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Smart Observations of Management Impacts on Peatland Function (SmartBog)

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Lead organisations: Trinity College Dublin, Dublin City University, University College Dublin and National Parks and Wildlife Service



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Government of Ireland

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5. Office of Communications and Corporate Services

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What did the research aim to address?

Peatlands in Ireland have been significantly impacted by land use change and are vulnerable to both long-term climate change and extreme weather events. These factors impact the ability of peatlands to support key ecosystem services and, in particular, to store carbon and minimise greenhouse gas (GHG) emissions, a key aspect of our national climate mitigation strategy.

The SmartBog project aimed to assess the extent, condition and use of raised bog ecosystems in Ireland and to enhance our understanding of the impact of management and climatic variability on the climate mitigation potential of these systems. The project used an innovative and interdisciplinary approach, integrating remote sensing data, machine learning and object-based image analysis to better understand the spatial extent and condition of raised bogs and to identify drainage status and habitat change over time. This work was combined with in situ and published studies of gaseous and fluvial carbon and GHG emissions to better inform peatland GHG reporting and to understand the efficacy of land-based mitigation strategies such as rewetting. Low-cost internet-of-things sensors were used to further validate and inform the remote sensing and in situ GHG measurements, and a web-based interactive data visualisation dashboard was developed to support decision-making to enhance the sustainable management of peatlands.

What did the research find?

The SmartBog project developed a new land use classification system and map for Irish peatlands, which, when combined with default emission factors from the Intergovernmental Panel on Climate Change wetlands supplement and literature-based emission factors for key land use classes of raised bog, highlighted a difference in estimated total CO2 emissions of ~1.2 Mt CO_2-C y^{-1} using these respective approaches.

The in situ measurements showed that our wetlands are both vulnerable and resilient to climatic variability, with changing hydrological conditions influencing the carbon source or sink strength of these ecosystems. This work also highlighted the time-dependent benefits of peatland rehabilitation in reducing carbon emissions, and that carbon losses through the fluvial pathway can constitute up to 10% of the annual net ecosystem carbon sink.

This research is highly relevant for policy-related and land management decisions on peatland rehabilitation; however, the work also highlights the need for further measurements to capture the variability in emissions between sites and, in the long term, to better understand site-specific drivers of emissions and the influence of the interaction between management and climate on the source/sink emission dynamics of these systems.

How can the research findings be used?

The Smartbog project provided a framework to inform the assessment of peatland use and management and how this can be further integrated into our national GHG emission reporting framework and land-based climate mitigation strategies.

This work needs to be expanded to other peatland types and supported by long-term monitoring and experimental activities to reduce uncertainties surrounding the site-specific variability in drivers of emissions and the impacts of exceptional and extreme climatic events, and to better assess the time-dependent impact of a variety of peatland rehabilitation strategies.

This work should align with other national and international observational networks such as the National Agricultural Soil Carbon Observatory and the Integrated Carbon Observing System, and the outputs from such work need to be harmonised and compiled in a national data repository that will provide information to the extensive array of stakeholder groups working with peatland systems.

Project code: 2018-CCRP-LS.2

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Smart Observations of Management Impacts on Peatland Function (SmartBog)

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Prepared by

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and National Parks and Wildlife Service



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This report is based on research carried out/data from March 2019 to December 2023. More recent data may have become available since the research was completed.

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Executive Summary

This report presents the outputs of the SmartBog – Smart Observations of Management Impacts on Peatland Function – project, a multidisciplinary endeavour that focused on the need to better understand the extent, condition and use of peatland ecosystems, in particular raised bogs, in Ireland and to assess how management and climate have influenced the provision of ecosystem services, with a particular focus on the climate change mitigation potential of these systems.

Raised bogs are important ecosystems that support a wide range of ecosystem services, including those related to biodiversity status, wider hydrological dynamics and climate mitigation through the long-term storage of carbon. However, many raised bog ecosystems have been degraded due to drainage and conversion to agriculture or forestry or extraction for energy and horticulture. While it is estimated that up to 95% of the peatlands in Ireland have been degraded to some extent, in reality there are few peatlands in Ireland that have not been impacted by human influence. It is therefore important to better understand where these ecosystems are located, how they are being used and if they are having a positive or negative impact on the climate through the uptake or release of carbon and greenhouse gases (GHGs). The SmartBog project addressed this by monitoring peatland sites across Ireland that represent a gradient of peatland conditions, including a near-natural peatland site, a degraded peatland and a peatland undergoing rehabilitation (Figure ES.1), and by integrating multiple remotely sensed datasets in combination with machine-learning and deep-learning techniques to produce a new land use classification system/map for Irish peatlands. The map was also used to estimate CO_2 emissions for four classes constituting 85% of raised bogs – cutover, cutaway, grassland and forestry – using the Intergovernmental Panel on Climate Change wetlands supplement and literature-based emission factors to give an estimate of total emissions of ~1.92 Mt CO_2-C y^{-1} (95% confidence interval (CI): 1.58–2.27 Mt CO_2-C y^{-1}) and ~0.68 Mt CO_2-C y^{-1} (95% CI: 0.44–0.91 Mt CO_2-C y^{-1}), respectively.

This work was further enhanced by the measurement of ecosystem-scale and point-source emissions of



Figure ES.1. Locations of SmartBog monitoring sites. Produced by Dr Wahaj Habib.

carbon dioxide (CO_2) and methane (CH_4), using eddy covariance (EC) techniques and portable analysers/chambers, across a raised bog with near-natural vegetation (Clara Bog), industrial post-extraction sites (Garryduff) and sites under rehabilitation (Cavemount and Lullymore). This work showed that Clara Bog was sensitive to climatic variability and, in particular, fluctuations in water table depth (WTD). In this study, the area of Clara Bog measured by the eddy covariance tower (the flux footprint) was a carbon source (53.51 g C m^{-2} y^{-1}) in a climatologically dry year where a near-continuous increase in WTD (< 5–15 cm) over the growing season was observed, while in other study years the study area acted as a carbon sink, assimilating between –49.72 and –135.93 g C m^{-2} y^{-1}. EC measurements at the Cavemount rehabilitation site over the 2-year study period indicated that the area measured (the flux footprint) acted as a small carbon source (18.27 g C m^{-2} y^{-1}) in one year and was carbon neutral (–0.34 g C m^{-2} y^{-1}) in another. This highlights the time-dependent benefits of peatland rehabilitation in reducing carbon emissions.

The levels of CH_4 emitted from the Garryduff post-extraction site were low (0.29 g CH_4-C m^{-2} y^{-1}) due to the increased WTD and aerobic soil conditions, while CH_4 emission levels were observed to be slightly higher at the Lullymore rehabilitation site (0.79 g CH_4-C m^{-2} y^{-1}) and were highest at Clara Bog (6.62 g CH_4-C m^{-2} y^{-1}). This increase in CH_4 emission levels from the most to the least degraded sites is as expected given historical management activities, decreasing WTD and associated anaerobic conditions of the peat substrate.

Both the EC and chamber data were integrated with Earth observation data products in an attempt to (i) upscale the chamber-derived emission levels from the point-source scale to the ecosystem scale using a weighted area approach and (ii) predict the carbon assimilation potential of near-natural peatlands by validating Earth observation predictions of carbon uptake. Both of these approaches were achieved with a high degree of accuracy (> 90%), providing a platform on which these methods can be extrapolated and upscaled across a wider array of peatland systems.

In order to provide a more holistic assessment of the carbon/GHG dynamics of peatland systems, the export of carbon and the evasion of GHGs through the fluvial pathway were also assessed. This work trialled the use of fluorescent dissolved organic matter sensors with the aim of developing a proxy for real-time measurements of non-particulate organic carbon. The combination of this work and the use of floating chambers to measure the rate of evasion of CO_2 and CH_4 from water leaving the sites indicated that approximately 11% of the carbon assimilated at the Clara site was lost through the fluvial pathway.

The utility of low-cost, low-power internet-of-things sensors in enhancing the temporal and spatial resolution of the measurement of key variables that drive the GHG dynamics of peatland ecosystems was assessed. This work tested multiple types of sensors that measure CO_2 concentrations, temperature and WTD, and it highlighted the need for appropriate calibration, data screening and a structured machine-learning data pipeline to provide robust curated low-cost datasets that provide greater insight into the wider peatland environment.

The project produced multiple data products, and an online dashboard was developed to provide a platform capable of integrating multiple data streams and compiling these into a useable interface for multiple stakeholders. Finally, the project led to a series of recommendations being made on further extending and enhancing work in this area, as detailed in Chapter 7.

1 Introduction

Peatlands account for 50–70% of terrestrial wetland ecosystems across the globe (Joosten and Clarke, 2002; Šimanauskienė *et al*., 2019). They are characterised by the accumulation of organic material that forms peat under waterlogged conditions (Charman, 2002; Evans *et al*., 2021). Peatlands are important ecosystems at the global, national and local scales, as they provide a range of ecosystem services, including those related to climate mitigation, water regulation and biodiversity. From a climate perspective, peatlands are space-efficient carbon stocks, containing approximately 455 Pg of carbon while covering only 2–3% of the global land area (Gorham, 1991). However, peatlands are being exploited annually by human activities, meaning that they are being degraded 10 times faster than they are expanding, on average (Joosten and Clarke, 2002).

In Ireland, raised bogs and blanket bogs account for the majority of peatlands and cover approximately 1.66 Mha (Gilet *et al*., 2024). However, 95% of that area has already been degraded to some extent due to land use activities (Fluet-Chouinard *et al*., 2023). These activities include artificial drainage, conversion to land for forestry or agriculture, peat extraction and the development of infrastructure such as roads (Renou-Wilson *et al*., 2011; Renou-Wilson and Byrne, 2015; Mackin *et al*., 2017; Connolly, 2018). The artificial drainage of peatlands represents an initial step in peatland degradation and is followed by further anthropogenic modifications (Parry *et al*., 2014; Turetsky *et al*., 2015). Drainage facilitates the release of dissolved organic carbon and particulate organic carbon, contaminating freshwater supplies. It also leads to a lowering of the water table, which increases the depth of the aerobic layer in peat, contributing to an increase in carbon and greenhouse gas (GHG) emissions. Moreover, drained sites can act as significant GHG hotspots (Jauhiainen and Silvennoinen, 2012; Evans *et al*., 2016; Leifeld *et al*., 2019). These activities significantly modify the ecological and hydrological characteristics of peatlands, changing them from moderate carbon sinks to large carbon sources (Wilson *et al*., 2013). Furthermore, drainage disrupts the ecosystem services provided by peatlands.

The European Union (EU) has established legislative frameworks and directives that aim to address peatland conservation and sustainable management. For example, the EU Habitats Directive (Council Directive 92/43/EEC) and the Water Framework Directive (Directive 2000/60/EC) underscore the critical importance of peatlands in achieving broader environmental objectives. The EU Biodiversity Strategy for 2030 and the LIFE programme both contribute to the broader goal of preserving and restoring these unique habitats. In addition, under the EU Monitoring, Reporting and Verification Regulation (Regulation (EU) No 525/2013) and the EU 2030 Climate Change Framework, Member States are obligated to report GHG emissions and removals resulting from land use, land use change and forestry activities (Leifeld *et al*., 2019). Despite this, there has been limited success in peatland conservation at the national scale due to a lack of peatland-specific policies or plans. Challenges include incomplete information on peatland characteristics, locations, extents and conditions (UNEP, 2022); a lack of data on sites' carbon/GHG dynamics influenced by drainage and management; the need for a wider assessment of lateral carbon exports, particularly in the fluvial pathway; the need to scale data in space and time; and the need to provide information directly to key stakeholders in real time when it is required.

To help to address these issues, the SmartBog – Smart Observations of Management Impacts on Peatland Function – project had a number of overarching aims, which are addressed in the following chapters. These aims included:

- developing a new spatial assessment of peatland area, land use and condition (Chapter 2);
- assessing the impact of climate and peatland condition on carbon/GHG uptake and release (Chapter 3);
- integrating Earth observation and GHG data as an approach to upscaling emissions (Chapters 2 and 3);
- assessing new technological and methodological approaches to measure fluvial carbon losses (Chapter 4);

- investigating the role and utility of low-cost sensors to enhance the spatial and temporal assessment of variables that drive peatland function (Chapter 5);
- developing an online stakeholder platform to promote the dissemination and use of data/project products (Chapter 6).

2 Geospatial Analysis of Peatland Land Use and Drainage Extent, and the Normalised Difference Vegetation Index

2.1 Introduction and Aims

Peatlands are usually located in isolated and remote areas, which presents difficulties in accessing and mapping them using traditional survey and mapping techniques. Remote sensing, which provides a suitable alternative for mapping these ecosystems, comes with its own set of challenges. These challenges are related to trade-offs between image resolution (spatial, temporal and spectral) and atmospheric conditions, for example persistent cloud cover in some regions. Furthermore, remote sensing-based land use/land cover classification methods are difficult to generalise and need to be adapted depending on the environmental and geographical conditions. This makes the process of image classification across space and time very challenging (Lam, 2008). Globally, remote sensing data have been used extensively to study peatlands (Lees *et al*., 2018). However, there is a severe lack of spatially explicit information on the extent and status of land use in peatlands (Minasny *et al*., 2023). Very few studies have focused on developing techniques to map land use (especially artificial drainage) (Connolly and Holden, 2017; Connolly, 2018; Artz *et al*., 2019; Robb *et al*., 2023). These studies either focused on small areas or used low-resolution satellite imagery for large-scale mapping. Some studies have mapped artificial drainage and land use in tropical peatlands (Miettinen *et al*., 2012, 2016; Dadap *et al*., 2021). However, these methods are not directly applicable to Irish peatlands because of the differences in geographical/environmental conditions and management practices. For example, artificial drainage in Indonesian peatlands is on a significantly larger scale and is achieved through creating what are referred to as "canals" (Dadap *et al*., 2021).

Several studies have been conducted to map the spatial extent of peatlands in Ireland (e.g. Hammond, 1981; Connolly and Holden, 2009); however, there is a significant gap in knowledge on land use extent and status within these peatlands, due to the absence of comprehensive (wall-to-wall) spatially explicit data (Renou-Wilson *et al*., 2014; Aitova *et al*., 2023). Therefore, we developed a set of methodologies that can map and quantify the spatial distribution of artificial drainage sites and land use within the vast expanses of these ecosystems. Previous attempts to map land use in peatlands in Ireland using optical remote sensing imagery have been limited by persistent cloud cover, and wall-to-wall coverage could not be achieved (Cawkwell *et al*., 2018; Connolly, 2018). Connolly (2018) identified and mapped four major land use classes; however, the maps produced lack coverage of the western seaboard region due to cloud cover issues. To achieve more comprehensive mapping of peatlands with further segregation of land use into multiple levels with full geospatial coverage, the development of a robust peatland land use classification taxonomy is necessary. Furthermore, the recent introduction of planetary-scale cloud computing platforms and the application of machine-learning and deep-learning techniques in remote sensing image processing (Cheng and Han, 2016; Gorelick *et al*., 2017) offer promising prospects for overcoming these challenges. This research focused on developing a classification taxonomy – that is, a land use classification system for Irish peatlands (LUCIP) and associated methodologies based on cloud computing (Google Earth Engine) to produce cloud-free mosaics of medium- to high-resolution remote sensing satellite imagery. These mosaics served as a basis for mapping land use across multiple temporal and spatial scales, providing a complete assessment of the coverage of peatlands in Ireland.

In the context of mapping artificial drainage sites, techniques for mapping linear features (e.g. roads, powerlines and canals) using remote sensing exist; these techniques focus on using semi-automated object-based image analysis, edge-detection methods and, more recently, semantic segmentation (Fischler *et al*., 1987; Mohammadzadeh *et al*., 2004; Ma *et al*., 2019; North *et al*., 2019). However, the artificial drainage of peatland ecosystems poses a unique

scenario in which the drainage features can be linear (industrial peat extraction sites) or non-linear (hand-cut peat extraction sites) in nature. Moreover, the spectral signature of drains can vary under different conditions, for example under dry or wet conditions, or with vegetation cover. This poses challenges for mapping artificial drains using traditional remote sensing methods. A study conducted by Connolly and Holden (2017) successfully used traditional semi-automatic object-based image analysis techniques to map linear drains on selected blanket bog sites. This study was the first test case in Ireland demonstrating the use of remote sensing techniques to map artificial drains in a degraded peatland environment. However, it was limited to a few sites and used time- and computation-intensive semi-automated traditional remote sensing techniques. More recently, linear artificial "canals" have been mapped in tropical peatlands using deep-learning techniques applied to semantic segmentation techniques (Dadap *et al*., 2021), and non-linear drainage sites have also been mapped separately using similar techniques on highland blanket bogs in the UK (Robb *et al*., 2023). However, none of these methods has been applied to a study site presenting a diverse range of shapes and sizes of artificial drainage ditches, such as Irish raised bogs. Therefore, the development of a new robust model that integrates deep-learning and remote sensing techniques was required. This research focused on applying fully automated deep learning to semantic segmentation techniques to identify artificial drainage using very high-resolution aerial imagery. This will help to advance research in the realm of the optical remote sensing of peatlands by developing methods that can be efficiently implemented and generalised for peatland environments and tailored to variations in geographical and environmental conditions, which is currently not possible.

Lastly, a significant amount of research has been carried out in Ireland to study the land–atmospheric carbon/greenhouse gas (GHG) dynamics of peatlands under various land uses at the local scale (Laine *et al*., 2007; Wilson *et al*., 2013; Jovani-Sancho *et al*., 2021). However, there is a need to assess these dynamics at a national scale. This work also focused on developing baseline datasets – that is, land use and artificial drainage maps that were used to calculate carbon and GHG emission levels at a national scale using the literature (Aitova *et al*., 2023) and Intergovernmental Panel on Climate Change (IPCC) default emission factors (Hiraishi *et al*., 2014). This helped to address a severe knowledge gap related to understanding the status and spatial extent of drained raised bogs and their implications for carbon and GHG emissions at a national scale.

The main aim of this work was to use a novel set of remote sensing image-processing methods to map land use and artificial drainage networks on peatlands in Ireland. Therefore, the work focused on the development of baseline datasets, including on peatland land use (at multiple scales), using satellite imagery of medium (Landsat, 30 m) and high (Sentinel-2, 10 m) spatial resolutions. Additionally, remote sensing aerial imagery of a very high spatial resolution (Bluesky imagery, 0.25 m) was used to map artificial drainage in raised bogs. The resulting dataset was further used for the geospatial assessment of the status of land use in these ecosystems. The output, an artificial drainage network dataset, underwent quantitative and qualitative assessments using geospatial techniques to identify the drainage density/hotspots (high and low concentration of drainage sites). The drainage dataset was also combined with the land use dataset to assess the spatial distribution of artificial drainage across different land uses.

The specific objectives of the geospatial work were to:

- develop a peatland land use classification taxonomy and map land use in peatlands using multispatial, multitemporal remote sensing, cloud computing technology and machine-learning algorithms;
- utilise novel deep-learning algorithms to map artificial drainage on raised bogs at a national scale using very high-resolution aerial imagery;
- conduct a comprehensive geospatial analysis of the land use and drainage patterns in peatlands, to evaluate the status and temporal evolution of these ecosystems at a national scale;
- integrate spatially explicit land use information and data on carbon dioxide (CO_2) emissions using emission factors proposed by the IPCC and literature sources.

2.2 Materials and Methods

2.2.1 Study site description

This research focused on Irish peatlands, found within Ireland's temperate maritime climate, which

is characterised by mild winters, cool summers and abundant rainfall throughout the year. There have been numerous estimates of peatland extent in Ireland, and in this work the spatial extent of peatlands was delineated using the Derived Irish Peat Map Version 2 (DIPMv2) (Connolly and Holden, 2009). This map classifies peatlands into three distinct classes: (i) high-level montane blanket bog, (ii) low-level Atlantic blanket bog and (iii) raised bog. Blanket bogs are characterised by their extensive coverage with a "blanket-like" continuous layer of peat. They represent most of the Irish peatlands – 926,700 ha (65%) – and are present mostly near low-lying coastal plains and across gentle slopes and mountain plateaux (Connolly and Holden, 2009). In contrast, raised bogs, known for their dome-shaped accumulation of peat, cover ~533,300 ha (35%) of the peatlands in Ireland and are situated mostly in the inland areas (midlands) (Feehan and O'Donovan, 1996; Connolly and Holden, 2009). Minerotrophic peatlands are also present; these fens cover approximately 22,180 ha (Foss, 2007). However, minerotrophic peatlands were excluded from Connolly and Holden's (2009) work on DIPMv2 and therefore were not considered in this work.

