USING HIGH FREQUENCY IN-SITU MONITORING TO GAIN NEW INSIGHTS INTO IRISH AQUATIC SYSTEMS

Jennings, E., de Eyto, E., Dillane, M., Mellander, P. E., Regan, F., Wilkes, R., O'neill, M., Briciu-Burghina, C., Antunes, P., Jordan, P., Arnscheidt, J., Linnane, S., McCarthy, V., McElarney, Y., Huallacháin, D., Rolston, A., & Wynne, C. (2022). USING HIGH FREQUENCY IN-SITU MONITORING TO GAIN NEW INSIGHTS INTO IRISH AQUATIC SYSTEMS. *Biology and Environment*, *122B*(3), 201-221. https://doi.org/10.1353/bae.2022.0014

Link to publication record in Ulster University Research Portal

Published in:
Biology and Environment

Publication Status:
Published (in print/issue): 21/12/2022

DOI:
10.1353/bae.2022.0014

Document Version
Author Accepted version

Title: Using high frequency in-situ monitoring to gain new insights into Irish aquatic systems

Authors:
Eleanor Jennings[1], Elvira de Eyto[2], Mary Dillane[2], Per-Erik Mellander[3], Fiona Regan[4], Robert Wilkes[5], Maria O'Neill[4], Ciprian Briciu-Burghina[4], Patricia Antunes[1], Phil Jordan [6,] Joerg Arnscheidt[6], Suzanne Linnane[1], Valerie McCarthy[1], Yvonne McElarney[7], Daire Ó hUallacháin[3], Alec Rolston[8], Caroline Wynne[9]

1. Centre for Freshwater and Environmental Studies, Dundalk Institute of Technology, Dundalk, Ireland.
2. Marine Institute, Newport, Mayo, Ireland.
3. Teagasc, Johnstown Castle Environmental Research Centre, Wexford, County Wexford, Ireland.
4. Water Institute, Dublin City University, Glasnevin, Dublin, Ireland.
5. Environmental Protection Agency, Castlebar, Mayo.
6. School of Geography and Environmental Sciences, Ulster University, Coleraine, Northern Ireland, UK.
7. Agri-Food and Biosciences Institute, Belfast, Northern Ireland.
8. Goyder Institute for Water Research, Adelaide, Australia.
9. Environmental Protection Agency, Richview, Dublin.

Corresponding author: Eleanor Jennings, Centre for Freshwater and Environmental Studies, Dundalk Institute of Technology, Dublin Rd., Dundalk. Email: eleanor.jennings@dkit.ie. Phone: + 353 42 9370306. https://orcid.org/0000-0002-9344-2056

CITATION

Jennings, E., de Eyto, E., Dillane, M., Mellander, P-E., Regan, F., Wilkes, R., O'Neill, M., Briciu-Burghina, C., Antunes, P., Jordan, P., Arnscheidt, J., Linnane, S., McCarthy, V., McElarney, Y., ÓhUallacháin, D., Rolston, A. and Wynne, C. 2022. Using high frequency in-situ monitoring to gain new insights into Irish aquatic systems. Biology and Environment: Proceedings of the Royal Irish Academy, Vol. 122, No. 3, 201–221. 10.1353/bae.2022.0014

ABSTRACT

Until recent decades, most monitoring of surface waters relied exclusively on samples analysed in the laboratory for ecologically and management-relevant parameters. It is now possible, however, to automatically monitor many parameters using in-situ sensors and to provide remote web-based access to these data. Such data are typically provided at frequencies of minutes rather than at the weekly, fortnightly or monthly intervals typical of traditional monitoring and therefore capture both short-term change and, for inter-annual deployments, long-term trends. Here we give an overview of the use of high frequency monitoring (HFM) in Ireland and present case studies from a set of four sites, representative of the catchment-stream-lake-estuary continuum, to illustrate new insights that such deployments can provide. These include 1. effects of cattle access on stream turbidity, 2. biogeochemical processing in agricultural streams, 3. effects of summer storms on dissolved organic matter in a catchment and lake, and 4. changes in a trophic index in an estuarine setting. We discuss the additional information provided by such systems when compared to traditional monitoring, some of the challenges related to their use, and assess the future use of HFM to inform management and policy of aquatic systems on the island of Ireland.

INTRODUCTION

Surface waters are vital global resources. They not only provide critical ecosystem services for the human population (Reynaud and Lanzanova 2017), but are also important in terms of biodiversity (Dudgeon *et al.* 2006), and are the site of key processes for carbon and nutrient cycling. There have been ongoing declines in the quality of surface freshwater systems for many decades, both globally (Cross *et al.* 2015) and on the island of Ireland (EPA 2019; NIEA 2021; Rippey *et al.* 2022). These declines have been attributed to a range of pressures including those from land cover change, increased pollution and global warming (IPCC 2022). Until relatively recently, monitoring programmes in surface waters relied exclusively on the collection of discrete samples that were then analysed in the laboratory. These include programmes used to support, for example, the Water Framework Directive (WFD) (CEC 2000) (Brack *et al.* 2017). Sampling frequency has generally been at relatively long time intervals (weekly, fortnightly or monthly) due to time and budget constraints. Low frequency data have, in fact, informed much of the current understanding of how aquatic systems operate. For example, data at relatively long intervals were used to identify the causal relationship between increased nutrients and algal biomass (Dillon and Rigler 1974; Vollenweider 1976) and the effects of seasonal changes in climate on thermal stratification in lakes (Imberger 1994). These low frequency data, however, will miss the effects of short-term changes on aquatic ecosystem functioning, such as the impacts of sudden climate extremes like storms and heatwaves, episodic and random pressures due to human management, or the occurrence of within system events such as toxic algal blooms. The impacts of such events are often highly non-linear in behaviour and therefore key process dynamics can be missed (Krause et al. 2015). Ecosystem theory which is based on more traditional lower frequency sampling will therefore potentially be biased, as by definition short-lived or unpredictable events, which can have extreme and unexpected consequences, will be missed (Jennings *et al.* 2012; Marcé *et al.* 2016; Jennings *et al.* 2022). Understanding the effects of such events is becoming more urgent given current and projected increases in the frequency and severity of climate extremes due to global warming (IPCC 2022). In addition, many of the more rapid changes in aquatic systems are regulated by organisms such as bacteria and phytoplankton that have generation times in hours or days and therefore will show rapid fluctuation.

Technological developments in recent decades now make it possible to automatically monitor ecologically and management-relevant parameters in rivers and lakes using sensors, and to provide web-based access to these data in near real time (Marcé *et al.* 2016; Rode *et al.* 2016). In contrast to traditional monitoring, sampling frequencies are typically sub-hourly. High frequency monitoring (HFM) systems in lakes and reservoirs are generally located close to the deepest point, with a suite of sensors measuring, for example, water temperature, dissolved oxygen, pH, turbidity and chlorophyll fluorescence (Marcé *et al.* 2016). Until recently, most lake systems were deployed from a buoy or other floating station at a fixed depth (typically *c.* 1m from the surface), with often a chain of temperature sensors to capture changes in the thermal profile with depth. However, winched systems, where all sensors move up and down through a single point in the water column, are now becoming more common (e.g. Brentrup *et al.* 2017; de Eyto *et al.* 2019). High frequency monitoring can be particularly useful in rivers and streams where conditions are dynamic and change even more rapidly than in lakes (Rode *et al.* 2016). River monitoring stations generally consist of *in-situ* deployments of sensors in submerged cages (e.g. Ryder *et al.* 2014), or in bankside installations where water is pumped to the station and then back into the river (Jordan *et al.* 2007; Jordan *et al.* 2012). The suite of water quality sensors used in riverine systems is generally similar to those used in lakes, with water level sensors providing data for quantifying stream discharge.

The key to the wider use for *in-situ* HFM in Europe and on the island of Ireland was the development of improved control and communication systems in the 1990s. Some of the most sophisticated early systems were developed for a set of European lakes (i.e. 18 stations across Europe funded by a series of EU projects (Rouen *et al.* 2004)) and included two in the Republic of Ireland: one in Lough Lein (Kerry) and one in Lough Feeagh (Mayo). The system on Feeagh has been maintained by the Marine Institute in the decades since and is now one of the longest running HFM platforms in Europe (de Eyto *et al.* 2020). In 2003, three river HFM stations were also established in the same catchment while a winched system was established on Lough Furnace, the coastal lake that lies between Feeagh and the sea at Clew Bay, in 2008. Together with a network of water level gauges, precipitation gauges and river water temperature sensors, these are the key components of the Burrishoole Ecological Observatory, which has provided new insights in lake and catchment functioning using data that are both high frequency and multiannual including, for example, on the effects of storms (de Eyto *et al.* 2016; Andersen *et al.* 2020; Calderó -Pascual *et al.* 2020; Hoke *et al.* 2020) and global warming (Kelly *et al.* 2020). The Burrishoole is a site member of the Global Lake Ecological Observatory Network (GLEON), with the resulting data been used in many multi-site publications (e.g. Jennings *et al.* 2012; O'Reilly *et al.* 2015). Other HFM studies of note on Irish lakes have included a three-year investigation of water column mixing and internal phosphorus loading in Lough Namachree, a small drumlin lake in County Monaghan (Crockfort *et al.* 2015), and deployments in Lough Ine (County Cork) which investigated changes in conditions during seasonal stratification (Sullivan *et al.* 2013). More recently, a HFM system was deployed in Lough Neagh in 2019 to help determine the nitrogen threshold at which phosphorus was released from lake sediment (Thompson 2022).

Some of the longest running HFM deployments on Irish rivers are those in the Teagasc Agricultural Catchment Programme (ACP) funded by the Irish Department of Agriculture Food and the Marine (Mellander *et al.* 2022). These include high-resolution water quality monitoring stations at the outlets of six study catchments continuously monitored since 2009. The stations include a wet chemistry based system to monitor two fractions of phosphorus (P) (total P and total reactive P) and total oxidised nitrogen (TON), a system that was first trialled on the island of Ireland in the Lough Neagh catchment (Jordan *et al.* 2005). The stations also have sensors to monitor turbidity, total organic carbon (a proxy for dissolved organic matter, DOM), temperature, and electrical conductivity on a sub-hourly basis, together with river discharge (Mellander *et al.* 2012, 2022). The ACP programme has provided a wealth of data on nutrient export from agriculture (e.g. Mellander *et al.* 2012; Mellander and Jordan 2021; Shore *et al.* 2017) and has expanded more recently to include eddy flux covariance towers for gaseous emissions measurements from agricultural land. In addition to these long-term ACP stations, other shorter studies in Irish rivers have included the DEPLOY project in the River Lee (Cork) (e.g. Regan *et al.* 2009), a demonstration project that aimed to highlight the capability of multi-sensor systems to remotely monitor variations in water quality. Targeted deployments in the Burrishoole catchment have also been successfully used to capture impacts of forestry management practices (O'Driscoll *et al.* 2016) which are often apparent at sub-daily time steps and not captured by routine sampling. Separate to the use of HFM in water bodies, there has also been an increase in the use of sensor data and camera observations to provide information in agricultural settings. Williams *et al.* (2020), for example, used cameras to track cattle behaviour at a drinking trough and calculate water in-take, while Rice *et al.* (2021) combined motion-capture cameras and terrestrial laser scanning to assess impacts of cattle access on stream bank modifications at three Northern Ireland catchments.

Whilst Irish participation in networks such as GLEON has been strong, to date there has been no collaborative publication that investigates the potential of information from HFM systems in an Irish context. Ireland's temperate oceanic climate, high rainfall, high organic soils and reliance on livestock-based agriculture mean that HFM may be particularly well suited to understanding the pressures on Irish aquatic ecosystems. Here, we present a set of four new case studies that demonstrate the potential use of HFM from differing catchments that are representative of site types along the catchment-stream-lake-estuary continuum: (1) at the field to small stream scale, (2) within the stream system, (3) at the larger river and lake scale, and (4) in the lower reaches of a large river. These aim to illustrate the capacity for HFM to (1) capture sudden changes, in this case related to cattle access and separately to storms, (2) provide new insights into biogeochemical processing in catchments, (3) inform on load estimation and the sampling design of monitoring programmes, and (4) be used to provide useful indices of trophic status in estuarine waters. We then further review the potential use of such data to inform Irish water resource management and policy.

