NO_3-N in Whitehead (2018) covered a range from <17 to >354 mg/m^3, whereas the range for NH_4-N was <3 to >10 mg/m^3.

Whitehead (2018) mapped NO_3-N and DRP in six categories, with automatic selection of boundaries so that each category contained the same number of nzsegments. Both the nutrient and periphyton predictions were mapped to show nzsegments with stream order 3 or higher (for clarity). The highest category of NO_3-N mapped by Whitehead (2018) had a relatively low threshold (354 mg/m^3) compared to the range of observed geometric means in each region (see Appendix B). The range of DRP mapped by Whitehead (2018) (<3 to >17 mg/m^3) was more representative.

A qualitative comparison of the spatial distribution of Chla_92 (Figure 6-4) with NO_3-N and DRP (Figures 4-9 and 4-11 in Whitehead (2018)) shows that predicted Chla_92 in bands C and D (orange and red in Figure 6-4) corresponds to predicted NO_3-N ranging from 61 to > 354 mg/m^3 and to predicted DRP ranging from 4 to >17 mg/m^3. Such variability illustrates the high complexity of periphyton – nutrient relationships and suggests that limit-setting may be equally complex.

The periphyton models developed in this report are relatively weak. Therefore, a more quantitative comparison with modelled nutrient concentrations is premature. We suggest that such a quantitative comparison may be appropriate following future modelling efforts.

7 General discussion, synthesis and recommendations

The requirement in MfE's initial RfP for the work provided in this report was: "Nuisance algae: Provide a report on analysis of current periphyton data (collected in Outcome 1[9]) and the further development of statistical and/or mechanistic models that can be used to predict periphyton biomass for all river segments (in the River Environment Classification)."

To meet that requirement, in this report, we modelled nuisance periphyton across all of New Zealand using two empirical statistical approaches: multiple linear regression and RF. Both methods required substantial datasets of observed data. Nuisance periphyton was defined as periphyton chlorophyll *a* that exceeded the bottom line defined in the periphyton attribute in the NPS-FM (NZ Government 2017). We also considered periphyton cover, and defined nuisance periphyton as WCC that exceeds a threshold defining "poor" ecological condition (Matheson et al. 2012).

This section is in three parts. We first discuss the statistical approaches used in this analysis, and their advantages and potential drawbacks for predicting periphyton nationally and across regions in New Zealand.[10] The second part comprises a brief synthesis of the outcomes of the statistical modelling. In the third part, we summarise recommendations arising from the analysis and results.

Further discussion on different modelling approaches is provided in the report on Part 2 of this project (Kuczynski 2019), which focuses on the development of mechanistic models (i.e., mathematical models that describe the processes driving periphyton growth and losses in rivers), rather than the empirical, statistical approach (i.e., purely data-based, and reliant on correlations) taken in this report. The potential for adopting a more mechanistic approach for deriving national predictions of periphyton is also covered by Kuczynski (2019).

7.1 Statistical approaches

7.1.1 Linear regression: multiple and stepwise

In Section 5, we used stepwise linear regression techniques to look for relationships between periphyton chlorophyll *a* and WCC at a national scale. Linear regression (with its variants, including multiple linear regression) is one of the oldest techniques used by ecologists to build predictive relationships between biota and environmental variables (Guisan et al. 2002). Although many other techniques are now available (see below), linear regression still has utility because of its ease of use and interpretation compared with more complex techniques (Aertsen et al. 2010, Huang et al. 2014), and superior predictive ability in some cases (Sharma et al. 2008). A useful potential output from multiple regression models is straightforward relationships (equations) that can be used to (a) estimate the dependent variables (in this case Chla_92, Chla_mean, WCC_92 and WCC_mean) at new sites, or (b) estimate levels of one of the predictor variables typically associated with set levels of the dependent variable. A relevant application of (b) is estimation of nutrient (DIN or DRP) concentrations associated with a periphyton target (such as the NPS-FM thresholds). This application was trialled in an analysis of periphyton data from the Horizons region (Appendix L in Kilroy et al. 2018). One limitation of such application of regression relationships is that care needs to be taken to restrict predictions to conditions that fall within the range of the data used to develop the relationship. For example, we identified in Section 5.1 that a limited range of DIN in the data used to

[9] Outcome 1 was a parallel task in the larger MfE project. The objective of outcome 1 was to update water quality state and trends, where water quality included periphyton. Insufficient data were available to include periphyton in outcome 1 and the analysis was transferred to the present project (outcome 2).
[10] Note that the discussion on statistical techniques is largely based on text from Kilroy et al. (2018).

develop existing periphyton models for New Zealand rivers (Biggs 2000a) means that application of the equations should be limited to low-DIN systems.

The requirements and assumptions of linear regression also limit its application for developing predictive relationships. Requirements of linear regression include: (a) normally distributed residuals (difference between observed value of the predicted variable and the predicted value); (b) homoscedasticity in the variance of the independent variable (i.e., even scatter of individual values around the mean value); (c) a linear relationship between the dependent and explanatory variables, which in many cases is not supported by data and observations. In addition, ideally there would be minimal collinearity among the independent variables.

Failure to meet requirements (a) and (b) can often be overcome by appropriate transformations of the data. Assumption (c) can also be addressed by data transformation, or the addition of polynomial or interaction terms to the model so that the dependent variable can display a non-linear pattern as the parameter increases linearly. Collinearity can make it difficult to identify optimal sets of explanatory variables from a range of candidate environmental parameters and can mask the effects of strong predictors (Graham 2003).

When datasets comprise biological observations along with a broad suite of potential explanatory variables, stepwise multiple regression can be used to try to identify the combinations of variables that best explain the observations. In stepwise regression, significant explanatory variables are in turn added (in forward selection) or non-significant terms are taken out (in backward removal) until a single, supposedly optimal, model is arrived at. Statistics assessing model fit, such as Akaike Information Criteria (AIC), are used at each step to assess whether terms improve model fit and thus should be retained or removed. The procedure is available in most statistical packages and is commonly applied in ecological studies. However, the drawbacks of stepwise multiple regression have been known for decades (e.g., Hocking 1976) and numerous authors have recommended that it should not be used (James and McCulloch 1990, Whittingham et al. 2006, Mundry and Nunn 2009).

The problems include:

1. inflation of Type 1 errors (inferring an effect when there is none) through inflating statistical significance by ignoring the fact that multiple tests are run (at each step) using the same data (this problem gets worse as the number of explanatory variables increases, especially if variables are correlated, Whittingham et al. 2006);
2. inability to select the true "best subset" and to show that alternative subsets of variables may provide solutions with similar explanatory power (refer to Whittingham et al. 2006, and Mundry and Nunn 2009, for more details).

Both problems are reduced when the sample size is very large, the effects of the predictors on the dependent variable are strong, and the number of predictor variables is small (Thompson 1995). The second problem (selection of an appropriate model) can be solved by using an information theoretic (IT) approach in which complete multiple linear regression is run on all subsets of the candidate variables, and the outputs are ranked according to various criteria that indicate an optimum or "best" model. Criteria include R^2 and adjusted R^2, the Akaike Information Criterion (AIC, Akaike 1974), Mallows' C_p (see Geyer 2003 for an explanation of each).

In the present analyses, the two main problems with stepwise multiple regression were minimised by meeting two of the criteria suggested by Thomson (1995) (see above): strong effects and small number of predictor variables. In addition, we used an IT approach (see Section 5.3) to reconfirm that the stepwise approach did indeed select optimal models.

It is important to realise that identifying the best model using an IT approach in no way increases the chances that the relationship represents cause and effect. In fact, no technique can distinguish cause-effect relationships from correlations (Graham 2003), particularly when multiple predictor variables are correlated. In the present analysis we are confident that there will be an element of cause and effect because decades of experimental and observational research have established that flows and nutrients influence periphyton chlorophyll *a* (see review by Larned 2010). An exception is that in this analysis conductivity was also included as a predictor in most of the best models. Current understanding of the mechanism behind the apparent positive effect of conductivity on periphyton standing crop is limited. The correlation has been observed in previous studies (e.g., Biggs and Price 1987, Chetelat et al. 1999) and it appears to be largely independent of DIN concentrations (which can influence conductivity). Refer to Kilroy et al. (2018) for further discussion.

