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Optimising sampling frequency for change detection of variables in lake monitoring programs

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ABSTRACT

A lake monitoring regime optimised to detect natural and anthropogenic variations in water quality is critical for supporting and understanding the impact of lake restoration actions. It can support efficient investment in monitoring by minimising the time required for change detection of lake water quality attributes. The objective of this study was to develop tools and resources to support the development of optimised lake monitoring programs tailored for individual monitored and unmonitored lakes in New Zealand, targeted to detecting change in key water quality attributes in response to restoration actions. We used monitoring data collected routinely from 148 lakes and modelled variability of chlorophyll-a (chl-a), total nitrogen (TN), total phosphorus (TP), and Secchi disk depth (SDD). Using a gradient boosted regression tree (BRT) procedure, we estimated the number of samples per year required over a 5-year and 20-year period to detect improvement in water quality equivalent to meeting thresholds for minimum acceptable water quality states in national policy. At monitored sites, chl-a monitoring to detect improvements within five years was estimated to increase current costs by over 16 times and over 3 times to detect improvements within 20 years. Monitoring to document the effects of restoration actions is important for justifying investments in restoration. Our assessment indicates the importance of monitoring frequency for the level of investment and duration with what is possible to detect the resulting changes in water quality.

1. Introduction

Lakes are sentinels for human induced environmental change (Adrian et al., 2009; Carpenter et al., 2007). Globally, lake ecosystems are facing intense pressure from water extraction, accelerated land clearance, and agricultural intensification in their catchments as well as climate change (Jenny et al., 2020). Legacies from historical land use activities also impact lake ecosystems as additional nutrients deposited in bottom sediments are remobilised through physical and biogeochemical processes (Jarvie et al., 2013). The associated eutrophication and anoxia of bottom waters affect the health and biodiversity of lakes (Li et al., 2010). Symptoms of eutrophication can be associated with collapse of benthic fauna and blooms of potentially toxic cyanobacteria (Rastogi et al., 2015; Wood et al., 2020). At an individual level, however, lakes respond in specific ways to anthropogenic pressures making it difficult to predict the extent of water quality impairment and responses to restoration actions (Adrian et al., 2009; Schallenberg, 2021). Monitoring is key to understanding and predicting lake responses, and the design of monitoring programs requires careful consideration of frequency and duration to reflect the complex interactions between hydrological and biogeochemical processes (Deleersnijder et al., 2001) and natural and human-induced climate variations.

The United Nations Decade on Ecosystem Restoration (2021–2030) emphasises protecting and restoring lakes and other freshwater ecosystems regionally and nationally to address the Sustainable Development Goals (specifically SDGs 6 and 15). The United Nations

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Environment Assembly Resolution on Sustainable Lake Management of 2 March 2022 (UNEP/EA.5/Res.4) has reinforced the urgency of restoration by recognising the deteriorating state of lake water quality to an extent that threatens human health, biodiversity, and the environment generally. At a national level in New Zealand, several studies have identified a rapid decline in freshwater quality from increases in diffuse nutrient pollution (Gluckman, 2017; Snelder et al., 2023) including for lakes (Wood et al. 2023). As a result, the 2020 National Policy Statement for Freshwater Management (NPS-FM, 2020) has undergone several iterations since it was first passed in legislation in 2011 and has been designed to provide direction to manage New Zealand's freshwater resources including improving waterbodies identified as degraded to minimum standards (termed National Bottom Lines).

To attempt to arrest eutrophication and restore the health, services and biodiversity of lakes, restoration programs are being implemented throughout New Zealand. The level of investment made in individual lakes can amount to many millions of dollars, as documented globally (Feeney et al., 2023; Hartig et al., 2020; Zhang et al., 2000) and in New Zealand (Hamilton et al., 2016). Monitoring programs are required to support the development of restoration actions and assess their effectiveness, including the time scales of lake responses to restoration, but in many cases, the level of follow-up monitoring has fallen short of requirements and even been non-existent (Poikane et al., 2024). A well-designed monitoring program will contribute to understanding the natural and anthropogenic variability of water quality attributes but poses several challenges. First, the ability to characterise the variability in water quality attributes is dependent on how frequently samples are taken. For example, in some shallow lakes, even fortnightly measurements may be inadequate to capture significant changes in water quality due to discharges or pollutant inflows (Diamantini et al., 2018). Second, some monitoring programs may not be of sufficient duration to detect trends in water quality, even after several years of monitoring (Kundzewicz and Krysanova, 2010). Thus, implementation of an optimised monitoring frequency (how often) and duration (how long) is critical for cost-effective detection of water quality changes.

Conventional lake monitoring involving collection of grab samples for 'state of the environment' reporting is usually undertaken on a fixed quarterly or monthly frequency and usually requires many years of sampling to detect water quality changes. To demonstrate the effects of restoration practices on water quality, sampling can be costly and infeasible for large numbers of lakes, particularly when regulatory requirements or funding are inadequate. Automated high-frequency sensor monitoring is valuable to address some of the inadequacies of conventional lake monitoring programs as it can capture short-lived, episodic, or unpredictable events (Dubelaar et al., 2004; Marcé et al., 2016; Seifert-Dähnn et al., 2021), but it also has substantial capital and maintenance requirements and methodologies are not routinely available for several key water quality attributes.