METHODS AND MATERIALS

CASE STUDY SITE DESCRIPTIONS

Case Study 1: Commons River

This case study focused on a cattle drinking site in a third order stream on the Commons River, County Louth, in the northeast of Ireland (53°50'01.7"N, 6°25'04.9"W) (Table 1, Fig. 1a). Precipitation at the site was typical for eastern Ireland with annual rainfall of 756mm $year^{-1}$ in 2017 and rainfall occurring on 244 days. The study field was used for grazing cattle and had 25 heifers and between 2 and 6 cows in the study period. The field was bordered on its north-eastern side by the stream, a small tributary of the White River (stream width between 1 and 3m depending on water level). The cattle drinking point was only accessible from the study field side of the bank. Electric fencing also prohibited cattle from going further upstream or downstream. This site was selected as cattle movement was confined but it also had sufficient water level for sensor deployment on the streambed. The stream waters at the site had relatively high nutrient concentrations during two sampling occasions in April and June 2017 (TP: 0.080, 0.258mg L^{-1} respectively; TON: 1.82, 2.00mg L^{-1} respectively) (Ó hUallacháin *et al.* 2019).

Case Study 2: Ballycanew River

The Ballycanew catchment (area 11.9km^2) is situated in the Brackan sub-basin of the Owenavoragh (36 km^2) catchment (52°37′7″N, 6°18′51″W), County Wexford, in southeast Ireland (Table 1, Fig. 1a). It was chosen to represent intensively managed agricultural land on poorly drained soils as part of the Teagasc Agricultural Catchments Programme (ACP). Most of the land (97%) is used for agriculture and of that 78% is used for grass production. The main farm enterprises are beef and dairying with a mean livestock unit of 1.28ha^{-1}. The remaining land is used for arable crops (mainly spring barley). About two thirds of the catchment has poorly-drained Gleysols. One third of the catchment, on the elevated land, has well-drained Cambisols. Where the two soils meet, there is a spring line with numerous small springs feeding tributaries to the main stream. The catchment has an extensive ditch/tile drainage network that increases hydrological connectivity (Shore *et al.* 2014). The hydrology is flashy (high ratio of storm flow to base flow magnitudes) and the hydrological pathways are dominated by quick surface pathways. The catchment is therefore at risk for loss of P despite relatively low soil P sources (Mellander *et al.* 2015), and for loss of sediment, mainly eroded from the riverbanks (Sherriff *et al.* 2016).

Case Study 3: Black River and Lough Feeagh

The Black River flows into Lough Feeagh (53°55'46.6''N, 9°34'24.6''W), the largest freshwater lake in the Burrishoole catchment, Co. Mayo (Table 1, Fig 1a). Its catchment area is 48.3km^2 and includes uplands with an altitude range of 8m - 627m (Doyle *et al.* 2019). Blanket bog represents 64% of land cover, commercial afforestation covers 17%, and the remainder is made up of agricultural and semi-natural grasslands. Rainfall is high reflecting the oceanic location. Doyle *et al.* (2019) estimated that annual precipitation from 2011 to 2017 was 2,623mm $year^{-1}$. The Black River typically has high levels of humic materials but low levels of nutrients. The range for colour reported by Doyle *et al.* (2019) was 15-257mg PtCo L^{-1} while that for dissolved organic carbon (DOC), a proxy for DOM, was 2-25mg DOC L^{-1}. The Black River flows into Lough Feeagh, which has mean and maximum depths of 14.5m and 46m respectively, a surface area of 3.92km^2, and a retention time of approximately five months (de Eyto *et al.* 2016; de Eyto *et al.* 2020). It is also highly coloured (ca. 80mg L^{-1} PtCo, with a mean DOC concentration of 8.82mg L^{-1}). The lake water is slightly acidic (pH = ca. 6.7) with low alkalinity (< 20mg L^{-1} $CaCO_3$) (de Eyto *et al.* 2016).

Case study 4: Moy Estuary
The monitoring site used for the current study was in the lower reaches of the River Moy, downstream from the marina in Ballina town, in an area with highly variable salinity (54°8'6.4''N, 9°8'16.6''W) (Table 1, Fig. 1a). North of Ballina town, the River Moy flows to the sea via a long, narrow estuarine channel. After approximately 8km, the estuary widens to form a north-facing triangular bay. The Moy and Killala Bay catchment includes the area drained by the River Moy and all streams entering tidal water in Killala Bay between Benwee Head and Lenadoon Point, Co. Sligo. This drains a total area of 2,345km^2. Given the urban location, the total population of the catchment is relatively high at approximately 77,260. A long sandy island (Bartragh Island) separates the south-western side of the bay from the open water. Much of the inner part of the bay is intertidal. The estuary is classified at Moderate status under current WFD monitoring (Wan *et al.* 2017; EPA 2019).

CASE STUDY METHODS AND DATA ANALYSES

Case Study 1: cattle access site on Commons River
Two multi-parameter sondes (YSI 6600 EDS V2-2), each of which included a turbidity sensor measuring in nephelometric turbidity units (NTU), were deployed in the stream from June 2017 to June 2018: one placed 3m upstream from the upper boundary of the cattle access point and the second 1m downstream of the lower boundary. These were first calibrated in the laboratory following manufacturer recommendations using an NTU standard (YSI, Part number 607300) and deionised water. Prior to deployment, the sensors were run overnight in the same sample to ensure the readings were consistent and there was no significant inter-sensor variability. In the stream, each sonde was placed in a specially constructed steel cage (Fig. 1b) to ensure that probes were completely submerged and were not dragged along the riverbed. Site visits were made every four weeks to clean the sensors and download data. The sondes were set to record at 15-min intervals. The data used here were for a ten-day period from 8 to 17 August 2017. The nephelometer data were first corrected for drift due to fouling (Wagner *et al.* 2006). River discharge and precipitation data were available from an ACP monitoring station approximately 280m downstream from the cattle access site (Mellander *et al.* 2022). The 5th percentile of discharge for the study year was used as a measure of low flow at the site.

Three motion-activated infrared cameras (Bushnell Trophy Cam™ HD, Model 119676) were placed at different angles to record presence of cattle or other species in the stream. The cameras also captured images during darkness. The data extracted from the image files included date and time, and the number of cattle in the stream. Access by other species was also noted. As the nephelometer data were recorded at 15-min intervals, cattle data were summarised (mean and maximum number) for the 15-min period prior to a nephelometer reading for plotting. To avoid pseudoreplication for statistical analyses, the data were then classified into 'events', defined as a period of continuous cattle access that was separated by at least 30min. The gaps between events ranged from 30min to 23h, with a median of 4h 50min. The maximum and mean number of cattle during an event were used as metrics of cattle pressure. The relationships between these metrics and the maximum difference between the upstream and downstream nephelometer readings for any event were assessed using generalised additive models (package mcgv, Wood 2011) with a cubic regression spline in R (Version 4.0.2, R Core Team, 2020). The models were assessed for any breaches of assumptions and a variance structure was added to account for a breach of the assumption of heterogeneity (Zuur *et al.* 2009).

Case Study 2: nutrient dynamics in the Ballycanew River

The catchment outlet at Ballycanew is equipped with a wet chemistry bankside P analyser (Jordan *et al.* 2013) (Fig. 1c) that uses Hach Sigmatax-Phosphax instruments to analyse river water samples for total P (TP) and total reactive P (TRP) concentrations, giving three TP and three TRP analyses per hour by alternating the digestion step. The detection limit is 0.010mg P L^{-1} and the measuring range is 0.010mg P L^{-1} to 5.000mg P L^{-1}. The bankside kiosk is also equipped with optical sensors for monitoring of TON, turbidity and total organic carbon TOC (Hach UVAS SC sensor), all on a 10-min basis. A Hach Nitratax SC-Plus UV was used to monitor TON with a measuring range of 0.1 - 50mg l^{-1}. The TON data were assumed to be equivalent to nitrate nitrogen (NO_3-N) concentration based on comparison with nitrite nitrogen (NO_2-N) concentrations (Melland *et al.* 2012). Turbidity was monitored using a Hach Solitax calibrated to laboratory base suspended sediment (SS) concentration (Sherriff *et al.* 2016). Stream water level was recorded on a 10-min basis with OTT Orpheus Mini vented-pressure instruments installed in stilling wells. Stream discharge was calculated via rating curves, developed in WISKI-SKED software, on Corbett non-standard flat-v weirs using the velocity-area method with OTT Acoustic Doppler Current meters. Standard weather data (including rainfall) were collected on a 10-min basis from a BWS200, Campbell Scientific weather station (www.acpmet.ie) located in the central lowlands of the catchment. The aim of this Case Study was to demonstrate the use of high frequency *in situ* monitoring to gain insight into the processes driving nutrient and sediment loss. The direction, slope and amplitude of plots of concentration (C) versus stream discharge (Q) can provide useful information on temporal and spatial mobilisation and transfer of nutrients and sediments during runoff events, generally referred to as hysteresis relationships (Hashemi *et al.* 2020). A clockwise C-Q loop in the plot indicates a quick or short transfer of nutrients and sediment from the streambed or riparian areas while an anticlockwise loop indicates a slow response or a transport from more distant sources.

Case Study 3: dissolved organic matter monitoring in the Black River and Lough Feeagh

The Automatic River Monitoring Station (ARMS) located on the Black River had a suite of instrumentation and included a sensor measuring chromophoric DOM (CDOM) fluorescence, a proxy for DOC concentration (Seapoint CDOM UV fluorometer). The CDOM data were logged at two minute intervals. River water temperature data were collected from the same site by a multi-parameter sonde (Hydrolab DS5, OTT). Water level was measured on the adjacent Glenamong River every 15 min using a data logger (Orpheus mini, OTT Hydromet). The water level for that site was converted to stream discharge using an established rating curve. The Black River discharge was then estimated using the drainage area ratio method (Hirsch 1979) and the Glenamong data. The 95th percentile value was calculated as an indicator of high flow rates.

An Automatic Water Quality Monitoring System (AWQMS) on Lough Feeagh, situated at the deepest point of the lake (46m), collected high frequency sensor information every 2min which was transmitted back to a logging computer (Fig 1d). Vertical temperature profiles were measured using 12 platinum resistance thermometers (PRTs, Lab facility PT100 1/10DIN 4 wire sensor, www.labfacility.co.uk) at 2.5, 5, 8, 11, 14, 16, 18, 20, 22, 27, 32, and 42m. The AWQMS also had a multiparameter sonde situated at 0.9 m (Environmental Hydrolab Data Sonde X5), which included measurement of water temperature. CDOM data were also available from the AWQMS at 2min intervals from a second Seapoint sensor. All sensors were cleaned fortnightly.

The fluorimeter output in mV from the CDOM sensors was first corrected for a fluorescence reading in distilled deionized water (clear water correction) and further corrected for temperature quenching using stream and lake surface water temperature (Watras *et al.* 2011; Ryder *et al.* 2012). The two-minute corrected CDOM data were then aggregated to hourly means. Dissolved organic carbon concentration was estimated separately for each sensor. The CDOM fluorescence data were converted to estimated DOC concentration using separate relationships for each site as described in Jennings *et al.* (2020). These used DOC data from multiple filtered water samples that were analysed within 48h in the laboratory using a Sievers TOC Analyser. Estimated DOC data from 1 May to 30 September 2018 were used in the current study. Values for five hypothetical weekday sampling programmes were extracted from the hourly mean data for the Black River by sub-setting the data to produce five datasets with one data point per day (midday) for each day between Monday and Friday inclusive. Data were also extracted for all events where stream discharge was greater than the 95th percentile (5.8m^3 s^{-1}) to assess whether any weekly sampling scenario coincided with the extreme high stream discharge events and therefore would have captured any resultant change in concentration. Estimated daily DOC loads were calculated for the Black River as the product of total daily discharge and mean daily estimated DOC concentration.

Case Study 4: using high frequency monitoring to provide an index of estuarine eutrophication

The deployment in the Moy estuary site used a Hydrolab DS5x Datasonde equipped with sensors to collect temperature, salinity in practical salinity units (psu), dissolved oxygen (DO), and pH. The sonde was attached to a mooring buoy just out of the main navigation channel and was suspended at a depth of 1m below the surface. Data were recorded to the internal memory every 20 min and the deployment was from February to August 2013. The mooring was visited every 4 to 6 weeks to clean the sensors, download the internally logged data and replace the batteries. In some cases, the sensors required more maintenance than could be undertaken in the field and therefore there were some gaps in the deployment.

The data for the months from February to August 2013 were used in the current case study. The sensor setup was chosen to allow for the calculation of an index that uses pH and dissolved oxygen data to assess eutrophication state. This phDO index was developed using a range of pH (as pH units) and DO saturation (as % O_2) values observed in multiple water bodies across Ireland (O'Boyle *et al.* 2013). To remove the effects of outliers, the range for each variable was first calculated based on the lower 5th and upper 95th percentile values at the study site. The monthly index (i) was calculated by adding together the normalised parameter ranges for each month and dividing that value by two (Eq. 1). Index values therefore ranged from 0–100, with 0 indicating no variation in either variable and 100 representing the maximum observed variation in both variables.

i = [((range pHi)/(max range pHn/100))+((range DOi)/(max range DOn/100))]/2 (Eq. 1),

where range pHi and range DOi are the difference between the 5th and 95th percentile values for pH and DO respectively for the Moy case study data, and max range pHn and max range DOn are the maximum range for the full set of values from across Irish estuaries that were used to create the model.

