



Trinity College Dublin
Coláiste na Tríonóide, Baile Átha Cliath
The University of Dublin

Multi-Spatial-Temporal Remote Sensing and Machine Learning for Mapping Management Impacts on Peatlands in Ireland

A thesis submitted to Trinity College Dublin, the University of Dublin, in candidature
for the Degree of

Doctor of Philosophy

2024

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Declaration

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Acknowledgments

As I reflect on the four-year rollercoaster that was my PhD journey, it is impossible not to express my deepest gratitude to the incredible individuals who made it interesting, pleasant, and unforgettable.

Firstly, I extend my deepest gratitude and appreciation to my supervisor, Dr. John Connolly, without his “bog-nificent” mentorship, care, and support this work would not have been possible. I would also like to extend special thanks to my Co-supervisor Dr Kevin McGuinness, who although sadly no longer with us, provided vital input in shaping the trajectory of the work related to artificial drainage mapping. A special note of thanks to Dr. Catherine Farrell, whose ecological expertise served as a “lens”, allowing me to understand and visually interpret peatland land use through satellite and aerial remote sensing imagery. Her guidance and discussions on the development of LUCIP have been invaluable to this work.

I would like to extend my gratitude to the Environmental Protection Agency (EPA) of Ireland. This work was supported by funding under the EPA Research Programme 2014-2020 (Grant no. 2018-CCRP-LS-2). The EPA Research Programme is a Government of Ireland initiative, funded by the Department of Communications, Climate Action, and Environment. I would also like to thank the French Embassy in Ireland for generously providing the French Research Residency Award, enabling the execution of part of the study’s research activities at the French National Research Institute for Agriculture, Food, and the Environment in Montpellier, France. I would also like to thank Rémi Cresson, for his support and guidance during the research visit.

Acknowledgments would be incomplete without expressing gratitude to my colleagues and friends who have been an essential part of this academic odyssey. Charm, Connor, Abbie, Alexia, Alex, Orla, Tommy, Benji, Louis, and Kate—your friendship and support made this journey not only academically enriching but also a delightful and memorable experience.

Finally, I owe an immense debt of gratitude to my family. To my parents (*Ammi* and *Abbu*), whose unwavering encouragement and belief in my abilities have been a constant source of strength. To my siblings, whose support and understanding have

been the pillars of my resilience. This achievement is as much yours as it is mine, and I am grateful for the love and support that has sustained me throughout this incredible journey.

آپ سب کا بہت شکریہ

Abstract

Peatlands, constituting over half of terrestrial wetland ecosystems across the globe, hold critical ecological significance and are large stores of Carbon (C). In Ireland, the wetland landscape is dominated by rare oceanic raised bogs and blanket bogs, covering ~21% (1.46 Mha) of the land surface area. These ecosystems account for 50-75% of the soil organic carbon stock of Ireland and offer numerous ecosystem services including C storage, biodiversity support and water regulation. However, more than 90% of these ecosystems have been degraded over centuries due to artificial drainage ditches followed by land use activities like peat extraction, afforestation, and agriculture. This has an overall negative impact on the functioning of these ecosystems, shifting them from a moderate sink of C to a large source of C. Recognising the importance of these ecosystems, efforts are underway to conserve them through measures such as rewetting, restoration, and rehabilitation. Furthermore, Ireland needs to meet its 2030 climate energy framework targets related to GHG emissions from land use, land use change, and forestry, including wetlands. Despite Ireland's voluntary decision to include peatlands in this system in 2020, spatially explicit information on land use activities and associated GHG emissions from peatlands is lacking. The implementation of conservation efforts and accurate accounting of C stores and GHG emissions requires accurate identification and mapping of artificial drainage ditches and associated land use activities.

The main objective of this study is to develop a robust set of methods capable of mapping and monitoring peatland land use changes using novel cloud computing, artificial intelligence (Machine Learning (ML) and Deep Learning (DL)) and multi-temporal-spatial remote sensing. The study begins with the development of a multi-level land use classification taxonomy, namely Land Use Classification for Irish Peatlands (LUCIP). The four-level classification system was used to identify land use activities. Each level of LUCIP corresponds to the spatial resolution of the sensor employed in the mapping of land use activities at that level. By utilising cloud computing, temporal mosaicking, Landsat and Sentinel data, this study developed a robust methodology that overcame cloud contamination and produced the first peatland land use and artificial drainage maps of Ireland with wall-to-wall coverage.

At LUCIP level-2 four peatland land use classes were identified: industrial peat extraction, forest, grassland, and residual peatland. These were then mapped and assessed using medium resolution (30 m) Landsat (5 and 8) data combined with Google Earth Engine (GEE) and random forest ML. These four land uses were assessed across three time periods: 1990, 2005 and 2019. 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 due to the unavailability of high-resolution reference data. The results indicate that extensive management activities have taken place in peatlands over the past three decades. There is no notable change between 1990 and 2005. However drastic changes were observed between 2005 - 2019, with exposed peat area on Bord na Mona (BnM) landholding decreasing while afforestation and grassland increasing on these sites. Overall, there is an increase in forests and a decrease in grasslands on peatlands.

The study then scopes down further to raised bogs. At LUCIP level-3 seven land use activities on Irish raised bogs peatlands were identified: cutaway, cutover, forest, grassland, remnant peatlands, waterbodies, and built-up. These were mapped using high-resolution (10m) Sentinel-2 imagery, random forest ML and GEE. The results revealed that agricultural grassland comprised 43% of the land use on raised bogs, followed by, forestry (21%), cutover (11%), cutaway (10%) remnant peatlands (13%), waterbodies and built-up ~1% each. The overall accuracy of the map was 89%. The map was also used to estimate CO₂ emissions for four classes constituting 85% of raised bogs: cutover, cutaway, grassland, and forestry using the IPCC wetlands supplement and literature-based emission factors, estimated emissions were at ~1.92 and ~0.68 Mt CO₂-C-yr⁻¹ respectively. This is the first study to spatially quantify land use and related emissions from raised bogs. The results revealed widespread degradation of these globally rare oceanic raised bogs habitats, making them net emitters of CO₂.

Lastly, the study utilises very high-resolution (0.25m) aerial imagery and a DL approach based on U-net to map the artificial drainage (LUCIP level 4) on 523,000 ha of raised bogs at a national scale. The results show that -drainage is widespread with approximately 20,000 km of drains mapped. This is the first study to map diverse sizes and patterns (regular and irregular) of artificial drains using DL methods on three peatland land use categories i.e., cutaway, cutover, and remnant peatlands. The results

show that over 70% (1300 km) of the artificial drainage ditches exist on Bord na Móna-based raised bogs alone. The overall accuracy of the model was 80% on an independent testing dataset. The data was also used to derive the $Frac_{ditch}$ which was 0.03 (fraction of artificial drainage on industrial peat extraction sites). This is lower than IPCC Tier 1 $Frac_{ditch}$ and can be used for IPCC Tier 2 reporting for Ireland.

The degradation of peatlands in Ireland through land use activities is widely acknowledged. However, due to the unavailability of spatially explicit information on artificial drainage ditches and land use, there is an overall ambiguity in the accurate accounting and reporting of emissions from these ecosystems and the status of land use activities. The study develops a robust set of methods capable of mapping and monitoring the artificial drainage and land use activities on Irish peatlands. The maps developed here are vital for the conservation of these ecosystems, and the methodologies can also be applied to other regions with similar peatland land use issues. This also has the potential for regional and global applications, providing maps that could help understand unsustainable management practices on peatlands and their impact on GHG emissions.

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List of Abbreviations

ALOS	Advanced Land Observing Satellite
ANN	Artificial Neural Network
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
BOA	Bottom of Atmosphere
CAP	Common Agricultural Policy
CCI	Climate Change Initiative
CCS	Climate Change Science
CLC	Corine Land Cover
CNN	Convolutional Neural Network
CORINE	Coordination of Information on the Environment
CSA	Canadian Space Agency
DAR	Differential Absorption Radar
DEM	Digital Elevation Model
DIC	Dissolved Inorganic Carbon
DIPMv2	Derived Irish Peat Map version 2
DL	Deep Learning
DN	Digital Number
DOC	Dissolved Organic Carbon
DT	Decision Tree
DTM	Digital Terrain Model
EEA	European Environment Agency
EEC	European Economic Community
EF	Emission Factor
EMR	Electromagnetic Radiation
EPA	Environmental Protection Agency
ESA	European Space Agency
ETM	Enhanced Thematic Mapper

EU	European Union
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization of the United Nations
GEE	Google Earth Engine
GHG	Greenhouse Gas
GIS	Geographic Information System
GMES	Global Monitoring for Environment and Security
GPU	Graphics Processing Unit
GSD	Ground Sample Distance
HRV	High-Resolution Visible
HSI	Hyperspectral Imaging
IGBP	International Geosphere-Biosphere Programme
IPCC	Intergovernmental Panel on Climate Change
IR	Infrared
IRS	Indian Remote Sensing satellite
ISMI	Indicative Soil Map of Ireland
LAI	Leaf Area Index
LiDAR	Light Detection and Ranging
LU	Land Use
LUCIP	Land Use Classification for Irish Peatlands
LULUCF	Land Use, Land-Use Change and Forestry
MERIS	Medium Resolution Imaging Spectrometer
ML	Machine Learning
MODIS	Moderate Resolution Imaging Spectroradiometer
MS	Multispectral
MSI	Multispectral Instrument
MSS	Multispectral Scanner
NASA	National Aeronautics and Space Administration
NCP	Nature's Contributions to People

NDVI	Normalised Difference Vegetation Index
NDWI	Normalised Difference Water Index
NIR	Near-Infrared
NISAR	NASA-ISRO Synthetic Aperture Radar
NLC	National Land Code
NLCD	National Land Cover Database
NNIR	Near and Near-Infrared
NPWS	National Parks and Wildlife Service
OA	Overall Accuracy
OBIA	Object-Based Image Analysis
OLI	Operational Land Imager
PA	Producer's Accuracy
PALSAR	Phased Array type L-band Synthetic Aperture Radar
PAN	Panchromatic
PCAS	Peatland Climate Actions Scheme
POC	Particulate Organic Carbon
QA	Quality Assurance
RADAR	Radio Detection and Ranging
RADARSAT	Radar Satellite
RBF	Radial Basis Function
RF	Random Forest
RS	Remote Sensing
RVI	Ratio Vegetation Index
SAC	Special Area of Conservation
SAEA	Stratified Area Estimator Analysis
SAED	Stratified Area Estimator Design
SAR	Synthetic Aperture Radar
SC	Scene Classification
SEEA	System of Environmental-Economic Accounting

SEPAL	System for Earth Observation Data Access, Processing and Analysis for Land Monitoring
SLC	Single Look Complex
SMILE	Statistical Machine Intelligence and Learning Engine
SOC	Soil Organic Carbon
SPOT	Satellite Pour l'Observation de la Terre
SRTM	Shuttle Radar Topography Mission
SVM	Support Vector Machine
SWIR	Shortwave Infrared
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
TOA	Top of Atmosphere
TP	True Positive
UA	User's Accuracy
UAS	Unmanned Aircraft System
UNEP	United Nations Environment Programme
UNFCC	United Nations Framework Convention on Climate Change
USGS	United States Geological Survey
VHR	Very High Resolution
VI	Vegetation Index
VIN	Vegetation Index Normalised
WCMC	World Conservation Monitoring Centre

List of Publications

Journal articles

1. **Habib, W.**, Connolly, J. A national-scale assessment of land use change in peatlands between 1989 and 2020 using Landsat data and Google Earth Engine—a case study of Ireland. *Reg Environ Change* **23**, 124 (2023).
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<https://doi.org/10.1038/s41598-024-51660-0>

5. **Habib, W.**, Cresson, R., McGuinness, K., Connolly, J. Mapping artificial drains in peatlands – A national-scale assessment of Irish raised bogs using sub-meter aerial imagery and deep learning methods. *Remote Sensing in Ecology and Conservation* (2024). <https://doi.org/10.1002/rse2.387>

Conference presentations/posters

1. **Habib, W.** & Connolly, J. (2024). Automated mapping of artificial drainage in peatlands using deep learning and very high-resolution aerial imagery, *EGU General Assembly, Vienna, Austria, 15th to 20th April 2024* <https://doi.org/10.5194/egusphere-egu24-21619>
2. **Habib, W.**, McGuinness, K. & Connolly, J. (2023). Mapping artificial drainage on Irish raised bogs using very high-resolution aerial imagery and deep learning methods, *American Geophysical Union Fall Meeting (AGU2023), San Francisco, CA (Online) – 11th to 15th December 2023*
3. **Habib, W.** & Connolly, J. (2023). From pixels to peat: Discerning management practices and their implications in peatlands using machine learning and multi-temporal spatial remote sensing, *Royal Geographical Society (RGS-IBG) Annual International Conference, Royal Geographical Society, London, UK - 29th to 1st September 2023*
4. **Habib, W.**, Ruchita, I., Saunders, M., & Connolly, J. (2022). Mapping vegetation communities across a drainage gradient in Irish raised bogs using PlanetScope Imagery, *14th Irish Earth Observation Symposium, Technological University Dublin, Ireland, 3rd & 4th November 2022*
5. **Habib, W.**, Connolly, J., & McGuinness, K., (2022). Machine learning and deep learning for multi-temporal-spatial assessment of anthropogenic stressors on peatlands – A case study of Ireland. *Flow Country Research Conference,*

University of the Highlands and Islands, North Highland, Thurso, Scotland – 25th to 28th October 2022

6. **Habib, W.**, Ruchita, I., Saunders, M., & Connolly, J. (2022). Mapping vegetation communities Irish raised bogs using PlanetScope imagery and Google Earth Engine, *32nd Irish Environmental Researchers Colloquium, Ulster University Belfast, 20th to 22nd June 2022* (**Best overall oral presentation award winner**) ([ONLINE](#))
7. **Habib, W.**, Ruchita, I., Saunders, M., & Connolly, J. (2022). Mapping vegetation communities across a drainage gradient in Irish raised bogs, *Irish Geosciences Early Career Symposium, University College Cork, Ireland - 9th to 10th June 2022*
8. **Habib, W.**, & Connolly, J. (2021). Spatio-temporal assessment of management impacts on peatlands - A case study of Ireland, *Open Data Science Europe, Wageningen, Netherlands - 6th to 11th September 2021*.
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Assembly, Vienna, Austria (Online), 25th to 30th April 2021.

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14. **Habib, W.**, McGuinness, K., Saunders, M., Delaney, D., Regan, S., & Connolly, J. (2019). Smart Observations of Management Impacts on Peatland Function (SmartBog). *13th Irish Earth Observation Symposium, the National University of Ireland, Galway, 5th to 6th December 2019.* <http://doras.dcu.ie/24003/>

Chapter 1. Introduction

1.1 Background

Peatlands account for 50-70% of the terrestrial wetland ecosystems across the globe (Joosten and Clarke 2002; Šimanauskienė et al. 2019) and are characterised by the accumulation of organic material (peat) in waterlogged conditions (Charman 2002; Evans et al. 2021). Peatlands are increasingly being considered a highly significant ecosystem at global, national, and local scales. They provide a range of ecosystems, including climate and water regulation as well as land atmospheric exchange of carbon (C) and greenhouse gas (GHG). Peatlands are space-efficient global C stocks, containing approximately 455 Pg of C and cover only 2-3% of the land area (Gorham 1991). Currently, an additional 5000 km² is being exploited annually by human activities, meaning that peatlands are being degraded ten times faster than their average expansion rate (Joosten and Clarke, 2002). In Ireland, raised bogs and blanket bogs account for the majority of the peatlands. They cover approximately 1.46 (Mha), however, 95% of that has already been degraded to some extent due to land use activities (Fluet-Chouinard et al. 2023). These activities include artificial drainage, forestry, agriculture, peat extraction, and infrastructure development (e.g., roads) (Renou-Wilson et al. 2011; Renou-Wilson and Byrne 2015; Mackin et al. 2017; Connolly 2018). Artificial drainage in peatlands is the initial step that leads to further anthropogenic modifications (Parry et al. 2014; Turetsky et al. 2015). These drains facilitate the release of dissolved organic carbon (DOC) and particulate organic carbon (POC), contaminating freshwater supplies. They also contribute to C and GHG emissions and are 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, turning them from a moderate C sink to a large C source (Wilson et al., 2013). Furthermore, this also harms several ecosystems regulating and supporting services provided by peatlands.

In the global context, the conservation of peatland is vital to meeting temperature goals outlined in the Paris Agreement and fulfilling international commitments to combat

1.2 Rationale

climate change. European Union (EU) has established legislative frameworks and directives which could address peatland conservation and sustainable management. Policies such as the EU Habitat Directive (92/43/EEC) and the Water Framework Directive (2000/60/EC) underscore the critical importance of peatlands in achieving broader environmental objectives. EU Biodiversity Strategy for 2030 and the LIFE program contribute to the broader goal of preserving and restoring these unique habitats. Moreover, under the EU Monitoring, Reporting, and Verification Regulation (MRV) (525/2013) and EU Climate Change Framework 2030, member states are obligated to report greenhouse gas emissions and removals resulting from Land Use, Land Use Change, and Forestry (LULUCF) activities (Leifeld et al. 2019). Despite this, there is limited success in peatland conservation at the national scale due to the lack of peatland-specific policies or plans. Challenges include incomplete information on peatland characteristics, location, extent, and condition (UNEP 2022).

1.2 Rationale

Peatlands are usually located in isolated and remote areas, presenting difficulties in accessing and mapping them using traditional survey and mapping techniques. Remote sensing, which provides a suitable alternative for mapping these ecosystems, also 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 are required to be adapted depending on the environmental and geographical conditions. This makes the process of image classification across different times and spaces extremely 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. 2023b). Very few studies have focused on developing techniques to map land use (especially artificial drainage) (Connolly 2018; Artz et al. 2019; Robb et al. 2023). These studies have either focused on small areas or used low-resolution satellite imagery for large-scale mapping. Similarly, 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 of significantly larger dimensions and is referred to as “canals” (Dadap et al. 2021).

Studies have been conducted to map the spatial extent of peatlands in Ireland (Hammond 1981; Connolly and Holden 2009). While these studies provide the spatial extent of peatlands, there is a significant knowledge gap due to the absence of comprehensive (wall-to-wall) spatially explicit on land use extent and status within these peatlands (Aitova et al. 2023; Renou-Wilson et al. 2014). Therefore, there is a need for the development of methodologies that can map and quantify the spatial distribution of artificial drainage 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's (2018) study maps in particular identify and map four major land use classes; however, they lack coverage of the western seaboard region. To achieve a more comprehensive mapping of peatlands with further segregation of land use into multiple levels with wall-to-wall 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 (ML) and Deep Learning (DL) techniques in remote sensing image processing (Cheng and Han 2016; Gorelick et al. 2017), offers a good prospect to overcome these challenges. This study focused on developing a classification taxonomy i.e., Land Use Classification for Irish Peatlands (LUCIP) and methodologies based on cloud computing (GEE) to produce a cloud-free mosaic of medium-to-high-resolution satellite remote sensing imagery. These mosaics served as a basis for mapping land use across multiple temporal and spatial scales, providing comprehensive wall-to-wall coverage.

In the context of mapping artificial drainage, techniques for mapping linear features (e.g. mapping of roads, powerlines, and canals) exist in remote sensing which focuses 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, artificial drainage of the peatland ecosystem poses a unique scenario in which it can be linear (industrial peat extraction

sites) and non-linear (hand-cut peat extraction sites) in nature. Moreover, the spectral signature of drains can vary under different conditions, for example, dry, wet, 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, depicting the use of remote sensing techniques to map artificial drains in a degraded peatland environment. However, this study was limited to a few sites and used time/computation-intensive semi-automated traditional remote sensing techniques. More recently, a linear artificial “canal” has been mapped in tropical peatlands using DL applied to semantic segmentation techniques (Dadap et al. 2021), and non-linear drainage has also been mapped separately using similar techniques on highland blanket bogs in the UK (Robb et al. 2023). However, these methods have not been applied to a study site presenting a diverse range of shapes and sizes of artificial drainage ditches, such as Irish raised bogs. Hence, the development of a new robust model with the implementation of DL techniques in remote sensing is required. This research focused on using fully automated DL applied to semantic segmentation techniques for the identification of artificial drainage using very high-resolution aerial imagery. This will help advance research in the realm of optical remote sensing of peatlands by providing methods that can be efficiently implemented and generalised in peatland environments, catering to variations in geographical and environmental conditions which are currently non-existent.

Lastly, a significant amount of research has been carried out in Ireland to study the land-atmospheric C and GHG dynamics of peatlands on different land uses at local scales (Laine et al. 2007; Wilson et al. 2013; Jovani-Sancho et al. 2021). However, there is a need to assess these factors on a national scale. This study also focused on developing baseline datasets i.e., land use and artificial drainage maps which were used to calculate C and GHG emissions at a national scale using the literature (Aitova et al. 2023) and the IPCC default emission factors (Hiraishi et al. 2014). This helped address a severe knowledge gap related to understanding the status and spatial extent of drained raised bogs and its implications on C and GHG emissions at a national scale. This will be directly fed into the National Inventory Reporting of Ireland which currently uses the default IPCC values for reporting emissions.

1.3 Research questions

The research questions addressed in this study were as follows:

1. How can novel cloud computing, machine learning (ML), and medium-to-high-resolution optical satellite imagery be effectively employed to map peatland use at a national scale, ensuring complete coverage despite the persistent cloud cover conditions in Irish peatland habitats?
2. What is the spatial pattern and temporal evolution of land use activities in Irish peatlands over the past three decades (1989-2020), and how have they affected peatland ecosystems?
3. What is the status and spatial extent of land use in Irish raised bogs and its implications on C and GHG emissions at a national scale?
4. How can novel deep learning (DL) techniques be effectively combined with very high-resolution optical aerial imagery to accurately delineate the spatial extent of artificial drainage, considering the diverse sizes and shapes of drainage across Irish raised bogs?
5. What is the condition of artificial drainage in raised bogs under various land uses, including the fraction of drainage ditches in industrial peat extraction areas, and how does this relate to GHG emissions?

1.4 Hypothesis

Widespread management activities have significantly degraded peatlands in Ireland, harming its many ecosystem services and leading to substantial C and GHG emissions. The use of novel planetary-scale cloud computing technology (GEE) with ML techniques and multi-scale (medium to high spatial resolution) optical remote sensing

1.5 Aims and Objectives

data will enable comprehensive mapping (wall-to-wall coverage) of peatland land use at a national scale, even under persistent cloud cover conditions. The spatial patterns and temporal evolution of land use activities in Irish blanket and raised bogs from 1989 to 2020 will reveal significant changes over time. These changes in land use activities are likely to have substantial impacts on peatland ecosystems, altering their composition, structure, and functioning. The analysis of land use on Irish raised bogs with higher resolution imagery will demonstrate a varied spatial extent and status. The implication of these diverse land uses on C storage and GHG emissions at a national scale is anticipated to be substantial, highlighting the environmental consequences of these land use practices. Finally, integrating advanced DL techniques with very high-resolution optical aerial imagery will provide an accurate spatial delineation of artificial drainage systems, accounting for the varied sizes and shapes of these drainage structures within Irish raised bogs. The condition of artificial drainage on raised bogs will vary across different land uses, with higher proportions of drainage ditches expected in industrial peat extraction areas resulting in a high $Frac_{ditch}$ (fraction of artificial drainage ditches).

1.5 Aims and Objectives

The main aim of this study was to use a novel set of remote sensing image processing methods to map land use and artificial drainage networks on peatlands in Ireland. As such, this study focused on the development of baseline datasets including peatland land use (at multiple scales) using medium (Landsat, 30m) and high (Sentinel-2, 10m) spatial resolution satellite imagery. Additionally, very high spatial resolution (BlueSky imagery, 0.25m) aerial remote sensing imagery 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 artificial drainage network dataset underwent quantitative and qualitative assessments using geospatial techniques to identify the drainage density/hotspots (high and low concentration of drainage). The drainage dataset was also combined with the land use dataset to assess the spatial distribution of artificial drainage across different land uses.

Following are the four specific objectives of this study:

1. To develop peatland land use classification taxonomy and map land use in peatlands using multi-spatial-temporal remote sensing, cloud computing technology, and machine learning (ML) algorithms.
2. To utilise novel deep learning (DL) algorithms to map artificial drainage on raised bogs at a national scale using very high-resolution aerial imagery.
3. To 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.
4. Integration of spatially explicit land use information and CO₂ emissions using emission factors proposed by the Intergovernmental Panel on Climate Change (IPCC) and literature sources.

1.6 Literature Review

This section provides a brief overview of the literature on peatlands, remote sensing of peatland use, and artificial drainage. It starts by discussing peatlands in general and their distribution from the global level to the Irish peatlands. The chapter then continues to discuss the main scientific methods and techniques (i.e., remote sensing) used here to study peatlands more specifically peatland land use and artificial drainage. The current state of knowledge and gaps in remote sensing of peatlands are also discussed. Additionally, the literature specific to each chapter is presented in the Introduction section.

1.6.1 Peatlands

“Mire” is a generic term which was first coined by Godwin (1941) in English and referred to as fen, bog, swamp, muskeg, moor and peatland (Clymo 1983). The term is now widely used for peatland ecosystems and is a type of ecosystem where peat is actively accumulating and formed (Joosten and Clarke 2002). One of the features used to distinguish peatland from other wetlands and histosol ecosystems is usually peat depth, with the minimum depth ranging between 30 and 40 cm (Charman 2002; Gorham 1991; Hammond, 1981; Wilson et al. 2011). Whereas, the global average peatland depth is estimated to be around 1.3 – 1.4 m (Lappalainen 1996). The main physical condition which regulates peatlands is the water table, which changes depending on weather conditions and the time of year (Mackin et al. 2015). High-water tables create waterlogging and anaerobic conditions which are essential factors in the formation of peatlands (Gorham 1991; Moore and Bellamy 1974; Rydin and John 2013). Anaerobic conditions impede the activities of decomposing organisms, which in turn limits decomposition (Joosten 2017).

Peatlands are further segregated into multiple types. The variation in peatland types on a global scale makes it challenging to classify peatlands in one particular way, and a globally accepted classification of peatlands still does not exist (Joosten 2017). The classification of peatlands varies based on geographical location, and most countries have developed their own classification systems (Charman 2002). Hence, it is suggested that the more generic term *peatlands*, rather than mire, should be used to describe them (Bridgham et al. 1996; Joosten and Clarke 2002).

There are several different ways in which peatlands are classified and sub-classified (Thomas et al. 2003; Millard and Richardson 2015; Lindsay 2016): including classifications based on the source of nutrients, water and hydro-morphology. The most fundamental basis for peatland classification relates to the water source and nutrient status, namely, ombrotrophic and minerotrophic (Charman 2002). In ombrotrophic peatlands, nutrients and water are primarily acquired from precipitation and are referred to as “bog” (Figure 1.1a). The water received via direct rainfall, snow, fog, or mist exceeds evapotranspiration and runoff, creating waterlogged conditions (Holden 2006). The dependency of ombrotrophic peatlands on

precipitation for water and nutrient sources is because inputs to the peatlands ecosystem are usually higher than the outputs, resulting in the accumulation of dead plant material, and eventually raising the existing surface (vegetation) where groundwater cannot reach (Charman 2002; Lindsay 2018). Minerotrophic peatlands, on the other hand, depend on groundwater as the main source of nutrients and water and are referred to as “fen” (Figure 1.1b) (Charman 2002; Lindsay 2018). Minerotrophic peatlands (fen) have higher nutrient contents than bogs. These nutrients are either supplied by subsoils and bedrock, or solutes which are flushed through focused surface seepage by the adjacent surface water source (Lindsay 2018). Based on nutrient levels, fens are further sub-classified into oligotrophic (nutrient-poor) and eutrophic (nutrient-rich) (Charman 2002).

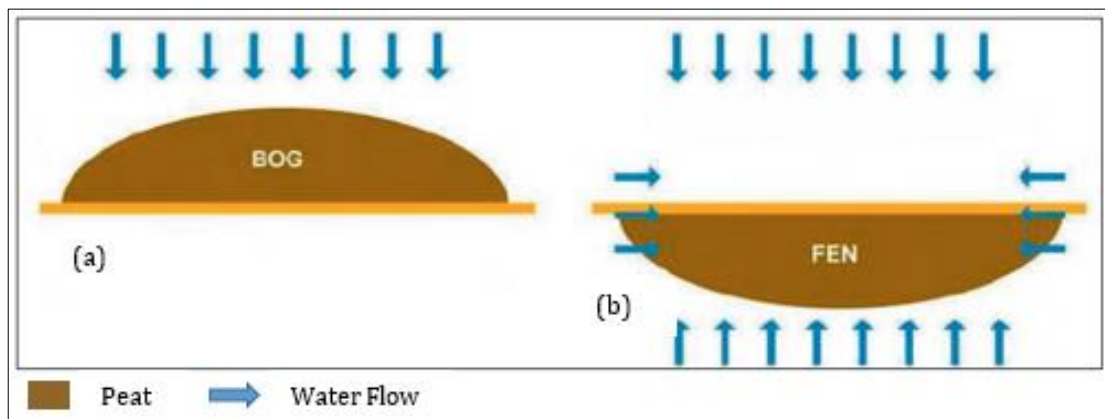


Figure 1.1: Schematic representation of (a) Bog and (b) Fen, depicting water flow and peat accumulation in both type of peatlands.

Earlier use of these two terms (bog and fen) was based on the acidity level rather than the water source (Rietz and Einar 1954). The term “Fen” was linked to peatland environments with low alkaline to moderately acidic and “bogs” related to highly acidic environments. However, more recently, these terms have been used to define two broad classes based on the source of water (along with a level of acidity) such as ombrogenous (precipitation as water source) and minerogenous (groundwater as water source) (Charman 2002; Lindsay 2018).

Peatlands habitat types can also be linked to two complex environmental gradients and can be classified based on that. The first is based on aeration and wetness; the second gradient is related to a combination of base saturation, calcium (Ca) content and pH

(Rydin and John 2013). Bridgham et al. (1996) proposed classifying peatlands based on water source and pH (moderately acid, strongly acid, circumneutral) rather than nutrient level. Fen, due to its strong connection with groundwater, has circumneutral pH (range) with an abundance of Ca, Mg (Magnesium) and base cations (Bridgham et al. 1996; Craft 2015). Contrary to that, the bog is more acidic with less amount of Ca and Mg (Charman 2002; Craft 2015)

1.6.2 Peat soils

The term peat, as defined by the EPA-funded Bogland project, is “a sedentarily accumulated material consisting of at least 30% (dry mass) of dead organic material” (Connolly and Holden 2009; Renou-Wilson et al. 2011). The accumulation of organic matter is due to incomplete decomposition under relatively acidic water-saturated anaerobic conditions (Charman 2002; Rydin and John 2013). Peat is an organic substance that is predominantly formed by the remains of plants that accumulate in situ (Clymo 1983; Page and Baird 2016; Warner 2001). Whereas peatland is “a geographical area where peat soil occurs and for mapping purposes, a peatland should cover a minimum spatial extent of 1 ha” (Connolly and Holden 2009). Peat soils fall under the category of organic soils, usually comprising ≥ 20 mass percentages (Canadian System of Soil Classification 1978). According to the Food and Agricultural Organization of the United Nations (FAO) guidelines for soil description and taxonomy (Survey 1999; FAO 2006), organic soils belong to histosols in the order of taxonomy. Peat has a set of unique physical properties such as high total porosity, low bulk density, and the ability to shrink and swell with drying or wetting, respectively (Rezanezhad et al. 2016). Hence, the methods and concepts used to describe the porous media properties of mineral soils may often be inadequate for defining peat soils. These soils contain organic materials with variable depths. Holman (2009) categorises peat soils into four different types (i) Peat soils that have a thickness of more than 100cm are known as – “Deep” peat; (ii) If the depth of peat soil is less than that of 100cm, it is categories as – “Thin” peat; (iii) Soils that encompass peat layers that are within the soil horizon and, covered by largely alluvial minerals that is more than 30cm,

it known as – Peat at “depth” (iv) Lastly the “remnant peat” - which are wasted to mineral soils and humose soils due to serious erosion, otherwise known as skirt lands.

1.6.3 Peatland hydrology

The most distinctive feature of peatlands is that they are wet (Wheeler 2005). They contain 90%–98% water by weight (Charman, 2002; Holden 2006). In an intact bog, the water table is very high i.e., it is a few centimetres from the surface (Feehan and O'Donovan 1996; Holden 2006). Moreover, the position of the water table, near-surface, and surface moisture is part of peatland hydrology (Wheeler 2005). Moreover, in an intact peatland, the water table remains close to the surface for 75% of the year, and only for short periods (during summer) does it drop below these levels (Holden 2006).

Water balance in peatlands, in its simplest form, depends on three components: influx, efflux, and water storage (Eggelsmann et al. 1993) The balance of these three components is important and depicted as,

$$\text{Influx} - \text{Efflux} - \text{Changes in storage} = 0 \quad 1.1$$

Here, the influx is designated as recharge, whereas the efflux is designated as discharge.

Depending on the specific bog system and site, there may be a large amount of variability in the overall water balance. A slightly complex peatland system of a raised bog with doomed relief can be represented by Eq. 1.2 (Streefkerk and Caspire 1989). The water movement there can be represented by the following equation:

$$P - E - R - D = \Delta S \quad 1.2$$

Where ΔS is the change in the water storage capacity. P = precipitation, E = evapotranspiration, R = surface runoff or supply, D = downwards vertical seepage.

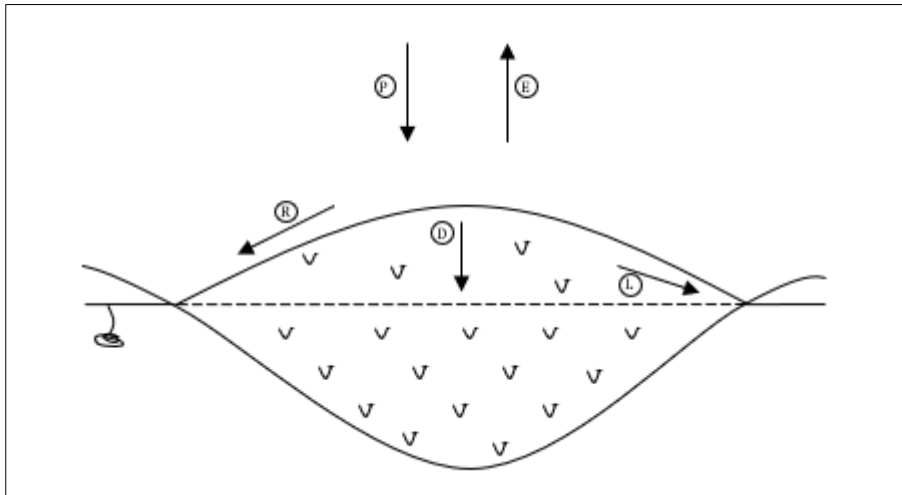


Figure 1.2: Diagrammatic representation of the movement of water in Bogs, representing supply and discharge of water (adapted from Streefkerk and Caspire 1989).

There is a key anatomical difference in the profile between the acrotelm and the catotelm, which also influences hydrology (Charman 2002). The acrotelm (partly living) actively grows on the surface (Figure 1.3) and is 0.1 to 0.3 m deep. More recently, Clymo and Bryant (2008) proposed a transitional layer known as mesotelm (Figure 1.3). It is a dynamic layer situated below the acrotelm (0.3 to 0.5 m deep) which may or may not contain oxygen. The underlying layer, known as the catotelm (anaerobic layer), is composed of saturated peat with minimal water movement (Feehan and O'Donovan 1996; Holden and Burt 2003). Although the catotelm is not as active (in terms of growth of vegetation because of anoxic conditions) as the upper layer would be, it is misleading to think that this layer is inactive, as the process of decay and change continues to occur in this layer (Tallis et al. 1997).

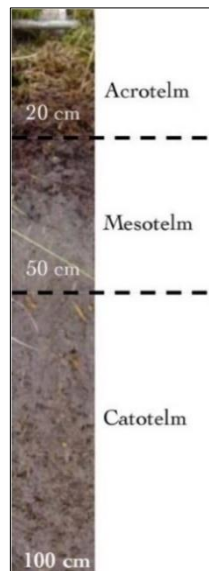


Figure 1.3: Typical profile of peatland, depicting three distinct layers: Acrotelm (the top layer), Mesotelm (transitional/middle layer) and Catotelm (bottom layer)(Zaouk et al. 2018).

Peat accumulation occurs when, over the long term, the water table is just above, below, or at the ground surface (Ivanov 1981; Sjörs 1990; Lamers et al. 1999; Joosten 2017). Hydrology also determines the type of plants that grow on peatlands, the amount of biomass produced, and whether peat accrues (Joosten 2017). In peatlands, the movement of water regulates the diffusion rates of gas and oxygen, the nutrient cycle and availability, redox status, and species diversity and composition. Moreover, it is essential for stream water quality, flooding, and water resource management (Hammond et al. 1990; Bragg et al. 1992). This also means that slight changes in the water table may lead to large changes in the carbon fluxes in peatlands (Evans et al. 1999; Schouten 2002).

1.6.4 Peatland ecosystem function and services

An ecosystem is defined as “a dynamic complex of plant, animal, and microorganism communities and their non-living environment interacting as a functional unit” (Millenium Ecosystem Assessment 2005). In contrast, ecosystem services are simply benefits derived by people from the ecosystem (Costanza et al. 1997; Mace et al. 2012). In a peatland ecosystem, all the components that function in an acrotelm or catotelm

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(be it abiotic or biotic) combine to form an ecosystem function (Connolly 2006). Therefore, they contribute to peatland ecosystem services (Table 1.1).

Table 1.1: Peatland ecosystem services and related functions (Kimmel and Mander 2010)

Ecosystem services of inland wetlands (Millenium Ecosystem Assessment, 2005)	Beneficial functions of peatlands (Joosten and Clarke 2002)	Explanation/Examples
Provisioning services	Production functions	
Fibre and fuel	Peat extracted and used/wild plants (including forests and energy biomass)	Peat used in horticulture, agriculture, domestic heating and energy generation/ raw material for industry and energy generation; medicine
Food	Wild plants/wild and domestic animals	Used as food for people and domestic animals/wood, fur, and medicine
Freshwater	Water Peat substrate	Public water supply is obtained from reservoirs draining peatlands Peatland space is used for agriculture, horticulture, and forestry
	Carrier functions	Space in peatlands for water reservoirs, infrastructure, waste deposits, landfills and military exercises and defence
Regulating services	Regulation functions	
Climate regulation	Regulation of global climate/ regional and local climates	Regulation of greenhouse gases, regulation of climatic processes
Water regulation	Regulation of catchment hydrology	Water storage, groundwater recharge and discharge
Water purification and waste treatment	Regulation of catchment hydrochemistry	Retention, recovery and removal of excess nutrients and pollutants
Cultural services	Informational functions	
Recreational and aesthetic	Recreation and aesthetic functions	Opportunities for recreation and tourism; appreciation of nature
Spiritual and inspirational	Spiritual and existential functions	Personal feelings and well-being: the religious significance
Educational	Signalization and cognition functions	Opportunities for education, training, and research
Supporting services		
Biodiversity		Habitats for species
Soil formation		Accumulation of organic matter
Nutrient cycling		Storage, recycling. processing and acquisition of nutrients

There are three main components of the peatland ecosystem: water, plants, and peat. They are mutually interdependent and closely related (Figure 1.4). Alterations in one

component may trigger changes in the ecosystem services associated with that component and the other two components, such as water quality, flow, regulation, and change in habitat provision for wildlife (Ivanov 1981; Joosten 2017).

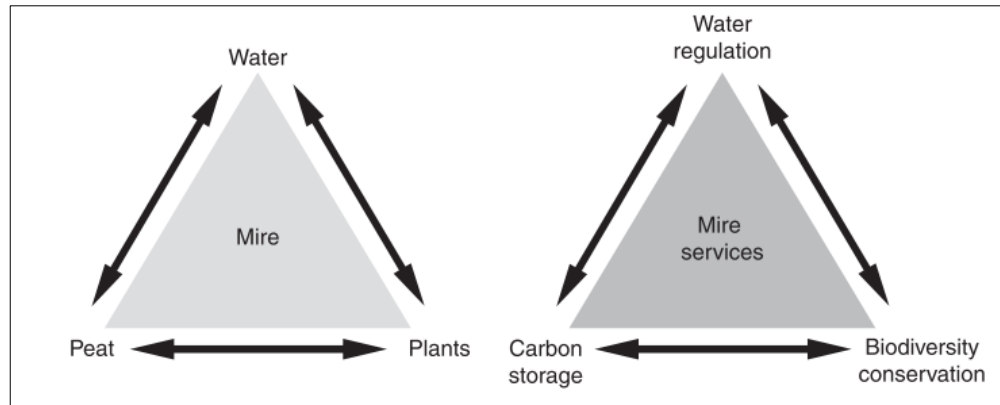


Figure 1.4: Components of Peatlands ecosystem and their relationship with each other and ecosystem services (Joosten 2017).

The triangle on the right in Figure 1.4 also shows the ecosystem functioning of peatlands through the interconnection of these three components. For example, if the water level is reduced below the optimal conditions, it will directly affect the growth of vegetation and, hence, peat formation, and vice versa. Consequently, this will affect the water regulation part of peatland ecosystem services which will have a direct impact on the biodiversity conservation and carbon storage capacity of peatlands. One of the main reasons for the disturbance in one of these three components is anthropogenic utilisation, for example, water is drained to enable agricultural, domestic use, or peat extraction, which in turn upsets the whole ecosystem.

