Environmental Protection Agency

Extrapolation of water status to unmonitored river water bodies

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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 (RBMP) and programme of measures to be developed and implemented, with the status of every identified 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.

Ireland has a total of 3192 WFD river water bodies (RWBs). It is not economically feasible, and nor is it expected that every RWB would be monitored for every quality element, and around 25% of RWBs are not monitored at all, or only for selected quality elements. In the absence of sampling data, the status of unmonitored RWBs must be "extrapolated" using an appropriate approach.

For Cycle 1 reporting in 2008, the Environmental Protection Agency (EPA) used a statistical algorithm (k-means clustering) to group RWBs into 20 groups based on their typology, catchment pressures and risk assessments; unmonitored RWBs were then assigned a status from the closest nearby RWB that was found within the same cluster and within the same hydrometric area (Bradley & Wilkes, 2022). This is termed the "donor extrapolation" method. A similar approach, with additional validation using supplementary data, was used more recently to classify unmonitored RWBs for the 2013-2018 reporting period. In the final assessment, 3,113 out of 3192 RWBs (98%) were assigned an ecological status. A total of 2,381 RWBs had their status defined using available monitoring data (EPA & NIEA) while 514 RWBs were defined using donor extrapolation. A further 218 RWBs were defined using expert judgement, with 79 RWBs remaining unassigned (Bradley & Wilkes, 2022).

The EPA has recently been considering alternative methods for applying WFD status to unmonitored water bodies. As part of this, APEM was commissioned by the EPA to assign a WFD status to unmonitored Irish lakes. That study (APEM, 2022a) successfully developed and applied a new regression-modelling approach, which provided new insights into the key factors determining the trophic status of lakes and was also able to quantify the degree of confidence in the status class predictions.

This report builds on that study (APEM, 2022a) by developing and applying a series of statistical regression models to predict the ecological status of unmonitored RWBs.

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 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 alongside other physical features and anthropogenic stressors to calibrate statistical models that are capable of predicting the status of unmonitored RWBs 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 rivers.

The specific objectives were to:

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

1.4 Scope

This study focused on a population of 3192 RWBs. These cover the whole of the Republic of Ireland and include 26 RWBs which cross the border into Northern Ireland, plus three which are located entirely within Northern Ireland (Crilly Feeder, Fury River, Derryhooley Tributary). Data sources were incomplete for some cross-border RWBs, so results for these RWBs should be treated with caution.

The study focused on predicting the WFD status class of the two quality elements that most commonly determine the overall ecological status of RWBs: Molybdate Reactive Phosphorus (MRP) and macroinvertebrates (Q-values). Nitrate is another important nutrient affecting the WFD status of surface water bodies[1], but it was not included in this study because there is no Environmental Quality Standard (EQS) for nitrate in rivers, and because phosphorus rather than nitrogen is usually the limiting nutrient in

[1] The EPA considers a three year average of <0.9 mg/l as N to be indicative of High status and <1.8 mg/l as N indicative of Good status. In 2019-2021, nitrate was monitored at 1557 sites in 667 RWBs, of which 892 sites were classed as Good or better.

freshwaters. The status class predictions for the two quality elements were combined using the one-out, all-out rule to predict an overall ecological status for RWBs that were unmonitored for MRP and/or macroinvertebrates.

Of the 3192 RWBs assessed, 2281 are covered by the EPA's national river monitoring programme. The study used monitoring data collected between 2019 and 2021 to calibrate statistical models, which were then used to predict the ecological status of unmonitored RWBs 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 chemical/physical attributes.

1.5 Report structure

This report is structured to illustrate the process through which RWB 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 WFD typology, including the approach and analysis undertaken to calculate typology where this information was not available, and a description of the different RWB characteristics tested as potential predictors of status.
- **Chapter 3: Classification of RWBs based on anthropogenic stressors and physical features.** This chapter outlines the methods used to model MRP concentration and status, and macroinvertebrate Q-value status. 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 river (more detail is provided in the Appendices). It also includes the classification of river with high uncertainty. This chapter provides a framework to assist with expert judgement, where a predicted RWB status has a large margin of error associated with it.
- **Chapter 4: Discussion and Recommendations.** This chapter discusses the different model performances, the strength of this approach, and the associated limitations. 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 as an Excel spreadsheet which forms an electronic appendix to this report.

2. Data sources and data processing

2.1 Conceptual model

To aid decisions about which variables to include when developing a predictive model of WFD status, a conceptual framework was built based on existing knowledge of the mechanisms of river eutrophication, and other anthropogenic pressures.

In Ireland, the most commonly encountered forms of pollution in rivers are eutrophication and organic pollution. Less frequently encountered are non-organic types of pollution such as toxic pollution (e.g., by sheep treatment or industrial chemicals), siltation (e.g. arising from livestock access, over-grazing, drainage and erosion, or quarrying operations) and acidification in sensitive afforested areas. Additionally, hydromorphological alteration to river channels can have influential and adverse effects on aquatic organisms (Feeley et al, 2020; Trodd *et al.*, 2022). Given these pressures, the key quality elements used by the EPA for assessing the status of Irish rivers are MRP concentration and the macroinvertebrate Q-value metric, which is based on the sensitivity of invertebrate taxa to reduced oxygen concentrations (Toner *et al.*, 2005), used as a general indicator of biological quality in rivers (Trodd & O'Boyle, 2021) and known to be responsive to catchment urbanisation, agricultural intensity, and water quality (Donohue *et al*., 2006)

The most recent Water Quality in Ireland report (Trodd *et al.*, 2022) indicated that 50% of RWBs were at less than Good status, with declines in both number of High and Good status water bodies, and identified declines in overall quality. The quality element responsible for determining ecological status in the largest number of RWBs was macroinvertebrate Q-value, and overall physico-chemical status of rivers was influenced primarily by their nutrient status (Trodd *et al.*, 2022). However, as a biological metric, the Q-value is not a determinant of quality in its own right, but an indicator of quality, in this case the processes affecting the chemical and physical condition of the river. It is important therefore to understand the key pressures and processes influencing the status of RWBs.

The source / pathway / receptor model describes the variables driving the response of a receptor (such as a river and its ecological status) to a source of pollution, 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 is linked to a receptor e.g., for the example above, runoff pathways that can result in excess fertiliser entering the river.
- **Receptor:** the element of the receiving environment that is affected and the impact on it, e.g., for the above example, nutrient enrichment from fertiliser

leading to excessive algal or bacterial growth and deterioration of riverbed habitat in rivers.

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 use a knowledge of these processes to predict the overall ecological status of unmonitored RWBs.

The Source Load Apportionment Model (SLAM) is a modelling framework developed by the EPA that predicts nutrient inputs from different sources within the catchment to receiving water bodies (Mockler *et al.*, 2016, 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 characterise source-pathway-receptor relationships. SLAM also takes into account the effect of wastewater treatment processes in reducing phosphorus losses from effluent discharges. The output of the model is an estimate of the annual average nutrient load to each RWB.

SLAM estimates load of total phosphorus (TP), which provides a direct predictor of nutrient enrichment and, as much nutrient input is associated with other forms of pollution such as organic inputs, can also provide somewhat of a proxy for these. Where it is important to distinguish largely nutrient inputs (e.g., inorganic fertiliser spraying, treated effluent discharge) from inputs associated with organic matter (e.g. sludge spreading, direct losses from farmyards) then levels of oxygen saturation and ammonia concentration, where measured, can be used to distinguish these.

The SLAM model accounts only for TP, however for rivers the WFD environmental quality standard is based on biologically available MRP. TP will always be greater than MRP, and the phosphorus that is biologically available will be reduced over time, for example through its incorporation in particulate matter which removes phosphorus from the water. These processes are not explicitly modelled within the SLAM framework, but post-hoc adjustments can be made to account for phosphorus retention within larger rivers. For the purposes of this project, TP was used as a proxy for MRP, which allows a reasonable worst-case scenario to be modelled.

Although SLAM is unable to calculate loads of biologically available MRP, it is able to calculate the relative contribution of various point sources (such as wastewater and industrial discharges) and diffuse sources (such as forestry, pasture, arable land, diffuse urban sources and septic tank systems), which typically have differing proportions of dissolved and particulate phosphorus. Partitioning the SLAM-modelled TP loads in this way therefore provides an indirect way of accounting for differing levels of bio-availability from different sources, and of gauging the relative contribution of different sources to measured in-river MRP concentrations.

The processes by which anthropogenic nutrient enrichment results in adverse effects on the biological communities of rivers are highly complex, with effects on the competitive balance between plant species, consequent effects on the fauna dependent on the plant community for food, shelter and reproduction, and the influence of biological feedback mechanisms and a range of environmental factors (some themselves anthropogenically influenced) on the manifestation of key eutrophication symptoms (Mainstone, 2010). Ecological communities are fundamentally shaped by the natural characteristics of the river, which are driven by factors such as catchment and site geology. Key factors are the nature of the flow regime (flashy, stable etc,), substrate types, alkalinity and pH, all of which are highly inter-related.

In the absence of data for many of these variables, and in an attempt to simplify a complex set of interactions, the present study used river typology as a surrogate for ecological sensitivity to nutrient enrichment. In Ireland, the river water body typology is based on water hardness (using % calcareous geology as a proxy) and channel slope (Kelly-Quinn *et al.,* 2005; see Section 2.4 for details). Although there is active scientific debate regarding the relative sensitivity of hard water and soft water rivers to elevated nutrient concentrations (Mainstone, 2010), water hardness has a fundamental influence on the composition of ecological communities in rivers, and is a proxy for geochemical processes that affect the mobilisation and transport of nutrients within the catchment. Channel slope influences in-stream hydraulic habitat (water depth, velocity) and substrate, which in turn influences the composition of the macroinvertebrate community (Kelly-Quinn *et al.*, 2019) and opportunities for nutrient retention via uptake and sedimentation (Brett & Benjamin, 2008).

As well as responding to changes in chemical water quality, macroinvertebrate communities are influenced by physical habitat quality, and adversely impacted by artificial modifications such channelisation, land drainage, barriers, culverts, embankments, overgrazing and bank erosion, which combine to reduce longitudinal and lateral connectivity, decrease habitat diversity and suitability, and lower ecological resilience to high and low flow events (e.g. Donohue *et al*., 2006; Dunbar *et al.*, 2010). During 2016-2021 hydromorphology was assessed at 384 river sites using the River Hydromorphological Assessment Technique (RHAT). This is a supporting element for high-status sites and resulted in 146 RWBs being classed as Good rather than High status (Trodd *et al.*, 2022). In the present study, the EPA's Morphological Quality Index (MQI) was used to characterise the hydromorphological condition of RWBs. MQI is a desk-based technique that yields a suite of hydromorphological condition assessment scores (Quinlan and Mockler, 2020), which were then used as predictors of macroinvertebrate status.

The contribution of the above factors to models of MRP concentration and macroinvertebrate status are illustrated in Figure 1.

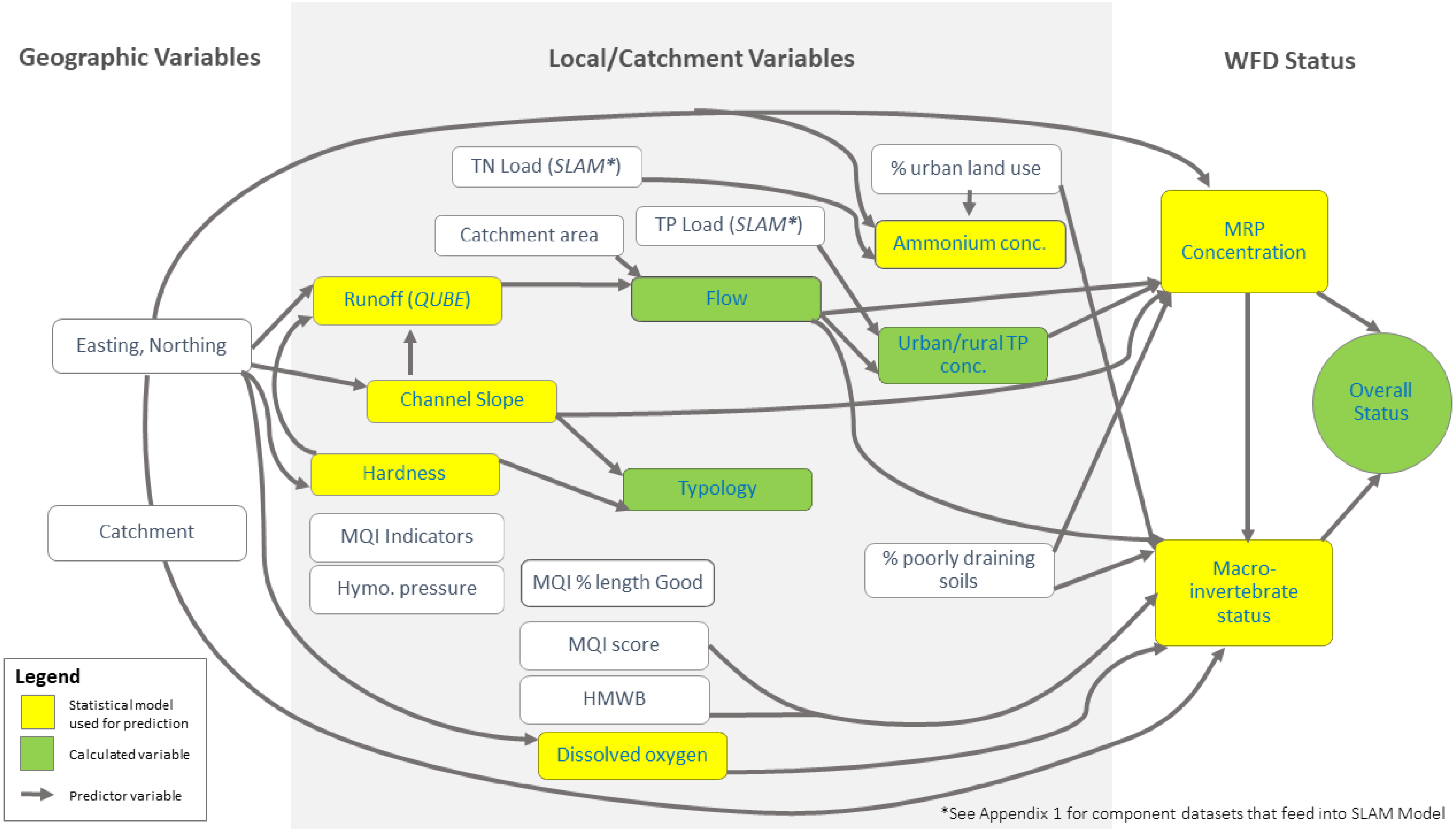

Figure 1: Flow chart summarising the variables used to predict the ecological status of unmonitored RWBs

For clarity the arrows only denote the factors retained in the final models.

2.2 WFD monitoring programme

2.2.1 Phosphorus

Phosphorus in rivers is reported as a concentration of the phosphorus component of the biologically reactive form, MRP, based on a three-year mean. The EQS is <0.025 mg/l P for High status and <0.035 mg/l P for Good status (Environmental Protection Agency, 2019; Table 1).

Table 1: WFD Environmental quality standards for MRP

MRP concentration (mg/l P)	Status class
<0.025	High
<0.035	Good
<0.05	Moderate
<0.1	Poor
≥0.1	Bad

During 2019-21, MRP was monitored in 1317 RWBs (41% of the total). Based on results for the *defining station* in each RWB (i.e. the furthest downstream), 858 RWBs were classed as Good or better, with 646 achieving High status. (Figure 2; Table 2). The remaining 1875 (or 59%) of RWBs were unmonitored.

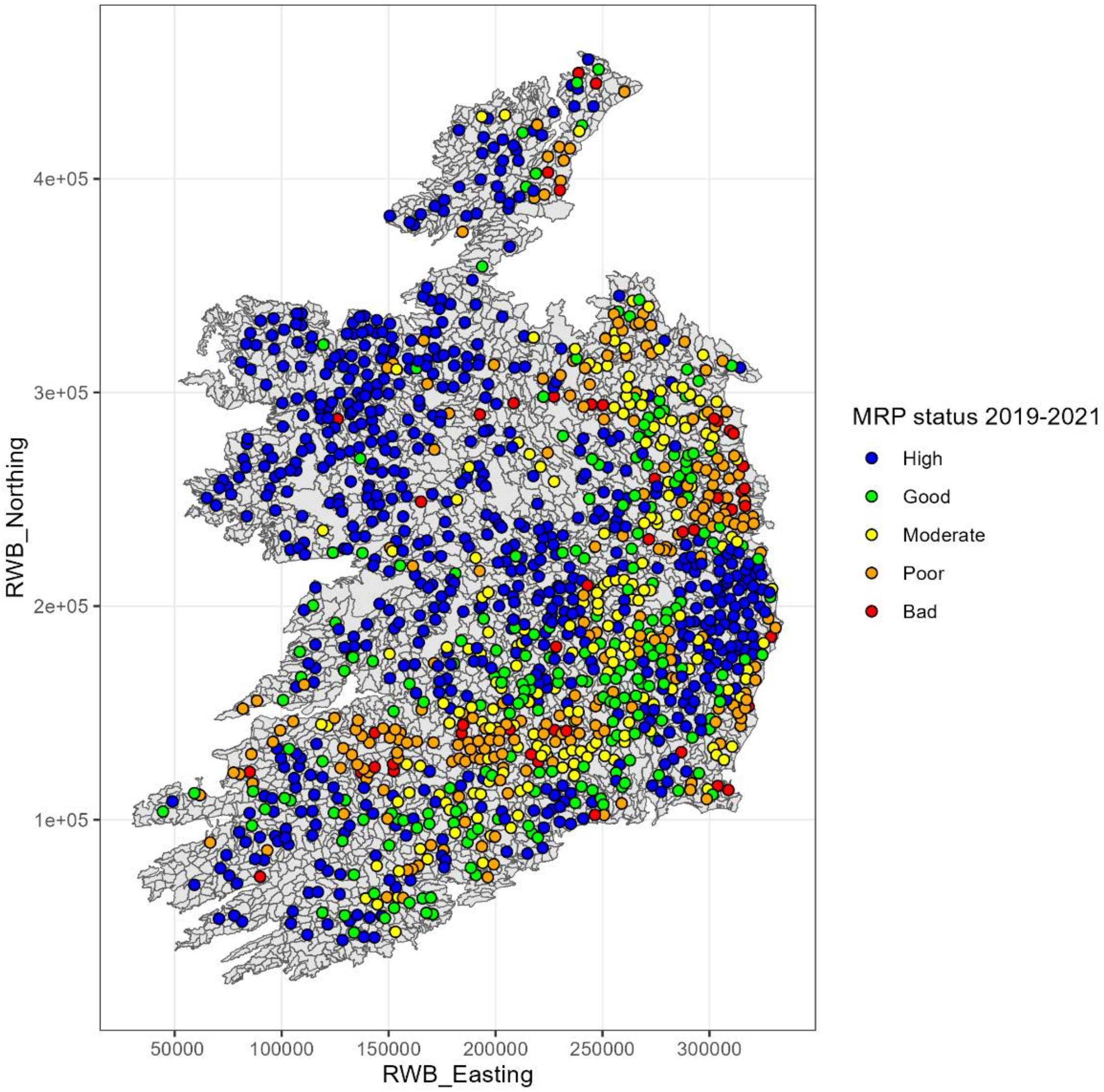

Figure 2: Map of water body-scale 2019-21 MRP status in monitored RWBs

Table 2: Summary of 2019-21 MRP status, by RWB

WFD status class	No. of monitored RWBs
High	646
Good	212
Moderate	189
Poor	223
Bad	47
Total	**1317**

2.2.1 Macroinvertebrates

Benthic macroinvertebrates are the main biological quality element used to assess the WFD status of rivers in Ireland. The Q-value system, described by Toner *et al*. (2005) and Feeley *et al.* (2020), is a qualitative assessment technique that combines information about the diversity and abundance of different macroinvertebrate taxonomic groups to yield a Quality (Q) value between 1 and 5. Other observational information (algae, macrophytes, sewage fungus, dissolved oxygen saturation and siltation) may also be used by the surveyor to increase the confidence in their assignment. These Q-values are then converted to EQRs and, in turn, to WFD status classes, as shown in Table 3.

Table 3: Macroinvertebrate Q-values and associated EQRs and WFD status classes

Q-value score	EQR	WFD status	Pollution gradient
Q4-5, Q5	≥ 0.90	High	Unpolluted
Q4	0.80 – 0.89	Good	Unpolluted
Q3-4	0.70 – 0.79	Moderate	Slightly polluted
Q2-3, Q3	0.50 – 0.69	Poor	Moderately polluted
Q1, Q1-2, Q2	<0.50	Bad	Seriously polluted

Adapted from Feeley et al., 2020

During 2019-21, a total of 2896 sites in 2370 RWBs were classified for macroinvertebrates using the Q-values. Where two or more sites were monitored within a RWB, the poorest performing site determined the status class of the RWB. This may or may not be the *defining station*, the furthest downstream monitoring site in the RWB. As the present study utilises a range of other datasets that describe conditions at the water body outlet, it was decided to model macroinvertebrate status at the defining station within each monitored RWB. Using the defining station results only, 1394 RWBs were classed as Good or better, none were classed as Bad. Over two-thirds of monitored water bodies fell into either the Good or Moderate status bands, indicating that many RWBs were close to the Good Ecological Status (GES) boundary (Figure 3; Table 4). The remaining 822 (or 26%) of RWBs were unmonitored.

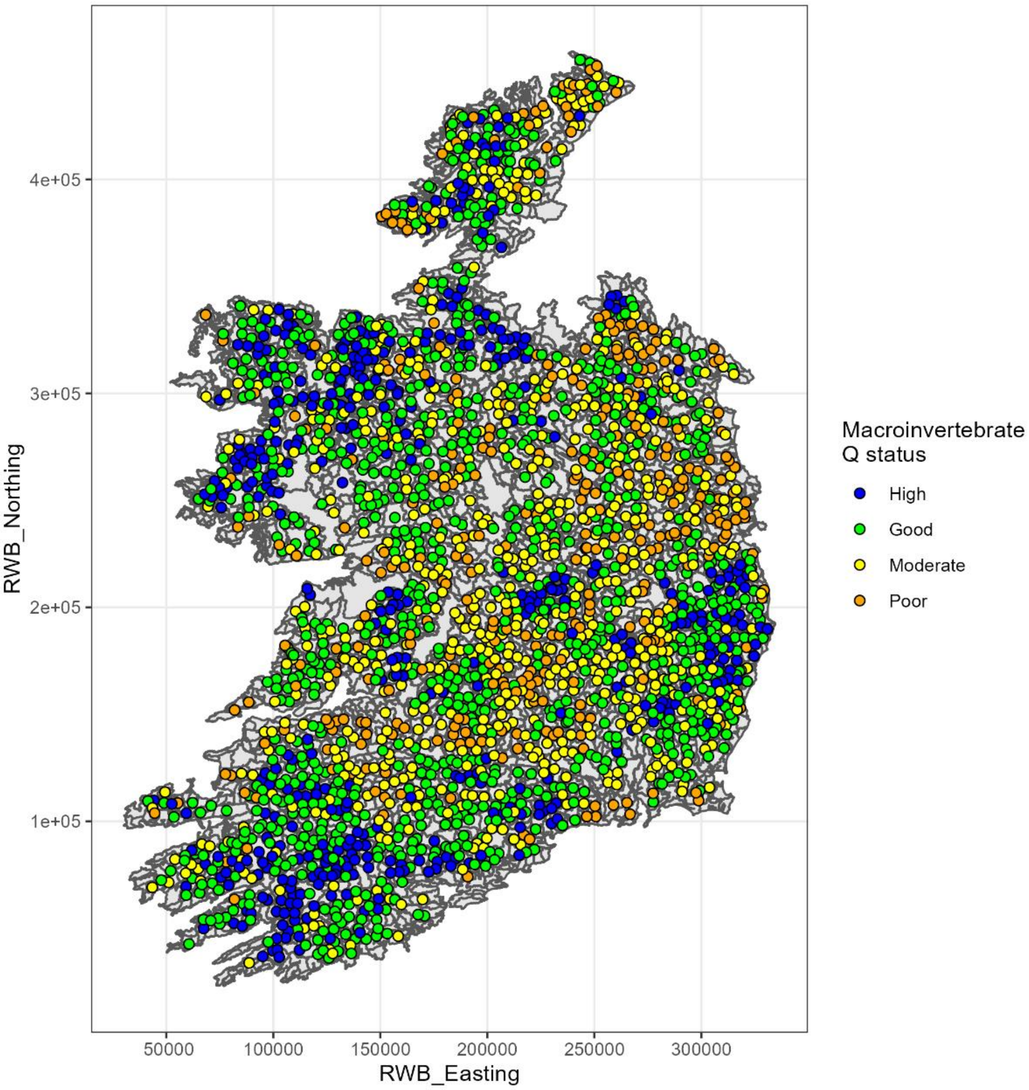

Figure 3: Map of 2019-21 macroinvertebrate status at defining stations in monitored RWBs

Table 4: Summary of 2019-21 macroinvertebrate status at defining stations, by RWB

WFD Status class	No. of monitored RWBs
High	435
Good	959
Moderate	630
Poor	346
Bad	0
Total	**2370**

Overall, 1317 RWBs were monitored for MRP and 2370 for macroinvertebrates and, of these, 1212 RWBs were "fully monitored" for both quality elements.

2.3 River and catchment characteristics

A variety of variables, listed in Table 5, were assembled to describe the characteristics of each RWB and its upstream catchment. Full details of how these variables were derived are provided in Appendix 1.

Table 5: National-, catchment- and local-scale variables used to model MRP concentration and macroinvertebrate status

Variable (units)	Description and derivation	Relevance	References
National Variables			
Easting, Northing	River centroid location (projected in TM65 / Irish National Grid)	Used to account for large-scale geographic variation among rivers.	
Catchment Variables – describe the characteristics of each RWB's catchment			
Catchment	The overall catchment of each RWB. There are 40 catchments defined, as the Shannon is split into several catchments.	To account for catchment-scale differences.	
Catchment area (km^2)	The catchment area draining to the water body outlet. 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 estimate flow in each water body.	Foy *et al*. (2003); Nõges (2009)
Runoff ($m^3/km^2/yr$)	Annual mean naturalised runoff across the upstream catchment, estimated for 2802 RWBs using the QUBE model and predicted using a statistical model for the remaining 390 RWBs.	Influences the mobilisation and transport of nutrients.	Bree (2018)
Flow (m^3/yr)	The annual mean discharge at the RWB outlet, calculated by multiplying the modelled annual runoff by the RWB's catchment area.	A proxy for river size. Influences dilution of phosphorus loads and time available for nutrient update/retention.	

Variable (units)	Description and derivation	Relevance	References
Soil type (%)	The percentage of peaty, well-drained, poorly drained and very poorly drained subsoils within the catchment.	Influences run-off, land use, mobilisation and transport of nutrients, and susceptibility to acidification impacts.	Hem (1985); Meybeck *et al*. (1996)
Upstream urban/rural total phosphorus loading (mg/l)	SLAM v303 provided an estimate of the annual load (kg/yr) of total phosphorus (TP) from land within each RWB. TP is worst-case estimate of MRP loading to the RWB. These loads were aggregated across each RWB's upstream catchment (i.e., excluding loads from the focal RWB itself). Headwater RWBs have no water bodies upstream and so have a loading of 0. SLAM allows TP from different sources to be estimated. The TP load was therefore split into "urban" sources from homes and businesses (wastewater, diffuse urban, septic tanks and other licensed discharges) and "rural" land-based sources (pasture, arable, forestry, peatlands and atmospheric deposition on water). The annual TP load (kg/yr, converted to mg/yr) was then divided by the annual flow (m3/yr, converted to l/yr) at the RWB outlet to estimate the annual mean flow-weighted TP concentration in each RWB (mg/l) due to "upstream" sources.	Estimate of external nutrient pressure from the catchment area upstream of each RWB.	Mockler *et al*. (2017)
Total nitrogen loading (mg/l)	SLAM v303 provided an estimate of the annual load (kg/yr) of total nitrogen (TN) from all sources for each RWB catchment. This load was then divided by the annual flow (m3/yr, converted to l/yr) at the RWB outlet to estimate the annual mean flow-weighted TN concentration in each RWB (mg/l).	Estimate of external nutrient pressure on each RWB.	Mockler *et al*. (2017)

Variable (units)	Description and derivation	Relevance	References
Upstream MRP	The measured MRP concentration in the RWB immediately upstream of the focal RWB. Where an RWB had more than one upstream RWB, the measurement for the largest RWB was used.	Estimate of MRP flowing into an RWB from upstream sources.	

