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Seeing is Predicting: Water Clarity-Based Nowcast Models for *E. coli* Prediction in Surface Water

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Abstract

Given the 24–48 h turn-around time of conventional surveillance approaches, methods are needed that improve the timeliness and accuracy of recreational water quality risk assessments. Although one useful approach is to combine existing monitoring programmes with predictive faecal indicator bacteria (FIB) models, these models are largely 'top-down' in their approach to safeguarding public health. Beyond being simply 'advised when to avoid swimming', there is an increasing awareness amongst the general public regarding the role they can play in water quality monitoring. Using quantile, maximum value and optimized incremental modelling approaches, this study reports on the possibility of developing intuitive, public-friendly models that are based on the physical appearance of water (clarity), to estimate 8103 nation-wide *E. coli* concentrations in rivers, and to assess whether water is safe to swim in. If swimmers were to avoid river waters with <1.1 m black disc visibility during autumn and summer, and river waters with values <0.5 m black disc visibility during spring and winter, they would also avoid microbial hazards that are associated with exceedances of the 540 CFU/100 mL single sample bathing water standard. Regardless of the climatic season, stream order classification, catchment land cover or geology of streams considered, the clarity-based *E. coli* models performed well as they presented with sensitivity, specificity and accuracy values of at least 72%. The developed models offer the benefit of providing a faster method for estimating *E. coli* concentration, potentially engaging the public in water monitoring, and allowing them to make informed decisions on whether it is safe to swim.

Keywords: faecal indicator bacteria, water clarity, predictive model, water quality, public health

1. Introduction

Surface waters are prone to contamination from various point and nonpoint sources and can therefore serve as a vehicle for transmission of potentially pathogenic bacteria (Dada & Hamilton, 2016; Devane, Gilpin, & Moriarty, 2015; Praveena et al., 2018). Consequently, beach monitoring programmes have been adopted and implemented in many nations to protect beachgoers from health risks caused by potentially harmful bacteria. In New Zealand, policies such as the National Policy Statement on Freshwater (NPS, 2014) provide guidelines for regulators to ensure that monitoring programs are in place to warn the public about the risk of exposure to these pathogens during recreational contact. Current risk assessment is based on microbiological culturing of *Escherichia coli*, and results are thus used to inform the issuance of swimming advisories to reduce the risks of exposure to potentially pathogenic bacteria at recreational sites. However, given the 24–48 h turn-around time before swimming advisories are released, advisories issued to protect public health effectively only indicate 'it may be unsafe to swim yesterday'. Thus, while dissemination of accurate and timely information is critical to preventing illness, water quality advisories often do not present accurate assessments of such risk in a timely manner.

Predictive modelling for faecal indicator bacteria (FIB) concentrations can complement the current culture-based monitoring approach to recreational water risk assessment. Predictive FIB models provide a rapid estimation of the bacteriological condition, potentially assisting local beach managers in the decision process related to the issue of swimming advisories. In recent years, many beach managers have increasingly adopted predictive tools, of which the most widely applied are models developed through multi-variable linear regression (e.g., Olyphant, 2005; Nevers & Whitman, 2005; Feng et al., 2015). Process-based models, which couple hydrodynamic models with a microbe transport-fate model involving microbial loading, transport, and fate processes, have also been demonstrated to make predictions (e.g., Sanders et al., 2005; Hipsey et al., 2008; Feng et al., 2013, 2015; Thupaki

et al., 2013).

While these predictive faecal indicator bacteria (FIB) models have been used to estimate bacteriological water-quality, they have largely adopted a 'top-down' approach to safeguarding public health (i.e. models are run by science staff of regulatory bodies who simply advise the public when it's safe or not safe to swim). Beyond being simply 'advised when to avoid swimming', there is an increasing awareness amongst the general public regarding the role they can play in water quality monitoring. This presents novel opportunities for citizen participation in predictive FIB modeling. This study presents a classic example of developing intuitive, 'public-friendly' and 'public-usable' models, using the physical appearance of water (as measured by water clarity) as a way of estimating *E. coli* concentrations in surface water, to assess whether water is safe to swim in. The goal of this study was to evaluate the possibility of using clarity models for *E. coli* nowcast prediction, at both a local and national scale throughout New Zealand. This will constitute a milestone in efforts geared towards developing and deploying site-specific river clarity-based *E. coli* models at local scales for nowcast prediction of *E. coli* concentrations at popular recreational sites in New Zealand and other nations worldwide.

2. Methods

2.1 Study Sites

A total of 145,040 water quality datasets, which have been routinely collected by regional authorities from as early as the late 1980s for most New Zealand rivers and tributaries (https://data.mfe.govt.nz/), was used in the analysis. These datasets contained measured values for several parameters including ammoniacal nitrogen, total nitrogen, nitrate-nitrogen, dissolved reactive phosphorus, total phosphorus, and E.coli. All E.coli datasets were extracted (n=8170). Of these, a total of 8103 E.coli datasets that had corresponding discharge data were subsequently used for the analysis. E.coli data used thus spanned the period 2005 to 2013 at a total of 77 freshwater swimming sites representing 49 rivers and tributaries throughout New Zealand. The frequency of sampling varied across the sites represented in the dataset from fortnightly to quarterly. While constraints and objectives associated with the design of regional sampling programs tend to influence variability in the geographical coverage of the sites in the database (as noted in McDowell et al., 2017) (Figure 1), we consider that the sites in our dataset adequately represent river sites nationally. Climatological, geological and land use characteristics for the sites are as described in the NZ River Environment Classification scheme (McDowell et al 2017).

2.2 Determination of E. coli and Water Clarity

As part of the national bathing site *E. coli* surveillance program, water samples from New Zealand rivers and tributaries are collected during recreational seasons and low flow months, particularly between October and March of every year (Davies-Colley, 1988). Microbiological water quality analyses are completed using the membrane filtration method (EPA, 2002) for *E. coli*. Counts are recorded as colony forming units (CFU/100 mL) and entered into spreadsheets. At these sites, water clarity is typically measured using a black disc which is placed in the water and viewed through an underwater viewing box at increasing distances until the black disc disappears from sight (Davies–Colley, 1988).

2.3 Data Management, Statistical Analysis, and Modeling

E. coli concentrations rarely fit into a normal distribution. Hence, they were log transformed before any exploratory data analysis was done to achieve normality (following Francy et al., 2013). Data applied were split in a ratio 2:1 between model development and validation (Gramatica, 2007). To fit the 8103 *E. coli* datasets based on their clarity, three approaches were used (as schematically represented in Figure 2).

i. **Quantile approach:** A classification scheme was applied that resolved the water clarity datasets into quantiles. To achieve this, quartiles were determined on the basis of stream order. Hence, quartile classes specific to each stream order were applied. Water clarity values less than the first, second, third and fourth quartiles were designated as Q1, Q2, Q3 and Q4, while water clarity values higher than the fourth quartile were designated as Q5.

ii. **Maximum value approach:** The maximum observed log *E. coli* concentrations per unique water clarity values were fitted using a linear regression model. This produced specific equations that predicted *E. coli* concentrations using water clarity values.

iii. **Gradient/incremental approach:** Incremental 'trigger' values or water clarity 'thresholds' (i.e. from lowest to highest) were applied as 'thresholds' to predict exceedances and non-exceedances of the national bathing water standard. These triggers or thresholds are water clarity values that would warrant additional site-based investigation, as they are indicative of

conditions of elevated faecal indicator bacteria levels higher than the national bathing water standard of 540 CFU/100mL.