2.3 Results

2.3.1 A national-scale assessment of land use change in peatlands between 1990 and 2019 using Landsat data and Google Earth Engine: a case study of Ireland

Note: This work is published as an open-access journal article and can be found here: https://link.springer.com/article/10.1007/s10113-023-02116-0.

In this work, Landsat (5 and 8) data, integrated using Google Earth Engine and machine-learning approaches, were used to examine and quantify land use on Irish peatlands across three years: 1990, 2005 and 2019 (Figure 2.1). Four peatland land use classes were mapped and assessed: (i) areas characterised by industrial peat extraction, (ii) areas characterised by forestry, (iii) grasslands and (iv) residual peatlands (revegetated and abandoned peatlands and other land use categories that could not be detected at the resolution used). The overall accuracy of the classification was 86% and 85% for the 2005 and 2019 maps, respectively. The accuracy of the 1990 dataset could not be assessed because high-resolution reference data were not available. The results indicate that extensive management activities have taken place in peatlands over the past three decades and that these have had negative impacts on peatlands' ecological integrity and the many ecosystem services they provide. Afforestation increased between 1990 and 2019 (from 12.4% to 15.3%), and grasslands accounted for over half of the land use in peatlands in all three years assessed (Figure 2.2). Industrial cutaway activities, which have been detrimental to the integrity of peatlands, were also widespread, although a substantial amount of industrial cutaway sites have been converted to other land uses in the past decade or so as a result of the reduction in and subsequent cessation of Bord na Móna activities. By utilising cloud computing, temporal mosaicking and Landsat data, this work developed a robust methodology that overcomes cloud contamination and has produced the first peatland land use maps of Ireland with wall-to-wall coverage. This has the potential for regional and global applications, providing maps that could improve our understanding of unsustainable peatland management practices and the impact of such practices on GHG emissions and CO_2 removals.

2.3.2 Quantifying peatland land use and CO_2 emission levels in Irish raised bogs: mapping insights using Sentinel-2 data and Google Earth Engine

Note: This work is published as an open-access journal article and can be found here: https://www.nature.com/articles/s41598-024-51660-0.

In this work, a seven-class LUCIP was developed and mapped using Sentinel-2 imagery, random forest machine learning and Google Earth Engine. The results reveal that agricultural grasslands account for 43% of land use on raised bogs, with forestry (21%), cutover peatlands (11%), cutaway peatlands (10%), remnant peatlands (13%), waterbodies and built-up areas (~1% each) accounting for the rest (Figures 2.3 and 2.4). The overall accuracy of this mapping was 89%.

This mapping was also used to estimate CO_2 emission levels for four land use classes constituting 85% of land use on raised bogs: cutover peatlands, cutaway peatlands, grasslands and forestry. Using the IPCC wetlands supplement and literature-based emission

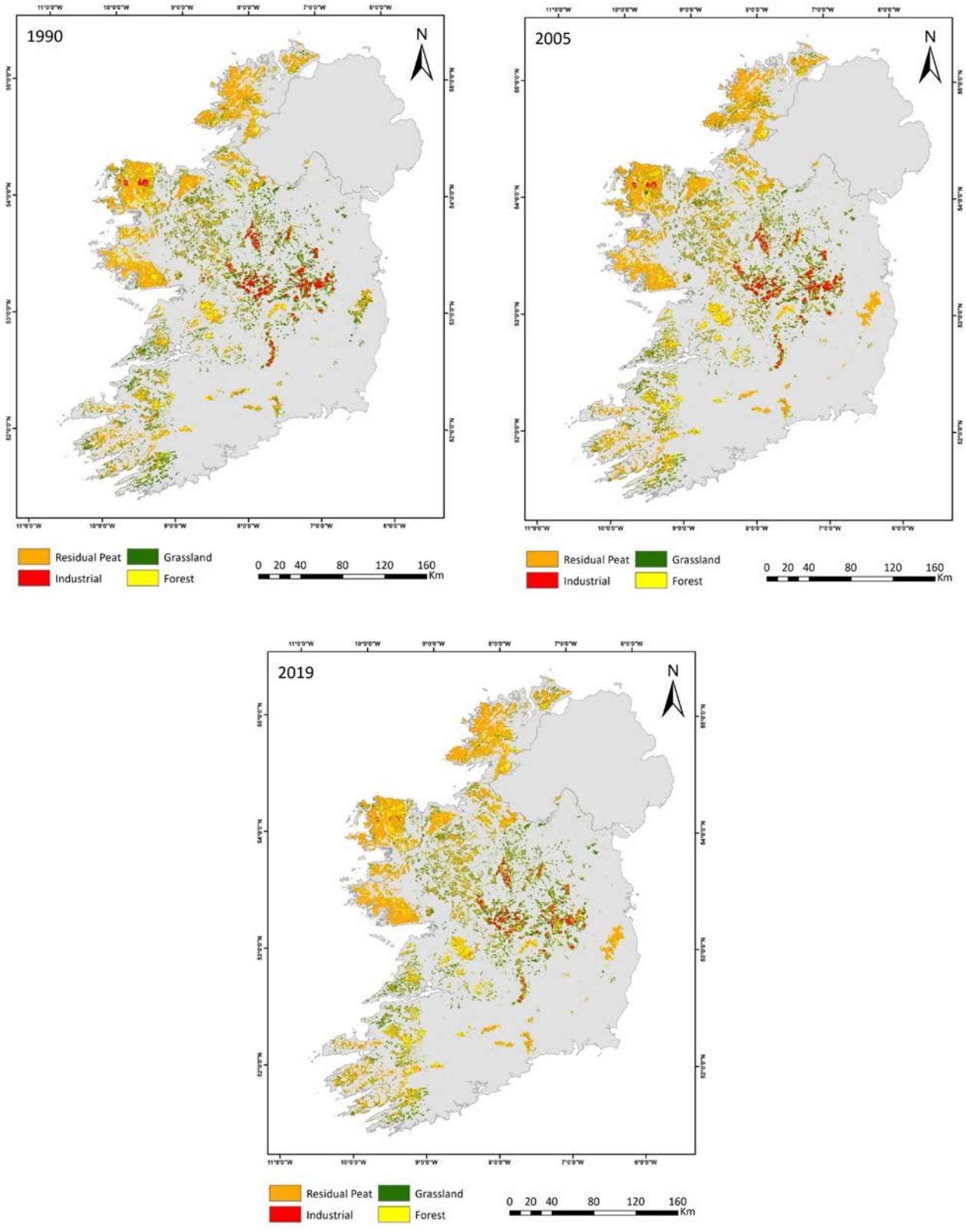

Figure 2.1. Maps showing land use on peatlands in 1990, 2005 and 2019, revealing major land use changes. Reproduced from Habib and Connolly (2023); licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

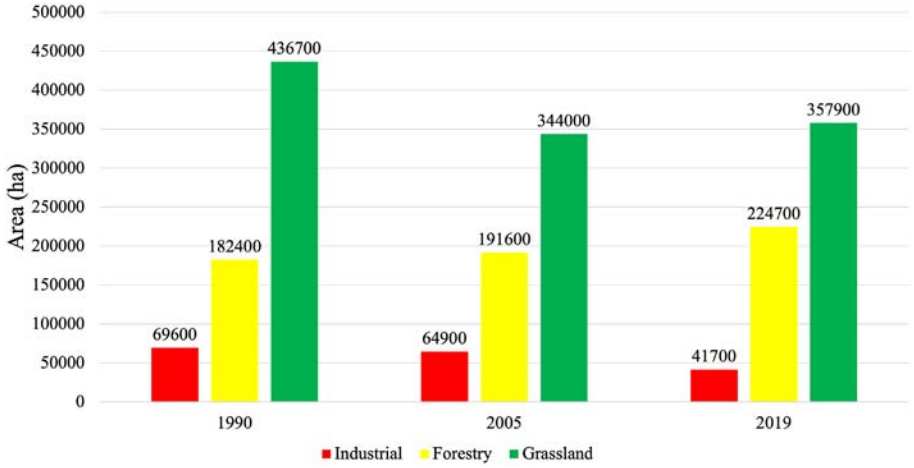

Figure 2.2. Comparison of land use areas classified industrial, forest and grassland. Reproduced from Habib and Connolly (2023); licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

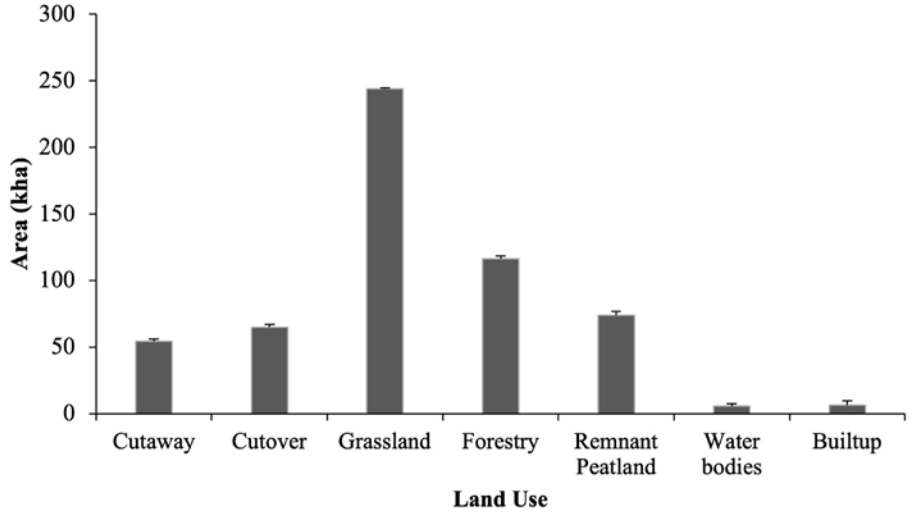

Figure 2.3. Comparison of land use on raised bogs in Ireland by land use area class. Error bars for standard errors are in kha. Reproduced from Habib *et al*. (2024a); licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

factors derived from Aitova *et al*. (2023), we estimated total emission levels to be ~1.92 Mt CO_2-C y^{-1} (95% confidence interval (CI): ±1.58–2.27 Mt CO_2-C y^{-1}) and ~0.68 Mt CO_2-C y^{-1} (95% CI: ±0.44–0.91 Mt CO_2-C y^{-1}), respectively. This is the first study to spatially quantify land use and related emission levels from raised bogs using remotely sensed data and methods. The results reveal widespread degradation of these globally rare habitats, which has led to them becoming net emitters of CO_2. This mapping is vital for informing the conservation of these ecosystems through restoration efforts, and the methodology can also be applied to other regions with similar peatland land use issues.

2.3.3 Mapping artificial drainage on peatlands: a national-scale assessment of Irish raised bogs using sub-metre aerial imagery and deep-learning methods

Note: This work is published as an open-access journal article and can be found here: https://zslpublications.onlinelibrary.wiley.com/doi/10.1002/rse2.387.

This work utilised very high-resolution (25 cm) aerial imagery and a deep-learning (U-Net) approach to map the visible artificial drainage (unobstructed by

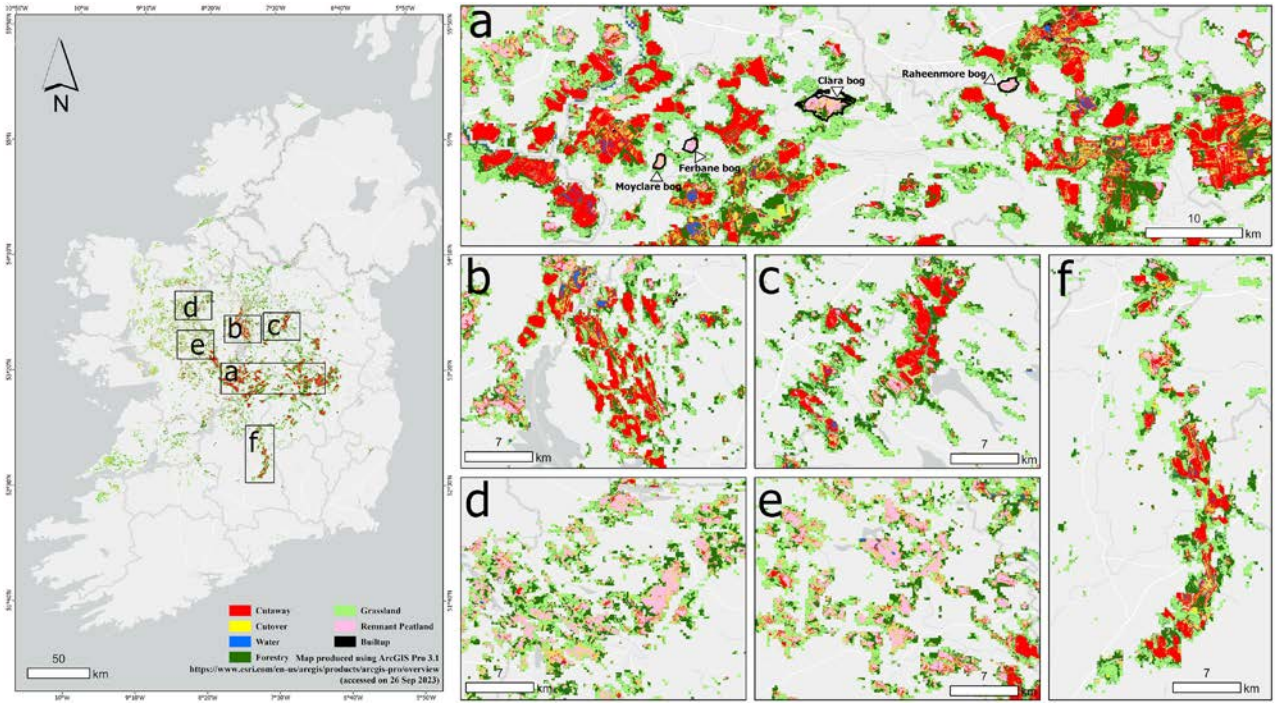

Figure 2.4. Land use on raised bogs in Ireland in 2020. Panels a, b, c and f show areas dominated by industrial peat extraction sites (mostly those of Bord na Móna), whereas panels d and e show areas dominated by remnant peatlands (high bogs). Reproduced from Habib *et al*. (2024b); licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

vegetation or infill) in raised bogs at a national scale. The results show that artificial drainage is widespread, with ~20,000 km of drains mapped (Figure 2.5). The overall accuracy of the model was 80% on an independent testing dataset. The data were also used to derive a country-specific value for the fraction of artificial drainage on industrial peat extraction sites ($Frac_{ditch}$), which was 0.03. This is lower than the IPCC Tier 1 $Frac_{ditch}$ value and will be useful in IPCC Tier 2 reporting for Ireland. This is the first study to map drainage sites with diverse sizes and patterns on Irish raised bogs using optical aerial imagery and deep-learning methods. The mapping data will serve as an important baseline dataset for evaluating artificial drainage ditch conditions and will prove useful in informing sustainable management and conservation efforts and refining estimations of GHG emission levels. The model's capacity for generalisation means that it offers potential for mapping artificial drains on peatlands at regional and global scales, thereby enhancing the comprehension of the global effects of artificial drainage ditches on peatlands.

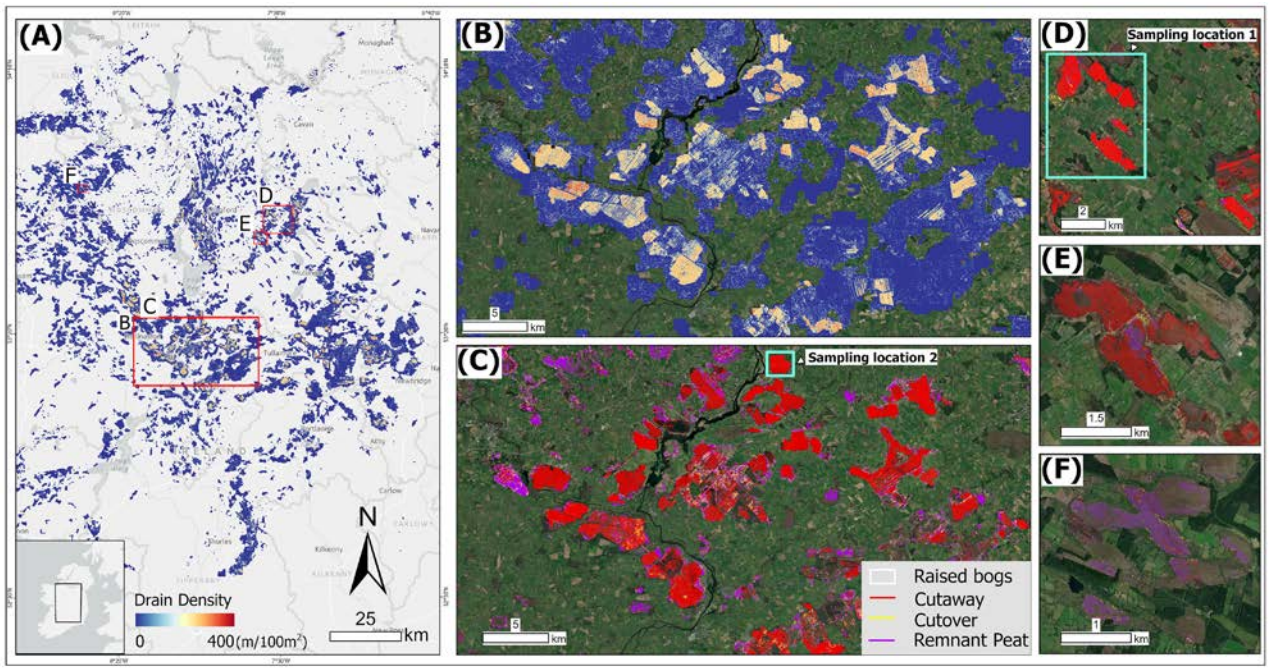

Figure 2.5. Drainage density map, peat extraction areas and sampling locations. Panel A shows the drainage density map (m 100 m^{-2}). Bord na Móna industrial peat extraction areas are shown in panel B (drainage density) and panel C (individual ditches). Sampling locations 1 and 2 are shown in panels D and C. Non-Bord na Móna industrial peat extraction sites are shown in panel E. Panel F shows a remnant peatland (high bog) area with extensive drainage. Data were derived for the years 2015–2020. This figure is reproduced from Habib *et al*. (2024b); licensed under CC BY-NC-ND 4.0 (https://creativecommons.org/licenses/by-nc-nd/4.0/deed.en).

3 Carbon and Greenhouse Gas Dynamics

3.1 Introduction and Aims

Peatlands play an important role in the land–atmosphere exchange of carbon and other radiatively important greenhouse gases (GHGs), such as methane (CH_4) and nitrous oxide (N_2O). The drainage and subsequent management of peatlands significantly alters their hydrological and ecological characteristics, which in turn modifies the carbon/GHG dynamics of these ecosystems, typically switching them from moderate sinks to net sources of GHGs (Wilson *et al*., 2013). A significant amount of research has been undertaken in Ireland to assess the carbon/GHG dynamics of peatland land use categories, such as pristine blanket and raised bogs, grassland systems on peat soils, drained and rewetted forest systems, and both industrial and domestic peat extraction sites, and this research has recently been synthesised by Aitova *et al*. (2023). These studies provide insight into the net ecosystem exchange (NEE) of carbon and hotspots of GHG uptake/release associated with these land use types and have further extended our knowledge on the peatland characteristics that drive the GHG dynamics of these systems.

The main objectives of this work were to:

- assess the impacts of climate and land management on net ecosystem carbon dynamics;
- investigate point-source CH_4 emission levels from sites across a drainage gradient and develop an approach to spatially upscale emissions and therefore derive ecosystem-scale emission estimates;
- integrate eddy covariance (EC) and Earth observation (EO) data to develop models that can be used to predict carbon assimilation by peatland/wetland systems.

