Extrapolation of Unmonitored Lake Ecological Status

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Executive Summary

Background

Under the EU Water Framework Directive (WFD), 812 lakes in Ireland are designated as WFD water bodies and their ecological status must be assessed and reported on a six-year cycle. As it is not economically feasible to monitor every water body, 224 lakes are currently classified based on the results of direct monitoring, and the remaining 588 unmonitored lakes have status assigned by a combination of extrapolation from monitored lakes and expert judgement.

Aims and objectives

Building on previous research (Wynne & Donohue, 2016) which used cluster analysis to extrapolate status classifications from monitored (donor) lakes to similar unmonitored (recipient) lakes, the EPA commissioned APEM Ireland to design and implement a methodology for assigning a WFD ecological status class to unmonitored Irish lakes.

The specific objectives of the project were to:

- establish a conceptual framework for predicting the status of unmonitored lakes;
- set out a methodology and stepwise process to be used in assigning status;
- predict the status of unmonitored WFD lakes; and
- provide recommendations for future improvements of the process.

The analysis focused on predicting the status class of the three quality elements that are most sensitive to nutrient enrichment: total phosphorus (TP), chlorophyll-*a*, (a key component of the phytoplankton quality element) and macrophytes. The project used 2016-2018 monitoring data as this was the most recent period for which concurrent data was available on catchment characteristics, land-use and diffuse and point source phosphorus loads.

Approach

To aid decisions about which variables were important to include in designing a statistical approach to predicting status, a **conceptual framework** was built based on existing knowledge of the mechanisms of lake eutrophication. The conceptual model adopted a source-pathway-receptor approach to describe how diffuse and point sources of nutrients combine with hydrogeomorphological factors to determine influent and in-lake phosphorus concentrations and, in turn, the chlorophyll-a and macrophytes status of each lake.

To account for natural variation in ecological conditions, the **WFD typology** of each lake was determined based on surface area, mean depth and alkalinity, with statistical regression models used to predict alkalinity and depth for lakes that lacked measured data.

For each quality element in turn, spatial variation among monitored lakes was analysed using Generalised Additive Models (GAMs), a flexible **regression modelling** technique that allows non-linear relationships to be described by smooth curves. The conceptual model of lake eutrophication was used to guide the selection of candidate predictor variables, and model selection was then used to optimise the predictive accuracy of the models. The final models were used to predict TP concentration, chlorophyll-a EQR and macrophyte EQR for the unmonitored lakes. These predictions were then converted to WFD status classes, combined using the 'one-out, all-out' rule to predict the 'overall status' of each unmonitored lake, and used to quantify the confidence that each lake was achieving Good status.

Finally, a structured checklist was developed to allow other **local/supporting information** (including expert judgment) to be used as part of a weight of evidence process to validate, or potentially override, the predictions from the statistical models.

Results

In-lake TP concentration was strongly associated with influent TP concentration, but the effect of external nutrient loading on lake water quality was strongly moderated by residence time. All else being equal, lakes in Cavan and Monaghan (and to a lesser extent southern Cork) had higher in-lake TP concentrations than those in the western coastal counties of Donegal, Mayo, Galway and Kerry. Together these factors explained 69.1% of the variation among lakes. The final model predicted the correct status class with 61% accuracy and predicted with 89% accuracy whether or not a lake was achieving Good status for TP.

There was a strong negative relationship between TP concentration and **chlorophyll-a EQR**, which was steepest for very high (>200 mg/l) and moderate (ca. 50 mg/l) lakes, plus a weak positive relationship between chlorophyll-a EQR and colour. Together these factors explained 69% of the variation among lakes. The final model predicted the correct status class with 69% accuracy and predicted with 89% accuracy whether or not a lake was achieving Good status for chlorophyll-a.

Macrophyte EQR decreased strongly with increasing TP concentration and to a lesser extent colour, and was marginally lower in moderate alkalinity lakes. After accounting for these effects, lakes in the western coastal areas of Donegal, Galway and Cork had higher predicted macrophyte EQRs than lakes in inland and eastern areas, and lakes in Monaghan had particularly low predicted EQRs, all else being equal. Together these factors explained 78.2% of the variation among lakes. The final model predicted the correct status class with 64% accuracy and predicted with 86% accuracy whether or not a lake was achieving Good status for macrophytes.

Typology, depth and area were not retained in the final models, indicating that the modelled relationships were common across all lake types. Inspection of the residuals showed that the models were equally good at predicting for lakes in karst and non-karst catchments, for large and small lakes, and for lakes in each of the 12 typology groups.

For monitored lakes, the models predicted the correct **overall WFD status** class with 64% accuracy and predicted with 86% accuracy whether or not a lake was achieving at least Good status. In only 2 out of 224 cases (0.89%) was the model prediction out by more than 1 status class. Around 75% of unmonitored lakes were predicted to be achieving Good overall status, compared with 52% of monitored lakes. Low alkalinity lakes had the highest proportion at Good or High overall status, whereas moderate alkalinity lakes and small, shallow high alkalinity lakes had the lowest proportion. For both monitored and unmonitored lakes, macrophytes and/or TP were the most common driving elements. The models were able to determine whether or not Good overall status was being achieved with reasonable (at least 75%) certainty for 85% of lakes.

Conclusions and recommendations

A key achievement of this study was the successful integration of a variety of EPA datasets and modelling tools; most notably, the EPA's SLAM nutrient loading model was combined with estimates of catchment run-off generated by the QUBE model to yield an estimate of the influent TP concentration, which proved to be a strong predictor of lake status. Furthermore, the application of statistical models to determine missing values for many of the variables has yielded a complete and up-to-date set of catchment and lake characteristics which are available for use in future studies.

Whilst the approach was successful in predicting the status of unmonitored lakes, some predictor variables were incomplete or had other data quality issues, and other potentially important variables could not be quantified. Recommendations were therefore made for improving and updating component datasets. The 224 monitored lakes used to calibrate the statistical models generally cover the full range of characteristics of the 812 WFD lakes, which means the models can be used with confidence to predict the status of unmonitored lakes. The only exception is the relatively poor coverage of lakes with very low modelled influent TP concentrations. Suggestions are made for targeting future monitoring activities to optimise model calibration.

Finally, the statistical modelling workflow developed in this study is fully documented, auditable and reproducible, meaning that the approach can be used to classify the status of new lakes or produce updated classifications in future reporting cycles.

1. Introduction

1.1 Background to this project

The EU Water Framework Directive (WFD; 2000/60/EC) is delivered in six-year cycles, each cycle requiring a new River Basin Management Plan and programme of measures to be developed and implemented, with the status of every designated water body to be assessed and reported on. The primary means through which status is assessed is through the results of monitoring. Operational monitoring must be undertaken for all water bodies that have been identified as being at risk of failing the relevant environmental objectives under Article 4 of the WFD.

It is not economically feasible to monitor all water bodies for all conditions, and many are not directly monitored. In Ireland, there are 812 lakes designated as WFD water bodies, of which only 224 have status assigned based on the results of direct monitoring. The remainder have their status determined by a combination of extrapolation from monitored lakes and expert judgement.

In order to facilitate assessment of unmonitored lakes, the Environmental Protection Agency (EPA) commissioned a study by Wynne & Donohue (2016), which examined options for classifying lakes based on typology, and then extrapolated results from monitored lakes to others. This approach was then applied to the previous and most recent reporting cycle.

More recently, the Centre for Ecology and Hydrology (Taylor *et al.*, 2021) conducted a study to demonstrate an approach to establish WFD-compliant nutrient management objectives for achieving Good Ecological Status (GES) in lakes. This study's findings, in particular on the biological response of algae and macrophytes to water transparency and colour in Irish lakes, led to the inclusion of water colour as a parameter in the modelling of biological elements. In addition, CDM Smith (2019) examined Irish lakes at risk of not achieving GES due to historic accumulation of phosphorus pools leading to a lag time in the response to measures. This study highlighted the importance of considering lake residence times in modelling their phosphorus concentration, and of understanding historic phosphorus inputs and possible internal phosphorus loading in lakes.

Since the Wynne & Donohue (2016) study was completed, new datasets have become available and the EPA wished to review and update its assessment process for unmonitored lakes. APEM Ireland was commissioned to develop an updated approach for assigning ecological status to unmonitored Irish lakes. This report provides the outcome of that work, designing and applying a series of statistical models to extrapolate the overall ecological status of unmonitored Irish lakes.

1.2 Water Framework Directive guidance

It is recognised that it is not economically feasible to monitor all water bodies for all conditions. Therefore, the Directive allows the grouping of water bodies based on type (see Section 2.4 for details of the WFD lake typology) and on similar hydrological, geomorphological, geographical or trophic conditions (European Commission, 2003a). Intuitive (expert judgment) approaches or more sophisticated multivariate classification procedures can be used for identifying groups of similar water bodies, although guidance from the Common Implementation Strategy (CIS) warns that 'black box' approaches should be used with caution, as there is no guarantee that the composition of the resulting groups will have a recognisable or obvious rationale (European Commission, 2003a). Whatever the method by which the water bodies are grouped, the guidance states that it is essential that sufficient representative water bodies are monitored within a group to provide an accurate assessment of status for that group. Where grouping is not possible, then the latest WFD Reporting Guidance indicates that “modelling” (including “statistical analysis”) or “expert judgement” can also be used to assign status (European Commission, 2022, p. 51).

In this study, we adopt a regression modelling approach, which considers the effect of typology (directly, and also indirectly by incorporating the effects of lake depth, alkalinity and area) alongside other physical features and anthropogenic stressors to yield a statistical model that is capable of predicting the status of unmonitored lakes with a quantified level of accuracy and confidence.

1.3 Study aim and objectives

The aim of this study was to design and implement a methodology for assigning a WFD ecological status class to unmonitored Irish lakes.

The specific objectives were to:

- establish a conceptual framework for predicting status of unmonitored lakes;
- set out a methodology and stepwise process to be used in assigning status;
- predict the status of unmonitored WFD lakes; and
- provide recommendations for future improvements of the process.

The project built on existing knowledge gained from previous research, particularly that of Wynne and Donohue (2016), which looked at almost exactly the same set of lakes as examined in this work and developed a methodology to select donor lakes representative of groups of unmonitored lakes.

1.4 Scope

It is estimated that there are 12,217[1] lakes in Ireland. Of these, 812 are currently identified as WFD water bodies in the Republic of Ireland. However, one of these lakes, Lower Erne Kesh, lies in Northern Ireland, and was therefore excluded from this study, leaving 811 lakes for analysis. Of these, 23 are designated as Heavily Modified Water Bodies (HMWBs), and one (Sevenchurches) is designated as an Artificial Water Body (AWB). A total of 224 lakes are monitored and 587 are unmonitored and require extrapolation to assign a WFD status class.

Nutrient enrichment is one of the most important stressors affecting the ecological status of lakes. The study therefore focused on predicting the status class of the three quality elements that are most sensitive to nutrient enrichment and therefore important drivers of overall ecological status: total phosphorus (TP), chlorophyll-*a*, (a key component of the phytoplankton quality element) and macrophytes. In addition, the status class predictions for the three quality

[1] As derived from the EPA’s ‘lake segments’ shapefile

elements were combined using the one-out, all-out rule to predict an "overall status"[2] for each unmonitored lake.

The study used monitoring data collected between 2016 and 2018 to determine the status of lakes during this same three-year reporting period. This was the most recent period for which concurrent data was available on catchment characteristics, land-use and diffuse and point source phosphorus loads.

1.5 Report Structure

This report is structured to illustrate the process through which lake status has been extrapolated and is laid out as follows:

- **Chapter 2: Conceptual framework, data sources and data processing.** This chapter summarises the conceptual framework on which the analysis was based. It identifies the data sources used in the analysis (details of the steps taken to derive the data are provided in the Appendices). It includes a section on lake typology, including the approach and analysis undertaken to predict alkalinity concentration and mean depth for each lake where this information was not available, allowing a prediction of typology category for each unmonitored lake.
- **Chapter 3**: **Classification of lakes based on anthropogenic stressors and physical features.** This chapter outlines the methods used to model TP concentration and status, chlorophyll-*a* status and macrophyte status of each unmonitored lake. It presents the results of this approach, testing the predicted results against the monitored data, mapping the residuals and analysing confidence intervals for predictions. It provides an overall status for each unmonitored lake (more detail is provided in the Appendices).
- **Chapter 4**: **Classification of lakes with high uncertainty.** This chapter provides a framework to assist with expert judgement, where a predicted lake status has a large margin of error associated with it.
- **Chapter 5**: **Discussion and Recommendations**. This chapter discusses the different model performances, the strength of this approach, and the limitations that are associated. It provides recommendations for further research and for improving the monitoring programme.

The report concludes with a series of appendices detailing methods and results. A full set of results is included in the Excel workbook which forms an electronic appendix to this report.

[2] In the context of WFD, "overall status" usually refers to a lake's overall ecological and chemical status, but this study uses the term more narrowly to refer to a lake's response to nutrient enrichment.

2. Data sources and data processing

2.1 Conceptual model of lake eutrophication

To aid decisions about which variables were important to include in designing a statistical approach to predicting status, a conceptual framework was built based on existing knowledge of the mechanisms of lake eutrophication.

Nutrient enrichment is one of the primary anthropogenic pressures affecting freshwaters globally (Schindler, 2006; Smith *et al.*, 2006). The most recent national monitoring programme of water quality in Ireland identified nutrient pollution as the principal pressure on water bodies (EPA, 2019). The relationship between catchment land-use and nutrient enrichment of water bodies has been well documented (OECD, 1982; Johnes and Heathwaite, 1997; Donohue *et al.*, 2006).

The source / pathway / receptor model describes the variables driving the response of a receptor (such as a lake and its ecological status) to a source, such as nutrient runoff from fertilised soil. The parameters of this approach are defined as follows:

- **Source:** the origin of a potential effect (noting that one source may have several pathways and receptors) e.g. an activity such as application of fertiliser to pasture.
- **Pathway:** the means by which the effect of the activity could influence a receptor e.g. for the example above, runoff pathways that can result in excess fertiliser entering the lake.
- **Receptor:** the element of the receiving environment that is affected e.g. for the above example, nutrient enrichment from fertiliser leading to algal blooms or suppression of non-competitive macrophyte species in lakes.

Different drivers influence the source of pollution and the pathways, influenced by hydrogeomorphological factors, through which the pollutant can be transported, attenuated or intercepted before delivery to the ultimate receptor, as well as the response of the receptor to this pollutant. The aim of the modelling conducted in this study is to predict the overall ecological status of each lake, through predicting the status of different quality elements such as the TP concentration as well as its the biological response in the form of the macrophyte Ecological Quality Ratio (EQR) and the chlorophyll-*a* (phytoplankton) EQR. The contribution of all variables to this outcome is illustrated in Figure 1.

The Source Load Apportionment Model (SLAM) developed by the EPA is a modelling framework that predicts nutrient inputs from different sources within the catchment to receiving water bodies (Mockler *et al.*, 2016, Mockler *et al.*, 2017). It uses an export coefficient approach to integrate catchment data such as land use, soil type, geology and hydrological connectivity with stressor information from point discharges and diffuse sources to enable characterisation of source-pathway-receptor relationships. The TP sources considered include point sources such as wastewater and industrial discharges, plus diffuse sources such as forestry, pasture, arable land, diffuse urban sources and septic tank systems.

SLAM involves not only calculating the available annual average nutrient loads from each sector within the catchment, but accounting for treatment where present (e.g. wastewater) and attenuation of the nutrients into the environment, through integrating the hydrogeological pathways for nutrient transport. The output of the model is a prediction of nutrient load inputs to receiving water bodies (identifying the sources) after accounting for attenuation or treatment. This model, which considers both the source and the pathway of nutrients, has been run for the 811 lakes included in this study, to predict annual TP loads and their sources (more detail on the SLAM model is documented in Appendix 1, Phosphorus loading). The contribution of the modelled TP load, derived from the SLAM model, to the model predicting overall status is illustrated in Figure 1.

Several factors need to be considered to convert the modelled TP load into the receiving water bodies into a predicted lake TP concentration (directly affecting the lake receptor). A number of studies have modelled this, considering factors such as lake depth, area, and flushing rate as well as influent concentration (Vollenweider, 1976). Here, these were re-arranged as influent TP concentration (estimated using SLAM-modelled TP loads and modelled flows), and mean residence time (accounting for lake depth, area and flushing rate (Brett & Benjamin, 2008)), estimated using modelled flows. The evolution of this calculation, and the final calculation used (log transformed, including an interaction factor) is discussed in detail in Section 3.2. The contribution of lake depth, area, flow and lake residence time to the model predicting overall status is also illustrated in Figure 1.

Lake residence time influences how much phosphorus settles to the bottom as sediment (with a potential then to be cycled internally) and how much phosphorus is exported. Inflowing phosphorus contains dissolved reactive phosphorus (taken up by plants and other primary producers) and particle-bound phosphorus (which may settle at the lake bottom via the process of sedimentation). Phosphorus exits lakes as dissolved reactive phosphorus in outflowing rivers, as particulate P in phytoplankton cells that are carried in outflowing rivers, and as sediment-bound phosphorus where lake residence times are short. Lakes with shorter hydraulic retention times are likely to have lower relative phosphorus retention in the sediment than lakes with slower flushing rates and shorter recovery times (Søndergaard *et al.*, 2001; Spears *et al.*, 2006). Lakes with longer hydraulic retention times have greater phosphorus retention and lakes with larger relative depths retain more phosphorus than larger, shallower lakes (Kõiv *et al.*, 2011). However, shallow, windswept lakes may be well mixed (McCarthy *et al.*, 2001) and thus at greater risk of eutrophication due to re-suspension of bottom sediments. Nutrient concentrations increase in lakes across Europe with increasing catchment size and decreasing depth and water residence time (Nõges, 2009). This is thought to be as a result of the potential for a greater nutrient load from land-use activities, with an increased number of pathways for nutrients to enter water bodies (Johnes, 1999; Foy *et al.*, 2003).

Many other catchment and in-lake processes are important to consider when modelling lake ecological status, influencing the sources, transport, attenuation and interception of nutrients to each lake. This project was built on the work of Wynne and Donohue (2016), who analysed a large number of hydrogeomorphological characteristics at catchment and lake scale, as well as land-use characteristics. Some of the hydrogeomorphological and all of the land-use characteristics were incorporated into the SLAM model. The remaining hydrogeomorphological characteristics were included or excluded based on how they performed in Wynne and Donohue's (2016) models. These variables are described in detail in Section 2.3 and their contribution to the model predicting overall status are illustrated in Figure 1.

Upstream hydrology, through the processing and retention of nutrients in upstream rivers, lakes and wetlands, can be an important predictor of in-lake nutrient concentrations (Soranno *et al.*, 1999; Venohr *et al.*, 2005; Zhang *et al.*, 2012). Proxies such as upstream lake density, and stream density were, therefore, included as candidate predictor variables in the models to represent the effect of upstream hydrology, shown in Figure 1.

Finally, the biological response of a lake, as a receptor, is influenced by not only the nutrient input and the characteristics of the catchment that influence the pathways from the source into it, but by its typology. In Ireland, this is based on lake alkalinity, mean depth and surface area (Free *et al.*, 2006; discussed in detail in Section 2.4). In addition, Taylor *et al.*, (2021) included water colour in their analysis of ten Irish lakes and found that algal and macrophyte communities in some lakes were possibly limited more by water colour than by nutrient availability in the more highly peat-stained waters. They also found that water transparency was affected more by water colour than by the turbidity caused by algal cells and other suspended matter and suggested that algal and macrophyte production in at least some lakes was likely limited by light attenuation rather than nutrient availability. For this reason, colour was also included in the chlorophyll-a and macrophyte models (Figure 1). The aim of the modelling is to predict not only the TP concentration of the lake as a measure of its ecological status, but also its biological response (macrophyte EQR and chlorophyll-*a* (phytoplankton) EQR). The contribution of these typological variables to the overall model, and overall ecological status prediction is illustrated in Figure 1.

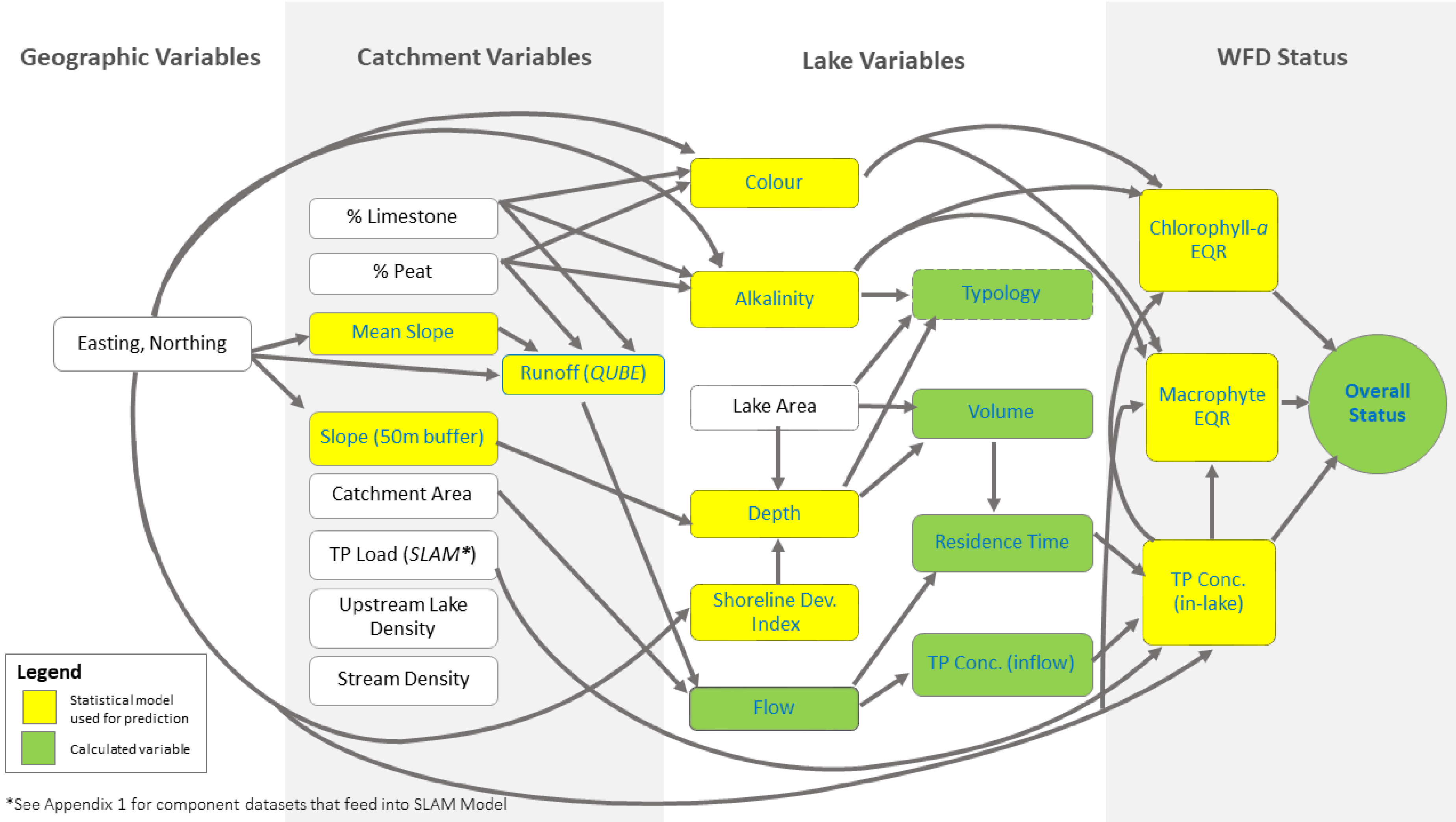


Figure 1: Flow chart summarising the variables used to predict the overall ecological status of unmonitored lakes.
For clarity the arrows only denote the factors retained in the final models.

2.2 WFD monitoring data

Of the 811 lakes designated as WFD water bodies in Ireland that are the focus of this study, 224 were directly monitored in the period between 2016 and 2018 under the EPA's national monitoring programme. TP and chlorophyll-*a* were sampled at all 224 monitored lakes, and macrophytes were monitored at all but three (Corconnelly, Gorman and Cummernamuck). The data from this 2016-2018 monitoring period form the basis of the models described in this report.

Figure 2 illustrates the ecological status of the different quality elements, showing the ecological status of biological quality elements (macrophyte and chlorophyll-*a*), and physico-chemical quality elements (TP) as well as the overall status for the three elements, which defaults to the worst status of the three elements. There are clear geographic patterns in the distribution of status, with the majority of High and Good status lakes situated along the west coast of Ireland, particularly in the more remote locations of the north-west, west and south-west. The majority of lakes with an ecological status of Moderate or worse are located in the north-east, especially in Cavan and Monaghan.

The quality element(s) driving the overall (worst) status is shown in Figure 3. The status of macrophytes and/or TP appear to drive status for most lakes, with the exception of the south-west, where chlorophyll-*a* appears to be driving the status of many lakes.

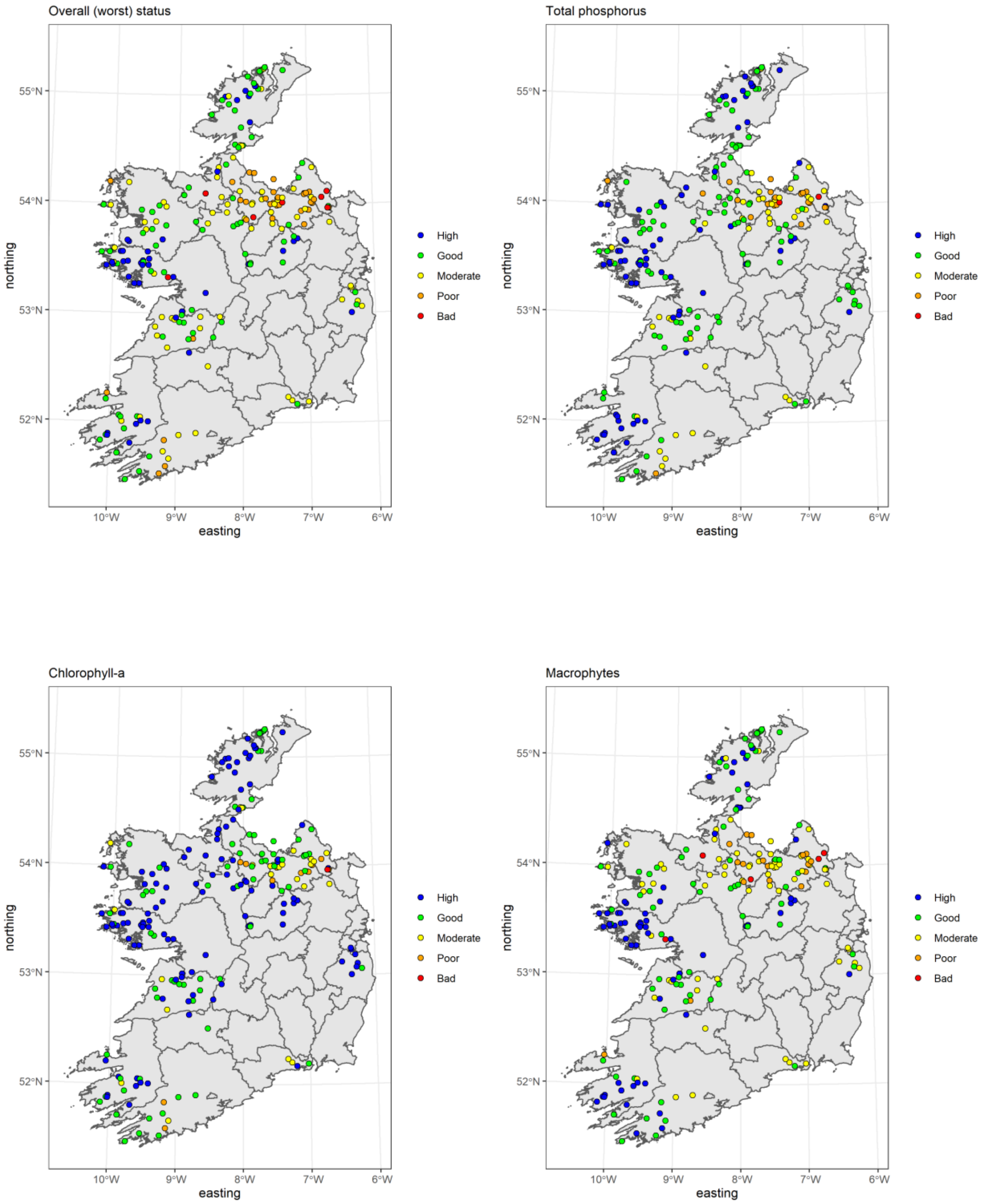


Figure 2: Maps of monitored lakes showing overall (worst) ecological status and the corresponding ecological status of the different quality elements

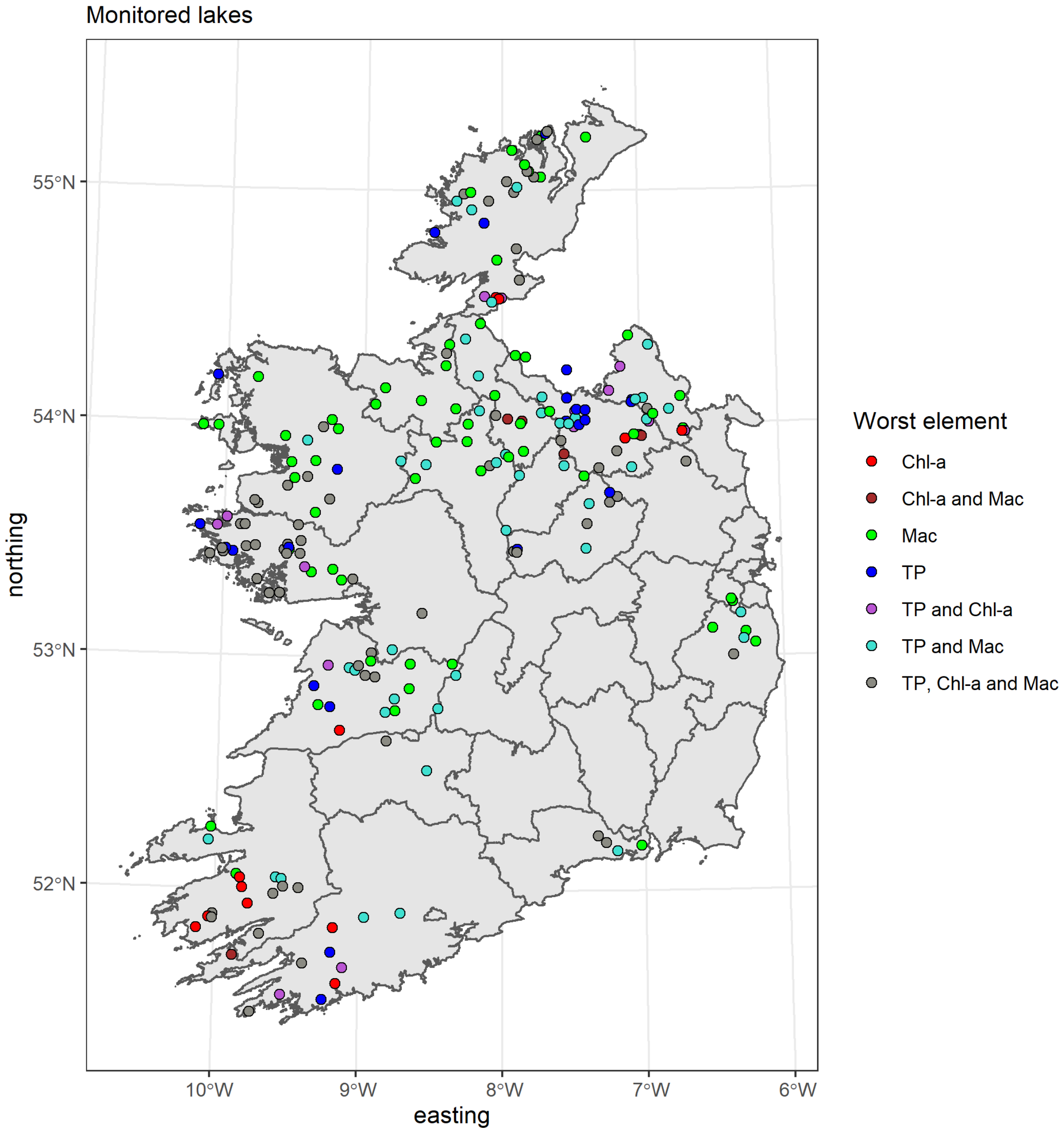


Figure 3: Map displaying the quality element(s) driving overall (worst) status in each of 224 monitored lakes

(TP = total phosphorus, chl-a = chlorophyll-*a* and mac = macrophytes)

2.3 Lake and catchment characteristics

A variety of relevant variables, listed in Table 1, were assembled to describe the characteristics of each lake and its upstream catchment. Details of how these variables were derived are provided in Appendix 1.

This exercise took as its starting point the dataset of physical and hydromorphological variables derived by Wynne and Donohue (2016) for 769 lakes. Data gaps were then filled using a combination of geospatial (GIS) analysis and statistical modelling. These analyses used: the WFD lake water bodies Cycle 3 layer, lake segments layer (including a total of 12,217 segments), and nested catchments layer (v2), from the EPA's catchment products geodatabase; and the river segments layer (RivNetRoutes; a river network layer with 102,108 river segments delineated from the OSI Discovery Series source) from the EPA's GeoPortal (Environmental Protection Agency, Ireland (EPA) Geoportal).

These datasets were downloaded and used in the geospatial analysis to derive hydrological and morphological characteristics to describe how water and pollutants might be transported and/or processed in these systems. All geospatial analyses were done using QGIS 3.24 and all statistical modelling used R 3.6.1 (R Core Team, 2022).

Table 1: Geographic, catchment and lake variables used in this study

Variable (units)	Description and derivation	Relevance	References
Geographic Variables			
Easting, Northing	Lake centroid location (projected in TM65 / Irish National Grid)	Used to account for large-scale geographic variation among lakes.	
Catchment Variables			
Catchment area (km^2)	The catchment area upstream of the lake outflow – i.e. the total land area draining to the lake. Derived from the 2022 catchment products geodatabase provided by the EPA, and using the nested catchments v2 layer.	Larger catchments are likely to have more heterogenous land cover and land uses. Used to calculate flow from each lake.	Foy *et al*. (2003); Nõges (2009)
Mean catchment slope (°)	The average slope across the upstream catchment. Calculated for 759 lakes by Wynne & Donohue (2016), who used geospatial analysis using a 5 m DTM and the nested catchments v2 layer, and predicted for the remaining 52 lakes using a statistical model.	Catchment slope may influence the hydrology within the catchment, including run-off potential and the importance of surface water pathways.	Sobek *et al*. (2011); Greene *et al*. (2013)

Variable (units)	Description and derivation	Relevance	References
Range in slope in near lake buffer (°)	The range in slope within 50 m of the lake shore. Calculated for 759 lakes by Wynne and Donohue (2016), who used geospatial analysis using a 5 m DTM, a 50 m buffer around each WFD lake, and the previous version of the nested catchments layer. Predicted for the remaining 52 lakes using a statistical model.	An indicator of the possible steepness of the lake littoral zone, and a predictor of lake depth.	Sobek *et al*. (2011)
Density of upstream lakes (km^2/km^2)	The proportion of the upstream catchment area that is lakes. Wynne and Donohue (2016) calculated this variable as the total area (km^2) of all lake segments (using the lake segments layer) upstream of the lake and within its nested catchment, and divided this by the lake's catchment area (km^2). Using the nested catchments v2 layer, the same methodology was adopted to estimate the density of upstream lakes for all 811 lakes.	Proxy for in-lake retention of nutrients as they are transported through the upstream catchment.	Kratz *et al*. (1997); Zhang *et al*. (2012)
Stream density (km/km^2)	The density of streams in the upstream catchment. Wynne and Donohue (2016) calculated this variable as the total length (km) of all river lines (using the RivNetRoutes layer) upstream of the lake and within its nested catchment, and divided this by the lake's catchment area (km^2). Using the nested catchments v2 layer, the same methodology was adopted to estimate stream density for the 53 lakes that were not included in the research by Wynne and Donohue (2016).	Indicative of the importance of surface water pathways. Proxy for in-stream retention of nutrients as they are transported through the upstream catchment.	Venohr *et al*. (2005)
Limestone (%)	The % of limestone bedrock within the upstream catchment. Wynne and Donohue (2016) used the intersection tool in ArcGIS 10.1 to estimate the % of limestone bedrock (utilising the GSI hydrostatic rock units layer) in each nested catchment from the previous version of the nested catchments layer. The same methodology was adopted to estimate % cover of limestone bedrock for all 811 lakes, but with the nested catchments v2 layer.	Predictor of alkalinity and colour, and a strong indicator of groundwater interactions.	Hem (1985); Meybeck *et al*. (1996); Tedd *et al*. (2014)

Variable (units)	Description and derivation	Relevance	References
Peat (%)	The % of peaty subsoils within the upstream catchment. Wynne and Donohue (2016) used the intersection tool in ArcGIS 10.1 to estimate the % of peaty subsoils (utilising the Subsoils.ie layer) in each nested catchment from the previous version of the nested catchments layer. The same methodology was adopted to estimate % cover of peat subsoil for all 811 lakes, but with the nested catchments v2 layer.	Influences run-off potential. Also a predictor of alkalinity and colour.	Hem (1985); Meybeck *et al*. (1996)
Karst (%)	The % of karst aquifers within the upstream catchment. Wynne and Donohue (2016) used the intersection tool in ArcGIS 10.1 to estimate the percentage of karst aquifers (utilising the groundwater resources bedrock aquifer layer) in each nested catchment from the previous version of the nested catchments layer. The same methodology was adopted to estimate % cover of karst aquifers for all 811 lakes, but with the nested catchments v2 layer.	Influences flow pathways. Catchment watersheds can be difficult to delineate in karst areas, leading to potential errors in flow estimation.	
TP load (kg/ha/yr)	Estimated total annual load of TP from the upstream catchment as estimated by SLAM v303.	Estimate of external nutrient pressure acting on each lake from point and diffuse sources.	Mockler *et al*. (2017)
Runoff ($m^3/km^2/yr$)	Annual mean naturalised runoff from the upstream catchment, estimated for 667 lakes using the QUBE model and predicted using a statistical model for the remaining 144 lakes.	Runoff influences the rate of TP transport.	Bree (2018)
Flow (m^3/yr)	The annual mean discharge at the lake outflow, calculated by multiplying the modelled annual runoff by the lake catchment area.	Influences TP dilution and lake residence time.	
Lake Variables			
Alkalinity (mg/l)	Long-term (2007-2015) mean alkalinity, calculated for 223 lakes using EPA sample data, and predicted using a statistical model for the remaining 588 lakes.	One of the most important factors in explaining natural variation in lake biological communities.	Free *et al*. (2006)

Variable (units)	Description and derivation	Relevance	References
Lake area (km^2)	Lake area, derived from the WFD lake water bodies layer.	Lake area, and its relationship to lake volume can impact cycling of nutrients through, increased wind and wave action, varying stratification regimes and dilution.	Håkanson (2005)
Depth (m)	Mean lake depth, based on EPA bathymetry data for 584 lakes, and predicted using a statistical model for the remaining 227 lakes.	Used to calculate lake volume, and part of the lake typology. As is the case with lake area, depth impacts the processing of nutrients once they reach the lake. One of three factors that determine WFD typology.	Håkanson (2005)
Influent TP concentration (mg/l)	The annual flow-weighted mean TP concentration in the water flowing into each lake, calculated by dividing the annual TP load (kg/yr, converted to mg/yr) by the annual flow (m^3/yr, converted to l/yr).	The primary external control on in-lake phosphorus concentration.	Vollenweider (1976); Brett and Benjamin (2008)
Residence time (years)	The average time taken for water to pass through the lake, calculated by dividing the estimated lake volume (m^3) by the estimated annual flow at the lake outlet (m^3/yr).	Influences how much of the influent phosphorus is retained within the lake in bed sediments.	Vollenweider (1976); Brett and Benjamin (2008)
Colour (Hazen)	Mean (2016-2018) lake colour based on EPA monitoring data for 224 lakes, and predicted using a statistical model for the remaining 587 lakes.	Affects light penetration, which can potentially influence community structure of phytoplankton and submerged macrophytes.	Alahuhta *et al*. (2013); Taylor *et al*. (2021)
Shoreline development index (SDI)	The ratio of the lake perimeter to the circumference of a circle of area equal to the surface area of the lake. Larger values indicate more irregular shore outlines. Calculated for 759 lakes by Wynne and Donohue (2016) and predicted using a statistical model for the remaining 52 lakes.	The extent of littoral habitat increases with an increasing SDI. Potential predictor of lake depth.	Shilland *et al*. (2009); Wynne and Donohue (2016)

2.4 WFD Typology

The WFD requires that surface water bodies be differentiated according to type, so that changes in biological indicator communities would detect changes in pressure, rather than reflecting natural variation (European Commission, 2003a). Natural variation in biological communities occurs along hydrogeomorphological gradients, and thus water body types must characterise elements of the water body's natural hydrogeomorphology at reference condition to reflect this natural variation (European Commission, 2003b).

The WFD typology of lakes in Ireland is based on Free *et al.* (2006), who showed that lake alkalinity, mean depth and surface area were the most important factors explaining natural variation in lake biological communities (Table 2).

Table 2: WFD typology for Irish lakes

Parameter	Boundaries											
Alkalinity (mg/l $CaCO_3$)	<20				20-100				>100			
Mean depth (m)	<4		>4		<4		>4		<4		>4	
Area (ha)	<50	>50	<50	>50	<50	>50	<50	>50	<50	>50	<50	>50
Type	1	2	3	4	5	6	7	8	9	10	11	12

For this project, it was important to know the typology of all lakes so that any influences of alkalinity, depth and area could be taken into account when predicting the status. Surface area is easily derived from maps and is therefore known for every lake, but alkalinity and depth have only been measured for a fraction of WFD lakes, and therefore statistical regression models were developed to predict alkalinity and depth for lakes with missing data.

Alkalinity measurements (mg/l) were available for 223 monitored lakes from the EPA's AQUARIUS database. The measurements for the monitored lakes were averaged over a 9-year period (2007-2015) to give an estimate of long-term mean alkalinity for each lake. Using these data, a GAM regression model was developed to understand and quantify the causes of variation in alkalinity from lake to lake. Alkalinity was modelled as a function of the following predictor variables:

- % peat (an indicator of the extent of peaty spoils in the upstream catchment);
- % limestone (an indicator of the geology of the upstream catchment); and
- easting/northing (to account for other sources of spatial variation).

%peat and %limestone were chosen as candidate predictors because Wynne and Donohue (2016) used them successfully to predict the alkalinity category of lakes using a regression tree model. The model was used to predict alkalinity (in mg/l) for the 588 unmonitored lakes. The predictions were then converted to categories (low, moderate, high) using the boundaries in Table 2. The full method used to model alkalinity is described in Appendix 1.

Mean depth estimates (in m) were provided by the EPA for a total of 584 WFD lakes; data for 204 of these lakes were derived from the EPA's 2013 monitored bathymetry database and the remaining 380 values were derived from the EPA's typology data update in 2016. Using these data, a GAM regression model was developed to understand and quantify the causes of variation in mean depth from lake to lake. Specifically, mean depth was modelled as a function of the following predictor variables:

- lake area (log_{10}-transformed);
- range in slope (50m buffer; log_{10}-transformed); and
- shoreline development index (SDI).

The approach followed is an advance on the previous study (Wynne and Donohue, 2016), which was unable to develop a sufficiently accurate model for lake depth. At that time, bathymetry data was unavailable, and their model was based on maximum depths recorded using a handheld depth sounder for 201 lakes.

The final model, which explained 41.4% of the variation among lakes, was used to predict mean depth (m) for the remaining 227 lakes. The predictions were then converted to categories (shallow, deep) using the boundaries in Table 2. The full method used to model depth is described in Appendix 1.

Using a combination of measured and predicted data, each of the 811 WFD lakes was assigned to a typology category (Figure 4). Small, shallow, low alkalinity lakes are the most numerous, accounting for ~32% of all WFD lakes. The EPA's lake monitoring programme includes at least 10 lakes in each of the 12 typology groups, although for every alkalinity/depth group a higher proportion of large lakes are monitored than small lakes (that is, small lakes are under-represented in the monitoring programme).

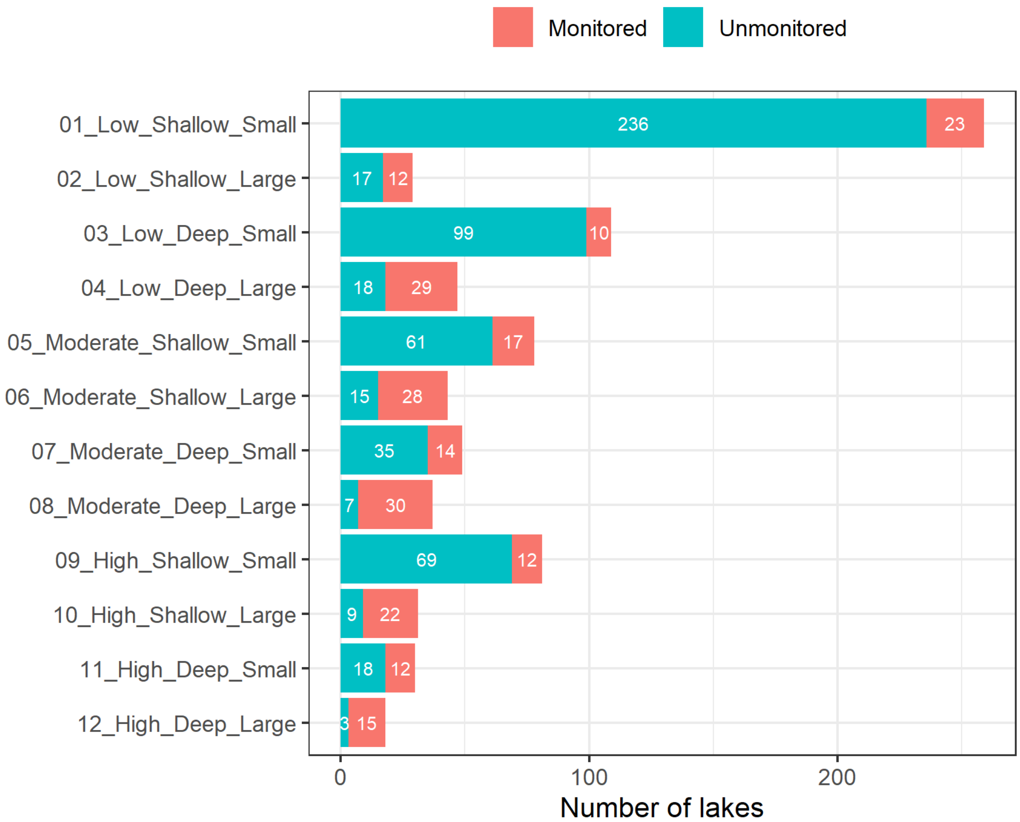


Figure 4: Number of lakes within each lake typology category

Figure 5 shows the geographic distribution of the different lake types. There is a clear geographic pattern in the distribution of the different lake alkalinity categories. Low alkalinity lakes are mostly found along the west coast of the country, with the largest proportions in Donegal, Galway and Kerry. Deeper low alkalinity lakes (both large and small) are most frequently found in Kerry and Donegal with a number also in Wicklow, whereas there are more small shallow low alkalinity lakes in Connemara (Galway), as well as in Donegal. Most of the moderate and high alkalinity lakes are found in the midlands, with a high concentration of small shallow lakes around the border in Monaghan and Cavan, and significant numbers of all types of moderate and high alkalinity lakes in Leitrim, Roscommon, Mayo and Clare.

