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Trends and influential factors of high ecological status mobility in Irish Rivers

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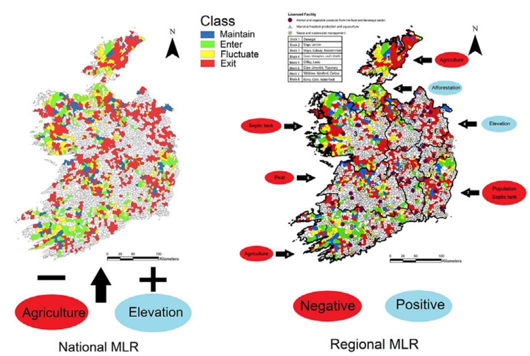
HIGHLIGHTS

- The trend and mobility of high status rivers have been visualised.
- Agriculture and elevation affect the mobility at national scale.
- Regional MLR models reveal different pressures in different regions.

GRAPHICAL ABSTRACT



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ABSTRACT

The decline in high ecological water status in rivers is a significant concern in European countries. It is thus important to investigate the factors that cause sites to lose high status in order to undertake measures to protect and restore high status water quality. Analysis of 20 years of water quality data reveals strong mobility between high status and non-high status (especially good status) rivers. Associations between this mobility and socio-economic and physical environmental variables were estimated by multinomial logistic regression at national scale and regional scale. Based on reported changes in water quality status cross across 1990, 2000 and 2010, four classes of the mobility of high status were defined in this study: those sites that maintain high status (maintain), enter high status (enter), fluctuate between high and non-high status (fluctuate) and exit from high status (exit). The national results indicate that agricultural activity as indicated by variables representing intensity of livestock farming (organic nitrogen) and tillage farming (cereal share) and elevation had significant negative impacts on high status rivers. Meanwhile, significant differences in population density and septic tank density between 'exit', 'maintain', 'fluctuate' and 'enter' classes indicate that these factors played important roles in the stability of high status rivers. The regional outcomes reveal differential significant pressures across regions. For example, rainfall and elevation had positive impacts on high status rivers in the north-west region, while organic nitrogen had a negative effect in the south-west. This paper demonstrates the challenge in achieving the Water Framework Directive goal of maintaining high status rivers, given the sensitive and highly differentiated nature of areas that have lost high status or fluctuated in and out of high status. This paper also suggests the necessity for localised policies and mitigation measures.

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1. Introduction

River water quality deterioration is a global concern (Diamantini et al., 2018; Hutchins et al., 2018; Jin et al., 2018). The status of rivers in Europe declined since economic activities flourished in the second half of the 20th century (Grizzetti et al., 2017). To meet the needs of society and pursue environmental sustainability, the primary goal of the Water Framework Directive (WFD) (2000/60/EC) is to achieve 'good' ecological status across all waters. Meanwhile, the WFD also seeks to maintain existing 'high' status that reflect natural background or minor disturbance by anthropogenic influences, according to ecological classifications (OJEC, 2000). However, a decrease in the number of high status rivers is widely observed in European countries such as Estonia, Latvia, Slovenia and Ireland (EEA, 2012; EEA, 2018; EPA, 2019). The loss of high status at river monitoring sites is a key environmental concern as it reflects water quality degradation, loss of pristine status, and loss of high quality reference sites vital for research and management (Hering et al., 2010). Such high (and pristine) status rivers are not only important for biodiversity and ecological integrity, they also provide valuable ecosystem services and public goods, including clean drinking water, landscape and recreational benefits.

To date, research on river water quality has largely focused on the investigation of 'good' status across all levels of water quality at varied scales. These include small catchment scale (less than 100 km^2) (Freni et al., 2012; Dewi Yustika et al., 2019), large catchment scale (1.8 million km^2) (Yang et al., 2015) and worldwide scale (Khan et al., 2017). It is however unclear whether these study conclusions are transferable to high status rivers. In addition, the secular downward trend in the share of high status sites is accompanied by some upward movement of lower ecological water quality status to better ecological status (EPA, 2019). The mobility between high status and non-high (good, moderate, poor, bad) status has not previously been examined, nor have the factors influencing such mobility. In order to deliver on the objectives for high status rivers, a comprehensive understanding of the mobility of high status rivers and the drivers of status change is required.

Water quality is influenced by a range of factors, from socio-economic factors to the physical environment. A number of studies focus only on socio-economic influences on water quality responses to land use change (Wilson, 2015; Mainali and Chang, 2018), but neglect natural controls, such as elevation (Varanka and Luoto, 2012) and rainfall (Panagopoulos et al., 2015). Farzin and Grogan (2013) investigated the relationships between water quality and socioeconomic factors in California at the county level for the years 1993–2006, finding that agricultural activities, land use and population density were all significantly correlated with various water quality indicators. Zhou et al. (2012) assessed the effects of landscape pattern on water quality in China and found that urban land use exerted a large influence. In relation to climatic impacts, seasonal or short-term variation in water quality has been observed due to accidental releases (Jirka and Weitbrecht, 2005), water turbidity (Iida et al., 2011) and hurricanes (Shiller et al., 2012; Dimitriou and Mentzafou, 2016).

Our study used Ireland as a case study because it contains a high proportion of the high status rivers found in the EU. However, the proportion of high status rivers in Ireland has declined dramatically in recent years (EPA, 2019), leading to a call for management strategies for the protection of high status water bodies (White et al., 2014). In order to provide a better understanding of the factors impacting on high status water quality, this analysis simultaneously took into account the influences of socio-economic, geological, hydrological and climatic factors.

Previous Irish studies (Daly et al., 2002; Roberts et al., 2017) have documented links between declining water quality and landscape variables such as soil type, hydrology, land use and nutrient use. O'Donoghue et al. (2021) found that river water quality was influenced by geomorphological (e.g. elevation, slope), climatic (e.g. rainfall, temperature) and anthropogenic factors (e.g. agricultural activities, septic tanks and forest cover) based on an analysis of longitudinal data sets. Roberts et al. (2016) examined the effects of land use on high status rivers in Ireland between 2001 and 2012 at 508 water quality monitoring sites across the country, and concluded that grassland negatively affected the maintenance of high status. However, the relationship with land use in Roberts et al. (2016) cannot fully explain fluctuations between high status and non-high status at river monitoring sites, especially those sites that enter high status from non-high status. There are also other local factors at play that affect the mobility of high status in rivers that cannot be elucidated with larger, national scale data analyses. Therefore, our analysis extended the explanatory variables to explore their influences at both national and regional scales.

Our study contributed to the gap in the literature by focusing not only on high status rivers but also examining the mobility between high status and non-high status as well as the stability of high status. To achieve the aim of restoring and retaining the high status requires a more detailed regional scale analysis, which has not been conducted previously. Building on earlier work that examined the relationship between rural economic activities and river water quality in Ireland (O'Donoghue et al., 2021), we used an Irish longitudinal water quality dataset (1990–2010) that exhibited a decline from 574 high status rivers in 1990 to 95 rivers in 2010, in order to examine the trend as well as the factors influencing changes in high status rivers. Our study objectives were (a) to visualise the trend in the change of water quality status and the mobility between high status and non-high status, and (b) to assess the main factors associated with the mobility of high status rivers, with multinomial logistic regression (MLR) models at both national scale and regional scales.

2. Data and methodology

2.1. Study area

The focus of our study is on water quality in the Republic of Ireland. Ireland is located in northwestern Europe, with mountainous, marginal farming areas in the west (Fig. 1a & b), contrasting with more lowland, fertile free-draining soils in the southeast (Fig. 1b). Annual rainfall is high, with drier areas in the east and wetter in the west (Fig. 1c). Based on the Corine land use map, a simplified land use map of the study area is classified and shown in Fig. 1a.

