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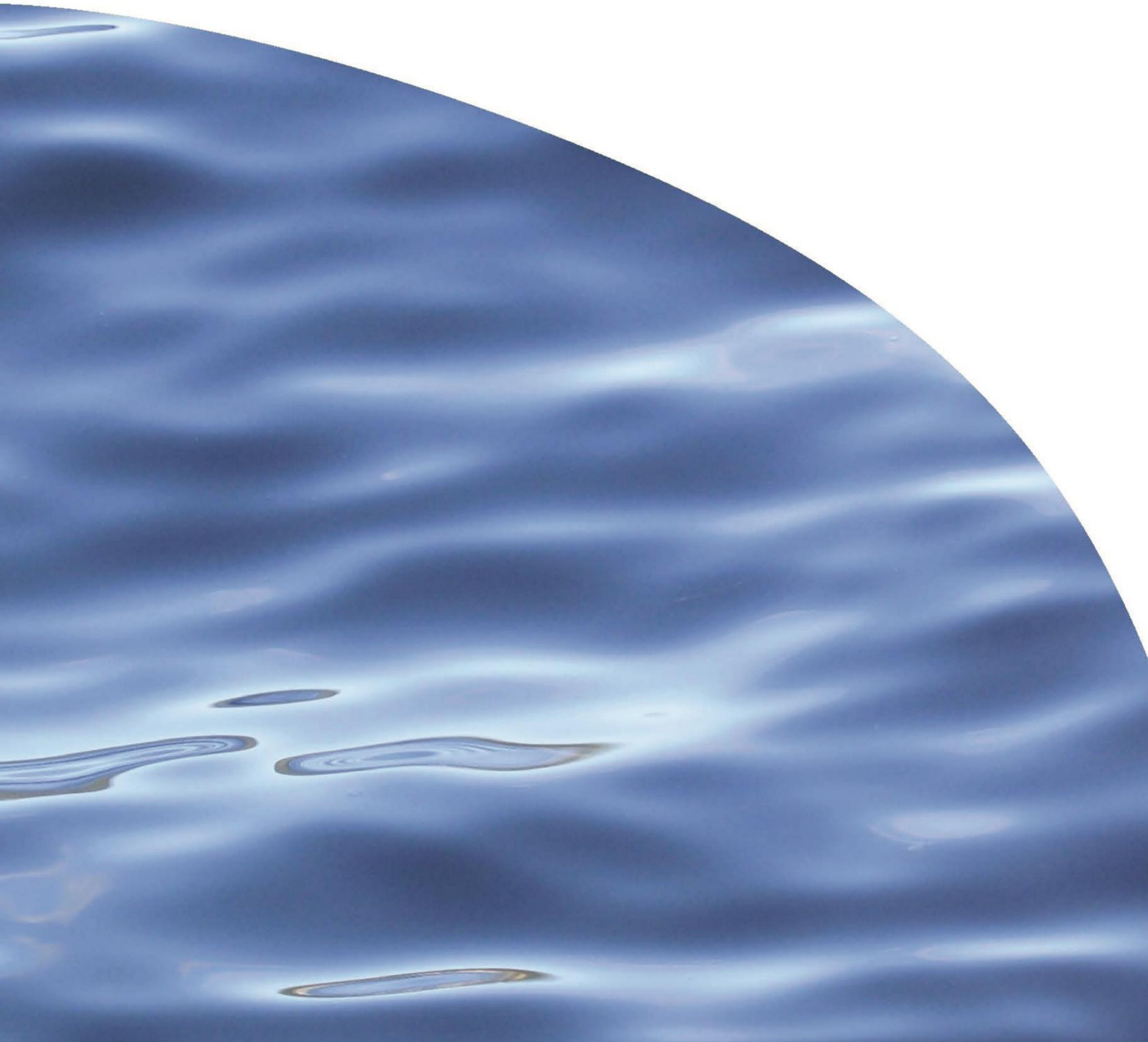
DRIVERS OF *PHORMIDIUM* BLOOMS IN SOUTHLAND RIVERS AND THE DEVELOPMENT OF A PREDICTIVE MODEL



DRIVERS OF *PHORMIDIUM* BLOOMS IN SOUTHLAND RIVERS AND THE DEVELOPMENT OF A PREDICTIVE MODEL

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EXECUTIVE SUMMARY

The prevalence of toxic benthic cyanobacteria blooms has increased in New Zealand rivers over the last decade. These blooms are most commonly formed by the genus *Phormidium. Phormidium* produces natural neurotoxins, known as anatoxins, which are powerful neuromuscular-blocking agents that pose a severe risk to both human and animal health. Potentially toxic *Phormidium* are known to be present at several sites in the Southland region. Concentrations of toxins at some Southland sites are extremely high and it has been shown that they can accumulate in aquatic organisms. Under the National Policy Statement for Freshwater Management, Environment Southland is required to manage freshwater resources to safeguard human and freshwater ecosystem health. To help achieve this goal, Environment Southland asked the Cawthron Institute to:

- Investigate the environmental drivers of *Phormidium* cover in Southland rivers using an existing dataset of *Phormidium* cover and physico-chemical variables for 31 river sites in the Southland region.
- Develop a real-time web-based predictive *Phormidium* cover model for two locations in the Southland region: Mataura River at the Seaward Downs and Aparima River at Thornbury.
- Provide a summary of Southland-specific information from a national model that was developed to predict stream susceptibility to *Phormidium* blooms.

The analysis of environmental drivers revealed a marked seasonal pattern with peak *Phormidium* cover at the end of the summer and strong site-to-site variability. The relationships with physico-chemical variables was in general very weak. This may be because sites were only sampled monthly, which increases the likelihood of *Phormidium* not being detected. The analysis indicated an increase in *Phormidium* cover with increasing water temperature up to 15 ºC, increasing dissolved inorganic nitrogen up to c. 0.05 mg L^{-1} and conductivity up to c. 150 µS cm^{-2}, whereas dissolved reactive phosphorus had a negative effect on *Phormidium* cover. In general, these findings aligned with patterns described for other rivers nationwide.

To increase knowledge on drivers of blooms, we recommend weekly surveying/sampling of a selection of sites (the ideal would be approximately 10) that have varying amounts of *Phormidium* cover.

Our mechanistic model was developed from data from rivers in other regions, because of a lack of observational data for the Mataura and Aparima rivers. The model provides relatively realistic real-time estimates of *Phormidium* cover. A web-based application which uses *in situ* continuous data from Environment Southland was developed to display the real-time estimations: (https://cawthron.shinyapps.io/Southland_Phormidium/). Model predictions should be

treated as preliminary until the model can be validated with site-specific data. We strongly recommend validation and on-going refinement of the model using site specific observational data.

Finally, we provide an overview of a national stream susceptibility model to *Phormidium* blooms developed in 2017 for the context of Southland streams. In general, the model confirmed our current knowledge of *Phormidium* in Southland, suggesting blooms are more likely to occur in lowland Eastern regions. The model outputs, in concert with local knowledge and observational data, may be useful for identifying rivers likely to be susceptible to *Phormidium* blooms.

Enhancing knowledge on the ecology and drivers of *Phormidium* blooms, and developing predictive warning tools for Southland rivers may help to safeguard humans and animals and ultimately lead to management strategies which reduce bloom formation.

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1. INTRODUCTION

Benthic cyanobacteria that produce toxins and form blooms have increased in prevalence in New Zealand rivers in the last decade. The most common bloom forming toxin-producing benthic cyanobacteria in New Zealand is *Phormidium* (McAllister et al. 2016). *Phormidium* forms thick black-brown cohesive mats that may cover many kilometres of the riverbed and it commonly produces neurotoxins collectively known as anatoxins. These toxins pose a human health risk through ingestion and skin contact.

Extensive blooms and high toxin concentrations have been reported in several Southland rivers. Sudden deaths of dogs were reported at the Mataura River in 1999 and 2000. Benthic *Oscillatoria*-like species mats were collected and mouse bioassays confirmed their high toxicity (death within 5 minutes, Hamill 2001). However, detailed taxonomic identification of the causative species was not undertaken. Species in the order Oscillatoriales are notoriously difficult to identify based on morphology alone, and it is likely that the *Oscillatoria*-like species documented in that study was actually *Phormidium.*

Heath and Wood (2010) reviewed *Phormidium* cover and anatoxin data from five rivers in the Southland region: Oreti, Makarewa, Waikaia, Mataura and Aparima. These rivers were sampled weekly (Oreti and Makarewa) or monthly in the summer of 2009/10. Anatoxins were detected at the Oreti, Waikaia and Mataura sites, with highest concentrations at Oreti River [0.71 mg kg^{-1} dried weight (dw)].

Wood and Puddick (2018) sampled the Mataura River at the Seaward Downs site every 2 to 3 hours for a 26-hr period. At the time of sampling *Phormidium* mats covered > 50% of the substrate and the bloom appeared to continue for many kilometres upstream from the sampling site. Anatoxin concentrations in *Phormidium* mat samples were extremely high, with the maximum concentration of 1,684 mg kg^{-1} dried weight being twice as high as previous nationwide records (McAllister et al. 2016). Additionally, anatoxins were detected in all water samples.

Environment Southland (ES) has a requirement under the National Policy Statement for Freshwater Management to manage freshwater resources to safeguard human and freshwater ecosystem health. National guidelines have been produced to establish monitoring protocols to manage risk from cyanobacteria on recreational activities (Ministry for the Environment and Ministry of Health 2009). The guidelines use a three-tier surveillance, alert and action sequence where monitoring and management requirements increase in response to severity and higher risk to human health. However, *Phormidium* blooms may undergo rapid changes in extent between infrequent sampling rounds, and ES does not always have the resourcing to monitor weekly. A better understanding of *Phormidium* ecology in Southland rivers will help to predict where and when to expect blooms and assist with making risk assessments. The aims of this project were to:

- investigate the environmental drivers of *Phormidium* cover in Southland rivers using an existing dataset of *Phormidium* cover and physico-chemical variables for 31 river sites in the Southland region
- develop a real-time web-based predictive *Phormidium* cover model for two locations in the Southland region: Mataura River at the Seaward Downs and Aparima River at Thornbury
- provide a summary of Southland-specific information from a national model that was developed to predict stream susceptibility to *Phormidium* blooms.