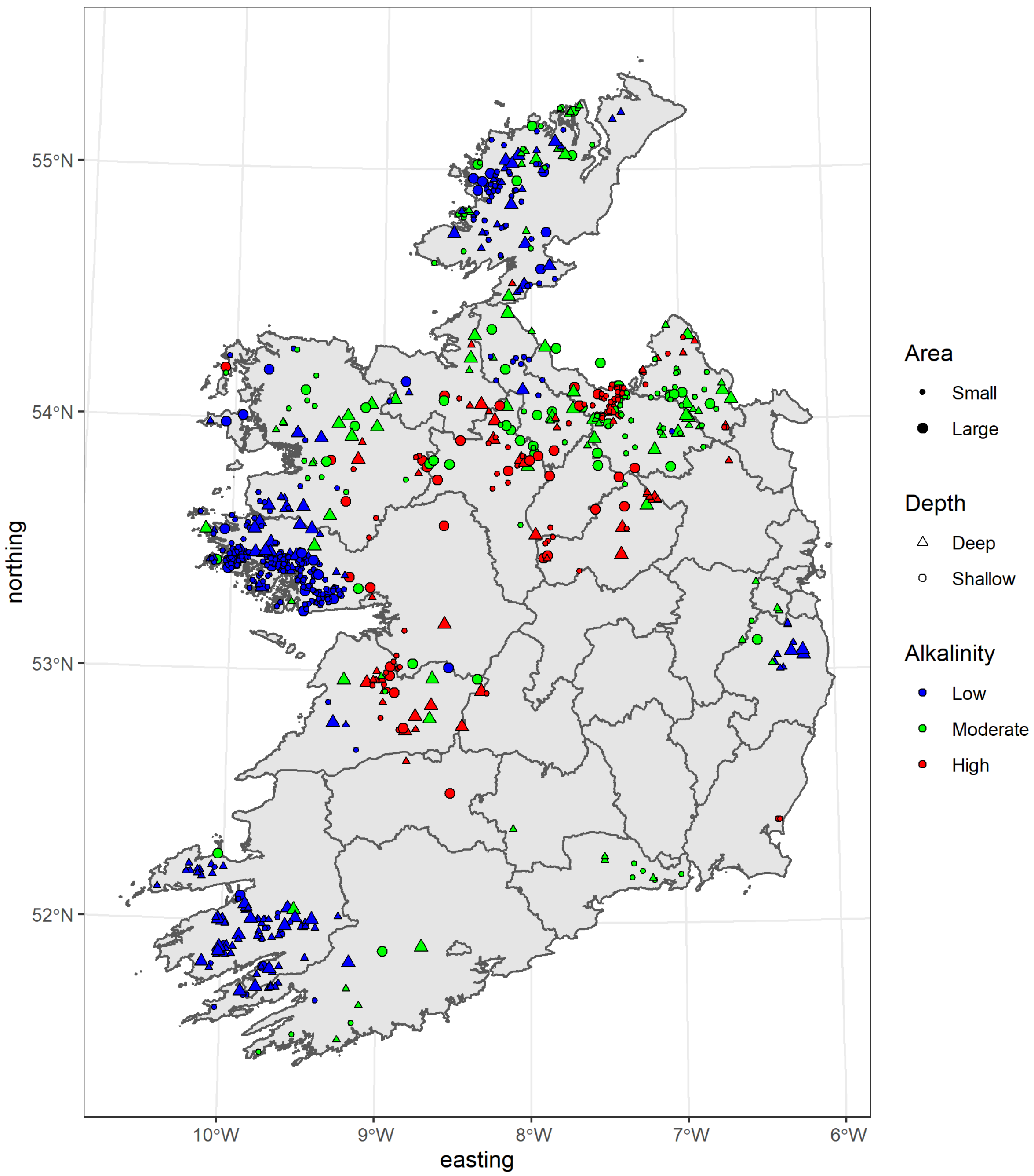


Figure 5: Map of WFD typology of all 811 lakes

3. Classification of lakes based on anthropogenic stressors and physical features

3.1 Approach

This section describes the approach used to develop statistical models of TP concentration, chlorophyll-*a* EQR and macrophyte EQR, and then apply those models to predict the status of unmonitored lakes.

Based on the one-out-all-out principle, Wynne and Donohue (2016) focused on the worst-performing quality element for each monitored lake and used a combination of k-means clustering and hierarchical clustering to group lakes according to their hydrogeomorphological characteristics. Whilst the approach was successful in identifying donor lakes that could be used to infer the WFD status of similar unmonitored lakes, it did not attempt to differentiate the responses of TP concentration, chlorophyll-a and macrophytes to anthropogenic stressors, and was unable to provide clear insight into the factors or processes driving variation in WFD status among lakes.

This study builds on the work of Wynne and Donohue (2016) in two main ways. First, to better understand the underlying mechanisms of nutrient enrichment and eutrophication in Irish lakes, we developed separate predictive models for each of the three quality elements. Moreover, to represent the chain of causation leading to impacts on biological receptors, predictions from the TP model were used as an input to the chlorophyll-a and macrophyte models, and predictions from the chlorophyll-a model were used as an input to the macrophyte model. Second, statistical regression models were used in preference to cluster analysis techniques to quantify causal relationships between nutrient enrichment pressure, lake water quality (TP concentration) and biological community composition (chlorophyll-a and macrophyte EQRs).

For each quality element in turn, spatial variation among monitored lakes was analysed using Generalised Additive Models (GAMs). GAMs are an extension of standard linear regression models that allow relationships between the explanatory variables and the response to be described by smooth curves (Wood, 2017). By flexibly describing non-linear relationships non-parametrically, without making *a priori* assumptions about the form of the relationship, GAMs offer a middle ground between simple linear models and complex machine-learning techniques, which has led to them being widely used to model complex ecological systems (Pedersen *et al.*, 2019).

For each model, the conceptual model of lake eutrophication was used to guide the selection of candidate predictor variables that had a plausible, scientific basis for inclusion in the model. Candidate variables were screened to identify and eliminate any that were strongly correlated or had high concurvity (where one variable was a smooth function of another). Continuous predictors were modelled as smooth functions using thin plate regression splines, with the degree of smoothing optimised using restricted maximum likelihood (REML; Wood, 2011). Two-dimensional isotropic smooths were used to model geographic variation (i.e. easting/northings), and a tensor product smooth was used to model interactions between variables measured on different scales.

A full model containing all candidate predictor variables was simplified using backward model selection to yield a final, parsimonious model containing only the most useful predictor variables. Model selection was based on the Bayesian Information Criterion (BIC) rather than the Akaike Information Criterion (AIC) because it penalises model terms more heavily and because simpler models tend to be more transferable and give better predictions when applied to new locations outside the training set (Millidine *et al.*, 2016; Jackson *et al.*, 2017). The model with the lowest BIC was selected as the final model. The accuracy of the final models was quantified by comparing the predicted and measured status classes for the 224 monitored lakes in the calibration dataset.

The final models were used to predict TP concentration, chlorophyll-a EQR and macrophyte EQR for the 587 unmonitored lakes, plus macrophyte EQR for the three monitored lakes that lacked macrophyte sample data. These predictions were then converted to WFD status classes as shown in Table 3 and, in turn, used to assess whether or not each lake was achieving GES. The degree of confidence in the classification results was quantified using prediction intervals and summarised in the form of certainty bands.

Finally, the status class predictions for the three quality elements were combined using the one-out, all-out rule to predict the overall status of each unmonitored lake.

All analyses were performed in R 3.6.1 (R Core Team, 2022), and the GAM models were fitted using the `gam` function from the `mgcv` package (Wood, 2022).

Table 3: WFD standards and criteria for TP, chlorophyll-a and macrophytes

WFD standard	TP concentration (mg/l)*	Chlorophyll-a (normalised EQR)	Macrophytes (normalised EQR)
High	0.010	0.8	0.8
Good	0.025	0.6	0.6
Moderate	0.050	0.4	0.4
Poor	0.100	0.2	0.2

*From EPA (2019)

3.2 TP status

Numerous studies have attempted to determine the factors that exert the greatest impact on in-lake TP concentrations, dating back to the seminal work of Vollenweider (1976), who developed the following mathematical model of phosphorus loading:

$$TP_{lake} = \frac{L}{D(\rho + \sigma)} \quad \text{(eqn. 1)}$$

where TP_{lake} = the TP concentration in the lake and its outflow (mg m^{-3} or µg L^{-1}), L = the areal TP loading rate (mg TP m^{-2} year^{-1}), D = mean lake depth (m), ρ = lake flushing rate (year^{-1}) and σ = first-order rate coefficient for TP loss from the lake (year^{-1}). Vollenweider's model assumes that the lake is well mixed and at steady state, so that the TP concentration throughout the lake and in the outlet stream can be characterized by a single value. It also assumes that TP can be lost from the lake in only two ways: via advection (i.e. in the outlet stream) or via one or more first-order processes occurring within the lake (principally sedimentation of phosphorus-containing particles in the lake).

Brett & Benjamin (2008) showed that eqn. 1 can be re-arranged as:

$$TP_{lake} = \frac{TP_{in}}{1 + \sigma\tau} \quad \text{(eqn. 2)}$$

where TP_{in} = the flow-weighted TP influent concentration (mg m^{-3} or µg L^{-1}) and τ = mean hydraulic residence time (years). As has been pointed out by several authors, eqn. 2 is identical to the classic result from chemical engineering for the relationship between the inlet and outlet concentrations of a substance that undergoes a first-order decay reaction in a continuous flow stirred tank reactor (Brett & Benjamin, 2008). Usefully, eqn. 2 expresses the in-lake concentration (as measured by the EPA's monitoring programme) as a function of the influent concentration (as estimated using SLAM-modelled TP loads and QUBE-modelled flows), and the lake's residence time (as estimated using QUBE-modelled flows); only the loss coefficient (σ) cannot be estimated directly for Irish lakes.

However, taking logarithms of eqn 2. gives:

$$\log(TP_{lake}) = \log(TP_{in}) - \log(1 + \sigma\tau) \quad \text{(eqn. 3)}$$

and by furthermore assuming that the loss coefficient (σ) is either a constant or a function of the lake's hydraulic residence time (τ) (Larsen & Mercier 1976; Brett & Benjamin, 2008), the in-lake TP concentration can be modelled using just influent concentration and residence time.

Using estimates of mean TP concentration (2016-18) available for 224 monitored lakes, TP was therefore modelled as a function of the **modelled influent TP concentration** ($\log_{10}$-transformed) and **residence time** (also $\log_{10}$-transformed). An interaction between these two predictors (as a 2D smooth) was also included. In addition:

- **typology** was included as a main effect to account for possible differences in nutrient dynamics and TP concentrations among lake types (main effect only, as there were insufficient data to test for a three-way interaction between influent TP concentration, residence time and typology);

- as an alternative to typology, **alkalinity** and **mean depth** ($\log_{10}$-transformed) were included as main effects to account for possible TP gradients across lake types;
- **stream density** ($\log_{10}$-transformed) and **upstream lake density** ($\log_{10}$-transformed) were included as proxies for nutrient processing and retention in streams and lakes in the upstream catchment (processes not accounted for in the SLAM model); and
- **easting** and **northing** were included as a 2D smooth to account for other sources of spatial variation.

There were insufficient data to test whether and how the interacting effects of influent TP concentration and residence time varied among lake types.

TP concentration was $\log_{10}$ transformed to satisfy the model's assumptions of normally distributed errors and heterogeneous variables (see Appendix 2 for residuals plots), and heavily skewed predictor variables were $\log_{10}$-transformed to reduce the influence of outliers.

Backward model selection using BIC was used to retain only the most relevant predictor variables. For TP concentration, the variables retained in the final model were:

- modelled influent TP concentration;
- residence time;
- modelled influent TP concentration x residence time interaction; and
- easting/northing.

Typology, alkalinity and depth were not retained in the final model. This was not unexpected, as depth was indirectly accounted for via residence time, and there is no clear mechanism by which alkalinity directly affects in-lake TP concentration. The effects of the predictors in the final model were therefore common across all lake types.

Stream density and upstream lake density were also dropped from the model, a result suggesting either that nutrient retention is relatively unimportant, or that these variables are poor proxies for upstream nutrient retention.

Overall, the final model explained 69.1% of the variation in TP concentration (Figure 6; Appendix 2).

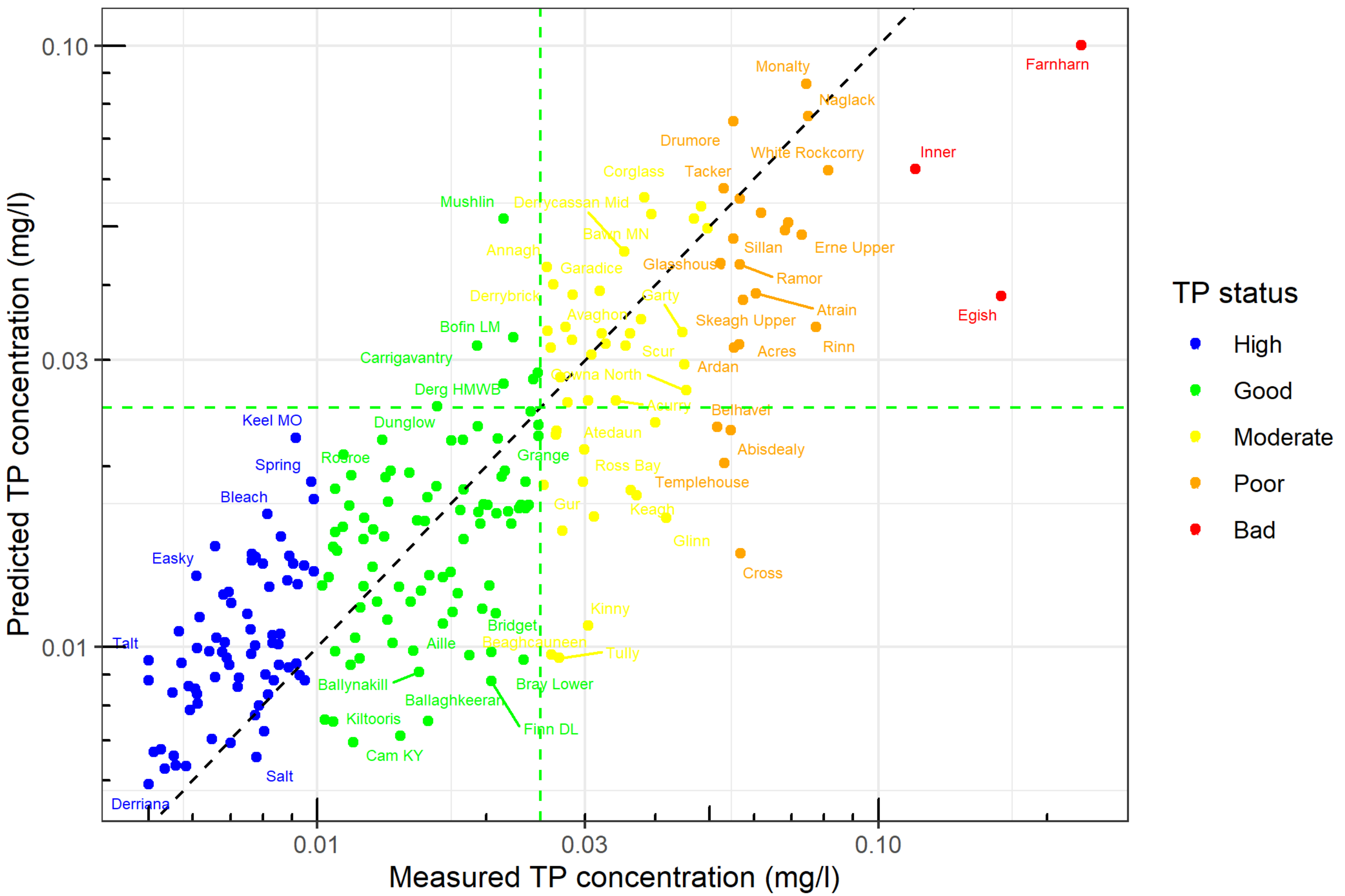


Figure 6: Predicted vs measured TP for the 224 monitored lakes

Figure 7 illustrates the effect influent concentration and residence time on in-lake TP concentration whilst holding easting/northing constant. The five curves represent lakes with residence times of 1 day, 1 week, 1 month, 1 year and 5 years (only seven lakes had an estimated residence time of less than 1 day, and only four lakes had an estimated residence time more than 5 years; see Appendix 1 for a full distribution). Overall, in-lake TP concentrations increased with influent TP concentration, but the effect of external nutrient loading on lake water quality was strongly moderated by residence time. Specifically, lakes with short residence times (< 1 month) had TP concentrations that were strongly driven by the influent TP concentration, whereas lakes with long residence times (> 1 year) were predicted to be relatively insensitive to TP inputs. Although the flat purple line in Figure 7 implies that increasing (or decreasing) TP inputs would have no effect on TP concentration in lakes with very long residence times (ca. 5 years), there are very few such lakes in the calibration dataset, so there is considerable uncertainty in this result; in fact, the confidence intervals around the purple line mean it is not possible to say whether the relationship between influent TP concentration and in-lake TP concentration is positive, negative or flat.

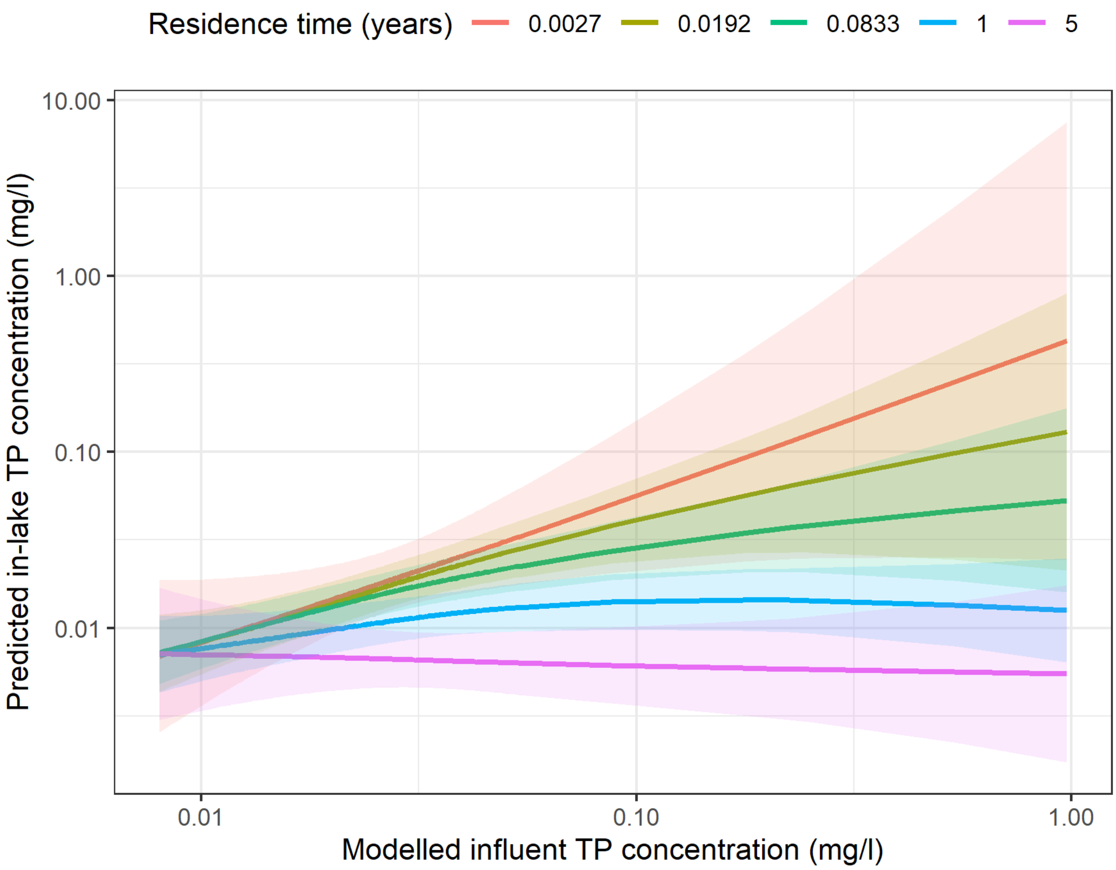


Figure 7: Partial effects plot showing the effect of influent concentration and residence time (1 day, 1 week, 1 month, 1 year and 5 years) on in-lake TP concentration

Figure 8 illustrates the geographic variation in measured TP concentration after accounting for the effect of influent TP concentration and residence time. All else being equal, lakes in Cavan and Monaghan (and to a lesser extent southern Cork) had higher in-lake TP concentrations than those in the western coastal counties of Donegal, Mayo, Galway and Kerry. The reason for this marked geographic variation could reflect spatial differences in soil geochemistry or historically high phosphorus inputs to lakes in the more intensively farmed regions of the country, or could be due to the under-estimation by the SLAM model of TP loads from some agricultural sources. Regardless of the cause, the final TP model accounts for this unexplained geographic variation in its TP predictions for each lake.

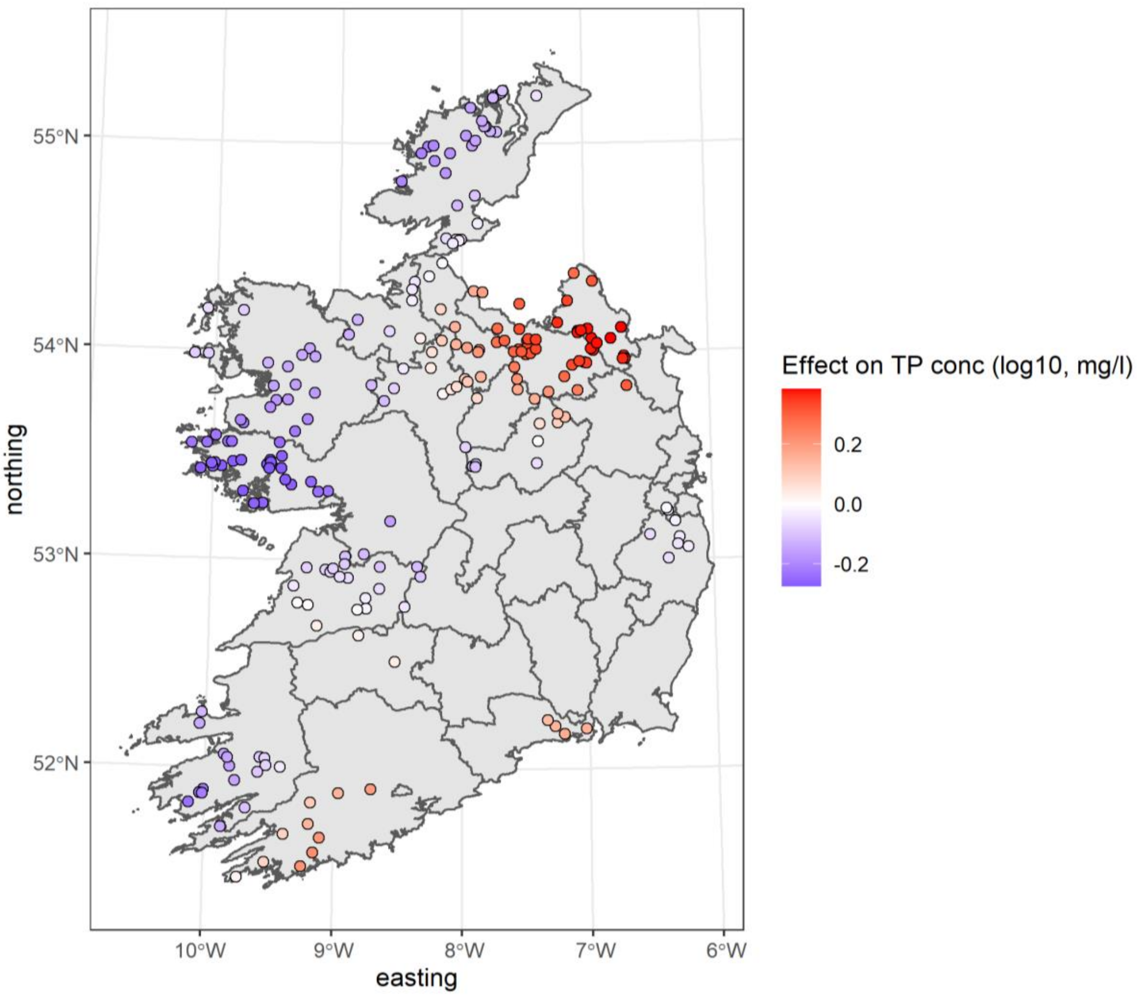


Figure 8: Partial effects plot showing the effect of easting/northing on TP concentration in monitored lakes

The predictive performance of the model was assessed by comparing the measured status class of the 224 monitored lakes with the class predicted by the final model (Figure 9). Overall, the model predicted the correct TP status class with 61% accuracy and predicted with 89% accuracy whether or not a lake was achieving Good status for TP. There was a slight tendency to over-predict status more than under-predict, particularly for more impacted lakes, but in only 8 out of 224 cases (3.5%) was the model prediction out by more than 1 status class. Appendix 2 lists the lakes with the largest positive and negative residuals (i.e. those where the TP concentration was proportionally under- and over-estimated the most).

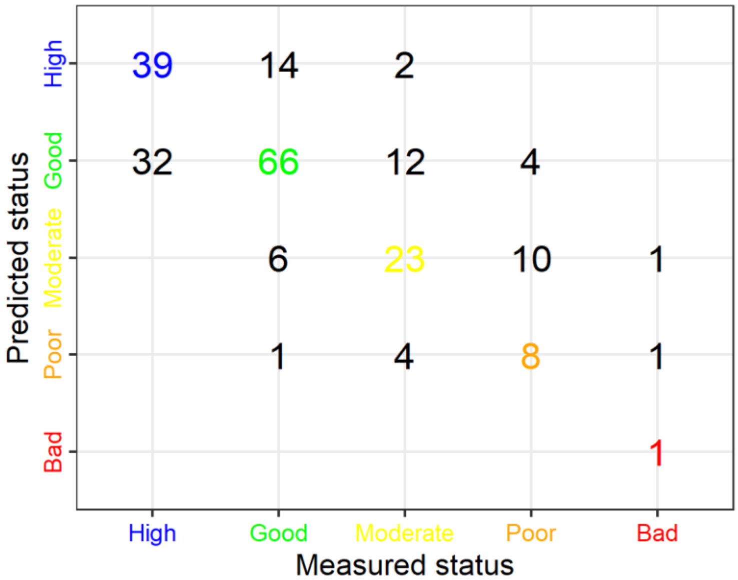


Figure 9: Matrix of measured and predicted TP status class for the 224 monitored lakes

Inspection of the model residuals showed that the model was equally good at predicting TP concentration for lakes in karst and non-karst catchments, for large and small lakes, and for lakes in each of the 12 typology groups (see Appendix 2 for details). This confirms that the model has general applicability and does not appear to be biased for any particular type of lake.

The final model was used to predict TP concentration for the 587 unmonitored lakes. 82% of these were predicted to be achieving Good status for TP, compared with 71% of monitored lakes (Figure 10). Overall, low alkalinity lakes had the highest proportion at High or Good status, and moderate alkalinity shallow lakes had the lowest proportion at GES (Figure 11).

Figure 12 maps measured and predicted TP status for all 811 lakes and reveals strong geographic variation in TP status which broadly reflects regional variation in the intensity of land use and level of TP loading from point and diffuse sources

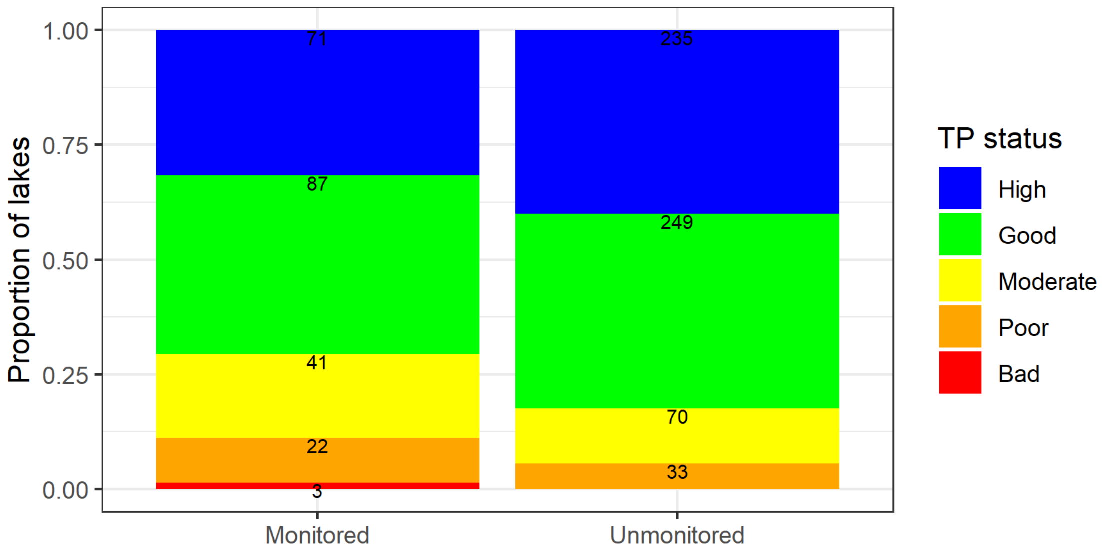


Figure 10: Summary of TP status for monitored and unmonitored lakes

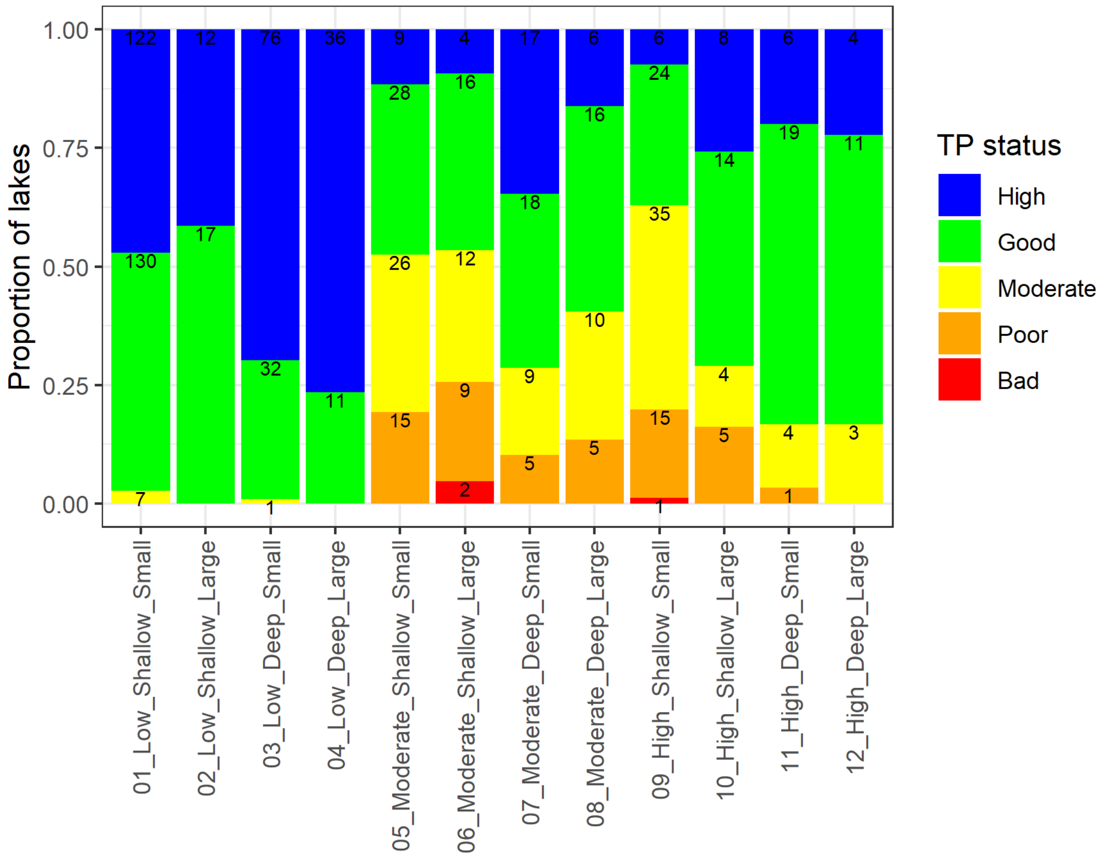


Figure 11: Summary of TP status for all 811 lakes, by WFD typology

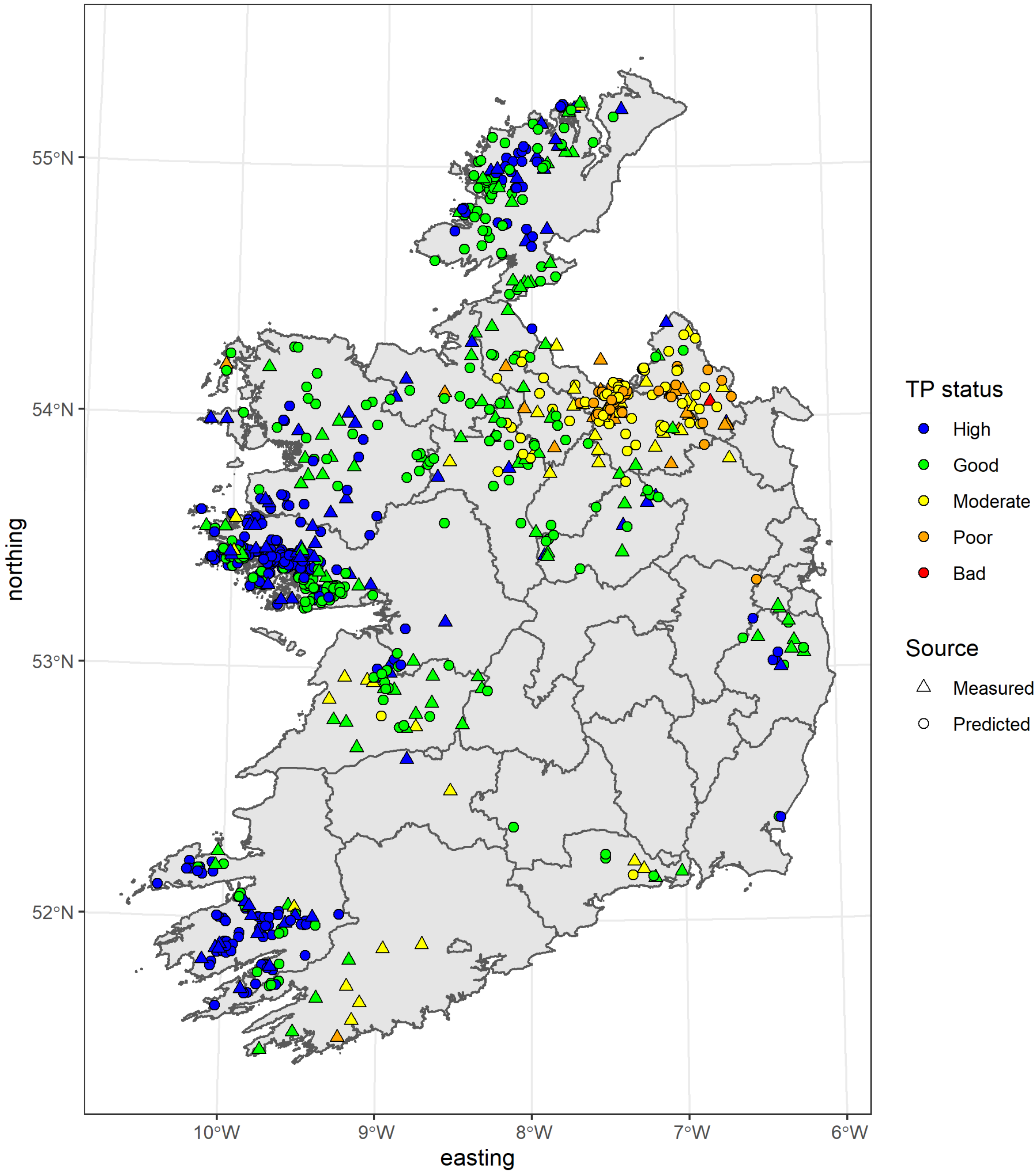


Figure 12: Map of measured and predicted TP status for all 811 lakes

3.3 Chlorophyll-a status

Chlorophyll-a EQR was used as the response variable in preference to chlorophyll-a concentration because it accounts for natural variation in chlorophyll-a concentration among lake types, and therefore provides a standardised metric that translates directly into a WFD status class.

Using estimates of mean EQR (2016-18) available for 224 monitored lakes, chlorophyll-a EQR was modelled as a function of the following predictor variables:

- **TP concentration** (log_{10}-transformed) to represent annual mean nutrient concentrations within the lake;
- **typology** was included as a main effect to account for possible differences in status among lake types;
- as an alternative to typology, **lake area** (log_{10}-transformed), **alkalinity** and **mean depth** (log_{10}-transformed) were included as main effects to account for natural gradients in chlorophyll-a EQR across lake types; **alkalinity** was also included as an interaction with **TP concentration**, to test for differential sensitivity of chlorophyll-a to nutrient enrichment;
- **residence time** (log_{10}-transformed) was included to account for possible effects on nutrient processing and nutrient uptake;
- **colour** (log_{10}-transformed, as a main effect and interaction with **TP concentration**) was included to account for possible effects of light limitation (Taylor *et al.*, 2021); and
- **easting** and **northing** were included as a 2D smooth to account for other sources of spatial variation.

Backward model selection using BIC was used to retain only the most relevant predictor variables. For chlorophyll-a EQR, the variables retained in the final model were:

- TP concentration;
- alkalinity;
- TP concentration x alkalinity interaction; and
- colour.

Typology, area, depth, residence time, and easting/northing, were not retained in the final model, so the effects of the above predictors were common across lakes of different areas and depths. Notably, alkalinity was a better predictor when fitted as a continuous term than when fitted as a categorical predictor (low, moderate, high).

Overall, the final model explained 69% of the variation in chlorophyll-a EQR (Figure 13; Appendix 3). As shown in Figure 13, the model predicted chlorophyll-a EQR well for lakes with a measured status of Good or High, but tended to over-predict chlorophyll-a EQR for lakes with a measured status of Moderate or worse.

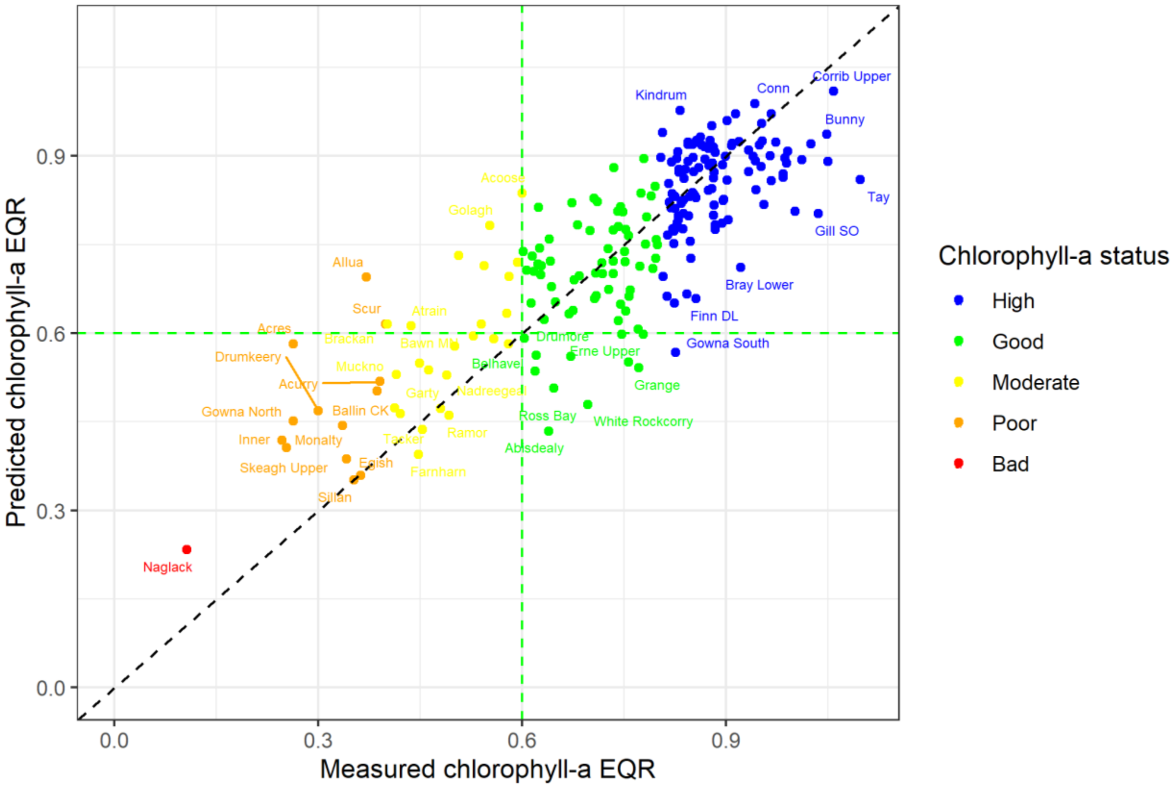
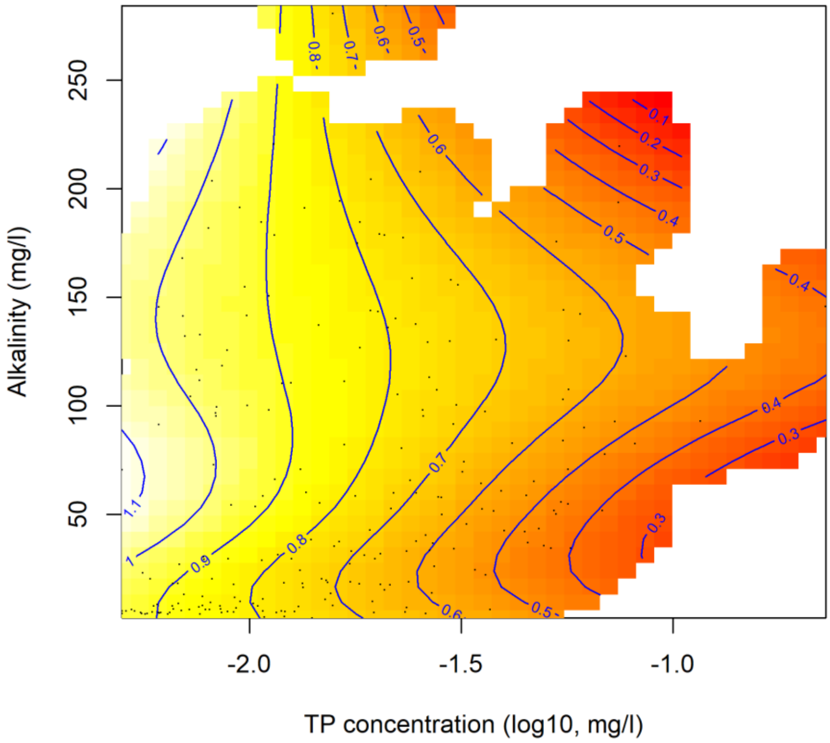


Figure 13: Predicted vs measured chlorophyll-a EQR for the 224 monitored lakes

Figure 14 illustrates the interacting effects of TP concentration and alkalinity on predicted chlorophyll-a EQR (whilst holding colour constant at a mean value of 36 mg/l). As expected, there was a strong negative relationship between TP concentration and chlorophyll-a EQR, which was approximately linear on a $\log_{10}$-scale. The slope of this relationship varied depending on the alkalinity of the lake, being slightly steeper for very high (>200 mg/l) and moderate (ca. 50 mg/l) lakes, and less steep for high (100-150 mg/l lakes). Thus the TP concentration and alkalinity interaction was relatively weak, and its inclusion in the model improved the accuracy of the model predictions by only 1%.

After controlling for the effects of TP concentration and alkalinity, there was a weak positive relationship between chlorophyll-a EQR and colour (Figure 15).