Variable (units)	Description and derivation	Relevance	References
Local variables – describe the characteristics of each RWB			
Hardness	Percentage calcareous geology in bedrock, derived from 2017 GIS data. Also available categorised (low, medium and high hardness) for RWB typology.	An indicator of catchment geology and therefore water chemistry.	Kelly-Quinn *et al*. (2005)
Mean channel slope (m/m)	The average slope of the river. Derived from 2017 GIS data. Also available categorised (low, medium, high and very high slope) for RWB typology.	Catchment slope may influence the hydrology within the catchment, including run-off potential and the importance of surface water pathways.	Greene *et al*. (2013) Kelly-Quinn *et al*. (2005)
Local urban/rural total phosphorus loading (mg/l)	SLAM v303 provided an estimate of the annual load (kg/yr) of total phosphorus (TP) from land within each RWB (i.e., excluding the upstream catchment). TP is worst-case estimate of MRP loading to the RWB. SLAM allows TP from different sources to be estimated. The TP load was therefore split into “urban” (wastewater, diffuse urban, septic tanks and other licensed discharges) and “rural” (pasture, arable, forestry, peatlands and atmospheric deposition on water) sources. The annual TP load (kg/yr, converted to mg/yr) was then divided by the annual flow (m3/yr, converted to l/yr) at the RWB outlet to estimate the annual mean flow-weighted TP concentration in each RWB (mg/l) due to “local” sources.	Estimate of external nutrient pressure within each RWB.	Mockler *et al*. (2017)
Dissolved oxygen saturation (%)	The average percentage saturation of dissolved oxygen in the RWB, averaged over a 3 year period (2019-21). Measured for 1393 RWBs and predicted using a statistical model for the remaining 1799 RWBs (see Appendix 1 for details).	Potential water quality stressor on macroinvertebrate communities.	

Variable (units)	Description and derivation	Relevance	References
Ammonium concentration (mg/l N)	The annual mean ammonium concentration in the river water, averaged over a 3 year period (2019-21). Measured for 1320 RWBs and predicted using a statistical model for the remaining 1872 RWBs (see Appendix 1 for details).	Potential water quality stressor on macroinvertebrate communities.	
Abstraction pressure	A flag indicating whether or not abstraction is having a significant influence on flows in the RWB.	Potential flow stressor on macroinvertebrate communities.	
Morphological Quality Index (MQI)	An indication of habitat quality as a result of anthropogenic alterations to the form of an RWB. Measured on a scale from 0-1, with one indicating high habitat quality.	Potential habitat stressor on macroinvertebrate communities.	Rinaldi *et al.* (2013)
Length of the RWB assessed as good for MQI	The percentage of the overall length of the RWB which was assessed as being at least of Good quality for MQI	Potential habitat stressor on macroinvertebrate communities.	
Hydro-morphological pressure	A flag indicating the presence (1) or absence (0) of different hydromorphological pressures: channelisation, land drainage, barriers, culverts, embankments, overgrazing and bank erosion.	Potential habitat stressor on macroinvertebrate communities.	
MQI Indicators	MQI sub-scores assessing the impact of different hydromorphological pressures on the overall habitat quality. The indicators used were: F1: Longitudinal continuity in sediment and wood flux; F3: River corridor connectivity; F5: Presence of a potentially erodible corridor; F7: Planform pattern and cross-section variability; A13: Historic modification (within cut/reclaimed peat).	Potential habitat stressor on macroinvertebrate communities.	Quinlan and Mockler (2020)
Soil type (%)	The percentage of poorly drained subsoils within the RWB.	Influences run-off, land use, mobilisation and transport of nutrients, and susceptibility to acidification impacts.	Hem (1985); Meybeck *et al*. (1996)

Variable (units)	Description and derivation	Relevance	References
Urban land use (%)	Percentage of land within the focal RWB which has been urbanised	Indicator of potential stressors on macroinvertebrate communities.	
Heavily modified water body	A flag indicating whether the RWB is considered to be heavily modified. The reasons for this flag being assigned include navigation, flood protection, arterial drainage and water storage.	Indicator of potential flow and/or habitat stressors on macroinvertebrate communities.	

2.4 WFD Typology

The WFD requires that surface water bodies be differentiated according to type, so that any differences in biological indicator communities are able to detect differences 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 rivers in Ireland is based on Kelly-Quinn *et al.* (2005), who showed that river hardness and mean channel slope were the most important factors explaining natural variation in river biological communities (Table 6). Hardness is grouped into categories, labelled from 1 to 3 based on increasing calcareous geology in the catchment. Slope is similarly divided into categories labelled from 1 to 4 based on increasing gradient. Each RWB is assigned a two-digit typology category, with the first digit relating to the hardness category and the second to slope category.

Table 6 Typology of Irish river water bodies, based on hardness and channel slope

Hardness (% calc. geology)		Slope (m/m)			
Codes		1	2	3	4
	Code values	<0.005	0.005-0.02	0.02-0.04	>0.04
1	0%	11	12	13	14
2	1-25%	21	22	23	24
3	>25%	31	32	33	34

For this project, it was important to know the typology of every RWB so that any influences of hardness and slope could be taken into account when predicting WFD status. Typology information was provided by the EPA for all except the 26 cross-border RWBs where the slope and water hardness categories were instead derived from modelled estimates of slope and % calcareous geology (See Appendix 1).

Using a combination of measured and predicted data, each of the 3192 RWBs was assigned to a typology category (Figure 4). Hard water rivers with gentle slopes (types 31 and 32) are the most numerous, accounting for ~43% of all RWBs.

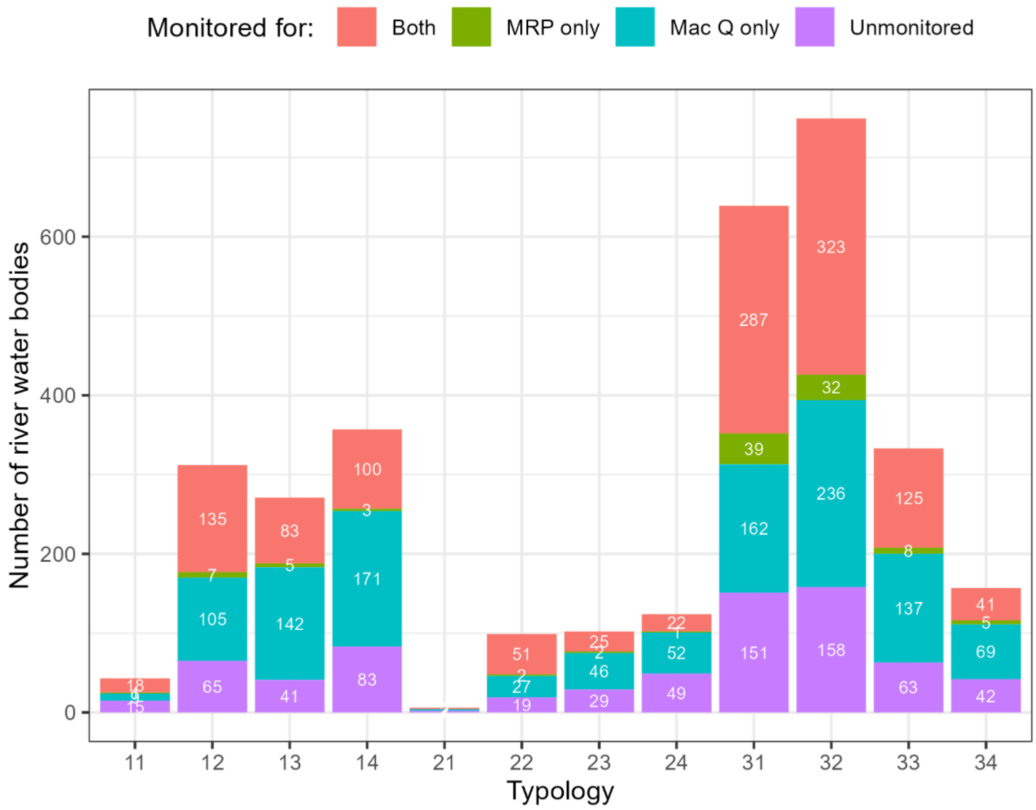

Figure 4: Number of RWBs, by river typology category and presence/absence of monitoring

Figure 5 shows the geographic distribution of the river types. There is a clear geographic pattern in the distribution of the different river categories, with gently sloping, hardwater rivers dominating in the centre of Ireland, and soft water rivers mainly present in the more mountainous areas in the west and south-east.

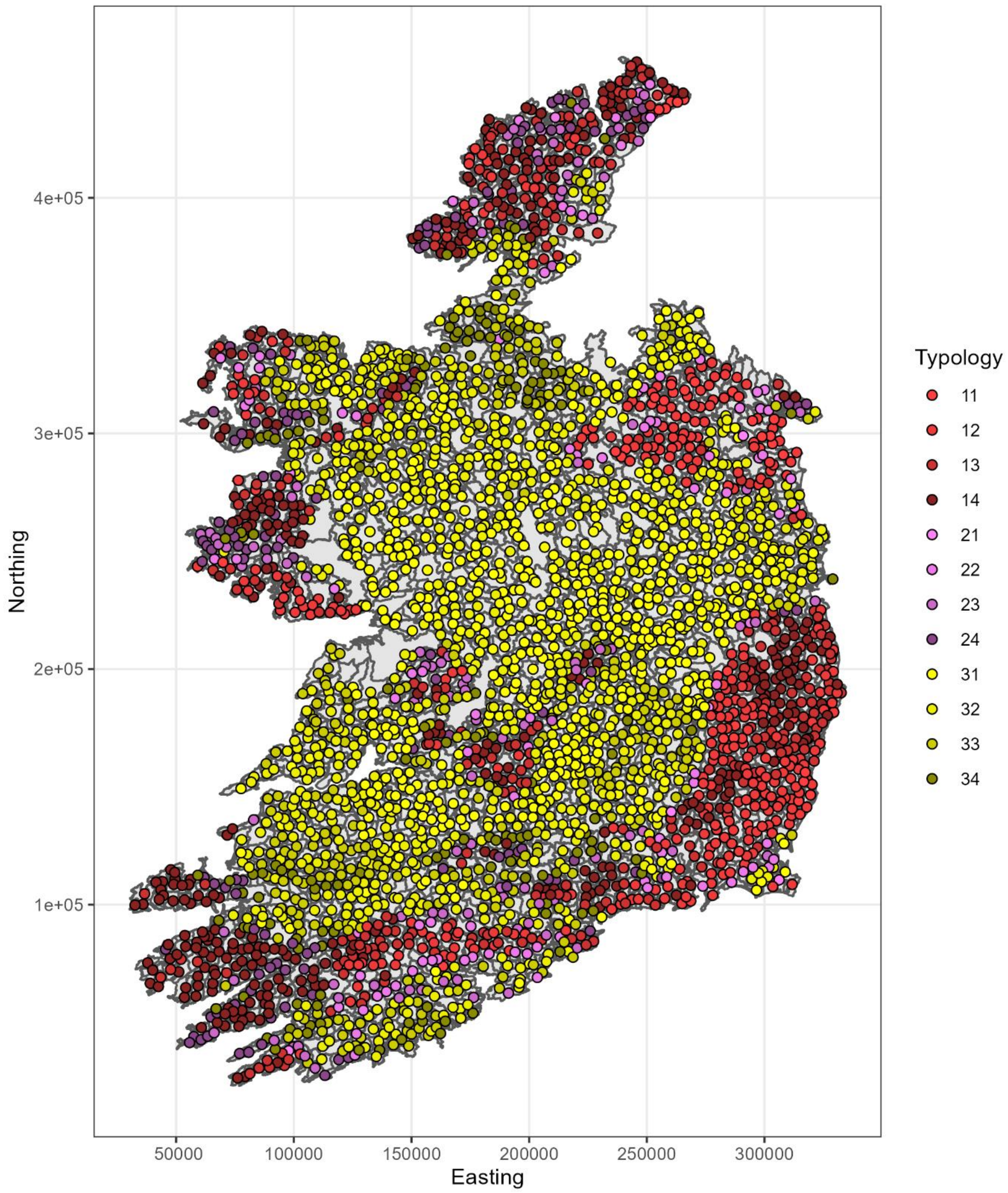

Figure 5: WFD typology map of all 3192 river water bodies

3. Methodology and results

3.1 Approach

This section describes the approach used to develop statistical models of MRP concentration and macroinvertebrate status, and then apply those models to predict the status of unmonitored river water bodies. The approach is very similar to the one used by APEM to predict the WFD status of unmonitored lakes (APEM, 2022a).

For both quality elements, spatial variation among monitored RWBs 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).

A standard gaussian error distribution was used to model MRP concentration. By contrast, the macroinvertebrate model focused on predicting Q-value status classes, which have a natural order (High, Good, Moderate, Poor and Bad), and so an ordered categorical (ocat) model was used instead (see Section 3.3.1 for further details).

For each model, the conceptual model 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 monitored rivers in the calibration dataset.

The final models were used to predict MRP and macroinvertebrate status for the unmonitored RWBs and, in turn, to assess whether or not each RWB was achieving GES. The degree of confidence in the classification results was quantified using prediction intervals (for MRP) or prediction probabilities (for macroinvertebrates) and summarised in the form of certainty bands.

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

All analyses were performed in R 4.2.1 (R Core Team, 2022), and the GAM models were fitted using the gam function from the mgcv package (Wood, 2022).

3.2 Phosphate status

3.2.1 Model fitting

A total of 1317 RWBs were monitored for MRP. The three-year (2019-21) mean MRP concentration (mg/l) was modelled as a function of the following predictor variables (see Table 5 for details):

- The **TP loading to each water body** was broken down into four separate variables in order to understand the relative importance of **urban vs rural** sources from the **local vs upstream** catchment. The four variables were expressed as concentrations (mg/l) and $\log_{10}$-transformed.
- To account for spatial differences in phosphorus mobilisation and transport, a 2D smooth was included to represent a possible interaction between local rural TP loading and the **local percentage of poorly draining soils** (and, alternatively, the **local percentage of very poorly draining soils**).
- Larger watercourses typically have longer residence times, with greater opportunity for MRP to be lost from the water column via sedimentation and biological uptake. Annual mean naturalised **flow** was therefore used as an indicator of river size and proxy for residence time and included as an interaction with each of the four phosphorus loading variables.
- **Typology** was included as a main effect to account for possible differences in nutrient dynamics and MRP concentrations among river types. As an alternative to typology, **slope** (m/m) and **hardness** (% calcareous geology) were included as main effects to account for possible differences among river types.
- To account for hydrological connectivity and upstream water quality, the measured mean (2019-21) **MRP concentration in immediately upstream water bodies** was included as a predictor, where available. (A dummy variable was used for headwaters and other water bodies with no upstream MRP monitoring data).
- The presence/absence of **abstraction pressure** was included as a main effect to account for the possible effect of water abstraction on dilution capacity.
- To account for other sources of spatial variation, **easting** and **northing** were included as a 2D smooth and, alternatively, **catchment** was included as a factor.

MRP concentration was log_{10}-transformed to satisfy the model's assumption of normally distributed errors and heterogenous variation (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 a BIC was used to retain only the most relevant predictor variables.

3.2.2 Final model

The variables retained in the final model were:

- local urban phosphorus loading;
- upstream urban phosphorus loading;
- local rural phosphorus loading x local percentage of poorly draining soils;
- flow;
- slope; and
- easting and northing.

Figure 6 shows the independent partial effect of each variable on MRP concentration. **Urban phosphorus loading** had a strong positive association with MRP concentration, with "local" loading from the immediate RWB having a stronger effect than "upstream" loading from the upstream catchment. This is not surprising given that loads from the upstream catchment may be attenuated by nutrient retention before reaching the focal RWB.

Overall, "urban" emissions from homes and businesses had a stronger influence on MRP concentration than "rural" land-based sources, possibly because wastewater and septic tank discharges typically contain a higher proportion of dissolved phosphorus than run-off from agricultural and forestry land.

"Local" rural loading had a strong positive association with MRP concentration, but this effect was moderated by soil type (Figure 7). The four curves in Figure 7 illustrate the modelled relationship for RWBs with differing **proportions of poorly draining soils**, ranging from 1% to 99%. In RWBs with well-draining soils, the SLAM-modelled phosphorus loads had little influence on in-river MRP concentration, but as the proportion of poorly drained soils increased, MRP concentration become increasingly sensitive to phosphorus loading from local rural sources. This result concurs with previous EPA assessments, which found the highest phosphorus concentrations in areas that have a high proportion of poorly draining soils such as Limerick, Monaghan, the area north west of Dublin and Wexford (EPA 2021b).

Phosphorus loading from **upstream rural sources** was not significantly associated with MRP concentration and so was dropped from the final model. Again, this is likely because loads from the upstream catchment are attenuated by nutrient retention before reaching the focal RWB. Also, the rate of attenuation may be even stronger for land-based rural sources than for urban sources from homes and businesses, because the former typically have a higher proportion of particulate phosphorus, which is less biologically available and more readily deposited.

After accounting for the influence of nutrient pressures, there was a very strong negative association between MRP concentration and **river flow** (Figure 6). River flow is an indicator size and proxy for residence time. Although none of the river flow x phosphorus loading interactions were retained in the final model (possibly due to low statistical power), this strong main effect is consistent with the idea that larger watercourses have longer residence times and function similarly to lakes, with greater opportunity for MRP to be lost from the water column via sedimentation and biological uptake.

Channel **slope** was also retained in the final model, even though it had a relatively weak negative association with MRP concentration (Figure 6). The cause of this relationship is unclear; steeper land might be expected to have less intensive land use and lower phosphorus losses, but this kind of geographic variation is accounted for in the SLAM model, and hence in the phosphorus loading variables. The other typology variable – **hardness** – was not significantly associated with MRP concentration and so was not retained in the final model; again this may be because hardness is correlated with land use intensity and phosphorus losses, which are already accounted for by the SLAM model.

Easting/northing proved to be a better predictor of MRP concentration than **hydrological catchment** because it is better able to describe continuous changes in nutrient loading and water quality across the country. Figure 8 illustrates the regional variation in measured MRP concentration after accounting for the effect of other predictors. All else being equal, RWBs in Tipperary, Limerick and Kilkenny had higher in-river MRP concentrations than those in the western coastal counties of Mayo and Sligo, central counties such as Offaly, and also County Wicklow. This regional variation could reflect spatial differences in soil geochemistry and/or historically high phosphorus inputs to RWBs in more intensively farmed regions of the country and/or under-estimation by the SLAM model of phosphorus loads from some agricultural sources. Regardless of the cause, the final model accounts for this unexplained regional variation in its predictions of MRP concentration for each RWB.

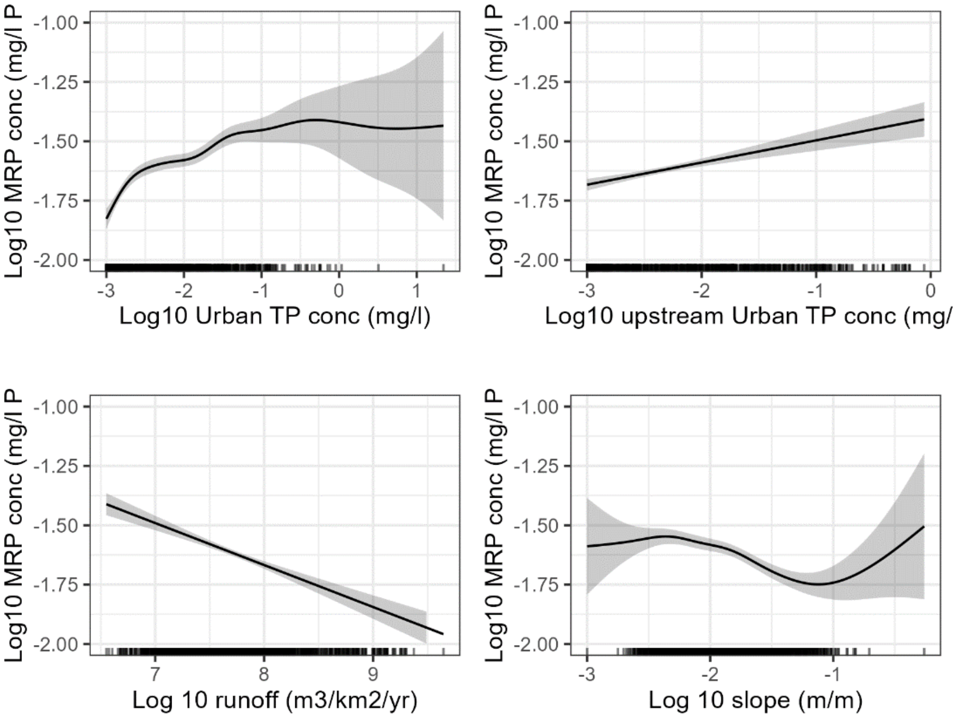

Figure 6: Partial effects plots showing the modelled relationship between each predictor variable and $\log_{10}$ MRP concentration when other variables are held constant at their mean values

Grey shading shows 95% confidence intervals

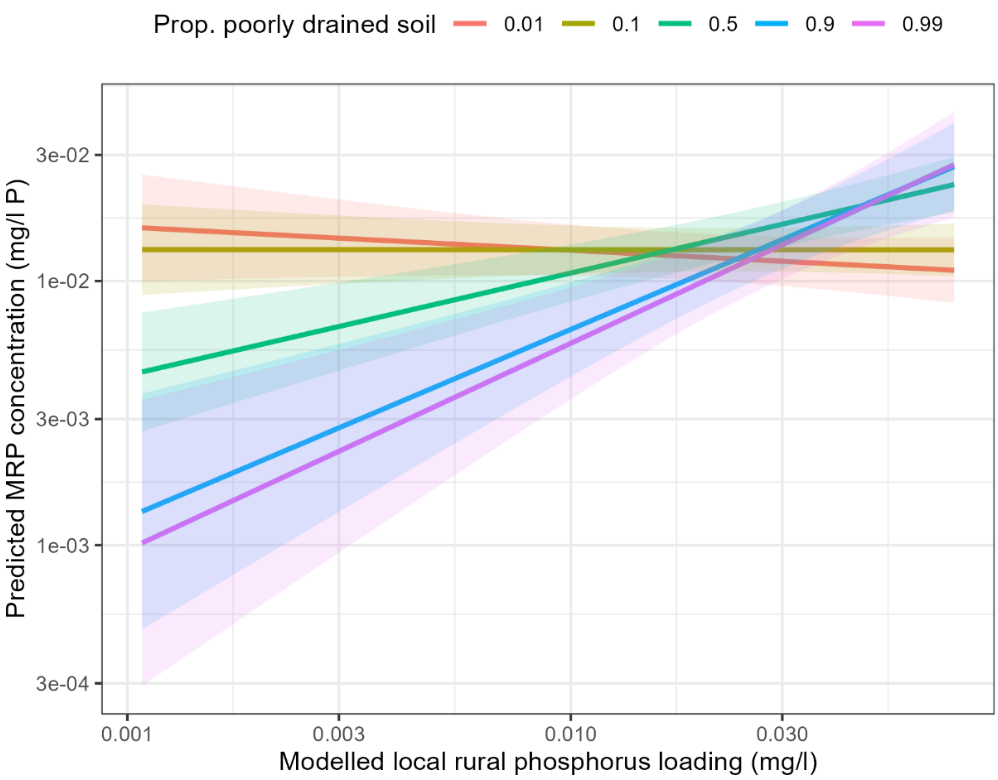

Figure 7: Partial effects plot showing the modelled relationship between local rural phosphorus loading, local percentage poorly draining soils and in-river MRP concentration, when all other variables are held constant at their mean values

Coloured shading shows 95% confidence intervals

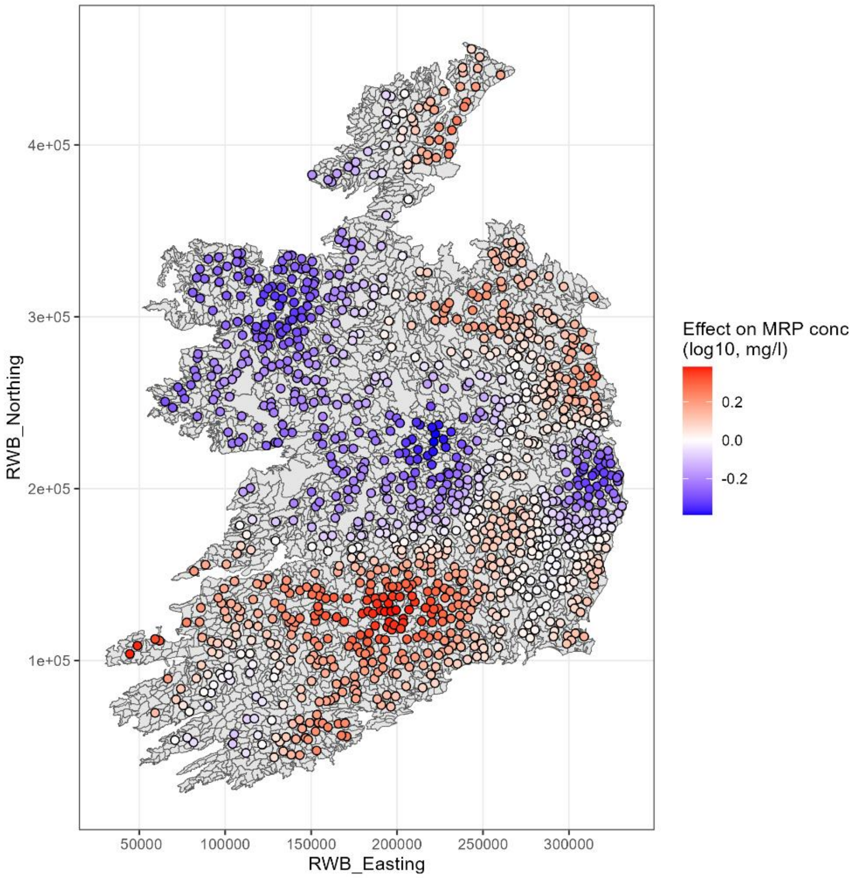

Figure 8: Partial effects plot showing the modelled effect of easting/northing on $\log_{10}$ MRP concentration

– i.e. the regional variation in MRP that is not explained by the other variables in the model

Abstraction pressure and upstream MRP concentration were not retained in the final model. **Abstraction pressure** is a relatively crude indicator of possible abstraction effects on dilution capacity, and this pressure does not appear to be very widespread (only 10.1% of RWBs were flagged as being at risk from abstraction pressure). Similarly, data on **upstream MRP concentration** was only available for 24.4% of RWBs because not all RWBs were monitored and some are headwaters that, by definition, do not have any upstream RWBs. Furthermore, upstream MRP concentration is correlated with phosphorus loading, so the water quality influence from upstream RWBs is also captured via that variable.

3.2.3 Model performance

Overall, the model explained 68.3% of the variation in MRP concentration (Figure 9).

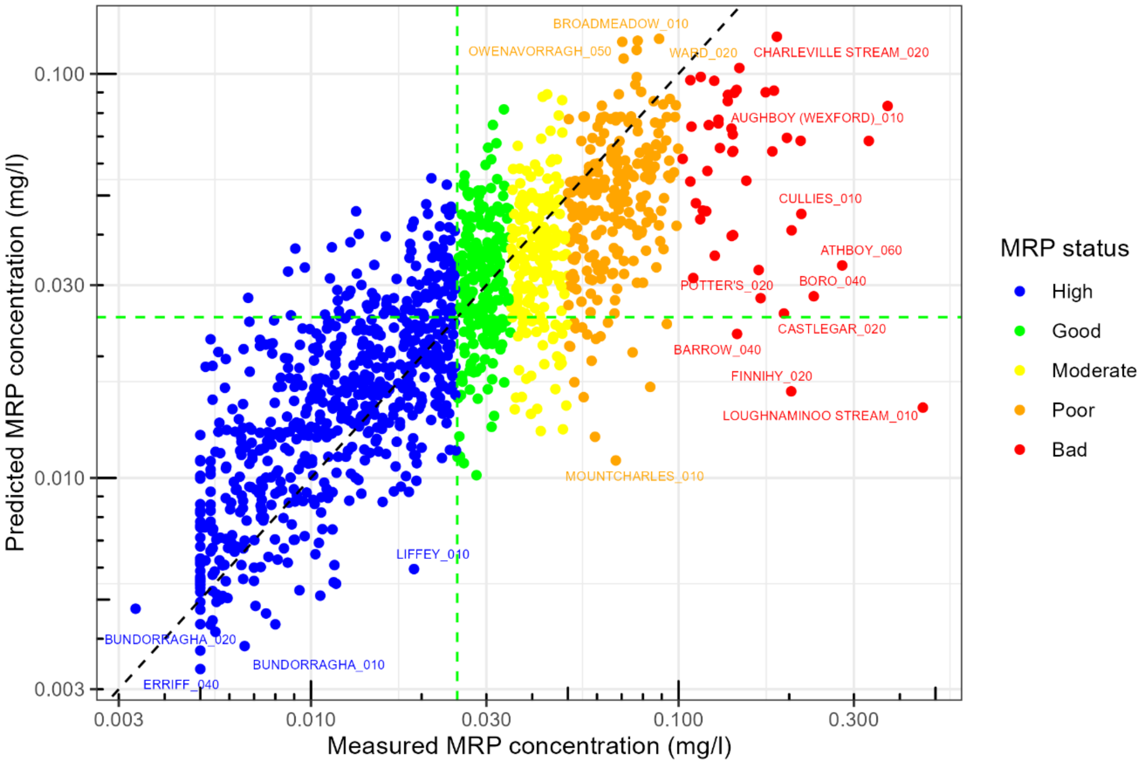

Figure 9: Predicted vs measured MRP concentration for monitored RWBs

The predictive performance of the model was assessed by converting the predicted concentrations to WFD status classes (using the EQSs in Table 1) and comparing the predicted and measured status classes of the 1317 monitored RWBs (Figure 10). Overall, the model predicted the correct status class with 59.8% accuracy and predicted with 80.1% accuracy whether or not a RWB was achieving Good status. There was a slight tendency to over-predict status more than under-predict, but in only 12.4% of cases was the model prediction out by more than one status class.