Figure 1. 77 New Zealand freshwater swimming sites (49 rivers and tributaries) in the *E.coli* predictive modeling using water clarity as a predictor variable

2.4 Model Performance and Swimming Advisory Assessment

Exceedances of bathing water thresholds applied in this study were compared against national and international guidelines. An exceedance (or a positive model outcome) was recorded when sampled or predicted *E. coli* levels exceeded the bathing water standard (BWS) of 235 CFU/100 mL (USEPA guidelines), or 260 and 540 CFU/100 mL (as stipulated in the New Zealand National Policy Statement for Freshwater Management) (NPS, 2014). A type I error (or a false positive outcome) was identified when the modelled *E. coli* level was above the thresholds, but the observed *E. coli level* was below the thresholds. When the modelled and observed *E. coli* levels were both above the thresholds, this was considered a true positive. On the other hand, a false negative result (type II error) was inferred when the modeled *E. coli* level was less than the thresholds but the observed *E. coli* level was higher. In such a case, potential microbial contamination would be undetected by the model and no swimming advisory would be issued. When the modeled and observed *E. coli* levels are both below the thresholds, this is identified as a true negative.

Model accuracy was determined in the study as the percentage of correct advisory predictions. Sensitivity and specificity are defined as the rates of correctly predicted exceedances and non-exceedances, respectively. Specificity, sensitivity, and accuracy of the model were determined using the following equations:

$$Model\ Sensitivity\ (\%) = \frac{\text{Number of True Positives} * 100}{(\text{Number of True Positives} + \text{Number of False Negatives})}$$

$$Model\ Specificity\ (\%) = \frac{\text{Number of True Negatives} * 100}{(\text{Number of True Negatives} + \text{Number of False Positives})}$$

$$Model\ Accuracy\ (\%) = \frac{(\text{Number of True Negatives} + \text{ Number of True Positives}) * 100}{(\text{Total number of observations})}$$

One-way analysis of variance (ANOVA) was conducted to compare significant differences between the modelled and observational results. Additionally, the correlation coefficient, R^2 (an estimate of the proportion of total variation in the data series which is explained by the model) and the residual root mean square error (RMSE) were used to measure the goodness-of-fit of the FIB models developed. The RMSE is a measure of variation of the observed *E. coli* concentration from its model-predicted value.

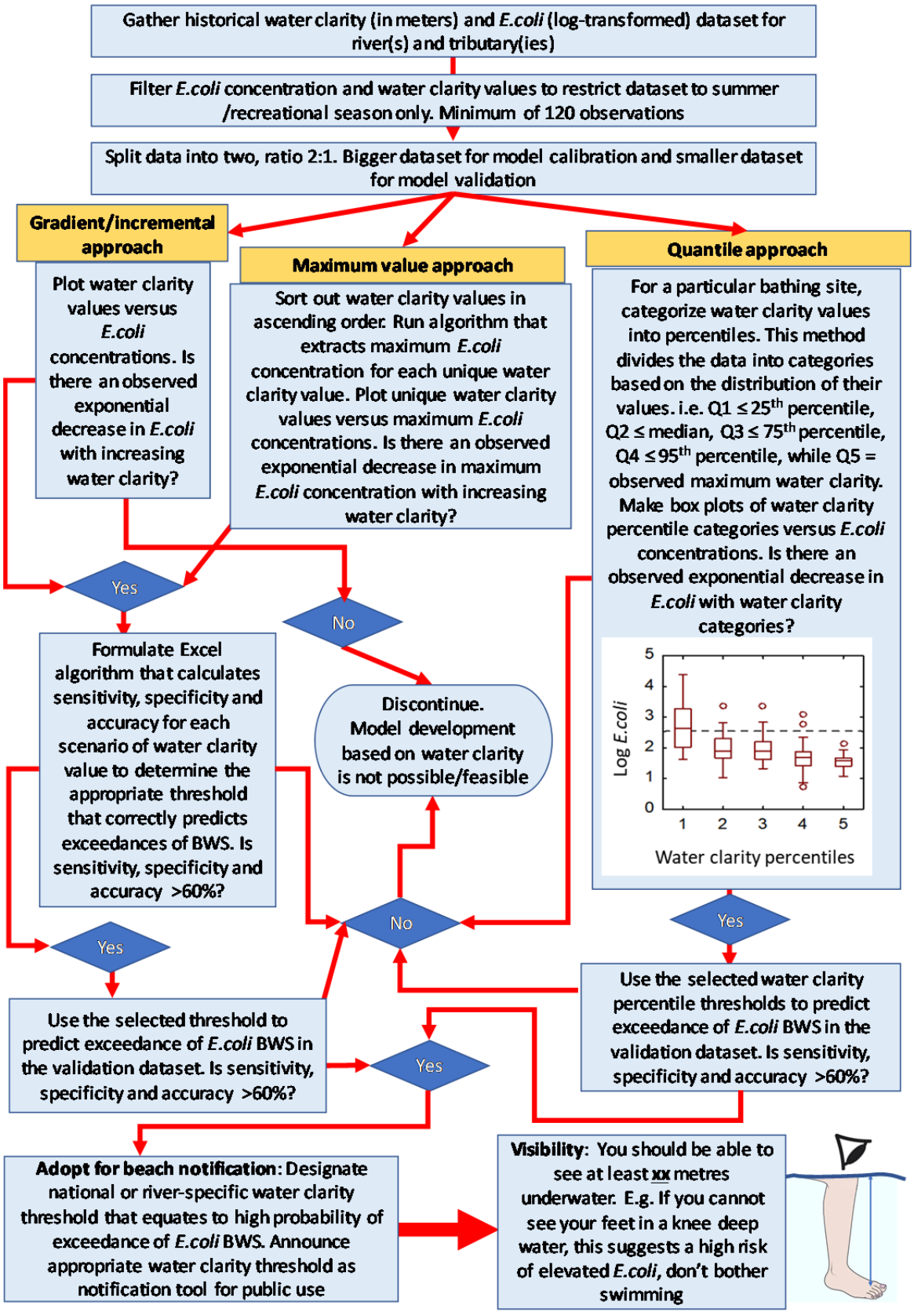


Figure 2. Methodology for Determining Water Clarity-based *E. coli* Predictions

3. Results

3.1 E. coli Concentrations in 49 Rivers Designated as Swimming Sites

On the whole, the Clutha, Waitaki and Waikato Rivers had the highest nine-year mean *E. coli* concentrations (2.59, 2.53 and 2.38 CFU/100 mL, respectively). However, rivers with the highest yearly summer average *E. coli* concentrations were Waikohu, Waihou, Sutton Stream, Waitara, Haast and Opihi. Monowai, a river flowing through non-pastoral catchments in the South Island, presented with the lowest yearly summer average *E. coli* concentrations. The proportion of samples with *E. coli* concentrations that exceed bathing water standards was highest for Waitara, Waipa, Waihou, and Waikohu as more than 30% of exceedances were observed during the nine-year period included in this study (Figure 3).

A=Waipapa, B=Opihi, C=Tarawera, D=Buller, E=Clutha, F=Shotover (3.49), G=Hakataramea (2.88), H=Opuha, I=Hurunui, J=Mohaka(3.74), K=Motueka (2.81), L=Waimakariri (1.90), N= Whiriniki (3.74), O=Rangitaiki (1.88), P=Wairau (1.60). Numbers in brackets and in the figure are proportions (%) of samples exceeding the recreational bathing water standards, text in the figure and beneath are 49 nationwide freshwater bodies included in the study.

Figure 3. Proportion of samples exceeding the NZ-NPS 540 CFU/100mL single sample bathing water standard (2005-2013)

3.2 Relationship Between E. coli and Clarity

A correlational analysis of 8103 *E. coli* and clarity datasets collated nationwide for a total of 49 rivers that have been routinely sampled at 77 sites by regional authorities in New Zealand was also done in this study. Results from the quartile approach indicate that river *E. coli* concentrations were inversely proportional to river water clarity, with a simply fitted spline accounting for more than 60% of the variability in the national *E. coli* dataset (Figure 4). *E. coli* concentrations declined with increasing water clarity, as assessed using clarity quartile categories (Figure 4). Water clarity quartile classification of rivers had a strong negative relationship with median faecal bacteria levels (Figure 4). Median *E. coli* concentrations were closer to the bathing water standard for water samples having water clarity values that fell within the first quartile (Figure 4). This inverse trend was also readily observable when box plots of *E. coli* concentrations versus water clarity quartiles were plotted for all different regions in New Zealand (Supplementary Figure 1), as well as for rivers categorized by land use (Supplementary Figure 2a), geology (Supplementary Figure 2b) and stream order classifications (Supplementary Figure 3).