2. FACTORS DRIVING TEMPORAL AND SPATIAL VARIATION IN *PHORMIDIUM* COVER IN SOUTHLAND RIVERS

2.1. Methods

The dataset obtained from ES contained *Phormidium* cover data for 31 sites collected at approximately monthly intervals (n = 721). A list of all sites is provided in Appendix 1. Sampling dates ranged from 1 November 2014 to 9 September 2017, with from 1 to 33 surveys undertaken at each site (Appendix 1). Corresponding environmental data were available for 27 of the 31 sites. Data were not available for the Makarewa River at Counsell Road, Oreti River at Branxholme, Oreti River at Wallacetown and Waimatuku Stream at Waimatuku Township Road sites. Additionally, *Phormidium* cover and environmental data survey dates did not always correspond, thus in these instances environmental data was averaged at the month-year-site level and matched with the monthly *Phormidium* data. Because of the limited number of sites where *Phormidium* was recorded, and the low cover of *Phormidium* observed in most surveys, we chose to focus only on variables where relationships with cover have previously been observed (Wood et al. 2017a, 2017b). These included month of the year, water temperature, dissolved reactive phosphorus (DRP), dissolved inorganic nitrogen (DIN), turbidity and conductivity. Initial exploration of the relationship between *Phormidium* cover and environmental variables was conducted using the full dataset.

Generalised additive mixed models (GAMM, Hastie & Tibshirani 1990; Zuur et al. 2014) were used to model non-linear trends in percentage cover data only at sites where *Phormidium* was detected and associated environmental data were available (22 sites and n = 528). GAMMs were constructed using cubic splines, log normal distributed errors, in the 'gamlss' package (Rigby & Stasinopoulos 2005) within the software R (R Core Team 2016). Month of the year was included in the model as a continuous covariate to account for seasonal trends. The effects of nutrients were incorporated as log-transformed concentrations of DIN and DRP in mg L^{-1}. Water temperature and conductivity (a measure of dissolved salts) were both included as continuous covariates and 'Site' as a random effect with 22 levels. No hydrological variables (e.g. time since last fresh) were included in this analysis (largely because of the monthly resolution of the data), despite knowledge that it can influence *Phormidium* cover (Wood et al. 2017b; McAllister et al. 2018). Models were selected using a stepwise procedure based on the generalised Akaike Information Criteria and were validated by inspecting the deviance residuals. Final models were presented as partial effects plots, which show the effect of each predictor variable conditional to others already in the model. The partial effect of each predictor is displayed as cubic splines showing either negative or positive effects relative to the response variable overall mean (i.e., the intercept of the model) centred on zero. Partial plots also show standard errors around the fitted spline and residuals for each observation.

2.2. Results

2.2.1. *Phormidium* cover at all sites

The highest *Phormidium* cover recorded over the sampling periods was 72% at Dipton Stream at South Hillend-Dipton Road, 70% at Mataura River at Mataura Island Bridge, 50% at Waikaia River upstream of Piano Flat, and 49% at Upukerora River at Te Anau Milford Road (Appendix 1 and Figure 1). Average *Phormidium* cover across the sampling sites was generally low (max. 4.8%, Mataura River at Mataura Island Bridge). There was a high proportion of zeros in the dataset (86%) and *Phormidium* was not recorded in nine out of the 31 surveyed sites (Appendix 1). Figure 1 shows monthly *Phormidium* cover for sites with mean cover > 1%.

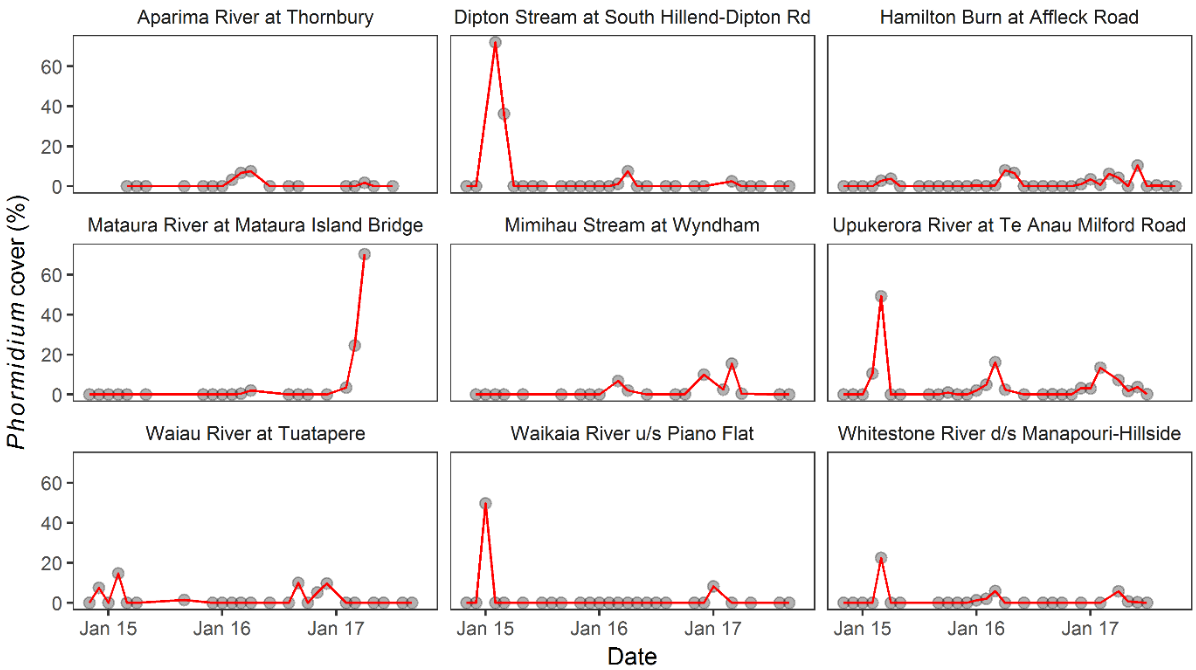

Figure 1. *Phormidium* cover at sites in the Southland region with mean cover > 1% (note sampling periods vary among sites, see Appendix 1).

2.2.2. Relationships between Phormidium cover and physico-chemical variables (all sites)

The relationships between *Phormidium* and physico-chemical parameters were generally weak and variable (Figure 2). This was primarily because of the large number of zero *Phormidium* cover values (shown at the bottom of each panel of Figure 2). Cover was generally higher during summer months compared to the rest of the year (Figure 2). Conductivity ranged between a minimum 0.1 µS cm^{-2} and a maximum of 116 µS cm^{-2}, however it did not show a clear relationship with *Phormidium* cover (Figure 2). There was a slight tendency for greater *Phormidium* cover at high DRP concentrations, which ranged between 0.002 and 0.15 mg L^{-1}. However, this apparent trend was driven by three data points with relative high cover and DRP: two at Dipton Stream at South Hillend-Dipton Rd (72% and 36% cover with corresponding DRP of 0.03 mg L^{-1}) and one at Mimihau Stream at Wyndham (10% cover and 0.04 mg L^{-1} DRP). River water temperature across the study sites and sampling periods ranged between 0.4 and 22.1ºC and generally had a positive relationship with *Phormidium* cover, with highest cover values recorded between 12.5 and 15.5ºC. DIN did not show a clear relationship with *Phormidium* cover across all 31 sites, where concentrations ranged between 0.006 and 7.9 mg L^{-1}.

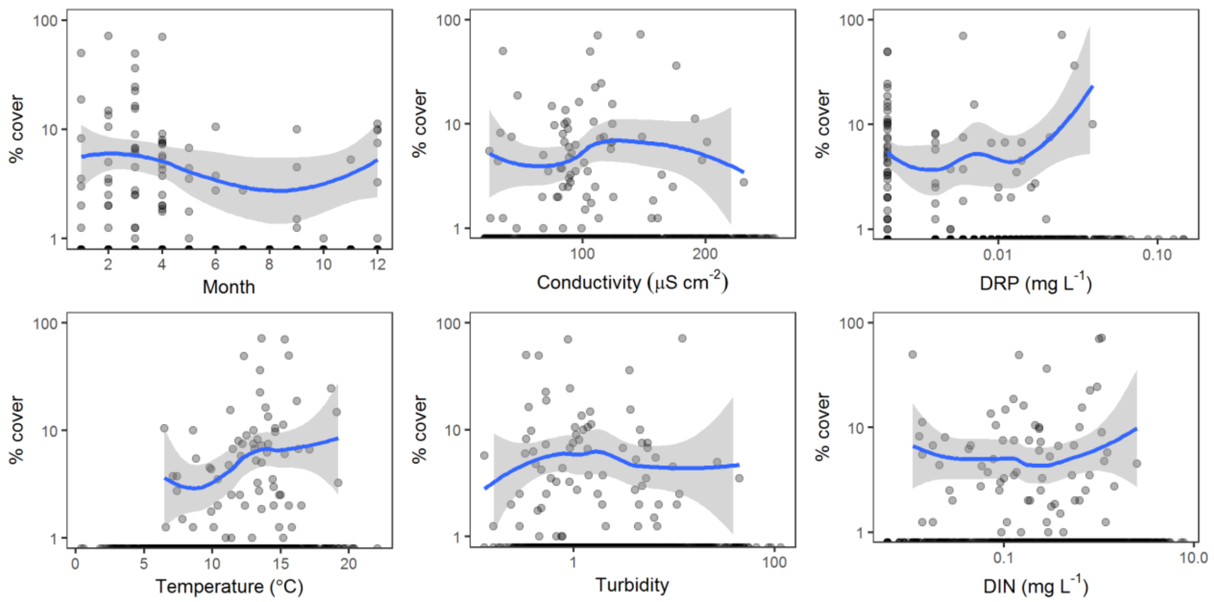

Figure 2. Relationship between *Phormidium* cover (%) and selected variables: month of the year, conductivity, dissolved reactive phosphorus (DRP), temperature, turbidity and dissolved inorganic nitrogen (DIN). The blue line is a loess-smoothed local polynomial regression and grey shading represents the pointwise 95% confidence interval around the smooth line. Note the y-axis is log scaled.