1.6.5 Historical formation of peatlands in Ireland

Peat formation in Ireland can be traced back to the onset of the post-glacial period, which occurred shortly after 10,000 BP. (Hammond 1981; Feehan and O'Donovan 1996; Renou-Wilson 2018). Raised bogs initially began to form in lakes and hallows, which were left by the retreating ice that covered most of the midlands of Ireland

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(Feehan and O'Donovan 1996; Renou-Wilson 2018). This process is depicted in Figure 1.5.

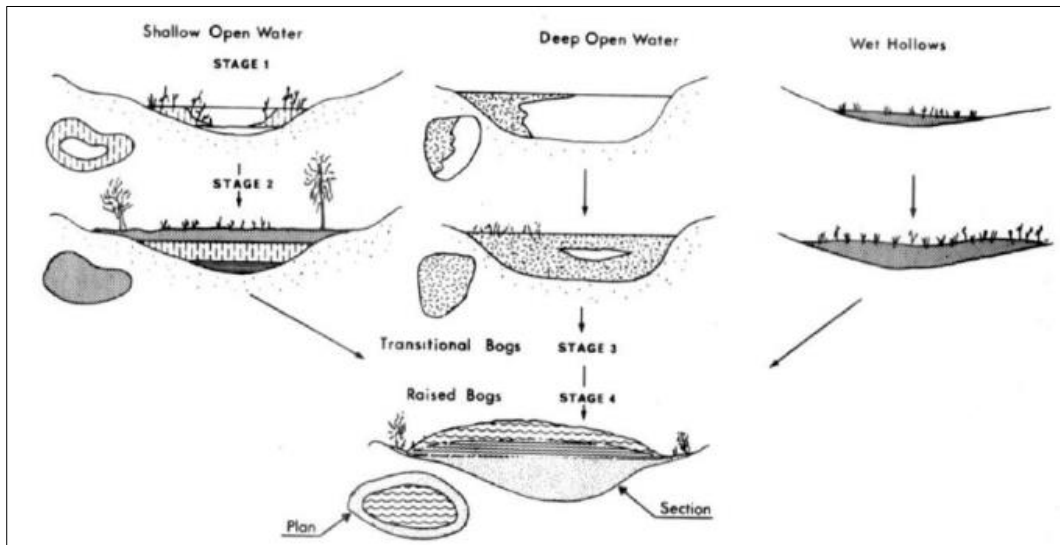


Figure 1.5: Succession in raised bog formation: showing the transformation of a shallow open water body into a raised bog over time (Hammond 1981).

Many of the post-glacial lakes, such as the Lough Boora, Lough Ree-Derg and Greater Lough Allen, covered large areas of the Midlands along the River Shannon (Feehan and O'Donovan 1996; Knight 2003). These lakes were fed by the groundwater that originated from calcareous glacial drift (Mitchell and Ryan, 1997).

The post-glacial birch period (birch began to become the dominant tree in the post-glacial landscape) marked the beginning of Marl accumulation in lakes (Feehan and O'Donovan 1996). This was followed by the Boreal Period (Post-glacial period between 8800–7500 B.P.). The development of fen peat started with reed peat when the sedges and reed encroached around the edges of the lake and their remains fell into the water where their partial decomposition happened (Feehan and O'Donovan 1996; Renou-Wilson 2018). The changeover from minerogenous fen to ombrogenous bog was initiated around the periphery between the Boreal and Atlantic periods ~7,000 – 5000 B.P.. (Feehan and O'Donovan 1996; Charman 2002).

The accrual of undecayed remains and the upward growth of other plants and sedges (sphagnum and brown moss) 'raised' the peat surface above the reach of the groundwater eventually turning them into ombrogenous raised bogs up to 14 m deep

(averaging 6-7 m) (Renou-Wilson 2018). The development of a raised bog can be linked to Terrestrialisation, a process which converts shallow water bodies into bogs via a successional accrual process of inorganic and organic substance deposition (Feehan and O'Donovan 1996; Charman 2002).

The development of blanket bogs started about 4000 - 7000 years ago in Ireland (Hammond 1981; Mitchell and Ryan 1997; Renou-Wilson 2018; Thorp and Glanville 2003), and these bogs are found along the western seaboard and in upland areas of the country (Feehan and O'Donovan 1996). They formed in areas with high rainfall, as shown in Figure 1.6. The development of these bogs can be linked to Paludification, a process in which peat from raised bogs spreads to the surrounding waterlogged mineral soils; as a result, they have a shallow blanket peat layer of approximately 2.5 m but can be up to 6 m deep (Feehan and O'Donovan 1996; Wilson 2018).

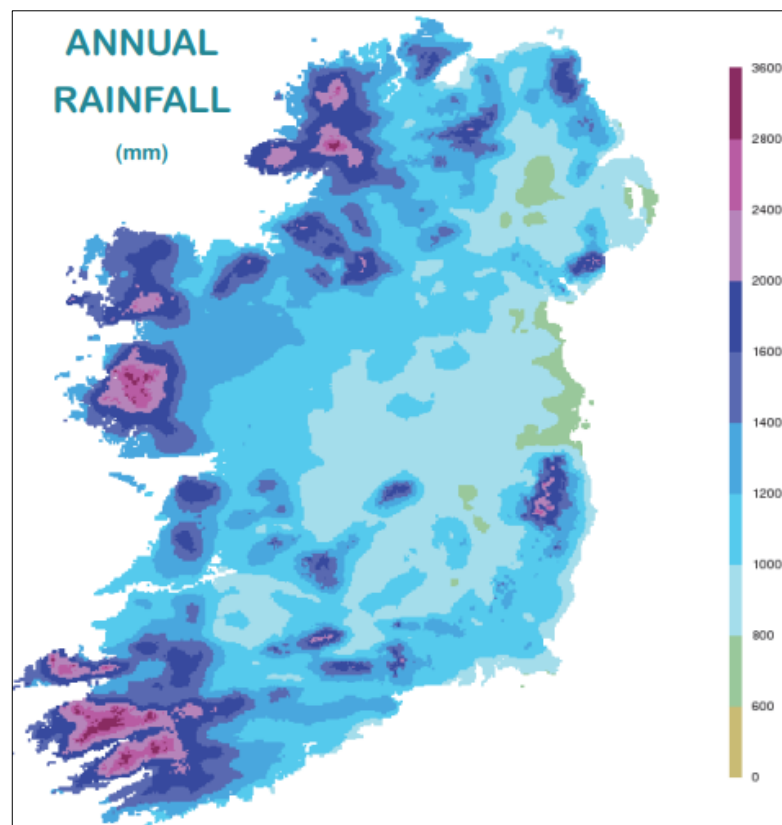


Figure 1.6: Annual rainfall average in Ireland between 1981- 2010, with highest average rainfall in west coast high elevation areas (Walsh 2012).

Similar to raised bogs, blanket bogs also begin as hollows that are gradually filled (Figure 1.7), causing the bog to spread outwards and connect with nearby formations to develop a blanket of peat (Moore 1987). The development of blanket bogs is primarily influenced by climatic factors, more specifically cool summers along with high levels of precipitations (Figure 1.6) on slopes with gradients less than 20 degrees and impeded drainage (Feehan and O'Donovan 1996).

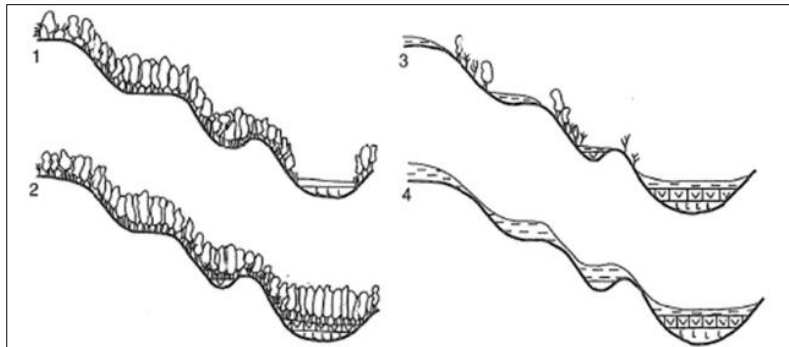


Figure 1.7: The developmental stages of blanket bogs and the forest-to-blanket bog transition across an upland terrain with varied topography. V symbols represent vegetation in shallow depressions, while L symbols denotes lake clay (Moore 1987).

1.6.6 Anthropogenic activities in peatlands

Globally, about 80% of the peatlands are in natural conditions, including those located in remote parts of Alaska, Canada, and Siberia (Joosten 2017). However, an additional 5000 km² is being exploited annually by human activities, meaning that peatlands are being degraded ten times faster than their average expansion rate (Joosten and Clarke 2002). In Europe, some 44% of peatlands are no longer able to accumulate peat (Joosten 2017). Tanneberger et al. (2021) indicated that the European Union accounts for about half of the Globally degraded peatlands. Consequently, degraded peatlands worldwide contribute significantly to current anthropogenic GHG emissions, potentially accounting for up to 5% of global emissions (Huang et al. 2021; Strack et al. 2022)

The impact of anthropogenic disturbances on peatlands in Ireland can be traced back to prehistoric times when peatlands were primarily used as a source of fuel (Feehan

and O'Donovan 1996; Wilson 2018). As early as 1685 these landscapes were considered as 'unproductive land that should be put to more productive usages' (King 1685). A recommendation was put forward by the Bog Commissioners in the early 1800s (1810-1814) to drain and convert the vast bogs in the midlands of Ireland to agricultural land (Figure 1.8), to produce raw material required by the British in their wars against Napoleon (Horner 2005).

Likewise, much of the degradation between 1814 and 1940 can be attributed to the artificial drainage of bogs for agricultural use (Carroll-Burke 2002). Post-1940s, about 40,000 ha of raised bogs were subject to land use change as a 'major investment was made to develop the peat fuel industry' (Hammond 1981). Agriculture is one of the oldest land uses of peatlands due to population pressure, and the industrialisation of both agriculture and peat harvesting for electricity production intensified the degradation of peatlands in the 1950s (Feehan and O'Donovan 1996; Renou-Wilson 2018).



Figure 1.8: Example of agricultural grassland on a raised bog (Lullymore, Co. Kildare).

Industrial peat extraction is facilitated by the installation of drainage ditches (Figure 1.9a), which reduce the moisture content (80–95%) due to lowering of the water table (Wilson et al. 2013). The history of large-scale industrial peat extraction activities on Irish raised bogs can be traced back to the mid-20th century as the demand for peat as a fuel source for electricity and domestic fuel increased (Hammond 1981). With the establishment of the Turf Development Board in 1934, which was later dissolved and replaced with BnM in 1946, huge areas of raised bogs were converted into a “major fuel production complex” (Kearns 1978). Mechanical peat extraction activities intensified after World War II, particularly for the use of peat for electricity generation.

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The majority of peatlands that were being utilised for peat extraction (~80%) for energy production and horticulture, were owned by BnM (Bord na Móna, 2010). On the other hand, domestic peat extraction (Figure 1.9b) also has a long history in Ireland, with evidence of peat being cut and used as a fuel for heating and cooking dating back to the 7th century and probably becoming the main source of fuel in the 17th century (Feehan and O'Donovan 1996). Most of this peat was cut using hand tools until the 1970s when extraction using heavy machinery became more common (Höper et al. 2008). The total area of peatland that is disturbed through domestic peat extraction by hand and mechanical cutting is poorly known, for LULUCF reporting it is around 400 ha however, other estimates show it to be around half a million hectares (Wilson et al. 2013; Malone and O'Connell 2009).



Figure 1.9: Artificial drainage on peat extraction sites showing (a) drain on a cutover site with growth and infill and (b) drain on industrial bare peat site (Co. Roscommon).

In terms of forestry on peatlands (Figure 1.10 (a and b)), between the 1950s and 1990, approximately 200,000 ha of peatlands were afforested under the state afforestation



Figure 1.10: (a) Afforested peatlands, drains, clear fell, and wind turbines in the background (b) drain in afforested peatland (Moher East, Co. Tipperary).

program initiated in 1948 (Farrell and Boyle 1990; Neeson 1991). An estimate from Foss et al. (2001) indicated that 8% of raised bogs and 21% of blanket bogs were severely degraded. The Bogland report 10 years later found that intact raised bogs in Ireland no longer exist, and blanket bog areas, although unknown, are also likely to have reduced (Renou-Wilson et al. 2011). The more recent uses of peatland range from industrial infrastructure development to housing and wind farms (Figure 1.10 (a)), recreation, tourism, and military exercises (Foss 2007; Wilson 2018). Moreover, each year, over 500,000 tons of peat were cut every year to heat approximately 20,000 households (most of them in rural areas) until late 2010 (Bullock et al. 2012). However, there was a gradual decline in the total household peat consumption by 2.9% (Howley et al. 2009). It is also estimated that 50% of the horticulture industry output is dependent on peat, which is used as a growing medium by professional and amateur gardeners and growers (Government of Ireland, 2019).

All the aforementioned anthropogenic land use also had an overall negative impact on peatland carbon sequestration and storage. It disturbs ecosystem function and may turn peatlands from a natural carbon sink to a source and trigger high GHG emissions (Leifeld and Menichetti 2018). More specifically, the disturbances caused by drainage can affect the microclimate, hydrology, and physical peat properties (Price 1996). Drainage ditches increase the aerobic zone in the upper layers of peatlands which results in increased decomposition; hence, the loss of CO₂ accelerates (Waddington et al. 2001). Drained peatlands continue to degrade until the peat deposit is completely leached and oxidised (Erkens et al. 2016). Consequently, the excavation and oxidation of peat causes GHG emissions which accumulate over decades to centuries (Leifeld et al. 2019). Drainage networks are also conduits of terrestrial carbon mobilisation in the form of particulate and dissolved organic carbon (POC and DOC) and Dissolved Inorganic Carbon (DIC) (Waldron et al. 2019).

More recently, with the cessation of large-scale industrial activities carried out by BnM, some sites are undergoing rewetting, including, for example, rewetting schemes such as PCAS. As a result, the exposed peatlands are being revegetated or show surface water due to these activities (Figure 1.11).



Figure 1.11: A former industrial peat extraction site rewetted, with exposed peat on the right and stagnant water as well as vegetation growth on the left (Lullymore, Co. Kildare).

1.6.7 Remote Sensing

Introduction

Remote sensing is broadly defined as the process of collecting information about a distant object, area, or phenomenon (earth and other planetary surfaces) without physical contact with them. However, within the scope of this study, the following definition by Campbell and Wynne (2011) is the most relevant.

“Remote sensing is the practice of deriving information about the Earth’s land and water surfaces using images acquired from an overhead perspective, using electromagnetic radiation in one or more regions of the electromagnetic spectrum reflected or emitted from Earth’s surface.”

The electromagnetic spectrum (Figure 1.12) covers the entire range of electromagnetic radiation (EMR) and is divided into distinct regions based on frequency. Moreover, each portion of EMR is associated with the wavelength of the electromagnetic spectrum (Jensen 1996; Lillesand et al. 2000; Campbell and Wynne 2011; Richards 2013). The lower end of the spectrum represents the portion of the EMR with longer wavelengths, such as ultraviolet, X-ray, and gamma rays. The upper end represents EMR with shorter

wavelengths, including microwave, infrared (IR), television, and radio waves. Visible light occurs in a very small part of the EMR (ranging from 0.4 to 0.7 μm). The visible range is further divided into a blue band with wavelength ranging from 0.4 - 0.5 μm , a green band from 0.5 - 0.6 μm and a red band ranging from 0.6 - 0.7 μm (Lillesand et al. 2000; Mather and Koch 2011; Campbell and Wynne 2011).

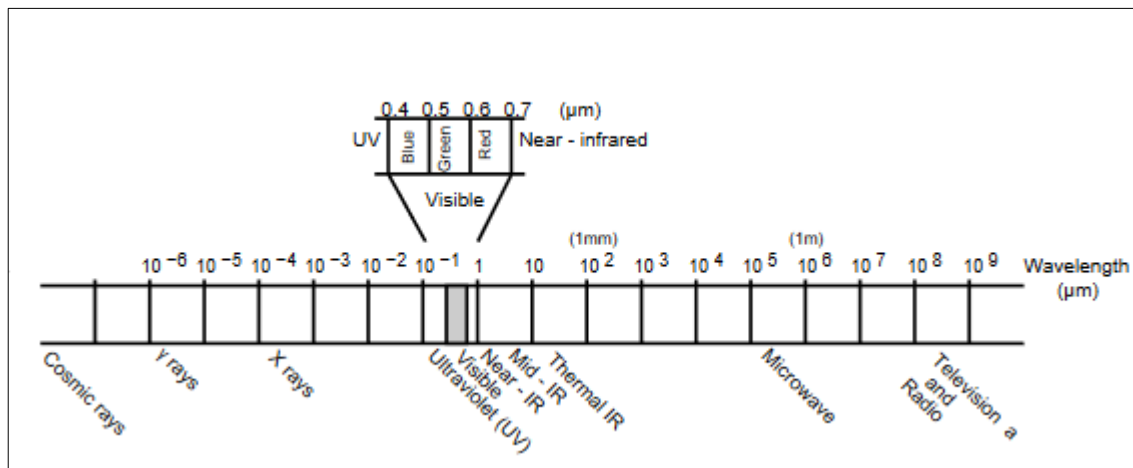


Figure 1.12 The electromagnetic spectrum (Lillesand et al. 2000).

Platforms and Sensors

Remote sensing is one of the main sources of spatial information about Earth's surface cover (Schmidt and Skidmore 2003). The term remote sensing was traditionally used for airborne and satellite-based platforms (Toth and Józków 2016). More recently, however, with the rapid advancement in remote sensing technology, a new platform system UAS (Unmanned Aircraft System) has also been introduced (Colomina and Molina 2014; Pajeres 2015). These platforms carry digital sensors onboard, which collect the visible and invisible portions of electromagnetic energy (Longley et al. 2005; Lagro 2011; Richards 2013; Liang 2017).

In satellite-based platforms, the sensor is onboard a spacecraft or satellite orbiting the Earth (Liew 2001). These have been around for more than forty years now; for example, Landsat-1 was launched in 1972 (Lulla et al. 2012). A remote sensing system can be based on a single satellite or multiple satellites (constellation) which allows for multiple observations in a day (Toth and Józków 2016). Airborne remote sensing, on

the other hand, uses sideward or downward-looking sensors that are on board an aircraft. Until the introduction of commercial remote sensing satellite systems, such as the launch of Ikonos in 1999, airborne remote sensing was the primary source of geospatial data acquisition in developed countries (Toth and Józków 2016).

Characteristics of remote sensing data

The features of the sensor and platform determine the different types of resolutions of the data that is acquired. There are four types of resolution: spatial, spectral, radiometric, and temporal (Liang et al. 2012). The spatial resolution plays a key role in determining the physical characteristics of an object being imaged. This is the measure of the smallest object/area that can be imaged by the sensor (Lillesand et al. 2000; Campbell and Wynne 2011). The spectral resolution refers to the width and number of spectral bands covered by the sensor system. (Jensen 1996; Richards 2013). The radiometric resolution describes the dynamic range or degree of intensity of the radiation that the sensor can distinguish (Campbell and Wynne 2011). It is represented as the number of bits e.g., in 8-bit data, the DN (Digital Number) has a range between 0-255, where each pixel can have values from $2^8 = 256$ total possible numbers. Lastly, temporal resolution refers to the frequency or repetition of the cycle of revisits over the same point on Earth by the sensor (Liang, 2017).

Active and passive remote sensing

Remote sensing can be further divided into two distinct types based on the instruments that capture energy: active and passive (Figure 1.13). Active remote sensing refers to the sensor illuminating the terrain with energy generated by the sensor itself (Campbell and Wynne 2011; Kumar and Shukla 2015; Liang 2017) for example, LIDAR (Light Detection and Ranging) and RADAR (Radio Detection and Ranging) are two common types of sensors that are used for this purpose, an example of some of the satellites are Sentinel-1, RADARSAT, TerraSAR-X see Table 1.2. Passive remote sensing refers to the detection of reflected solar radiation in the form of microwave or thermal

radiation, or visible light from objects on the Earth's surface (Maini and Agrawal 2011; Campbell and Wynne 2011; Liang 2017).

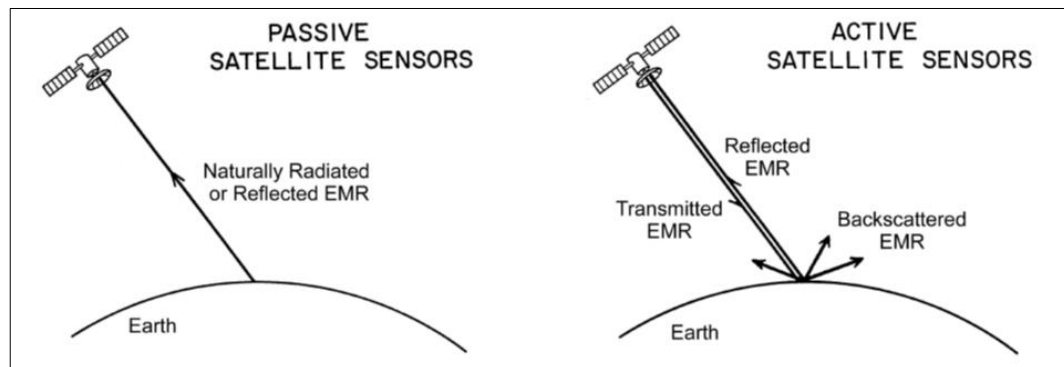


Figure 1.13 Active and passive satellite sensors (Wilson et al. 2020)

Optical sensors which work on the principle of passive remote sensing detect a range of radiation from visible to thermal infrared (IR), using both emitted and reflected radiation from targets in the overlying atmosphere and on the ground to generate images (Rajendran 2009; Emery and Camps 2017).

Depending on the number of spectral bands (also called spectral channels) used in the process of imaging, optical remote sensing can be classified as either a single-band or multi-band image e.g., a Panchromatic or Multispectral Imaging system. The Panchromatic system is based on a sensor that is sensitive to radiation in a single channel covering a broad range of wavelengths e.g., Landsat 7 panchromatic band covers wavelength between 0.52-0.90 nanometres. Examples of such satellites with sensors include Ikonos PAN, SPOT HRV-PAN etc. On the other hand, sensors that can sense radiation in multiple channels, with each channel covering narrow wavelength bands, are known as multispectral imaging systems, such as Copernicus Sentinel-2 A/B, LANDSAT-8, and Ikonos-2 (Table 1.2).

Table 1.2 Earth Observation Sensors (selected), as modified from (Toth and Józków 2016). PAN: Panchromatic; MS: Multispectral, HSI: Hyperspectral Imager, SAR: Synthetic Aperture Radar

Name	Launch	Constellation	Sensor	GSD range (m)	Swath width (km)	Revisit time (day)
Ikonos-2	1999	Single	PAN	0.8×0.8	11.3	3
			4 MS	3.2×3.2		
SPOT 6	2012	Dual	PAN	1.5×1.5	60	1-5
SPOT 7	2014		4 MS	6×6		
Landsat-8	2013	Single	PAN	15×15	185	16
			11 MS	30×30		
Sentinel-2	2015	Dual	13 MS	10×10	290	10
				20×20		
	2016			60×60		5 (dual)
Terra (MODIS)	1999	Single	14 MS (IR)	15×15	60	16
				30×30		
			36 HSI ³	90×90		
				250×250		
				500×500		
				1000×1000		
Aqua (MODIS)	2002	Single, part of A-Train	36 HSI	250×250	2330	1-2
				500×500		
				1000×1000		
RADARSAT-2	2007	Single	C-band SAR	3×3	20	24 (orbit repetition)
				100×100	500	
	2007	Single		1×1	5×10	11

Name	Launch	Constellation	Sensor	GSD range (m)	Swath width (km)	Revisit time (day)
TerraSAR-X			X-band SAR	16×16	1500×100	
TanDEM-X	2010	Single, tandem with TerraSAR-X	X-band SAR	1×1	5×10	11
				3×3	1500×30	
				16×16	1500×100	
Sentinel-1	2014	Dual	C-band SAR	5×5	80	12
	2016			5×20	250	
						6 (dual)

A sensor which has sensing capability in even more channels (typically > 10) with narrower wavelength coverage than multispectral sensors is known as a super-spectral imaging system. Some examples are MODIS and MERIS sensors, which acquire images covering hundreds of channels (also called an “imaging spectrometer”) and are known as hyperspectral sensors. The level of spectral information captured by these HSI sensors is precise and can be used to better identify and characterise targets (Rajendran 2009).

Sentinel-2

The Sentinel-2 constellation is part of the space component of the Global Monitoring of Environment and Security (GMES) program (ESA 2015). Sentinel-2 satellites are equipped with Multispectral Instrument (MSI) sensors. They perform various services that depend on the observation of terrestrial surfaces using multispectral high-spatial-resolution optical sensors (Drusch et al. 2012).

The Sentinel-2 MSI captures information from 13 distinct spectral channels (Drusch et al. 2012). The spatial resolution varies between these different bands, and each band

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covers a specific region of the electromagnetic spectrum. The spatial resolution of the blue, green, red, and NIR bands is 10m, while the shortwave infrared (SWIR) bands have a spatial resolution of 20m, and the remaining bands have a resolution of 60m see Table 1.3) (Drusch et al. 2012; ESA 2015).

Table 1.3: Characteristics of Sentinel-2 bands

Bands	Central wavelength (µm)	Spatial Resolution (m)
Band 1 - Coastal aerosol	0.44	60
Band 2 - Blue	0.49	10
Band 3 - Green	0.56	10
Band 4 - Red	0.66	10
Band 5 - Vegetation red edge	0.70	20
Band 6 - Vegetation red edge	0.74	20
Band 7 - Vegetation red edge	0.78	20
Band 8 - NIR	0.84	10
Band 8A - Vegetation red edge	0.86	20
Band 9 - Water vapor	0.94	60
Band 10 - SWIR - Cirrus	1.37	60
Band 11 - SWIR	1.61	20
Band 12 - SWIR	2.19	20

Landsat-5 and 8

USGS Landsat satellite data provide one of the richest archives of medium-resolution multispectral satellite imagery, with imagery dating back to 1972 (Wulder et al. 2016). Landsat-5 satellite, which was launched in 1984, carried two sensors: the Thematic Mapper (TM) and the Multi-Spectral Sensor (MSS). Data acquisition by the MSS sensor ended in 1999 (USGS, 2016). In this study, data captured with the TM sensor were used for 1989-1991 and 2004-2006 images. The TM sensor captured images in six spectral bands with a 30-meter spatial resolution. This study mainly utilised bands 1-5 and 7 (Table 1.4).

Landsat-8 satellite, launched in 2014, includes two sensors: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) instruments. In this study, data captured with the OLI sensor were used for the 2017-2020 period. The OLI sensor captured images in 11 spectral bands with a spatial resolution of 15-30 meters. The study mainly utilised bands 2-7 (Table 1.4).

Table 1.4: Characteristics of Landsat -5 and 8 images

Satellite	Bands	Wavelength (µm)	Spatial Resolution (m)
Landsat-5 (TM)	Band 1 – Blue	0.45-0.52	30
	Band 2 – Green	0.52-0.60	30
	Band 3 – Red	0.63-0.69	30
	Band 4 – Near Infrared (NIR)	0.76-0.90	30
	Band 5 – Shortwave Infrared (SWIR) - 1	1.55-1.75	30
	Band 6 – Thermal	10.40-12.50	120 (30)
	Band 7 – Shortwave Infrared (SWIR) - 2	2.08-2.35	30
Landsat-8 (OLI)	Band 1 – Ultra Blue	0.43-0.45	30
	Band 2 – Blue	0.45-0.51	30
	Band 3 – Green	0.53-0.59	30
	Band 4 – Red	0.63-0.67	30
	Band 5 – Near Infrared (NIR)	0.85-0.87	30
	Band 6 – Shortwave Infrared (SWIR) - 1	1.56-1.65	30
	Band 7 – Shortwave Infrared (SWIR) - 2	2.10-2.29	30
	Band 8 – Panchromatic	0.50-0.67	15
	Band 9 – Cirrus	1.36-1.38	30
	Band 10 – Thermal Infrared (TIRS) - 2	10.60-11.19	100 (30)
	Band 11 – Thermal Infrared (TIRS) - 2	11.50-12.51	100 (30)

Limitations

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Remote sensing-based systems have both strengths and weaknesses associated with them. Some of the issues that are inherent with remotely sensed images are discussed by Kerr and Ostrovsky (2003) (e.g., since these measurements are taken at a substantial height from space, there is a problem of scale mismatch associated with in-situ measurements from ecological sensors and data obtained via satellite images. There are negative impacts of clouds and cloud shadows (CCS) associated with optical data. This is a problem, especially in temperate countries such as Ireland (McGovern et al. 2002; Wang et al. 2009). Moreover, some of the problems inherent to remote sensing data are related to trade-offs between spatial, temporal, and spectral resolutions which limits the use of this technology; for example, higher spatial and spectral resolutions are difficult to achieve simultaneously (Newland 1999; Cenci et al. 2018; Durgun et al. 2020).

Additionally, issues related to sensor and platform functions are characteristic of remote sensing data. Errors associated with sensor malfunctions, poor sensor calibration, atmospheric influences, and image registration can also lead to serious problems (Lillesand et al. 2000; Miura et al. 2000). For example, in Landsat 7 imagery, on 31 May 2003, the failure of the Scan Line Corrector (SLC) led to huge data gaps being introduced to the data (Scaramuzza and Barsi 2005). Similarly, owing to an issue with the MODIS sensor, there was a complete loss of data between Julian days 177 and 193 in 2001 (Wan et al. 2004).

Active remote sensing systems such as radar and LiDAR can overcome some of the limitations posed by optical data, such as CCS because these systems can penetrate cloud cover and do not require solar energy to illuminate features on Earth. However, there are also some limiting factors associated with these systems; SAR, for example, requires long-term observation to distinguish between noise and displacement signals, and the temporal data are still limited as SAR-based satellites have been introduced more recently (the early 1990s) (Zhou 2013).

Nonetheless, despite these limitations, remote sensing provides a multitude of measurements that are ecologically valuable, such as biophysical characteristics and habitat details (land cover classification and ecosystem measurements), along with the capacity to identify natural and human-induced changes across landscapes (Kerr and Ostrovsky 2003). Moreover, to overcome the trade-offs between the strengths and weaknesses of different ground-, space-, and aerial-based sensors, they are sometimes

used in combination to complement each other (Harris and Bryant 2009; Bourgeau-Chavez et al. 2017; Hribljan et al. 2017; Millard et al. 2018).

1.6.8 Remote Sensing Image classification

Remote sensing image classification is a complex process that takes many different factors into account (Lu and Weng 2007). The classification process involves multiple steps (Figure 1.14). One of the first steps of the process is the selection of a remote-sensing imagery and classification system. The decision for the selection of remotely sensed data is based on the different characteristics discussed in previous sections, i.e., spatial resolution intended needs of use, and scale are some of the most important (Estes et al. 1999; Althausen 2002; Lefsky and Cohen 2003).

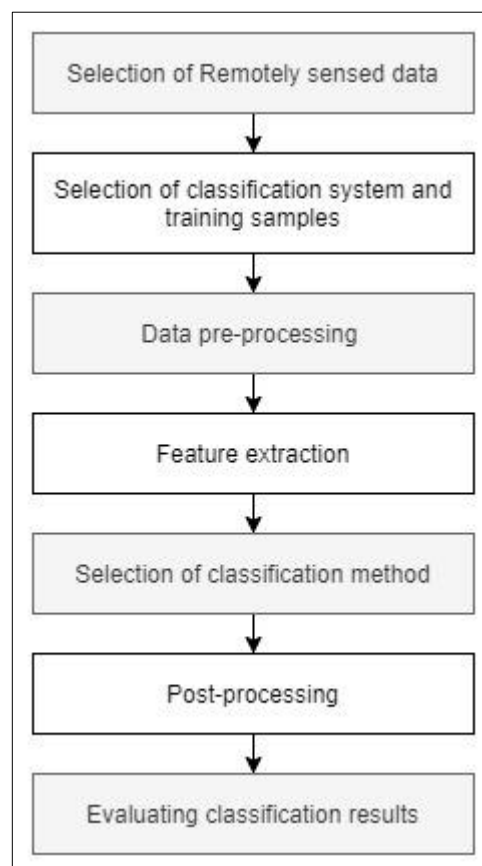


Figure 1.14 Image classification process, adapted from (Lu and Weng 2007)

Classification system (taxonomy) and training samples

One prerequisite for successful remote sensing image classification is the identification or development of a suitable classification system (taxonomy) (Lu and Weng 2007). A classification system should have the capacity to be applied over wide-ranging extents, compromised by a hierarchical set of classes that would allow aggregation and an extensive range of classes. Thus, all areas can fit within a class, which can eventually provide results in a consistent and repeatable manner through time, and there is a reasonable level of accuracy between the classes (Anderson 1976).

For example, a land use classification system should be broad enough to represent at least four main ways that a human can interact with its environment: production, built-up, recreation, and construction. Production: producing or removing natural resources from an area, such as grazing, agriculture, peat extraction; built-up: construction of buildings for inhabiting or working; tourism or recreation: visiting an area for enjoyment but not using it for any significant construction; conservation: setting aside places with the purpose of protecting natural systems and wildlife habitat (Theobald 2014).

In general, the classification system should be exhaustive, informative, and have the ability to discriminate between highly detailed land-cover classes (Jensen 1996; Rochon et al. 2003). Furthermore, the selection of an adequate number of training samples and their representativeness are also of critical importance (Rochon et al. 2003; Pal et al. 2013). The strategy adopted for the collection of training samples influences the result of image classification, particularly in the case of very high spatial resolution imagery, since it contains more ground details; classification strategies can be based on a polygon or a single-pixel or a point, depending on the analysis (Chen and Stow 2002). Therefore, for the selection of training samples, the important factors to be considered are the spatial resolution of the imagery, the complexity of the landscape, and the availability of ground reference data (Lu and Weng 2007).

Feature extraction is one of the most critical steps in remote-sensing image classification (Guo et al. 2019). Traditionally, the features discernible in aerial photographs were collected using manual photogrammetric methods (analytical) on an analogue film; however, these techniques are very time-consuming and require highly skilled operators (Taylor and Ruzgiene 2012). However, with the introduction

of digital aerial photography and modern computing capabilities, feature extraction techniques have become more sophisticated and vary from semi-automatic (integration of computer-based models and humans) to automatic (Leymarie et al. 1996; Gruen and Agouris 1997; Trinder and Wang 1998; Mayer 1999; Sha et al. 2020). Humans and computers complement each other's strengths; while humans are good at distinguishing objects and scanning large areas, computers work best at repetition, optimisation, and detailed delineation (Greve 1996). Automated, manual, or combined feature extraction can be an extremely involved process (Quackenbush 2004). Manual extraction utilises the interpretation skills of a human operator, which can be time-intensive and hence costly to achieve (Baumgartner et al. 1999). On the other hand, automated feature extraction from imagery has been the subject of research since the 1970s. It offers the possibility of saving time as well as labour and includes the prospect of enhanced accuracy and consistency in planimetric data (Yee 1987).

Classification methods

In remote sensing, the selection of an image classification method is a process that requires the consideration of many factors, such as the spatial and spectral resolution of remote sensing data, the availability of classification software, the sources of data, and the type of classifier to be used (upon which the results are dependent) (Lu and Weng 2007). There are several classification methodologies, including pixel-, subpixel-, and object-based. Moreover, classification methods can also be based on the type of learning (supervised and unsupervised learning) and the assumption of data distribution, that is parametric and non-parametric.

Linear feature extraction

Extraction of linear features, such as drainage, streams, and road lines, is an important technique in remote sensing image processing (Niu et al. 2007). One of the main motivations for the development of automated linear feature extraction methodologies is the need to assess the condition and location of roads in our society, and the

importance of having up-to-date databases on roads (Pigeon et al. 1999). Nevertheless, several challenges are associated with mapping linear features in remote sensing images (Park et al. 2002). One particular challenge is related to the spatial resolution of imagery. To identify and extract a feature from the imagery, the spatial resolution should be sufficiently high to resolve the object. This means that the success of extracting linear features is specifically associated with the spatial resolution of the imagery (Wang and Zhang 2000).

Extensive research has been conducted on linear feature extraction and wide-ranging techniques have been developed to address this issue (Fischler et al. 1987; Ohlhof et al. 2003; Mohammadzadeh et al. 2004; Murphy et al. 2008). While most of the research focuses on extracting specific features, such as roads, some considered techniques for generalising the extraction of linear features, such as railroads, canal runways, and peatland drains (Connolly and Holden 2017; Fischler et al. 1987). Quackenbush (2004) reviewed the various techniques used to extract linear features from remotely sensed imagery, some of which are discussed here. (i) Mathematical morphology: A filtration process is used to extract the features using a kernel, and the result is reliant on the match between the operation performed, the image, and the kernel. The process was developed to extract roads from panchromatic images (O'Brien 1989). (ii) The Hough transform is another technique that was developed to identify the direction of linear features using a parametric approach and hence works with any type of feature that can be parameterised. This method was specifically developed to extract geological features (Karnieli et al. 1996). (iii) Multiresolution techniques: involve resampling of high-resolution imagery (in which roads are represented as homogenous features) to low-resolution imagery and identification of roads are done using edge detection techniques (Baumgartner et al. 1999; Gibson 2003). (iv) Template matching is a technique that is guided by a template defining the general attributes (shape, size intensity, etc.) of features of interest. Linear features are identified by moving the template over the image and further similarity measures are used to find the suitable location of the features (Suetens et al. 1992). (v) Pixel swapping utilises the combination of both the spatial and spectral information that is generally available with the remotely sensed data. This is different from other techniques because spatial information is usually not considered (Iisaka and Sakurai-Amano, 1995). (vi) Knowledge integration is a technique that uses contextual knowledge that can be incorporated as ancillary information to optimise the identification of specific features.

A study conducted by Fischler et al. (1987) developed a numerical score-based approach to identify the likelihood of a pixel being a part of the feature of interest. (vii) Classification-based approaches specifically exploit the multispectral nature of most satellite images. These have been mostly used for pre-processing in the feature identification process (for example, the segmentation of high-resolution imagery into objects based on spectral information). However, with recent advances and the advent of artificial intelligence-based techniques in image classification, it has proven successful in the identification of objects from remotely sensed data (Cheng and Han 2016). Furthermore, along with the spectral bands in multispectral or hyperspectral imagery, many other possible variables can be used in the image classification process, including vegetation indices, contextual or textual information, ancillary data (e.g. elevation), and spectral signatures (Lu and Weng 2007).

Supervised and unsupervised classification

The most commonly used classification methods are based on the type of learning (Hasmadi et al. 2009). They are further divided into two distinct categories: supervised and unsupervised. Unsupervised classification is an automated classification approach in which the user's prior knowledge is not required to assign the pixels to a certain category of classes (Richards 1991; Lillesand et al. 2000). In this process, an algorithm classifies pixels based on the statistical grouping of the data (Lillesand et al. 2000). Spectral similarity or spectral distance, a scalar measure used to determine the resemblance of spectra between two pixels, is used to group pixels (Jensen 1996). In the feature space, a scatterplot with a dot for every pixel in the image between two chosen bands of an image is used to group the data into classes (Richards 1991; Jensen 1996). The basic principle of this approach is that the different classes should be relatively well separated in a feature/measurement space, as shown in Figure 1.15, whereas the values within a given class should be close together (Lillesand et al. 2000). Examples of this classification include ISODATA and K-means clustering.

In supervised classification, the analyst or user 'supervises' the classification process by specifying the pixels that are to be classified into a certain category (Jensen 1996; Lillesand et al. 2000; Tadesse et al. 2003; Boori et al. 2018).

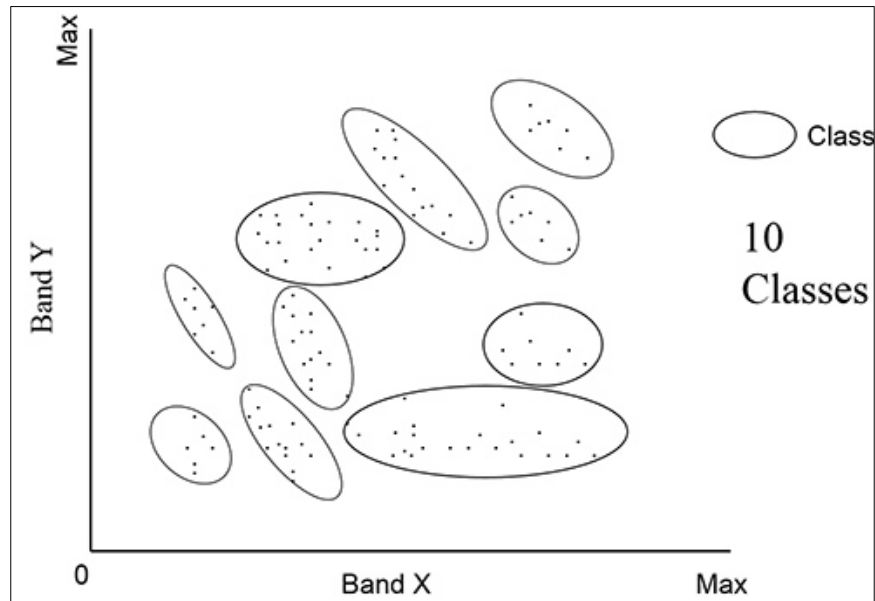


Figure 1.15 Illustration of feature space

This technique is preferred for quantitative remote sensing and mapping of land cover, which is of interest to users (Richards 1991). The spectral signature for known land cover types is manually labelled by the user. These labelled regions are used as a training set for the classification process (Lillesand et al. 2000; Boori et al. 2018). This type of classification is dependent on the availability of a sufficient number of labelled pixels to train the classifier (Richards 1991). Examples of supervised classification algorithms used in remote sensing include maximum likelihood, parallelepiped, and minimum distance (Jensen 1996). Supervised classification provides the user with added control over the classification process and usually delivers more accurate results than unsupervised classification (Mather and Tso, 2016).