3.2 Methodology

3.2.1 Study sites

This work utilised a range of raised bog sites across the Irish midlands that represent a range of land use types and various states of degradation. These sites include those with near-natural hydrological and ecological conditions (Clara Bog), industrially extracted sites (Garryduff) and former extraction sites undergoing rehabilitation (Lullymore and Cavemount). Clara Bog is a special area of conservation located in County Offaly in the Irish midlands. It is considered one of the largest (> 400 ha) near-natural raised bogs remaining in Ireland. The site has some remedial drainage and is divided by a road. This study was undertaken on the western part of the bog. The vegetation communities at Clara were classified using the approach of Schouten (2002) and linked to the hydrological characteristics of the bog (Regan *et al*., 2020). Garryduff is in County Galway, where peat was industrially mined until 2021. Prior to entering a rehabilitation programme, the site was under a pumped drainage regime and, during this study, much of the site comprised bare peat with some emerging pioneer vegetation. The Lullymore site is in County Kildare and represents a former industrially mined site that has undergone phased rehabilitation involving drain blocking over a 15-year period. The site is dominated by bog woodlands, emergent macrophytes and wet shrub vegetation, and areas of open water. The Cavemount site is in County Offaly and has a similar land use history to that of Lullymore, with peat extraction ceasing in 2015 and rehabilitation being undertaken through drain blocking. The site is following a similar ecological transition to Lullymore. Details of all the sites and measurement approaches used to assess carbon/GHG exchange are provided in Table 3.1.

3.2.2 Techniques for measuring gas exchange

Eddy covariance

Measurements of the NEE of carbon dioxide (CO_2) were conducted using the EC technique at the Clara and Cavemount sites. This instrumentation consisted of a sonic anemometer (WindMaster, Gill Instruments, Lymington, UK), measuring wind speed and direction in three dimensions, and an embedded closed-path infrared gas analyser (LI-7200, LI-COR, Lincoln,

Table 3.1. Study sites and techniques used to measure carbon/GHG exchange in the SmartBog project

Site name	Site type	Location (latitude/longitude)	Measurement technique
Clara Bog	Near natural	53°19′N, 7°36′W	EC and chamber based
Garryduff	Industrially extracted	53°15′N, 8°3′W	Chamber based
Lullymore	Undergoing rehabilitation	53°16′N, 6°57′W	Chamber based
Cavemount	Undergoing rehabilitation	53°32′N, 7°23′W	EC based

Nebraska, USA). The raw EC data were collected at 10 Hz and processed using EddyPro version 7.0.6. The EC tower was equipped with a range of ancillary sensors for measuring environmental and meteorological conditions every 30 minutes. The variables measured included precipitation (measured using a tipping bucket rain gauge, RM Young, Traverse City, Michigan, USA); air temperature and humidity (both measured using the CS215, Campbell Scientific, Shepshed, UK); volumetric water content of the soil (measured using the CS616 water content reflectometer, Campbell Scientific, Shepshed, UK); soil heat flux (measured using the HFP01, Hukseflux, Delft, the Netherlands); soil temperature (measured using the 105E, Campbell Scientific, Shepshed, UK); photosynthetically active radiation (PAR) (measured using the Skye Quantum Sensor, Skye Instruments, Llandrindod, UK); and net radiation (measured using the NR Lite, Kipp & Zonen, Delft, the Netherlands).

The meteorological data were recorded using a CR3000 micrologger (Campbell Scientific, Shepshed, UK) at 30-minute intervals. Water table depth (WTD) was measured and recorded at hourly intervals using Orpheus Mini vented-pressure level transducers (OTT Hydromet, Kempten, Germany) located in phreatic tubes.

Chamber measurements

Point measurements of CO_2 and CH_4 were made using the LI-7810 $CH_4/CO_2/H_2O$ trace gas analyser (LI-COR, Lincoln, Nebraska, USA) coupled with the LI-COR smart chamber to facilitate soil gas flux measurements. Permanently installed polyvinyl chloride (PVC) collars (with an outer diameter of 21.34 cm and a height of 11.43 cm) were used to seal the smart chamber and soil surface during each measurement. At each site where chamber measurements were made, the PVC collars were installed across a representative range of ecotopes to allow for the spatial upscaling of the data. An overview of the ecotopes sampled at each site can be found in Table 3.2.

3.3 Results

3.3.1 Impacts of climate and management on the net ecosystem exchange of carbon

The EC towers were operational as part of the SmartBog project in 2018–2023 and 2020–2021 at the Clara and Cavemount sites, respectively. At Clara, the EC footprint was dominated by the subcentral ecotope, which constitutes the dominant ecotope at this site, and during the study period the area acted as

Table 3.2. Ecotopes and associated vegetation communities sampled as part of the chamber-based measurement campaign

Site	Ecotopes	Dominant vegetation	Number of collars
Clara Bog	Central	*Sphagnum cuspidatum*	6
	Subcentral	*Sphagnum magellanicum*	6
	Submarginal	*Narthecium ossifragum* and *Sphagnum tenellum*	6
	Marginal	*Calluna vulgaris* and *Trichophorum germanicum*	6
Lullymore	Bare peat	Bare peat	4
	Shrub	Mosaic of pioneer *Juncus*, *Eriophorum angustifolium*, emergent *Betula pubescens* and *Salix* spp. scrub	4
	Bog woodlands	*Betula pubescens*, *Pinus sylvestris* and *Pinus contorta*	4
Garryduff	Bare peat	Bare peat	8
	Vegetated	Mosaic of pioneer *Juncus*, *Eriophorum angustifolium*, *Carex rostrata*, emergent *Betula pubescens* and *Salix* spp. scrub	8

both a carbon source and a carbon sink on an annual basis. The study area acted as a carbon source in 2018, emitting 53.5 g C m^{-2}, but over the remainder of the study period (2019–2023) the study area acted as a net carbon sink of varying strength, assimilating between –49.7 and –135.9 g C m^{-2} y^{-1} (Figure 3.1; by convention, a negative sign denotes the net uptake of carbon by an ecosystem and a positive sign denotes carbon loss from a system). The tower was active during two hydrologically exceptional years, 2018 and 2021, when precipitation was approximately 10.6% and 31.7% lower, respectively, than the 30-year mean for the period. The reduction in precipitation coupled with continued evapotranspiration increased the WTD to a maximum of 15 cm and 21 cm below the surface in 2018 and 2021, respectively (Figure 3.2). One key difference between these measurement years is that, while in 2021 the site received less precipitation in total than in 2018, the changing water table dynamics in 2018 had a greater impact on the NEE of carbon.

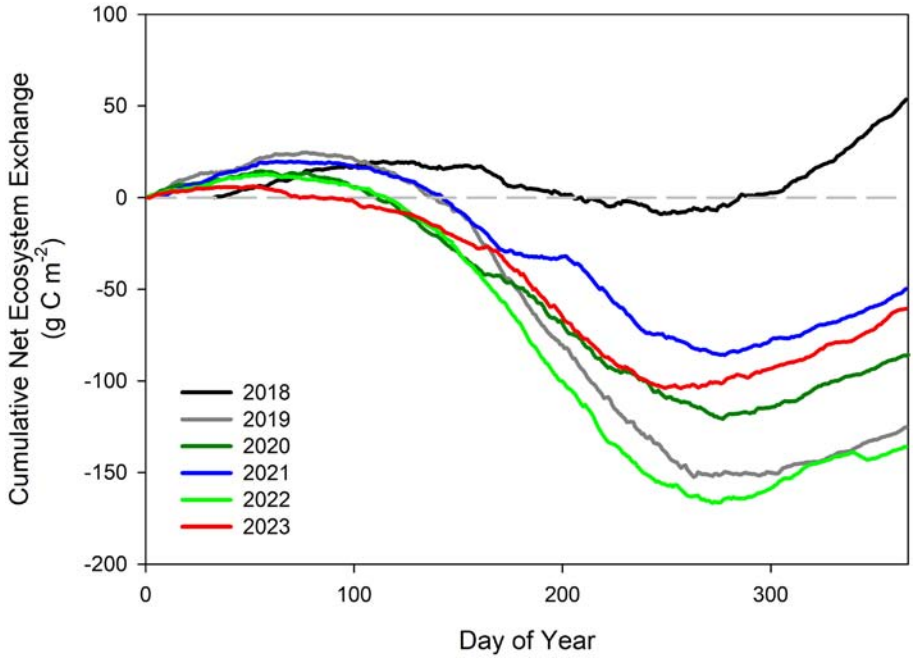

Figure 3.1. NEE of carbon at the Clara Bog site over the study period.

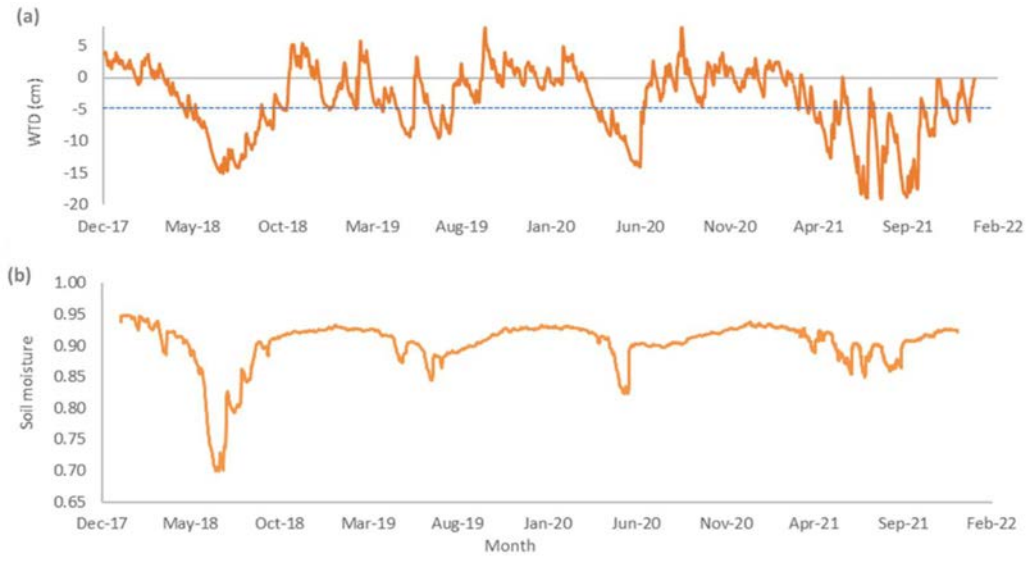

Figure 3.2. WTD (a) and surface (0–20 cm) soil moisture content (b) measured at the EC tower location on Clara Bog, 2018–2022. Reproduced from Ingle (2023).

In 2018, the WTD increased and remained at 5 cm or more below the peat surface for a consecutive period of 109 days during the growing season, coinciding with peak summer air temperatures driving water loss through evapotranspiration. In comparison, in 2021 the WTD fluctuated more and, while total precipitation was lower, the timing of rain events replenished the water table so that it reached the surface of the bog several times during the growing season (Figure 3.2). Similar patterns were also observed in the fluctuations of the surface (0–20 cm) soil volumetric moisture content in both 2018 and 2021, with a more pronounced drop in soil moisture content in 2018. This variability in hydrology had a greater impact on the rate of carbon loss from the system through ecosystem respiration than the rate of carbon assimilation through photosynthesis (gross primary productivity (GPP)) (Table 3.3). This highlights the sensitivity of these sites to climate-induced variability in hydrology and water availability, as extended periods of an increase in WTD coupled with higher temperatures in the growing season have the potential to stimulate an increase in the decomposition of the peat substrate.

The Cavemount site acted as a small carbon source or could be considered carbon neutral over the two study years, with the carbon dynamics ranging from a source of 18.3 g C $m^{-2}y^{-1}$ and a negligible sink of –0.34 g C $m^{-2}y^{-1}$ (Figure 3.3). This work highlights the potential emission savings that can be made

Table 3.3. Components of NEE of carbon at the Clara and Cavemount sites

Site	Year	GPP (g C m^{-2})	R_{eco} (g C m^{-2})	NEE (g C m^{-2})
Clara	2018[a]	–753.09	806.60	53.51
	2019	–824.32	699.14	–125.18
	2020	–775.04	698.23	–85.81
	2021	–725.64	675.92	–49.72
	2022	–812.59	676.66	–135.93
	2023	–700.48	639.88	–60.60
Cavemount	2020	–492.27	510.54	18.27
	2021	–607.04	606.70	–0.34

Negative values represent a carbon sink and positive values represent a carbon source.

[a]Annual estimates based on data derived from February to December 2018.

R_{eco}, the rate of carbon loss through ecosystem respiration.

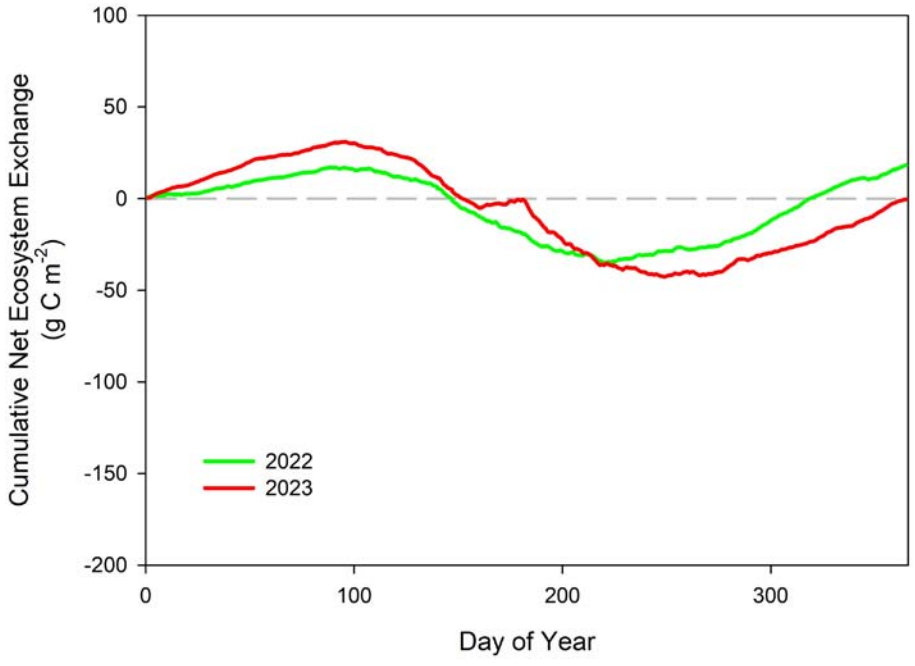

Figure 3.3. NEE of carbon at the Cavemount site over the study period.

through the rehabilitation of former peat extraction sites, as a decrease in WTD has the potential to reduce carbon losses, and the recolonisation of the site by vegetation acts to balance these losses over time.

3.3.2 Spatial upscaling of methane emission measurements

Wetlands represent a significant source of atmospheric CH_4, but in many studies measurements of emission levels using both chamber- and EC-based approaches are often not aggregated to estimate emission levels at the ecosystem scale. This study developed a methodology using PlanetScope imagery and machine-learning tools to map dominant vegetation communities and to upscale emission measurements using a weighted area approach. Full details on the methodology used can be found in Ingle *et al*. (2023a). This work was undertaken at the Clara, Garryduff and Lullymore sites over a 2-year period (2020 and 2021). The ecological maps produced (Figure 3.4)

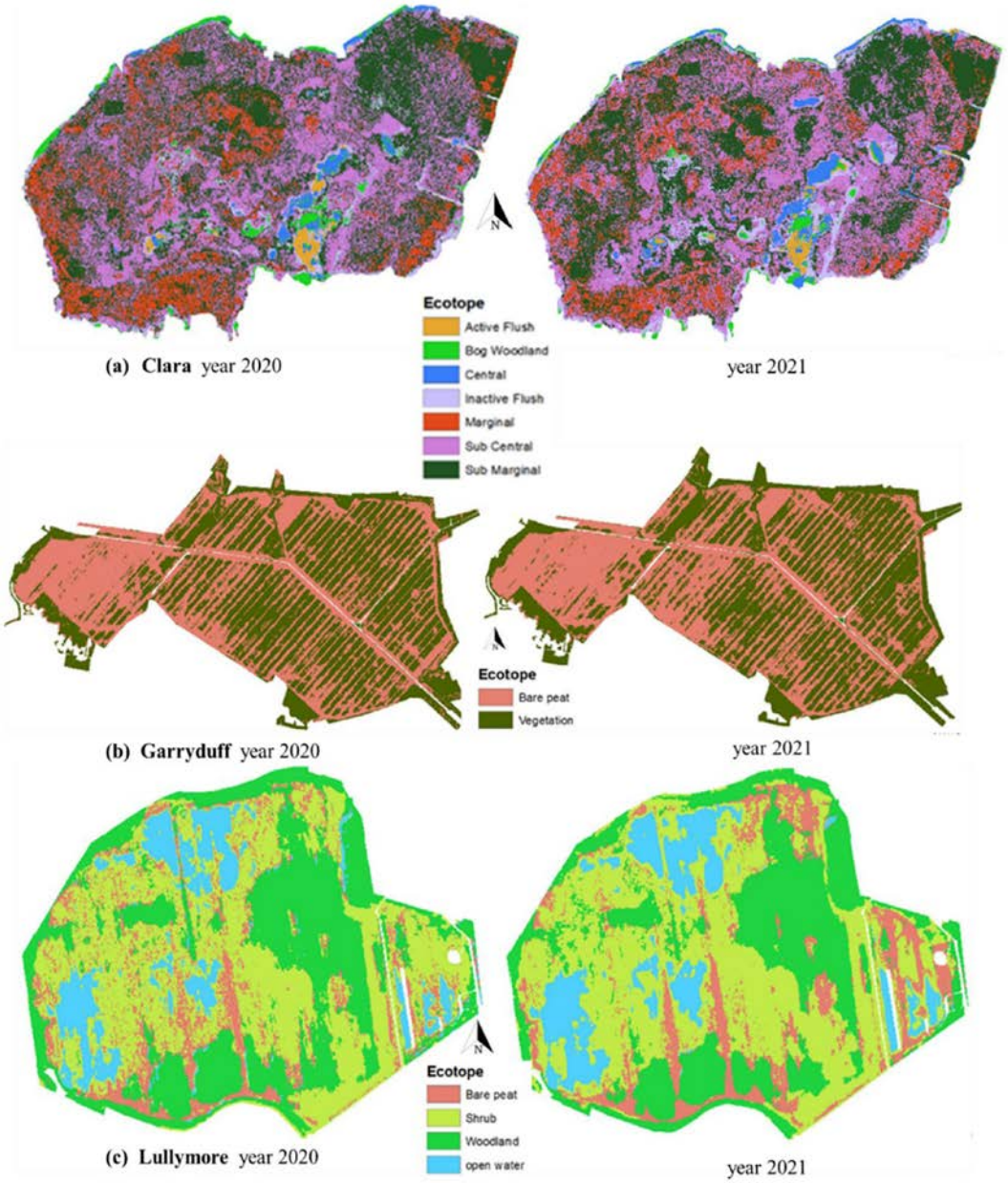

Figure 3.4. Annual ecotope maps produced in 2020 and 2021 for the Clara (a), Garryduff (b) and Lullymore (c) sites. Reproduced from Ingle *et al*. (2023a); licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

had an accuracy that ranged from 89%, for the near-natural site, where the ecological composition was more heterogenous, to 99%, for the degraded site, which was dominated by bare peat. The measured CH_4 fluxes observed were highest at Clara Bog (2.25 and 3.80 g CH_4-C m^{-2} y^{-1}) while lower rates of emission were observed at the rehabilitation (Lullymore, 0.17 and 0.31 g CH_4-C m^{-2} y^{-1}) and degraded (Garryduff, 0.15 and 0.27 g CH_4-C m^{-2} y^{-1}) sites (Figure 3.5).