(a)



(b)

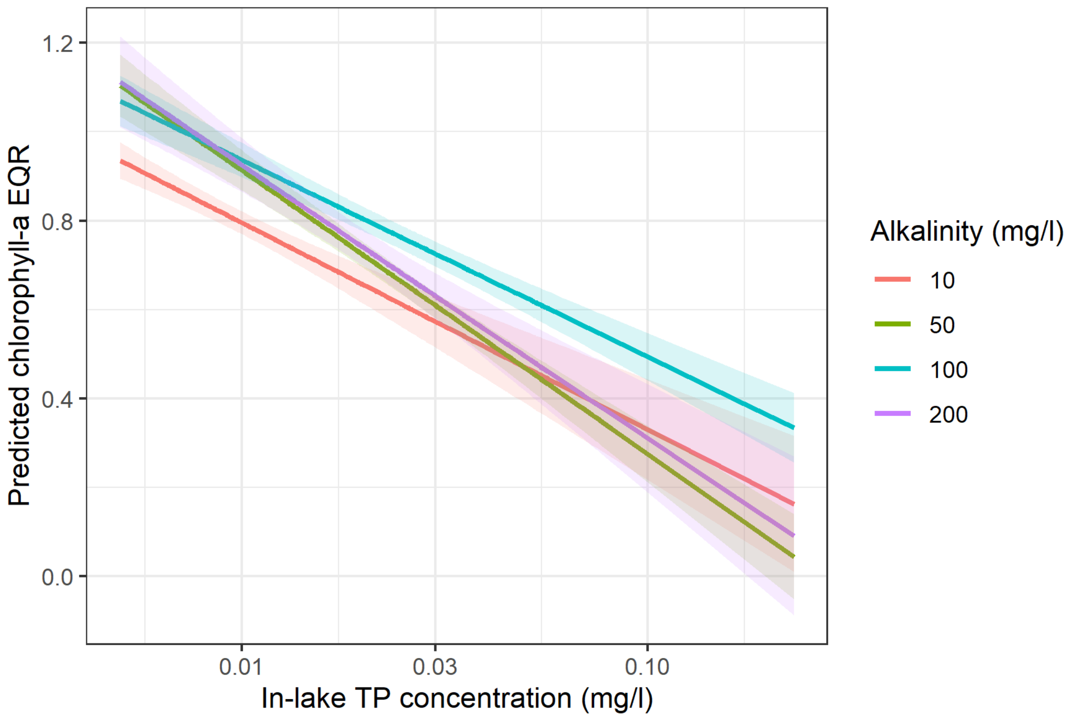


Figure 14: Contour plot (a) and model predictions (b) showing the effect of TP concentration and alkalinity on chlorophyll-a EQR

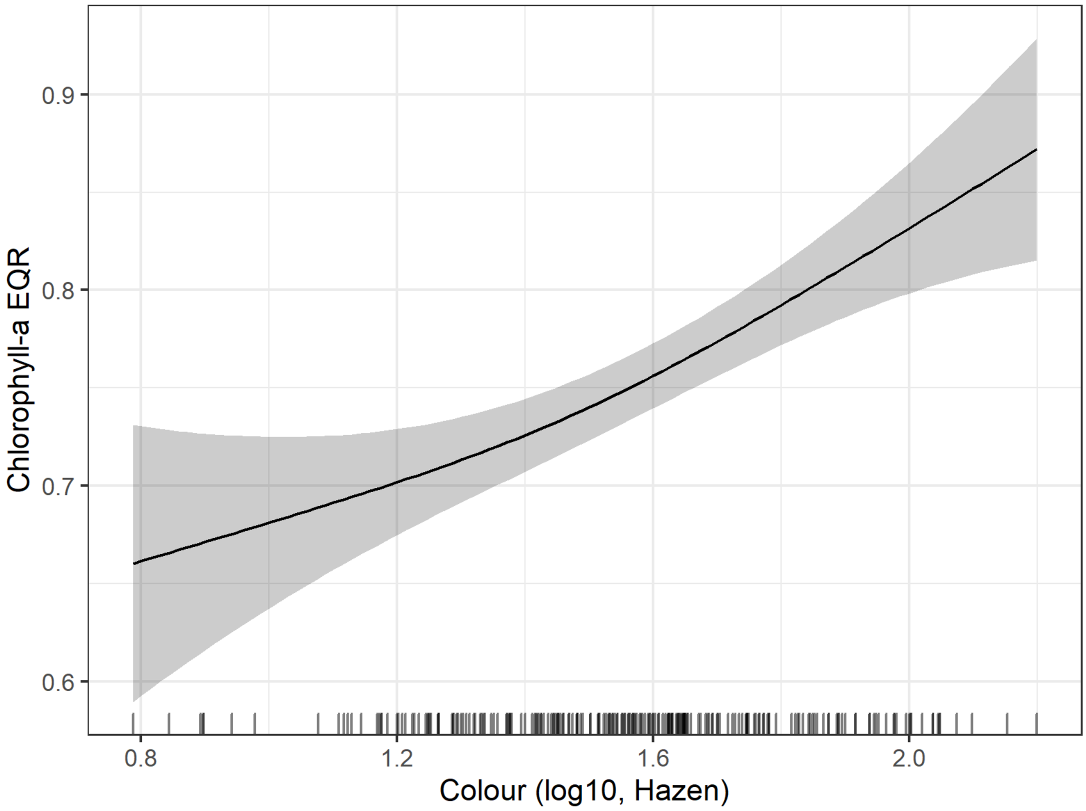


Figure 15: Partial effects plot showing the effect of colour on chlorophyll-a EQR

The predictive performance of the model was assessed by comparing the measured status class of the 224 monitored lakes with the class predicted by the final model (Figure 16). Overall, the model predicted the correct WFD status class with 69% accuracy and predicted with 89% accuracy whether or not a lake was achieving Good status for chlorophyll-a. Over- and under-estimates were roughly evenly balanced, but there was a tendency to over-predict the status of more impacted lakes. In only 4 out of 224 cases (1.8%) was the model prediction out by more than 1 status class. Appendix 3 lists the lakes with the largest positive and negative residuals (i.e. those where the chlorophyll-a EQR was under- and over-estimated the most).

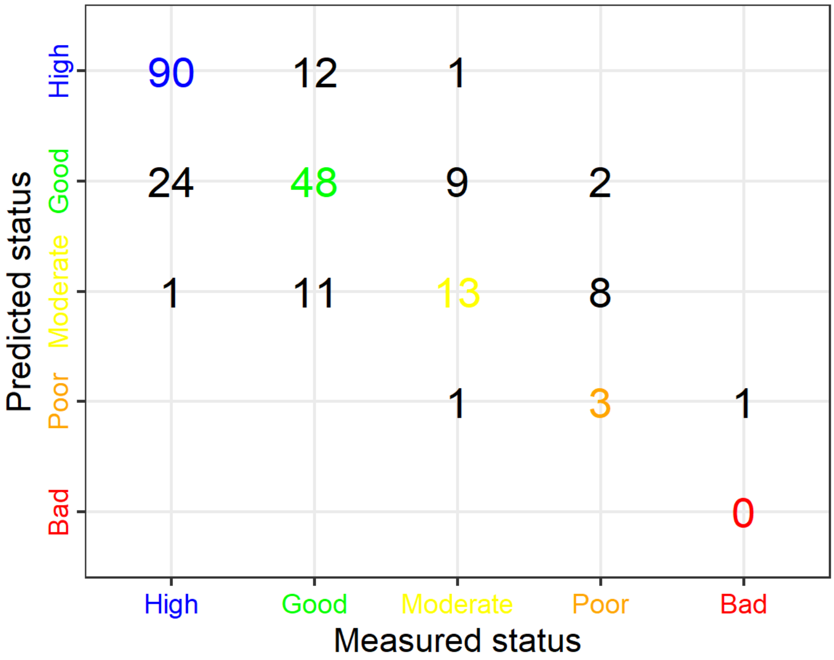


Figure 16: Matrix of measured and predicted chlorophyll-a EQR status class for the 224 monitored lakes

Inspection of the model residuals showed that the model was equally good at predicting chlorophyll-a EQR for lakes in karst and non-karst catchments for large and small lakes, and for lakes in each of the 12 typology groups (see Appendix 3 for details). This confirms that the model has general applicability and does not appear to be biased for any particular type of lake.

The final model was used to predict chlorophyll-a EQR for the 587 unmonitored lakes. 90% of these were predicted to be achieving Good status for chlorophyll-a, compared with 83% of monitored lakes (Figure 17). Overall, low alkalinity lakes had the highest proportion at High or Good status, and small, shallow lakes of moderate-to-high alkalinity had the lowest proportion (Figure 18).

Figure 19 maps measured and predicted chlorophyll-a status for all 811 lakes and reveals strong geographic variation in status which broadly reflects regional variation in the intensity of land use and level of TP loading from point and diffuse sources.

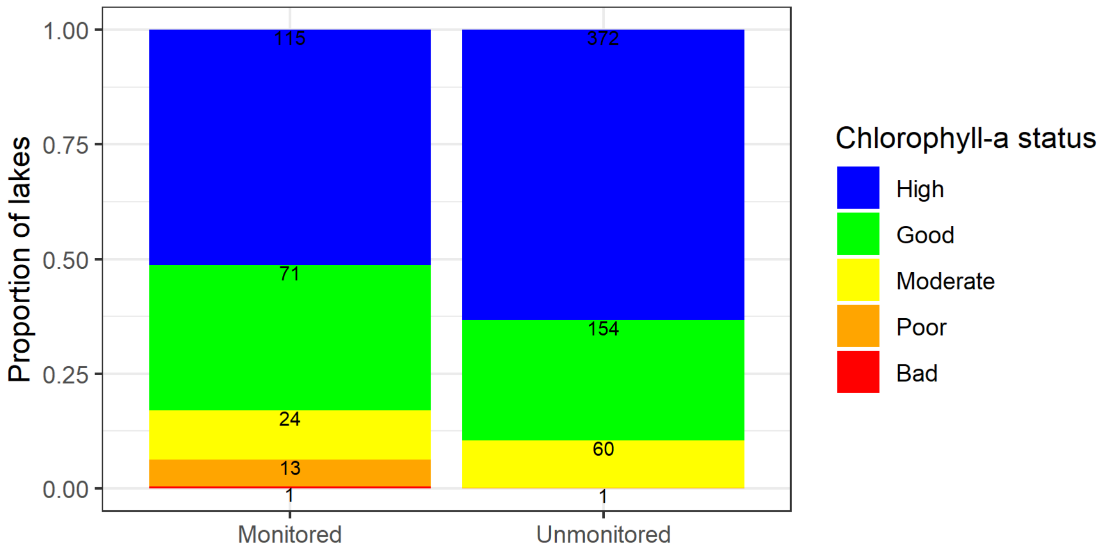


Figure 17: Summary of chlorophyll-a status for monitored and unmonitored lakes

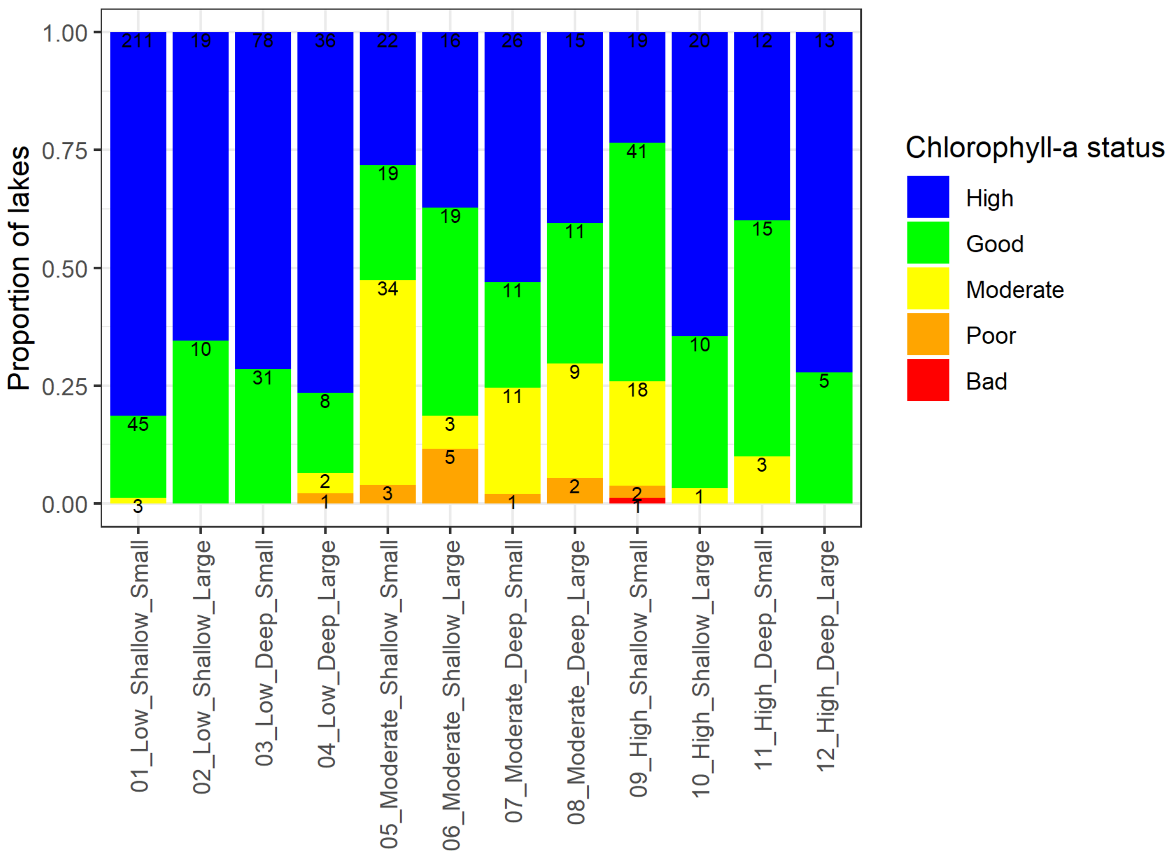


Figure 18: Summary of chlorophyll-a status for all 811 lakes, by WFD typology

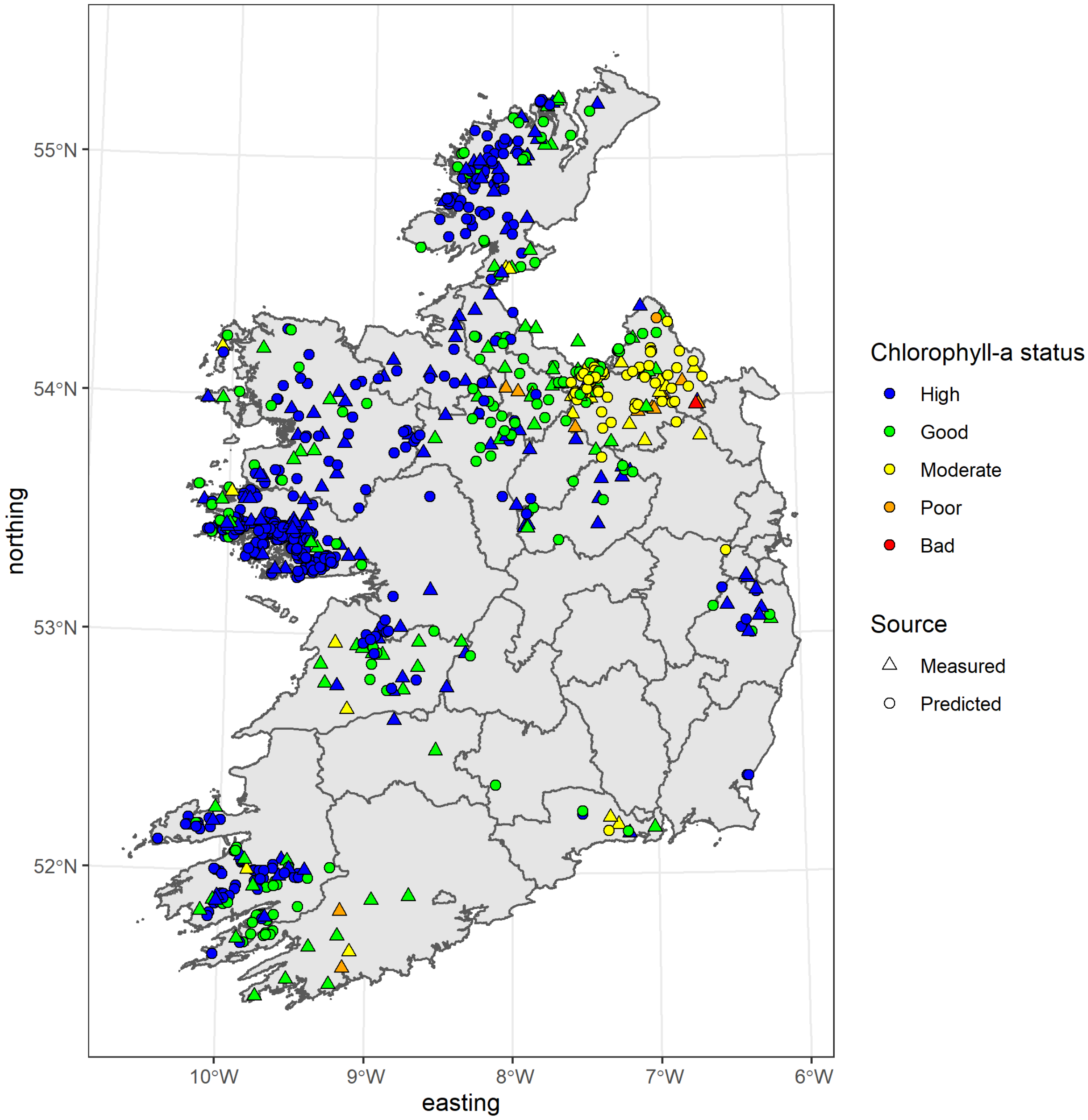


Figure 19: Map of measured and predicted chlorophyll-a status for all 811 lakes

3.4 Macrophyte status

Macrophyte EQR was used as the response variable to provide a standardised metric that translates directly into a WFD status class.

Using the measured EQR (2016-18) available for 221 monitored lakes[3], macrophyte EQR was modelled as a function of the following predictor variables:

- **TP concentration** (log_{10}-transformed) to represent annual mean nutrient concentrations within the lake;
- **typology** was included as a main effect to account for possible differences in status among lake types;
- as an alternative to typology, **lake area** (log_{10}-transformed), **alkalinity** and **mean depth** (log_{10}-transformed) were included as main effects to account for natural gradients in macrophyte EQR across lake types;
- **alkalinity** was also included as an interaction with **TP concentration**, to test for differential sensitivity of macrophyte communities to nutrient enrichment;
- **residence time** (log_{10}-transformed) was included to account for possible moderating effects on nutrient processing and nutrient uptake;
- **colour** (log_{10}-transformed, as a main effect and as an interaction with **TP concentration**) was included to account for possible effects of light limitation (Taylor *et al.*, 2021);
- **chlorophyll-a EQR** was included to represent the potential limiting effect of phytoplankton on macrophyte growth; and
- **easting** and **northing** were included as a 2D smooth to account for other sources of spatial variation.

Backward model selection using BIC was used to retain only the most relevant predictor variables. For macrophyte EQR, the variables retained in the final model were:

- TP concentration;
- colour;
- alkalinity; and
- easting/northing.

Typology, area, depth, and residence time were not retained in the final model, so the effects of the above predictors were common across lakes of different areas and depths. Notably, alkalinity was a better predictor when fitted as a continuous term than when fitted as a categorical predictor (low, moderate, high). There was no evidence that the relationship between TP concentration and macrophyte EQR was moderated by alkalinity or colour, nor that the chlorophyll-a status of the lake influenced macrophyte status.

Overall, the final model explained 78.2% of the variation in macrophyte EQR (Appendix 4). As shown in Figure 20, the model had a tendency to under-predict macrophyte EQR for lakes with a measured status of Good or High, and to over-predict for lakes with a measured status of Poor or Bad.

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[3] Three lakes (Corconnelly, Cummernamuck and Gorman) were monitored for TP and chlorophyll-a but not macrophytes.

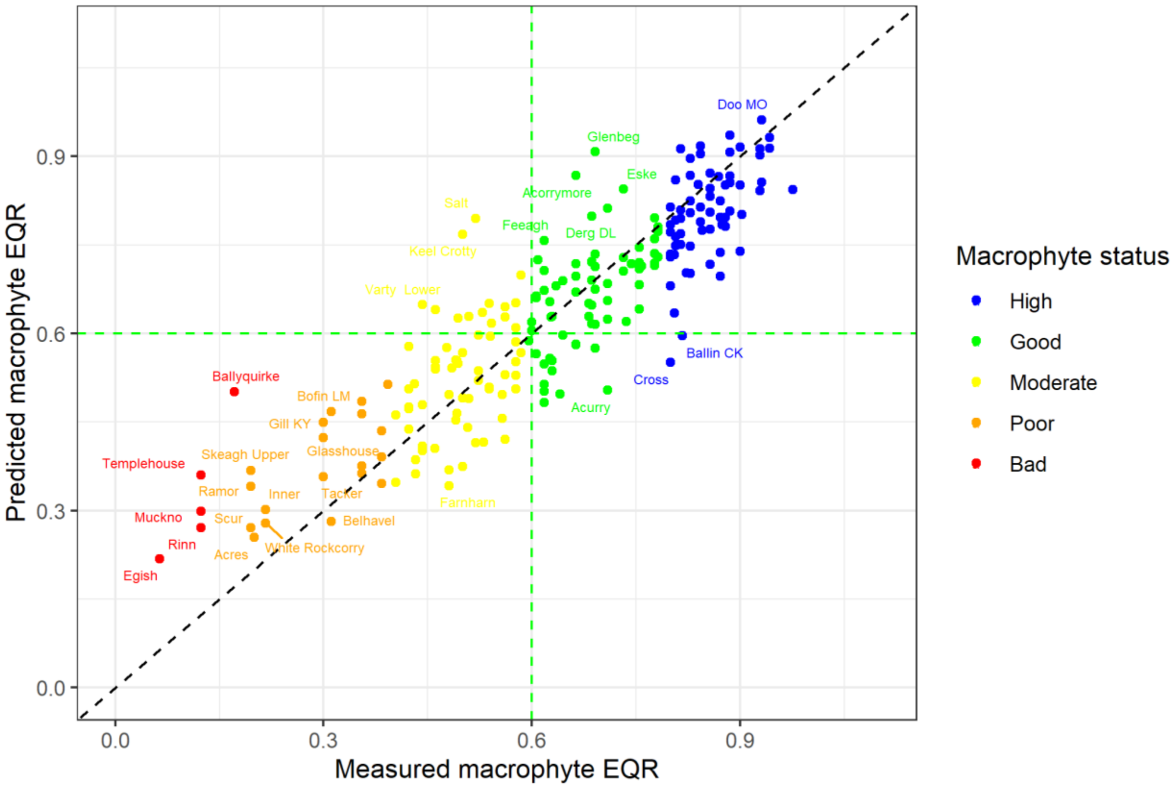

Figure 20: Predicted vs measured macrophyte EQR for the 221 monitored lakes

Figure 21 illustrates the relationship between macrophyte EQR and each variable whilst holding the other retained predictor variables constant at their mean values. As expected, TP concentration had the strongest influence on macrophyte EQR, with the negative relationship being roughly linear on a $\log_{10}$ scale. In contrast to chlorophyll-a, colour had a negative effect on macrophyte EQR, suggesting that macrophyte growth may be reduced in lakes where high colour limits light penetration. Finally, the relationship between macrophyte EQR and alkalinity was weak and unimodal, with the lowest EQR predicted for lakes with an alkalinity of ca. 70 mg/l.

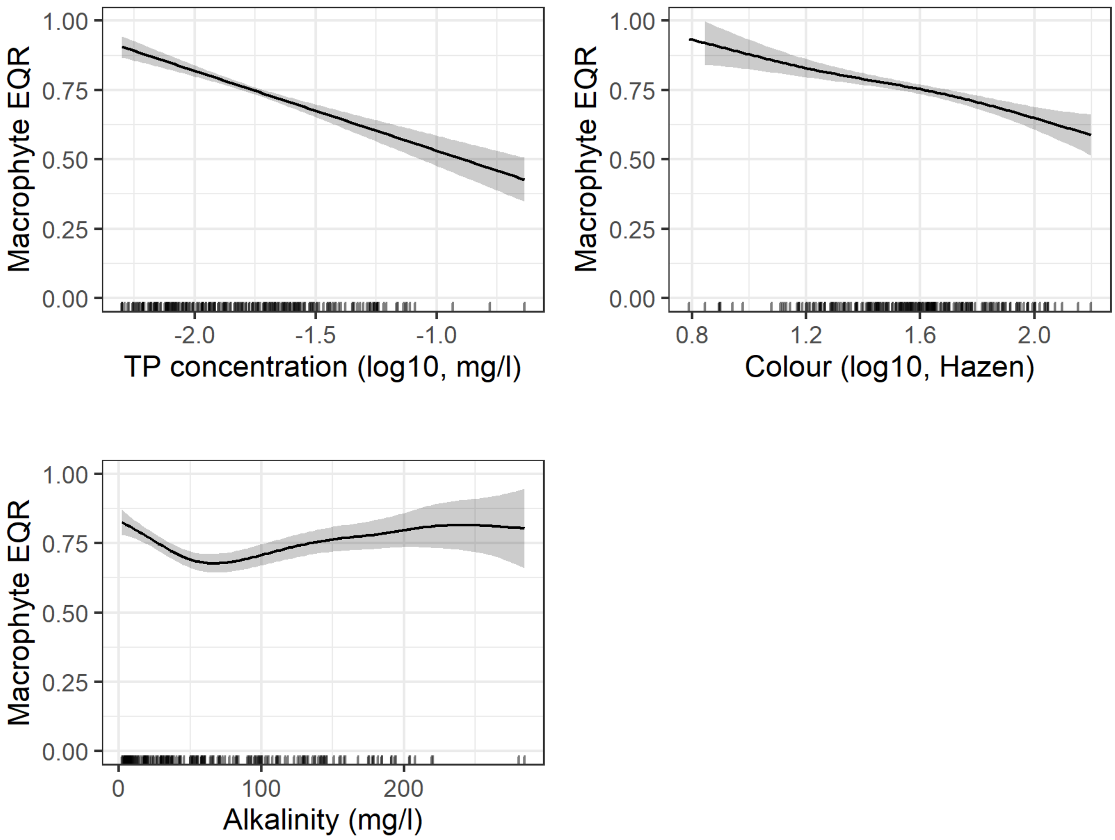

Figure 21: Partial effects plots showing the effect of each variable on macrophyte EQR

Figure 22 illustrates the geographic variation in macrophyte EQR after accounting for the effects of in-lake TP concentration, colour and alkalinity. All else being equal, lakes in the western coastal areas of Donegal, Galway and Cork had higher predicted macrophyte EQRs than lakes in inland and eastern areas, and lakes in Monaghan had particularly low predicted EQRs. The reason for this marked geographic variation is unclear, but could possibly reflect spatial variation in historical nutrient inputs and the extent of internal nutrient loading from lake sediments. Regardless of the mechanism, the final macrophytes model accounts for this unexplained geographic variation in its EQR predictions for each lake.

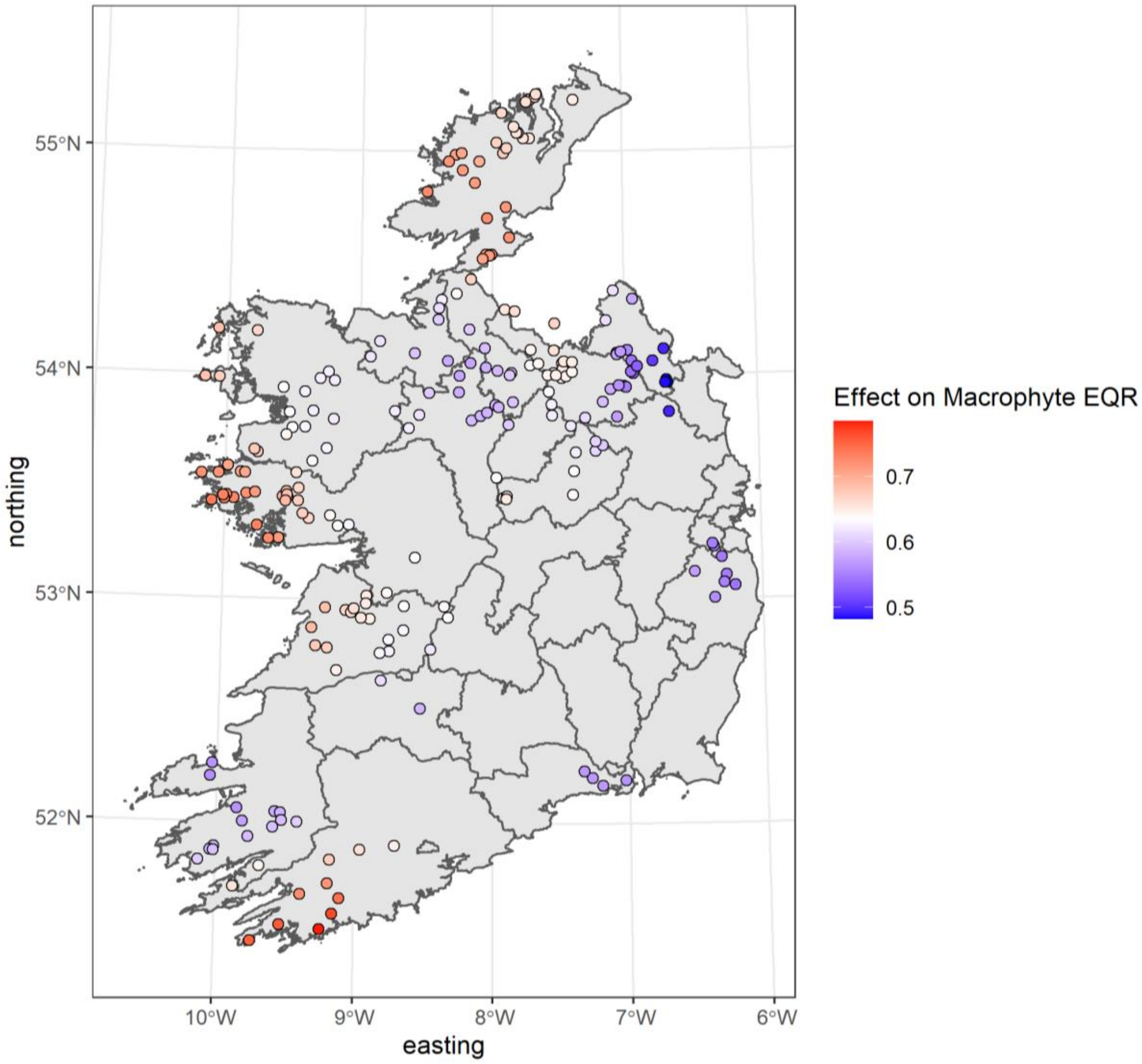

Figure 22: Partial effects plot showing the effect of easting/northing on macrophyte EQR in monitored lakes

The predictive performance of the model was assessed by comparing the measured status class of the 221 monitored lakes with the class predicted by the final model (Figure 23). Overall, the model predicted the correct WFD status class with 64% accuracy and predicted with 86% accuracy whether or not a lake was achieving Good status for macrophytes. There was a slightly tendency to under-predict more than over-predict, but in only 3 out of 221 cases (1.4%) was the model prediction out by more than 1 status class. Appendix 4 lists the lakes with the largest positive and negative residuals (i.e. those where the macrophyte EQR was under- and over-estimated the most).

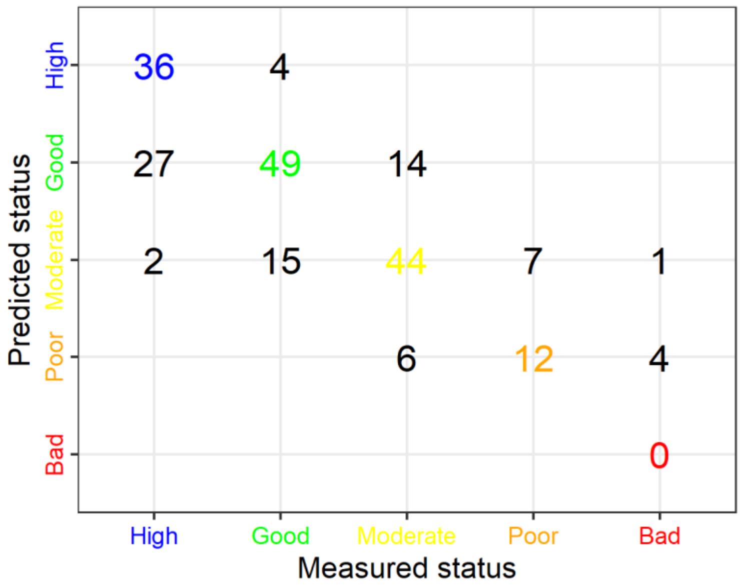

Figure 23: Matrix of measured and predicted macrophyte-EQR status class for the 221 monitored lakes

Inspection of the model residuals showed that the model was equally good at predicting macrophyte EQR for lakes in karst and non-karst catchments for large and small lakes, and for lakes in each of the 12 typology groups (see Appendix 4 for details). This confirms that the model has general applicability and does not appear to be biased for any particular type of lake.

The final model was used to predict macrophyte EQR for the 590 lakes lacking macrophyte data. Overall, 77% of unmonitored lakes were predicted to be achieving Good status for macrophytes, compared with 60% of monitored lakes (Figure 24). Overall, low alkalinity lakes had the highest proportion of lakes at Good or High status, whereas moderate alkalinity lakes and small, shallow high alkalinity lakes had the lowest proportion (Figure 25).

Figure 26 maps measured and predicted macrophyte status for all 811 lakes and reveals strong geographic variation in macrophyte status which broadly reflects regional variation in the intensity of land use and level of TP loading from point and diffuse sources.

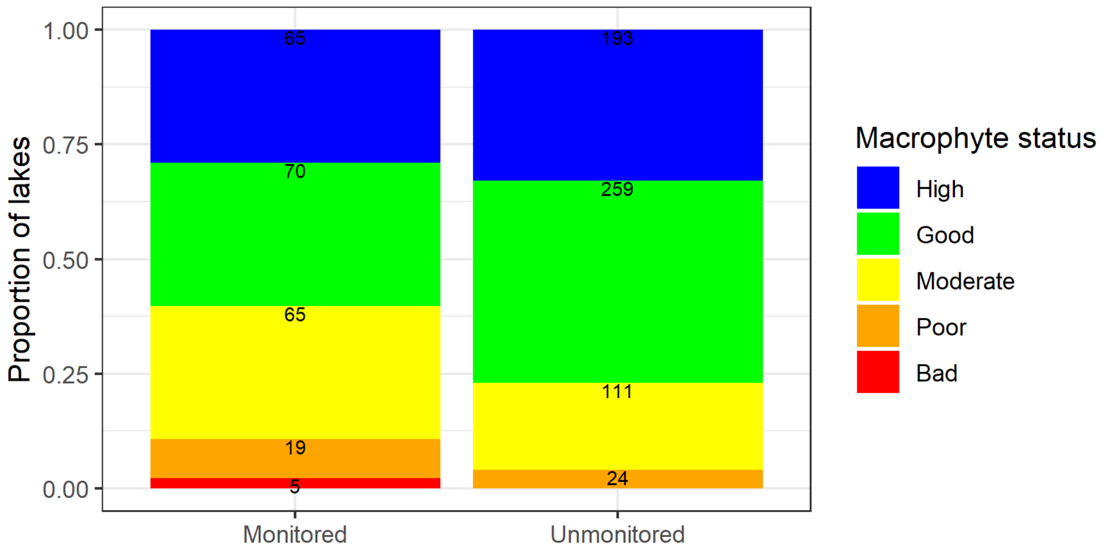

Figure 24: Summary of macrophyte status for monitored and unmonitored lakes

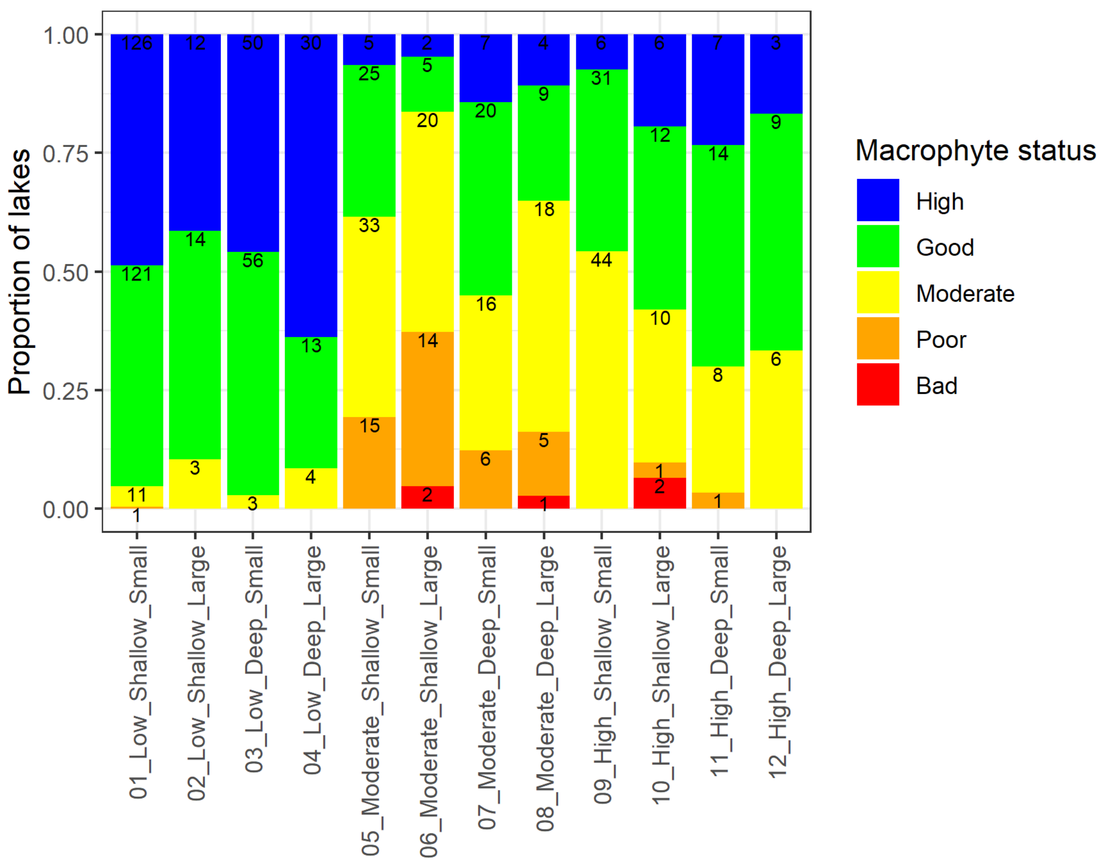

Figure 25: Summary of macrophyte status for all 811 lakes, by WFD typology

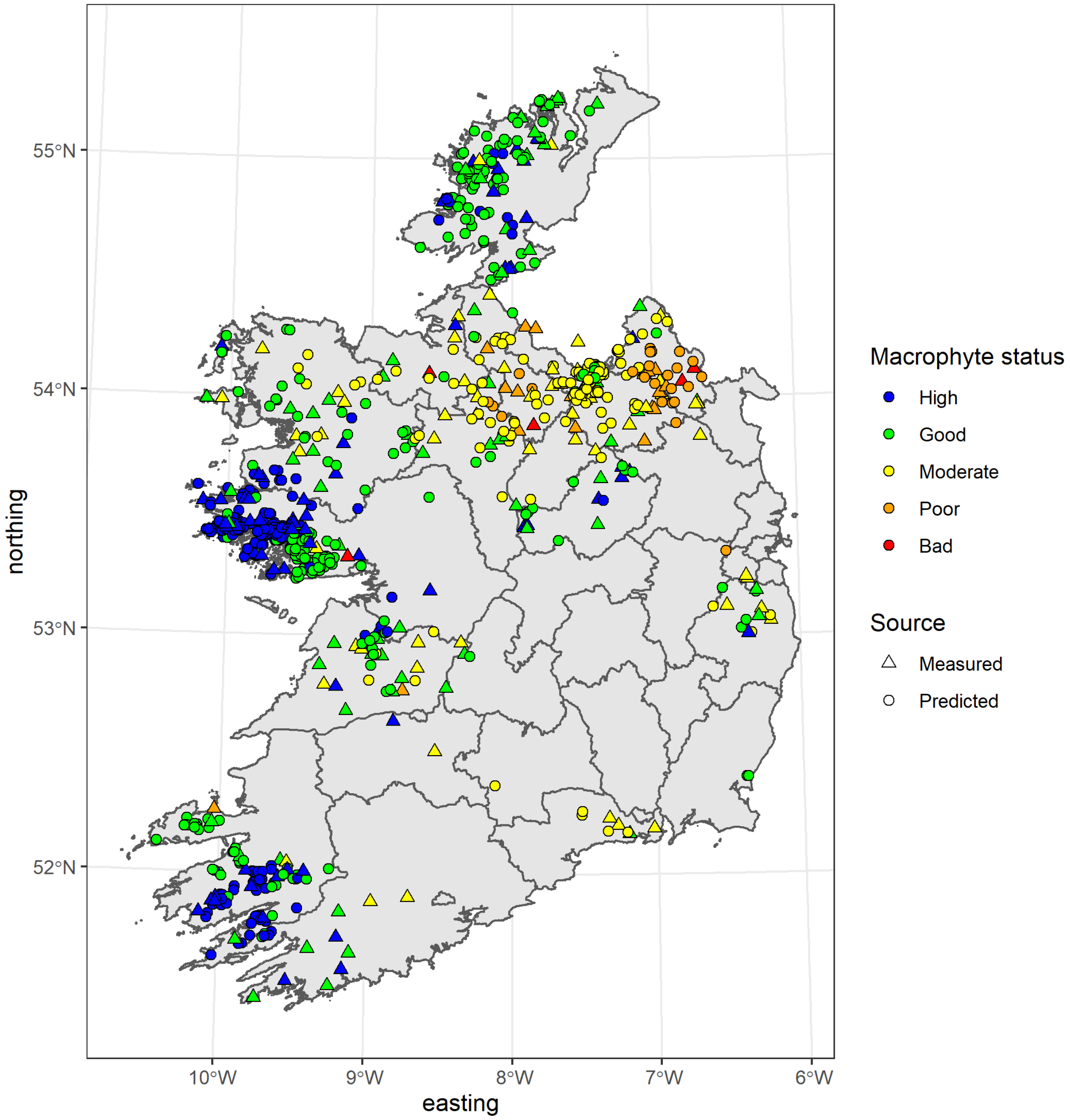

Figure 26: Map of measured and predicted macrophyte status for all 811 lakes

3.5 Overall status

The predicted status classes for the three quality elements (TP, chlorophyll-a and macrophytes) were combined using the one-out, all-out rule to predict an "overall status"[4] for every unmonitored lake.

For monitored lakes, the models predicted the correct overall WFD status class with 64% accuracy and predicted with 86% accuracy whether or not a lake was achieving at least Good status. In only 2 out of 224 cases (0.89%) was the model prediction out by more than 1 status class (Figure 27).

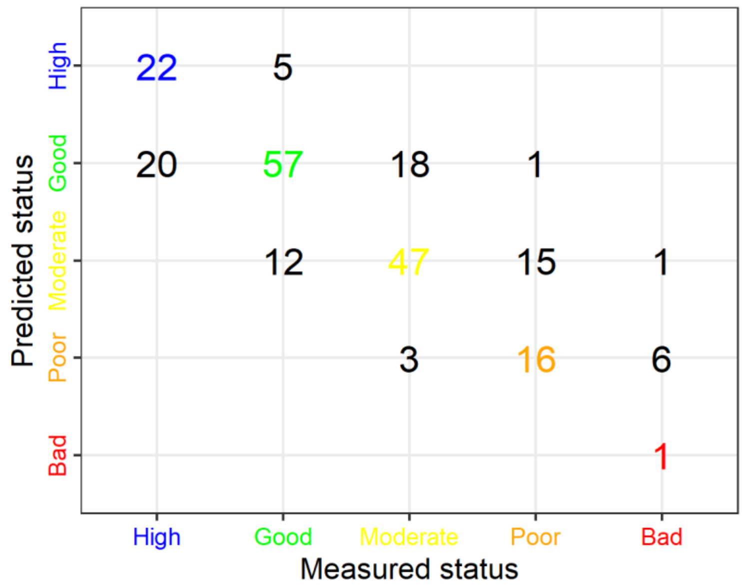

Figure 27: Matrix of measured and predicted overall status class for the 224 monitored lakes

Around 75% of unmonitored lakes were predicted to be achieving Good overall status, compared with 52% of monitored lakes (Figure 28). Low alkalinity lakes had the highest proportion at Good or High overall status, whereas moderate alkalinity lakes and small, shallow high alkalinity lakes had the lowest proportion (Figure 29). Figure 30 maps the measured and predicted overall status for all 811 lakes. Overall status shows marked geographic variation reflecting, predominantly, the intensity of land use and level of TP loading from point and diffuse sources.

[4] In the context of WFD, "overall status" usually refers to a lake's overall ecological and chemical status, but this study uses the term more narrowly to refer to a lake's overall response to nutrient enrichment.