The design of monitoring programs to assess lake restoration efforts has not received the attention needed to effectively inform sampling to meet policy at a national scale. The objectives of this study were therefore to: 1) determine the factors accounting for the variability of lake water quality attributes at monitored sites, 2) use these factors to model variability of water quality attributes at unmonitored sites, 3) use monitoring data in statistical power analyses to estimate the likelihood of detecting changes in water quality over time, and 4) package this information in a web application (https://www.monitoringfreshwater.co.nz/lakes) to support the design of lake water quality monitoring programs tailored to optimise the detection of changes in water quality (e.g., from mitigation actions) at individual lakes. We extend our analysis to estimate the number of samples and associated monitoring costs required over a 5- and 20-year period for two scenarios of improvement in total nitrogen, total phosphorus and chlorophyll-a concentrations, and Secchi depth across New Zealand lakes. The scenarios include (1) a level of improvement to meet minimum acceptable state set in national freshwater policy (NPS-FM, 2020) for concentrations of total nitrogen (TN), total phosphorus (TP), chlorophyll-a (chl-a), and Secchi disk depth (SDD), and (2) a nominal 30 % improvement in each of these water quality attributes (commensurate with the national average achievable improvements via actions to mitigate contaminant losses from land to water (McDowell et al., 2021)).

2. Material and methods

2.1. Study area

New Zealand has approximately 3800 lakes > 1 ha in area (MfE, 2020) of which 322 are fed by ≥ 3rd-order streams and rivers. Freshwater lakes in New Zealand have significant cultural, recreational, and social values. Lakes support agriculture, water supply, tourism, and hydroelectricity generation. There is also a documented history of cultural eutrophication of lakes in New Zealand (Wood et al., 2023). Land use intensification for agriculture, establishment of non-native species, and climate change pose major challenges for maintaining or improving the trophic status of the lakes (Hamilton et al., 2013; Gluckman, 2017). Land use intensification over the past two decades has been associated with increased irrigation and fertiliser use for agricultural production (McDowell et al., 2023). Lake water quality also varies naturally due to a range of catchment and within-lake factors, such as geomorphology and water depth (Abell et al., 2020). To account for this variability based on water depth, we classified lakes as shallow (mean depth ≤ 7 m and maximum depth ≤ 20 m) or deep for remaining cases, following Abell et al. (2020). We also used geomorphological origin as a variable to assess trophic state. Volcanic eruptions have contributed to the formation of many large North Island lakes, while the South Island large lakes are mostly of glacial and alluvial outwash origin. There are also landslide, peat, shoreline, and riverine lakes throughout New Zealand (Fig. 1).

The trophic status was assessed using water quality attributes of nutrient concentration (TN, TP), algal biomass (using a proxy of chl-a), and water clarity (SDD). Together these attributes are part of the Trophic Level Index commonly used for assessing lake trophic status and management responses at a regional level in New Zealand (Burns et al., 1999). Three of these attributes (TN, TP, chl-a) are used in the NPS-FM (2023) to define the level of departure of a lake from a near-pristine state, i.e., from a category of 'A' for water quality that is close to a reference state, 'B' for slightly impacted, 'C' for impacted but acceptable, and 'D' for unacceptably poor water quality. A management plan is required for a D state or when the state (i.e., B or C) does not meet agreed expectations.

2.2. Data preparation

Data for this study were sourced from all Regional Councils in New Zealand for 2006–2020 via the Land, Air, Water, Aotearoa website (https://www.lawa.org.nz). We restricted our database to samples taken between 2006 and 2020. This period allowed for the greatest consistency in analytical methods and reporting. We chose 15 years as a period to account for trends owing to land use or climatic variation (Scarsbrook et al., 2003; Wilcock et al., 2013). The analytes included in our analysis were TN, TP, chl-a, and SDD.

We used four steps to inspect, clean, and filter the data (Fig. 2):

1. When multiple locations (up to 4 sites) were sampled on a single day on a lake, a mean value was calculated. This occurred in 17 lakes.
2. The data were inspected for outliers (more than three times the interquartile range) or mislabelled values (e.g., text or incorrect < or > signs). There were few (<1%) outlier values, so we chose not to remove them. However, we did correct (viz. clean) any mislabelled data (also < 1 % of values).
3. Values at or below the detection limit were set to half the detection limit.