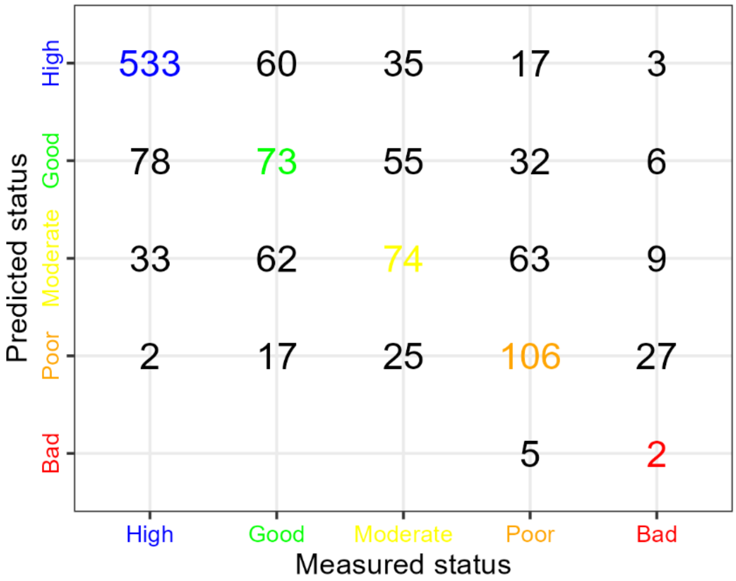

Figure 10: Matrix of measured and predicted MRP status class for the 1317 monitored RWBs

3.2.4 Model predictions

The final model was used to predict MRP concentration for the 1875 unmonitored RWBs. Of these, 77.6% of these were predicted to be achieving Good status for MRP, compared with 65.15% of monitored RWBs (Figure 11), which suggests that the EPA's monitoring programme disproportionately samples RWBs that are at risk of not achieving Good status.

Across the 12 typology categories, RWBs with steep slopes (types X3 and X4) had the highest proportion achieving at least Good status, and more gently sloping RWBs had the lowest proportion achieving Good status (Figure 12).

Figure 13 maps measured and predicted MRP status for all 3192 RWBs, revealing strong geographic variation in MRP status which broadly reflects regional variation in the intensity of land use and level of phosphorus loading from point and diffuse sources, and the hydrology of the soils.

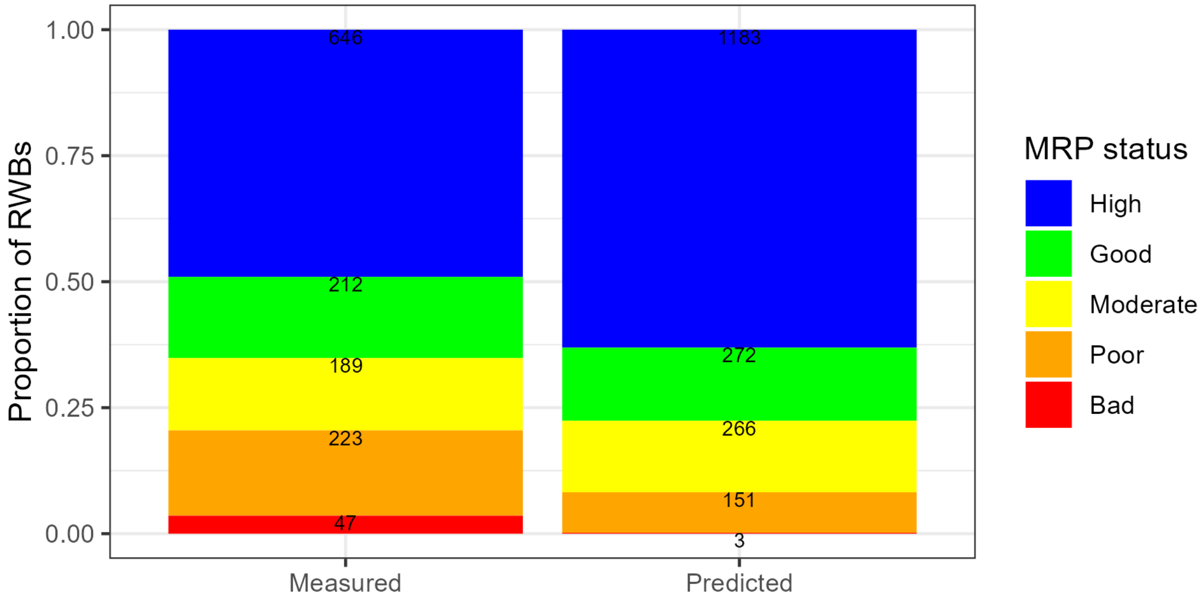

Figure 11: Summary of MRP status for monitored (measured) and unmonitored (predicted) RWBs

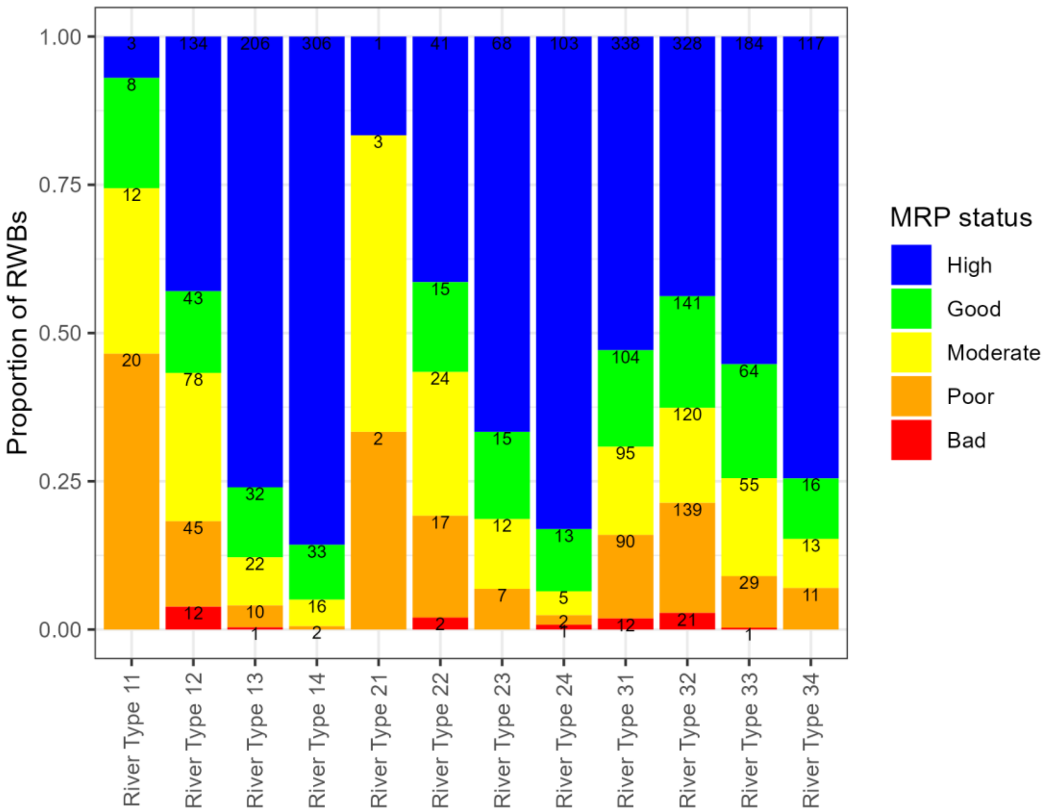

Figure 12: Summary of MRP status for all RWBs, by WFD typology

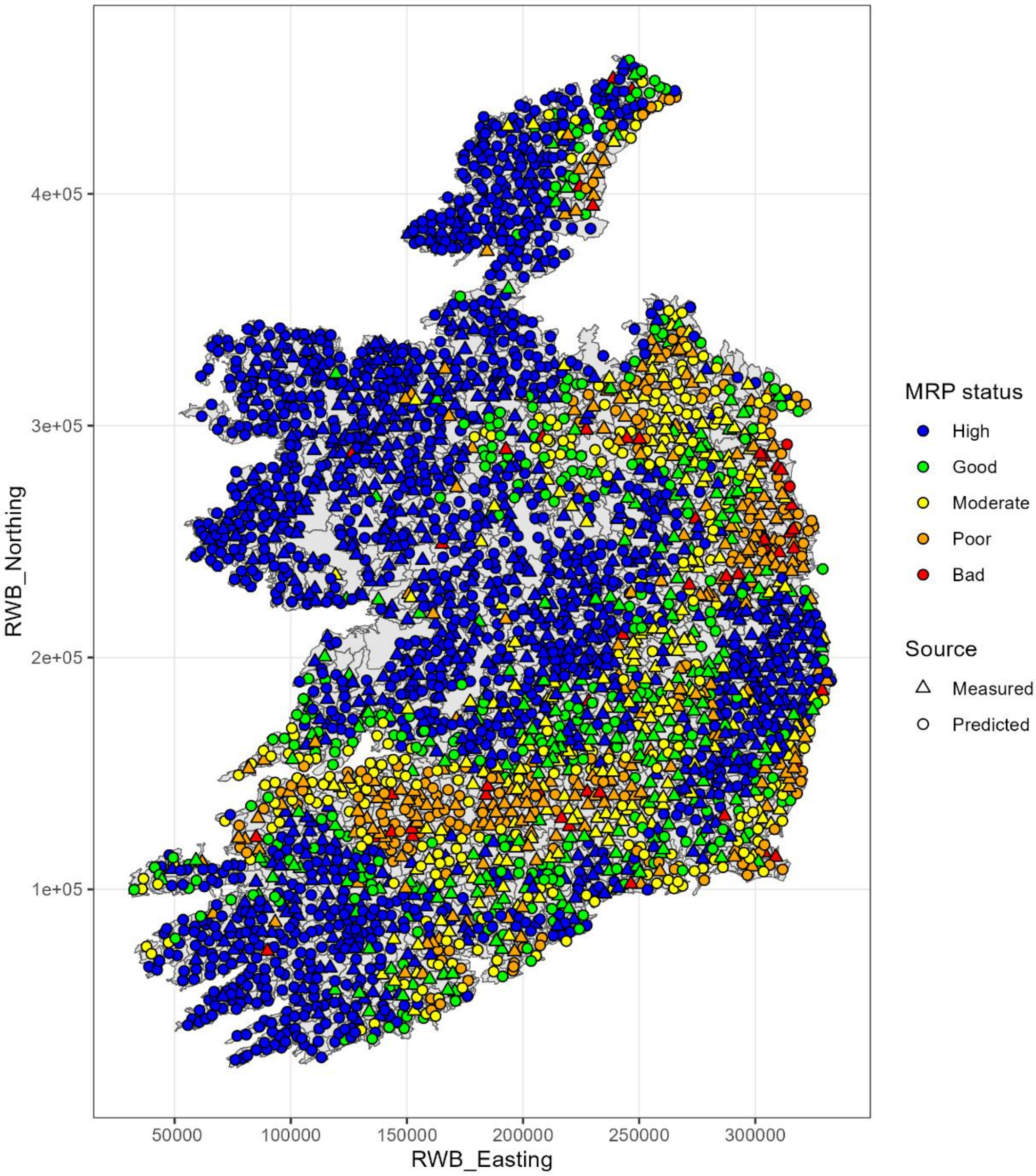

Figure 13: Map of measured and predicted MRP status for all RWBs

3.3 Macroinvertebrate status

3.3.1 Model fitting

Macroinvertebrates were monitored in 2370 RWBs. Q-values are non-continuous (i.e. they take only certain, discrete values between 1 and 5; see Table 3), meaning that a standard GAM with a gaussian error distribution is inappropriate for modelling Q-values (or their corresponding EQRs). Instead, an ordered categorical ('ocat') model was used to directly predict the probability of a RWB being in each of four WFD status classes (High, Good, Moderate and Poor – no monitored RWBs were at Bad status in 2019-21).

Using Q-value *status class* as an ordered categorical response variable, the ocat model calculates a continuous *latent variable*, which takes values from +∞ to -∞ and represents a gradient in macroinvertebrate status. Following a logistic distribution, the probability of this latent variable lying between certain cut-points provides the probability that the status class is High, Good, Moderate or Poor (Table 7). The cut-points are estimated alongside the model smoothing parameters using the same criterion. In the following sections, it is this latent variable which is displayed as the response variable, rather than actual Q-values themselves.

Table 7: Cut-points used to split the ocat model's latent variable into WFD status classes

Q-value score	WFD status	Latent variable
Q4-5, Q5	High	> 3.49
Q4	Good	0.94 to 3.49
Q3-4	Moderate	-1.00 to 0.94
Q2-3, Q3	Poor	< -1.00
Q1, Q1-2, Q2	Bad	NA

Q-value status class was modelled as a function of the following predictor variables (see Table 5 Table 5: National-, catchment- and local-scale variables used for details):

- Water quality pressures were represented using three separate variables describing three-year (2019-21) mean concentrations: (i) **MRP concentration** (log_{10} transformed), either measured or predicted by the MRP model described in Section 3.2.1 above; **dissolved oxygen** saturation, either measured or predicted using a simple interpolation model (see Appendix 1); and (iii) **ammonium concentration,** either measured or predicted using a simple regression model (see Appendix 1).
- Morphological pressures were represented using a number of alternative variables (see Table 5 for details): (i) the **MQI** score at the defining station; (ii) the **percentage of the length of the RWB which was assessed as at least**

Good status for MQI; (iii) a suite of five **MQI indicator sub-scores**; (iv) a suite of seven **hydromorphological pressure** indicator variables; and (v) whether or not the RWB is designated as **Heavily Modified**.

- The presence/absence of **abstraction pressure** was included as a main effect to account for the possible effect of flow alteration.
- **Typology** was included as a main effect to account for possible differences in nutrient dynamics and macroinvertebrate community composition among river types. As an alternative to typology, **slope** (m/m) and **hardness** (% calcareous geology) were included as main effects to account for possible differences among river types.
- To account for hydrological connectivity and upstream water quality, the measured **macroinvertebrate status in immediately upstream water bodies** was included as a predictor, where available. (A dummy variable was used for headwaters and other water bodies with no upstream monitoring data).
- Annual mean naturalised **flow** was used as an indicator of river size.
- The influence of soil type and land use within the RWB catchment were represented using the **% of poorly draining soils** and **% urban land use**, respectively.
- To account for other sources of spatial variation, **easting** and **northing** were included as a 2D smooth and, alternatively, **catchment** was included as a factor.

Backward model selection using BIC was again used to retain only the most relevant predictor variables.

3.3.2 Final model

The variables retained in the final model were:

- MRP concentration;
- dissolved oxygen saturation;
- flow;
- slope;
- local % poorly draining soils;
- local % urban land use;
- Heavily Modified Water Body;
- MQI score; and
- easting and northing.

Figure 14 shows the independent (partial) effect of each variable on macroinvertebrate status when other variables are held constant at their mean values. Specifically, the vertical axis shows the expected value of the ocat model's latent variable, which represents a gradient in macroinvertebrate status, rather than Q-values themselves.

These charts show a strong negative effect of increasing **MRP concentration** and a strong positive effect of **dissolved oxygen saturation**. Although **ammonium**

concentration was not retained in the final model, it is strongly correlated with MRP concentration and therefore indirectly captured through this variable. Together, these variables indicate that water quality is the single most important pressure influencing macroinvertebrate status. However, it is not currently possible to rank the relative influence of MRP, dissolved oxygen and ammonium due to the correlations between them.

Of the various alternative measures of morphological pressure, two were retained in the final model. All else being equal, **Heavily Modified Water Bodies** had lower macroinvertebrate status than other RWBs, and **MQI score** (indicating better quality habitat) had a weak positive effect on macroinvertebrate status (Figure 14). Interestingly, the overall MQI score, which is a simple aggregate of various sub-scores, was a better predictor of macroinvertebrate status than individual variables that scored specific kinds of morphological alteration. This suggests either that the methods used to record different types of morphological alteration may be too crude to be useful predictors in their own right or, more likely, that channelisation, land drainage, barriers, culverts, embankments etc., interact in complex ways to produce ecological responses that vary from river to river and site to site, and which cannot easily be deconstructed into simple additive effects. On top of these effects, **% urban land use** had a strong, but uncertain negative effect on macroinvertebrate status, with impacts appearing to be greatest when urban land use in the RWB was >50%.

Macroinvertebrate status increased with channel **slope** (Figure 14). The cause of this relationship is unclear; steeper land might be expected to have less intensive land use, less pollution and more natural channel morphology, but this kind of geographic variation should be accounted for by other variables in the model. The other typology variable – **hardness** – was not significantly associated with macroinvertebrate status and so was not retained in the final model.

After accounting for other influences, there were weak positive effects of **river flow** and **% poorly drained soils** on macroinvertebrate status, the mechanisms for which are unclear (Figure 14). **Abstraction pressure** was not retained in the final model; this was unsurprising given that this variable provides a relatively crude indicator of possible abstraction effects, and this pressure does not appear to be very widespread (only 10.1% of monitored RWBs were flagged as suffering from abstraction pressure).

Easting/northing proved to be a better predictor of macroinvertebrate status than **hydrological catchment** because it is better able to describe continuous changes in anthropogenic pressures, landscape characteristics and ecological communities across the country. Figure 15 illustrates the regional variation in macroinvertebrate status that cannot be explained by the other variables in the model. All else being equal, (i.e. after accounting for geographic variation in water quality and other pressures) macroinvertebrate status was higher in RWBs around Cavan/Monaghan, central Connaught, eastern Cork and Wicklow/Wexford, and lower in RWBs around the west coast, particularly in Donegal. This regional variation may reflect natural differences in the sensitivity of different macroinvertebrate communities to water quality and other pressures, and/or the influence of other pressures missing from, or not fully accounted for in the model. Together, these land use and landscape characteristics give rise to different water quality and ecological responses in each region. Regardless of the underlying cause, the final model accounts for this unexplained regional variation in its predictions of macroinvertebrate status for each RWB.

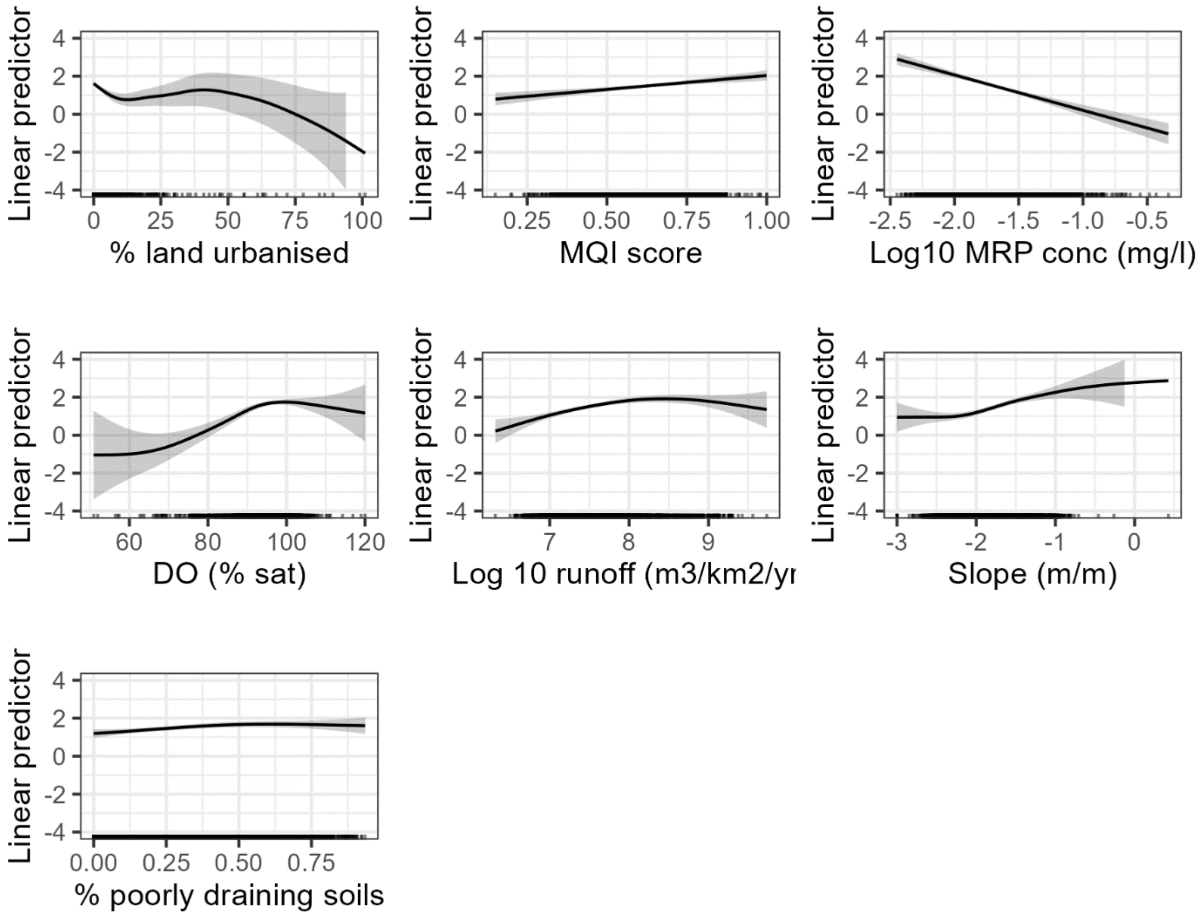

Figure 14: Partial effects plots showing the modelled relationship between each predictor variable and macroinvertebrate status (as represented by a continuous latent variable or 'linear predictor') when other variables are held constant at their mean values

Grey shading shows 95% confidence intervals

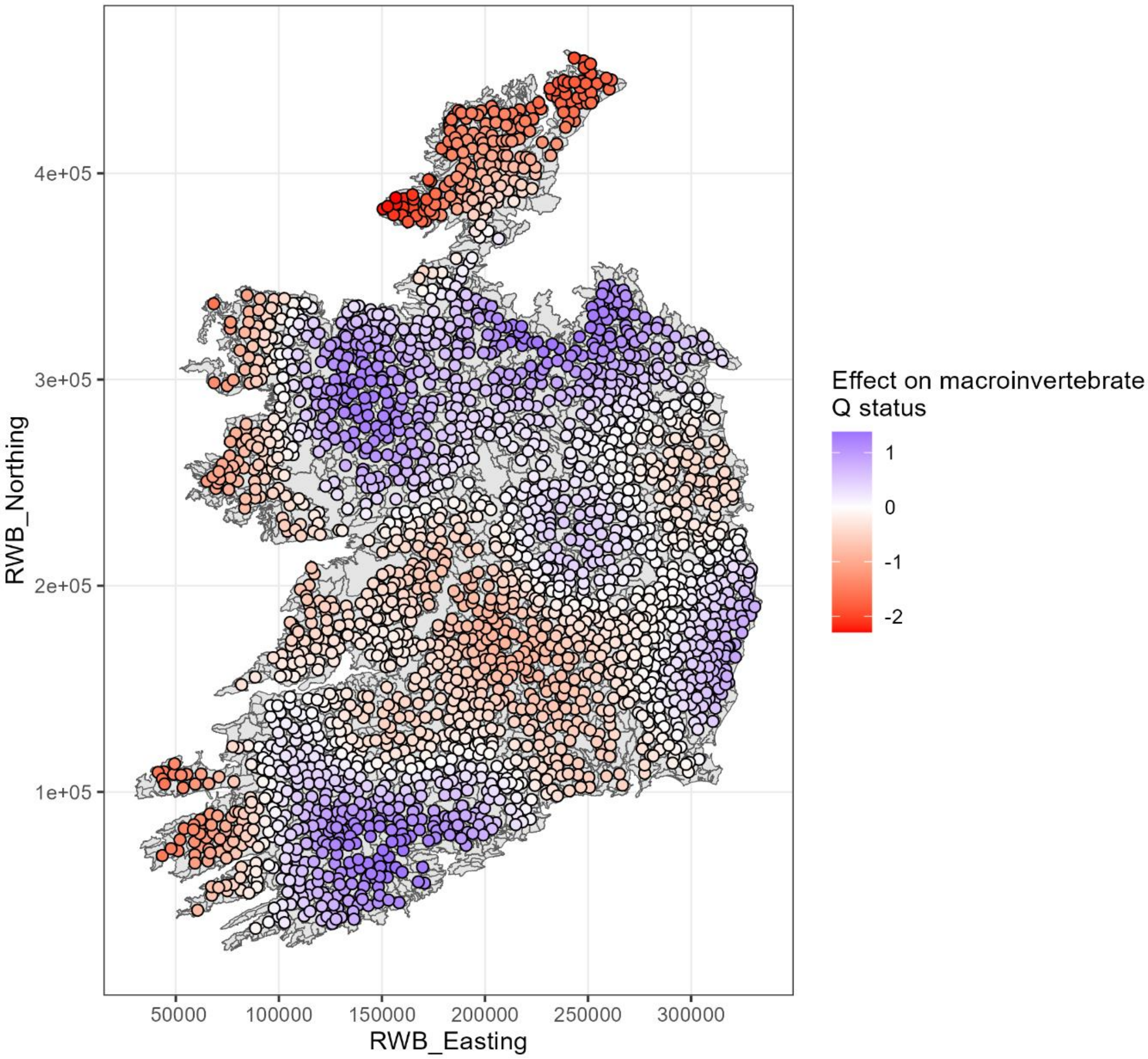

Figure 15: Partial effects plot showing the modelled effect of easting/northing on macroinvertebrate status – i.e. the regional variation in macroinvertebrate status (as represented by a continuous latent variable) that is not explained by the other variables in the model

3.3.3 Model performance

Overall, the model explained 21.9% of the variation in the calibration dataset. Although this is much lower than the 68.3% of variation explained by the MRP model, the two figures are not directly comparable because the MRP model assumes a Gaussian error distribution, whereas the macroinvertebrate model uses a logistic error distribution.

A better, and more comparable, measure of predictive performance is gained by comparing the measured status class of the 2370 monitored RWBs with the class predicted by the final model (Figure 16). Overall, the model predicted the correct macroinvertebrate status class with 49.9% accuracy. This performance is slightly lower than that achieved by the MRP model, despite there only being four macroinvertebrate status classes (no monitored RWBs were at Bad status); we speculate that this may be because macroinvertebrates respond in more complex ways to a wider range of pressures than MRP concentration, which makes status harder to predict.

The macroinvertebrate model predicted with 75.1% accuracy whether or not an RWB was achieving Good status, which again was worse than for the MRP model. This may in part be because a high proportion (67.1%) of monitored RWBs were at Good or Moderate status for macroinvertebrates, and these “borderline” cases are inherently more difficult to classify as “Good” and “Not Good” than RWBs at High or Poor status.

Overall, there was a slight tendency to over-predict status more than under-predict, but in only 5.1% of cases was the model prediction out by more than one status class. This is actually better than the 12.4% achieved by the MRP model, probably due to the lack of a fifth status class.