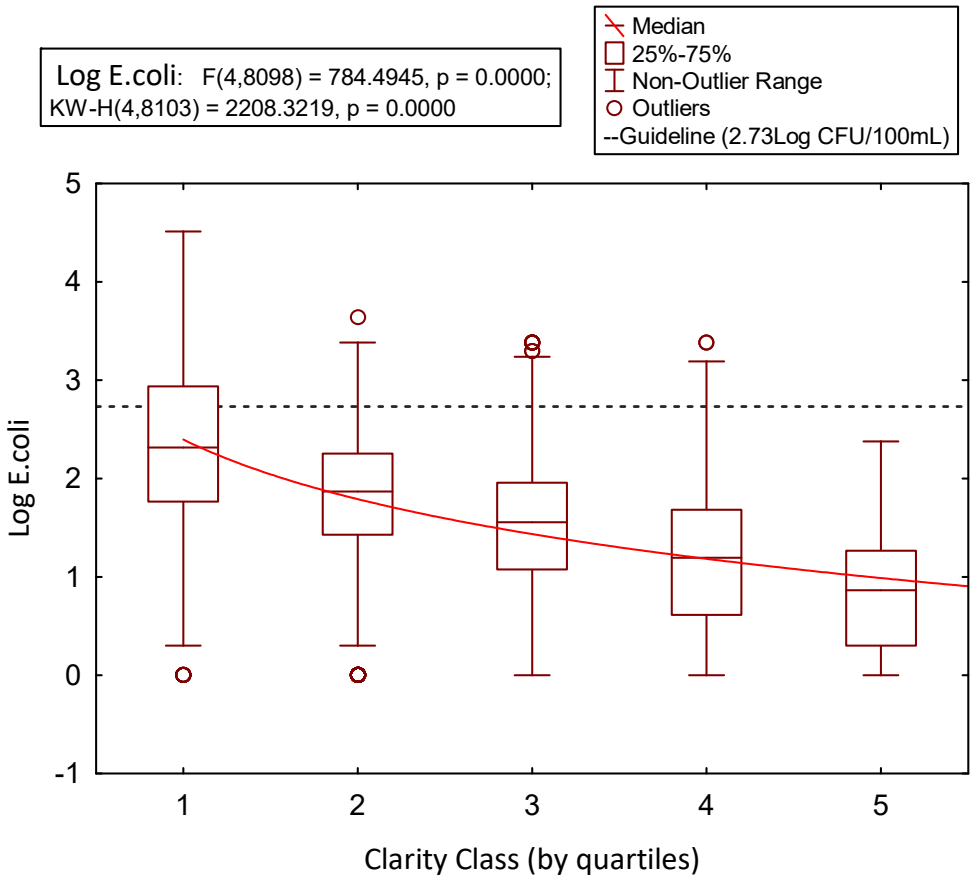


Figure 4. Plots of 8103 *E.coli* concentrations versus quartile distribution of water clarity. R-squared = 0.613. Red line is the line of fit that runs across median *E.coli* concentrations at different water clarity quartiles

3.3 Nation-Wide Trigger Values: Application of Clarity-Based Model for Estimating E. coli Concentrations in New Zealand Rivers

The applicability of water clarity-based *E. coli* models for use on a national scale was tested using the datasets described earlier. This was done with a view to developing a clarity-based classification scheme that could potentially identify exceedances of bathing water standards in recreational water using an easily measured indicator. This approach thus identifies trigger clarity ranges or thresholds that could initiate further investigation to confirm whether there is a problem related to faecal contamination.

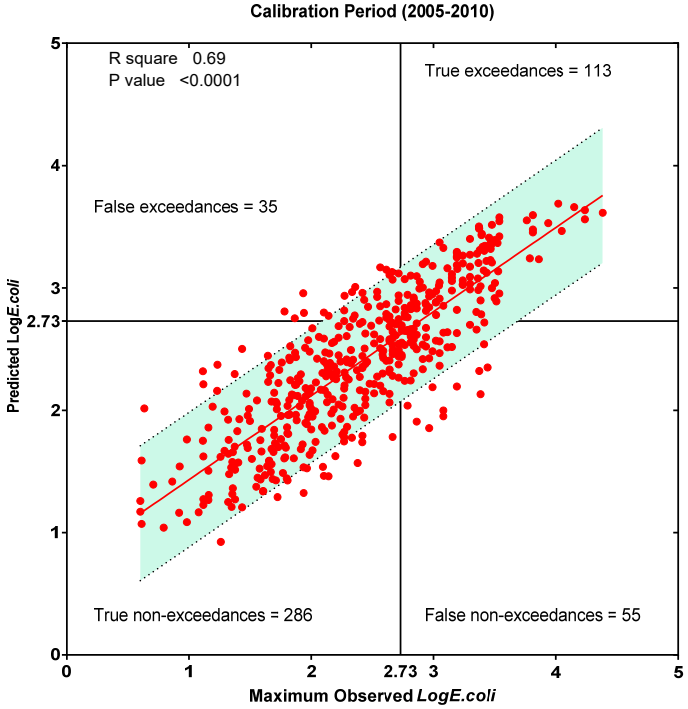
Using the maximum value approach stated in Section 2.3, maximum *E. coli* concentrations per unique water clarity value (in meters) were fitted using a regression model. Based on unique water clarity values, a predictive *E. coli* model was developed for rivers and tributaries in New Zealand with the equation below:

$$\text{Maximum Log}E.coli = 3.82 - 0.91 * Squaredroot[WaterClarity(m)]$$

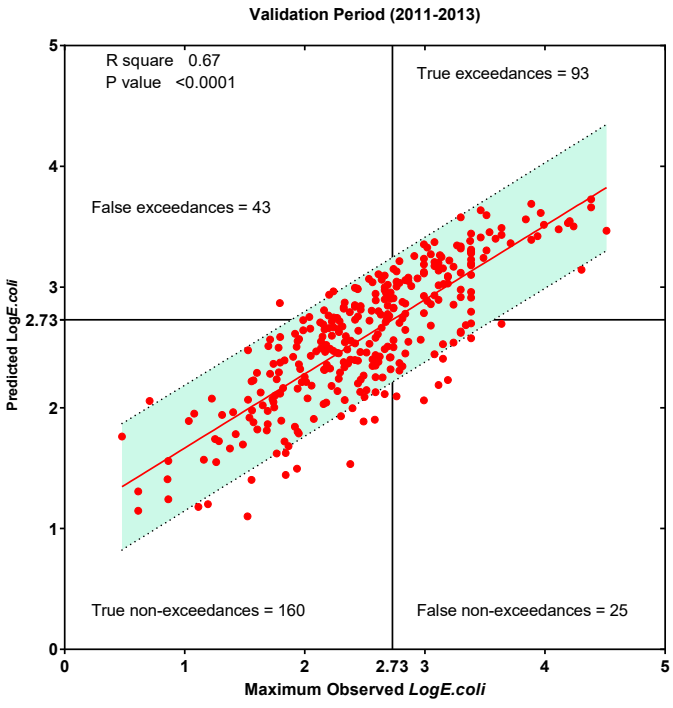
The water clarity-based *E. coli m*odel adequately captured the variability in *E. coli* data during the modeling period. Based on the obtained R-squared values, nearly 70% of the variability in maximum *E. coli* concentrations was explained by the model (Table 1 and Figure 5a). When model performance was assessed against the NZ NPS-FM bathing water criterion of 540 CFU/100 mL, a total of 113 out of the 168 exceedances (67%) in the calibration period were correctly predicted by the model (Figure 5a), with a sensitivity and specificity of 67 and 89%, respectively. The model was at least 81% accurate as it correctly predicted 399 exceedances and non-exceedances out of the 489 observations in the calibration period (Figure 5a).