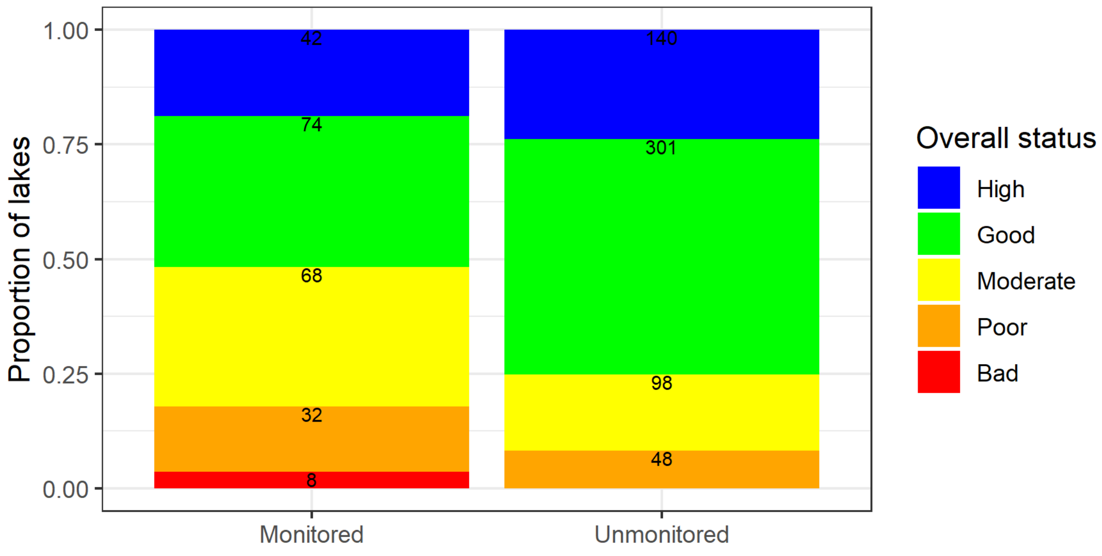

Figure 28: Summary of overall status for monitored and unmonitored lakes

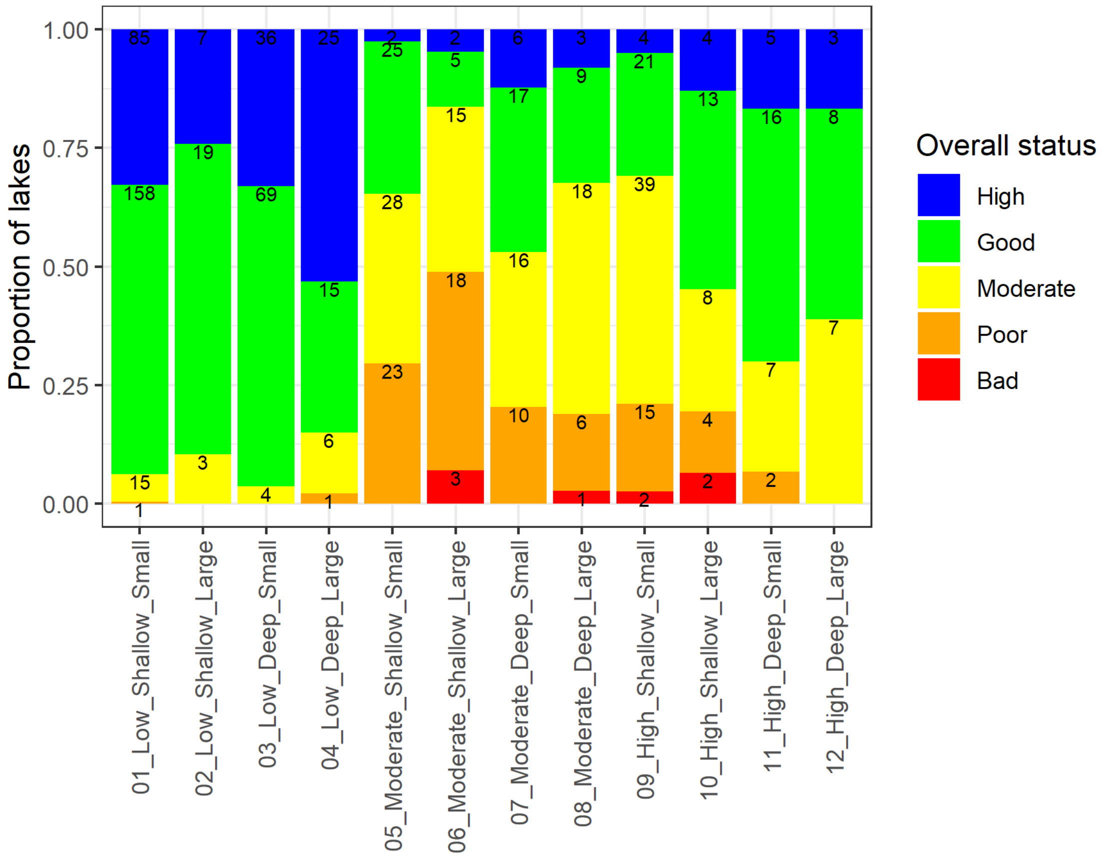

Figure 29: Summary of overall status for all 811 lakes, by WFD typology

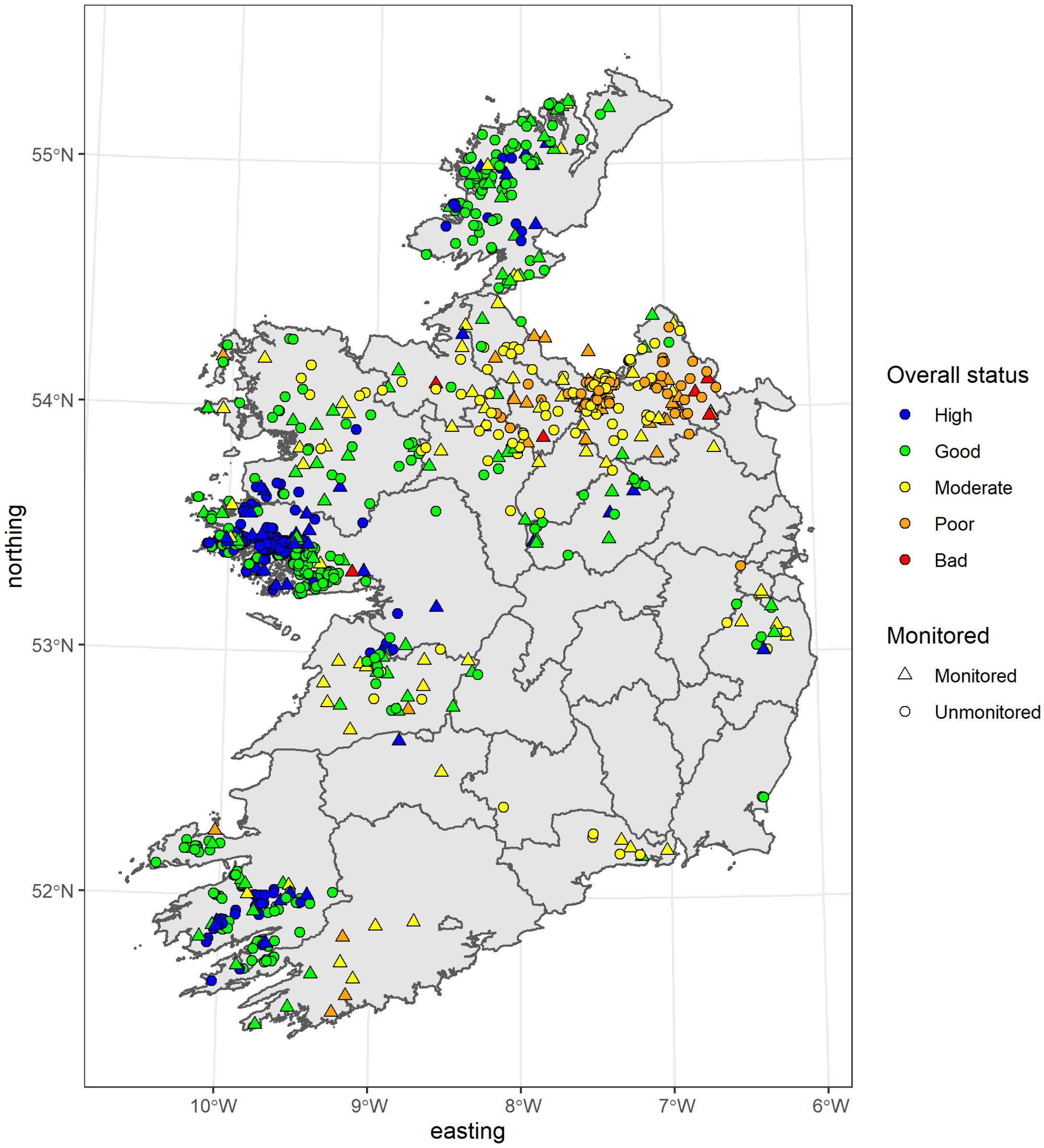

Figure 30: Map of overall status for all 811 lakes

The quality element(s) driving the overall (worst) nutrient status of monitored and unmonitored lakes are tabulated in Table 4. For both monitored and unmonitored lakes, macrophytes and/or TP were the most common driving elements. However, the model predictions for unmonitored lakes tended to have a slightly higher level of agreement across the three elements, with 37% (209 out if 587) of lakes having identical status classes for all three elements, compared to just 29% of monitored lakes. We suspect this is because the three models are ultimately based on the same predictor variables. Chlorophyll-a was a more common driving element for lakes in the south-west (Figure 31).

Table 4: Worst element(s) driving overall nutrient status

Worst element(s) driving overall nutrient status	Monitored lakes	Unmonitored lakes	All lakes
Chlorophyll-a	12	17	29
Chlorophyll-a and macrophytes	5	2	7
Macrophytes	61	134	195
TP	24	48	72
TP and chlorophyll-a	14	23	36
TP and macrophytes	44	146	190
TP, chlorophyll-a and macrophytes	64	217	281
TOTAL	**224**	**587**	**811**

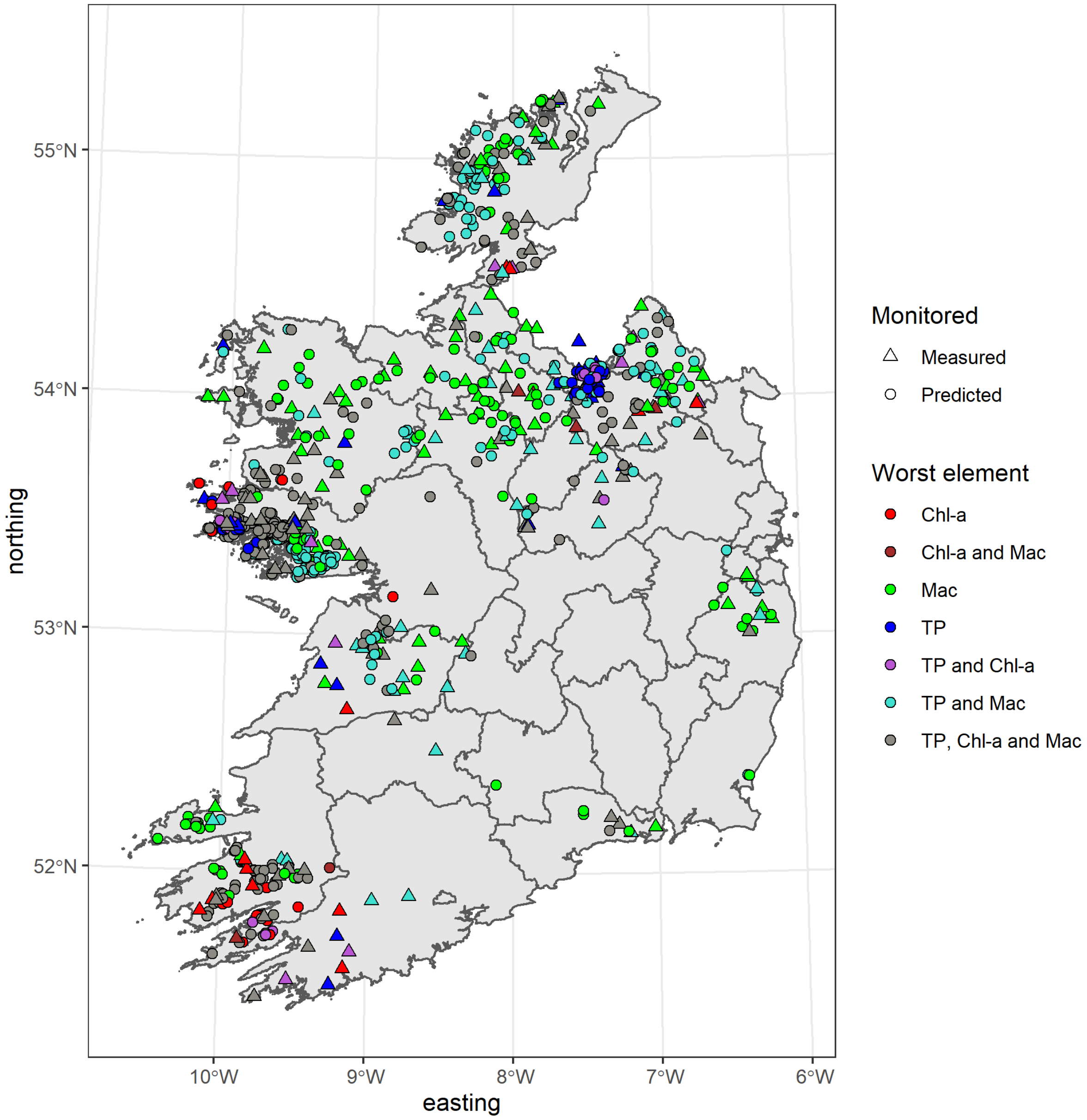

Figure 31: Worst element(s) driving overall nutrient status for all 811 lakes

3.6 Uncertainty in status classifications

One of the advantages of GAMs over hierarchical clustering (as used by Wynne and Donohue, 2016), and other classification techniques such as k-nearest neighbours and classification trees, is that the models yield not only a central estimate of the response for each lake, but are also able to quantify the degree of certainty (or margin of error) in the predictions (for both monitored and unmonitored lakes).

As an illustration, Figure 32 plots the TP model predictions for a representative sample of five monitored lakes. The degree of certainty in the predictions is shown by the 95% prediction intervals which, on average, include the true, measured TP concentration (marked ‘x’) for 95% of lakes; in other words, for any individual lake there is a 5% chance that the true TP concentration will fall outside the calculated prediction interval. Note that because TP concentration is modelled on a $\log_{10}$ scale, the prediction intervals are asymmetrical, and tend to be wider for lakes with higher TP concentrations. Note too that the model has a slight tendency to under-predict TP concentration (and therefore over-predict status). In the case of Ramor this leads to a mis-classification of status, although it should be remembered that measured status is also subject to error, so it is not possible to say definitely whether the measured or predicted status is correct, only that there is a disagreement.

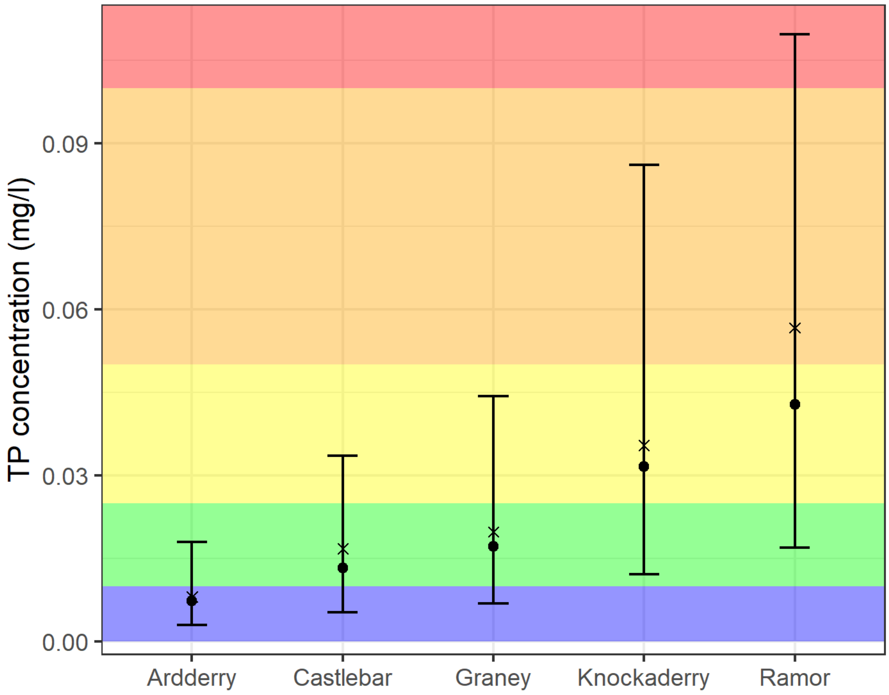

Figure 32: Measured (x) and predicted (●, with 95% prediction intervals) in-lake TP concentration for selected lakes

When assigning a WFD status class to unmonitored lakes, the prediction intervals can be used to quantify the degree of confidence that a lake is in each of the five predicted WFD status classes and, by extension, the confidence that it is achieving predicted Good status. These calculations mirror the confidence of class results calculated by the EPA for monitored lakes, but take account of the prediction error of the statistical model rather than the sampling error of the field measurements.

By way of illustration, Table 5 details the confidence of class results for the same five lakes shown in Figure 32 (all five are monitored, but they serve to illustrate the information that can be generated for unmonitored lakes). Ardderry, which has a low predicted TP concentration, is very certain to be achieving Good status, whereas Ramor, which has much higher predicted TP concentration, is quite certain not to be achieving Good status. Knockaderry and Ramor are both predicted to be of Moderate status, with 50% confidence, but their confidence of class profiles indicate that Ramor is 19% less likely to be achieving Good status than Knockaderry.

Table 5: Confidence of class assessment for predicted TP status for selected lakes

Lake	Confidence that TP status is…						Certainty band
	High	Good	Mod	Poor	Bad	Good or better	
Ardderry	0.74	0.26	0.00	0.00	0.00	1.00	Very certain pass
Castlebar	0.28	0.63	0.09	0.00	0.00	0.91	Quite certain pass
Graney	0.13	0.66	0.20	0.01	0.00	0.79	Quite certain pass
Knockaderry	0.01	0.31	0.50	0.17	0.01	0.32	Uncertain fail
Ramor	0.00	0.13	0.50	0.33	0.04	0.13	Quite certain fail

Prediction intervals and confidence of class were calculated separately for TP, chlorophyll-a and macrophytes, and the full results are included in the Excel workbook that forms an electronic appendix to this report. As a summary, Table 6 categorises the 587 unmonitored lakes according to the degree of certainty that each is achieving at GES. Overall, the models were able to determine whether or not Good status was being achieved with reasonable (at least 75%) certainty for the vast majority of lakes; only 9% of lakes were an uncertain pass or fail for TP, 11% for chlorophyll-a and 19% for macrophytes (Table 6).

Table 6: Certainty of status predictions for unmonitored lakes

Certainty band (confidence that lake is achieving GES)	TP	Chlorophyll-a	Macrophytes	Overall[1]
Very certain pass (>95%)	316	422	250	219
Quite certain pass (75-95%)	133	77	150	173
Uncertain pass (50-75%)	35	27	52	49
Uncertain fail (25-50%)	20	24	53	37
Quite certain fail (5-25%)	70	35	43	63
Very certain fail (<5%)	13	2	39	46
TOTAL	**587**	**587**	**587**	**587**

[1] The overall certainty band is the worst of the certainty bands for the three quality elements

The information shown in Table 6 may be used to prioritise lakes for expert judgment review (see Section 0), focusing attention on those borderline cases in the 'uncertain pass' and 'uncertain fail' categories.

4. Classification of unmonitored lakes with high uncertainty

The statistical modelling approach described above is able to predict an overall WFD status class for each unmonitored lake, and also quantify the degree of confidence that it is achieving GES.

The models generally performed well and for the majority of lakes were able to determine with reasonable (at least 75%) confidence whether or not the lake was achieving GES (Table 6). For 86 (15%) of the 587 unmonitored lakes, however, confidence was less than 75% because the driving element(s) was categorised as an uncertain pass or uncertain fail (Table 6).

High uncertainty in the assessment of GES can occur when the statistical models have a high prediction error (particularly for lakes that have unusually high or low scores for some of the predictor variables), but more commonly occurs when the predicted concentration or EQR is close to the Good/Moderate boundary (since the risk of mis-classification is greatest for ‘borderline’ lakes).

For these lakes, we recommend that other local/supporting information (including expert judgment) to be used as part of a weight of evidence process to validate, or potential over-ride, the predictions from the statistical models. The following checklist provides a structured approach for incorporating these additional lines of evidence.

1. Is it possible to identify why a lake has high uncertainty around its predicted status?

- ☐ Are the predictor variables used in the models reliable/valid? In particular, sense-check any values that have been predicted by the statistical models in Appendix 1 as outliers can lead to inflated model prediction errors. Focus especially on lake depth and flow as these variables strongly influence both nutrient dilution and lake residence time.
- ☐ How much agreement is there among the three quality elements? If all three elements give the same status class, then this could be considered to provide a greater level of confidence, even if individual elements have high uncertainty.
- ☐ Which quality element(s) have high uncertainty? The chlorophyll-a and macrophyte models are inherently less certain because they take TP concentration as an input, which is itself predicted. So if the most uncertain element is chlorophyll-a or macrophytes, then consider whether overall status should be based on TP, as it comes earlier in the stressor-response framework.

2. Can the status class predictions be validated?

- ☐ How does the predicted status compare with the measured/predicted status of similar monitored/unmonitored lakes? Ideally focus on other lakes of the same WFD type, and check that the hydrological regime, level of nutrient pressure and any mitigation measures are comparable.
- ☐ Is there a hydrologically-connected monitored lake within the catchment that could be used as a donor lake instead? Check that any candidate donor lake is of the same WFD type, and has a hydrological regime, level of nutrient pressure and mitigation measures that are similar to the recipient lake.

3. Are there any known characteristics or stressors that have not been fully/properly accounted for within the modelling?

- ☐ Does the nutrient load apportionment from SLAM concur with local knowledge of the stressors acting within the catchment? In particular, does SLAM adequately describe the influence of wastewater discharges and pig/poultry farming within the catchment? Are there any significant sources of nutrients within the immediate vicinity of the lake shore whose effect may be under-estimated by SLAM?
- ☐ Is the lake a Heavily Modified Water Body (HMWB), or been subject to hydromorphological alteration?
- ☐ Is there any evidence of invasive species impacts?
- ☐ Is there any evidence of acidification, especially in area of high coniferous plantation forestry?
- ☐ Has there been recent forestry activity or land-use change within the catchment?
- ☐ Is the lake in a karstic catchment, or does it have strong groundwater influence?
- ☐ Are there any major abstractions or water transfers to/from the catchment?
- ☐ Could high historical nutrient inputs be contributing to internal nutrient loading?
- ☐ Is there a large lake upstream that could be influencing nutrient retention and downstream water quality?

4. What mitigation measures have been undertaken within the catchment?

- ☐ Is the lake part of an Area for Action (AfA) or has it been in the past? If so, when was it added?
  - Are there already improvements in progress in this catchment, and what stage is the work at? Could this have altered the status of the lake?
  - What is likelihood of the intervention having been successful and improving status? Consideration should be given to the lag time, wind exposure, stratification and historical nutrient inputs.
- ☐ Is the lake on an Irish Water Capital Improvement Plan (plant upgrade)? Has this work been completed (at the time for which status is being predicted)?
  - Is there an agglomeration associated with any planned upgrades to the collection network (and when is this planned for)?
  - If so, what is the area of the agglomeration that intersects with the lake catchment (what % of the lake catchment area does this represent)? This could be interpreted as a proxy for urban pressures on the lake.
- ☐ Does the lake overlap with a river sub-basin that is in an AfA? If so, what % of the catchment does this apply to and what is the likelihood of it improving lake status?

5. Discussion and recommendations

5.1 Strengths of the approach

This study used a regression modelling approach to identify and quantify the causes of spatial variation among lakes in TP concentration, chlorophyll-a EQR and macrophyte EQR. This approach is a departure from the donor-recipient approach used to date by the EPA to classify the status of unmonitored lakes (Wynne and Donohue, 2016) in that it does not seek to define discrete groups of lakes. Instead, regression modelling unlocks the full potential of the data collected by the EPA's lakes monitoring programme by explicitly revealing the key factors that determine a lake's trophic status and modelling how status changes along a gradient of nutrient enrichment pressure. In this sense, the approach is consistent with WFD guidance (European Commission, 2003a) because the predicted status of unmonitored lakes is based upon empirical data from hydrologically, geomorphologically, and geographically similar lakes.

The choice of GAMs offers a number of advantages over hierarchical clustering (as used by Wynne and Donohue, 2016) and commonly-used classification techniques such as k-nearest neighbours and classification trees:

- GAMs provide a flexible, data-driven way of describing non-linear relationships. Relationships are not constrained to be linear, and the analyst is not required to make (and subsequently test) any prior assumptions about the form of the relationship. Furthermore, in-built regularisation of predictor functions helps avoid overfitting (that is, the wiggliness of the curves is optimised automatically).
- Spatial variation caused by unknown factors can be modelled explicitly, which is helpful not only for boosting the fit of the model, but also for suggesting additional predictor variables (or refinements to existing ones).
- GAMs are easy to interpret. In contrast to some 'black-box' machine learning techniques, the curves produced by GAMs clearly show how the predictor variables act, individually and in combination, to drive variation in the response. Furthermore, their flexibility means that GAMs are adept at revealing ecological thresholds.
- The GAM models developed in the present study have proven to be capable of achieving a reasonably high degree of classification accuracy, ranging from 86% to 89% when classifying lakes at Good or better versus Moderate or worse.
- Finally, GAMs, like other regression-based techniques, yield a central estimate of the response for each subject (lake), but are also able to quantify the degree of certainty (or margin of error) in the predictions. As illustrated in Section 3.6, prediction intervals can be calculated and used to quantify the degree of confidence that an unmonitored lake is truly in each of the five WFD status classes.

A key achievement of this study was the successful integration of a variety of EPA datasets and modelling tools. Notably, the EPA's SLAM model, which has previously been used to model nutrient load to rivers and estuaries (Mockler *et al.*, 2016; Mockler *et al.*, 2017), was combined with estimates of catchment run-off generated by the QUBE model (Bree, 2018) to yield an estimate of the influent TP concentration, which proved to be a strong predictor of in-lake concentration. Notwithstanding some limitations of these datasets and models (discussed in Section 5.2 below), these results validate the use of the SLAM model for understanding phosphorus dynamics in Irish lakes, and illustrate the potential benefits of integrating datasets and tools that originally may have been developed for other purposes. Furthermore, the application of statistical models to impute missing values in many of the variables (detailed in Appendix 1) has yielded a complete and up-to-date set of catchment and lake characteristics which are available for use in future studies.

5.2 Limitations of the approach

Whilst the approach was successful in predicting the status of unmonitored lakes, some predictor variables were incomplete or had other data quality issues. Other potentially important variables could not be quantified, and the regression-modelling methodology itself rests on some important assumptions. These limitations are discussed in further detail below.

5.2.1 Data issues

Geographic proximity. As noted by Wynne and Donohue (2016), the catchment variables derived for each lake do not currently consider the proximity to the lake itself. For example, carbonate-rich rocks such as limestone can have a disproportionately large influence on lake alkalinity when present in the immediate vicinity of the lake. Similarly, the SLAM Framework predicts phosphorus losses based on the percentage land use within the catchment but does not consider how close these sources are to the lake, and therefore the potential for nutrient transport.

TP Load Estimation from Agricultural Activity. The SLAM framework covers all major sources of TP from point and diffuse sources (see Appendix 1 for details) and so provides a reasonably comprehensive assessment of TP loads. The model includes estimates of TP losses from farms, but these figures assume compliance with regulatory limits on the spreading of waste to land; excess spreading is not accounted for, and the model is therefore likely to under-estimate TP loads from these sources by an unknown amount for some lakes.

TP loads from wastewater discharges. The SLAM framework was configured to include discharges within a 2 km buffer around the catchment (a legacy of the original national-scale modelling study), which meant that TP from wastewater was over-estimated for a small minority of lakes.

The EPA subsequently undertook a sensitivity analysis in May 2022 to quantify the effect this had on estimated TP loads (D. Cunningham, *pers. comm.*). Of the 844 lake catchments assessed, there was no change in TP load for 764 of lakes, an increase in 14 lakes and a decrease in 66 lakes. Of the decreases, 44 were solely due to wastewater emissions from points near (but outside) the lake catchment. Of the remaining 22, the decreases may have been due to lower 2018 emissions and/or the exclusion of some emission points.

The list of 44 lakes was then filtered to identify six unmonitored lakes of Moderate or worse predicted status where the total TP load decreased by more than 10% (Table 7).

Consequently, there is a high risk that that the over-estimation of TP from wastewater discharges led to these lakes being erroneously assigned as not achieving GES.

Table 7: Unmonitored lakes of Moderate or worse predicted status where TP loads were over-estimated by more than 10%

EU water body code	Lake name
IE_NB_03_90	Lambs
IE_SH_27_123	Ballybeg
IE_NB_03_79	Glaslough
IE_SE_17_6	Ballinlough
IE_EA_10_30	Lower
IE_EA_09_69	Leixlip Reservoir

QUBE flow/runoff estimates. It is assumed that the QUBE (EPA HydroTool) model is a good indicator of outflow for each of the lakes. It is also assumed that the extent a lake is hydrologically connected within the sub-basin will control the appropriateness of some of the datasets. There were 144 lakes where the EPA HydroTool model did not return flow data, which could have been due to: a) the lake being in a karstic catchment; b) absence of a QUBE flow estimate point within the lake's contributing catchment; c) the lake not lying within a recognised contributing hydro catchment upstream of a flow estimation point; or d) significant groundwater influence. The EPA HydroTool model points are not necessarily directly associated with the outflow of the lakes, due to the location of the points frequently being situated further upstream in the catchment.

Catchment stream density. The size and complexity of the RivNetRoutes file (downloaded from the EPA GeoPortal) meant that we took the decision to calculate stream density only for the nested lake catchments that were missing stream density values from the previous research by Wynne and Donohue (2016). As a result, it is possible that if the stream densities had been calculated for the nested lake catchments that had existing stream density values, we would assume discrepancies would be due to the changes in nested catchment area values for each lake following the recent updating of catchment delineation.

Lake depth. Lake levels fluctuate naturally and the measured depths are assumed to represent typical or average conditions for each lake. The bathymetric survey data were collated in 2013 and pre-date the other datasets, although they are not expected to have changed appreciably since then. The model that was used to estimate mean depths for 204 lakes without depth data was not as successful at accurately predicting mean depths compared to other statistical models. The collection of depth data for these lakes would better refine the depth model (see Section 5.3.1 for further detail).

Inter-drumlin lakes. Inter-drumlin lakes, which are particularly prevalent in Cavan and Monaghan, have a distinctive glacial moraine geology, and often have extensive nutrient-rich wetlands, both fringing and elsewhere in the catchment. This may render estimates of flows, TP loading and TP influent concentration unreliable.

Nested catchment boundaries. Following the modelling work, the EPA identified delineation issues in the nested catchments v2 layer for three lakes: Creggan, Doonis, and Scur. In all three cases, the catchments were fragmented into multiple polygons (Figure 33; Figure 34; Figure 35). Catchment characteristics for these lakes will therefore not be representative of the true catchment area.

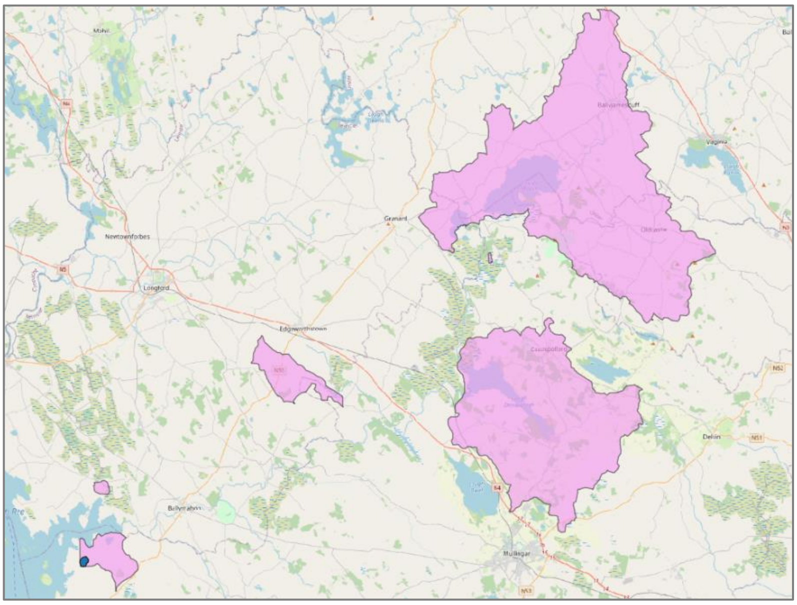

Figure 33: Map of Lake Creggan's multi-part nested catchment

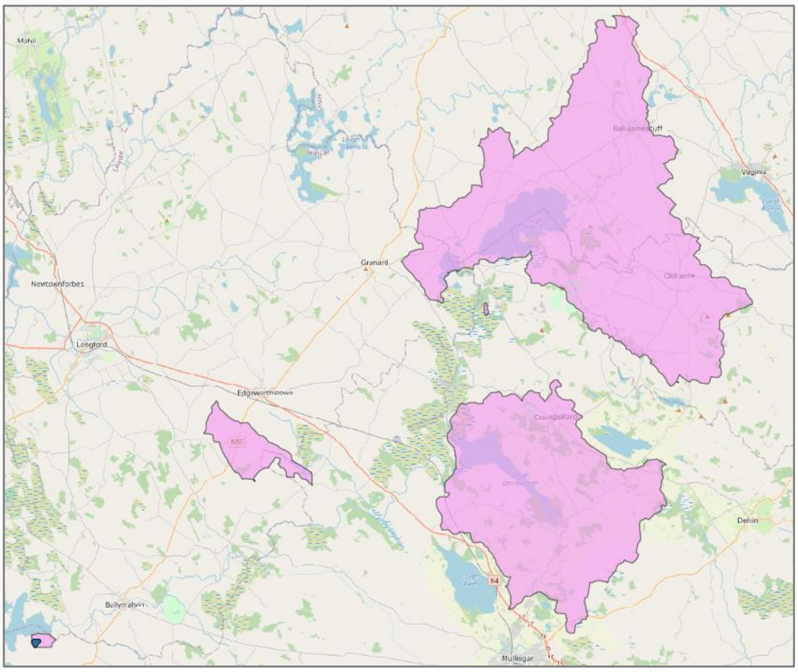

Figure 34: Map of Lake Doonis' multi-part nested catchment

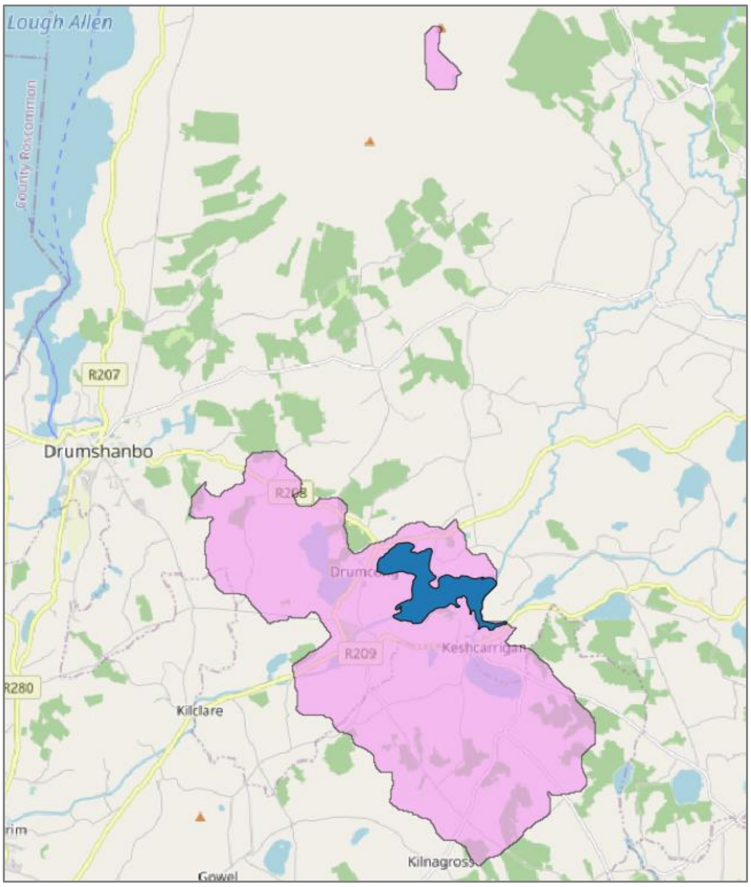

Figure 35: Map of Lake Scur's multi-part nested catchment

5.2.2 Missing factors

Other stressors. Stressors such as hydromorphology, acidification and invasive species can potentially influence the ecological status of chlorophyll-a and macrophytes, but these factors were not included in the predictive regression models because it was not possible to categorise or quantify the strength of these pressures for every lake. In particular, zebra mussels (*Dreissena polymorpha*) are becoming widespread in Ireland (Minchin *et al*., 2003; CDM Smith, 2019; Figure 36), especially in high alkalinity lakes (D. Tierney, EPA, *pers. comm.*) and can quickly become abundant (CDM Smith, 2019). Quagga mussels (*Dreissena rostriformis bugensis*) are now present in Ireland (Baars *et al*., 2022) and likely to expand their distribution rapidly. Their ability to filter large volumes of water all year round can reduce concentrations of nutrients, phytoplankton and chlorophyll-a, and increase water transparency, with positive consequences for macrophytes (Zhu *et al*., 2006; Higgins and Zanden, 2010; Salgado *et al*., 2018). Conversely, they are also capable of mobilising sediment-bound phosphorus through their feeding action, and can be responsible for increasing internal loading of phosphorus and increasing in-lake TP concentrations (Taylor *et al*., 2012, cited by CDM Smith, 2019). The overall effect of these mussel species is, therefore, difficult to predict and will depend on factors such as the trophic status of the lake when the invasion began, the number and size of the established population, and presence of predators, parasites or other competitors (CDM Smith, 2019).

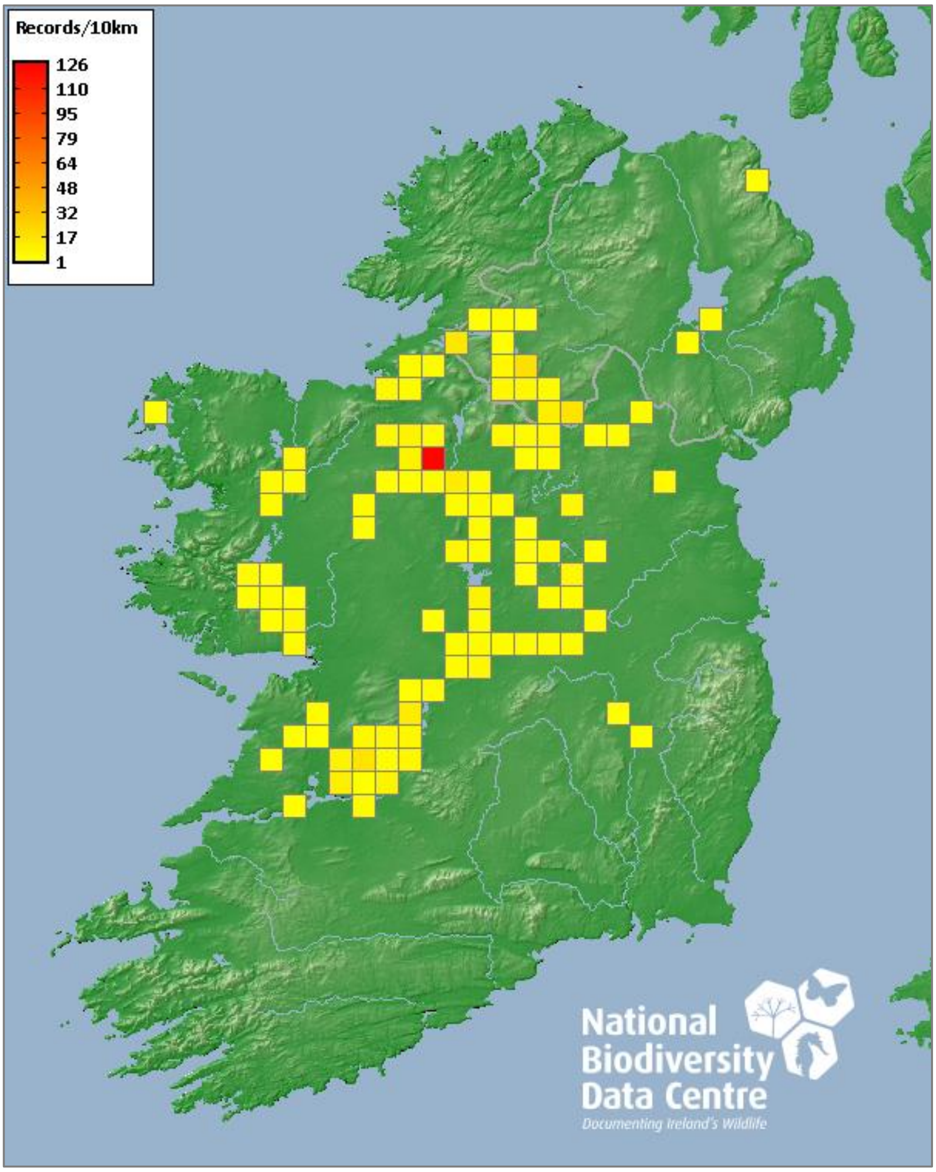

Figure 36: Distribution of invasive zebra mussels in Ireland (National Biodiversity Data Centre, 2022)

Upstream retention. The SLAM framework includes a simple lake retention model which reduces loads from catchments draining through all lakes above a threshold size of 50 ha. The retention factors used (24% for TP and 10% for nitrogen) are derived from studies in the Lee catchment (Sullivan *et al*., 1995) and whilst they provide a useful approximation at a river basin or national scale, the level of retention in individual lakes is likely to vary considerably, dependent on factors such as residence time (Foy, 1992). For this reason, the TP load estimates used in this study had the retention factor set to 0%, meaning that total TP loads were over-estimated by an unknown amount for some lakes (especially those which have a large lake in close proximity upstream).

Instead of accounting for nutrient retention in the SLAM model, the statistical regression models included stream density and upstream lake density as proxies for nutrient retention in the upstream catchment. In practice, both stream density and upstream lake density were found to be poor predictors of in-lake TP concentration and were not retained in the final TP model (Section 3.2). This does not necessarily mean that the predictions of TP concentration are systematically biased, however, because the overall regression relationship between modelled influent TP concentration and in-lake measured TP concentration will adjust to compensate for the over-estimation of TP loads. Rather, the predictions of TP concentrations for unmonitored lakes will be less precise than they would otherwise be if the level of nutrient retention was known for each lake catchment.

Internal TP loading. The SLAM framework used recent (ca. 2018) data on anthropogenic pressures to estimate external TP loads contemporary with the measured (2016-2018) data on lake status. Historical nutrient enrichment of lakes was not accounted for in the modelling. Contemporary TP loads are expected to provide a good prediction of in-lake TP concentration for a majority of lakes. In other lakes, however, internal phosphorus loading from lake sediments may be a significant additional source of TP, particularly in lakes that have experienced high TP loadings over a prolonged period, and in lakes where anoxic conditions and/or wind-driven re-suspension of sediment promote phosphorus release (Marsden 1989; CDM Smith, 2019; McElarney *et al*., 2021). Internal TP loading may be especially important in inter-drumlin lakes; for example, a high frequency monitoring programme at Namachree Lough (Co. Monaghan) found that lake sediments provided 300% more soluble reactive phosphorus (SRP) than external sources loading during spring and summer (CDM Smith, 2019).

Seasonal and inter-annual variation. The present study focused on assessing status over a three-year reporting period (2016-2018) and used data from SLAM and QUBE representing long-term annual average TP loads and flows. The regression models do not, therefore, capture seasonal and inter-annual variability in nutrient loads that can be important in determining water quality and ecological responses on a lake-specific basis. Irish lakes exhibit diverse seasonal patterns in TP concentrations including winter maxima, summer maxima, as well as no clear seasonal patterns (Irvine *et al*., 2001). The extent and timing of seasonal peaks in TP can aid in understanding the relative importance of external and internal TP loading (CDM Smith, 2019), as well as the contribution of different catchment sources (e.g. point sources may dominate inputs during low flows and diffuse sources may dominate inputs under high flow conditions). The flexibility of GAMs means, however, that the regression models could be extended to also consider temporal as well as spatial variation in TP concentration, which could potentially help to improve predictions of status for individual lakes.

5.2.3 Statistical modelling

Under-estimation of effect sizes. The statistical regression models developed in this study are based on other models and datasets which themselves are subject to a variety of systematic and random errors. Error in the measurement of predictor variables results in weaker regression relationships and reduces their statistical significance, so it is possible that the effect of some variables has been under-estimated, or that more subtle effects of other variables may have been overlooked altogether. Despite this, the final models were able to successfully identify a small number of variables that explained a high proportion of the variation in TP, chlorophyll-a and macrophytes among lakes.

Confidence intervals. The calculated confidence intervals around the TP, chlorophyll and macrophyte predictions assume that all the predictor variables for each lake are known without error. In reality, many predictors are subject to measurement or modelling errors, which will propagate through to add uncertainty to the model predictions. Unfortunately, these errors are often difficult or impossible to quantify, making it difficult to undertake a comprehensive assessment of uncertainty. This issue of predictor uncertainty is partially mitigated through the use of log-transformations, which reduce the sensitivity of the predictions to small changes in the values of those predictor variables.

Representativeness. Using data from monitored lakes to predict the status of unmonitored lakes implicitly assumes that the 224 monitored lakes are representative of the full population of 811 lakes. However, a higher proportion of large lakes are monitored than small lakes, and a higher proportion of high alkalinity lakes are monitored than low alkalinity lakes (see Figure 4), so there is a risk that the models will be biased towards the behaviour of larger, higher alkalinity lakes. This risk is partially mitigated by the inclusion in the models of typology as a candidate predictor, so that any systematic differences among typology groups can be accounted for. More difficult to control for is the risk of bias if there is tendency for monitoring to target, within a type, those lakes that are known to exhibit symptoms of eutrophication.

Extrapolation. The modelled regression relationships hold true over the range of characteristics represented by the monitored lakes in the calibration dataset, but care must be taken when extrapolating the models to predict the status of unmonitored lakes that have more extreme characteristics. This is particularly the case with GAMs because their flexibility permits the ends of the curves to be heavily influenced by individual lakes when data are sparse. In addition to the risk of bias that this poses, the predictions will be less certain and the prediction intervals will be wider. Figure 37 shows, however, that the 224 monitored lakes do, generally, cover the full range of characteristics of the 811 WFD lakes, which means the models can be used with confidence to predict the status of unmonitored lakes; the only exception is the relatively poor coverage of lakes with very low modelled influent TP concentrations (the log_modelled_tp_mg_l variable in Figure 37), where some extrapolation beyond the calibration dataset is required.

Figure 37: Distribution and coverage of monitored (blue) and unmonitored lakes (red) with respect to the key variables used for modelling lake status

5.3 Recommendations

5.3.1 Model refinements

Given the limitations discussed in Section 5.2 above, there is clearly potential to refine the regression models and further improve the accuracy of the status class predictions for unmonitored lakes. Further refinements are likely to deliver diminishing returns, and so the following recommendations are therefore ranked in descending priority order, starting with activities that are relatively straightforward and/or expected to yield the biggest improvements.

It is worth noting that including additional predictor variables is not guaranteed to improve the fit and predictive performance of the models; additional predictors will only be beneficial if they are uncorrelated with existing predictors, and if they explain variation among lakes that is not already explained by geographic location (i.e. easting/northing).

1. It is recommended that the **catchment delineation** of lakes in the nested v2 layer be checked and, if necessary, the catchment-scale variables be re-calculated for any lakes where the delineation is incorrect.

2. **Residence time** has been shown to be a key factor, but is poorly estimated for lakes that lack measured depths or modelled flows. **Annual average flow** appears to be estimated reasonably well by QUBE for most lakes, but may be less reliable for inter-drumlin lakes and others with strong groundwater influences. In these cases, QUBE may not be the most appropriate tool, and field measurements or groundwater models may be able to provide a better quantification of residence time, and also influent TP concentration. Similarly, predictions of **mean depth** from statistical models have appreciable error and residence time estimates would be improved if depths could be measured directly or if better predictors of depth could be found.

3. Given the strong influence of **influent TP concentrations** on in-lake TP concentration, it is recommended that the EPA explores options for improving the estimation of TP loads. For example, the SLAM-modelled TP loads may be improved by excluding TP inputs from wastewater discharges located outside the lake catchment boundary, better accounting for agricultural waste and, crucially, accounting for upstream retention. The SLAM framework currently includes the facility to apply a fixed retention factor to reduce loads from catchments draining through all lakes >50 ha, but greater success may be achieved by developing lake-specific retention factors that take into account residence time (as derived in this study). If refinements to SLAM model were able to account for some of the currently unexplained spatial variation in influent TP concentration, then this may also provide greater confidence about the exact shape of the residence time effect and, in particular, clarify how sensitive long residence time lakes are to TP inputs.

4. It is recommended that the fit of the current models is examined in detail in order to identify potentially important **factors that may be missing or poorly represented** at present. Focusing on lakes with the largest residuals (see Appendices) may be especially instructive. For example, where under-prediction of TP concentration indicates a potentially important unknown source of phosphorus, a lake-specific assessment is recommended to determine whether an important catchment source has not been represented fully within the SLAM model or whether a significant internal release of phosphorus from lake sediments is the more likely cause. Similarly, the tendency of both the chlorophyll-a and macrophyte models to over-predict status could reflect the influence of other pressures which not currently accounted for in the models. Any factors identified then either be incorporated into the regression models (if they can be quantified) or else taken into account when deciding whether to apply an expert judgment over-ride (see Section 0).

5. **Zebra mussels** can strongly influence concentrations of nutrients and chlorophyll-a, and indirectly benefit macrophyte communities. Information on their distribution is readily available from the National Biodiversity Data Centre and it is recommended that this and other data are used to categorise the presence/absence of zebra mussels in each lake (e.g. confirmed, probable, not currently known). This information could then be included as an additional

predictor variable in the chlorophyll-a and macrophyte models. The potential impact of quagga mussels is unknown, but they may become equally important in the future.