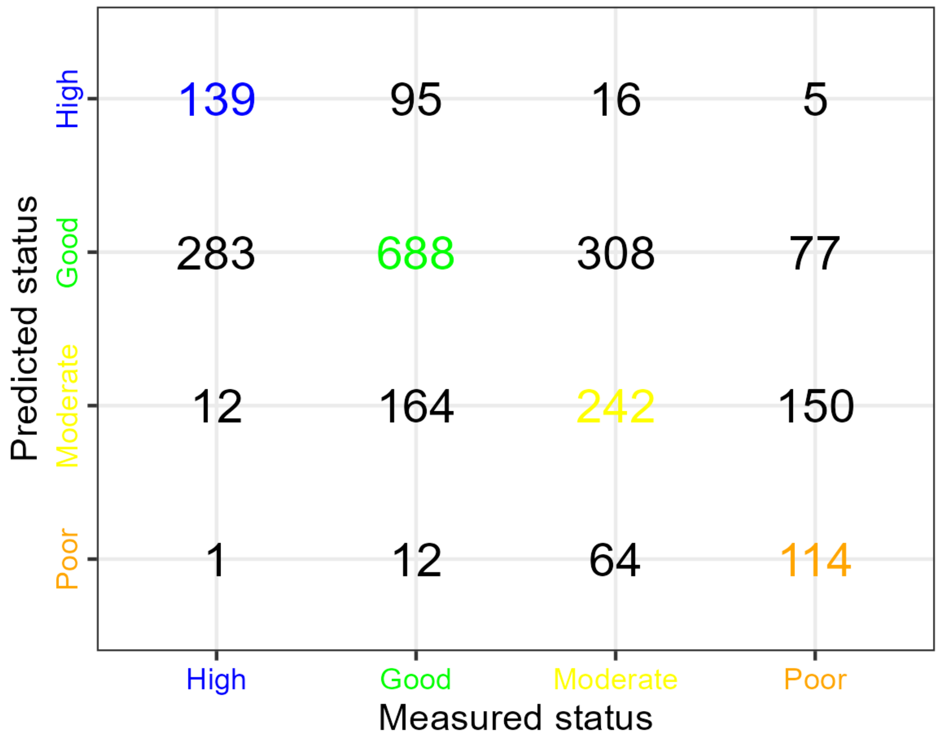

Figure 16: Matrix of measured and predicted macroinvertebrate status class for the 2370 monitored RWBs

3.3.4 Model predictions

The final model was used to predict macroinvertebrate Q-value status for the 822 unmonitored RWBs. The macroinvertebrate model was based on data from the monitoring station furthest downstream within the RWB (the defining station), rather than the poorest performing site within the RWB, which is the one used to determine status for WFD reporting. Consequently, the figures presented below do not necessarily match the official WFD status classification reported by the EPA.

Overall, 61.8% of unmonitored RWBs were predicted to be achieving Good status for macroinvertebrates, compared with 50.1% of monitored RWBs (Figure 17), which suggests that the EPA's monitoring programme disproportionately samples RWBs that are at risk of not achieving Good status.

Across the 12 typology categories, RWBs with steep slopes (types X3 and X4) had the highest proportion achieving at least Good status, and more gently sloping RWBs had the lowest proportion at Good status (Figure 18).

Figure 19 maps measured and predicted macroinvertebrate status for all 3192 RWBs, revealing strong geographic variation in macroinvertebrate status which broadly reflects regional variation in the intensity of land use, landscape characteristics and level of TP loading from point and diffuse sources.

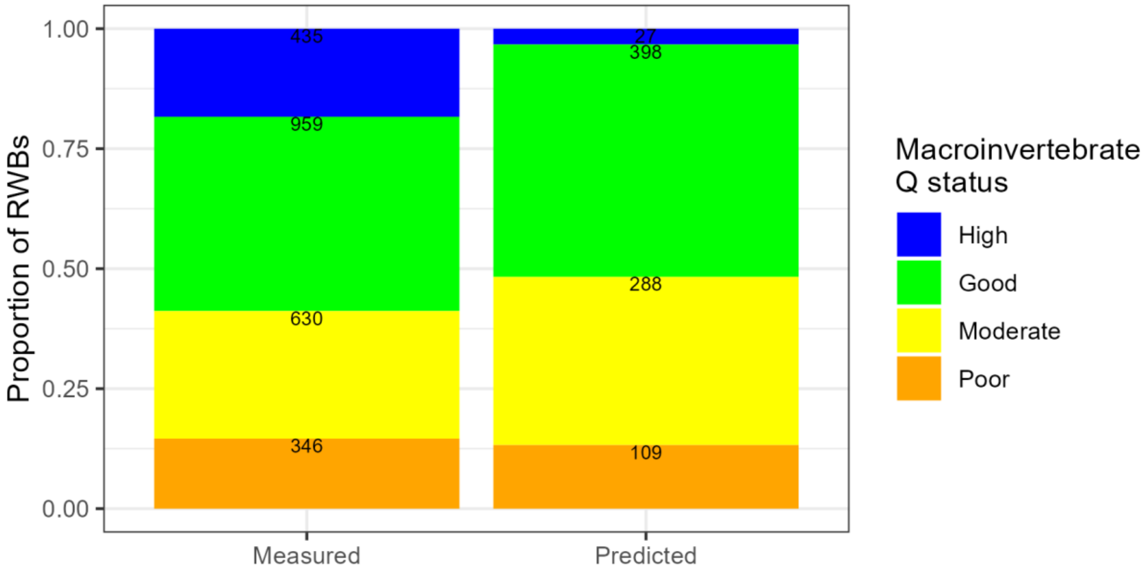

Figure 17: Summary of macroinvertebrate status for monitored (measured) and unmonitored (predicted) RWBs

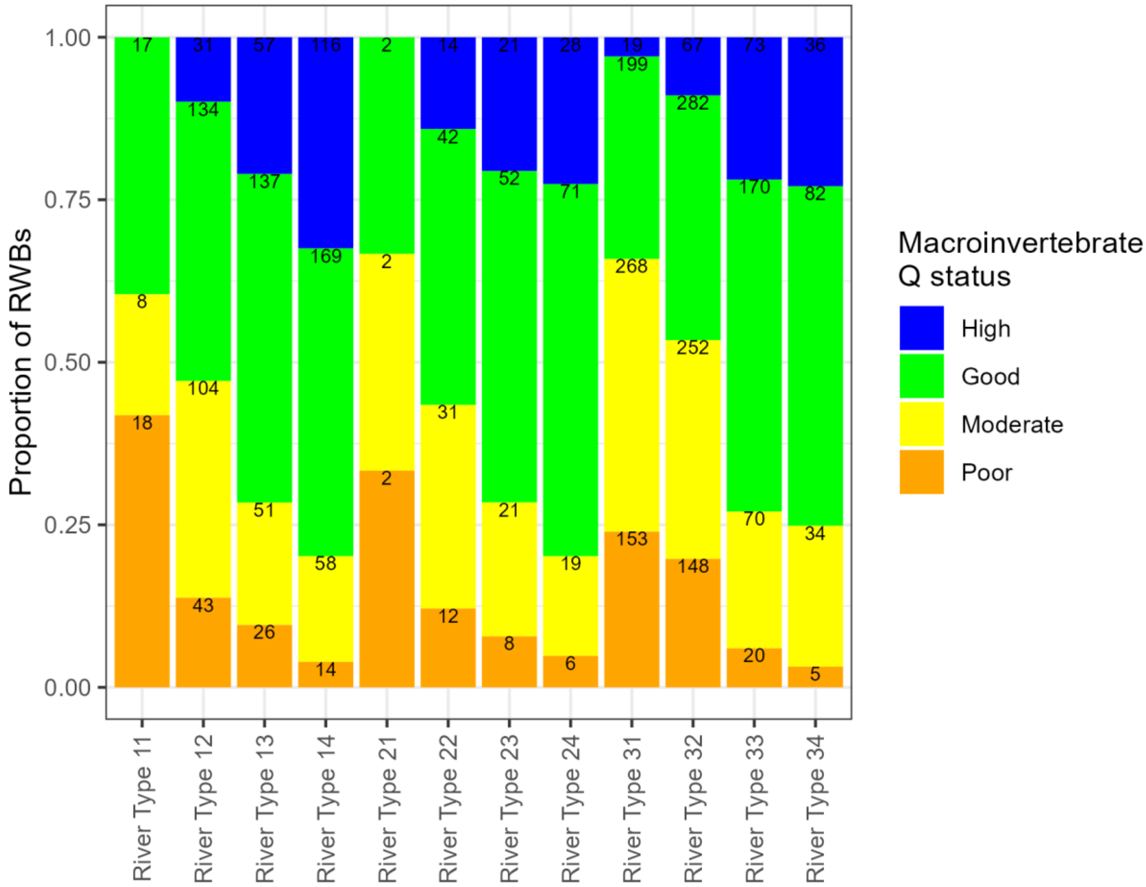

Figure 18: Summary of macroinvertebrate status for all RWBs, by WFD typology

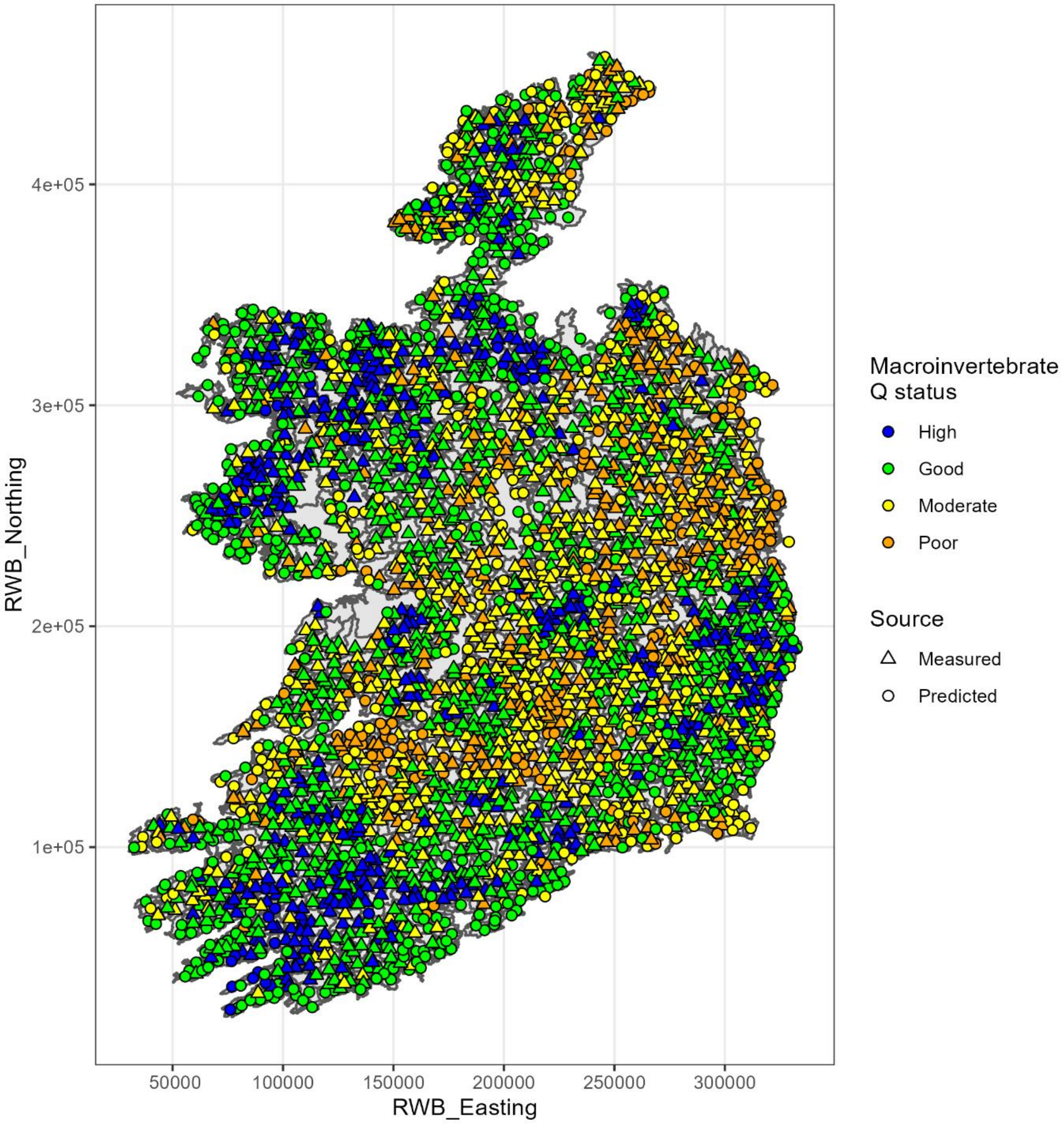

Figure 19: Map of measured and predicted macroinvertebrate status for all 3192 RWBs

3.4 Overall status

The measured and predicted status classes for the two quality elements (MRP and macroinvertebrates) were combined using the one-out all-out rule to predict an "overall status" for every RWB. Although MRP is not ordinarily allowed to stand on its own in formal one-out all-out status assessments, given the strong influence of MRP concentration on macroinvertebrate status, combining the two sets of results in this way provides an integrated assessment of the influence of phosphorus enrichment on the ecological status of RWBs. Using the 1212 RWBs that were "fully monitored" for both MRP and macroinvertebrates, it is then possible to assess the ability of the two models to predict a RWB's overall status class. As shown in Figure 20, the models predicted the correct overall WFD status class with 49.8% accuracy and predicted with 76.2% accuracy whether or not a RWB was achieving at least Good status.

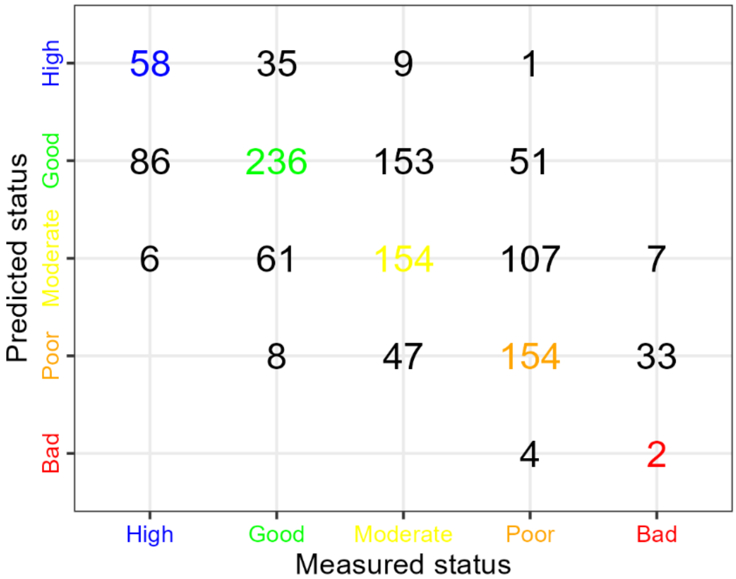

Figure 20: Matrix of measured and predicted overall status class for the 1212 RWBs monitored for both MRP and macroinvertebrates

Around 59.0% of the 1980 "unmonitored" RWBs (i.e. RWBs lacking measured data for one or both quality elements) were predicted to be achieving Good overall status, compared with 40.4% of 1212 "fully monitored" RWBs (Figure 21). Across the 12 typology categories, steeply sloping RWBs (types X3 and X4) had the highest proportion achieving at least Good status, whereas more gently sloping RWBs had the lowest proportion (Figure 22). This is in line with the results of the individual quality elements. Figure 23 maps the measured and predicted overall status for all 3192 RWBs. Overall status shows marked geographic variation reflecting, predominantly, the intensity of land use, the landscape characteristics and level of phosphorus loading.

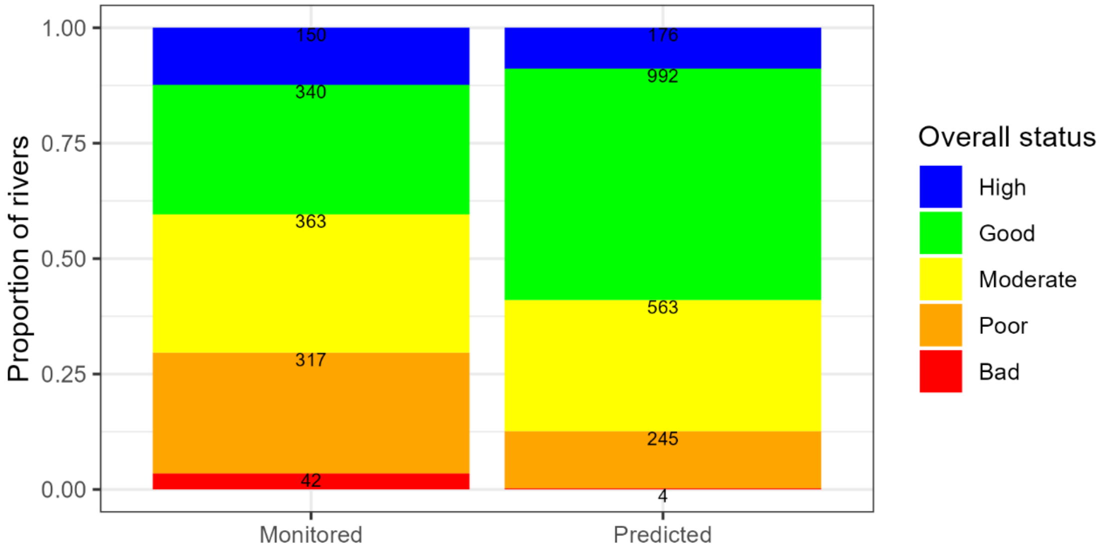

Figure 21: Summary of overall status for monitored and unmonitored RWBs

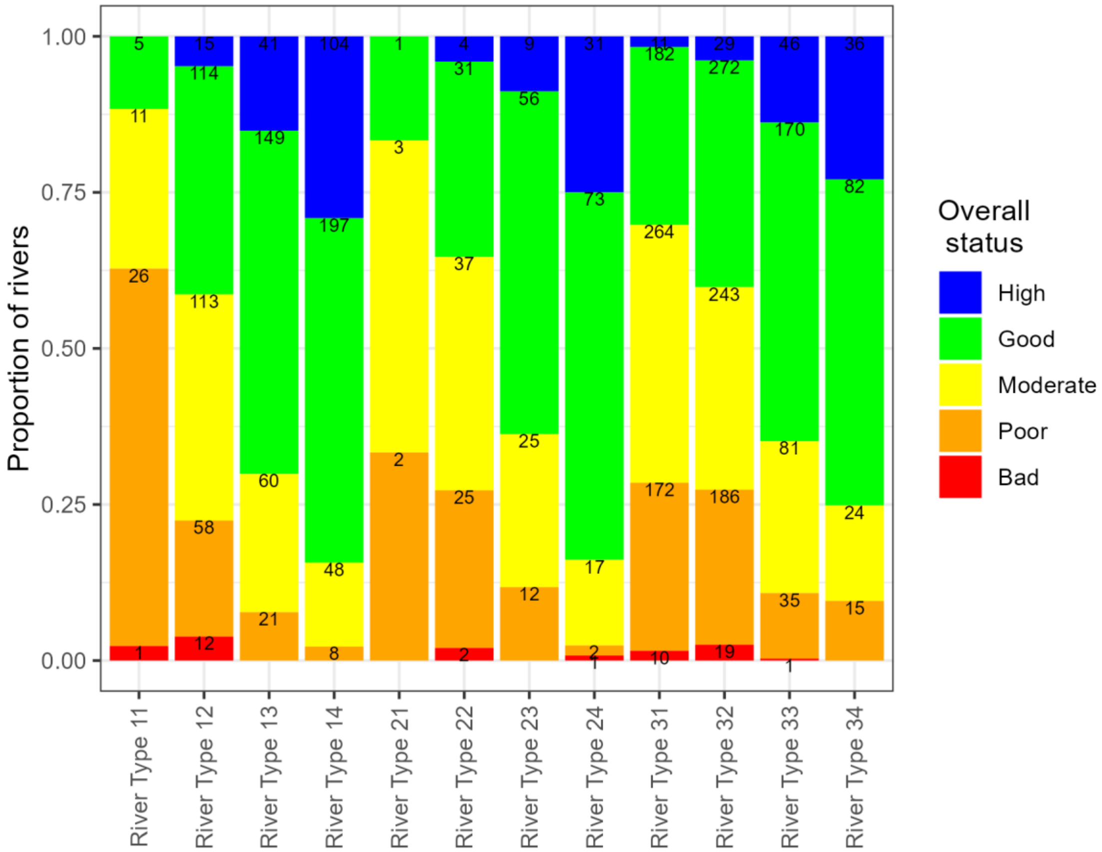

Figure 22: Summary of overall status for all 3192 RWBs, by WFD typology

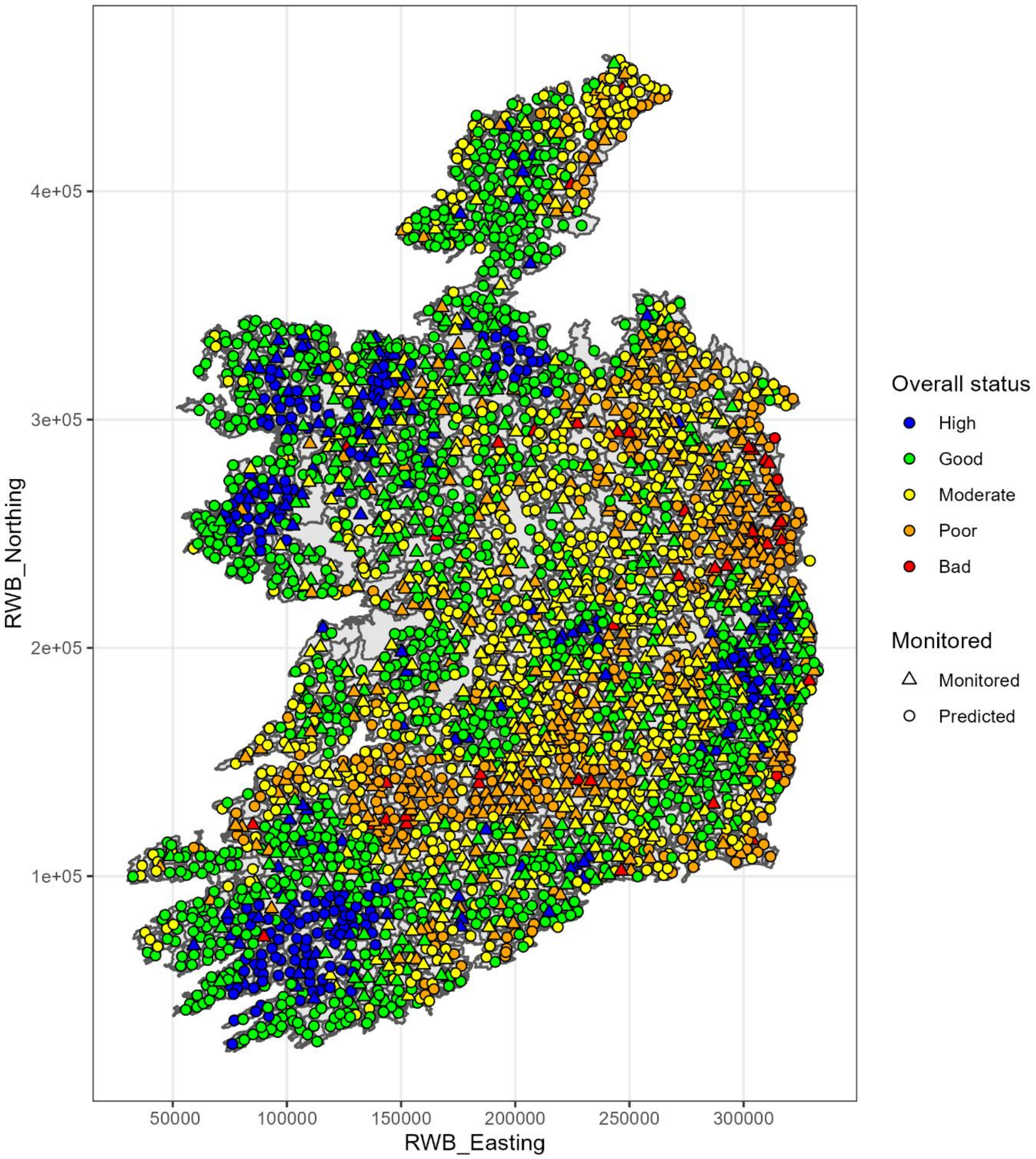

Figure 23: Map of overall status for all 3192 RWBs

The quality element(s) driving the overall (worst) status of monitored and unmonitored RWBs are tabulated in Table 8 and mapped in Figure 24. For both monitored and unmonitored RWBs, macroinvertebrates were the most common driving elements. MRP was a more common driving element for RWBs across south-central Ireland, the south east and around Monaghan/Cavan.

Table 8: Worst element(s) driving overall status

Worst element(s) driving overall status	Monitored RWBs	Unmonitored RWBs	All RWBs
MRP	183	223	406
Macroinvertebrate	643	1216	1859
Both	386	541	927
Total	**1212**	**1980**	**3192**

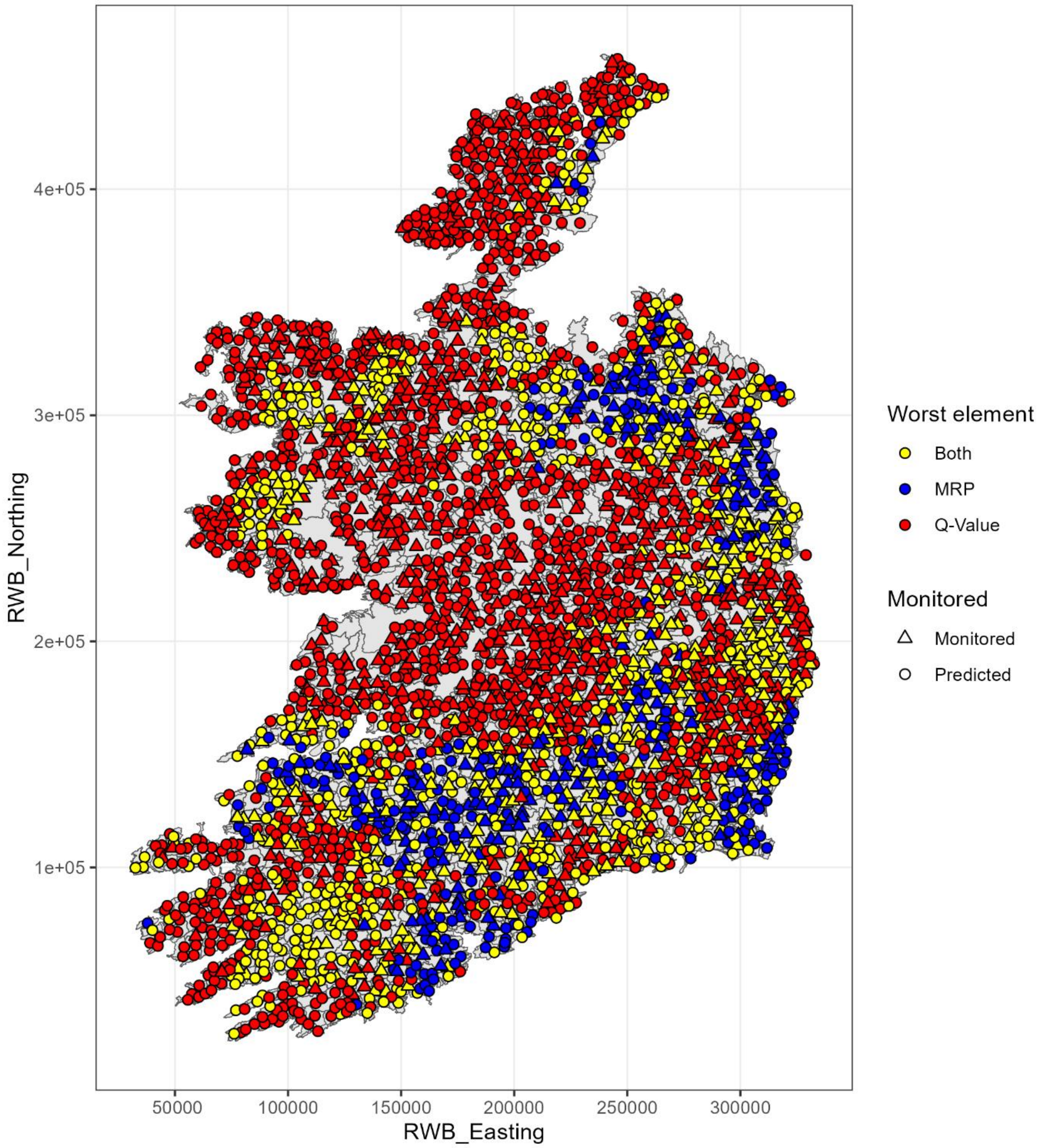

Figure 24: Worst element(s) driving overall status for all 3192 RWBs

3.5 Uncertainty in status classifications

One of the advantages of GAMs over classification techniques such as k-nearest neighbours and classification trees is that the MRP model yields not only a central estimate of the response for each RWB, but is also able to quantify the degree of certainty (or margin of error) in the predictions (for both monitored and unmonitored RWBs).