The model also performed well when validated against the *E. coli* concentrations measured in rivers and tributaries during the validation period, 2011-2013 (Figure 5b). For instance, the model accurately predicted more than 75% of all exceedances in the *E. coli* data (Table 1) when assessed against the NPS-FM and USEPA bathing water

criteria. The root mean square errors of prediction for modeled mean *E. coli* concentrations were also low (0.02 LogCFU/100 mL).



(a)



(b)

Figure 5. Model performance plots fitted for New Zealand wide dataset using maximum value modelling approach: (a) Calibration Period, 2005-1010. (b) Validation Period, 2011-2013. Light green error bar indicates the 90% prediction interval

Table 1. FIB model performance during calibration (2005-2010) and validation (2011-2013) period. Performance of the classification scheme was assessed against a BWS of 540 CFU/100 mL, 260 CFU/100 mL, and 235 CFU/100 mL, respectively as in the New Zealand National Policy Statement on Freshwater Management and the USEPA guidelines

Model Statistics	Calibration Period (2005-2010)			Validation Period (2011-2013		
	NPS-540	NPS-260	USEPA-235	NFP-540	NPS-260	USEPA-235
Sensitivity (%)	67.26	82.86	82.94	78.81	85.41	87.37
Specificity (%)	89.10	84.02	79.75	78.82	62.50	60.31
Accuracy (%)	81.60	83.44	81.39	78.82	75.70	76.32
RMSE (LogCFU/100mL)	0.02	0.02	0.02	0.02	0.02	0.02
R Squared	0.69	0.69	0.69	0.67	0.67	0.67
Pearson Correlation	0.83	0.83	0.83	0.82	0.82	0.82

Figure 6 presents the receiver operating characteristic (ROC) curve of sensitivity, specificity and accuracy obtained when incremental water clarity 'thresholds' were applied to predict exceedances and non-exceedances of 8103 *E. coli* datasets, against a national bathing water standard of 540 CFU/100 mL, for each season. Table 2 summarizes the model performance data.

With increasing water clarity 'trigger value', the sensitivity of the model increases: there is an increase in the proportion of correctly predicted true exceedances but a concomitant reduction in the specificity of the model; i.e. decreases in the proportion of correctly predicted BWS non-exceedances. A plot of sensitivity and specificity versus potential trigger values quite easily delineated a crossover value. This crossover value is the optimum decision threshold where the maximum number of exceedances are correctly identified and is a reasonable trade-off between sensitivity, specificity, and accuracy (Arad, Housh, Perelman, & Ostfeld, 2013). Regardless of the season considered, the *E. coli* clarity models performed well as they presented with at least 75% sensitivity, specificity and accuracy at the crossover value (Figure 6, Table 2).

During summer and autumn, the crossover (trigger) value was observed to be 1.1m (Figure 6); i.e. on a nation-wide scale, there is a high likelihood that elevated levels of faecal indicator bacteria, above the *E. coli* BWS, would be present in rivers when the stream or river water clarity was lower than 1.1m. At this trigger value, 324 out of the 423 total *E. coli* BWS exceedances observed in the summers and autumns of the 9-year period were correctly predicted (i.e. 133 +191, see Table 2).

During winter and spring, the crossover (trigger) value was observed to be lower; 0.5m and 0.6m respectively (Figure 6), i.e. on a nation-wide scale, during these seasons, there is a high likelihood that elevated levels of faecal indicator bacteria, above the *E. coli* BWS, would be present in rivers when the stream or river water clarity is lower than 0.6m. At this trigger value, at least 383 out of the 465 exceedances observed in the winters and springs over the 9-year period were correctly predicted (i.e. 195+198, see Table 2). This trigger value also correctly predicted a high proportion of the non-exceedances observed in the winters and springs of the 9-year period, with a minimum specificity of 79% (Table 2). Regardless of the scenario of river catchment land use, geology, and stream order classifications considered in this study, the *E. coli* clarity models performed well as they presented with sensitivity, specificity and accuracy that ranged between 72.82% and 100% (Table 2).

On the whole, these results show that if swimmers were to avoid river waters with <1.1 m black disc visibility during summer and autumn or river waters with <0.5m black disc visibility during spring and winter, they would also avoid microbial hazards that are associated with exceedances of the 540 CFU/100 mL single sample bathing water standard (Table 2).

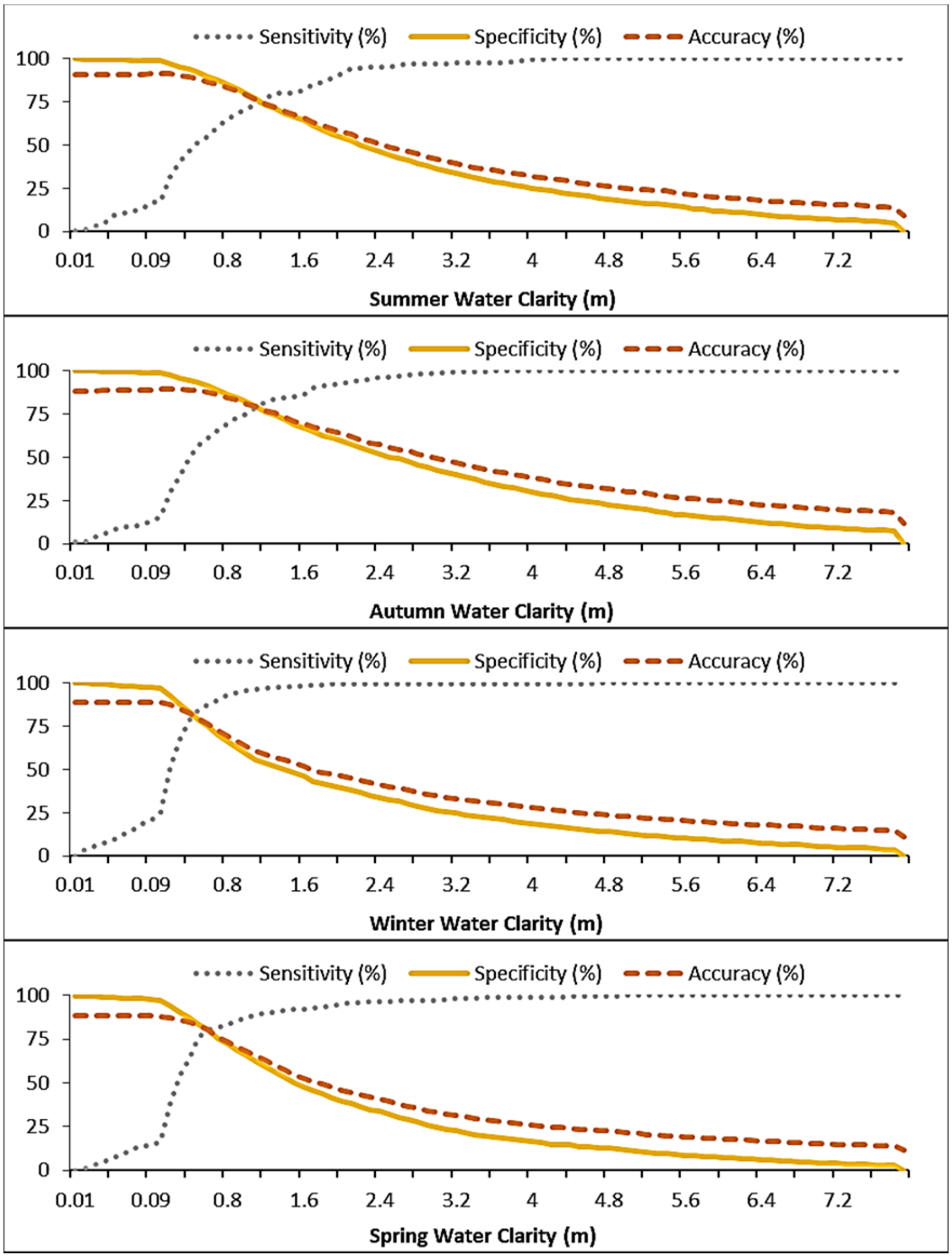


Figure 6. Receiver operating characteristic (ROC) plots of sensitivity, specificity, and accuracy versus incremental water clarity 'trigger' values that predict *E.coli* BWS exceedances at 77 freshwater sites nationwide during different seasons. Performance of the classification scheme was assessed against a BWS of 540CFU/100 mL as in the New Zealand National Policy Statement on Freshwater Management (2014)