2.2. Dependent variable (water quality)

Data from more than 3000 water quality monitoring sites on about 13,200 km of main river channels are examined by the current WFD monitoring programme (EPA, 2008). The monitoring sites are selected in all river basins of Ireland to depict national water status, aiming to assess the measures of point source pollution, diffuse pollution, hydromorphological pressures and the retention of high and good status (EPA, 2006). The 'Q-value' quality rating system which is primarily based on measurements of tolerant macroinvertebrates is adopted for the WFD ecological classification (Flanagan et al., 1972). The macroinvertebrate index, ranging from 0 to 1, represents taxonomic composition and abundance and the ratio of sensitive to insensitive taxa (EPA, 2006). The different biological, physical and chemical indices are aggregated in the calculation of our sampling to the overall Q-Value. The trend and change of Q-values are analysed on a tri-annual basis. The monitoring programme visits more than 1000 monitoring sites (one third) every year, sampling biological elements, such as macroinvertebrates and fish to generate measures of the overall water quality for Ireland. Q-values range from 1, indicative of extremely poor ecological quality to 5, indicative of minimally impacted conditions (i.e. pristine/unpolluted) (Table 1S, EPA, 2008). A time-series of Q-value river quality monitoring data collected by the Environmental Protection Agency (EPA) over the period 1971 to 2018 were used in this study to illustrate the long-term changes in Q-value, focusing on EPA high status river

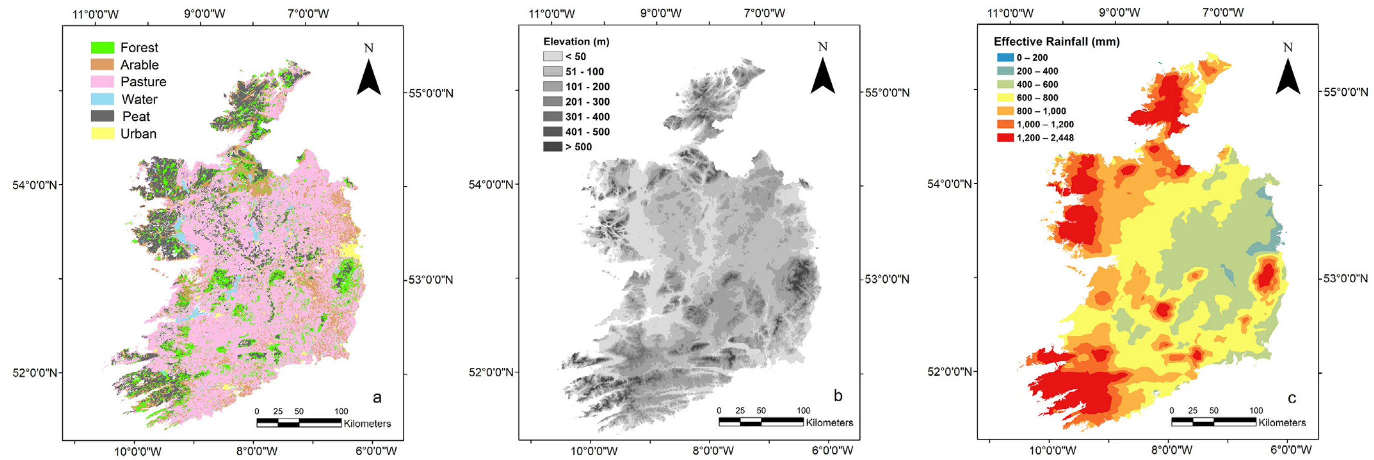

Fig. 1. Maps showing background of study area: a) simplified land use map; b) elevation map; c) effective rainfall map.

monitoring sites whose Q-values are equal to or above 4.5 during the period 1990–2010.

High status monitoring sites were classified by the change of Q-value on the basis of tri-annual water quality of 1990, 2000 and 2010. In this way, four mobility classes were created: 1) maintain - sites that maintain high status in 1990, 2000 and 2010, 2) enter - sites that exhibit improved water quality and achieve high status in either 2000 or 2010, 3) fluctuate - sites that fluctuate between high status and a lower status in 1990, 2000, and/or 2010, 4) exit - sites that exhibit decline in water quality from high to a lower status in 2000 or 2010 (Table 1). On the basis of the WFD objective of maintaining high status water, the 'maintain' class is stable; the 'enter' class indicates improvement; the 'fluctuate' class is unstable and the 'exit' class suggests deterioration.

2.3. Explanatory variables

2.3.1. Agricultural data (organic nitrogen (N) and cereal share)

Due to the high proportion of grassland-based ruminant livestock in Ireland, agriculture is one of the main pressures on ecological status in rivers (Donohue et al., 2006; Álvarez-Cabria et al., 2016; EPA, 2020). Organic animal manure (slurry) and inorganic fertilisers are the main sources of diffuse N losses (Daly et al., 2002; Fenton et al., 2017; Roberts et al., 2017). In contrast to grassland-based farm activities, cereal production requires larger applications of chemical fertilisers with higher concentrations of most major nutrients due to high crop uptake, however, poor management of nutrients and soil conditions in tillage systems can lead to significant losses to water (Roberts et al., 2017; Ulén and Mattsson, 2003).

The Irish Census of Agriculture collects information on farm structures from all farm holdings on a ten-year cycle. Our analysis used data from the 1991, 2000 and 2010 Census of Agriculture at Electoral Division (ED) level, which is the lowest level of spatial disaggregation for publicly provided data in Ireland. The total number of EDs of Ireland in the 2011 National Census of Population is 3409, with an average area of 20.4 km^2. Agricultural activity in Ireland is comprised of both livestock and tillage systems. The annual organic N load is used as a proxy for the intensity of livestock agriculture and is calculated as the number of livestock units per hectare multiplied by livestock nutrient excretion factors (Table 2S) (Government of Ireland, 2010). Tillage farming is represented as the cereal share, defined as the proportion of crop-land coverage in each ED.

2.3.2. Population density and septic tank density

High status water bodies are sensitive to population and relatively low-intensity activities, such as septic tanks (Curtis and Morgenroth, 2013). The National Census of Population conducted by the Central Statistics Office (CSO), collects detailed data of every residential dwelling in Ireland at five-year intervals since 1951. Housing variables including domestic wastewater treatment (septic tank) facilities in each ED are included in the small area population statistics (SAPS). The specific variables used in this analysis were population density and septic tanks density in each ED of 1991, 2002 and 2011.

2.3.3. Forest data

The relationship between water quality and afforestation has been studied by others (e.g. Baillie and Neary, 2015; Duffy et al., 2020; O'Donoghue et al., 2021). To investigate afforestation within each ED, the Forest Inventory Planning System and Irish Forest Soils (FIPS-IFS) project developed by Teagasc was employed. The FIPS-IFS dataset was based on field sampling and was created using GIS and remote sensing, with a mapping unit of 1 ha. The variable used was annual afforestation, reflecting the percentage area of newly planted forest in each ED (Upton et al., 2014).

2.3.4. Environmental data

Apart from human activities, the physical environment, including soil type, bedrock geology, landscape, hydrological and climatic factors all affect river water quality (Silva and Williams, 2001; Moses et al., 2011; Rankinen et al., 2015). In terms of hydrological characteristics, the N groundwater (GW) pathway factor is a coefficient which is

Table 1
Mobility class criteria of the dependent variable – water status.

Class	1990	2000	2010	Description	Number of EDs
Maintain	Q ≥ 4.5	Q ≥ 4.5	Q ≥ 4.5	Maintain high status	131
Enter	Q ≤ 4	Q ≥ 4.5	Q ≥ 4.5	Enter high status in 2000	242
	Q ≤ 4	Q ≤ 4	Q ≥ 4.5	Enter high status in 2010	
Fluctuate	Q ≥ 4.5	Q ≤ 4	Q ≥ 4.5	Exit from high status in 2000, then enter to high status in 2010	240
	Q ≤ 4	Q ≥ 4.5	Q ≤ 4	Enter high status in 2000, then exit from high status in 2010	
Exit (reference)	Q ≥ 4.5	Q ≤ 4	Q ≤ 4	Exit from high status in 2000	944
	Q ≥ 4.5	Q ≥ 4.5	Q ≤ 4	Exit from high status in 2010	
Not included in model	Q ≤ 4	Q ≤ 4	Q ≤ 4	Non-high status	1834

dependent on subsoil permeability and depth to bedrock (Table 3S). GW vulnerability represents how easily GW may be contaminated by human activities. For example, Mockler et al. (2017) pointed out that high permeability and thin depth to bedrock lead to greater transport of N to water, while Packham et al. (2015) stated a rate of 75% of soil N residues in poorly drained soil (25% of soil N removal through denitrification), with 15% and 5% of soil N residue in moderate and well drained soils, respectively.