As an illustration, Figure 25 plots the MRP model predictions for a representative sample of five monitored RWBs. The degree of certainty in the predictions is shown by the 95% prediction intervals which, on average, include the true, measured MRP concentration (marked 'x') for 95% of RWBs; in other words, for any individual RWB there is a 5% chance that the true MRP concentration will fall outside the calculated prediction interval. Note that because MRP concentration is modelled on a $\log_{10}$ scale, the prediction intervals are asymmetrical, and tend to be wider for RWBs with higher MRP concentrations. Note too that the model has a slight tendency to under-predict MRP concentration (and therefore over-predict status) in more polluted watercourses. In the case of Lyreen_020 this leads to a misclassification of status (the model predicts Poor when the measured status is Bad), although it should be remembered that measured status is also subject to sampling error, so it is not possible to say definitely whether the measured or predicted status is correct, only that there is a disagreement.

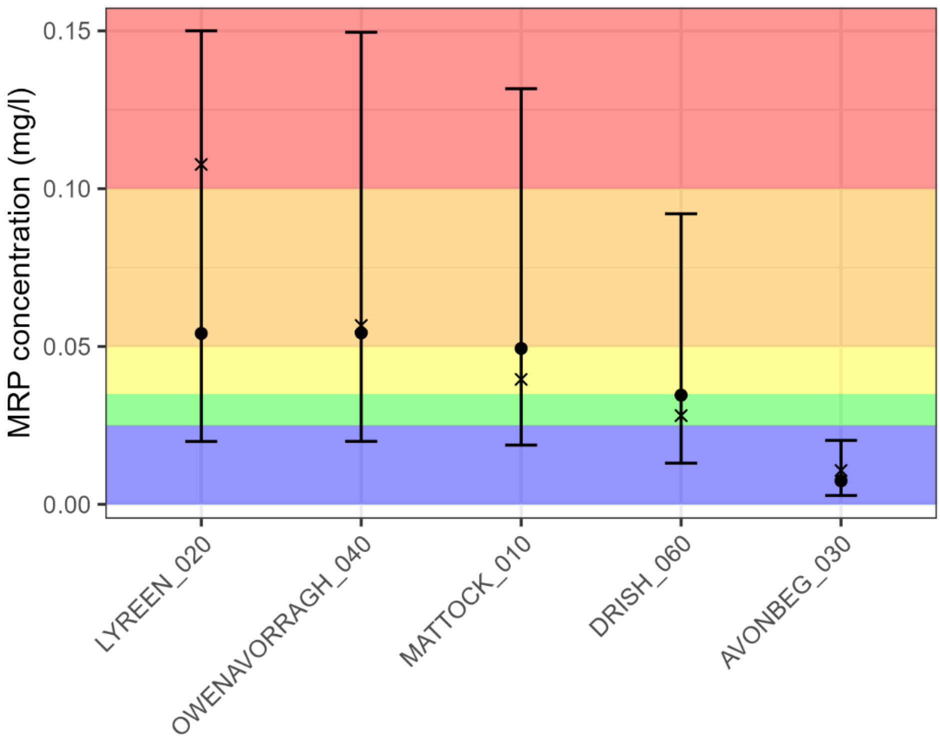

Figure 25: Measured (x) and predicted (●, with 95% prediction intervals) in-river MRP concentration for selected RWBs

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

For macroinvertebrates, the ocat model works slightly differently: rather than predicting a Q-value score with associated predictions intervals, it makes a probabilistic prediction of WFD status class for each RWB, as illustrated in Table 9 below for three RWBs. The most probable class is taken to be the predicted "face value" class, and the sum of the probabilities for the High and Good classes gives the degree confidence that the RWB is achieving at least Good status. One quirk of this method is that for some "borderline" RWBs which are close to the Good/Moderate boundary (e.g. Ballinagh_010), it is possible for the most probable "face value" class to be Good, but for the combined probabilities of Moderate and Poor to be >0.50, which yields a confidence band of "uncertain fail". A total of 46 unmonitored RWBs exhibit this apparent contradiction, which is simply an artefact of two status classes both having similar probabilities.[2]

Table 9: Predicted status class probabilities from the macroinvertebrate model for selected RWBs

RWB Name	Probability of being					Face value class	Certainty band
	High	Good	Moderate	Poor	At least Good		
STONY_010	0.67	0.29	0.03	0.01	**0.96**	High	**Very certain pass**
BALLINAGH_010	0.07	0.42	0.38	0.13	**0.49**	Good	**Uncertain fail**
SKANE_010	0.01	0.10	0.35	0.54	**0.11**	Poor	**Quite certain fail**

[2] An alternative method for assigning a WFD status class, which ensures there is never a mis-match between the face value class and the confidence band, involves calculating the cumulative probability (from High to Poor, or from Poor to High, it doesn't matter), and finding the status class where the cumulative probability crosses the 0.5 threshold. This can be thought of as the status class that is at the centre of the predicted probability distribution from the model. In the case of Ballinagh_010, the cumulative probability approach would give a face value class of Moderate, which is consistent with the "uncertain fail" certainty band. The downside of this approach is that it is arguably a less simple and intuitive approach that is more difficult to communicate to stakeholders.

Confidence of class calculations were performed separately for MRP and macroinvertebrates and the full results are included in an Excel workbook that forms an electronic appendix to this report (Appendix 4). As a summary, Table 10 categorises the unmonitored RWBs according to the degree of certainty that each is achieving GES. Overall, the MRP model was able to determine whether Good status was being achieved with reasonable (at least 75%) certainty for 70.8% of unmonitored RWBs, but the macroinvertebrate model achieved the same level of certainty for only 44.5% of unmonitored RWBs. Again, we suspect that the lower degree of certainty for the macroinvertebrate results is due, in part, to a high proportion of "borderline" RWBs that are close to the Good/Moderate boundary and therefore inherently more difficult to classify as "Good" or "Not Good".

Table 10: Certainty of status predictions for unmonitored RWBs

Certainty band (confidence that RWB is achieving GES)[1]	MRP	Macroinvertebrate
Very certain pass (>95%)	660	10
Quite certain pass (75-95%)	511	151
Uncertain pass (50-75%)	282	218
Uncertain fail (25-50%)	265	238
Quite certain fail (5-25%)	145	190
Very certain fail (<5%)	12	15
TOTAL	**1875**	**822**

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

The information shown in Table 10 may be used to prioritise RWBs for expert judgment review, focusing attention on those borderline cases in the 'uncertain pass' and 'uncertain fail' categories.

4. Discussion and recommendations

4.1 Strengths of the approach

This study used a regression modelling approach to identify and quantify the causes of spatial variation among RWBs in MRP concentration and macroinvertebrate status. This approach is the same as was used previously by APEM to model the variation in lake quality elements (APEM, 2022a). Regression modelling unlocks the full potential of the data collected by the EPA's river monitoring programme by explicitly revealing the key factors that determine a RWB's trophic status and modelling how ecological 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 RWBs is based upon empirical data from hydrologically, geomorphologically, and geographically similar RWBs.

As discussed in the lake extrapolation report (APEM, 2022a) 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: around 50-60% when predicting individual status classes, and around 75-80% when classifying rivers as Good or better vs. Moderate or worse.
- Finally, GAMs, like other regression-based techniques, are also able to quantify the degree of certainty (or margin of error) in the predictions. As illustrated in Section 3.5, using this approach it is possible to quantify the degree of confidence that an unmonitored RWB 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 flow-weighted mean TP concentration, which proved to be a strong predictor of in-river MRP concentration. Notwithstanding some limitations of these datasets and models (discussed in Section 4.2 below), these results validate the use of the SLAM model for understanding phosphorus dynamics in Irish rivers 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 RWB characteristics which are available for use in future studies.

4.2 Limitations of the approach

Whilst the approach was successful in predicting the status of unmonitored RWBs, 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.

4.2.1 Data issues

Water body connectivity. Some variables, most notably the SLAM-modelled TP loads, were available at an RWB-scale and needed to be aggregated to characterise influences at a catchment-scale. Aggregation was achieved using a 'linkages table' listing the RWBs that are immediately upstream of, and therefore hydrological connected to, each focal RWB. Unfortunately, the linkages table was not fully complete and contained both missing and spurious linkages. Using catchment area estimates from the QUBE model as external validation allowed some of the linkages to be fixed, but upstream-aggregated variables were still over- or under-estimated for a small proportion of RWBs.

Geographic proximity. As also noted for lakes by Wynne and Donohue (2016), the catchment variables derived for each RWB do not currently consider the proximity to the river itself. For example, the SLAM Framework predicts phosphorus losses based on the percentage land use within the RWB catchment but does not consider how close these sources are to the river itself, and therefore the potential for nutrient transport.

QUBE flow/runoff estimates. It is assumed that the QUBE (EPA HydroTool) model provides a good estimate of flow at the defining station in each RWB. However, the EPA HydroTool model points are not always located at (or close to) the RWB outflow and, in some cases, are located on tributary streams which can give a potentially misleading estimate of flow if not identified (see Appendix 1).

TP vs MRP. The EPA uses Molybdate Reactive Phosphorus (MRP) to classify the phosphorus status of RWBs, whereas the SLAM framework estimates losses of Total Phosphorus (TP). By definition, TP provides a worst-case estimate of biologically available phosphorus, but will over-estimate MRP by a variable amount depending on the mix of particular and dissolved phosphorus fractions from different sources. To some extent this shortcoming is mitigated by the use of GAMs, which can flexibly model non-linear relationships rather than assuming a linear or 1:1 relationship between TP and MRP concentration, and by using different variables to represent "urban" and "rural" sources of phosphorus. Nonetheless, the predictive performance of the MRP model might be expected to improve if it were possible to estimate MRP instead of TP loads.

TP load estimation from agricultural activity. The SLAM framework covers all major sources of TP from point and diffuse sources (see Appendix 1) 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 may therefore under-estimate TP loads from these sources by an unknown amount for some RWBs.

4.2.2 Missing factors

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 RWBs (especially those which have a large lake in close proximity upstream).

Other stressors. Stressors such as acidification, invasive species and pesticides can potentially influence the status of macroinvertebrate communities, 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 RWB.

Seasonal and inter-annual variation. The present study focused on assessing status over a three-year reporting period (2019-21) 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 river-specific basis. Notably, the extent and timing of seasonal peaks in MRP concentration can aid in understanding the relative importance of external and internal phosphorus loading, 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 MRP concentration, which could potentially help to improve predictions of status for individual RWBs.

4.2.3 Statistical modelling

Representation of catchment networks. Being hydrologically connected, the ecological status at any given location on the river network is influenced by conditions upstream (and potentially downstream as well). In this study, various approaches were used to try to account for this spatial correlation: (i) variables describing conditions in immediately upstream RWBs were included in the models, but they were of limited predictive value because 44.2% of RWBs are headwaters that lack an upstream RWB, and because not all upstream RWBs are monitored; and (ii) hydrological catchment was included as a predictor to represent systematic differences among catchments, but this is probably too coarse for modelling status at a RWB scale. Due to the shortcomings of these approaches, the final models simply include a 2D easting/northing smooth to represent unexplained geographic variation in MRP concentration and macroinvertebrate status, but this too can be criticised on the grounds that it smooths across catchment watersheds (i.e., predictions are influenced by straight-line distance to other monitored RWBs, and ignore whether or not a nearby RWB is hydrologically connected or even in the same catchment).

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 MRP concentration and macroinvertebrate status among RWBs.

Confidence intervals. The calculated confidence intervals around the MRP predictions assume that all the predictor variables for each river 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 RWBs to predict the status of unmonitored rivers implicitly assumes that the monitored RWBs are representative of the full population of 3192 RWBs. Figure 4 confirms that the EPA's monitoring programme is broadly representative of the 12 WFD river typology groups. Generally, 70-80% of RWBs are monitored for MRP and/or macroinvertebrates, however this is lower (60-70%) for the less common RWB types 11, 21 and 24. There is a small risk that the models will be biased towards the behaviour of the more common river types. This risk is partially mitigated by the inclusion in the models of slope and hardness as candidate predictor variables, 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 RWBs that are known to exhibit symptoms of eutrophication.

Extrapolation. The modelled regression relationships hold true over the range of characteristics represented by the monitored RWBs in the calibration dataset, but care must be taken when extrapolating the models to predict the status of unmonitored RWBs 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 RWBs 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 26 (MRP) and Figure 27 (macroinvertebrates) show, however, that the monitored rivers do, generally, cover the full range of characteristics of the 3192 WFD rivers, which means the models can be used with reasonable confidence to predict the status of unmonitored RWBs.

Figure 26: Distribution and coverage of monitored (green) and unmonitored (red) RWBs with respect to the key predictor variables used for modelling MRP

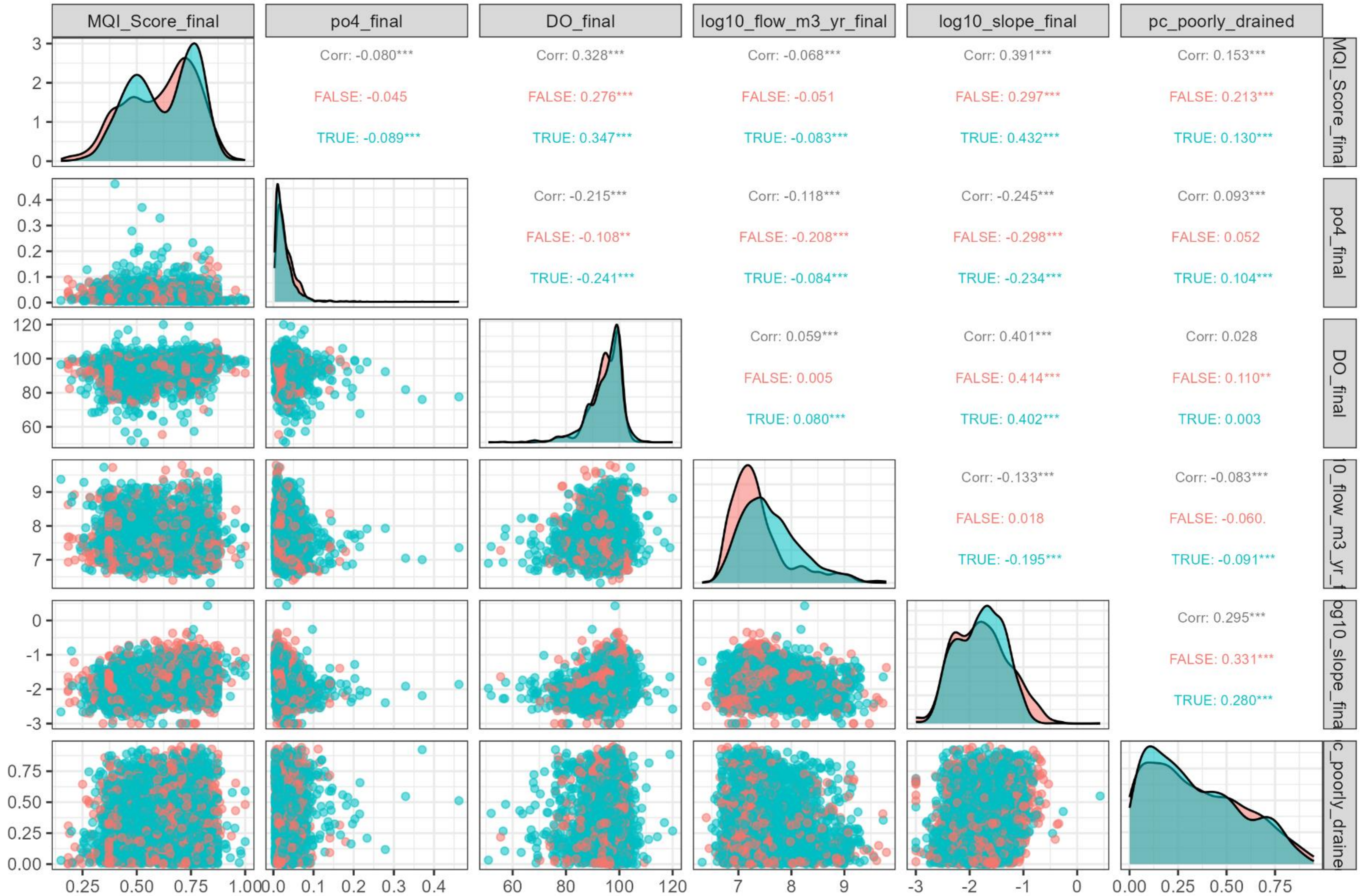

Figure 27: Distribution and coverage of monitored (green) and unmonitored RWBs (red) with respect to the key predictor variables used for modelling macroinvertebrate Q-value status

4.3 Recommendations

4.3.1 Model refinements

Given the limitations discussed in Section 4.2 above, there is clearly potential to refine the regression models and further improve the accuracy of the status class predictions for unmonitored RWBs. Further refinements are likely to deliver diminishing returns, however, 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 RWBs that is not already explained by geographic location (i.e., easting/northing).

1. In the short term, it is recommended that the **RWB linkages file**, which lists immediately upstream RWBs, is checked and refined to correct any missing or spurious linkages. This would immediately allow the catchment-scale variables to be re-calculated and more accurate estimates of catchment characteristics and upstream water quality to be used as predictors in the current models. It would also facilitate the use of locally averaged Markov Random Field (MRF) smooths, which model data over discrete spatial units such as RWBs, and use data from neighbouring units to predict responses in the focal unit.
2. In the longer term, the development of a complete and continuous **river network layer** would support the use of spatial stream network (SSN) models. SSN models are a class of advanced regression model that explicitly represent spatial autocorrelation within dendritic drainage networks using a covariance structure based on e.g., along-channel distance or the degree of hydrological connectivity (Isaak *et al*., 2014; O'Donnell *et al*., 2014). By providing a much more sophisticated representation of spatial variation in water quality and ecological status within river catchments, SSN models have been shown to achieve superior predictive performance to other spatial modelling techniques and are also capable of yielding predictions at any point on the river network, not just at the defining (downstream) station within each RWB. SSN models have been used successfully to model spatio-temporal variation in river nutrient concentrations (O'Donnell *et al*., 2014), water temperature (Jackson *et al*., 2017) and macroinvertebrate indices (Frieden *et al*., 2014) but critically they require a complete (unbroken) river network layer in order to calculate the covariance structure.
3. **Dissolved oxygen (DO)** saturation is an important factor influencing macroinvertebrate status but is relatively poorly estimated for unmonitored RWBs. At present only 1393 (~44%) of 3192 RWBs are currently monitored for DO, and DO saturation for unmonitored RWBs was infilled using a very simple

spatial interpolation model. An improved understanding and representation of the factors that influence DO – for example the degree of groundwater contribution (Jenny Deakin *pers. comm.*) – would allow an improved model to be developed for the infilling process, which should in turn lead to improvements to the macroinvertebrate model.

4. Similarly, **ammonium concentration** is expected to have a strong influence on macroinvertebrate status. In this case, 1320 (~41%) of RWBs are monitored for ammonium, and as part of this project ammonium concentrations were modelled for RWBs where this data was missing. This model comprised geographic position (easting/northing), total organic nitrogen loading as calculated from the SLAM model, and the percentage of the surrounding RWB that is urbanised, and explained just 28.9% of the variation in ammonium concentration. An improved understanding and representation of the factors that influence ammonium concentration – for example, drained organic soils can be an important source of elevated ammonium (Jenny Deakin *pers. comm.*) – would allow an improved model to be developed for the infilling process, which should in turn lead to improvements to the macroinvertebrate model. it should be noted, however, that ammonium and MRP concentrations were strongly correlated with each other, so the modelled relationship between MRP and macroinvertebrate status may already partially account for the influence of ammonium.
5. Given the strong influence of TP loads on in-river MRP concentration and macroinvertebrate status, it is recommended that the EPA explores options for improving the estimation of **phosphorus loads** to better account for agricultural loadings, accounting for nutrient retention in upstream lakes and rivers and, crucially, adjusting the export coefficients to estimate biologically available MRP instead of TP.
6. 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 RWBs with the largest residuals (see Appendices 2 and 3) may be especially instructive. For example, where under-prediction of MRP concentration indicates a potentially important unknown source of phosphorus, an investigation is recommended to determine whether an important catchment source has not been represented fully within the SLAM model. For example, RWB LOUGHNAMINOO STREAM_010 (IE_WE_34L040200) in County Mayo returned the highest residuals from the MRP model (Figure 56, Table 11), and a brief desk-based investigation revealed that the defining station for this RWB was downstream of a livestock mart which may be contributing to the higher concentrations of phosphorus than currently indicated by the SLAM model. Any factors identified can 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.

4.3.2 Future monitoring

The ability to predict, with reasonable accuracy, the status class of unmonitored RWBs presents the EPA with new options for designing 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 RWB 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 RWBs 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 RWBs could be selected for monitoring in a way that maximises gains in predictive performance across the set of 3192 RWBs. Similar approaches have been used for designing river water temperature networks in Scotland (Jackson *et al*., 2016) and England (APEM, 2022b), and optimising the national electrofishing programme in Wales (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.

4.4 Application in future reporting cycles

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

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

- updated MRP and DO concentrations and macroinvertebrate Q-values for monitored RWBs for the relevant reporting period;
- updated TP loads (from SLAM) for all RWBs (to align with the new reporting period); and
- updated MQI scores (if there have been any changes).

This is the minimum amount of data required; the physical (flow, slope etc.) and chemical (hardness etc.) characteristics of the RWBs 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 (especially the column names) 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 RWB. 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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6. Abbreviations used in this report

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BQE	Biological Quality Elements
CIS	Common Implementation Strategy
CORINE	Coordination of Information on the Environment
DO	Dissolved Oxygen
EPA	Environmental Protection Agency
EQR	Ecological Quality Ratio
EQS	Environmental Quality Standards
GAM	Generalised Additive Model
GES	Good Ecological Status
GIS	Geographic Information System
MQI	Morphological Quality Index
MRF	Markov Random Field (GAM smooth)
MRP	Molybdate Reactive Phosphate
NIEA	Northern Ireland Environment Agency
RBMP	River Basin Management Plan
RHAT	River Habitat Assessment Technique
RWB	River Water Body
SANICOSE	Source Apportionment of Nutrients in Irish Catchments for On-Site Effluent model
SLAM	Source Load Apportionment Model
SSN	Spatial Stream Network
TP	Total Phosphorus
WFD	Water Framework Directive

Appendix 1 Data sources and data processing

Catchment area

A “linkages table” with details of the immediately upstream water bodies of each focal RWB was provided by the EPA. This was restructured into a matrix in R with both vertices labelled with the water body codes. From this it was possible to generate a list of *all* the upstream water bodies for each RWB. Using this structure, the catchment areas were aggregated to calculate the total catchment area (in km^2) for each RWB (see Table 5). From this data, headwaters were identified (where the catchment area was the same as the area of the focal RWB), and an “upstream” area was calculated for each RWB by subtracting its area from the total catchment area.

The catchment area calculations were validated using catchment areas derived from the QUBE flow model. Figure 28 highlights differences between the calculated catchment area (on the x-axis) and the QUBE hydrological catchment area (on the y-axis). As the QUBE flow estimation points are not always located at the defining stations used for WFD monitoring, slight differences between the two values were to be expected (shown in red). More problematically, however, there were known issues with the linkages file; these included breaks (where a link is missing) and loops, which caused the calculated area to be much smaller than the QUBE catchment area (shown in blue), and also spurious connections, which caused the calculated area to be much larger than the QUBE catchment area (shown in green). The latter situation was more difficult to diagnose because some QUBE points were found to be on a tributary stream, which resulted in the QUBE catchment area under-estimating the true catchment area of the RWB.

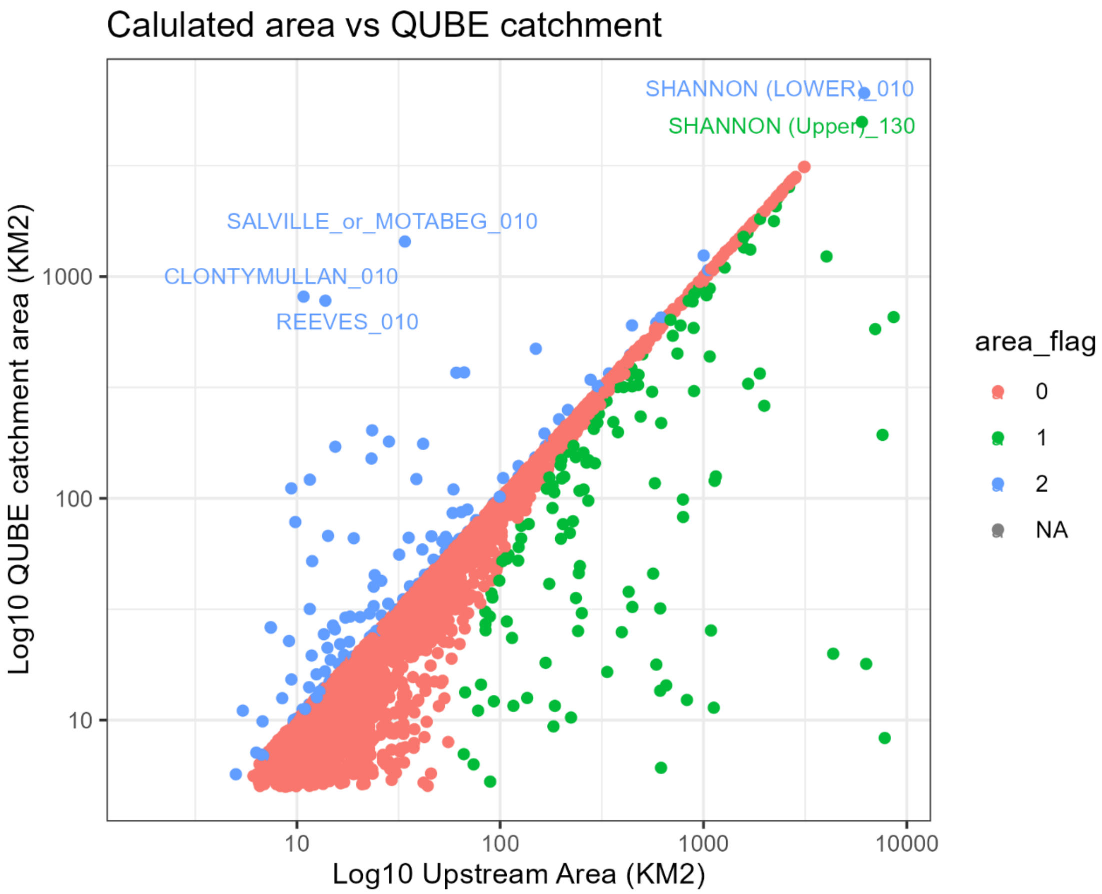

Figure 28: Validation of calculated catchment areas against QUBE hydrological catchment areas

Area flags: 0 = calculated catchment and QUBE areas similar (difference is <1% and <50 km^2); 1 = QUBE area >50 km^2 smaller than the calculated catchment area; 2 = QUBE area >1% larger than the calculated catchment area

Channel slope

Data on mean channel slope, measured in m/m, was available for the majority of RWBs, with data missing only for the 26 cross-border rivers.

A simple GAM was developed to interpolate the missing RWBs, with slope modelled as a function of easting/northing to account for spatial variation (Figure 29, Figure 30). Overall, the model explained 47.7% of the variation in slope (Figure 31). Figure 32 illustrates the relationship between slope and easting/northing. The final model was used to predict channel slope for the remaining 26 rivers.