Table 2. Model performance of seasonal water clarity trigger values used to fit exceedances and non-exceedances of *E.coli* data

Land cover						
	EF	P	S	IF		
Trigger Value (m)	1.1	0.9	1	0.7		
True Exceedances of BWS	11	296	7	380		
Total number of exceedances	11	391	9	476		
Total number of observations	106	4306	207	3484		
Sensitivity (%)	100	75.7	77.78	79.83		
Specificity (%)	90.53	72.82	78.79	80.55		
Accuracy (%)	91.51	73.08	78.74	80.45		
Season						
	Summer	Autumn	Winter	Spring	All seasons	
Trigger Value (m)	1.1	1.1	0.5	0.6	0.8	
True Exceedances of BWS	133	191	195	188	698	
Total number of exceedances	181	242	231	234	887	
Total number of observations	1952	2064	2043	2044	8103	
Sensitivity (%)	73.48	78.93	84.42	80.34	78.69	
Specificity (%)	76.76	79.36	79.08	80.22	77.63	
Accuracy (%)	76.46	79.31	79.69	80.23	77.75	
Stream order						
	1	2	3	4	5	6
Trigger Value (m)	0.6	0.6	1	0.7	0.6	0.8
True Exceedances of BWS	25	100	174	241	118	31
Total number of exceedances	32	133	230	301	154	37
Total number of observations	526	839	2518	2428	1266	526
Sensitivity (%)	78.13	75.19	75.65	80.07	76.62	83.78
Specificity (%)	79.35	76.35	74.83	79.5	79.84	83.44
Accuracy (%)	79.28	76.16	74.9	79.57	79.45	83.46
Geology						
	VA	SS	PI	HS	VB	AL
Trigger Value (m)	0.7	0.8	N/A	0.6	1.8	0.8
True Exceedances of BWS	75	298	0	132	5	174
Total number of exceedances	97	398	0	179	6	207
Total number of observations	950	2846	207	1372	106	2622
Sensitivity (%)	77.32	74.87	0	73.74	83.33	84.06
Specificity (%)	75.85	77.61	N/A	77.03	87	81.78
Accuracy (%)	76	77.23	N/A	76.6	86.79	81.96

EF= exotic forest, P = Pastoral, S = Scrub, IF= Indigenous forest, VA = Volcanic acidic, VB = Volcanic basic, Pl = Plutonics, HS = Hard sedimentary, ss = Soft sedimentary, AL = Alluvium, as in McDowell et al (2017), N/A = Not applicable, since no exceedances were observed for streams and rivers with plutonic geology throughout the entire 9-year modelling period. Trigger values were obtained from cross over plots for each scenario of river land use type, season, stream order and geology. Performance of the classification scheme was assessed against a single sample BWS of 540 CFU/100 mL as in the New Zealand National Policy Statement on Freshwater Management (NPS 2014).

4. Discussion

The goal of this study was to develop predictive models, based on the visual clarity of a waterbody, which could be used by the general public, as well as by the water science staff in regulatory institutions to predict the concentrations of *E. coli* in rivers and tributaries before water quality tests results are ready or during days when monitoring is not conducted. One critical goal was to build the model using relatively basic numerical concepts that could be relayed to and be useable by the public. In this way, the public can make smarter, faster decisions on the bacteriological quality of water at their favourite swimming spot.

In order to achieve this objective, this study focused on water clarity as a potential environmental surrogate for *E. coli* in the development of predictive FIB models. The use of water clarity to predict stream bacteriological water quality in our study is logical since it has been shown that this variable is strongly correlated with turbidity, which also influences water quality in a water body (Dada & Hamilton, 2016), and is related to *E. coli* concentration. A number of studies have previously shown strong relationships between *E. coli* and turbidity (Christensen, 2001; Rasmussen and Ziegler, 2003, Riverkeeper et al., 2008) and between *E. coli* and other variables that influence turbidity, including antecedent rainfall, suspended solids, and phosphorus nutrient enrichment. Gregory and Frick (2000) reported that faecal coliform bacteria densities in the Chattahoochee River were highest after rainstorms, when the river was turbid. Dada and Hamilton (2016) reported an increase in total phosphorus (TP) and suspended solids at some streams in New Zealand in relation to *E. coli.* For example, like phosphorus, faecal bacteria tend to be bound to particulate matter, and are often transported in a particle-facilitated manner (Hong et al., 2010). Also, suspended solids include a wide variety of material (such as silt, decaying plant and animal matter and wastes) (Kannel et al., 2007), which could provide attachment surfaces for bacteria, a process important for the growth and survival of organisms in the aquatic environment. With increased concentrations of suspended solids in these streams, *E. coli* may be able to attach to more particle surfaces by adsorption. Fries et al. (2006) reported that 34 to 42 percent of *E. coli* in surface-water samples were attached to particles in the water column. The presence of suspended solids in the water column increases the survival rates of *E. coli* by limiting the inactivating effects of sunlight (Sinton et al., 2002; Stapleton et al., 2004; Kay et al., 2005; Liu et al., 2006).

Unlike turbidity or suspended solids, however, water clarity can be easily measured with very minimal training and basic equipment. Additionally, in instances where there is no equipment, a water clarity-based predictive system, when translated into specific meter measurements, could potentially help the public make fast, informed decisions on the bacteriological quality of the water they are about to wade into. For instance, regional authorities can harness historical water clarity and *E. coli* data to mathematically determine water clarity thresholds that tend to be mostly associated with exceedances of the bathing water standard. In this study, our results show that if swimmers were to avoid river waters with <1.1 m black disc visibility during autumn and summer or river waters with <0.5 m black disc visibility during spring and winter, they would also avoid microbial hazards that are associated with exceedances of the 540 CFU/100 mL single sample bathing water standard. These water clarity thresholds could then be used by relevant authorities to build an early warning system, which could be communicated to the public. This could result in warnings like, 'if you cannot see your feet in ankle-deep water, don't go swimming' (see Figure 2).

We used water clarity to calibrate and validate FIB models to predict *E. coli* concentrations on a nation-wide scale for all rivers in New Zealand. The *E. coli* model built using the maximum value approach showed high predictive power, which could account for more than 67% of the variability in the *E. coli* data (R^2 ranged between 0.67 and 0.69 during the calibration and validation period). Based on a recent literature study, de Brauwere et al. (2014) reported that the performance (adjusted R^2) of multiple linear regression models varies widely, ranging from 0.29 to 0.99, thus emphasizing their extreme case-sensitivity.