To account for geological, hydrological and climatic characteristics in the model, spatial variables are generated. GW and bedrock data from the Geological Survey of Ireland (GSI) were used to derive variables on hydrological, geological and climatic characteristics respectively, such as N GW pathway factor, peat-or-non-peat soils, and annual effective rainfall. The attributes of each ED were obtained through intersecting with polygon-based data. Elevation was sourced from an Irish digital elevation model (DEM) at a 25 m resolution. In terms of raster data, the average and median values were calculated across each ED.

2.3.5. Summary

The explanatory variables examined were: agricultural activity (organic N; cereal share), afforestation, population density, septic tank density, elevation, effective rainfall, GW pathway factors, non-peat and GW vulnerability (Table 2). These data were obtained from outside sources and linked using GIS techniques.

2.4. Data merging

The shapefiles of river sub-basins and EPA monitoring sites and the excel file of biological Q-values were downloaded from the EPA website. After linking EPA monitoring sites with Q- values, each station was joined to the river sub-basin in which it fell. Thus, a dataset relating Q-values to the characteristics of the relevant river sub-basin was generated. Notably, the EDs were linked to river sub-basins on the basis of the ED centroids that fall within the river sub-basin. EDs with centroid elevation greater than the centroid elevation of the river sub-basin were determined to be upstream. The average Q-values of monitoring points within river sub-basins were derived to link the upstream ED for the analysis. All the GIS data were projected to the same coordinate of the Irish National Grid System in ArcGIS® software (ver. 10.2), and the basic analysis unit was the ED level. All maps were produced by ArcGIS® software (ver. 10.2).

The 1991, 2000 and 2010 Census of Agriculture data were matched to the closest data collection years within the Census of Population, namely the 2000/2002 and 2010/2011 datasets.

2.5. Statistical analyses

2.5.1. Multinomial logistic regression (MLR)

MLR is frequently used for the analysis of categorical response data with continuous or categorical explanatory variables, where each category is assigned a probability between 0 and 1 with the sum adding to one (Walker and Duncan, 1967). In our study, MLR was used to model the relationships of four water status mobility classes (maintaining high status, entering high status, fluctuating between high status and non-high status, and exiting from high status), with economic and environmental explanatory variables using SPSS (Tables 1 & 2). The logit (ℓ) is the logarithmic function of the ratio between the probability (P) that an observation (i) is a member of a class (j) and the probability that it is not ($1 - P$). In the MLR model, the 'exit' class was set as the reference class, in order to interpret the categorical response with explanatory variables more clearly. The MLR model is expressed as follows (Hosmer and Hjort, 2002):

$$\ell_{ij} = \text{In}\frac{P_{ij}}{1-P_{ij}} = \beta_j + \beta_{1j}X_{1i} + \beta_{2j}X_{2i} + \ldots + \beta_{nj}X_{ni} \quad (1)$$

where β_j indicates the intercept of the regression curve for the water status class j, $\beta_{1j\ldots nj}$ are the coefficients associated with the n^{th} explanatory variable and n is the total number of covariates that significantly correlate with the given water status class j. This model is analogous to a logistic regression model except that the dependent variable has more than two classes.

MLR is considered a powerful and widely used non-parametric statistical test. However, the independence of irrelevant alternatives (IIA) is an important assumption of MLR, illustrating that the probability of choosing a category is independent of more or less choices (Ray, 1973). The IIA assumption was tested with the Hausman-McFadden test and passed the test. The significance of the regression coefficient of each explanatory variable is set as 0.1. The goodness of fit of the model (pseudo R^2) was calculated using Nagelkerke pseudo R-squared measures. The regression coefficient of each explanatory variable leads to a positive or negative change in the odds ratio of the dependent variable while holding all other explanatory variables in the model constant. The greater the absolute value of coefficient (β), the greater its influence.

MLR was also carried out for eight blocks (regional scale), which were divided according to the mobility class distribution pattern as well as the boundaries of sub-catchment and county (Fig. 6). To aid comparison, the explanatory variables used in each model were the same.

Table 2
Description, sources and summary statistics of explanatory variables used in the MLR model.

Explanatory variable	Description	Input data & source	Mean	Median	Min	Max	SD
Organic N	Average organic N density per ha of ED (kg)	1991, 2000 and 2010 Census of Agriculture	97.83	100.48	16.00	169.33	28.35
Cereal Share	Proportion of ED land area under arable crops (%)	1991, 2000 and 2010 Census of Agriculture	0.04	0.004	0	0.5	0.08
Afforestation	Area of new planting forest on formerly agricultural land of ED (ha)	The FIPS–IFS dataset (Upton et al., 2014)	60.14	34.22	0	4073.51	138.06
Population density	Population density per km2 per ED	1991, 2002 and 2011 Census of Population	32.88	20.33	1.43	702.64	54.68
Septic tank density	Septic tank density per km2 per ED	1991, 2002 and 2011 Census of Population	6.03	5.40	0.41	37	3.75
Elevation	Average elevation of ED (m)	Irish digital elevation model (DEM)	105.46	94.19	8.45	398.73	58.62
Effective rainfall	Average annual effective rainfall of ED (mm)	Geological Survey of Ireland (GSI)	884.70	814	345	2361	335.17
Nitrate GW pathway factors	Dependent on subsoil depth to bedrock and soil permeability (Mockler et al., 2017)	Geological Survey of Ireland (GSI)	–	–	–	–	–
Non peat	Peat or non-peat	Geological Survey of Ireland (GSI)	–	–	–	–	–
GW vulnerability	Extreme/low/moderate/high/water	Geological Survey of Ireland (GSI)	–	–	–	–	–

Table 3
Results of trend in the shares of water quality status from Daniel's trend test.

	Bad status	Poor status	Moderate status	Good status	High status
R	−0.953	0.513	0.875	0.912	−0.920
Z	−0.142	0.076	0.130	0.136	−0.137
Trend	Decreasing	Increasing	Increasing	Increasing	Decreasing

2.5.2. Daniel's test for trend analysis

Daniel's test for trend is a nonparametric test on the basis of Spearman's correlation coefficient computed as a rank statistic and is used to test if the changing trend of water status fluctuates randomly or has a upward/downward direction in this study as described in Eqs. (2) and (3)(Wang et al., 2015):

$$r = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n^3 - n} \tag{2}$$

$$d_i = X_i - Y_i \tag{3}$$

where r is the rank correlation coefficient, d_i is the difference between X_i and Y_i, X_i is the ascending rank of percentage of water status, Y_i is the rank of the year, and n is the number of observations in the time series. If $r > 0$, the trend is increasing. If $r < 0$, the trend is decreasing. In our case, the n was greater than 30, the test statistic was calculated as follows:

$$z = \frac{r}{\sqrt{n-1}} \tag{4}$$

If $|z|$ is greater than $z_{\alpha/2}$ (significant level α), the time series does exhibit significant trend.

2.5.3. One-way analysis of variance (ANOVA)

ANOVA was employed as needed to determine differences of the seven key explanatory variables (organic N, cereal share, afforestation, population density, septic tank density, elevation and effective rainfall) among the four water status mobility classes. The seven key explanatory variables do not follow a normal distribution. Therefore, the normal score transformation is used in the ANOVA analysis. Subsequently, Tukey's multiple comparisons method is employed to further observe differences among water status mobility classes.