3.3.3 Predicting carbon assimilation using Earth observation and eddy covariance data

Remote sensing techniques can be used to better understand the impacts of climate and management on the NEE of carbon, and the key components of NEE, such as GPP. This work assessed the relationship between GPP estimated by remote sensing techniques, using high-resolution Sentinel-2 imagery, and that inferred from EC flux measurements at Clara Bog. Full details of the methodology used can be found in Ingle *et al*. (2023b). In brief, multiple regression analyses that included remotely sensed indices such as the normalised difference vegetation index, the enhanced vegetation index and the normalised difference water index were integrated with literature-based light use efficiency (LUE) models to create a hybrid-based approach for estimating GPP. The modelling framework included six satellite-derived indices, three literature-based LUE parameters and site-specific PAR data, from which GPP was modelled using Equation 3.1:

$$GPP_{Modelled} = \varepsilon * f_{PAR} * PAR \quad (3.1)$$

where $GPP_{Modelled}$ is LUE-modelled GPP; ε is the radiation use conversion efficiency of the vegetation (g C MJ^{-1}), also referred to as the LUE parameter; f_{PAR} is the fraction of incident PAR absorbed by the canopy (MJ m^{-2}); and PAR represents the incident irradiance at the canopy. This information was incorporated into a modelling framework (Figure 3.6) to develop proxies for f_{PAR} that could be used to model GPP; this framework included both model calibration and validation steps.

The comparison of modelled and EC-derived GPP using the three literature-based LUE parameters for the validation years (2019 and 2020) is shown in the correlation matrices in Figure 3.7. The estimates of GPP using models based on the enhanced vegetation index and normalised difference water index 2 (used for models 2 and 4, respectively, in Figure 3.7) show a

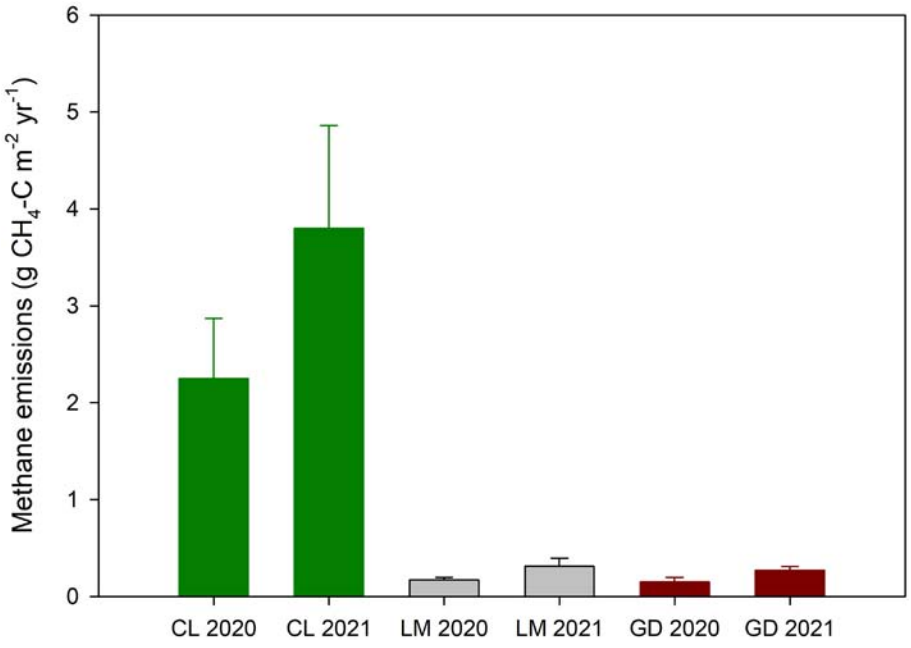

Figure 3.5. Aggregated CH_4 fluxes at the Clara (CL), Lullymore (LM) and Garryduff (GD) sites in 2020 and 2021 (error bars represent upscaled uncertainty estimates).

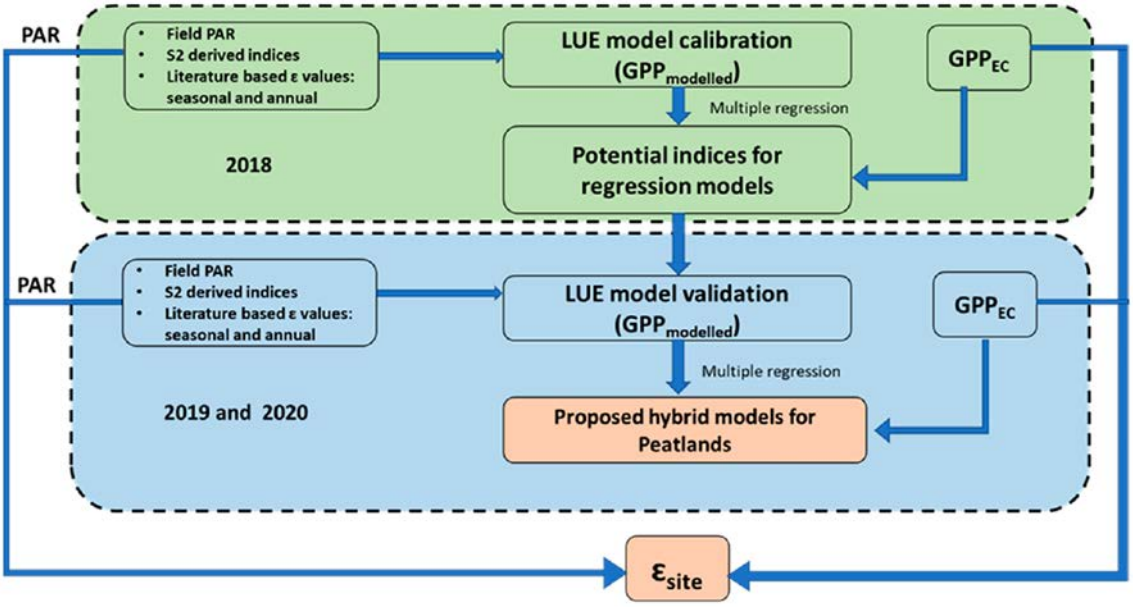

Figure 3.6. Framework used to derive the hybrid models and site-specific LUE parameters. The orange boxes represent the key objectives of the work, while the blue and green boxes show the time frames and data series used for calibration and validation, respectively. Reproduced from Ingle *et al*. (2023b); licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

strong correlation with the EC-inferred GPP data using all three LUE parameters, with Spearman's correlation coefficients of 0.96 and 0.98, respectively (Figure 3.7).

This work showed that utilising multiple EO indices in a hybrid approach is of benefit when trying to model GPP and that a combination of normalised difference vegetation index and normalised difference water index imagery correlated well with the EC-derived GPP data as such imagery can capture the variability in vegetation cover and water at the site. Furthermore, the estimation of GPP using the hybrid model approach was based on literature-based values of LUE derived from similar site typologies. Having the EC tower running in the long term allowed for the development of site-specific LUE parameters across contrasting climatological years, and the development of LUE values from the SmartBog EC tower and other peat-based EC towers across Ireland will further support the application of the hybrid models developed in this study to other wetland systems, such as blanket bogs, fens or turloughs, to enable a broader spatial and temporal scaling of EO-derived GPP for a wider array of peatland systems.

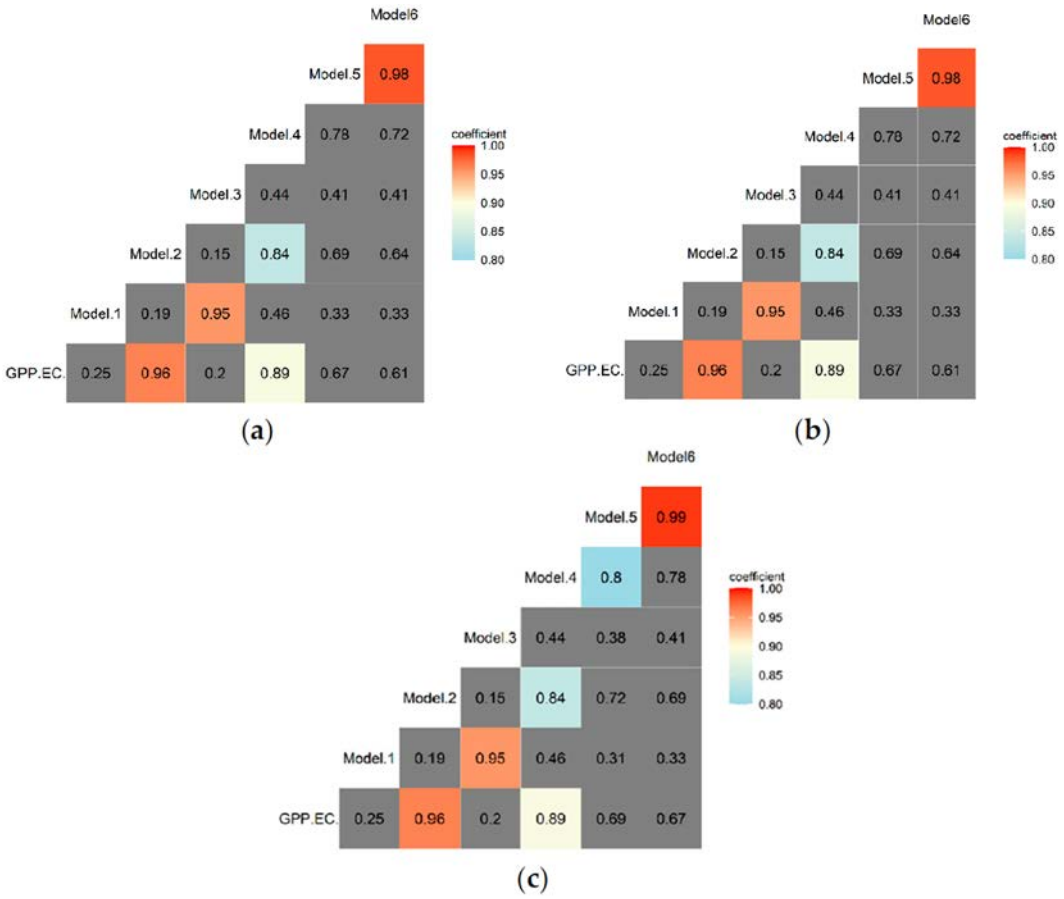

Figure 3.7. Correlation matrices for modelled and EC-derived GPP at Clara Bog in 2019 and 2020 using three literature-based LUE parameters: ε = 0.61 (a), ε = 0.83 (b) and ε = 1.2 (c). The warmer colours indicate a strong positive correlation, blue and yellow indicate moderate positive correlation and grey colours represent correlation values of less than 80%. Reproduced from Ingle *et al.* (2023b); licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

4 Estimation of Carbon Fluxes from Fluvial Pathways

4.1 Introduction and Aims

Considering the national emphasis on peatland restoration, there is a need to improve the technical basis for monitoring sites during rehabilitation to quantify the fluxes of carbon within peatland systems. The net ecosystem carbon balance of peatlands consists of net ecosystem exchange (NEE) (which is the balance between gross primary productivity and ecosystem respiration in terms of carbon dioxide (CO_2)), net methane (CH_4) consumption or efflux, and the net gain or loss of carbon in water inputs and run-off (including total organic carbon, dissolved inorganic carbon and CH_4) (Chapin *et al*., 2006). The NEE – the difference between the fixation of carbon via photosynthesis and the emission of carbon through ecosystem respiration – of peatland systems is relatively well researched compared with the other components. However, carbon losses via fluvial pathways have not been adequately quantified and remain a key knowledge gap. This area of research is important, as fluvial carbon has been shown to account for 15–50% of all greenhouse gas emissions from drained and rewetted peatlands (Evans *et al*., 2016) and in some cases can change annual carbon budgets of peatlands from sinks to sources of carbon when included (Billett *et al*., 2006). There are two fluvial pathways through which carbon can leave systems: in the form of dissolved or particulate carbon as water flows out of the system and as evaded gasses through surface water to atmosphere exchange.

The main objectives of this work were to:

- assess whether levels of fluorescent dissolved organic matter (fDOM), measured using a flurometric instrument, can be used as a proxy for accurately and continuously monitoring the concentration of non-particulate organic carbon (NPOC) leaving temperate raised bogs;
- investigate the influence of the ecohydrology of raised bogs undergoing different levels of rehabilitation on the export of fluvial carbon;
- collate NPOC, CO_2 and CH_4 evasion findings with information on the ecohydrology of three raised bogs to determine and compare their overall fluvial carbon budgets.

4.2 Methodology

4.2.1 Study sites

The studies on fluvial carbon export were undertaken on three raised bogs in different states of degradation and restoration. These sites include those with near-natural conditions (Clara Bog), industrially extracted sites (Garryduff) and former extraction sites undergoing rehabilitation (All Saints). Clara Bog is a special area of conservation located in County Offaly in the Irish midlands. It is considered one of the largest (> 400 ha) near-natural raised bogs remaining in Ireland. The site is divided by a road and this study was undertaken on the western part of the bog. The vegetation communities at Clara were classified using the approach of Schouten (2002) and linked to the hydrological characteristics of the bog (Regan *et al*., 2020). Garryduff is in County Galway, where peat was industrially mined until 2021. The site was under a pumped drainage regime and, during this study, much of the site comprised bare peat with some emerging pioneer vegetation. The site has three pumps, which dominate the hydrology of the system; therefore, it did not have a natural ecohydrological regime during the study period. At the beginning of the study period, the bog consisted of sparse vegetation in the form of wet and dry grasslands, bog woodlands (birch and willow species), some conifer trees, sedge/reed beds and gorse. Due to the cessation of pumping at the site at the end of the study period, the extent and make-up of the vegetation communities are now in the process of changing. The majority of the footprint of former peat production during the study period was bare peat, making up approximately 50% of the bog's area and containing active drainage channels. Most of Garryduff Bog is classed as cutaway peatlands, with only small pockets of peat with a depth in excess of 2 m remaining. The degraded nature of this raised bog site makes it a good representation of degraded raised bog hydrology. All Saints Bog – a lowland raised bog – is a special area of conservation, protected under the Habitats Directive for its orchid-rich calcareous grasslands, raised bogs, *Rhynchosporion* vegetation and bog woodlands. The bog lies on poorly productive

limestone aquifer bedrock. All Saints Bog features large birch- and pine-dominated bog woodlands, classified under Annex 1 to the Habitats Directive, covering 14.34 ha. Until recently, peat cutting (for use in horticulture), drainage and quarrying to the south of the high bog were responsible for the degradation of the bog. The current conservation objective for All Saints Bog is to restore the area of active raised bog and bog woodlands to its state at the time of the Habitats Directive coming into force in 1994. All Saints was selected to represent a rehabilitation site, as it is currently going through the process of enhanced rehabilitation using berms/bunding across the cutover bog.

4.2.2 Instrumentation

Discharge

Flow (discharge) rate was measured in flumes placed in stream outlets from exemplar subcatchments for the different areas of the three bogs under examination (Figure 4.1 shows the installed flume at All Saints Bog). Pressure transducers were used to continuously log water level upstream of the flumes. Flow rate was then calculated using a predetermined laboratory-based relationship between water depth and flow rate as well as periodic manual field measurements of discharge to produce rating (flow rate vs depth) equations. It should be noted that at Garryduff Bog the flume was installed at the exit of a settling pond, which was fed by two pumps that intermittently pumped out water from the bog that continually drained to the pump sump.



Figure 4.1. Installed flume in an outlet stream from All Saints Bog.

Non-particulate organic carbon

Measurements of fDOM were taken every 30 minutes at the three sites using EXO2 multiparameter sondes (Xylem Inc., Washington, DC, USA) installed in stilling wells just before the flow-monitoring flumes. The fDOM sensor measures the fraction of the dissolved organic carbon (DOC) that absorbs light in the UV range of 365 nm ± 5 nm and emits light at 480 nm ± 40 nm. A wiper installed on the sonde reduced the risk of biofouling the sensors. The sensors were all removed, inspected and calibrated every 12 months in the laboratory using quinine sulfate standards. Discrete water samples were taken every 2 weeks by hand. The samples were filtered in the field through Minisart 0.45 µm syringe filters (Millex, Ireland), acidified through the addition of two drops of 2 M hydrochloric acid and refrigerated until they could be analysed using a Shimadzu TOC-L analyser (Shimadzu, Kyoto, Japan) back in the laboratory, with a manufacturer DOC detection limit of 0.5 mg l^{-1}. A further 10 ml of the filtered sample was then used to determine absorbance at 254 nm in the laboratory using a spectrophotometer, for later correction of the fDOM values.

Meteorological measurements

Two automated weather stations (Campbell Scientific) were installed in Clara Bog and All Saints Bog to record key meteorological parameters required for hydrological analysis of the bogs. These included

rainfall, wind speed and direction, relative humidity, air temperature, air pressure, incident photosynthetically active radiation and net radiation. For Garryduff Bog, meteorological data from the nearest Met Éireann station, in Gurteen (25 km away), were used.

Micrometeorological measurements

Net ecosystem measurements of evapotranspiration were made using the eddy covariance (EC) technique for Clara Bog and All Saints Bog. The EC instrumentation consisted of a three-dimensional sonic anemometer (WindMaster, Gill Instruments, Lymington, UK) and an enclosed infrared gas analyser (LI-7200, LI-COR, Lincoln, Nebraska, USA). Further details on the Clara EC instrumentation can be found in section 3.2. Garryduff Bog had no EC instrumentation and so evapotranspiration was estimated using the crop coefficients determined at the nearby All Saints Bog (~3 km away), which presented a similar predominance of bare-peat surface during the project.

Fluvial gas flux evasion

A trace gas analyser (LI-7810, LI-COR, Lincoln, Nebraska, USA) was used to measure CH_4 (ppb), CO_2 (ppm) and water vapour (H_2O) (ppm). During each site visit, evasion at the stream outlets was quantified by a series of measurements taken along a transect away from the flumes using a floating collar constructed using a polystyrene float that sat on the water. For Clara, there were seven points (extending a distance of 360 m away from the bog) along the transect and for Garryduff there were four points based on accessibility and distance from each sampling point. All Saints was not assessed due to time constraints and the ongoing rehabilitation works.

4.3 Results

4.3.1 Flow measurements and catchment determination

Flow rate

The time series of the flow measurements taken at the three bogs are shown in Figure 4.2. As described in Cox (2024), basic filtering was performed on the discharge measurement data and outliers were detected and removed using published methods (Bae and Ji, 2019). As shown in Figure 4.2, Garryduff had the highest flow rate (median 23.02 l s^{-1}, maximum 407 l s^{-1}), All Saints had the second highest flow rate (median 1.64 l s^{-1}, maximum 110.52 l s^{-1}) and the Clara site had the lowest flow rate (median 0.86 l s^{-1}, maximum 45.6 l s^{-1}), with the differences between the sites reflecting the differences in catchment areas, as expected.

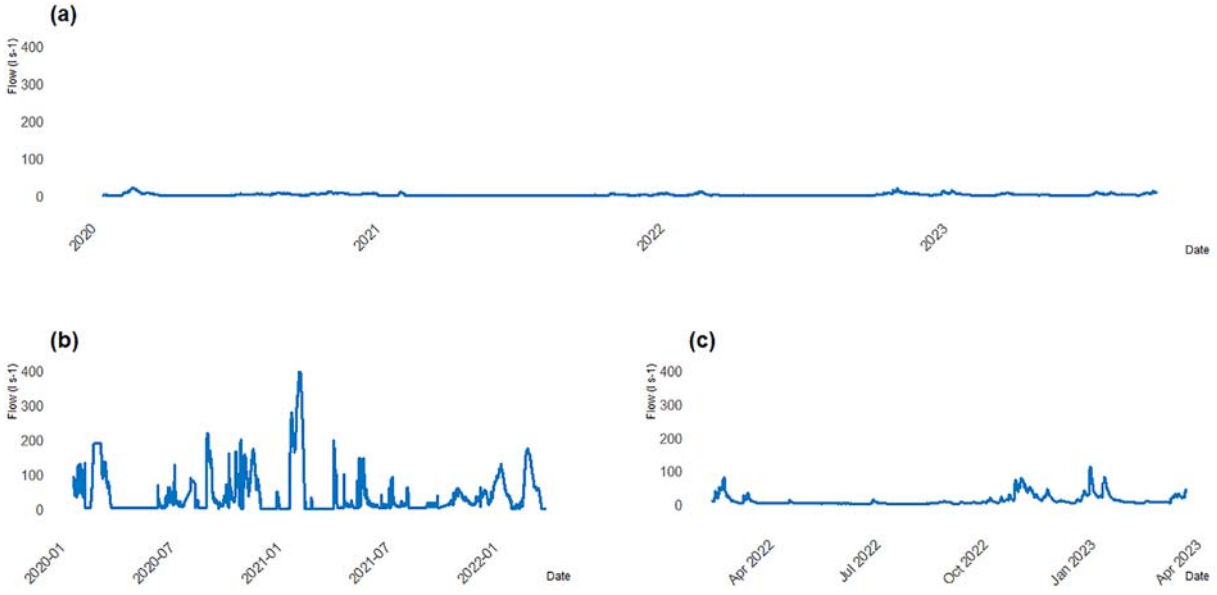

Figure 4.2. Flow rates at the outlet flumes for (a) Clara, (b) Garryduff and (c) All Saints across the monitoring period.