Finally, an important step in all model development is model validation, i.e., testing predictive performance on independent data. When very large datasets are available, an option is to use cross validation. The dataset is divided into two or more subsets. The model is developed using one subset, and its predictive ability tested on the other subsets. With smaller datasets, the standard technique is leave-one-out cross validation (or k-fold cross validation, where k = 1) (Arlot and Celisse 2010), and that was the approach used in the present analyses.

7.1.2 Other statistical techniques

More recently developed statistical techniques for the analysis of large and complex datasets such as the New Zealand periphyton dataset include classification and regression trees (De'ath and Fabricius 2000) and their variants (boosted regression trees (BRT), RF) and Artificial Neural Networks (ANN). These methods have the advantage that no distributions are assumed for the data and therefore transformations need not be applied to the predictor variables. Machine-learning techniques can outperform traditional regression methods (Cunningham et al. 2009, Leclere et al. 2011). Different techniques have been applied and compared in a range of studies (e.g., Segurado and Araujo 2004, Aertsen et al. 2010). It is worth noting that the use of these more complex techniques does not guarantee that a strong or usable model will be identified (Oppel et al. 2012). Breiman (2001b) provides a useful discussion on the merits and drawbacks of regression-based and machine-learning techniques.

RF models often perform well in terms of the strengths of relationships identified and their utility lies in accurate classification (i.e., prediction) at new sites (Cutler et al. 2007). In this study, it was possible to predict periphyton for the entire REC network to obtain intuitively sensible national estimates of periphyton. However, in contrast to regression models, which can be easily applied to management (e.g., scenario testing) through the use of simple equations, prediction using RF is not available as a simple management tool. On the other hand, while simple regression models can easily be applied by managers, it is unlikely that a single model can successfully estimate national patterns or even regional patterns.

Further comparison of different modelling techniques is provided in Kucsynski (2019).

7.2 Synthesis of analysis

This study comprised analyses carried out in a series of steps. In **steps 1 and 2** periphyton and associated environmental data from six regional councils (Northland, Bay of Plenty, Horizons, Greater Wellington, Canterbury and Southland) were assembled a national dataset. We required monthly time series, ideally spanning three years or more. To extend the number of sites, some shorter time series were included. The final usable dataset comprised 194 sites. Representation was biased toward lowland sites in pastoral catchments, but there was reasonable representation across all REC climate, source of flow, geology and land cover classes. Flow data were available at 136 sites.

In **step 3**, we used flow data to identify at each site (if possible) the characteristic flow magnitude that reduces periphyton chlorophyll a to low levels. The flow magnitude (called the effective flow, EF) was expressed as multiples of the long-term median flow at each site. We identified the magnitude of the EF at 109 of the 136 sites with a flow record. The magnitude of the EF ranged from 1.5 to 16 x median flow. An EF was identified at almost all sites in Greater Wellington, Canterbury and Southland (61 of 65 sites with flow records). An EF could not be identified at 22 of the remaining 71 sites in Northland and Horizons region. We attempted to develop a random forest (RF) model to predict EF across the whole REC network but were unable to identify a useful model.

In **step 4**, multiple regression techniques (with cross validation) were used to develop relationships between chlorophyll *a* and periphyton cover (as weighted composite cover, WCC) and measured environmental variables. Periphyton variables were the 92nd percentiles and means of chlorophyll *a* and WCC calculated from the time series data (Chla_92, WCC_92, Chla_mean, WCC_mean). Predictor variables focussed on those known to influence periphyton growth rates and accrual and included mean accrual period calculated from the EF (at sites where it was identified), along with measured DIN, DRP, conductivity, substrate composition and temperature. The dataset size varied from 94 to 194 because not all sites had all predictor variables available. Key results were:

- across all available data, chlorophyll *a* was more predictable than WCC, but the strongest relationships were relatively weak (less than 40% of variance explained);
- no model was identified in which WCC was predictable;
- predictor variables in the strongest national models for chlorophyll *a* included DIN, DRP, conductivity and accrual period calculated from EF;
- all regional datasets except the Canterbury dataset out-performed the overall dataset in terms of model strength and predictive ability for chlorophyll *a* (but note that some datasets were very small, e.g., n < 10);
- DRP and (less often) DIN were included in some models with a negative coefficient, which is counterintuitive to our understanding of drivers of periphyton growth. This was attributable to a statistical feature of multiple regression models, but may also have been caused by species composition differences between rivers and regions.

We concluded that simple regression models performed too poorly across multiple regional datasets to produce useful national predictions. However, the results from datasets within regions were more promising consistent with earlier studies (from a comparison in **step 5**).

The initial plan for **step 6** was to use the regression models developed in steps 4 to make national predictions of periphyton abundance by substituting modelled predictor variables available from the

REC network database for the measured variables used to develop the models. In view of the weak performance of the regression models, and failure to identify a useful model for predicting EF across the network, the plan was changed. We used RF to derive predictions of periphyton chlorophyll *a* across the entire New Zealand river network, using modelled variables as predictors. The RF models for both chlorophyll *a* and WCC had average performance (on a scale proposed by Li, 2016) and were relatively unbiased. The most important predictor variables for Chla_92 and Chla_mean were conductivity, nitrate-N, TN and rainfall variability, in that order. Inclusion of two highly correlated variables representing N supply was discussed. The strongest predictors in the WCC models differed from those for chlorophyll *a*, and from each other. One variable (usTmin) was common to the top four predictors for WCC_92 and WCC_mean.

Spatial predictions derived from the RF models of Chla_92, WCC_92, Chla_mean across WCC_mean across the REC network produced patterns that were generally intuitively sensible. However, very few reaches were predicted to fall below the bottom line (band D) in the NPS-FM. Low prediction rates of sites in band D was attributed mainly to a feature of RF models that prevents predictions outside the range of the training data. In addition, only 6% of the sites in the training dataset were in Band D, despite a bias in the dataset towards lowland rivers in pastoral catchments.

Areas of potentially high chlorophyll *a* were highlighted better when Chla_mean was mapped, with Chla_mean >50 mg/m^2 predicted for south eastern North Island and coastal north Canterbury. Lowest Chla_mean (< 7.5 mg/m^2) was predicted to be concentrated in the eastern mountainous areas of the North Island, and the central mountain / foothills and western coastal areas of the South Island. Predicted mean WCC differed in that all of the eastern foothills of the South Island were predicted to have higher WCC than western areas and highest WCC was concentrated along most of the east coast and northern North Island, especially western Bay of Plenty.

Discrepancies between the spatial distributions of chlorophyll *a* and WCC were attributed partly to regional discrepancies in the relationship between WCC and chlorophyll *a*. For example, sites in Bay of Plenty had lower chlorophyll *a* relative to WCC than other regions. Potential reasons for the discrepancies may include differences in sample collection and analysis methods, and regional differences in periphyton community composition.

7.3 Summary of recommendations

Key findings from the analysis have prompted recommendations that extend to collection and analysis of periphyton data in general, as well as to future analysis of national datasets.

The first key finding was that simple regression relationships for predicting periphyton biomass from environmental variables performed better at a regional than at a national scale. Therefore, our first recommendation is that the **current effort to develop straightforward regression relationships for predicting periphyton within regions is justified and should continue** (e.g., Kilroy et al. 2017, 2018). The recommendation relates in particular to the need for councils to set nutrient limits for managing periphyton. A related recommendation is that the **current effort by regional councils to accumulate robust datasets should continue**, as the present analysis could potentially be improved if all the sites had datasets of equivalent quality (e.g., sufficiently long record, and including measures of substrate and shading (or preferably light at the streambed) at each site[11]).