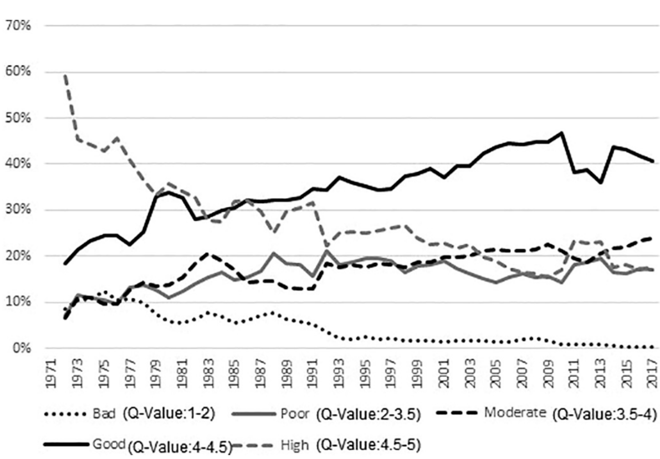

Fig. 2. Shares of water quality status per year based at EPA river monitoring sites.

3. Results and discussion

3.1. Trend analysis

3.1.1. Trends in shares of different water quality status

The Daniel's trend test can determine if any significant trends occur in the share of water quality status from a particular statistical approach. In this analysis, the Daniel's test is applied to trends in the shares of different water quality status and also to trends in the mobility of water quality status. The results in relation to the trends in shares of different water quality status showed clear temporal variation across all water quality status, although the significance does not reach 10% level because the absolute Z values were not greater than the statistic Z values (Table 3). The share of poor, moderate and good water quality status exhibited a non-significant increase from 1971 to 2017 revealed by the positive R values, while the share of bad and high water status exhibited a non-significant decrease during this period, indicated by the negative R values (Table 3).

Examining the trends in shares in more depth, the overarching trend was one of an increase in the share of good status river monitoring stations, increasing from 18.4% in 1971 to 40.6% in 2017, except for a drop for a short period from 2011 to 2013 (Fig. 2). However, the trend of high status was the opposite, with a secular decline from 59% in 1971 to 17.9% in 2017 (Fig. 2).

The share of bad status river monitoring sites was consistently around 5% until the late 1980s before halving in the period post 1990 (Fig. 2). This decline in bad status was associated with regulation and upgrading of municipal wastewater treatment plants. However there was an increase in poor and moderate water quality, coinciding with the expansion of agriculture after the entry of Ireland into the European Economic Community in 1973 until price related market supports ended in the early 1990s. From the 1990s onwards, although the share of high status rivers was still decreasing (but more gently), there was a secular upward trend in good status. This upward trend likely reflects environmental policy interventions such as voluntary agri-environment schemes from the early 1990s, together with the introduction of regulations such as the Nitrates Directive in 1991 and Cross Compliance with EU payment schemes in 2000 (Alons, 2017).

Despite these measures, the share of high status EPA river monitoring sites was continuously declining, albeit for a short-term recovery in the number of high status monitoring sites from 2010 to 2013, which possibly reflects reduced economics activity during the economic crisis in Ireland (Whelan, 2014). However, owing to the lack of Census of Agriculture data beyond 2010, it is not possible to assess recent socio-economic impacts on high status rivers. While our study is limited to the 1991 to 2010 period for which Census data are available, this period captures many important changes in both agricultural policies and in economic and population-related drivers.

3.1.2. Mobility of water quality status between high status and non-high status

Applying the Daniel's test to the mobility or water quality status showed temporal variation in the mobility of water quality status between high status and non-high status, although the results are not

Table 4
Results of trend in the mobility of water quality status between high status and non-high status from Daniel's trend test.

	Exit	Enter	Exit to bad status	Exit to poor status	Exit to moderate status	Exit to good status	Enter from bad status	Enter from poor status	Enter from moderate status	Enter from good status
r	−0.417	0.823	−0.877	−0.590	−0.748	0.830	0.069	−0.436	−0.737	0.736
z	−0.068	0.134	−0.137	−0.092	−0.117	0.130	0.010	−0.066	−0.112	0.112
Trend	Decreasing	Increasing	Decreasing	Decreasing	Decreasing	Increasing	–	Decreasing	Decreasing	Increasing

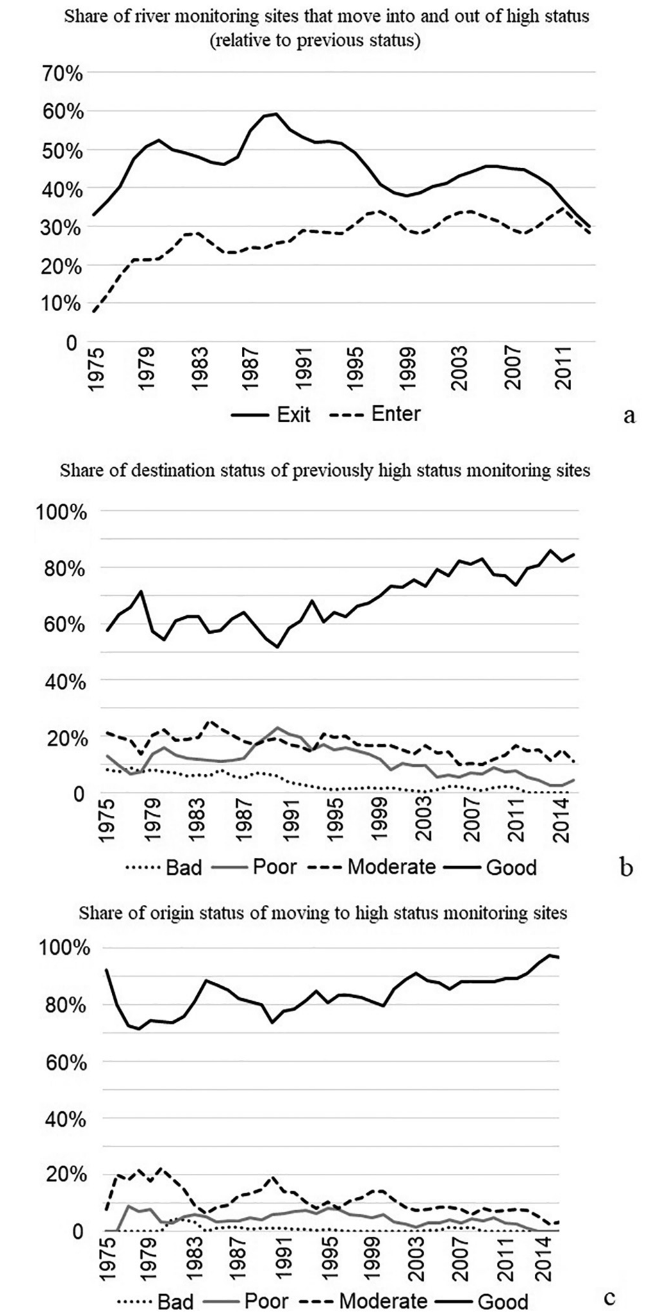

Fig. 3. Flows between high status and non-high status rivers.

significant at 10% level (Table 4). In general, the share of monitoring sites that 'exit' high status showed a non-significant decrease and the share of 'enter' sites displayed a non-significant trend in the opposite direction (Table 4). In particular, a high proportion of previously high status sites declined to good status over time, while a high proportion of good status improved to high status over time (Table 4).

Going beyond the share of sites in the different water quality status classes, the flows between high status and non-high status revealed further information on status mobility. While mobility can be caused by natural phenomena such as weather, the exit rate from high status rose from about 32% in the early 1970s to a peak of 59% in 1991 (Fig. 3a), coinciding with agricultural expansion in the aftermath of entry to the EU. From then onwards, the exit rate fell during the 1990s before increasing slightly again in the 2000s (Fig. 3a). During the first half of the 2010 decade, the exit rate decreased (Fig. 3a). During this period, agri-environment schemes were implemented from the mid-1990s onwards while environmental protection regulations were also introduced.