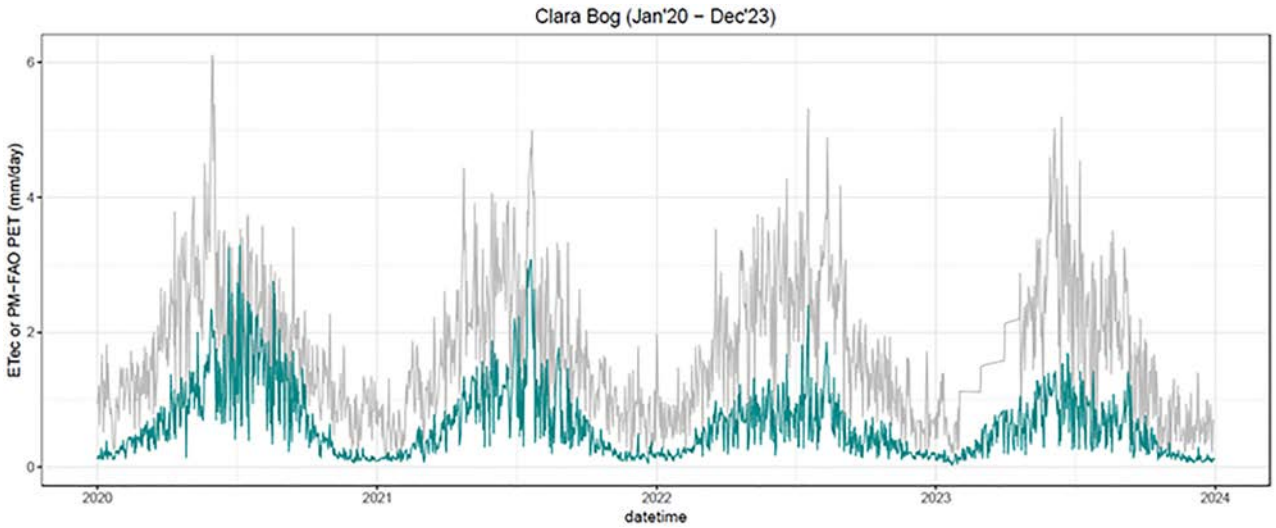

Figure 4.3. ET_{ec} rates and PET rates (Penman–Monteith FAO-56 formulation, short-grass reference) at Clara Bog.

Evapotranspiration

Evapotranspiration measurements were captured by EC flux towers (ET_{ec}) at Clara and All Saints as well as derived in the form of potential evapotranspiration (PET) values calculated through the Penman–Monteith equation using meteorological parameters. Figure 4.3 shows the comparison between the ET_{ec} values, measured by the EC flux tower in the middle of Clara Bog, and the PET values calculated using the Penman–Monteith formula. The comparison between PET and ET_{ec} trends reveals that PET values seem to significantly overestimate the rate at which *sphagnum* evapotranspires, evidenced by crop coefficients of between 0.32 and 0.45 for Clara Bog and All Saints Bog. There has been significant discussion in the hydrology field about the use of the Penman–Monteith FAO-56 method versus in-field measurements using lysimeters or EC towers. In this study, estimates of the catchment sizes and water-balance calculations using rainfall and discharge data suggest that ET_{ec} values appear to be more representative of evapotranspiration rates than PET values derived from the Penman–Monteith model.

Catchment areas

Catchment areas for each of the sites were determined using annual water balances from the cumulative discharge over a hydrological year (as quantified by the flume measurements at the catchment outlets), annual cumulative evapotranspiration and annual cumulative rainfall (Table 4.1).

4.3.2 Continuous measurement of fluorescent dissolved organic matter

The time series for the fDOM measurements from the sondes at the three bog outlet monitoring stations are shown in Figure 4.4. Note that the measurements shown are the final corrected data with outliers removed and gaps filled using linear interpolation, and with corrections for conductivity, turbidity and temperature applied, following De Oliveira *et al*. (2018).

The results in Figure 4.4 show relatively minor fluctuations in concentrations throughout the year at all sites, with the highest mean DOC proxy measurement (in quinine sulfate units) being seen at the more

Table 4.1. Catchment areas (km²) derived for each flume outlet

Year	Clara	Garryduff	All Saints
2020	0.152	1.65	NA
2021	0.143	1.88	0.439
2022	0.089	NA	0.656
2023	0.119	NA	0.653
Average	**0.126**	**1.76**	**0.58**

NA, not available.

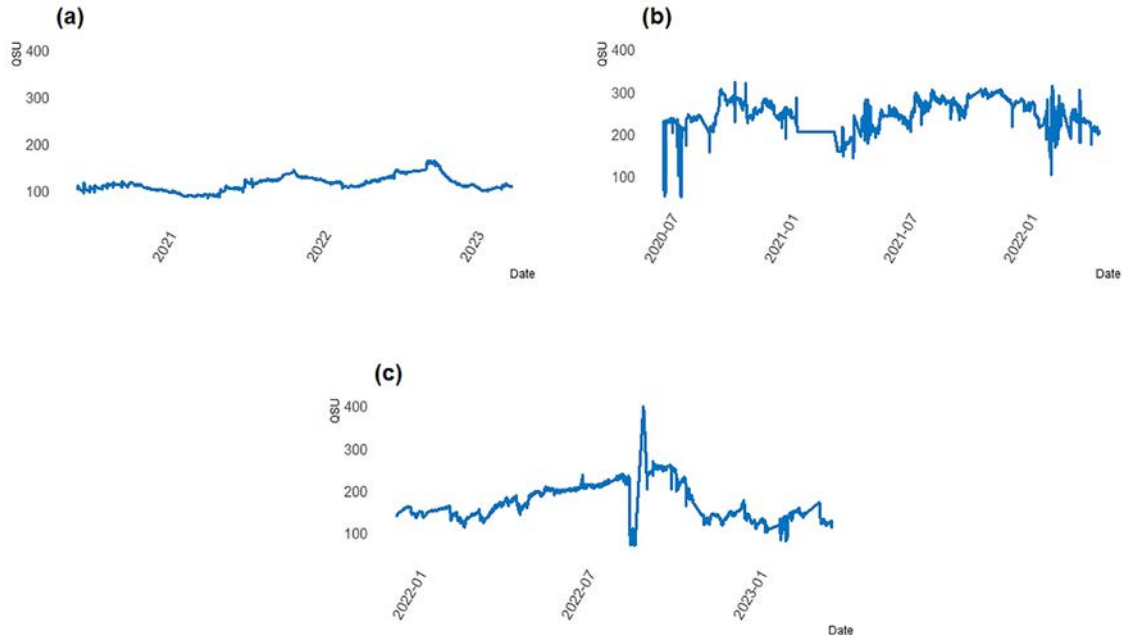

Figure 4.4. fDOM monitoring results (in quinine sulfate units (QSU)) at (a) Clara, (b) Garryduff and (c) All Saints Bogs with outliers removed and gaps filled with linear interpolation, and with corrections for conductivity, turbidity and temperature applied.

degraded sites: Garryduff Bog is highest, followed by All Saints and then the near-natural Clara Bog.

4.3.3 Conversion of measurements of fluorescent dissolved organic matter to non-particulate organic carbon concentrations

Correlation between fluorescent dissolved organic matter measurements and non-particulate organic carbon concentrations

The measured NPOC concentrations and corrected fDOM data were plotted to produce an initial estimate of the correlation between NPOC concentrations and fDOM measurements for the three sites (Figure 4.5). The relationships were not statistically significant for any of the sites and so a multivariate analysis was undertaken to see if this could demonstrate a more robust relationship using some additional variables.

Multivariate analysis

The approach assumes that there is a relationship for each site in terms of the input vector (i.e. the predictor: observed NPOC data) and the output (i.e. what is predicted: fDOM sensor data), but the predictor and what is predicted are expressed as (initially unknown) probability density functions of other variables, such as conductivity, discharge, water temperature and rainfall, that influence water quality parameters. Since these relationships are highly non-linear, a support vector regression (SVR) model was developed to search for the optimal combination of variables and the time window used to develop the functions at each data point. Table 4.2 shows the results from the analysis for the Clara site for all different combinations to give an optimum Nash–Sutcliffe efficiency (NSE) metric (a normalised statistic commonly used to assess the predictive skill of hydrological models) of 0.811 using the expectation function variables of fDOM (EY) and rainfall (ER) considered over a 3-hour window. Hence, this combination of variables over that time window should be used to develop the SVR model for the best predictive performance. Likewise, for Garryduff the highest NSE value, of 0.866, was obtained using the expectation function of fDOM (EY) and the variance of the fDOM data over a 36-hour period; for All Saints, the highest NSE value, of 0.930, was obtained using the fDOM data, the expectation functions of fDOM (EY) and electrical conductivity (EC) over a 12-hour window. Therefore, different NSE/expectation functions are required for the different sites to achieve the best simulation results, which reiterates the uniqueness

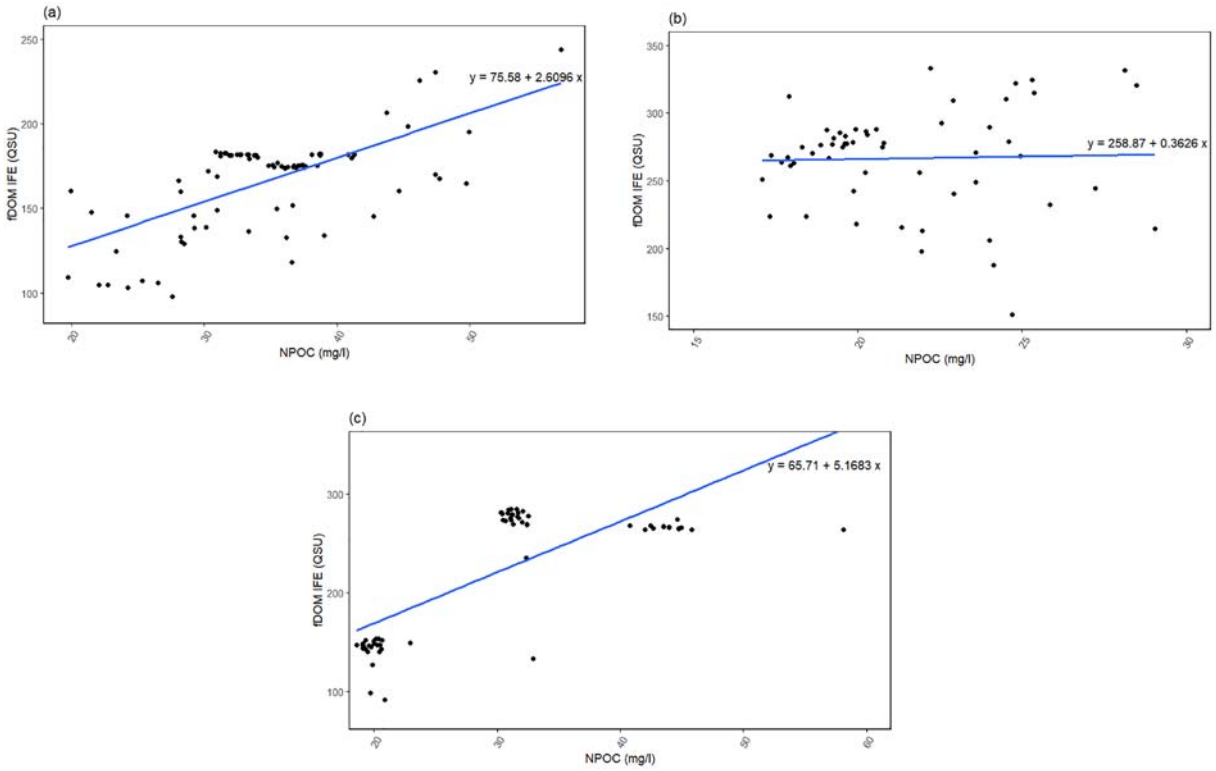

Figure 4.5. Scatterplots of the fully corrected fDOM measurements (in quinine sulfate units (QSU)) vs laboratory-measured NPOC concentrations for (a) Clara, $r^2 = 0.427$; (b) Garryduff, $r^2 = 0.0009$; and (c) All Saints, $r^2 = 0.575$.

Table 4.2. NSE-based goodness-of-fit results for the different models used for determining the variables that best described the relationship between fDOM measurements and NPOC concentrations for Clara Bog

Model	3 hours	6 hours	12 hours	24 hours	36 hours	48 hours
Fy, y	0.790	0.764	0.674	0.649	0.691	0.698
Fy, y, EY	0.809	0.794	0.758	0.742	0.755	0.757
Fy, y, EY, Var(Y)	0.667	0.727	0.772	0.807	0.814	0.776
Fy, y, EY, Var(Y), $E[Y-EY]^3$, $E[Y-EY]^4$	0.662	0.731	0.764	0.813	0.778	0.724
Fy, y, EY, E[C]	0.791	0.798	0.775	0.807	0.809	0.821
Fy, y, EY, ET	0.216	0.296	0.413	0.354	0.336	0.339
Fy, y, EY, EQ	0.657	0.538	0.480	0.459	0.435	0.424
Fy, y, EY, ER	**0.811**	0.579	0.704	0.312	0.698	0.661
Fy, y, EY, EC, ET, EQ, ER	0.495	0.475	0.495	0.453	0.476	0.475
Fy, y, EY, EC, ET, EQ, ER, Var(C), Var(T), Var(Q), Var(R)	0.500	0.413	0.442	0.407	0.499	0.541
Fy, y, all moments (mean, Var and third and fourth of Y, C, T, Q and R)	0.476	0.358	0.392	0.356	0.497	0.605

The optimum fit is marked in bold.

C, conductivity; E, expectation function; Fy, cumulative distribution function of y; Q, discharge; R, rainfall; T, water temperature; Var, variance of the data; y, fDOM sensor data; Y, fDOM.

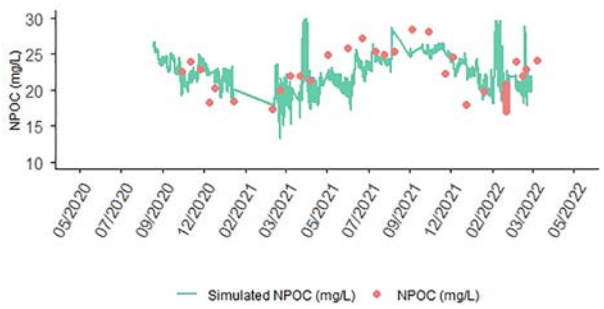

Figure 4.6. Time series of simulated (green) and laboratory-measured (red) NPOC concentrations for Garryduff.

of individual sites. Using the optimised multivariate SVR modelling approach, the modelled NPOC time series for Garryduff was correlated with the laboratory-measured NPOC time series, as shown in Figure 4.6.

Non-particulate organic carbon flux measurements

The final derived flux values ($g\,C\,m^{-2}\,y^{-1}$) for each site's catchment area using the fDOM and NPOC correlation before multivariate analysis and after multivariate analysis are presented in Table 4.3.

The full annual results from the three sites reveal similar NPOC flux values for all sites, which are in different states of degradation/restoration. Values were slightly higher for All Saints than for other sites, presumably due to the significant level of bund construction activity that was taking place during the monitoring period at this site. Values were marginally higher for Clara Bog than for Garryduff, which is somewhat surprising, as values for Clara Bog might have been expected to be more than just marginally higher, as the water interacts through a fully formed bog and has longer contact times than at Garryduff, with very fast run-off characteristics and no living acrotelm.

Fluvial gas flux evasion

The results from measuring rates of CO_2 and CH_4 gas evasion at the flumes at Clara and Garryduff, reported as CO_2 equivalents (CO_2eq) determined over a 100-year period, are shown in Tables 4.4 and 4.5.

The average total flux of CO_2 eq ($g\,CO_2\,eq\,m^{-2}\,day^{-1}$) was higher at Clara than at Garryduff over the study period, with emissions of $94.2 \times 10^{-6}\,g\,CO_2\,eq\,m^{-2}\,day^{-1}$ and $20.6 \times 10^{-6}\,g\,CO_2\,eq\,m^{-2}\,day^{-1}$ from these sites, respectively. At Clara, the highest total flux was observed in autumn ($164 \times 10^{-6}\,g\,CO_2\,eq\,m^{-2}\,day^{-1}$), when compared with all seasonal averages, with spring having the second highest total flux ($122 \times 10^{-6}\,g\,CO_2\,eq\,m^{-2}\,day^{-1}$). At Garryduff, the highest flux was observed in winter ($37.9 \times 10^{-6}\,g\,CO_2\,eq\,m^{-2}\,day^{-1}$), with autumn having the second highest total flux ($17.8 \times 10^{-6}\,g\,CO_2\,eq\,m^{-2}\,day^{-1}$).

Table 4.3. NPOC flux values for the three sites derived using 30-minute continuous fDOM measurements converted into NPOC concentrations before and after multivariate analysis was undertaken, multiplied by the respective flow rates measured at the flumes

	Clara flux ($g\,C\,m^{-2}\,y^{-1}$)		Garryduff flux ($g\,C\,m^{-2}\,y^{-1}$)		All Saints flux ($g\,C\,m^{-2}\,y^{-1}$)	
Year	Pre-analysis	Post-analysis	Pre-analysis	Post-analysis	Pre-analysis	Post-analysis
2020	8.16[a]	7.93[a]	4.12[c]	4.25[c]	NA	NA
2021	**10.57**	**10.68**	**9.46**	**9.49**	NA	NA
2022	**9.44**	**9.29**	4.16[d]	4.21[d]	**10.63**	**12.00**
2023	2.24[b]	2.21[b]	NA	NA	2.02[e]	3.40[e]
Average	10.00	9.99	9.46	9.49	10.63	12.00

Figures in bold are for whole-year (12-month) monitoring.
[a]June to December 2020.
[b]January to February 2023.
[c]June to December 2020.
[d]January to March 2022.
[e]January to February 2020.
NA, not available.

Table 4.4. Average seasonal flux for CO_2 and CH_4 and annual average for Clara Bog

Season	CO_2 flux ($g\,CO_2\,eq\,m^{-2}\,day^{-1} \times 10^{-6}$)	CH_4 flux ($g\,CO_2\,eq\,m^{-2}\,day^{-1} \times 10^{-6}$)	Total flux ($g\,CO_2\,eq\,m^{-2}\,day^{-1} \times 10^{-6}$)
Winter	43.0	9.2	52.2
Spring	9.58	26.6	122.0
Summer	34.7	3.35	38.0
Autumn	152.0	12.3	164.0
Average	81.3	12.9	94.2

The flux values given are per m^2 of stream surface.

Table 4.5. Average seasonal flux for CO_2 and CH_4 and annual average for Garryduff Bog

Season	CO_2 flux ($g\,CO_2\,eq\,m^{-2}\,day^{-1} \times 10^{-6}$)	CH_4 flux ($g\,CO_2\,eq\,m^{-2}\,day^{-1} \times 10^{-6}$)	Total flux ($g\,CO_2\,eq\,m^{-2}\,day^{-1} \times 10^{-6}$)
Winter	3.17	6.2	37.9
Spring	13.9	1.8	15.7
Summer	8.2	2.8	10.9
Autumn	14.9	2.9	17.8
Average	17.2	3.4	20.6

The flux values given are per m^2 of stream surface.

Table 4.6. Net fluvial carbon flux and total cumulative carbon export (catchment loss) for all three sites during their measurement periods for complete annual measurements

	Clara Bog		Garryduff Bog		All Saints	
Year	Flux ($g\,C\,m^{-2}$)	Catchment loss ($kg\,C\,y^{-1}$)	Flux ($g\,C\,m^{-2}\,y^{-1}$)	Catchment loss ($kg\,C\,y^{-1}$)	Flux ($g\,C\,m^{-2}\,y^{-1}$)	Catchment loss ($kg\,C\,y^{-1}$)
2021	12.07	1520.8	9.49	16,702.4	NA	NA
2022	10.69	1346.9	NA	NA	12.91	7074.7

NA, not available.