[11] Detailed guidelines on measuring light at the streambed are in Matheson et al. (2012).

Expansion of datasets especially applies to the RF analysis and models. Despite relatively weak statistical performance, the model predictions appeared to be intuitively sensible at the national scale. The patterns were especially clear when Chla_mean and WCC_mean were mapped to show lower levels of biomass and cover. **Further rounds of modelling and mapping are likely to be informative**, especially if further robust regional council data becomes available. Other machine learning based regression techniques may be more appropriate than RF, particularly in relation to the limitation of RF models that they cannot predict outside the range of the observation data. For example, predictions from **multivariate adaptive regression splines (MARS)** models extrapolate beyond the observation data. If more robust models can be developed then **quantitative comparisons between modelled nutrient concentrations and modelled periphyton** may also be informative in relation to nutrient limit setting.

A second key finding was that we identified differences in predictor variables between chlorophyll *a* and WCC in both the regression models and RF models. For the RF models, differences were especially noticeable when the models were used to predict back onto the REC network. We identified that one driver of the differences was inconsistent relationships between WCC and chlorophyll *a*. Potential reasons for the inconsistencies were discussed. These included regional discrepancies in sample collection and analyses, even though all regions use the same general methodologies. To eliminate or confirm sources of differences we recommend **prioritising development and completion of a National Environmental Monitoring Standard (NEMS) for periphyton**. The document is underway and will cover a wide range of aspects of field and laboratory methodologies related to periphyton.

Related to the second key finding, we also suggest that **periphyton community composition data may also be useful for understanding regional differences in periphyton – environment relationships.** Such data need not be exhaustive: an account of dominant taxa present at times of peak biomass is likely to be sufficient.

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Appendix A List of regional council sites with periphyton data

RCid = regional council (BOP, Bay of Plenty; ECAN, Environment Canterbury; ES, Environment Southland; GWRC, Greater Wellington Regional Council; HRC, Horizons Regional Council; NRC, Northland Regional Council).

N (samples) refers to the number of chlorophyll *a* collected between the Start and Finish dates. N (months) is the period in months over which data were used in the analysis. In most cases this was all of the available data. In the HRC dataset we used data since 2015 only. % missing is the percentage of months for which there was no periphyton observation. EF = effective flow (in multiples of median flow) calculated as set out in Section 4.

Grey shaded sites were omitted from the analysis due to insufficient data.

	RC	Site name	E	N	REC1_ reachID	REC2_ segment	Linked flow site	Flow site name	Start_date	Last_date	N (samples)	N (months)	% missing	EF
1	BOP	Aongatete at Lockington Rd Quarry	1857715	5831495	4000540	4057509	NA		20-Oct-15	16-May-18	26	32	20	
2	BOP	Atuarere at Waiotahe Valley Rd	1967055	5773144	4012873	4089671	NA		15-Oct-15	24-May-18	24	33	27	
3	BOP	Horomanga at Galatea Rd	1928934	5746403	4020577	4110272	NA		23-Oct-15	14-Jun-18	17	33	49	
4	BOP	Horomanga u/s Troutbeck Rd	1934078	5741985	4021429	4113518	NA		23-Oct-15	14-Jun-18	17	33	49	
5	BOP	Manganuku u/s SH2	1983542	5752821	4019101	4105411	NA		26-Nov-15	23-May-18	15	31	52	
6	BOP	Mangaonuku at Takaputahi	2002005	5776006	4011811	4087410	NA		14-Oct-15	21-May-18	21	33	36	
7	BOP	Mangapae at Ruatahuna Rd	1937300	5716700	4026013	4133924	NA		22-Oct-15	22-May-18	20	32	38	
8	BOP	Mimiha at Ruatahuna Rd	1941150	5714900	4026248	4135233	NA		22-Oct-15	22-May-18	19	32	41	
9	BOP	Ngamuwahine at Reserve	1864551	5811383	4002930	4065653	NA		19-Oct-15	19-Mar-18	18	30	41	
10	BOP	Ohutu at Troutbeck Rd	1932945	5743875	4021106	4112374	NA		23-Oct-15	14-Jun-18	14	33	58	
11	BOP	Omaukora at Wairata	1979653	5755127	4018403	4103023	NA		17-Dec-15	10-Apr-18	16	29	45	
12	BOP	Oruamanganui at Waiotahe Valley Rd	1966683	5774951	4012220	4088222	NA		15-Oct-15	24-May-18	26	33	21	
13	BOP	Otangimoana at Forestry Rd*	1896603	5706057	4027146	4141467	NA		21-Oct-15	17-Oct-16	8	13	39	
14	BOP	Otangimoana at Matea Rd	1899007	5700775	4027587	4144926	NA		21-Oct-15	20-Apr-18	18	31	43	
15	BOP	Owhakatoro at Owhakatoro	1945029	5771567	4013425	4090767	NA		27-Nov-15	18-May-18	16	31	49	
16	BOP	Raroa at Raroa Rd	1954977	5768611	4014644	4093368	NA		27-Nov-15	18-May-18	17	31	45	
17	BOP	Tauranga at Wardlaw Glade	1954452	5774619	4012286	4088396	NA		9-Oct-15	13-Apr-18	13	32	59	
18	BOP	Te Rereatukahia at SH2	1857084	5837121	4000415	4056302	NA		20-Oct-15	15-May-18	25	32	23	

	RC	Site name	E	N	REC1_ reachID	REC2_ segment	Linked flow site	Flow site name	Start_date	Last_date	N (samples)	N (months)	% missing	EF
19	BOP	Tuapiro at Farm Bridge	1855187	5844992	4000199	4054525	NA		20-Oct-15	16-May-18	26	32	20	
20	BOP	Tutaetoko at Tutaetoko Rd	1981261	5775544	4011954	4087679	NA		13-Oct-15	23-May-18	17	33	48	
21	BOP	Waiaua d/s Oiratiti	1990496	5779697	4010618	4085103	NA		13-Oct-15	21-May-18	19	33	42	
22	BOP	Waihua at Galatea Rd	1934850	5759950	4017064	4099121	NA		20-Nov-15	15-Jun-18	19	32	41	
23	BOP	Waikokopu at Galatea Rd	1936322	5762575	4016456	4097515	NA		20-Nov-15	15-Jun-18	22	32	32	
24	BOP	Waiotahe at 1100 Waiotahe Valley Rd	1966899	5773685	4012417	4088645	NA		24-Nov-15	24-May-18	17	31	46	
25	BOP	Waiotahe d/s Kahunui Village Trust	1966171	5770448	4013691	4091375	NA		15-Oct-15	24-May-18	20	33	39	
26	BOP	Waitekohe at SH2	1857397	5834637	4000461	4056794	NA		19-Oct-15	15-May-18	29	32	10	
27	BOP	Waitukuaruhe at Ngaupokotangata confluence	2000387	5770726	4013781	4091580	NA		14-Oct-15	21-May-18	23	33	30	
28	BOP	Whakatane at Pekatahi Bridge	1949980	5781507	4010027	4083343	NA		9-Oct-15	10-Apr-18	10	31	68	
29	BOP	Whirinaki u/s Waiparera confluence	1922500	5714250	4026415	4136274	NA		25-Nov-15	22-May-18	16	31	49	
30	ECAN	Ashburton River North Branch SH72 bridge	1481476	5170855	13048738	13130188	68810	North Ashburton at Old Weir	26-Jul-11	17-Mar-14	31	33	7	3
31	ECAN	Ashburton River SH1 (Upstream discharge)	1498697	5137363	13058883	13148714	68801	Ashburton at SHBr	26-Jul-11	18-Jun-14	33	36	9	3
32	ECAN	Ashley R at Gorge bge	1537356	5213583	13036021	13111660	66204	Ashley at Gorge	22-Jul-11	20-May-14	32	35	10	3
33	ECAN	Conway River - SH1	1634333	5283594	13014759	13080679	64304	Conway at SH1	25-Mar-03	1-Jun-14	32	36	10	11
34	ECAN	Cust River Skewbridge Road	1569960	5197841	13040638	13118112	66417	Cust Main Drain at Threlkelds Rd	29-Jul-11	17-Jun-14	35	36	3	6
35	ECAN	Forkes Stream at SH8	1392505	5124833	13507097	13154190	71129	Forks at Balmoral	28-Jul-11	27-May-14	32	35	10	3
36	ECAN	Hae Hae Te Moana - Glentohi	1448565	5121786	13061335	13155759	69644	Te Moana at Glentohi	27-Jul-11	28-May-14	33	36	7	7
37	ECAN	Hurunui River	1607788	5250678	13023716	13094546	65101	Hurunui at SH1 Br	22-Jul-11	1-Jun-14	32	36	11	1.5
38	ECAN	Mason River At SH 70	1605361	5279773	13015738	13082259	64622	Mason at d/s Lottery River Confluence	28-Jul-11	20-Mar-14	29	33	13	10
39	ECAN	Opihi River at Rockwood bridge	1435674	5107413	13063543	13163015	69618	Opihi at Rockwood	27-Jul-11	26-May-14	33	35	7	7
40	ECAN	Opihi River SH1	1461845	5097378	13064793	13168406	69607	Opihi at No1 SHB	25-Jul-11	29-May-14	33	36	7	6
41	ECAN	Orari River Parke Rd	1471543	5100493	13064298	13166097	69514	Orari at U/S Ohapi Ck Confluence	25-Jul-11	29-May-14	34	36	5	6