RESULTS

Case Study 1: cattle access effects on turbidity in the Commons River

Stream discharge over the ten-day study period was generally low and below the 5th percentile of annual discharge in 2017 (0.004m^3 s^{-1}). It increased on 14-15 August following rainfall of 19.2mm on the 14 August (Fig. 2a). Turbidity also increased at both the upstream and downstream nephelometers in response to increased flow on the 14 August to daily maxima of 12.7NTU and 20.8NTU respectively (Fig. 2b). There was also a smaller increase in turbidity at the upstream nephelometer only on 13 August, the initial day of rainfall, but before discharge had increased. However, multiple other spikes in turbidity were recorded only by the downstream nephelometer throughout the study period during low flows. These spikes coincided with 46 occasions when cattle were also recorded in the stream by the cameras (Fig. 2b). The number of cattle in the stream ranged from 1 to 8 head 15-min^{-1}, with a median of 2 head 15-min^{-1}. The maximum difference between upstream and downstream turbidity for any 15-min period that coincided with cattle access was +164NTU, with a median of +7NTU. In total there were 22 cattle events i.e. discrete periods with continuous cattle access. The model between the downstream-upstream difference in turbidity and the maximum number of cattle during an event (range: 1 to 8 cattle) had an $r^2_{adj.}$ of 0.59 ($p<0.0001$, n = 22) (Fig. 2c). This relationship was positive and slightly non-linear, indicated by an estimated degrees of freedom (edf) of greater than 1 (edf = 1.38). The model with the mean number of cattle as the co-variate (range: 1 to 4.4 cattle) had a lower r^2adjusted of 0.50 (p = 0.00011, n =22).

Case Study 2: Ballycanew, Agricultural Catchments Programme

Changes in stream discharge and in concentrations of TP, TRP, NO_3-N, TOC and SS were captured during two successive rainfall events in August 2020 (Fig. 3a). The first event (*Event I*) produced a total streamflow of 26.7mm over 48h and the second (*Event II*) 38.4mm over 61h and both events had maximum flows that were above the 95th percentile for the period 1 October 2010 to 30 September 2020. In-stream TP, TRP, SS and TOC concentrations were generally elevated during these events, while the NO_3-N concentrations in contrast were diluted, increasing again after discharge had subsided (Fig. 3b-d). Compared to a long-term annual average mass load for 2010 to 2019, the total mass load during the two events combined was 27% for TP and 30% for TRP (Table 2). For both TP and TRP, there was a higher percentage lost in *Event II*. The loss of SS was 16% of the long-term annual average and again there was a larger loss in *Event II*. The loss of NO_3-N was 7% of the long-term annual average, while that for TOC was 16%.

For the two events, the concentration to stream discharge (C-Q) hysteresis loop for TP was clockwise with a positive slope, indicating rapid transfer from sources closer to the stream (Fig. 4a). Concentrations of TP were lower in *Event II* than *Event I*, likely due to source depletion. For TRP, the pattern was similar, but in *Event II* there was a weak figure-of-8 C-Q loop, a pattern indicative of more distant and slowly transferred sources that only became connected at higher flows (Fig. 4b). The plot for SS also showed a positive and clockwise C-Q hysteresis, but with an amplitude that increased in *Event II*, suggesting proximal sources of sediments with connection to high availability sources that increased in the second event (Fig 4.c). In contrast to P fractions and SS, the C-Q hysteresis for NO_3-N was anticlockwise (Fig. 4d), with a negative slope in both events and a lower amplitude in *Event II*, a pattern that indicated the sources were distant or slowly transferred and were depleting as the event progressed. The loop for NO_3-N also appeared as chemo-static (i.e. a horizontal C-Q relationship) when at stream discharge rates of 2 to 5$m^3 s^{-1}$. The pattern for TOC was similar to TRP, with a positive slope and a clockwise direction for *Event I* and a weak figure-of-8 pattern for *Event II* (Fig. 4e). While the patterns differed between the parameters, for all the pollutants there was a change in slope at discharge rates of *ca*. 2$m^3 s^{-1}$, indicating a switch to quick-flow transfer pathways (surface runoff, drain flow etc.) above this threshold.

Case Study 3: estimation of DOC concentration and loads, River Black and Lough Feeagh, Mayo

The weather in the study period for Case Study 3 (1 May and 30 September 2018) was exceptional due to the co-occurrence of two extreme weather events: 1. a drought from 22 May to 14 July broken by 2. a summer storm, Storm Hector, between 13 to 19 June (Fig. 5a). Discharge from the Black River was generally low in the dry periods before and after Storm Hector, but increased immediately following the storm with high flows on 18 and 19 June. In addition, there were seven other occasions when mean daily discharge in the Black River exceeded the 95th percentile value (5.8$m^3 s^{-1}$): two in May (1 and 20), three in August (1, 17 and 18) and two in September (8 and 17) (Table 3). The last of these was the highest mean daily discharge (22.22$m^3 s^{-1)}$ and was associated with the highest rainfall over the period (28.8mm day^{-1}).

The estimated DOC concentration in the river was highly variable. It increased during the high discharge events in May, but decreased during higher flows on, for example, 17 and 18 August, and 16 September (Fig. 5b). The response of concentration during Storm Hector in June was more complex.

Concentrations increased for an initial period on the 13 June to 11.8mg L^{-1} but then declined to very low levels of < 3mg L^{-1} on 16 June before increasing again. A similar decline with increased flow occurred during the largest discharge event on 17 September. Concentrations declined from 15 mg L^{-1} on the 16 September to 4.3mg L^{-1} on the 17 September before increasing again. Six of the nine events were captured by at least one sampling programme, but, interestingly they would have been missed by all others, while events that occurred at weekends would have been missed entirely (Table 3). The timing of events during any day also had implications for monitoring. On 20 May (a Monday), for example, estimated DOC concentrations started to increase at 4.00 and peaked at 18.4mg L^{-1} at 23.00, but had declined again by 8.00 on the 21 May and would not have been captured by a Tuesday midday sample (Table 3). Despite these fluctuations in DOC concentration, the pattern in the estimated DOC loading to the lake was dominated by the effect of day-to-day changes in stream discharge (Fig. 5d). However, while the mean daily DOC load using all HFM data was 0.38kg ha^{-1} day^{-1}, the estimated values based on the five weekly sampling scenarios ranged from 0.31kg ha^{-1} day^{-1} (Friday sampling) to 0.62kg ha^{-1} day^{-1} (Thursday sampling), an underestimation of -24% and overestimation of 51% respectively (Table 3).

Water temperature profiles from Lough Feeagh showed that the lake first began to stratify in mid-May, with an initial period of strong stratification occurring from 29 May to 12 June (Fig. 5c). By 7 June the water temperature at 0.9m was 19.4^{o}C, while that at 8m was six degrees lower at 13.1^{o}C. Stratification broke down during Storm Hector and by 19 June, the water temperature at 0.9m was 14.7^{o}C while that at 8m was 14.5^{o}C. Temperatures then increased from 21 June and remained relatively high until the lake began to cool in September. Despite these changes in lake physical structure, and the variation in DOC loading from the main inflow, the estimated DOC concentration in the lake surface waters remained relatively constant from 1 May to mid-June (Fig. 5d). Over the full study period, the median estimated DOC concentration in Feeagh was 10.1mg DOC L^{-1} (interquartile range 9.6 to 10.8mg DOC L^{-1}), while that in the Black River was 11.7mg DOC L^{-1} (interquartile range 6.1 to 13.8mg DOC L^{-1}). There was a small increase in concentration in the lake following higher flows associated with Storm Hector in mid-June, and again after the high flow event in mid-July. The estimated DOC concentration in the lake then began to increase to *c.* 13-14mg DOC L^{-1} in August and September, reflecting the more consistent increase in daily loading during that time. But it then declined and became variable following the largest inflow event on 16 September, a date which had the highest daily DOC load (Fig. 5d) but actually resulted in decreased concentrations as the large volume of lower DOC concentration water from the river (Fig. 5b) diluted the lake.

Case Study 4: using HFM to provide an index of eutrophication in the River Moy

Water temperatures at the River Moy estuary monitoring site gradually increased in the period from February to August 2013 (Fig. 6a). Over that same period, salinity levels increased from values of less than 1psu in February and March, reflecting a predominance of freshwater sources to the river, to values over 25psu in August, reflecting an increasing influence of tidal waters. Dissolved oxygen concentrations declined gradually over the sampling period from above 100% saturation in February to approximately 60% saturation in mid-July to August (Fig. 6b). While pH was variable, it stayed above 8.2 for much of the period, but declined continuously over the month of July to a low of 7.8 in mid-August. From February to June, the index based on DO and pH data showed that the estuary had little or no indication of being eutrophic, with all index values in the ‘unpolluted’ range (Fig. 6c). Only in April, did the index go above the unpolluted/intermediate boundary (i.e. an index value 40) at 41.1, corresponding to a time when a spring phytoplankton bloom would be expected. There was a large increase in the index values to 77.6 in July and 65.3 in August, indicating a tendency towards eutrophication in those months, a time when opportunistic macroalgal growth peaks (Bermejo *et al.* 2019).

DISCUSSION

The case studies presented here were selected from large data archives to illustrate some of the key benefits that HFM can provide (Table 4). They have highlighted the capacity for *in-situ* automated systems to capture the effects of episodic or extreme events, such as livestock movement (Case Study 1) and storms (Case Study 3), and to track the propagation of these events through linked aquatic systems, as in Case Study 3. They also have demonstrated how HFM systems not only provide data on current water quality status, but can also be used to gain new insights into catchment processes (Case Study 2), improve the design of monitoring programmes (Case Study 3) and be combined to provide indices of trophic status (Case Study 4). Moreover, these benefits are enhanced where data from multiple sensors are combined, as was the case in all of our examples. Stream discharge and lake temperature profile data, for example, were used to provide the physical context for interpretation of the information captured by high frequency nutrient monitoring and CDOM sensors, while automated image capture gave a visual context to Case Study 1. In that example, the automated image capture linked what might otherwise be interpreted as random noise in stream turbidity levels to cattle movements.

A particular advantage of combining HFM of water quality and hydrometric parameters in rivers is that it allows the capture of the effects of sudden and rapid flow events without skewing the information provided through having only a few data points (Cassidy and Jordan 2011). It then becomes possible to very accurately quantify nutrient and sediment losses in the stream or river throughout the year, or during single events, and relate this to annual losses that include both low and high flow periods (Case Study 2). Concurrent monitoring of chemistry and stream flow further allows the use of methods such as our example C-Q analysis to gain insights into underlying mobilisation and transfer processes. The data can also facilitate other methods that analyse and quantify contaminant transfer pathways and concentrations, for example, Loadograph Recession Analysis (Mellander *et al.* 2012). Such analyses can facilitate a process-based understanding of nutrient and sediment loss that is essential for the identification of critical source areas (e.g. Thomas *et al.* 2016) and critical transfer times (e.g. Shore *et al.* 2016) and can be used to support targeted mitigation strategies. In Case Study 3, daily mean stream discharge and estimated DOC concentrations were also used to assess the implications of weekly versus HFM for load estimation. Of particular note was the magnitude of the large over- and under-estimations in estimations of daily DOC loads from the Black River when hypothetical weekly sampling frequencies were used. Indeed, initial periods of HFM would be invaluable in informing monitoring design and quantifying the uncertainty in concentration and load estimates where monitoring programmes will rely on lower frequency data in the longer term (Jordan and Cassidy 2011).

Concurrent HFM datasets from lakes and their inflows are still relatively rare in the literature generally. In Case Study 3, the availability of both data types also highlighted the damping and integrating effect of lake retention time (five months in the case of Feeagh) on lake concentrations. The lower variability in the data from the lake sensor when compared to the inflow was striking, with relatively small increases in the lake after high loading events such as Storm Hector in mid-July. Concentrations only increased substantially once loading was consistently high in autumn. In contrast to the effect on DOC, Storm Hector resulted in an immediate but short lived disruption in lake stratification as indicated by the temperature changes with depth. Temperature sensors are among the most reliable and widely used sensors in lakes and are widely used to capture changes in lake physical structure (Jennings *et al.* 2017). The effects of Storm Hector on lake biota in Lough Feeagh in 2018 were variable, with disruption of the phytoplankton community (Calderó-Pascual *et al.* 2020) while bacterioplankton were generally less impacted (Hoke *et al.* 2020). A previous multi-year study of the effects of a 1-in-250 year rainfall event during summer also showed that Feeagh was relatively resilient and that conditions reset after the winter mixing period (de Eyto *et al.* 2016). In addition to the benefits that we have highlighted, existing HFM station infrastructure may also be used as testbeds for new technologies thus supporting new advances in HFM research (e.g. O'Boyle *et al.* 2014) while HFM can also be used to calibrate and validate models that can then be used to simulate past and future changes in, for example, lake water temperature (Kelly *et al.* 2020) (Table 4).