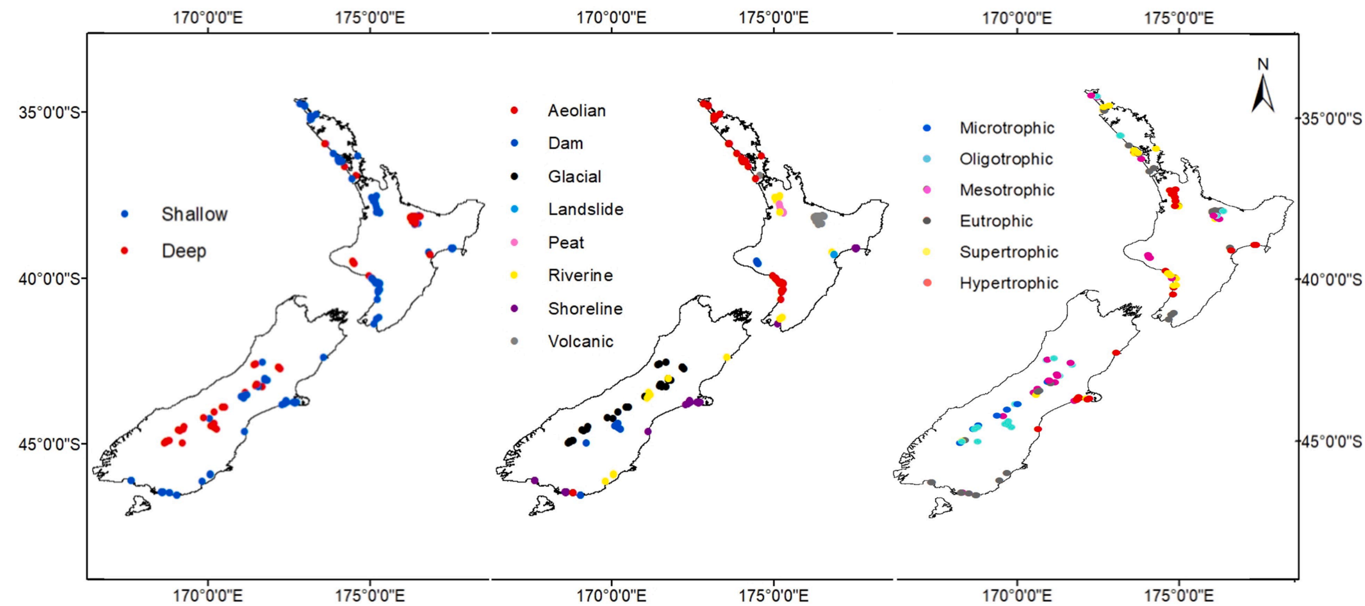

Fig.1. Locations of monitored sites showing lakes classified according to maximum depth, trophic level, and geomorphic origin.

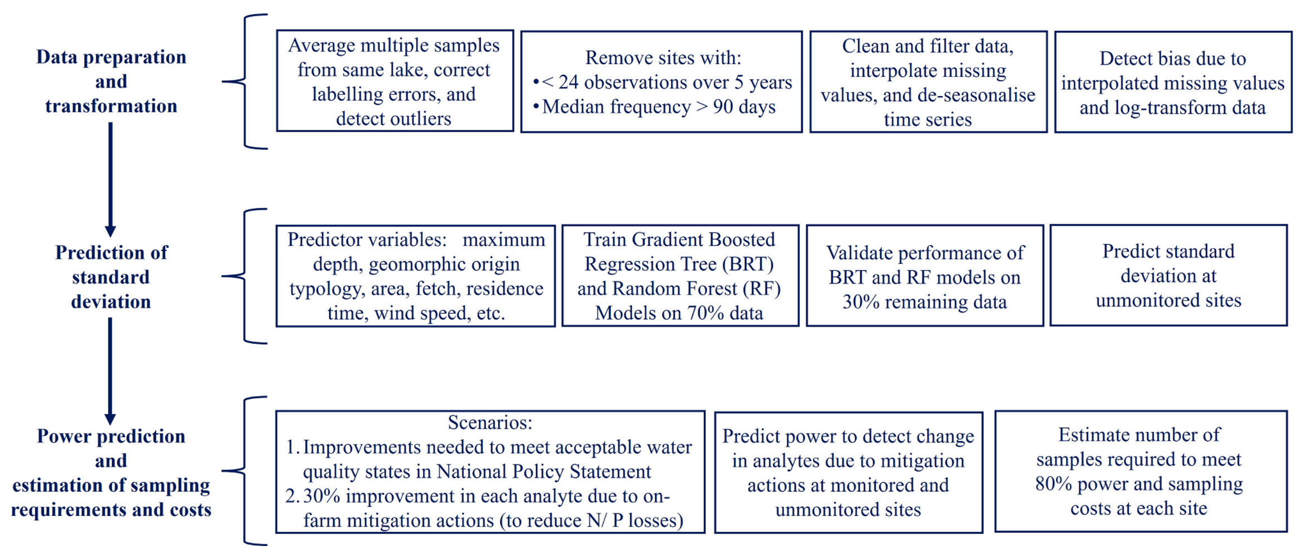

Fig.2. Flowchart summarizing key steps in methodology adopted for predicting variability (standard deviation) of four water quality analytes (TP, TN, chlorophyll-a, and Secchi disk depth), predicting power, and estimating sampling requirements and costs at each site.

4. Finally, we removed sites with fewer than 24 observations over 5 years or a median measurement frequency > 90 days.

Cleaning and filtering the data (steps 2–4) resulted in the removal of 17, 4, 15, and 20 sites for chl-a, SDD, TN, and TP, respectively, leaving 106, 70, 108, and 103 lakes, respectively, for modelling purposes. Across all analytes, there was a total of 148 monitoring sites across 116 lakes. Lake attributes were derived from the FENZ dataset (Leathwick, et al., 2010). This dataset provided 3,457 lakes with necessary attributes for further analysis (e.g. depth, area, and type).