2.2.3. Generalised additive mixed model (GAMM) for sites where Phormidium was present

The GAMM model explained 27% of the total variation in the *Phormidium* cover data and included six significant predictor variables ($p < 0.05$): month, temperature, DIN, DRP, conductivity and site (Figure 3). Turbidity was dropped from the model during the selection process. Partial plots show the effect of each predictor variable conditional to others already in the model (Figure 3). Relatively large residual values indicated high variability in the data and relatively small partial effects (i.e., > -2 and < 2) indicates a weak predictors effect. Month of the year had the strongest positive effect, with highest *Phormidium* cover predicted in April. Increasing temperature up to 15 ºC was predicted to result in greater *Phormidium* cover, after which further increases had no effect. DIN had a positive effect on *Phormidium* cover up to a concentration of c. 0.05 mg L^{-1} and negative effect at higher concentrations. The effect of DRP on *Phormidium* was negative, with highest cover predicted at low DRP concentrations. The effect of conductivity was positive up to c. 150 µS cm^{-2} after which it decreased. The random effect of site was significant, indicating that there was a large variability between sites that could not be explained by any of the other predictor variables included in the model (Figure 3).

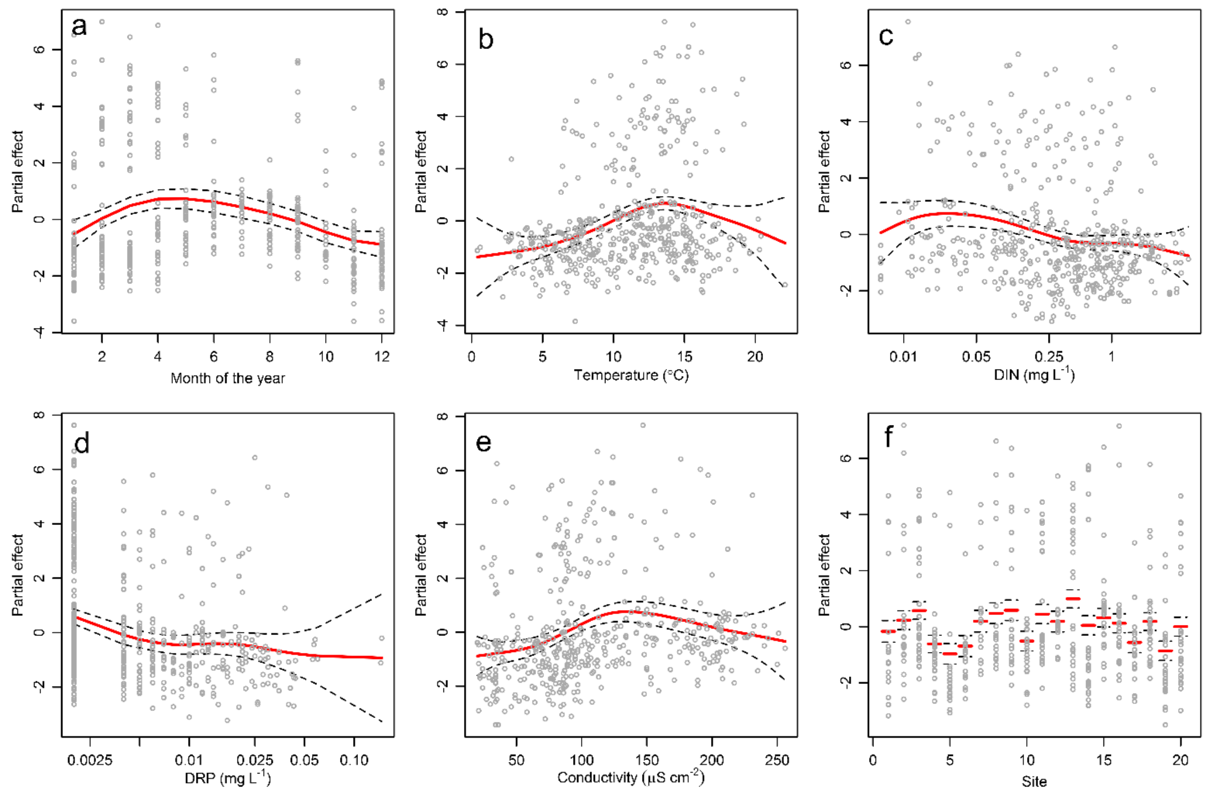

Figure 3. Partial plots for the effects of: a) month of the year, b) temperature, c) dissolved inorganic nitrogen (DIN), d) dissolved reactive phosphorus (DRP), e) conductivity, and f) site on *Phormidium* cover. Red lines represent cubic splines (± standard error, dotted lines) fitted using a log normal generalised mixed additive model. See methods section for description of the y-axis partial effect scale. Note differences in scales on the y-axes.

2.2.4. Comparisons with other studies

The GAMMs had a low explanatory power compared to other studies (Wood et al. 2017b; McAllister et al. 2018). There are several possible explanations:

- When monthly or sporadic sampling is undertaken there is a higher likelihood of missing periods when *Phormidium* cover is high. This presumably will reduce the effectiveness of the model in identifying meaningful relationships with environmental predictors.

- The basic model for the control of periphyton biomass in cobble-bed rivers identifies hydrologic disturbance as the primary regulator, whilst nutrients operate within this by influencing the rate of biomass accrual during stable periods (Biggs 1995). Previous studies (Wood et al. 2017b; McAllister et al. 2018) have included a flow predictor in their models. No flow data were included in this study, largely because the data had only monthly resolution. In the future, maximum flow during the week prior to sampling could be included as a predictor variable, which may help to explain the variability in the *Phormidium* data.
- Site emerges as an important predictor (random effect), indicating that different variables or river-specific features (e.g., substrate stability) that are not included in the models are likely important in explaining much of the observed variability. This pattern has also been observed in similar studies (Wood et al. 2017b; McAllister et al. 2018).

Despite the relatively low explanatory power of the model, general patterns and significant predictor variables matched those identified in our previous analyses, i.e., month, temperature, DIN, DRP, conductivity and site. However, there are some notable difference among regions, for example, the present study predicted blooms in Southland during late summer, whereas in the Maitai River (Nelson) blooms are predicted to occur in spring (Thomson-Laing et al. 2018). In general, the patterns observed for DIN (increases in cover up to certain thresholds), DRP (blooms more common when DRP is low) and increases in cover with temperature and conductivity, agree with patterns observed elsewhere, albeit the trends in Southland are generally weaker, likely for the reasons discussed above.

3. PREDICTIVE MODEL DEVELOPMENT

3.1. Training datasets

Based on previous ecological knowledge of the drivers of *Phormidium* (Wood et al. 2017a), a mechanistic model was conceptualised and subsequently the optimal model parameters found. There were insufficient *Phormidium* cover data available for the two Southland sites of interest (Mataura River at the Seaward Downs and Aparima River at Thornbury (hereafter 'test rivers'); Table 1 and Figure 4). Although there were limited data available from a site close to Mataura River at the Seaward Downs, (i.e. Mataura River at Mataura Island Bridge, see Figure 1), there were no continuous flow data available for this site. Therefore, we selected three datasets with weekly sampling resolution that had similar substrates to the two Southland sites. The data from these sites (hereafter 'training sites') were used to find the optimal model parameters. These three training sites were: Makakahi River at Hamua and Mangatainoka River at State Highway 2 (Manawatu) and Opihi River (Canterbury; Table 1 and Figure 4). The three datasets were collated from two different studies:

1. Opihi River - this was from a study of rivers in the Canterbury region (Figure 4) that comprised weekly measurements from a single site in each of eight rivers in the Canterbury region. These rivers were sampled from November 2014 to June 2015. Locations and detailed sampling methods are described in McAllister et al. (2016). The Opihi River experiences severe *Phormidium* blooms, and its substrate is dominated by cobbles and gravel (McAllister et al. 2016). It is a medium size stream with c. 60% of its catchment in pastoral land-use (Table 1).
2. Makakahi River and Mangatainoka River – these two sites were part of a study undertaken in the Manawatu region (Figure 4). The study comprised one or two sites at each of seven rivers sampled weekly between January 2012 and June 2013. Locations, sampling and analyses methodology are described in detail in Wood and Young (2012), Wood et al. (2014) and Wood et al. (2017b). The Makakahi River and Mangatainoka River are medium size streams, with cobbles being the dominant substrate. The catchment of both streams is predominantly (60%) in pastoral land-use, with c. 20% in native vegetation (Table 1).

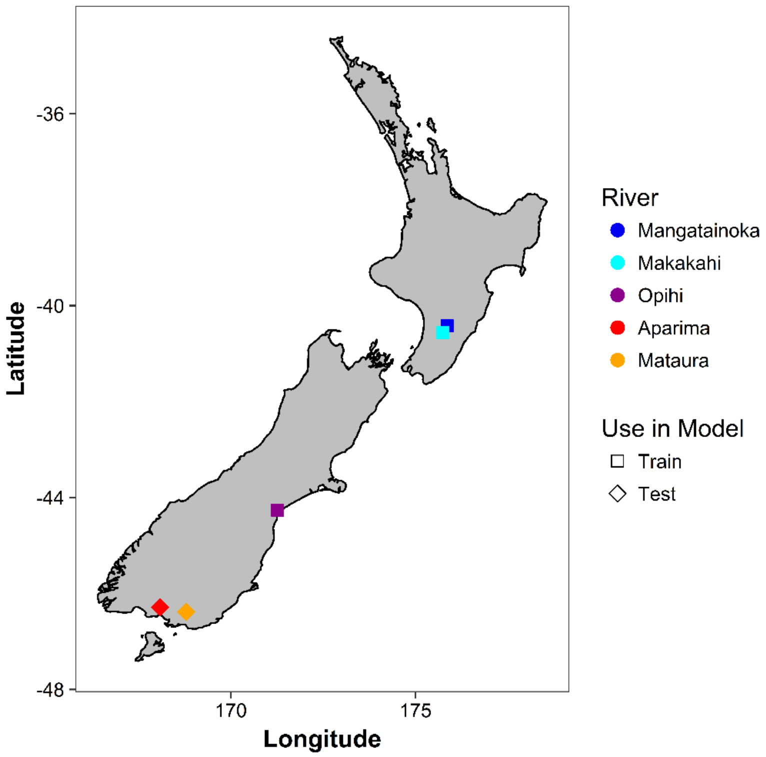

Figure 4. Location of rivers used as 'training sites' (square symbols) to develop the *Phormidium* predictive model for the two 'test' river sites (diamond symbols) in the Southland region.