Challenges for the use of HFM in surface water systems

While our case studies were selected to showcase advantages of automated HFM systems, it is well recognised that there are also challenges related to their use. These include issues related to deployment moorings, sensor failures and performance issues, technical maintenance, data processing, and equipment and personnel costs (Table 4). The original in-stream cage in one of the Burrishoole rivers, for example, was damaged on several occasions during high flows resulting in data gaps (Jennings *et al.* 2020), while the moorings of the Lough Lein system referred to earlier also were damaged during storms and the deployment was eventually abandoned in 2005. We note, however, that successful long-term deployments in the Burrishoole and the ACP catchment have been in place for more than 15 years, attributed to strong, in-house technical support. Vandalism can also be a factor for some automatic stations, for example in one study by Teng *et al.* (2009) 8 of 19 oceanic mooring failures were attributed to this, but this issue has not been frequently encountered by the study authors. Sensor failure or issues related to reliability can also compromise HFM data. The data for our Case Studies 2 and 4 had gaps due to failure or maintenance requirements, while in the year previous to our Case Study 4, the pH sensor at the Moy failed completely. Even where a sensor does not fail, the performance of all water quality sensors should be benchmarked against other measurements regularly. A detailed study assessing the performance of a set of commercially available nephelometers, for example, reported considerable variability between instruments, results that have implications for inter-study comparisons (Rymszewicz *et al.* 2017).

Sensor maintenance, data collation and quality assurance-quality control measures to minimise signal drift are other cost relevant issues which are frequently underestimated, even for sensor-based systems that do not require the consumables needed for wet chemistry methods. The technical support of sensors on HFM platforms requires a different set of skills than is traditional in aquatic science, including continuous maintenance and often electronic troubleshooting. Thus, having access to electronic engineering expertise is crucial for long term programmes, whether that be in-house or on an outsourced contractual basis. If it is outsourced, delays in getting instrumentation fixed and redeployed can be an issue. This can be overcome by having duplicate instruments and a rolling calibration/maintenance schedule. Fouling can be a particular problem for optical sensors (Delgado *et al.* 2021) although the introduction of wipers to these sensors has improved this. The use of optical proxy parameters may also require site specific calibration, for example the relationship between turbidity and suspended solid concentration will vary between catchments, while removing the effect of temperature quenching in DOM fluorometer data can require both site- and sensor-specific correction values (Ryder *et al.* 2012). Indeed, it should be noted that HFM compliments rather that replaces laboratory-based analyses of grab samples, which will continue to be essential in order to, for example, ground truth measurements and calibrate sensors. Data processing has its own challenges (Table 4). McBride and Rose (2018) noted that a single lake platform measuring 20 variables every 5min will produce more than half a million individual observations per year and that these datasets require meticulous error detection, correction, interpolation, and/or data transformations before publication. All of the above will add to the economic cost of automated HFM systems, and therefore to the decision on whether it is worth undertaking given the aims of a particular study. Seifert-Dähnn *et al.* (2020) conducted a cost benefit analysis on HFM at three European sites that supplied drinking water (including one Irish site, Lough Gara) that included costs for infrastructure, data handling/storage, and technical expertise. They concluded that the benefits for drinking water provision outweighed costs only where reservoirs served a sufficiently large population. It should be noted, however, that they did not include any benefit from additional information gained such as identification of long-term trends or controlling factors, analyses that would also require additional expert resources.

The use of automated in-situ HFM systems for routine monitoring
A major advantage of automated HFM in complementing national monitoring efforts is that water quality parameters are measured at frequencies and times that could not be achieved with usual manual sampling. This ensures that data are obtained for routinely monitored variables during times when traditional manual monitoring cannot be carried out, such as during storms or when restrictions on fieldwork are in place, as for example, during the recent COVID pandemic. National monitoring programmes, such as those required for the WFD, generally specifically aim to characterise general conditions, using mean values with the aim of ensuring that water bodies do not fail to meet WFD objectives. Events such as acute pollution incidents and storm flows have the potential to hugely affect assessment outcomes, and conversely samples taken on the basis of what might be one-off events do not well describe the most common conditions in a water body.

The data generated by national monitoring programmes also often provide little evidence as to the source, timing or magnitude of the major pressure that is causing any impact. This affects programmes like the WFD in two ways: in the first instance the characterisation process, whereby the risk of each water body not achieving their WFD objectives, can be hampered by the low number of points used to provide information on seasonal variation and longer-term trends. Short-lived events such as heat waves or storms can have large impacts on water quality and ecosystem functioning as we have shown and these events can result in pulses of nutrients and carbon which likely impact WFD metrics, but are largely missed by monthly sampling efforts (Bergkemper and Weisse 2018). Secondly, where WFD Programmes of Measures are required to improve or protect water bodies, specific information about the delivery mechanisms and timing of inputs are required to ensure that the appropriate measure is put in place. Added value from HFM can also include improving stakeholder engagement and raising the profile of government funded monitoring efforts. The response from key stakeholders such as the Lough Neagh Fishermen's Co-Operative Society to the deployment of a HFM buoy in Lough Neagh (N. Ireland), for example, has been very positive. Members frequently access information from a free public portal, especially meteorological variables, before and during fishing (Thompson *et al.* 2021).

Although assessment methods for WFD aim to describe the general condition of the water body over a three-year period, the methods used need to be able to detect impacts along a gradient of pressure, so that the most impacted sites are identified with as high confidence as the least. In this capacity, HFM has the potential to support tool development by capturing rapid and variable changes. Our case study from the R. Moy showed how having continuous data from two commonly used sensors can provide useful index values to assess trophic status and inform WFD status. The primary drivers of trophic status at this location have been phytoplankton communities and elevated macroalgal growth (Wan *et al.* 2017). Routine assessment of *in-situ* parameters, sampled 4 times per year, had not however shown any elevated concentration of nutrients in the estuarine waters. The index used in our case study, based on pH and dissolved oxygen data, was developed to allow for an assessment of eutrophication state (O'Boyle *et al.* 2013). This index value can be calculated from data obtained during low frequency site visits. However, as our case study shows, the two parameters show high levels of variability, variability that single grab samples would miss. Continuous HFM data in this case showed the potential to provide an additional line of evidence to identify pressures acting on the estuarine environment. While traditional broad scale monitoring had clearly indicated that the Moy estuary status was being impacted negatively, these finer scale data were useful in helping identify exactly when these pressures were acting and when impacts were occurring within the water body. However, while the 2013 HFM on the Moy deployment was successful, it should be noted that a deployment in the previous year had issues when the pH sensor failed to function and no data were collected, highlighting the need for regular maintenance for any long-term sensor deployment.

The use of HFM to inform policy, management and the public

Our case studies highlighted individual applications of HFM for water quality monitoring, although the implementation of such systems on the island of Ireland is still relatively limited. Their full potential is only realised when the information they provide is also used to inform policy and management (Marcé *et al.* 2016). Currently, real-time river discharge data and hydrographs, for example, provide not only site specific information, but help to inform flood policy, management actions and emergency responses. It is also of note that many of these challenges related to cost, maintenance and expertise also apply to existing automated meteorological and hydrometric networks, but such networks are now long established. As of 2017, automated recorder stations measuring water level or discharge in the Republic of Ireland were employed in 99.3% of 950 hydrometric stations (Nasr and Hynds 2017).

Our case studies moreover identify the potential for HFM to provide policy relevant information for key parameters such as DOM and nutrients that can impact on drinking water quality. This is particularly the case for DOM concentrations in raw water which, although not a contaminant of public health concern in itself, can impact on for example drinking water quality through taste, appearance (colour) and the formation of disinfectant by-products (DBPs) which are potentially carcinogenic for humans (Villanueva *et al.* 2015). In the Republic of Ireland, approximately 80% of drinking water is abstracted from surface water sources (DHPLG, 2018; Rolston and Linnane 2020). In 2020, the EU escalated an infringement case against the Republic of Ireland for persistent exceedance of trihalomethanes (THMs), toxic disinfection by-products that can be formed when drinking water is treated using chlorine, by issuing a reasoned opinion on the country's failure to fulfil its obligations under the Drinking Water Directive (EC 2020). Installation of HFM of DOM in drinking water catchments at risk would both provide managers with the potential to implement actions to reduce the risk at times when that is highest (e.g. after heavy rainfall following dry periods), but also would provide new information to inform policy.

The installation of any HFM station network on the island of Ireland could require a policy change to augment current programs. This would also need a significant financial investment, not just for the installation period, but also for the equipment maintenance and data management processes. Yet, automated HFM in real-time could not only fill data gaps currently present within catchment-scale monitoring, but also provide water managers with improved information to implement management actions. Indeed, systems and tools to automate measurement of DOM and other parameters in drinking water management are now becoming mainstream (e.g. Cascone *et al.* 2022) while water supply companies such as Northern Ireland Water now maintain networks of controlled HFM optical sensors for 'now-casting' source water supplies into treatment plants, with alarm systems to reduce or change water input if thresholds are exceeded (O'Donoghue 2015). There is also the scope for real-time provision of HFM for parameters of public health interest such as faecal coliforms (Briciu-Burghina *et al.* 2019), which significantly impact on bathing water quality throughout the Republic of Ireland. Providing a public information tool with real-time bathing water quality would potentially help to reduce health risks and increase awareness of the issues impacting on local water quality. The potential for using data from multiple HFM sites to inform policy has also been highlighted by the wealth of high impact publications that have arisen from the GLEON network and the ACP (e.g. Jordan *et al.* 2005; Jennings *et al.* 2012; O'Reilly *et al.* 2015; Mellander *et al.* 2022). Multi-site studies using lake temperature profile data, including from Feeagh, have also been central to increasing understanding of the impacts of climate extremes on lakes (e.g. O'Reilly *et al.* 2015; Jennings *et al.*

2022), literature that has contributed to the recent IPCC 6th report thus informing future policy at national and global scales (IPCC 2022).

RECOMMENDATIONS AND CONCLUSIONS

Despite the challenges identified above, the benefits we have described provide scope for the increased use of HFM in water quality applications on the island of Ireland. While sensors for some key chemical and biological parameters such as P are still under development, operating a suite of key operational sites using tried and tested HFM technology can only benefit water quality monitoring, reporting and research. Undertaking HFM continually at all monitoring sites in national programmes would likely be prohibitive in terms of budget and human resources (Seifert-Dähnn *et al.* 2020; Jordan and Cassidy 2022), but we believe the benefits of extending HFM in Ireland outweigh the costs and would ensure that Irish aquatic systems are included in future key policy decisions. Data from HFM sites can help to contextualise other sites with lower frequency data and can make important contributions to national and global trend analysis including wider cause and effect interpretation. As the effects of climate extremes continues to impact on aquatic systems, HFM may prove to be a crucial tool in climate change attribution and adaptation as it enables data collection at time scales necessary for calibrating models of aquatic systems, which, in turn, allow projections of climate impacts on aquatic ecosystems to be developed. The maintenance of any new network and existing sentinel HFM sites will facilitate the detection of response patterns in Ireland's complex natural water systems, as shown by the wealth of publications already based on the Burrishoole Ecological Observatory and the ACP programmes. In summary, we believe that sustained strategic investment in a suite of HFM monitoring sites, at multiple scales, would serve to underpin water research and surveillance in Ireland and ensure its scientific quality and global relevance.

ACKNOWLEDGEMENTS

Funding: the work in Case Study 1 was supported by the Environmental Protection Agency grant 2014-W-LS-6 (COSAINT). Case Study 2 was made within the Agricultural Catchments Programme (ACP) funded by the Irish Department of Agriculture, Food and the Marine (DAFM). DkIT (Case Study 3) received funding support from the Marine Institute under the Marine Research Program by the Irish Government under the name BEYOND 2020 (Grant-Aid Agreement No. PBA/FS/16/02). Automated monitoring in Lough Neagh was funded by the Department of Agriculture, Environment and Rural Affairs Northern Ireland. The long-term monitoring of the Burrishoole catchment is enabled by core Marine Institute funding. The work of Jessica Sullivan (DkIT) in collating cattle images is also gratefully acknowledged.

REFERENCES

Andersen, M.R., de Eyto, E., Dillane, M., Poole, R. and Jennings, E. 2020 13 years of storms: an analysis of the effects of storms on lake physics on the Atlantic fringe of Europe. *Water* **12**, 318.