Classification based on assumptions on the data distribution

Another classification method assumes the distribution of the data in the feature (band) space. Further sub-categorisations include parametric and non-parametric classifiers. Parametric classifiers are based on the assumption of a normal (Gaussian) distribution of data and are often based on strong statistical assumptions (Jensen 1996;

Richards 2013). These classifiers work mostly when the assumptions about the data distribution hold; however, in the case of a complex landscape and with high variance in classes they are not very effective (Hansen et al. 1996). Examples of parametric classifiers include maximum likelihood classifiers and minimum distances (Mather and Tso, 2016). Among these, maximum likelihood is one of the most widely used classification algorithms in remote sensing image classification (Wang 1990; Hansen et al. 1996; Jensen 1996).

Non-parametric classifiers, in contrast, are not dependent on the assumption of a normal distribution of the data and hence overcome the dependence on the statistical assumptions by parametric classifiers (Jensen 1996; Lu and Weng 2007; Richards 2013). Several studies have shown that these methods produce better results in complex landscapes as compared to the traditional parametric classifiers (Foody 2002; Mather and Tso 2016; Mondal et al. 2012; Murthy et al. 2003; Paola and Schowengerdt 1995). Additionally, because no statistical parameters are required to distinguish the image classes, they are more suitable for incorporating additional non-spectral and ancillary information to enhance the classification results (Lu and Weng 2007). Examples of these classifiers include ML-based algorithms, such as artificial neural networks (ANNs), Support Vector Machines (SVMs), decision Tree), and random forests (RF).

ML is a computational method that learns or improves the performance of data (Hastie et al. 2009; Wilson and Keil 2001). Mitchell (1997) defines ML as “a computer program can learn from experience E , concerning some class of tasks T , and performance measure P ”. Machine learning is used in remote sensing to map land cover and land use based on optical remote sensing images. It is known to deliver more accurate results as compared to the traditional classification methods discussed before (Huang and Jensen 1997; Pal 2005; Mountrakis et al. 2011; Maxwell et al. 2018).

A typical ML modelling process (Figure 1.16) starts with the acquisition of the target variable which is known as the dependent variable, response variable, or ground truth data, which are usually collected through field surveys (Kuhn and Johnson 2013). Predictors, descriptors, and independent variables are then used as inputs to a prediction equation to estimate the response variable (Kuhn and Johnson 2013). The initial dataset is formed using the response and predictor variables. This is subdivided

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into training and testing data. The training data is used to train the ML model, while the testing data is used to test or validate the performance of the model.

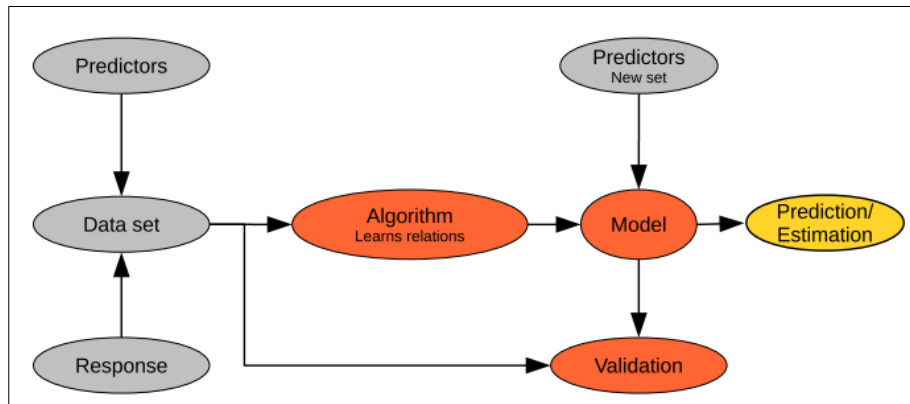


Figure 1.16 Machine learning process workflow (Meyer 2017).

In ML, the algorithm learns the relationship between the predictors and the response based on the training data, which is known as model training, building, or parameter estimation, as shown in Figure 1.16. Hyperparameters are used to control the complexity of the model, for example, the number of estimators in a Random Forest. Overfitting can occur when complex models fit errors or noise into the training data (James et al. 2013; Burkov 2019). To avoid overfitting, the data can be split into several folds or resamples. Each fold or iteration has its own specific set of hyperparameters which use all the data except for one-fold, which is used to evaluate the performance of the model. This aids in the retrieval of an optimal set of hyperparameters and the preparation of the final model (James et al. 2013; Kuhn and Johnson 2013; Kamusoko 2019).

Artificial Neural Network

Artificial Neural Networks (ANNs) are a form of artificial intelligence which is typically conceptualised as the mathematical equivalent of axons and synapsis (representing many interconnections) in an animal's brain (Atkinson and Tatnall 1997; Civco 1993; Foody and Arora 1997). ANNs have “neurons” or processing units that are organised

as input, output, and hidden layers, see Figure 1.17 (Maxwell et al. 2018). The neurones in a particular layer are connected by a link that has a weight assigned to it, and a given layer is linked to all neurones in adjacent layers (Maxwell et al. 2018).

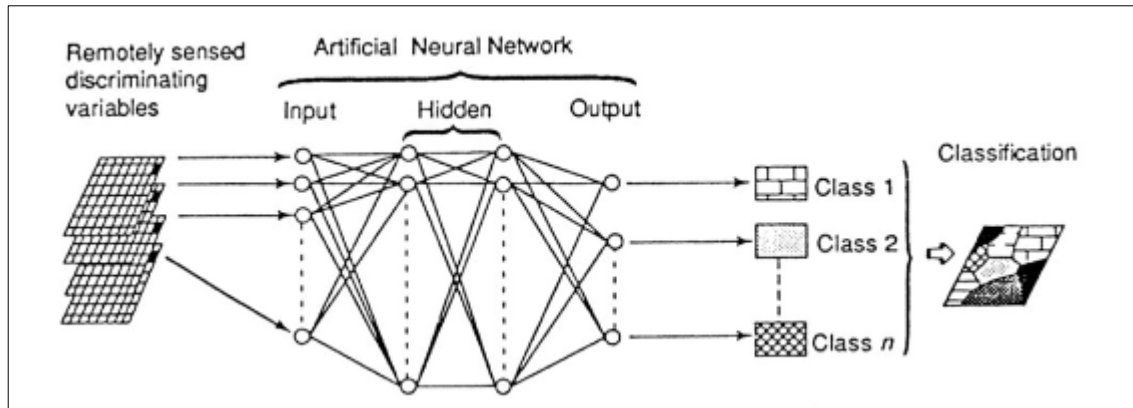


Figure 1.17 Workflow of an Artificial Neural Network (ANN) for Remote Sensing (RS) image classification. (Foody, 1999).

During the training phase, the regularities related to the data are learned by the ANN with the help of the training data, and rules are constructed based on those regularities which are then extended to unknown data (Foody and Arora, 1997). Some of the challenges associated with ANN are that they can easily overfit the classification results and can be slow to train and produce undesired results (Maxwell et al. 2018). However, the problem of overfitting has largely been solved with the use of modern neural network architecture and regularisation and learning techniques, such as batch normalisation, dropout, transfer learning, and pretraining (Shao et al. 2014; Srivastava et al. 2014; Ioffe and Szegedy 2015).

Support Vector Machine

A Support Vector Machine (SVM) is a type of discriminative supervised learning technique (Mountrakis et al. 2011). The focus of SVM classification is specifically on training samples that are nearest to the optimal boundary between classes in the feature space (Huang et al. 2002; Pal and Mather 2005; Vapnik 2013).

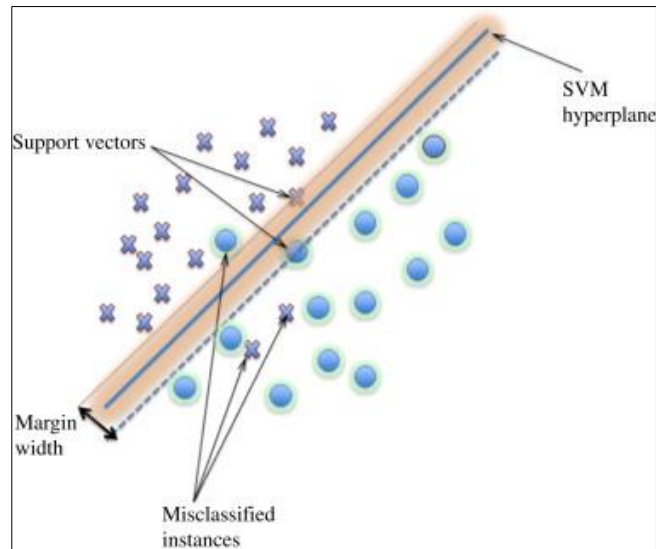


Figure 1.18 Illustration of Linear Support Vector Machine (SVM), which attempts to separate two categories of data using a hyperplane. (Mountrakis et al. 2011).

The SVM classifier is a linear binary (two-class) classifier that was initially designed to solve binary problems by identifying a single boundary (i.e., hyperplane) between two classes, see Figure 1.18. In remote sensing, a sample data instance is often an individual pixel obtained from hyperspectral or multispectral images (Mountrakis et al. 2011). The pixel is depicted as a pattern vector and contains a set of numerical measurements for each band of the imagery. Moreover, based on spatial relationships, for example, texture, there might be other discriminative variable measurements present in the elements of the feature vector space (Mountrakis et al. 2011). The limitation of the SVM classifiers is that they are designed to identify linear class boundaries. This was addressed by projecting the feature space to a higher dimension (i.e., kernel trick), which assumes that a linear boundary may still exist in a feature space at a higher dimension (Maxwell et al. 2018). There are many possible kernels with many requiring user-specified hyperparameters (Kavzoglu and Colkesen 2009; Karatzoglou et al. 2016). In remote sensing, the most commonly used kernels are radial basis function (RBF) and polynomial kernels (Davis et al. 2002).

Decision Trees (DTs) are a kind of classification algorithm that splits the datasets into smaller subsets recursively (Friedl et al. 1997; Pal 2005; Maxwell et al. 2018). The subsets are based on tests defined at every branch (node) (Friedl et al. 1997). As shown in Figure 1.19, the composition of a tree is based on a node that is formed from all the data, called a root node, a set of internal nodes known as splits, and finally a set of terminal nodes called leaves (Friedl et al. 1997). The analogy of a tree is used for the description of the overall pattern of the recurring splits, where branches depict the path through the splits, while leaves (or branch termini) are the ultimate target values (Pal and Mather 2003; Maxwell et al. 2018).

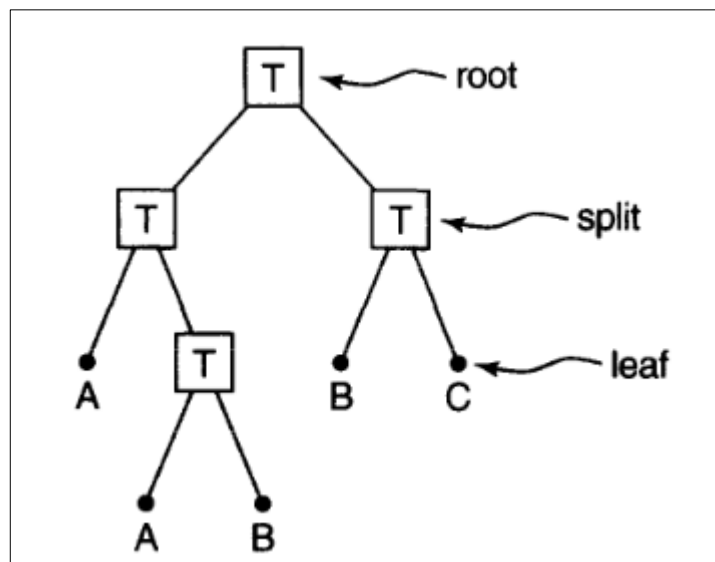


Figure 1.19 Illustration of a Decision Tree classifier. The data is classified by following a path through the tree (T), starting at the “root” node and making decisions at each “split” node based on the features of the data. The “leaf” nodes represent the final classifications (Friedl et al. 1997).

In remote sensing, data can be split based on a pixel value in a certain band that is below or above a threshold (Maxwell et al. 2018). Compared to the classification algorithm discussed previously, DTs have an added advantage in that the logic of the model can be easily visualised as a combination of if-then rules, and the rules can then be easily interpreted to filter the data into suitable classes (Yang et al. 2003). However,

one of the disadvantages is that they are prone to overfitting (Maxwell et al. 2018). However, the overfitting issue can be ameliorated with a pruning technique in which one or more layers of splits are removed. This generally reduces the accuracy of the classification of training data but improves generalisation (Pal and Mather 2003). Another disadvantage of DTs is that they are high-variance classifiers, which means they are strongly influenced by the specifics of the training examples.

Random Forest

The Random Forest (RF) is an ensemble classifier i.e., it combines the decisions from a set of classifiers by a voting system (weighted or unweighted) to classify the unknown examples (Pal 2005). To overcome the weakness of a single DT, random forest uses a large number of DTs (Belgiu and Drăgu 2016; Breiman 2001; Cutler et al. 2007; Pal 2005). Owing to their processing speed and excellent classification results, RF classifiers have received increasing attention over the last two decades (Belgiu and Drăgu, 2016). By aggregating multiple trees, the variance of the model output is significantly reduced, thereby improving the performance of the model (Hastie et al. 2009).

The advantage of RF over DT is that, because there are multiple trees present, there is no need to prune an individual tree (Maxwell et al. 2018). However, a disadvantage is that visualising a tree effectively is no longer possible because of the presence of many trees (Breiman, 2001). RF has been used widely in both active and passive remote sensing imagery to solve many problems, such as land cover, habitat, soil, and biomass mapping using optical satellite remote sensing data (Frazier et al. 2014; Amani et al. 2019) and oil spill and land cover mapping using SAR data (Waske and Braun 2009; Topouzelis and Psyllos 2012).

Deep learning (Convolutional Neural Networks)

In contrast to the previously discussed “shallow” ML classifiers, DL classifiers are based on “deep” neural networks, which comprise a significantly increased series of neural

nets (Kattenborn et al. 2021). The most commonly used DL classifier for spatial pattern recognition in remote sensing is a convolutional neural network (CNN), which comprises three parts: convolutional, pooling, and fully connected layers (Li et al. 2018). Within the convolutional layers, input images undergo a series of transformations with trainable kernels and are subsequently passed through activation functions to generate the resultant maps (Ma et al. 2019; Cresson 2020; Kattenborn et al. 2021). CNNs are designed to recognise and learn spatial patterns based on the shape, size, edges, and textural features of target features (Kattenborn et al. 2021). An increasing number of network architectures have been proposed over the past decade, such as U-net (Ronneberger et al. 2015) and ResNet (He et al. 2016). U-net was first developed to process biomedical imagery. However, it has been increasingly used for remote sensing imagery and has shown good results with a limited amount of sampling (Shamsolmoali et al. 2019; Dadap et al. 2021; Robb et al. 2023). The model architecture is “U” shaped (Figure 1.20). It has two major parts: the left part is the contracting part (down-sampling), which is made up of a general convolutional process, whereas the right part is expansive (up-sampling) composed of transposed 2D convolutions.

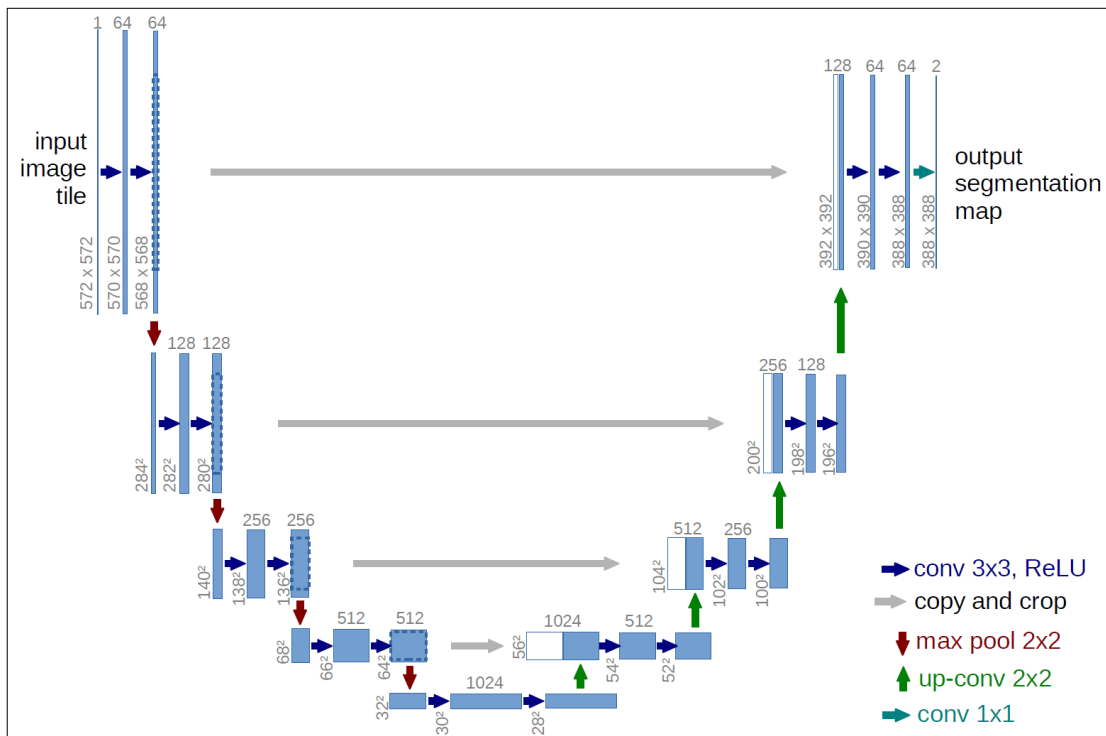


Figure 1.20: U-Net architecture (Ronneberger et al. 2015).

1.6.9 Vegetation Indices

Vegetation Indices (VIs) are quantitative measurements that depict the vigour, activity, and relative abundance of vegetation (Running et al. 1994; Campbell and Wynne 2011). They depict enhanced sensitivity for the detection of biomass, as compared to individual spectral bands, allowing the assessment of canopy structure and terrestrial photosynthetic activity at spatial and temporal scales (Asrar et al. 1984; Huete 2012). In other words, these indices are designed to convert spectral information into a form that is easily interpretable (Bannari et al. 1995). The first use of vegetation in remote sensing is attributed to Pearson and Miller (1972) who developed ratios from various RS channels i.e., Vegetation Index Number (VIN) Eq.(1.3) and Ration Vegetation Index (RVI) Eq.(1.4), to monitor and vegetation cover.

$$VIN = \frac{NIR}{R} \quad 1.3$$

$$RVI = \frac{R}{NIR} \quad 1.4$$

Where NIR is the mean reflectance in the near-infrared band and R is the mean reflectance in the red band.

These indices are sensitive to ground optical properties; however, they are less affected by illumination conditions and enhance the contrast between vegetation and the ground (Baret and Guyot 1991). VIs can be calculated as simple ratios or in other algebraic forms such as arctangent ratios, log ratios, and normalised differences (Goetz et al. 1975; Wecksung and Breedlove 1977). These ratio types are functionally equivalent but differ nonlinearly (Perry and Lautenschlager 1984). Among these ratio types, the normalised difference has become the standard and is most widely used (Crippen 1990). The most frequently used normalised difference ratio are NDVI the normalised difference vegetation index (NDVI) in Eq. (1.5) and its improved version, that is, the Enhanced Vegetation Index (EVI) in Eq. (1.6).

$$NDVI = \frac{NIR - R}{NIR + R} \quad 1.5$$

$$EVI = G \times \frac{NIR - R}{NIR + (C1 \times R) - (C2 \times B) + L} \quad 1.6$$

Where B is the reflectance in the blue channel, G is the gain, C1 and C2 are the fitting coefficients, and L is the background canopy adjustment.

NDVI was first proposed by Rouse (1973) and subsequently used to study ecological phenomena involving vegetation (Rouse et al. 1975; Tucker 1979). On the other hand, EVI is an improved version of NDVI that overcomes its limitations, that is, the open-loop structure (no feedback) of the equation makes it vulnerable to uncertainty and large error sources (Liu and Huete 1995). Therefore, EVI is based on a feedback-based approach, which incorporates both atmospheric resistance and background adjustment concepts by incorporating coefficients (G, L, C1, C2) into the equation (Huete et al. 1999; Liu and Huete 1995). It shows improved capability in vegetation monitoring and better sensitivity to high-biomass regions via the reduction in atmospheric influences and decoupling of the canopy background signal (Huete et al. 1999). VIs are also used to enhance the classification results by adding them as additional variables (bands) to existing image bands.

1.6.10 Remote Sensing of Peatlands

Remote sensing was used as a tool to assess, monitor, and inventory peatlands as early as the 1960s (Minasny et al. 2023b). In a study by Sjörs (1959), bogs and fens in Hudson Bay, Canada were mapped using aerial images. Satellite remote sensing has also been used quite extensively to examine the spatial extent condition, vegetation, and hydrology of peatlands (Howland 1980; Palylyk and Crown 1984; Glaser 1989; Cruickshank and Tomlinson 1990)

The main criterion for a wetland to be classified as a peatland is peat depth, and it is not possible to estimate depth using optical data alone (Krankina et al. 2008). To overcome this, proxy variables such as geomorphological, hydrological, and floristic

characteristics have been used to study peatlands (Matthews 1989; Sheng et al. 2004; Prigent et al. 2007). Several other studies have also been conducted in which automated classification techniques have proven to be successful (Connolly 2018; Mahdianpari et al. 2020; Markon and Derksen 1994; Poulin et al. 2002). Moreover, the combination of optical data with RADAR has provided significant results in the identification and classification of peatlands (Li and Chen 2005; Mahdianpari et al. 2020).

Remote sensing of peatlands with passive sensors

Peatlands have been studied using various types of passive sensors (Pflugmacher et al. 2007; Asapo and Coles 2012; Minasny et al. 2019). Over the last three to four decades, a combination of remote sensing data and expert knowledge has been used to delineate peatland vegetation (Aitkenhead 2017). Primarily, imagery from high-resolution sensors, such as the Indian Remote Sensing (IRS) Satellite, Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+), and Multispectral Instrument (MSI) onboard Landsat and Sentinel-2 satellites, and medium-to-low-resolution sensors, such as MODIS, have been used to study peatlands (Connolly 2018; Lahteenoja and Page 2011; Langner et al. 2007; Wijedasa et al. 2012). Moreover, there is a new generation of very-high-resolution (VHR) satellite imagery (spatial resolution < 10 m) with multispectral sensors. These provide a good prospect of mapping and delineating peatland with even better accuracy and precision, examples of such sensors include SkySat (spatial resolution of 0.72 m) and Doves (spatial resolution of 3 m) by Planet Lab, Ikonos (spatial resolution of 4 m), Worldview (spatial resolution of 2 m) etc. (FAO 2020a).

Multispectral Remote Sensing

Landsat provides one of the largest temporal inventories of multispectral high-resolution satellite imagery. It has been used in many studies related to peatlands, including peatland use land cover classification, change detection to characterise carbon balance, determination of carbon storage, and detection of biotic and

hydrogeochemical properties of peatlands (Glaser 1989; Jaenicke et al. 2008; Crichton et al. 2015). Additionally, there is also an example of Landsat imagery being used in combination with high spatial resolution optical data. Cruickshank and Tomlinson (1990) used Landsat TM combined with SPOT imagery to map changes over peatlands in Ireland. Because there is a trade-off between high spatial resolution and high spectral resolution, as pointed out by Newland (1999), this means that sensors with very high spatial resolution, such as Ikonos, Quickbird, and Worldview, are used for mapping peatlands with object-based classification, unlike multispectral sensors which are more suitable for pixel-based classification. The panchromatic band in these sensors is suitable for an object-based classification approach, as it has a substantially higher spatial resolution than the other bands. Dissanska et al. (2009) used an object-based classification approach to evaluate changes in the structure of peatlands using very high-resolution panchromatic imagery obtained using imagery acquired with Quickbird satellite. The study concluded that imagery proved useful for mapping structural components and transitional zones in peatlands. Frick et al. (2011) used the combination of images from Quickbird, Worldview-1 and SPOT for land use classification of peatlands. Multiple classification approaches were assessed, along with the use of VHR images. They concluded that all sensors performed substantially well with different machine-learning-based classification techniques. However, the use of a combination of VHR imagery, such as QuickBird, with multispectral imagery yielded better results than SPOT imagery.

Similarly, Ikonos which is one of the first commercial-based satellites with very high spatial resolution, has also been used in combination with other aerial and satellite imagery to perform mapping over peatlands. Beilman and Robinson (2003) used aerial photographs along with Ikonos imagery to map peatland landforms and permafrost thaw in the permafrost region of Canada. Although remote sensing with multispectral sensors, such as Sentinel-2, Landsat, and SPOT, provides a good prospect for mapping peatlands at a finer resolution, they have been used to map peatlands at local and regional scales (Markon and Derksen 1994; Poulin et al. 2002).

Hyperspectral Remote Sensing

Hyperspectral remote sensors (aerial and satellite) have good potential because they collect data across a much wider range of wavelengths compared to traditional sensors, allowing for more detailed identification and analysis of target features on Earth's surface. There are several examples in which these sensors have been used for mapping various peatland characteristics. Harris et al. (2015) used an airborne (AISA) hyperspectral sensor to map the floristic gradient in peatlands. This helped to visualise the key species of vegetation in the northern peatlands. Middleton et al. (2012) applied a classification approach using data acquired through a Hyperspectral Mapping (HyMap) hyperspectral sensor to map biotope classification across all northern peatlands. Biotope classification can aid in capturing species diversity and monitoring the changes that occur through artificial management. Other examples include peat humification (which is helpful in carbon budget mapping), plant composition, and species diversity mapping (McMorrow et al. 2004; McPartland et al. 2019).

Super-spectral Remote Sensing

Super-spectral sensors like MODIS (Moderate Resolution Imaging Spectroradiometer) have a lower spatial resolution (250 – 1000 m) compared to the sensors mentioned above, which means that mapping is limited to mapping larger landscape features (Pflugmacher et al. 2007). However, it has an advantage over other sensors in that it has a higher temporal resolution (1 day). This facilitates the possibility of acquiring data in densely cloud-covered regions (Townsend and Walsh 2001). The long-term availability of the data (the early 2000s) also means that it has the potential to model habitat conditions (Artz et al. 2019). Several processed MODIS products are produced, such as surface reflectance, sea ice extent, surface temperature, vegetation indices (NDVI and EVI), net primary productivity, and fraction of absorbed photosynthetically active radiation (fPAR) / leaf area index (LAI) (Morissette et al. 2002). The availability of these products also makes them suitable for studying Gross Primary Productivity in peatlands which is useful in determining the carbon emission status of peatlands (Harris and Dash 2011; Lees et al. 2019). Anthropogenic disturbances in peatlands that

are related to industrial and domestic use (discussed in the previous chapter) and natural disturbances, such as fire and flood, are also mapped using imagery and products obtained through MODIS (Tansey et al. 2008; Connolly et al. 2011). Connolly et al. (2011) used EVI (Enhanced Vegetation Index) with the combination of univariate image differencing and other statistical methods to create a probability map and monitor disturbances like overgrazing, forestry, drainage, and turf cutting in Ireland.

Remote sensing of peatlands with active sensors

Due to rapid advancements in remote sensing imaging systems, several spaceborne radar sensors have become valuable tools for mapping various aspects of peatlands (Table 1.5). It has been used in many studies carried out over peatlands all over the globe. The application of radar systems for mapping different aspects of peatland depends on the wavelength of the sensor; for example, L-band radar systems (ALOS/PALSAR) with a longer wavelength are more suitable for mapping peatlands with dense forest cover, such as tropical regions (Ayunda et al. 2019; Waqar et al. 2020). In particular, radar systems have been used for peatland habitat and carbon assessment, surface movement, and subsidence mapping to understand the chemistry of water, vegetation, and soil moisture mapping (Cooper and Andrus 1994; Bubier et al. 2006; Fiaschi et al. 2019).

Table 1.5 RADAR based sensor suitable for peatland mapping (FAO 2020a)

Satellites/ Sensors	Country	Period of operation	Band	Wave- length (cm)	Polarisation	Spatial resolution (m)	Orbit al repe at (day s)
ALOS / PALSAR	Japan	2006- 2011	L	23.6	Single, Dual, Quad	10-100	46
ALOS-2 PALSAR-2	Japan	2014- present	L	23.8	Single, Dual, Quad	1-100	14
NISAR	NASA India	Start in 2021	L	23.8	Single, Dual, Quad	3-10	12
Sentinel-1	Europe	2014- present	C	5.6	Single, Dual, Quad	W-20	12(6)
RADARSAT Constellation	Canada	2019- present	C	5.6	Single, Dual, Quad	1-100	12(4)
TerraSAR-X TanDEM-X	Germany	2007- present 2010- present	X	3.1	Single, Dual	1-16	11
PAZ	Spain	2019- present	X	3.1	Single, Dual	1-16	11
COSMO-SkyMed	Italy	2007- present	X	3.1	Single, Dual	1-100	16

Page et al. (2000) used a combination of SAR and Landsat imagery to assess the impact of fire using images obtained pre- and post-fire and mapping changes that occurred in land use due to fire. More recently, Widodo et al. (2019) used imagery from ALOS-2/PALSAR-2 data in combination with real-time depth information obtained using an in situ sensor to determine the degradation occurring in tropical peatlands due to fire. However, radar systems with X and C bands have shorter wavelengths than the L-band; hence, it is difficult to use them to observe peatlands under a dense tree canopy. Therefore, they are preferred in regions with peatlands with no overlying tree cover. Two of the more recent X-band-based radar satellites, Sentinel-1 and RADARSAT by ESA and the Canadian Space Agency (CSA) have been used for peatland mapping. Asmuß et al. (2018) used time series backscatter measurement from Sentinel-1 to monitor groundwater depth in peatlands in Germany. The study showed the potential of the imagery to measure temporal variation in water level effectively. Poggio et al. (2019) explored the possibility of mapping peatland extent using Sentinel-1 (SAR) data as an alternative to optical remote sensing to overcome the problem faced by cloud

cover in Northern regions. The study showed significant results with the use of Sentinel-1 with morphological features. Finally, a sensor with data in the X-band region onboard satellites TerraSAR-X and COSMO-SkyMed (Table 1.5) acquires images with a relatively high spatial resolution. Nonetheless, these images have smaller coverage in terms of area and are used for applications that require high to very high spatial resolutions (FAO 2020a). Typical applications in terms of peatland mapping using radar with X-band include characterisation of different types of peatlands, mapping the distribution of peatlands at a regional scale, and carbon stock assessment (Wijaya et al. 2010a; Kalia et al. 2012; Englhart et al. 2014; Wohlfart et al. 2018).

Light Detection and Ranging (LiDAR), similar to radar, is based on the principle of active remote sensing. However, unlike radar, it has laser sensors that produce a cloud of points that are three-dimensional and can be used to depict the vertical and horizontal distribution of the Earth's surface (vegetation and elevation) with a high spatial resolution (Liang and Wang 2019). LiDAR sensors are mostly airborne because they are quick and accurate methods for generating elevation models of land surfaces. Moreover, it is more effective in built-up and vegetated areas where satellite-based radar systems are not useful, for example, ASTER and SRTM (Yamazaki et al. 2017; Vernimmen et al. 2019). In terms of peatlands, LiDAR has applications in the production of Digital Terrain Models (DTM), detecting peatland drainage in combination with high-resolution aerial photographs, obtaining burn scars in peatlands affected by fire, ecohydrology, land use classification, and delineating peatland lag boundaries (Aitkenhead et al. 2016; Langlois et al. 2017; Vernimmen et al. 2019). However, the high cost associated with airborne lidar systems makes them less suitable for large-scale studies, which can sometimes be overcome by taking measurements at a fraction of the study area and modelling upscaling it to a larger scale using modelling techniques (Mitchell et al. 2015; Zande et al. 2009).

Fusion of active and passive sensor

The data from these VHR sensors have been used for various studies successfully, sometimes used individually, and combined with data from another sensor. This includes mapping of vegetation composition and distribution, as well as

characterisation, C and GHG flux mapping, and quantification (Bubier et al. 2006; Brosseau et al. 2010; Frick et al. 2011). Since 2015, the launch of Sentinel-2 by ESA has helped to deliver optical imagery with higher resolution than other free sensors such as Landsat and MODIS. When these optical data are combined with SAR data such as Sentinel 1, it has led to improvements in the mapping and inventory of peatlands on local and national scales (DeLancey et al. 2019; Mahdianpari et al. 2020). Wijaya et al. (2010b) combined Landsat ETM data with SAR data to study peat under thick forests in Indonesia with significant results. Radar can penetrate vegetation; therefore, when fused with multispectral imagery from Landsat forested peatlands, it could be classified. Anderson et al. (2010) combined Ikonos data with LiDAR data to devise a multispectral-structural approach to map the conditions of peatlands. The elevation information of the landscape was obtained from LiDAR data which was then assimilated with multispectral data from Ikonos to carry out maximum likelihood classification. These classification results improved substantially, with an accuracy assessment of 88%, as opposed to 71% accuracy when using only Ikonos data.

1.6.11 Peatlands distribution and mapping

Global distribution of peatlands

The global distribution of peatlands is not accurately known, particularly in tropical areas (Charman 2002). Peatlands are found in 90% of countries across the globe; however, the spatial distribution of peatlands is unknown for parts of South America, Africa, and the mountainous region of Central and South East Asia (Joosten 2017). Most of the estimates suggest that, on a global scale, peatlands cover an area (Figure 1.21) between 3.8 and 4.8 million km² (~3%) of the terrestrial area (Feehan and O'Donovan 1996; Parish et al. 2008; Wu et al. 2017; Joosten 2017; Xu et al. 2018; UNEP 2022). The most recent report by suggests the area to be about 4.8 million km² (UNEP 2022). This assessment suggests that Northern peatlands span over 3 million km². However, many

countries in the Southern Hemisphere lack detailed maps of peatlands, despite the prevalence of medium-small sized peatlands (Minasny et al. 2023).

Moreover, within the boreal forest region, about 25-30% of the total area of its landscape is covered by peatlands (Gorham 1991; Wieder and Vitt 2006). Peatlands are scarcely found in the southern hemisphere due to a lack of suitable land in cooler latitudes (Joosten 2017). Whereas 11% of the global peatlands are found in the tropics, of these, some of the largest extents are in lowland Southeast Asia (Page et al. 2006) and the Amazon basin (Lähteenoja et al. 2009). In Africa, the lowland peatland area is vastly unknown, apart from the Congo Basin, where the recent estimate of the peatland area is around 14,5000 km² (Dargie et al. 2017). Peatlands are also found in high-elevation areas, with Tropical alpine peatlands situated in mountain ranges such as Andes, Africa and many tropical islands (Smith and Young 1987; Chimner 2004; Chimner and Karberg 2008).

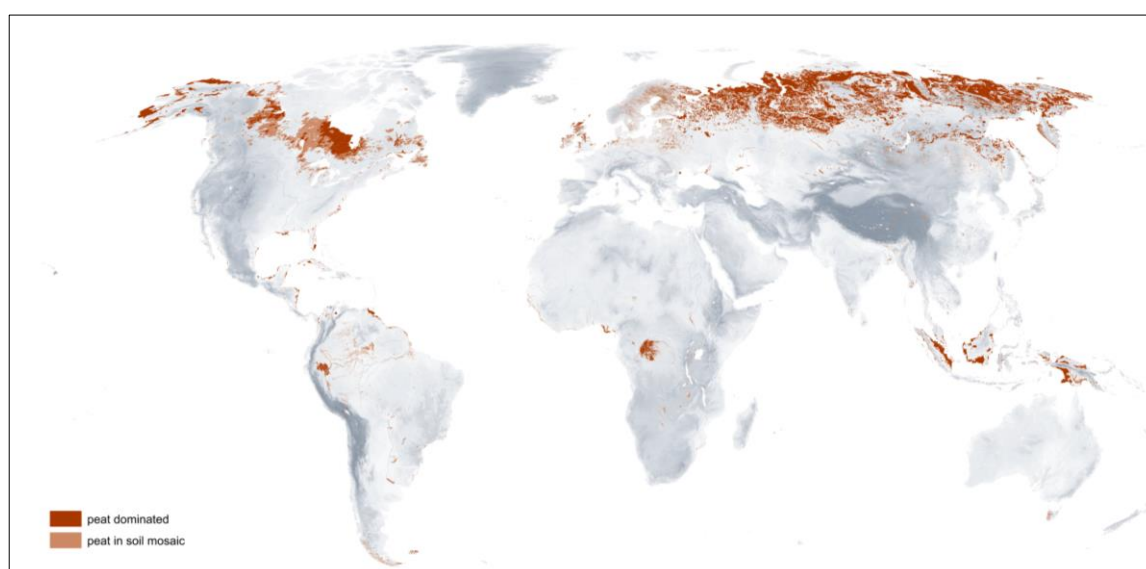


Figure 1.21: Spatial distribution of peat-dominated areas across the globe (UNEP 2022).

The estimate by UNEP (2022) shows that the continent of Asia and North America account for most of the peatland area with approximately 33.01% and 32.43% of the global peatland cover, respectively. The continental Europe covers 12.05%, followed by Latin America and Caribbean (LAC) comprising 12.99%, Africa with 8%, and Oceania and containing 1.49% of the peatland area see Table 1.6. Overall, six countries account for approximately 93% of the total peatland extent worldwide, namely Canada,

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Russia, Sweden, Finland, the USA, and Indonesia (Joosten and Clarke 2002; Wieder et al. 2006).

Table 1.6: Peatland area (km²) coverage (UNEP 2022).

Continent/Region	Peatland Area (km ²)	Percentage
Asia	1,610,302	33.01
North America	1,582,008	32.43
Latin America and the Caribbean (LAC)	633,731	12.99
Europe	587,556	12.05
Africa	390,373	8.00
Oceania	72,859	1.49
Sub-Antarctic Islands	712	0.01
WORLD	487,754	

Peatlands situated in tropical regions of South America are mostly found in high-elevation areas, and those located in Southeast Asia and Africa are found in lowland landscapes (Chavez et al. 2018; Cooper et al. 2012; Lahteenoja and Page 2011). Tropical peatlands are classified into three main classes based on the landscape: basin peatlands, high-elevation peatlands, and coastal peatlands (Page et al. 1999). Northern peatland classes include paludified shallow peatlands (Tundra), polygon mires, peat plateau and palsa mires, patterned string fen (aapa mire), raised bogs, and thermokarst kettle hole peatlands (Minayeva et al. 2017).

Peatland distribution across Europe

Previously the estimated the extent of peatlands in Europe was between 1.0 and 1.8 million km² (Lappalainen 1996). However, recent estimates suggest the spatial extent to be 0.5 to 0.6 million km², which is 5.2% to 5.4% (Figure 1.22) of the total land area

of Europe (Tanneberger et al. 2017; Xu et al. 2018). These peatlands account for 12% of the global peatlands. Peatlands are distributed unevenly across the region, with a graded concentration observed in the Northern regions, highland and coastal areas (Figure 1.22), and less prevalent in steppe and broadleaved forest zones (Joosten et al. 2017). Most peatlands are in European Russia (185,809 km²), covering ~2% of the land area of Europe, followed by Finland (71,911 km²), and Sweden (60,819 km²), covering approximately 0.7% and 0.6%, respectively (Xu et al. 2018).