On the positive side, there was a significant number of river monitoring sites that entered high status over this period, while the entry rate to high status increased from less than 10% to nearly 35% of river monitoring sites by 2013 (Fig. 3a). It should be noted that the number of monitoring sites can vary between surveys as new monitoring sites are added to the network over time. While the number of new sites may be small, they are often new high status sites or sites that were not previously monitored.

Between the 1970s and 1990s, over 50% of river monitoring sites that exited high status moved to good status (Fig. 3b). This share increased to about 80% in the 2000s, but the trend declined between 2005 and 2011 (Fig. 3b). The share of monitoring sites entering high status from previously non-high status is presented in Fig. 3c with about 80% of the newly high status sites moving from good status. A lower percentage of low status (bad, poor or moderate) entered high status in comparison with the greater number that exited to low status.

The strong mobility between high and non-high status (especially good status) may reflect variations in water quality due to natural weather (Lee et al., 2016) and climatic change (Yang et al., 2019), as well as forest harvesting, land drainage or idiosyncratic events such as waste treatment system failures or environmental risk events (Pascual-Benito et al., 2020). Given that EPA river monitoring sites are sampled on a three-year cycle, it is difficult to ascribe changes in status to either short-term (seasonal) changes (Moss, 2008) or long-term changes. These trends also reflect the complex influence of underlying socio-economic and physical environmental characteristics that drive changes in water quality in the medium to longer term.

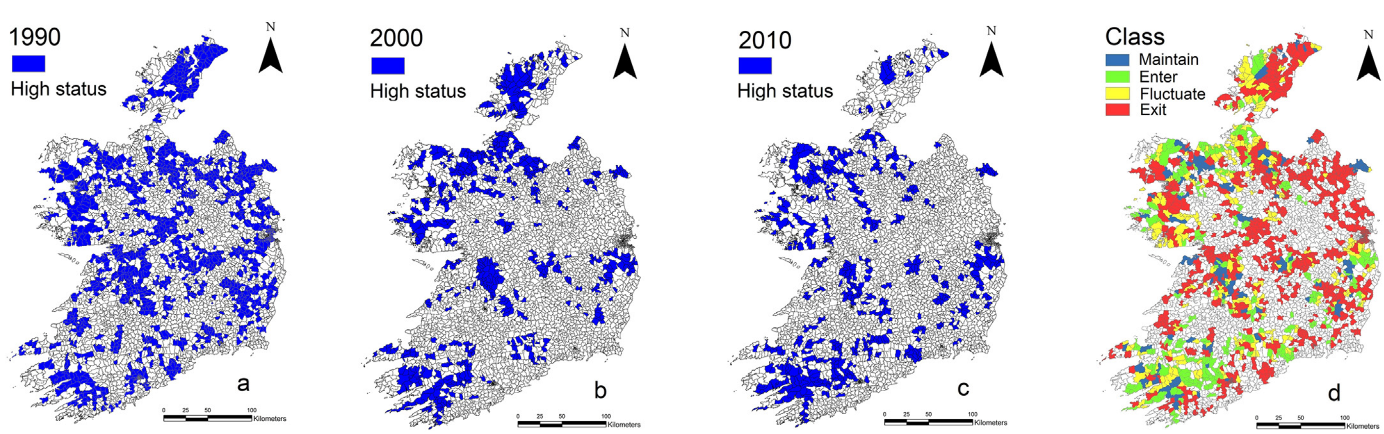

Fig. 4. EDs with high status river (Q 4.5 & Q5) in 1990 (a), 2000 (b) and 2010 (c) and classes of high status mobility by decade during the period 1990–2010 (d).

Table 5
The coefficient (β) and significance of explanatory variables obtained by the national MLR model.

	β_Maintain	β_Enter	β_Fluctuate
Organic N	−0.016***	0.005	−0.010**
Cereal Share	−5.771**	−2.898*	−3.870**
Afforestation	0.000	0.001	0.000
Population density	0.000	−0.001	−0.004
Septic tank density	0.012	−0.011	0.036
Elevation	0.011***	0.006***	0.004**
Effective rainfall	0.001	0.002***	0.001**
N GW pathway factors	1.365**	−0.493	0.320
Not peat	0.326	0.352	0.073
GWV_E	−0.201	0.413	0.195
GWV_L	1.273	0.016	0.125
GWV_M	0.823	0.307	0.335
GWV_H	0.868*	0.788*	0.500
GWV_W	0.831	−0.327	0.763
Intercept	−3.632	−4.229***	−2.002
N	1557		
pseudo R^2	0.187		

Note: i) * $p < 0.1$; ** $p < 0.05$; *** $p < 0.001$; ii) GWV: groundwater vulnerability, including E: extreme; L: low, M: moderate, H: high, W: water.

Table 6
The ANOVA results of seven key explanatory variables of the four mobility classes.

Explanatory variables	R^2	F	P
Organic N	0.7%	5.2	< 0.01
Cereal Share	1.4%	9.3	< 0.001
Afforestation	6.6%	41.5	< 0.001
Population density	9.0%	57.8	< 0.001
Septic tank density	1.4%	9.0	< 0.001
Elevation	11.6%	76.6	< 0.001
Effective rainfall	16.5%	114.7	< 0.001

3.1.3. Spatial trends

In 1990, there were 1335 EDs containing high status rivers, however, the number decreased rapidly to 518 and 500 in 2000 and 2010, respectively (Fig. 4a, b & c). In 1990, the locations of high status rivers were relatively evenly distributed in Ireland. In 2000 and 2010, a large number of high status rivers in the north-east were disappearing, likely due to intensive agriculture and a high population density. The high intensity of both animal waste (manure) and human sewage from wastewater treatment facilities can have a serious impact on water resources, due to leaching or nutrient run-off and loss to water, leading to excess nutrients in water causing eutrophication (Kato et al., 2009). Mockler et al. (2017) found that wastewater was the main source of nutrients in the north-east area of Ireland. While nutrients such as N and P are necessary for plant growth, eutrophication causes excessive growth of plants and algae, which when decomposed result in increased biochemical oxygen demand and the death of ecological indicator species.

The 'maintain', 'enter' and 'fluctuate' classes were mostly located in the west of the country (Fig. 4d) with a large share of high altitude areas (Fig. 1b), while the 'exit' class was largely located in the east in low altitude areas (Fig. 1b). This reflects the greater pressure on water quality in low-elevation catchments due to urbanization and more fertile lowlands that allow for more intensive agriculture (Larned et al., 2004). Combined with the rainfall map (Fig. 1c), the counties containing the highest number of high status rivers were located on the western seaboard where there is higher rainfall than the east and more peat and poorly drained marginal soils (Roberts et al., 2016). While heavy rainfall can exacerbate nutrient runoff through overland flow, leading to water deterioration (Zhou et al., 2015), Roberts et al. (2016) found that rainfall was a significant positive factor influencing high status in Irish rivers.