Bergkemper, V. and Weisse, T. 2018 Do current European lake monitoring programmes reliably estimate phytoplankton community changes? *Hydrobiologia* **824**,143—162.

Bermejo, R., Heesch, S., O'Donnell, M., Golden, N., MacMonagail, M., Edwards, M.D., Curley, E., Fenton, O., Daly, E. and Morrison, L. 2019 *Nutrient dynamics and ecophysiology of opportunistic macroalgal blooms in Irish estuaries and coastal bays (Sea-MAT).* Environmental Protection Agency.I Wexford, Ireland.

Brack, W., Dulio, V., Ågerstrand, M., Allan, I., Altenburger, R., Brinkmann, M., Bunke, D., Burgess, R.M., Cousins, I., Escher, B.I. and Hernández, F.J., 2017 Towards the review of the European Union Water Framework Directive: recommendations for more efficient assessment and management of chemical contamination in European surface water resources. *Science of the Total Environment* **576,** 720—737.

Brentrup, J.A., Williamson, C.E., Colom-Montero, W., Eckert, W., de Eyto, E., Grossart, H.P., Huot, Y., Isles, P.D.F., Knoll, L.B., Leach, T.H., McBride, C.G., Pierson, D., Pomati, F., Read, J.S., Rose, K.C., Samal. N.R., Staehr, P.A., Winslow, L.A. 2016 The potential of high-frequency profiling to assess vertical and seasonal patterns of phytoplankton dynamics in lakes, an extension of the Plankton Ecology Group (PEG) model. *Inland Waters* **6**, 565—580.

Briciu-Burghina, C., Heery, B., Duffy, G., Brabazon, D. and Regan, F. 2019 Demonstration of an optical biosensor for the detection of faecal indicator bacteria in freshwater and coastal bathing areas. *Analytical and Bioanalytical Chemistry* **411,** 7637—7643.

Calderó-Pascual. M., de Eyto, E., Jennings, E., Dillane, M., Andersen, M.R., Kelly, S., Wilson, H.L. and McCarthy, V. 2020 Effects of consecutive extreme weather events on a temperate dystrophic lake, A detailed insight into physical. chemical and biological responses. *Water* **12**, 1411. doi.org/10.3390/w12051411.

Cascone, C., Murphy, K.R., Markensten, H., Kern, J.S., Schleich, C., Keucken, A. and Köhler, S.J. 2022 AbspectroscoPY, a Python toolbox for absorbance-based sensor data in water quality monitoring. *Environmental Science: Water Research & Technology* **8***,* 836—848.

Cassidy, R. and Jordan, P., 2011 Limitations of instantaneous water quality sampling in surface-water catchments: Comparison with near-continuous phosphorus time-series data*. Journal of Hydrology* **405,** 182—193.

Council of the European Communities [CEC] 2000 Directive of the European Parliament and of the Council establishing a framework for Community action in the field of water policy. L327. *Official Journal of the European Communities* **43(22/12/2000),** 1—73.

Crockford, L., Jordan, P., Melland, A.R. and Taylor, D. 2015 Storm-triggered, increased supply of sediment-derived phosphorus to the epilimnion in a small freshwater lake. *Inland Waters* **51**, 15—26.

Cross, W.F., Hood, J. M. Benstead, J.P. Huryn, A.D. and Nelson D. 2015 Interactions between temperature and nutrients across levels of ecological organization. *Global Change Biology* **21**, 1025–1040.

de Eyto, E., Jennings, E., Ryder, E., Sparber, K., Dillane, M., Dalton, C. and Poole, R., 2016 Response of a humic lake ecosystem to an extreme precipitation event, physical. chemical. and biological implications. *Inland Waters* **6**, 483—498.

de Eyto, E., Kelly, S., Ryder, E., Dillane, M., Archer, L., O'Cathain, D., Daly, S., Lyons, K., Obrador, B., Brentrup, J. and Naumoski, A., 2019 High frequency monitoring reveals fine scale spatial and temporal dynamics of the deep chlorophyll maximum of a stratified coastal lagoon. *Estuarine, Coastal and Shelf Science,* **218**, 278—291.

de Eyto E., Jennings, E., Dalton, D., McGinnity, P., and Poole, R. 2020 The Burrishoole catchment. In M. Kelly-Quinn and J.D, Reynolds (eds.) *Ireland's Rivers.* Dublin. UCD Press.

Department of Housing, Local Government and Heritage [DHPLG]. 2018 *River Basin Management Plant for Ireland 2018–2021*. Dublin. Government of Ireland.

Dillon, P.J. and Rigler F.H. 1974 The phosphorus-chlorophyll relationship in lakes. *Limnology and Oceanography* **19,** 767—773.

Doyle, B.C., de Eyto, E., Dillane, M., Poole, R., McCarthy, V., Ryder, E. and Jennings, E. 2019 Synchrony in catchment stream colour levels is driven by both local and regional climate. *Biogeosciences*, **16,** 1053—1071.

Dudgeon, D., Arthington, A.H., Gessner, M.O., Kawabata, Z.-I., Knowler, D.J., Lévêque, C., Naiman, R.J., Prieur-Richard, A.-H., Soto, D., Stiassny, M.L.J. and Sullivan, C.A. 2006 Freshwater biodiversity, importance, threats, status and conservation challenges. *Biol. Rev. Camb. Philos. Soc*. **81,** 163—82.

European Commission [EC] 2020 *Infringements Package: Key Decisions*. Available online: https://ec.europa.eu/commission/presscorner/detail/en/inf_20_859 (Accessed on 23 August 2022).

Environmental Protection Agency [EPA] 2019 *Water Quality in Ireland 2013—2018*. Environmental Protection Agency of Ireland. Wexford, Ireland.

Hashemi F., Pohle I., Pullens J.W.M., Tornbjerg H., Kyllmar K., Marttila H., Lepistö A., Kløve B., Futter M., and Kronvang B. 2020 Conceptual mini-catchment typologies for testing dominant controls of nutrient dynamics in three Nordic Countries. *Water* **12**, 1776.

Hirsch, R.M. 1979 An evaluation of some record reconstruction techniques*. Water Resources Research* **15***,* 1781—1790.

Hoke, A., Woodhouse, J., Zoccarato, L., McCarthy, V., de Eyto, E., Calderó-Pascual. M., Geffroy, E., Dillane, M., Grossart, H.P. and Jennings, E. 2020 Impacts of Extreme Weather Events on Bacterial Community Composition of a Temperate Humic Lake. *Water* **12,** 2757.

Imberger, J. 1994. Transport processes in lakes – a review. In. R. Margalef (ed.) *Limnology now – a paradigm of planetary problems*. 99—139, Elsevier. Amsterdam.

Intergovernmental Panel on Climate Change [IPCC]. 2022 Summary for Policymakers [H.-O. Pörtner, D.C. Roberts, E.S. Poloczanska, K. Mintenbeck, M. Tignor, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem (eds.)]. In H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. *Climate Change 2022, Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. Cambridge.

Jennings, E., Jones, S., Arvola, L., Staehr, P.A., Gaiser, E., Jones, I.D., Weathers, K.C., Weyhenmeyer, G.A., Chiu, C.Y. and De Eyto, E. 2012 Effects of weather-related episodic events in lakes: an analysis based on high-frequency data. *Freshwater Biology* **573**, 589—601.

Jennings, E. de Eyto E., Laas, A., Pierson, D., Mircheva, G., Naumoski, A.,Clarke, A.,Healy, M., Šumberová, K., and Langenhaun D. 2017 The NETLAKE metadatabase—a tool to support automatic monitoring on lakes in Europe and beyond. *Limnology and Oceanography Bulletin* **26**, 95—100.

Jennings, E., E. de Eyto, T. Moore, M. Dillane, E. Ryder, N. Allott, C. N. Aonghusa, M. Rouen, R. Poole, and D. C. Pierson. 2020 From highs to lows, Changes in dissolved organic carbon in a peatland catchment and lake following extreme flow events. *Water* **12,** 2843.

Jennings, E., de Eyto, E., Jones, I., Ibelings, B., Adrian, R. and Woolway, R.I., 2021. Ecological consequences of climate extremes for lakes. In: M.E. Perga and D. Bouffard (eds.) *Encyclopedia of Inland Waters. 2nd ed.* Amsterdam. Elsevier. https://doi.org/10.1016/b978-0-12-819166-8.00027-x

Jordan, P., Arnscheidt, J., McGrogan, H. and McCormick, S. 2005 High-resolution phosphorus transfers at the catchment scale: the hidden importance of non-storm transfers. *Hydrology and Earth System Sciences* **9**, 685—691.

Jordan P., Arnscheidt J., McGrogan H.J. and McCormick S. 2007 Characterising phosphorus transfers in rural transfers using a continuous bank-side analyser. *Hydrol Earth Syst Sci.* **11,** 372—81.

Jordan P. and Cassidy R. 2011 Technical Note: Assessing a 24/7 solution for monitoring water quality loads in small river catchments. *Hydrol. Earth Syst. Sci.* **15**, 3093—3100.
Jordan P., Melland A.R., Mellander P.-E., Shortle G. and Wall D.P. 2012 The seasonality of phosphorus transfers from land to water, implications for trophic impacts and policy evaluation. *Science of the Total Environment* **434,** 101—109.
Jordan P., Cassidy R., Macintosh, K.A. and Arnscheidt J. 2013 Field and laboratory tests of flow--proportional passive samplers for determining average phosphorus and nitrogen concentration in rivers. *Environmental Science & Technology* **47**, 2331—2338.
Jordan P and Cassidy R 2022. Perspectives on water quality monitoring approaches for behavioural change research. *Frontiers in Water* **4**, 917595. doi.org/10.3389/frwa.2022.917595.
Kelly, S., Moore, T.N., de Eyto, E., Dillane, M., Goulon, C., Guillard, J., Lasne, E., McGinnity, P., Poole, R., Winfield, I.J. and Woolway, R.I. 2020 Warming winters threaten peripheral Arctic charr populations of Europe. *Climatic Change* **163,** 599—618.
Krause, S., Lewandowski, J., Dahm, C.N. and Tockner, K. 2015 Frontiers in real-time ecohydrology - a paradigm shift in understanding complex environmental systems. *Ecohydrology* **8**, 529—537 DOI: 10.1002/eco.1646.
Marcé, R., George, G., Buscarinu, P., Deidda, M., Dunalska, J., de Eyto, E., Flaim, G., Grossart, H.P., Istvanovics, V., Lenhardt, M., Moreno-Ostos, E., Obrador, B., Ostrovsky, I., Pierson, D.C., Potužák, J., Poikane, S., Rinke, K., Rodríguez-Mozaz, S., Staehr, P.A., Šumberová, K., Waajen, G., Weyhenmeyer, G.A., Weathers, K.C., Zion, M., Ibelings, B.W., and Jennings E. 2016 Automatic high frequency monitoring for improved lake and reservoir management *Environmental Science and Technolo*gy **50,** 10780—10794.
McBride, C.G. and Rose, K.C., 2018 Automated high-frequency monitoring and research. In D.P. Hamilton, K.J. Collier, J.M. Quinn and C. Howard-Williams (eds), *Lake Restoration Handbook*, (419-461). Cham. Springer.
Melland, A.R., Mellander, P.-E., Murphy, P., Wall, D.P., Mechan, S., Shine, O., Shortle G. and Jordan P. 2012 Stream water quality in intensive cereal cropping catchments with regulated nutrient management. *Environmental Science and Policy*, **24,** 58—70.
Mellander, P.E., Melland, A.R., Jordan, P., Wall, D.P., Murphy, P.N. and Shortle, G. 2012 Quantifying nutrient transfer pathways in agricultural catchments using high temporal resolution data. *Environmental Science and Policy* **24,** 44—57.
Mellander, P.E., Jordan, P., Shore, M., Melland, A.R. and Shortle, G. 2015 Flow paths and phosphorus transfer pathways in two agricultural streams with contrasting flow controls. *Hydrological Processes*, **29**, 3504—3518.
Mellander, P.E., Jordan, P., Bechmann, M., Fovet, O., Shore, M.M., McDonald, N.T. and Gascuel-Odoux, C. 2018 Integrated climate--chemical indicators of diffuse pollution. *Nature Scientific Reports* **8**, 944.
Mellander, P.E. and Jordan, P. 2021 Charting a perfect storm of water quality pressures in Ireland. *Science of the Total Environment* **787**, 147576.
Mellander P-E, Lynch B, Galloway J, Žurovec O, McCormack M, O'Neill M, Hawtree, D, Burgess E. 2022 Benchmarking a decade of holistic agro-environmental studies within the Agricultural Catchments Programme. *Irish Journal of Agricultural and Food Research* DOI: 10.15212/ijafr-2020-0145
Nasr, A.E. and Hynds, P.D. 2017 *Assessment of the Hydrometric Network and Hydrodynamic Behaviour of Small Irish Catchments. EPA Research Report 218*. Wexford. Environmental Protection Agency.
Northern Ireland Environment Agency [NIEA] 2021 *Water Framework Directive Statistics Report December 2021*. Available online: https://www.daera-ni.gov.uk/publications/northern-ireland-water-framework-directive-statistics-report-2021 (accessed 10 August 2022).
O'Boyle, S., Trickett, P., Partington, A. and Murray, C. 2014 Field testing of an optical in situ nitrate sensor in three Irish estuaries. *Biology and Environment: Proceedings of the Royal Irish Academy* **114**, 53—59.