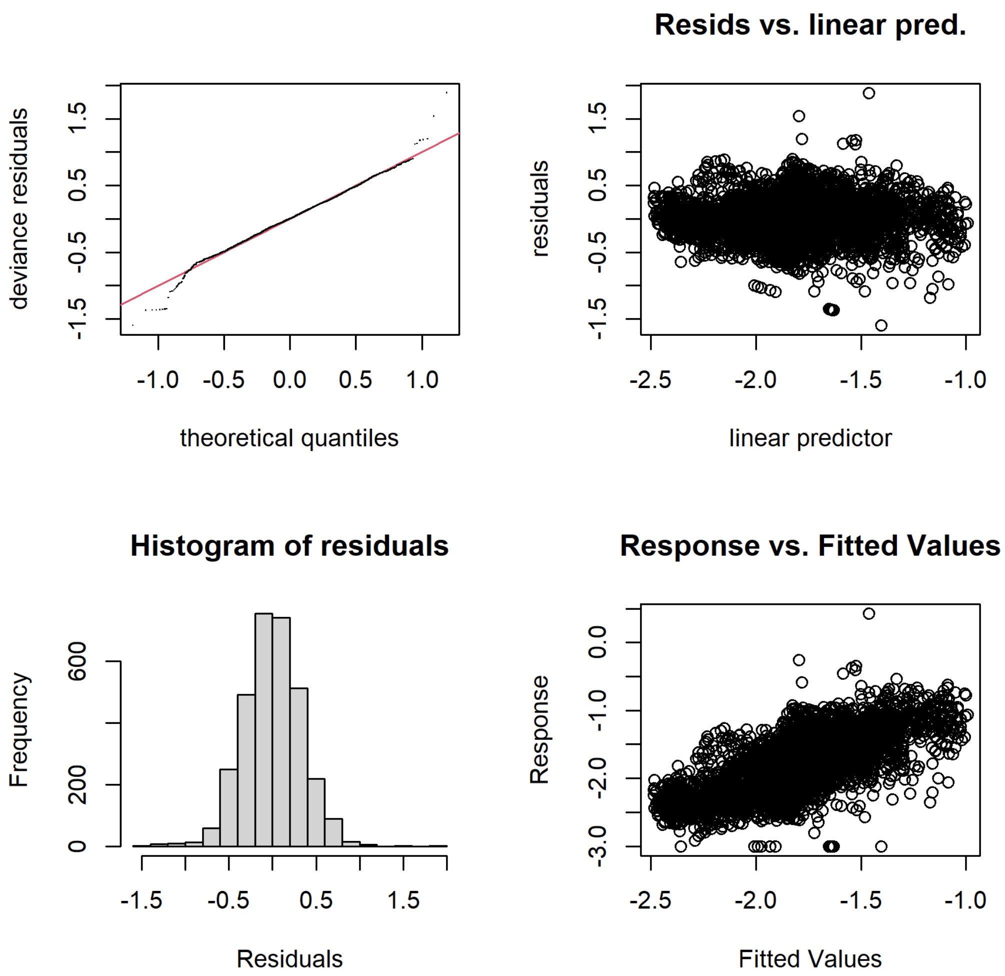

Figure 29: Residuals plots for the slope model

```
Family: gaussian
Link function: identity

Formula:
log10_slope ~ s(RWB_Easting, RWB_Northing)

Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.791739   0.005869  -305.3   <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(RWB_Easting,RWB_Northing) 28.17  28.96 97.85  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.472   Deviance explained = 47.7%
-REML = 1051.7  Scale est. = 0.10907   n = 3166
```

Figure 30: Statistical summary of the slope model

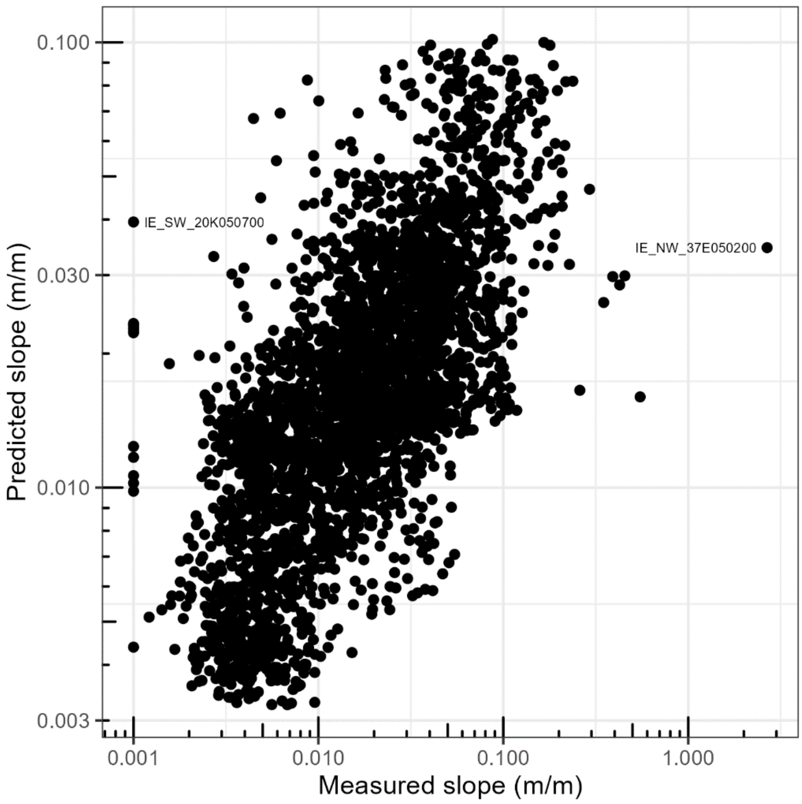

Figure 31: Predicted vs measured slope

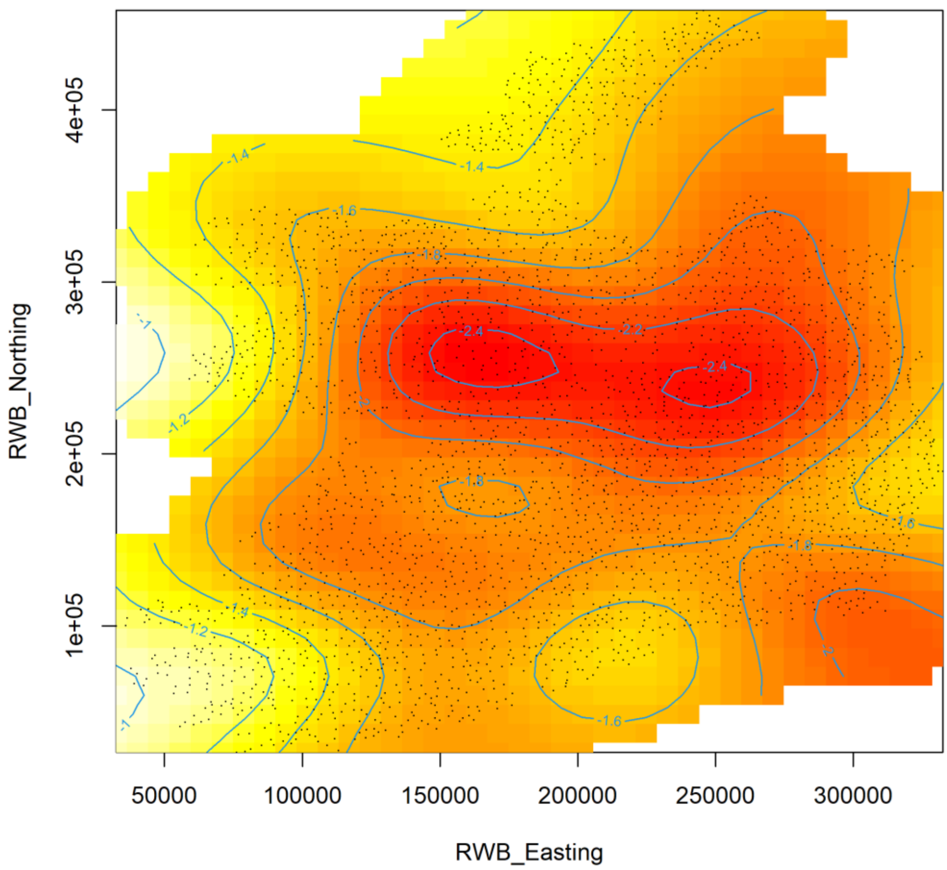

Figure 32: Partial effects plots showing the modelled effect of easting/northing on channel slope

Hardness

Data on water hardness (as indexed by the percentage of calcareous geology) **within the immediate RWB** was available for all RWBs except 26 cross-border RWBs.

The hardness data were logit-transformed, and a simple GAM was developed to infill the missing RWBs. Hardness was modelled as a function of easting/northing to account for spatial variation (Figure 33, Figure 34). Overall, the model explained 56.1% of the variation in hardness (Figure 35).

Figure 36 illustrates the relationship between hardness and easting/northing. The final model was used to predict hardness for the remaining 26 rivers.

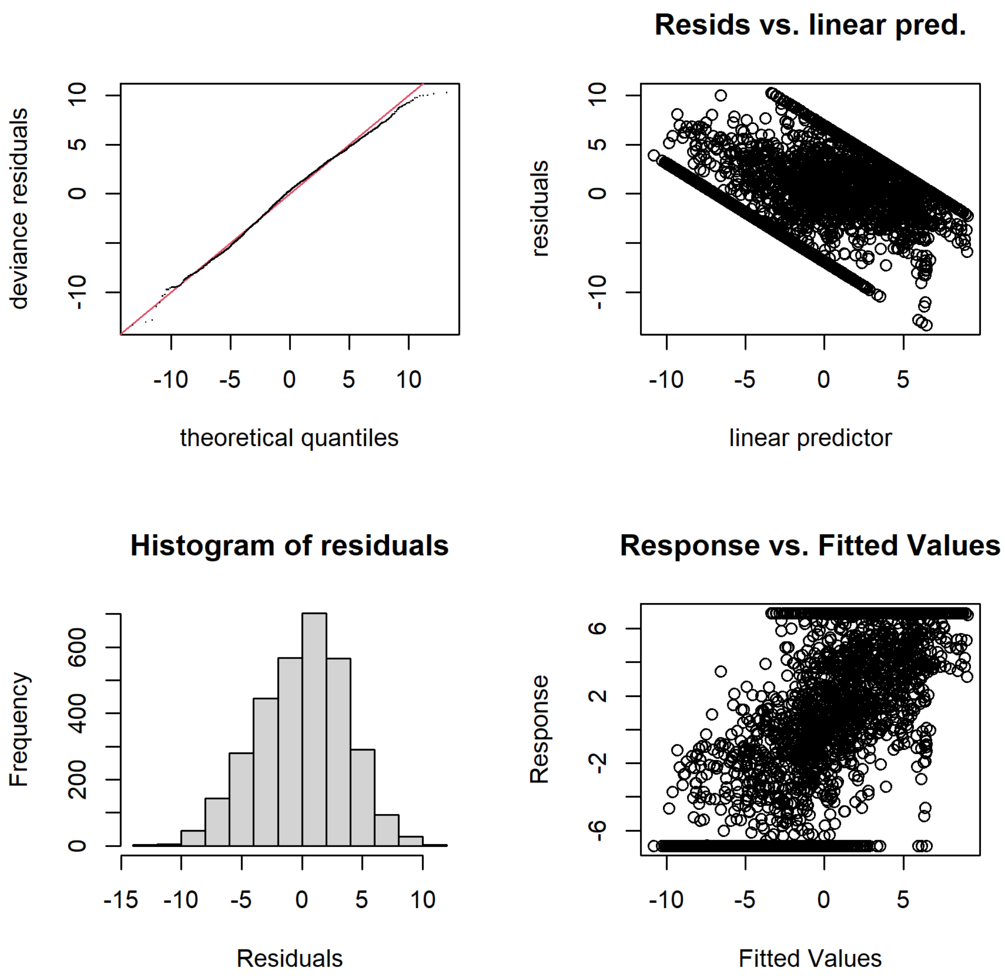

Figure 33: Residuals plots for the hardness model

```
Family: gaussian
Link function: identity

Formula:
trans_calcareous_pct ~ s(RWB_Easting, RWB_Northing)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.12817    0.06521   1.965   0.0495 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df     F p-value
s(RWB_Easting,RWB_Northing) 28.6   28.99 137.4  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.557   Deviance explained = 56.1%
-REML = 8677.8  Scale est. = 13.465    n = 3166
```

Figure 34: Statistical summary of the hardness model

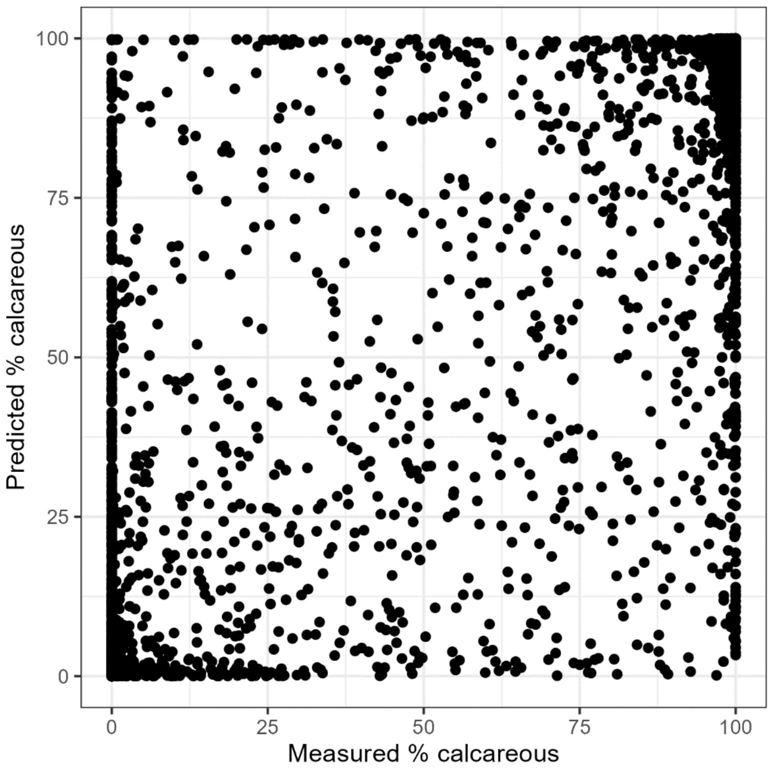

Figure 35: Predicted vs measured hardness

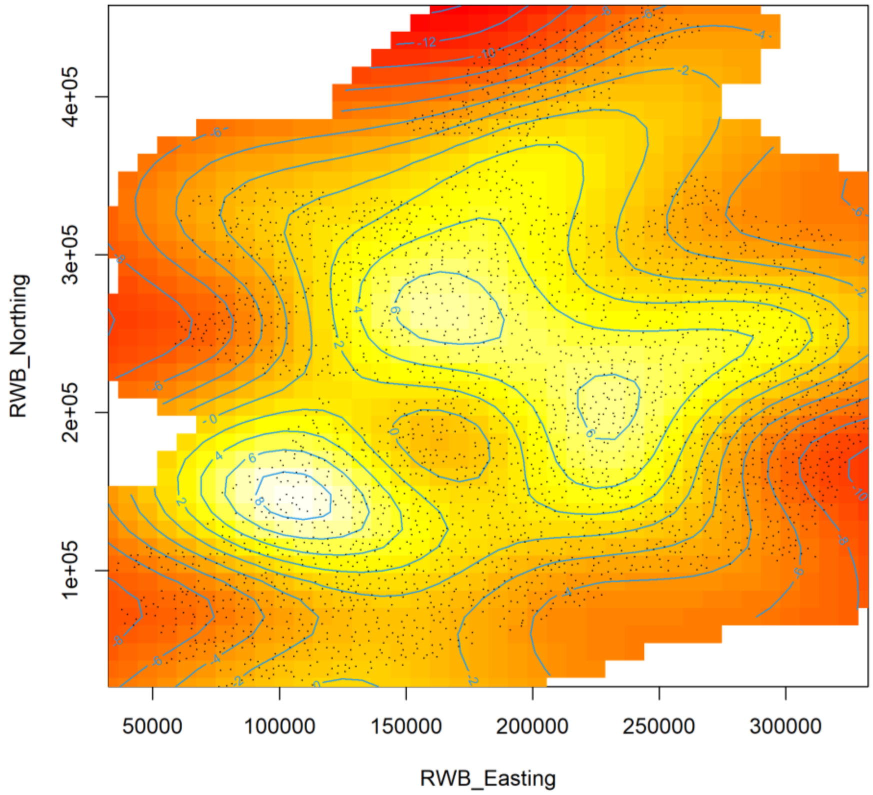

Figure 36: Partial effects plots showing the modelled effect of easting/northing on hardness

To estimate hardness at a **catchment scale**, the area (in km^2) of calcareous geology in the immediate RWB was calculated, then aggregated across all upstream RWBs (using the same “linkages” method used to calculate catchment area, see above) and expressed as a percentage of the total catchment area.

Runoff

Flow data was provided by the EPA and included QUBE data. 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 river, the naturalised annual mean flow (NATAMF) in m^3/s (converted to m^3/yr) was extracted from the QUBE estimation point that was closest to the downstream end of the RWB. Data was available for 2811 rivers. QUBE data for nine rivers was removed after being identified as incorrect during the validation of the catchment area calculation (see above).

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 runoff could be derived for the 390 rivers lacking QUBE data.

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

- mean catchment slope (log_{10}-transformed);
- upstream hardness (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 three variables were retained in the final model (Figure 37; Figure 38). Overall, the model explained 78% of the variation in runoff (Figure 39). Figure 40 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 390 rivers; Figure 41 maps measured and predicted runoff for all 3192 rivers.

The annual average flow (m^3/yr) for all 3192 WFD river outlets was then calculated by dividing the annual runoff (either modelled or predicted, $m^3/km^2/yr$) by the river catchment area (km^2). As the position of the QUBE estimation points varied within an RWB, this calculation assumes that runoff across the hydrological catchment (upstream of the QUBE estimation point) is constant.

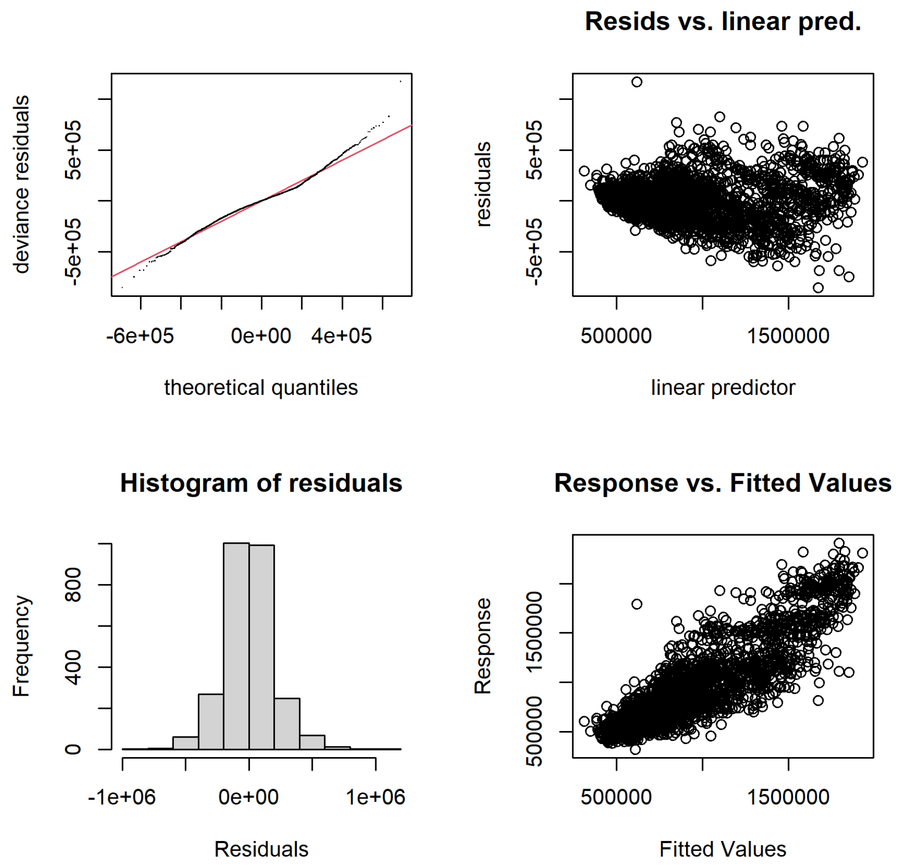

Figure 37: Residuals plots for the runoff model

```
Family: gaussian
Link function: identity

Formula:
runoff_m3_km2_yr ~ s(RWB_Easting, RWB_Northing) + s(log10_slope_final) +
    s(upstream_calcareous_pct)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   913091       3763   242.6   <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(RWB_Easting,RWB_Northing) 28.265 28.964 133.73  <2e-16 ***
s(log10_slope_final)         7.297  8.339  50.83  <2e-16 ***
s(upstream_calcareous_pct)   7.664  8.536  19.11  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.777   Deviance explained =   78%
-REML =  36207  Scale est. = 3.7684e+10  n = 2661
```

Figure 38: Statistical summary of the runoff model

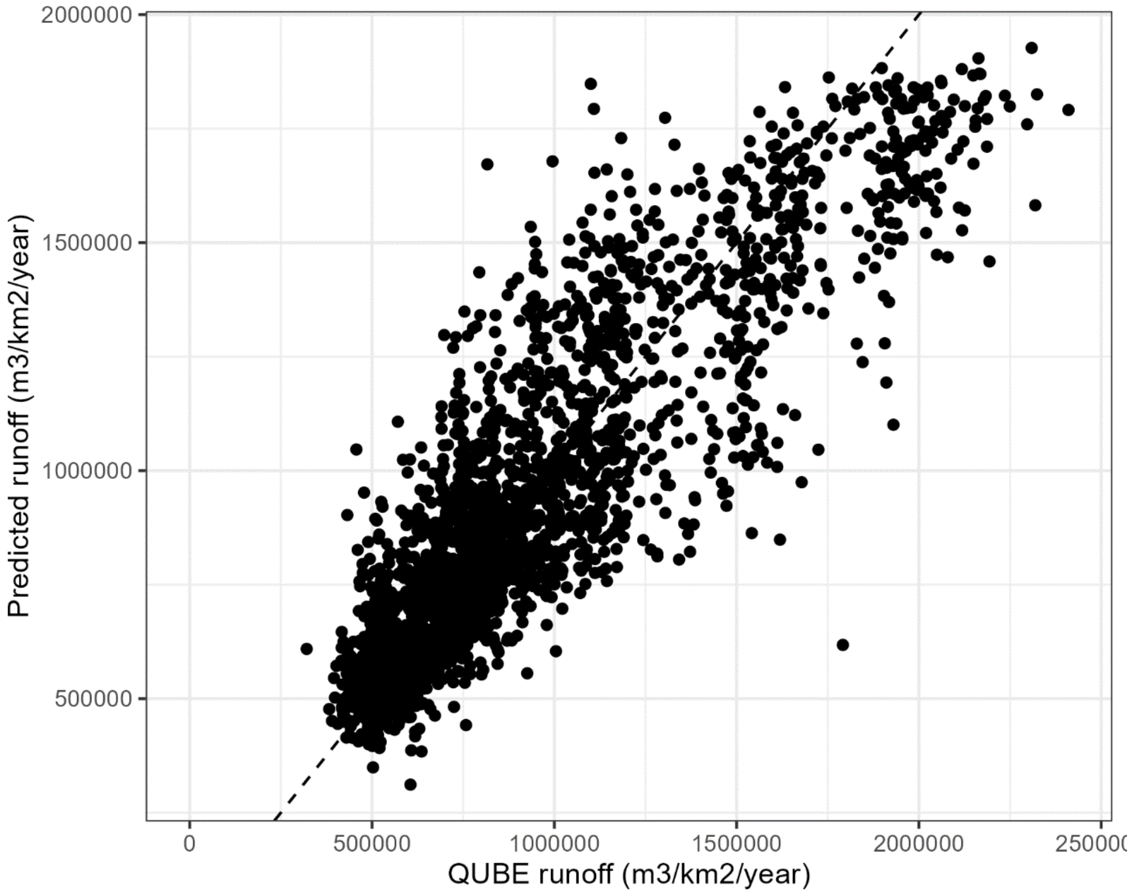

Figure 39: Predicted vs measured runoff for the rivers with QUBE data

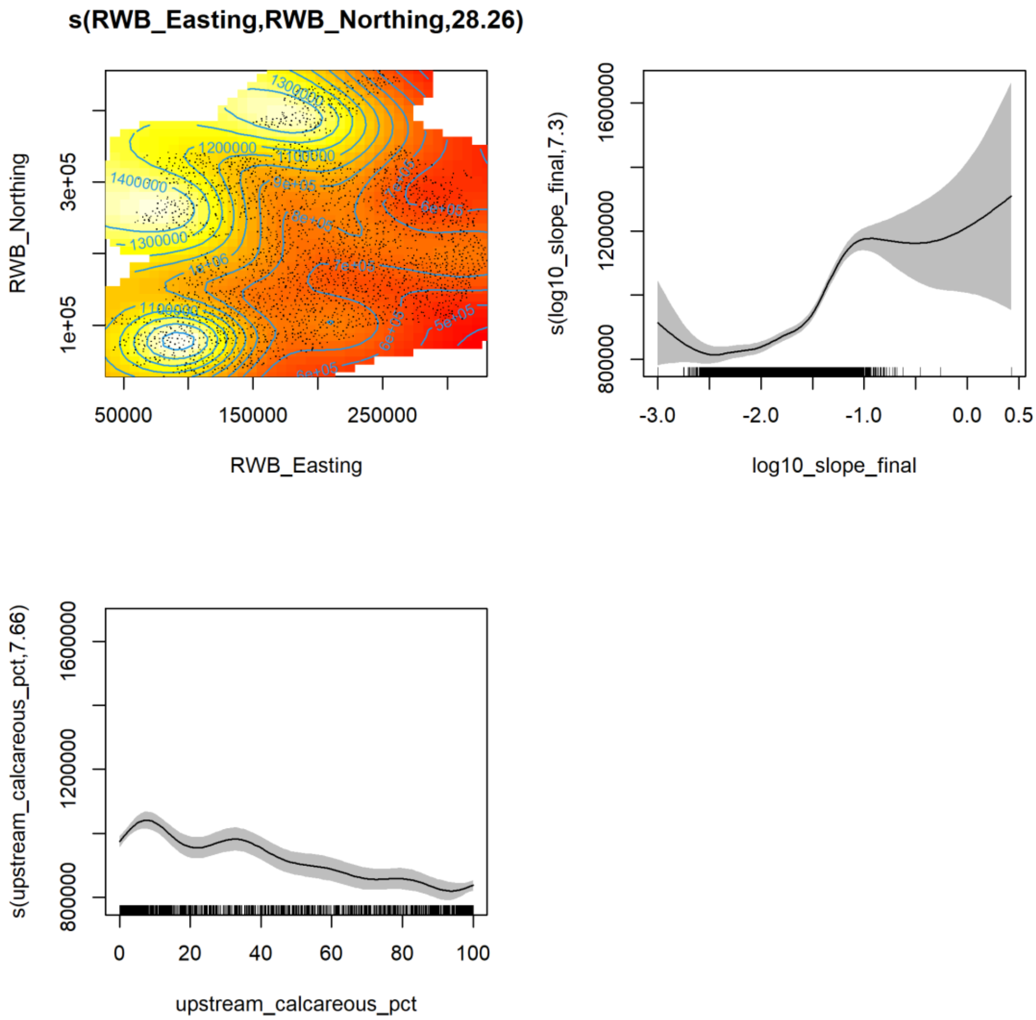

Figure 40: Partial effects plots showing the effect of each variable on runoff

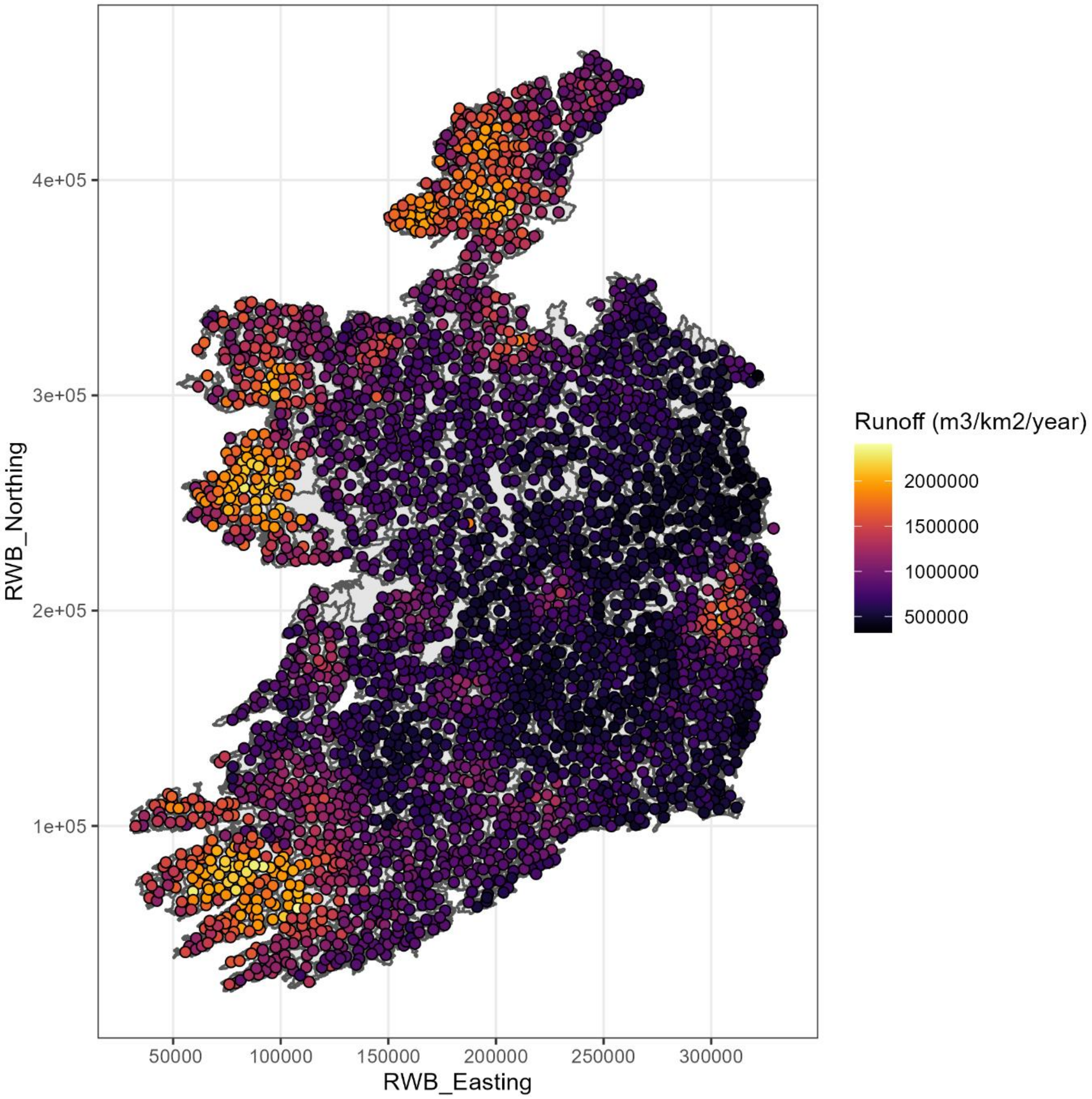

Figure 41: Map of measured and predicted runoff for all 3192 rivers

Phosphorus loading

The EPA's Source Load Apportionment Model (SLAM, v303) was used to estimate the total annual TP load entering each WFD RWB 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 Waterbody layer, the SLAM framework collated the following spatial datasets to characterise the land-use and physical characteristics of each WFD RWB:

- 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 was used to estimate 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 estimate the total annual TP loading (in kg/ha/yr) from land within each RWB from "urban" sources from homes and businesses (wastewater, diffuse urban, septic tanks and other licensed discharges) and "rural" land-based sources (pasture, arable, forestry, peatlands and atmospheric deposition on water). However it should be noted that for cross-border RWBs, only the fraction of the RWB area within the Republic of Ireland can be modelled by SLAM, so the loads for these RWBs are under-estimates.