The models developed in this study were also able to advise on exceedances or non-exceedances of existing BWS. Model performances, in terms of predicting whether a warning should be issued, varied among the rivers and streams considered depending on the season, land cover, geology and stream order classification. However, in most instances, the model sensitivity and specificity were higher than 70% in most scenarios of season, land cover, geology and stream order classification. The variability observed in our model performance is in agreement with the observations of Thoe et al. (2014).

Also, model performances, in terms of predicting whether a warning should be issued, varied among the modelling approaches used. For instance, while model specificity, specificity and accuracy ranged from 67.26% to 89.1% for the gradient modelling approach, higher values of model specificity, specificity and accuracy (range 72.8% - 100%) were recorded for the incremental modelling approach. These results suggest that the best approach to using water clarity to predict E. coli concentrations is the incremental modeling approach, coupled with an ROC-curve

optimization to determine water clarity 'thresholds' that best predict exceedances of the bathing water standard.

From a public health protection perspective, Thoe et al. (2014) suggested that a model ready for management applications should predict a greater percentage of beach postings (water quality warnings) than the current method, without the expense of excessive 'false alarms'. Given this background, criteria were proposed by Thoe et al. (2014) to determine whether a model is effective for beach management. These conditions require that the selected model should have (i) sensitivity greater than 30% and (ii) specificity greater than 80%. The water clarity-based FIB models developed in this study using the incremental approach largely satisfy these criteria.

Despite the performance of these models, some exceedances of the bathing water standards were still missed. This suggests that there are factors other than clarity affecting *E. coli* concentrations, which are not captured by the model. Notwithstanding this limitation, our model was able to accurately predict more than 75% of the exceedances and non-exceedances recorded at these sampling sites (1990-2013); hence, it is a useful tool for bacteriological water quality management. Under varying scenarios of water clarity conditions, water science managers and the public at large can make a reliable prediction of current *E. coli* concentrations faster than the turn-around period of currently available, conventional assay-based methods. We believe that the approach used in this study could be adapted for wide-spread use in local water bodies in New Zealand and beyond.

While a number of studies globally have reported correlations of *E. coli* concentrations with the physical appearance of water (e.g. turbidity and water clarity), these studies are often site-specific (Collins, 2003, Dwivedi et al 2013, Francy et al 2013). It thus becomes logical to argue that strong correlations reported for one site do not necessarily mean the same is true for other rivers not covered in any given study. Besides, the characteristics of every river will differ, typically reflective of the catchments they run through. Our unique approach goes beyond exploring water clarity and *E. coli* concentrations at a site-specific level and covers entire national datasets, capturing multi-river considerations and differing land use, geology, river order classification and seasons.

A recent article (Davies-Colley et al., 2018) published during the preparation of this paper, operates at a national level. Davies-Colley et al. (2018) described a uniform water clarity threshold across different conditions, suggesting that 'if swimmers were to avoid river waters <1.6 m black disc visibility, they would also avoid microbial hazards about 99% of the time'. The current study advances these findings reported by Davies-Colley et al. (2018) by showing that there are differences in the ability of water clarity to predict *E. coli* concentrations depending on climatic seasons, land use, geology, and stream order classifications. Kelly et al. (2018) reported that swimming site geomorphology was highly associated with exceedance of regulatory standards. Similarly, Paule-Marcado et al. (2016) and Donahue et al. (2017) reported that faecal indicator bacteria exceedances were associated with land use.

Our study also successfully applied receiver operating characteristic (ROC) curves to optimize the determination of water clarity 'thresholds' that predict exceedances of the bathing water standard (as in Figure 6). This ROC-guided crossover value is the optimum decision threshold where the maximum number of exceedances are correctly identified and is a reasonable trade-off between sensitivity, specificity, and accuracy (Arad, Housh, Perelman, & Ostfeld, 2013). The ROC approach was able to optimize the water clarity thresholds in this report, rather than applying a single uniform water clarity threshold across different seasons and land use conditions. For instance, applying a single threshold of 1.6m without the ROC optimization will predict that a stream is safe for recreation when it actually contains *E. coli* at concentrations above the bathing water standard (at least half of the predicted times, based on the low model specificity and accuracy of 47.7% and 52.5%, respectively (see supplementary sheet)). The findings of this research have important policy implications because site-specific considerations for water clarity-based E. coli prediction could be implemented in other parts of the country and around the world to augment conventional culture-based approaches in a way that improves the timeliness of swimming water advisories.

We note however that there are potential limitations to the modelling approach in our study. For instance, in summer, 133 out of 183 exceedances of the BWS were predicted by the water clarity-based model. This suggests that there are situations when water clarity may prove to be a poor model for *E. coli* levels (i.e. erosion of sediments with little microbial input or clear water in urban systems despite high concentrations of microbial pollutants). Also, while our focus was to model the relationship between water clarity and faecal indicator bacteria, it does not differentiate between contributions of faecal bacteria from the sediment bed and from the watershed. There was also no delineation between free and particle-associated faecal bacteria. In the future, sediment deposition and resuspension fluxes of faecal bacteria across the sediment bed–water interface at river-specific levels could be incorporated into the model. Based on this, it would be possible to apply the model to hypothetical scenarios that can potentially evaluate the impact of varying catchment management conditions as well as settling

and resuspension conditions on *E. coli* concentrations observable in the water column.

Another limitation to our approach is spatial variability. For instance, bacteriological water quality at designated sampling sites is thought to be representative of that particular water body. However, considerable spatial variability has been documented over scales of 10 m and more (Schang et al, 2018; Boehm et al 2009). It is thus hoped that future studies will combine *E. coli* and water clarity data with geographic information systems in a way that dynamically captures both spatial and temporal dimensions. A similar approach was adopted by Money et al. (2009) in a study that combined *E. coli* and turbidity data in a river-based space/time geostatistical framework for basin-wide assessment of faecal contamination. This can harness the power of aerial photography and satellite-based remote sensing to provide real-time aerial prediction of *E. coli* conditions.

We note that the assessment of recreational water, depending on the location, may require consideration for other parameters apart from *E. coli*. These include, for instance, nuisance algae and floating trash that may contribute to the overall suitability of a water body for contact recreation. In the future, studies will emerge that attempt to aggregate a range of environmental variables other than *E. coli* into a single index that comprehensively assesses risk and that is understandable to the public and decision makers. The use of comprehensive contact recreation attributes rather than single *E. coli*-based measures have recently emerged (e.g. SafeSwim-Auckland Council, Milne et al., 2016, 2017; Lopes et al., 2018) and show potential for national and global application.

5. Conclusion

In this study, a direct negative correlation between water clarity and *E. coli* concentrations was observed for most major rivers and tributaries in New Zealand. This correlation was used to develop predictive models that can produce estimates of *E. coli* concentrations rather than waiting for the 24-48-hour reporting time that conventional monitoring procedures require. Water clarity trigger values defined by the model can be used by authorities to alerts recreational users of possible high faecal bacteria values. Water clarity trigger values defined for specific bathing sites can also be incorporated into early warning systems, which could be communicated to the public. This could result in warnings like, ‘if you cannot see your feet in ankle-deep water, don’t go swimming’. The developed models can provide a faster estimation of *E. coli* concentrations, allowing the public to engage in water quality monitoring, and also to make informed decisions on whether it is safe to swim at their favourite swimming spot.

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Competing Interests Statement

The authors declare that there are no competing or potential conflicts of interest.