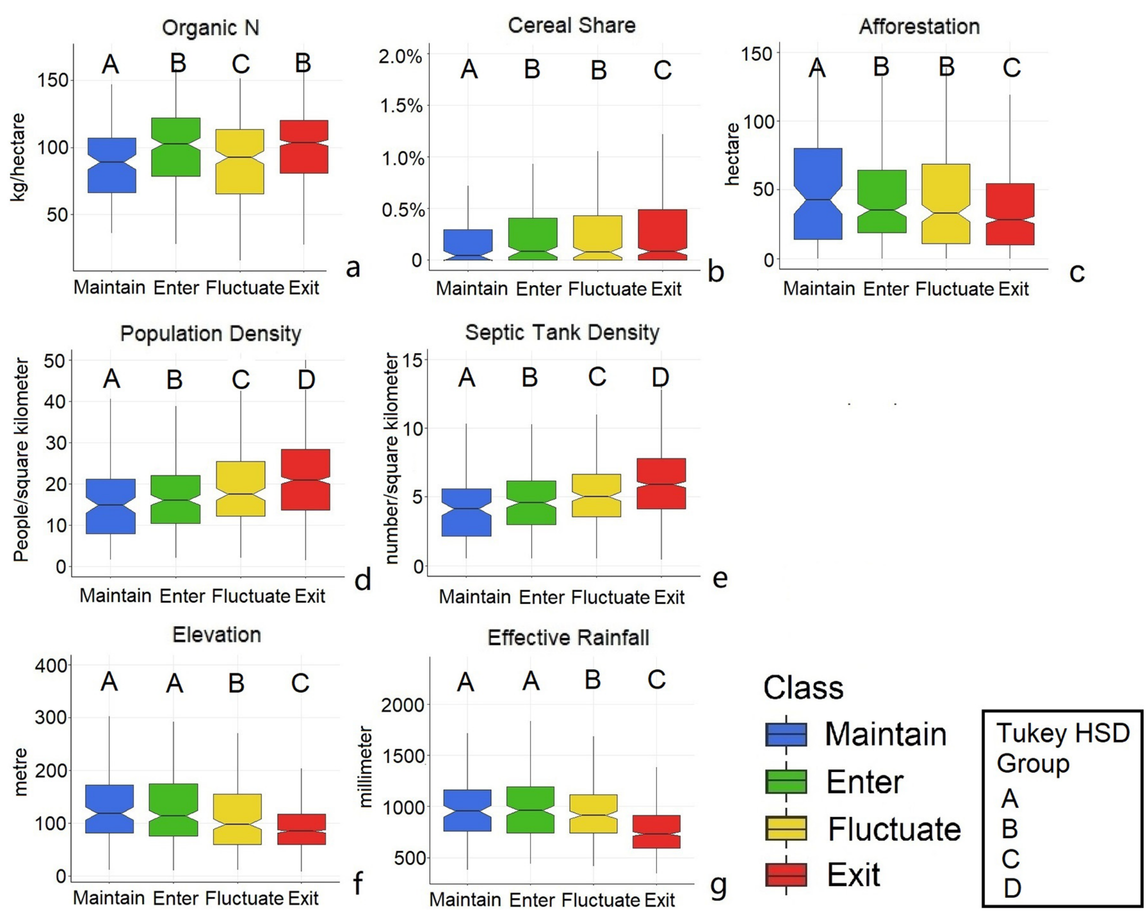

Fig. 5. Boxplots of key explanatory variables of mobility classes.

Table 7
The coefficient (β) and significance of explanatory variables obtained by the regional MLR model.

	Block 1			Block 2			Block 3			Block 4		
	Donegal			Sligo, Leitrim			Mayo, Galway, Roscommon			Cavan, Monaghan, Louth, Meath		
	β_M	β_E	β_F	β_M	β_E	β_F	β_M	β_E	β_F	β_M	β_E	β_F
Organic N	−0.007	0.011	−0.046**	−0.473	−0.050*	−0.048*	−0.001	−0.008	−0.007	−0.041	−2.351	−0.113
Cereal Share	−7.863	−8.785	12.433	5.580	−4.656	−5.326	−8.124	−14.134	−4.415	−5.703	−5.469	−1.727
Afforestation	−0.013	0.000	0.005	0.044*	0.001	−0.003	0.000	0.000	0.000	−0.025	−0.939	−0.006
Population density	0.000	−0.101	−0.030	−0.012	−0.114	0.004	0.011	0.014	−0.004	0.007	−0.771	−0.076
Septic tank density	0.012	0.278	0.145	1.838	−0.714*	0.360	−0.220*	−0.008	0.000	−0.278**	11.588	0.386
Elevation	0.017	−0.015	−0.016*	0.116	−0.007	0.000	−0.002	0.000	−0.011*	0.028**	−0.437	0.042
Effective rainfall	−0.006**	0.003*	−0.001	−0.024	0.007**	0.004	0.002	0.002	0.002*	0.003	−0.098	−0.014
Nitrate GW pathway factors	1.904	9.038	−8.717	6.864	−2.073	−0.423	4.889	−0.007	−2.634	−19.853	−6.383	−3.351
Not peat	−1.012	0.352	−0.617	−0.691	0.128	0.245	0.314	0.491	0.534	27.648	−22.395	14.593
GWV_E	2.203	−0.094	−2.762	−5.991	0.489	0.165	2.366**	3.552**	1.070	16.836	7.084	1.937
GWV_L	–	–	–	–	–	–	6.759	3.206	−1.113	−0.271	6.448	−17.803
GWV_M	−1.313	2.775	–	1.460	−1.667	–	3.571	3.242**	−0.105	–	–	–
GWV_H	−11.550	−12.984	−8.222	−4.331	1.733	−0.918	3.422**	2.735*	−0.044	17.415	−2.424	−14.288
GWV_W							1.151	1.679	1.528*	–	–	–
Intercept	−10.783	−22.040	52.138	8.184	−9.860	−9.860	−8.794	−5.011	0.057	−11.519	10.686	−0.604
N	118			110			240			135		
pseudo R^2	0.527			0.621			0.224			0.561		

Note:
i) β_M: β_Maintain; β_E: β_Enter; β_F: β_Fluctuate;
ii) * $p < 0.1$; ** $p < 0.05$; *** $p < 0.001$;
iii) GWV: groundwater vulnerability, including E: extreme; L: low, M: moderate, H: high, W: water.

In summary, the location of high status rivers is not merely dependent on individual physical environmental factors such as elevation or rainfall, but happens as a result of a combination of complicated socio-economic and physical environmental factors. The 'fluctuate' class is the most unstable class. These fluctuations may be due to natural phenomena, anthropogenic impacts, or both. The trend analysis revealed that the secular decline of high status rivers since the early 1970s was relatively complex with considerable churn into and out of high status in parallel with this secular trend, but accompanied by strong mobility. However, the low sampling/ monitoring frequency of rivers may be inadequate to capture individual events that can cause disturbance to sensitive ecological communities (Snell et al., 2014; Arnell and Gosling, 2016). More frequent surveillance of streams and rivers could potentially record natural churn and enable detection of statistically significant increases or decreases in the water quality status of streams and rivers over time.

3.2. Multinomial logistic regression (MLR)

3.2.1. National scale

For the 'maintain' class, the higher intensity of organic N and cereal share was associated with a lower probability of maintaining high status (Table 5). This is consistent with agriculture being the primary cause of poor water quality in water bodies in European countries (Lennox et al., 1998; Volk et al., 2008; Zia et al., 2013). In Ireland, freshwater ecosystems are -limited, meaning that P largely drives ecological health and in turn Q-value. As shown by Ulén et al. (2007), P often accompanies N in agricultural land. However, P and N impact on hydrology in different ways. In this context, it should be noted that as the organic N variable is a summary measure of intensity, representing nutrient load, it could be picking up the associated impact of P, rather than just an N effect. This possibly explains the lower probability of maintaining high status associated with higher intensity organic N. In a similar way, P and other contaminants impacting high status waters (e.g. dissolved oxygen and sediment) are delivered by surface-water rather than N groundwater pathways, thus the volumes of water flushing through the landscape may also be contributing to impacts on water quality status. However, due to data constraints, it is not currently possible to further disaggregate this complexity.

Elevation had a significantly positive influence on the 'maintain' class, in agreement with O'Donoghue et al. (2021). Arocena et al. (2018) found that watersheds with high-elevation and less intense land use have better water quality than lowland streams in Uruguay. Gill and Mockler (2016) modeled nutrient transport to rivers in three pathways: direct, subsoil and GW. The N GW pathway factor is significantly positive for the 'maintain' class. This class was mainly located in areas receiving heavy rainfall (Fig. 1c) and median GW recharge areas that is helpful in releasing the diffuse nutrient burden (Mockler et al., 2017). It should be noted that diffuse N load is also derived from surface and near-surface pathways, apart from GW, and is influenced by many factors.

Notwithstanding the potential addition of new high status sites from survey to survey, for the 'enter' class, the physical environmental factors had significant impacts. The higher elevation and effective rainfall were associated with a higher probability of entering into high status. This result suggests that it is a challenge to improve ecological status in low-elevation areas, owing to greater pollutant loads in areas with less rainfall (less dilution) and more intensive agricultural and urban land use (Glińska-Lewczuk et al., 2016).