Table 1. Catchment and hydrological conditions at training and test river sites used for developing the predictive model. Catchment data were retrieved from the Freshwater Ecosystems of New Zealand database (Leathwick et al. 2011) and the Land Cover Database V3.

	River	Region	Latitude	Longitude	Type	Catchment area (km^2)	Heavy pastoral land use (%)	Native vegetation land use (%)	Other land use (%)	Median flow (m^3 s^{-1})
Training	Makakahi River at Hamua	Manawatu	40°33'54.9"S	175°44'44.1"E	Training	163	79	18	3	3.18
	Opihi River at SH1 Bridge	Canterbury	44°15'51.9"S	171°16'05.5"E	Training	1740	61	35	4	8.7
	Mangatainoka River at SH2	Manawatu	40°25'17.1"S	175°51'47.2"E	Training	413	76	20	4	8.9
Test	Mataura River at the Seaward Downs site	Southland	46°23'09.0"S	168°47'27.8"E	Test	5149	52	8	40	69.6
	Aparima River at Thornbury	Southland	46°17'08.8"S	168°05'00.0"E	Test	1254	57	15	28	13.6

3.2. Model training

3.2.1. Logistic growth model

Because there was a lack of data available for the test sites to allow the development of an empirical model (i.e., using observed data), we used a mechanistic growth model. Mechanistic models are based on an understanding of the behaviour of a system's components and parameterised accordingly, whereas empirical models are based on direct observation, measurement and extensive data records.

The growth model was based on the logistic function, which is commonly used in the field of population dynamics ecology. In the logistic growth model, population regulation is a density-dependent process, meaning that growth rates are regulated by the density of a population. The initial stage of growth is approximately exponential; then, as saturation begins, the growth slows, and at maturity, growth stops at the carrying capacity or homeostasis of the system (Figure 5). Thus, the model follows a common sigmoid shape up to a river carrying capacity and has a function with the differential equation:

$$dN/dt = r \cdot P \cdot [(K - P) / K]$$

where r is the exponential growth rate, P is *Phormidium* percentage cover (%), K the carrying capacity (or maximum cover) for the site and T is time. Rearranging the equation:

$$N_t = [K \cdot N_0 \cdot e^{(r \cdot t)}] / [K + N_0 \cdot (e^{r \cdot t} - 1)]$$

Where N_t and N_0· are cover at time t and 0, K remains the maximum cover and r the exponential rate of cover increase. Cover at any one time thus depends on the time since expansion began, the population at t = 0, the growth rate, and the proximity to K. Population growth rate is highest at ½ K and zero around K (Figure 5). The initial value for *Phormidium* cover (t = 0) was set using a negative binomial distribution function with an expected mean cover of 2.5%.

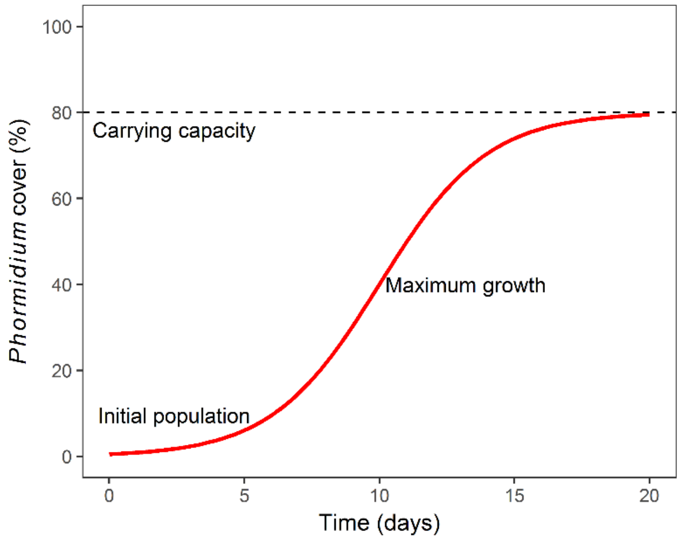

Figure 5. Schematic representation of the logistic growth model sigmoid curve for *Phormidium* showing carrying capacity (*K*), initial population and maximum growth rate (*r*).

3.2.2. Flow-related cover removal events

River flow has been identified as a major driver of *Phormidium* mat removal events (Wood et al. 2017a, 2017b). A common measure to relate the magnitude of river flow required to reduce *Phormidium* cover is 'times median flow', i.e., the maximum flow obtained from daily mean flow data between sampling periods divided by the long-term median flow for a given site. In the logistic growth model *Phormidium* cover removal events were modelled by flow events, which had varying impact depending on the cover of the *Phormidium* mat. The flow removal rate function was specified as:

$$\textit{Cover removal rate} = L / (1 + \exp((-1 * \textit{k-flow}) * (x - x0))) - 1$$

Where *x* is river flow, *L* maximum effect size constant, set at 99.5%, *k-flow* is the steepness of curve, *x0* is the flow midpoint of effect curve, which was calculated as the ratio the carrying capacity (*K*) and cover at a given time.

3.2.3. Model parameters optimisation

A general solver for ordinary differential equations (Hindmarsh 1983; Petzold 1983) was used to integrate the logistic growth model over time. For this purpose the lsoda method was specified in the ode function from the library deSolve (Soetaert et al. 2010) within the software R (R Core Team 2016). For each river, the model was fitted with all combinations of a wide range of values for each of the logistic growth model unknown parameters *r* and *k-flow*. Based on preliminary data exploration, a total of 18,847 model parameters combinations were tested, with *K* ranging from 1 to 98% and *k-flow* from 1 to 49. After modelling using the large combination of parameters, optimal parameters were selected based on the combination with the lowest root mean squared error of predictions (RMSE) expressed in terms of *Phormidium* percent cover (Table 2). Combined optimal parameters were calculated as the average of the optimal parameters for each training river, weighted by the inverse RMSE (Table 2). The exception was *K* which was determined based on expert assessment of the likely maximum *Phormidium* cover expected at each site, based on river catchment and hydrological conditions (Table 1) and previous *Phormidium* data (Figure 1).

Table 2. Optimal parameters for each training river site based on the lsoda method to integrate equation logistic growth model over time for each of the three training river sites. r is the optimal growth rate, *k-flow* is the flow-related cover removal parameter and *K* is the carrying capacity. Average error is expressed is terms of *Phormidium* cover (%). *K* was determined based on expert knowledge of the likely maximum *Phormidium* cover at each site.

River site	r	*k-flow*	Average error	*K*
Makakahi at Hamua	0.22	21.44	6.81	31
Opihi	0.48	1.299	14.96	70
Mangatainoka at SH2	0.45	25.00	9.44	44
Combined	0.36	14.39	9.48	70

Predicted and observed *Phormidium* cover by the logistic growth model with optimal parameters for each training river is shown in Figure 6, illustrating that observed and predicted cover timeseries follow similar trajectories over time at each site. Relative river flow (times median flow) is also shown below each *Phormidium* timeseries. Cover data were available between January 2012 and June 2013 for the Makakahi and Mangatainoka sites, whereas for Opihi data were only available from November 2014 to June 2015. Highest *Phormidium* cover values were observed and predicted for Opihi, which also had considerably lower relative river flow than the two other sites. Generally, *Phormidium* cover declined after significant flow events, showing that this process was well captured by the flow-related cover removal function. Validation using linear regression between observed and predicted *Phormidium* cover for each river indicated that model performance was moderate. Regression coefficient of determinations (R^2, proportion of variance explained) were 0.39, 0.55 and 0.23 for Makakahi, Opihi and Mangatainoka, respectively (Figure 7). There was under-estimation of cover at all three sites, particularly at higher *Phormidium* cover values (Figure 7).