	RC	Site name	E	N	REC1_ reachID	REC2_ segment	Linked flow site	Flow site name	Start_date	Last_date	N (samples)	N (months)	% missing	EF
42	ECAN	Pahau River - u/s Top Pahau Ford Rd	1582183	5265432	13019274	13087814	165122	Pahau at u/s Hurunui Confluence (Dalzells)	28-Jul-11	16-Jun-14	34	36	6	3
43	ECAN	Pareora River at Huts	1445310	5080560	13066255	13178049	70105	Pareora at Huts	27-Jul-11	30-May-14	32	36	10	4
44	ECAN	Rakaia R at the gorge < the bge	1491507	5180781	13046130	13126316	68526	Rakaia at Fighting Hill	21-Jul-11	17-Jun-14	34	36	7	3
45	ECAN	Rangitata River - Arundel SH72	1463785	5129533	13060064	13151719	69302	Rangitata at Klondyke	26-Jul-11	18-Jun-14	29	36	20	1.5
46	ECAN	Selwyn River - Whitecliffs	1510418	5187383	13043804	13122878	68001	Selwyn at Whitecliffs	21-Jul-11	17-Jun-14	35	36	4	9
47	ECAN	Temuka River Manse Bridge	1461765	5099435	13064432	13166783	69602	Temuka at Manse Br	25-Jul-11	29-May-14	34	36	5	8
48	ECAN	Tengawai River - Clelands bridge	1439869	5093098	13065189	13170715	69635	Tengawai at Cave Picnic Grounds	28-Jul-11	27-May-14	34	35	4	8
49	ECAN	Twizel River Downstream SH8 Bridge	1369324	5095663	13511847	13169345	71117	Twizel at L Poaka	28-Jul-11	27-May-14	33	35	7	7
50	ECAN	Waiau River - Above Second Bridge Leslie Hills	1583600	5273854	13017244	13084605	64602	Waiau at Marble Point	28-Jul-11	16-Jun-14	29	36	20	1.5
51	ECAN	Waihao River - McCullochs Bri	1439921	5037243	13069160	13202880	70902	Waihao at McCulloughs Br	27-Jul-11	1-Jun-14	34	36	5	14
52	ECAN	Waimak> Gorge	1523033	5198766	13040507	13117926	66401	Waimakariri at Old Highway Br	21-Jul-11	17-Jun-14	32	36	12	1.5
53	ECAN	Waipara at Teviotdale bge	1582016	5224963	13032346	13106425	65904	Waipara at Teviotdale	22-Jul-11	20-May-14	33	35	7	9
54	ES	Aparima River at Thornbury	1221246	4862422	15057386	15312336	78901	Aparima River at Thornbury	1-Nov-14	31-Jan-18	27	41	33	6
55	ES	Cromel Stream at Selbie Road	1239102	4942045	15027427	15264496	1	Cromel Stream at Selbie Road	4-Dec-14	12-Feb-18	34	40	15	8
56	ES	Dipton Stream at South Hillend-Dipton Rd	1236924	4897175	15045350	15294225	2	Dipton Stream at South Hillend-Dipton Road	6-Nov-14	12-Feb-18	33	41	19	10
57	ES	Dunsdale Stream at Dunsdale Reserve	1260283	4881576	15051163	15302981	3	Dunsdale Stream at Dunsdale Reserve	9-Dec-14	28-Feb-18	33	40	18	5
58	ES	Hamilton Burn at Affleck Road	1226219	4918606	15036486	15280148	4	Hamilton Burn at Affleck Road	1-Nov-14	12-Feb-18	39	41	5	3
59	ES	Hedgehope Stream 20m u/s Makarewa Confl	1249666	4866258	15056334	15310842		Hedgehope Stream 20m u/s Makarewa Confluence	1-Nov-14	25-Jan-18	27	40	33	
60	ES	Irthing Stream at Ellis Road	1243785	4931366	15031719	15271780	78637	Irthing Stream at Ellis Road	5-Dec-14	12-Feb-18	36	40	10	6
61	ES	Lill Burn at Lill Burn-Monowai Road	1187270	4891852	15047441	15297404	5	Lill Burn at Lill Burn-Monowai Road	11-Nov-14	24-Jan-18	24	40	40	0
62	ES	Longridge Stream at Sandstone	1258724	4909162	15040542	15286902	6	Longridge Stream at Sandstone	3-Nov-14	16-Jan-18	28	40	30	0
63	ES	Makarewa River at Counsell Road	1243565	4861168	15057721	15312789	78634	Makarewa River at Counsell Road	13-Jan-15	21-Feb-18	22	39	43	10
64	ES	Mararoa River at Weir Road	1186895	4936043	15029370	15267818	79737	Mararoa at The Cliffs (NIWA/Meridian operated)	30-Nov-14	21-Dec-17	20	38	48	5