2.3. Data analysis

The purpose of the data analysis was to estimate the sampling variability at each lake for use in future predictions of statistical trends due to mitigation actions designed to improve lake quality. The sampling variability needed to represent a probability distribution that could be randomly sampled to determine if upstream mitigations significantly improved the lake water quality from baseline conditions. We defined this monitoring variability as the standard deviation of the Gaussian distribution of the log-transformed monitoring data. We observed that some sites had long-term and seasonal trends, which we wanted to remove when estimating our sampling probability distribution. We used non-parametric regression methods to first detrend/de-seasonalise monitoring data and calculate the detrended residual variances for each lake. These residual variances were used for fitting predictive models, which were used to calculate lake-specific residual variances for all lakes for the power analysis. We used a seasonal-trend decomposition filter with locally estimated scatterplot smoothing (LOESS) to separate the log-transformed data into long-term trends, seasonal trends, and residuals at each site using the STL (Season-Trend decomposition using LOESS) function in the python package ‘statsmodels’ (Cleveland et al., 1990). We then estimated the standard deviations per site from the residuals.

About 20 % of sites had missing observations, which were filled with linear interpolation in time. To test if interpolation introduced bias in the de-seasonalised residuals, we removed an equivalent amount of data from the remaining (80 %) sites with monthly data and compared the residuals from this test with those for the interpolated data (see Supplementary Table ST1).

The standard deviations derived from the residuals at the monitoring sites were used to predict the standard deviations for the 3,457 lakes in the FENZ dataset (see Table 1) using a gradient-boosted regression tree (Friedman, 2002) and random forest model (Breiman, 2001). The models were trained on 70 % of the data, with the remaining 30 % reserved to validate model performance.

We used the observed and predicted standard deviations at individual lakes to output power predictions for the monitored (1 1 6) and unmonitored (3,457) lakes, respectively (Fig. 2). We also output the number of samples required to meet 80 % statistical prediction power for each site assuming a level of significance of 5 % ($\alpha = 0.05$) and reductions phased over 5 and 20 years (or maintaining the current sampling regime for lake attributes above the threshold), commensurate with Government goals for water quality to improve over 5 years and stabilise within a generation assumed here to be 20 years (MfE, 2020).

The targets were set in two scenarios:

1. Improvements required to meet the NPS-FM (2023) thresholds for minimum acceptable water quality states (also called national bottom lines), where the bottom line corresponding to the C-D transition is 12 mg m^{-3} chl-a, 750 or 800 mg m^{-3} TN (stratified/brackish or polymictic lakes, respectively), and 50 mg m^{-3} TP. We also included a SDD of 1.6 m as a threshold for bottom-line values for water clarity, which is equivalent to the boundary between mesotrophic and eutrophic lake states in Burns et al. (1999). All attribute values correspond to median values.
2. Improvement of 30 % in each attribute, which corresponds to the estimated national average reduction of TN and TP losses arising from the implementation of on-farm mitigation actions (McDowell et al., 2021).

Table 1
Parameters used in the gradient boosted tree and random forest models to predict the standard deviation of each analyte. Description from Leathwick et al. (2010).

Parameter	Description
Lawa_id	Land, Air, Water, Aotearoa (LAWA) identifier
Site_id	Site number identifier
LFENZID	Unique lake identifier
Indicator	Analyte or attribute
Stdev	Standard deviation
Name	Lake name (if known)
Current5	Current classification level 4 (A.1.1.1.1 to G.2.1.1.1)
GeomorphicType	The geomorphic formation typology for the lake according to the classes aeolian (wind-formed, dune) (0), dam (1), geothermal (2), glacial (3), landslide (4), peat (5), riverine (6), shoreline (7), tectonic (8), and volcanic (9). Data from lake atlases by Irwin (1975), Livingston et al (1986a; 1986b), and Viner (1987)
MaxDepth	Maximum lake depth (m)
LakeArea	Lake area (m^2)
DecTemp	Estimated December air temperature (^{o}C)
DecSolrad	Estimated December solar radiation (MJ/m^2/d)
Fetch	Maximum lake fetch (m)
SumWind	Estimated summer wind (m/s)
CatBeech	Estimated catchment cover of forest dominated by *Nothofagus* species (percentage)
CatGlacial	Estimated catchment cover of glaciers (%)
CatHard	Average rock hardness in the upstream catchment (1 weak to 5 very strong)
CatPeat	Estimated catchment cover of peat soils (%)
CatPhos	Average phosphorus content of rocks in the upstream catchment (1 low to 5 high)
CatSlope	Average slope in the upstream catchment (degrees)
CatAnnTemp	Average annual air temperature in the upstream catchment (^{o}C)
DirectDistCoast	Shortest distance to the coast (km)
ResidenceTime	Estimated lake residence time (yr)
Urban	Cover of built up (urban) sites in the upstream catchment derived from LCDB2_1 (%)
Pasture	Cover of high producing exotic grassland in the upstream catchment derived from LCDB2_40 (%)
LakeElevation	Lake elevation (m)
MeanWind	Estimated mean annual wind speed (m/s)

The percentage reductions used median values for the last five years of data with a start year of 2021 or a significant linear trend between 2006 and 2020. If the site already met the national bottom line for each attribute, we assumed sampling at two-month intervals was adequate. This frequency of monitoring equates to the dominant one used for most current monitoring regimes. We combined the number of samples needed to reach 80 % power in each scenario with an estimate of sampling costs collated from four Regional Councils (see Supplementary Tables ST2 and ST3). Cost estimates were obtained for staff time and included preparation, travel to get to sites, sample/measurement collection, data entry and QA/QC procedures, and analytical costs including equipment purchase for in-field measurements and commercial analytical costs. Costs associated with the development or maintenance of databases or data systems were excluded. We derived an average travel time and mileage cost per site and per sampling event based on the total distance covered and total number of sites in each Regional Council network.