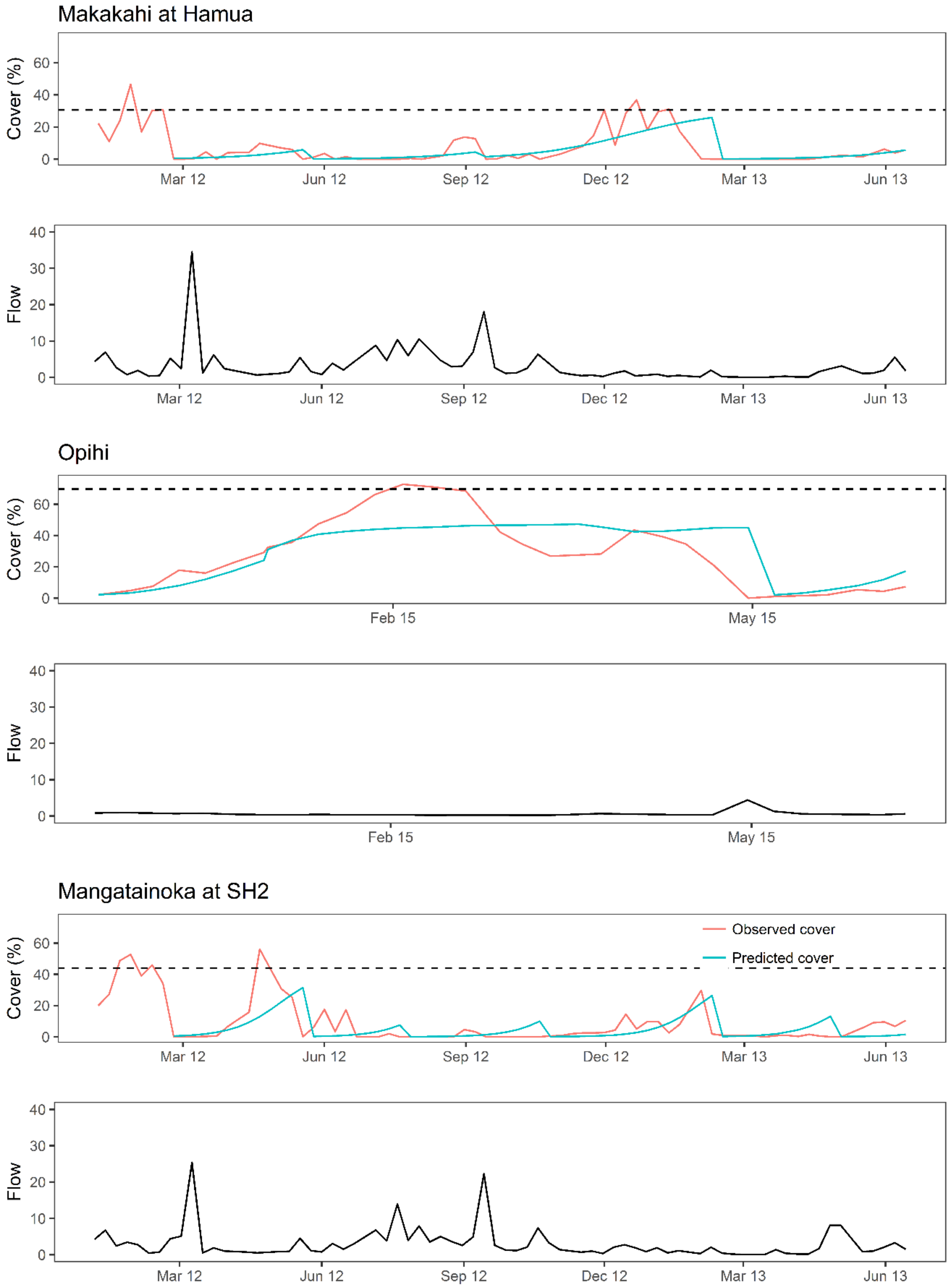

Figure 6. Results of the logistic growth model for *Phormidium* cover at each the three training river sites : Makakahi at Hamua (top), Opihi (middle) and Mangatainoka at SH2 (bottom) using optimal growth rate (r) and flow removal effect (*k-flow*) model parameters. The red and blue lack lines are observed and predicted *Phormidium* cover, respectively. Flow times median and the river carrying capacity is shown black solid and dotted lines, respectively. Note differences in x-axis between sites.

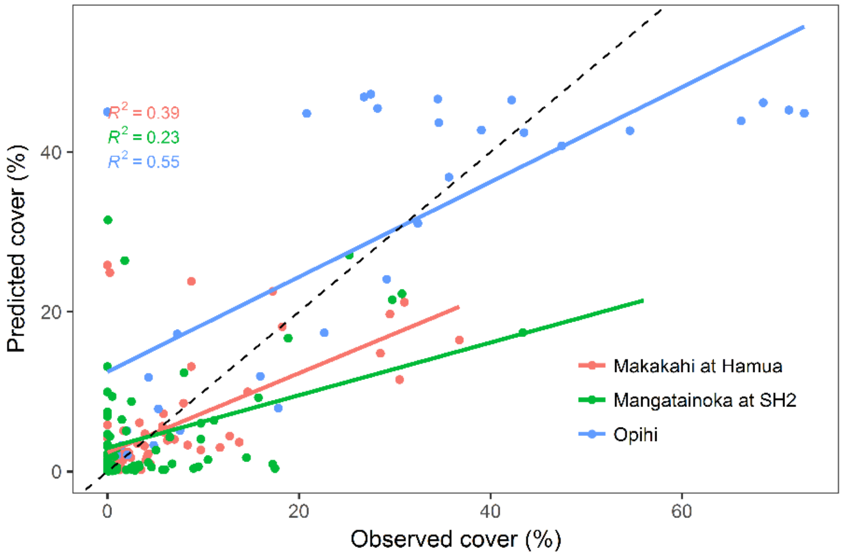

Figure 7. Observed versus predicted *Phormidium* percent cover. The colour lines are ordinary least square regression; fitted values and the R^2 is the coefficient of determination. The black dotted line is the one-to-one relationship.

3.3. Model predictions

The logistic growth model was used to predict *Phormidium* cover in two test river sites (Mataura River at the Seaward Downs and Aparima River at Thornbury) using the combined optimal r and *k-flow* model parameters (Table 2). Predictions were obtained between February 2012 and March 2017, when river flow data were available. Predicted *Phormidium* cover timeseries data for each test river is shown in Figure 8, together with observed river flow data obtained from continuous flow loggers. Predicted *Phormidium* increased according to a logistic growth function until flow events reset its cover to initial low cover values c. 0.5%. During periods of low flow predicted *Phormidium* cover approached maximum cover values, set as the carrying capacity (i.e., 70%, dotted lines in Figure 8)

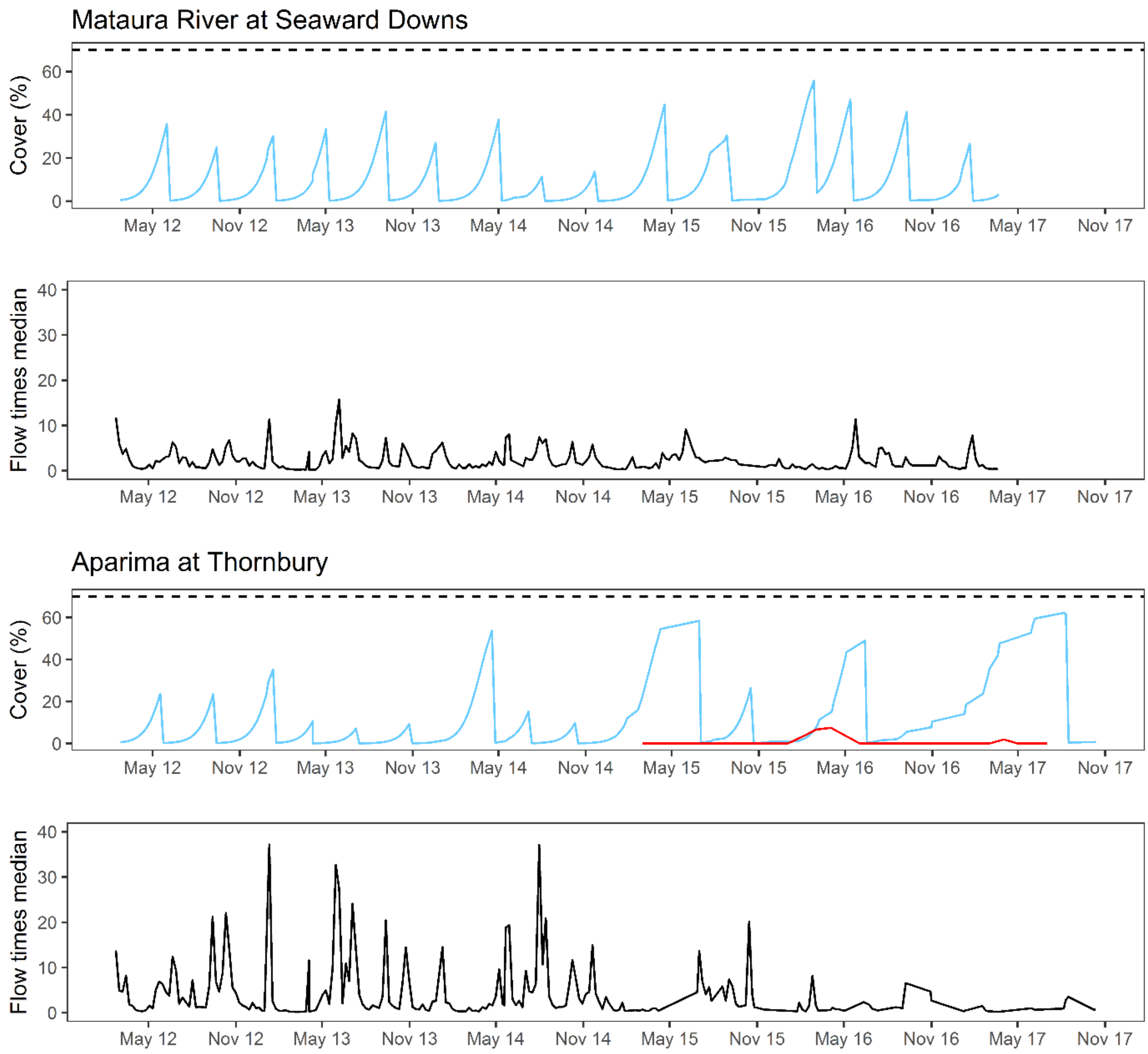

Figure 8. Logistic growth model predictions for *Phormidium* cover at each of the two Southland test river sites: Mataura River at the Seaward Downs (top) and Aparima at Thornbury (bottom) using combined optimal growth rate (*r*) and flow removal effect (*k-flow*) model parameters. Observed *Phormidium* cover data for Aparima at Thornbury is shown in red. Observed relative flow (i.e., times long term median) is shown for each site below the respective cover timeseries. *Phormidium* carrying capacity (*K*) is indicated (dashed black line).

3.4. Real-time predictive web application

The *Phormidium* predictive model outputs are displayed interactively in a web application created using Shiny (Chang et al. 2015). Shiny is an open source solution allowing easy creation of interactive web applications using R code (www.rstudio.com/shiny). Cawthron has a Shiny account that can host several applications. Displaying live data on a web application allows end users to view predicted *Phormidium* cover in real-time (Figure 9). The data are stored in the Shiny server from where it can automatically be drawn by the web application. The web application can be accessed at https://cawthron.shinyapps.io/Southland_*Phormidium*/

Flow data are obtained from ES flow gauge (at Mataura River at the Seaward Downs and Aparima River at Thornbury) xml document downloaded by the Shiny web app from http://odp.es.govt.nz/data.hts?Service=Hilltop&Request=GetData&Collection=CyanoForecastCawthron.