Net fluvial carbon budget

Table 4.6 shows the net fluvial carbon loss from the three sites for the years where complete 12-month monitoring data were available. Calculations were carried out for the fluvial gas flux evasion over the course of a year. The multiple sampling locations away from the bog, how they varied across the year and the surface area of the stream were accounted for, but it was revealed that their contribution to the net fluvial carbon flux was negligible. For example, along a 360 m stretch of river leaving Clara Bog the average annual flux resulted in just $12.7\,g\,C\,eq\,y^{-1}$ for combined CO_2 and CH_4 gas evasion (based on the 2022 measurements).

5 Low-cost Sensor Validation

5.1 Introduction and Aims

Low-cost internet-of-things (IoT) devices are deployed for the purpose of data collection over a wide range of domains, including the industrial, automotive and environmental monitoring and assessment domains. Their application in environmental monitoring projects is growing steadily due to the benefits they present in terms of the cost of deployment and access to collected data. IoT devices are equipped with sensors that measure specific environmental features, and with a wireless communications component that can send sensor measurements to a central location (data server or data distribution hub) in real time. This facilitates continuous access to current data from the sensor location. IoT data have been used in several national and pan-European environmental monitoring projects including the Carbosense (Müller *et al.*, 2020) and Integrated Carbon Observation System projects.

The advent of IoT devices for environmental monitoring presents many opportunities for data collection. Once deployed in the field, IoT devices will collect and send data to an accessible location. As lower-cost devices enter the market, IoT sensors will have the potential to provide datasets of high spatial and temporal resolution to environmental monitoring networks at lower costs. These devices can be used to supplement current collection techniques or extend data collection to otherwise logistically or economically unviable locations. To fully leverage the opportunities provided by IoT sensors in environmental monitoring, the community must address several existing weaknesses. One major challenge is addressing the dearth of knowledge and experience in integrating IoT sensors into both Irish and peatland contexts. Other key challenges include ensuring the accuracy and reliability of sensor data, as IoT devices can be susceptible to calibration drift, environmental interference and periods of missing data. Calibration drift can lead to inaccurate readings over time, necessitating regular calibration and maintenance protocols. Environmental interference, such as that resulting from temperature fluctuations and humidity, and electromagnetic interference, can also affect sensor performance. Implementing robust algorithms for data validation and error correction can mitigate these issues. Additionally, developing standardised protocols for sensor deployment and data collection will enhance consistency and reliability, ensuring that IoT sensors provide dependable data and therefore robust insights.

The main objectives of this work were to:

- evaluate the performance of and validate the data collected by a range of carbon dioxide (CO_2) and soil moisture IoT sensors;
- inform best practices and enhance the efficacy of IoT sensors in similar environmental contexts;
- develop a context-specific toolset for processing data from IoT sensors in peatlands.

5.2 Methodology

In the context of the SmartBog project, data validation is the process of ensuring that the data collected from CO_2 and soil moisture IoT sensors are accurate, reliable and consistent. This involves several steps, including the following:

- **Error detection:** this involves implementing algorithms to detect and correct errors or anomalies in the data caused by environmental interference or sensor malfunctions.
- **Cross-verification:** sensor data can be compared with reference measurements or data from other reliable sources to identify discrepancies.
- **Consistency checks:** this involves ensuring that data collected over time remain consistent and follow expected patterns or trends.
- **Calibration and environmental adaptation:** sensors should be calibrated to maintain accuracy and account for any drift, including by adjusting data-processing techniques to account for the unique conditions of peatlands, such as high moisture levels and variable conditions, which can affect sensor readings. Specific calibration leads to a robust dataset by ensuring that the sensor data accurately reflect real-world conditions and provides reliable data for use in monitoring and modelling applications.

IoT deployment in the SmartBog project consisted of locating an array of CO_2 and soil moisture sensors over two sites. At the Clara Bog site, two CO_2 sensors and one soil moisture sensor were placed on each of the peat ecotopes (central, subcentral and marginal), with two additional sensors being located at the eddy covariance (EC) tower. Two CO_2 sensors and one soil moisture sensor were placed at a grassland site and four CO_2 and one soil moisture sensor were deployed at a forest site, with both sites being located in Lullymore Heritage and Discovery Park. Soil moisture sensors were used for reference while the majority of the methodological steps detailed above were designed for and applied to the CO_2 sensor data, as these data were in most need of correction.

5.3 Results

5.3.1 Data-processing pipeline

The SmartBog project developed a data-processing pipeline for data validation and calibration in the peatland context. This pipeline applies machine-learning tools to enhance data accuracy and reliability, following a structured set of processing steps tailored for the specific features of the peatlands. The pipeline consists of five key steps, as presented in Figure 5.1. The codebases for the data tools are publicly available under the MIT License (SmartBog, 2024).

The output of the pipeline is a set of data corrected for calibration errors and its use may be extended to application modelling for specific use cases.

Outlier detection

This step involves identifying and removing anomalous data points that deviate significantly from the expected range, ensuring that the dataset remains clean. Such data points are considered erroneous and cannot be corrected through the calibration and data correction process. These data will not be used for any further inference or modelling. Outlier detection is particularly necessary for pervasive CO_2 sensing. Such sensors use non-dispersive infrared (NDIR) technology for determining CO_2 levels in ambient air. This requires passing air through a small chamber where an infrared beam is directed through the air sample and onto a sensor. Due to the mechanics of the sensor, high relative humidity conditions, such as those seen on peatlands, may result in distorted or corrupted readings. As shown in Figure 5.2, sensor data exhibit significant numbers of outliers in conditions above 85% relative humidity, with 70% of all outliers within the CO_2 dataset occurring above this threshold.

High water vapour concentrations can interfere with the measurement of CO_2 levels by broadening the absorption spectrum. This could lead to distorted or corrupted readings, especially in conditions of high humidity, as the water vapour absorbs infrared radiation in similar regions of the spectrum to CO_2. This issue arises from the inherent mechanics of NDIR sensors, where high humidity can distort CO_2 readings due to interference with the sensor's optical path. While this problem is specific to NDIR technology, it highlights the importance of considering sensor-specific limitations when designing a general sensor data-processing pipeline. When removing outliers from data, it is crucial to account for the unique characteristics and potential frailties of each sensor type, as these can significantly impact data accuracy.

Data imputation

Missing data in a dataset can occur due to sensor malfunctions or failures, leading to gaps in data collection. Environmental interference, such as that resulting from adverse weather conditions, can disrupt sensor readings. Data transmission issues, including

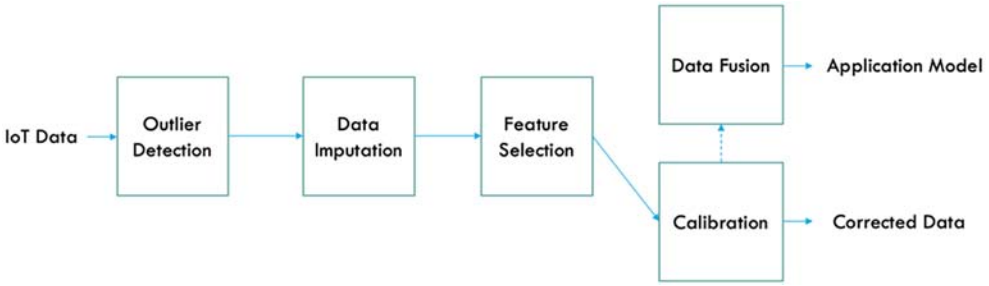

Figure 5.1. Data-processing pipeline for IoT sensor data.

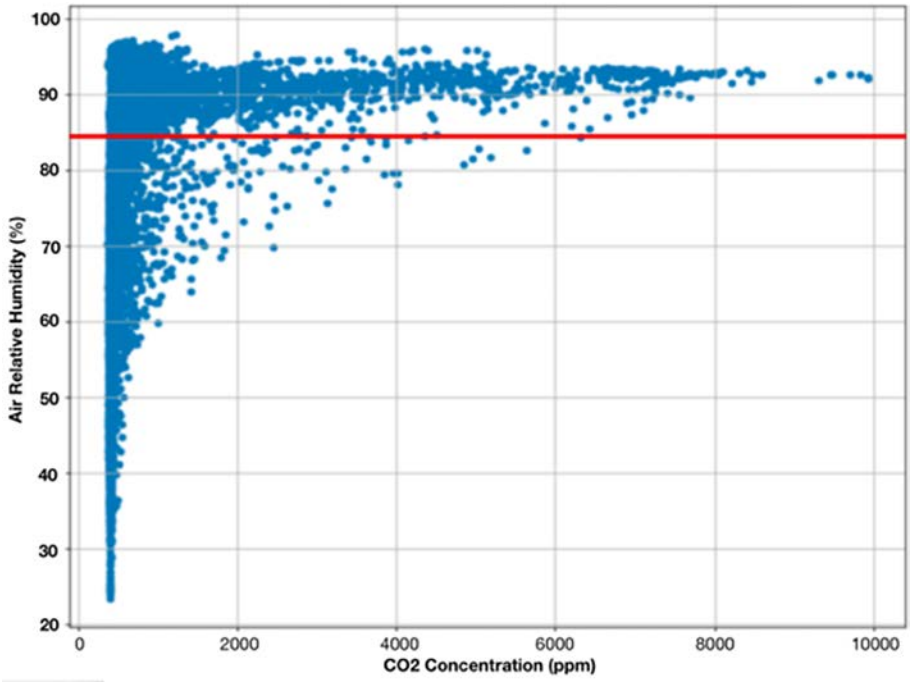

Figure 5.2. Measured CO_2 concentrations (ppm) with respect to ambient relative humidity at time of measurement.

connectivity problems, can result in incomplete data being recorded. Furthermore, additional gaps in the dataset can emerge as a result of removing outliers during the data-cleaning process. Analysis and model development are impeded by missing data, particularly when relying on correlations in time series data such as those used in sensor data analysis. Recent practice has been to reconstitute the missing data before further processing (García-Laencina *et al*., 2010). To address this issue in the SmartBog data-processing pipeline, this step applies a neural network approach to data imputation. A variational autoencoder is applied, which leverages the correlations over multiple collocated sensors to fill gaps in the dataset before further processing (Okafor and Delaney, 2021). It is important to note that imputed data are used solely for downstream calibration model development and do not appear in the final corrected dataset.

Feature selection

This step involves identifying and selecting the most relevant variables ("features") from the collected dataset that either impact the accuracy of sensor readings or are useful for calibrating those readings. In this context, features refer to measured environmental variables (e.g. temperature, humidity, wind speed) that influence sensor performance at a given time, rather than intrinsic properties of the sensor location/site itself. Specifically, for the NDIR CO_2 sensors used in this project, relative humidity, wind speed and wind direction are the primary environmental features that affect measurement accuracy. To identify the most important features, the exhaustive feature selection technique is applied, which systematically evaluates all possible combinations of features to determine the best set for use in future calibration models. This technique tested favourably compared with forward feature and backward feature selection in this context (Okafor *et al*., 2020).

Calibration

This step involves adjusting the sensor data to correct for any measurement errors or drift, ensuring that the readings accurately reflect real-world conditions. The result of this is a corrected dataset that may be used in environmental data collection projects. The sensor readings are calibrated against CO_2 chamber measurements. A machine-learning approach is used to develop relationships between key features, sensor CO_2 readings and ground-truth measurements. An extreme gradient boost-based machine-learning technique is applied in this case to leverage the distributed nature of the deployment for sensor calibration. Applying the calibration technique results

in a significant reduction in recorded error compared with the ground-truth measurements, as shown in Figure 5.3.

Data fusion

Application-specific modelling involves integrating data from various sensors to enhance the accuracy and robustness of models tailored to specific applications. This process leverages the strengths of different data sources, providing a more detailed and comprehensive dataset for complex environments where single-sensor data may be insufficient for precise modelling and analysis. The SmartBog project implemented a long short-term memory recurrent neural network prediction model, which aims to model the processed outputs from an EC tower located on Clara Bog using an array of sensors located on the same site (Okafor *et al*., 2022). This is an example of how calibrated sensor readings can be used in further downstream processes and highlights long short-term memory as an effective tool for time series environmental data prediction modelling; however, the model itself should be considered experimental.

5.3.2 The cost benefits of deploying sensors

Low-cost IoT sensors can offer cost benefits compared with traditional methods of data collection. Firstly, IoT sensors reduce the need for frequent on-site visits to manually collect measurements, cutting down on labour and travel costs. This automation enables continuous data collection without the logistical challenges and delays associated with periodic site visits. Secondly, low-cost sensors enable widespread deployment across multiple locations, providing a richer and more comprehensive dataset. In contrast, deploying more expensive equipment in fewer locations limits the spatial resolution and coverage of the data, potentially leading to localised variations and trends being missed. Additionally, the affordability of IoT sensors makes it feasible to replace or upgrade them regularly, ensuring access to the latest technology and maintaining data accuracy over time.

The outlay costs consist of the costs of the sensor devices, which are placed *in situ*, and additional costs related to facilitating the communication of the data. Communication-related costs are dependent on the technology used and are typically (i) per-unit monthly costs charged by a third-party network owner/operator or (ii) one-off costs for site network infrastructure. Owning and operating the site infrastructure require expertise and therefore ownership is more likely to be beneficial for the deployment of sensors for long-term data collection. The current costs of IoT devices for data collection are detailed in Table 5.1.

It is clear that overall costs are dominated by sensor device costs, which are dependent on the number of sensors deployed. Testing and monitoring over the duration of the project showed that no difference in data quality was observed between the more expensive Decentlab and less expensive SenseCAP sensor devices. This may indicate where savings can be made in IoT deployments, with further reductions in cost per device expected as worldwide demand and subsequent supply increases.

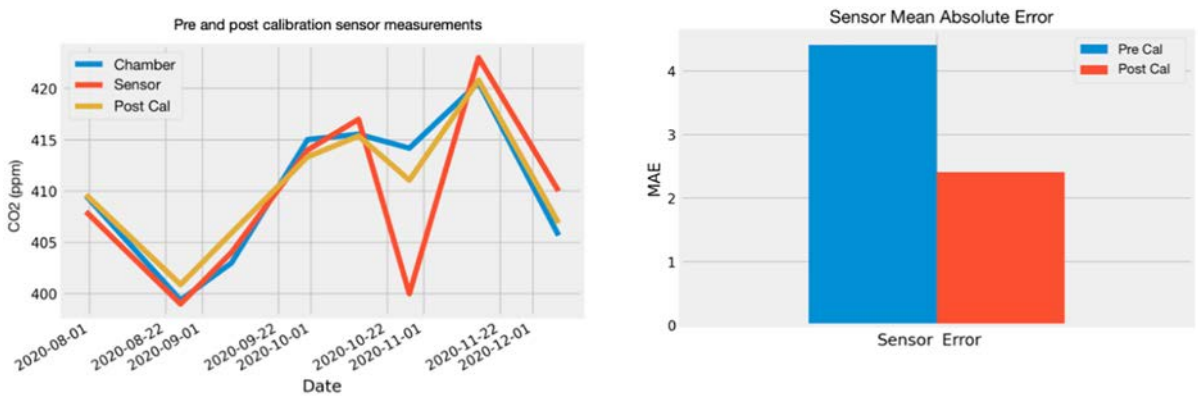

Figure 5.3. Direct comparison of ground-truth measurements and pre-calibrated and post-calibrated sensor data (left panel) and comparison of mean absolute error between ground-truth measurements and pre-calibrated and post-calibrated sensor data (right panel).

Table 5.1. Costs associated with IoT sensors and infrastructure used for data collection

Device	Location	Cost
Antenna for site communication (Wirnet iBTS – LoRaWAN, Kerlink, Thorigné-Fouillard, France)	Clara, Lullymore	€1500 per site
CO_2 sensor (Decentlab, Dübendorf, Switzerland)	Clara, Lullymore	€505 per sensor
Soil moisture sensor (Decentlab, Dübendorf, Switzerland)	Clara	€590 per sensor
CO_2 sensor (SenseCAP, Lefkoşa, Cyprus)	Clara, Lullymore	€290 per sensor
Soil moisture sensor (SenseCAP, Lefkoşa, Cyprus)	Lullymore	€350 per sensor

6 Stakeholder Platform

The activities of the SmartBog project produced a range of data streams that included high-resolution imagery; outputs of machine-learning models used in automatic land use classification and peatland drain detection; and the integration of greenhouse gas and meteorological data from two eddy covariance (EC) stations, periodic measurements and internet-of-things sensors. These outputs could be of use to a variety of decision-makers and stakeholders, and the main objective of this part of the project was to develop a web-based interactive data visualisation dashboard to present project outputs in an accessible format and therefore support additional scientific endeavours (e.g. the provision of data for modelling activities), help stakeholders to meet reporting requirements and aid in the development of decision-making tools.

A pilot web-based user interface was developed to facilitate the integration of multiple data streams and products, with the purpose of demonstrating how these products could be made available to key stakeholders (Figure 6.1).

The web-based platform was initially designed around the exemplar measurement sites, with site-specific information and metadata on the study sites being displayed in both list-based (Figure 6.2) and geospatial (Figure 6.3) formats. The capability to integrate multiple levels of data within the platform was included, with an option to integrate raw/live/real-time data into the visualisation. The intention was for users to have the ability to query, filter and view time-specific datasets. An example of this is shown in Figure 6.4, which displays a single variable: 30-minute soil temperature data from the Clara Bog EC tower in 2022. The platform was also designed to have the capability to compare variables, so that users could explore relationships between variables without needing to download all data independently. Figure 6.5 shows how the platform could be used,

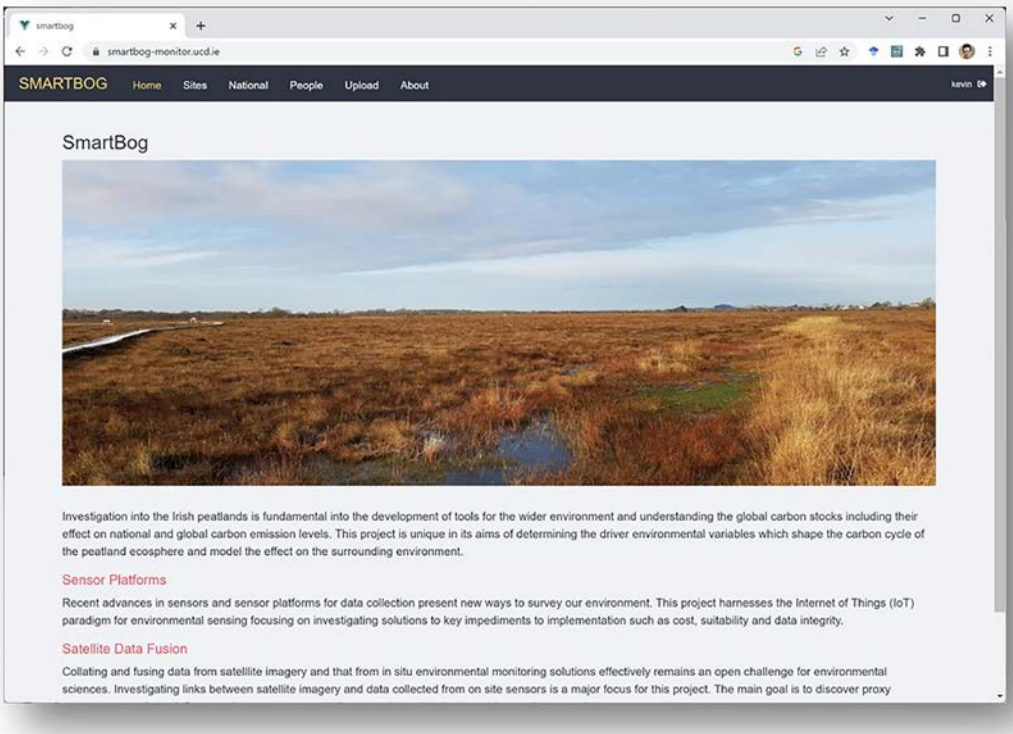

Figure 6.1. A screenshot of the SmartBog user interface landing page.