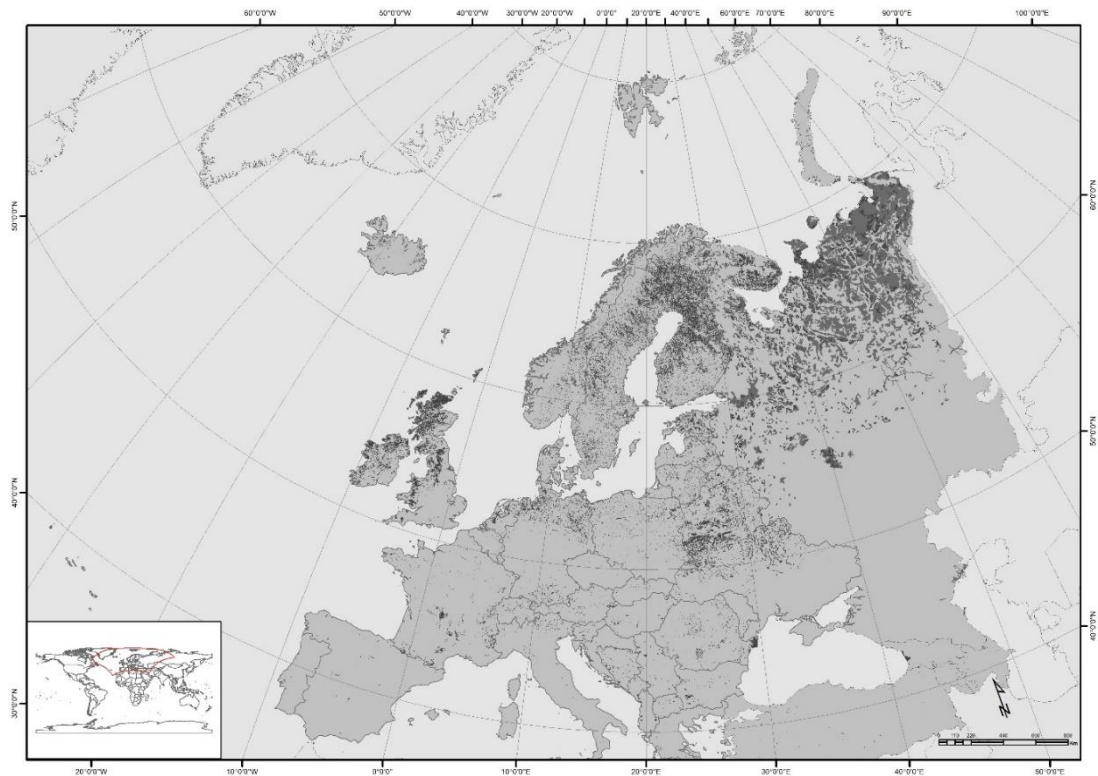


Figure 1.22: Peatland Map of Europe (Tanneberger et al. 2017).

Peatland distribution in Ireland

In Ireland, peat soils are defined by depth; in areas which are drained, the depth should be more than 30 cm, while in undrained areas, peat depth should be greater than 45 cm (Renou-Wilson et al. 2011). The different peatland soils are assigned to several different soil series by Irish soil scientists, for example, the Atlantic blanket bog (which is in the west of Ireland and spread over mountainous areas, valleys, and low-lying coastal areas) is allocated to the Glenamoy Series. The montane blanket bog was assigned to the Aughty series (Feehan and O'Donovan 1996). In Ireland, peatlands

1.6 Literature Review

cover approximately 14,664 km² (~20.6%) of the total land area see Figure 1.23 (Connolly and Holden 2009), which is the second largest peatland area relative to the size of a country in Europe, second only to Finland (Tanneberger et al. 2017). The peatland distribution pattern has been influenced by the combination of glaciation and bedrock geology (Hammond 1981). Peatlands in Ireland account for approximately 3% of the total peatland area in Europe and < 1% (~0.40%) in the world (Tanneberger et al. 2017; Xu et al. 2018).

There are two dominant types of ombrotrophic peatlands in Ireland; blanket and raised bog (Connolly and Holden 2009). Blanket bogs consisting of, Atlantic blanket bogs and montane blanket bogs cover approximately 5,902 and 3,298 km², respectively (Hammond 1981; Feehan and O'Donovan 1996).

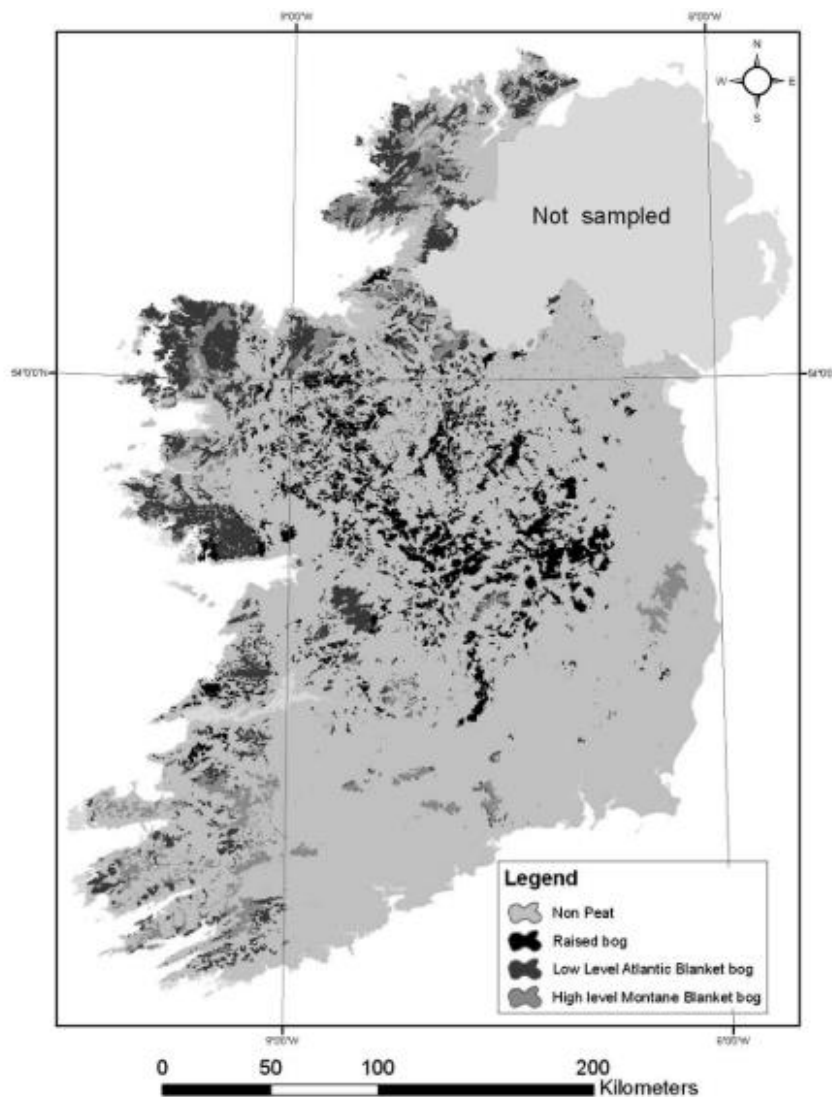


Figure 1.23: Derived Irish peat Map Version 2 (Connolly and Holden 2009).

Blanket bogs represent the vast majority of Irish peatlands (~65%) and are present mostly near low-lying coastal plains and across gentle slopes and mountain plateaus (Hammond 1981; Renou-Wilson et al. 2011).

Raised bogs cover approximately 5333 km² of peatlands in Ireland and are situated mostly in inland areas (midlands) (Wilson et al. 2011). There is also the presence of minerotrophic peatland; fens which covers approximately 200 km² (Foss 2007). These peatlands were excluded from Connolly and Holden's (2009) work on DIPMv2, and hence will not be considered in this study. Most of the low-level Atlantic blanket bog is located in three counties; Mayo, Donegal and Galway, these are situated along the western coastal plains and valley of mountainous areas of Ireland (Hammond 1981; Renou-Wilson et al. 2011). The peatland distribution in Ireland varies significantly by region and county. Mayo and Donegal are the counties with the largest areas of peatlands in Ireland (Table 1.7) with 16% and 14% respectively (Connolly and Holden 2009). Following this county, Galway contains approximately 13% of the total peatlands. The table below (derived from DIPMv2) shows the areal extent of peatland in all counties with peatlands equal to or greater than 1%.

Table 1.7: Peatland area with respect to counties (Connolly and Holden 2009).

County	Area (km ²)	Percent of total peatland area
Mayo	2373	16%
Donegal	2060	14%
Galway	1952	13%
Kerry	1255	9%
Offaly	821	6%
Cork	753	5%
Clare	694	5%
Roscommon	673	5%
Sligo	576	4%
Leitrim	558	4%

County	Area (km ²)	Percent of total peatland area
Westmeath	422	3%
Kildare	327	2%
Longford	302	2%
South Tipperary	262	2%
Laois	257	2%
Wicklow	252	2%
Cavan	227	2%
Limerick	222	2%
North Tipperary	175	1%
Waterford	132	1%
Meath	98	1%
Total	14664	

Peatland land use mapping

Land use mapping has always been desirable; it is mostly focused on how people use the land (Fisher and Unwin 2005). The easy access to satellite data in the last few decades means that there is a growing international commitment to the development of different land use and land cover maps on local and regional scales, for example, the National Land Cover Dataset (NLCD) by the United States Geological Survey (USGS), the European CORINE (Co-ordinated Information on the Environment (CORINE) land cover dataset, and the international land use land cover change dataset by IGBP are few examples among many different datasets (Bossard et al. 2000; Loveland et al. 2000; Fry et al. 2009).

With the development of these different datasets, there is also growing confusion in the core terminology: land use and land cover (Fisher and Unwin 2005). These terms are often used interchangeably; however, there are differences with regard to technical and ontological aspects (Comber et al. 2005). The System of Environmental-Economic

Accounting-Experimental Ecosystem Accounting (SEEA-EEA) (UNEP-WCMC 2015) which is primarily based on the definitions of land use and land cover by Gregorio and Jansen (1998) and Herold et al. (2006), respectively, has the following definitions.

“Land cover refers to the observed physical and biological cover of the Earth’s surface and includes natural vegetation and abiotic (non-living) surfaces. At its most basic level, it comprises all individual features that cover the area within a country. For land cover statistics, the relevant country area includes only land and inland waters. The area of coastal waters is excluded. (SEEA CF 5.257)”

While “Land use reflects both (a) the activities undertaken and (b) the institutional arrangements put in place for a given area for the purposes of economic production, or the maintenance and restoration of environmental functions. In effect, “use” of an area implies the existence of some human intervention or management. Land in use, therefore, includes areas, for example, protected areas, as they are under the active management of institutional units of a country for the purpose to conserve biodiversity and other environmental values, excluding an economic or human activity from that area (SEEA CF 5.246)”

Peatland mapping, as a distinct class of land cover, is challenging (Frey and Smith, 2007). it is mostly represented as a single class of peatland or sometimes under a broad category of wetlands, for example, it is represented under the broad category of wetlands in NLCD and IPCC land cover maps (Fry et al. 2009; López-Calderón and Riosmena-Rodríguez 2016). Similarly, the CORINE land cover dataset, which is used as one of the sources of land cover in Ireland, represents peatlands under a broad category of wetlands and is depicted as peat bogs (Bossard et al. 2000). Owing to this underrepresentation, there have been several efforts to develop peatland-specific maps at national, regional, and global scales (Montanarella et al. 2006; Connolly and Holden 2009; Wu et al. 2017; Chavez et al. 2018; Mahdianpari et al. 2020). Similarly, in terms of mapping land use on peatlands, very few studies have focused on developing peatland-specific maps. More specifically, land use has been mapped on tropical peatlands using GEE, Landsat, and MODIS data (Langner et al. 2007; Miettinen and Liew 2010; Miettinen et al. 2012). However, temperate peatlands, such as those in

Ireland, lack peatland use mapping studies, despite the huge proportion of these ecosystems being degraded by land use activities.

In Ireland, there are national-scale peatland maps that represent broad peatland classifications (Connolly and Holden 2013; Dwyer 1962; Hammond 1981) i.e., raised bogs, blanket bogs and fens. Moreover, some efforts have been made to conduct peatland use and degradation mapping at the local scale using high-medium resolution satellite imagery i.e., IRS (23m); however, due to persistent cloud conditions, the map lacked coverage of peatlands in the western seaboard region (Connolly 2018). This has resulted in a severe lack of spatially explicit information on peatland land use activities and associated GHG emission estimations (Wilson et al. 2015; Aitova et al. 2023). This was also reflected in the National Inventory reporting from LULUCF. As such peat extraction activities have been reported under the “managed wetland” category and the area reported under these activities is ~80,000 ha (Duffy et al. 2022). Despite having multiple other uses on peatlands in Ireland (e.g., agriculture and forestry), the current focus of reporting is only industrial peat extraction activities (Aitova et al. 2023).

Peatland drainage mapping

Drainage on peatlands that are developed artificially is one of the forms of anthropogenic disturbance (Connolly and Holden 2013, 2017; Holden et al. 2004). This artificial drainage, which is one of the initial steps towards opening a peatland for exploitation, has been carried out for many centuries. Peatlands have been exploited for their energy and horticulture properties, agricultural demand, and forestry (Holden et al. 2004; Parry et al. 2014; Turetsky et al. 2015). The drains, which are linear features (in most cases), have various widths, and this can vary depending on the location. In Ireland, drains are up to 2m wide and in Indonesia up to 20m (Renou et al. 2005; Ismail et al. 2018).

Peatlands have been put under stress all over the globe due to these artificial drains (Borger and Guus 1992; Broadhead et al. 1989; Holden et al. 2004). These drains affect the hydrology of peatlands and disturb water balance which is the most important component of peatland ecosystems (Luscombe et al. 2016). Moreover, they also release

carbon into the natural drainage system in the form of DOC and POC which affect drinking water quality and cause carbon dioxide emissions (Evans et al. 2016; Holden et al. 2007). Because of the impacts of drainage on the peatland ecosystem and their consequential effect on the environment due to C and GHG emissions, it is important to identify the extent, location, and density of these drainage networks (Crowe et al. 2008; Holden et al. 2007).

The artificial drainage ditches in Southeast Asia's tropical peatlands, referred to as 'canals', also contribute significantly to disturbance (Jauhiainen and Silvennoinen 2012). In Indonesia, thousands of hectares of peatland have been drained using these artificial drainage systems. Peatlands are planted with plantation estates (Miettinen et al. 2011). In these areas, mapping peatland drainage with remotely sensed data is a challenging task, especially with optical data which cannot penetrate the thick canopy of a forest in tropical peatlands (Sinha et al. 2020). However, the use of a Digital Elevation Model (DEM) derived using LiDAR has been successful in mapping artificial drainage in wetlands (Poppenga et al. 2010; Lang et al. 2012). Some studies use a combination of aerial images; LiDAR and stream network modelling techniques have even higher accuracy than space-borne satellite images (Murphy et al. 2008; Persendt and Gomez 2016). In a study conducted by Ismail et al. (2018), a wide range of active and passive remote sensing data were used to map tropical peatland drainage using visual interpretation techniques. Both active and passive sensors were successful in mapping drains, with some trade-offs.

However, mapping peatland drainage in Europe with remotely sensed data is difficult because of persistent cloud cover (Tolnai et al. 2016). Moreover, the small size of artificial drainage ditches means that most of the freely available medium-(Landsat: 30m) to high-resolution satellite images (Sentinel – 2:10m) are unable to capture these drains. A recent study conducted by Carless et al. (2019) on peatlands in the UK mapped different types of peatland disturbances, including peat cutting, drainage, and erosional gullies. A combination of hyperspectral and digital elevation model (DEM) data derived from LiDAR was used. Although automated classification techniques were used to map the erosional gullies, the drains were manually digitised using visual interpretation. It is evident from these studies that drain mapping is normally carried out using manual on-screen digitising, which is a laborious and time-consuming task.

1.7 Scope of the research

The introduction of ML-based linear feature extraction techniques allows the automated mapping of small linear features (Mohammadzadeh et al. 2004; Quackenbush 2004; Romero et al. 2015). Peatland drain density has also been mapped using medium to low spatial resolution imagery (Landsat-MODIS) in Scotland; however, the study concluded that it is a challenging task because of limited coverage due to persistent cloud coverage (Aitkenhead et al. 2016). A recent study conducted by Connolly and Holden (2017) used very high-resolution satellite imagery (spatial resolution of 10m) and semi-automatic OBIA (Object-Based Image Analysis) techniques to map drains in Ireland. However, these techniques require manual intervention and are time- and resource-intensive for national-scale applications. More recently, a combination of very high-resolution satellite imagery (PlanetScope 3m) and DL methods applied to semantic segmentation has been successfully used to map artificial drainage canals at a national scale in Indonesia (Dadap et al. 2021). Similarly, Robb et al. (2023) utilised these DL modelling approaches to map small artificial drains on UK-based highland bogs. However, the application of DL is focused either on artificial drains with regular structures and large dimensions or irregular and small drains on highland bogs. The model has not been tested on a diverse study area with different dimensions of drains and irregular and regular shapes and sizes, such as those usually found in Irish-raised bogs.

1.7 Scope of the research

The scope of the research and novelty are covered in the following points.

- It is clear from the literature review that only a limited number of studies exist on peatland use mapping, particularly in Ireland, where only one such study exists. Recognising this gap, this research necessitated the development of a peatland use-specific classification system and mapping for Irish peatlands.
- Existing literature emphasises the challenge of cloud cover in peatland habitats, hindering the mapping of these ecosystems through passive optical remote sensing sensors. Consequently, an effective cloud removal methodology was

developed to ensure wall-to-wall coverage for comprehensive spatiotemporal land use mapping and assessment at a national scale.

- The literature review revealed a significant knowledge gap concerning spatially explicit information on artificial drainage and land use in Irish peatlands, leading to the underreporting of C and GHG emissions. This study addresses this deficiency by providing detailed land use maps along with associated emissions, thereby contributing to a more comprehensive understanding of these ecosystems.
- Prior studies relying on medium spatial resolution satellite imagery, such as IRS (23m) and Landsat (30m) used in this study were limited to mapping only four major land use classes in peatlands. To overcome this limitation, this study employed higher resolution (10m) Sentinel-2 data, integrating effective cloud removal methods utilised for Landsat mapping.
- Earlier research in Ireland and elsewhere focused on mapping artificial drainage using small study sites, semi-automated object-based image analysis (OBIA), which requires manual intervention, or automated DL methods focused on mapping either regular (canals) or irregular drainage features. In contrast, this study aimed to develop a more generalisable single DL model capable of mapping both regular and irregular artificial drainage in raised bogs, providing a broader and more applicable approach.
- In the National Inventory Report of Ireland, the current value used for $Frac_{ditch}$ is based on the IPCC default value. By mapping land use and associated artificial drainage, this study proposes a country-specific value that offers a more accurate basis for estimating GHG emissions from artificial drainage on peatlands in Ireland.

1.8 Overall methodology

The overall methodology for land use and artificial drainage was principally based on remote sensing-based image classification see Figure 1.24. Remote sensing image classification is a complex process that takes many different factors into account (Lu

1.8 Overall methodology

and Weng 2007). The classification process involves multiple steps: (i) selection of remotely sensed data, (ii) data pre-processing, (iii) selection of the classification method and classification system (taxonomy), (iv) accuracy assessment, and (v) post-processing. The decision for the selection of remotely sensed data is based on distinctive characteristics, that is, spatial resolution, smallest feature to be mapped, temporal resolution, temporal archive, and scale are some of the most important (Estes et al. 1999; Althausen 2002; Lefsky and Cohen 2003). To develop land use maps at different scales, remote sensing imageries with spatial resolution of 30m, 10m, and 0.25m were chosen. The selection of these different image data is based on the trade-offs associated with each type of data. First, aerial image data provide the highest resolution and are acquired under clear weather conditions. However, the high cost associated with the acquisition of such data means that continuous (repeatable) coverage can be difficult. These data were mainly acquired to map small features, that is, artificial drainage. Second, although high-resolution Sentinel-2 data provide high temporal and spatial resolution data, it lacks the historical temporal archive as it was launched more recently (2015). Finally, Landsat data has a low spatial and temporal resolution but contains the largest temporal archive, dating back to the 1970s (Wulder et al. 2016). Multiscale analysis facilitated overcoming the trade-offs associated with these datasets. The selection of classification methods is based on the scale at which mapping is performed. Multitemporal medium-to-high-resolution maps were developed using satellite imagery (Sentinel-2 and Landsat-5 and 8). This was based on pixel-based image classification (random forest). A high-resolution artificial drainage map is developed using aerial imagery and novel semantic segmentation techniques.

As depicted in the data processing workflow Figure 1.24, the workflow used for satellite image classification was consistent with the remote sensing image classification steps mentioned earlier. (i) Remote sensing imagery (Landsat-5, Sentinel-2, and BlueSky aerial imagery) was acquired from various sources (Table 1.8). (ii) Following the acquisition of the image data, pre-processing was performed, which included constraining the image data to peatland sites (raised and blanket bogs) and mosaicking the datasets collected over various periods. (iii) In the next step, image classification was performed, that is, pixel-based classification for the satellite remote sensing image data (Landsat-5 and Sentinel-2) for mapping land use, whereas a DL-based approach was used on very high-resolution image data to map the artificial drainage on raised bogs. Concurrently, a peatland land use classification taxonomy:

Land Use Classification for Irish Peatlands (LUCIP) was also developed. LUCIP is a hierarchical classification taxonomy (consistent with multiscale land use mapping) and was implemented at various levels to produce a multiscale peatland use map. Furthermore, in step (iv), the classification results are evaluated using an accuracy assessment. For this purpose, data collected through visual interpretation of high-resolution satellite imagery were used.

Accuracy assessment is an integral part of remote sensing image classification process (Cihlar 2000). The process helps in identification and quantification of uncertainties arising from classification process. It also helps in identifying the uncertainties introduced by spectral similarities, where different land cover classes may exhibit similar light reflection making it difficult for classification algorithm to distinguish between them. Furthermore, the spatial resolution also plays a role in uncertainty i.e., coarse resolution may not capture the details of small features leading to misclassification. Lastly, the use of specific classification algorithm also introduces uncertainty while labelling a pixel as certain land cover class. Nevertheless, a robust sampling and error quantification methods were used in this study to quantify the uncertainty i.e., error matrix was used for Seninel-2 and Landsat (Cochran 2007). Whereas for the artificial drainage mapping using high resolution aerial imagery, the F_1 score was used. This metric offers a balanced view of both precision and recall, making it suitable for assessing performance in imbalanced datasets that might be common in land cover classification.

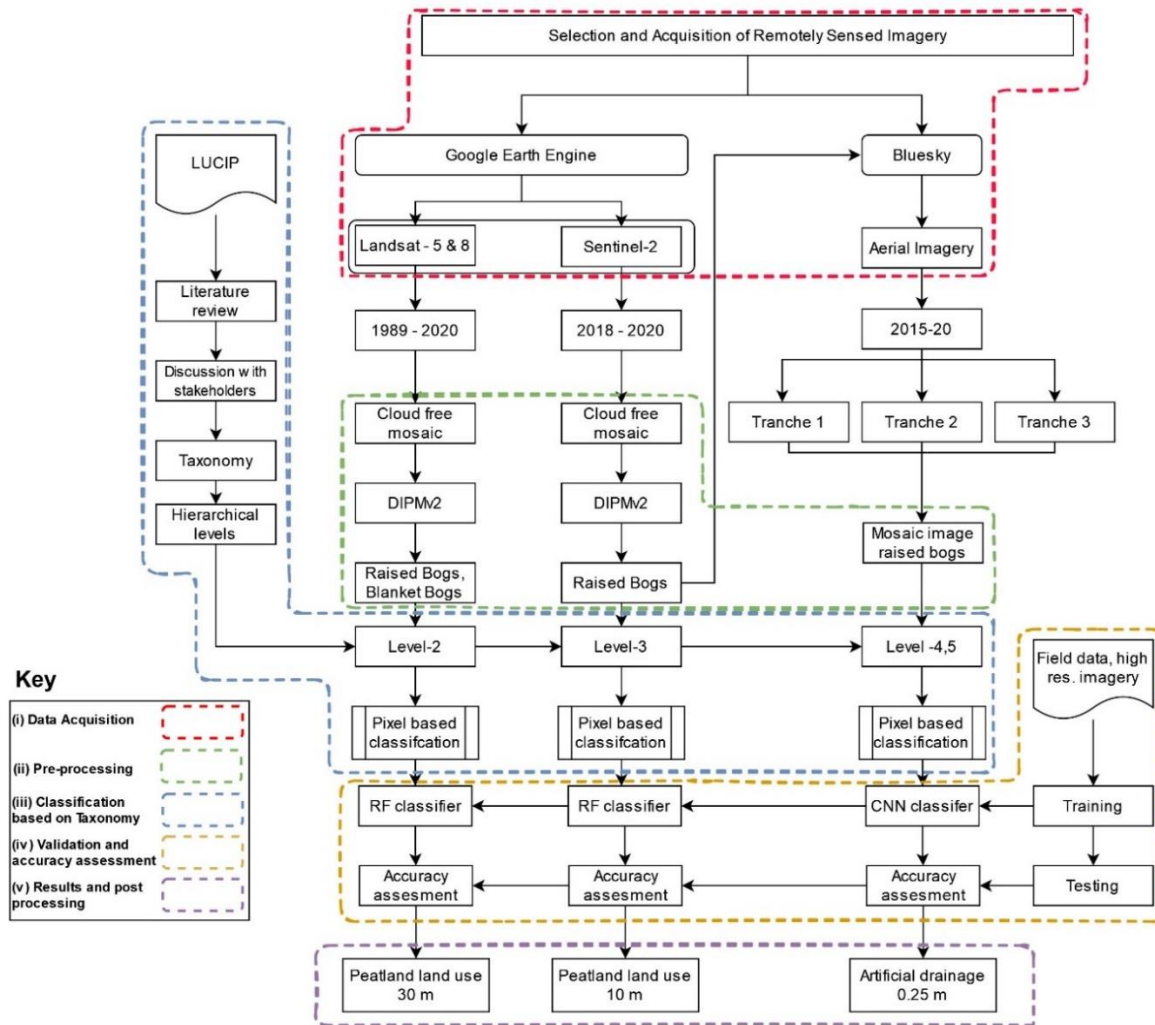


Figure 1.24 Overall classification workflow. DIPMv2: Derived Irish Peat Map version 2, LUCIP: Land Use Classification for Irish Peatlands, RF: Random Forest, CNN: Convolutional Neural Network

1.8.1 Study area

The study area covers peatlands (blanket and raised bogs) in Ireland. For this purpose, the derived Irish peat map version-2 (DIPMv2) was used (Figure 1.23). The DIPMv2 map was developed to map the spatial extent of peat soils in Ireland. This dataset was then used to define the study area. DIPMv2 is an updated version of the DIPM (Connolly and Holden 2017). The DIPM was developed using the General Soil Map of Ireland, Peatland Map of Ireland (Hammond 1981) and CORINE landcover (CLC; Bossard et al. 2000), 1990. DIPMv2 was updated using the same rule-based decision tree methodology as DIPM; however, with the updated version of CLC (2000), the general

soil map was replaced with an indicative soil map of Ireland (ISMI) (Connolly and Holden 2009).

However, DIPMv2 is the most accurate map to depict the spatial extent of peatlands across Ireland. This map has some limitations. These limitations were rendered from the low-resolution (e.g., CLC, 25 ha) datasets that were used to develop the map. This means that the coverage of peatlands is limited along the boundaries. Furthermore, the overall accuracy of DIPMv2 is 88%. Nonetheless, the methodologies developed in this study could facilitate updates of land use maps concurrent with future updates to the DIPMv2.

1.8.2 Datasets

Three remotely sensed optical images were used in this study. Landsat-5, 8 and Sentinel-2 were used for satellite imagery. The primary sources of these images were the U.S. Geological Survey (USGS) and the European Space Agency (ESA). These data were accessed through the Google Earth Engine (GEE) data catalogue. In contrast, very high-resolution aerial imagery was procured from Bluesky International Limited after conducting a spatial analysis of the area of interest (see *Appendix A: Spatial Analysis* for procuring aerial imagery). Table 1.8 depicts the datasets acquired for this study. The specifications of each dataset are discussed below.

Table 1.8: List of datasets used in the study

Dataset	Data period	Spatial resolution (m)	Source
Landsat-5	2004-06 1989-91	30	USGS
Landsat-8	2018-20	30	
Sentinel-2	2017-20	10	ESA
Aerial Image data	2015-20	0.25	BlueSky Geospatial
DIPMv2	2009	300	EPA/(Connolly and Holden 2009)

1.9 Development of peatland land use taxonomy (LUCIP)

Ireland recently released a high-resolution national land cover (NLC) map. Although the NLC consists of peatland cover classes such as cutover, it does not specifically map other land uses on peatlands, such as artificial drainage, grassland, forest, and industrial peat extraction. Furthermore, the map is based on high-resolution aerial imagery and semi-automated methods which makes it time- and cost-inefficient. Europe wide land use/land cover products, for example, CLC and ESA Climate Change Initiative (CCI) land cover data (300 m), are medium-to low-resolution products. Although these products provide information on land cover at regional and national scales, they lack details related to anthropogenic activities on peatlands, such as drainage and industrial and domestic peat extraction. As a result, these products are insufficient for estimating C and GHG emissions and for developing rehabilitation, rewetting, and restoration activities for peatlands. This requires a detailed land use classification taxonomy that includes these activities. LUCIP was developed and used to assess land use at multiple spatial scales (medium (30 m) to very high (0.25 m)). The initial draft of the peatland use taxonomy for this study was developed based on the study conducted by Connolly (2018). The study classified the peatland land use into grassland, forest, industrial (peat extraction) and residual classes. The schema was used as the basis for level-2 classification, as shown in Table 1.9. Further stratification at lower levels (levels 3-5) was conducted based on discussions with various stakeholders (NPWS and BnM) and an ecologist with expertise in peatlands. Land-use classification was performed at different hierarchical levels. Landsat data were used to perform the classification at level-2 since the resolution of the data was the lowest among the remote sensing datasets used in this study. Classification at level-3 was performed using a higher-resolution Sentinel-2. Finally, the classification at level-4 and 5 (mainly drains) was based on very high-resolution aerial imagery. The development of LUCIP was primarily theoretical, for mapping purposes, only the classes that could be mapped with the limited spatial resolution of the sensor were picked and mapped. Owing to the limitations of time and scope of the study, only artificial drainage was mapped at levels 4 and 5. However, the methods used for drainage classification can be applied for fine-scale mapping of other land use classes, and future studies may expand upon LUCIP taxonomy for mapping.

Table 1.9: Classification taxonomy

Level - 0	Level - 1	Level - 2	Level -3	Level- 4	Level - 5 (proposed for peat extraction)
Peatlands	Degraded	Peat Extraction	Active/ Inactive Cutover	Hand cut - drains	Mechanical face bank extraction
					Sausage Extraction
					Other (Methods of extraction)
					Manual face bank Extraction - method 1
					Manual face bank Extraction - method 2
					Scrubland (abandoned peat extraction sites)
			Active/ Inactive Cutaway	Industrial - drains	Sod extraction
					Milling
			Transitional		
		Agricultural	Grassland/Pasture	Grazing	
				Silage	
				Wild/Natural Grassland	
			Crop/ Tillage	Crop/Tillage	
		Forestry	Coniferous & Mixed	Coniferous	Commercial/stage of growth/Condition
				Mixed	silver birch/transition from industrial
				Transitional	
				Broadleaf Forest	
			Broadleaf/	Scrub	

1.10 Organisation of the thesis

Level - 0	Level - 1	Level - 2	Level -3	Level- 4	Level - 5 (proposed for peat extraction)
			Scrub & Linear Woodland	Hedgerows	
				Treelines	
		Artificial Surfaces	Buildings		
			Windfarms		
			Roads		
		Water Bodies	Permanent	Lakes/Ponds	
				River/Canals	
			Rewetted (flood)		
	Near Natural	Remnant Peatland			

1.10 Organisation of the thesis

The main work of this thesis is presented in four subsequent chapters. Chapters 2-4 are standalone chapters with an introduction which includes a literature review, rationale, background, novelty, scope of the studies and comprehensive discussions at the end of each chapter.

- Chapter 2: This chapter extensively examines the application of novel cloud computing (GEE), ML and medium resolution (Landsat-5 and 8) optical remote sensing for mapping peatland land use (LUCIP level 2) at a national scale, overcoming persistent cloud cover challenges in Irish peatland habitats. It also investigates the spatial and temporal dynamics of land use activities in Irish peatlands over the past three decades (1989-2020).
- Chapter 3: The methods introduced in Chapter 2 were employed in this Chapter to further scope down the analyses of raised bogs. Seven land use classes were mapped using Sentinel-2 data. The classes were based on LUCIP level-3. Furthermore, CO₂ emissions were also estimated for the four major land use classes (cutaway, cutover, grassland, and forestry) using emission factors available in the IPCC wetland supplement and the recently updated literature-based emission factors for Ireland. This study fills a much-needed knowledge gap in terms of spatially explicit information on Irish peatland use.

- Chapter 4: This chapter focuses on utilising state-of-the-art DL methods combined with high-resolution aerial imagery to map artificial drainage ditches on raised bogs. The study further utilised the data produced in Chapter 4 to analyse the spatial distribution of drainage on three distinct land uses on raised bogs: cutaway, cutover, and remnant peatlands. Furthermore, geospatial analysis was performed on the resultant drainage maps to identify the drainage hotspots (high density) and calculate $Frac_{ditch}$.
- Chapter 5: This chapter presents the conclusions of the thesis. A summary of different studies carried out in the previous chapter, along with a critical evaluation of the work, is presented. Additionally, the chapter makes recommendations for future work utilising the methods developed in this study are presented in this chapter.
- All supplementary information is outlined in the Appendix.

Chapter 2. A national-scale assessment of land use change in peatlands between 1989 – 2020 using Landsat data and Google Earth Engine – a case study of Ireland¹

2.1 Abstract

Over the centuries, anthropogenic pressure has severely impacted peatlands on the European continent. Peatlands cover ~21% (1.46 Mha) of Ireland's land surface, but 85% have been degraded due to land use. Ireland needs to meet its 2030 climate energy framework targets related to greenhouse gas (GHG) emissions from land use, land use change, and forestry, including wetlands. Despite Ireland's voluntary decision to include peatlands in this system in 2020, information on land use activities and associated GHG emissions from peatlands is lacking. This study strives to fill this information gap by using Landsat (5 and 8) data with Google Earth Engine and ML (Machine Learning) to examine and quantify land use on Irish peatlands across three time periods: 1990, 2005 and 2019. Four peatland land use classes were mapped and assessed: industrial peat extraction, forestry, grassland, and residual peatland. 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 due to the unavailability of high-resolution reference data. The results indicate that extensive management activities have taken place in peatlands over the past three decades, which may have negative impacts on its ecological integrity and the many ecosystem services provided. By utilising cloud computing, temporal mosaicking, and Landsat data, this study developed a robust methodology that overcomes cloud contamination and produces 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

¹ This chapter corresponds to the paper published on 20 September 2023, in *Regional Environmental Change* (2023) [1]

help understand unsustainable management practices on peatlands and the impact on GHG emissions.

2.2 Introduction

Peatlands are one of the most space-efficient carbon stores in the world and play an important role in the global carbon cycle (Limpens et al. 2008; Yu et al. 2011). These ecosystems cover about 3% or 4.23 million km² of global land surface area (Xu et al. 2018) and store approximately 455 to 582 Peta grams of carbon (Gorham 1991; Jackson et al. 2017). For centuries, management-related activities have exerted severe pressure and caused the degradation of peatlands (Tanneberger et al. 2021). Consequently, peatland ecosystems are projected to shift from a carbon sink to a carbon source within this century (Loisel et al. 2021).

Emissions from peatlands where substantial land use change occurred, e.g., forestry and agriculture, have a greater impact on global land atmospheric greenhouse gas (GHG) emissions than previously thought (Ribeiro et al. 2021). Afforestation of natural peatlands and intensive forest harvesting also increase CO₂ emissions and affect water quality (Jovani-Sancho et al. 2021; Palviainen et al. 2021). Furthermore, drained peatlands used for industrial and domestic peat extraction are conduits of fluvial C and GHG emissions. They are also associated with higher risks of carbon loss through fire (Waddington et al. 2001; Turetsky et al. 2015; Wilson et al. 2015; Tubiello et al. 2016; Regan et al. 2019; Peacock et al. 2021b). Tiemeyer et al. (2016) analysed GHG emissions from several bog and fen sites dominated by grasslands and reported high emissions. These peatland land uses play a significant role in fluvial C and GHG dynamics.

Legislative changes in the EU's 2030 Climate Change Framework mean that wetlands are now included in the quantification of GHG emissions and removals from LULUCF (Land Use, Land Use Change Forestry: EU 2018). Additionally, the EU Nature Restoration law aims to restore the degraded ecosystem across the EU (EU 2022), while the EU biodiversity strategy for 2030 (2020/2273(INI)) offers comprehensive guidance on the restoration of wetland ecosystems. On a national scale, the Government of Ireland made two major announcements: (1) the allocation of funding for rehabilitation activities on managed peatlands (Government of Ireland 2020) and, (2) to report emissions from managed wetlands, including peatlands (Ireland and Government of Ireland 2021). Given the increased need to accurately quantify

emissions from peatlands, as well as carry out rehabilitation, restoration, and rewetting activities, it is necessary to map the spatial and temporal changes in peatland land use.

Despite these requirements, there is a lack of spatial information on land use and land use change within these ecosystems (Fluet-Chouinard et al. 2023). Peatlands are not thoroughly represented in global, regional, and national land use and land cover classification maps (Krankina et al. 2008; Pflugmacher et al. 2007; UNEP, 2022). This is also evident in the efforts to develop peatland-specific global and regional maps (Xu et al. 2018; Montanarella et al. 2006; Tanneberger et al. 2017), as they are often underrepresented in land cover databases. One of the reasons for this underrepresentation is that peatlands have undergone land use conversion to agriculture, forest, or have been mined and thus the land cover has changed (Connolly 2018). Therefore, it is these land cover types that are represented in land cover maps and not the peatlands which are effectively “hidden” beneath (UNEP, 2022). This results in an underestimation of peatland area in land cover maps such as the NLCD (National Land Cover Database: Loveland et al. 2000); the European CORINE (Co-ordinated Information on the Environment: Bossard et al. 2000) land cover dataset and the international land use land cover change dataset by IGBP (Fry et al. 2009). Where they are represented such as in the NLCD or the IGBP land cover maps, it is under the broad classification of wetlands. Similarly in CORINE land cover, which is one of the principal sources of land cover information in Europe, peatlands are categorised under wetlands and are classified as peat bogs (Bossard et al. 2000). Additionally, the CORINE land cover dataset is low resolution with a minimum mapping unit of 25 ha. In many areas across the globe, peatlands that have undergone land use change, still contain a large stock of carbon (Hastie et al. 2022). Consequently, as these land cover maps do not adequately represent peatland extent and thus land use on peatlands, it prompts the need to develop peatland land use-specific maps to track land use change over time.

In Ireland, peatlands account for ~21% or 1.46 Mha of the total land surface (Connolly and Holden 2009). However, 85% has already been degraded due to land use activities, such as drainage and subsequent conversion to agriculture, forestry, and extraction (domestic/industrial) (Malone and O’Connell 2009; Davies et al. 2014; Connolly 2018; Fluet-Chouinard et al. 2023). Large areas of peatland are managed by semi-state companies, namely Bord na Móna (BnM), and Coillte. BnM was responsible for

2.2 Introduction

industrial peat extraction until 2020 when extraction ceased. Coillte, the semi-state forestry company, has afforested a substantial portion of the peatlands in Ireland (Connolly and Holden 2011). There are also several medium and small private companies still actively involved in peat extraction as well as numerous smaller landowners, who manage peatlands for a variety of land uses such as agriculture, afforestation, and peat extraction (Malone and O'Connell 2009). However, the spatial extent of these activities has not been mapped.

The Derived Irish Peat Map version 2 (DIPMv2: Connolly and Holden, 2009), was used here to delimit peatland areas and then to track land use change since 1990. Land use maps can be produced using readily available satellite remote sensing data. However, persistent cloud cover is a serious impediment to detecting land use change using remote sensing, especially in Europe and more specifically in Ireland (Tolnai et al. 2016). This is also clear from previous Irish land use and land cover mapping efforts which used remote sensing methods (Walsh et al. 2021; Cawkwell et al. 2018; Cawkwell et al. 2010; Fealy et al. 2009). Cloud cover was also an issue for the Connolly (2018) peatland land use study, which was the first map of land use on peatlands in Ireland and used imagery from 2005/6. In that map, four major land use classes were mapped: industrial peat extraction, grassland, forestry, and residual peatland. However, areas along the western seaboard were omitted due to cloud cover. Given that areas contain extensive blanket bogs which contain some of the largest peatland soil organic carbon stocks in Ireland, it is essential to track and monitor the land use there (Renou-Wilson and Byrne 2015).

The past decade has seen a paradigm shift in remote sensing from change detection to monitoring and tracking change through time (Woodcock et al. 2020). This has been paralleled and facilitated by the development of planetary-scale cloud computing platforms such as Google Earth Engine (GEE: Gorelick et al. 2017) and the Geo-Microsoft Planetary Computer Program (Lukacz 2022). These platforms provide readily accessible computing capabilities and integrated remote sensing image archives thus facilitating the processing and analysis of earth observation imagery for large spatial scales. Furthermore, there has been a substantial rise in freely accessible remote sensing data sources like Sentinel-2 and Landsat-8 and 9, contributing to a notable increase in remote sensing based peatland mapping and monitoring (Dronova 2015; Czapiewski and Szumińska 2021). To address the issue of cloud contamination,

temporal mosaicking functions within GEE can be employed. Amani et al. (2019) and Mahdianpari et al. (2020) utilised these mosaicking functions in GEE to create cloud-free mosaics using seasonal imagery and successfully performed large scale wetland mapping with wall-to-wall coverage.