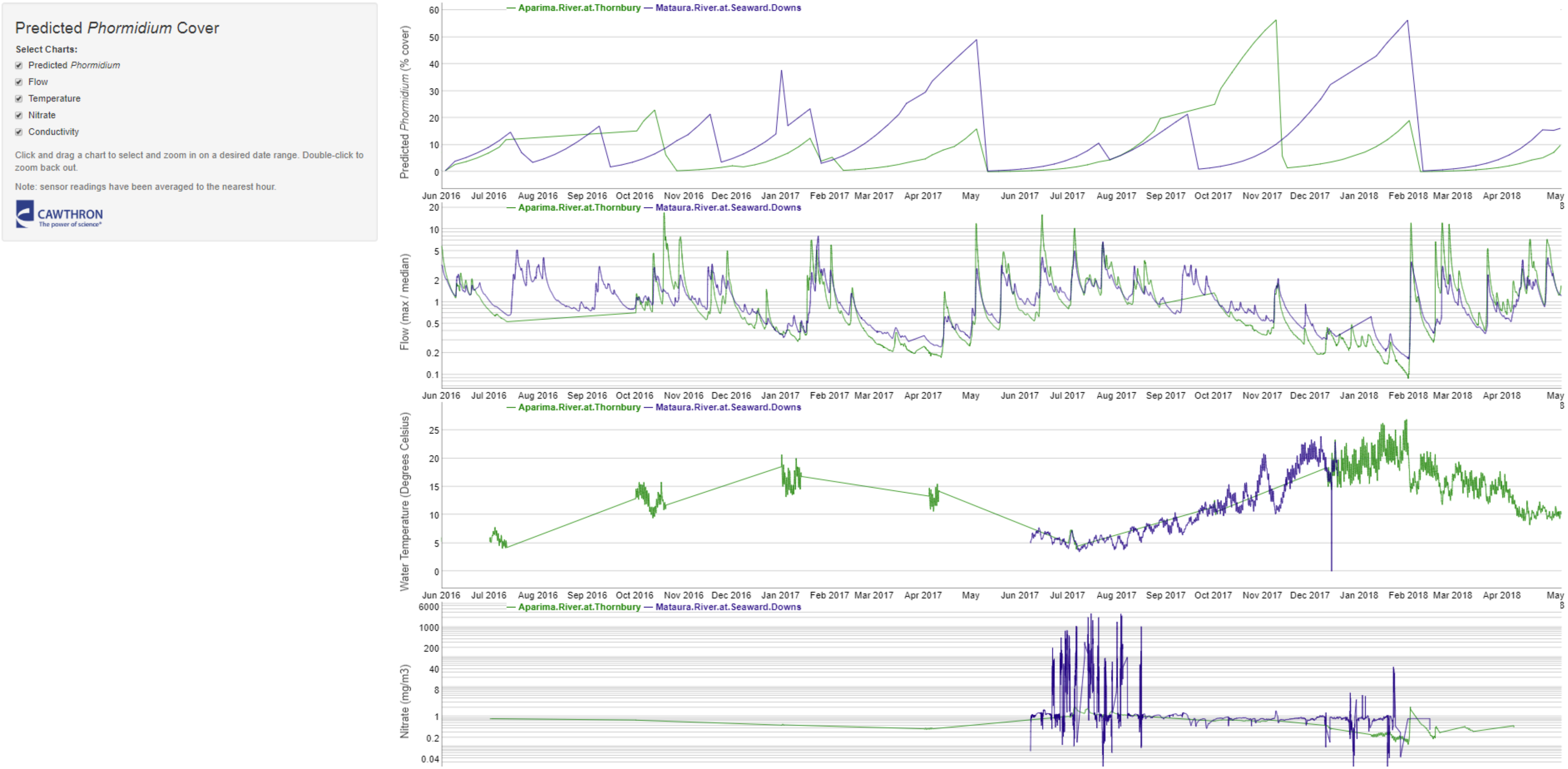

Figure 9. Screenshot from shiny R application showing predicted *Phormidium* cover at the two test river sites in Southland: Mataura River at the Seaward Downs site and Aparima River at Thornbury (https://cawthron.shinyapps.io/Southland_Phormidium/).

3.5. Caveats and how to interpret and utilise the data from the predictive model

Given the considerable intrinsic natural variability of *Phormidium*, the developed model had moderate predictive ability for training sites. The model explained 39%, 55% and 23% of the variance in the data for Makakahi, Opihi and Mangatainoka, respectively.

An advantage is that the model only requires flow data that are continually measured by flow gauges, thus it is a very cost-efficient way to estimate *Phormidium* cover. Initially we also investigated including temperature in the model, but it did not improve the model performance, and was therefore excluded.

The major limitation of the model is the lack of observed *Phormidium* cover data for the two test sites in Southland, which precluded model validation. Thus, the model performance in the two ES test rivers remains unknown and its predictions, as displayed in the web-based app, should be interpreted with caution. Extrapolating statistical relationships outside the range of observed data leads to higher uncertainty in the predictions, as it requires strong assumptions; in this case, the assumption being that the model will continue to be equally adequate in a different region from where it was developed. Undoubtedly estimating *Phormidium* cover in the Southland rivers based on flow and a logistic growth function from data obtained from different regions represents a simplified approach that probably results in high uncertainty in predictions.

Therefore, we recommend validating the model using *Phormidium* data collected in the two test rivers and further model refinement which may involve the inclusion of other parameters. A predictive model was recently developed for a site in the Maitai River (Nelson) that experiences *Phormidium* blooms. In that study data were available for five summers, allowing an empirical model approach to be utilised (Thomson-Laing et al. 2018). The model incorporated flow and week of the year and explained 62% of the deviance in the data. The validation process indicated that the model performance was good (R^2 = 0.56) and there was a mild under-estimation of cover, particularly at higher cover values. As actual *Phormidium* cover data are obtained for these sites we recommend exploring this as an alternative approach. We suggest at least two years of weekly data is needed and ideally these data should be collected year-round.

3.6. National model of susceptibility of streams to *Phormidium* blooms

A national model to predict stream susceptibility to *Phormidium* blooms was developed for the Ministry for the Environment by Wood et al. (2017a). The model was developed based on data from 493 sites across the North and South islands and used to predict maximum *Phormidium* cover in all stream segments in New Zealand.

The methods and analysis of this model are comprehensively described by Wood et al. (2017a) so just a brief summary of the model development is provided here. *Phormidium* cover datasets were collated from 11 regional councils including information from a total of 493 stream sites. Number of sites and sampling effort differed considerably between councils. The sample data provided by the councils were collected as part of State of the Environment monitoring, recreational bathing sampling, and specific periphyton or *Phormidium* monitoring programmes; therefore, the frequency of sampling and the types of environmental data collected in parallel varied greatly. Most regional councils used the transect method outlined in Ministry for the Environment and Ministry of Health (2009) to collect sample data. Some regional councils also used a bankside visual estimate of *Phormidium* cover. When both sampling methods were used, the authors selected the higher *Phormidium* cover value for analysis. Maximum *Phormidium* cover was calculated if sites had data from at least five independent observations (493 sites).

Catchment and segment-scale environmental descriptors were extracted from the Freshwater Ecosystems of New Zealand database (FENZ; Leathwick et al. (2011)). A total of 20 predictor variables were considered in the analyses, based on our knowledge of the potential drivers of *Phormidium* blooms (for more detail see Wood et al. 2017a). Land cover variables were derived from the Land Cover Database Version 3 (LCDB3). Generalised additive modelling (GAM) was used to model maximum percent *Phormidium* cover in relation to environmental and land use variables for each sampled stream segment (Wood et al. 2017a). Maximum *Phormidium* percentage cover was then predicted for 68,631 stream segments across the country, excluding still and backwater habitats, stream order < 3, and segments with glacial mountains as the source of flow.

The final GAM model included 19 predictor variables (Appendix 2) and explained 67% of deviance in maximum *Phormidium* cover data. The GAM predictions had a satisfactory performance, as indicated by the determination coefficient value (R^2) of 0.51 for the regression between observed and predicted values. The final model had a Nash-Sutcliffe efficiency value of 0.5, which is also indicative of satisfactory performance (Moriasi et al. 2007).

For this report the Southland-specific data was extracted. Maximum *Phormidium* percentage cover was predicted for 7,705 river segments across ES (Figure 10). Table 3 and Figure 11 detail the top 30 streams predicted to have the highest maximum *Phormidium* cover in the Southland region. In general, the model predictions match our expectations. Most rivers in Fiordland have low likelihood of experiencing blooms, whereas those in the regions with greater agriculture on the eastern side of Southland had a moderate likelihood. The models predicted low risk for the Mataura River at the Seaward Downs test site (maximum of 10% cover), whereas it predicted medium risk for Aparima River at Thornbury (43% cover). There are several sites with moderate risk of *Phormidium* blooms where the catchment is entirely native vegetation; it seems unlikely that blooms would occur in these, e.g., Red Pyke River and Eglinton River East Branch (Table 3). See Section 3.7 for further discussion on caveats and interpretation of the model predictions.