O’Boyle, S., McDermott, G., Noklegaard, T. and Wilkes, R. 2013 A simple index of trophic status in estuaries and coastal bays based on measurements of pH and dissolved oxygen. *Estuaries and Coasts* **36**, 158—173.

O'Donoghue, N., Phillips, D.H. and Nicell, C., 2015. Reducing SCADA system nuisance alarms in the water industry in Northern Ireland. *Water Environment Research* **87**, 751—757.

O’Driscoll, C., O’Connor, M., Asam, Z.-Z., de Eyto, E., Brown, L. E., and Xiao, L. 2016 Forest clearfelling effects on dissolved oxygen and metabolism in peatland streams. *Journal of Environmental Management* **166**, 250—259. doi: 10.1016/j.jenvman.2015.10.031.

O'Reilly, C.M., Sharma, S., Gray, D.K., Hampton, S.E., Read, J.S., Rowley, R.J., Schneider, P., Lenters, J.D., McIntyre, P.B., Kraemer, B.M., Weyhenmeyer, G.A. et. al. 2015 Rapid and highly variable warming of lake surface waters around the globe. *Geophysical Research Letters* **42,** 10—773.

Ó hUallacháin, D., Jennings, E., Antunes, P., Green, S., Kilgarriff, P., Linnane, S., O’Callaghan, P., O’Sullivan, M., Regan, F., Ryan, M. and Kelly-Quinn, M. 2019 *COSAINT Project Final Technical Report: Cattle access to Watercourses, Environmental and Socio-economic Implications*. Wexford. Environmental Protection Agency.

R Core Team 2020 *R, A language and environment for statistical computing.* Vienna, Austria. R Foundation for Statistical Computing. URL: https,//www.R--project.org/.

Regan, F., Lawlor, A., Flynn, B.O., Torres, J., Martinez-Catala, R., O'Mathuna, C. and Wallace, J. 2009 A demonstration of wireless sensing for long term monitoring of water quality. *IEEE 34th Conference on Local Computer Networks* 819—825.

Reynaud, A. and Lanzanova, D. 2017 A global meta-analysis of the value of ecosystem services provided by lakes. *Ecol. Econ*. **137,** 184—194. https,//doi.org/10.1016/j.

Rice, A.R., Cassidy, R., Jordan, P., Rogers, D. and Arnscheidt, J. 2021 Fine-scale quantification of stream bank geomorphic volume loss caused by cattle access. *Science of The Total Environment* **769**, 144468.

Rippey, B., McElarney, Y. Thompson, J., Allen, M., Gallagher, M. and Douglas, R. 2022 Recovery targets of Lough Neagh and other lakes. *Water Research* **222**. *118858.*

Rode, M., Wade, A.J., Cohen, M.J., Hensley, R.T., Bowes, M.J., Kirchner, J.W., Arhonditsis, G.B., Jordan, P., Kronvang, B., Halliday, S.J., Skeffington, R.A., Rozemeijer, J.C., Aubert, A.H., Rinke, K., Jomaa, S., 2016 Sensors in the stream, the high-frequency wave of the present. *Environmeantal Science and Technology* **50,** 10297—10307.

Rolston, A. and Linnane, S. 2020 Drinking water source protection for surface water abstractions: an overview of the group water scheme sector in the Republic of Ireland. *Water* **12,** 2437; doi:10.3390/w12092437.

Rouen, M., George, G., Kelly, J., Lee, M. and Moreno-Ostoa, E. 2004 High-resolution automatic water quality monitoring systems applied to catchment and reservoir monitoring. *Freshwater Forum* **23,** 320—337.

Ryder, E., Jennings, E., de Eyto, E., Dillane, M., NicAonghusa, C., Pierson, D.C., Moore, K., Rouen, M. and Poole, R. 2012 Temperature quenching of CDOM fluorescence sensors: temporal and spatial variability in the temperature response and a recommended temperature correction equation. *Limnology and Oceanography: Methods* **10**, 1004—1010.

Ryder, E., de Eyto, E., Dillane, M., Poole, R. and Jennings, E. 2014 Identifying the role of environmental drivers in organic carbon export from a forested peat catchment. *Science of the Total Environment*, **490**, 28—36.

Rymszewicz, A., O'Sullivan, J.J., Bruen, M., Turner, J.N., Lawler, D.M., Conroy, E. and Kelly-Quinn, M. 2017. Measurement differences between turbidity instruments, and their implications for suspended sediment concentration and load calculations: A sensor inter-comparison study. *Journal of Environmental Management* **199**, 99—108.

Seifert-Dähnn, I., Furuseth, I.S., Vondolia, G.K., Gal. G., de Eyto, E., Jennings, E. and Pierson, D., 2021 Costs and benefits of automated high-frequency environmental monitoring–The case of lake water management. *Journal of Environmental Management* **285,** 112108. doi/abs/10.1080/03323315.2021.1932549

Sherriff, S.C., Rowan, J.S., Fenton, O., Jordan, P., Melland, A.R., Mellander, P.E. and Ó hUallacháin D. 2016 Storm event suspended sediment--discharge hysteresis and controls in three agricultural watersheds, implications for watershed scale sediment management. *Environmental Science and Technology* **50,** 1769—1778.

Shore, M., Jordan, P., Mellander, P.E., Wall, D., Murphy, P. and Melland, A.R. 2014 Source and transport factors influencing storm phosphorus losses in agricultural catchments. *Science of the Total Environment* **490,** 405—415.

Shore, M., Murphy, S., Mellander, P.E., Shortle, G., Melland, A.R., Crockford, L., O'Flaherty, V., Williams, L., Morgan, G. and Jordan, P. 2017 The relative and combined impacts of rural diffuse and point sources on stream ecology in agricultural catchments. *Science of the Total Environment* **590/591**, 469—483.

Sullivan, T., Broszeit, S., O'Sullivan, K.P., McAllen, R., Davenport, J. and Regan, F. 2013 High resolution monitoring of episodic stratification events in an enclosed marine system. *Estuarine, Coastal and Shelf Science **123***, 26—33.

Teng, C.C., Cucullu, S., McArthur, S., Kohler, C., Burnett, B. and Bernard, L., 2009 Buoy vandalism experienced by NOAA national data buoy center. In *OCEANS 2009,* 1—8. IEEE.

Thomas, I.A., Mellander, P.E., Murphy, P.N.C., Fenton, O., Shine, O., Djodjic, F., Dunlop, P. and Jordan, P., 2016. A sub-field scale critical source area index for legacy phosphorus management using high resolution data. *Agriculture, Ecosystems & Environment* **233,** 238—252.

Thompson, J., McElarney, Y., Mellor, A. 2021 *Automatic high frequency monitoring in Northern Irish lakes. Evidence and Innovation Project, 16/4/02 (48122).* Summary Report to Department of Agriculture Environment & Rural Affairs, N. Ireland.

Thompson, J. 2022. *Timescales of recovery and the use of automatic high frequency monitoring in N. Irish lakes. Evidence and Innovation Project, 16/4/02 (48122).* Supplementary Technical Report to Department of Agriculture Environment and Rural Affairs, Northern Ireland.

Villanueva, C., Cordier, S. Font-Ribera, L., Salas, L.A. and Levallois, P. 2015 Overview of Disinfection By-products and Associated Health Effects. *Curr. Environ. Health Rep.* **2,** 107–115.

Vollenweider R.A. 1976 Advances in defining critical loading levels for phosphorus in lake eutrophication. *Memorie dell' Istituto Italiano di Idrobiologia* **33,** 58—83.

Wagner, R.J., Boulger Jr, R.W., Oblinger, C.J. and Smith, B.A. 2006 Guidelines and standard procedures for continuous water-quality monitors, station operation, record computation, and data reporting No. 1, D3. USGA. Virginai, USA.

Wan, A.H., Wilkes, R.J., Heesch, S., Bermejo, R., Johnson, M.P. and Morrison, L. 2017 Assessment and characterisation of Ireland's green tides (Ulva species). *PLoS One* 12, e0169049. https://doi.org/10.1371/journal.pone.0169049.

Watras, C.J., Hanson, P.C., Stacy, T.L., Morrison, K.M., Mather, J., Hu, Y.H. and Milewski, P., 2011 A temperature compensation method for CDOM fluorescence sensors in freshwater. *Limnology and Oceanography: Methods* **9,** 296-301.

Williams, L.R., Moore, S.T., Bishop-Hurley, G.J. and Swain, D.L. 2020 A sensor-based solution to monitor grazing cattle drinking behaviour and water intake. *Computers and Electronics in Agriculture* **168,** 105141.

Wood, S. N. 2011 Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society (B)* **73**, 3—36.

Zuur, A. F., Ieno, E. N., and Walker, N. 2009 Mixed effects models and extensions in ecology with R, Springer, New York, NY, USA.

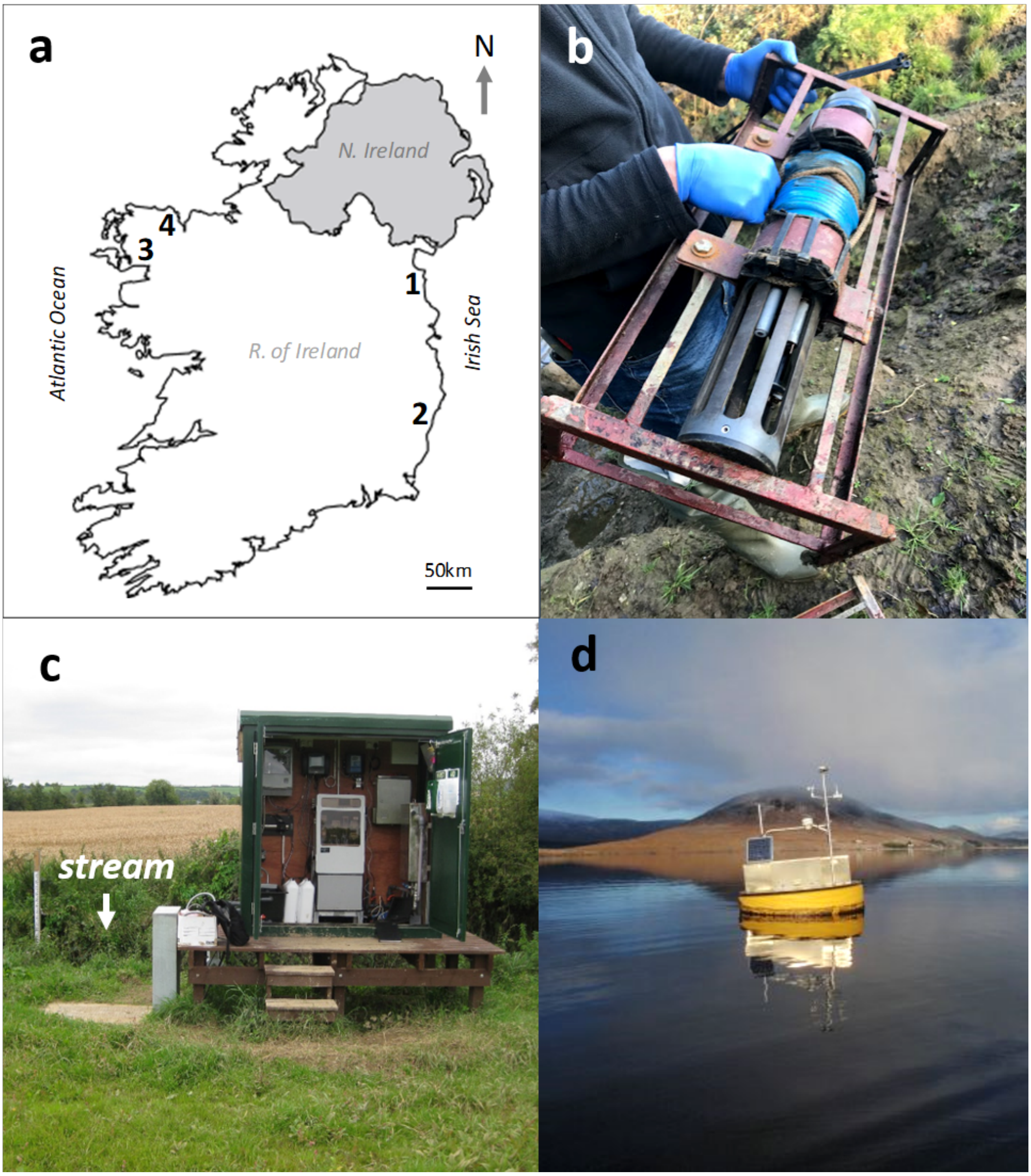

Fig. 1— a. map showing case study locations (numbers); b. sonde in metal cage ready for in-stream deployment at Dunleer, Case Study 1; c. bankside measurement hut in Ballycanew, Case Study 2; d. lake monitoring buoy, Lough Feeagh, Case Study 3.