In this study, GEE was used with Landsat data (5 and 8) and a ML-based classification algorithm (i.e., random forest) to assess, monitor, and track land use change on Irish peatlands from 1990, 2005 and 2019. The rationale for choosing these key years is that they relate to baseline data requirements for both the Kyoto Protocol and the Paris Agreement. Additionally, the EU 2030 climate and energy framework aims to reduce (at least 40% cuts) GHG emissions to 1990 levels (UN 1992; EU 2018). The baseline year for quantification of GHG emissions from LULUCF for the Paris Agreement is 2005. Lastly, 2020 has been included for a more recent comparison. To address the issue of cloud cover, a three-year time period (TP) was selected to facilitate the development of wall-to-wall cloud-free images using the GEE mosaicking functions. These TPs consisted of one year before and one year after the key years i.e., TP1 = 1989-1991, TP2 = 2004-2006 and TP3 = 2018-2020. The results demonstrate the evolution of land use on peatlands and its current status (TP3), providing accurate spatial data for informed decision-making in sustainable land use management in peatlands.

2.3 Material and methods

2.3.1 Study area

This research focuses on Irish peatlands, found within Ireland's temperate maritime climate, which is characterised by mild winters, cool summers, and abundant rainfall throughout the year. The spatial extent of peatlands was delineated using 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

2.3 Material and methods

mountain plateaux. In contrast, raised bogs, known for their dome-shaped peat accumulation, 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). There is also the presence of minerotrophic peatland (i.e., fens) which cover approximately 22,180 ha (Foss 2007). These were excluded from Connolly's (2009) work on DIPMv2 and therefore are not considered in this study.

2.3.2 Satellite image data

Landsat-5 and 8 multitemporal and multispectral optical remote sensing satellite images were used in this study. Six spectral bands were selected for the land use classification: Red, Green, Blue, Near Infrared and both Short-Wave Infrared. The swath width of the sensor is 185 km and has a spatial resolution of 30 meters (USGS 2016). Atmospherically corrected Landsat-5 and Landsat-8 products were used including Tier 1 Surface Reflectance from the TM (Thematic Mapper) and OLI (Operational Land Imager). The atmospheric correction of TM and OLI products is based on the Landsat Ecosystem Disturbance Adaptive Processing System and Landsat-8 Surface Reflectance Code respectively (Masek et al. 2006; Vermote et al. 2016; Foga et al. 2017). It includes snow, water, cloud, and shadow masks that are based on the per-pixel saturation mask and CFMask (C Function of Mask) algorithm (Foga et al. 2017). The QA (Quality Assessment) band is used to represent these masks within the Level-1 data. The CFMask has been validated by Foga et al. (2017) and shown to have the best overall accuracy among different cloud masking algorithms. Topographic effects can also have an impact on the classification results (Álvarez-Martínez et al. 2018). However, most of the study area did not have significant terrain variations, so topographic corrections were not explicitly considered for this study. The entire study area was covered by 9450 columns and 14341 rows of Landsat imagery for each TP.

2.3.3 Methodology

A remote sensing-based image classification approach was used here (Lu and Weng 2007). This included the acquisition and processing of satellite imagery which was conducted in GEE. The imagery was processed to mask out the clouds using the *pixel_qa* band. It was then constrained to the peatland areas in Ireland using the DIPMv2. After defining training areas using heads-up digitisation, a classification of land use was performed using the Statistical Machine Intelligence and Learning Engine (SMILE) random forest algorithm. Accuracy assessment of the results was performed using System for Earth Observation Data Access, Processing and Analysis for Land Monitoring (SEPAL) (Figure 2.1).

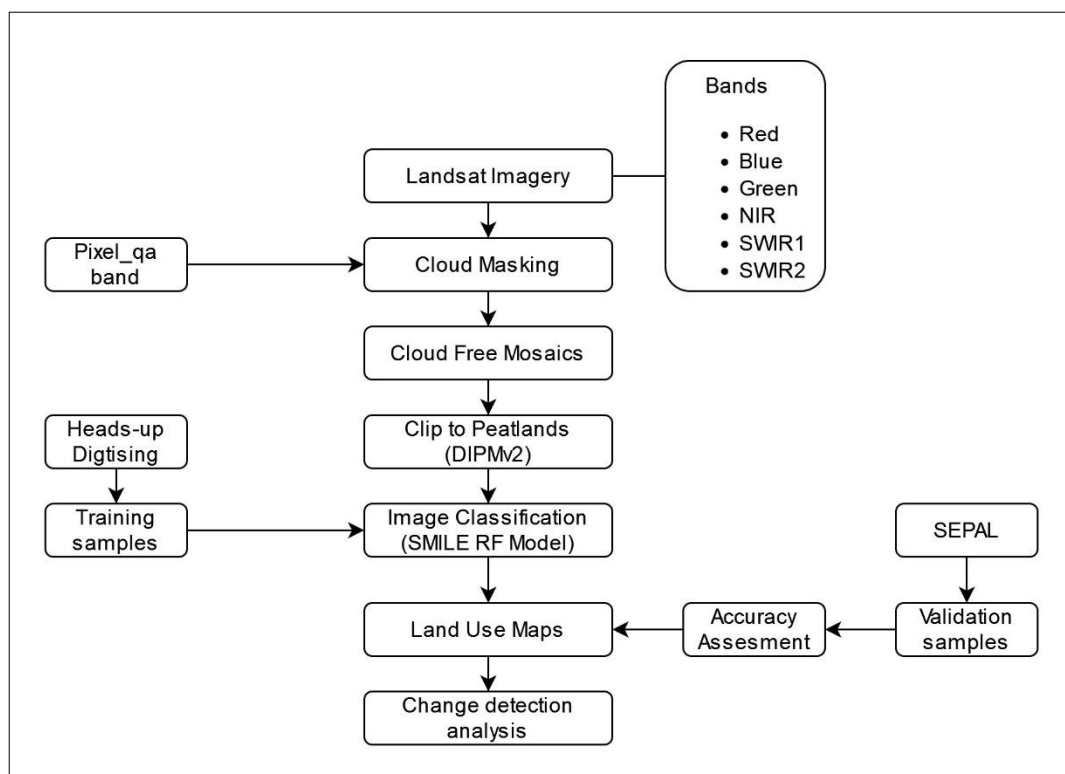


Figure 2.1: A schematic representation of the data processing workflow based on the processing of the data in the GEE and validation and accuracy assessment using the SEPAL platform.

2.3.4 Training data

The spatial resolution of the Landsat data (30 m) means that only certain features on the ground can be discriminated. In this case, only four classes could be identified: industrial peat extraction, forestry, grassland, and residual peatland (Table 2.1). These classes are also consistent with the land use map developed by Connolly (2018) which used a relatively higher spatial resolution (23 m) imagery but did not provide wall-to-wall coverage due to cloud cover contamination along the western seaboard.

Table 2.1: Description of each land use class mapped in the study. Land Use Classification for Irish Peatlands (LUCIP) level-2.

Land Use class	Description
Industrial	Land that has been subjected to peat extraction, with the peat removed and the land left bare, with a thin layer of soil. Managed by BnM with large-scale mechanised peat extraction.
Forest	Land covered with trees; afforested areas are mostly covered by evergreen tree species.
Grassland	Natural and/or agricultural grassland that is used for pasture or hay, silage, and grazing
Residual Peatland	Mosaics of revegetated areas (heath, scrub etc.), exposed peat through domestic peat extraction, remnant peatlands (high bog)

The training data was derived from randomly distributed polygons digitised by an expert operator using the visual interpretation (Richards 2013) of Landsat imagery available for each TP. Training samples based on these polygons were created for each land use class and each TP in GEE enabling image classification. Figure 2.2 depicts the spectral reflectance values of the training samples at different wavelengths. There is a significant difference in reflectance values between grassland, forestry, and industrial classes at different wavelengths more noticeable in the NIR region. Residual peatland class, on the other hand, may exhibit some similarities with other land use classes at specific wavelengths, given it includes cutover and dynamic vegetation environment. Nevertheless, the differences in spectral reflectance between all classes are

prominently discernible. Hence, the variation observed indicates potential effectiveness in distinguishing the mapped land use types in this study.

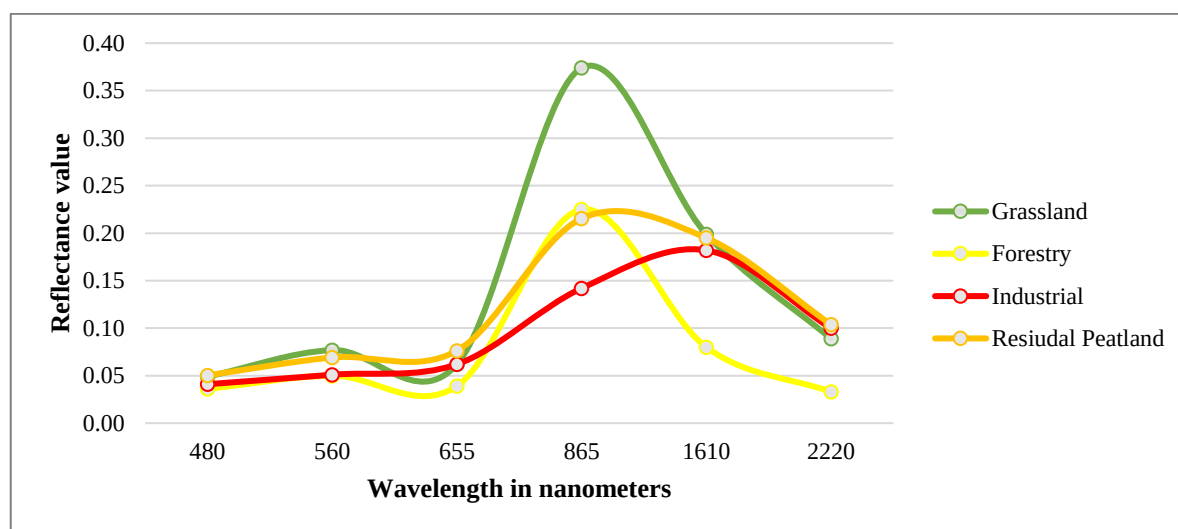


Figure 2.2: Spectral reflectance of the land use types across the six spectral bands.

2.3.5 Satellite image processing

To address the issue of persistent cloud cover in Landsat imagery, an efficient cloud removal methodology is crucial in regions where cloudy conditions are prevalent (Amani et al. 2019). Recent studies have shown that a period of three years (for a particular season) is optimal to create a cloud-free mosaic for national-scale mapping (Amani et al. 2019; Mahdianpari et al. 2020). Therefore, in this study, GEE was utilised to access imagery with less than 10% cloud cover over each TP to create cloud-free mosaics. It is also pertinent to mention that most peatlands investigated in this research do not experience land use change on short temporal scales. Hence it was also suitable to use imagery over the entire year as opposed to being constrained to a specific season. This also allowed for the acquisition of wall-to-wall coverage of cloud-free imagery without any gaps created due to the application of cloud masks. The table shows the temporal coverage of images on each TP (Table 2.2).

2.3 Material and methods

Table 2.2: Temporal coverage of the imagery used for each TP. TM: Thematic Mapper, OLI: Operational Land Imager.

Time Period (TP)	Spacecraft	Sensor	Temporal selection	Total images
TP-1	Landsat-5	TM	01/01/1989 – 31/12/1991	387
TP -2	Landsat-5	TM	01/01/2004 – 31/12/2006	358
TP -3	Landsat-8	OLI	01/01/2018 – 31/01/2020	500

Based on the selection criterion of temporal (Table 2.2) and cloud coverage (less than 10%), several hundred images were available for each TP. Two cloud masking functions in GEE were used to mask out the clouds: `cloudMaskL457` and `maskL8sr`, which use a QA band denoted as *pixel_qa* (Figure 2.1). These were implemented for the Landsat-5 and Landsat-8 data, respectively. Finally, a single cloud-free composite image was generated for each TP using the GEE median (*ee.reducer*) composite function. The function calculates the median value of all the pixels in matching bands across the image stacks and eliminated pixels with extreme value. It also removes any remaining artefacts in the imagery. Hence, each TP image represented pixels with no or minimum cloud cover (or shadow).

Image classification

A pixel-based Random Forest classification model approach was used in this study (Breiman 2001). It is one of the most widely used classification algorithms in remote sensing and has also shown reliable results in wetland mapping (Amani et al. 2019; Mahdianpari et al. 2020). It is an ensemble classifier that uses a large number of decision trees that combine decisions from a set of classifiers using a voting system (Breiman 2001; Pal 2005). GEE has implemented a slightly modified version of the algorithm known as the SMILE random forest (Li 2016), which was used here. It closely resembles the original algorithm in structure but includes decision tree size regularisation through the *maxNode* and *nodeSize* parameters.

The optimum value for the two most important parameters in the random forest classifier, namely the number of trees and number of variables, were adjusted using a trial-and-error method and the square root of the number of features, respectively. A value of 20 was finally used for the number of trees. The model was trained for each TP using the training samples. Due to spectral similarities between the industrial peatlands and many residual peatland sites, most of the areas not identified as industrial extraction sites (containing bare peat on the surface and mostly non-industrial) were classified as such. To resolve this issue, boundary data from BnM was used to delineate the spatial extent of the industrial peat extraction sites on raised bogs and blanket bogs. Any bare (exposed) peat areas, outside the BnM industrial extraction sites that were classified as industrial peatlands, were merged with residual peatlands. This is due to the coarse spatial resolution of the imagery and could be improved in future studies with higher spatial resolution datasets. National scale peatland land use maps at 30 m spatial resolution were thus created for each TP. The output maps from this analysis depict the spatial extent and temporal trend of four major land use categories on Irish peatlands over a 30-year period.

Accuracy assessment using validation data

An overall accuracy assessment was conducted for the output maps using independent data. The maps were uploaded to the SEPAL platform (FAO 2020b) which is a cloud computing-based platform developed for the automated mapping, monitoring, and assessment of land cover. There are several tools available on the platform for land cover analysis. In this study, the following tools were used; Stratified area estimator–design (SAED) and stratified area estimator–analysis (SAEA). SAED was used to create a sampling point. The tool uses Eq. 2.1 (Cochran 2007), to calculate the overall sample size (n). It ensures that enough sample points (validation data) are created for each stratum (class).

$$n = \frac{(\sum W_i S_i)^2}{[S(\widehat{O})]^2 + \left(\frac{1}{N}\right) \sum W_i S_i^2} \approx \left(\frac{(\sum W_i S_i)}{Ss(\widehat{O})} \right)^2 \quad 2.1$$

Where n is the total number of validation points, N is the number of pixels for each class in the classified raster representing the spatial unit, $S(\widehat{O})$ represents the standard error of the estimated overall accuracy, S_i is the standard deviation of each class (stratum), $S_i = \sqrt{U_i(1 - U_i)}$, where U_i is the conjectured value of the user's accuracy for a land use class and W_i is the proportional area of each class i that is mapped (Olofsson et al. 2014). 1704 sample points were generated which were used for accuracy assessment (Table 2.3).

Table 2.3: Distribution of validation sample points for each land use derived using the SEPAL.

Land Use Class	Sample Points
Forest	219
Grassland	394
Industrial	100
Residual Peatland	991
Total	1704

The labelling of validation data was carried out using Collect Earth, a desktop-based tool combining Google Earth and GEE (Bey et al. 2016). This was conducted employing visual interpretation of high-resolution imagery in the Google Earth desktop application in both 2005 and 2019. Each point was carefully assessed by a single expert operator. For areas with low spatial resolution imagery, the temporal archive and GEE were utilised to ascertain the specific class, however, these points were less than 10% of the total. Upon completion of the labelling process, the points were further analysed in the SEPAL platform using the SAEA tool. This was used to obtain a confusion matrix

and estimate the overall, producer and user accuracies. The simplest statistic is the overall accuracy which defines the proportion of locations that are correctly predicted by the model. The producer's accuracy indicates the probability of a correctly classified reference pixel. Whereas, the user's accuracy defines the probability of the pixel classified on the map agreeing with the class on the ground (Story and Congalton 1986; Congalton 1991).

2.4 Results

This study is the first to quantify land use on raised and blanket bogs separately across Ireland over three decades. The resulting maps (depicted in Figure 4.3 (a, b, c)) provide insights into the intensity, extent, and trends of land use on peatlands during this period. The prevalence of industrial peat extraction sites can be seen in the midland region, where most of the raised bogs are situated. These peatlands are transitioning into grassland and forestry, as evident in the 2019 map (Figure 2.3 (c)). Within these midland areas, grassland primarily occupies the peripheries of industrial peat extraction sites. Additionally, grassland emerges as a predominant land use category across both peatland types. Along the western seaboard's blanket bog regions, afforestation and residual peatland remain prevalent.

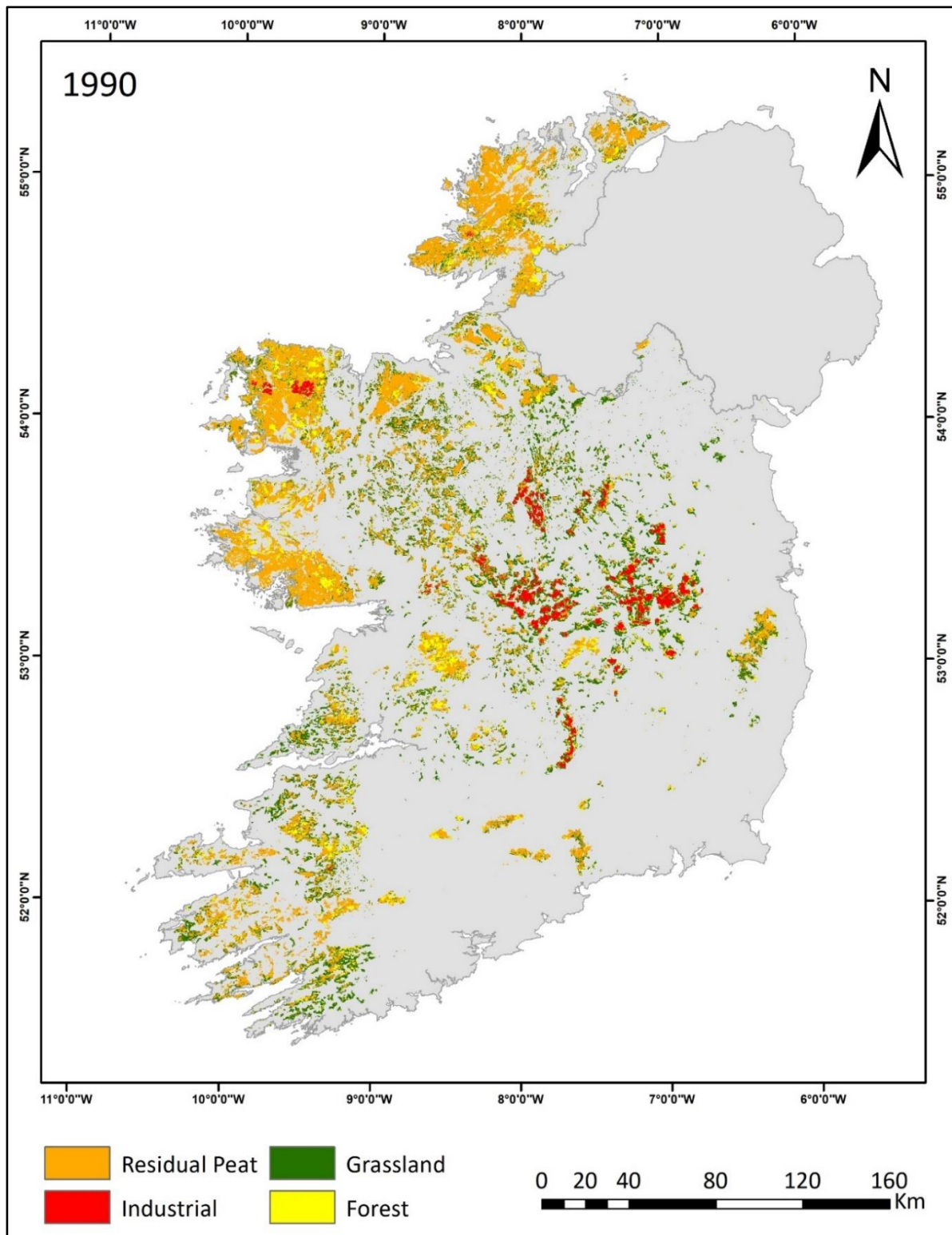


Figure 2.3 (a): Peatland Land use map 1990.

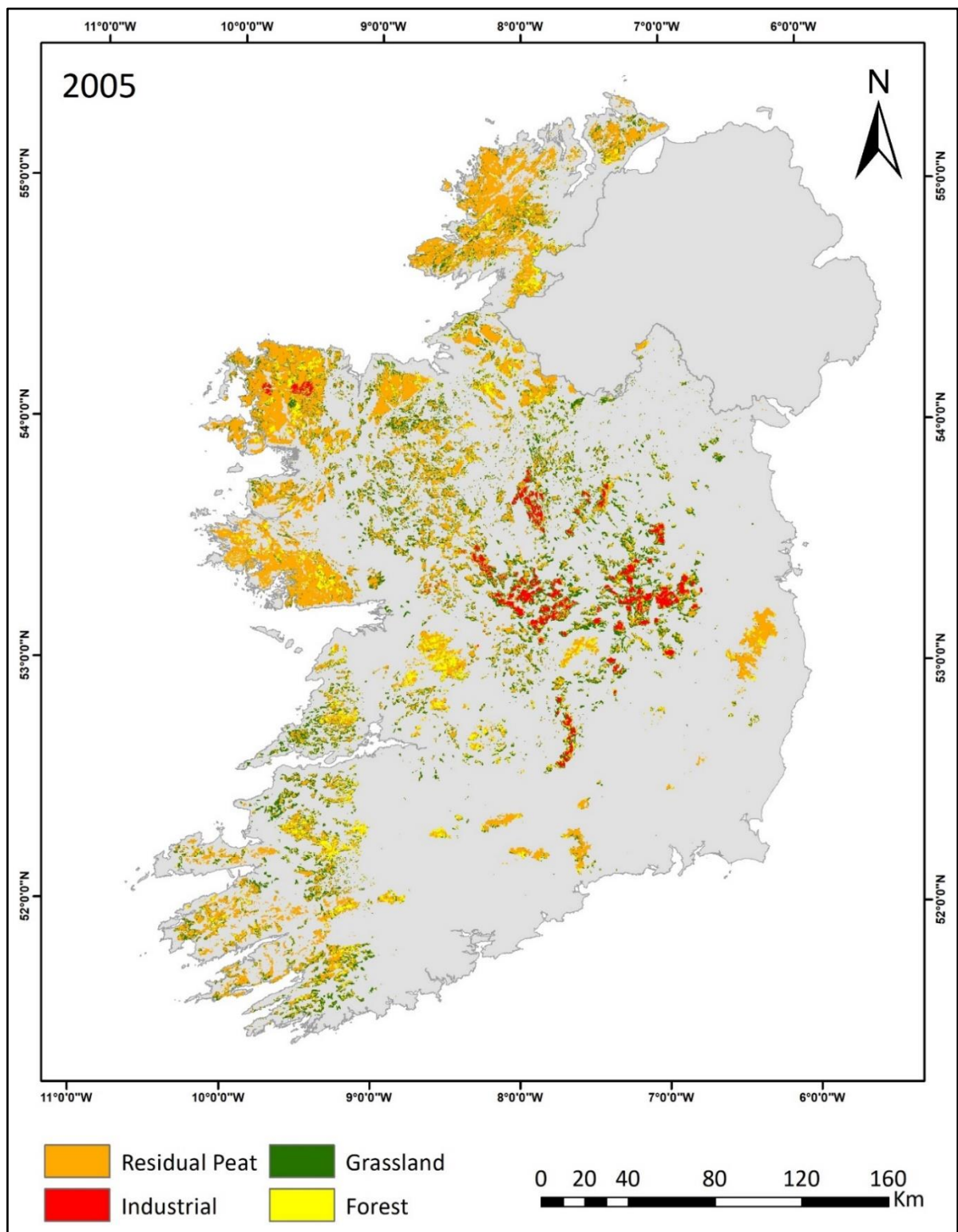


Figure 2.3 (b): Peatland land use map 2005.

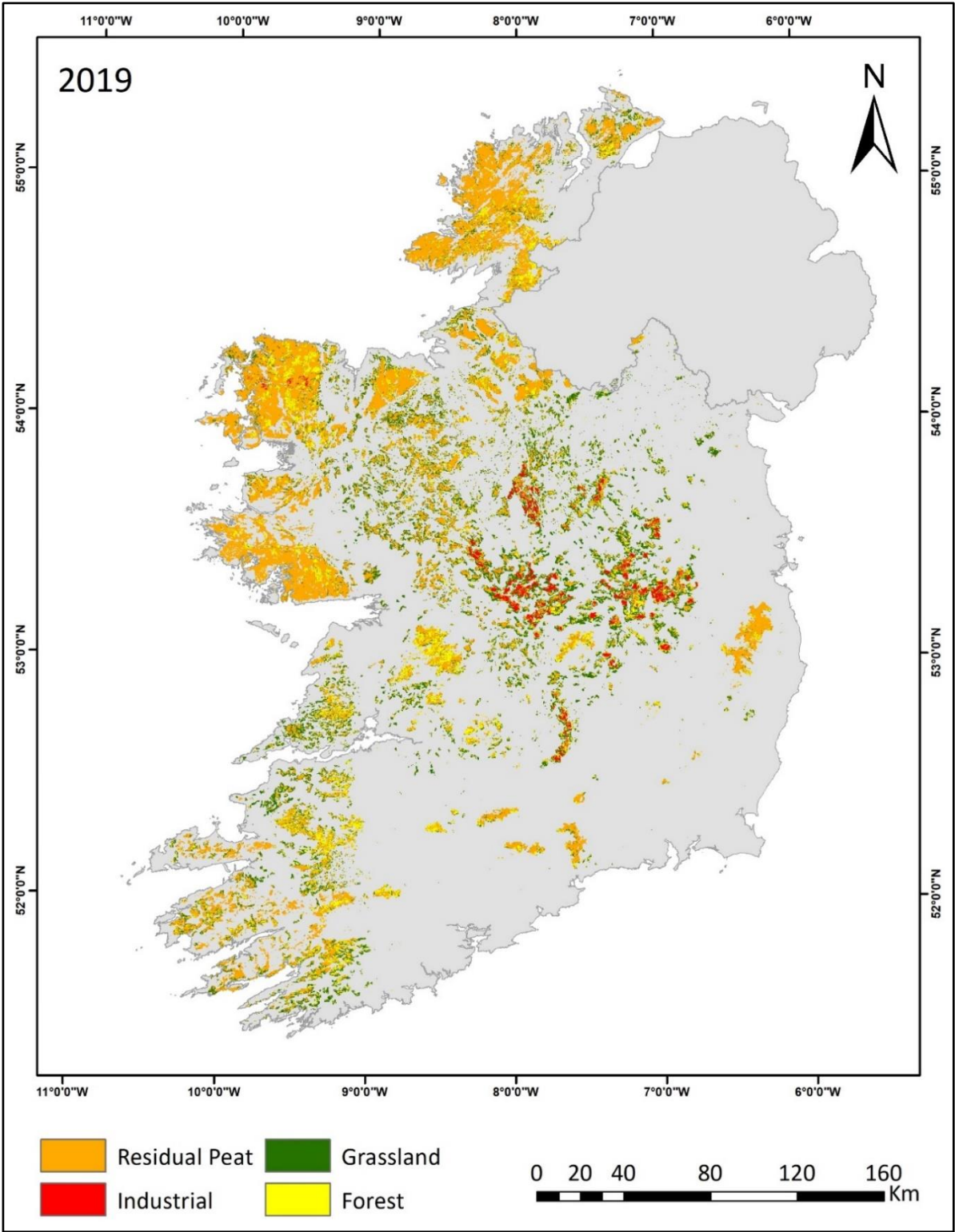


Figure 2.3 (c): Peatland land use map 2019.

The spatial extent of each peatland land use category was assessed for each TP. The industrial peatland extraction sites managed by BnM have undergone a significant transition. One key indicator of this change is the steady reduction in exposed bare peat areas, which have decreased by almost 40%, from 69,600 ha to 41,700 ha between 1990 and 2019 (Figure 2.4). Afforestation increased by 17% between 2005 and 2019 from 191,600 ha to 224,700 ha, respectively. Over the past 30 years, the grassland area has decreased from 436,700 ha to about 357,900 ha (Figure 2.4).

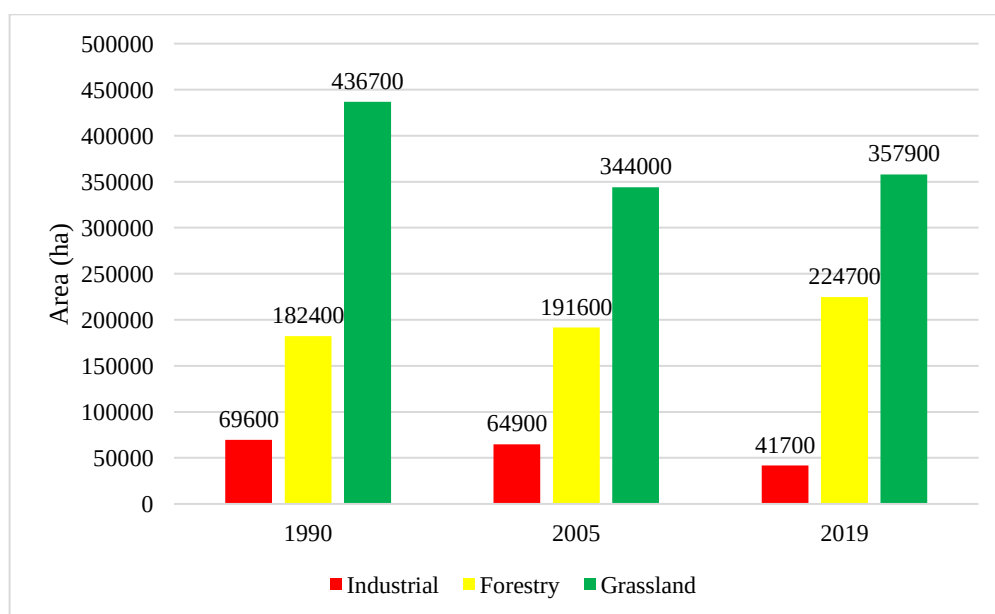


Figure 2.4: Comparison between land use areas for industrial, forest and grasslands.

Land use change dynamics between 1990 to 2005 and 2005 to 2019 are depicted in Table 2.4 and 5, respectively. These tables show the major land use change between the four mapped land use classes. The bold values along the diagonal line in the tables indicate the land use categories that remained constant and were consequently subjected to the same land use. The cumulative area represented by these constant values is estimated to be approximately 1 Mha between 1990 and 2005, and 1.1 Mha between 2005 and 2019. This constitutes ~71% of the total peatland area, identified at this spatial resolution.

The other ~30 % of the peatland area has experienced a change in land use. The largest change between 1990 and 2005 was a 27% reduction in the grassland sites due to afforestation, i.e., 40,700 ha. Afforestation showed a 5% increase in 2005 compared to

2.4 Results

1990. The conversion of grassland to residual peatland, in some cases could be attributed to differences in the spectral signature and is discussed in detail later. Meanwhile, the industrial peat extraction sites underwent substantial land use change between 2005 and 2019 (Figure 2.3 (b, c)). Almost one-third (36%) of these sites were converted to forest, grassland, and residual peatlands. The increase in afforestation is also apparent as 34,700 ha of grasslands and 5,100 ha of industrial peat extraction sites converted to forestry (Table 2.5).

Table 2.4: Land use (LU) change (ha) in Irish peatlands from 1990 to 2005. The emboldened diagonal elements represent constant land use.

		Land use 2005				
		Grassland		Industrial	Residual Peat	Total
LU Class		Forest				(1990)
Land use 1990	Forest	95,300	21,500	700	64,900	182,400
	Grassland	40,700	273,300	1,100	121,600	436,700
	Industrial	2,300	400	59,700	7,200	69,600
	Residual Peat	53,300	48,800	3,400	665,800	771,300
	Total (2005)	191,600	344,000	64,900	859,500	1,460,000
Change (ha)		9,200	-9,270	-470	88,200	0
Change (%)		5	-27	-7	11	0

Table 2.5: Land use (LU) change (ha) in Irish peatlands from 2005 to 2019. The emboldened diagonal elements represent constant land use.

		Land use 2019				
		Forest	Grassland	Industrial	Residual Peat	Total (2005)
LU 2005	Forest	119,200	22,300	300	49,800	191,600
	Grassland	34,700	249,300	0	60,000	344,000
	Industrial	5,100	2,800	39,500	17,500	64,900
	Residual Peat	65,700	83,500	1,900	708,400	859,500
	Total (2019)	224,700	357,900	41,700	835,700	1,460,000
	Change (ha)	33,100	13,000	-2,320	-2,380	
	Change (%)	17	4	-36	-3	

2.4.1 Raised bogs

Grassland (agriculture) has been the dominant land use in raised bogs, accounting for ~43% of the total area of raised bogs in 1990 and 47% in 2019 (Table 2.6). A smaller but significant area has been afforested, increasing from ~8% in 1990 to ~14% in 2019. Peat soil exposed through industrial peat extraction constituted ~12% in 1990 reducing to ~7% in 2019. Approximately 90% of the BnM industrial peat extraction sites occur on raised bogs, in the midlands. However, there has been a notable decrease in industrial bare peat sites, as they transition to other land use types.

Table 2.6: Land use (LU) on raised bogs over three decades.

LU classes	1990		2005		2019	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Industrial	61,900	11.5	58,100	10.8	39,900	7.4
Forest	42,000	7.8	51,500	9.6	73,400	13.6
Grassland	255,900	47.5	206,900	38.4	232,800	43.2
Residual Peat	179,100	33.2	222,400	41.3	192,800	35.8
Total	538,900	100	538,900	100	538,900	100

2.4.2 Blanket bogs

Much less land use change can be detected in blanket bogs (Table 2.7) at this spatial resolution. Grasslands on peatlands have decreased from 20% in 1990 to 14% in 2019. Afforested areas have increased marginally from 16% to 17%. The residual peat area increased slightly between 1990 and 2019 from 64% to 70%. However, as with the raised bogs, the residual peat category is a catchall for many peatland land use categories that cannot be detected at this spatial resolution. The BnM industrial areas at Bellacorrick, Co. Mayo, are now captured under the residual peatland category. These industrial peat extraction sites on blanket bogs account for between 0.2 and 0.8% of the total area of BnM landholdings. However, peat extraction ceased there in 2003 and there has been a transition from industrial to forest and residual peatlands. This may depict revegetation through rehabilitation activities after the cessation of extraction in 2003 (Farrell and Doyle 2003).

Table 2.7: Land use on blanket bogs over three decades.

LU Classes	1990		2005		2019	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Industrial	7,300	0.8	4,400	0.5	1,700	0.2
Forest	144,000	15.6	140,800	15.3	151,500	16.4
Grassland	181,200	19.7	143,200	15.5	126,900	13.8
Residual Peat	588,600	63.9	632,700	68.7	641,000	69.6
Total	921,100	100	921,100	100	921,100	100

2.4.3 Accuracy assessment

The accuracy of the map is calculated by comparing the mapped classes against the reference data. The overall accuracy was 86% and 85% for the 2005 and 2019 maps respectively (Table 2.8). In both the 2005 and 2019 maps, the forest class exhibited the highest user's accuracy, with values of 95% and 88%, respectively. The producer's accuracy, on the other hand, was highest for residual peatland class in both 2005 and 2019 maps i.e., 95% and 93% respectively. The accuracy assessment of the 1990 map was not carried out due to the unavailability of high-resolution reference data.

Table 2.8: Accuracy assessment results for 2005 and 2019 results.

	Accuracy (%)			
LU Classes	2005		2019	
	User's	Producer's	User's	Producer's
Forest	95	60	88	74
Grassland	89	84	85	90
Industrial	86	83	82	64
Residual Peatland	82	96	86	93
Overall Accuracy	86		85	

2.5 Discussion

This study seeks to address the lack of robust spatial data on land use and land use change on peatlands in Ireland. It uses freely available Landsat satellite imagery and the GEE cloud computing platform. A novel and robust method was developed in GEE using the random forest ML approach to identify four peatland land use classes and to track land use dynamics over thirty years from 1989 to 2020. The use of these methods in GEE enabled the study to overcome the challenges posed by persistent cloud cover and obtain accurate wall-to-wall land use maps for Irish peatlands. Several studies have found cloud cover to be a major issue with using remote sensing in Ireland (Cawkwell et al. 2018; Connolly 2018; Walsh et al. 2021). The findings demonstrate significant changes across all four peatland land use categories examined here. The accuracy assessment results from the 2005 and 2019 datasets show a particularly good agreement between the land use maps and the reference data, however, high-resolution reference data was not available to conduct the accuracy assessment of 1990 land use results. Table 2.4 provides information on the direction and magnitude of changes in land use class. That facilitates the evaluation of the consistency of the land use classification for that particular TP. The transition from forest to grassland observed may be linked to policy incentives for agricultural production (Donnellan et al. 2015; Renou-Wilson and Byrne 2015). Whereas small changes in bare peat in

industrial areas between 1990 – 2005 are consistent with the policy regarding industrial peat extraction (Bullock et al. 2012).

In TP2: 2005, grassland covers 23% (~342,800 ha) of the peatland area, forestry covers 13% (~188,800 ha), and industrial peat extraction covers 4% (~65,500 ha). However, a previous study by Connolly (2018) reports higher estimates for grassland and forestry areas: 437,000 ha and 337,000 ha, respectively. Similarly, the industrial peat extraction area was estimated to be ~50,000 ha but did not include BnM landholdings on blanket bogs. Therefore, our study estimated an accurate BnM industrial peat extraction area of 63,900 ha. The remaining 59% (~864,500 ha) consists of degraded remnant and cutaway peatland areas, which were not detectable in either study due to the coarse spatial resolution of the imagery. We believe that the utilisation of robust ML-based pixel classification techniques, coupled with cloud-free wall-to-wall coverage, as employed in our study, enables more accurate estimations of the four land use categories when compared to the previous study (Connolly 2018).

Peatlands have been under considerable land use pressure in Ireland, particularly over the past several decades with the introduction of mechanised peat extraction (Smith and Crowley 2020). There are varying spatial and temporal changes across raised and blanket bogs. Industrial peat extraction areas are being converted to grassland, forestry, and residual peatlands (revegetated, and abandoned). Whereas grasslands and forestry, located on peatlands, can be replaced with each other. According to this pixel-based approach, approximately 30% or 400,000 ha of Ireland's peatlands have experienced a change from one type of peatland land use to another in the past 30 years. Of the remaining 70%, about 47% were classed as residual peatlands. The land use changes that occur in those areas are relatively small scale e.g., domestic peat extraction and are not detectable using Landsat data. However, they are extensive and should be examined using higher-resolution imagery in future studies. The remaining 23% represent land use on peatlands including industrial, forested or grassland, that has remained stable over the study period. The driving factors for the land use change detected in this study could be linked to land use policy changes related to peat mining, afforestation, and agricultural production over the last thirty years.

2.5.1 Industrial

The assessment of Industrial land use was limited to the BnM landholding. The increase of afforestation on these lands has mainly occurred in the past 15 years. This could be attributed to the afforestation of former industrial peat extraction sites by BnM in collaboration with Coillte as depicted in Figure 2.5. It also shows the transition from industrial peat extraction sites to grassland and residual peatland. Between 1990 and 2005, there were minor changes in the east of the midlands in the areas (outlined by the blue box in Figure 2.5). However, between 2005 and 2019 there was a marked increase in forestry (yellow) and residual peat (orange) in this area. Given the relatively rapid land use change detected between 2005 and 2019, it would be prudent to track and monitor this on all industrial peatland sites using this methodology, particularly as all extraction activities on these sites officially ended in 2021 (BnM 2021).

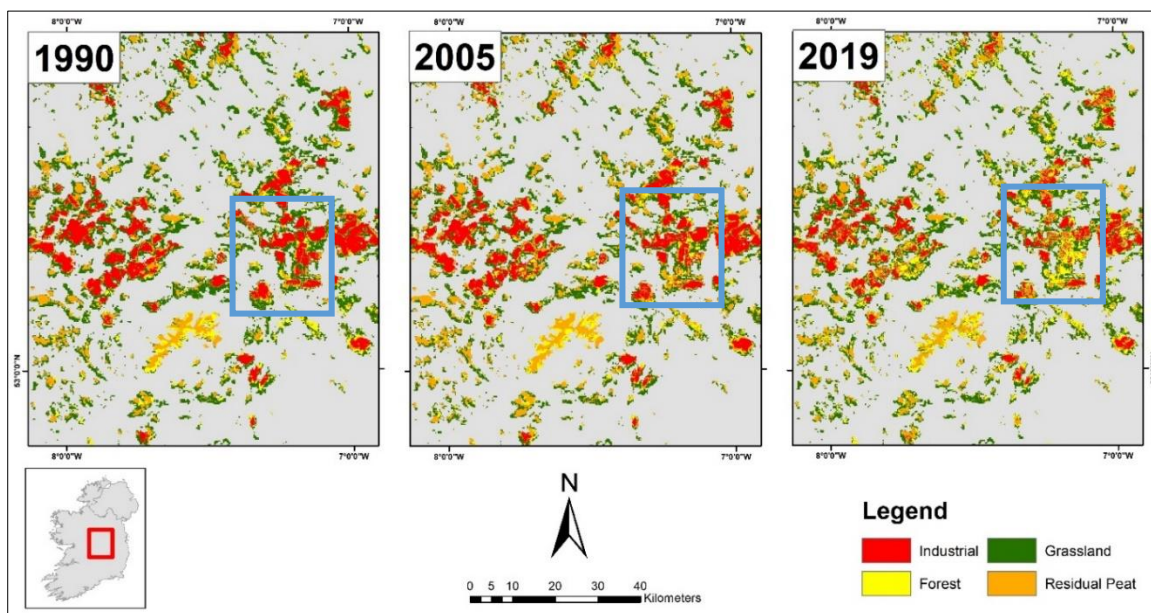


Figure 2.5: Peatland land use change in the Midlands.