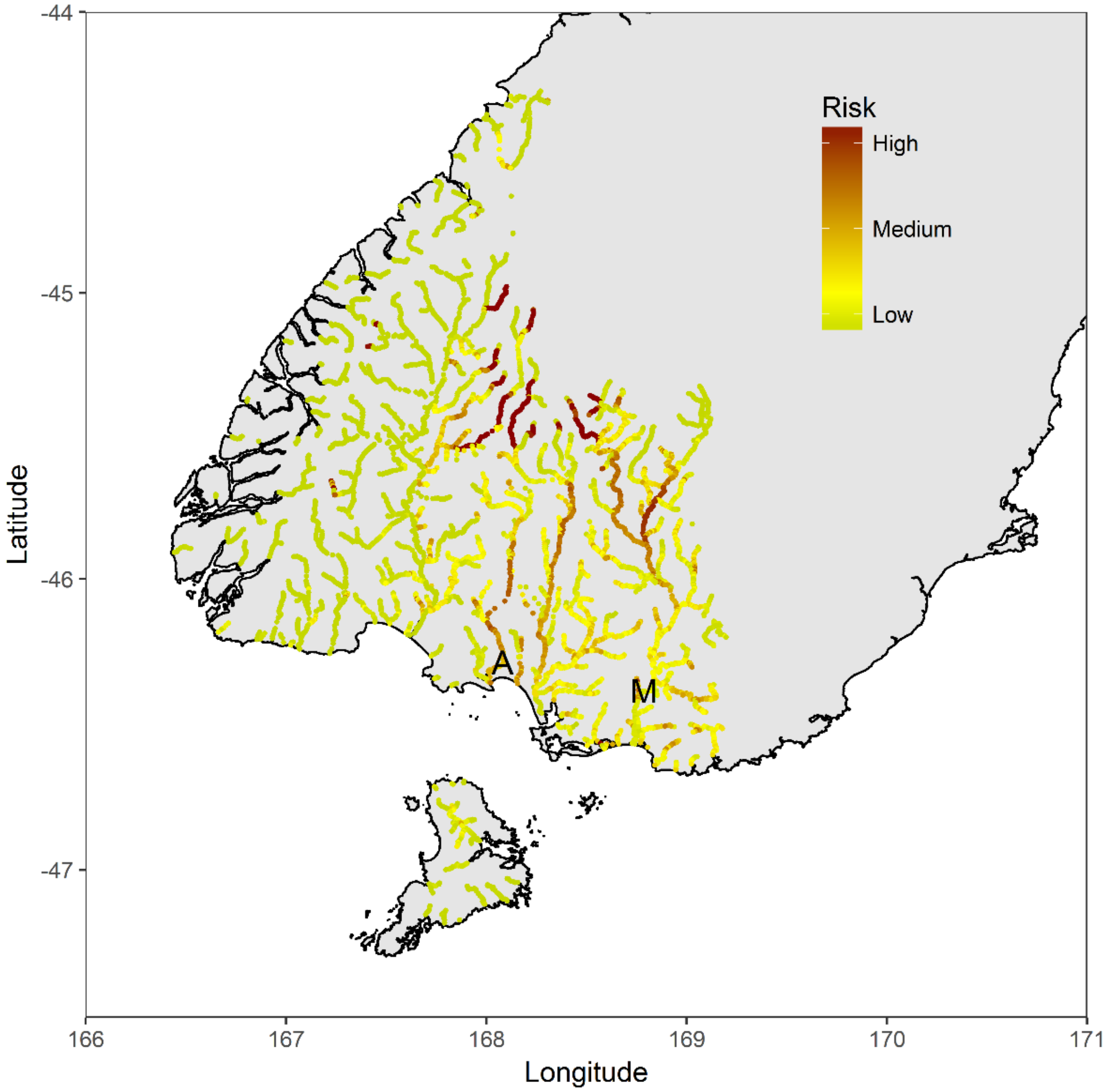

Figure 10. Map of *Phormidium* risk for Southland rivers based on national generalised additive model developed by Wood et al. (20017a) using *Phormidium,* environmental and landuse data from 493 sites across the North and South Island. The two river test sites Mataura River at the Seaward Downs and Aparima River at Thornbury are shown as an A and M, respectively.

Table 3. The top 30 streams in the Southland region identified in the national model used to predict stream susceptibility to *Phormidium* blooms (Wood et al. 2017a).

River Site	NZ Reach No.	Predicted maximum *Phormidium* cover (%)
Acton Stream	15031249	82.6
Allen Creek	15017777	83.4
Alton Burn	15050217	74.8
Aparima River	15053508	85.3
Argyle Burn	15029661	68.9
Ashton Burn	15018131	100.0
Cleddau River	15004281	75.2
Cromel Stream	15022108	100.0
Dome Creek	15028564	90.0
Doon River	15011423	99.9
Eglinton River East Branch	15009004	100.0
Eyre Creek	15023721	100.0
Florence Stream	15035200	89.0
Florence Stream North Branch	15034030	99.9
Gow Burn	15026253	88.4
Grassy Creek	15044398	69.1
Henry Creek	15014246	76.6
Mimihau Stream	15056512	75.9
Otautau Stream	15050301	76.0
Pig Creek	15019666	100.0
Red Pyke River	15000363	99.9
Terrace Creek	15052166	68.5
Upukerora River	15013853	100.0
Waikaia River	15034198	95.5
Waikaka Stream East Branch	15043155	77.1
Waikawa River West Branch	15061436	71.2
Waimatuku Stream	15058867	67.4
Whitestone River	15016611	100.0
Windley River	15023480	100.0
Woodrow Burn	15013274	98.7

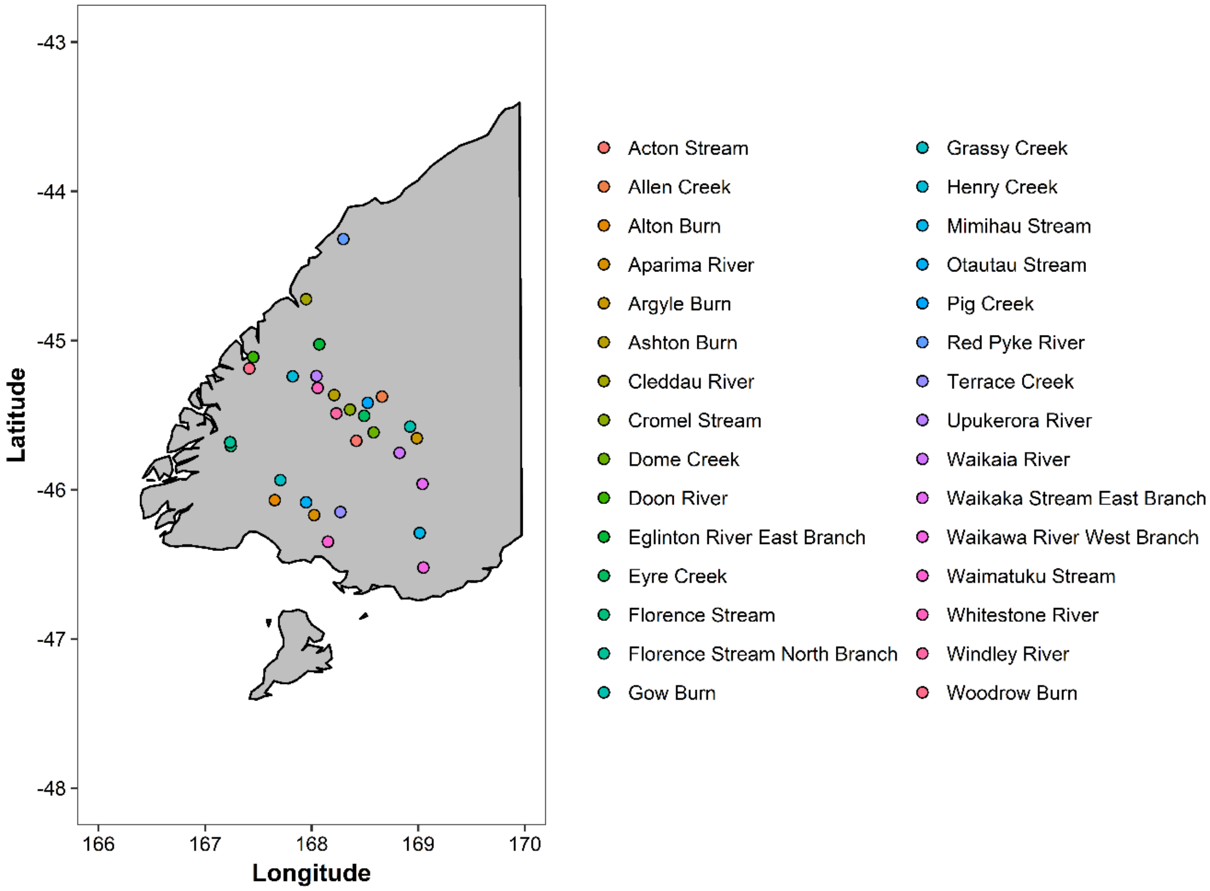

Figure 11. The location of the top 30 streams in the Southland region identified in the national model of stream susceptibility to *Phormidium* blooms (Wood et al. 2017a).

To ground truth the model, 30 unmonitored sites identified in the national risk susceptibility model as being likely to experience *Phormidium* blooms were visited during the summer of 2016 to 2017 when *Phormidium* percent cover was assessed and general site characteristics were observed (Wood et al. 2017a). Of the 30 sites visited, 6 streams were in the Southland region (Table 4). Only one of the sites contained *Phormidium*. At some sites, e.g., Alton Burn, the habitat was deemed unsuitable based on expert judgement, i.e., sandy substrate, slow-flowing small stream. However, other sites are known to have experienced *Phormidium* blooms, i.e., Oreti River, but none was observed during the site visit. This highlights the limitations of trying to undertake a model validation study when sites are only visited once.

Table 4. Rivers visited in Southland during independent model validation with predicted and observed *Phormidium* cover.

Name	**Region**	**Predicted *Phormidium (%)***	**Actual *Phormidium* (%)**
Otautau Stream	Southland	76	0
Waimatuku Stream	Southland	67	0
Alton Burn	Southland	75	0
Aparima River	Southland	85	0
Wairaki River	Southland	4	3
Oreti River	Southland	54	0

3.7. Caveats and how to interpret and utilise the data from the stream susceptibility model

The predictions made using the stream susceptibility model provide a description of regional to national scale patterns in rivers which might experience *Phormidium* proliferations. The predictions should be interpreted with caution at a site scale, as other processes are not included in the model, e.g., water column nutrients can influence *Phormidium* proliferations. Additionally, seasonal and inter-annual variability is not accounted for in the models. Recent flow and climatic conditions, i.e., time since a flushing flow, will also impact whether a site experiences a proliferation at a given point in time. Despite these caveats the stream-scale predictions provide some guidance on where proliferations might occur and in concert with local knowledge might be useful for ES to guide the selection of monitoring sites.

4. CONCLUSIONS AND RECOMMENDATIONS

4.1. Improving knowledge on environmental drivers and effects of blooms in Southland rivers

The analysis in this study showed that potentially-toxic *Phormidium* are known to be present at 22 sites in the Southland region. However, the low abundance of *Phormidium* cover in these datasets, and monthly resolution of data made investigating drivers of *Phormidium* proliferations challenging.

To improve knowledge on environmental drivers, we suggest more targeted studies focusing on rivers with known *Phormidium* blooms. These studies should collect weekly resolution *Phormidium* cover data including corresponding site descriptors such as water depth, slope and substrate. Physiochemical water column variables e.g., flow and nutrients, should also be measured. Multiple sites on a river with an increasing abundance of *Phormidium* could be targeted i.e., down the Mataura River. These data would enable more in-depth analysis such as the approaches used in Wood et al. (2017b) and McAllister et al. (2018).