Organic N and cereal share also had significantly negative impacts on the 'fluctuate' class, while elevation (less economic activity) and rainfall had significantly positive influences on this class. As the 'fluctuate' class included the most changeable Q-values of the EPA river monitoring sites, they may be more sensitive to agricultural intensification. In particular, the 'fluctuate' class was mostly located in upland area with high rainfall that are sensitive to the effects of agriculture (Roberts et al., 2016). In such areas, innovative technologies, adaptive management, and policy all play critical roles in balancing agricultural intensification and high water quality status (Salmoral and Garrido, 2015).

The relationship with afforestation was not strong, consistent with Roberts et al. (2016). Hughes and Quinn (2019) suggested that forest management disturbances such as planting or harvesting interventions can lead to soil disturbance, sediment erosion, and nutrient runoff. Forests can also contribute to the artificial acidification of run-off waters if planting is undertaken on acid-sensitive soils (Saarinen et al., 2013). However, O'Donoghue et al. (2021) reported that increased afforestation replacing livestock agriculture can have a small positive impact over time, due to the reduction in the risk of loss of agricultural nutrients to water on planting and infrequent management disturbances over forest life-cycles.

Block 5			Block 6			Block 7			Block 8		
Offaly, Laois			Clare, Limerick, Tipperary			Wicklow, Wexford, Carlow			Kerry, Cork, Waterford		
β_M	β_E	β_F	β_M	β_E	β_F	β_M	β_E	β_F	β_M	β_E	β_F
0.018	0.805	−0.027	−0.029	0.021	−0.012	0.009	−0.024	−0.025	−0.038**	−0.014*	−0.021**
−40.784	7.920	−0.452	−17.092	−5.792	6.347	3.746	−16.324**	−10.415	−2.498	−2.990	−15.596**
0.000	0.501	−0.003	0.003	−0.001	0.000	−0.004	0.014*	0.019**	−0.001	−0.004	−0.004
−0.004	0.119	−0.452	−0.016	0.006	−0.008	−0.041	0.092	−0.081**	−0.009	−0.032**	−0.008
0.193	−3.639	0.242	−0.166	0.084	0.069	−0.088	−0.024	−0.704**	0.173	−0.208**	0.100
0.008	0.845	0.027	0.005	0.030***	0.008	0.025*	−0.007	0.002	0.018**	0.014***	0.012**
0.008	−0.310	−0.003	−0.003	−0.003	0.001	0.001	0.004	−0.001	0.001	−0.001	−0.001
−3.470	−19.104	23.621	0.815	−4.136	1.768	−2.266	−6.211**	0.628	2.022	1.061	3.270**
−2.846	−16.159	−1.189	1.345*	0.848	1.329*	2.821	0.948	−0.529	0.175	−0.607	−1.040
–	–	–	−0.367	20.367***	1.843*	18.019***	17.881	−2.722	0.969	−0.976	−0.857
–	–	–	0.979	16.555***	0.816	18.340	12.724	−20.609	3.969	−0.741	1.684
–	–	–	0.177**	19.154***	1.857	–	–	–	1.785	−0.347	1.406
6.454	60.741	−19.124	0.389	19.179***	0.915	−1.392	18.910	−2.038	1.093	−0.410	0.549
–	–	–	2.064*	–	0.952	–	–	–	–	–	–
−7.788	−8.313	−17.247	2.704	−22.133***	−4.926*	−25.152**	−10.169	6.865	−4.943	1.189	0.020
86			158			110			284		
0.785			0.477			0.633			0.355		

ANOVA results show that there were significant differences among the four mobility classes related to the seven key explanatory variables (organic N, cereal share, afforestation, population density, septic tank density, elevation and effective rainfall) (Table 6). The highest proportion of variance from the ANOVA was found in effective rainfall, indicating that effective rainfall exerted a strong impact on mobility. The second strongest influential factor was elevation and the third was population density. The groups sharing different letter (A, B, C or D) have significantly different means (Fig. 5). Tukey HSD results indicated that the 'exit' class had notably higher organic N, cereal share, population density and septic tank density than other classes (Fig. 5a, b, d & e). In contrast, the 'exit' class had significantly lower afforestation, rainfall and elevation than other classes (Fig. 5c, f & g).

Compared to other classes, the 'exit' class had relatively high organic N and cereal share as reported in the results of Tukey HSD test (Fig. 5a & b), reflecting that agriculture was a main pressure on high status rivers over the period examined. The 'exit' class contained relatively low afforestation (Fig. 5c), indicating a potential long-term positive effect of afforestation over time in Ireland as observed by (Duffy et al., 2020), despite short-term potentially negative impacts of forest disturbances on water quality if appropriate management practices are not followed. This is consistent with Bastrup-Birk and Gundersen (2004) who found that increased forest cover can have a positive impact on water quality in the long term, where forests displace agriculture and reduce the N concentration in rivers. This result is also indicative of historic planting on marginal agricultural land, often in sparsely populated areas.

Population density and individual septic tank density follow the same pattern, increasing in magnitude across the 'maintain', 'enter', 'fluctuate' and 'exit' classes (Fig. 5d & e). The pattern suggests that the population density and septic tank density had negative effects on the stability of high status. High population density in urban areas poses a significant threat to river water quality (Liyanage and Yamada, 2017). Human sewage and industrial wastes were primary factors influencing water quality in urban areas, while agriculture is the dominant factor in rural areas (Chen et al., 2016). This is also consistent with other studies that found that the presence of septic tanks can have a significant negative impact on water quality (Clabby et al., 2008; Macintosh et al., 2011; Curtis and Morgenroth, 2013). This is largely due to historically poorly designed wastewater disposal infrastructure (O'Donoghue et al., 2021). Under the National Inspection Plan for Domestic Wastewater Treatment Systems (DWWTSs) set up in Ireland to meet WFD requirements, risk-based inspections of septic tanks and other on-site treatment systems have been carried out. Naughton and Hynds (2014) recommended that such inspections should be concentrated in areas where wastewater discharges present a high risk to human health or the environment.

The 'maintain', 'enter' and 'fluctuate' classes had higher effective rainfall and elevation than the 'exit' class. This reflects the location of many high status sites in upland areas, clustered along the western seaboard in areas with little urbanization and heavy rainfall, that are marginal for agricultural production. In Ireland, the combination of high elevation and heavy rainfall is generally positive for high status rivers, however, the impact of high rainfall is influenced by soil and landscape. Heavy rainfall in poorly-drained areas leads to high nutrient loss to surface water, while heavy rainfall in well-drained areas results in nutrient loss mostly to GW systems. Rainfall is a complex factor as heavy rainfall can carry more organic carbon (from peat soils) and sediment to receiving waters in agricultural catchments, leading to water quality degradation (Delpla et al., 2011). Alternatively, high rainfall and surface water levels can dilute nutrient concentrations (Park et al., 2011), and water quality may improve following rainfall, if dissolved oxygen increases (Ling et al., 2017).

3.2.2. Regional scale

The pseudo R^2 of MLRs at regional scale is much larger than at the country scale (Table 7), indicating that the regional models accounted for a greater proportion of variability. Additional detail for the coefficients for each explanatory variable, their standard errors and significance levels is presented in Table 5S.

Organic N and cereal share had a negative impact on water quality in block 8 (Fig. 6), while the water quality deterioration in block 7 and 8 (Fig. 6) was associated with increases in population and septic tanks (Table 7). These results indicate that the high status in these areas is very sensitive to activity (farm and population). The assimilation capacity for nutrients in oligotrophic water bodies is very low, and White et al. (2014) suggested that many were close to or have exceeded their capacity for further agricultural intensification. In the south-west (block 8, Fig. 6) which has the highest dairy cow population (ICBF, 2020), agriculture is exerting pressure on water quality. Block 8 had the largest area of high risk of N loss arising from diffuse agricultural sources consistent with (Archbold et al., 2007), while Pavri et al. (2013) found that increasing population and housing activities had negative influences on vulnerable freshwater resources. Water quality in western Ireland was also sensitive to streamflow and microbial activity (Coffey et al., 2016). According to Roberts et al. (2016), the protection of these high quality sites through more sustainable agricultural planning may also need to be considered if the aim of maintaining high ecological status at river sites is to be achieved.