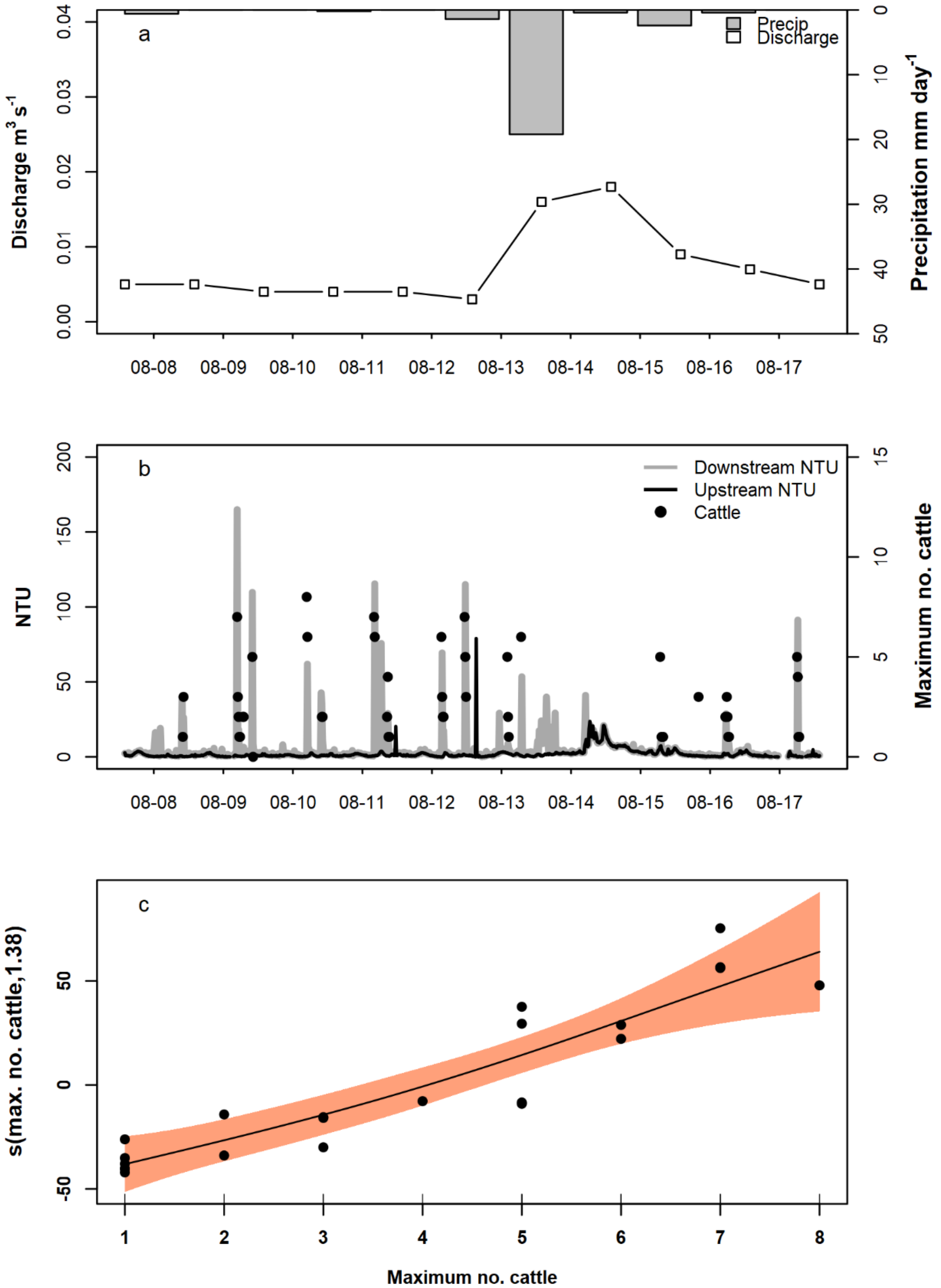

Fig. 2—a. daily precipitation and stream discharge for the study period, 8 to 17 August 2017; b. turbidity data (NTU) from upstream (black) and downstream (grey) of the cattle access site, together with the maximum number of cattle in the stream in any 15-min period (black circles); c. the smoother for the relationship between the upstream to downstream difference in turbidity and the maximum number of cattle in the stream during an access event, with model residuals (black). The y-axis units are the scaled smoother, with the estimated degrees of freedom (edf).

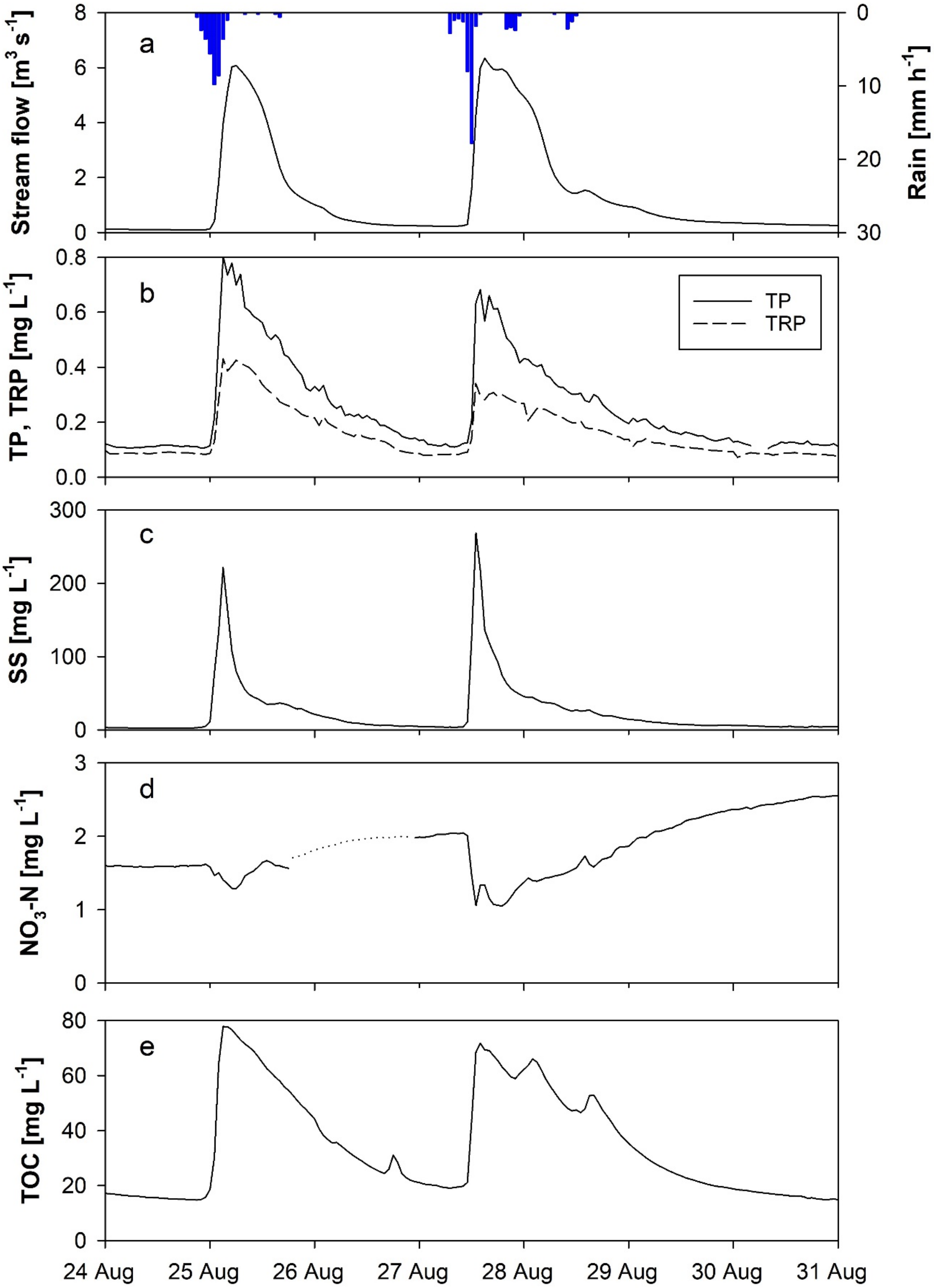

Fig. 3—a. hourly stream discharge, rainfall and concentrations of b. total phosphorus (TP), c. total reactive P (TRP), d. NO_3-N, suspended sediments (SS) and d. total organic carbon (TOC) during two flow events in August 2020 in Ballycanew catchment. NO_3-N data were gap filled with modelled data during the recession of the first flow event (dotted line) due to a logging failure.

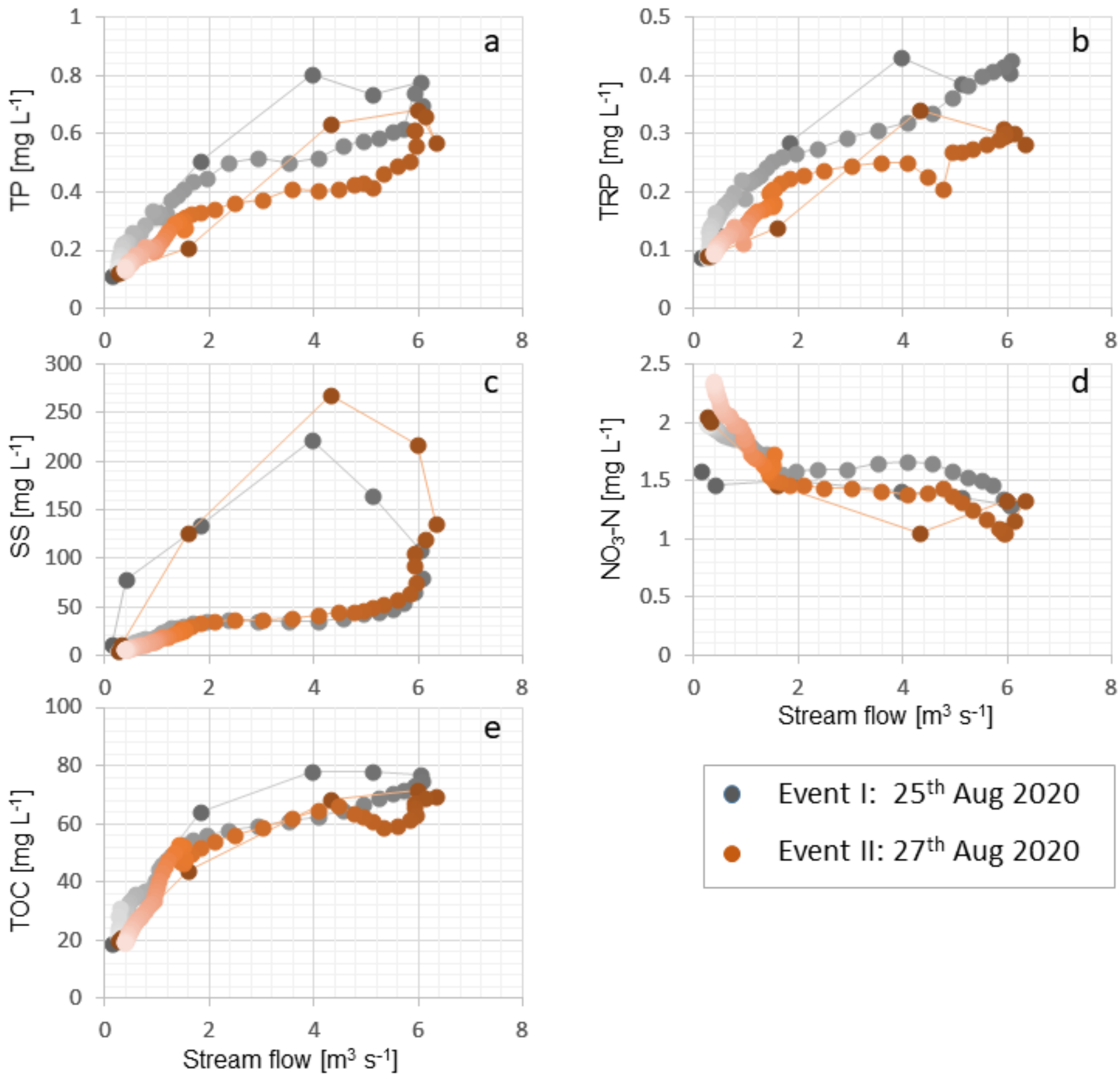

Fig. 4—Example of concentration-streamflow (C-Q) hysteresis plots for a. total phosphorus (TP), b. total reactive P (TRP), c. NO3-N, d. suspended sediments (SS) and e. total organic carbon (TOC) during two high flow events in August 2020 in the Ballycanew catchment. Grey = event I (25 August 2020) and red = event II (27 August 2020). The order of the measurements is indicated by the colour intensity, with the darkest colours at the start of an event and intensity getting lighter as the event progresses.