For each lake, we estimated TN and TP response times as lakes do not respond instantaneously to mitigation actions that improve the water quality in the inflows. Response times are influenced by complex interactions among lake morphology, nutrient forms (e.g., dissolved or particulate material), water retention time, and sedimentation rates. Various empirical or semi-mechanistic formulae that relate in-lake nutrient concentrations to inflow concentrations have been used to generalise relationships for large numbers of lakes (e.g., Jones 1976) and can usefully be applied here. The water residence time τ_w (yr) is defined as:

$$\tau_w = V/Q \tag{1}$$

where V is the water volume (m^3) and Q is the inflow (m^3 yr^{-1}). The residence time of phosphorus and nitrogen in the lake is different from the value of τ_w due mostly to the net sedimentation rate, noting that in some cases bottom sediments can release large quantities of nutrients into the water and that nutrient losses also occur through processes like denitrification of nitrate. Verburg et al. (2018) provide formulae for the retention of phosphorus and nitrogen:

$$R_{TP} = \frac{\sqrt{\tau_W}}{(1 + \sqrt{\tau_W})} \tag{2}$$

$$\text{and } R_{TN} = 1 - exp\left(\frac{-a\tau_W}{z}\right) \tag{3}$$

where R_{TP} and R_{TN} are the in-lake net retention of phosphorus and nitrogen, respectively, z is the mean depth ([m], = V/A, the lake volume divided by area, and a is a coefficient with a value of 6.83 for lakes. The value of a is higher in reservoirs but for the overall purpose of an estimate of response time, we adopt the lake value which has more conservative (longer) values of response time. The mass of phosphorus and nitrogen in the lake can now be determined from the inflow concentration and the lake retention values as:

$$M_{TP} = TP_{in}(1 - R_{TP})V \tag{4}$$

$$\text{and } M_{TN} = TN_{in}(1 - R_{TN})V \tag{5}$$

and the load in the inflow can be assigned as:

$$L_{TP} = TP_{in}Q \tag{6}$$

$$L_{TN} = TN_{in}Q \tag{7}$$

The residence time is given by the mass in the lake (Eq. 4 or 5) divided by the load (Eq. 6 or 7):

$$\tau_{TP} = \frac{(1 - R_{TP})V}{Q} \tag{8}$$

$$\text{and } \tau_{TN} = \frac{(1 - R_{TN})V}{Q} \tag{9}$$

Therefore, the time required to reach an arbitrary value of 95 % of the steady state concentration is $-\ln(0.95)\tau_{TP}$ and $-\ln(0.95)\tau_{TN}$, or approximately 3 x τ_{TP} or 3 x τ_{TN}, respectively. These 'response times' are provided in a webapp, so that the user can consider the time for a mitigation action to generate a response in nutrient inflow concentrations and in concentrations within the lake. Of the 148 monitored and 791 unmonitored sites, we calculated response times for 99 monitored and 505 unmonitored sites as Q was not defined for other sites (e.g., these sites had catchments of negligible area or were seepage lakes).

3. Results

Boosted Regression Tree (BRT) and Random Forest (RF) models were used for predicting standard deviation of the four analytes at unmonitored sites. There was little difference in the performance of either method. However, the BRT tended to yield a higher coefficient of determination, especially for SDD ($r^2 = 0.83$) compared with the RF approach (Table 2). On the other hand, the RF approach had marginally lower mean absolute error (MAE) and root mean squared error (RMSE) (Table 2). Except for SDD, the performance of the BRT and RF models was modest and therefore the outputs for TN, TP, and chl-a in unmonitored lakes should be treated with caution. Predicted variability and power analyses at monitored sites are based on actual monitoring data and should generally be ascribed greater confidence than at unmonitored sites. These may be used to guide operational decisions regarding monitoring design. Results at unmonitored sites should be treated with caution, especially those relating to TN, TP, and chl-a due to modest model performance. These may be used to guide initial monitoring design decisions relative to monitoring frequency, which should be reviewed after a few years once actual data have been collected from the sites.

For the monitored lakes, 105, 119 and 56 sites met bottom lines for chl-a, TN, and TP, respectively. The number of samples required per year to detect change within a period of five years and with a power of 80 % was higher than the total sample size required for change detection within the 20-year period. A minimum of six samples per year is required to detect a change in SDD within 5 years with $\geq$ 80 % power (Table 3). Among the four attributes, chl-a required the greatest number of samples for change detection at sites not meeting bottom lines, with 26 samples required to detect a change within 5 years. Chlorophyll-a measurements contribute over 30 % of total annual monitoring costs while SDD measurements contribute least (<22 %) using change detection within 5 years. Annual monitoring costs are slightly lower (<5%) for a 20-year monitoring program under scenario 1 (Table 3).

Table 2
Performance (coefficient of determination (r^2), mean absolute error (MAE), and root mean squared error (RMSE)) of the Boosted Regression Tree (BRT) and Random Forest (RF) models in predicting the standard deviation (SD) of each attribute. Mean absolute error (MAE), root mean squared error (RMSE), and mean standard deviation (SD_{mean}) are log-transformed values.