An experimental approach could also be used. For example, we have recently developed a technique which involves inoculating rocks with a constant amount of *Phormidium.* This involves drilling a small hole (c. 5 mm dia. and 5 mm depth; Figure 12) into the cobble which is then filled with *Phormidium* mat (sourced from the river where the experiment will be undertaken).

Figure 12. Cobble showing a 5-mm diameter hole which is then filled with *Phormidium* mat. Photo: T. McAllister, Canterbury University.

In recent pilot studies, the mat-inoculated cobbles have been placed in slow, medium and fast flowing sections of Canterbury rivers with different nutrients (Tara McAllister, Canterbury University, unpub. data). *Phormidium* expansion rates can then be determined by revisiting each cobble every 3-4 days, taking photos for image analysis and evaluating biomass by sacrificing certain rocks at less frequent intervals.

Experimental investigations into the role of nutrients (and other factors) in facilitating blooms could involve comparative studies in rivers where *Phormidium* is known to proliferate with those that are seemingly suitable for proliferations to occur (i.e., nutrients are within optimal ranges), but do not. Another alternative would be rivers with nutrient gradients (e.g., Mataura River), where *Phormidium* proliferations do not occur in the upper reaches but are prevalent in lower reaches. The result of a suite of these experiments would help determine the relative contribution of flow and water column nutrients on accrual rates.

Wood and Puddick (2018) detected extremely high levels of anatoxin in *Phormidium* mat samples from the Mataura River in 2017. The highest value (1,684 mg kg^{-1} dw) was over twice the maximum recorded previously in a nationwide collation of data (McAllister et al. 2016), and only slightly below the national maximum of 2,116 mg kg^{-1} dw from the Hutt River (Wellington). All river water samples collected in their study also contained toxins. Collectively the results from Wood and Puddick (2018) demonstrated the high human risk that these blooms pose in the Mataura River. Further information on the potential human health risk posed by benthic cyanobacteria in Southland is given in Wood (2017).

As part of their study Wood and Puddick (2018) undertook a preliminary assessment of the potential for anatoxin to bioaccumulate in three freshwater species at the Mataura River site: the mayfly *Deleatidium* sp., the freshwater snail *Potamopyrgus antipodarum*, and the flatworm Platyhelminthes. Specimens were maintained in river water for 24 hrs (to purge digestive tracts of food and possible *Phormidium* cells), and washed c. 5 times in Milli-Q water and analysed using chemical methods for anatoxins. All tested positive for anatoxins. As the data are preliminary and the method is not yet validated they cannot provide actual concentrations. Based on these preliminary data we strongly recommend that further research is undertaken to assess the effects of anatoxins on a variety of freshwater species, to validate anatoxin extraction methods for use in those species, and to investigate the accumulation of anatoxins, particularly in freshwater species such as trout and eels harvested for human consumption.

4.2. Refining the real-time *Phormidium* cover estimation model

A mechanistic predictive model that utilised a logistic growth model and flow-related cover removal events to predict the cover of *Phormidium* was developed for two sites in Southland: Mataura River at the Seaward Downs and Aparima River at Thornbury. Despite the lack of observational data for these two sites, relatively realistic real-time predictions of cover are being estimated, and these are available in a web-based application https://cawthron.shinyapps.io/Southland_*Phormidium*/.

Given the limited *Phormidium* cover data for either site the model will require ongoing validation and development. Collection of at least two full years of data is recommended. Ideally, in addition to *Phormidium* cover other water quality parameters such as nutrients and suspended solids should be collected. Collection of a high-resolution dataset may allow other, potentially more robust predictive models to be developed, such as the one recently developed for the Maitai River in Nelson (Thomson-Laing et al. 2018). It is anticipated that once the model has been fully validated, it could be used to reduce reliance on site surveys.

The selection of the carrying capacity of the model is an important aspect to consider in relation to predictive performance, because cover estimates will be bounded this upper growth limit. Site and river specific carrying capacity is expected to be affected by habitat suitability (e.g., slope, flooding regime and substrate stability), rather than by resource availability. These physical attributes tend not to be routinely measured in monitoring programmes. An improved understanding of how these attributes are linked to site specific carrying capacity will assist in enhancing knowledge on *Phormidium* blooms and assist in further development of predictive models.

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7. APPENDICES

Appendix 1. Summary statistics of *Phormidium* cover (%) over sampling period for survey sites (start and end dates) in the Southland region. Max. = maximum cover (%), S.D. = standard deviation of the mean, n = number of samples.

Site	Start	End	Mean	Max.	S.D.	n
Aparima River at Thornbury	Mar-15	Jul-17	1.2	13.3	3.3	21
Cromel Stream at Selbie Road	Dec-14	Sep-17	0.0	0.0	0.0	31
Dipton Stream at South Hillend-Dipton Road	Nov-14	Sep-17	4.3	72.0	15.0	28
Dunsdale Stream at Dunsdale Reserve	Dec-14	Sep-17	0.0	0.0	0.0	29
Hamilton Burn at Affleck Road	Nov-14	Oct-17	1.4	10.5	2.7	35
Hedgehope Stream 20m upstream Makarewa Confluence	Nov-14	Sep-17	0.0	0.0	0.0	24
Irthing Stream at Ellis Road	Dec-14	Sep-17	0.1	3.5	0.6	32
Lill Burn at Lill Burn-Monowai Road	Nov-14	Aug-17	0.6	11.3	2.5	20
Longridge Stream at Sandstone	Nov-14	Aug-17	0.0	0.0	0.0	27
Makarewa River at Counsell Road	Jan-15	Aug-17	0.0	0.0	0.0	20
Mararoa River at Weir Road	Nov-14	Mar-17	0.1	1.0	0.2	19
Mataura River at Gore	Dec-14	May-17	0.9	9.0	2.4	17
Mataura River at Mataura Island Bridge	Nov-14	Apr-17	4.8	70.3	15.9	21
Mimihau Stream at Wyndham	Dec-14	Sep-17	1.8	15.5	4.1	21
Orauea River at Orawia Pukemaori Road	Nov-14	Sep-17	0.3	6.8	1.4	22
Oreti River at Branxholme	Dec-14	May-17	0.9	9.1	2.4	17
Oreti River at Three Kings	Dec-14	Oct-17	0.7	8.5	1.8	30
Oreti River at Wallacetown	Jun-16	Jun-16	0.0	0.0	-	1
Otamita Stream at Mandeville	Nov-14	Oct-17	0.0	0.0	0.0	31
Otautau Stream at Otautau-Tuatapere Road	Nov-14	Oct-17	0.3	2.8	0.8	24
Upukerora River at Te Anau Milford Road	Nov-14	Jul-17	4.3	49.3	9.8	28
Waiau River at Tuatapere	Nov-14	Sep-17	2.0	14.8	4.1	25
Waikaia River at Waikaia	Nov-14	Sep-17	0.8	18.8	3.7	26
Waikaia River upstream of Piano Flat	Nov-14	Sep-17	2.1	49.8	9.6	27
Waikaka Stream at Gore	Dec-14	Sep-17	0.0	0.5	0.1	21
Waikawa River at Progress Valley	Dec-14	Aug-17	0.0	0.0	0.0	19
Waimatuku Stream at Waimatuku Township Road	Nov-14	Sep-17	0.0	0.8	0.2	28
Waimea Stream at Mandeville	Nov-14	Oct-17	0.2	4.5	0.8	31
Wairaki River downstream of Blackmount Road	Nov-14	Aug-17	0.2	2.5	0.6	24
Waituna Creek at Marshall Road	Dec-14	Sep-17	0.0	0.0	0.0	18
Whitestone River downstream of Manapouri-Hillside	Nov-14	Jul-17	1.5	22.5	4.7	25

Appendix 2. Predictor variables included in the generalised additive national model of susceptibility of streams to *Phormidium* blooms. Data were obtained from the Freshwater Ecosystems of New Zealand database (Leathwick et al. 2011) and the New Zealand Landcover Database version 3 (http://www.lcdb.scinfo.org.nz/home).

Predictor	**Abbreviation**	**Description**	**Units**
Climate and flow	SEGJANAIRT	Average summer (January) air temperature	°C
	SEGRIPSHAD	Riparian shading proportion	%
	USDAYSRAIN	Days/year with rainfall greater than 25 mm in the upstream catchment to indicate the likely frequency of elevated flows	Days/year
	SEGFLOWSTA	Annual low flow/annual mean flow (ratio)	
	USAVGSLOPE	Average slope in the upstream catchment	degrees
	SEGLOWFLOW	Mean annual 7-day low flow	m^3/sec
	SEGSLOPE	Segment slope	degrees
Land cover	T2ExoticForest	Proportion of catchment occupied by exotic forest	%
	T1NativeVeg	Proportion of catchment occupied by native vegetation	%
	T1Urban	Proportion of catchment occupied by built-up area, urban parkland, surface mine, dump and transport infrastructure	%
	T2PastoralHeavy	Proportion of catchment occupied by heavy pasture	%
	T1BareGround	Proportion of the catchment with bare ground	%
	CATCHAREA	Catchment area	m^2
Geography and topography	USPHOSPHOR	Phosphorus content of surface rocks	Ordinal
	LOCSED	Weighted average of proportional cover of bed sediment using categories of: 1–mud; 2–sand; 3–fine gravel; 4–coarse gravel; 5–cobble; 6–boulder; 7–bedrock	Ordinal
	LOCHAB	Weighted average of proportional cover of local habitat using categories of: 1–still; 2–backwater; 3–pool; 4–run; 5–riffle; 6–rapid; 7–cascade	Ordinal
Geology	USCALCIUM	Calcium content in surface rocks	Ordinal
	USHARDNESS	Average hardness (induration) of surface rocks	Ordinal
	LOGNCONC	Log10 transformed values of nitrogen concentration (ppb) as estimated from CLUES, a leaching model combined with a regionally-based regression model, implemented within a catchment framework (Woods et al. 2006)	ppb