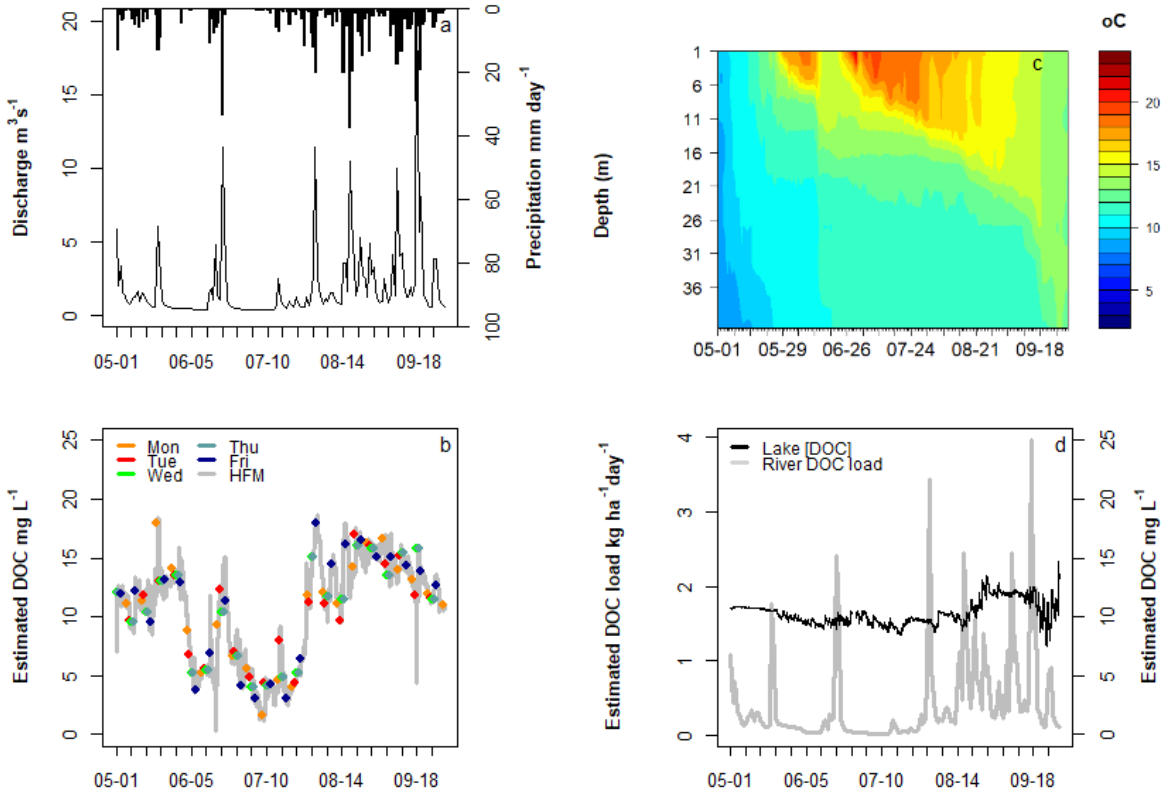

Fig. 5—a. daily total precipitation and mean daily river discharge for the Black River; b. mean hourly estimated DOC concentration (grey, based on HFM CDOM fluorescence) in the Black River, with five datasets for hypothetical weekly sampling programmes (each at 12.00, Monday to Friday), generated by sub-setting the full dataset; c. contour plot of water temperature by depth in Lough Feeagh; d. mean hourly estimated DOC concentration ([DOC]) in Lough Feeagh (black) and daily DOC load in the Black River (grey, kg DOC ha^{-1} day^{-1}). All data run from 1 May 2018 and 30 September 2018.

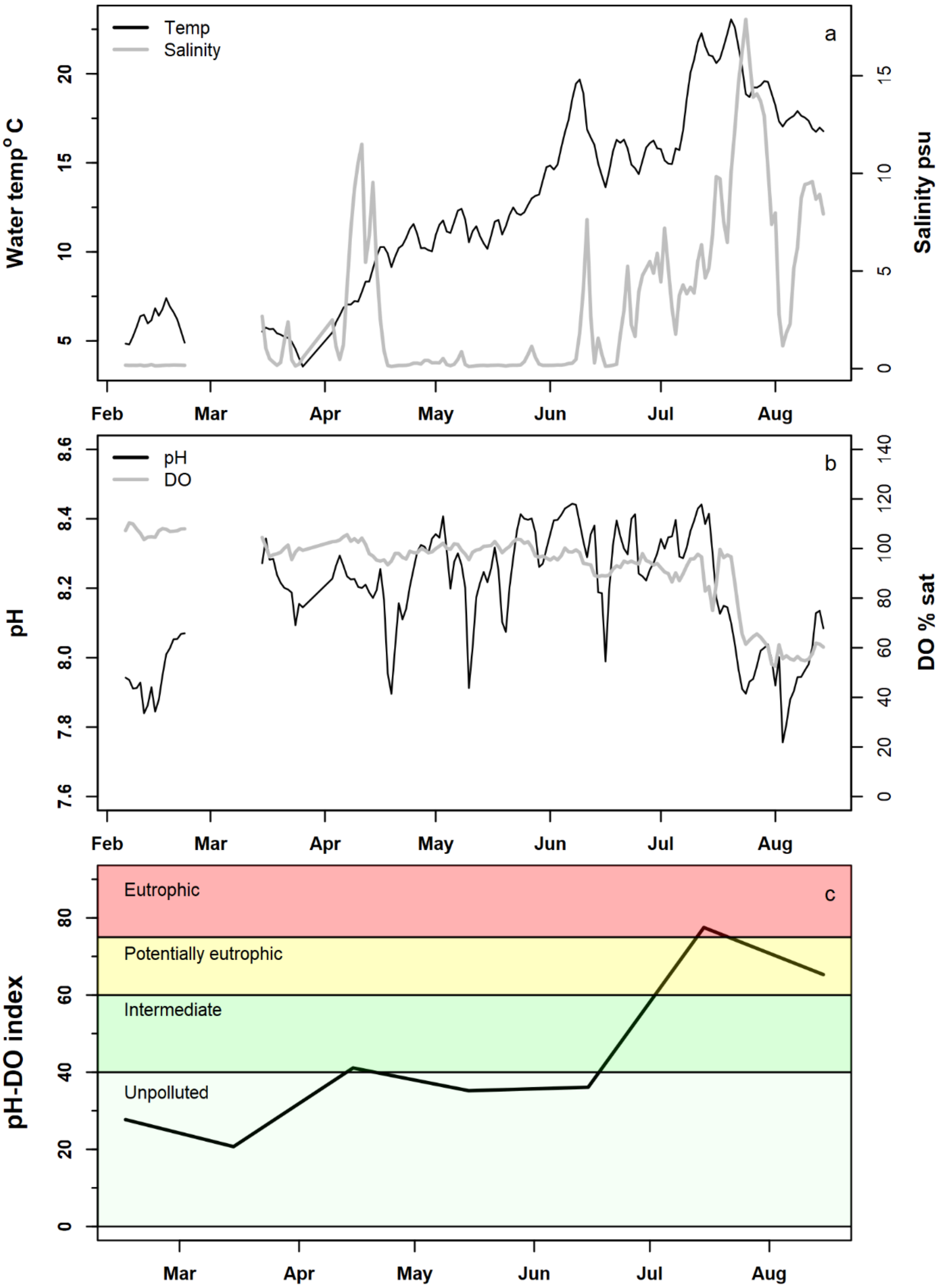

Fig. 6—a. water temperature (black) and salinity (grey) measured at the Moy station sonde from 1 February to 31 August 2013; b. pH (black) and dissolved oxygen (% saturation) (grey); c. index of trophic status based on measured pH and DO data.

Table 1—Case Study details including number, spatial scale, location, station type, deployment timescale and aim, and Case Study outputs (this paper).

Case no.	Spatial scale	County/ catchment/ coordinates	Station type	Deployment timescale, aim	Case study outputs
1	 Field	Louth, Commons, 53°50'1.7"N, 6°25'4.9"W	In-stream cage	Short-term, research	Relationship of turbidity to cattle movement
2	 River	Wexford, Ballycanew, 52°37′7″N, 6°18′51″W	Bankside hut	Long-term, research	Load calculation/ catchment nutrient processing
3	 Inflow/ lake	Mayo, Burrishoole, 53°55'46.6''N, 9°34'24.6''W	River: bankside hut Lake: buoy	Long-term, research	Load calculation/ storm impacts
4	 Lower reach	Mayo, Moy, 54°8'6.4''N, 9°8'16.6''W	Buoy	Short-term, national monitoring	Index value for trophic status

Table 2—Case Study 2: event loss of total phosphorus (TP), total reactive P (TRP), nitrate-N (NO_3-N), total organic carbon (TOC) and suspended sediment (SS) as a percentage of the annual average mass load from 2010 to 2019 (2018-2020 for TOC).

Event no./date	TP	TRP	SS	NO_3-N	TOC*
I: 25 Aug 2020	12.7%	14.5%	6.2%	3.0%	7.1%
II: 27 Aug 2020	14.3%	15.2%	10.0%	3.9%	9.2%

*(percentage of average annual loss for 2018-2020).

Table 3—Case Study 3: date of each event where stream discharge was greater than the 95th percentile value (5.8 $m^3 s^{-1}$) between 1 May and 30 September 2018; event weekday, daily total precipitation and daily mean river discharge. Sampling day indicates whether a given weekday sampling programme captured that event and resultant changes in DOC concentration (Y and shaded = yes; N = no).

Date	**Event weekday**	**Precip.**	**Stream discharge**	**Sampling scenario day**				
		mm day^{-1}	$m^3 s^{-1}$	Mon	Tues	Wed	Thu	Fri
01/05/2018	Thu	12.7	5.89	N	N	N	**Y**	**Y**
20/05/2018	Mon	12.8	6.03	**Y**	N	N	N	N
19/06/2018	Thu	33.2	11.46	N	N	N	**Y**	N
20/06/2018	Fri	1.8	6.06	N	N	N	N	**Y**
01/08/2018	Thu	19.8	11.42	N	N	N	**Y**	N
17/08/2018	Sat	37.0	10.43	N	N	N	N	N
18/08/2018	Sun	19.3	6.64	N	N	N	N	N
08/9/2018	Sat	17.0	10.02	N	N	N	N	N
17/9/2018	Mon	28.8	22.22	**Y**	N	N	N	N
Mean daily load using weekly 12.00 sample (± S.E.)				0.39 ±0.13	0.49 ±0.22	0.49 ±0.14	0.61 ±0.19	0.31 ±0.07

Table 4— Advantages and challenges for the use of HFM in aquatic systems (CS = Case Study).

Advantage	Example	Reference	Challenge	Example	Reference
Use of HFM data for monitoring/ modelling	All CS Modelling past/future	*This study* *Kelly et al. 2020*	Mooring failure	1. Gaps in CDOM data due to storm damage 2. Vandalism	Jennings et al. 2020 Teng et al. 2009
Episodic/ extreme events	CS 1 & 3	*This study*	Sensor failure	CS 2 & 4	*This study*
Accurate load estimation	CS 2 & 3	*This study*	Sensor performance	Assessment of variation between nephelometers	*Rymszewicz et al. 2017*
New insights into key processes	CS 1 & 2	*This study*	Sensor maintenance /fouling	Example of drift due to biofouling	*Delgado et al. 2021 (review)*
Station use as testbed	Testing NO_3 sensor	*O'Boyle et al. 2014*	Data processing/ QA-QC	Multiple processing steps required	*McBride and Rose 2018*
Benefits exceeding costs	Cost-benefit analysis: Erken & Kinneret examples	*Seifert-Dähnn et al. 2021*	Cost exceeding benefits	Cost-benefit analysis: Gara example	*Seifert-Dähnn et al. 2021*