6. As **easting/northing** was retained as a predictor variable in the TP and macrophyte statistical models, a possible future refinement would be to investigate the possible causes of this currently unexplained spatial variation among lakes, and which geochemistry variables this predictor variable may be representing.

5.3.2 Future monitoring

The ability to predict, with reasonable accuracy, the status class of unmonitored lakes presents the EPA with new options for its WFD monitoring programme. "**Model-based monitoring**" refers to a monitoring strategy whose goal is to collect, as efficiently as possible, the data necessary to calibrate a predictive model. Any future changes to the lakes monitoring network could therefore be made with a view to optimising the predictive performance of the regression models.

For instance, should the EPA wish to reduce its monitoring budget, then existing lakes could be screened to identify those that provide redundant information, thereby reducing costs whilst minimising loss in predictive performance. Conversely, if the EPA wished to expand its monitoring network, new lakes could be selected for monitoring in a way that maximised gains in predictive performance across the set of 811 lakes. Similar approaches have been used for designing river water temperature networks in Scotland (Jackson *et al*., 2016) and England (APEM, 2022), and optimising Wales's national electrofishing programme (APEM, 2019).

A further recommendation, proposed by CDM Smith (2019), is to align operational monitoring of rivers and lakes to ensure, wherever feasible, that the inflowing rivers to lakes are monitored for flow and nutrients as well as the lakes themselves, particularly in the inter-drumlin landscape.

Lakes that still have a high level of uncertainty around whether they are 'Not at risk/At risk' after consideration of the factors outlined in Section 4.1 should be considered for:

- Further investigation through one-off sampling/site visit;
- Inclusion in the national monitoring programme.

5.4 Application of approach to new lakes and future reporting cycles

The statistical modelling workflow developed in this study is coded in R, available to run as a .Rmd script file and therefore fully documented, auditable and reproducible.

To apply the existing models to classify the status of *new* lakes, the following data will need to be assembled for each new lake:

- lake location (easting and northing);
- lake area;
- catchment area;
- % limestone and % peat (unless alkalinity, colour and run-off are all known); and
- TP load (from SLAM);

This is the minimum amount of data required; all other variables that directly or indirectly feed into the predictive models (see Figure 1) can, if required, be imputed using the statistical models described in Appendix 1, although it is preferable to use measured data where possible. The new lakes can be simply be appended to the master input data table, and the script run to generate a fresh set of predictions for the 587+ unmonitored lakes.

To classify the status of the existing 587 unmonitored lakes in future reporting cycles, the following data will need to be assembled:

- updated TP concentrations, chlorophyll-a EQRs and macrophyte EQRs for monitored lakes; and
- updated TP loads (from SLAM) for all lakes (to align with the new reporting period).

This is the minimum amount of data required; the physical (flow, depth, residence time etc) and chemical (alkalinity, colour etc) characteristics of the lakes and their catchments may be assumed to be unchanged, but newer, improved estimates should be used if available. Additional variables could also be assembled and used as predictor variables in the models if desired. The structure of the master input data table must not be changed; only the data should be updated.

Using the updated dataset, the models can then be updated before being applied to predict the status of each unmonitored lake. The script automates most of this workflow, the exceptions being (i) the need to manually repeat the model selection process to determine which variables should be retained in the final models, and (ii) the need to confirm that the models remain fit-for-purpose (i.e. have acceptable accuracy and are not unduly biased).

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7. Abbreviations used in this report

BIC	Bayesian Information Criterion
CIS	Common Implementation Strategy
CORINE	Coordination of Information on the Environment
EPA	Environmental Protection Agency
EQR	Ecological Quality Ratio
GAM	Generalised Additive Model
GES	Good Ecological Status
GIS	Geographic information system
GSI	Geological Survey of Ireland
HMWB	Highly Modified Water Body
P	Phosphorus
SANICOSE	Source Apportionment of Nutrients in Irish Catchments for On-Site Effluent model
SDI	Shoreline Development Index
SLAM	Source Load Apportionment Model
TP	Total Phosphorus
WFD	Water Framework Directive

Appendix 1 Data sources and data processing

Mean slope

The previous research by Wynne and Donohue (2016) created a slope raster from a 5 m DEM to derive summary statistics of the mean catchment slope (in °) for 759 lakes based on the original version of the nested catchments layer.

Using these data, a GAM regression model was developed to predict the mean catchment slope for the lakes with missing data values. Slope was modelled as a function of the easting/northing predictor variable. Mean catchment slope was $\log_{10}$ transformed to satisfy the model's assumptions of normally distributed errors and heterogeneous variables.

The statistical model explained 58.9% of the variation in mean catchment slope (Figure 38; Figure 39; Figure 40). Figure 41 illustrates the relationship between mean catchment slope and easting/northing.

The final model was used to predict mean catchment slope for the remaining 52 lakes; Figure 42 maps the measured and predicted slope for all 811 lakes.

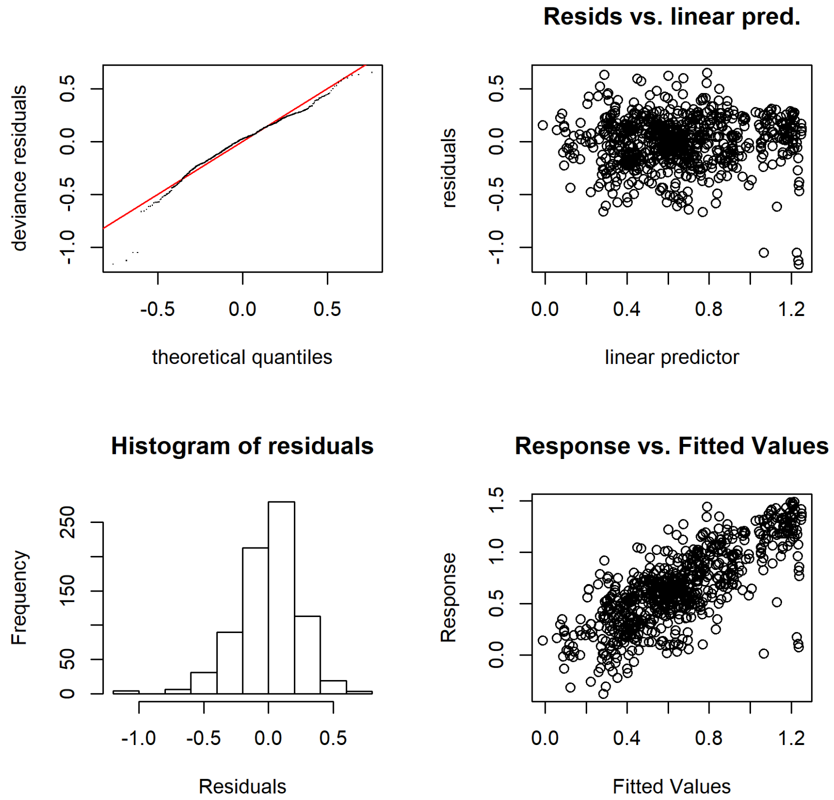

Figure 38: Residuals plots for the mean catchment slope model

```
Family: gaussian
Link function: identity

Formula:
log_mean_slope ~ s(easting, northing)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.648842   0.008615   75.31   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                       edf Ref.df     F p-value
s(easting,northing) 26.88   28.7 35.51  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.574   Deviance explained = 58.9%
-REML = 39.307  Scale est. = 0.056337  n = 759
```

Figure 39: Statistical summary of the mean catchment slope model

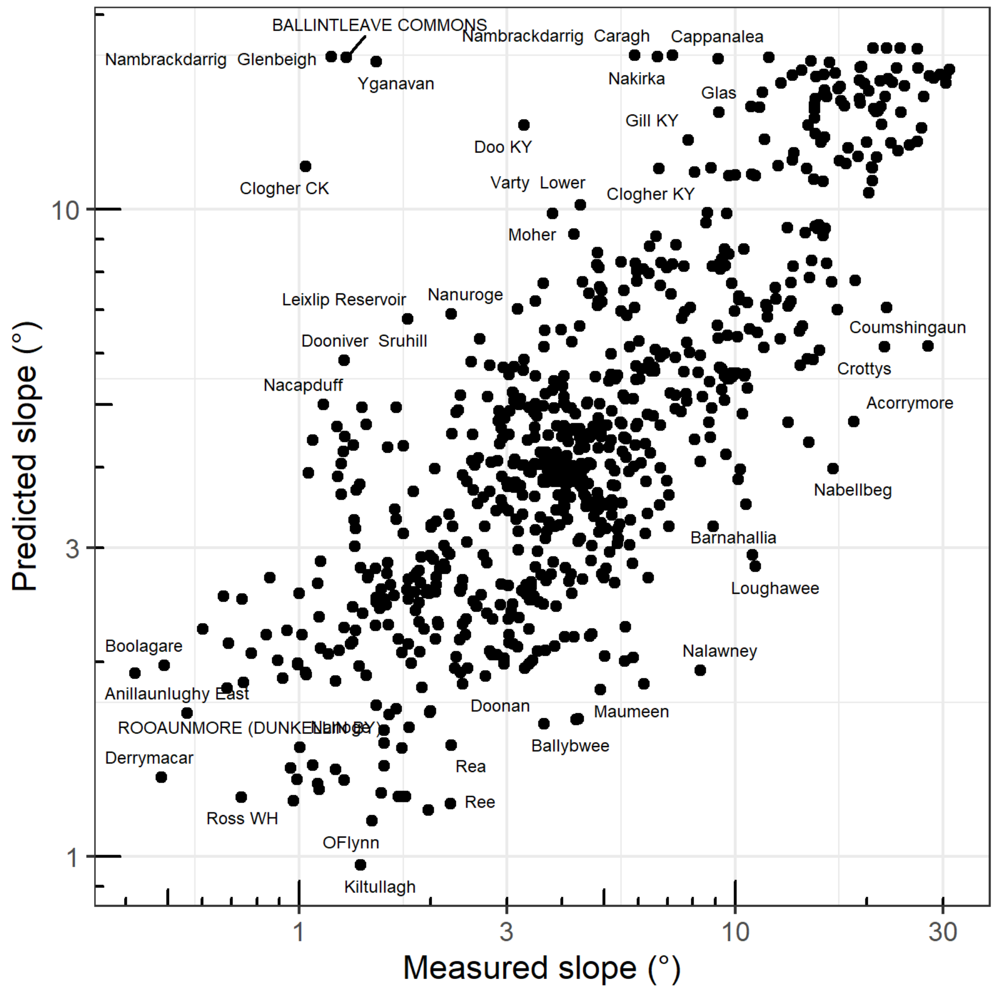

Figure 40: Predicted vs measured slope for the 759 lakes with mean catchment slope values

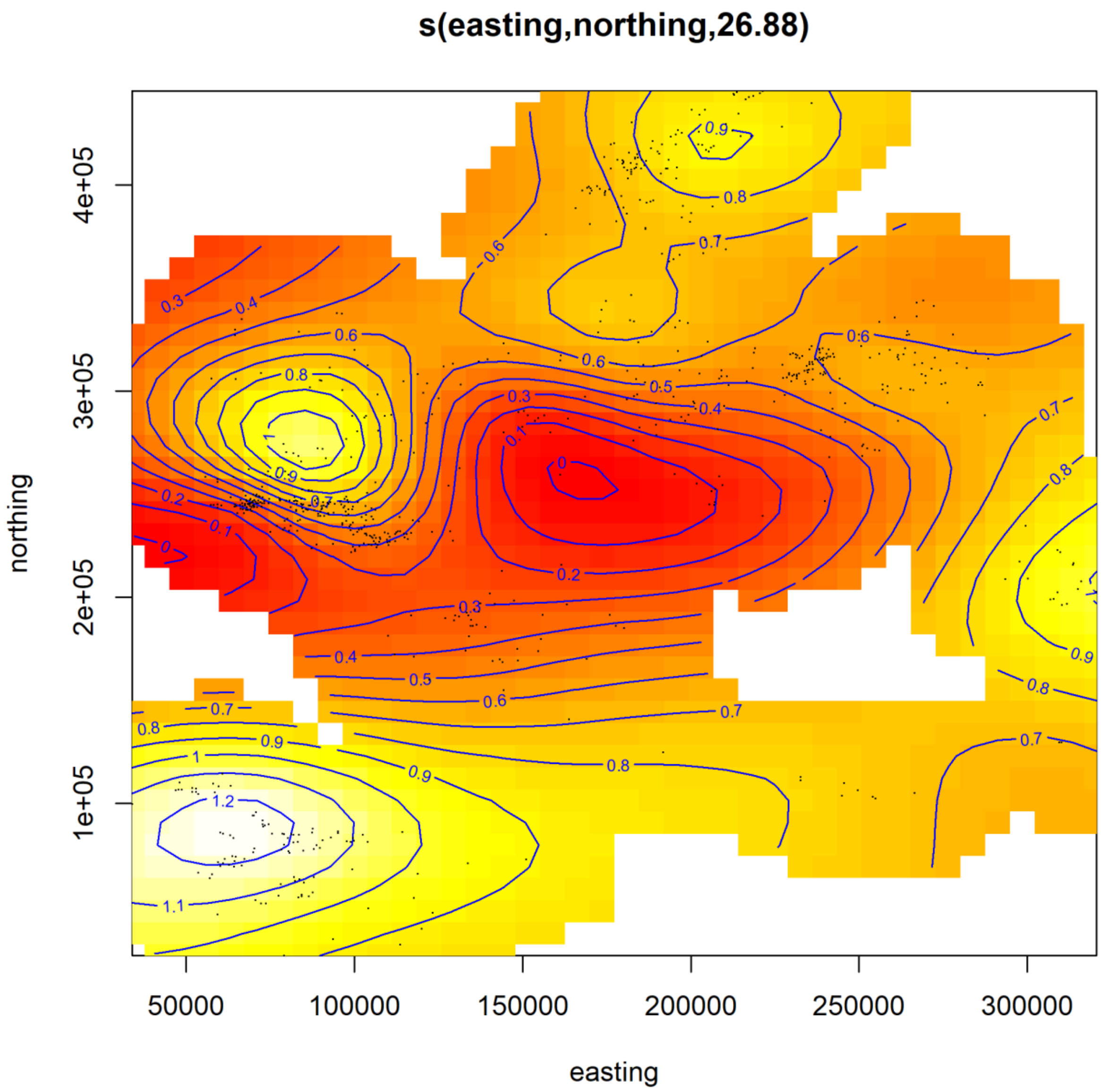

Figure 41: Partial effects plot showing the effect of easting/northing on mean catchment slope

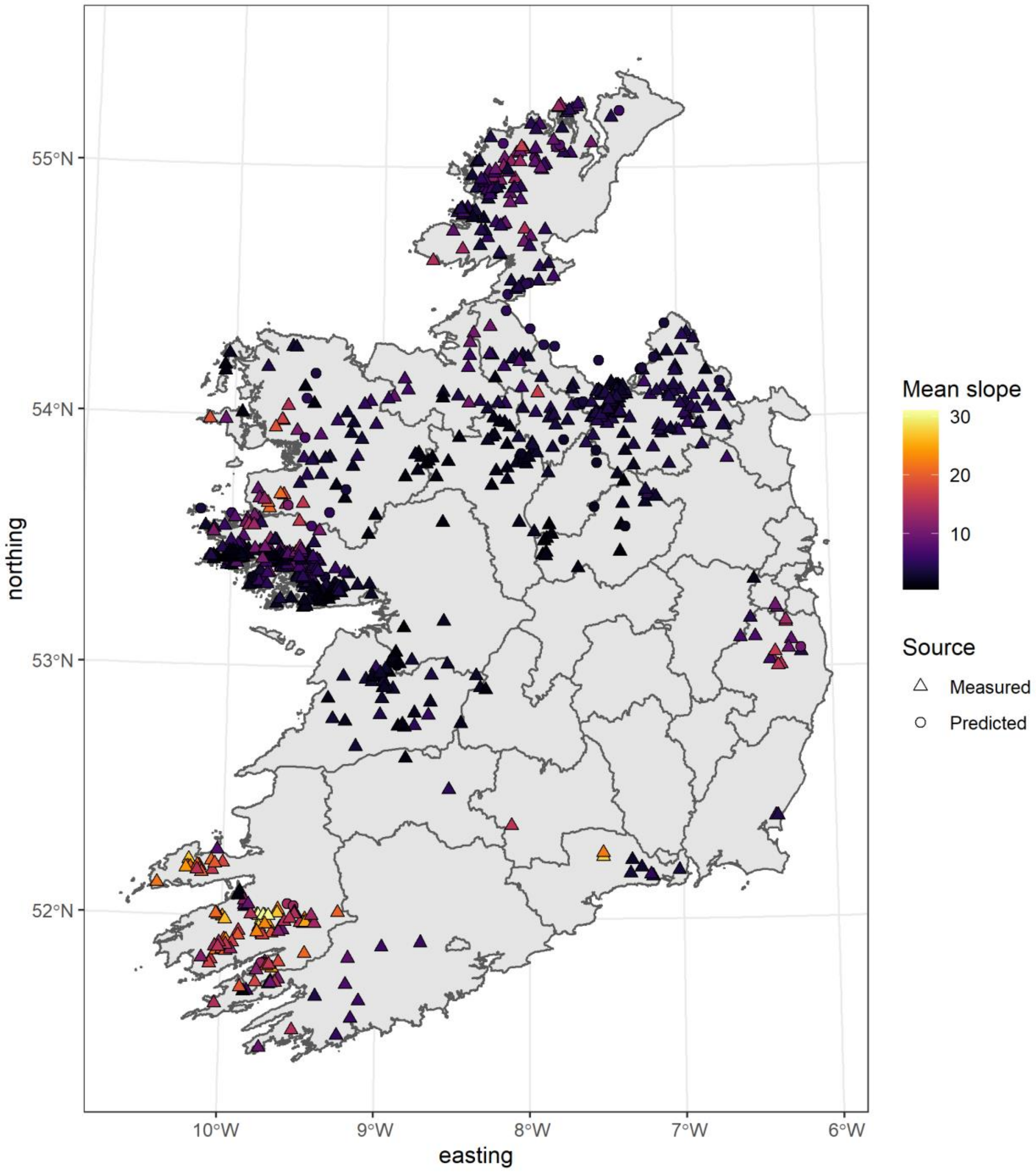

Figure 42: Map of measured and predicted mean catchment slope for all 811 lakes

Range in slope (50 m buffer)

The previous research by Wynne and Donohue (2016) created a slope raster from a 5 m DEM to quantify the range in slope within 50 m of the lake shore (in °) for 759 lakes.

Using these data, a GAM regression model was developed to predict the range in slope (50 m buffer) for the lakes with missing data values. Range in slope (50 m buffer) was modelled as a function of the easting/northing predictor variable. Range in slope (50 m buffer) was $\log_{10}$ transformed to satisfy the model's assumptions of normally distributed errors and heterogeneous variables.

The statistical model explained 39.2% of the variation in range in slope (50 m buffer) (Figure 43; Figure 44; Figure 45). Figure 46 illustrates the relationship between range in slope (50 m buffer) and easting/northing.

The final model was used to predict mean catchment slope for the remaining 52 lakes; Figure 47 maps measured and predicted range in slope (50 m buffer) for all 811 lakes.

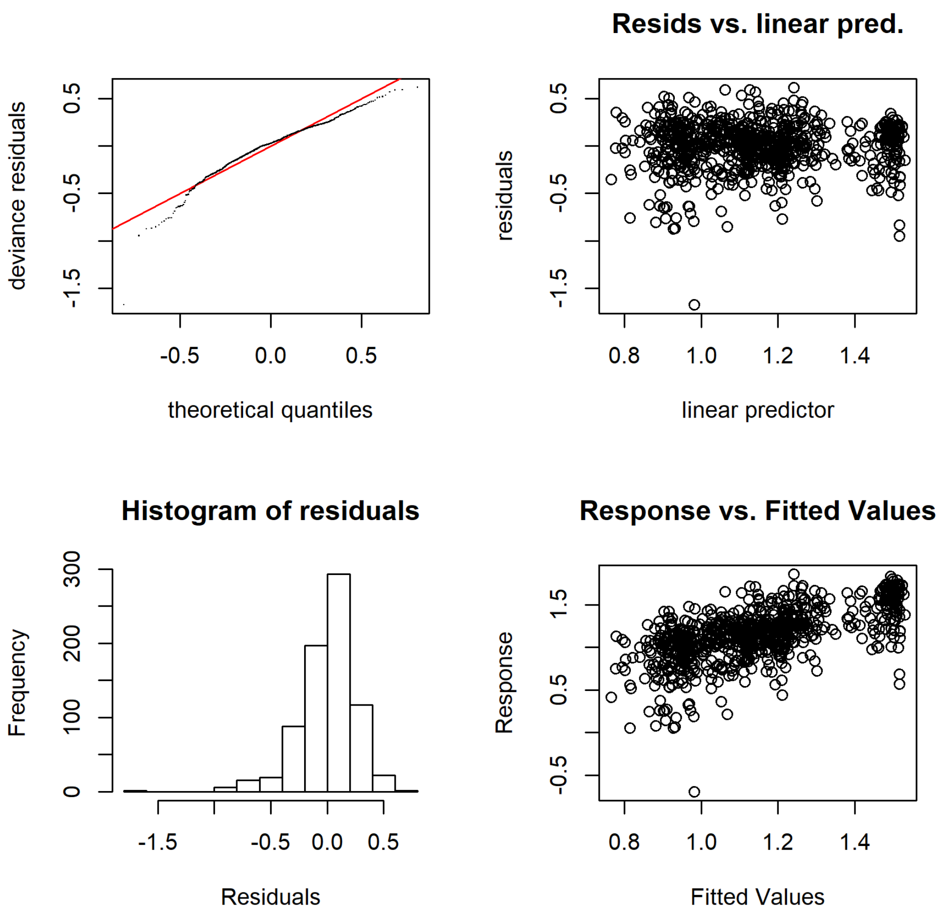

Figure 43: Residuals plots for the range in slope (50 m buffer) model

```
Family: gaussian
Link function: identity

Formula:
log_range_slope_50 ~ s(easting, northing)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.147809   0.009119   125.9   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                      edf Ref.df     F p-value
s(easting,northing) 22.92  26.82 16.7  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.373   Deviance explained = 39.2%
-REML = 66.266  Scale est. = 0.06312    n = 759
```

Figure 44: Statistical summary of range in slope (50 m buffer) model

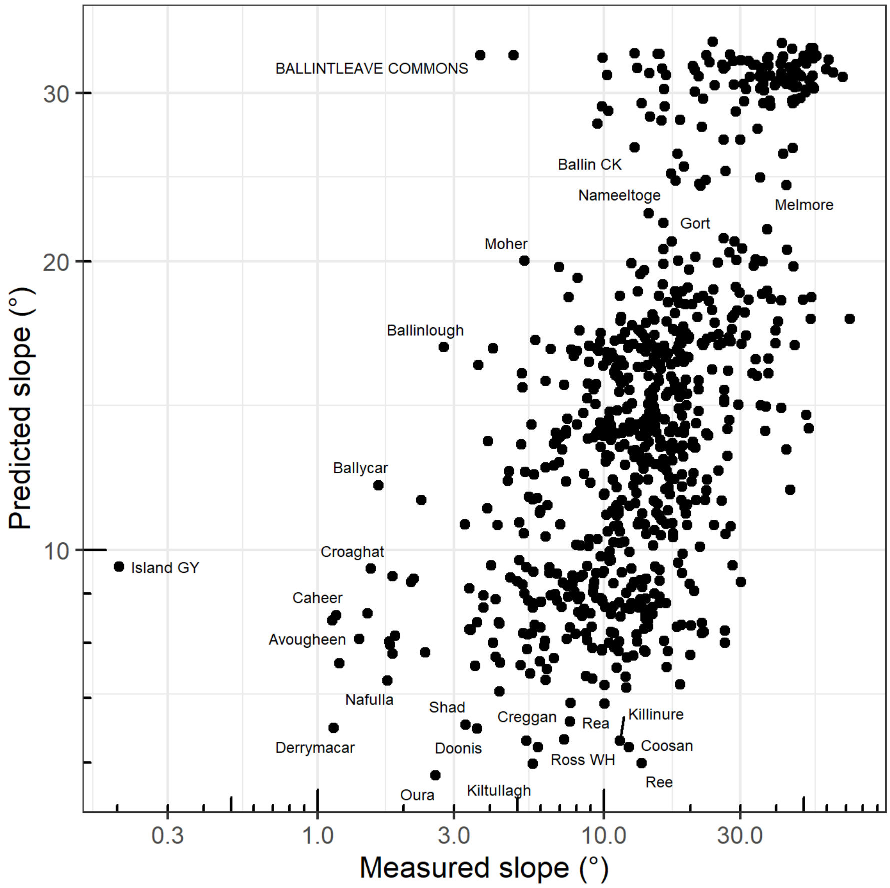

Figure 45: Predicted vs measured range in slope for the 759 lakes with range in slope (50 m buffer) values

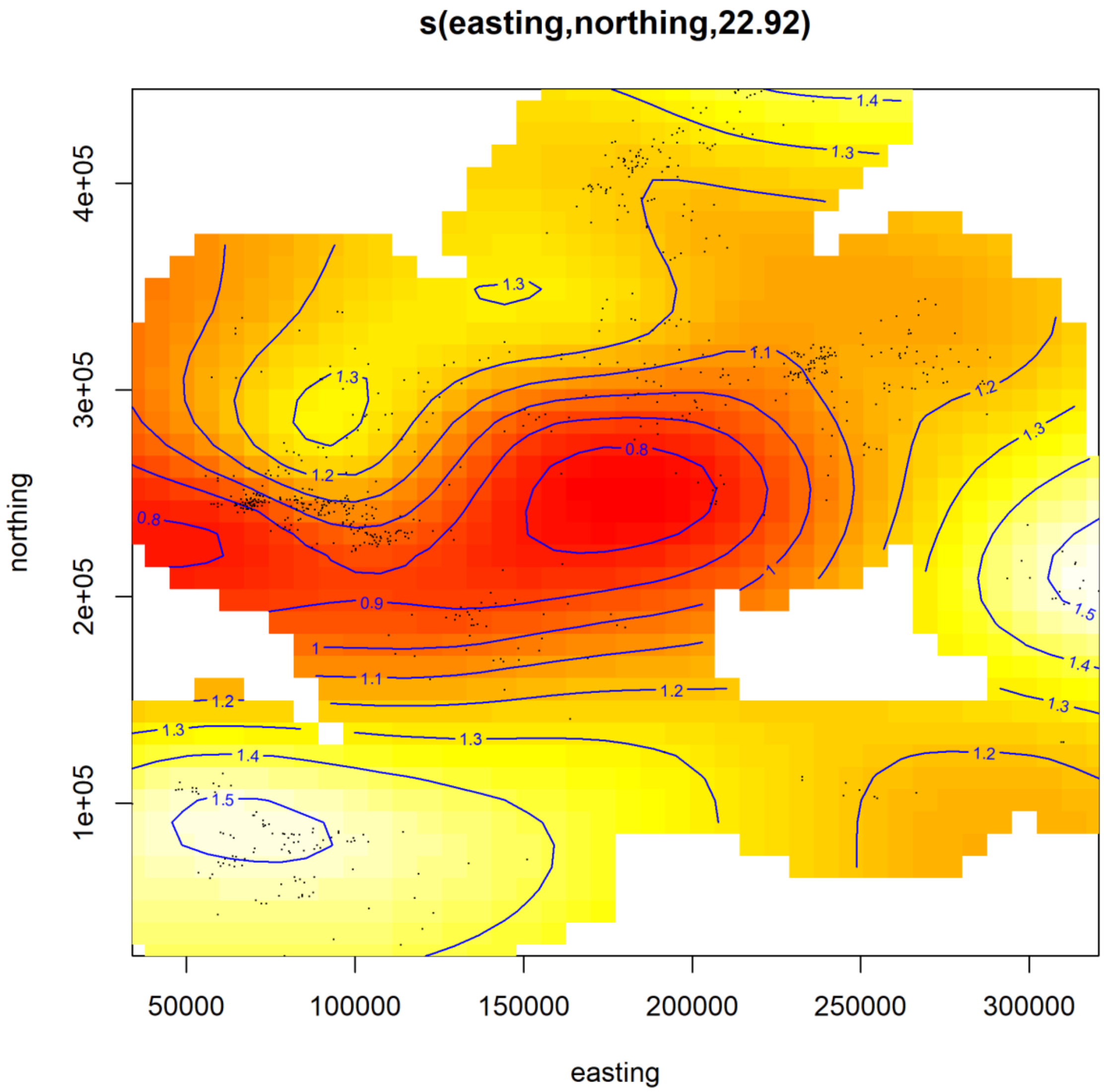

Figure 46: Partial effects plot showing the effect of easting/northing on range in slope (50 m buffer)

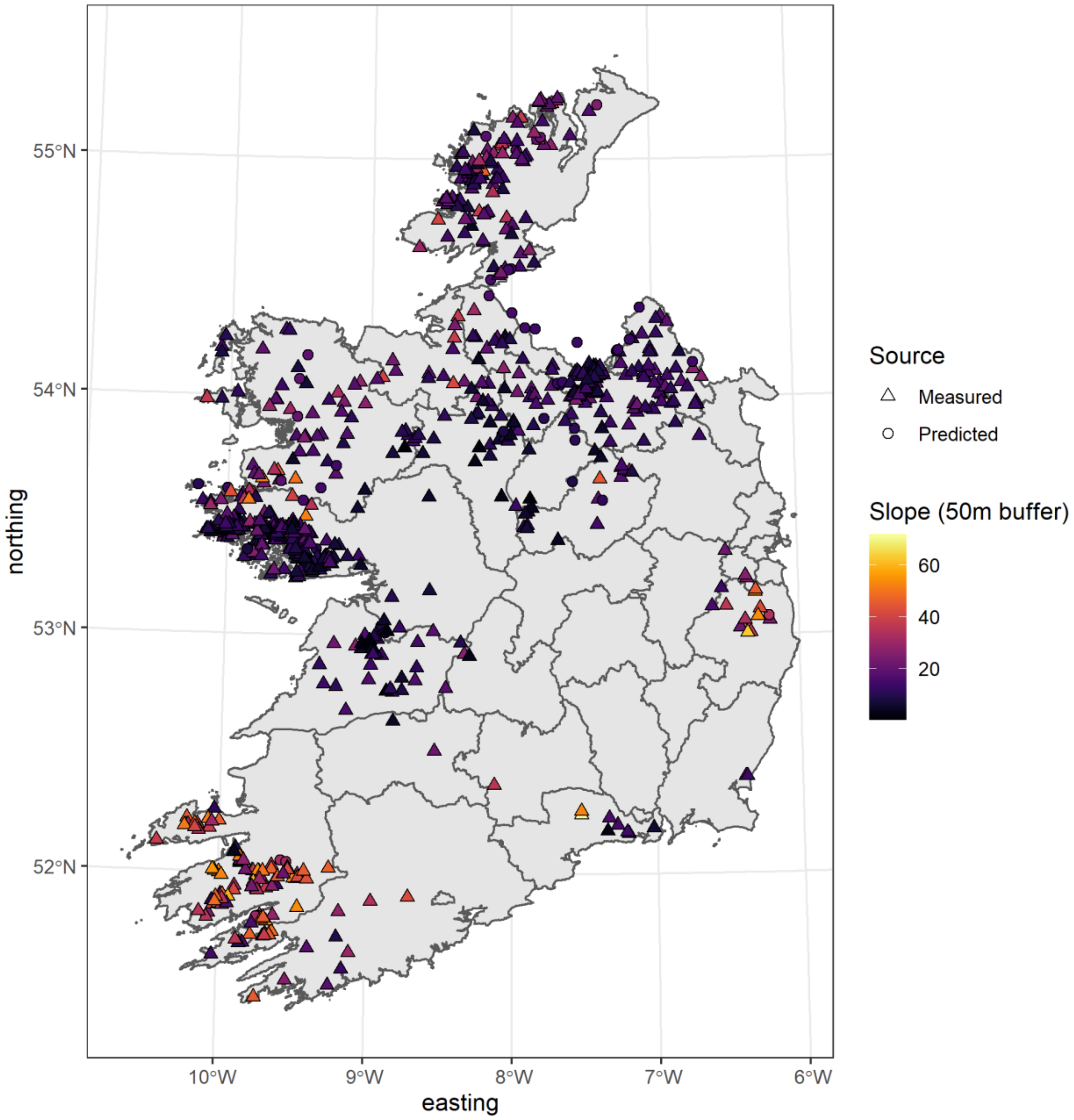

Figure 47: Map of measured and predicted range in slope (50 m buffer) for all 811 lakes

Density of upstream lakes

The GIS methodology used by Wynne and Donohue (2016) was adopted to estimate the density of upstream lakes for all 811 lakes, but with the nested catchments v2 layer. The latest lake segments layer had 12,217 segments, including ponds, reservoirs, lakes, and null values. Due to size of the datasets, spatial indices were created before each tool was run on the layers, and columns that weren't needed in the shapefiles were removed where necessary. The lake segments were clipped to the extent of the nested catchments v2 layer to reduce the size of the file to only those segments that were within the catchments of interest. Area values (in km^2) for the lake segments were added as a column to the layer. Using eu_code as the common ID attribute, the lake area values from the WFD lake water bodies layer was joined onto the nested catchments v2 layer. This joined layer was exported as a new shapefile.

A spatial join of the lake segments layer onto the new shapefile was performed, and the lake segments area was summed for each nested catchment. This gave a total area for all lakes within each WFD lake catchment (km^2). The area of the WFD lake itself was then subtracted from the total lake area. The result was then expressed as a proportion of the catchment area (km^2), as illustrated in Figure 48.

In a few instances (e.g. Ballaghkeeran, Castle CN, Killinure, Tap South), the proportion exceeded 1 because these lakes were a part of a larger lake or directly linked to a conglomerate of lakes that were deemed to be the same catchment during the spatial join because a part of their feature was within and/or touching the lake catchment polygon. To resolve this issue, upstream lake segments were identified and extracted manually.

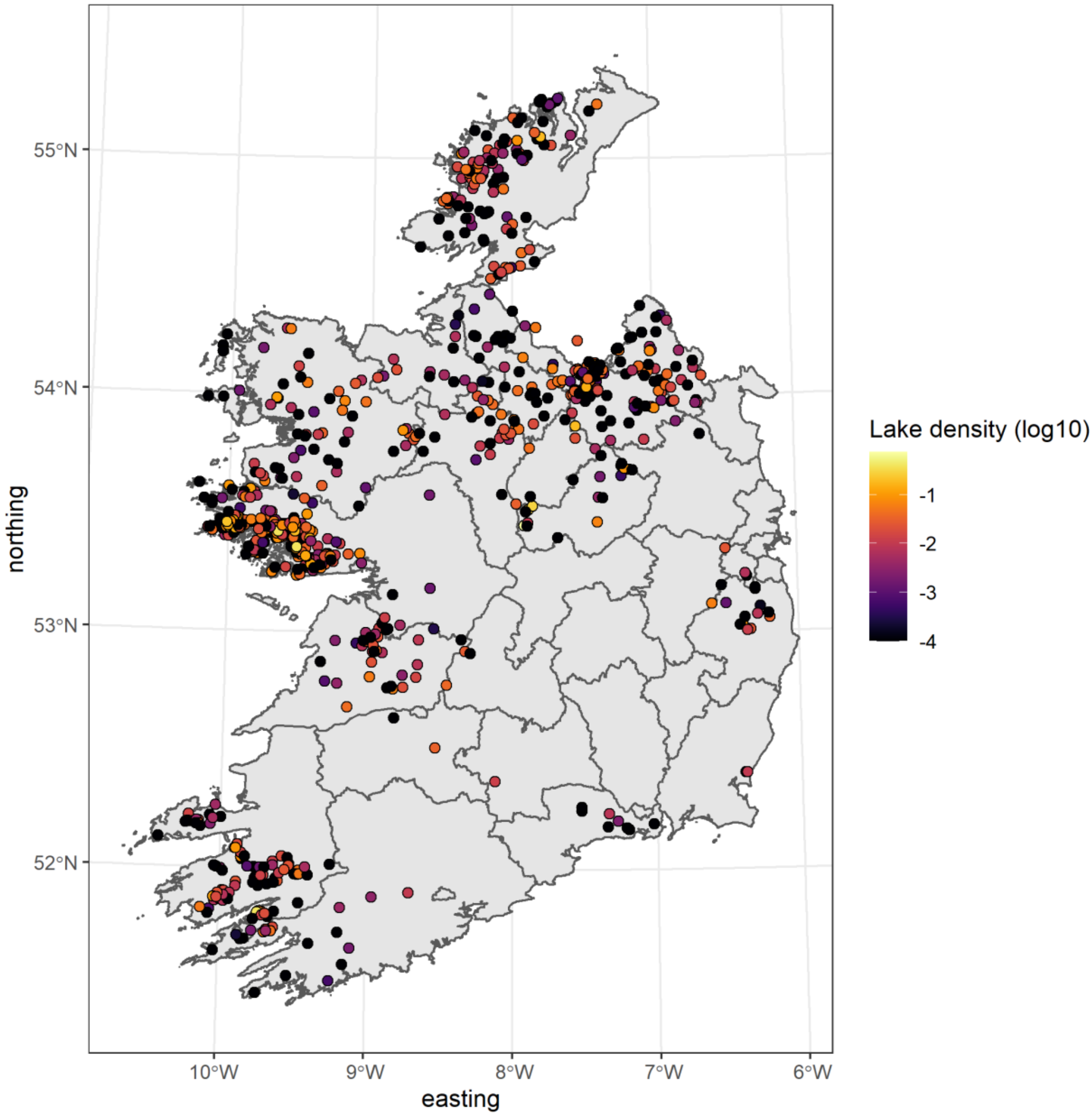

Figure 48: Map of lake density for all 811 lakes

Stream density

Wynne and Donohue (2016) calculated stream density for 758 lakes using the previous version of the nested catchments layer. Due to the time required to process the RivNetRoutes layer, the present study only calculated stream density for the remaining 53 lakes, using the same GIS methodology as Wynne and Donohue (2016) but with the nested catchments v2 layer.

The RivNetRoutes layer was used to find the total length (km) of all streams within each WFD lake catchment. This value was then divided by the catchment area (km^2) to give the density of streams per km^2 of catchment (km/ km^2; Figure 49).

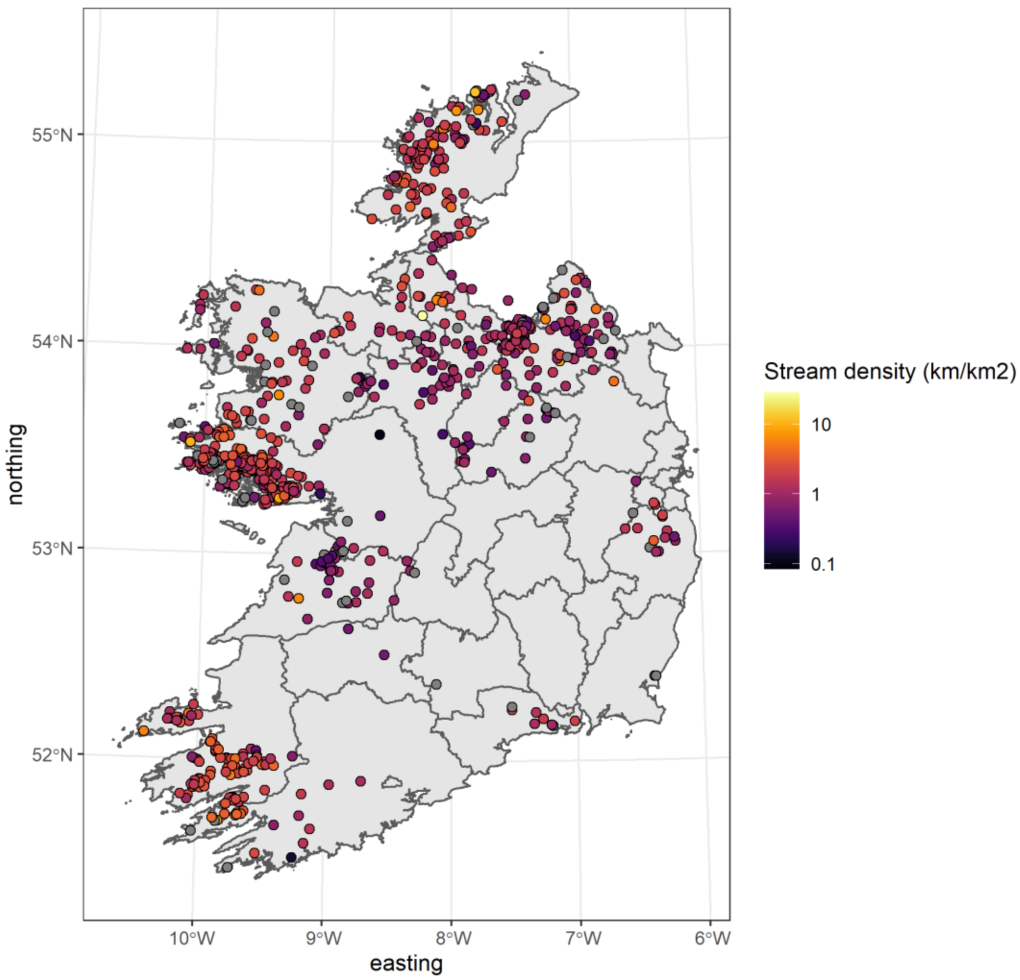

Figure 49: Map of stream density for all 811 lakes

Limestone

The GIS methodology used by Wynne and Donohue (2016) was adopted to estimate the percentage cover of limestone bedrock for all 811 WFD lakes, but using the nested catchments v2 layer.

The GSI hydrostatic rock units layer was downloaded from the EPA GeoPortal. The following categories from the DESCRIPT column in the Groundwater_Rock_Units_ITM layer were taken to be limestone:

- Dinantian (early) sandstones, shales, and limestone;
- Dinantian dolomitised limestones;
- Dinantian lower impure limestones;
- Dinantian mixed sandstones, shales, and limestones;
- Dinantian pure bedded limestones;
- Dinantian pure unbedded limestones;
- Dinantian shales and limestones; and
- Dinantian upper pure limestones.

These categories were dissolved to create one feature, which was then intersected with the nested catchments v2 layer to give the total area (km^2) of limestone in each catchment. This was then expressed as a proportion of the total catchment area (km^2).

Small discrepancies between the calculated figures and those produced by Wynne and Donohue (2016) could be due to the use of slightly different bedrock categories (Wynne and Donohue did not document which they used) and/or the use of the updated nested catchments v2 layer.

Peat

The GIS methodology used by Wynne and Donohue (2016) was adopted to estimate the percentage cover of peaty subsoils for all 811 WFD lakes, but using the nested catchments v2 layer.

The Subsoils.ie layer was downloaded from the EPA GeoPortal. The following categories from the PAR_MAT column were taken to be peat:

- BktPt (blanket peat);
- RsPt (raised peat);
- FenPt (fen peat); and
- Cut (cutover peat).

These categories were dissolved to create one feature, which was then intersected with the nested catchments v2 layer to give the total area (km^2) of peat subsoil in each catchment. This was then expressed as a proportion of the total catchment area (km^2).

Small discrepancies between the calculated figures and those produced by Wynne and Donohue (2016) could be due to the use of slightly different subsoil categories (Wynne and Donohue did not document which they used) and/or the use of the updated nested catchments v2 layer.

Karst

The GIS methodology used by Wynne and Donohue (2016) was adopted to estimate the percentage cover of karst aquifers for all 811 WFD lakes, but using the nested catchments v2 layer.

The GSI groundwater resources bedrock aquifer layer (IRL_AQUIFER_BEDROCK_ITM shapefile) was downloaded from the EPA GeoPortal. The following aquifer units from the AQUIFER_CAT column were taken to be karst:

- Rkc (Regionally Important Aquifer - Karstified (conduit);
- Rkd (Regionally Important Aquifer - Karstified (diffuse);
- Rk (Regionally Important Aquifer - Karstified);
- Lk (Locally Important Aquifer - Karstified);
- Rf/Rk (a border of karstified and fissured bedrock regionally important aquifers);
- RkNI;
- RkcNI; and
- LkNI.

The Ballyshannon Limestone Formation was the only feature in the dataset listed as Rf/Rk. The features with an 'NI' suffix were either cross border or entirely within Northern Ireland.

These categories were dissolved to create one feature, which was then intersected with the nested catchments v2 layer to give the total area (km^2) of karst aquifers in each catchment. This was then expressed as a proportion of the total catchment area (km^2).

Lakes with >25% karst were then categorised as karst lakes.

Small discrepancies between the calculated figures and those produced by Wynne and Donohue (2016) could be due to the use of slightly different aquifer categories (Wynne and Donohue did not document which they used) and/or the use of the updated nested catchments v2 layer.

Phosphorus loading

The EPA's Source Load Apportionment Model (SLAM, v303) was used to estimate the total annual TP load entering each WFD lake following attenuation or treatment (Mockler *et al.*, 2017; Mockler and Breun, 2018). The model contains a number of sub-models that take account of point source discharges from wastewater treatment works, industrial sources, surface water overflows, and septic tanks (using a model called SANICOSE, Gill & Mockler, 2016). The 'Catchment Characterisation Tool' was used to produce sub-models for pasture and arable land-use (Archbold *et al.*, 2016).

Using the nested catchments v2 layer, the SLAM framework collated the following spatial datasets to characterise the land-use and physical characteristics of each WFD lake catchment:

- PIP models (developed initially by the Pathways and CatchmentTools Research Projects, and by the EPA Catchments Unit) (Mockler *et al.*, 2017)
- CORINE land use update 2018;
- Good Agricultural Practice Regulations;

- Agricultural LPIS and AIM;
- soil classification and natural soil drainage map;
- depth to bedrock map;
- subsoil permeability (K) map;
- national recharge map;
- potential bedrock denitrification map; and
- aquifer bedrock boundaries.

Using these datasets, SLAM estimated TP loads from the following point and diffuse sources:

- municipal wastewater treatment plants;
- septic tank systems;
- other licensed discharges;
- pasture;
- arable;
- forestry;
- peatlands;
- urban diffuse; and
- atmospheric deposition on water.

These estimates were combined to provide an estimate of total TP loading to each lake (in kg/ha/year).

The version of SLAM used in this research did not consider the following pressures:

- non-licenced industries;
- water treatment plants;
- WWTP emergency overflows;
- non-compliance not captured by AERs;
- human burials;
- animal burials;
- abstractions/diversions;
- aquaculture; or
- Historically Polluted Sites.

For reference, Figure 50 lists the input data that was included in SLAM v303, including the calculation methods and time period of each data input.