Analyte	Model	r^2	MAE	RMSE	SD_{mean}
Chlorophyll *a* (mg/m^3)	BRT	0.28	0.310	0.248	0.870
	RF	0.25	0.266	0.217	0.850
Secchi depth (m)	BRT	0.83	0.410	0.165	0.340
	RF	0.28	0.366	0.150	0.360
Total nitrogen (mg/m^3)	BRT	0.28	0.365	0.113	0.330
	RF	0.24	0.336	0.098	0.320
Total phosphorus (mg/m^3)	BRT	0.34	0.275	0.128	0.480
	RF	0.22	0.247	0.117	0.480

The number of samples required per year to detect change in chl-a, TP and SDD within 5 years at monitored or unmonitored sites is four times higher than that required for detecting the change within 20 years under scenario 2 of a 30 % improvement in each attribute (Table 3). To detect a change in TN within 5 years requires twice the number of samples per year than for a 20-year period. On average, over the four attributes, 42 samples per year would be required to detect a change at monitored sites within 5 years (power $\geq$ 80 %), but only 11 samples per year would be required for change detection within 20 years. For scenario 2, an average over the four attributes of 31 additional samples per year would be required to detect change in five years compared with the 20-year period (Table 3). For the 30 % reduction, the largest sample size ($n = 104$ per year) for change detection within 5 years is for chl-a and the smallest is for TN ($n = 12$), which compares with $n = 26$ for chl-a and $n = 6$ for TN over a 20-year period. For scenario 2, the annual average cost for a five-year monitoring program is four times higher than the annual cost for a 20-year monitoring program, due to higher sampling requirements to detect change over a short duration (Table 3). However, total monitoring costs of a 20-year monitoring program would be slightly (<5%) higher than the total monitoring costs of a 5-year monitoring program under scenario 2 (Table 3).

Many monitored and unmonitored sites have water residence time $\leq$ 0.5 years ($\leq$6 months) (Fig. 3). Over 70 % of monitored sites and 90 % of unmonitored sites have water residence time < 2 years (Fig. 3). On average, >70 % of monitored sites have response time < 2 years to reach 95 % steady state TP and TN concentrations. Similarly, >90 % of unmonitored sites have response time of < 2 years to reach 95 % steady state TP and TN concentrations. These data infer that response time will not have much of an effect in delaying change detection.

4. Discussion

To improve the understanding of restoration outcomes, there is a need for long-term records which may also help understand the key processes and functions that drive changes within lakes (Jaiswal et al., 2021). These records are particularly important in the context of natural variability of climate affecting water quality trends and complicating direct attribution to anthropogenic impacts, e.g., effects of land use and intensity (Snelder et al., 2022). Our method used 15 years of data to make inferences about detecting change over 5-year and 20-year monitoring periods. Although 15 years is a long time compared to many monitoring regimes, it may not be long enough if there are gradual or long-term changes in contaminant concentrations. It is also possible that lake concentrations may be influenced by first or second order streams, which we did not account for.

Improvements in lake trophic state due to restoration actions (e.g., upstream land use management) depend on several factors related to catchment and lake size and lake residence time (Macintosh et al., 2018). Sampling at different frequencies may be needed to match with the timeline on which practitioners wish to demonstrate improvements. In our national scenarios, short duration (5-year) monitoring of chlorophyll-a would need more frequent sampling (twice a week), but sampling at two-week intervals would meet minimum requirements of a long-term (20-year) chlorophyll-a monitoring program (Table 3). Considering different analytes, monthly sampling would be adequate to detect change in TN at monitored sites over five years while sampling at fortnightly intervals would be needed for TP (Table 3). Optimized bimonthly sampling at monitored lakes with less variable nutrient levels would be sufficient to detect long-term (20-year) change in nutrient concentrations. Our calculated response times for TN and TP had a mode around 6 months in both monitored and unmonitored sites across small lakes (Fig. 3), implying that monthly or fortnightly sampling would

Table 3
Outputs of Scenario 1 (improvements required to meet the NPS-FM (2023) thresholds for minimum acceptable water quality states (*national bottom lines)) which lists the mean (median) number of samples per year across monitored sites (degraded sites only [14, 16 and 7 for chlorophyll-a, total N and total P, respectively] and all sites [up to 148]) required to meet a minimum power of detection of ≥ 0.80 for water quality thresholds[1] (or maintain current sampling where above the threshold) over duration of 5 and 20 years for each attribute, and Scenario 2 (improvement of 30 % in each attribute) which lists the mean (and median in parentheses) number of samples per annum across monitored (up to 148 sites) and modelled sites (up to 791 sites) required to meet a minimum power of detection of ≥ 0.80 for a 30 % reduction (Scenario 2) in either 5 or 20 years for each contaminant. The sum and annualised cost ($m NZD) per contaminant assume individual laboratory charges, Opex, and labour and mileage associated with the sampled contaminant at a site.