	RC	Site name	E	N	REC1_ reachID	REC2_ segment	Linked flow site	Flow site name	Start_date	Last_date	N (samples)	N (months)	% missing	EF
65	ES	Mataura River at Gore	1286933	4886837	15049483	15300394	77504	Mataura River at Gore	16-Dec-14	21-Feb-18	23	40	42	1.5
66	ES	Mataura River at Mataura Island Bridge	1275360	4854054	15059279	15315077	77518	Mataura River at Mataura Island Bridge (NIWA)	19-Dec-14	22-Jan-18	20	39	48	2
67	ES	Mimihau Stream at Wyndham	1281312	4861933	15057618	15312637	7	Mimihau Stream at Wyndham	9-Dec-14	28-Feb-18	25	40	38	13
68	ES	Orauea River at Orawia Pukemaori Road	1197286	4884169	15050335	15301693	79751	Orauea River at Orawia Pukemaori Road	10-Nov-14	24-Jan-18	24	40	40	1.5
69	ES	Oreti River at Branxholme	1236806	4862307	15057362	15312337	8	Oreti River at Branxholme	22-Dec-14	31-Jan-18	20	39	49	3
70	ES	Oreti River at Three Kings	1219662	4955860	15021776	15254930	78608	Oreti River at Three Kings	4-Dec-14	7-Feb-18	35	40	12	7
71	ES	Otamita Stream at Mandeville	1276655	4897687	15045155	15293926	9	Otamita Stream at Mandeville	6-Nov-14	14-Feb-18	34	41	17	7
72	ES	Otautau Stream at Otautau-Tuatapere Road	1211972	4879606	15051985	15304031	10	Otautau Stream at Otautau-Tuatapere Road	1-Nov-14	12-Feb-18	27	41	34	6
73	ES	Upukerora River at Te Anau Milford Rd	1188503	4958017	15020897	15253881	11	Upukerora River at Te Anau Milford Rd	30-Nov-14	31-Jan-18	31	40	22	4
74	ES	Waiau River at Tuatapere	1189518	4877680	15052505	15305046	79701	Waiau River at Tuatapere	10-Nov-14	24-Jan-18	27	40	33	7
75	ES	Waikaia River at Waikaia	1276430	4928356	15032882	15273874	12	Waikaia River at Waikaia	13-Nov-14	11-Jan-18	29	40	27	2
76	ES	Waikaia River u/s Piano Flat	1290026	4948314	15024871	15260248	77563	Waikaia River at Piano Flat	13-Nov-14	8-Feb-18	31	40	23	6
77	ES	Waikaka Stream at Gore	1287349	4886052	15049464	15300377	13	Waikaka Stream at Gore	19-Dec-14	21-Feb-18	26	40	34	10
78	ES	Waikawa River at Progress Valley	1304746	4834934	15062197	15319599		Waikawa River at Progress Valley	19-Dec-14	19-Feb-18	24	40	39	
79	ES	Waimatuku at Waimatuku Township Road	1228428	4859573	15057950	15313130	15	Waimatuku at Waimatuku Township Road	1-Nov-14	27-Feb-18	30	41	28	3
80	ES	Waimea Stream at Mandeville	1274804	4898793	15044772	15293344	77525	Waimea Stream at Mandeville	3-Nov-14	14-Feb-18	34	41	17	0
81	ES	Wairaki River ds Blackmount Road	1189126	4899512	15044418	15292848	14	Wairaki River ds Blackmount Road	11-Nov-14	21-Dec-17	26	39	33	10
82	ES	Waituna Creek at Marshall Road	1258129	4838488	15061706	15318943	77602	Waituna Creek at Marshall Road	22-Dec-14	22-Aug-17	16	33	52	3
83	ES	Whitestone River d/s Manapouri-Hillside	1190428	4944699	15026001	15262148	16	Whitestone River d/s Manapouri-Hillside	30-Nov-14	31-Jan-18	26	40	34	3
84	GWRC	Horokiri Stream at Snodgrass	1761804	5450652	9009035	9259111	30912	30912	23-Aug-16	17-May-18	20	22	9	7
85	GWRC	Huangarua River at Ponatahi Bridge	1807009	5435213	9012636	9262975			16-Aug-16	3-May-18	18	22	18	1.5
86	GWRC	Hutt River at Boulcott	1761038	5437628	9012031	9262382	29809	29809	24-Aug-16	16-May-18	17	22	23	1.5

	RC	Site name	E	N	REC1_ reachID	REC2_ segment	Linked flow site	Flow site name	Start_date	Last_date	N (samples)	N (months)	% missing	EF
87	GWRC	Kaiwharawhara Stream at Ngaio Gorge	1749069	5431077	9013489	9263922	100	100	24-Aug-16	17-May-18	20	22	9	4
88	GWRC	Kopuaranga River at Stuarts	1826760	5469569	9004627	9254500	29264	29264	18-Aug-16	8-May-18	19	22	13	1.5
89	GWRC	Mangaroa River at Te Marua	1778726	5448590	9009586	9259708	29830	29830	24-Aug-16	16-May-18	18	22	18	5
90	GWRC	Mangatarere Stream at SH2	1809768	5452160	9008718	9258789	1504591	1504591	23-Aug-16	4-Apr-18	17	21	18	5
91	GWRC	Otaki River at Mouth	1777982	5485886	9000731	9250231	31807	31807	23-Aug-16	7-Jun-18	21	23	8	5
92	GWRC	Parkvale Stream at weir	1813515	5449469	9009215	9259306	1505742	1505742	23-Aug-16	4-Apr-18	15	21	27	
93	GWRC	Porirua Stream at Wall Park	1754366	5443031	9010725	9260915	30701	30701	23-Aug-16	17-May-18	20	22	9	
94	GWRC	Ruamahanga River at Gladstone	1820883	5449878	9009060	9259193	29201	29201	16-Aug-16	3-May-18	14	22	36	6
95	GWRC	Ruamahanga River at Waihenga	1804604	5436519	9012311	9262654	29202	29202	16-Aug-16	3-May-18	17	22	22	5
96	GWRC	Waikanae River at Greenaway Rd	1771223	5472915	9003856	9253695	31504	31504	23-Aug-16	7-Jun-18	21	23	8	6
97	GWRC	Wainuiomata River d/s White Bridge	1757315	5415739	9016527	9267124	29605	29605	24-Aug-16	6-Jun-18	18	23	21	9
98	GWRC	Waiohine River at Bicknells	1810614	5448099	9009625	9259732	29224	29224	16-Aug-16	4-Apr-18	15	21	28	3
99	GWRC	Waipoua River at Colombo Rd Bridge*	1825018	5462890	9006301	9256259	29257	29257	27-Jul-17	8-May-18	8	11	24	
100	HRC	Kumeti at Te Rehunga	1856499	5543295	7036367	7234284	1032501	Kumeti at Te Rehunga	10-Dec-08	10-Apr-17	99	49	3	3
101	HRC	Makakahi at DOC Reserve	1819444	5489684	7048874	7249258	1032518	Makakahi at Hamua	13-Aug-13	11-Apr-17	61	46	6	8
102	HRC	Makakahi at Hamua	1832591	5505688	7044946	7244807	1032518	Makakahi at Hamua	9-Dec-08	11-Apr-17	107	49	9	
103	HRC	Makotuku at Raetihi	1796646	5633817	7017142	7193268	33119	Makotuku at Raetihi	17-Dec-08	18-Apr-17	85	49	7	
104	HRC	Makotuku at SH49	1800443	5639220	7015868	7189858	33117	Makotuku at SH 49A Br	17-Dec-08	18-Apr-17	100	49	3	
105	HRC	Makotuku d/s Raetihi STP	1796948	5631615	7017619	7194503	33119	Makotuku at Raetihi	17-Dec-08	20-Mar-17	90	48	8	
106	HRC	Makotuku u/s Raetihi STP	1796711	5632113	7017619	7194503	33119	Makotuku at Raetihi	19-Jul-10	18-Apr-17	76	49	5	
107	HRC	Makuri at Tuscan Hills	1848497	5509791	7044151	7244003	1032591	Makuri at Tuscan Hills	19-Dec-08	11-Apr-17	92	49	16	7
108	HRC	Manawatu at Hopelands	1851798	5527796	7039708	7238779	32504	Manawatu at Hopelands	11-Dec-08	13-Mar-17	108	48	10	4
109	HRC	Manawatu at Opiki	1810011	5520560	7041173	7240461	1032560	Manawatu at Teachers College	18-Dec-08	13-Apr-17	78	49	32	2
110	HRC	Manawatu at Teachers College	1824387	5526978	7039938	7239118	1032560	Manawatu at Teachers College	15-Dec-08	12-Apr-17	86	49	30	2