Catchment Nutrient Model Input data

SLAM Input	Calculation Method	Main Data sets	Time period of data
WWTP AER	Loads reported in AER	WWTP AER spreadsheet	2018
WWTP PE	Load calculated from PE	LEMA	2018
SWO AER	Loads estimated from measured overflow volume in AER & diluted influent concentrations	WWTP AER spreadsheet	2018
SWO Estimated	Loads estimated from PE	LEMA	2018
Diffuse Urban sources	Corine landcover with factors	Corine 2018	2018
Section 4s	25% of ELV loads	December 2015 draft from national abstractions & discharges study	Limits as of 2014/2015
IPPC	From PRTR database (& limits)	PRTR database custom extract	2018
DWTS	SANICOSE model	Geodirectory, DTB, Subsoil permeability, karst features, river water bodies, lake segments, GSI recharge map	~2017
Pasture	From PIP-P v303 / PIP-N	LPIS&AIM 2018 data, 2018 Sheep data	2018
Arable	From PIP-P v303 / PIP-N	LPIS	2018
Forestry	Corine landcover with nutrient export factors	Corine 2018 **DRAFT model based on Forestry/LPIS data**	2018
Peat	Corine landcover with nutrient export factors	Corine 2018	2018
Deposition on water	Atmospheric deposition directly on open water bodies	Atmospheric deposition map of TN (Hernry & Aherne, 2014) & uniform rates of TP deposition are estimated as 0.5 kg ha-1 yr-1 (Jordan, 1997). Open water is defined by the lake segment dataset.	

Figure 50: SLAM v303 input data

Runoff and flow

Flow data was requested from the EPA. The flow data received and downloaded included QUBE data and an EPA nested hydro catchments dataset.

QUBE (formerly known as the EPA HydroTool) is a model that generates natural flow duration curves in ungauged catchments from flows at 145 gauged catchments of similar character, using a procedure called Region of Influence which is based on catchment descriptors (Bree, 2018). The model does not take into account artificial influences, for example abstractions or discharges.

For each WFD lake, the naturalised annual mean flow (NATAMF) in m^3/s (converted to m^3/yr) was extracted from the downstream QUBE estimation point that was closest to the lake outflow. Data was available for 667 lakes (NATAMF data for Quivvy was not available in the QUBE data download, but a value was taken from the QUBE point associated with Erne Upper; Quivvy is therefore included in the total 667 lakes with data). Of the remaining 144 lakes, 75 lakes were not situated within a recognised contributing hydro catchment upstream of a flow estimation point, and 69 lakes did not have a QUBE estimation point within the hydro catchment (e.g. because there were significant groundwater influences that could not be modelled).

The annual mean flow (m^3/yr) was divided by the hydrological catchment area upstream of the QUBE estimation point (km^2) to give a standardised measure of annual runoff ($m^3/km^2/yr$). Eliminating the effect of catchment size in this way allowed geographic variation in run-off to be modelled so that estimates of flow could be derived for the 144 lakes lacking QUBE data.

Using the QUBE data, a GAM was developed to understand and quantify the causes of variation in runoff from lake to lake. Specifically, runoff was modelled as a function of the following predictor variables:

- mean catchment slope (log_{10}-transformed);
- % peat (as an indicator of the soil type in the upstream catchment);
- % limestone (as an indicator of the geology of the upstream catchment); and
- easting/northing (to account for other sources of spatial variation).

Backward model selection using BIC was used to retain only the most relevant predictor variables; in this case, all four variables were retained in the final model (Figure 51; Figure 52). Overall, the model explained 86.5% of the variation in runoff (Figure 53). Figure 54 illustrates the relationship between runoff and each variable whilst holding the other variables constant at their mean values.

The final model was used to predict runoff for the remaining 144 lakes; Figure 55 maps measured and predicted runoff for all 811 lakes.

The annual average flow (m^3/yr) for all 811 WFD lake outlets was then calculated by dividing the annual runoff (either modelled or predicted, m^3/km^2/yr) by the lake catchment area (km^2). As the QUBE estimation points were a variable distance downstream of the lake outlet, this calculation assumes that runoff across the hydrological catchment (upstream of the QUBE estimation point) is constant, and a good estimate of runoff from the smaller (nested) lake catchment.

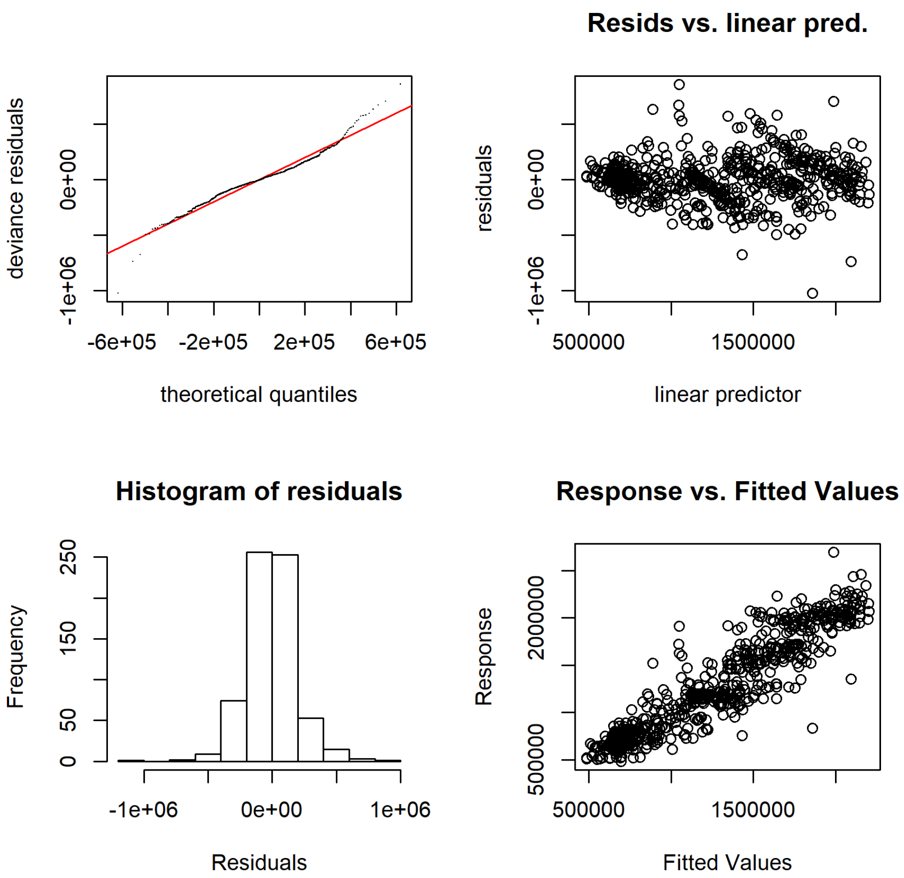

Figure 51: Residuals plots for the runoff model

```
Family: gaussian
Link function: identity

Formula:
runoff_m3_km2_yr ~ s(easting, northing) + s(mean_slope_final) +
    s(peat_pc) + s(limestone_pc)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1277267       7537   169.5   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                        edf Ref.df      F  p-value
s(easting,northing) 27.832 28.897 34.287  < 2e-16 ***
s(mean_slope_final)  4.645  5.732 12.660  < 2e-16 ***
s(peat_pc)           1.872  2.361 10.594 1.39e-05 ***
s(limestone_pc)      3.194  3.900  9.221 9.56e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.858   Deviance explained = 86.6%
-REML =   9067  Scale est. = 3.7888e+10  n = 667
```

Figure 52: Statistical summary of the runoff model

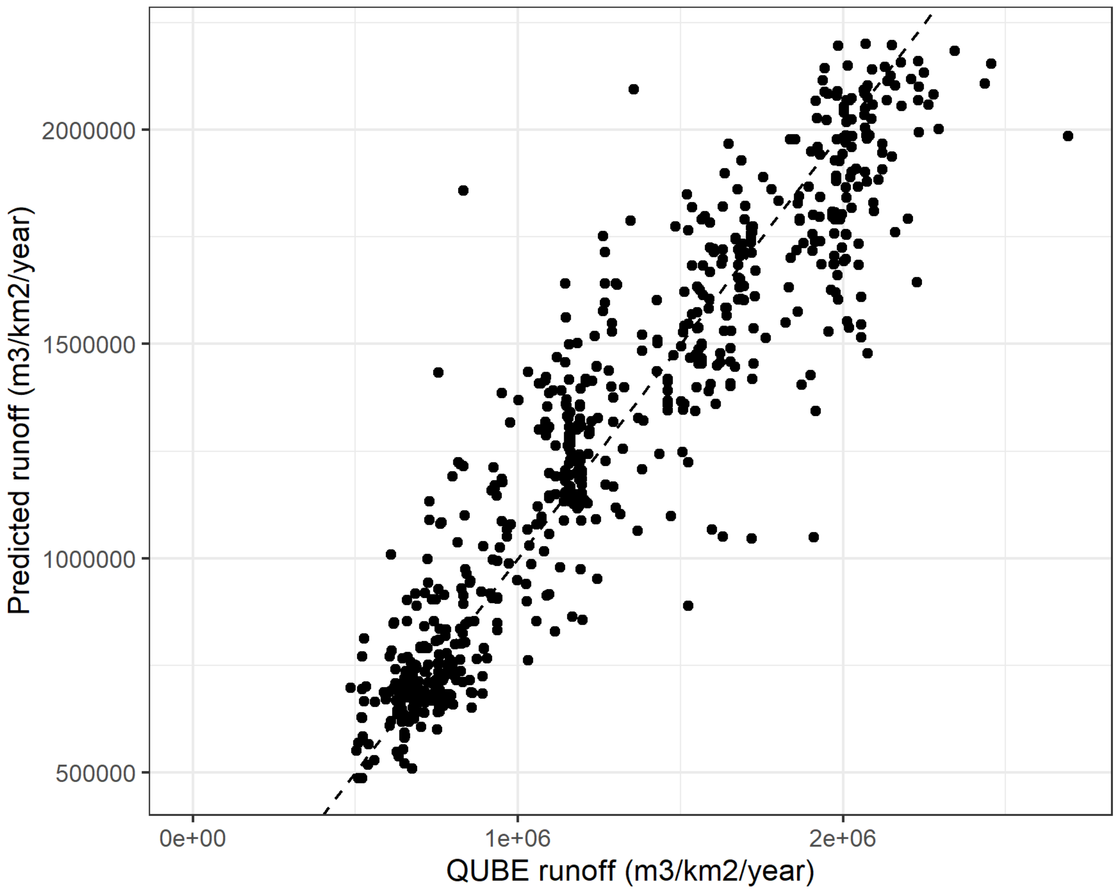

Figure 53: Predicted vs measured runoff for the 667 lakes with QUBE data

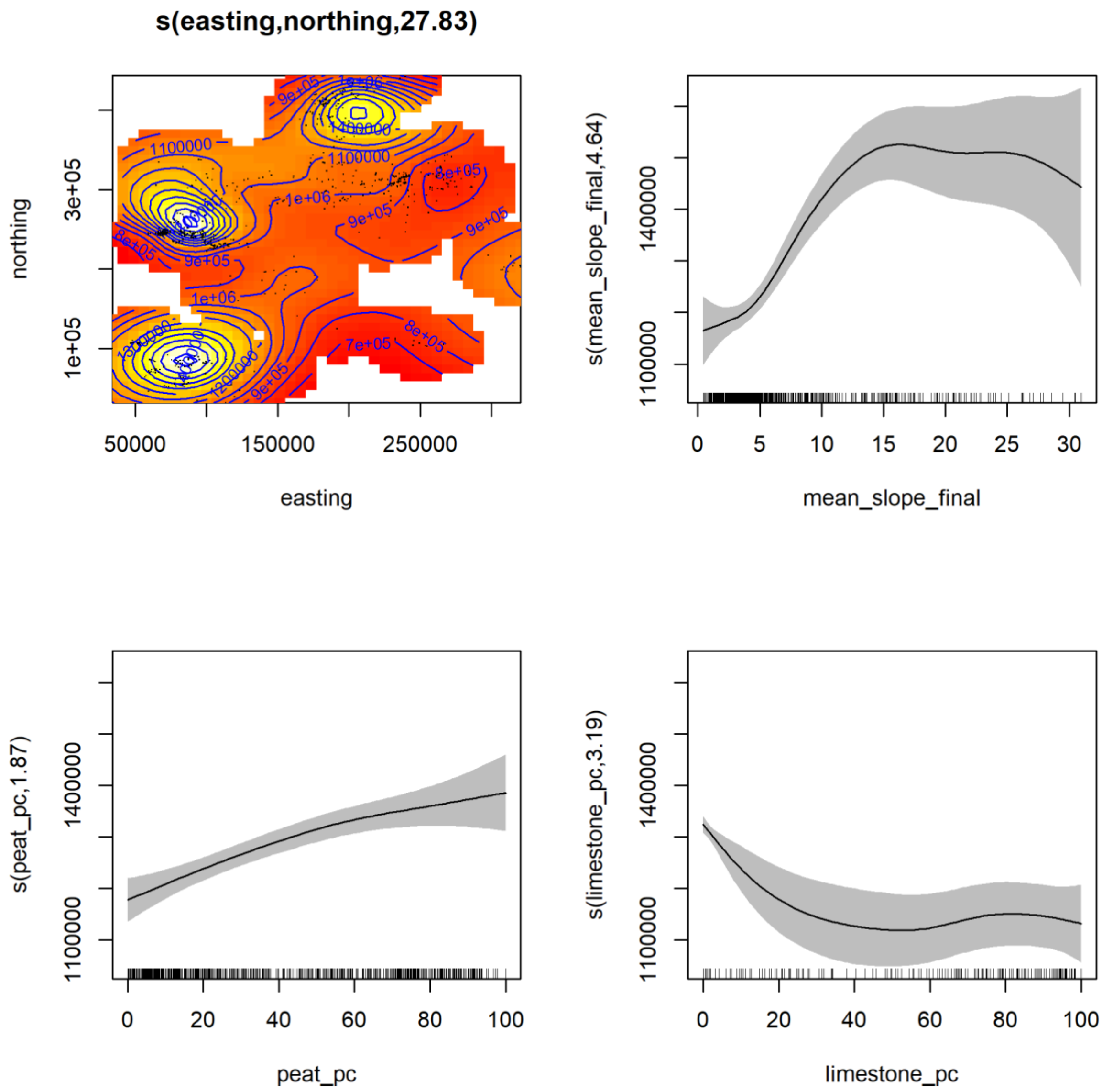

Figure 54: Partial effects plots showing the effect of each variable on runoff

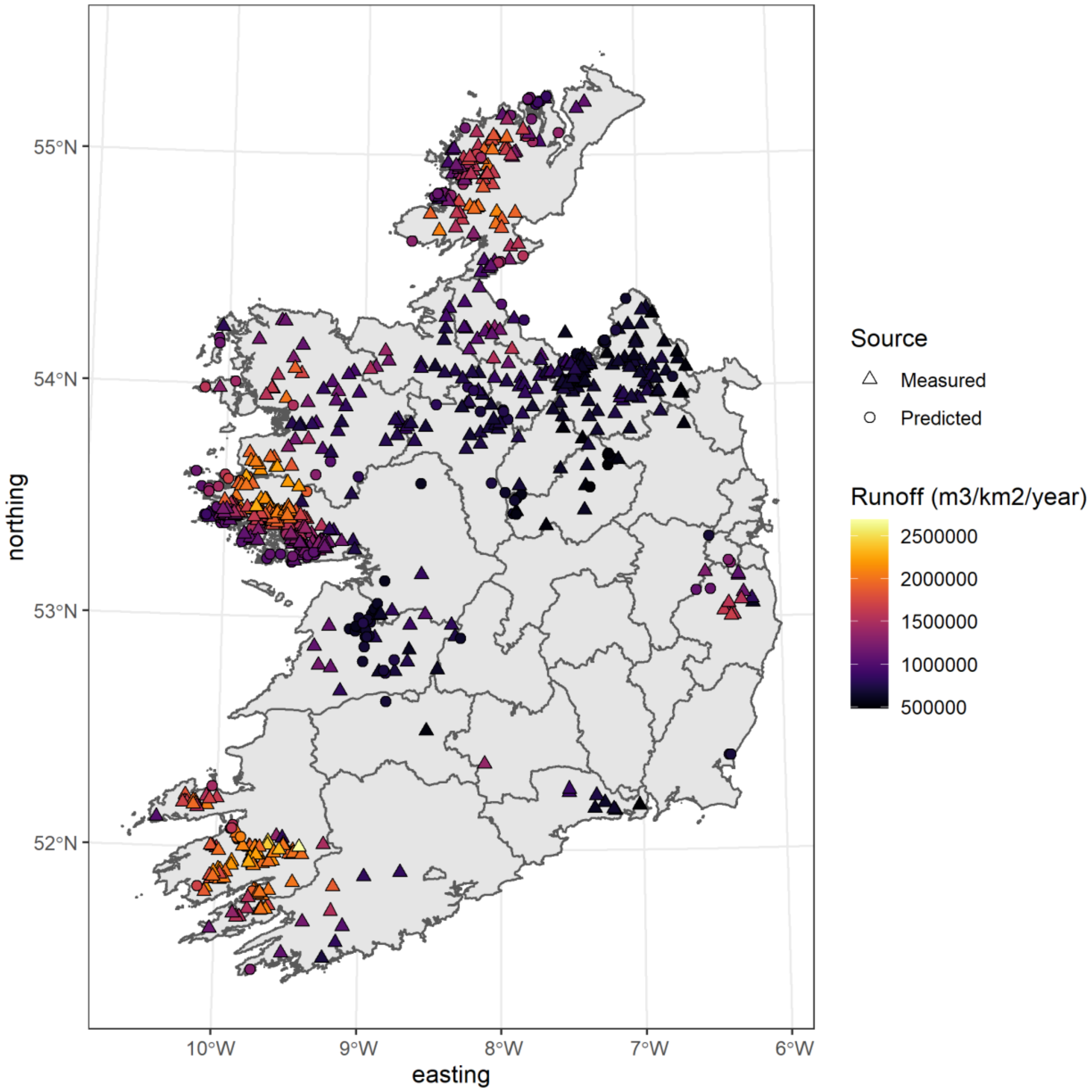

Figure 55: Map of measured and predicted runoff for all 811 lakes

Alkalinity

Alkalinity measurements (mg/l) were available for 223 monitored lakes from the EPA's AQUARIUS database. The measurements for the monitored lakes were averaged over a 9-year period (2007-2015) to give an estimate of long-term mean alkalinity for each lake.

Using these data, a GAM regression model was developed to understand and quantify the causes of variation in alkalinity from lake to lake. Alkalinity was modelled as a function of the following predictor variables:

- % peat (as an indicatory of the extent of peaty spoils in the upstream catchment);
- % limestone (as an indicatory of the geology of the upstream catchment); and
- easting/northing (to account for other sources of spatial variation).

%peat and %limestone were chosen as candidate predictors because Wynne and Donohue (2016) used them successfully to predict the alkalinity category (low, moderate, high) of lakes using a regression tree model. Alkalinity was $\log_{10}$ transformed to satisfy the model's assumptions of normally distributed errors and heterogeneous variables.

Backward model selection using BIC was used to retain only the most relevant predictor variables; in this case, all three variables were retained in the final model (Figure 56; Figure 57). Overall, the model explained 85.9% of the variation in alkalinity (Figure 58). Figure 59 illustrates the relationship between alkalinity and each variable whilst holding the other variables constant at their mean values.

The final model was used to predict alkalinity for the remaining 588 lakes; Figure 60 maps measured and predicted alkalinity for all 811 lakes.

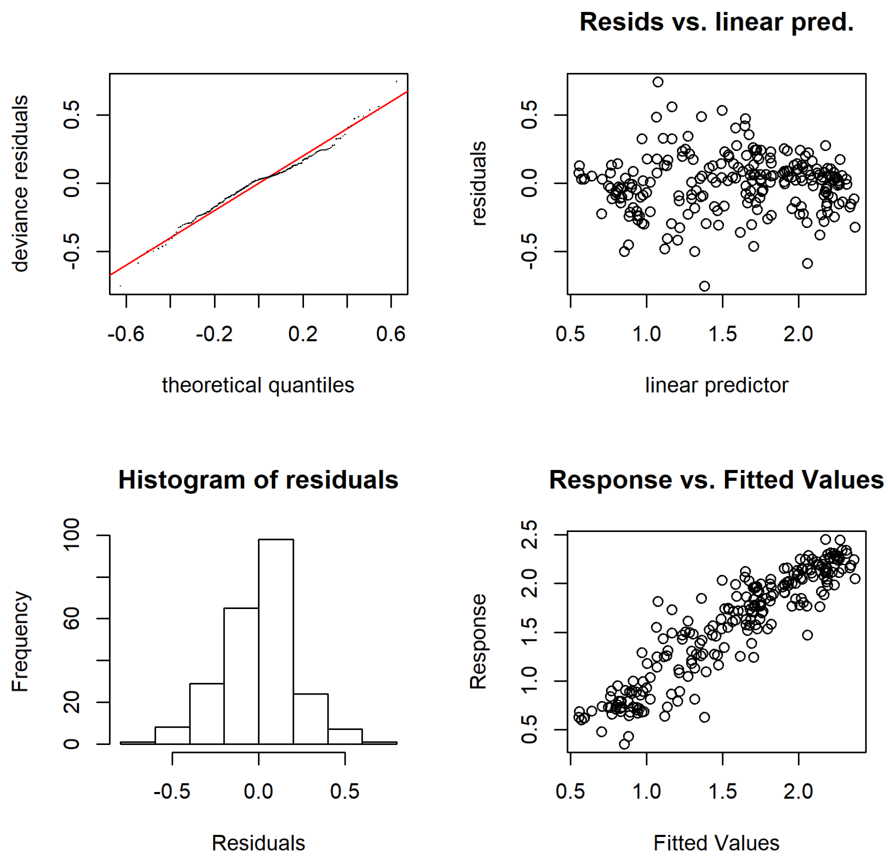

Figure 56: Residuals plots for the alkalinity model

```
Family: gaussian
Link function: identity

Formula:
log_alkalinity ~ s(peat_pc) + s(limestone_pc) + s(easting, northing)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.57734    0.01433     110   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                        edf Ref.df      F p-value
s(peat_pc)            2.471  3.054 28.879  <2e-16 ***
s(limestone_pc)       2.845  3.470 38.190  <2e-16 ***
s(easting,northing) 19.600 24.168  8.878  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.842   Deviance explained = 85.9%
-REML = 14.187  Scale est. = 0.047868  n = 233
```

Figure 57: Statistical summary of the alkalinity model

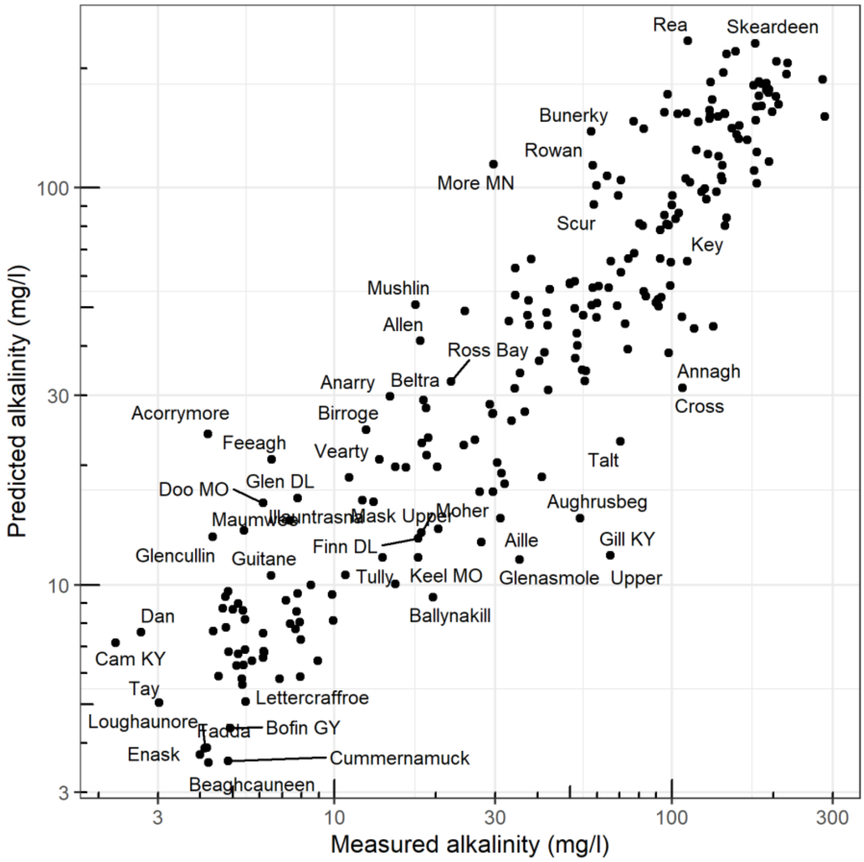

Figure 58: Predicted vs measured alkalinity for the 223 lakes with measured alkalinity

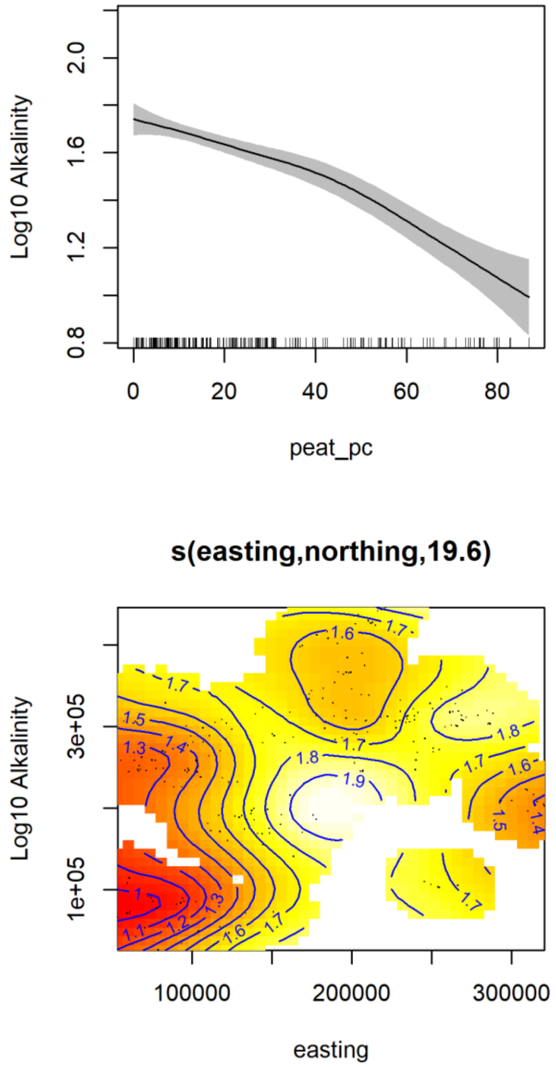

Figure 59: Partial effects plots showing the effect of each variable on alkalinity

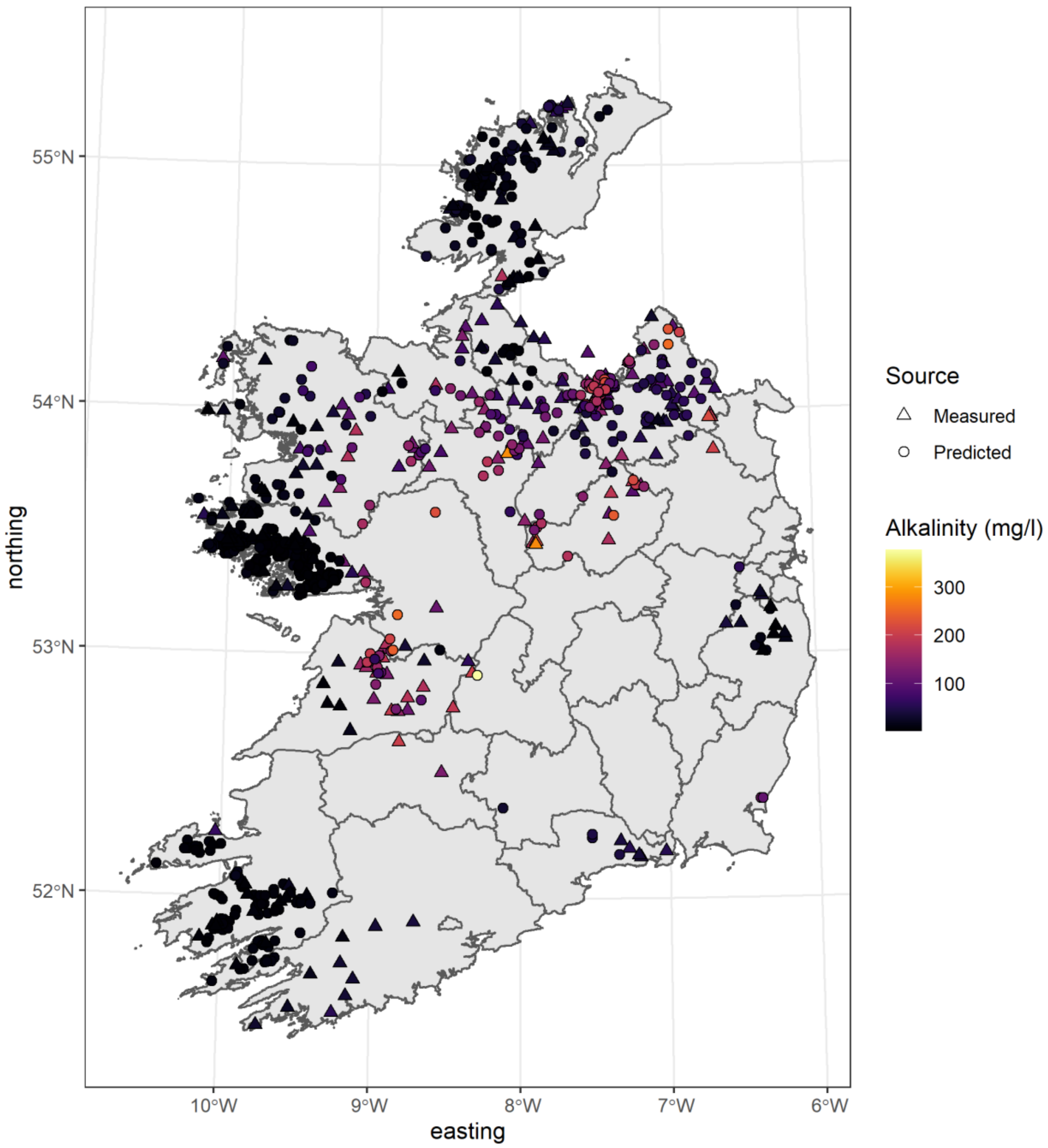

Figure 60: Map of measured and predicted alkalinity for all 811 lakes

Depth

Mean depth estimates (in m) were provided by the EPA for a total of 584 WFD lakes; data for 204 of these lakes were derived from the EPA's 2013 monitored bathymetry database and the remaining 380 values were derived from the EPA's typology data update in 2016.

Using these data, a GAM regression model was developed to understand and quantify the causes of variation in mean depth from lake to lake. Specifically, mean depth was modelled as a function of the following predictor variables:

- lake area (log_{10}-transformed);
- mean catchment slope (log_{10}-transformed);
- range in slope (50m buffer; log_{10}-transformed; included as a main effect and also as an interaction with lake area);
- SDI; and
- easting/northing (to account for other sources of spatial variation).

Depth was log_{10} transformed to satisfy the model's assumptions of normally distributed errors and heterogeneous variables.

Backward model selection using BIC was used to retain only the most relevant predictor variables. The final model included lake area, range in slope (50 m buffer), and SDI (Figure 61; Figure 62). Overall, the model explained 41.4% of the variation in mean depth (Figure 63). Figure 64 illustrates the relationship between mean depth and each variable whilst holding the other variables constant at their mean values.

The final model was used to predict mean depth for the remaining 227 lakes; Figure 65 maps measured and predicted mean depth for all 811 lakes.

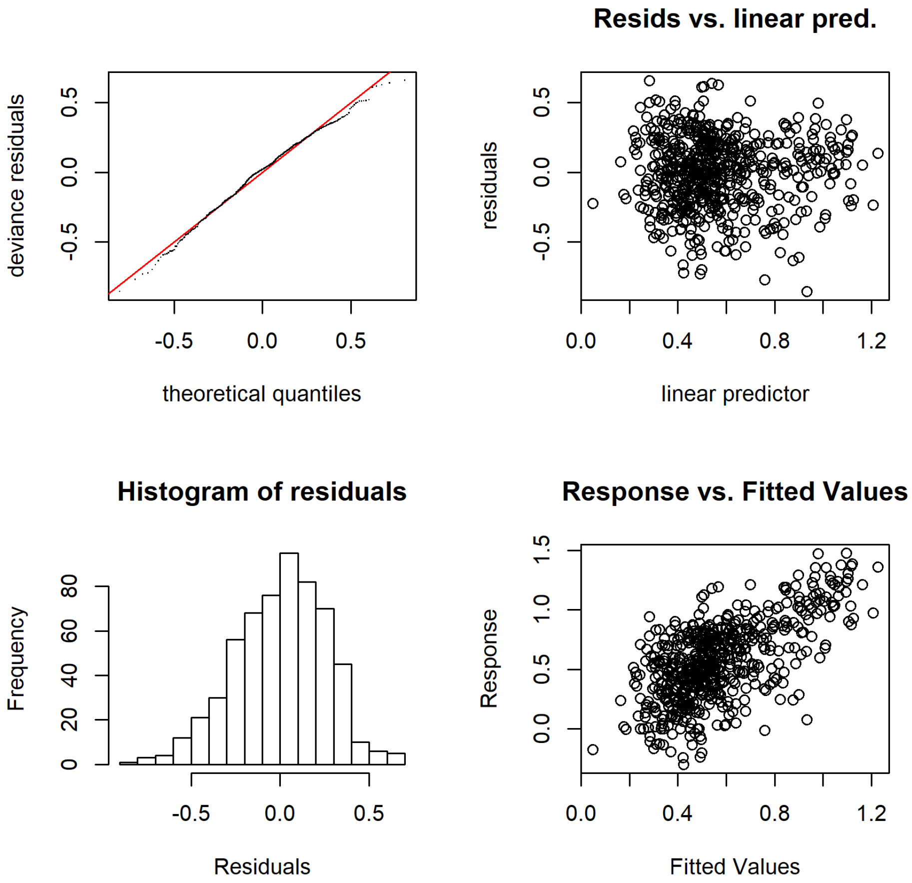

Figure 61: Residuals plots for the mean depth model

```
Family: gaussian
Link function: identity

Formula:
log_mean_depth ~ s(log_lake_area_ha) + s(log_range_slope_50_final) +
    s(log_sdi_final)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.56364    0.01065   52.94   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df     F  p-value
s(log_lake_area_ha)         2.428  3.129 10.36 1.21e-06 ***
s(log_range_slope_50_final) 4.226  5.232 55.70  < 2e-16 ***
s(log_sdi_final)            1.000  1.000 26.75 5.25e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.406   Deviance explained = 41.4%
-REML = 52.777  Scale est. = 0.066194  n = 584
```

Figure 62: Statistical summary of the mean depth model

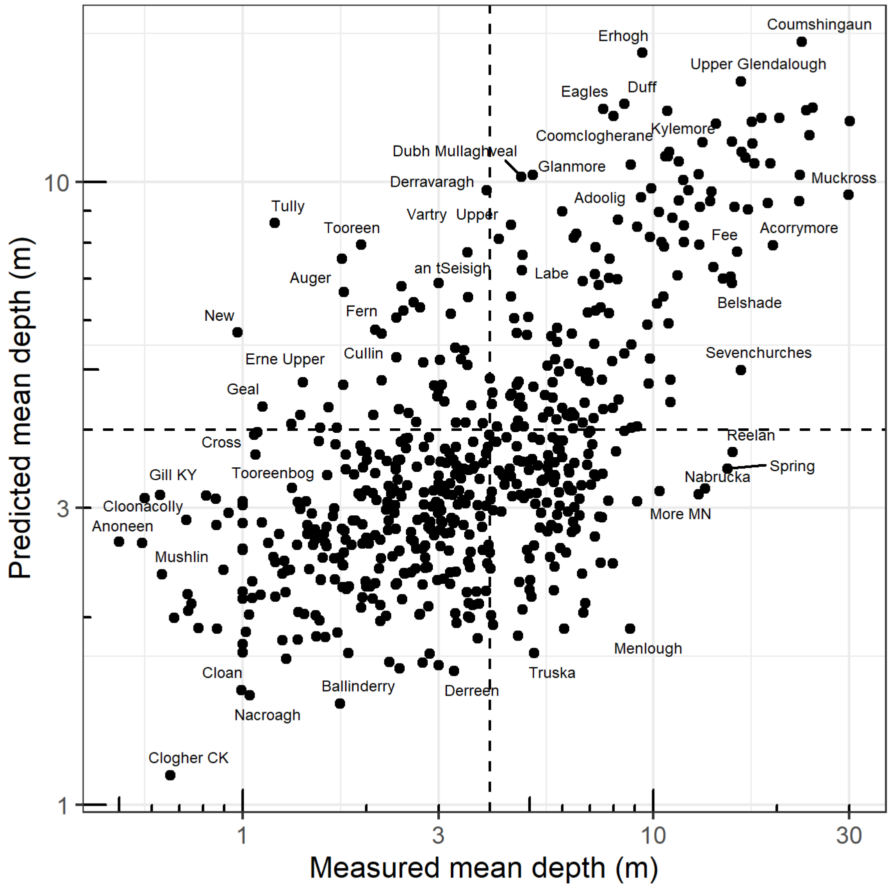

Figure 63: Predicted vs measured mean depth for the 584 lakes with measured depth

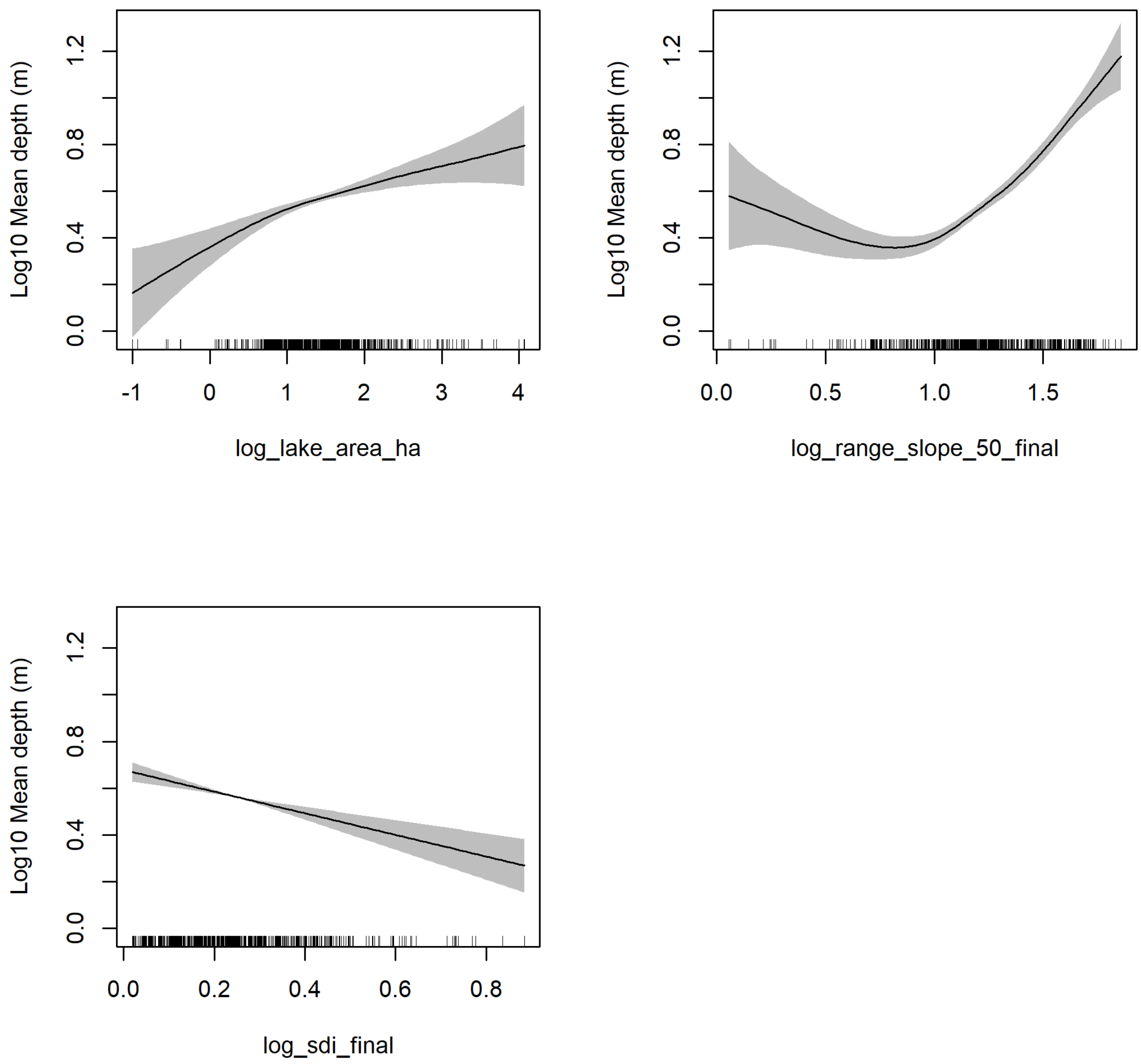

Figure 64: Partial effects plots showing the effect of each variable on mean depth

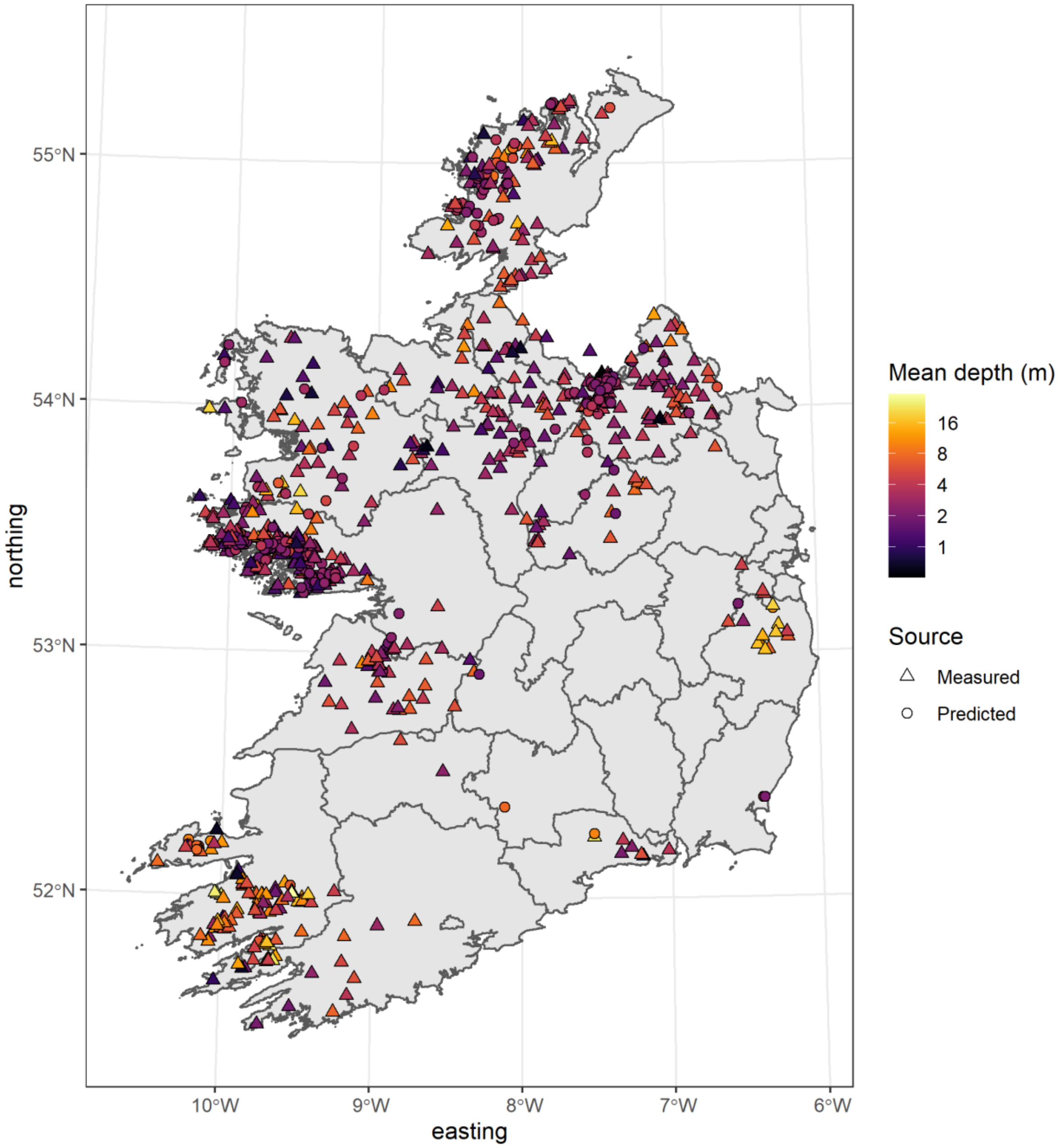

Figure 65: Map of measured and predicted mean depth for all 811 lakes

Residence time

The average hydraulic residence time (in years) of water in each lake was calculated by dividing the estimated lake volume by the estimated annual outflow. Residence times ranged from less than 1 day (= 0.027 years) to 10 years (Figure 66). Figure 67 maps the spatial distribution of residence times.