Attribute / cost	Scenario 1				Scenario 2			
	Change within 5 years		Change within 20 years		Change within 5 years		Change within 20 years	
	Min no. samples	Annual cost	Min no. samples	Annual cost	Min no. samples	Annual cost	Min no. samples	Annual cost
	Degraded sites				Monitored sites			
Chl-a	26 (57)	0.25	12 (40)	0.11	104 (158)	10.47	26 (32)	2.62
TN	6 (15)	0.06	6 (7)	0.06	12 (16)	1.15	6 (9)	0.57
TP	6 (21)	0.06	6 (9)	0.06	26 (39)	2.50	6 (7)	0.58
Secchi depth	6 (6)	0.03	6 (6)	0.03	26 (30)	2.41	6 (10)	0.56
	All sites				Modelled sites			
Chl-a	6 (17)	0.60	6 (10)	0.60	104 (197)	55.94	26 (43)	13.98
TN	6 (7)	0.57	6 (6)	0.57	12 (25)	6.15	6 (8)	3.07
TP	6 (7)	0.58	6 (6)	0.58	52 (48)	26.76	13 (13)	6.69
Secchi depth	6 (6)	0.56	6 (6)	0.56	26 (26)	12.85	6 (7)	2.97
Sum: all sites assuming costs for min. no. of samples for each contaminant					Sum: all sites assuming costs for min. no. of samples for each contaminant			
Annualised cost ($m NZD)		2.71		2.58	Monitored annual cost ($m NZD)	16.52		4.32
					Modelled (unmonitored) annual cost ($m NZD)	101.7		26.71

* Bottom lines are the thresholds between C and D class waters in the NPS-FM (2023), listed as the median of 12 mg m-3 chl-a, 750–800 mg m-3 total nitrogen (brackish and polymictic lakes, respectively), and 50 mg m-3 total phosphorus. We also included a Secchi depth of 1.6 m as a threshold for clarity, as this is equivalent to the boundary between mesotrophic and eutrophic states (Burns et al., 1999).

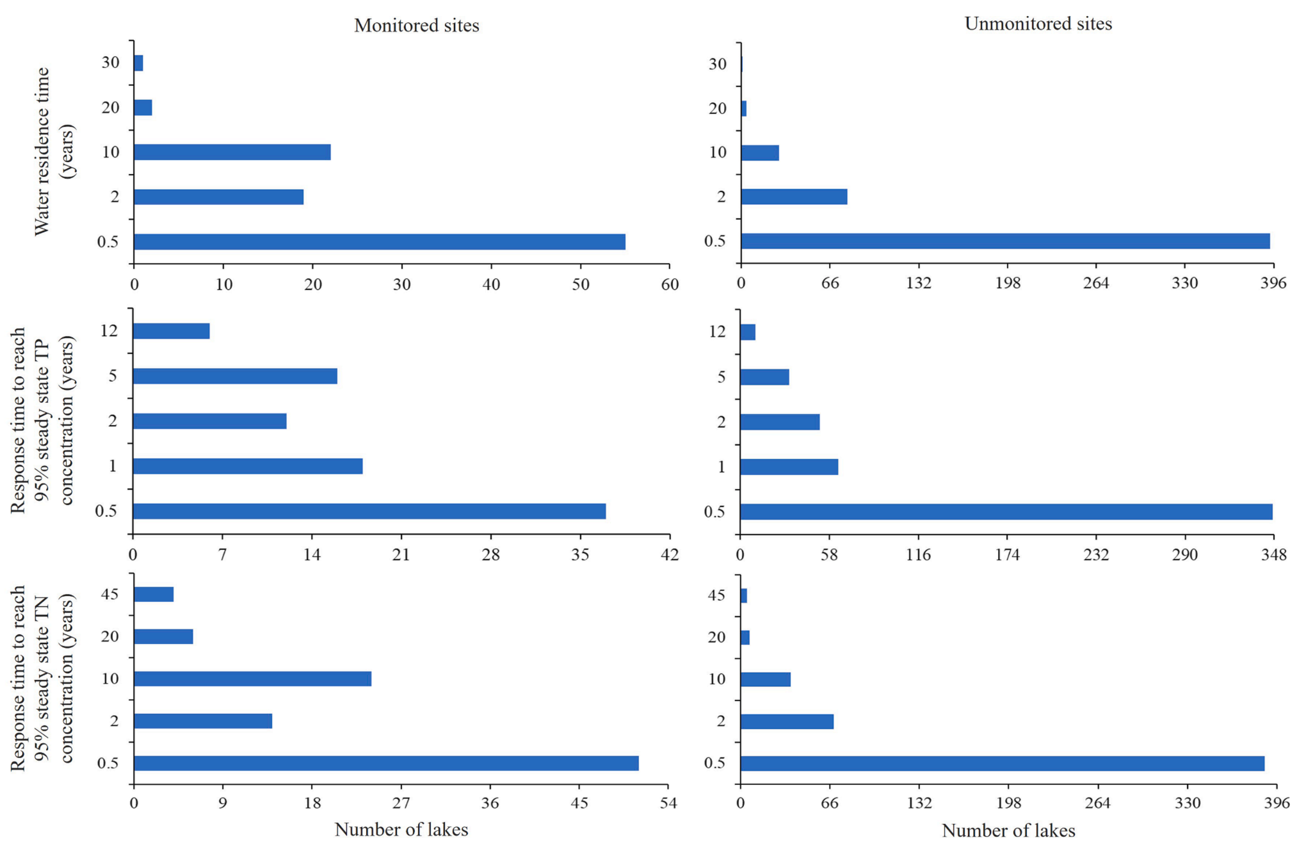

Fig.3. Residence time and response times (at monitored and unmonitored sites) to reach around 95 % of steady state concentration in response to a nutrient reduction in the inflows (the response time is approximately 3 x τ_{TP} or 3 x τ_{TN}, respectively, where τ_{TP} and τ_{TN} are the retention times of total phosphorus and total nitrogen, respectively).

provide a good chance of detecting change in nutrient levels at small lakes over a 5-year period (Fig. 3, Table 3). Greater TN (>2 years) and TP (>1 year) response times at monitored and unmonitored sites, mostly associated with large lakes, require bi-monthly or monthly sampling over longer periods to detect changes in nutrient concentrations (Fig. 3, Table 3).