	RC	Site name	E	N	REC1_ reachID	REC2_ segment	Linked flow site	Flow site name	Start_date	Last_date	N (samples)	N (months)	% missing	EF
111	HRC	Manawatu at Upper Gorge	1839584	5530866	7039002	7237871	1232566	Manawatu at Upper Gorge	11-Dec-08	12-Apr-17	90	49	18	3
112	HRC	Manawatu at Weber Road	1865100	5540804	7037199	7235487	32503	Manawatu at Weber Rd	10-Dec-08	13-Mar-17	91	48	10	7
113	HRC	Manawatu d/s PNCC STP	1819388	5525095	7040389	7239702	1032560	Manawatu at Teachers College	15-Dec-08	12-Apr-17	92	49	24	4
114	HRC	Manawatu u/s PNCC STP	1819873	5526036	7039919	7239092	1032560	Manawatu at Teachers College	15-Dec-08	12-Apr-17	95	49	16	2
115	HRC	Mangapapa at Troup Road	1842110	5530306	7039229	7238188	1232563	Mangapapa at Troup Rd	19-Dec-08	10-Apr-17	100	49	3	10
116	HRC	Mangatainoka at Hukanui	1830063	5505684	7044988	7244863	1032555	Mangatainoka at Larsens Br	13-Aug-13	11-Apr-17	60	46	3	10
117	HRC	Mangatainoka at Larsons Road	1820866	5497913	7046821	7246861	1032555	Mangatainoka at Larsens Br	13-Aug-13	11-Apr-17	60	46	3	12
118	HRC	Mangatainoka at Pahiatua Town Bridge	1840277	5518541	7041713	7241237	1132511	Mangatainoka at Pahiatua	13-Aug-13	17-Jan-17	56	43	9	4
119	HRC	Mangatainoka at Putara	1815488	5493385	7048086	7248192	1032555	Mangatainoka at Larsens Br	13-Jan-09	11-Apr-17	112	49	7	16
120	HRC	Mangatainoka at Scarborough Konini Road	1837153	5515563	7042591	7242238	1032555	Mangatainoka at Larsens Br	13-Aug-13	11-Apr-17	57	46	10	14
121	HRC	Mangatainoka at SH2	1843011	5521292	7041260	7240726	1132511	Mangatainoka at Pahiatua	9-Dec-08	11-Apr-17	114	49	5	10
122	HRC	Mangatainoka d/s DB Breweries	1843596	5521694	7041260	7240726	1132511	Mangatainoka at Pahiatua	9-Dec-08	11-Apr-17	97	49	9	10
123	HRC	Mangatainoka d/s Pahiatua STP	1841651	5519576	7041558	7241056	1132511	Mangatainoka at Pahiatua	9-Dec-08	11-Apr-17	89	49	14	10
124	HRC	Mangatainoka u/s Pahiatua STP	1841264	5519731	7041605	7241121	1132511	Mangatainoka at Pahiatua	9-Dec-08	11-Apr-17	97	49	9	10
125	HRC	Mangatainoka u/s Tiraumea confl	1845834	5523649	7040681	7240042	1132511	Mangatainoka at Pahiatua	14-Jan-11	11-Apr-17	69	49	14	10
126	HRC	Mangatepopo d/s Genesis Intake	1820933	5674368	7008526	7164935	1033399	Mangatepopo Intake at Spillweir	24-Sep-10	20-Apr-17	76	49	5	
127	HRC	Mangatera d/s Dannevirke STP	1863973	5542486	7036883	7235055	NA	NA	10-Dec-08	10-Apr-17	98	49	3	
128	HRC	Mangatera u/s Dannevirke STP	1863960	5542672	7036883	7235055	NA	NA	12-Jan-09	10-Apr-17	99	49	3	
129	HRC	Mangawhero at DoC	1808048	5635824	7016679	7192145	33149	Mangawhero at Pakihi Rd Br	17-Dec-08	18-Apr-17	100	49	3	
130	HRC	Mangawhero at Pakihi Road Bridge	1800047	5632619	7017464	7194090	33149	Mangawhero at Pakihi Rd Br	17-Dec-08	18-Apr-17	87	49	14	9
131	HRC	Mangawhero d/s Ohakune STP	1805147	5635016	7016830	7192527	33149	Mangawhero at Pakihi Rd Br	17-Dec-08	18-Apr-17	97	49	3	
132	HRC	Mangawhero u/s Ohakune STP	1805583	5634912	7016972	7192890	33149	Mangawhero at Pakihi Rd Br	17-Dec-08	18-Apr-17	100	49	3	
133	HRC	Moawhango at Waiouru	1839008	5631360	7017746	7195026	32732	Moawhango at Waiouru	22-Oct-10	5-Apr-17	60	47	27	
134	HRC	Ohau at Gladstone Reserve	1797784	5495787	7047475	7247560	32106	Ohau at Rongomatane	18-Dec-08	19-Apr-17	116	49	2	4

	RC	Site name	E	N	REC1_ reachID	REC2_ segment	Linked flow site	Flow site name	Start_date	Last_date	N (samples)	N (months)	% missing	EF
135	HRC	Ohau at Haines Farm	1785787	5496172	7047460	7247544	32106	Ohau at Rongomatane	17-Dec-12	19-Apr-17	58	49	12	3
136	HRC	Ohau at SH1	1789583	5495187	7047669	7247769	32106	Ohau at Rongomatane	18-Dec-08	19-Apr-17	114	49	4	10
137	HRC	Oroua at Almadale	1826786	5549299	7035276	7232687	32514	Oroua at Almadale	11-Dec-08	13-Apr-17	91	49	16	3
138	HRC	Oroua at Apiti Gorge	1850190	5574817	7030716	7224620	32514	Oroua at Almadale	11-Dec-08	13-Apr-17	94	49	14	3
139	HRC	Oroua at Awahuri Bridge	1814585	5538400	7037684	7236108	NA	NA	11-Dec-08	13-Apr-17	90	49	18	2
140	HRC	Oroua d/s Feilding STP	1816094	5539897	7037436	7235818	NA	NA	11-Dec-08	13-Apr-17	90	49	20	3
141	HRC	Oroua u/s Feilding STP	1816667	5539958	7037428	7235694	NA	NA	11-Dec-08	16-Mar-17	83	48	33	3
142	HRC	Oruakeretaki at SH2	1858238	5539507	7037487	7235868	1232581	Oruakeretaki at SH2(Napier)	10-Dec-08	10-Apr-17	96	49	3	4
143	HRC	Pohangina at Mais Reach	1837110	5543456	7036595	7234641	32576	Pohangina at Mais Reach	15-Dec-08	12-Apr-17	98	49	7	4
144	HRC	Pohangina at Piripiri	1850837	5562129	7033068	7228878	NA	NA	15-Dec-08	12-Apr-17	94	49	14	
145	HRC	Porewa d/s Hunterville STP	1819486	5574766	7030743	7224660	NA	NA	3-Oct-12	15-Mar-17	48	48	14	
146	HRC	Porewa u/s Hunterville STP	1819615	5575154	7030646	7224518	NA	NA	3-Oct-12	15-Mar-17	51	48	8	
147	HRC	Rangitikei at Mangaweka	1840482	5589420	7027408	7218183	32702	Rangitikei at Mangaweka	16-Dec-08	8-Mar-17	91	48	10	3
148	HRC	Rangitikei at McKelvies	1795844	5537388	7037579	7235983	32760	Rangitikei at McKelvies	28-Jan-09	9-Mar-17	83	48	16	4
149	HRC	Rangitikei at Onepuhi	1811373	5560691	7033375	7229701	32703	Rangitikei at Onepuhi	19-Dec-08	9-Mar-17	87	48	18	4
150	HRC	Rangitikei at Pukeokahu	1861485	5608938	7023107	7208135	32763	Rangitikei at Pukeokahu	16-Dec-08	8-Feb-17	87	47	10	4
151	HRC	Tamaki at Reserve	1858597	5554208	7034557	7231558	NA	NA	10-Dec-08	10-Apr-17	99	49	3	
152	HRC	Tamaki at Stephensons	1860916	5540162	7037329	7235652	1332556	Tamaki at Stephensons	12-Jan-09	10-Apr-17	93	49	9	4
153	HRC	Tiraumea at Ngaturi	1847745	5516222	7042471	7242086	32529	Tiraumea at Ngaturi	19-Dec-08	14-Feb-17	72	47	34	4
154	HRC	Tiraumea d/s Mangatainoka confl*	1845825	5523873	7040656	7240009	#N/A	#N/A	19-Dec-08	4-May-10	11	NA	100	
155	HRC	Tokiahuru at Karioi	1815390	5627270	7018762	7197395	NA	Tokiahuru at Whangaehu Junct	23-Jan-09	21-Oct-14	69	18	7	
156	HRC	Tokomaru at Horseshoe Bend	1814282	5514659	7042760	7242415	2232510	Tokomaru at RiverlandFarm	18-Dec-08	13-Apr-17	100	49	1	13
157	HRC	Waikawa at North Manakau Road	1788884	5491087	7048450	7248627	1432008	Waikawa at Nth Manakau Rd	18-Dec-08	19-Apr-17	116	49	4	4
158	HRC	Waitangi d/s Waiouru STP	1828838	5628442	7018473	7196591	NA	NA	16-Dec-08	18-Apr-17	100	49	3	
159	HRC	Waitangi u/s Waiouru STP	1828826	5628643	7018473	7196591	NA	NA	16-Dec-08	18-Apr-17	100	49	3	