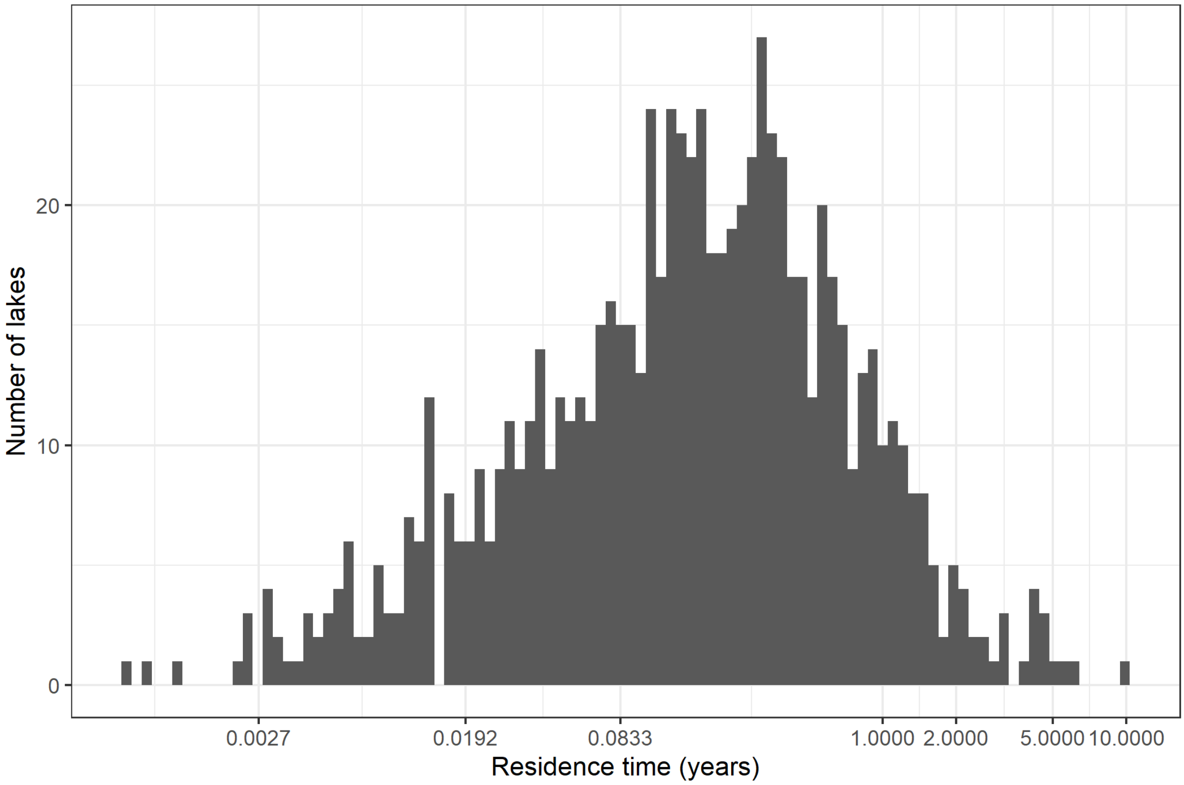

Figure 66: Distribution of estimated hydraulic residence times all 811 lakes

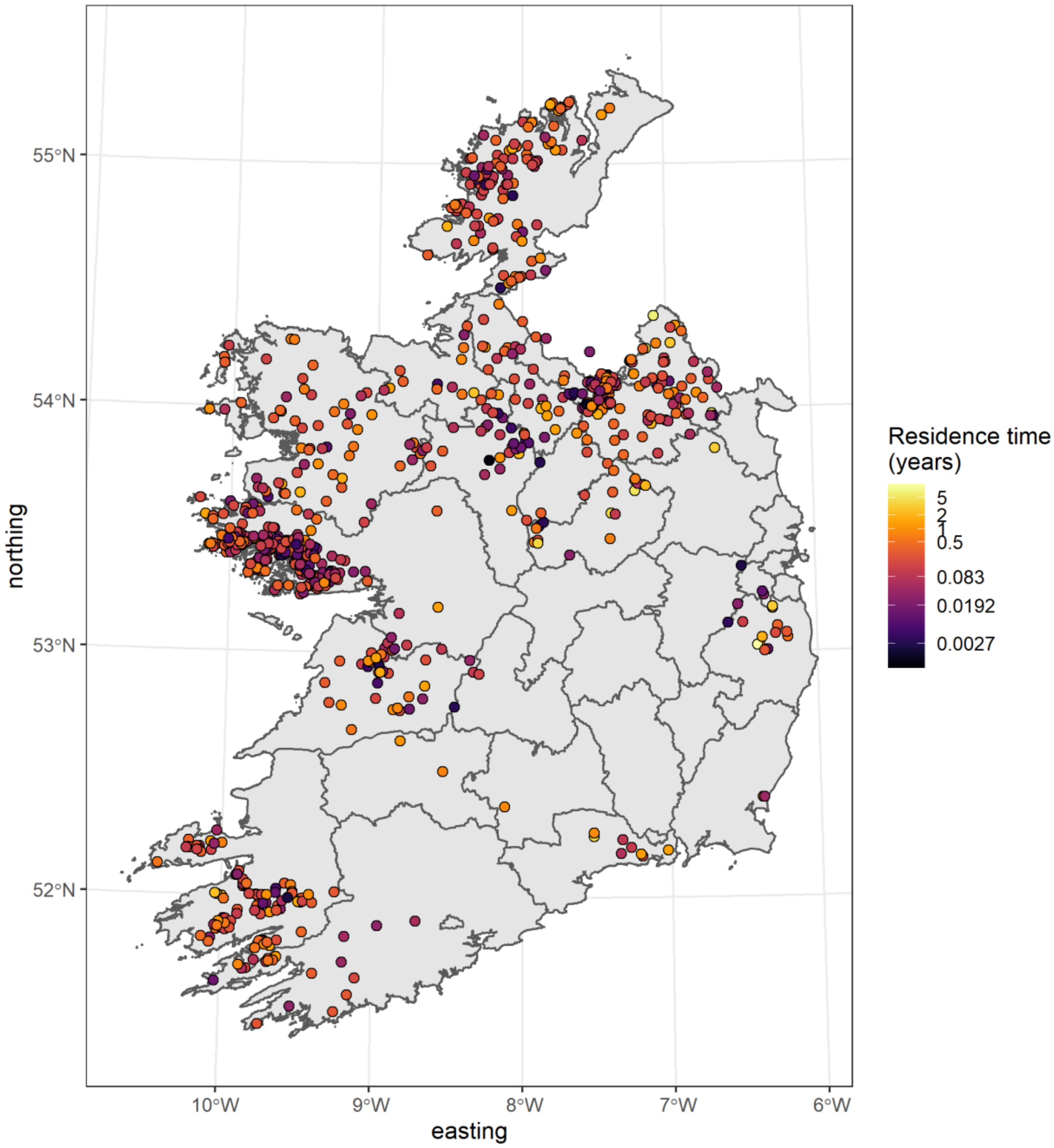

Figure 67: Map of hydraulic residence times for all 811 lakes

Colour

Colour measurements (Hazen) were available for 224 monitored lakes from the raw chemistry general physical conditions (GPC) master dataset supplied by the EPA. The colour measurements for the monitored lakes were averaged over a 3-year period from 2016-2018.

Using these data, a GAM regression model was developed to understand and quantify the causes of variation in colour from lake to lake. Specifically, colour was modelled as a function of the following predictor variables:

- % peat (as an indicatory of the extent of peaty soils in the upstream catchment);
- % limestone (as an indicatory of the geology of the upstream catchment); and
- easting/northing (to account for other sources of spatial variation).

Colour was $\log_{10}$ transformed to satisfy the model's assumptions of normally distributed errors and heterogeneous variables.

Backward model selection using BIC was used to retain only the most relevant predictor variables; in this case, all three variables were retained in the final model (Figure 68; Figure 69). Overall, the model explained 60% of the variation in colour (Figure 70). Figure 71 illustrates the relationship between colour and each variable whilst holding the other variables constant at their mean values.

The final model was used to predict colour for the 587 unmonitored lakes; Figure 72 maps measured and predicted colour for all 811 lakes.

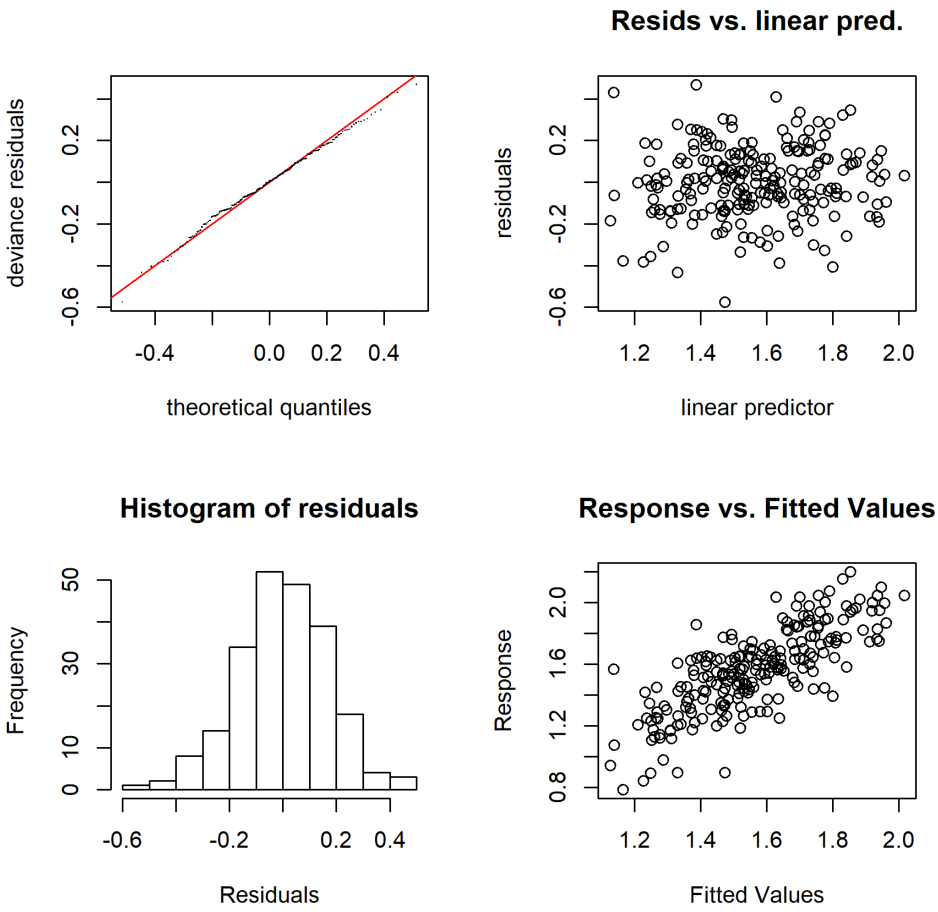

Figure 68: Residuals plots for the colour model

```
Family: gaussian
Link function: identity

Formula:
log_colour ~ s(peat_pc) + s(limestone_pc) + s(easting, northing)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.56286    0.01206   129.6   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                       edf Ref.df      F  p-value
s(peat_pc)           2.572  3.189 23.724  < 2e-16 ***
s(limestone_pc)      1.000  1.000 14.837 0.000158 ***
s(easting,northing) 20.252 24.806  4.087  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.552   Deviance explained =   60%
-REML = -27.956  Scale est. = 0.032564  n = 224
```

Figure 69: Statistical summary of the colour model

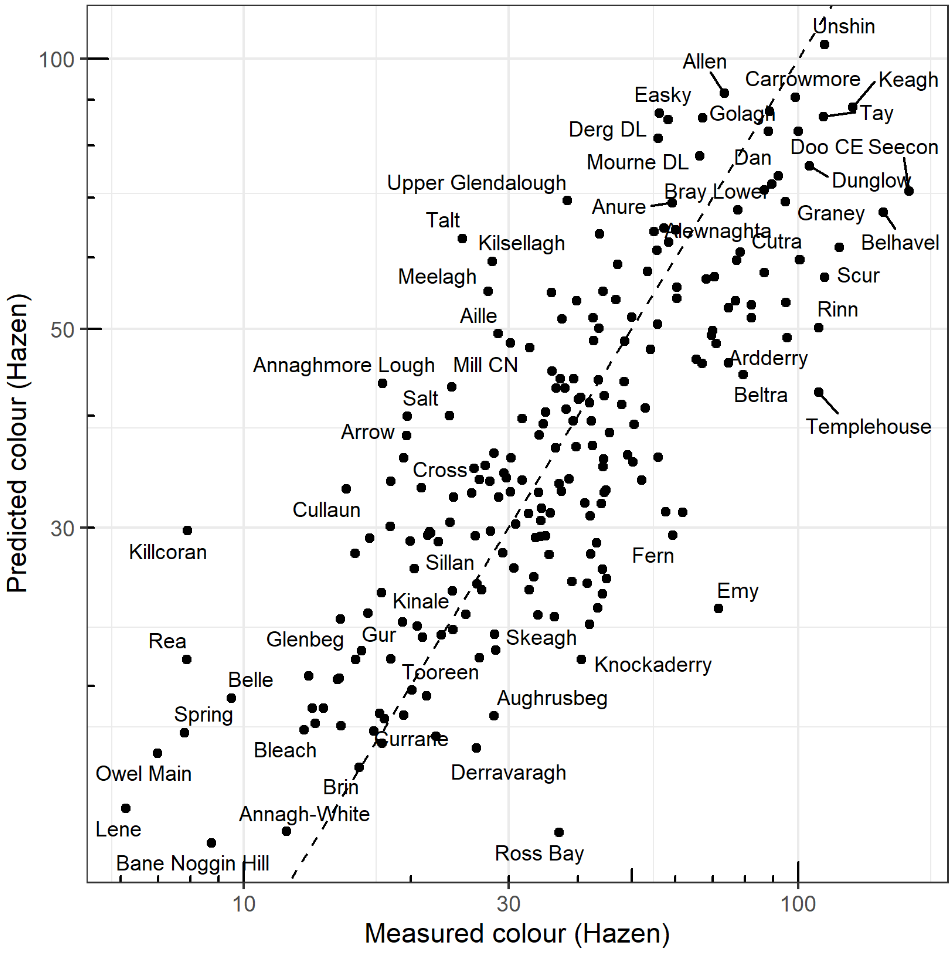

Figure 70: Predicted vs measured colour for the 224 monitored lakes

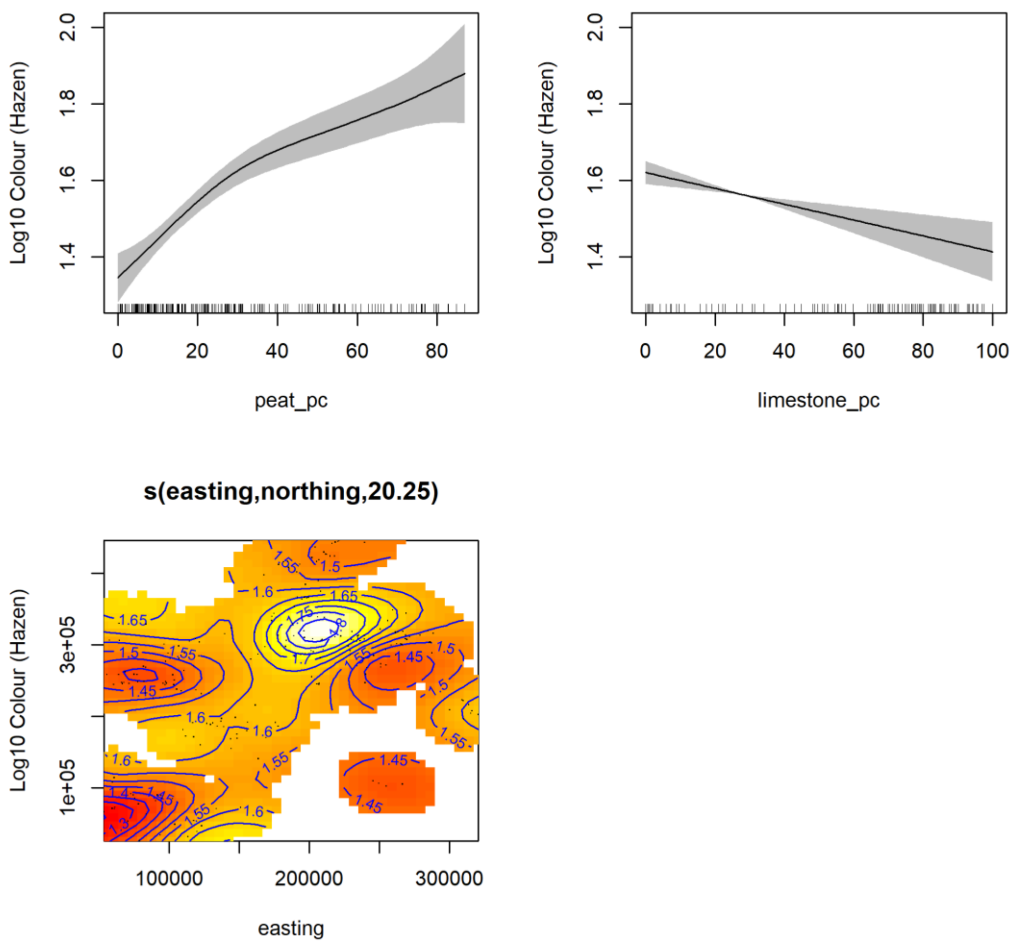

Figure 71: Partial effects plots showing the effect of each variable on colour

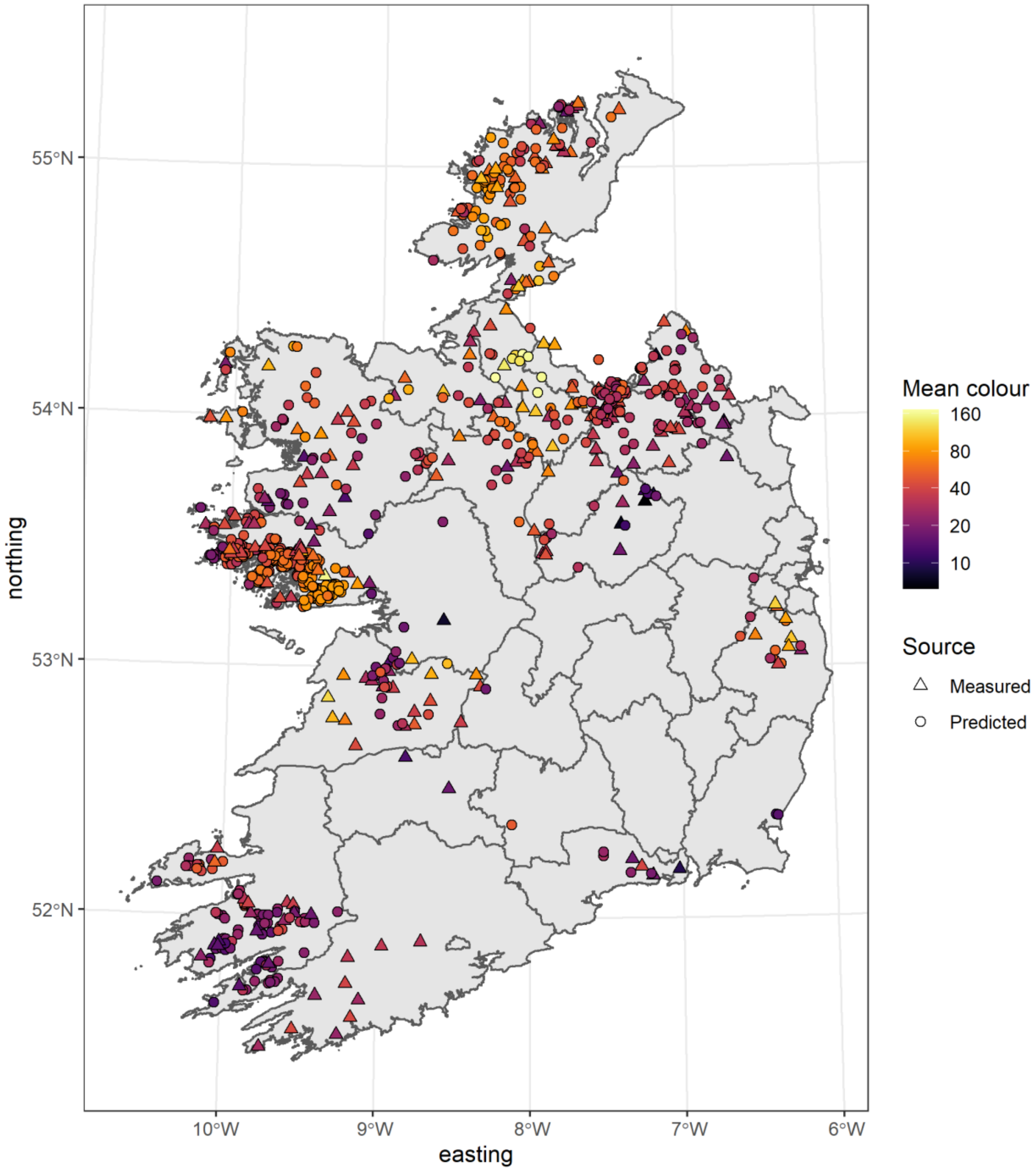

Figure 72: Map of measured and predicted colour for all 811 lakes

Shoreline development index (SDI)

The SDI is a measure of the extent of littoral areas of a lake shoreline (Shilland *et al.*, 2009). SDI is defined as the ratio of the shoreline length to the circumference of a circle of area equal to the surface area of the lake. SDI therefore takes values ≥1; the higher the SDI ratio, the more dendritic the lake shoreline is.

Wynne and Donohue (2016) calculated the SDI for 759 WFD lakes using the EPA's WFD lake water body layer to derive values for lake shoreline (km) and lake area (km^2) and then calculating SDI as:

$$SDI = \frac{Shoreline}{2\sqrt{\pi Area}}$$

Using these data, a GAM regression model was developed to predict SDI for the lakes with missing data values. SDI was modelled as a function of the easting/northing predictor variable. SDI was $\log_{10}$ transformed to satisfy the model's assumptions of normally distributed errors and heterogeneous variables.

The statistical model explained 17.1% of the variation in range in SDI (Figure 73; Figure 74; Figure 75). Figure 76 illustrates the relationship between SDI and easting/northing.

The final model was used to predict SDI for the remaining 52 lakes; Figure 77 maps measured and predicted colour for all 811 lakes.

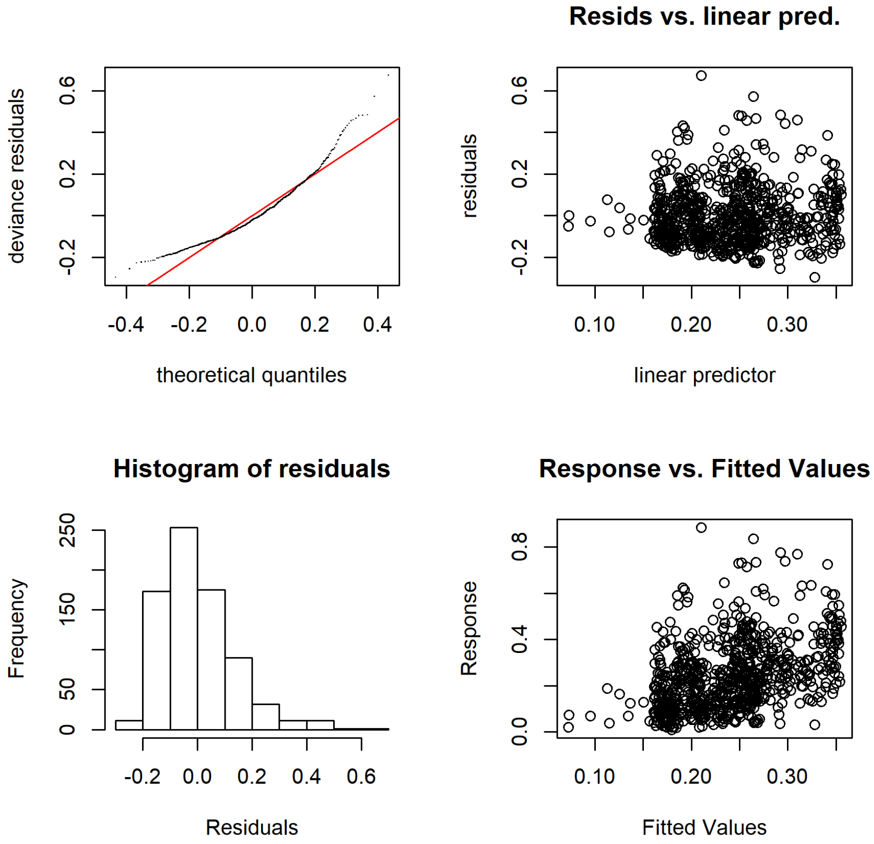

Figure 73: Residuals plots for the SDI model

```
Family: gaussian
Link function: identity

Formula:
log_sdi ~ s(easting, northing)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.240361   0.004918   48.88   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                        edf Ref.df     F p-value
s(easting,northing) 18.59  23.32 5.598  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.151   Deviance explained = 17.2%
-REML = -409.77  Scale est. = 0.018333  n = 758
```

Figure 74: Statistical summary of the SDI model

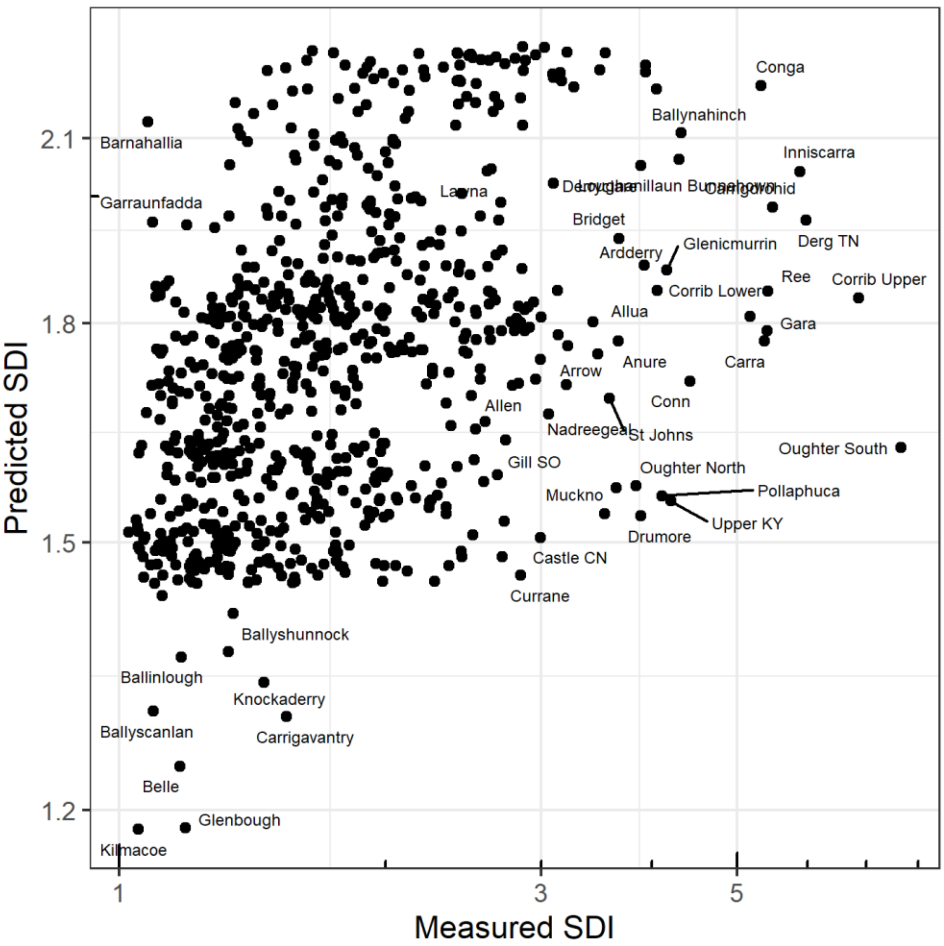

Figure 75: Predicted vs measured SDI for the 759 lakes with measured SDI values

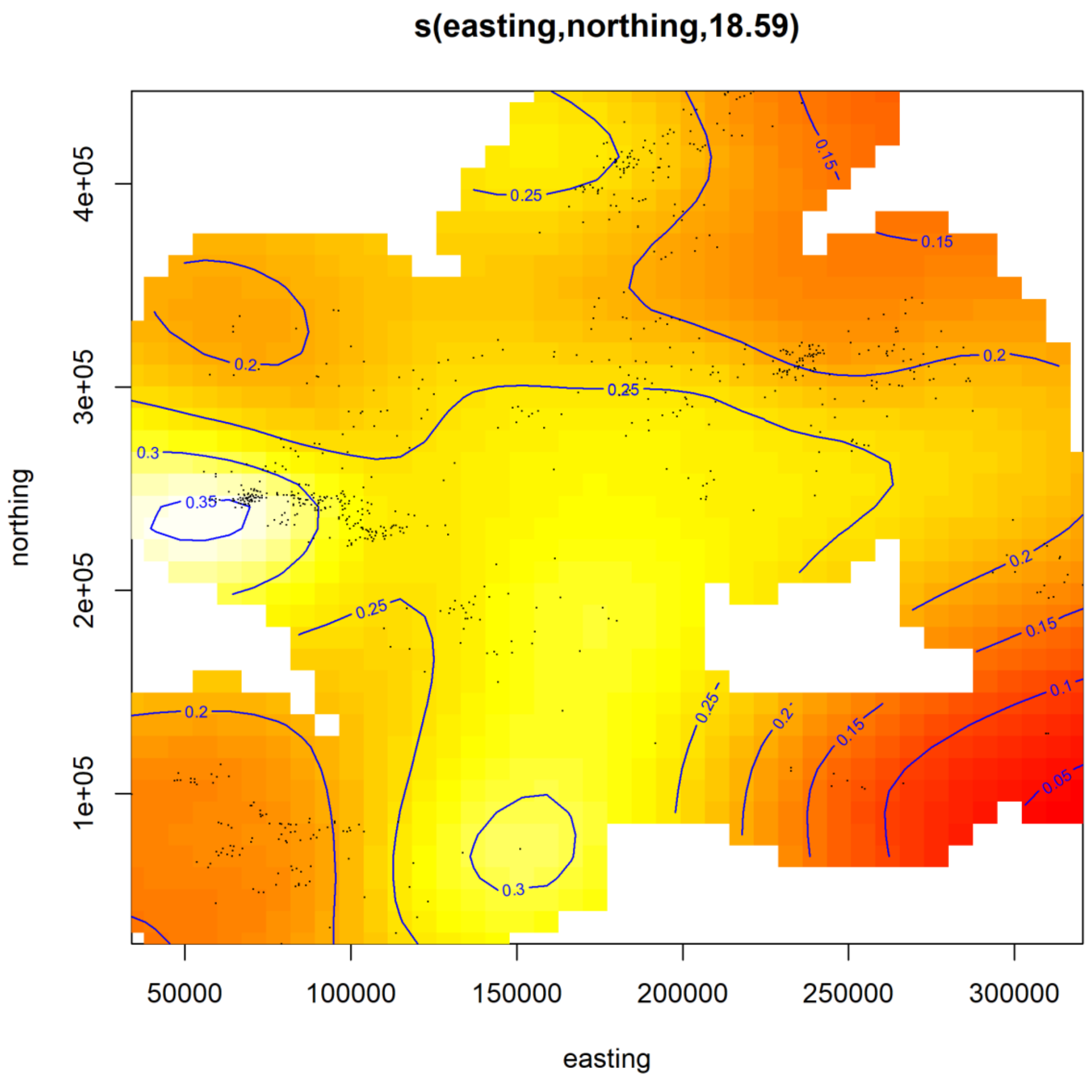

Figure 76: Partial effects plot showing the effect of easting/northing on the SDI

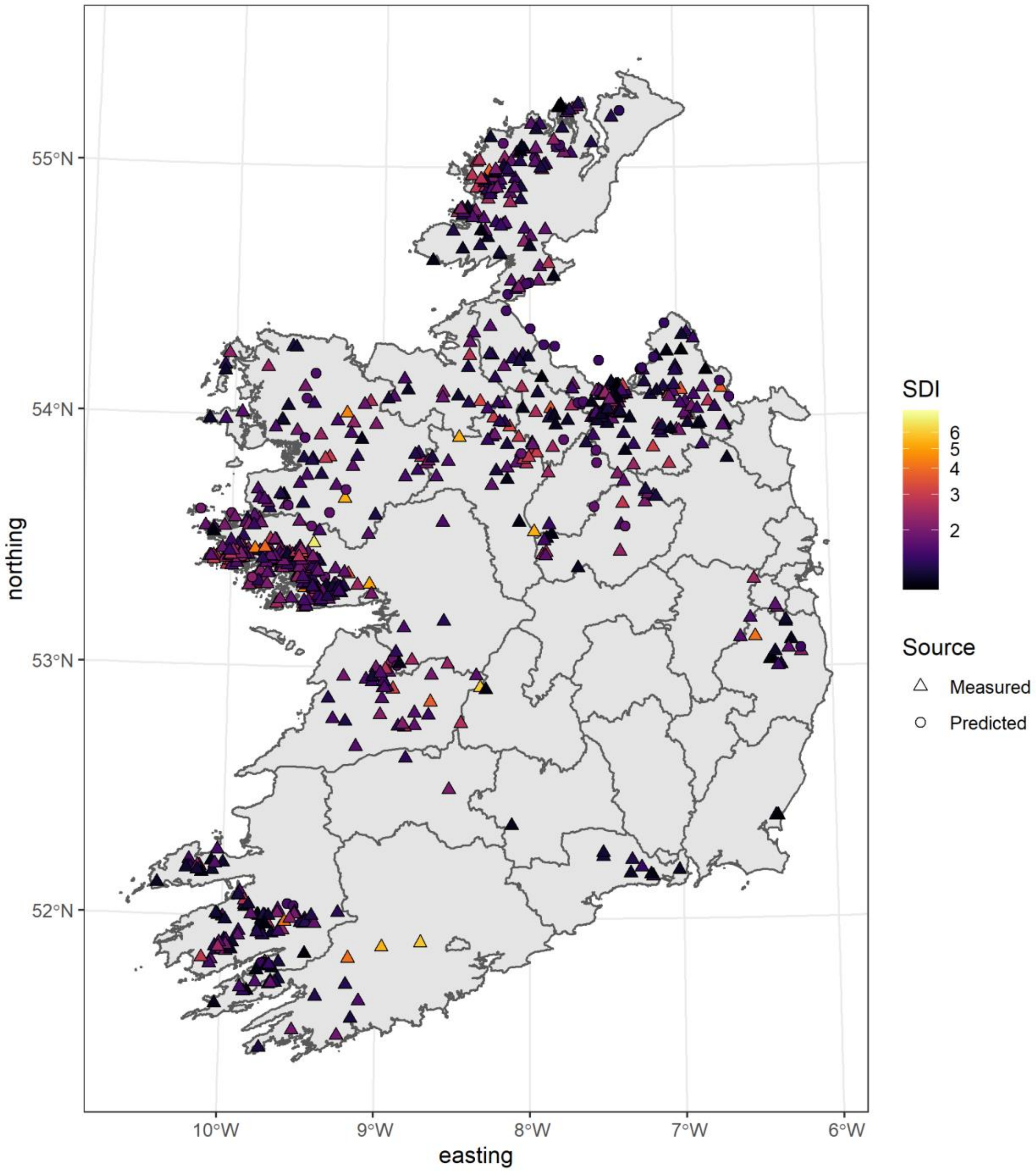

Figure 77: Map of measured and predicted SDI for all 811 lakes

Appendix 2 TP model

```
Family: gaussian
Link function: identity

Formula:
log_tp_mg_l ~ s(easting, northing) + te(log_modelled_tp_mg_l,
    log_residence_time_yr)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.77708    0.01318  -134.8   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                                             edf Ref.df     F p-value
s(easting,northing)                        17.69 22.352 8.221  <2e-16 ***
te(log_modelled_tp_mg_l,log_residence_time_yr)  6.91  8.868 9.420  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.653   Deviance explained = 69.1%
-REML = -16.096  Scale est. = 0.038936   n = 224
```

Figure 78: Statistical summary of the TP model

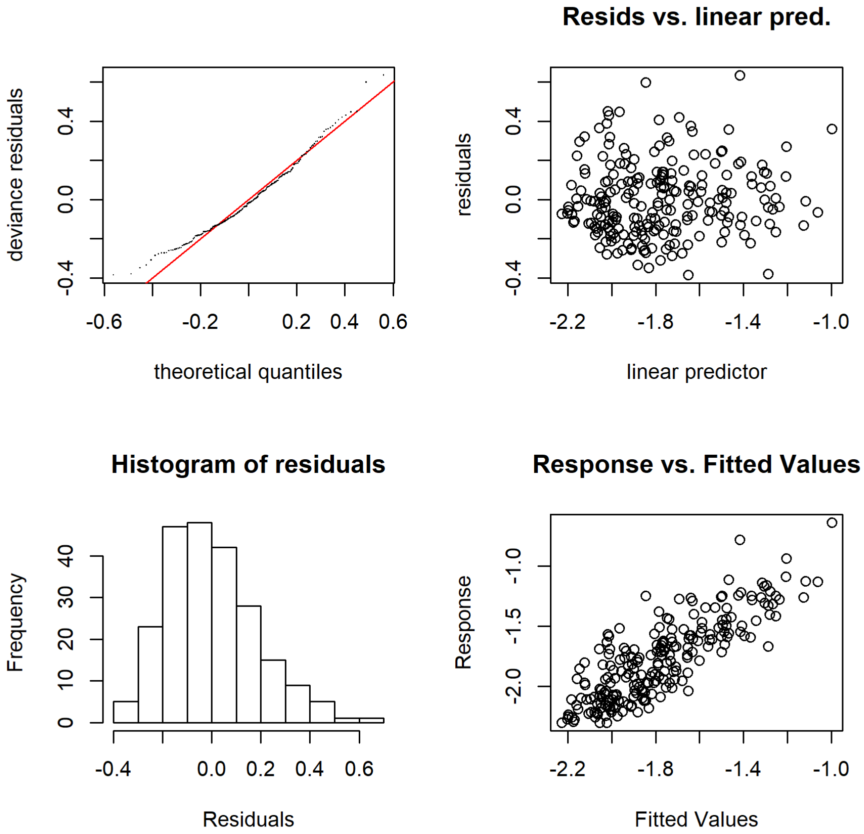

Figure 79: Residuals plots for the TP model

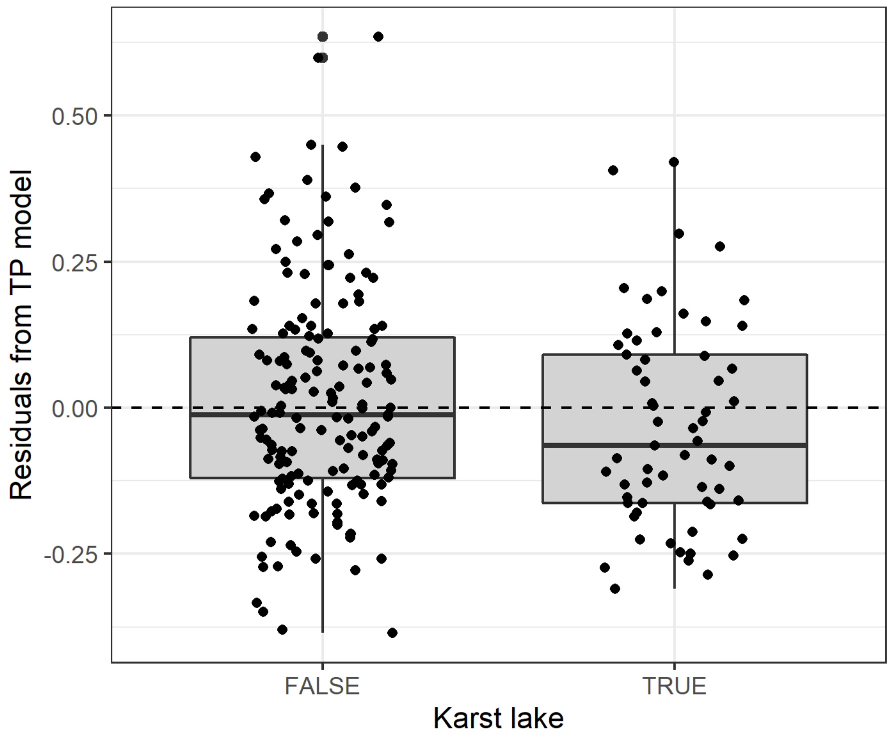

Figure 80: Comparison of residuals from the TP model for lakes in karst catchments (>25% karst geology) and non-karst catchments

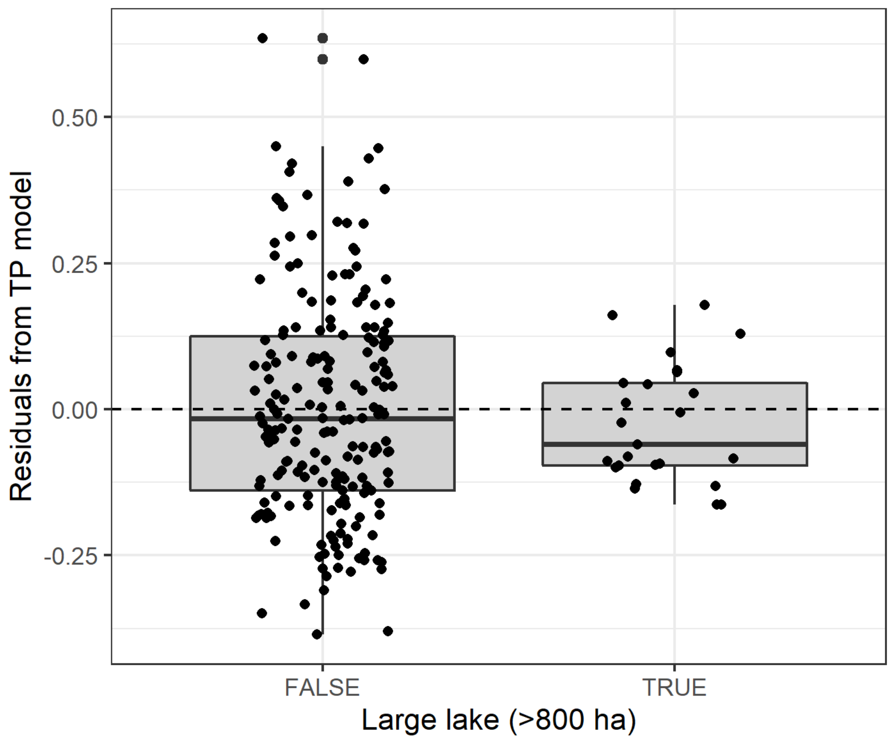

Figure 81: Comparison of residuals from the TP model for the 25 largest lakes and the rest

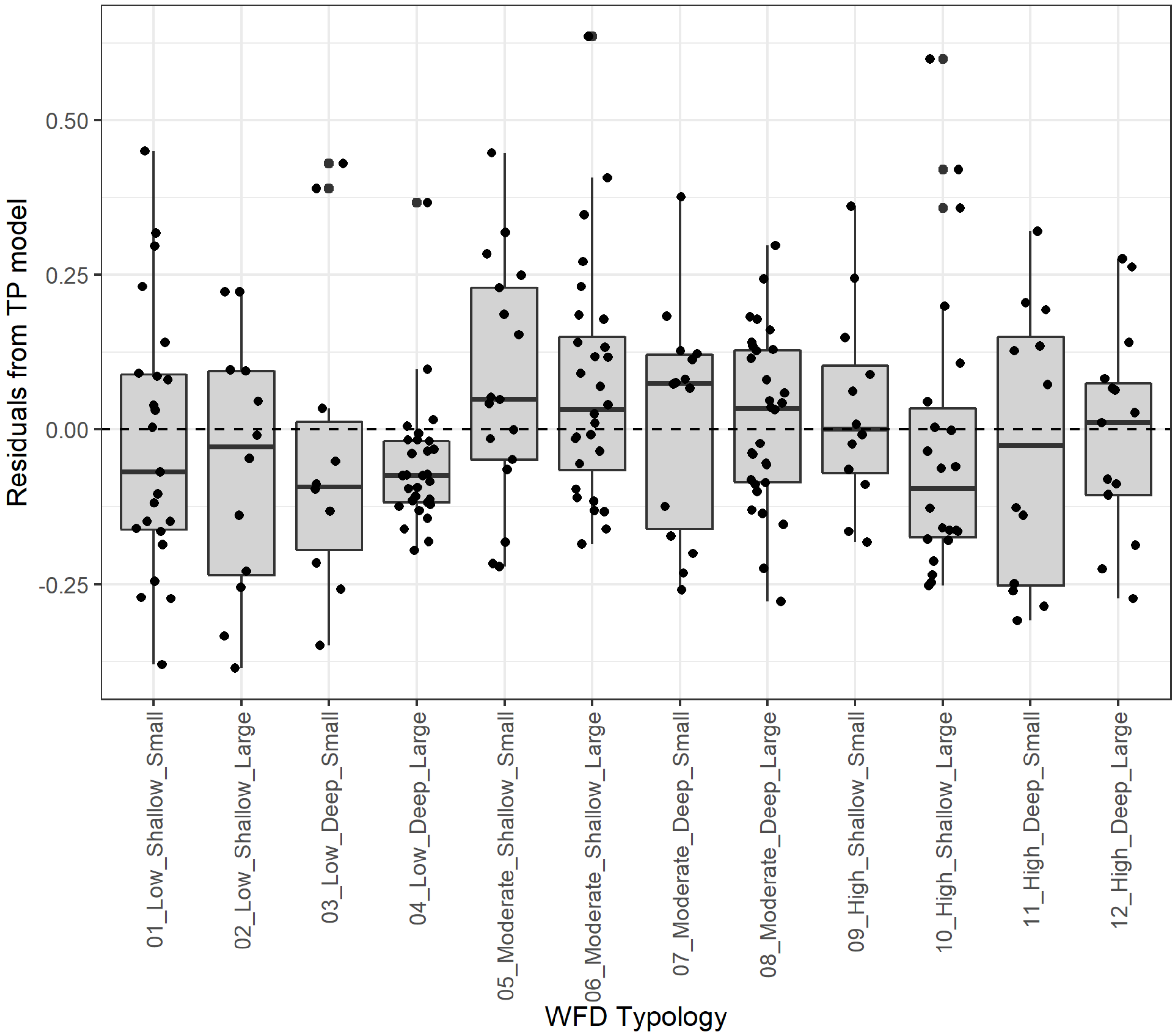

Figure 82: Comparison of residuals from the TP model for the 12 WFD typology groups