Using the catchment area data, the "local" (RWB-scale) loads were summed to estimate the total TP load to each RWB (in kg/yr) from the upstream catchment. Both the “local” and “upstream” loads (kg/yr, converted to mg/yr) were then divided by the annual flow (m3/yr, converted to l/yr) at the RWB outlet to estimate the annual mean flow-weighted TP concentration in each RWB (mg/l) due to local and upstream sources.

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 42 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 42: SLAM v303 input data

Dissolved oxygen saturation

Measured data on 3-year mean DO saturation, was available for 1393 RWBs. Using the available data, a GAM was developed to infill the missing RWBs. DO saturation was modelled as a function of easting/northing to account for spatial variation (Figure 43, Figure 44).

Overall, the model explained 35.8% of the variation in DO saturation (Figure 45). Figure 46 illustrates the relationship between DO saturation and easting/northing. The final model was used to predict DO saturation for the remaining 1799 RWBs, as illustrated in Figure 47.

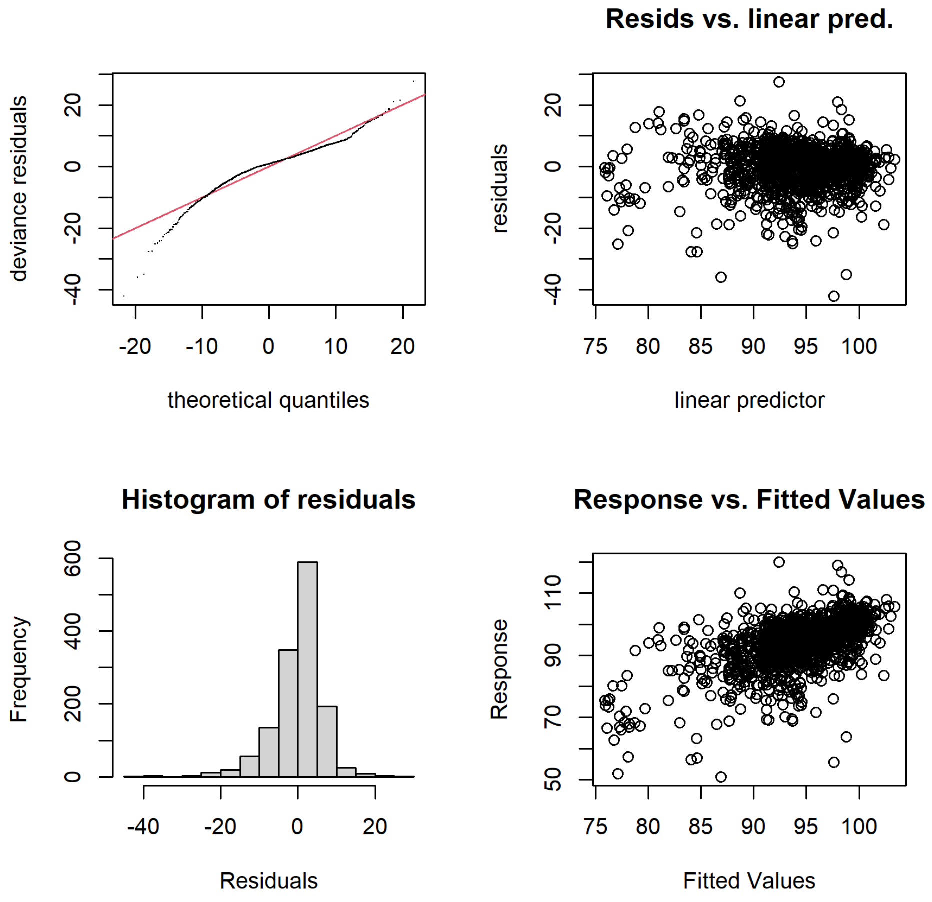

Figure 43: Residuals plots for the DO model

```
Family: gaussian
Link function: identity

Formula:
Av_3Year_DO ~ s(RWB_Easting, RWB_Northing)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  94.6811     0.1716   551.9   <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(RWB_Easting,RWB_Northing) 27.15  28.79 25.64  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.345   Deviance explained = 35.8%
-REML = 4608.6  Scale est. = 41.004    n = 1393
```

Figure 44: Statistical summary of the DO model

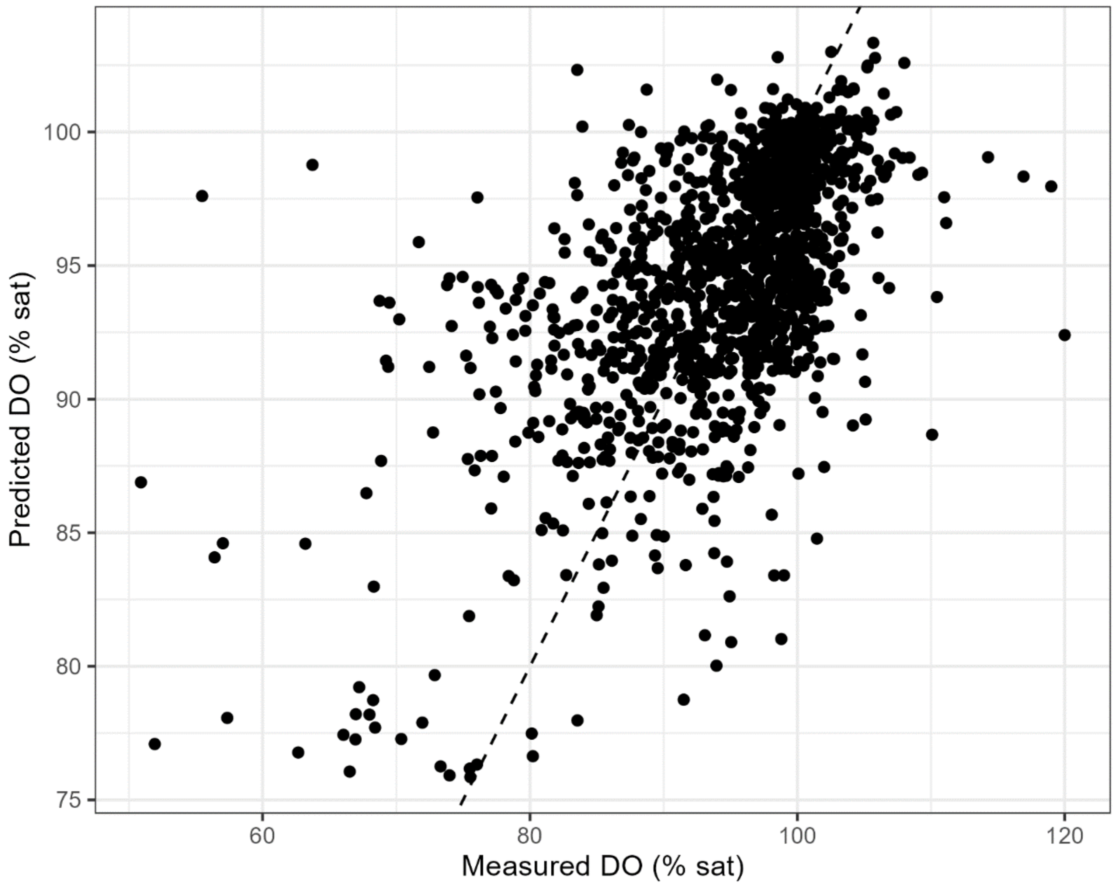

Figure 45: Predicted vs measured DO saturation

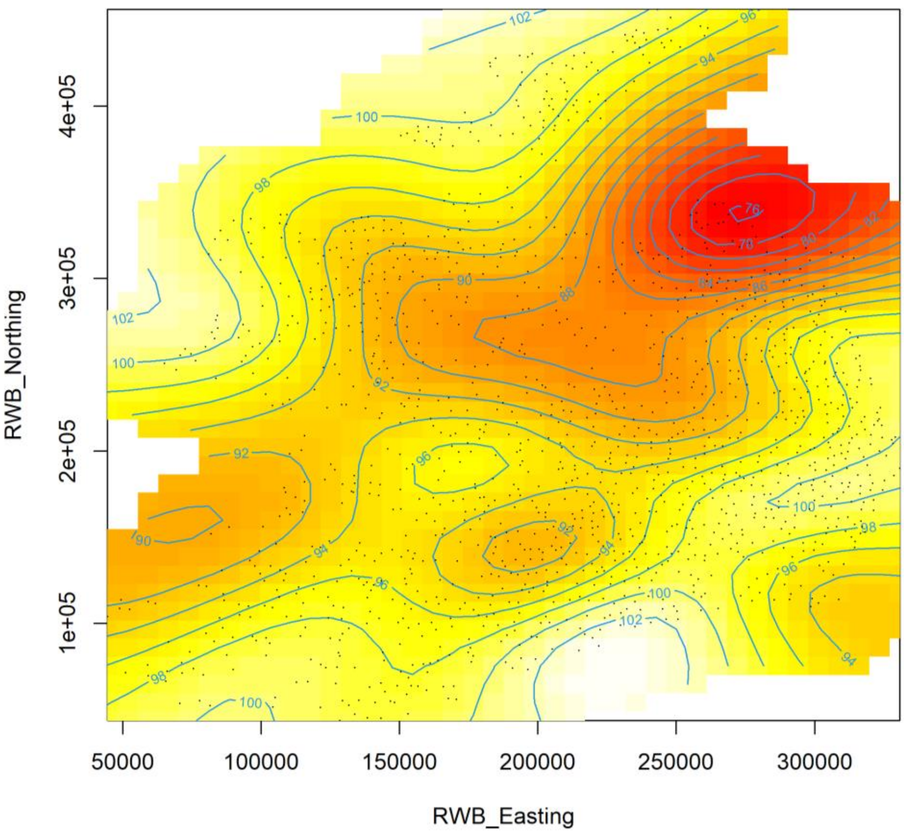

Figure 46: Partial effects plot showing the modelled effect of easting/northing on DO saturation

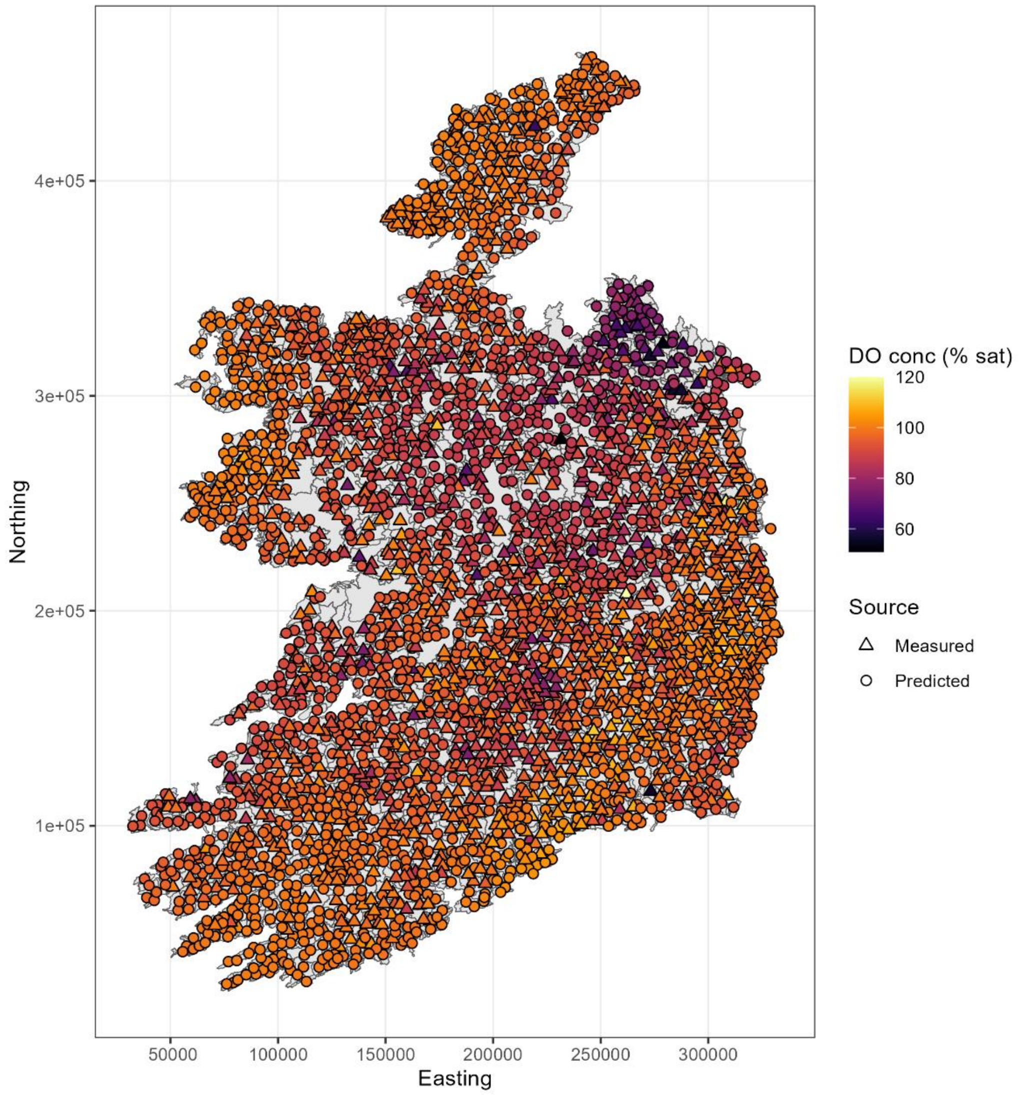

Figure 47: Map of measured and predicted DO saturation for all 3192 RWBs

Ammonium concentration

Measured data on 3-year mean ammonium concentration, was available for 1320 RWBs. Using the available ammonium data, a GAM was developed to infill the missing RWBs. Ammonium concentration was modelled as a function of: (i) easting/northing to account for spatial variation, (ii) the percentage urban land use in the RWB, and (iii) the SLAM-modelled Total Nitrogen (TN) loading from the RWB, expressed as a flow-weighted annual mean concentration and $\log_{10}$-transforemed to reduce skew (Figure 48, Figure 49).

Overall, the model explained 28.4% of the variation in ammonium concentration (Figure 50), and concentration increased strongly with TN loading and percentage urban land use (Figure 51). The final model was used to predict ammonium concentration for the remaining 1872 rivers, as illustrated in Figure 52.

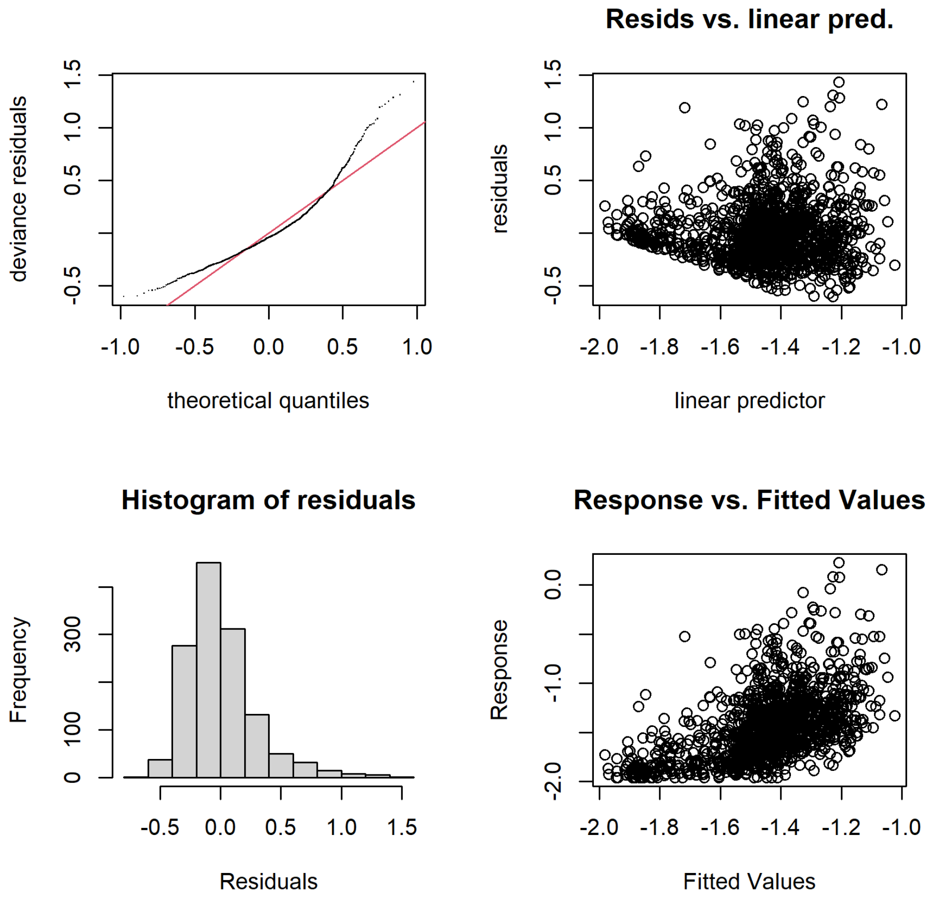

Figure 48: Residuals plots for the ammonium model

```
Family: gaussian
Link function: identity

Formula:
log_Av_3Year_NH4 ~ s(RWB_Easting, RWB_Northing) + LU_Urbanisation +
    s(log_tn_mg_l)

Parametric coefficients:
                  Estimate Std. Error  t value Pr(>|t|)
(Intercept)     -1.4627216  0.0087717 -166.755  < 2e-16 ***
LU_Urbanisation  0.0041117  0.0009337    4.403 1.15e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                               edf Ref.df      F p-value
s(RWB_Easting,RWB_Northing) 23.098 27.021  9.528  <2e-16 ***
s(log_tn_mg_l)               3.693  4.696 16.270  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.269   Deviance explained = 28.4%
-REML = 290.82  Scale est. = 0.084465  n = 1320
```

Figure 49: Statistical summary of the ammonium model

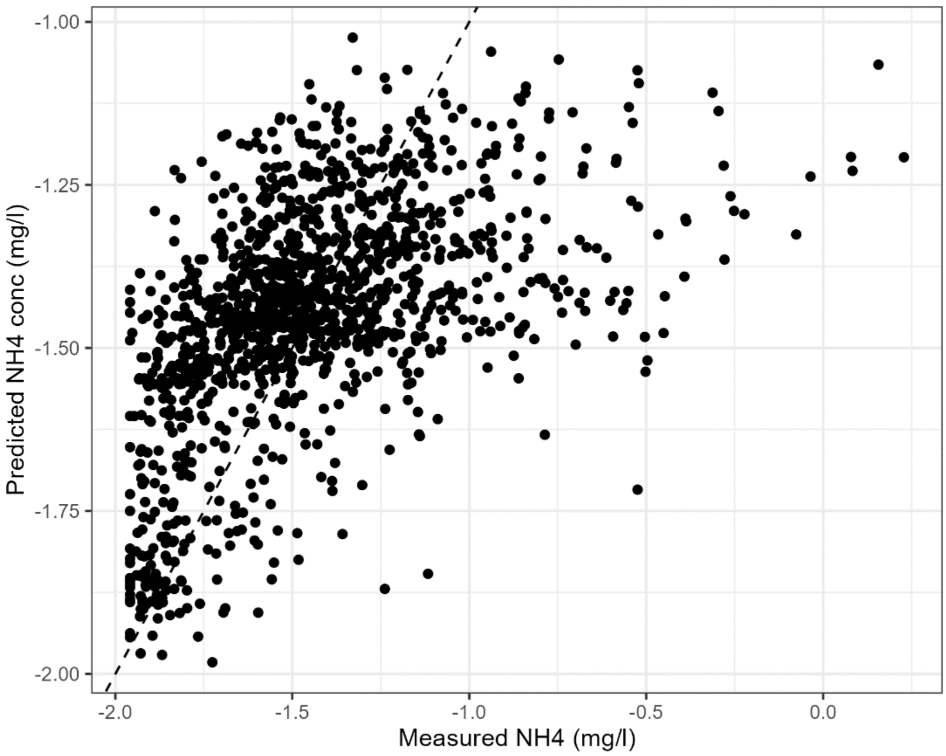

Figure 50: Predicted vs measured ammonium concentration (log-log scale)

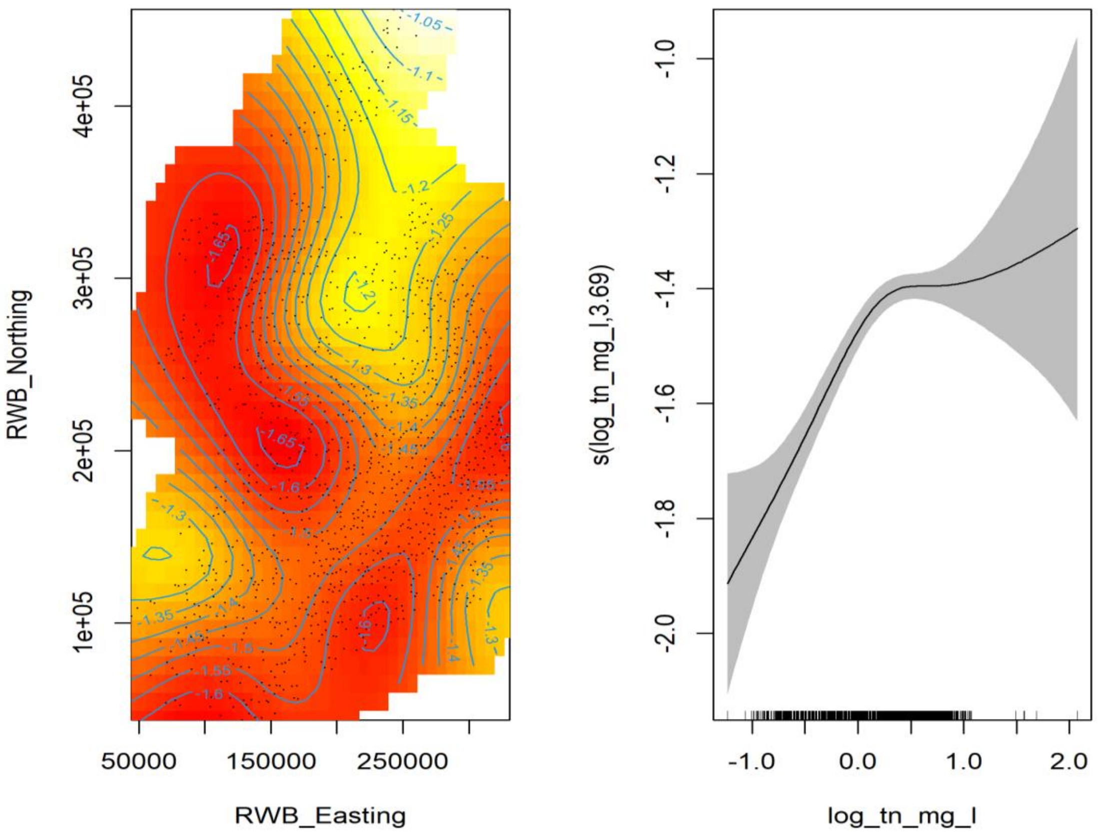

Figure 51: Partial effects plots showing the modelled effect of easting/northing and $\log_{10}$ transformed Total Nitrogen loading on ammonium concentration

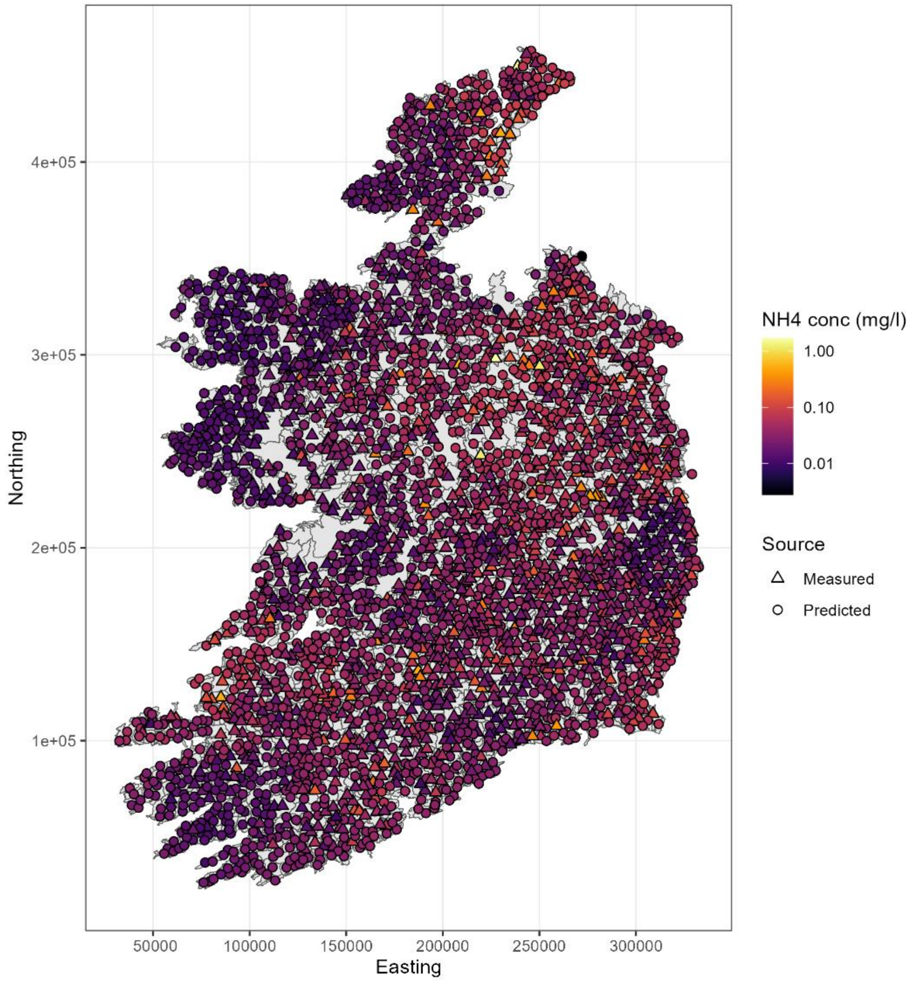

Figure 52: Map of measured and predicted ammonium concentration for all 3192 RWBs