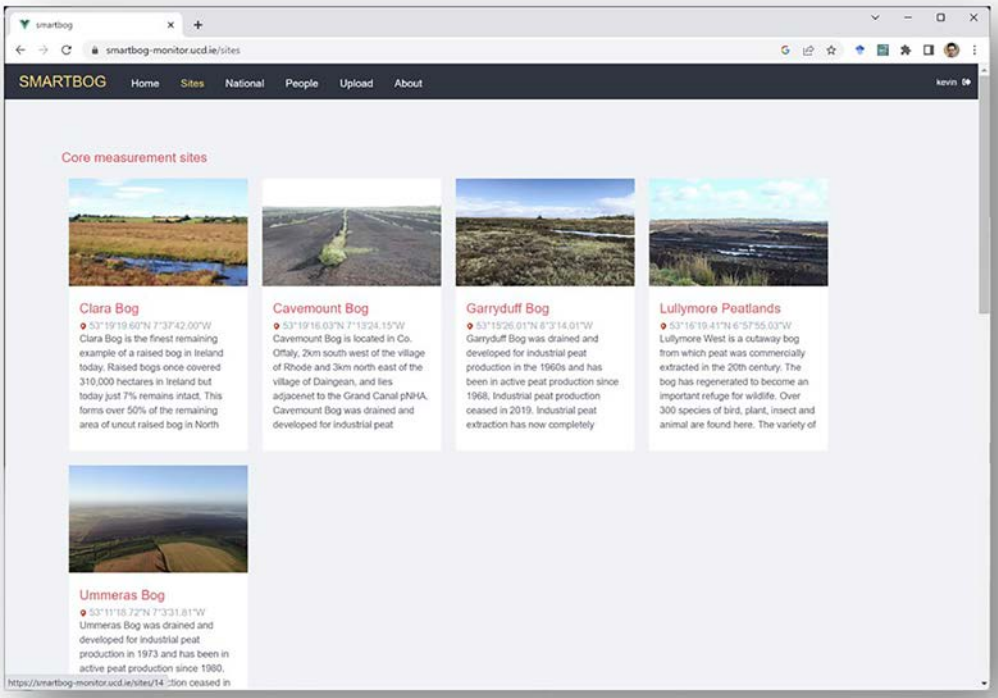

Figure 6.2. The list-based overview of exemplar study sites on the SmartBog platform.

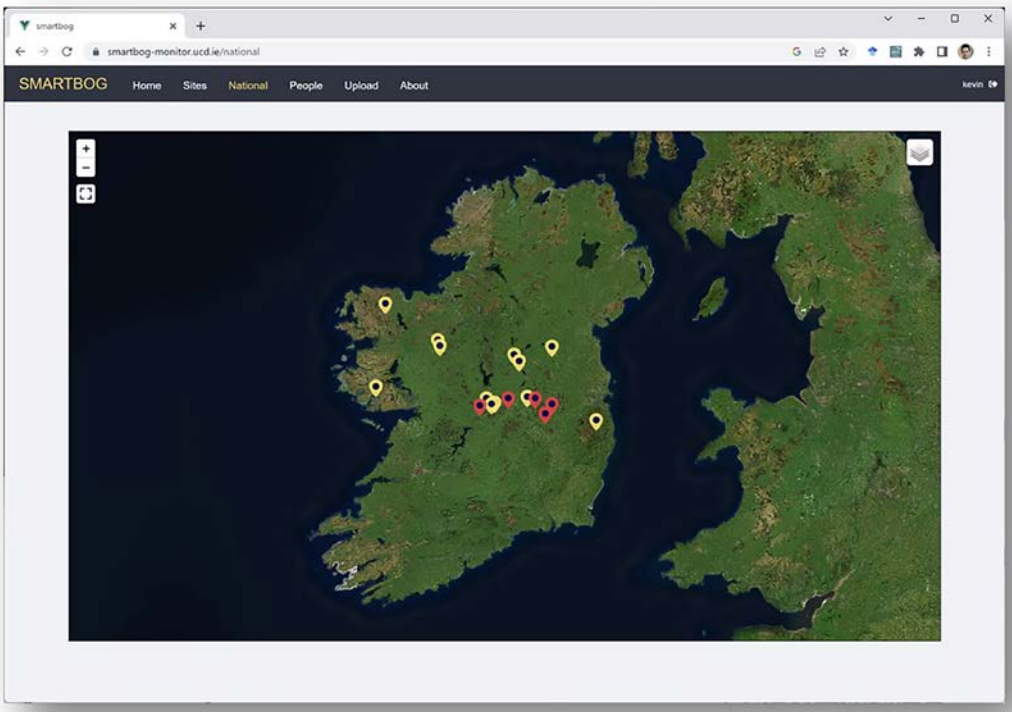

Figure 6.3. A geospatial overview of the core (red pins) and ancillary (yellow pins) SmartBog study sites on the SmartBog platform.

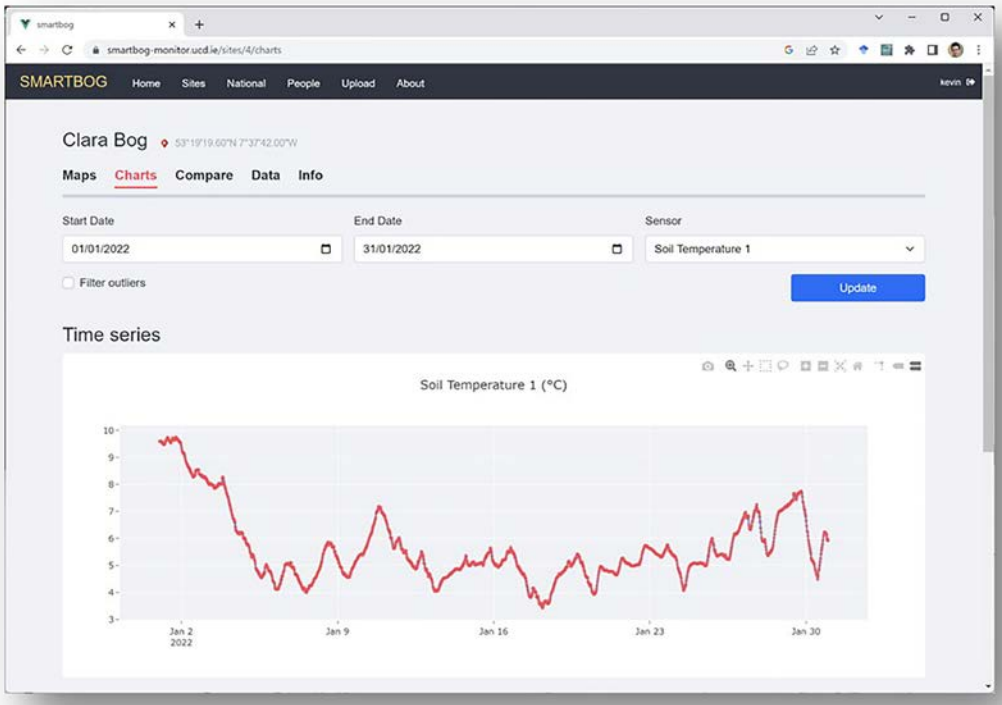

Figure 6.4. Time series soil temperature data from the Clara Bog study site in 2022 displayed using the SmartBog platform.

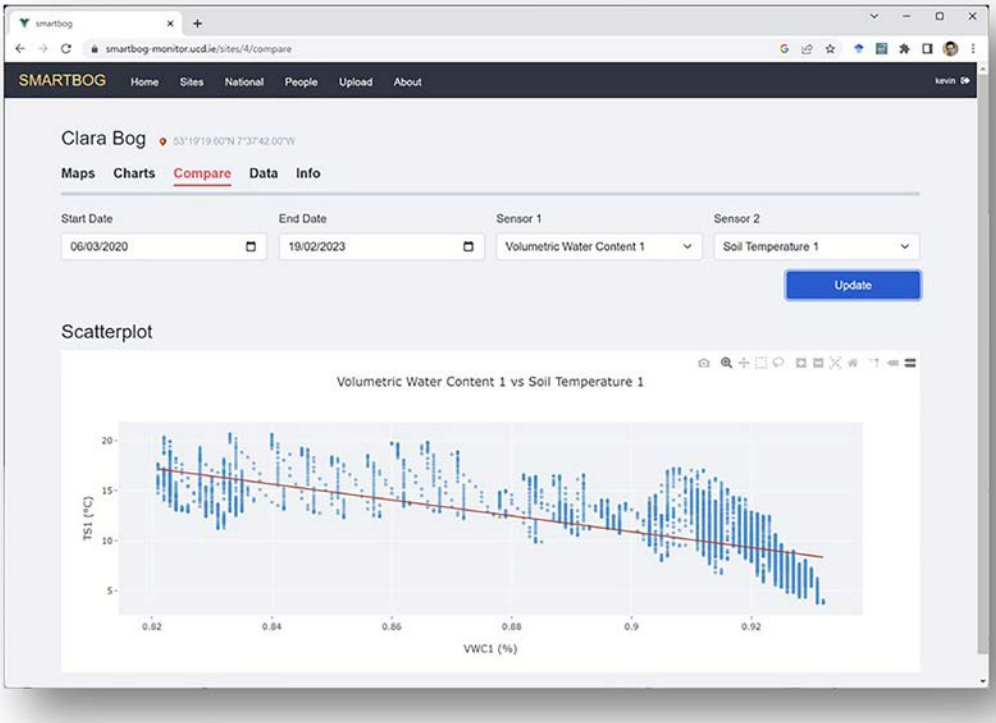

Figure 6.5. Comparison of volumetric soil moisture content and soil temperature at the Clara site using the SmartBog platform.

for example, to investigate the relationship between volumetric soil moisture content and soil temperature at the Clara site.

Geospatial data can also be accessed through the platform, with satellite-based and unmanned aerial vehicle-based maps being available in vector and raster overlays. This information was used to show both ecological comparisons of key sites, such as the ecotope maps for Clara Bog (Figure 6.6), and the impacts of human intervention/management through drain mapping (Figure 6.7). Finally, the platform was equipped with a download function for users to access and download datasets of interest.

As stated in the acknowledgements section, Dr Kevin McGuinness sadly passed away during the project and the web platform remains in pilot/demonstration mode only.



Figure 6.6. The ecotope map of Clara Bog, derived from the integration of ground-based surveys and remote sensing data using the SmartBog platform.

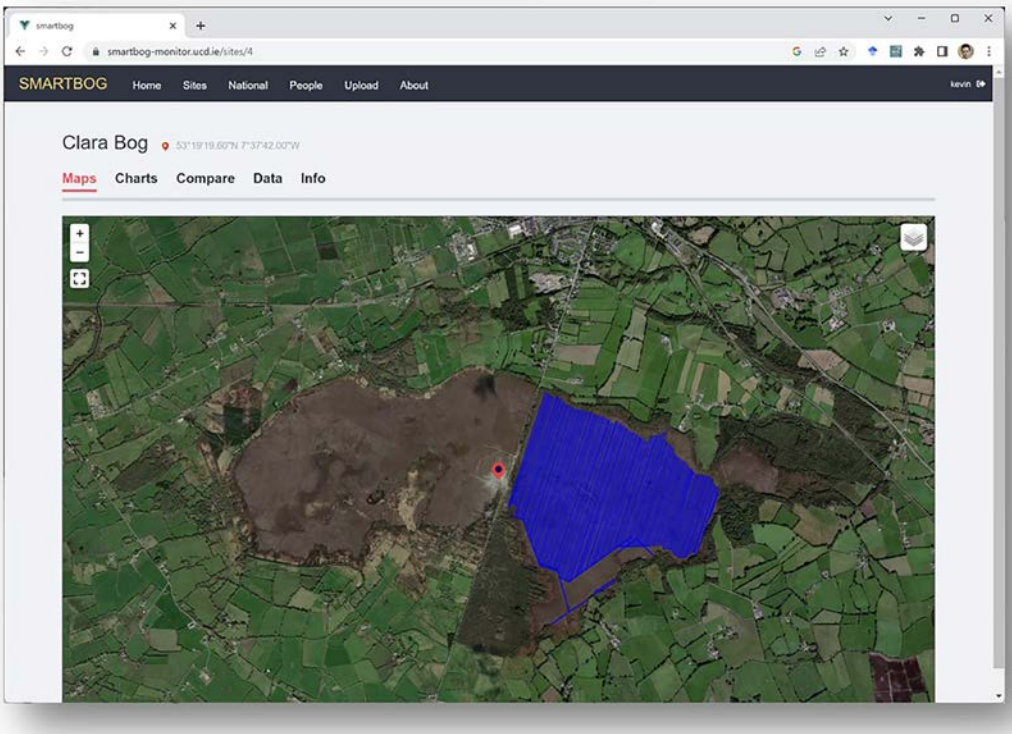

Figure 6.7. A map of surface drains at the Clara Bog site, demonstrating how some of the outputs of the geospatial work of the SmartBog project could be presented for use by stakeholders on the SmartBog platform.

7 Summary, Conclusions and Recommendations

7.1 Geospatial Analysis of Peatlands

Overall, the much-needed baseline data produced in this work will provide information on peatland extent and condition at a national level. This information will (i) support policy-related decision-making on the sustainable management of these ecosystems, for example by identifying degraded peatlands and informing restoration prioritisation, and (ii) account for emissions based on robust spatially explicit data. Furthermore, the methods developed here could potentially be applied globally to map land use on peatlands and fill the knowledge gap related to spatially explicit information on these rare and vital ecosystems. Application in other peat-rich regions would require an existing peatland extent layer, locally derived training data and region-specific emission factors. The use of free satellite archives ensures scalability, particularly in data-poor regions. The utilisation of freely available Landsat and Sentinel-2 imagery in a planetary-scale cloud computing platform (Google Earth Engine) provides a readily accessible and efficient method for monitoring and mapping land use activities on peatlands at a national level, and this was proven to be both time- and cost-effective. Significant changes observed between 2005 and 2020 using Landsat imagery, particularly in areas used for industrial peat extraction, are expected to persist. Landsat data remain pertinent for monitoring and mapping these ongoing changes. The higher-resolution Sentinel-2 data, along with the methods developed here, will be useful for monitoring progress on current rewetting and rehabilitation activities following industrial peat extraction, such as those being undertaken as part of the Peatlands Climate Action Scheme (PCAS) (www.bnmpcas.ie). Finally, the method developed for artificial drainage mapping, which is conducted using high-cost, very high-resolution imagery, could serve as an effective tool for monitoring peatland conditions and assessing rewetting activities, such as ditch blocking and damming. This is particularly relevant for restoration measures carried out under the drainage management plans prepared by Bord na Móna, especially if the analysis is repeated every few years. The baseline dataset developed here will also serve as an explanatory variable for future studies, for example on the susceptibility of these fragile ecosystems to natural disasters such as fire and (peat) landslides due to degradation induced by human or natural pressures.

The peatland extent map used as the basis of this work – that is, Derived Irish Peat Map Version 2 (DIPMv2) (Connolly and Holden, 2009) – was the most recently updated map of peatlands in Ireland at the time of the study. The overall accuracy of the map was 88%, and it underestimated areas smaller than 7 ha. It has further potential to be expanded using information published after the study was undertaken (e.g. Gilet *et al*., 2024). The use of medium-resolution Landsat imagery meant that some land use classes, such as land used for small-scale domestic peat extraction and remnant peatlands (high bogs), could not be mapped. An assessment of the accuracy of the Landsat imagery included in the study was not conducted because of the unavailability of high-resolution imagery. To mitigate these limitations, high-resolution Sentinel-2 data were used. However, forestry land was not further segregated into distinct types at this level because of the unavailability of training data to ground-truth the imagery for these classes. Emission levels were calculated for only four land use classes (cutaway peatlands, cutover peatlands, forests and grasslands) because of the unavailability of emission factors for other classes. Due to the use of optical aerial imagery, only the drains that were “visible” in the imagery could be detected. Hence, only the drains in the bare-peat areas were mapped. The fraction of artificial drainage on industrial peat extraction sites ($Frac_{ditch}$) emission levels were calculated for only Bord na Móna industrial peat extraction areas, since the drains in these areas are mostly present in bare-peat areas and their presence can be verified against Bord na Móna drainage management plans. A substantial knowledge gap remains in terms of mapping land use and artificial drainage on blanket bogs using high-resolution satellite imagery and very high-resolution aerial imagery. This could not be remedied in this study due to time constraints and the complexity of the large and heterogeneous blanket bog landscape.

7.2 Greenhouse Gas Emissions

The measurements obtained for the net ecosystem exchange (NEE) of carbon at the Clara Bog site are comparable to those reported by other published studies on raised bog systems and, importantly, demonstrate both the vulnerability and the resilience of intact peatlands to climatic variability. Over the course of this work, the flux footprint at Clara Bog, which was dominated by the subcentral ecotope, showed that this area was vulnerable to prolonged increases in the water table depth (WTD), particularly over the course of the growing season. In 2018 (a drought year), this caused the study area to act as a net source of carbon, amounting to 53.51 g C m^{-2} y^{-1}. In contrasting years, when the WTD did not fluctuate to such a degree, or when it returned closer to the surface of the bog during the growing season, the study area acted as a net sink of carbon, assimilating between –49.72 and –135.93 g C m^{-2} y^{-1}, with the lower values in this range occurring during the drier years (e.g. 2021). The NEE measurements taken at the Cavemount site highlight the beneficial impact of peatland rehabilitation on reducing carbon emissions from post-industrial extraction sites. In this study, NEE values at Cavemount suggested that over the study years this site varied from being a small source of carbon (18.27 g C m^{-2} y^{-1}) to a negligible sink (–0.34 g C m^{-2} y^{-1}). The variability in these values is due to both the heterogeneity of the study site – which comprises bare peat, areas of natural revegetation and open water, which will influence the flux footprint and cumulative NEE value derived – and interannual climatic variability (e.g. temperature and water availability), which will influence the processes that drive both carbon assimilation and carbon release. The range of NEE values reported here are encouraging, as they highlight the time-dependent carbon emission reduction potential of peatland rehabilitation, in particular where rehabilitation activities could be considered more passive as the ecology of the site changes through natural succession post-rewetting. It is important to maintain and support the operation of ecosystem-scale experimental sites such as these in the long term (decadal scales) in order to (i) capture the impacts of climatic variability as they occur in greater frequency, magnitude and duration, and (ii) assess how rehabilitation activities, such as those associated with PCAS, are making a positive contribution to meeting Ireland's land-based emission targets. This long-term vision, which will support research infrastructure across the operational, information, knowledge and societal domains at experimental sites such as those in this study, will allow such sites to be integrated into and contribute to wider international networks such as the Integrated Carbon Observation System (ICOS) network and the Long Term Ecological Research (LTER) Network. The ICOS network represents an integrated research infrastructure that spans the atmospheric, ecosystem and ocean domains and aims to produce standardised, high-precision and long-term data that underpin our understanding of the carbon cycle and greenhouse gas (GHG) dynamics to support environmental policymaking and decision-making on combating the impacts of climate change. Ireland's membership of the ICOS network is coordinated by the EPA (https://meta.icos-cp.eu/resources/stations/ES_IE-Cra), and the Clara raised bog ecosystem is an associated site within this network (https://meta.icos-cp.eu/resources/stations/ES_IE-Cra). The LTER Network (https://lternet.edu) is grounded in the knowledge that can be accrued through observation and investigation of ecosystems over decadal time frames; the aim is for the knowledge created to inspire environmental solutions and cultivate wider learning. There is a significant opportunity, through sustained and coordinated resourcing, to integrate the activities of Irish observational/experimental sites into these wider networks, which in turn would lead to greater impact at both the national and global scales.

This study focused on the ecosystem-scale emission dynamics of carbon dioxide (CO_2); however, it is also important to assess the magnitude and drivers of emissions of other important GHGs emitted from these ecosystems, such as methane (CH_4) and to a lesser extent nitrous oxide (N_2O). While other active projects are assessing emissions of these gases (e.g. the EPA-funded CH_4Peat and ASPEN projects), investment in infrastructure such as automated chambers that can capture facilitated emissions of CH_4 from stands of large emergent vegetation such as *Typha latifolia* and *Phragmites australis*, which can naturally colonise and dominate rehabilitation sites, would be beneficial, as the data collected could be integrated with ecosystem-scale flux measurements.