	RC	Site name	E	N	REC1_ reachID	REC2_ segment	Linked flow site	Flow site name	Start_date	Last_date	N (samples)	N (months)	% missing	EF
160	HRC	Whakapapa d/s Genesis Intake	1813243	5667184	7009900	7170971	33320	Whakapapa at Footbridge	22-Oct-10	20-Apr-17	72	49	9	
161	HRC	Whanganui d/s Genesis Intake	1825224	5676985	7007984	7162188	1033369	Whanganui R. at D/S Intake	24-Sep-10	20-Apr-17	77	49	1	
162	NRC	Awanui at FNDC	1625095	6113439	1004333	1004707	1316	Awanui at School Cut	27-Mar-08	22-Feb-18	39	39	33	
163	NRC	Hakaru at Topuni	1734330	5992416	1026482	1029172	46020	Hakaru at Topuni Creek Farm	26-Mar-08	16-May-18	46	41	20	
164	NRC	Hatea at Mair Park	1720284	6047290	1018018	1019677	5538	Hatea at Whareora Road	14-Apr-09	17-May-18	47	41	11	
165	NRC	Kaeo at Dip Road	1670326	6115833	1003935	1004253	2624	Kaeo at Fire Station	20-Nov-14	17-May-18	40	41	6	
166	NRC	Kaihu at Gorge	1661946	6042161	1019201	1020914	46611	Kaihu at Gorge	25-Mar-08	19-Apr-18	54	40	6	15
167	NRC	Kerikeri at Stone Store	1687631	6102447	1006289	1006886	3506	Maungaparerua at Tyrees Ford	14-Apr-09	17-May-18	52	41	6	
168	NRC	Mangahahuru at Main Road	1718886	6055192	1016447	1018024	46674	Mangahahuru at County Weir	17-May-18	17-May-18	39	41	6	
170	NRC	Mangakahia at Twin Bridges	1677333	6056762	1015928	1017446	46618	Mangakahia at Gorge	15-Apr-09	17-May-18	51	41	11	13
171	NRC	Mangakino at Mangakino Lane	1719727	6053270	1016854	1018555			18-Nov-14	24-May-18	41	42	4	
172	NRC	Mangamuka at Iwitaua Road	1649247	6103622	1006091	1006665			27-Mar-08	17-May-18	51	41	11	
173	NRC	Ngunguru at Coalhill Lane	1729072	6054775	1016568	1018140	4901	Ngunguru at Dugmores Rock	18-Nov-14	22-Mar-18	39	40	4	6
174	NRC	Opouteke at Suspension Bridge	1678503	6049460	1017632	1019255	1046651	Opouteke at Suspension Bridge	14-Jan-10	19-Apr-18	45	40	21	
175	NRC	Oruaiti at Sawyer Road	1655830	6121640	1003228	1003562			20-Nov-14	11-Apr-18	35	40	15	
176	NRC	Oruaiti at Windust Road	1654906	6125632	1002580	1002765			20-Nov-14	9-May-18	39	41	8	
177	NRC	Otaika at Otaika Valley Road	1715476	6039940	1019622	1021389	5659	Otaika at Kay	19-Aug-13	16-May-18	45	41	3	5
178	NRC	Pekepeka at Ohaeawai	1680346	6086802	1009328	1010345			21-Nov-14	9-May-18	42	41	0	
179	NRC	Peria at Honeymoon Valley Road	1645966	6111291	1004660	1005099			20-Nov-14	9-May-18	42	41	0	
180	NRC	Pukenui at Kanehiana Drive							21-Jul-16	17-May-18	23	23	1	
181	NRC	Punakitere at Taheke	1660001	6075453	1011729	1012993	47595	Punakitere at Taheke	11-Feb-13	14-Dec-17	31	36	42	2
182	NRC	Punaruku at Russell Road	1719724	6083074	1010009	1011158			21-Jul-16	17-May-18	22	23	5	18
183	NRC	Raumanga at Bernard Street	1718760	6044937	1018618	1020313	5528	Raumanga at Bernard Street	17-Nov-14	26-Apr-18	40	41	4	6
184	NRC	Ruakaka at Flyger Road	1726626	6029623	1021503	1023322	5901	Ruakaka at Flygers Road	26-Mar-08	16-May-18	51	41	3	
185	NRC	Stony Creek at Sawyer Road	1656071	6123396	1002927	1003147			20-Nov-14	9-May-18	41	41	3	

	RC	Site name	E	N	REC1_ reachID	REC2_ segment	Linked flow site	Flow site name	Start_date	Last_date	N (samples)	N (months)	% missing	EF
186	NRC	Tapapa at SH1	1643752	6105453	1005768	1006310			20-Jul-16	17-May-18	21	23	9	
187	NRC	Victoria at Victoria Valley Road	1637132	6110554	1004839	1005288	1351	Victoria at Victoria Valley Road	27-Mar-08	17-May-18	53	41	6	7
188	NRC	Waiarohia at Second Avenue	1719047	6046013	1018445	1020121	5527	Waiarohia at Lovers Lane	11-Feb-13	16-May-18	49	41	6	
189	NRC	Waiarohia at Whau Valley	1717568	6048671	1017919	1019541			6-Apr-09	24-May-18	50	42	4	
190	NRC	Waiaruhe at Puketona	1687317	6093001	1008155	1009326	3707	Waiaruhe at Puketona	21-Nov-14	9-May-18	39	41	7	
191	NRC	Waiaruhe downstream Mangamutu Confluence	1682873	6084561	1009776	1010922			21-Nov-14	9-May-18	34	41	20	
192	NRC	Waiharakeke at Stringers Road	1692604	6082806	1009997	1011114	3819	Waiharakaka at Willowbank	14-Apr-09	18-Apr-18	40	40	31	2
193	NRC	Waimamaku at SH12	1640666	6064914	1014099	1015604			17-Apr-09	19-Apr-18	41	40	16	
194	NRC	Waipao at Draffin Road	1701772	6045796	1018522	1020192	46641	Waipao at Draffin Road	19-Aug-13	18-Apr-18	44	41	6	
195	NRC	Waipapa at Forest Ranger	1662582	6096421	1008155	1009326	47804	Waipapa at Forest Ranger	17-Apr-09	17-May-18	52	41	8	3
196	NRC	Waipapa at Landing	1688150	6103986	1006063	1006630			14-Apr-09	17-May-18	52	41	6	
197	NRC	Waipapa at Waimate North Road	1682092	6095939	1007584	1008408			21-Nov-14	9-May-18	40	41	5	
198	NRC	Waipoua at SH12	1651633	6054443	1016579	1018149	46902	Waipoua at SH12 Bridge	25-Mar-08	17-May-18	54	41	1	
199	NRC	Waitangi at SH10	1686946	6093563	1008099	1008952	43602	Waitangi at SH10 Bridge	21-Nov-14	9-May-18	26	41	39	3
200	NRC	Waitangi at Waimate North Road	1681894	6093741	1008027	1008863	3725	Waitangi at Waimate North Road	11-Feb-13	18-Apr-18	42	40	23	6
201	NRC	Watercress at SH1	1687416	6086899	1009281	1010417			21-Nov-14	9-May-18	37	41	12	

Appendix B Data summary for each Regional Council dataset

Regional statistics (N, minimum, maximum, median, mean, standard deviation) are shown for the main variables used in the analyses. Nutrient statistics were calculated from geometric means at each site. Lines with median values in each region are highlighted in grey to aid comparisons. *Note that in the Northland dataset, conductivity values from two sites known to have tidal influence were removed from the dataset (Hatea at Mair Park, Kerikeri at Stone Store).