2.5.2 Forestry

While there has been an overall increase in forestry on peatlands over the past three decades, there was also a sub-trend where some afforested areas were converted to residual peatlands. For example, several EU LIFE-Nature projects have the aim of the “restoration of afforested bogs to their former status” including 1,976 ha of blanket bogs on the west coast and more recently the raised bogs sites in the midlands (Bullock et al. 2012; Griffin 2016). This increasing trend may be related to afforestation policy incentives offered on a national scale. These incentives began with the establishment of Coillte in 1989 (Ward 1989), a semi-governmental organisation for the management of state-owned forestry. The introduction of EU and national afforestation schemes and grants such as the farm compensatory allowance scheme in 1987, the forest premium in 1990 and more recently, the afforestation scheme 2014-2020 incentivised forestry for farmers/landowners (Government of Ireland 2022). In this study, a substantial increase in forestry on peatlands was detected in the past 15 years, mainly on raised bogs. There are further plans by BnM and Coillte e.g., to convert 1,500 ha of the former industrial area into native woodlands (BnM 2019). Therefore, this land use change trend will continue over the coming years.

2.5.3 Grassland

Irish Peatlands have been drained and reclaimed for agricultural development for centuries (Hammond 1981; Connolly 2018). This grassland category includes several types of grassland land uses including silage, hay, grazing, and pasture (Fealy Stuart Green et al. 2009). While the other land use categories exhibited either consistent downward or upward trends since 1990, the grassland area on peatlands in Ireland has experienced an overall decline between 1990 and 2019. However, between 2005 and 2019, an increase is observed. A more detailed examination of this phenomenon in Figure 2.6 highlights a continuous decrease in grassland on blanket bogs, while grasslands on raised bogs display a decrease between 1990 and 2005, followed by an increase in 2019.

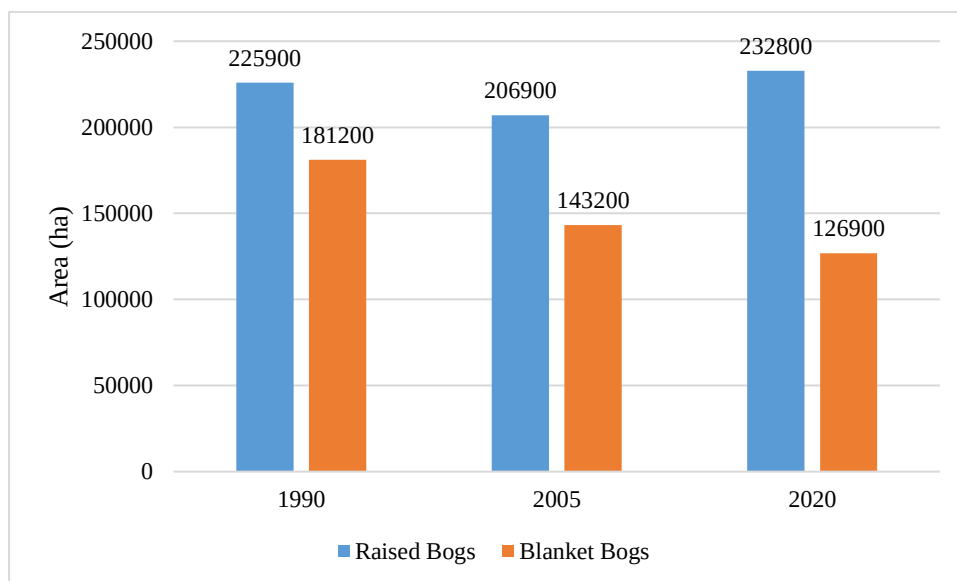


Figure 2.6: Grassland area on raised and blanket bogs.

To be precise, the land use conversion analysis (Table 2.5) shows that between 1990 and 2005, ~40,700 ha of grassland on peatland was converted to forestry. This could be attributed to afforestation incentives discussed earlier. The increase in grasslands on raised bogs between 2005 and 2019 could be explained by a national drive towards agricultural production with incentives such as the abolition of the milk quota (Donnellan et al. 2015). BnM also converted 2,500 ha of industrial cutaway land to agricultural grasslands (Renou-Wilson et al. 2015). Furthermore, government grant aids in the 1980/90 and payments through the EU Common Agricultural Policy (CAP), encouraged the conversion of large areas of peatland (mostly upland bogs) to grazing lands (Bullock et al. 2012).

2.5.4 Residual Peatland

The residual peatland class comprises a range of small-scale land use categories that make up a spatially complex and heterogeneous landscape (Connolly, 2018). These land use categories include domestic peat extraction, rewetted and rehabilitated areas, natural degradation, and bare peat which can be difficult to discriminate within the

Landsat imagery. Consequently, the spectral signature variations are likely the result of land use and revegetation associated with the rehabilitation or abandonment of these lands. This leads to a shift from one class to another within a particular TP, followed by a return to the same class. An example of this is a change from Grassland to Residual Peatland and then back to Grassland. Sites that are going through rehabilitation such as the former BnM industrial site at Bellacorrick, Co. Mayo have predominantly reverted to poor fen and scrub with embryonic peat-forming conditions and thus converted to the residual peatland category (Farrell and Doyle, 2003). The cutover and remnant peatland (high bog) areas present a dynamic landscape and detailed habitat (area of occupancy) mapping using high-resolution imagery is essential (Álvarez-Martínez et al. 2018; Ingle et al. 2023). COPENICUS Sentinel-2 or other higher-resolution imagery could be used for this purpose, but this was beyond the scope of this study. Future work could also include additional TPs and the analysis of the spectral signature over time.

Overall, the general spatial distribution and temporal trend of the four main land use classes show that peatland industrial areas, which are present mostly on raised bogs, are converting to residual peatland, forestry, and grassland. Although residual peatlands possibly show the rehabilitation, restoration and rewetting efforts being implemented. Furthermore, the use of blanket bogs for afforestation activities will also lead to ecosystem degradation and increasing peatland emissions (Jovani-Sancho et al. 2021). Degradation could be further exacerbated by climate change. For instance, periods of dry weather might render these ecosystems more susceptible to wildfires, and episodes of drought followed by heavy precipitation could increase their vulnerability to landslides (Connolly et al. 2021).

The overall accuracy for the maps in both 2005 and 2019 is 86% and 85%. However, more detailed information can be obtained by looking at the user and producer accuracy. The user accuracy for forestry and grassland is the highest in the 2005 (86%) and 2019 (85%) maps. The accuracy of the residual peat class is the lowest, primarily because this category is an amalgamation of multiple small-scale land uses. This is a limitation of using medium spatial resolution data (30 m). The industrial class also has lower accuracy. This class represents the exposed peat areas within the BnM landholdings. However, the peripheries of BnM sites still have domestic peat extraction activities ongoing which result in exposed peat. This is one cause of confusion between

2.5 Discussion

industrial peat extraction sites with residual peatlands, resulting in lower accuracy for both classes. Future work could use high-resolution satellite imagery and very high-resolution aerial imagery to improve the land use maps, and map residual peatland class in further detail. This includes domestic peat extraction and rehabilitation, restoration, and rewetting sites. The use of Landsat (medium resolution) for the hard classification of large areas may introduce uncertainties (Álvarez-Martínez et al. 2010). For example in heterogeneous land use classes such as the residual peatlands and grassland in this study, the allocation of pixels to specific land use classes may cause uncertainty (Bradley and Mustard 2005). This could introduce errors in classification results and eventually the confusion matrix. The elimination of these uncertainties using the methods proposed by Álvarez-Martínez et al. (2010) could lead to a more refined accuracy assessment and a more efficient analysis of the temporal evolution of changes. Additionally, this study uses an existing peatland map (DIPMv2) for the delineation of peatland areas. However, it is the latest and most reliable map of peatlands in Ireland with an overall accuracy of 88%. It underestimates the extent of peatlands with areas of less than 7ha (Connolly and Holden 2009). Therefore, this study can be expanded to these missing areas if that peat map is updated. Nevertheless, our study is an essential first step towards understanding peatland land use and offers a significant perspective and valuable insights into the dynamics of land use change on peatlands in Ireland.

While higher spatial resolution remote sensing data is available, this methodology outputs maps of the major land use categories on peatlands providing valuable information on how they are changing through space and time. It could be a useful dataset for the recently announced “Land Use Review” by the Government of Ireland (2023). This methodology could be used to identify hotspots of land use change to support policy-related decision-making, aid Nation Inventory Reporting, promote sustainable land use practices and implement the principles and actions outlined in the National Peatland Strategy of Ireland. Additionally, these maps could also be used to refine estimates of GHG emissions from peatlands using Intergovernmental Panel on Climate Change (IPCC 2003) methodologies. The method used here is robust and could be applied to track and monitor peatland land use and land use change over time both in Ireland and across the globe.

2.6 Conclusion

This study presents the first long-term spatiotemporal assessment of peatland land use and land use change for Ireland. It was conducted over a 30-year period from 1989 to 2020. The spatial extent of four major peatland land use categories (grassland, forestry, industrial peat extraction and residual peatlands) are quantified, for both blanket and raised bogs. The methodology integrates the DIPMv2 to delimit peatlands within the GEE cloud computing platform. The random forest ML algorithm is combined with Landsat data to classify the major land use classes. The results indicate that at least 30% of peatlands in Ireland have undergone major land use change in the last 30 years. The results clearly show the conversion of industrial peatlands (BnM-owned) as extraction ceases and the land is converted to several other land uses including rewetted areas. The forestry area has also increased, and grassland is one of the largest land use classes on peatlands in Ireland. The methodology also highlights how GEE can be used to overcome issues such as persistent cloud cover to deliver a national scale assessment of land use change on peatlands and identify hotspots of change. Future studies should use higher-resolution imagery that can then be applied to examine these areas in detail, particularly the residual peatland class where change is occurring but cannot be detected with Landsat data. This robust method could be used to generate peatland land use-specific maps for peatland areas across the globe using the available global and regional peatland extent maps.

Chapter 3. Quantifying peatland land use and CO₂ emissions in Irish Raised bogs: Mapping insights using Sentinel-2 data and Google Earth Engine²

3.1 Abstract

Ireland has >50% of the EU's oceanic-raised bogs; however, degradation through land use activities has turned them from carbon (C) sinks to sources. Given their significant role in climate mitigation, quantifying land use degradation and emissions is crucial. A seven-class land use classification system for Irish peatlands (LUCIP) was developed and mapped using Sentinel-2 imagery, random forest ML and Google Earth Engine. The results revealed that agricultural grassland comprised 43% of the land use on raised bogs, followed by, forestry (21%), cutover (11%), cutaway (10%) remnant peatlands (13%), water-bodies and built-up ~1% each. The overall accuracy of the map was 89%.

The map was used to estimate CO₂ emissions for four classes constituting 85% of raised bogs: cutover, cutaway, grassland, and forestry using the IPCC wetlands supplement and literature-based emission factors, we estimated emissions at ~1.92 and ~0.68 Mt CO₂-C-yr⁻¹ respectively. This is the first study to spatially quantify land use and related emissions from raised bogs. The results revealed widespread degradation of these globally rare habitats, making them net emitters of CO₂. The map is vital for 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 This chapter corresponds to the paper published on 12 January 2023, in *Scientific Reports* (2024) [4]

3.2 Introduction

European peatlands cover approximately 60 million ha (Tanneberger et al. 2017; Xu et al. 2018) with a substantial area degraded by unsustainable land use practices, including agriculture, forestry, and peat extraction. Consequently, almost 44% can no longer accumulate peat (Joosten 2017). Tanneberger et al. (2021b) indicated that degraded peatlands in the European Union (EU) represent half of the globally degraded peatlands. In Ireland, peatlands cover ~1.46 million ha (21% of Ireland) and consist of two types of bogs: blanket bogs (~900,000 ha) and the globally rare oceanic raised bog (~530,000 ha) (Connolly and Holden 2009; Bullock et al. 2012). It is estimated that they store between 60 to 75% of the national SOC (Soil Organic Carbon) stock (Tomlinson 2005; Eaton et al. 2008; Renou-Wilson et al. 2011) but land use practices have led to the degradation of about 95% of these peatlands (Malone and O'Connell 2009a; Bullock et al. 2012b; Davies et al. 2014; Connolly 2018; Fluët-Chouinard et al. 2023).

These land use activities harm the hydrological and ecological functioning of peatland ecosystems, turning them from a net sink to a source of C (Wilson et al. 2013). It also results in a consistently lowered water table, which accelerates peat decomposition, releases dissolved organic carbon (DOC) and particulate organic carbon (POC) and alters C and GHG fluxes (Holden et al. 2007; Mackin et al. 2015). Hence, these ecosystems, which in their natural condition are significant C stores and are crucial to the prevention of natural disasters such as landslides, fires, and floods (Tanneberger et al. 2021a), become susceptible to them (Turetsky et al. 2015; Connolly et al. 2021; Islam et al. 2022). Despite this, Irish peatlands still contribute to various hydrological and ecological functions and cultural, and socio-economic values (Bullock et al. 2012; Flood et al. 2021)

The land use practices on peatlands in Ireland are similar to those in Europe, including drainage for industrial and domestic peat extraction, agriculture (mostly grasslands), afforestation and infrastructure development (roads, wind farms, airports etc.,) (Connolly and Holden 2013; Joosten et al. 2017; Connolly 2018). As a result, it is estimated that less than 1% of raised bogs in Ireland are actively forming peat as of 2017 (NPWS 2017). This is particularly due to the intensification of land use through industrial peat extraction, afforestation and agriculture, which is a relatively recent

3.2 Introduction

development (since the 1940s) but has caused more damage in a short period of time (Connolly and Holden 2013). The establishment of Bord na Mona (BnM), a semi-state-owned company, in 1946, for industrial peat extraction had a notable impact on raised bogs. Approximately 90% of the BnM landholdings are situated on raised bogs and the majority of those (~90 %) have been drained and/or opened for peat extraction (Habib and Connolly 2023). BnM ceased extraction activities in 2021 (BnM 2021), however, there are still several medium-sized companies engaged in industrial peat extraction, including Harte, Klasmann-Deilmann, Bulrush, Clover, Erin, and Westland, as well as ~30 other small producers (Malone and O'Connell 2009; Wilson et al. 2013). Coillte, a semi-private afforestation company established in 1989, afforested approximately 30,000 ha of raised bogs. The provision of grants through the Common Agricultural Policy (CAP) for the reclamation of raised bog edges for agriculture has contributed to the intensification of land use in these ecosystems. However, spatially explicit data on the extent of these activities (especially non-BnM industrial activities) and domestic peat extraction activities is non-existent (Aitova et al. 2023). The absence of such data prevents accurate quantification of emissions from managed peatlands and hinders the formulation of effective conservation strategies.

As a signatory to the United Nations Framework Convention on Climate Change (UNFCCC), Ireland has an obligation to report and account for its GHG emissions and removals and meet its emission targets for Land Use, Land Use Change, and Forestry (LULUCF), including wetlands, as outlined in the EU's 2030 climate change framework (EU 2022). Several studies have been conducted on Irish raised bogs at small spatial scales to gain insights into the effect of land use conversion activities on C and GHG dynamics, such as losses through land, atmospheric, and fluvial emissions (Swenson et al. 2019; Wilson et al. 2022). These local-scale effects can have regional and global consequences; yet information on land use status and associated emissions from these ecosystems remains poorly understood at the national, regional, and global levels (Page and Baird 2016). To propagate local-scale emission measurements to a national scale and accurately account for peatland emissions, spatially explicit information on peatland land use is essential (Wilson et al. 2013; Aitova et al. 2023). Andersen et al. (2017) emphasise the importance of land use/cover data in understanding degradation and restoration. However, national and global land use/cover maps often exclude activities such as peat extraction, forest and abandoned peat extraction sites (Tanneberger et al. 2021b). This makes these datasets inadequate for understanding

degradation through land use, monitoring conservation activities (rehabilitation, restoration, and rewetting), and assessing C and GHG emission dynamics.

To report emissions from wetlands, the Intergovernmental Panel on Climate Change (IPCC) has proposed a system consisting of three tiers: Tier 1 (T1) includes default EF (Emission Factor) and is specifically for wetlands and Tier 2 (T2) EFs are country-specific and based on the emission data from case studies. The Tier 3 (T3) EFs use more complex and dynamic models. The default T1 EFs are derived from limited data available from sites with different geographical, climatic, and ecological conditions. Ireland reports emissions from peatlands based on T1 EFs except for industrial peat extraction sites and forests on drained peatlands, where country-specific EF values are being used (Duffy et al. 2021). However, the reliance on coarse spatial resolution (25 ha) CORINE (Co-ordinated Information on the Environment) land cover data and non-spatially explicit information for reporting purposes make the national emission estimates less accurate. Given these limitations, it is essential to develop peatland-specific land use maps that can be used for more accurate upscaling of emissions from site to regional, national, and global scales using IPCC methods. Furthermore, these maps are vital for supporting conservation activities, sustainable land management practices and policy-related decision-making.

This study aims to map the much-needed spatial distribution of land use on raised bogs in Ireland and quantify the corresponding C and GHG emissions (Hammond 1981; Feehan and O'Donovan 1996; Connolly and Holden 2009). The spatial extent of raised bogs is based on the DIPMv2 (Derived Irish Peat Map version 2), which is the latest peatland extent map integrating data from multiple sources (Connolly and Holden 2009). Irish raised bogs represent more than 50% of oceanic-raised bogs in the EU (Bullock et al. 2012). Spatially explicit information on land use can be obtained using remote sensing methods. However, the persistent cloud cover inherent to the temperate maritime climate of Ireland poses a challenge to the acquisition of frequent cloud-free optical remote sensing images (Fealy Stuart Green et al. 2009). As a result, it is particularly difficult to map national-scale land cover and land use. Previous attempts to map land cover at a national scale in Ireland have encountered similar difficulties and full coverage has not been achieved (Fealy Stuart Green et al. 2009; Cawkwell et al. 2010, 2018; Walsh et al. 2021). Connolly (2018) successfully mapped industrial, grassland and forestry on peatlands in Ireland, including raised bogs, but

3.3 Material and methods

was unable to map domestic peat extraction, because of the medium spatial resolution of the data (23m) and cloud cover issues.

Google Earth Engine (GEE), a planetary-scale cloud computing platform (Gorelick et al. 2017), integrates freely available high-resolution satellite imagery such as Sentinel-2, as well as ML algorithms such as random forest. By leveraging a vast archive of satellite imagery and employing temporal mosaicking functions within GEE, it is possible to obtain cloud-free imagery with wall-to-wall coverage and use it to map land use in areas where cloud cover impedes optical remote sensing (Amani et al. 2019b; Mahdianpari et al. 2020). This approach was used in this study to obtain cloud-free imagery by mosaicking annual images acquired for three years from 1st January 2018 – 31st December 2020. As a result, the first national-scale land use map of raised bog with seven classes was developed. The classes were derived from the Land Use Classification for Irish Peatlands (LUCIP), which was developed for this study through discussions with various stakeholders including NPWS, BnM, and ecologists. The classes on LUCIP include cutover, cutaway, grassland, forestry, remnant peatlands, water bodies, and built-up areas. The map enabled the assessment of the spatial extent of land use in raised bogs. It is further used to estimate CO₂ emissions using site-specific EFs from case studies in Ireland (Aitova et al. 2023), which are then presented along with IPCC T1 EFs. This work will provide better insight into C dynamics at the site scale, with an emphasis on the importance of high-resolution maps for area estimation and country-specific EFs.

3.3 Material and methods

3.3.1 Study area

The study area for this research was based on the spatial extent of raised bogs derived from DIPMv2 (Connolly and Holden 2009). Raised bogs are predominantly situated in the midlands of Ireland and are a distinctive feature of this inland region. They cover ~530,000 ha of the surface area and constitute ~35% of the total peatland area in Ireland and 8% of the total land surface area.

Satellite image data

Copernicus Sentinel-2-MSI (Multi-Spectral Instrument) optical remote sensing satellite images were used in this study and the images were acquired by Sentinel-2- A and B. The Sentinel-2 sensor has 13 spectral bands, 10 of which were used in this study: Red (R), Green (G), Blue (B), Near Infrared (NIR) and Narrow NIR, three of the Vegetation Red Edge, and two of the Short-Wave Infrared (SWIR) (Drusch et al. 2012). Table 3.1 shows the spectral and spatial resolutions of the bands used in this study. The RGB and NIR bands have a spatial resolution of 10 m while the rest were resampled from 20 m to 10 m. The sensor has a swath width of 290 km (Drusch et al. 2012).

Table 3.1: Characteristics of sentinel-2 bands(ESA 2015).

Bands	Central wavelength (μm)	Spatial Resolution (m)
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 - Vegetation red edge	0.705	20
Band 6 - Vegetation red edge	0.740	20
Band 7 - Vegetation red edge	0.783	20
Band 8 - NIR	0.842	10
Band 8a - NNIR	0.865	20
Band 11 - SWIR	1.610	20
Band 12 - SWIR	2.190	20

GEE provides the Sentinel-2-MSI image archive dating back to March 2017. This study used the atmospherically corrected products: Level-2A (L2A) S2_SR (Sentinel-2 Surface Reflectance). They are corrected for atmospheric, slope and adjacency effects.

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L2A processing is based on a two-step process i.e., (1) scene classification (SC), which is used to derive a pixel classification map for vegetation, snow, soil, cloud shadows and cloud and (2) Sentinel-2 Atmospheric Correction (S2AC) which is used to convert the Top of Atmosphere (TOA) reflectance to BOA (Bottom of Atmosphere) values. The S2AC process is based on the library for Radiative transfer (libRadtran) model (Mayer and Kylling 2005; Richter and Schläpfer 2005). It provides cloud, haze, and water removal methods. To enhance the classification process, a vegetation and water index was calculated and included as additional bands. The Normalised Difference Vegetation Index (NDVI) with values ranging from 0.1 to 1 indicates the presence and health of vegetation (Liu and Huete 1995) Eq. (3.1), while the Normalised Difference Water Index (NDWI) with values ≥ 0.5 indicates the presence of open water (Gao 1996) Eq. (3.2).

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad 3.1$$

$$NDWI = \frac{NNIR - SWIR1}{NNIR + SWIR1} \quad 3.2$$

3.3.2 Image classification methods

A remote sensing image classification-based approach was used in this study and implemented in GEE and ArcPro desktop version 2.7 (ArcPro from here onwards). It consisted of accessing, pre-processing and classification of land use using LUCIP, in GEE. The accuracy assessment was conducted using ArcPro. The imagery was accessed at a national scale and constrained to Irish-raised bogs using the DIPMv2. The overview of the process is presented in Figure 3.1.

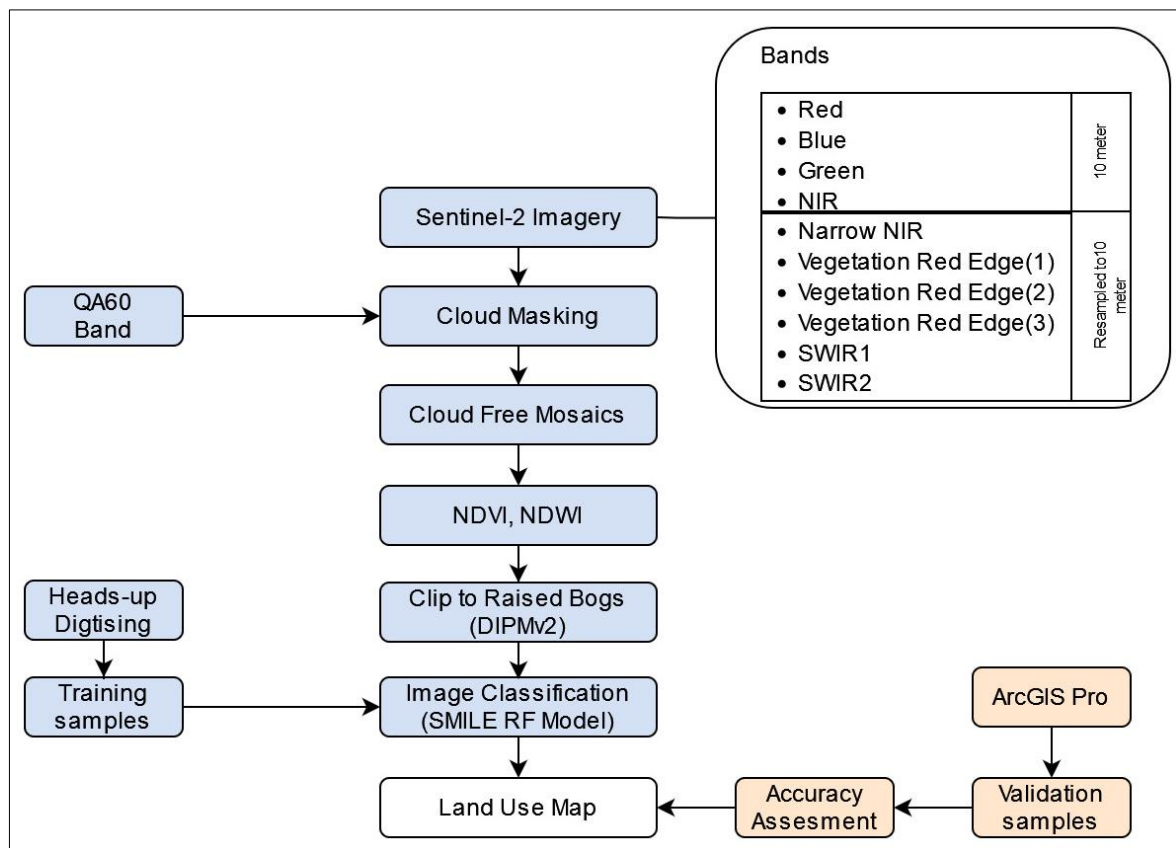


Figure 3.1: Data processing workflow. NIR (Near Infrared), SWIR (Shortwave Infrared), NDVI (Normalised Difference Vegetation Index), Normalised Difference Water Index (NDWI), QA60 (Quality Assessment) band for cloud and cirrus masking, and DIPMv2 (Derived Irish Peat Map version 2).

3.3.3 Image pre-processing

Despite the high temporal resolution (5 days) of Sentinel-2 (A and B), obtaining a cloud-free mosaic for wall-to-wall coverage of raised bogs in Ireland was challenging. To address this issue, it is important to develop an efficient cloud removal methodology. Accordingly, a temporal filter was applied to obtain imagery over three years (1st January 2018 – 31st December 2020). A selection criterion to obtain images with less than 10% cloud cover was also applied; a percentage more than this would return cloud-contaminated images that were not useful for analysis. Based on these criteria, 1483 images were available. The remaining cloudy pixels were masked out using a cloud masking function (*masksS2clouds*) which was based on the ‘QA60’ quality flag band used for cloud and cirrus. Finally, the images were stacked together to generate a single cloud-free composite using the median (*ee.reducer*) composite function available in GEE. This also helped eliminate pixels with extreme values, thus

removing the remaining artefacts. The final image was composed of pixels with minimal to no cloud cover.

3.3.4 Training sample data

The training and validation data used in this study were completely independent of one another. The training data was based on randomly generated sample polygons created within GEE for each land use class (Table 3.2). Validation sample points were generated using ArcPro. A classification schema (LUCIP) was developed to identify seven land use classes, cutover, cutaway, grassland, forestry, remnant peatlands (high bog) and built-up/infrastructure areas (Table 3.2)

Table 3.2: Description of land use classes based on the Land Use Classification for Irish Peatland (LUCIP) level-3 developed in this study.

Land use class	Description
Cutaway	Land that has been subjected to industrial peat extraction, with the peat removed and the land left bare or with a thin layer of soil, managed by BnM and other private companies with large-scale mechanised peat extraction
Cutover	Land that has been subjected to domestic peat extraction, hand-cut, small-scale mechanised, includes bare peat, interspersed woodland, heath, and scrub
Grassland	Agriculture grass-covered land that is used for pasture or hay, silage, and grazing
Forestry	Land covered with trees; afforested areas are mostly covered by evergreen tree species
Remnant Peatland	Land that has a high percentage of peat (near natural and high bog areas,) and is characterized by the

Land use class	Description
	presence of sphagnum mosses and other bog flora, not directly affected by human intervention. Revegetated areas of post-extraction activities
Water bodies	Land covered with water, including natural waterways and surface water on raised bogs that have appeared after rewetting activities and/or abandonment
Built-up/Infrastructure	Land used for human settlements and infrastructure, such as buildings, roads, windfarms etc.,

The collection of training data was based on the visual interpretation technique, which was used by an expert operator to generate randomly distributed sample polygons for each land use class (Richards 2013). The training data consisted of 366 polygons (148405 pixels) that were randomly distributed across the study area (Table 3.3).

Table 3.3: Characteristics of randomly distributed training and validation sample data.

Land use class	No. of training polygons	No. of training pixels (sum per training polygon)	No. of validation points
Cutaway	37	94672	197
Cutover	45	4345	130
Grassland	32	7320	660
Forestry	100	11627	252
Remnant Peatland	62	28038	121
Water bodies	64	1816	50

3.3 Material and methods

Land use class	No. of training polygons	No. of training pixels (sum per training polygon)	No. of validation points
Built-up/Infrastructure	26	587	50
Total	366	148405	1460

The spectral signature of each land use class is shown in Figure 3.2. The mean reflectance values across multiple Sentinel-2 bands demonstrate significant spectral separability in the visible and NIR bands range i.e., 0.49 to 0.78 μm . Notably, built-up areas consistently exhibit high reflectance, whereas water has consistently low reflectance, making them significantly distinguishable. Cutaway and grassland show high reflectance in the NIR region. Cutover and remnant peatlands, however, may exhibit some similarities, given that the cutover class includes a dynamic vegetation environment. The spectral separability for most of the classes diminishes for longer wavelength bands, specifically at 1.61 and 2.19 μm . Nevertheless, differences in spectral reflectance between all the classes remain prominently discernible, underscoring the effectiveness of the sampling procedure employed for land use classification.

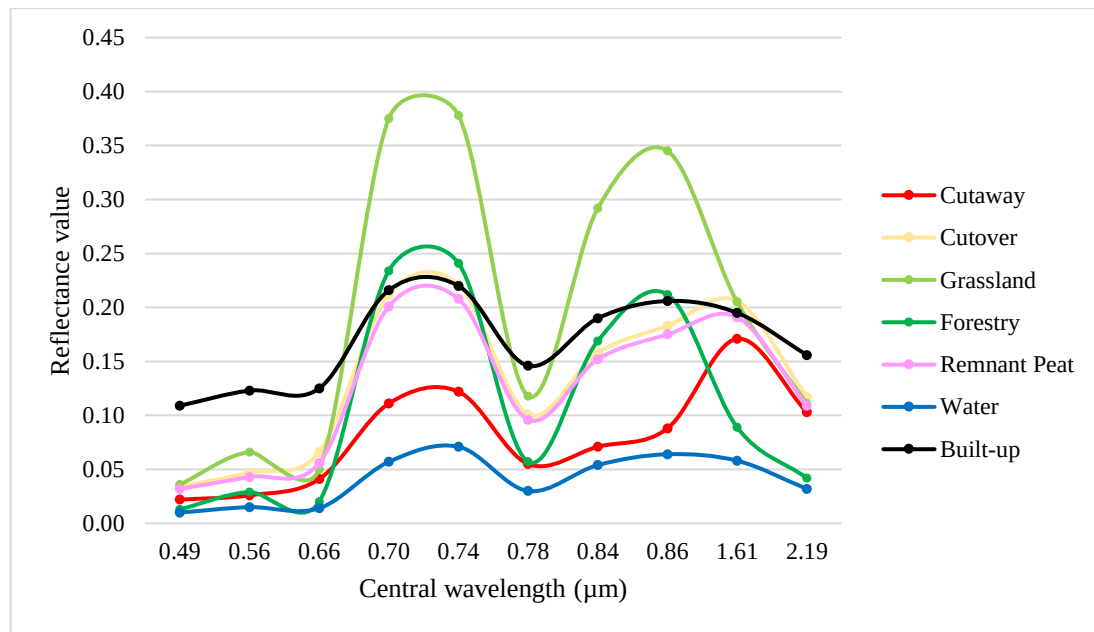


Figure 3.2: Spectral reflectance of the land use types across the ten spectral bands (Sentinel-2).

3.3.5 Classification of satellite imagery

The random forest classification model, an ensemble classifier (Breiman 2001; Pal 2005) was trained using training data. The random forest algorithm is based on an ensemble of several decision trees, each with multiple nodes (Breiman 2001). The classification was implemented using the GEE platform. A slightly improved version of the random forest model known as the Statistical Machine Intelligence and Learning Engine (SMILE) random forest algorithm was used for this study (Li 2016). The classification model was trained using the training data, with the number of variables and the number of trees being the two critical parameters. The optimal values of these parameters were determined using the square root of the number of features and the trial-and-error method. Based on these procedures, the optimal number of trees was determined to be twenty. Each tree in the model consists of multiple nodes, and each pixel is assigned a label by each tree. The final label for each pixel was determined by aggregating the labels assigned by all trees through a majority vote (Breiman 2001). The implementation of the random forest model and its optimization procedures were performed using GEE. The variable importance for all spectral bands, NDVI and NDWI

was also assessed. Spectral reflectance bands (5,12, 11 and 2) were ranked higher while NDVI and NDWI were ranked lower (*see Appendix B: Variable Importance and Error Matrix*). The accuracy of the final output map was assessed using validation data.

3.3.6 Validation (accuracy assessment)

After conducting a qualitative accuracy assessment (visual evaluation), the final map was downloaded from GEE and imported into ArcPro. An overall quantitative accuracy assessment was conducted using ArcPro using independent validation point sample data (Table 3.3). Yelena and Antonia (2016) emphasise the importance of using higher-quality reference data derived through a sampling approach to assess the accuracy of land use maps. They further noted that the data could be based on field sampling or a higher resolution spatial resolution aerial imagery. The latter approach was used in this study since the first approach could be laborious and time-consuming for national scale mapping. The “create accuracy assessment tool” in ArcPro was used with a stratified random sampling strategy (Olofsson et al. 2014). The tool generates random points, and the sample size is based on the proportion of the area for each class. This process ensures that a sufficient number of reference samples is created for each stratum (class) (Olofsson et al. 2014). In total, 1460 points were obtained (Table 3.3). Each validation sample data point was assessed and manually labelled through the visual interpretation of very high-resolution aerial imagery (25 cm) by a single expert operator. After completion of manual labelling, a confusion matrix for accuracy assessment was generated using the “compute confusion matrix” tool in ArcPro. This was done by comparing the classes obtained using the classification model with the ground truth data. Multiple statistics were derived from the confusion matrix to quantify map accuracy. These include Overall Accuracy (OA), overall agreement between classification (map) and ground truth for all classes. The User's accuracy (UA) measures the agreement between the classified pixels and the ground-truth data for a specific class from the user's perspective, whereas the Producer's accuracy (PA) measures the agreement between the classified pixels and the ground-truth data for a specific class from the producer's perspective (Story and Congalton 1986).

3.3.7 CO₂ emission calculations

CO₂ emissions were calculated using the IPCC T1 EFs and the literature-based T2 EFs using Equation (3.3). Four dominant land use classes (cutaway, cutover, forestry, and grassland), which cover ~85% of the total raised bog land use area (Figure 3.3) were used for emission estimation. For the remaining classes (remnant peatlands, water bodies, and built-up areas), neither T1 nor T2 emission factors were available; therefore, CO₂ emissions could not be estimated. T1 default EFs from the IPCC Wetland Supplement (2013) and T2 EFs by Aitova et al. (2023) which are based on case studies in Ireland for grasslands, cutover and cutaway sites were used. The EF for forestry is based on eight drained and afforested peatland sites in Ireland (Jovani-Sancho et al. 2021).

$$\begin{aligned} CO_2 \text{ emission } (t \text{ CO}_2 - C \text{ ha}^{-1} \text{ y}^{-1}) \\ = \text{land use area (ha)} \times EF (t \text{ CO}_2 - C \text{ ha}^{-1} \text{ y}^{-1}) \end{aligned} \quad 3.3$$

where t is tonnes, ha is hectare and y represent a year and EF is the land use-specific emission factor.

3.4 Results

The statistics for the area of each land use class on raised bogs are presented in Figure 3.3. Almost half of the raised bogs mapped in this study are covered by grassland i.e., 43% (244,100 ha). Forest covers about 21% (116,427 ha), whereas cutaway is 10% (54,302 ha) and cutover 11% (646,99 ha). The remnant peatlands (high bog) area covers about 13% (73,795) ha. Water bodies and built-up areas account for about 1% (1542 ha and 1358 ha, respectively). The water bodies here constitute both natural waterways included in the coarse resolution DIPMv2 and surface water on raised bog appearing possibly after rewetting activities.

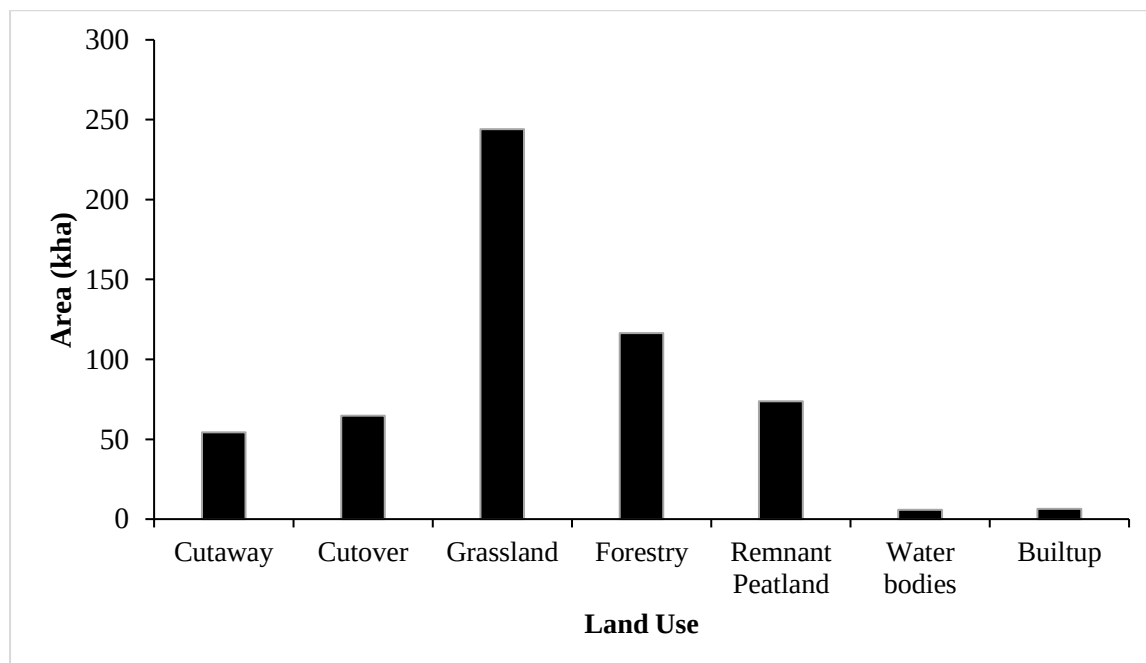


Figure 3.3: Land use area in kilo hectares (kha) for each class.

The prevalence of land use activities can be seen across all raised bogs in the midlands of Ireland (Figure 3.4). Industrial peatland extraction sites are primarily located in the midlands (Figure 3.4 (a)), and some parts of the North (Figure 3.4 (b and c)) and South (Figure 3.4 (f)) of the midlands. About 65% of these industrial extraction sites belong to BnM. The other 35% constitute non-BnM peat extraction carried out on an industrial scale similar to BnM (Figure 3.4 (d, e)). The BnM landholding and Special Area of Conservation (SAC) boundary data were used to further examine the distribution of land use to better understand the status and condition of raised bogs under different management regimes i.e., industrial and protected. Which is presented in the table below (Table 3.4). Additionally, Coillte landholding boundary data was also used to assess land use. It owns ~31,000 ha of raised bog areas accounting for about one-third of the total forestry on these bogs.

Table 3.4: Proportion of each land use on Bord Na Mona (BnM) and Special Area of Conservation (SAC) under the National Parks and Wildlife Services. All areas are in hectares (ha).

Class	BnM (ha)	SAC (ha)
Cutaway	42264	2460
Cutover	7303	4907
Grassland	2379	7318
Forestry	9067	3490
Remnant Peatland	6491	13053
Water bodies	1580	1340
Built-up/Infrastructure	388	197
Total	69472	32568

The exposed peat on BnM landholdings amounts to around 42,264 ha. The rest of the cutaway bogs totalling about 2,460 ha are in SAC, highlighting the existence of a substantial amount of bare peat on these “protected” bogs with active cutting also taking place (O’Sullivan 2023). The cutaway bogs in the midlands have interspersed forestry. (Figure 3.4 (a)). The areas on the edges of these bogs represent agricultural grasslands. The remnant peatlands in the midlands are mostly on SAC sites such as Clara Bog, Ferbane Bog, Moyclare Bog, and Raheenmore Bog (Figure 3.4 (a)). Overall, there is about 13,053 ha of remnant peatlands located on the SAC, which is approximately 1% of the total peatland area and most of the “actively forming raised bogs” are possibly located in these sites (Mackin et al. 2017a). The majority of the remnant peatlands are in the West of the midlands and are surrounded by peat extraction activities (Figure 3.4 (d and e)). Lastly, the scattered water bodies on cutaway sites in the Midlands and some parts in the North represented are possible signs of some of the rewetting activities being carried out by BnM (Figure 3.4 (a and b)).