The duration and frequency of the optimized sampling regime affects operational costs. For example, at monitored sites in New Zealand, chlorophyll *a* monitoring would cost NZ$ 10.47 m annually to detect changes assumed under either of our two scenarios within 5 years, an increase of 1645 percent over current costs, but substantially cheaper than the estimated annual cost to detect contaminant reductions of 30 % in New Zealand's rivers (McDowell et al., 2024). Long-term monitoring programs (monthly or two-monthly nutrient monitoring) could be a better choice for monitoring lakes with less variable nutrient levels and would incur lower (≤5%) annual costs. For example, to detect change in chlorophyll *a* concentration within 20 years, it would cost NZ$2.62 m annually at monitored sites at an increase of 337 percent over current costs. Although different annual costs can influence a choice of either the 5-year or 20-year monitoring programs, duration of monitoring can also be influenced by water quality goals. For example, a 5-year monitoring is more suitable to assess improvement in water quality against immediate anthropogenic impacts, whereas a 20-year period is needed to stabilise such improvements (changes) within a generation (MfE, 2020).

Instead of general targets, many jurisdictions (e.g., Europe) target driving water quality towards reference conditions, as deemed satisfactory for stakeholders, with restoration actions planned accordingly (McDowell and Hamilton, 2013). Optimized sampling regimes from this study can be adopted for collecting samples which can be used for routine periodic assessment of the trophic status of lakes against 'reference values' of TN, TP, chl-a, and Secchi depth (McDowell et al., 2013; NPS-FM, 2023; Wood et al., 2023). State of the Environment (SoE) monitoring assesses trophic state and long-term trends of nutrients (TP, TN), phytoplankton (chl-a), and water clarity (SDD) (NPS-FM, 2023). Outcomes from this study can also help to identify when (5-year or 20-year) restoration actions can have large desirable effects without excessive costs (sampling fortnightly, monthly, or bi-monthly) or to avoid being too restrictive where lakes are already close to reference conditions.

Routine monitoring practices (e.g., weekly, or monthly sampling) of some variables such as water clarity and chlorophyll-a are amenable to high frequency monitoring with sensors (Hamilton et al., 2014). However, there can be large capital costs in setting up high-frequency sensors, as well ongoing operational costs. Thus, high-frequency monitoring for many lakes may not be always feasible or affordable. The feasibility of remote sensing-based water quality monitoring has been demonstrated for synoptic coverage of chlorophyll-a at regional scale (Allan et al., 2009) and water clarity at national scale (Lehmann et al., 2018). Optimized monitoring regimes used in this study can be adopted for sampling at monitored sites and these samples can be used for ground truthing and validating water clarity and chlorophyll-a measurements at monitored sites against remote sensing measurements and models. This method could provide a cost-effective solution for examining temporal trends in water quality across many lakes where a conventional monitoring programme in all lakes is not feasible. Due to increased spatial resolution and frequency of image capture with remote sensing, a combination of an optimized water sampling program with spatial monitoring could provide observations at higher temporal and spatial resolution than anyone monitoring program alone.

Sampling requirements and monitoring costs from our study can help guide optimizing investments in freshwater monitoring in New Zealand as well as in other regions. To support efforts to arrest water quality decline, the New Zealand government announced NZ$700 m under freshwater reforms in 2020 (NZ Government, 2024a), and an additional NZ$2.5bn in 2021 to support local government transition through the freshwater reforms (NZ Government, 2024b). The New Zealand government also announced NZ$100 m to the freshwater improvement fund for monitoring water quality improvements (MfE, 2024). However, total investment in water quality monitoring is less than 3.2 % of the total investment in restoration (NZ$3.2bn). Our data on optimized sampling frequency and costs (Table 3) imply that more investment in monitoring is needed and that this could be afforded at the expense of putting more effort into unmonitored restoration efforts. Improvements in monitoring will ensure that restoration actions deliver water quality outcomes cost-effectively.

5. Conclusions

This study modelled in-lake variability of TN, TP, chl-a, and SDD and determined the optimum number of samples per year required to detect changes in water quality under two national-scale water quality improvement scenarios. An optimised 5-year monitoring regime would cost NZ$10.47 m/year while a 20-year monitoring would cost NZ$2.62 m/year to detect reduction in chlorophyll-a at monitored sites an increase of over 16 times and 3 times over current costs, respectively. This study provides a framework to realistically assess the large costs (and any lag times caused by response times) involved in monitoring to support investments in water quality restoration. Using statistical models and increasing the number of continuous and remote sensing technologies can help us detect short- and long-term change over large areas more cost-effectively.

CRediT authorship contribution statement

Rupesh Patil: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **David Hamilton:** Writing – review & editing, Supervision, Conceptualization. **Olivier Ausseil:** Writing – review & editing, Supervision, Conceptualization. **Michael Kittridge:** Writing – review & editing, Methodology, Formal analysis. **Deniz Özkundakci:** Writing – review & editing. **Richard W. McDowell:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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