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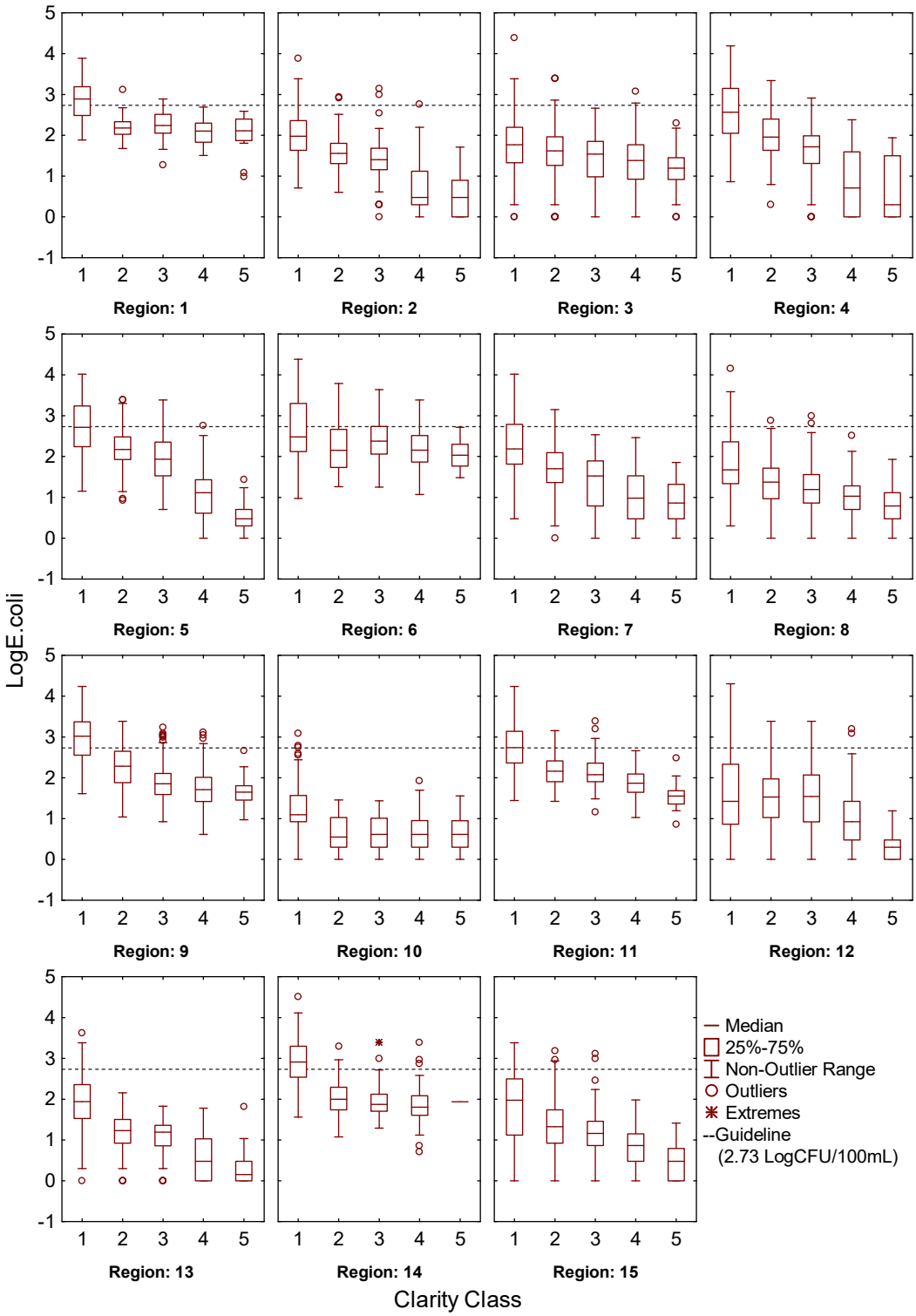
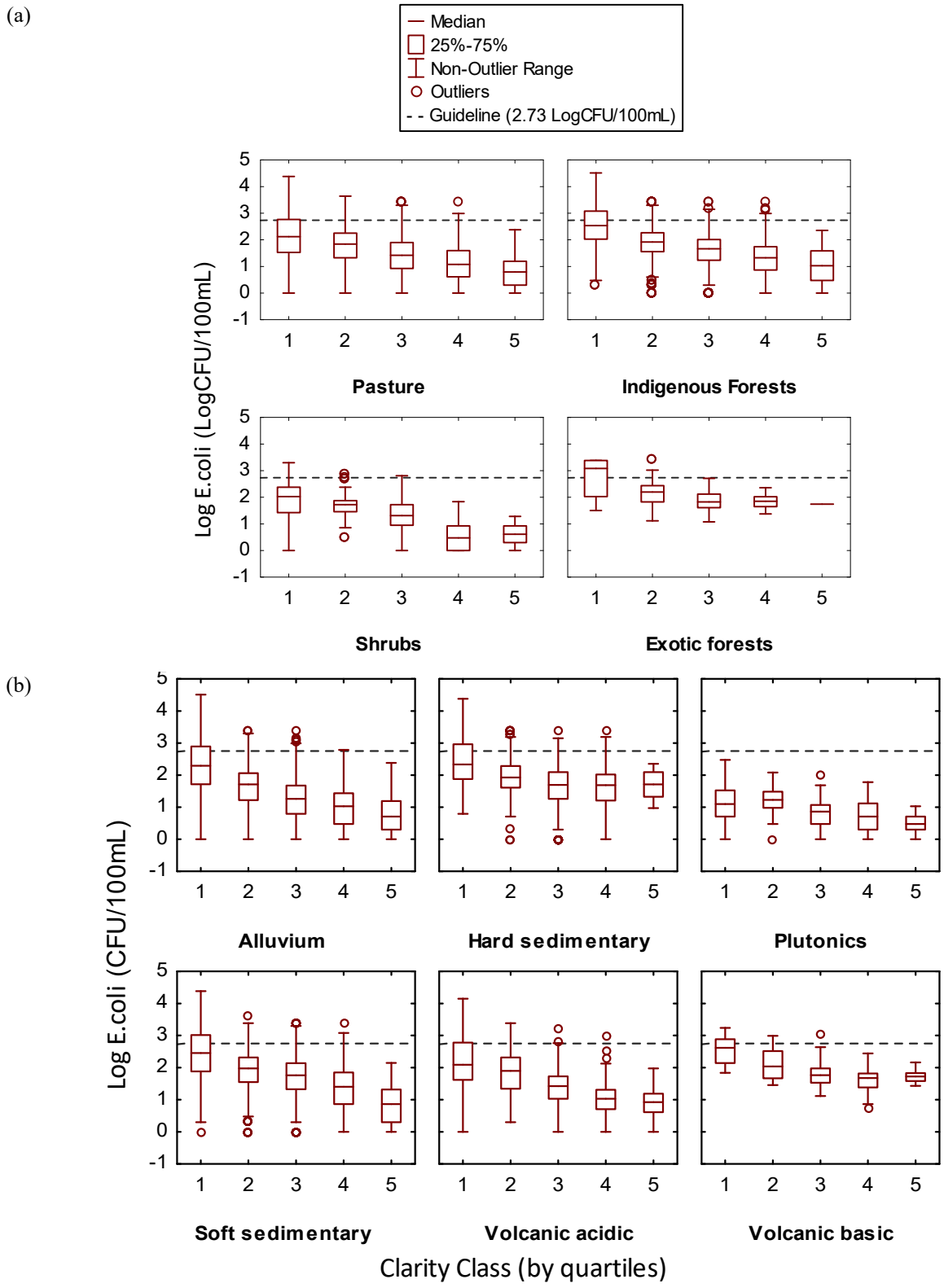
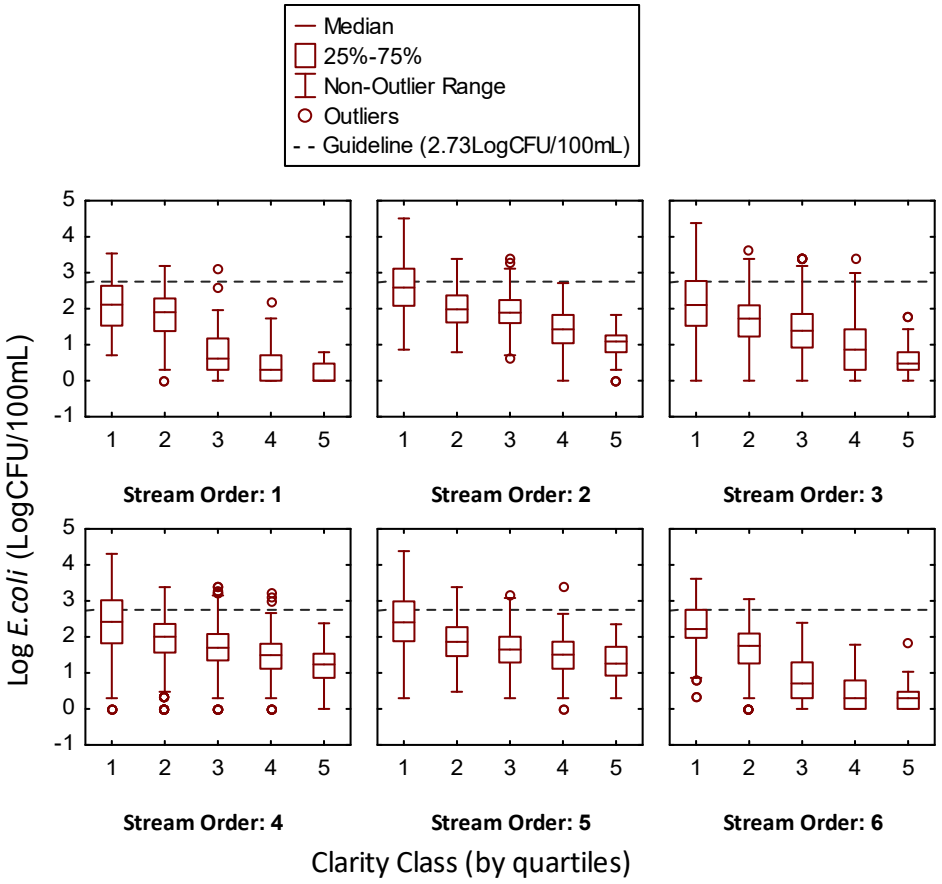
Supplemental Material