Statistic	Periphyton				Temperature					Cond (µS/cm)	Nutrients (mg/m³)				Substrate			Flow (m³/s)		Accrual (days)		
	chla_mean	WCC_mean	chla_92	WCC_92	mean	max	min	med	range		DRP	DIN	TN	TP	% coarse	% fine	Sand	mean	med	Da_EF	Da_3med	Da_10med
Northland Regional Council																						
N	38	38	38	38	38	38	38	38	38	36	38	38	38	38	37	37	37	22	22	12	22	22
Min.	0.6	0.3	4.3	1.2	13.9	18.7	5.8	13.7	7.1	60.4	4.7	3.2	66.3	9.7	0.0	0.0	0.0	0.4	0.2	15.4	14.6	31.4
Max.	96.7	57.1	717.0	94.4	17.3	24.2	11.8	17.3	17.8	233*	94.0	2393	2694	151.4	100.0	100.0	30.0	9.6	5.1	432	432	3894
Med.	7.2	10.0	54.3	34.2	16.1	21.6	9.7	16.1	12.1	112	12.5	88.9	293	25.7	10.0	35.0	10.0	1.4	0.7	38.6	18.6	60.5
Mean	11.9	12.8	86.0	36.4	15.9	21.6	9.6	15.9	12.0	121	18.4	245	442	31.8	23.2	42.2	12.0	2.7	1.4	91.2	38.6	244
SD	16.5	10.6	118.5	18.7	1.0	1.5	1.2	1.0	1.9	41.0	17.6	444	487	25.6	29.3	27.4	8.9	2.7	1.4	127	88.0	816
Bay of Plenty Regional Council																						
N	29	29	29	29	29	29	29	29	29	29	29	29	29	29								
Min.	0.1	0.5	3.1	0.0	10.8	11.7	0.0	11.1	1.2	46.5	4.1	11.0	40.5	9.2								
Max.	15.7	52.5	112	100	17.7	23.3	12.9	17.9	23.2	483.2	39.1	2174	2172	48.9								
Med.	1.7	6.1	22.6	21.6	14.5	18.6	8.6	15.4	10.5	74.5	26.9	40.6	88.4	37.4								
Mean	3.4	11.6	33.5	33.5	14.5	18.9	8.0	14.9	10.9	106.7	24.5	203	254	33.7								
SD	3.8	13.9	29.8	32.5	1.9	3.1	3.6	2.1	4.8	98.4	9.9	532	524	10.7								
Horizons Regional Council																						
N	61	61	61	61	61	61	61	61	61	61	59	59	56	56	61	61	61	45	45	37	45	45
Min.	0.2	0.0	2.0	0.1	8.5	10.7	2.9	8.2	5.0	52.0	4.9	5.8	55.1	0.0	0.0	17.0	0.0	0.5	0.3	14.0	9.9	32.3
Max.	52.1	28.7	220	81.6	17.3	24.7	9.5	18.3	19.2	335	188	1480	1853	255	40.0	62.0	13.0	103	67.2	287.3	41.1	433
Med.	3.0	3.5	40.5	12.4	12.6	19.2	6.5	11.7	13.0	117	10.5	186	493	20.6	12.0	30.0	2.0	6.7	4.1	37.4	19.3	86.4
Mean	9.6	5.6	60.8	16.6	12.3	18.9	6.4	11.9	12.5	136	16.3	339	571	29.0	14.0	31.4	2.4	22.3	14.3	51.1	20.0	155
SD	12.4	6.2	55.1	17.2	2.1	3.6	1.5	2.2	3.2	66.7	24.8	386	437	34.7	9.5	9.3	2.4	31.9	21.2	48.1	6.7	118

Statistic	Periphyton				Temperature					Cond (µS/cm)	Nutrients (mg/m³)				Substrate			Flow (m³/s)		Accrual (days)		
	chla_mean	WCC_mean	chla_92	WCC_92	mean	max	min	med	range		DRP	DIN	TN	TP	% coarse	% fine	Sand	mean	med	Da_EF	Da_3med	Da_10med
Greater Wellington Regional Council																						
N	14	14	14	14	14	14	14	14	14	14	14	14	14	14				13	13	12	13	13
Min.	0.8	1.0	11.3	3.3	13.2	18.5	6.7	12.5	9.6	67.6	2.1	41.1	113	5.8				0.2	0.2	8.4	10.9	66.2
Max.	126.9	27.6	593.2	69.8	17.8	25.8	10.2	18.6	16.6	400	34.8	1077	1296	40.9				74.3	49.0	102	28.2	544
Med.	6.8	7.3	125.6	22.8	14.6	21.4	8.4	13.7	13.4	117	6.3	370	546	13.4				4.3	2.3	34.8	18.1	87.9
Mean	18.0	9.5	153.5	27.3	14.6	21.8	8.4	14.3	13.4	164	9.0	451	633	15.5				15.3	9.3	37.4	18.4	127
SD	32.8	8.1	151.8	19.6	1.2	2.5	1.1	1.5	2.4	100	8.5	350	390.1	9.7				20.7	13.5	25.7	4.8	128
Environment Canterbury																						
N	24	24	24	24	24	24	24	24	24	24	24	24			24	24	24	24	24	24	24	24
Min.	0.1	1.3	6.1	2.6	8.0	14.3	1.2	9.0	11.1	21.2	1.1	9.3			0.0	21.0	1.0	1.2	0.5	13.3	23.9	57.7
Max.	24.2	38.5	271.1	77.8	14.5	22.6	7.1	15.8	18.6	300	23.1	4132			16.0	59.0	12.0	204	151	111	55.9	790
Med.	2.6	7.8	79.7	26.9	11.8	18.7	4.0	12.3	14.9	85.0	2.9	134			2.5	38.5	6.5	5.9	3.4	52.5	34.8	117
Mean	4.3	8.7	96.5	27.3	11.7	18.7	3.9	12.1	14.9	103	4.4	502			4.0	38.0	6.4	29.5	20.7	51.7	36.4	203
SD	5.5	7.6	76.3	18.5	1.5	2.1	1.6	1.6	2.4	63.0	4.5	903			4.3	11.6	3.4	50.0	37.6	25.6	7.0	186
Environment Southland																						
N	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	27	28	28	24	28	28
Min.	0.2	1.3	5.5	3.2	7.7	13.7	0.4	7.6	10.2	29.4	0.4	11.0	106.3	0.0	0.0	0.0	3.0	0.6	0.2	15.3	15.3	37.6
Max.	31.7	32.0	211	83.3	14.2	23.7	7.6	15.0	20.9	307.4	38.2	3624	4344	70.2	30.0	93.0	23.0	130	72.1	388	50.2	773
Med.	2.5	12.8	65.8	48.9	11.7	18.5	4.1	11.8	14.4	119	5.4	424	799	20.6	0.0	56.5	10.0	5.4	3.7	44.9	23.1	107
Mean	4.8	13.1	66.9	43.4	11.3	18.6	4.2	11.5	14.4	128	10.1	698	1046	26.9	3.8	51.8	10.1	17.4	11.3	75.4	26.5	209
SD	6.6	8.2	52.0	23.7	1.6	2.4	1.7	1.8	2.5	67.8	10.1	919	1063	21.0	6.5	23.9	5.5	29.1	18.7	86.6	9.3	205