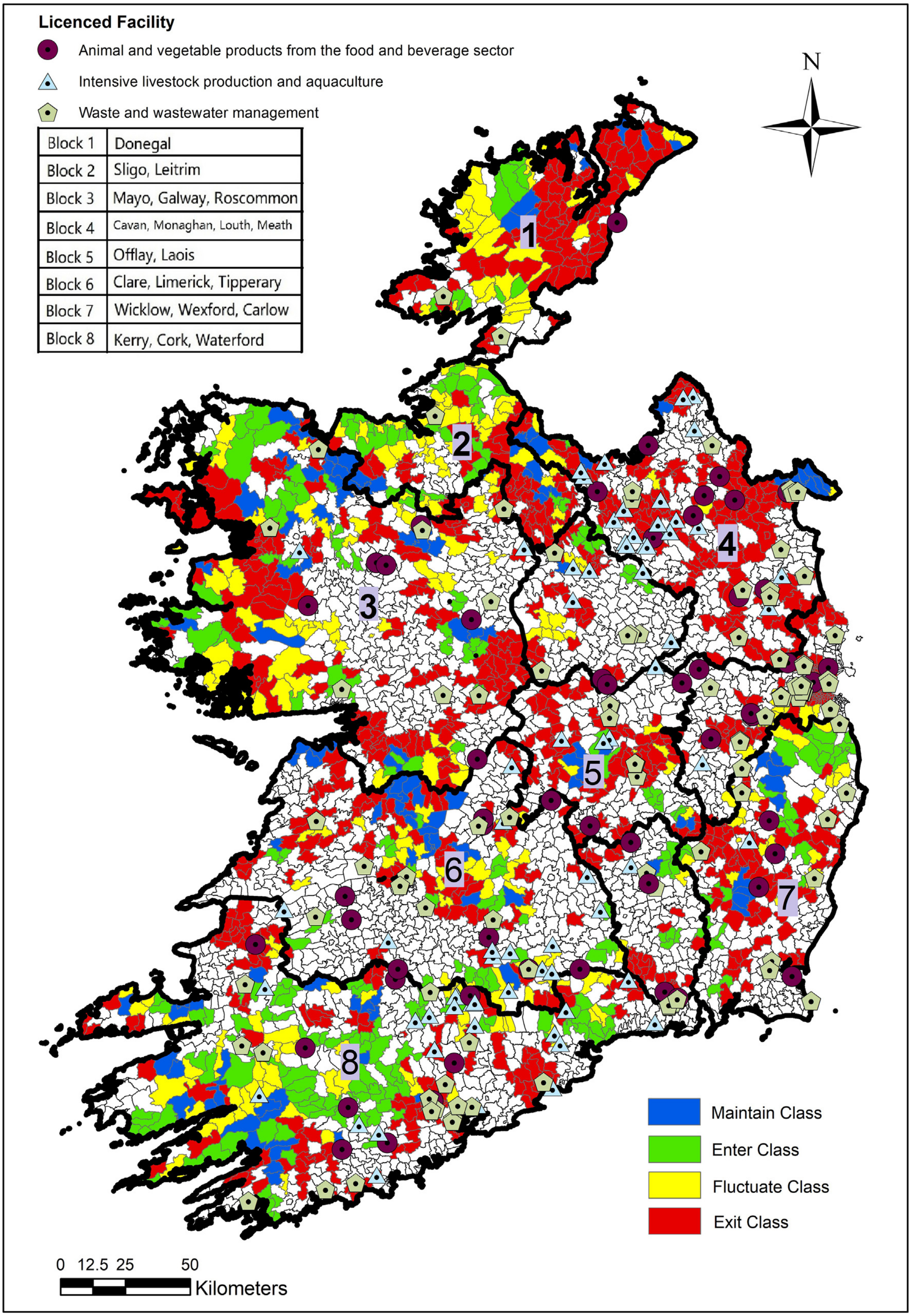

Fig. 6. Blocks of classes of high status (Q 4.5 & Q5) by decade during the period 1990–2010.

Natural environmental factors such as elevation and rainfall affected the high status in block 4 and 6. The northern part of block 4 had the highest density of wastewater treatment plants and intensive agriculture facilities, corresponding to one of the most serious losses of high status (Fig. 6) (EPA, 2015). In block 2, afforestation had a significant and positive impact on water quality.

Historically, the area covered by block 3 contained high numbers of monitored high status rivers (White et al., 2014), however, the water quality in this area deteriorated substantially over the period of this study. Septic tank density had a negative impact on the 'maintain' class, while elevation and rainfall also influenced the 'fluctuate' class in block 3.

No significant factors were found in block 5. In the midlands area, industrial peat extraction was historically facilitated by abundant land drains releasing ammonium and fine-grained suspended sediments, leading to the physical alteration of aquatic habitats (Collier and Scott, 2008; Page and Baird, 2016). Such hydromorphological modification of surface waters (e.g. channelisation, bank protection, dams, culverts and land drainage), is one of the main causes of the degradation of river ecosystems worldwide (González Del Tánago et al., 2016). The hydromorphological pressure map produced by the EPA illustrates that these hydromorphological modifications are clustered in block 4 and 5. Due to the complexity associated with hydromorphology, this variable was not included in the analysis. A Morphological Quality Index has recently been recommend (Belletti et al., 2018) and may have potential for future analysis.

In summary, these results suggest the need for better management of agricultural activities upstream of the high status sites, with a focus on septic tanks that are hydrologically connected to high status rivers. Moreover, different pressures in different areas were observed due to different agricultural activities, in addition to physical and climatic characteristics. More frequent sampling of high status sites in order to apply the most appropriate local measures and assess their effectiveness would be useful in these areas. In addition, systematic rehabilitation planning at smaller scales that incorporates socio-economic factors could lead to water quality improvements (Hermoso et al., 2012). These findings thus help to develop a stronger understanding of the diverse drivers in different regions, implying that policy solutions must be localised to be effective under different water quality pressures and environmental contexts.

4. Conclusions

Our study investigated the trend and the influential factors on high status mobility in Irish rivers, from both spatial and statistical perspectives, and at national and regional scales. The trend analysis revealed strong mobility of water status and suggests that more frequent monitoring in these areas would be needed to derive further information on the drivers of changes in status in areas with unstable water quality status.

High status mobility was captured at ED level by examining four mobility classes based on the variability of the Q-value using MLR models. The main findings of the MLR at national scale were that (a) agricultural activity (organic N, cereal share) were significantly negatively associated with the 'maintain' and 'fluctuate' classes; and (b) elevation was significantly positively associated with the 'maintain', 'enter' and 'fluctuate' classes. Moreover, ANOVA results showed that there were significant differences among four mobility classes. The 'exit' class had remarkably higher organic N, cereal share, population density and septic tank density and significantly lower afforestation. The 'enter' class had notably greater elevation than other classes.

Undertaking the MLR at regional scale, the results indicated different significant pressures in different areas. A range of socio-economic factors with multiple environmental impacts contribute to this heterogeneity. Improving the high status objective may require different policy solutions and site mitigation measures than those currently in operation for the achievement of good status (Riley et al., 2018). At present, some of the main EU policy levers such as the Nitrates Directive are defined and targeted at national scale, however, this study highlights the spatial complexity of changes in water quality, which requires more localised targeting to improve effectiveness.

CRediT authorship contribution statement

Cathal O'Donoghue: Conceptualization, Formal analysis, Writing – original draft. **Yuting Meng:** Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Mary Ryan:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Paul Kilgarriff:** Data curation. **Chaosheng Zhang:** Supervision. **Lyubov Bragina:** Resources. **Karen Daly:** Writing – review & editing.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.151570.

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