Supplemental Figure S1. Box plots of 8103 datasets of river *E.coli* concentrations grouped by clarity class and categorized by region. Region 1=AC, 2=BOP, 3=ECAN, 4=ES, 5=EW, 6=GDC, 7=GWRC, 8=HBRC, 9=HRC, 10=MDC, 11=NRC, 12=ORC, 13=TDC, 14=TRC, 15=WCRC



Supplemental Figure S2. Box plots of 8103 datasets of river *E.coli* concentrations grouped by clarity class and categorized by a) land use and b) geology.



Supplemental Figure S3. Box plots of 8103 datasets of river *E.coli* concentrations grouped by clarity class and categorized by stream order classification

Supplemental Table S1. Sensitivity, specificity, and accuracy associated with various incremental water clarity 'trigger' values (in meters) when used to predict *E.coli* BWS exceedances at 77 freshwater sites nationwide during spring.

Incremental water clarity values	True Exceedences of BWS	True Non-excceedances of BWS	False Non-exceedanceS of BWS	False exceedanceS of BWS	Total exceedances	Total non-exceedances	Total observations	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity - Specificity (%)
0.01	0	1808	234	1	234	1809	2043	0.00	99.94	88.50	-99.9
0.02	3	1803	231	6	234	1809	2043	1.28	99.67	88.40	-98.4
0.03	7	1799	227	10	234	1809	2043	2.99	99.45	88.40	-96.5
0.04	12	1793	222	16	234	1809	2043	5.13	99.12	88.35	-94.0
0.05	17	1789	217	20	234	1809	2043	7.26	98.89	88.40	-91.6
0.06	22	1786	212	23	234	1809	2043	9.40	98.73	88.50	-89.3
0.07	28	1781	206	28	234	1809	2043	11.97	98.45	88.55	-86.5
0.08	33	1777	201	32	234	1809	2043	14.10	98.23	88.60	-84.1
0.09	33	1773	201	36	234	1809	2043	14.10	98.01	88.40	-83.9
0.1	39	1763	195	46	234	1809	2043	16.67	97.46	88.20	-80.8
0.2	89	1698	145	111	234	1809	2043	38.03	93.86	87.47	-55.8
0.3	127	1635	107	174	234	1809	2043	54.27	90.38	86.25	-36.1
0.4	150	1584	84	225	234	1809	2043	64.10	87.56	84.88	-23.5
0.5	178	1517	56	292	234	1809	2043	76.07	83.86	82.97	-7.8
0.6*	188	1451	46	358	234	1809	2043	80.34	80.21	80.23	0.1
0.7	191	1370	43	439	234	1809	2043	81.62	75.73	76.41	5.9
0.8	195	1309	39	500	234	1809	2043	83.33	72.36	73.62	11.0
0.9	200	1245	34	564	234	1809	2043	85.47	68.82	70.73	16.6
1	205	1191	29	618	234	1809	2043	87.61	65.84	68.33	21.8
1.1	207	1129	27	680	234	1809	2043	88.46	62.41	65.39	26.1
1.2	211	1075	23	734	234	1809	2043	90.17	59.43	62.95	30.7
1.3	211	1016	23	793	234	1809	2043	90.17	56.16	60.06	34.0
1.4	214	964	20	845	234	1809	2043	91.45	53.29	57.66	38.2
1.5	216	900	18	909	234	1809	2043	92.31	49.75	54.63	42.6
1.6**	216	862	18	947	234	1809	2043	92.31	47.65	52.77	44.7
1.7	218	822	16	987	234	1809	2043	93.16	45.44	50.91	47.7
1.8	219	790	15	1019	234	1809	2043	93.59	43.67	49.39	49.9
1.9	220	752	14	1057	234	1809	2043	94.02	41.57	47.58	52.4
2	223	717	11	1092	234	1809	2043	95.30	39.64	46.01	55.7
2.1	224	689	10	1120	234	1809	2043	95.73	38.09	44.69	57.6
2.2	225	661	9	1148	234	1809	2043	96.15	36.54	43.37	59.6
2.3	226	630	8	1179	234	1809	2043	96.58	34.83	41.90	61.8
2.4	226	609	8	1200	234	1809	2043	96.58	33.67	40.87	62.9
2.5	226	581	8	1228	234	1809	2043	96.58	32.12	39.50	64.5
2.6	227	547	7	1262	234	1809	2043	97.01	30.24	37.89	66.8
2.7	227	523	7	1286	234	1809	2043	97.01	28.91	36.71	68.1
2.8	228	501	6	1308	234	1809	2043	97.44	27.69	35.68	69.7
2.9	228	471	6	1338	234	1809	2043	97.44	26.04	34.21	71.4
3	228	448	6	1361	234	1809	2043	97.44	24.77	33.09	72.7
3.1	229	423	5	1386	234	1809	2043	97.86	23.38	31.91	74.5
3.2	231	408	3	1401	234	1809	2043	98.72	22.55	31.28	76.2
3.3	231	394	3	1415	234	1809	2043	98.72	21.78	30.59	76.9
3.4	231	369	3	1440	234	1809	2043	98.72	20.40	29.37	78.3
3.5	232	354	2	1455	234	1809	2043	99.15	19.57	28.68	79.6
3.6	232	344	2	1465	234	1809	2043	99.15	19.02	28.19	80.1
3.7	232	330	2	1479	234	1809	2043	99.15	18.24	27.51	80.9
7.7	234	53	0	1756	234	1809	2043	100.00	2.93	14.05	97.1
7.8	234	49	0	1760	234	1809	2043	100.00	2.71	13.85	97.3
20	234	0	0	1809	234	1809	2043	100.00	0.00	11.45	100.0

Optimum threshold (spring), this study, **1.6m threshold reported in Davies-Colley et al (2018)