3.4 Results

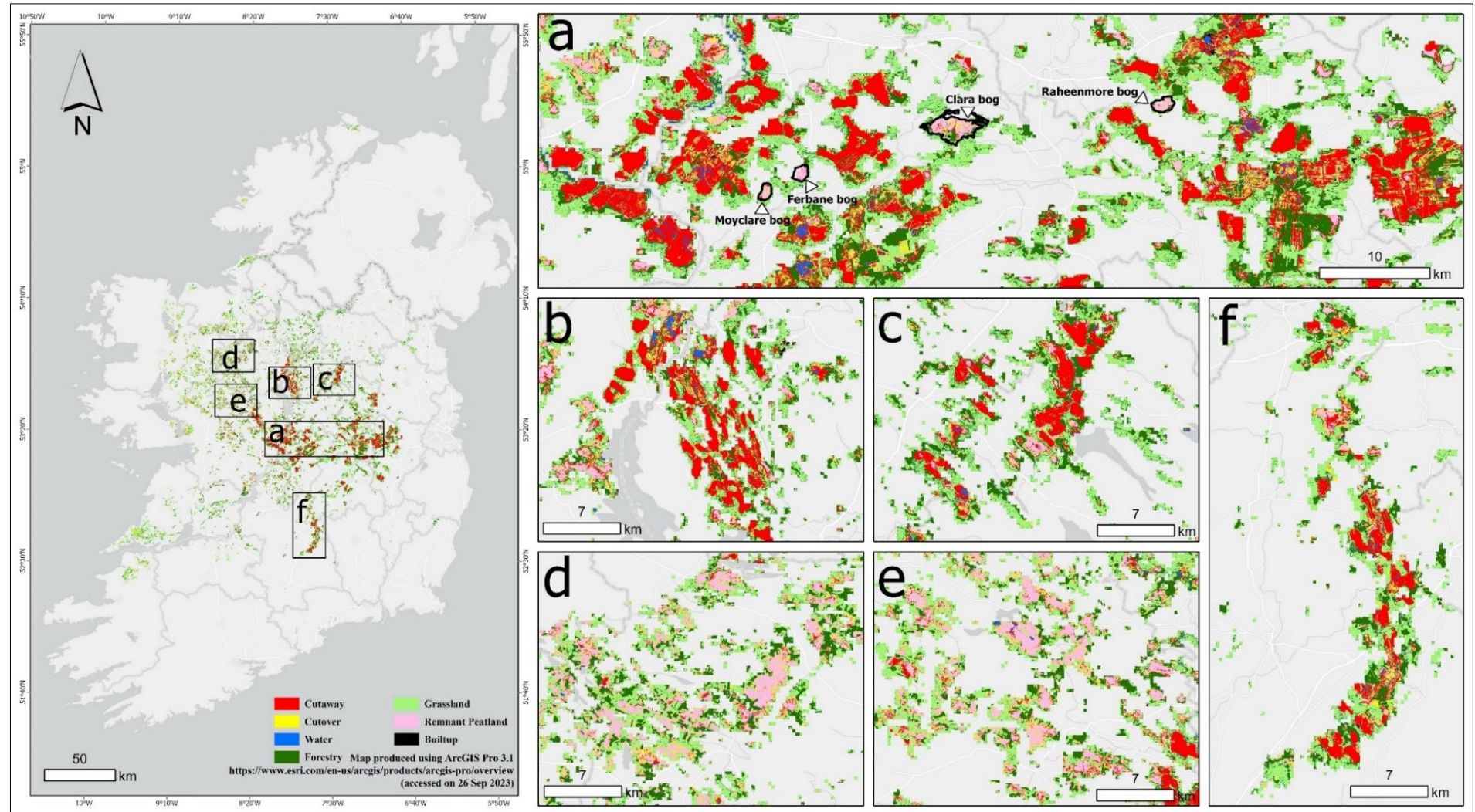


Figure 3.4: Land use on raised bogs. (a), (b), (c) and (f) are dominated by industrial peat extraction sites (mostly Bord na Mona), whereas (d) and (e) have a mix of remnant peatland, cutover, grassland, and forest. (a) labelled bog areas Special Area of Conservation (SAC)

3.4.1 CO₂ emissions

The CO₂ emissions presented in Table 3.5 are calculated using Equation (3.3) for the four land use classes. The area (ha) is estimated from the land use map (Figure 3.4). T1 emissions ranged between 303,710 to 1,293,730 t CO₂-C ha⁻¹ y⁻¹ with grassland being the highest emitters followed by forestry, cutover, and cutaway. T2 emissions were in the range of 65,705 to 317,330 t CO₂-C ha⁻¹ y⁻¹ with the highest emissions at grassland and lowest for the cutaway. The T1 emissions for grassland were four-fold higher than T2 emissions. The total CO₂ emissions from Irish-raised bogs based on the four land use classes mapped here account for 0.68 Mt CO₂-C ha⁻¹ y⁻¹ as per T2 and 1.92 Mt CO₂-C y⁻¹ as per T1.

Table 3.5: Emissions from four dominant land use classes, with Intergovernmental Panel on Climate Change (IPCC) Tier 1 and 2 (T1, T2) Emission Factors (EFs) with 95% confidence intervals values are shown in brackets, Emissions based on the area in hectares (ha) and EFs (in tonnes of CO₂-C per hectare per year).

Land Use	Area (ha)	T1 (IPCC) EFs	T1 Emissions (t CO ₂ -C ha ⁻¹ y ⁻¹)	T2 (literature) EFs	T2 Emissions (t CO ₂ -C ha ⁻¹ y ⁻¹)	No. of sites for T2 EFs	Literature source
Cutover	64699	2.8 (1.1 - 4.2)	181157	1.21 (0.4 - 2.0)	102871	3	(Aitova et al. 2023)
Cutaway	54302	2.8 (1.1 - 4.2)	152046	1.59 (1.2 - 2.0)	65705	4	(Aitova et al. 2023)
Forestry	116427	2.6 (2.0 - 3.3)	302710	1.68 (1.04 - 2.32)	195597	8	(Jovani-Sancho et al. 2021)
Grassland	244100	5.3 (3.7 - 6.9)	1293730	1.3 (0.04 - 2.55)	317330	3	(Aitova et al. 2023)

3.4.2 Accuracy assessment

The OA of the final land use map was 89% which is computed from the diagonal line of the confusion matrix (Table 3.6), representing the number of correctly classified classes. A total of 1303 out of 1460 points were correctly classified. These UA ranges from 70% (water and cutover) to 96% (forest), and PA ranges from 64% (built-up) to 97% (cutaway).

Table 3.6: Result of accuracy assessment for all the seven land use classes, including Overall Accuracy (OA), User's Accuracy (UA), and Producer's Accuracy (PA).

Class	A	B	C	D	E	F	G	Total	UA (%)
Cutaway (A)	164	12	1	8	2	10	0	197	83
Cutover (B)	0	91	0	4	15	19	1	130	70
Water (C)	1	0	35	8	2	0	4	50	70
Forest (D)	1	2	0	244	4	1	0	252	96
Grassland (E)	2	1	1	12	624	6	14	660	94
Remnant Peatland/High Bog (F)	1	2	0	2	5	111	0	121	91
Built-up (G)	0	0	0	3	13	0	34	50	68
Total	169	108	37	281	665	147	53	1303	OA (%)
PA (%)	97	84	94	86	93	75	64		89.2

The results show the highest PA for cutaway (97%) and grassland classes (93%) while remnant peatlands (75%) and built-up (64%) have the lowest PA. Whereas, forestry (97%), grassland (94%) and remnant peatlands/high bog (91%) all show high UA, while built-up (68%), cutover and water (70%) show low UA. The lower UA of the

cutover class (70%) can be attributed to the presence of heterogeneous vegetation, resulting in a mosaic landscape following the abandonment of extraction sites. As a result, this class is prone to misclassification, particularly with remnant peatlands (another landscape characterised by heterogeneity) (Figure 3.2). Whereas the lower UA of waterbodies (70%) and misclassification with forestry can be attributed to overlap in spectral signature in partially vegetated and surface water areas such as in Figure 3.4.

3.5 Discussion

The degradation of Irish-raised bogs due to centuries of human exploitation is widely acknowledged (Bullock et al. 2012b; Connolly 2018; Fluët-Chouinard et al. 2023). Nevertheless, a significant knowledge gap exists in the absence of “robust aerial data” for accurate assessment of land use on the raised bog (Wilson et al. 2013; Aitova et al. 2023). That gap in spatial data is addressed here through the development of the LUCIP taxonomy and its implementation in GEE using Sentinel-2 data. This research delivers the first high-resolution wall-to-wall coverage of land use on raised bogs in Ireland. The robust methodology presented here facilitates an accurate assessment of the magnitude and extent of land use and CO₂ emissions on these ecosystems. It utilises cloud computing (GEE), temporal mosaicking, ML (random forest and high-resolution remote sensing imagery (Sentinel-2) to overcome the issue of persistent cloud cover in Ireland. The accuracy assessment results (overall accuracy of 89%) show a good agreement between the map and reference data.

Currently, the Irish National Inventory Report (NIR) only considers peat extraction activities (industrial/domestic) in the “managed wetlands” category for all peatlands (blanket and raised bogs). This area is reported as 70,020 ha, out of which 400 ha is domestic cutover with the remainder being industrial cutaway, and emissions calculations in the NIR are also reliant on these area estimates (Duffy et al. 2021). In literature, this figure is ~80,000 ha, which is mainly the BnM landholding (Malone and O’Connell 2009b; Wilson et al. 2013; Connolly 2018; Duffy et al. 2021). However, the findings of our study which is just focused on raised bogs, indicate that the peat extraction (cutaways and cutover) is considerably more prevalent than currently

3.5 Discussion

reported and extends to approximately 119,000 ha. This is 70% more than the NIR-reported “managed wetlands” area figures for all peatlands. This reveals an overall ambiguity in land use information for Irish peatlands (especially peat extraction). Here we address this by providing accurate spatially explicit land use estimates based on robust remote sensing methods.

The results depict a heterogeneous picture of land use in raised bogs across Ireland. The midland raised bogs (Figure 3.4 (a-c, and f)) are dominated by industrial mining activities with extensive conversion to grassland and forestry. The more peripheral raised bog areas, to the west and northwest and southwest of the midlands are dominated by conversion to grassland and forestry. In general, the most extensive land use on raised bogs is agricultural grasslands which are distributed across the region. Grasslands mainly occur on the margins of cutaway, cutover and remnant peatlands. The remnant peatland class, which represents the remaining areas of the raised bogs, are not in pristine condition, and are more abundant towards the North and West of the midlands, away from the areas of intensive industrial peat extraction activities. The BnM Peatland Climate Action Scheme (PCAS) aims to restore degraded peatlands within BnM landholding and is a good start for mitigation and adaptation, it is these more intact raised bogs, in the north and west, that could be targeted for active restoration by policymakers, facilitating carbon retention in these ecosystems. It is also pertinent to mention that the PCAS was initiated on some of the former industrial peat extraction sites during the timeframe of this study. Most of these areas are still bare peat which means this data may act as baseline data for tracking and monitoring the PCAS over time. Overall, the maps show that the current level of human-induced degradation on these raised bogs, through land use change, requires immediate action in terms of sustainable management practices.

On BnM land holdings industrial extraction activities gradually started to cease over the past two decades with an announcement of complete cessation in 2020. The results of this cessation are beginning to be seen in the data here. At the Blackwater site (Co. Offaly) site (Figure 3.5), areas are being classified as remnant peatlands, which is an indication of revegetation after the cessation of extraction activities (pre-2000) and subsequent rewetting in 1999 (Renou-Wilson et al. 2019). These sites are going through a transformation with land use conversion to forestry or a diverse mosaic of vegetation communities composed of heather, shrubs, grasses, and interspersed larger

plants. The forestry areas in Figure 3.5, are on land owned by Coillte and are highlighted with a grey outline. Other areas with surface water are the signs of rewetting activities and are represented by surface water here (Figure 3.5). Vegetation cover at Blackwater has increased over the years, albeit slowly, with *Sphagnum* mosses and other bog species recolonising the area i.e., sparse remnant peatlands patches among the prevalent bare peat (cutaway) (Figure 3.5). This recovery process is not only important for carbon sequestration and climate change mitigation but also for the restoration of the unique biodiversity and ecosystem services provided by peatlands. An SAC site is outlined (white dotted line) in the bottom right (Figure 3.5) and shows a good example of what is considered a “near natural” raised bog e.g., intact centre but degraded margins where substantial cutting has taken place and areas converted to grassland. These changes can be seen using Sentinel-2 which demonstrates the utility of this methodology for tracking and monitoring land use change raised bogs over time.

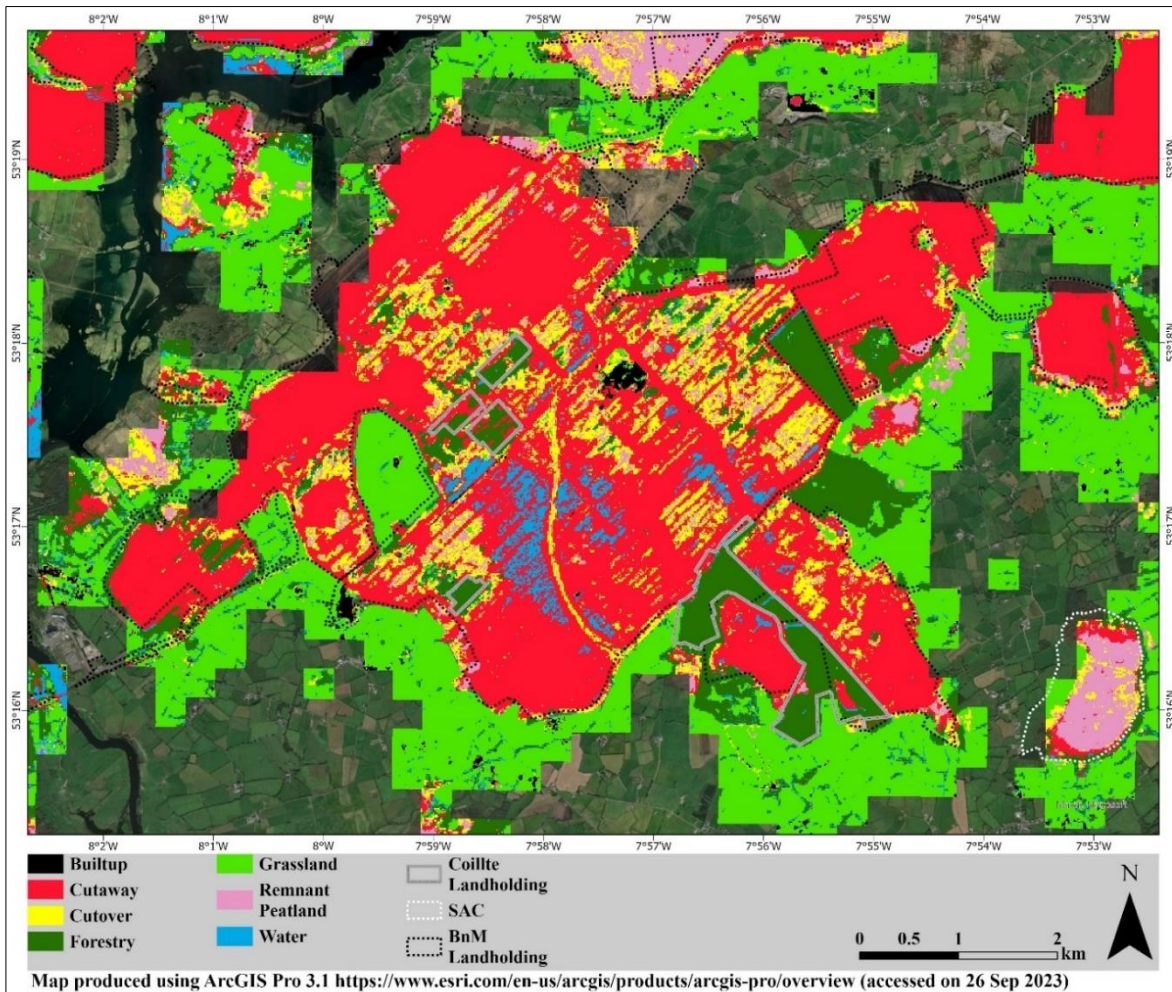


Figure 3.5: A typical example of a former industrial bog complex mapped in this study. The areas outlined by black dotted lines are within the BnM (Bord na Mona) landholdings whereas the white dotted lines in the Southeast section of the map show a bog under SAC (Moyclare Bog). The grey boundaries in the BnM landholdings and outside of it are Coillte landholdings.

The EU has established a range of regulations and initiatives that directly or indirectly require the restoration and sustainable management of peatlands. These include the Habitats Directive (Council Directive 92/43/EEC), Water Framework Directive (Directive 2000/60/EC), EU Biodiversity Strategy for 2030, Common Agricultural Policy (CAP), Natura 2000 Network (Directive 2009/147/EC), LIFE Programme, EU Climate Adaptation Strategy, and more recently the Nature Restoration Law which includes restoration of peatlands by binding targets and net zero CO₂ emissions form

these ecosystems by 2050. The effective implementation of these initiatives is only possible through robust mapping, tracking, and monitoring methodologies such as those proposed in this study.

The map produced here serves as an important indicator for determining the baseline status and condition of these ecosystems as well as providing a quantification of CO₂ emissions hotspots. By providing a detailed map of BnM/non-BnM industrial activities and domestic extraction activities, this study not only highlights these activities in a spatial context but also estimates emissions from them. The emissions calculated in this study based on IPCC T1 and Ireland-specific T2 EF show a substantial difference. The IPCC default emission factor is higher than the Irish T2 EF resulting in higher emission estimation. One of the limitations of using IPCC T1 EFs is that these EFs are based on limited case studies with diverse geographical locations, climatic conditions and ecology not necessarily suited to Irish Peatlands. The EFs proposed by Aitova et al. (2023) and the EFs from the study by Jovani-Sancho(2021) are based on measurements from specific sites in Ireland, the United Kingdom and Germany, and may not be a true representative of other sites in the country. For example, T1 EFs for grasslands (5.3 t CO₂-C ha⁻¹ y⁻¹) are mostly based on study sites from Germany, which are under more intensive management practices compared to Ireland (Renou-Wilson et al. 2014; Aitova et al. 2023). This possibly leads to a substantial difference when comparing T2 EFs for grasslands in Ireland (1.30 t CO₂-C ha⁻¹ y⁻¹) (Aitova et al. 2023). While these EFs could be refined specifically for Ireland, their use by Aitova et al. (2023) is a significant improvement compared to the T1 EFs. Finally, the delineation of the raised bog in this study relies on an existing peatland extent map i.e., DIPMv2. Although DIPMv2 is the most current peatland map in Ireland, with an overall accuracy of 88%, it tends to underestimate the presence of peatlands with areas smaller than 7 ha(Connolly and Holden 2009) . This study can be expanded to these missing areas if DIPMv2 is updated in the future.

Nevertheless, this study demonstrates the robustness and utility of earth observation methods to accurately map the land use on peatlands and to integrate these data with the latest T2 EFs thus refining estimates of CO₂ emissions from different land use on Irish peatlands. The LUCIP implemented in GEE facilitates the development of highly accurate land use maps that can aid the refinement of national-scale T2 reporting in these globally rare ecosystems. These integrated spatial datasets can help inform

3.6 Conclusion

decision-making for sustainable land management practices and conservation. Furthermore, the detailed habitat mapping of remnant peatland class using a high-resolution dataset and integrated Sentinel-1 and 2 approach could be useful for monitoring of active raised bog areas in SAC (Mahdianpari et al. 2020; Ingle et al. 2023). Future work using the LUCIP could address the large knowledge gap that is land use type and extent on blanket bogs, which account for ~70% of peatlands in Ireland and have not been studied at this level in Ireland. It is important that EFs and the emissions are assessed for these areas to identify C and GHG emission hotspots and areas for targeted restoration.

3.6 Conclusion

In this study, a spatially explicit dataset of land use on Irish raised bogs was created by integrating the DIPMv2 and Sentinel-2 satellite images collected over 2018-2020. Overall, the accurate results (OA=89%) of this study provide valuable insights into the spatial extent of land use on raised bogs in Ireland. These data were integrated with T2 EFs to refine the estimation of CO₂ emissions from four major land classes on raised bogs. These spatial data on land use can inform policies on land use and emissions on a national scale. The map also enhances the current understanding of the extent and scale of different land use (especially peat extraction activities) in a spatial context. The state and condition of raised bogs in Ireland present a pressing concern due to their substantial CO₂ emissions. Urgent measures are required to address this issue, including: (i). mitigating the emissions and (ii). implementing sustainable management practices to promote carbon sequestration within these ecosystems and prevent additional degradation. This spatial information can be used to inform the development of more sustainable approaches to peatland management in the country, the decision-making process for developing such policies and effective strategies to mitigate these management impacts.

Chapter 4. Mapping artificial drains in peatlands – A national scale assessment of Irish raised bogs using sub-meter aerial imagery and deep learning methods³

4.1 Abstract

Peatlands, constituting over half of terrestrial wetland ecosystems across the globe, hold critical ecological significance and are large stores of carbon (C). Irish oceanic raised bogs are a rare peatland ecosystem offering numerous ecosystem services, including C storage, biodiversity support, and water regulation. However, a significant proportion of these ecosystems have degraded over the centuries due to artificial drainage ditches, followed by land use activities such as peat extraction, afforestation, and agriculture. This has an overall negative impact on the functioning of these ecosystems, shifting them from a moderate C sink to a large C source. Recognising the importance of these ecosystems, efforts are underway to conserve them through measures such as rewetting, restoration, and rehabilitation while accurately accounting for C stock and greenhouse gas (GHG) emissions. However, the implementation of these efforts requires the accurate identification and mapping of artificial drainage ditches.

This study utilised very high-resolution (25 cm) aerial imagery, and a DL approach based on U-Net was used to map the artificial drainage of 523,000 ha of raised bogs at a national scale. The results showed that artificial drainage is widespread, with approximately 20,000 km of drains mapped. This is the first study to map diverse sizes and patterns (regular and irregular) of drainage using DL methods in three peatland land use categories, cutaway, cutover and remnant peatlands. The overall accuracy of the model was 80% on an independent testing dataset. The data was also used to derive the $Frac_{ditch}$ which was 0.03 (fraction of artificial drainage on industrial peat

³ This chapter corresponds to the paper published on 23 April 2024, in *Remote Sensing in Ecology and Conservation* [5].

extraction sites). This is lower than IPCC Tier 1 $Frac_{ditch}$ and can aid in IPCC Tier 2 reporting for Ireland. The map provides an important baseline dataset for assessing the condition of artificial drainage ditches but will also be vital for sustainable environmental management and governance, as well as for improving estimates of GHG emissions. The model's capacity for generalisation implies its potential in mapping artificial drains on peatlands at a regional and global scale, thereby enhancing the comprehension of the global effects of artificial drainage ditches on peatlands.

4.2 Introduction

Peatlands account for 50-70% of terrestrial wetland ecosystems across the globe (Joosten and Clarke 2002; Šimanauskienė et al. 2019) and are characterised by the accumulation of organic material (peat) in waterlogged conditions (Charman 2002; Evans et al. 2021). Peatlands are increasingly being recognised as important ecosystems due to the provision of many services, including carbon (C) storage, biodiversity support, and water regulation (Kimmel and Mander 2010; Page and Baird 2016; Flood et al. 2021; Minasny et al. 2023b). However, increased anthropogenic pressure initiated through artificial drainage and subsequent extensive land use practices, such as industrial/domestic peat extraction, agriculture, afforestation, and infrastructure development (roads etc.), has led to significant degradation of these ecosystems and their Nature's Contributions to People (NCP) (Chapman et al. 2003; Joosten 2017; UNEP 2022). Globally, degraded peatlands contribute significantly to current anthropogenic GHG emissions, accounting for 4 - 5% of the total global human-induced emissions (Huang et al. 2021; Strack et al. 2022).

Irish raised bogs are particularly important among the EU's peatlands as they comprise more than 50 % of the rare oceanic-raised bogs in the region (Bullock et al. 2012). They are one of the key components of Ireland's natural capital (Farrell et al. 2022) and account for a substantial amount of SOC stock of the country (Tomlinson 2005; Renou-Wilson et al. 2011). However, they have undergone widespread drainage, land use change and degradation (Fluet-Chouinard et al. 2023; Habib and Connolly 2023). Hydrology plays a crucial role in the functioning and preservation of raised bogs, significantly influencing vegetation growth and peat formation and maintaining a delicate balance between water, vegetation, and peat (Ivanov 1981; Joosten 2017; Regan et al. 2019). The development of artificial drainage to facilitate land use change leads to the lowering of water table and results in compaction, subsidence, and oxidation (Mackin et al. 2015). These artificial drains also function as conduits for dissolved organic carbon, particulate organic carbon and CH₄, shifting these ecosystems from C sinks to persistent sources source (Peacock et al. 2021a; Regan et al. 2019). Peacock et al. (2021b) reported that drainage ditches and canals account for 1% of the global anthropogenic CH₄ emissions and it can be much higher for high-density drained areas. Artificial drainage also shifts peatlands from water purifiers to

4.2 Introduction

potential sources of water pollution (Liu et al. 2023). Yet, much like European peatlands, centuries of artificial drainage have modified the hydrology of Irish raised bogs, leading to adverse effects on the entire ecosystem (Pschenyckyj et al. 2023; Tuohy et al. 2023). The past century has seen the intensification of artificial drainage for large scale industrial peat extraction activities, primarily carried out by Bord na Móna (BnM), a semi-state peat harvesting company (Common 1970; Connolly and Holden 2017). These ditches are extensive and regularly spaced at 15-30m intervals (Wilson et al. 2015). The majority of BnM landholdings are situated within raised bogs, and a substantial amount of these lands underwent drainage and/or peat extraction (Connolly and Holden 2011; Habib and Connolly 2023). These activities ceased in 2020 (BnM 2021); however, a number of small to medium-scale private industrial peat extraction companies continue to extract peat (Malone and O'Connell 2009).

Several EU regulations and directives mandate the conservation and protection of these rare ecosystems. For instance, the EU Habitat Directive (92/43/EEC) and Water Framework Directive (2000/60/EC) stress the importance of conservation and enhancing water quality. Similarly, the EU Biodiversity Strategy for 2030 and the LIFE program call for the preservation and restoration of these unique habitats. Furthermore, under the EU Monitoring, Reporting, and Verification Regulation (525/2013) and EU Climate Change Framework 2030, Ireland, like other EU member states, is required to report GHG emissions and removals from Land Use, Land Use Change, and Forestry activities.

Ireland reports emissions and removals from both managed/exploited (industrial) and unmanaged peatlands for its National Inventory Report (Duffy et al. 2022). Unmanaged peatlands (all peatlands excluding exploited) are assumed to be rewetted within five years of any anthropogenic impact with soil carbon loss also ceasing in that time (Duffy et al. 2022). In exploited peatland areas, dominated by BnM, GHG emissions are recorded (Duffy et al. 2022). Currently, these emissions from artificial drainage ditches are accounted for using Tier 1 (T1) reporting i.e., a default value is given for the “fraction of the total area of drained organic soil which is occupied by ditches” or $Frac_{ditch}$. This is derived from the “mean of all data within each land use class” from several studies (Hiraishi et al. 2014). Most of these studies were based in continental Europe, Russia, and Canada, with only two studies in the UK and none from Ireland. However, for Tier 2 (T2) and Tier 3 (T3) reporting countries are encouraged to develop

country-specific metrics. These data can include information on the spatial extent of artificial drainage ($Frac_{ditch}$), as well as characteristics including plants or algal growth within ditches and ditch maintenance activities. (Hiraishi et al. 2014). These spatially explicit data on artificial drainage is also useful for the implementation of conservation activities (e.g., drain blocking to facilitate rewetting). However, the data for T2 and T3 reporting currently not available for raised bogs in Ireland. Both Connolly and Holden (2017) and Robb et al. (2023) note that mapping artificial drains is difficult and expensive with traditional ground surveys. One reason is the extensive and diverse characteristics of artificial drainage ditches, including drainage density, intensity, and morphology which differ from region to region (Burke 1961). In Artificial drainage, the ditch morphology exhibits significant variability (Peacock et al. 2021c). This can be observed in Ireland, between industrial peat extraction areas (cutaway) and domestic peat extraction areas (cutover) i.e., regular vs. irregular patterns and sizes (Connolly and Holden 2011). However, these drains can be identified through visual interpretation of very high-resolution aerial imagery, and they can therefore be mapped using remote sensing techniques (Connolly and Holden 2017).

Advanced very high-resolution optical remote sensing data, coupled with semi-automated mapping techniques, such as Object-Based Image Analysis (OBIA) and, more recently, automated DL-based mapping techniques, have demonstrated the ability to map these drainage patterns efficiently (Connolly and Holden 2017; Dadap et al. 2021; Robb et al. 2023). Connolly and Holden (2017) used OBIA techniques to map regular patterned drains on Irish blanket bogs using very high-resolution Geoeye-1 satellite imagery. However, OBIA requires extensive manual intervention which poses limitations for large-scale mapping. Recent developments in automated mapping, such as DL applied to semantic segmentation have shown significant promise in effectively mapping artificial drainage ditches for example, in tropical peatlands (Dadap et al. 2021). These tropical drainage ditches, commonly referred to as “canals”, exhibit larger dimensions compared to those found in Ireland and the UK. They also have regular patterns and were successfully mapped using high-resolution PlanetScope satellite imagery (3m) and DL applied to semantic segmentation methods (Dadap et al. 2021). Additionally, highland blanket bogs in the UK, where drainage ditches are usually of smaller size and depict irregular patterns have also been mapped using DL applied to feature/object extraction (Robb et al. 2023). An artificial drainage network that has a diverse range of patterns and orientations, as well as regular and irregular

shapes/sizes, presents a considerable challenge for mapping using a single deep-learning model.

This research aims address the challenge of accurately mapping an extensive artificial drainage network in raised bogs on a national scale. Only the visible drainage network was mapped, that is, unobstructed by vegetation canopy or infill. The drainage network was mapped across multiple land use categories, including cutaway, cutover and remnant peatlands using very high-resolution optical aerial imagery and DL methods. A U-Net-based (Ronneberger et al. 2015) convolutional neural network (CNN) was used for the automated pixel-wise classification of drains with a spatial resolution of 0.25 m per pixel over an extensive area of 523,000 ha. A national scale artificial drainage map of Irish raised bog was created. This accurate spatial quantification and mapping will be useful for implementing key management strategies, such as drain blocking, to facilitate rewetting activities. This is crucial for promoting carbon sequestration and enhancing biodiversity (NPWS 2017). Furthermore, the country-specific $Frac_{ditch}$ value obtained here fills the knowledge gap by providing T2 and T3 metrics for Ireland. This will be useful for the accurate accounting of emissions from these ecosystems for National Inventory Reporting.

4.3 Material and methods

4.3.1 Study area

The study area consists of raised bogs in Ireland, delineated by the Derived Irish Peat Map version 2 (DIPMv2) (Connolly and Holden 2009). These bogs are spread across the midland region of Ireland, covering about 523,000 ha, constituting ~35% of the total peatland area and 8% of the land surface area of Ireland (Feehan and O'Donovan 1996; Connolly and Holden 2009).

4.3.2 Drainage types (land use)

The drainage assessment was primarily focused on three land use types: cutaway, cutover, and remnant peatland (Table 4.1). Different drainage patterns are associated with each land use. In cutaway areas, artificial drainage tends to exhibit more regular structure and spacing between drains, for example, 15 – 30m on BnM industrial peat extraction sites. In cutover areas where traditional manual digging of drains may have taken place in the past, irregular shapes and sizes can be seen. Furthermore, drainage orientation and spacing vary significantly between land use, and drainage conditions may change over time due to factors like drain collapse, vegetation cover and infill.

Table 4.1: Description of land use classes based on Land Use Classification for Irish Peatlands (LUCIP) level-4.

Land use class	Description
Cutaway	Land that has been subjected to peat extraction, with the peat removed and the land left bare or with a thin layer of soil; managed by BnM and other private companies with large-scale industrial/mechanised peat extraction
Cutover	Land that has been subjected to peat extraction with peat removed and the land left bare; hand-cut and other small-scale mechanised domestic peat extraction
Remnant/Revegetated Peatland	Land that has a high percentage of peat (near natural and high bog areas) and is characterized by the presence of sphagnum mosses and other bog flora, not directly affected by human intervention. Also, revegetated areas post extraction activities

4.3.3 Aerial Imagery

The spatial extent of artificial drainage on raised bogs was assessed using an extensive dataset of 5,111 aerial image tiles providing wall-to-wall coverage for raised bogs, as defined by the DIPMv2 (including an additional 50 m buffer to incorporate peripheral areas). The images were produced by Bluesky International Limited using a manned survey aircraft with gyro-stabilised mounted sensors i.e., Vexcel UltraCam MK3 (Gruber et al. 2012). The images were acquired between 2015 to 2021, with each image comprising 4 bands, i.e., Blue, Green, Red and NIR (R, G, B, NIR), with a size of $\sim 2 \times 2$ km and spatial resolution of 0.25 m. Pixel encoding was unsigned byte (8 bits, unsigned i.e., values ranging from 0 - 255) and no pre-processing was implemented. The total volume of the images was 1.3 terabytes. To efficiently manage, store, and access the images, a “mosaic dataset” was created using ArcGIS Pro version 3.1 desktop software. The very high spatial resolution (0.25 m) and limited to no cloud cover are the two salient features of this dataset for mapping narrow (<0.50 m width) drainage features in otherwise persistent cloud-obscured conditions in Ireland.

4.3.4 Training, testing and validation sample data

To the best of our knowledge, there is no publicly available dataset with accurate georeferencing depicting the spatial extent of artificial drainage in Irish raised bogs which could be used for training the model. Therefore, training data were developed for this study using the heads-up digitisation method by employing the visual interpretation technique on very high-resolution aerial imagery. It was collected by digitising drains with a diverse set of characteristics (size, orientation, etc.) covering ~ 400 km at two bog sites (Figure 4.1 (b and c)). The drainage lines were digitised at the centre of each drain and were extended by an additional 0.25 m using the “buffer” tool within ArcGIS Pro v3.1. This step transformed the lines into polygons and generated well-annotated data suitable for training a deep-learning model. Moreover, by incorporating the buffer, the resulting masks contained more pixels, providing efficient bank-to-bank coverage of the ditches and contributing to improved accuracy.

The training images and masks (created from digitised drains) were cropped into patches of 64×64 pixels.

The final training dataset consisted of 22,748 (64×64 pixels) 4-band images. The sampling dataset was divided into training, validation, and testing subsets by using a 70-15-15 split. The training subset, comprising 70% (15,924 image patches) of the data, allowed the model to learn patterns and adjust parameters. Meanwhile, the validation and testing subset which comprised the remaining 15% (3412 image patches), served as an independent benchmark to assess the model's performance on new data and choose the best model across training iterations. Finally, the model was tested on 15% of the completely independent testing data (3412 image patches) to evaluate the trained model. The training, validation, and testing data consisted of samples for all three types of land use (Table 4.1), and both uniform (industrial) and nonuniform (domestic) drainage were considered.

4.3.5 Classification of imagery

Convolutional Neural Network (CNN) model

Mapping of the spatial extent of artificial drainage using aerial imagery was accomplished using a U-Net model (Ronneberger et al. 2015). The model consisted of approximately 34 million parameters. This was used to predict the extent of artificial drainage for each pixel in the input image. For this task, a four-band image (R, G, B, NIR) with dimensions of 64×64 pixels and a spatial resolution of 0.25 m was employed as input. The training sample data underwent data augmentation, such as random brightness, contrast, hue, and random horizontal and vertical flips, before being fed to the model. For optimisation, the Adam optimiser was used, with a learning rate of 0.0001. A custom loss function consisting of the sum of the Binary Cross-Entropy Equation (4.1), and the Dice Loss in Equation (4.2) is used in Equation (4.3) to encourage accurate segmentation and effective boundary delineation.

$$BCE\ loss = -\frac{1}{N} \sum_{i=1}^N (y_{true} \cdot \log(y_{pred}) + (1 - y_{true}) \cdot \log(1 - y_{pred})) \quad 4.1$$

$$Dice\ loss = \left(1 - \frac{2 \cdot \sum(y_{true} \cdot y_{pred})}{\sum y_{true} + y_{pred} + \epsilon} \right) \quad 4.2$$

$$BCE\ Dice\ loss = BCE\ loss + Dice\ loss \quad 4.3$$

Where y_{true} is the ground truth, y_{pred} are predicted values (probability scores), ϵ is a small constant to prevent division by zero, and N is the total number of elements (pixels) in the tensors.

The entire network was trained for 600 epochs, with a batch size of 32 images over the training dataset. The training was concluded when loss values showed no further decrease over the validation dataset, and the model with the minimum loss across epochs was retained for inference. The model training was completed in less than a day using an NVIDIA RTX 2080 Graphics Processing Unit (GPU) equipped with 12 GB of memory.

The model produced a binary output with values ranging from 0 to 1, where a value of 1 indicated the presence of a drainage pixel. The model was implemented using the Keras framework in R language with the RStudio interface and TensorFlow version 2.8 (Allaire and Chollet 2019).

Model assessment

Previous studies that mapped the drainage network on peatlands have noted the challenges associated with the accuracy assessment of drainage lines using traditional methods (Connolly and Holden 2017; Dadap et al. 2021; Robb et al. 2023). Assessing the accuracy of these linear features is challenging, primarily because of the presence of a high proportion of true non-drainage pixels. The testing dataset was used to assess the model's accuracy. The accuracy was assessed using the F1 score in Equation (4.6), which is the harmonic mean of the precision in Equation (4.4), and recall Equation (4.5), which is a popular combination that symmetrically represents both precision and

recall in one metric. Precision is a measure that represents the proportion of true positive results (correctly predicted positive results) among the total predicted positives. The inverse of the precision is the error of commission. Recall, also known as sensitivity or true positive rate, represents the proportion of true positive results (correctly predicted positives) among the actual positives. The inverse of recall is the error of omission.

$$precision = \frac{tp}{tp + fp} \quad 4.4$$

$$recall = \frac{tp}{tp + fn} \quad 4.5$$

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall} \quad 4.6$$

Where tp are true positives, fp are false positives and fn are false negatives.

Inference

At the inference stage, the images with the original tile size (2×2 km) were used. For faster processing, inference was performed on bigger patch sizes than training: 512×512 pixels with a 64 pixels (16m) overlap to mitigate the border artifacts (Ronneberger et al. 2015). Inference was conducted on each sub-patch of each image patch, excluding the margins of the overlapped pixels. The final output patches were then mosaiced into a single binary image representing the drains map. The processing time for the imagery covering raised bogs at the national scale (523,000 ha) was approximately one month using a single RTX 2080 GPU.

4.3.6 Density mapping

The classification results were initially obtained in a raster format, representing drains and non-drains within the study area at the pixel level. To facilitate geospatial analysis, such as length calculation and density mapping, several post-processing steps were performed in ArcGIS Pro. Given the variable drain width, that is, ranging from one to three pixels, the 'thin' tool was used to extract the central pixels of the drain networks. The transition from raster to vector was completed using the 'raster to polyline' tool, resulting in drain-vector lines. These lines were further optimised by applying the 'smooth line' tool using Polynomial Approximation and Exponential Kernel with a smoothing tolerance of 0.75 m to achieve a more refined representation. Finally, the derivation of drain density maps was accomplished using the 'line density' tool with a cell size of 10 m to match the land use map. This process delivers a comprehensive visualisation of the peatland drain network distribution in the form of a density map of all raised bogs in Ireland (Figure 4.1 (a and b)). Furthermore, it allows for the quantitative assessment of drains in the form of the total length of drainage. This was further segregated for each land use based on high-resolution peatlands land use map (Habib et al. 2024)

4.3.7 Updating the fraction of drainage ditches

The 2013 wetland supplement, an extension of the 2006 IPCC guidelines, outlines a method to estimate C and GHG emissions and removals from drained inland organic soils (Hiraishi et al. 2014). An essential element of this calculation is $Frac_{ditch}$ Eq. (4.7). According to these guidelines, the estimation of emissions is based on multiple levels of detail. T1 relies on the default values of $Frac_{ditch}$ available in the wetland supplement. By contrast, T2 and T3 are based on country-specific values.

$$Frac_{ditch} = \frac{\text{Area covered by drainage ditches (ha)}}{\text{Area covered by land use class impacted by drainage ditches (ha)}} \quad 4.7$$

where the area covered by drains is equal to the width of the ditches multiplied by their total length (Hiraishi et al. 2014).