Chamber-based measurements of CH_4 from bare peat and low-stature vegetation aggregated at the ecosystem scale were comparable to measurements from other published studies such as Regan *et al*. (2020), and they showed that, on average across the study period, CH_4 emission levels were lower for the degraded site (0.29 g CH_4-C m^{-2} y^{-1}) than for the rehabilitation (0.79 g CH_4-C m^{-2} y^{-1}) or near-natural (6.62 g CH_4-C m^{-2} y^{-1}) sites. This work also shows that, as the WTD decreases post-rewetting, some small, but expected, increases in CH_4 production and emission levels occur and that CH_4 emissions from near-natural sites are dominated by ecotopes where the WTD is closer to the surface of the bog and where *Eriophorum* species are present. This also highlights the expected trade-offs between reducing carbon emissions and enhancing CH_4 production during peatland rehabilitation and rewetting activities. As the WTD decreases and stabilises, the activity of methanogenic bacteria in the anaerobic layers of peat will increase the production of CH_4 and – where plant species that can facilitate the emission of CH_4 to the atmosphere are present – net losses of CH_4 from peatland may increase. However, this is countered by the role that these plants play in the assimilation of carbon from the atmosphere and their role in active peat formation. This again highlights the need for long-term data on these ecosystem flux dynamics as sites change post-rewetting and against the backdrop of climate change.

This project also demonstrated the role that Earth observation (EO) data can play in the monitoring, upscaling and predicting carbon/GHG dynamics in peatlands. The work here integrated satellite-derived and ground-based data to map the ecology and ecotope classification of the sites, which allowed an accurate area-based assessment of net ecosystem CH_4 emissions to be carried out. This work also developed a new hybrid bog index that uses EO-derived spectral reflectance and surface moisture information to predict the carbon assimilation potential of these ecosystems. This index was validated against the ecosystem-scale measurements of NEE. The development of such indices, where EO-derived data are combined with observations from experimental sites, will enhance our understanding of how ecological change, driven by site hydrology, will influence carbon uptake/release and wider GHG dynamics, and how these respond to both climatic and management-related interventions. These approaches can be extrapolated and upscaled across a wider array of peatland systems to better understand ecological change, ecosystem health and wider climate benefits.

7.3 Fluvial Carbon Losses

This work focused on the utility of sensor technology to detect fluorescent dissolved organic matter (fDOM) in the water sources leaving ecosystems and how this could be used as a proxy for measuring the export of non-particulate organic carbon (NPOC) and therefore enable the estimation of fluvial carbon export from these ecosystems. The sensor technology was tested at a near-natural site (Clara) and at post-extraction sites (Garryduff and All Saints). The results show that the magnitudes of fluvial carbon losses from our study sites were comparable to those reported for other peatland systems globally. Higher NPOC concentrations were typically seen in run-off from Clara than from the other sites, but, given the lower discharge rate at Clara, its NPOC export rates were only slightly higher than for Garryduff (10.68 and 9.49 g C m^{-2} y^{-1}, respectively, for 2021, for example). Exports were higher in the winter for both sites due to the higher discharge rates, despite NPOC concentrations being lower in the winter than in the summer. This finding contrasts with those from other studies, where fluvial exports of carbon have been shown to be higher in degraded peatlands than in near-natural sites. The higher losses from Clara can probably be explained by the role that plants play in actively assimilating carbon from the atmosphere, which can enhance microbial activity, due to the increased availability of organic matter. The measurements at Clara also indicated that for 2021 and 2022 approximately 11% of the carbon assimilated through NEE was exported via the fluvial pathway.

In this study, a multivariate approach was used to determine a statistically significant relationship between fDOM measurements and NPOC concentrations. This is important, as it allows for the site-specific variability in precipitation, soil moisture, flow discharge, temperature and pH, and the hysteresis between those processes, to be accounted for when estimating fluvial carbon losses, and it is recommended that other studies using fDOM sensors consider this approach, not least because the relationship between fDOM measurements and

NPOC concentrations can be continually adjusted over time. It is also important to consider the flow regime of peatlands, and in particular how water moves through or is held within these systems and how the water interacts with the vegetation cover that is present. In addition, as there is a need for consistent grab sampling and autosampling to define the site-specific relationship between fDOM measurements and NPOC concentrations, a cost–benefit analysis of the fDOM sensor technology should be carried out based on the specific aims of projects using this technology.

7.4 Low-cost Sensors

The SmartBog project investigated the use of internet-of-things (IoT) devices to collect data on features relating to atmospheric CO_2 and soil moisture. Sensors were deployed on Clara Bog and on grassland and forest sites on peat in Lullymore Heritage and Discovery Park with the goal of validating IoT data collection methods for use in compiling environmental monitoring datasets. Analysis of the data collected over the project period shows that there is potential to integrate IoT data; however, feature- or sensor-specific processing is necessary, to clean and correct data before they are included in any dataset. The SmartBog project has developed a structured pipeline for the machine-learning processing of IoT data, including a suite of tools designed and tested specifically for CO_2 sensor devices in the peatland environment that could be applied at low cost and power requirements for providing greater information on the variables that drive the carbon/GHG dynamics of these ecosystems, and additional insight into how these systems respond to change at greater temporal and spatial scales.

7.5 Stakeholder Platform

The development of the SmartBog stakeholder platform demonstrates the potential of an online platform to integrate multiple data streams and products and to present these in a format that is of use to key end users and stakeholders. The platform was developed in pilot/demonstration mode only but was used to demonstrate the following capabilities: users can access site metadata; compare, contrast and download variables captured at the SmartBog experimental sites; and explore the integration of these data with key EO products. This platform could be further enhanced to enable online data acquisition; harmonised processing and analysis; and the compilation of data products that are required by multiple end users. For example, the provision of open-access, near-real-time, quality-controlled meteorological and flux data would be of direct benefit to the modelling community, and the aggregation of these data to provide higher-tier emission factors scaled using the SmartBog land use classification system for Irish peatlands (LUCIP) would then be of direct benefit for emission-reporting activities. Such a platform could act as a central focal point for land-based carbon/GHG emission and geospatial research and could support the development of synergies across sectors, institutes and end users.

7.6 Recommendations for Future Work and Conclusions

The recommendations from the SmartBog project for future work in this area include the following:

- Focus on addressing the limitations identified during the project, to enhance the accuracy and comprehensiveness of peatland land use and artificial drainage mapping.
- Incorporate a more comprehensive and finer-scale map of peatland extent for Ireland, if such a map becomes available, which accurately represents smaller areas, that is, areas under 7 ha.
- Further segregate forest and grassland classes, with both Landsat data and Sentinel-2 data. This would be possible with the availability of training data through the recently released National Land Cover Map of Ireland.
- Use higher-resolution satellite (e.g. PlanetScope) imagery for habitat mapping of remnant peatland (high bog).
- Use deep-learning methods combined with aerial imagery for higher-level mapping of cutaway and cutover methods, for example extraction methods (LUCIP level 5).
- Use machine-learning and deep-learning methods for mapping the natural degradation of peatlands, such as peat erosion on blanket bogs.
- In terms of emission mapping, this project focused only on four classes, and, as mentioned previously, these classes currently cover the majority of peatland use. However, this will change as rewetting, restoration and rehabilitation activities advance. Therefore, consider

incorporating the classification schema proposed by Aitova *et al*. (2023) into LUCIP to achieve a more comprehensive classification taxonomy that could be used to estimate emission levels from rewetted and nutrient-poor/nutrient-rich sites.
- Consider incorporating the deep learning-based mapping of artificial drainage with active remote sensing (e.g. lidar) data to map "hidden drains" (i.e. drains obscured by infill or vegetation).
- As emission factors are updated for other types of land use on peatlands, especially artificial drainage, consider using these emission factors to accurately estimate the level of emissions from the drains as well as from specific land use types.
- Given the generalising capability of the machine-learning and deep-learning methods used here, consider using these models to map land use and drainage on blanket bogs in Ireland and in peatlands regionally (Europe) and globally.
- Identify a suite of peatland sites that would form the basis of an integrated long-term observational network. This should be coordinated across organisations and research-performing organisations and harmonised across disciplines to develop standardised protocols and enable data curation and accessibility for end users.
- Provide financial support for the long-term operation of key ecosystem flux sites across the LUCIP classes. These sites are typically operated through short, fixed-term research projects, creating useful snapshots of information but limited long-term understanding. This is particularly important with regard to capturing the impacts of climatic extremes or the time-dependent aspects of peatland rehabilitation.
- Invest in the infrastructure required to measure plant-facilitated CH_4 emissions from large emergent macrophytes at greater temporal and spatial scales, to enhance our ability to integrate the influence of these emissions into estimates of net ecosystem carbon and GHG emission levels.
- Conduct an extended and more consistent campaign of chamber measurements of CO_2 and CH_4 evasion from standing water at degraded sites, and at different locations within each site, to assess variability in emission levels.
- Derive a more comprehensive estimate of the net carbon and GHG budgets for these systems, by integrating all elements of carbon and GHG uptake, release and export.
- Conduct further assessments to determine how frequently NPOC concentrations must be measured to ensure that fDOM measurements can be used as a reliable proxy for fluvial carbon export.
- Perform a cost–benefit analysis of fDOM technology that considers the amount of data required for validation.
- Carry out a parallel factor analysis of the UV absorption of dissolved organic matter in raised bog systems of different conditions.
- Carry out an assessment of the lag time between changes in variables that affect NPOC and changes in NPOC concentrations.
- Develop a model that better captures evapotranspiration in the types of temperate peatlands found in Ireland; this would be beneficial for understanding the ecohydrology more fully.
- Conduct a more in-depth analysis of the impact of lateral flow on discharge in these systems using microcosms.
- IoT sensors can be used to provide insights into variables that drive carbon/GHG dynamics in peatland systems, but careful consideration must be given to the cleaning and correcting of data before use in data-processing pipelines. To address these issues, develop an online platform that can act as a centralised data repository and online processing platform to acquire, integrate, process and carry out quality control on data, fill data gaps and analyse the depth and breadth of the data products produced in the SmartBog project. Moreover, provide an open-access platform to make the data products available to a diverse array of end users.

This project has highlighted the need to integrate a variety of data sources and methodologies to better understand the beneficial impacts of peatland rehabilitation on the hydrological and ecological status of these systems and how vulnerable or resilient they are to climatic variability. This work demonstrates that the rehabilitation of former industrial extraction sites through drain blocking and subsequent natural ecological succession will, over a time frame of more than 10 years, reduce gaseous carbon losses and position these systems on an emission-saving trajectory. Further work is however needed to elucidate the implications of this ecological change and the role this has in carbon uptake/release and associated

CH_4 emissions. Additional research is also required to determine how other rehabilitation techniques, such as the use of berms/bunds to manage the hydrology of the sites, will impact their function and wider ecosystem service provision. The outputs of the project provide insights into the depth and breadth of the monitoring approaches required to assess progress, detect change and support sustainable land management decision-making associated with key land use interventions such as PCAS and the proposed Nature Restoration Plan.

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Abbreviations

CI	Confidence interval
CO_2 eq	CO_2 equivalents
DIPMv2	Derived Irish Peat Map Version 2
DOC	Dissolved organic carbon
EC	Eddy covariance
EO	Earth observation
ET_{ec}	Evapotranspiration captured by eddy covariance flux towers
EU	European Union
fDOM	Fluorescent dissolved organic matter
$Frac_{ditch}$	Fraction of artificial drainage on industrial peat extraction sites
GHG	Greenhouse gas
GPP	Gross primary productivity
ICOS	Integrated Carbon Observation System
IoT	Internet of things
IPCC	Intergovernmental Panel on Climate Change
LTER	Long Term Ecological Research
LUCIP	Land use classification system for Irish peatlands
LUE	Light use efficiency
NDIR	Non-dispersive infrared
NEE	Net ecosystem exchange
NPOC	Non-particulate organic carbon
NSE	Nash–Sutcliffe efficiency
PAR	Photosynthetically active radiation
PCAS	Peatlands Climate Action Scheme
PET	Potential evapotranspiration
PVC	Polyvinyl chloride
SVR	Support vector regression
WTD	Water table depth

An Ghníomhaireacht Um Chaomhnú Comhshaoil

Tá an GCC freagrach as an gcomhshaol a chosaint agus a fheabhsú, mar shócmhainn luachmhar do mhuintir na hÉireann. Táimid tiomanta do dhaoine agus don chomhshaol a chosaint ar thionchar díobhálach na radaíochta agus an truaillithe.

Is féidir obair na Gníomhaireachta a roinnt ina trí phríomhréimse:

Rialáil: Rialáil agus córais chomhlíonta comhshaoil éifeachtacha a chur i bhfeidhm, chun dea-thorthaí comhshaoil a bhaint amach agus díriú orthu siúd nach mbíonn ag cloí leo.

Eolas: Sonraí, eolas agus measúnú ardchaighdeáin, spriocdhírithe agus tráthúil a chur ar fáil i leith an chomhshaoil chun bonn eolais a chur faoin gcinnteoireacht.

Abhcóideacht: Ag obair le daoine eile ar son timpeallachta glaine, táirgiúla agus dea-chosanta agus ar son cleachtas inbhuanaithe i dtaobh an chomhshaoil.

I measc ár gcuid freagrachtaí tá:

Ceadúnú

- Gníomhaíochtaí tionscail, dramhaíola agus stórála peitril ar scála mór;
- Sceitheadh fuíolluisce uirbigh;
- Úsáid shrianta agus scaoileadh rialaithe Orgánach Géinmhodhnaithe;
- Foinsí radaíochta ianúcháin;
- Astaíochtaí gás ceaptha teasa ó thionscal agus ón eitlíocht trí Scéim an AE um Thrádáil Astaíochtaí.

Forfheidhmiú Náisiúnta i leith Cúrsaí Comhshaoil

- Iniúchadh agus cigireacht ar shaoráidí a bhfuil ceadúnas acu ón GCC;
- Cur i bhfeidhm an dea-chleachtais a stiúradh i ngníomhaíochtaí agus i saoráidí rialáilte;
- Maoirseacht a dhéanamh ar fhreagrachtaí an údaráis áitiúil as cosaint an chomhshaoil;
- Caighdeán an uisce óil phoiblí a rialáil agus údaruithe um sceitheadh fuíolluisce uirbigh a fhorfheidhmiú
- Caighdeán an uisce óil phoiblí agus phríobháidigh a mheasúnú agus tuairisciú air;
- Comhordú a dhéanamh ar líonra d'eagraíochtaí seirbhíse poiblí chun tacú le gníomhú i gcoinne coireachta comhshaoil;
- An dlí a chur orthu siúd a bhriseann dlí an chomhshaoil agus a dhéanann dochar don chomhshaol.

Bainistíocht Dramhaíola agus Ceimiceáin sa Chomhshaol

- Rialacháin dramhaíola a chur i bhfeidhm agus a fhorfheidhmiú lena n-áirítear saincheisteanna forfheidhmithe náisiúnta;
- Staitisticí dramhaíola náisiúnta a ullmhú agus a fhoilsiú chomh maith leis an bPlean Náisiúnta um Bainistíocht Dramhaíola Guaisí;
- An Clár Náisiúnta um Chosc Dramhaíola a fhorbairt agus a chur i bhfeidhm;
- Reachtaíocht ar rialú ceimiceán sa timpeallacht a chur i bhfeidhm agus tuairisciú ar an reachtaíocht sin.

Bainistíocht Uisce

- Plé le struchtúir náisiúnta agus réigiúnacha rialachais agus oibriúcháin chun an Chreat-treoir Uisce a chur i bhfeidhm;
- Monatóireacht, measúnú agus tuairisciú a dhéanamh ar chaighdeán aibhneacha, lochanna, uiscí idirchreasa agus cósta, uiscí snámha agus screamhuisce chomh maith le tomhas ar leibhéil uisce agus sreabhadh abhann.

Eolaíocht Aeráide & Athrú Aeráide

- Fardail agus réamh-mheastacháin a fhoilsiú um astaíochtaí gás ceaptha teasa na hÉireann;
- Rúnaíocht a chur ar fáil don Chomhairle Chomhairleach ar Athrú Aeráide agus tacaíocht a thabhairt don Idirphlé Náisiúnta ar Ghníomhú ar son na hAeráide;
- Tacú le gníomhaíochtaí forbartha Náisiúnta, AE agus NA um Eolaíocht agus Beartas Aeráide.

Monatóireacht & Measúnú ar an gComhshaol

- Córais náisiúnta um monatóireacht an chomhshaoil a cheapadh agus a chur i bhfeidhm: teicneolaíocht, bainistíocht sonraí, anailís agus réamhaisnéisiú;
- Tuairiscí ar Staid Thimpeallacht na hÉireann agus ar Tháscairí a chur ar fáil;
- Monatóireacht a dhéanamh ar chaighdeán an aeir agus Treoir an AE i leith Aeir Ghlain don Eoraip a chur i bhfeidhm chomh maith leis an gCoinbhinsiún ar Aerthruailliú Fadraoin Trasteorann, agus an Treoir i leith na Teorann Náisiúnta Astaíochtaí;
- Maoirseacht a dhéanamh ar chur i bhfeidhm na Treorach i leith Torainn Timpeallachta;
- Measúnú a dhéanamh ar thionchar pleananna agus clár beartaithe ar chomhshaol na hÉireann.

Taighde agus Forbairt Comhshaoil

- Comhordú a dhéanamh ar ghníomhaíochtaí taighde comhshaoil agus iad a mhaoiniú chun brú a aithint, bonn eolais a chur faoin mbeartas agus réitigh a chur ar fáil;
- Comhoibriú le gníomhaíocht náisiúnta agus AE um thaighde comhshaoil.

Cosaint Raideolaíoch

- Monatóireacht a dhéanamh ar leibhéil radaíochta agus nochtadh an phobail do radaíocht ianúcháin agus do réimsí leictreamaighnéadacha a mheas;
- Cabhrú le pleananna náisiúnta a fhorbairt le haghaidh éigeandálaí ag eascairt as taismí núicléacha;
- Monatóireacht a dhéanamh ar fhorbairtí thar lear a bhaineann le saoráidí núicléacha agus leis an tsábháilteacht raideolaíochta;
- Sainseirbhísí um chosaint ar an radaíocht a sholáthar, nó maoirsiú a dhéanamh ar sholáthar na seirbhísí sin.

Treoir, Ardú Feasachta agus Faisnéis Inrochtana

- Tuairisciú, comhairle agus treoir neamhspleách, fianaise-bhunaithe a chur ar fáil don Rialtas, don tionscal agus don phobal ar ábhair maidir le cosaint comhshaoil agus raideolaíoch;
- An nasc idir sláinte agus folláine, an geilleagar agus timpeallacht ghlan a chur chun cinn;
- Feasacht comhshaoil a chur chun cinn lena n-áirítear tacú le hiompraíocht um éifeachtúlacht acmhainní agus aistriú aeráide;
- Tástáil radóin a chur chun cinn i dtithe agus in ionaid oibre agus feabhsúchán a mholadh áit is gá.

Comhpháirtíocht agus Líonrú

- Oibriú le gníomhaireachtaí idirnáisiúnta agus náisiúnta, údaráis réigiúnacha agus áitiúla, eagraíochtaí neamhrialtais, comhlachtaí ionadaíocha agus ranna rialtais chun cosaint chomhshaoil agus raideolaíoch a chur ar fáil, chomh maith le taighde, comhordú agus cinnteoireacht bunaithe ar an eolaíocht.

Bainistíocht agus struchtúr na Gníomhaireachta um Chaomhnú Comhshaoil

Tá an GCC á bainistiú ag Bord lánaimseartha, ar a bhfuil Ard-Stiúrthóir agus cúigear Stiúrthóir. Déantar an obair ar fud cúig cinn d'Oifigí:

1. An Oifig um Inbhunaitheacht i leith Cúrsaí Comhshaoil
2. An Oifig Forfheidhmithe i leith Cúrsaí Comhshaoil
3. An Oifig um Fhianaise agus Measúnú
4. An Oifig um Chosaint ar Radaíocht agus Monatóireacht Comhshaoil
5. An Oifig Cumarsáide agus Seirbhísí Corparáideacha

Tugann coistí comhairleacha cabhair don Ghníomhaireacht agus tagann siad le chéile go rialta le plé a dhéanamh ar ábhair imní agus le comhairle a chur ar an mBord.

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