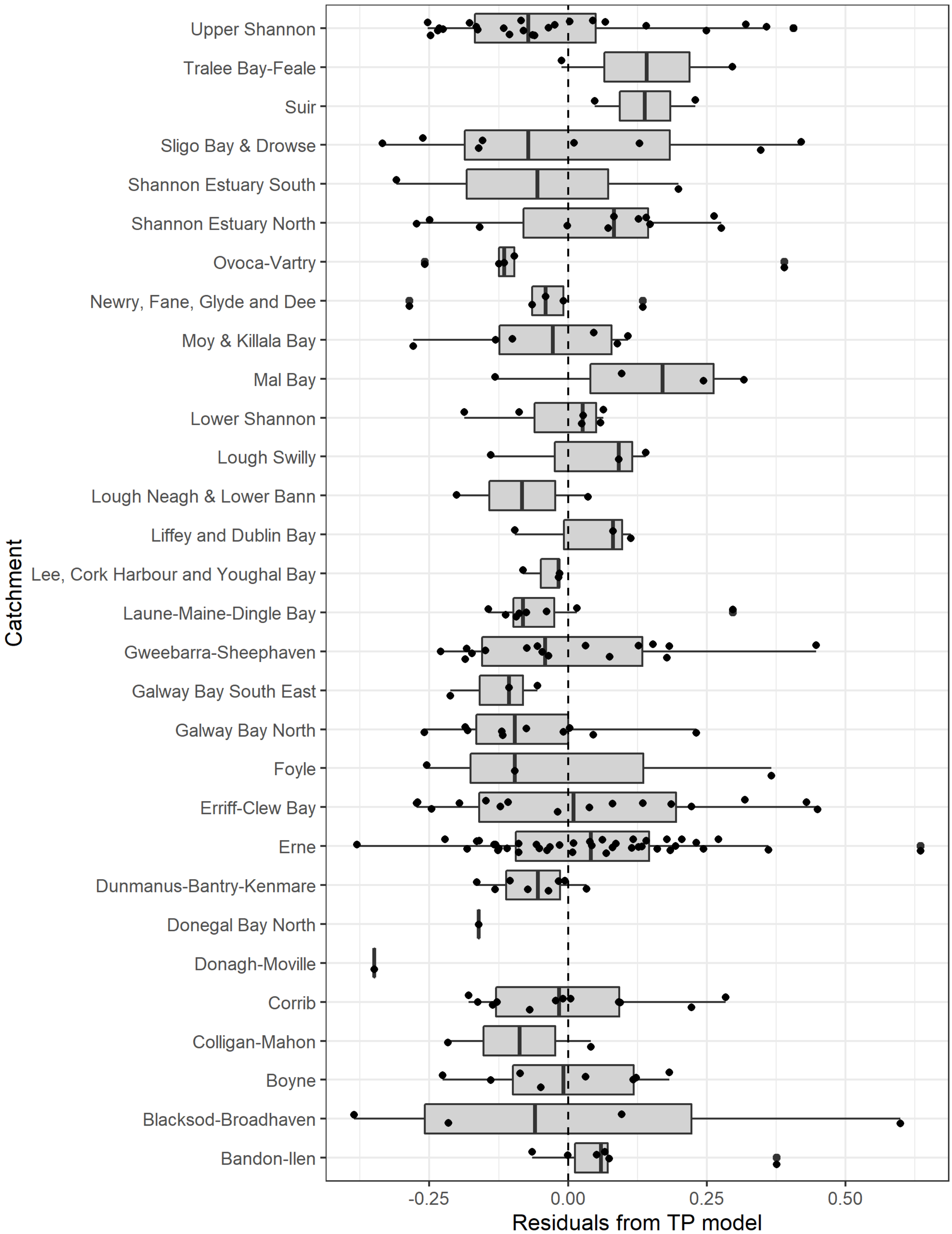

Figure 83: Comparison of residuals from the TP model for the 32 river catchments

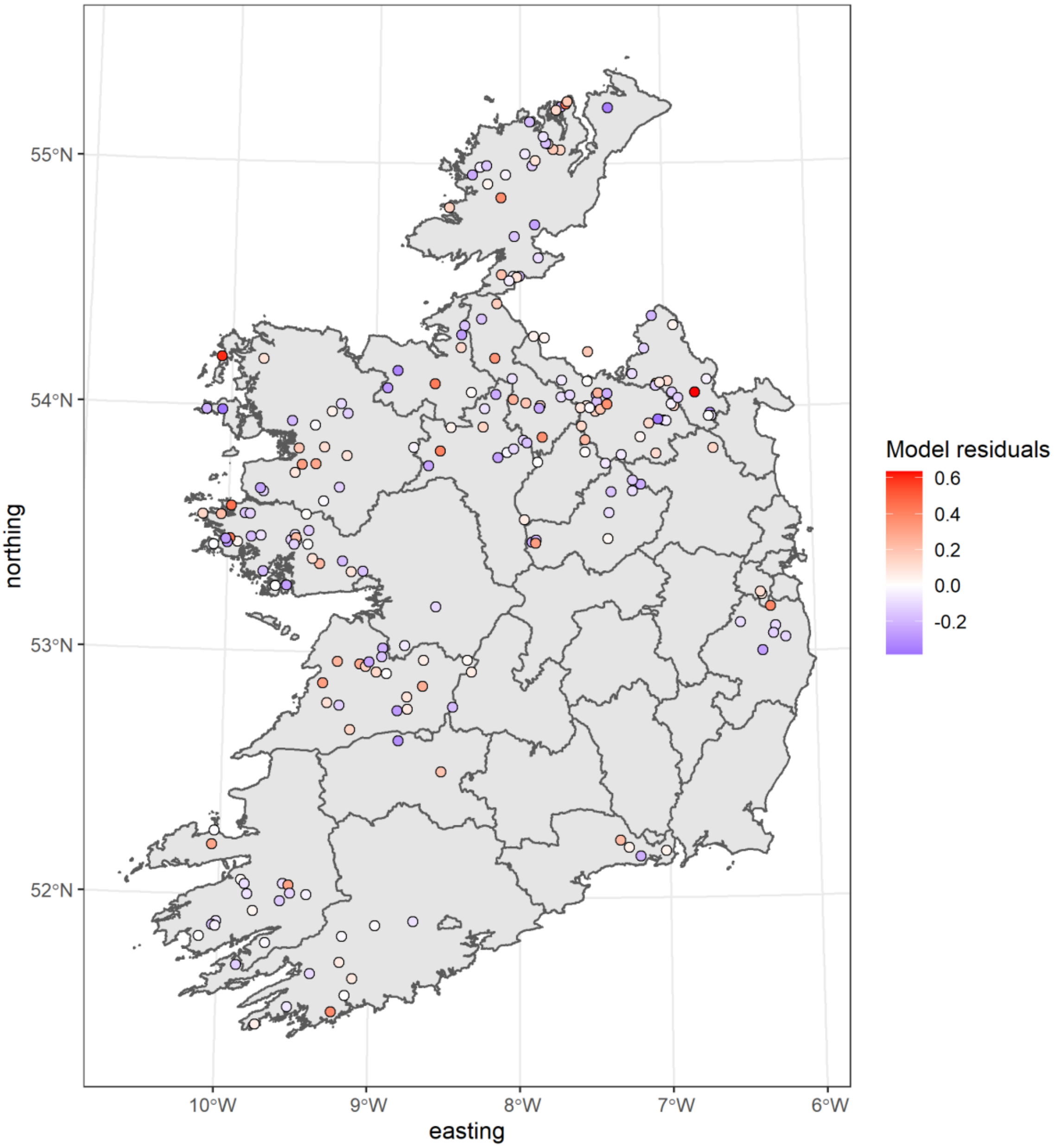

Figure 84: Map of residuals from the TP model showing the difference between measured and predicted log10 TP concentrations in monitored lakes

Table 8: Lakes with the top 10 largest positive and the top 10 largest negative residuals in the TP model

Lake code	Catchment area (km^2)	Lake name	Measured TP	Predicted TP	Residual (log scale)
NW_36_671	6.509	Egish	0.1654	0.0383	0.6348
WE_33_1889	3.039	Cross	0.0568	0.0143	0.5987
WE_32_474	1.878	Tully	0.0270	0.0096	0.4496
NW_38_59	3.315	Kinny	0.0304	0.0109	0.4467
WE_32_402	1.675	Beaghcauneen	0.0261	0.0097	0.4293
WE_35_157	272.653	Templehouse	0.0532	0.0202	0.4198
SH_26_661	2.764	Glinn	0.0418	0.0164	0.4063
EA_10_28	1.455	Bray Lower	0.0233	0.0095	0.3895
SW_20_148	5.827	Abisdealy	0.0545	0.0229	0.3759
NW_01_102	10.379	Finn DL	0.0204	0.0088	0.3662
WE_32_333	5.185	Enask	0.0076	0.0143	-0.2711
WE_32_501	4.607	Fadda	0.0057	0.0106	-0.2730
SH_27_120	51.044	Rosroe	0.0111	0.0209	-0.2732
WE_34_405	5.662	Talt	0.0050	0.0095	-0.2786
NB_06_198	0.57	Spring	0.0098	0.0188	-0.2859
SH_24_90	1.321	Bleach	0.0082	0.0166	-0.3095
WE_35_136	10.678	Easky	0.0061	0.0131	-0.3344
NW_40_2	3.158	Fad Meendoran	0.0066	0.0147	-0.3491
NW_36_272	0.214	Mushlin	0.0215	0.0516	-0.3805
WE_33_1895	12.383	Keel MO	0.0092	0.0223	-0.3855

Appendix 3 Chlorophyll-a model

```
Family: gaussian
Link function: identity

Formula:
chl_eqr ~ te(log_tp_mg_l, alkalinity_final) + s(log_colour_final)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.755042   0.007044   107.2   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                                  edf Ref.df     F  p-value
te(log_tp_mg_l,alkalinity_final) 7.876  8.555 53.23  < 2e-16 ***
s(log_colour_final)              1.706  2.153 13.01 3.16e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.676   Deviance explained =   69%
-REML = -166.77  Scale est. = 0.011115   n = 224
```

Figure 85: Statistical summary of the chlorophyll-a model

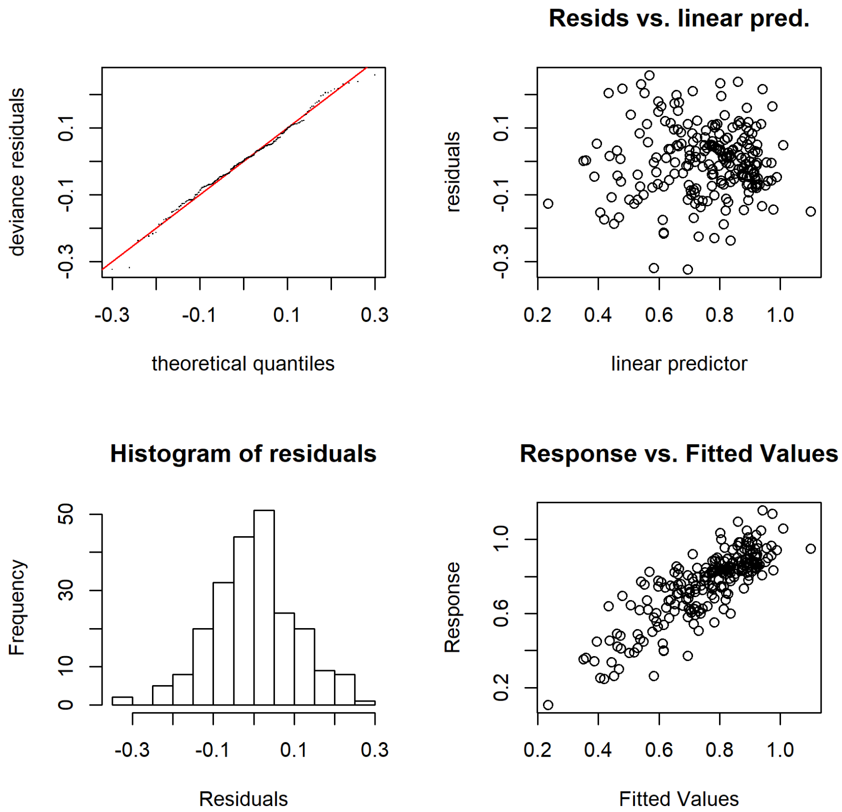

Figure 86: Residuals plots for the chlorophyll-a model

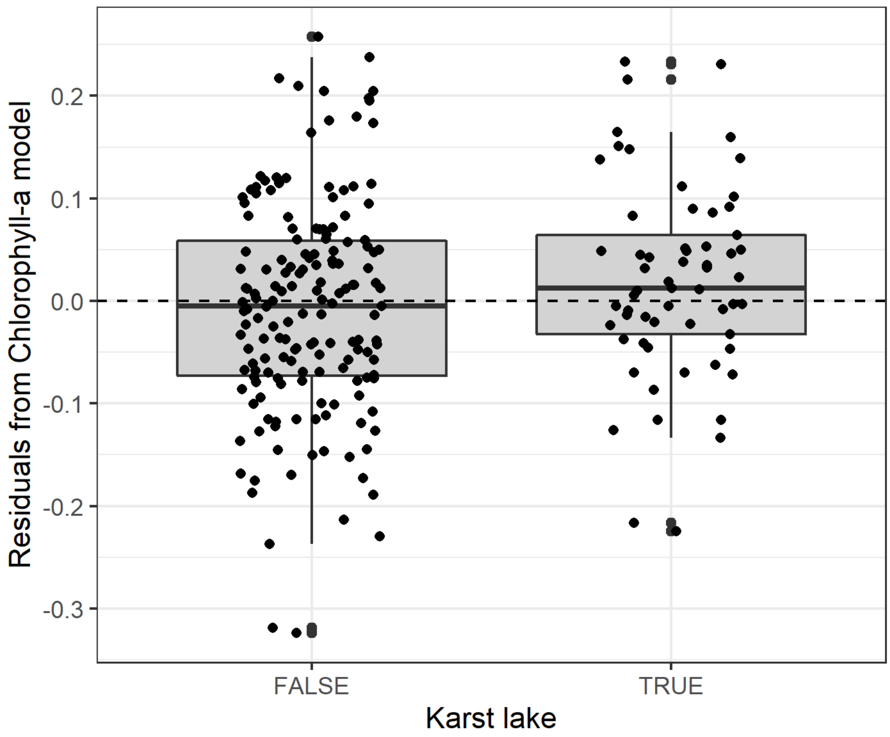

Figure 87: Comparison of residuals from the chlorophyll-a model for lakes in karst catchments (>25% karst geology) and non-karst catchments

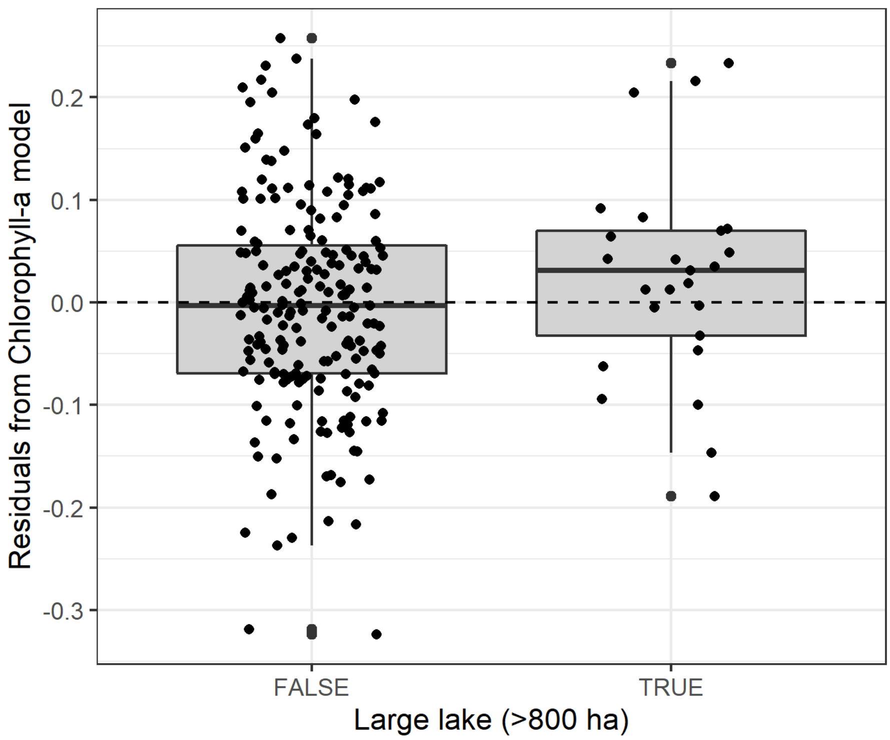

Figure 88: Comparison of residuals from the chlorophyll-a model for the 25 largest lakes and the rest

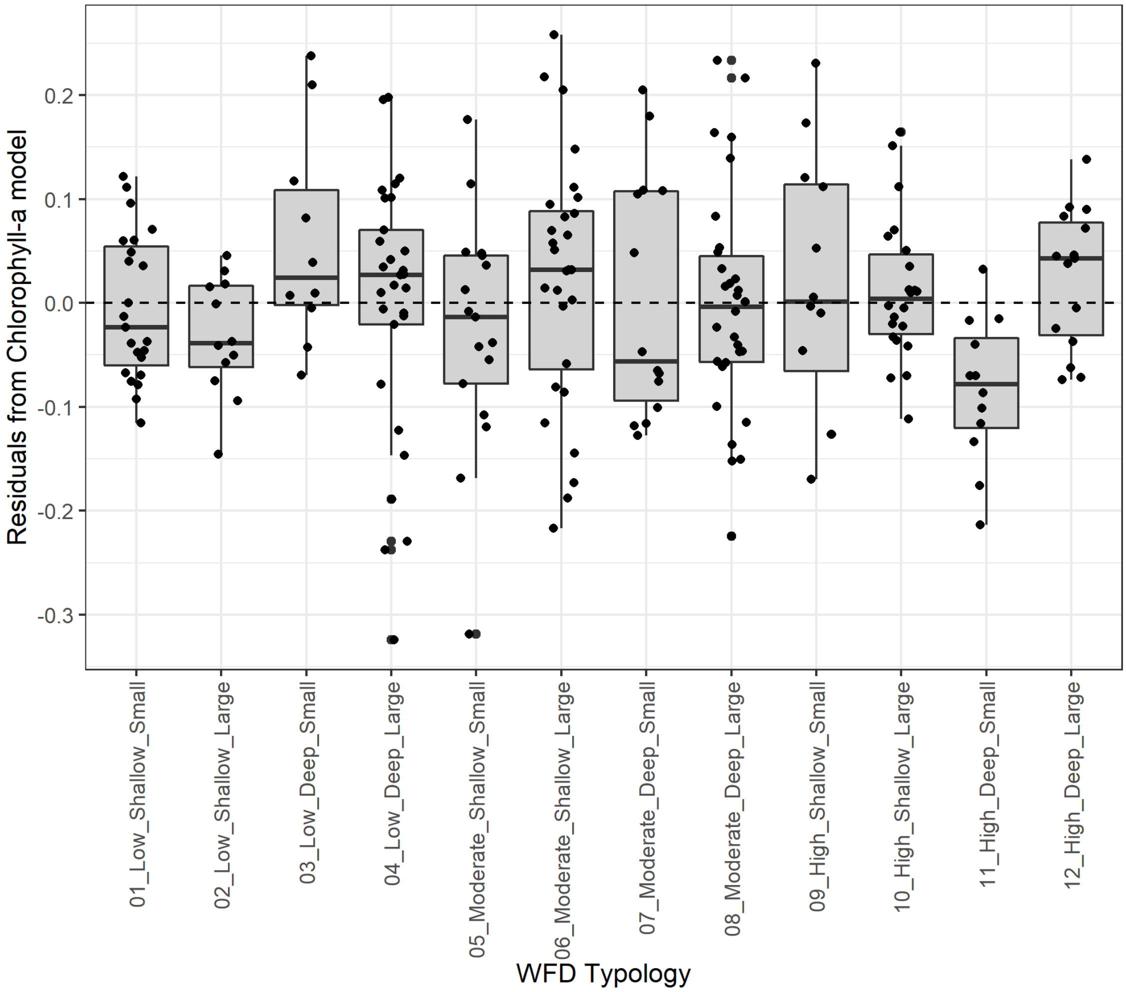

Figure 89: Comparison of residuals from the chlorophyll-a model for the 12 WFD typology groups

Figure 90: Comparison of residuals from the chlorophyll-a model for the 32 river catchments

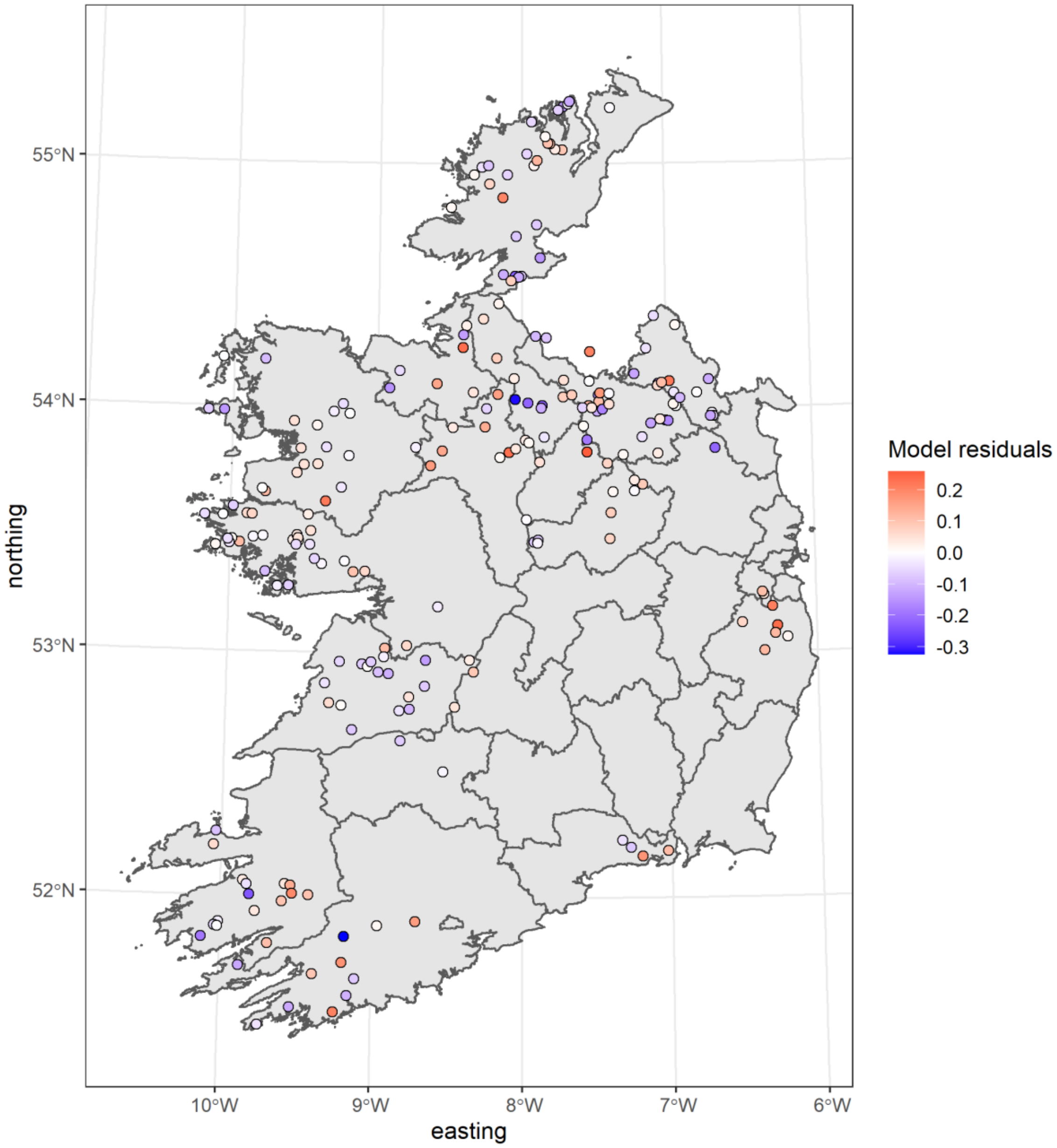

Figure 91: Map of residuals from the chlorophyll-a model showing the difference between measured and predicted chlorophyll-a EQR in monitored lakes

Table 9: Lakes with the top 10 largest positive and the top 10 negative residuals in the chlorophyll-a model

Lake code	Catchment area (km^2)	Lake name	Measured TP	Predicted TP	Log residuals
NW_36_724	254.893	Gowna South	0.8254	0.5677	0.2577
EA_10_25	20.049	Tay	1.0975	0.8600	0.2375
WE_35_158	363.195	Gill SO	1.0354	0.8020	0.2334
SH_26_706	2.772	Grange	0.7716	0.5409	0.2307
NW_36_647	122.615	White Rockcorry	0.6967	0.4795	0.2172
WE_30_665a	875.509	Mask	1.1576	0.9415	0.2161
EA_10_28	1.455	Bray Lower	0.9210	0.7112	0.2098
SW_20_148	5.827	Abisdealy	0.6389	0.4340	0.2048
NW_36_672	3339.332	Erne Upper	0.7562	0.5515	0.2048
NW_01_102	10.379	Finn DL	0.8558	0.6583	0.1975
NW_36_618	1.403	Atrain	0.4368	0.6123	-0.1755
NW_36_723	39.331	Gowna North	0.2633	0.4508	-0.1875
SW_21_457	103.908	Currane	0.6240	0.8131	-0.1891
NB_06_209	0.266	Brackan	0.4015	0.6148	-0.2134
NW_36_665	21.162	Scur	0.3988	0.6155	-0.2167
NW_36_614	2.179	Drumlaheen	0.5064	0.7310	-0.2247
NW_36_715	4.794	Golagh	0.5524	0.7819	-0.2295
SW_22_208	11.168	Acoose	0.5994	0.8368	-0.2374
SH_26_681	0.58	Acres	0.2634	0.5822	-0.3188
SW_19_4	106.956	Allua	0.3707	0.6945	-0.3239

Appendix 4 Macrophytes model

```
Family: gaussian
Link function: identity

Formula:
mac_eqr ~ s(easting, northing) + s(log_tp_mg_l) + s(log_colour_final) +
    s(alkalinity_final)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.635230   0.006602   96.21   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                       edf Ref.df      F  p-value
s(easting,northing) 18.486 23.184  2.975 2.28e-05 ***
s(log_tp_mg_l)       1.000  1.000 68.167  < 2e-16 ***
s(log_colour_final)  2.176  2.741 12.435 1.62e-06 ***
s(alkalinity_final)  4.573  5.561  5.337 7.20e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.753   Deviance explained = 78.2%
-REML = -154.62  Scale est. = 0.0096337  n = 221
```

Figure 92: Statistical summary of the macrophytes model

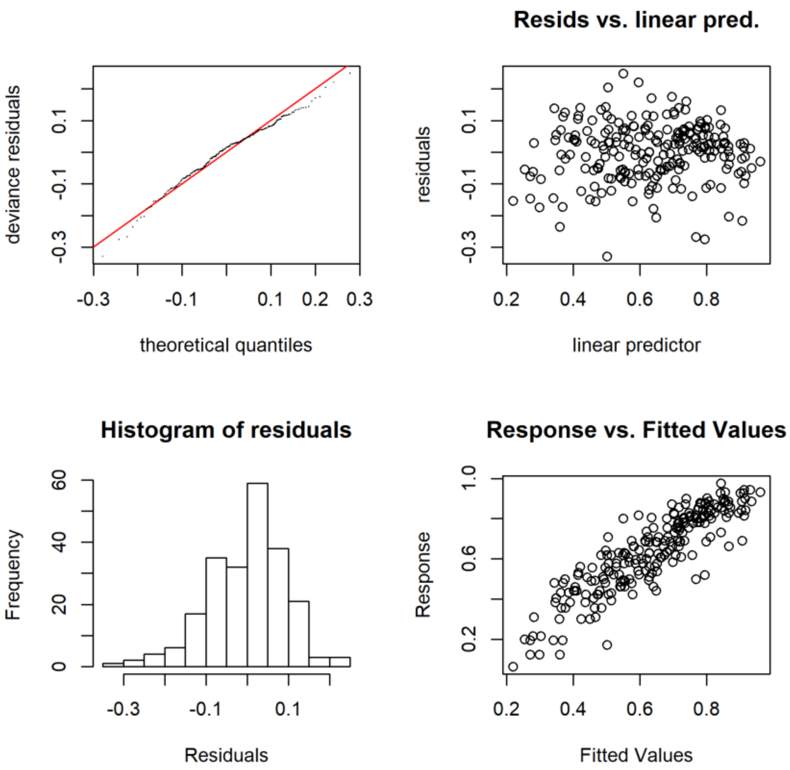

Figure 93: Residuals plots for the macrophytes model

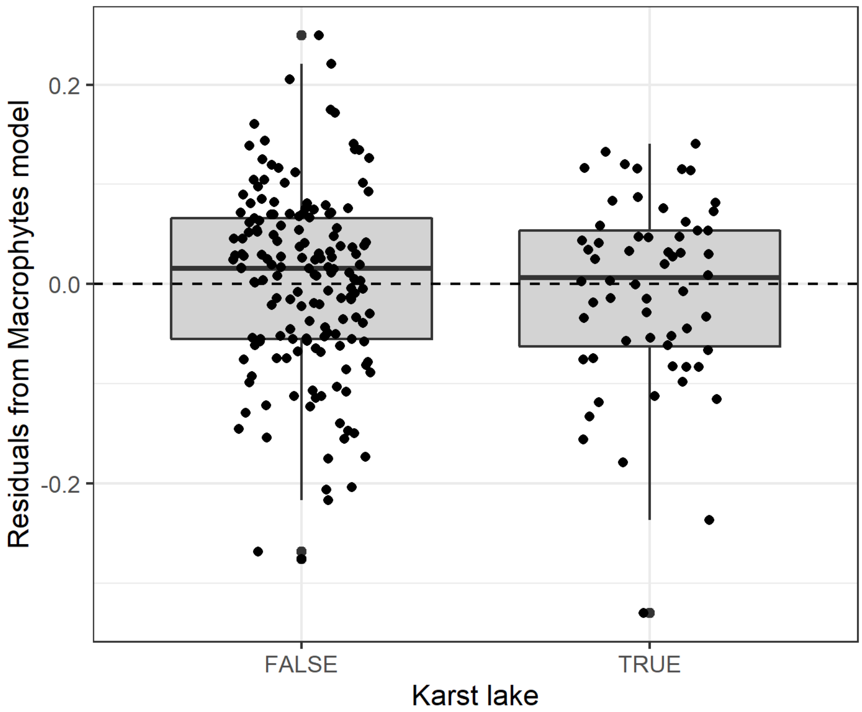

Figure 94: Comparison of residuals from the macrophytes model for lakes in karst catchments (>25% karst geology) and non-karst catchments

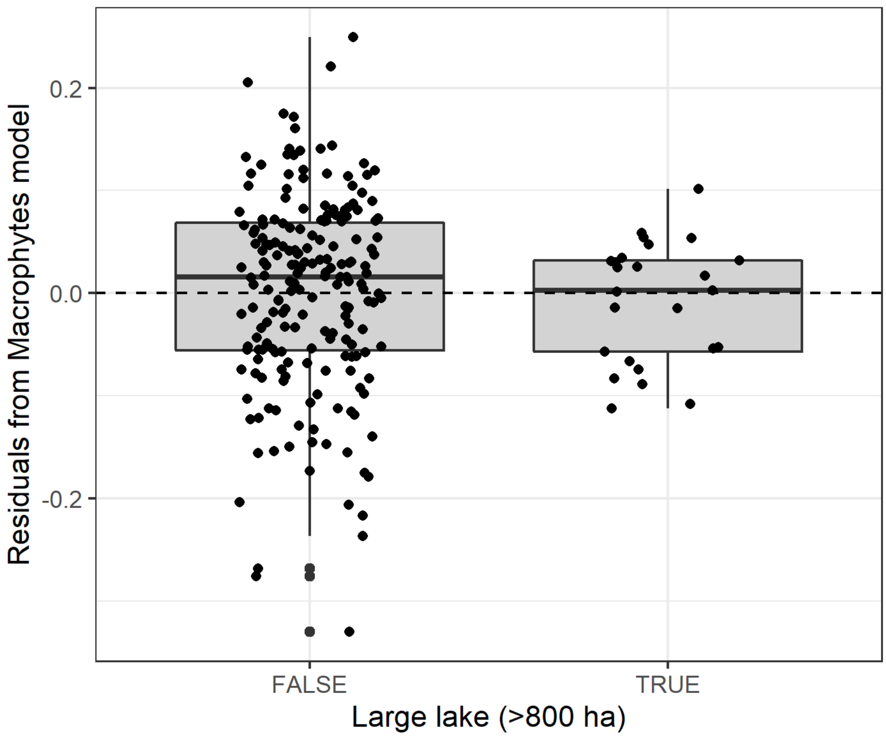

Figure 95: Comparison of residuals from the macrophytes model for the 25 largest lakes and the remaining lakes

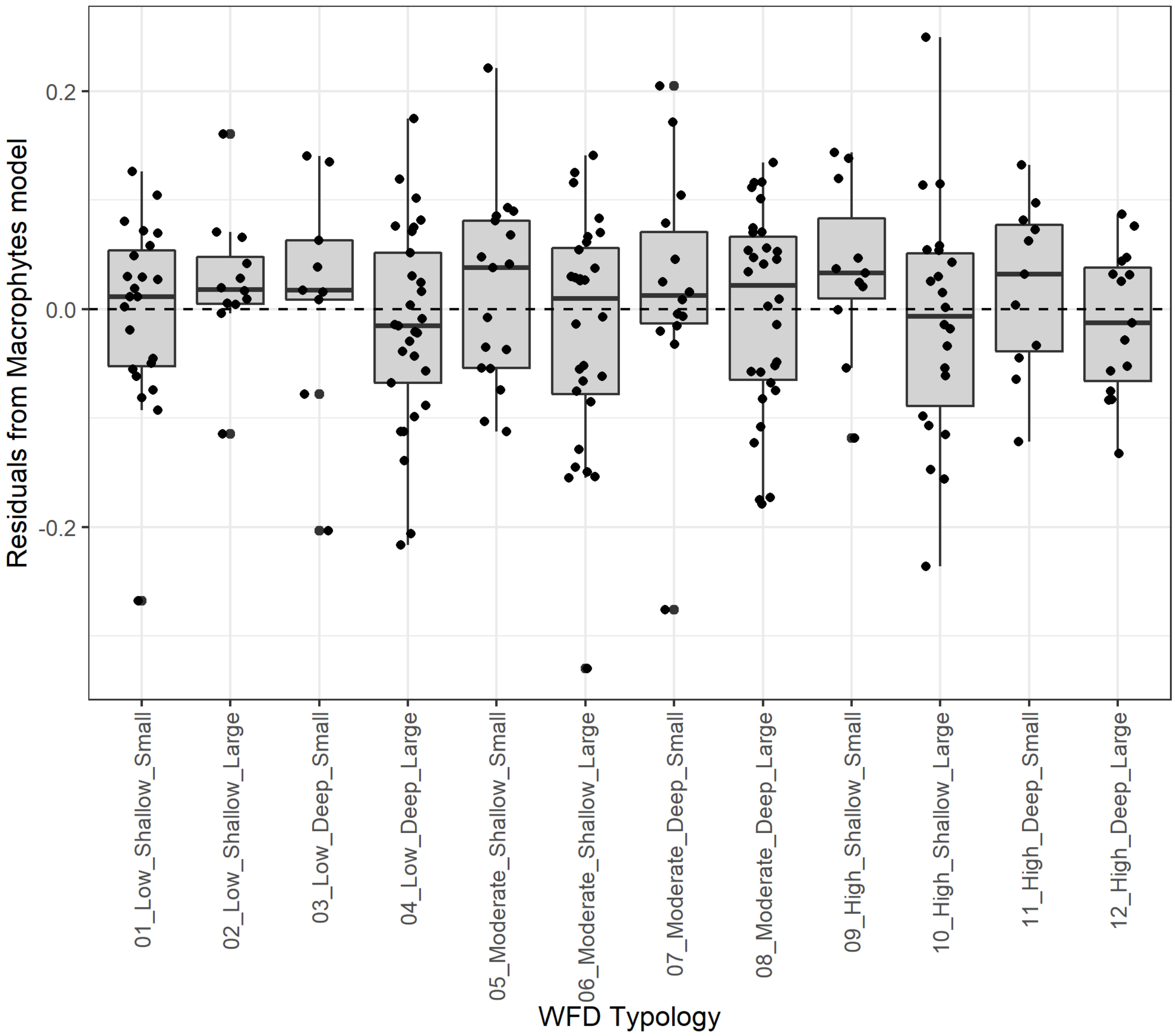

Figure 96: Comparison of residuals from the macrophytes model for the 12 WFD typology groups

Figure 97: Comparison of residuals from the macrophytes model for the 32 river catchments

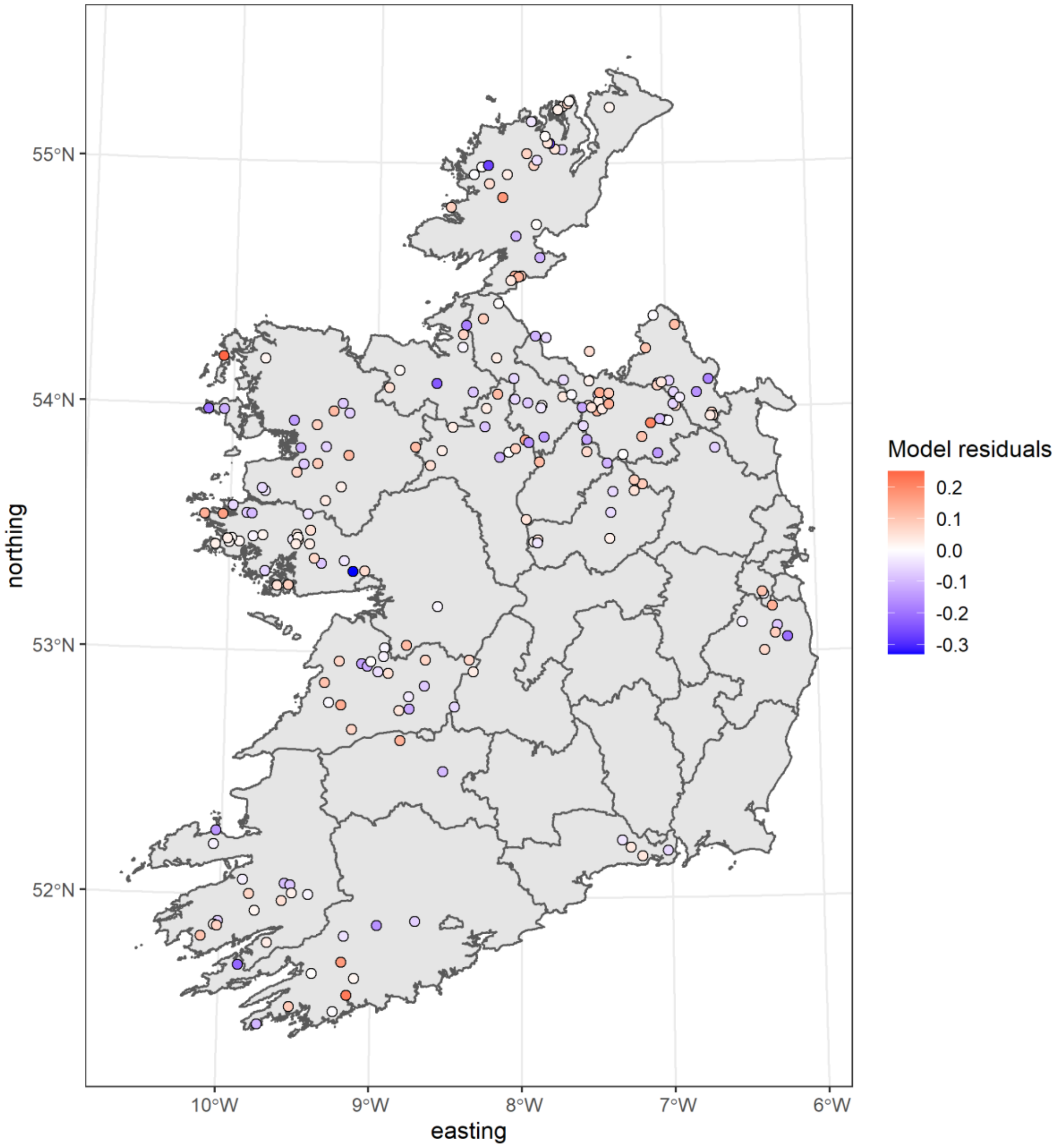

Figure 98: Map of residuals from the macrophytes model showing the difference between measured and predicted macrophytes EQR in monitored lakes

Table 10: Lakes with the top 10 largest positive and the top 10 largest negative residuals in the macrophytes model

Lake code	Catchment area (km^2)	Lake name	Measured TP	Predicted TP	Log residuals
WE_33_1889	3.039	Cross	0.8000	0.5505	0.2495
SW_20_150	1.279	Ballin CK	0.8171	0.5960	0.2211
EA_07_242	0.491	Acurry	0.7091	0.5040	0.2051
NW_01_102	10.379	Finn DL	0.8714	0.6964	0.1751
SW_20_153	3.013	Coolkellure	0.8057	0.6343	0.1714
WE_32_479	5.555	Ballynakill	0.9000	0.7392	0.1608
NW_36_432	1.019	Ardan	0.6409	0.4971	0.1438
SH_26_747b	1817.192	Boderg	0.5615	0.4206	0.1409
SH_28_87	0.898	Naminna	0.8571	0.7167	0.1404
NW_36_564	76.996	Farnharn	0.4808	0.3422	0.1386
EA_07_267	5.312	Skeagh Upper	0.1952	0.3681	-0.1729
NB_06_56	161.61	Muckno	0.1238	0.2987	-0.1749
WE_35_139	39.928	Glencar	0.4615	0.6405	-0.1789
WE_33_1892	1.826	Acorrymore	0.6636	0.8671	-0.2035
EA_10_10	35.502	Varty Lower	0.4423	0.6486	-0.2063
SW_21_444	7.516	Glenbeg	0.6909	0.9075	-0.2165
WE_35_157	272.653	Templehouse	0.1238	0.3601	-0.2363
NW_38_576	3.59	Keel Crotty	0.5000	0.7681	-0.2681
NW_38_649	0.924	Salt	0.5192	0.7950	-0.2758
WE_30_340	77.995	Ballyquirke	0.1714	0.5012	-0.3298

Appendix 5 Averaging status class results

The EPA currently adopts the 'one-out, all-out' method of using the worst performing quality element to determine the overall status of each lake water body. However, WFD guidance also permits the use of averaging for quality elements that respond to the same pressure. The three quality elements analysed in this study – TP, chlorophyll-a and macrophytes – all respond to nutrient enrichment plus the three GAM models are based on the same datasets and are inter-linked, and so there is an argument that the results should be averaged because they're providing similar assessments of trophic status.

For comparative purposes, the overall status class results presented in Section 3.5 (based on one-out, all-out method), were compared with those produced by averaging the status classes for TP, chlorophyll-a and macrophytes. In practice, averaging was achieved by converting the five WFD status classes (High to Bad) to numerical values (1 to 5), averaging the numerical values, rounding to the nearest integer, and then converting back to the corresponding WFD status class, as illustrated in Table 11 below. In most cases, this averaging method gives a higher (better) assessment of overall status than the one-out, all-out method, and is very similar to finding the median (middle) of the three status classes.

Table 11: Comparison of methods for combining results across three quality elements to derive an overall status class

Status classes of individual quality elements	Scores of individual quality elements	Average score	Average status	Worst (One-out, all-out) status	Median status
Moderate, Moderate, Moderate	3, 3, 3	3.00	Moderate	Moderate	Moderate
Good, Moderate, Moderate	2, 3, 3	2.67	Moderate	Moderate	Moderate
Moderate, Moderate, Poor	3, 3, 4	3.33	Moderate	Poor	Moderate
High, Moderate, Moderate	1, 3, 3	2.33	Good	Moderate	Moderate
Moderate, Moderate, Bad	3, 3, 5	3.67	Poor	Bad	Moderate
Good, Moderate, Poor	2, 3, 4	3.00	Moderate	Poor	Moderate
Good, Moderate, Bad	2, 3, 5	3.33	Moderate	Bad	Moderate
High, Moderate, Poor	1, 3, 4	2.67	Moderate	Poor	Moderate
High, Moderate, Bad	1, 3, 5	3.00	Moderate	Bad	Moderate
High, Good, Bad	1, 2, 5	2.67	Moderate	Bad	Good
High, Poor, Bad	1, 4, 5	3.33	Moderate	Bad	Poor

As expected, the averaging method gives substantially higher status class results (80% at High or Good status) than the one-out, all-out method (69% at High or Good status) for the 811 lakes considered in this project (**Error! Reference source not found.**).

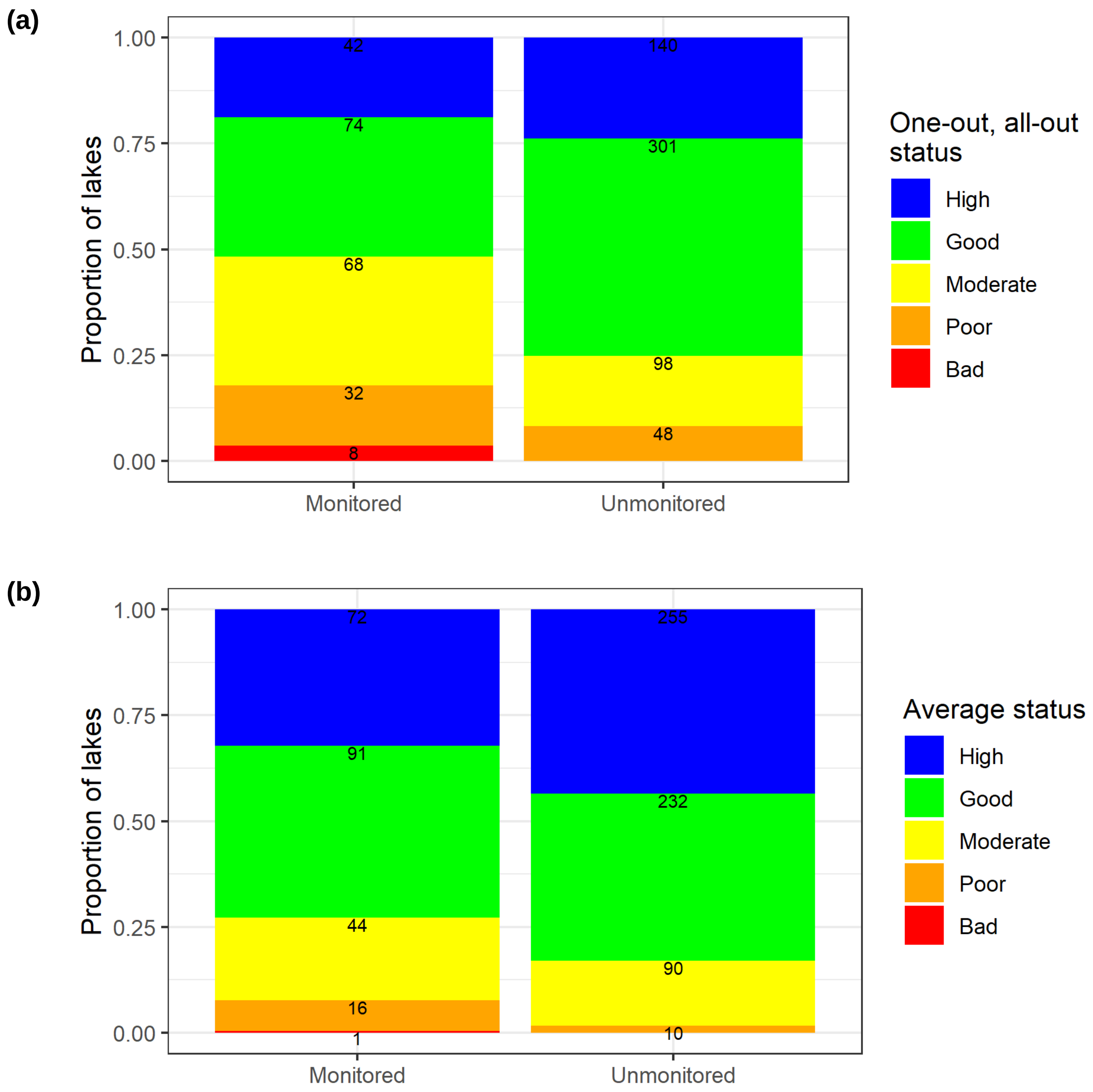

Figure 99: Overall status calculated using the one-out, all-out (a) and averaging (b) method