4.4 Results

Over 523, 000 ha of raised bogs were assessed using very high-resolution aerial imagery and DL applied to a semantic segmentation modelling approach. The total surface area covered by the drainage on raised bogs was approximately 2000 ha. This was calculated from pixels identified as drains. The total length of the detected and mapped drains was approximately 20,000 km. The drains were further segregated by land use categories based on the raised bogs land use map developed using Sentinel-2 (Habib et al. 2023 – under review). Cutaway bogs account for the majority of the mapped drains i.e., 16000 km (Figure 4.1(c)). The cutover drains account for ~ 1600 km and are mostly located at the periphery of the cutaway sites (Figure 4.1 (d-f)). The rest of the drains occur on remnant peatland sites i.e., ~ 2400 km.

The density map (Figure 4.1 (a)) reveals that the cutaway drains are systematically placed with the highest density of 400 m/ 100 m². The maximum drainage density for remnant peatlands (high bogs) was 250 m /100 m² and it was lowest for cutover bogs, that is, 200 m/100 m². The overall spatial distribution of drainage network density can be seen in Figure 4.1 (a). Drainage was more prevalent in the majority of the BnM peat extraction sites (Figure 4.1 (b)). There is also a presence of extensive drainage on non-BnM peat extraction sites. Figure 4.1 (e) shows one such site, owned by a private industrial peat extraction company i.e., Klasmann- Deilmanna.

4.4 Results

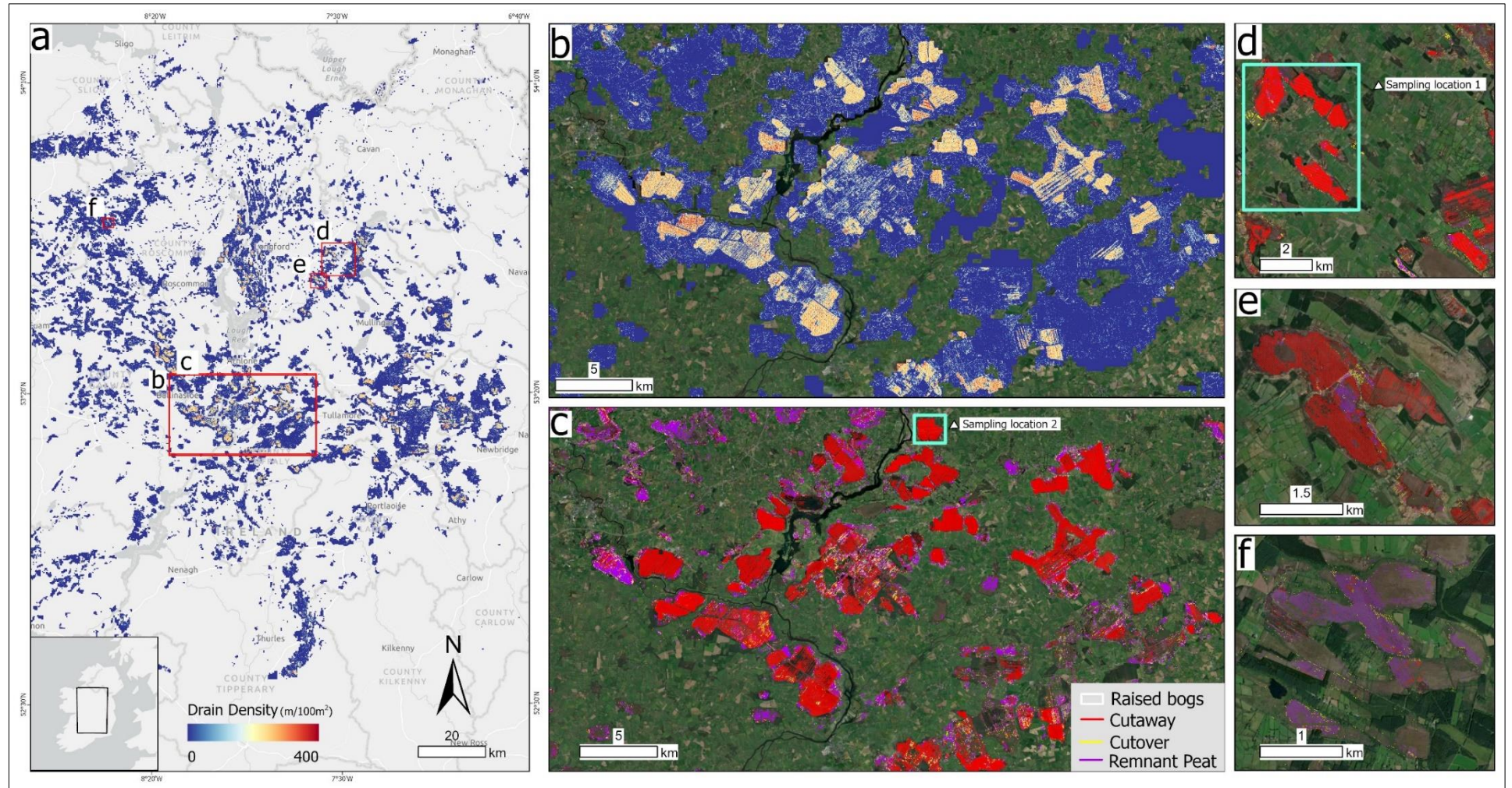


Figure 4.1: (a) Drainage density map (m/100m²), (b, c) BnM (Board na Mona) based industrial peat extraction areas, (b) shows the drainage density and (c) shows the individual ditches (d, c) sample locations 1 and 2 (e) non-BnM based industrial peat extraction activities, (f) remnant peatland (high bog) area with extensive drainage

To further examine the results, boundary data from BnM was used to assess the status of drainage under industrial exploitation. The results show that most of the drains mapped in this study exist on BnM-based industrial peat extraction sites i.e., approximately 14,000 km or 70% of the total drainage network identified. A relatively small proportion of remnant peatlands (high bog), and cutover drains are also present on BnM landholdings (Table 4.2).

Table 4.2: Proportion of drainage (ditch length value in km) within BnM (Bord na Mona) landholding

Land Use	BnM
Cutaway	14000
Remnant peatland	611
Cutover	514
Total	15125

4.4.1 Fraction of drainage ditches

The value for $Frac_{ditch}$ for BnM landholdings presented in Table 4.3 was calculated using Equation (4.7). Only the cutaway land use class was considered because most of the drainage networks at these sites were identifiable using optical aerial imagery. This is largely due to the presence of these artificial drainage ditches in bare peat sites, unobstructed by vegetation canopy or infill, etc., unlike cutover and remnant peatlands class. The land use class area was 42,264 ha, sourced from (Habib et al. 2024). The drainage ditch area for the same land use class was 1300 ha (Table 4.3) as calculated in this study from the total length of drainage on BnM peat extraction sites i.e., 13000 km and an average width of 1m (BnM 2016). The $Frac_{ditch}$ value obtained was 0.030.

Table 4.3: Fraction of ditches on BnM (Board na Mona) based cutaway sites

Cutaway (BnM) area (ha)	Drainage ditches (cutaway) area (ha)	$Frac_{ditch}$
42264	1300	0.030

4.4.2 Classification accuracy

The results were assessed both qualitatively (visual interpretation) and quantitatively. The qualitative assessment shows that the model can capture the details of spatial patterns in all land use types across the study area at a national scale (Figure 4.1 (c–f)). Both the regular patterns of cutaway peatlands and irregular patterns of cutover peatlands were accurately mapped. A quantitative assessment was conducted using the F1 score (Eq. (4.6)). The testing dataset yielded an F1 score of 0.80 (Table 4.4), indicating a good agreement between the drainage maps and reference data.

Table 4.4: Results of accuracy assessment (Precision, recall, and F_1 scores)

Metric	Value
Precision	0.76
Recall	0.85
F_1 Score	0.80

4.5 Discussion

This study presents the first map of an artificial drainage network across 523,000 ha of Irish-raised bogs. Over 20,000 km of small artificial drains (<1m wide) were detected and mapped using optical aerial imagery, with an overall accuracy (F_1 score) of 80%. To the best of our knowledge, this is the first drainage map of temperate European peatlands at this scale. The U-Net-based semantic segmentation model adapted for this study identified a drain network with good accuracy on an independent testing dataset, demonstrating the ability of CNN to map artificial

drainage features on peatlands (Dadap et al. 2021). Previous studies in Ireland utilising OBIA required extensive manual interventions and were applied to a smaller study area in blanket bogs (Connolly and Holden 2017). Whereas the DL-based applied to semantic segmentation for mapping was carried out by Dadap et al. (2021) on tropical peatlands assessed larger size (>5m wide) regular patterned drainage “canals”. On the other hand, Robb et al. (2023) used DL applied to feature/object detection to identify irregular pattern “drain features” on highland blanket bogs and was focused on a smaller area. However, the DL model used in this study provided very high-resolution (sub-metre) large-scale mapping of an artificial drainage network across multiple land use categories in raised bogs. The diversity of land use and drain types (range of size, orientation, and patterns) mapped, combined with the model’s high accuracy, shows its global application for mapping artificial drains across a variety of peatland types where drains are visible in optical imagery.

The results quantified the spatial extent and density of drains on raised bogs. This affirms the widely acknowledged drainage status of these ecosystems in Ireland (Common 1970; Wilcock 1979; Wilson et al. 2022). This study also addresses the knowledge gap by providing robust spatially explicit data for land use activities on peatlands in Ireland (Wilson et al. 2013; Aitova et al. 2023). Current C and GHG emission estimations from peat extraction-based artificial drainage ditches in Ireland rely on the T1 default $Frac_{ditch}$ value (0.05) available in the wetlands supplement (Hiraishi et al. 2014; Duffy et al. 2022). This is an average indicative value derived from several local scale studies conducted on temperate and boreal peatlands. In this study, the $Frac_{ditch}$ 0.03 was obtained for cutaway bogs in Ireland. This is lower than the IPCC default value (0.05) currently used in the National Inventory Report (Duffy et al. 2022). This new value also allows for more “rationalised and reflective estimates” of C and GHG emissions (Tuohy et al. 2023) from cutaway bogs and facilitates both T2 and T3 approaches for methane emissions from those areas (Hiraishi et al. 2014). However, the $Frac_{ditch}$ value was not calculated for the non-industrial areas because drainage in these areas could not be mapped comprehensively due to limitations of optical remote sensing data. Future work with the integration of active remote sensing data (e.g., LiDAR) with the very high-resolution aerial imagery (Carless et al. 2019) used here could provide enhanced detection of drainage ditches. This could lead to a refined $Frac_{ditch}$ values for both raised bogs and blanked bogs in Ireland.

4.5 Discussion

Distinct patterns of drains were identified within each of the three land use categories. The prevalence of regular patterned industrial drains, especially within BnM landholdings, stands out, while the presence of extensive drainage on cutover and remnant peatland sites (where detectable using optical imagery) provides valuable insights on domestic peat extraction and drainage of raised bogs. Industrial peat extraction sites (mainly BnM) accounted for the majority of high-density artificial drainage ditches, followed by remnant peatlands and cutover sites. This can be seen in the density maps (Figure 4.1(a and b))

4.5.1 Condition of drainage ditch network

Drainage maps can also be used to infer the condition of the drains (Connolly and Holden 2017). For example, the low drainage density areas on the cutaway and cutover sites could be interpreted as overgrown or deteriorated drains. Artificial drainage ditches can also impact peatland subsidence rates, with a clear correlation between drainage density and subsidence rates, as shown in regional studies (Dadap et al. 2021). The density map produced here could be used to infer the subsidence rates of raised bogs and the overall condition of raised bogs.

4.5.2 Cutaway drainage

Approximately 90% of the BnM sites were drained or subjected to peat extraction activities (Habib and Connolly 2023). These areas also have the highest density of drains at 400 m/100 m²; however, there are also low drainage density zones on BnM landholdings (Figure 4.1 (d)). These zones may indicate areas that have been inactive in peat extraction for the past 10-20 years (NPWS 2017). The abandonment of these areas may lead to drain structure degradation, occlusion, and partial collapse (Connolly and Holden 2017). This possibly facilitates revegetation (Figure 4.2 (a)) and infilling (Figure 4.2 (b)), making them less discernible in optical aerial imagery. Some of the sites are also going through rewetting and rehabilitation. At these locations intervention measures such as peat dams and borrow pits which can be seen in Figure

4.2 (c). Overall, the spatial extent of the drainage network and patterns was robustly measured for industrial peat extraction areas in both BnM and non-BnM landholdings. This may be because the majority of these drains are present on bare peats and are not obscured by vegetation canopies, infills, etc.

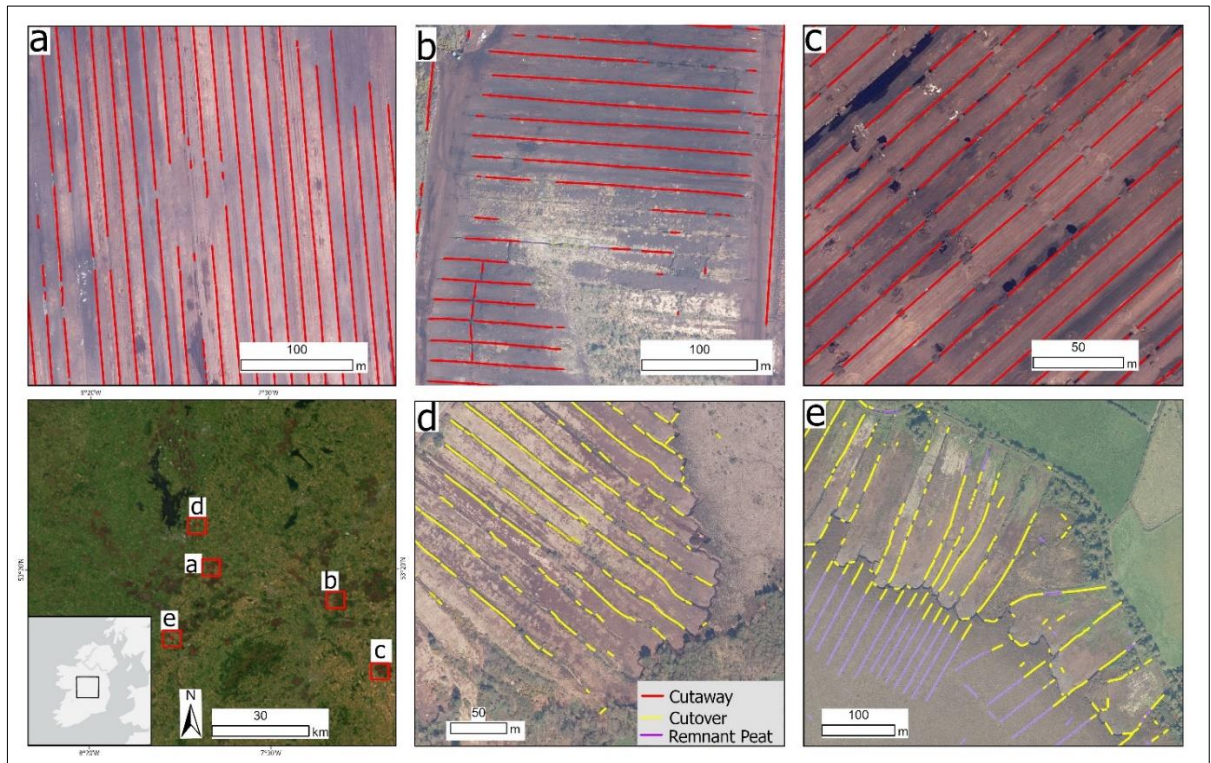


Figure 4.2: Different types of drainage conditions on each land use. (a) Industrial peat extraction site, drainage infilled with peat. (b) revegetation of former industrial peat extraction site owned by BnM. (c) Drains blocked with peat dams (borrow pits). (d) The pattern of drainage on a cutaway site with drains in-filled and covered with vegetation (e) cutover site with remnant peatland (high bog) towards the South and partially covered with vegetation on the North

4.5.3 Cutover drainage

Cutover sites exhibit a drainage network, characterised by haphazard patterns of various sizes (length and width). Some of these drains have been in use for centuries and display a range of conditions (Figure 4.2 (d and e)). The cutover sites exhibited the

lowest drainage density among the three land uses mapped in this study, yet this metric does not precisely reflect the true spatial extent of the drainage within this land use category. This is because many drains on cutover sites exhibit re-vegetation and embankment deterioration (Figure 4.2 (e)), making accurate detection and mapping challenging with optical aerial imagery. However, as Connolly and Holden (2017) observed, these broken line patterns may illustrate the drain condition. This could make these maps useful for monitoring sustainable management at these sites.

4.5.4 Remnant peatlands drainage

Drains traversing through high bogs and surrounding bog margins effectively reduce water tables within peat, impeding the hydrological conditions essential for peat accumulation (Mackin et al. 2017b). The density of the drainage network within remnant peatlands (high bog) exceeds that of cutover peatlands (250 m/ 100 m²), yet it is lower than that observed in cutaway peatlands. Nevertheless, this shows that the raised bogs within this land use category are not in pristine condition (Smith and Crowley 2020). The drainage pattern exhibits variability contingent upon proximity to peat extraction operations (both industrial and domestic), a systematic pattern observed in proximity to cutaway areas, while irregular patterns characterise areas near the cutover sites. One such site is shown in Figure 4.2 (d), a typical cutover peat extraction area. The drainage pattern here closely resembles the cutover regions towards North (Figure 4.2 (e)).

4.5.5 Implications of the study

The methods used in this study are a robust and cost-effective way for qualitative and quantitative assessment of artificial drainage ditches on raised bogs in Ireland. The methods are also fully automated and can be deployed at large scales; therefore, they could be applied to other artificially drained peatlands in Ireland (e.g., blanket bogs) across Europe and globally. It requires no manual intervention compared with the OBIA method (Connolly and Holden 2017) and can detect a wide range of artificial

drainage ditches with diverse characteristics compared with previous studies (Dadap et al. 2021; Robb et al. 2023). The output map provides valuable and much-needed spatially explicit information on the extent and fraction of drains which is useful for many stakeholders, including those restoring, managing, and monitoring peatlands, as well as for accurate National Inventory Reporting.

Local-scale studies have shown the effect of drainage on ecosystem services provided by peatlands, including C storage/sequestration and water provision (Regan and Johnston 2010). The drain map produced in this study can facilitate a wider-scale assessment of the implications of drainage on raised bogs for various land use activities and GHG emissions. Without drain blocking, peatlands are prone to becoming drier and more susceptible to fires over time, leading to increased C and GHG emissions (Price et al. 2003; Brown et al. 2015). Drains are also CH₄ hotspots (Cooper et al. 2014; Peacock et al. 2021a); therefore, mapping the extent and condition of artificial drains may facilitate the refinement of GHG emission estimation and reporting, as well as cost-effective restoration, rehabilitation, and rewetting activities.

The methodology can also be effectively used to monitor and track conservation activities (Figure 4.2 (c)). Artificial drainage ditch data will be a valuable resource for designing and implementing effective restoration and rehabilitation plans for Irish-raised bogs, leading to improved ecosystem function and enhanced carbon sequestration. Overall, as pointed out by Connolly and Holden (2017), the two main uses of the drain maps are (i) identification of C and GHG emission hotspots and (ii) identification of suitable areas for drain-blocking activities (rewetting). This work shows additional applications of the data by providing details ($Frac_{ditch}$) that are useful for both T2 and T3 reporting, ditch maintenance activities, capturing seasonal dynamics (particularly if the study was repeated) as well as assessing flow rates transport length of water (Hiraishi et al. 2014). The map produced here will also provide valuable information for land use policy and conservation efforts in Ireland, leading to more informed decision-making and better outcomes for raised bog ecosystems.

4.6 Conclusion

The significance of peatlands is increasingly being recognised due to their large stores of C and GHG emissions due to degradation. Peatland degradation starts with artificial drainage ditches. However, uncertainty exists regarding the status and condition of artificial drainage, and consequently, peatland ecosystems. Understanding the regional and global effects of artificial drainage ditches on peatlands is hindered by the lack of spatially explicit data. Mapping these drains accurately is time- and cost-prohibitive. However, utilising DL combined with very high-resolution aerial imagery offers a cost-effective way to map drains nationally, aiding the identification of the extent, condition, and emission hotspots. Such maps support spatial and temporal monitoring, which is crucial for conservation efforts. Incorporating artificial drainage maps into the National Inventory reporting aligns with the IPCC reporting guidelines, enhancing the reporting accuracy at the T2 and T3 levels. The DL method used in this study could detect small artificial drains (~1 m wide) in peatlands with a high degree of accuracy. It can also detect a diverse range of drain patterns and sizes (length and width) across three different land use categories in raised bogs. The ability of the model to generalise suggests its potential for mapping artificial drains on peatlands at regional and global scales. This could contribute to a better understanding of the global impact of artificial drainage ditches and facilitate their sustainable management.

Chapter 5. Conclusion

5.1 Critical reflection and inferences

5.1.1 Summary of the thesis

Mapping and monitoring of peatlands is important due to their vital role in the global carbon cycle and the various ecosystem services they provide, notably climate and water regulation. However, the integrity and ecological balance of peatlands, both globally and specifically in Europe, face significant threats due to land use activities. These activities negatively affect the ecosystem services provided by peatlands and render them more susceptible to future climatic variations such as increased temperatures and reduced water availability. The widespread degradation of these ecosystems due to land use activities is widely recognised. However, detailed spatially explicit information on these activities is currently lacking. This has wide-reaching implications, not only for the ecosystems themselves but also for the key stakeholder groups in Ireland, such as the NPWS, involved in the conservation of peatlands and dealing with conflicts related to domestic peat cutting in protected areas. Similarly, BnM is undertaking peatland conservation efforts following the cessation of drainage and extraction on its landholdings, while the EPA reports GHG emissions to the UNFCCC from various sectors, including land use.

However, the lack of accurate and robust areal figures on land use activities leads to ambiguity in the current state and reporting of C and GHG emissions from these ecosystems, as well as hinders effective planning for conservation activities (restoring, rewetting, and rehabilitating). At a global, regional, and national scale, land cover/use maps inadequately represent land use in peatlands. This underscores the necessity for the development of methodologies, including peatland use-specific classification taxonomies and remote sensing-based methods, to effectively identify and map various land use activities on peatlands. However, mapping peatlands through optical remote sensing sensors, which rely on sunlight to gather information about the Earth's surface, faces significant challenges due to persistent cloudy conditions in which peatland

habitats are usually located. The limitations imposed by atmospheric conditions hinder comprehensive coverage and detailed information retrieval regarding land use activities on peatlands. Recognising these challenges, this study is the first to establish a country-specific land use classification taxonomy for peatlands and subsequently develop methodologies and technique-based ML and DL approaches for mapping these land use activities through remote sensing.

5.1.2 Peatland land use dynamics

Initially, the study focused solely on raised bogs because of the complexity of mapping land use at a national scale (all peatlands). However, the developed methodologies proved effective not only for raised bogs but also for blanket bogs when using the LUCIP level 2 approach, resulting in accurate national-scale mapping of peatland use using Landsat data. The use of DIPMv2 within the GEE platform, along with ML, temporal mosaicking, and Landsat data, has proven effective in the classification and mapping of peatlands. This study provides a thorough assessment of land use and changes within Ireland's peatlands over a 30-year period. It offers a detailed understanding of how these areas have evolved and identifies significant land use changes. The findings reveal persistent land use shifts in 30% of the peatlands area, whereas for the rest of the areas, the land use remained constant. There has been a shift in industrial peat extraction areas (BNM-based), which are transitioning to alternative uses post-extraction with the rise in forestry and agricultural grasslands. There has been a consistent increase in forestry over the past three decades along with peatland restoration projects and national afforestation schemes. Grassland, on the other hand, accounts for half of the land use in peatlands. It is on an overall decline; however, it has particularly fluctuated over time, showcasing decreases and subsequent increases possibly influenced by agricultural incentives and shifts in land use policies. While the study produced a useful spatial understanding of the major land use activities and proved instrumental for long-term mapping, it remained limited in detailed classification due to the low spatial resolution of Landsat imagery (30m). For example, the residual peatland category covers a range of small-scale land use types, making it challenging to discriminate using Landsat imagery.

5.1.3 Quantification of land use and CO₂ emissions in raised bogs

The study then explored higher resolution Sentinel-2 datasets for land use mapping at level-3 (seven classes: cutaway, cutover, remnant peatlands, grassland, forestry, waterbodies and built-up). However, this was focused only on raised bogs because the inclusion of blanket bogs for such detailed mapping would have been a time-intensive task and was out of the scope of this study. Nonetheless, the methods developed for Landsat-based mapping (ML, temporal mosaicking, and GEE) also proved useful for Sentinel-2 mapping. Furthermore, the detailed seven-class land use mapping formed bases for estimating CO₂ emissions from four main land uses (cutaway, cutover, forestry, and grassland). The study was also the first to reveal robust areal-based estimates of these land uses, and it was used for accurate emission calculations, revealing raised bogs to be net emitters. The study also revealed discrepancies between reported peat extraction areas in the Irish National Inventory Report (NIR) and the actual extent of land use detected in the study, emphasising the prevalence of peat extraction activities. Furthermore, grassland is the dominant land use, accounting for almost half of the total land use on raised bogs. Industrial peat extraction areas are more prevalent in the midlands, where most BnM landholdings exist. However, this study for the first time quantifies non-BnM industrial and domestic peat extractions. The study not only refined areal figures but also robust methods that can track changes in these rapidly evolving landscapes.

5.1.4 Artificial drainage ditches in raised bogs

The study was further extended to map artificial drainage ditches on raised bogs using very high-resolution imagery (0.25 m) combined with advanced deep-learning methods. Pixel-based DL applied to semantic segmentation techniques has proven to be more suitable than the ML or OBIA techniques used with Sentinel-2 and Landsat data. Building on prior research with DL models, a single model was developed that accounted for diverse drainage patterns and sizes, which had not been previously

considered. This represents an important advancement in DL modelling approaches for remote sensing of peatlands, offering a more comprehensive and adaptable method for mapping drainage in Irish-raised bogs. The results confirm the significant drainage status of the Irish peatland ecosystems, with a particular focus on peat extraction (domestic/industrial) and high bogs. This study identified distinct patterns and conditions within different land use categories. Geospatial analysis of the output drainage data revealed high drainage density areas and the proportion of drainage across different land use categories. The research findings are also useful for refining GHG emissions from artificial drainage, challenging the current default values used for reporting in the National Inventory Report. The findings not only highlight the prevalence and impact of artificial drainage on Irish raised but also present a new, accurate, and automated methodology for mapping these features. This has significant implications for emission estimation, conservation, and policymaking, suggesting broader applications on a global scale for peatlands.

5.2 General conclusion, limitations, and recommendations

Overall, the much-needed baseline dataset produced in this study will prove vital at a national level to (i) support policy-related decision-making for the sustainable management of these vital ecosystems and (ii) accurately account for emissions based on robust spatially explicit data. Furthermore, the methods developed here could potentially be applied globally to map land use in peatlands and fill the knowledge gap related to spatially explicit information on these rare and vital ecosystems. The utilisation of freely available Landsat and Sentinel-2 imagery in a planetary scale cloud computing platform (GEE) provides a readily accessible and efficient method for monitoring and mapping land use activities on peatlands at a national level, proving to be both time- and cost-effective. Significant changes observed between 2005 and 2020 using Landsat, particularly in areas involved in industrial peat extraction, are expected to persist. Landsat data remains pertinent for monitoring and mapping these ongoing changes. The higher resolution Sentinel-2 data along with the methods developed in this study will be useful for monitoring ongoing conservation activities from industrial peat extraction activities such as PCAS. 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, 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, the susceptibility of these fragile ecosystems to natural disasters such as fire and land(peat)slides due to degradation induced by human or natural pressure.

5.2.1 Limitations

- The peatland extent map used in this study (i.e., DIPMv2) is the most recent updated map of peatlands in Ireland. The overall accuracy of the map was 88%, and it underestimated areas smaller than 7 ha. This study could be updated if a more comprehensive and finer-scale map of the peatland extent for Ireland becomes available.
- The use of medium-resolution Landsat imagery meant that some land use classes, such as small-scale domestic peat extraction and remnant peatlands (high bogs), could not be mapped.
- An accuracy assessment of TP-1 with Landsat imagery was not conducted because of the unavailability of high-resolution imagery.
- To mitigate these limitations mentioned in the previous point, high-resolution Sentinel-2 data were used. However, further segregation of forestry into distinct types was not performed at this level because of the unavailability of training data for classes.
- Emissions were calculated for only four land use classes (cutaway, cutover, forest, and grassland) because of the unavailability of EF for other classes.
- Due to the use of optical aerial imagery, only the drains that were “visible” in the imagery could be detected. Hence, the drains in the bare peat areas were mapped.
- The $Frac_{ditch}$ was only calculated for BnM-based industrial peat extraction areas, since these drains are mostly present in the bare peat areas.

- 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 achieved in this study because of time constraints and the complexity of the large and heterogeneous landscape that is covered by blanket bogs.

5.2.2 Recommendations and future work

Future work could focus on addressing the identified limitations to enhance the accuracy and comprehensiveness of peatland land use and artificial drainage mapping. The following are some specific recommendations.

- Incorporate a more comprehensive and finer-scale map of peatland extent for Ireland, if made available, which accurately represents smaller areas under seven hectares.
- Further segregation of forest and grassland classes, both with Landsat and Sentinel-2 data, possibly with the availability of training data through the recently released National Land Cover Map of Ireland.
- Use of higher resolution satellite (e.g., PlanetScope) imagery for habitat mapping of remnant peatland (high bog) areas as well as level-4 and 5 of LUCIP.
- The use of DL methods combined with aerial imagery for higher-level mapping of cutaway and cutover methods, for example, extraction methods (LUCIP level 5).
- ML and DL methods for mapping the natural degradation of peatlands, such as peat erosion on blanket bogs.
- In terms of emission mapping, the study focused only on four classes, as mentioned before; currently, these classes cover the majority of peatland use. However, this will change as conservation activities come into play, and the classification schema proposed by Aitova et al. (2023) could be incorporated with LUCIP to have a more comprehensive classification taxonomy that can be used to estimate emissions from rewetted and nutrient-poor/rich sites.

- The DL-based mapping of artificial drainage if incorporated with active remote sensing (e.g., LiDAR) data, could be used to map the “hidden drains” i.e., obscured by infill or vegetation.
- As the emission factors are updated for other land use on peatlands, especially for artificial drainage, it could be used for accurate national-scale estimation of emissions from the drains as well as land use.
- The generalising capability of the ML and DL methods used here means that these models could be used to map land use and drainage on blanket bogs in Ireland and expand further in peatlands regionally (Europe) and globally.

5.3 More recommendations (beyond peatland land use)

Previously, Ireland did not have a comprehensive, high-resolution land cover/use map on a national scale. However, this has been rectified by a recent release (2023) of the NLC map. However, the development of NLC relies on semi-automated (OBIA) methods and very high-resolution aerial imagery, which are time-, computation-, and resource-intensive. The methodologies employed in this study not only set a precedent for accurate wall-to-wall land use mapping in cloud-obscured Irish conditions, specifically for peatlands but also hold the potential for broader application beyond these ecosystems.

The successful implementation of the methodologies in this study sets the basis for a more extensive application of similar techniques. For example, the recent Phase 1 announcement of the Land Use Review by the Government of Ireland aims to “provides an evidence base to determine the environmental, ecological and economic characteristics of land types across Ireland”. The expansion of the methods used here could offer repeatable, comprehensive, high-resolution, and detailed national-scale land use maps that support land use reviews and various ecological, environmental, and economic studies. The execution of these recommendations could establish a foundation for a more comprehensive and accurate understanding of Ireland’s land use, aiding informed policymaking, environmental governance, and the sustainable management of diverse ecosystems beyond peatlands.

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Appendix

All supplementary analyses and results which could not be included in the main body of the thesis are presented in this section.

Appendix A: Spatial Analysis for procuring aerial imagery

Due to the limitations of DIPMv2, and to have the most accurate coverage of raised bogs. Rigorous spatial analysis was performed for the order of each tranche. The methodology for the spatial analysis is detailed here using a series of flow charts. The data were procured in two tranches for raised bogs, which provided coverage for raised bogs across Ireland as per the DIPMv2.

Analysis for Tranche-1:

The first order was made for SmartBog project sites across the Midlands. The point data of the Smartbog sites were first used to intersect the DIPMv2. This provided an area of interest (AOI) boundary which was overlaid with the image vendor's coverage area (national scale coverage was not available at that time). A series of buffer distances were created, including 50m, 100m, 150m and 200m along the area of interest, with visual interpretation, and the AOI with the best possible coverage was chosen i.e., 200 m. The final order was determined for an area of 700 km².

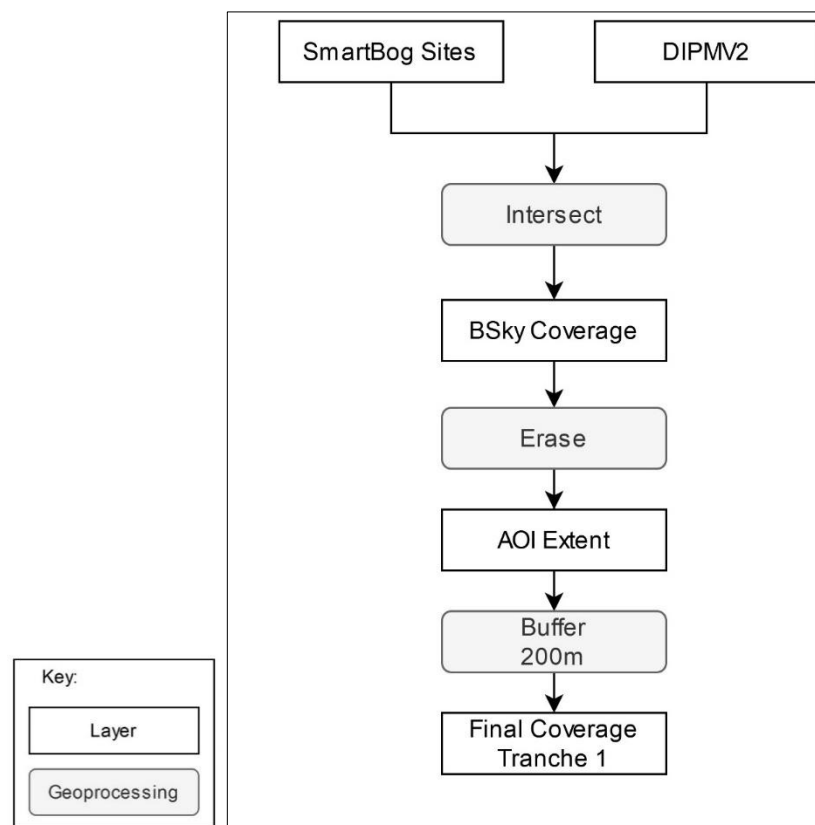


Figure 6.1: Workflow of analysis for Tranche-1

Analysis for Tranche-2:

A similar analysis was performed for the procurement of the second tranche. This order covered the rest of the raised bog area. The order was made for a much larger area, that is, $\sim 5593.36 \text{ km}^2$, keeping the budget limitation in mind. An AOI with a buffer distance of 50m was chosen.

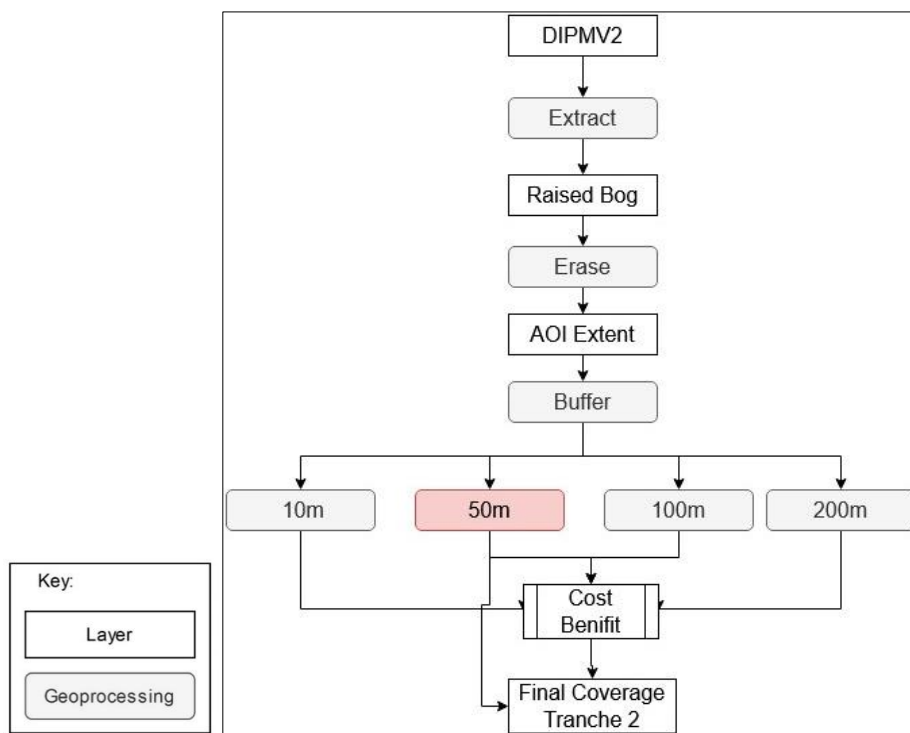


Figure 6.2: Workflow of analysis for Tranche-2

Appendix B: Variable Importance and Error Matrix

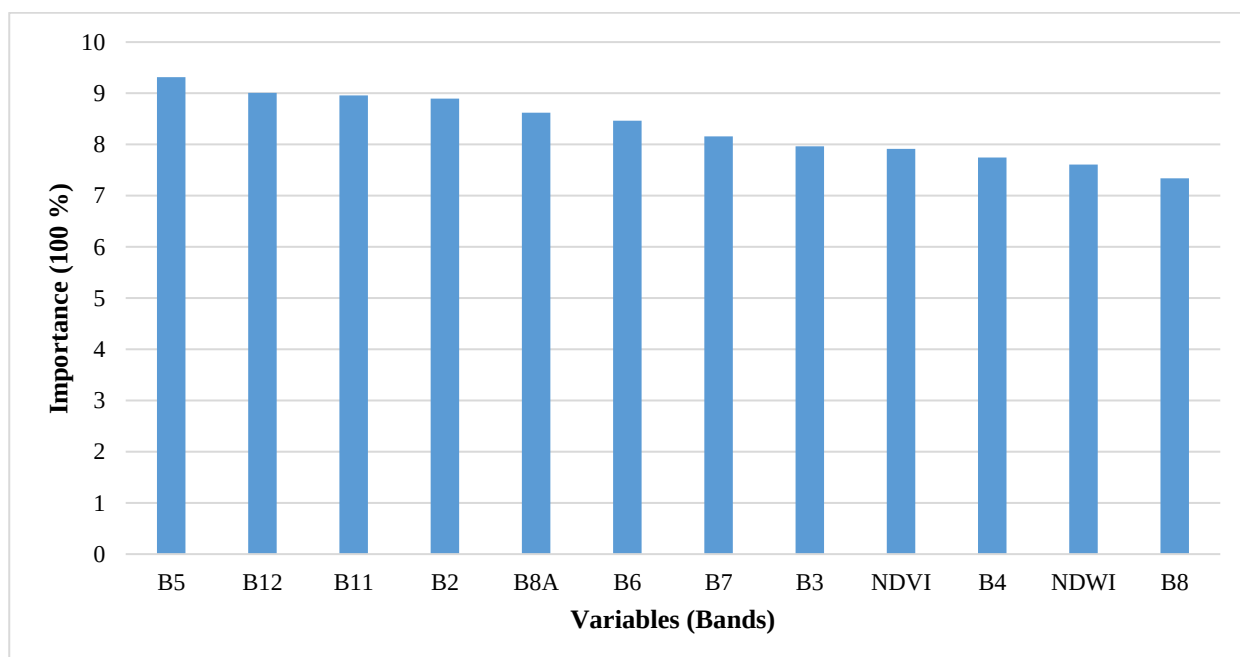


Figure 6.3: Variable importance in the Random Forest model trained with variables from 10 spectral reflectance bands, NDVI and NDWI

Table 6.1: Unbiased area estimates in hectares (ha), the table also presents standard error and 95% Confidence Interval values for each class

Area-based Error Matrix							
Classified	Cutaway	Cutover	Water	Forest	Grassland	Rem. Peat	Built up
Cutaway	0.0989	0.0072	0.0006	0.0048	0.0012	0.0060	0.0000
Cutover	0.0000	0.0553	0.0000	0.0024	0.0091	0.0115	0.0006
Water	0.0003	0.0000	0.0096	0.0022	0.0005	0.0000	0.0011
Forest	0.0008	0.0016	0.0000	0.1973	0.0032	0.0008	0.0000
Grassland	0.0014	0.0007	0.0007	0.0084	0.4351	0.0042	0.0098
Remnant Peatland	0.0009	0.0019	0.0000	0.0019	0.00	0.1050	0.0000
built-up	0.0000	0.0000	0.0000	0.0006	0.0026	0.0000	0.0068
Total Estimated Area Proportions	0.102	0.067	0.011	0.218	0.456	0.128	0.018
Class Area Estimates (ha)	54301.80	35385.73	5786.48	115458.44	242159.53	67674.29	9705.63
Standard Error of Area Estimates	0.00356	0.00422	0.00129	0.00418	0.00545	0.00308	0.00617
Standard Error of Area Estimates (ha)	1886.37	2240.05	682.93	2217.80	2889.98	1635.13	3274.76
95% Confidence Interval (ha)	3697.28	4390.51	1338.55	4346.89	5664.36	3204.86	6418.53