Appendix 2 Phosphate (MRP) model

```
Family: gaussian
Link function: identity

Formula:
log10_Av_3Year_PO4 ~ s(RWB_Easting, RWB_Northing, k = 50) + s(log10_tp_mg_l_urban) +
    s(log10_upstream_tp_mg_l_urban) + te(log10_tp_mg_l_rural,
    pc_poorly_drained) + s(log10_flow_m3_yr_final) + s(log10_slope_final)

Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.620440   0.006354    -255   <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(RWB_Easting,RWB_Northing)            41.861 47.214 15.347  <2e-16 ***
s(log10_tp_mg_l_urban)                  6.069  7.226 24.571  <2e-16 ***
s(log10_upstream_tp_mg_l_urban)         1.000  1.000 34.317  <2e-16 ***
te(log10_tp_mg_l_rural,pc_poorly_drained) 5.068  5.851  8.891  <2e-16 ***
s(log10_flow_m3_yr_final)               1.000  1.000 85.392  <2e-16 ***
s(log10_slope_final)                    4.677  5.869  8.648  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.666   Deviance explained = 68.3%
-REML = -28.997  Scale est. = 0.046921  n = 1162
```

Figure 53: Statistical summary of the MRP model

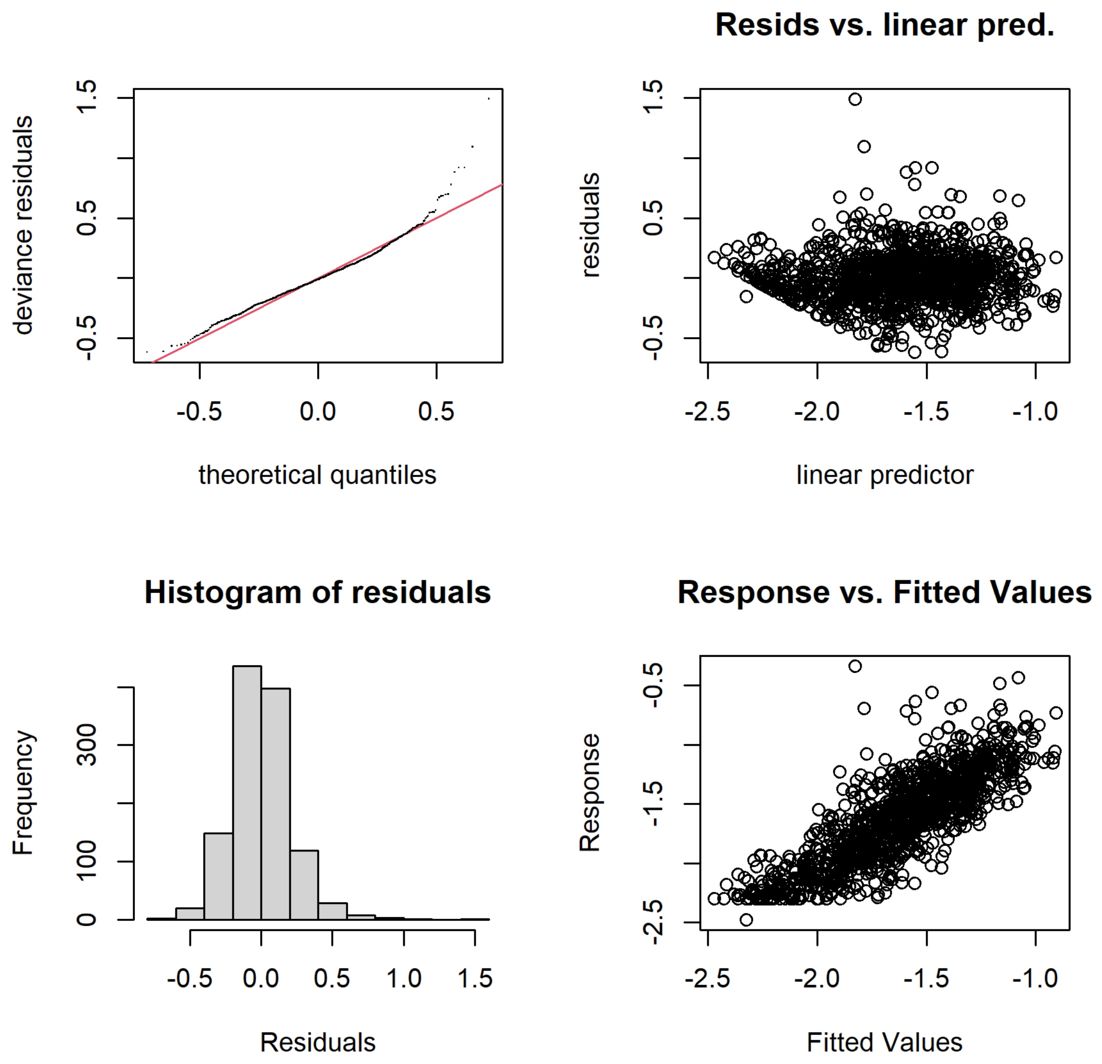

Figure 54: Residuals plots for the MRP model

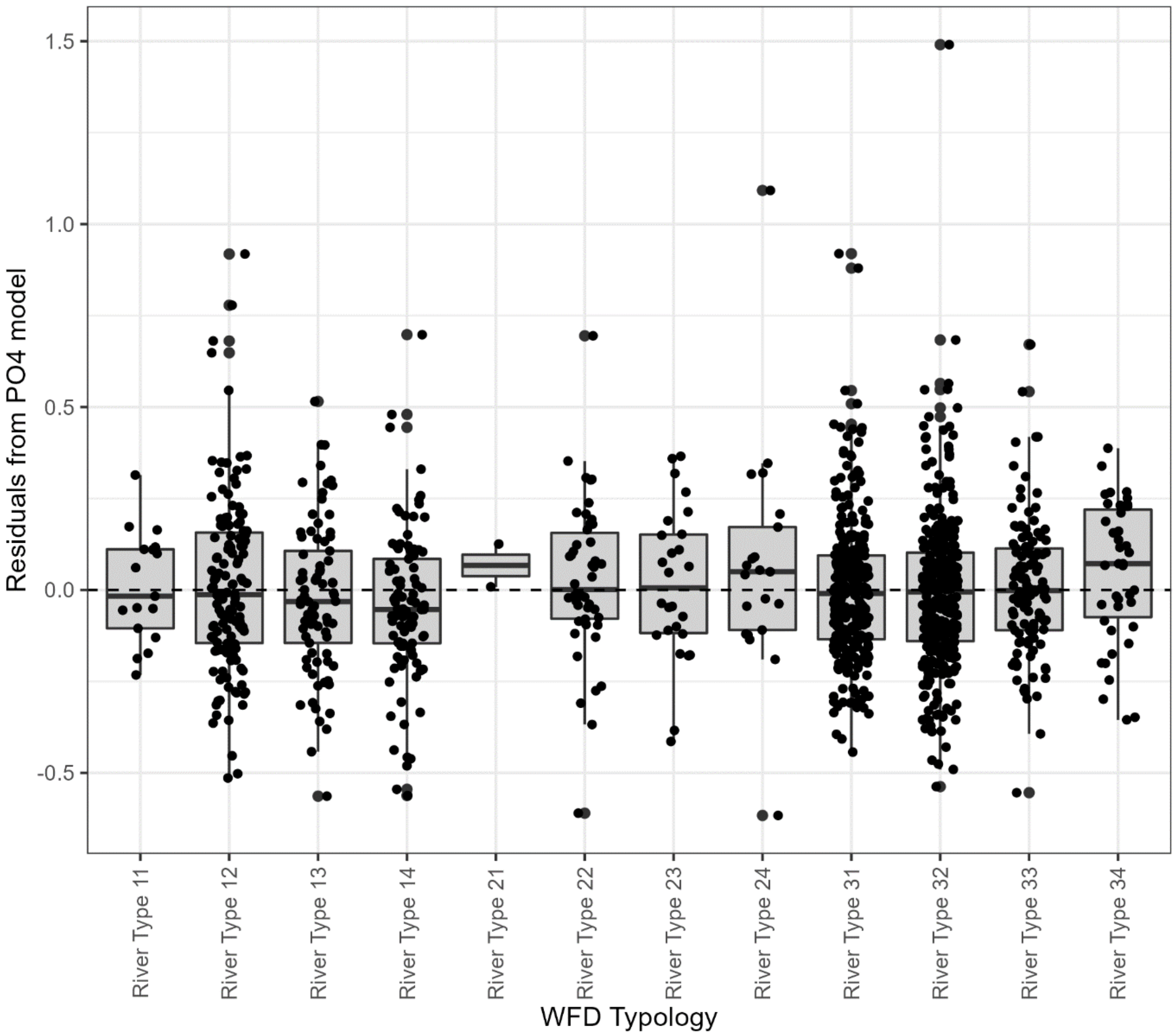

Figure 55: Comparison of the residuals from the MRP model for the WFD typology groups

Figure 56: Comparison of the residuals from the MRP model for the different river catchments

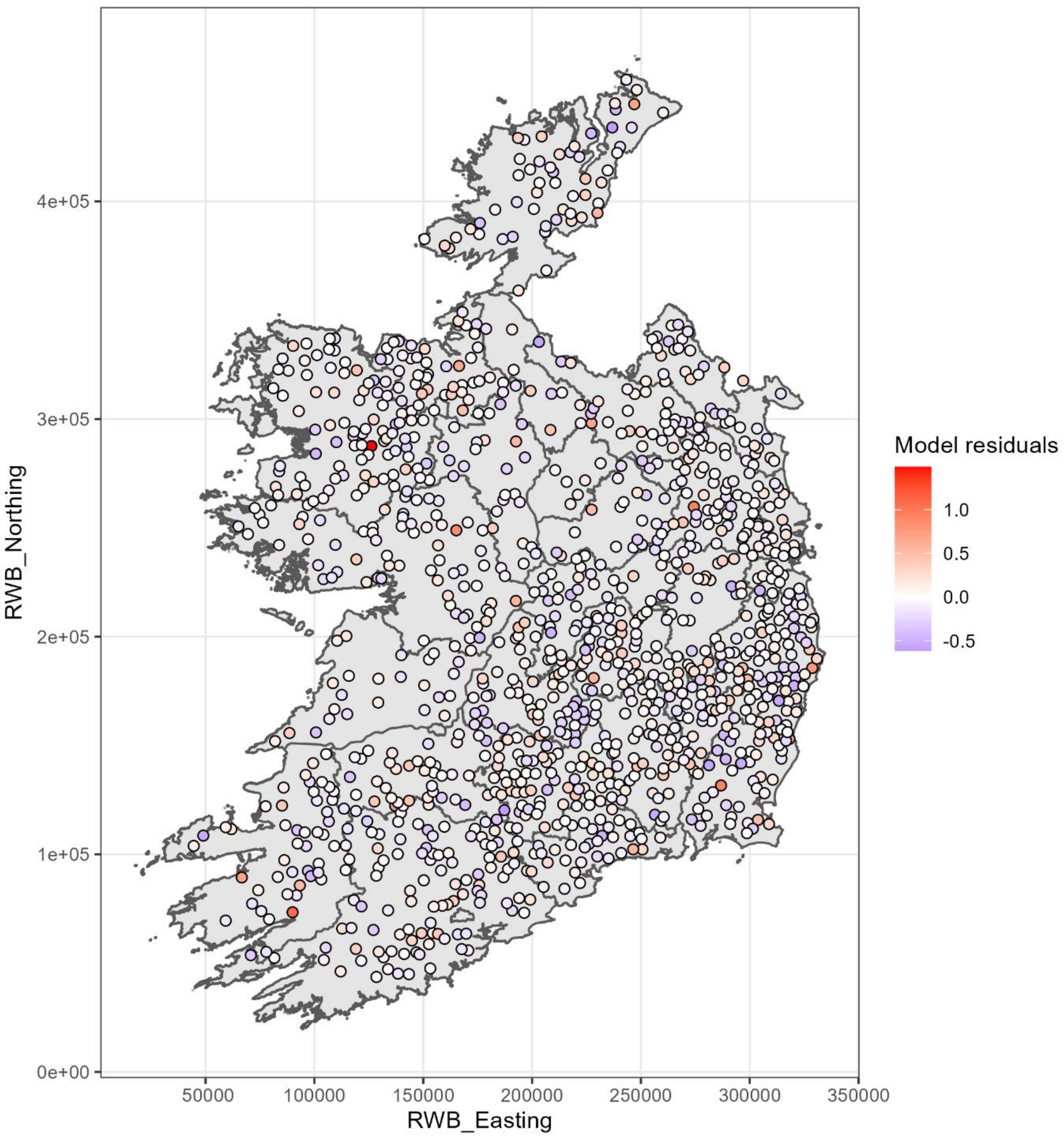

Figure 57: Map of residuals showing where the true measured MRP concentration is higher (red) or lower (blue) than the concentration predicted by the MRP model

Table 11: RWBs with the top 10 largest positive and negative residuals in the MRP model

RWB code	Catchment area (km^2)	River name	Measured MRP concentration	Predicted MRP concentration	Log residuals
IE_WE_34L040200	25.93	LOUGHNAMINOO STREAM_010	0.46205	0.014933	1.490546
IE_SW_21F010510	20.26	FINNIHY_020	0.2025	0.01638	1.092106
IE_EA_07A010500	34.56	ATHBOY_060	0.278725	0.033569	0.919235
IE_SE_12B020340	45.29	BORO_040	0.233239	0.028154	0.918259
IE_SH_26C030200	15.3	CASTLEGAR_020	0.193481	0.025529	0.879611
IE_EA_10P010500	18.3	POTTER'S_020	0.167205	0.02786	0.778271
IE_SW_22B021300	11.73	BEHY (KERRY)_030	0.08375	0.016795	0.697799
IE_NW_40D010400	11.81	DONAGH_030	0.203021	0.041003	0.694721
IE_SH_24A020800	11.81	AHAVARRAGA STREAM_010	0.329261	0.068263	0.683358
IE_NW_36C030300	35.47	CULLIES_010	0.21575	0.045018	0.680566
IE_SH_25R020200	15.11	ROCK (BIRR)_020	0.007933	0.024548	-0.49057
IE_EA_10A031050	18.91	AVOCA_020	0.006557	0.020842	-0.50224
IE_SE_12U010500	14.55	URRIN_050	0.0114	0.037226	-0.51394
IE_SE_16B020450	13.25	BLACKWATER (KILMACOW)_040	0.009625	0.033182	-0.5375
IE_SH_23O030300	30.33	OWENMORE (KERRY)_010	0.0054	0.018935	-0.54486
IE_NW_36R020200	11.51	ROO_010	0.0068	0.024354	-0.55406
IE_SE_12B020040	18.94	BORO_010	0.005167	0.018842	-0.56192
IE_SE_12B010100	15	BANN_010	0.0056	0.020504	-0.56365
IE_NW_39C020500	15.92	CRANA_030	0.009067	0.036946	-0.61012
IE_SW_18F050030	16.21	FUNSHION_010	0.00675	0.0279	-0.61631

Appendix 3 Macroinvertebrate model

```
Family: Ordered Categorical(-1,0.94,3.49)
Link function: identity

Formula:
Mac_Q_group ~ s(RWB_Easting, RWB_Northing, k = 50) + s(LU_Urbanisation) +
    HMWB + s(MQI_Score_final) + s(log10(po4_final)) + s(DO_final) +
    s(log10_flow_m3_yr_final) + s(log10_slope_final) + s(pc_poorly_drained)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.48828    0.04275   34.82  < 2e-16 ***
HMWB        -0.56435    0.14621   -3.86 0.000113 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq  p-value
s(RWB_Easting,RWB_Northing) 35.081 42.885 279.29  < 2e-16 ***
s(LU_Urbanisation)           4.115  5.003  28.75 2.48e-05 ***
s(MQI_Score_final)           1.002  1.004  18.00 2.29e-05 ***
s(log10(po4_final))          1.003  1.006  80.95  < 2e-16 ***
s(DO_final)                  4.093  5.205  54.08  < 2e-16 ***
s(log10_flow_m3_yr_final)    3.118  3.926  56.10  < 2e-16 ***
s(log10_slope_final)         3.315  4.276  42.36  < 2e-16 ***
s(pc_poorly_drained)         2.151  2.701  11.21  0.00702 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Deviance explained = 21.9%
-REML = 2620.1  Scale est. = 1         n = 2370
```

Figure 58: Statistical summary of the macroinvertebrate model

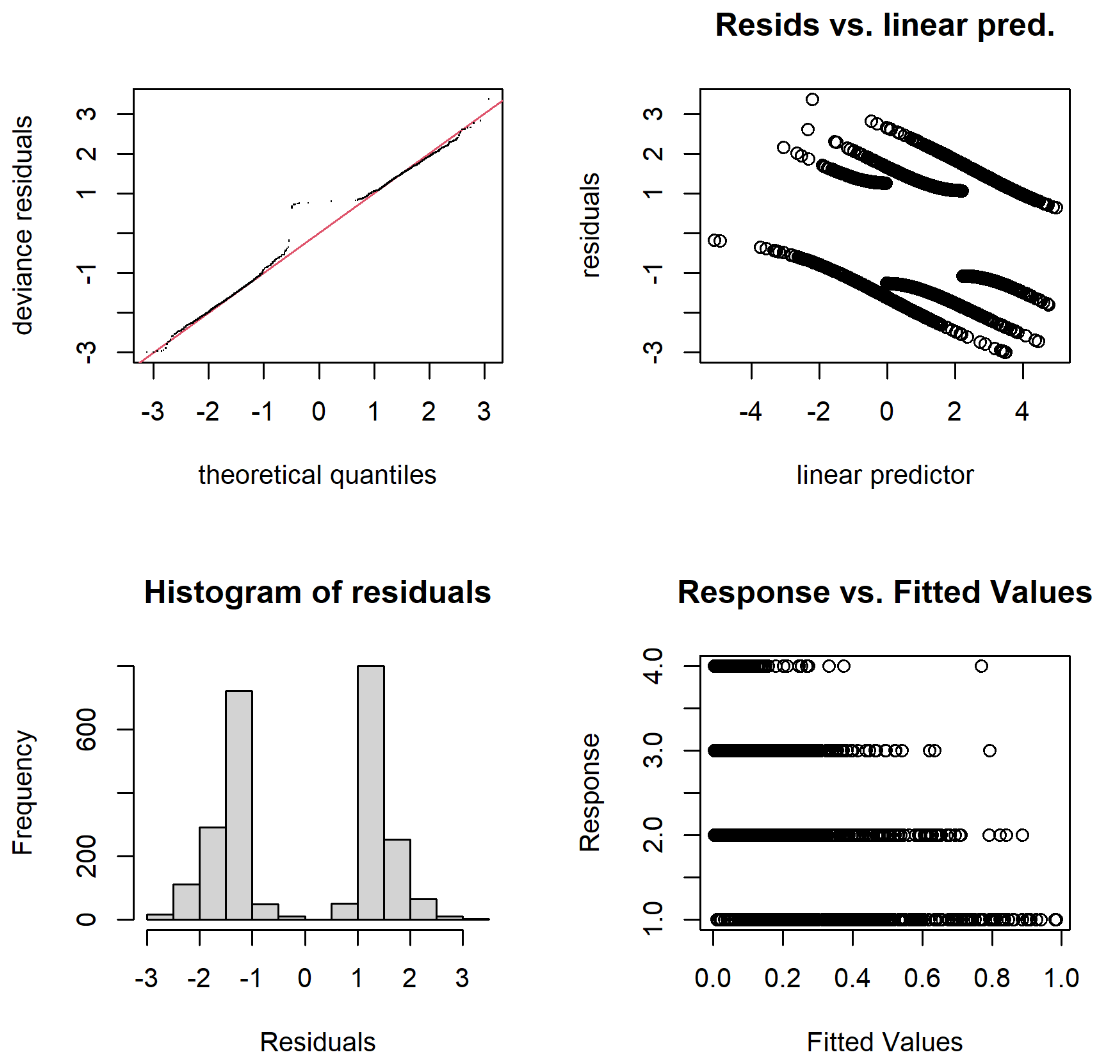

Figure 59: Residuals plots for the macroinvertebrate model

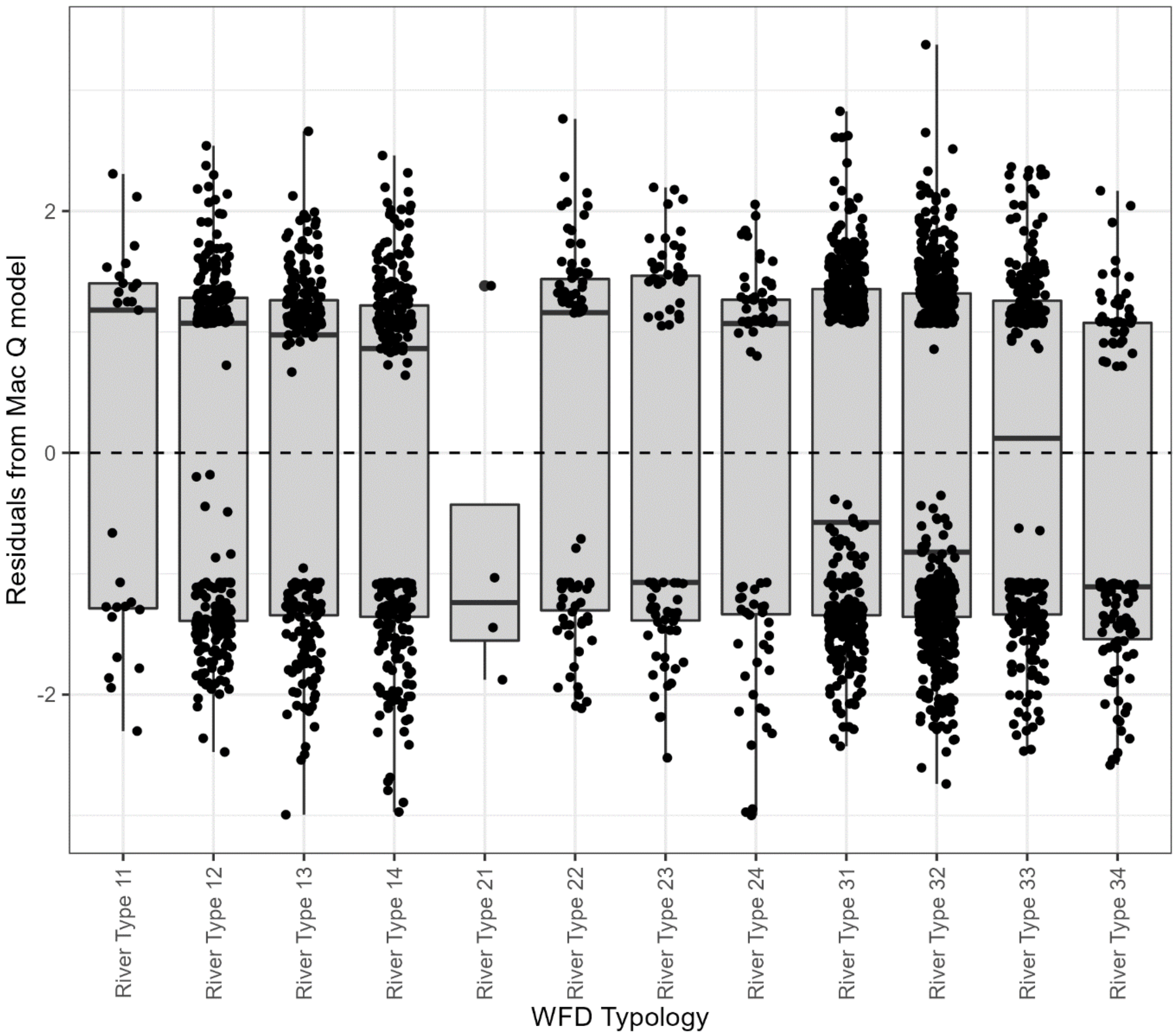

Figure 60: Comparison of the residuals from the macroinvertebrate model for the WFD typology groups

Figure 61: Comparison of the residuals from the macroinvertebrate model for the different river catchments

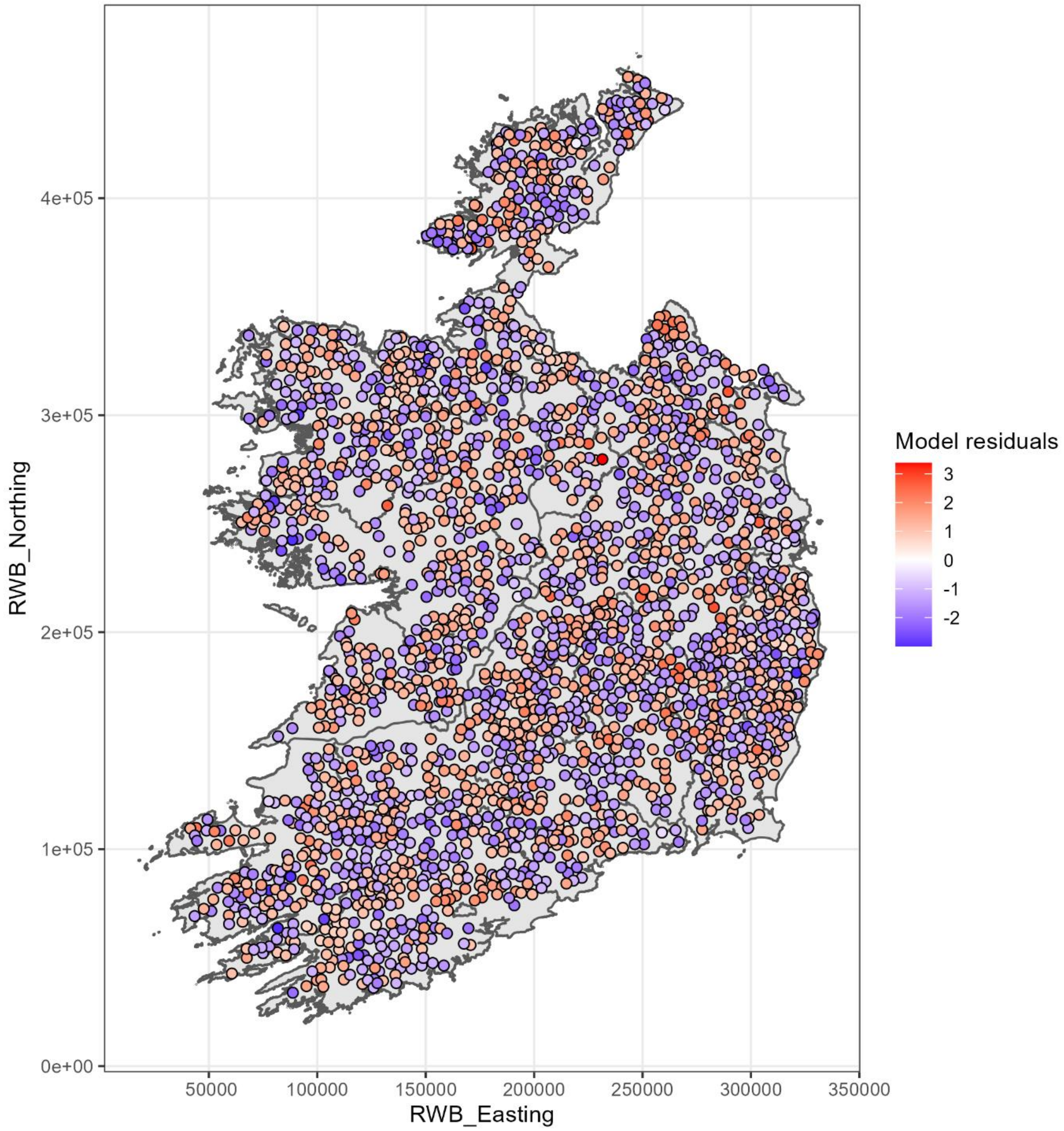

Figure 62: Map of residuals showing where the measured macroinvertebrate status (represented by a latent variable) is higher (red) or lower (blue) than that predicted by the macroinvertebrate model

Appendix 4 River water body results

An accompanying Excel spreadsheet provides a full set of input data and model predictions for all 3192 river water bodies.